Argumentative Learning with Intelligent Agents

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Abstract

Argumentation plays an important role in information sharing, deep learning and knowledge construction. However, because of the high dependency on qualified arguing peers, argumentative learning has only had limited applications in school contexts to date. Intelligent agents have been proposed as virtual peers in recent research and they exhibit many benefits for learning. Argumentation support systems have also been developed to support learning through human-human argumentation. Unfortunately these systems cannot conduct automated argumentations with human learners due to the difficulties in modeling human cognition.

A gap exists between the needs of virtual arguing peers and the lack of computing systems that are able to conduct human−computer argumentation. This research aimed to fill the gap by designing computing models for automated argumentation, develop a learning system with virtual peers that can argue automatically and study argumentative learning with virtual peers.

This research designed and developed four computing models for argumentation, which can be applied in building intelligent agents to conduct argumentation dialogues on learning topics. The research is ground breaking in the aspect of enabling computers to conduct argumentation dialogues automatically.

The computing models developed enabled studies on argumentative learning with virtual peers. In this research, a learning system was developed with an intelligent agent (modeled as a virtual peer) to argue with learners on science topics. Then, a study was conducted with secondary school students to investigate the argumentative learning between human learners and intelligent agents.

In summary, this multidisciplinary research is significant: it enables automated argumentation of computers by designing four computing models for argumentation; it makes the desirable argumentative learning practical by developing learning

systems with intelligent agents to facilitate human-computer argumentative learning; and for the first time, it investigated argumentative learning with intelligent agents which contribute to knowledge on argumentative learning between human learners and virtual peers.

Declaration

I, Xuehong Tao, declare that the PhD thesis entitled "Argumentative Learning with Intelligent Agents" is no more than 100,000 words in length including quotes and exclusive of tables, figures, appendices, bibliography, references and footnotes. This thesis contains no material that has been submitted previously, in whole or in part, for the award of any other academic degree or diploma. Except where otherwise indicated, this thesis is my own work.

Signature:

Date: 20 March 2014

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Published Outputs from Thesis

[1] Tao, X., Yelland, N. & Shen, Z. (2014). Learning outcomes and experiences while learning with an argumentative agent. In *Proceedings of World Conference on Educational Multimedia, Hypermedia and Telecommunications 2014* (pp. 2312-2322). Chesapeake, VA: AACE.

[2] Tao, X., Yelland, N. & Shen, Z. (2014). Do learners argue with intelligent virtual characters seriously? In *Proceedings of World Conference on Educational Multimedia, Hypermedia and Telecommunications 2014* (pp. 2302-2311). Chesapeake, VA: AACE.

[3] Tao, X., Miao, Y. & Zhang, Y. (2012). Cooperative-competitive healthcare service negotiation. *International Journal of Software and Informatics*, *6*(4), 553~570.

[4] Tao, X., Yelland, N. & Zhang, Y. (2012). Fuzzy cognitive modeling for argumentative agent. In *Proceedings of the 2012 IEEE International Conference on Fuzzy Systems*. Piscataway, New Jersey: IEEE.

[5] Tao, X., Shen, Z., Miao, C., Theng, Y. L., Miao, Y. & Yu. H. (2010). Automated negotiation through a cooperative-competitive model. In T. Ito, M. Zhang, V. Robu, S. Fatima, T. Matsuo & H. Yamaki (Eds.), *Innovations in agent-based complex automated negotiations* (pp. 161-178). Springer-Verlag Berlin Heidelberg.

[6] Tao, X., Theng, Y. L., Yelland, N., Shen, Z. & Miao, C. (2009). Learning through argumentation with cognitive virtual companions. In G. Siemens & C. Fulford (Eds.), *Proceedings of World Conference on Educational Multimedia, Hypermedia and Telecommunications 2009* (pp. 3179-3194). Chesapeake, VA: AACE.

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[8] Tao, X., Yelland, N. & Miao, Y. (2008). Adaptive learning through interest based negotiation. In *Proceedings of the 16th International Conference on Computers in Education* (pp. 191-192). Asia-Pacific Society for Computers in Education.

[9] Tao, X. & Miao, Y. (2008). Interest based learning activity negotiation. In *Proceedings of the International Conference on Cyberworlds 2008* (pp. 58-64). Los Alamitos, CA: IEEE Computer Society.

Note: This is a multi-disciplinary research which involves the development of computing models for argumentation automation, and the conducting of educational studies to investigate human-computer argumentative learning. Articles [3], [4], [5] and [7] are related to argumentation computing models and their applications, and articles [1], [2], [6], [8] and [9] are related to educational studies.

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Part I. Introduction and Background

Part I introduces the background of the research, reviews the related literatures, states the research aims and highlights the significance of this research.

1. Introduction

Argumentation plays an important role in education. Argumentative learning is a promising learning strategy in information sharing, deep learning, and knowledge construction. However, in an argumentative learning process, learners require qualified learning peers to conduct argumentative dialogues regarding the learning content. A qualified arguing peer should have argumentation skills, relevant knowledge levels and sufficient available time to ensure the effectiveness of argumentative learning. Student peers may not have the proper argumentation skills and knowledge levels to provide the right scaffolding to each other, and teacher peers may not always be available due to factors such as high teacher - student ratios. Because of the high dependency on qualified arguing peers, argumentative learning has only had limited applications in school contexts.

A possible solution is to apply intelligent agents as virtual learning peers. In recent research development, intelligent agents have been proposed as virtual learning peers and exhibited many benefits for learning. Studies have been conducted on various aspects of using virtual peers in learning, such as those where agents' appearances can have a profound impact on learners' motivation and learning transfer (Baylor & Plant, 2005; Rosenberg-Kima et al. 2008; Baylor & Kim, 2009). Argumentation is a high level intelligence and requires profound modelling of human's cognition. Currently, there is no intelligent agent that is able to conduct argumentation dialogues with learners. Argumentation support systems have also been developed to support learning through human-human argumentation. However, these systems also cannot conduct automated argumentations with human learners.

A gap exists between the needs of virtual peers to facilitate argumentative learning and the lack of computing systems that are able to conduct human−computer argumentation. The research presented here aims to fill this gap by advancing computer technologies to meet the needs of education.

This is a multidisciplinary research project. It designed four computing models to automate human-computer argumentation. With the computing models designed, the research developed learning systems with virtual peers to conduct argumentative dialogues with learners. The virtual peer can be largely "cloned" to meet the needs in argumentative learning. Furthermore, this research conducted studies with students and for the first time investigated argumentative learning between human learners and virtual peers.

1.1 Argumentative Learning and the Needs for Virtual Arguing Peers

Learning is a social process. Intellectual growth is achieved when learners are involved in learning activities with others (Vygotsky, 1978). Learning is socially constructed during interaction and activity with others. Dialogue and communication during the learning processes are important. As Yelland (2011) noted, "it is also essential that learners be provided with opportunities to share their strategies and to communicate and disseminate their ideas. This is important for the creation of knowledge building communities, and because we can learn a great deal from each other about the varied processes and strategies used, in order to evaluate their effectiveness" (p.35).

Recently, a new form of "learning by arguing" strategy was proposed by Andriessen (2006). In this learning approach, argumentation is described as a form of collaborative discussion in which both parties are working together to resolve an issue, and in which both parties expect to find agreement by the end of the argumentation. Andriessen (2006) termed it as collaborative argumentation to emphasise that it is different from a debate. In collaborative argumentation, students do not have to take sides and persuade others. They are free to explore positions and find mutually accepted solutions. In this thesis, such learning is noted as argumentative learning, or "learning by collaborative argumentation".

Collaborative argumentation can help students to think critically. A collaborative argumentation may contain a mixture of arguments, explanations and a variety of other activities. Students may critique different points of view and use arguments and/or counterarguments to resolve their conflicting opinions; they may also elaborate misconceptions and generate associations among new ideas and prior knowledge. These interactions will bring in new view points, and broaden and deepen their existing understandings. Research studies showed that there are significant benefits of argumentative learning: it promotes scientific thinking (Duschl & Osborne, 2002; Driver, Newton & Osborne, 2000); it leads to deep understandings and knowledge co-construction (Newton, Driver & Osborne, 1999); it fosters conceptual change (Asterhan & Schwarz, 2007); and it supports problem solving (Oh & Jonassen, 2007).

Although collaborative argumentation is regarded as being very beneficial to learning, it has not been widely applied in schools. Osborne (2010) pointed out that the lack of opportunities to develop the ability to reason and argue scientifically would appear to be a significant weakness in contemporary educational practices. However, there are some barriers that prevent argumentative learning from being widely applied in schools. On one hand, some students view argumentation as constituting discord and disagreement, so they are not willing to engage in argumentation (Nussbaum, Sinatra & Poliquin, 2008). On the other hand, as Duschl and Osborne (2002) noted, the discursive nature of argumentation requires both time to undertake the process, and time for reflection and consideration of the outcomes. Therefore, it is important for argumentative learning to be guided by experienced teachers to ensure that it is on the right track and achieve productive outcomes. Schools also have limited resources to accommodate argumentative learning in the current context.

An alternative approach to enable argumentative learning is to develop intelligent agents as virtual learning peers. There are multiple benefits if such virtual peers can be developed. Firstly, it is possible to largely clone the virtual peers once they are created. Secondly, students do not have to worry about the face to face disagreement with their friends. Thirdly, virtual peers can facilitate argumentative learning with more flexible time schedules.

Using virtual peers to facilitate learning is not new. A number of computer simulated virtual characters have been developed and studied in education. For example, virtual peers have been applied to bring in different competencies to scaffold students (Kim

& Baylor, 2006b), as trouble makers to encourage students to solve conflicts (Aïmeur, Frasson & Dufort, 2000), and as learners to promote learning by teaching (Blair et al., 2007). Researchers have discovered profound impacts of virtual peers on learning. For instances, the influence may come from the virtual characters' appearances, such as gender (Baylor, Shen & Huang, 2003), facial expression (Baylor & Kim, 2009), emotion (Alepis & Virvou, 2011), and the manners in which virtual characters communicate with students (Wang et al, 2008). Although progresses have been made in developing virtual learning peers and applying them in various studies, no argumentative learning peer has been reported.

There have been a few computer systems developed to support argumentation, such as InterLoc (Ravenscroft, McAlister & Sagar, 2010) and Reason!Able (Van Gelder, 2002). Some researchers have also applied intelligent agents as assistants for argumentation (e.g. Monteserin, Schiaffino & Amandi, 2010). However, the existing systems are, in fact, argumentation support systems. They either provide communication platforms to support human-human argumentation, or provide feedback on human's arguments. Due to the difficulties in modeling human cognitive processes with computers, there is no computer-based learning systems that are able to conduct argumentation dialogues with learners, especially for school science topics.

A clear gap exists between the needs of artificial peers to facilitate argumentative learning and the fact that there is a lack of computing systems that are able to conduct human−computer argumentation. This thesis aims to fill the gap by designing computing models for automated argumentation, developing learning systems with virtual peers that can argue automatically, and studying argumentative learning with virtual peers.

Yelland (2007, p.1) has suggested that, "in the information age or knowledge era, we should not be mapping the use of new technologies onto old curricula; rather, we need to rethink our curricula and pedagogies in light of the impact that we know new technologies can have on learning and meaning making in contemporary times." This research is to advance technologies to create innovation in a promising new way of learning − argumentative learning with intelligent agents.

1.2 Research Aims and Research Questions

To enable argumentative learning, computing models need to be developed for virtual peers to conduct argumentation with human learners automatically. Following on, studies can then be conducted to gain understandings on argumentative learning powered by intelligent virtual peers. This multidisciplinary research has two broad aims:

- firstly, to design and develop computing models that enable computer automated argumentation with human learners; and

- secondly, to implement a learning system with an intelligent agent that is able to conduct collaborative argumentation with learners; and to investigate the learning outcomes, the learner - agent interaction and learning experiences in this context.

Particularly, the research will address the following two broad issues and consider the four research questions posed in B below.

A. Computing models for argumentation automation

Knowledge is the basis of arguments. People argue based on their knowledge. Human beings have different types of knowledge. Some knowledge is in the form of chained components; some knowledge is based on fuzzy concepts; and some knowledge is hierarchically structured. Therefore, different computing models are needed to automate the corresponding knowledge based argumentation. In this research, four types of major computing models have been developed for argumentation automation.

- *Computing model for chained knowledge.* In our everyday life, there is some knowledge that describes sequences of items. For example, the knowledge that describes *eating* and *be eaten* relationship of a food web. In this case, the argumentation is around the issue of deciding a proper sequence to specify the order of a set of given items. Knowledge model for chained knowledge and algorithms to automate the argumentation dialogues were developed in this study.

- *Computing model for hierarchical knowledge.* The *If…Then* alike rules are widely used in expert systems and our lives. They are commonly understood as logical entailments, e.g. *If* an animal is warm blooded, has fur, feeds young with milk, *Then* this animal is a mammal. In addition to logical entailments, this kind of rule can also be used to represent a wide range of relationships among components, such as part and whole, or detailed description and abstract concept, and so on. One such rule shows the relationship between one component and other components. A set of such rules will show a hierarchical relationship among components. This kind of knowledge is termed as *Hierarchical Knowledge* in this thesis. The corresponding knowledge model, reasoning algorithms and argumentation algorithms were developed to automate the argumentation for hierarchical knowledge.

- *Computing model for fuzzy and dynamic knowledge.* Classical knowledge models use crisp concepts. When a rule states that a zebra is a mammal, there is no ambiguity. However, the most common concepts human beings possess are fuzzy concepts. For example, eating more vegetables is good for your health. Here, *more* and *good* are all fuzzy descriptions. Fuzzy Cognitive Map (FCM) is a knowledge model to represent fuzzy and dynamic knowledge, which has wide application in decision making systems such as medical systems, ecosystems and management systems. Based on FCM, this research developed the first FCM based argumentation model.

- *Computing model for collaborative optimisation.* When a group of people encounter a problem, they usually propose individual opinions, critique and evaluate each other's opinion, and collaboratively construct solutions by considering the shared knowledge of the group. In this case, people are often able to explore a wide range of possibilities, compare the advantages and disadvantages of different approaches, and choose an optimal solution based on the collective knowledge of the group. A computing model was developed in this thesis to automate argumentation dialogues for optimal solutions.

B. Educational studies on argumentative learning with virtual peers

By applying the argumentation computing models, a learning system was developed with an intelligent agent that was able to conduct automated argumentation. An intelligent agent that can conduct automatic argumentation is termed as *argumentative agent* in this thesis. The argumentative agent was modeled as a virtual learning peer in the developed learning system. Virtual learning peers have many advantages. They can be largely cloned at low cost; they can be specially designed to implement particular pedagogies; they can carry various domain knowledge thus can be applied in different learning subjects. However, virtual peers are different from human peers. Do students argue with the virtual peers seriously? Are the virtual peers beneficial to students' learning? Studies were carried out to investigate the argumentative learning with intelligent agents.

Particularly, this study focused on the following research questions:

- *Is learning with argumentative agents effective in improving learners' knowledge?* A main concern of the learning system was whether it could improve the learners' knowledge. This study was carried out to evaluate the learning gains while learning with the argumentative agent.

- *Are learners interested in arguing with the argumentative agent and do they argue with the agent seriously?* The argumentative agent was modeled as a virtual peer in the developed learning system. A virtual peer is different from a human peer. If the students didn't argue with the virtual peer seriously, there wouldn't be meaningful argumentative learning. Therefore, the learner – agent interaction was investigated.

- *What are the learners' learning experiences?* Because of lacking virtual peers that can conduct argumentation with students, there has been no study on learners' experiences while arguing with intelligent agents. For the first time, this research studied the qualitatively different ways of learning experiences while arguing with virtual learning peers. The learners' experiences provide feedback on argumentative learning from the learners' perspectives rather than the researcher's interpretation.

- *Do different activities have different impacts on learning?* The purpose of introducing the argumentative learning system was to improve the learners' learning. Therefore, the argumentative activities were expected to be positively related to the learners' achievement. Whether or not argumentative activities were main contributors to students' academic achievements was also examined in this study.

1.3 Research Methods

This is a multidisciplinary research. This thesis reports two major parts of research: one part was to develop computing models for automated argumentation so that argumentative virtual peers become possible; another part was to implement argumentative learning systems in a school context and study the effectiveness and learning experiences of argumentative learning with virtual peers. The research methods also include two parts as described below.

A. Research methods in argumentation computing modeling

This thesis adopts the theoretical method in computer science research (Dodig-Crnkovic, 2002) which adheres to the traditions of logic and mathematics, and seeks to find solutions or better solutions to complex problems through algorithms design and analysis. The key phases of argumentation computing model development are:

- *Identify the key requirements and components*,
- *Design the argumentative agent architecture*,
- *Design argumentation dialogue types and dialogue protocols*, and
- *Develop knowledge models and argumentation automation algorithms*.

Altogether, four computing models were developed in this research to represent four types of widely used knowledge, and to automate the argumentation processes. The development of each of the computing model had experienced multiple rounds of iterations on requirements identification, architecture design, dialogue design and algorithms development. The models or algorithms of each phase were revised and improved until a final mature model was established.

B. Research methods in educational studies

As this research aims to improve learning through the design and development of argumentative learning systems, design based research was employed as the overall methodology to guide the educational research process. The design based research methodology intends to bring together design and research in order to create a better improvement and understanding of the argumentative learning with virtual peers (modelled by intelligent agents).

The design based research involved two iterative cycles of design, development and evaluation. A pilot learning system was developed by applying an argumentation computing model. There was an argumentative intelligent agent in the learning system which was modeled as a virtual learning peer. The virtual peer was able to conduct argumentation with learners automatically. The software system development followed the iterative waterfall software engineering model (Sommerville, 2011) with each iteration including a number of phases: requirements analysis, system design, implementation, testing, and operation and maintenance/improvement. After the pilot system was implemented, a pilot study was conducted with 5 children. Both video recording and interviews were collected. The children's activities and perceptions to the learning system were investigated.

The findings from the first study informed the development of a second learning system. A further study was conducted on the second learning system with 33 secondary school students. Data were collected from multiple sources and the analysis was focused on learning outcomes, learner-agent interaction, learning activities and learning experiences. A Phenomenographic approach (Marton, 1981, 2001) was incorporated to analyse students' learning experiences.

Argumentative learning is a new way of learning. There is no report regarding the study of argumentative learning with intelligent agents in school based contexts. This research generated new understandings about human-agent argumentative learning and suggests guidelines for future argumentative learning systems design and development.

1.4 Significance of the Research

This research is significant in both computing models for argumentation automation and understandings about human-agent argumentative learning in education.

Firstly, the computing models developed will enable a wide range of applications. Argumentation is one of the most common human interactions. It is widely applied in knowledge building, decision making, business negotiation, conflict resolution and so on. However, computing models for human oriented argumentation automation remained unavailable. This research developed computing models for four typical human knowledge types, namely chained knowledge, hierarchical knowledge, fuzzy dynamic knowledge and knowledge for optimal solutions. The computing models provided mechanisms for computers to conduct argumentation dialogues automatically. This work will enable a wide range of applications in various areas, such as education, business and legal services.

Secondly, this research will make significant impacts on education by enabling a practical approach for widely adopting argumentative learning. It is known that argumentation plays an important role in information sharing, deep learning and knowledge construction. However, argumentative learning requires learning peers, who have the domain knowledge, skills to interact with students to promote learning and time to be with learners. Student peers may not have the proper knowledge level and argumentation skills. Teacher peers may not always be available considering many classrooms have the current student teacher ratio of 20:1 or more. Therefore, without intelligent virtual peers, argumentative learning is not practical. With the argumentative virtual peers, argumentative learning can be applied whenever needed.

Third, this research is a pioneer work on argumentative learning with intelligent agents. This research for the first time has studied students' learning with an argumentative agent. It will contribute to knowledge on the understandings of argumentative learning with virtual peers, and the design and development of future argumentative learning systems.

In summary, this multidisciplinary research is significant: it enables automated argumentation of computers by designing four computing models for argumentation; it makes the desirable argumentative learning practical by developing learning systems with intelligent agents to facilitate human-computer argumentation; and for the first time, it investigates argumentative learning with intelligent agents which contributes to knowledge on argumentative learning between human learners and virtual peers.

1.5 Organisation of the Thesis

This is a multi-disciplinary research project. To achieve the goal of using computer based virtual peers to support argumentative learning, this study involves research from the computer science area within the education context. Part I of the thesis introduces the background and related literature this research is situated; Part II presents the computing research on argumentation model design and development; Part III presents the educational studies on argumentative learning between human learners and computer based argumentative virtual peers; and Part IV concludes the thesis. Details are as follows:

Part I introduces the background of the study and reviews the related literature this study is situated.

Chapter 1 introduces the motivation, aims and research questions, as well as presents the significance of this research.

Chapter 2 reviews the theoretical foundation and benefits of argumentative learning. It summarises the current issues of applying argumentation in schools which are the situations this research attempts to improve.

Chapter 3 reviews the contemporary research on pedagogical agents. Pedagogical agents are animated virtual characters which help learners in computer based learning environments. The review covers the properties of pedagogical agents and the impact of different properties on learning. Pedagogical agents are potential technologies that can facilitate argumentative learning in schools.

Chapter 4 reviews the existing computer supported argumentation systems in the literature. These systems can only support human-human argumentation, or provide feedbacks to human's arguments. They lack the capability to support human-computer argumentation. To design and develop mechanisms for human-computer argumentation is a goal of this research.

Part II presents the design and development of argumentation computing models.

Chapter 5 introduces the fundamental concepts used in the computer science area regarding argumentation modeling, and the collaborative argumentation strategy used in this study. It presents the conceptual design of an argumentative agent.

Chapter 6 presents an argumentation computing model for chained knowledge, including the knowledge model and argumentation dialogue automation algorithms.

Chapter 7 presents an argumentation computing model for hierarchical knowledge, including the knowledge model, argumentation dialogue automation algorithms and illustrative examples.

Chapter 8 presents an argumentation computing model for fuzzy dynamic knowledge, including the knowledge model, argumentation dialogue automation algorithms and illustrative examples.

Chapter 9 presents an argumentation computing model for applications seeking optimal solutions, including the collaborative optimal seeking argumentation approach, knowledge model, argumentation dialogue automation algorithms and an illustrative example.

Part III presents the educational study by applying the designed and developed argumentative virtual peer in education contexts.

Chapter 10 presents the research methodology. Design based research is adopted and it guides the whole education study. The study included two iterative cycles of design, development and evaluation: a pilot study and a further study. Mixed methods research is applied to collect and analyse both quantitative and qualitative data. Data was collected from multiple sources including pre-testing, post-testing, questionnaires, screen recordings and interviews. The data was analysed with quantitative methods using statistics and a qualitative method including phenomenography.

Chapter 11 reports the pilot study. The pilot study confirms the potential for effective learning with argumentative virtual peers. The study also revealed valuable points of argumentative learning with intelligent agents that helped further design and develop the learning system and the study that followed.

Chapter 12 presents the improved argumentative learning system and the design of the educational study, including the study procedures, data collection and analysis methods and measurements.

Chapter 13 reports the analysis of results. The results cover learning gains, learner-virtual peer interaction, learning activities and learning experiences. The results show that learners were engaged in serious discussion with the virtual peer, and argumentative learning was effective in improving learners' knowledge. The results also reveal multi-dimensional learning experiences of the students who participated in this study.

Chapter 14 discusses the findings of this research, answers the research questions, and compares the results with related research.

Part IV concludes the thesis.

Chapter 15 highlights the main contributions and suggests future research.

2. Argumentative Learning

Argumentative learning can be traced back to 1978 when Vygotsky (1978) studied the important role of social interaction for intellectual growth. Since then, argumentative learning has been studied by researchers. Many benefits of argumentative learning have been identified. It has broadened human understanding of learning from knowledge transfer between teachers and students to knowledge construction through social activities. This chapter reviews the theoretical foundation, benefits and current issues of argumentative learning.

2.1 Learning through Argumentation

Peer learning has been a central theme in the learning sciences for a long time. Peer interactions have been shown to influence learning in the classroom and have been reported as beneficial to the learners (Howe et al, 1995; Thurston et al, 2007).

De Lisi and Golbeck (1999) highlighted four reasons for the prominence of peer learning: One reason is that a shift away from traditional learning approaches that focus on knowledge transmission from teachers to students, to the constructivist approaches that emphasize discovery learning and view knowledge acquisition as a social activity. Peer learning has become an important means of implementing constructivist educational approaches. A second reason is related to the fact that one of the fundamental goals that schools have is to prepare students for life after school in the workplace and in communities. Working cooperatively with peers is regarded as a very important skill in contemporary workplaces. A third reason is that schools have introduced many technologies into classrooms in recent years, especially computer technologies. Peer learning is necessary for sharing of technological resources. Finally, the Internet provides opportunities for students to access ideas of others and share ideas easily. That is, the Internet has removed some key restrictions of peer learning such as peer learning does not have to happen in class time nor require the peers to be physically present.

Argumentation is one of the most common interactions in peer learning. Andriessen (2006) proposes a new “learning by arguing” paradigm. Here argumentation refers to the dialogues that learners engage in when solving problems. In an argumentation process, learners can collaboratively explore and evaluate different perspectives. The goal is to reach an agreement on the problem solution. It is unlike a debate where people retain their own positions and attempt to persuade others, and to win the debate is the ultimate goal. Educators often use the term ‘collaborative argumentation’ to differentiate it with debating. Nussbaum (2008) defines collaborative argumentation as a social process in which individuals work together to construct and critique arguments. He explained that collaborative argumentation is unlike a debate, students do not have to take sides and persuade others, but are free to explore positions flexibly and to make concessions. Andriessen (2006) has a similar view and noted that when students collaborate in argumentation, they work together to critically explore and resolve issues which they all expect to reach agreement on. Ultimately, they are arguing to learn.

2.2 Theoretical Foundation

Argumentative learning involves two or more students collaboratively contributing ideas to solve issues. In the process of learning, students are usually surrounded by conflicting perspectives and arguments. They are encouraged to work together to evaluate these perspectives and reach a commonly agreed solution. Piaget's cognitive constructivism (1985) and Vygotsky's social constructivism (1978) are two of the most relevant theoretical foundations for argumentative learning.

2.2.1 Piaget’s Cognitive Constructivism

Jean Piaget was a Swiss psychologist who was one of the first to make a systematic study of the processes inherent to the acquisition of conceptual understandings in children. Piaget asserted that children develop their understanding through the processes of assimilation and accommodation, associated with the construction of internal schemas (Pritchard & Woollard, 2010). This was termed cognitive constructivism.

Piaget used assimilation and accommodation to describe the processes when new information is encountered. Piaget (1952) borrowed the term *assimilation* and *accommodation* from physiology. In terms of cognitive processes, Piaget used assimilation to refer to the collecting and classifying of new information. When new information is encountered, if it does not contradict with the existing schema, it is assimilated to the existing schema. Accommodation is the alteration of schemas in order for allowing new and contradictory information (Pritchard & Woollard, 2010).

Schema is an important concept in Piaget's theory. Schemas refer to the set of rules that human beings use to interpret their everyday surroundings. They are stored in long term memory. A schema is a representational model of all of the knowledge that an individual has on a topic. Schemas are organised around themes or topics; the elements of a schema are linked by a common theme. Human schemas are very large and constantly evolving. There are many links both within and among human schemas. (Pritchard & Woollard, 2010)

Piaget (1985) developed his cognitive development theory into what is often called an equilibration model. When children do not change very much, they assimilate more than they accommodate. Piaget referred to this steady period as a state of cognitive equilibrium. During periods of rapid cognitive change, children are in a state of disequilibrium, where they accommodate more than they assimilate. They have to frequently modify their current schemes due to the large amount of new information. Piaget referred to this back-and-forth movement from equilibrium to disequilibrium as equilibration (Bornstein & Lamb, 1999, p. 278). According to Piaget (1985), equilibration refers to the mental activity of changing and developing while regulating itself to maintain coherence. Cognitive development takes place by the subject's advancing from one stage of equilibrium to another. Equilibrium is thus never achieved except in temporary stages. The cycle of equilibrium - disequilibrium - new equilibrium thus goes on. Equilibration then reflects a process that involves the creation, or construction of new forms that lead to a better, improved state of equilibration (Kamii, 1986).

Piagetian theory implies the benefits of peer learning and provides a strong foundation for the use of peer learning in classrooms. Peer interactions provide rich and necessary contexts for students, reflecting on peer reactions and perspectives serves as a basis for a student to revise his or her schema. Such revisions would in turn, lead students to make new meanings (De Lisi & Golbeck, 1999). Specifically, peer interaction creates critical cognitive conflict. If learners are aware of a contradiction in their shared knowledge base, the experience creates disequilibrium. This disequilibrium motivates the learners to question their beliefs and to try out new ones. This leads to the existing cognitive structure being displaced and a new structure taking its place, hence leads learners towards internal cognitive development.

Argumentation constitutes a major source of cognitive conflict, and cognitive conflict is regarded as an important stimulus for learning (Veerman, 2000). Argumentation provides a context full of cognitive conflicts, and the cognitive conflicts stimulate learners' cognition advances from one equilibrium to another. Hence, Piaget's cognitive conflict theory provides a theoretical foundation for argumentative learning.

2.2.2 Vygotsky's Social Constructivism

Lev Vygotsky was a Russian psychologist. His theory of social development and particularly his work on learning in social contexts has become central to current thinking and practice in education. Vygotsky (1978) considered that social interaction as a fundamental aspect of successful cognitive and intellectual growth. He thought that cognitive and intellectual development is achieved when learners are involved in learning activities in which they interact with others. Learning is socially constructed during interaction and activity with others. His theory is usually labeled as social constructivism.

The major aspect of Vygotsky's theory is that social interaction, language and discourse play a fundamental role in the development of cognition. He stated that "every function in the child's cultural development appears twice: first, on the social level, and later, on the individual level; first, between people (inter-psychological), and then inside the child (intra-psychological). This applies equally to voluntary attention, to logical memory, and to the formation of concepts. All the higher functions originate as actual relations between human individuals." (Vygotsky 1978, p. 57). Vygotsky believed that all cognitive functions originate in social interactions, and human cognitive structures are essentially socially constructed. Different from the traditional belief that knowledge is transmitted from teachers to students, Vygotsky's theory advocates that knowledge is constructed during the interactions between students and teachers. Individuals learn by interacting, communicating, collaborating and negotiating meaning with each other in a social context. According to Vygotsky, learning environments should be designed to promote students' interactions (such as group discussion, argumentation, collaborative problem solving) so as to foster knowledge construction.

Another important aspect of Vygotsky's work is the idea that the potential for cognitive development depends on the zone of proximal development (ZPD). The concept of ZPD is at the center of learning and developmental processes. He believes that people learn and construct knowledge within the ZPD, which is "the distance between the actual developmental level as determined by independent problem solving and the level of potential development as determined through problem solving under adult guidance or in collaboration with more capable peers." (Vygotsky 1978, p.86).

The ZPD is a notional area of understanding, or cognitive development, that is close to, but just beyond a learner's current level of understanding. If learners are to make progress they must be helped to move into this zone and then beyond it to a new and higher level. In this new level there will be a new ZPD. Successful and timely movement across this notional zone is dependent upon social interaction. Learners can be assisted in the progress made across their ZPD in a given situation by a more knowledgeable other who can provide support that will make progress possible (Pritchard & Woollard, 2010). This assistance is known as scaffolding.

Dialogues within the ZPD are essential to cognitive growth. Vygotsky distinguished two interrelated groups of concepts that called scientific concepts and spontaneous concepts. Spontaneous concepts arise from everyday experience and they are rich in contextual associations but unsystematic. They follow a common sense logic and are expressed via informal language. Scientific concepts originate during highly structured activities within the culturally coordinated practices of a school. The ZPD represents the place where the child's empirical spontaneous concepts meet with the systematic and logic of adult reasoning. Through dialogue and tasks within the ZPD, the flaws of the child's spontaneous concepts and reasoning are made explicit and compensated by the strengths of the adult's scientific conceptions and reasoning. Then the child becomes socialised with scientific conceptualisations. Thus, by using dialogues and tasks, the teacher (or more capable peer) develops the child's spontaneous concepts into scientific conceptions (Ravenscroft, 2001).

Vygotsky's theory about social interaction and the ZPD laid the foundation for argumentative learning. Argumentation among peers provides a social learning environment for learners to carry out learning discourse. The dialogues or argumentation can generate hints, verify ideas or generate new ideas and help the learner reach the potential.

2.3 Benefits of Argumentative Learning

Argumentation is a popular subject of investigations in education. The interests can be found in many fields of expertise, such as argumentation theory itself, discourse analysis and psychology (Asterhan & Schwarz, 2007). Researchers and educators have studied argumentation practice in various subjects, including science (Driver, Newton & Osborne, 2000) and mathematics (Krummheuer 2007). Significant benefits of argumentative learning have been discovered.

2.3.1 Argumentation Promotes Scientific Thinking

Scientific knowledge is socially constructed and validated (Driver et al. 1994). Scientific knowledge does not directly exist in the natural world, it is constructed and developed by scientists to interpret and explain the nature world. Once such constructs have been validated and agreed on, they become part of the "take-for-granted" way of seeing things within that community (Driver et al. 1994).

In this social construction and validation process, argumentation is a core activity of the scientific community. When scientists invent concepts or models to interpret the world, these new scientific conjectures do not become public knowledge until they have been checked and generally accepted. The scientific community will carry out argumentative practices to validate the conjectures, such as an evaluation of conjecture in the light of available evidence; determination which conjectures present the most convincing explanations for particular phenomena in the world. These argumentative practices are essential in the establishment of knowledge claims (Newton, Driver & Osborne, 1999). Argumentative practice is also used in examining the appropriateness of an experimental design, or the interpretation of evidence in the light of alternative theories. Furthermore, scientists also extend argumentation beyond the scientific community to the public domain through journals, conferences and the wider media. It is through such processes of having claims checked and criticized that "quality control" in science is maintained (Driver, Newton & Osborne, 2000).

Since argumentation is essential in the social construction of scientific knowledge and argumentative practice is a key activity of scientists, it has been suggested that science education should largely involve argumentation. Driver et al. (1994) believed that the role of science education is to mediate scientific knowledge for learners, to help them to make personal sense of the ways in which knowledge claims are generated and validated. When learning science concepts it should not simply be a case of extending learners' knowledge of phenomena, or developing and organizing learners' commonsense reasoning. It should lead learners to a different way of thinking about and explaining the natural world, and help learners become socialized into the practices of the scientific community. Newton, Driver and Osborne (1999) also pointed out that it is not enough for students just to hear the explanations from experts, they should know both the questions and answers that scientists value, and practice using the questions and answers for themselves. Through practice in posing and answering scientific questions, students become active participants in the community of science rather than just passive observers. Furthermore, through taking part in activities that require them to argue the basis on which knowledge claims are made, students also begin to gain an insight into the epistemological foundations of science itself. Driver, Newton & Osborne (2000) concluded that if we intend to show the socially constructed nature of scientific knowledge, students should be given some insight into its epistemology, the practices and methods of science and its nature as a social practice through studies of science-in-the-making. Students should be given the opportunity for discursive practices in general and argumentation in particular.

Argumentation promotes epistemic knowledge and scientific thinking. Duschl & Osborne (2002) believed that "if the structures that enable and support dialogical argumentation are absent from the classroom, it is hardly surprising that student learning is hindered or curtailed. Or, put simply, teaching science as a process of enquiry without the opportunity to engage in argumentation, the construction of explanations and the evaluation of evidence is to fail to represent a core component of the nature of science or to establish a site for developing student understanding (p. 41)". They claimed that teaching science must address epistemic goals that focus on how we know what-we-know, and why we believe the beliefs of science. Engaging learners with conceptual and epistemic goals in argumentative learning environments can help make scientific thinking and reasoning visible. Driver, Newton and Osborne (2000) pointed out that when students engage in argumentation, they will learn not only what a phenomenon is, but also how it relates to other events, why it is important and how this particular view of the world came to be. Through argumentative learning, they practice the way that scientists do, promote scientific thinking and gain experience for their future scientific works.

2.3.2 Argumentation Leads to Deep Learning

Deep learning is regarded as a desirable goal for education. It enables learners to learn in an integrated way, and know how to apply the knowledge learned in a variety of contexts. Moon (1999) claimed that learning is a continuum ranging from surface learning to deep learning. The representation of surface learning is when bits of information may be recalled but the learner does not demonstrate it in a coherent or varied form, nor is it substantially related to their previous knowledge. Deep learning is represented as a coherent form because new ideas are meaningfully related to each other and also related to a network of relevant ideas in the learners' existing cognitive structures. In surface learning, learners simply memorise isolated ideas, while in deep learning learners integrate new ideas into their cognitive structures. Offir, Lev and Bezalel (2008) defined deep learning in distance education as a process that takes place when students translate new information into engraved concepts and relate it to their life experiences. Existing thinking schemes are changed during this process and the learned material is integrated within the students' perceptions web. Surface learning is the understanding and remembering of existing information, or primary absorption of new information at a simple level. It does not change the students' engraved thinking process. Neal (2005) suggests that effective learning is more likely to occur when students adopt a deep learning approach.

Deep learning happens when learning tasks are challenging. Neal (2013) stated that "surface learning approaches include tasks that involve low-level thinking – these primarily consist of reproducing information or memorising information; also, the student's sole intention is the completion of the task…. When given tasks demand more than routine effort and demand the use of higher cognitive strategies by challenging the students' thinking, these are considered to be deep learning approaches. Deep learning includes the intention to understand, relating previous knowledge to new knowledge, and discovering relationships between ideas." (p.27) Argumentation can promote deep learning because it challenges the learners to apply higher cognitive strategies, and when learners engage in argumentation, they seek to find evidence to prove a claim and they seek to infer from their existing knowledge base. This enables them to connect relevant information together and link new information with the existing ones.

Generating relations among knowledge, experience and existing knowledge are important for learning. Wittrock (1992) believes that the focus in learning is on generating relations, rather than on storing information. He proposed a generative model of learning and teaching, which deals with the effects of generation of meaningful relations, among concepts and between knowledge and experience. People actively and dynamically use generative learning processes to (a) selectively attend to events and (b) generate meaning for events by constructing relations between new or incoming information and previously acquired information, conceptions, and background knowledge. These active and dynamic generations lead to reorganisations and reconceptualisations and to elaborations and relations that increase understanding (Wittrock, 1992, p. 532). In his model, comprehension and understanding result from the processes of generating relations both among concepts and between experience or prior learning and new information.

Argumentation can provide different mechanisms that lead to deep learning:

- *Context*: Argumentation is context based. Discussing knowledge in specific contexts helps students to construct connections between knowledge and the context and apply the knowledge in appropriate contexts. In addition, Von Aufschnaiter et al. (2008) found that argumentation provides the opportunity for learners to use similar ideas in different contexts, and helps to make connections across (familiar) contexts. So argumentation enables the confirmation of the initially tentative ideas and consolidation of the existing knowledge.

- *Elaboration*: Argumentation provides a context within which students can elaborate their knowledge. When students engage in elaborative processing, they seek details and attempt to understand the reasons why something exists or happens, rather than simply accepting that it is the case. They go beyond what is explicitly stated in a text or conversation to re-produce knowledge that is more complex, integrated and ultimately more meaningful to them (Felton, 2011).

- *Explanation*: Explanation is a basic part of argumentation, for example, when learners explain and justify a claim, or they explain it to themselves to ensure they have a clear position regarding it. As mentioned by Duschl and Osborne (2002), the construction of an explanation requires students to clarify their thinking, to generate examples, to recognize the need for additional information and to monitor and repair gaps in their knowledge. Generating explanations can lead to deeper understanding when learning new content (Chi et al. 1994; Ploetzner et al. 1999). A recent study by Ainsworth and Burcham (2007) has confirmed the importance of self-explanation in learning. They explored the roles of self-explanation and text coherence for novices learning relatively complex material about structure and functioning of the human circulatory system. Their post-test included implicit questions and knowledge inference questions that required not only factual recall, but also inference and application of knowledge to a particular situation. They found that participants who had been trained to self-explain performed significantly better than participants who had not been trained.

- *Co-construction*: During argumentation, deeper understanding can be achieved via co-construction. Argumentation offers an opportunity for conjecture, argument and challenge. During argumentation, learners will articulate reasons for supporting particular conceptual understandings and attempt to justify their views. Others will challenge, express doubts and present alternatives so that a clearer conceptual understanding will emerge. In such a manner, knowledge is co-constructed by the group as the group interaction enables the emergence of an understanding whose whole is more than the sum of the individual contributions (Newton, Driver & Osborne, 1999). Knowledge co-construction can be evidenced from argumentation processes. Nykvist (2008, 2013) adapted an argumentation framework for online discourse analysis and identified evidence of knowledge building through the analysis of argumentations in students' online forums.

2.3.3 Argumentation Fosters Conceptual Change

One main benefit of argumentation is to foster conceptual change. Conceptual change occurs when learners change their understanding of concepts and the conceptual frameworks that encompass them, reorganizing their frameworks to accommodate new perspectives (Jonassen & Kim, 2010).

Piaget's developmental theory always considers cognitive conflict to be the central in cognitive development. Cognitive conflict is known as an important factor in conceptual change (Lee et al, 2003). Argumentation provides an environment rich of cognitive conflicts. These conflicts will stimulate learners to adjust their old cognitive structure to a new one to accommodate new concepts.

The effects of argumentation on conceptual changes have been recognised by researchers. For example, Driver, Newton & Osborne (2000) pointed out that conceptual change is dependent on the opportunity to socially construct and reconstruct one's own personal knowledge through a process of dialogic argument. Conceptual change can occur in science lessons when students are given the opportunity to tackle a problem in a group, or in a whole class situation. The teacher coordinates a discussion to identify different thoughts, invites students to evaluate these, and move toward an agreed outcome.

Empirical studies also evidenced the effectiveness of argumentation in promoting conceptual change:

- Nussbaum and Sinatra (2003) explored the potential of argumentation in science to promote conceptual engagement and ultimately conceptual change. Their results suggest that argumentation techniques have the potential to act as a conceptual change intervention. They believe this potential comes from the nature of argumentation. When someone argues for an alternative point of view, the processes necessary for producing conceptual change are naturally engaged. That is, when constructing an argument, individuals must consider both sides of the issue, explain aspects of the problem that are anomalous to their existing conception, and must be confronted with the discrepancy between their point of view and the alternative.

- Asterhan and Schwarz (2007) investigated the effects of argumentation-eliciting interventions on conceptual understanding in evolutionary theory. The study showed that students who participated in argumentation conditions have achieved greater gains in understanding of evolutionary concepts than control participants. And students in argumentative conditions were able to preserve the gains until the one week delayed post test, but control participants could not.

2.3.4 Argumentation Supports Problem Solving

Problem solving is generally regarded as the most important cognitive activity in everyday and professional contexts (Jonassen 2000). Problems can be generally classified as well structured and ill-structured problems. Well structured problems (Voss, 2005) are problems that

- the goal is well-defined, and generally the solution is agreed upon by the members of the respective community;
- constraints are usually stated in the problem statement or are readily apparent;
- operators are frequently mathematical or logic-based; and
- the problem solving is within computer simulation capabilities.

Mathematic problems are usually well structured. Hilbert et al (2008) showed the essential role of argumentation in mathematical proof. Proving is a highly important activity in mathematics. Hilbert et al. (2008) proposed a four stage model for proof finding in classrooms: production of a conjecture (includes the exploration of the problem situation, identification of arguments to support the evidence), formulation of the statement, exploration of the conjecture (includes identify appropriate arguments for the validation of the conjecture), and selection and combination of coherent arguments in a deductive chain. It is clear that argumentation is very important for well structured problems as this model is very much aligned with the argumentation activity of making claims, providing justifications, evaluation of different perspectives and drawing conclusions. There are also many well structured science problems which have well defined questions and agreed correct answers. Argumentation among each other can help to verify the different understandings and solutions to a problem.

Ill structured problems are problems that have vaguely stated goals; their solutions may vary considerably in the nature and content due to the solver's knowledge, beliefs and attitudes. The solutions typically are not right or wrong, and are usually regarded in terms of some level of plausibility or acceptability (Voss, 2005). Cho and Jonassen (2002) believed that ill-structured problems are more affected by argumentation than well-structured problems. Because ill-structured problems are dialectical in nature, with two or more opposing conceptualisations of the problem or its solution result, the production of arguments to support those differing conceptualisations is essential.

Empirical studies also confirmed that argumentation supports problem solving in the following ways:

- *Argumentation can enhance problem solving processes.* Cho and Jonassen (2002) applied an online argumentation system, the Belvédère system, in an undergraduate economics course on problem solving. They used four argument types (hypothesis, data, principles, unspecified) and three links (for, against, and) as constraints to scaffold the argumentation, and found strong connection between argumentation and problem solving. The groups with argumentation scaffold produced significantly more comments on the categories of problem definition, orientation, criteria development, solution development, solution approval and solution critique. That is, more problem solving processes appeared in the argumentation scaffolding groups. Oh and Jonassen (2007) carried out another study to investigate the effect of constraint-based argumentation on the type of problem solving processes (problem space construction, hypothesis generation, hypothesis testing, solution generation, solution verification). This time they used a constraint-based discussion board to scaffold pre-service teachers' online argumentation about behaviour management problems. The constraints required the students to post messages following the pre-defined message type and sentence openers. The six message types are: hypothesize cause, solution generation, verification, rebuttal, evidence and elaboration. Sentence openers are like "I agree because...", "I believe..." or "Research shows...". within comparison to the group without argumentation scaffolding, the scaffolded group significantly increased the processes of problem space construction, hypotheses generation and hypothesis testing.

- *Argumentation helps students think more in depth and breadth*. Munneke et al. (2007) studied the influence of representation tools on interactive argumentation of a wicked problem. Wicked problems are a subset of ill-structured problems with two unique features. Firstly, wicked problems have no right or wrong solutions that can be tested and revised. Secondly, they are problems which have many stakeholders who have their own views on both the problem and the solutions. The participants in the study of Munneke et al. (2007) were secondary school students who worked in pairs in computer supported collaborative learning (CSCL) environments discussing genetically modified organisms. There were two different tools, a diagram tool and a text outline tool, to support students' collaborative argumentation. Some students were assigned to use the diagram tool and others use the text outline tool. Students could talk and discuss in the chat space, collaboratively construct arguments using text-outline/diagram tool in the tool space, and finally collaboratively write an argumentative text in the text space. The research reported that in the tool space, students using the diagram tools generated significantly more claims, supportive theories, evidence, alternative theories and rebuttals than students using the text-outline tools. In addition, students using the diagram tools also argued more in depth and breadth about the topic of genetically modified organisms. Their study tells us that using appropriate presentation tools to scaffold argumentation can help students think deeper and broader.

- *Argumentation can lead to better solutions.* The process of argumentation allows people to consider alternative perspectives and come up with more complete picture of the problem. This makes it possible to generate more effective solutions to a problem. In addition, people collaboratively contribute ideas during the argumentation process which also increases the possibility of a better solution than an individualized solution. Nussbaum, Sinatra and Poliquin (2008) used brief instruction to scaffold argumentation and examined undergraduate students' physics problem solving about gravity and air resistance. Students worked in pairs in an online learning environment to collaboratively solve the problems. The treatment groups received written information about the criteria for sound scientific arguments while the control groups did not. The results showed that the treatment groups developed better arguments and considered on average twice as many ideas than the control groups. There were significantly more participants in the treatment group who adopted the correct answer to one of the two problems.

2.4 Barriers of Argumentative Learning in Education

Collaborative argumentation is thus regarded as being significant for learning and consequently can be regarded as being very important in school subject areas such as science. However, it is not widely applied in schools. Osborne (2010) pointed out that the lack of opportunities to develop the ability to reason and argue scientifically would appear to be a significant weakness in contemporary educational practices.

There are some barriers that prevent the argumentative learning from being widely applied in schools:

- *Students are not willing to engage in argumentation.* Some students view argumentation as constituting discord and disagreement, or an interaction involving winners and losers, so they do not appreciate the role of argumentation, as a consequence they often don't want to participate in argumentation; some students' epistemic beliefs are that knowledge is simple, certain and unchanging (instead of dynamic and constantly changing), they also tend to avoid argumentation (Nussbaum, Sinatra & Poliquin, 2008). Another possible reason may be that students are used to more traditional school tasks and they work for grades. They may have interpreted the learning tasks as a problem to solve quickly or aim at a product (such as essay, final solution), instead of understanding the space of the problem, therefore they are not really engage in argumentative activities (Munneke et al., 2007).

- *People have difficulties in arguing*. Kuhn (1991) reported an empirical study of people's informal reasoning. The study found a number of problems that people have in arguing. For example, people tend to give pseudo evidence (such as examples or descriptions of the theory) which do not support the theory. Another typical problem is that people often have difficulties to generate alternative theories, counterarguments and rebuttals (Baron, 1992).

- *Schools do not have sufficient teachers or resources to facilitate argumentative learning.* During argumentation, students might wander off the learning topic and turn to discuss other irrelevant topics. They may just want to get the task done quickly without any investigation or exploration. Occasionally, in some competitive situations they might just want to 'win' and thus take the fastest and easiest path to a solution. Therefore, each student group needs to be closely monitored and supported in their learning. This may become time challenging for teachers because argumentative learning does take a longer time than traditional learning. For example, students require time to organise evidence to support the claims, they also need time to present their ideas and consider different perspectives from each other. As Duschl and Osborne (2002) noted, the discursive nature of argumentation requires both time to undertake the process, and time for reflection and consideration of the outcomes. Schools may have difficulties in arranging argumentative learning in their busy schedules.

- *Argumentative learning may lead to incorrect learning outcomes.* Students in a group may have identical ideas thus no opportunity to experience cognitive conflicts during argumentation. Student peers may not able to provide the right scaffolding to each other. Sometimes, wrong arguments may seem to be more acceptable to students. Students may absorb the wrong idea if no experts' opinion presents. As Baker (2009) has pointed out, argumentation functions as a means of transforming the degree of acceptability of problem solutions from the points of view of students. It influences which solutions will be retained or rejected. There is nothing to guarantee that the best solutions are in fact not rejected. The better-argued (defended) solution might "win out" as a result of argumentation, and is mutually accepted.

The above mentioned barriers mainly come from the availability of qualified arguing peers. A qualified arguing peer should be able to conduct collaborative argumentation, make the students who tend to be shy comfortable for the argumentative interaction, apply proper knowledge and skills to direct students' knowledge construction and exploration to the solution. In practice, there is no sufficient resource to provide each student a qualified arguing peer.

Using intelligent agents to simulate human peers can be a solution. Intelligent agents may reduce students' worries while arguing with human peers, and they are always available which allow students to access their arguing peers when needed. One of the major aims of this thesis is to develop computing models for intelligent virtual arguing peers to enable argumentative learning in educational contexts.

3. Pedagogical Agents and Learning

3.1 Pedagogical Agents

Virtual characters are computer software components which take forms such as synthetic humans, animals, mythological creatures, and non-organic objects that exhibit lifelike properties. They are used in areas including education, entertainment, training and simulation (Dinerstein et al 2004). In educational systems, these virtual characters are also commonly called educational agents. An educational agent is a piece of educational software with lifelike characteristics that facilitate social learning (Chou, Chan & Lin, 2003).

Educational agents are classified as pedagogical agents and personal assistant agents, according to their roles and functions (Chou, Chan & Lin, 2003). Pedagogical agents are designed to be involved in social learning activities for a specific pedagogical purpose. They can play an authoritative role, such as a domain expert, a teacher, a tutor or a coach. They can also play a non-authoritative role to support collaborative or competitive learning activities, such as a teachable student, a collaborator or a competitor. Personal assistants are educational agents that provide users with information that pertains to the learning activities, but do not become directly involved in the learning activities. For example, a teacher's assistant can help to record each student's level of effort; a student's assistant can help to arrange collaborators or record homework.

Pedagogical agents can be designed to simulate social interactions. This will motivate the learners to engage in the learning task and consequently to enhance learning in computer-based environments. What makes pedagogical agents unique from conventional computer-based environments is their ability to simulate social interactions (Kim & Baylor, 2006). The studies that investigate the impact of pedagogical agents on learning exist in two broad categories. One category relates to the appearances of pedagogical agents and learning. In this category, the main functionalities of agents are demonstrated via the visual appearance, such as gender, facial expression, emotion, and so on. Another category relates to the cognitive aspect of pedagogical agents and learning. In this category, the main functionalities of agents are demonstrated via their cognitive capabilities, such as providing advice, encouraging reflection, and to simulate as a co-learner to present alternative answers.

This thesis will focus on non-authoritative pedagogical agents, which are usually called learning companions. A learning companion is defined as a computer-simulated character, which has human-like characteristics and plays a non-authoritative role in a social learning environment (Chou, Chan & Lin, 2003). To students, a learning companion is not a domain expert and may make mistakes.

3.2 Appearance of Pedagogical Agents and Learning

The agents' strong positive impacts on students' perception of learning has been recognised since the late 90s. One of the pioneer works was conducted by Lester et al. (1997) on Herman-the-Bug. They studied the pedagogical agent named Herman-the-Bug in a learning game called *Design a Planet*. Herman-the-Bug is shown in Figure 3.1 (Johnson, Rickel & Lester, 2000). The study provided significant evidence about the positive impact of the presence of animated pedagogical agents on students' perception of their learning experiences. Because these agents can provide students with customised advice in response to their problem solving activities, their potential to increase learning effectiveness is significant. The agents can also play a critical motivational role as they interact with students.

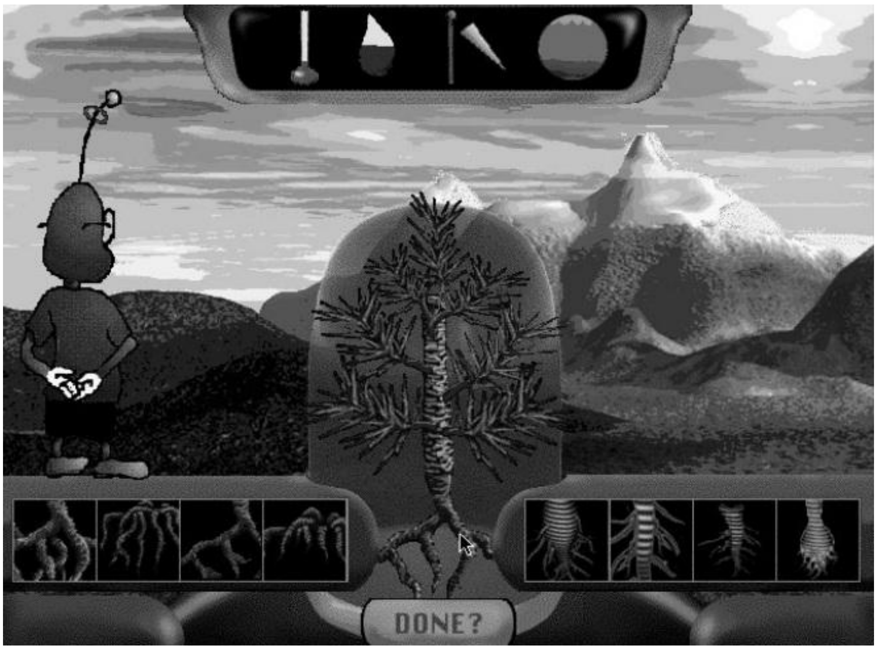


Figure 3.1 Herman the Bug

In recent years, researchers discovered that agents' appearances can have a profound impact on learners' motivation and learning transfer (Baylor & Plant, 2005; Rosenberg-Kima et al. 2008; Baylor & Kim, 2009). Various aspects of pedagogical agents have been examined. For example:

- *Gender*: Researchers found that girls tend to choose cartoon-like (as opposed to realistic) agents more than boys (Baylor, Shen & Huang, 2003) and students who worked with the realistic agents performed marginally better than students who worked with the cartoon-like agents (Baylor & Kim 2004).

- *Facial Expression*: Baylor and Kim (2009) studied the impact of facial expressions and deictic gestures. The pedagogical agents were designed in four different groups:

  - with deictic gestures and facial expressions,
  - with deictic gestures but no facial expressions,
  - with no deictic gestures, nor facial expressions, and
  - with no deictic gestures but with facial expressions.

The sample agents of the four different types are shown in Figure 3.2.

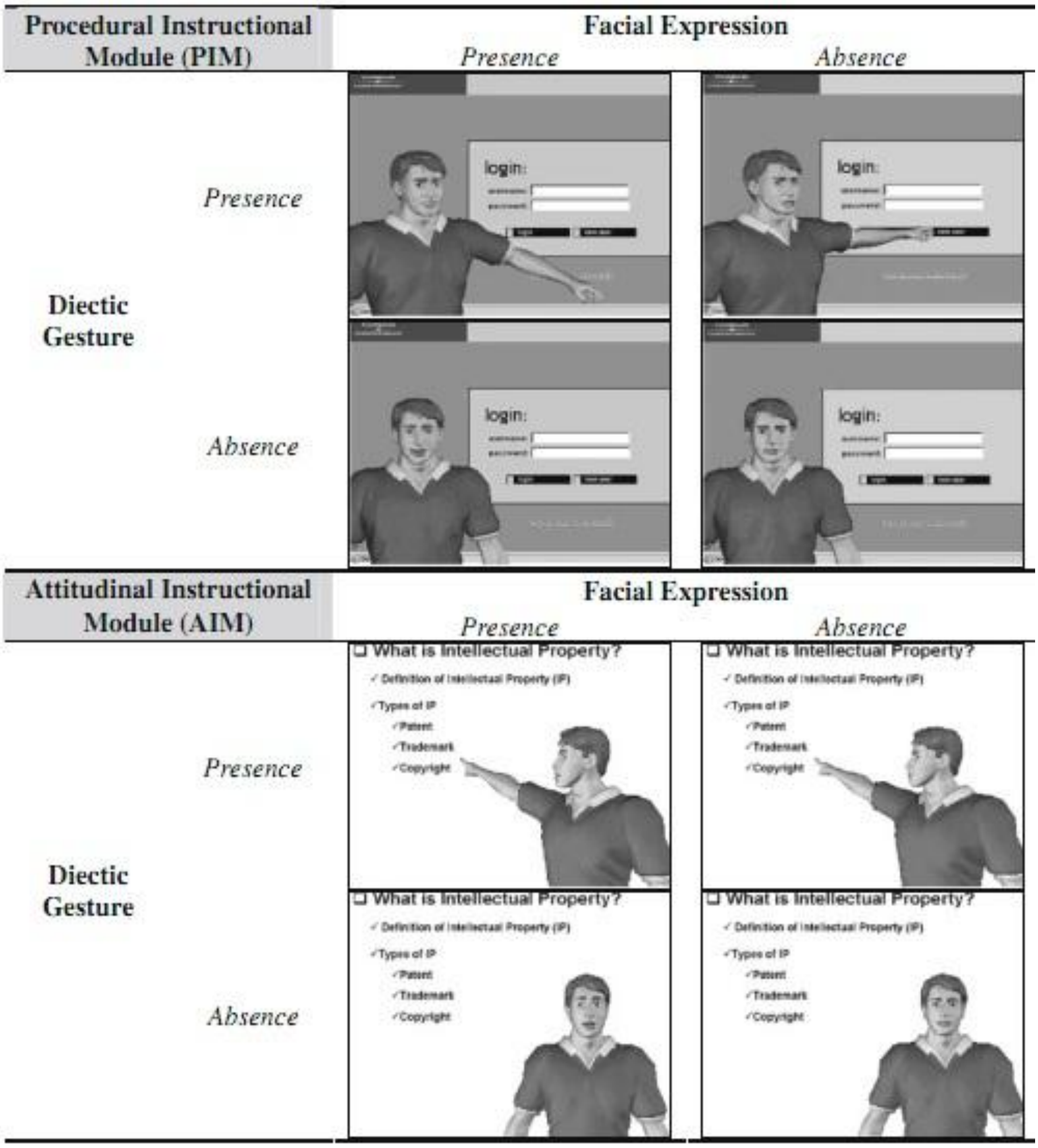


Figure 3.2 Agents with Different Facial Expression and Deictic Gesture

The agents are applied in two different contexts; in procedural instructional modules and in attitudinal instructional modules. The research found that in the procedural instructional modules, students who used an agent with deictic gestures but without facial expressions had the highest mean score on attitude toward the content. In the attitudinal instructional module, students who had an agent with neither gestures nor facial expressions, had the lowest mean score. Through further analysis, the results showed the effect of facial expressions positively influenced learning, and agent gestures enhanced procedural learning but was detrimental for attitudinal learning. Additionally, when facial expression was absent, the presence of agent gestures enhanced learning, and when facial expression was present, the absence of agent gestures enhanced learning.

- *Politeness*: The manner in which pedagogical agents communicate with students has an impact on learning. Wang et al (2008) compared the pedagogical agent online assistance in direct mode and in polite mode. They found that the students liked the polite mode better and the corresponding learning outcomes were also much better.

- *Emotion***:** Emotion is very important for realistic pedagogical agents. Some researchers have developed affective inference models for agents to derive their emotions dynamically. For example, Alepis and Virvou (2011) reported an emotional agent for e-learning, based on the OCC cognitive model of emotions (Ortony, Clore & Collins, 1990). The agent can express specific emotional states to students for the purpose of motivating them while they learn. In their study most students believed that the agent was very useful and user friendly.

The above examples show that agents' appearances do have an impact on learning motivation and/or learning outcomes. In addition to appearance, intelligence is another important aspect of pedagogical agents. The next section will introduce the cognition of pedagogical agents and their influence on students' learning.

3.3 Cognition of Pedagogical Agents and Learning

In addition to studying the appearance of agents, researchers have also studied the cognition of pedagogical agents. Agents are equipped with knowledge and collaborative learning strategies to provide learning content based interactions in educational contexts. A few studies are reviewed as outlined below:

- *Agent as a trouble maker:* Aïmeur and Frasson (1996) proposed a simulated student that plays the role of a troublemaker and introduced a "learning by disturbing" strategy. In their later work, Aïmeur, Frasson and Dufort (2000) summarised that the learning by disturbing strategy implicates three participants:

- the tutor agent who presents both the lessons and the exercises to be solved,
- the learner who is the human student who uses the intelligent tutoring system,
- the troublemaker agent who is a simulated student working with the human student.

The troublemaker has both pedagogical expertise and domain knowledge. The troublemaker uses the pedagogical expertise to maximise the impact of its interventions. The role of the troublemaker is to unsettle the student by proposing solutions that are sometimes truthful but other times erroneous. This tests the student's self-confidence and obliges him/her to defend his/her point of view. Aïmeur, Frasson and Dufort (2000) describe the learning by disturbing strategy in the following manner: A cognitive dissonance is triggered by the troublemaker's interventions; in order to reduce the dissonance, the learner is motivated to search for new information in his environment; through dialogue and debate with the troublemaker, the student is then convinced by the troublemaker or the student tries to convince the troublemaker. Aïmeur, Frasson and Dufort (2000) believe that the dialogue and debate through this process increases the student's motivation and improves the learning.

- *Agent as a learner taught by students:* Betty's Brain is a system which implements the "learning by teaching" paradigm to help school students develop cognitive and meta-cognitive skills in science domains (Biswas et al., 2005; Blair et al., 2007). In this system, the pedagogical agent is called a teachable agent, named Betty. Students teach Betty by creating a network of entities and their relations, much like a concept map. At any time, students can query Betty to see how well she has learned. Betty can answer queries based on what she has learned from students. Students can observe Betty's conclusions and decide whether they need to revise what they have taught Betty. Betty can also take a quiz composed by a classroom instructor that is automatically scored by the computer. So, students can watch Betty's performance and receive projective feedback on their own knowledge. The Teachable Agent Betty is shown in Figure 3.3 (Blair et al. 2007).

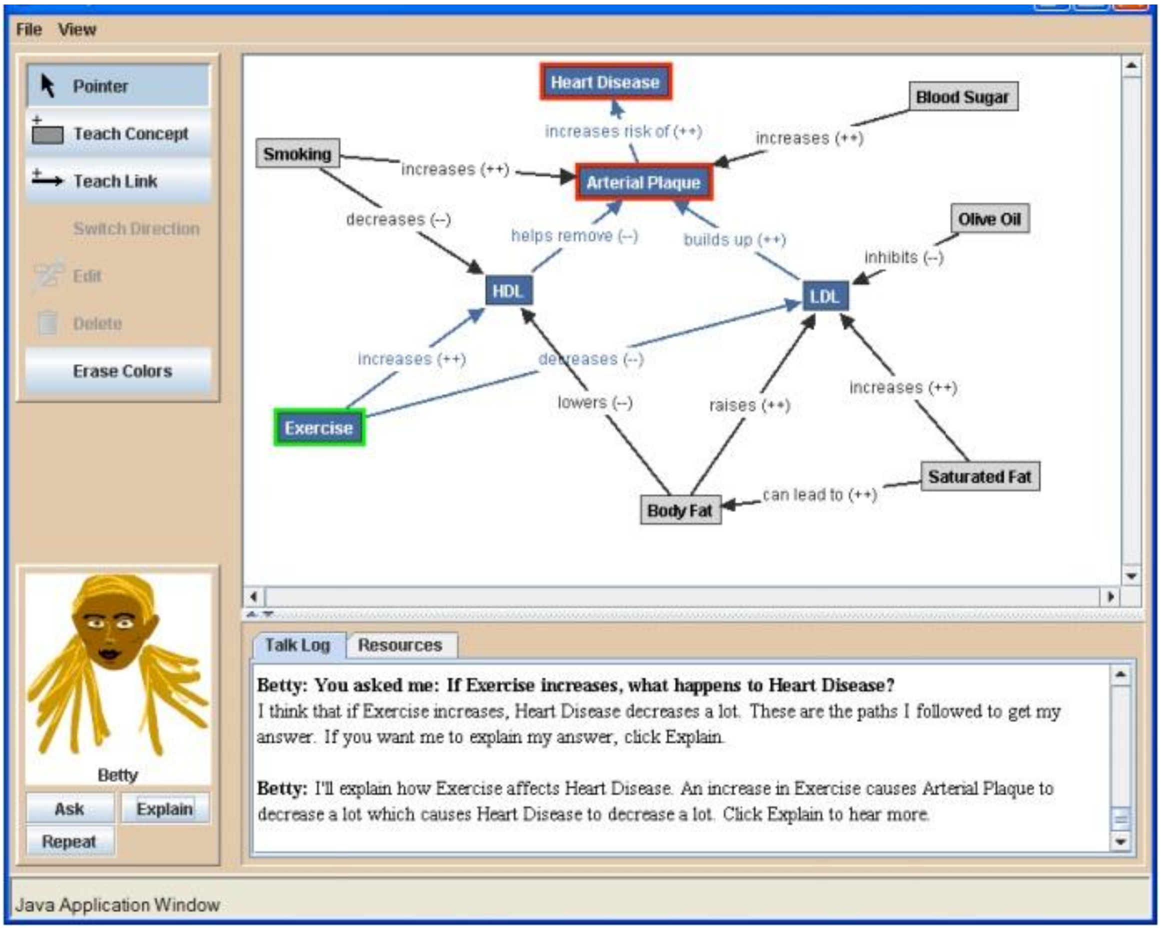


Figure 3.3 The Teachable Agent Betty

Studies have shown that both the query and quiz features from Teachable Agent Betty had beneficial effects on students' learning (Biswas et al 2005). The Learning-by-teaching paradigm was found to help students focus on making sure Betty (and themselves at the meanwhile) understand the information (deep learning) rather than just get the correct answers (surface learning). Through learning-by-teaching, students can make their own thinking explicit and exhibit more complex chains of causal reasoning on a post-test (Blair et al 2007).

- *Agent brings in different competencies:* Kim and Baylor (2006b) investigated the effects of the competency (low vs. high) and interaction type (proactive vs. responsive) of pedagogical agents as learning companions on learning, self-efficacy, and attitudes for undergraduates in an introductory computer-literacy course. Their results showed that a high competency learning companion is more effective for students to apply what they have learned; while a low competency companion can significantly enhance self-efficacy; and a proactive companion has a significantly positive impact on recall.

- *Agent prompts explanation:* Generating explanations can lead to deeper understanding when learning new content (Chi et al. 1994; Ploetzner et al. 1999). To encourage explanation, Holmes (2007) designed a conversational agent to request the learner to provide explanation. When learning, students often make an incomplete answer so the request for explanation helps their deeper thinking by making causal connections.

The above mentioned agents all mimic human like interactions to influence students' cognitive processes. These interactions help to create an engaging learning environment and enhance students' learning.

3.4 Important Features of Pedagogical Agents as Learning Peers

Pedagogical agents are animated life-like characters used in electronic learning environments to enhance learning. They can be modelled as peer learners to mimic social interaction and apply collaborative learning strategies. In addition to the appropriate appearance (such as facial expression, emotion), a knowledge focused virtual peer agent should have at least the following important features:

- *Being knowledgeable in the learning domain*. As a learning peer, the agent needs to have domain knowledge. If the agent is expected to be a learning peer for students to learn science, the agent needs to have knowledge on the related science topics. Depending on the pedagogy, the agent may be designed to have more or less knowledge as compared to the student. It is also possible for the agent to have some incorrect knowledge as a human peer could do.

- *Being able to conduct interactive discussions*. The agent needs to communicate with learners interactively. In contemporary literature, most pedagogical agents can only give one time responses, such as answer questions upon request, provide hints, and prompt students to explain. The agents cannot conduct several rounds of interactions based on the learner's response. This limits the depth of interaction. A virtual peer agent should be able to "discuss" with learners.

- *Being able to conduct inference based on its knowledge*. To help students construct knowledge and develop critical thinking skills, the agent learning peer is expected to conduct collaborative argumentation with students. Therefore, the agent needs to be able to conduct inference on the domain knowledge. When the agent's knowledge set is incomplete or mixed with flawed knowledge, the agent can generate various arguments through inference, for students to evaluate, critique, and make correction. The inference mechanism will provide the agent intelligence to present its "opinions" on learning topics.

Although there have been a number of pedagogical agent systems, none of the existing agents are able to conduct argumentations with learners. This research aims to develop a learning peer agent which can conduct interactive argumentation dialogue with learners regarding learning topics.

4. Computer Supported Argumentation Systems and Learning

Recognising the importance of argumentation in education, a few computer supported argumentation systems have been developed for educational environments. These systems are mainly argumentation support systems and are not able to conduct argumentations automatically with learners. This chapter reviews some of the systems and identifies the features that are missing in the existing systems in regard to supporting human-computer argumentative learning.

4.1 Collaborative and Single User Argumentation Systems

Researchers have developed some argumentation support systems. These systems are not able to conduct argumentations with learners, but they can provide support in argumentation processes. Among them, there are networked software applications that support human - human argumentation, e.g. Belvédère, and AcademicTalk/InterLoc. Other systems are mainly used for single users to practice reasoning skills with the assistance of computers, e.g. Convince Me, Rationale/Reason!Able and SenseMaker.

Belvédère: The Belvédère (Veerman, Andriessen & Kanselaar, 1999; Suthers et al 2001) software is a networked system that provides learners with shared workspaces for coordinating and recording their collaborations in scientific inquiry. Figure 4.1 shows the Interface of the Belvédère system. It has a diagram window for students to construct an "evidence map". The evidence maps are graphs that are similar to concept maps. Its nodes represent component statements (primarily empirical observations or hypotheses) of a scientific debate or investigation; and links represent the relations between the elements (consistency or inconsistency). A study on the Belvédère in an undergraduate Computer Based Learning course was conducted (Veerman, Andriessen & Kanselaar, 1999). The study result showed that the Belvédère system stimulated students to check and counter each other's information frequently. It also helped students to focus strongly on the meaning of concepts. Cho and Jonassen (2002) investigated the use of Belvédère in an undergraduate economics course on problem solving. They used four types of arguments (hypothesis, data, principles, unspecified) and three links (for, against, and) as constraints to scaffold the argumentation. They found that the groups with Belvédère produced significantly more comments on the categories of problem definition, orientation, criteria development, solution development, solution approval and solution critique, than the threaded discussion groups using only Bulletin Board System.

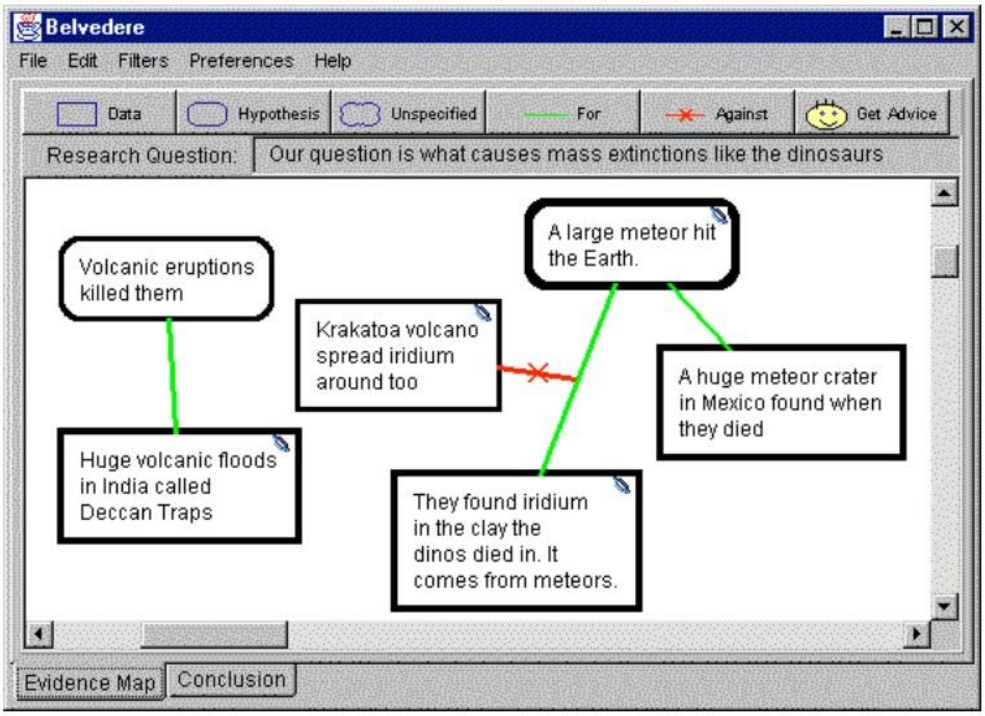


Figure 4.1 Interface of the Belvédère
(Suthers et al. 2001)

AcademicTalk/InterLoc: AcademicTalk (McAlister, Ravenscroft & Scanlon, 2004) is a critical reasoning game to promote critical discussions and reasoning. It guides student dialogues in ways that lead to improved argumentation and collaborative knowledge development. Figure 4.2 shows the interface of AcademicTalk. It presents learners with an interface of threaded discussions and predefined sentence openers. There are two viewing panes. The upper pane lists the latest message of each argument strand and when selected the strand is listed in the lower pane. AcademicTalk provides sentence openers to facilitate argumentation. The openers are grouped by intentions, such as inform, question, support and reason. It requires that the learner chooses a sentence opener for each new message then completes the message in his/her own words. Figure 4.2 shows the sentence openers in the question group.

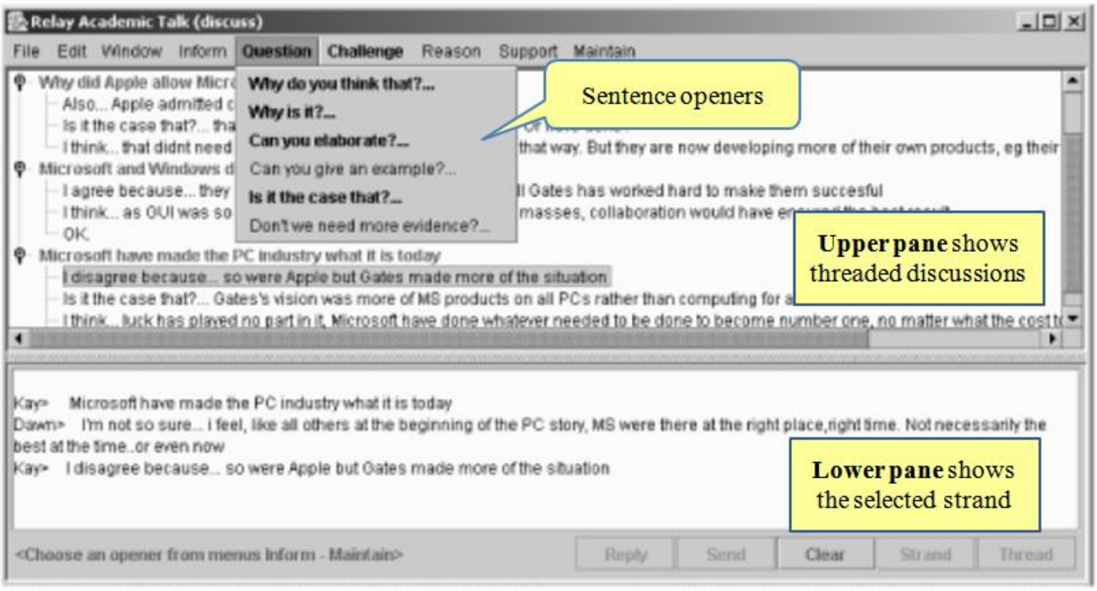


Figure 4.2 AcademicTalk Interface
(McAlister, Ravenscroft & Scanlon, 2004)

Its successor was the InterLoc (Ravenscroft & McAlister, 2005; Ravenscroft, McAlister & Sagar, 2010). InterLoc is a web-based tool supporting collaborative argumentation and other forms of real-time learning dialogues. InterLoc requires learners to select a locution opener (e.g. I think, I disagree because, My evidence, etc) from one of six predefined dialogue move categories (Inform, Question, Challenge, Reason, Agree, Maintain) to perform their contribution and then complete the message in their own words. Ravenscroft, McAlister and Sagar (2010) evaluated InterLoc from over 350 users in a rich and varied range of learning contexts. The evaluations showed that InterLoc succeeded in stimulating critical and collaborative thinking, elements of deep learning.

Convince Me: Convince Me (Schank & Ranney, 1995; Siegel & Ranney, 2003) is a "reasoner's workbench" computer program. It is a tool for generating and analyzing arguments for scientific reasoning. Users can use the program to enter their ideas, i.e. hypotheses and evidence. They can indicate which ideas support and which contradict others. If the statements support each other then they use explanation links; while if the statements conflict with each other, they use contradiction links. Learners can also rate the plausibility of a belief, that is, how strongly they believe each proposition and how reliable the evidence is. This process can help students to clarify their thoughts.

Convince Me also provides feedback to learners. Based on the feedback, users can modify their ratings and arguments. Schank and Ranney (1995) reported that Convince Me's feedback is critical for learning and the system makes people more effective at reasoning. Siegel and Ranney's (2003) study showed students' attitudes about science have significantly improved over time when using Convince Me. The results demonstrated that on average, students had a slightly more positive view of science and that it increasingly became more positive over the semester.

Reason!Able/Rationale: Reason!Able (Van Gelder, 2002) is an educational software that supports argument mapping to teach reasoning skills. Figure 4.3 shows the screenshot of Reason!Able. Reason!Able provides a workspace within which click and drag operations are used to build and modify hierarchical tree structures. The tree structures represent the inferential relationships among the various claims that make up arguments. The argument trees constructed by Reason!Able contain claims, reasons and objections. Reasons and objections are usually complex objects, made up of sets of claims (premises) working together. They can be unfolded to show the full set of premises. In the evaluation mode, Reason!Able can provide evaluations including strength of reasons/objections, degree of confidence in the truth of claims, and independent grounds for accepting a claim as true. Van Gelder (2002) reported that over the first three years of the study it was found that students on average improved their scores. The researcher claimed that using the Reason!Able approach accelerates growth in critical thinking skills, relative to undergraduate education. *Rationale* is the successor of Reason!Able (van Gelder, 2007). In Davies' (2009) study on Rationale, students reported that their understanding of the assessment task improved as a result of using Rationale, and they generally enjoyed the experience.

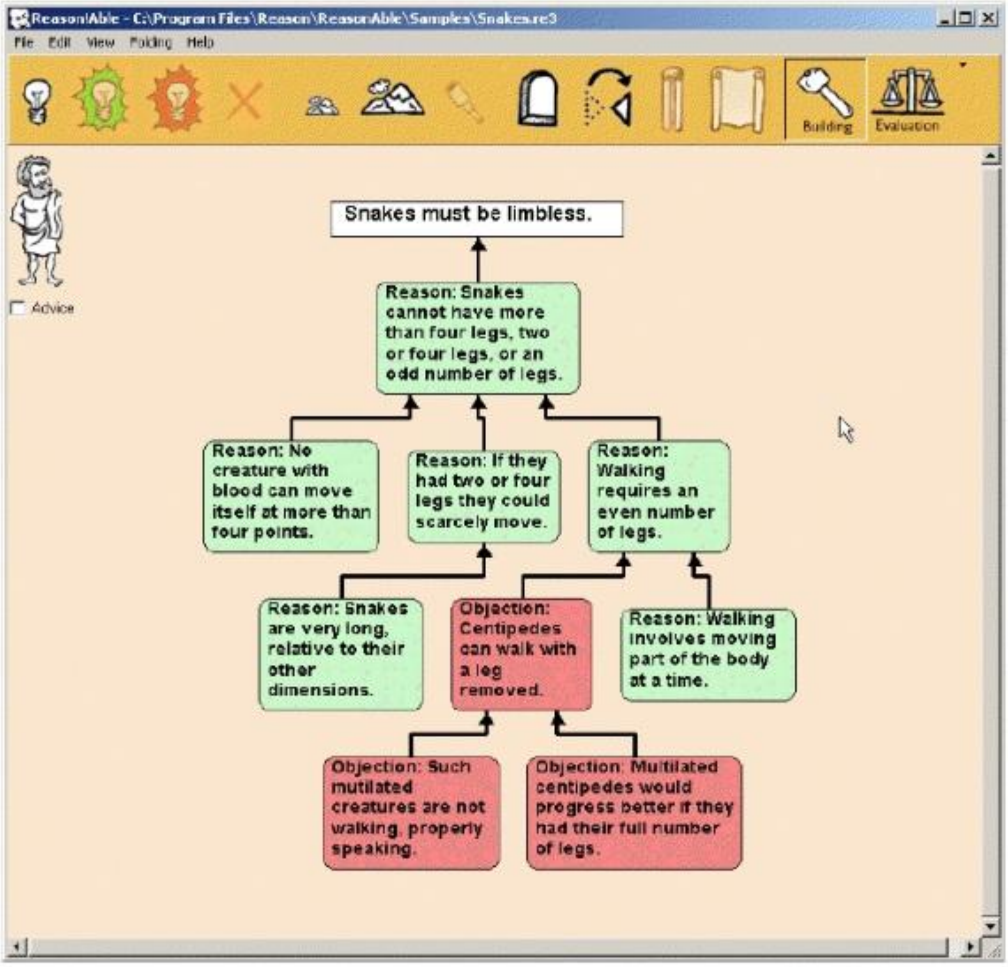


Figure 4.3 Screenshot of Reason!Able
(Van Gelder 2002)

SenseMaker: SenseMaker (Bell, 1997) is part of the Knowledge Integration Environment (KIE) (Bell and Linn, 2000) debate project. The project aims to promote middle and high school students' understanding of science. The successor of KIE is the Web based Inquiry Science Environment (WISE) (Linn, Clark & Slotta, 2003). SenseMaker supports the construction of scientific arguments with a graphical representation. Students can work individually or in small groups on the same computer. Bell and Linn (2000) investigated middle school students' learning on a light propagation topic. SenseMaker can make scientific thinking and reasoning visible. This contributed to their refinement of the images of science. The graphical arguments representation allows students to express and exchange their conceptual ideas. SenseMaker engages students in the construction of their arguments about a topic. As students elaborate their arguments, they are making their understanding of the evidence and the scientific ideas contained in the topic. The result showed that students acquired a more normative and robust understanding of how far light travels.

4.2 Agent Mediated Argumentation Systems

In order to better facilitate argumentation, some researchers have applied intelligent agents as assistants to support the argumentation process. The intelligent agents can help to make sure the argumentation progresses in the right direction, provides hints for refining/expanding arguments, and visualises the argumentation plan.

Yu and Chee (1999) developed an intelligent agent that can provide students with online argumentation strategies and rhetorical methods in a computer supported collaborative argumentation environment. Regular patterns are retrieved from the computer supported collaborative augmentation environment, and saved into the corpus of regular pattern. Each pattern is assigned with several argumentation strategies and rhetorical methods. When students write argumentative articles but have no idea on how to expand their arguments, they can request the intelligent agent for assistance. The agent will match regular patterns with the student's article. If a regular pattern is matched, the related argumentation strategies and rhetorical methods will be presented to students. Figure 4.4 shows an example of the agent’s suggestion to students. From the experimental result, Yu and Chee (1999) found that about 65% of argumentation strategies on average can be used by students to improve the quality of their arguments.

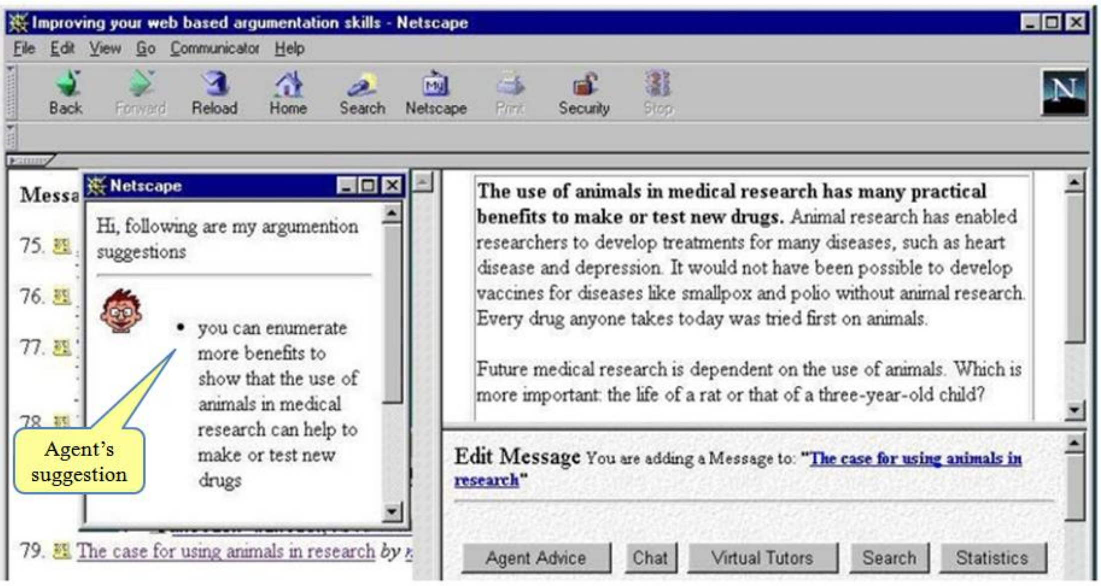


Figure 4.4 Agent Providing Advice
(Yu & Chee, 1999)

Constantino-Gonzales and Suthers (2001) developed a web based collaborative learning environment equipped with a virtual personal coach (a pedagogical agent). The virtual coach assists students to solve database modeling problems. It encourages argumentation among participants in the shared workspace when differences are detected. The evaluation showed that most of the students thought that the presence of the coach is helpful, especially in guiding the collaborative session and establishing the group dynamics required in collaborative learning.

Monteserin, Schiaffino and Amandi (2010) proposed a tutor agent that can build and present argumentation plans, which provides students an intuitive view of the problem solution and the conflicts needed to be resolved. The research result revealed that students reach consensus easier when an assistance of argumentation plan is presented. The argumentation plan allows students to decide which task could be agreed on, detects relations among different conflicts and facilitates conflict resolution.

4.3 Issues of the Current Argumentation Systems

The review of the existing argumentation systems shows that they are not able to be applied as peers in argumentative learning. The major issues of these systems are as follows:

- *Lack of ability to argue.* The existing systems are in fact argumentation support systems. They cannot automatically argue with people. These argumentation support systems can be regarded as being collaborative argumentation support systems or non collaborative argumentation support systems. Collaborative argumentation systems provide platforms for human peers to argue with each other. They are able to support the exchange of arguments, visualisation of arguments and identification for conflicts among peers. However, they cannot produce arguments to be used in the argumentation.

The non-collaborative argumentation systems provide interface for learners to construct arguments. These systems are able to support the argument construction with visual tools, or support the refinement/revision of arguments by providing feedback, which are based on the comparison of learner's arguments and expert's opinions stored in the system. They usually provide feedback upon request and cannot conduct argumentation with learners.

- *Lack of learning supervision*. Supervision is essential in argumentative learning. Unsupervised argumentative learning may lead to incorrect learning outcomes (Baker, 2009). Liu and Tsai (2008) also revealed that small groups with peer members in the high achievement level might not necessarily assure the success of group work, if they have inadequate group development skills and cannot reach consensus on a common process to solve the assigned problem. Teachers or moderators need to scaffold the process of peer interactions. Hmelo-Silver, Duncan and Chinn (2007) also pointed out the importance of scaffolding in problem based learning. However, the existing systems are clearly lacking of supervision functions.

- *Lack of an easy and motivational interface*. Argumentative learning is a challenging learning model. Students need to construct their own arguments, evaluate others arguments, talk with peers, work out solutions collaboratively, and negotiate many other features. If the system is complicated, students may not able to concentrate on their learning. Liu and Tsai (2008) studied the peer interaction patterns of university students in an on-line, small group discussion for solving computer programming problems. The study revealed that the most frequent interactions were related to questions or suggestions regarding how to effectively coordinate peer members, rather than discussions pertaining to the problem that needed to be solved. This finding suggests that even university students might not have sufficient competencies for web based team work or collaborative learning. What is more, the majority of the systems provide users with interfaces to construct argument diagrams or write argumentative texts. Most interactions are tedious diagram constructions or text writing. They are not attractive to learners, especially to school students.

This research is to advance the frontier by designing and developing intelligent models for agents to be able to conduct argumentation automatically, which in turn enable human-computer argumentative learning for the first time.

Summary of Part I

Part I reviewed the promising argumentative learning strategy, and the latest development in pedagogical agents and computer supported argumentation systems.

Learning is a process in which learners actively construct knowledge rather than passively receive knowledge from teachers. Argumentation is essential in learning processes, as it promotes epistemic knowledge and scientific thinking, facilitates deep learning and conceptual change. However, due to the high dependency on qualified arguing peers, argumentative learning has not been largely applied in schools.

Progresses have been made in the development of computer supported argumentation systems and pedagogical agents facilitated learning systems. However, no computer system is able to conduct argumentation with learners to facilitate argumentative learning. A clear gap exists between the needs of virtual arguing peers to facilitate argumentative learning and the lack of computing systems that is able to conduct human−computer argumentation.

The research presented here aims to fill the gap by making significant progress in computing models to enable argumentative learning with intelligent agents. This is a multi-disciplinary research. Part II is to present the argumentation computing model development and Part III is to present the educational studies on argumentative learning with intelligent agents.

Part II. Argumentation Computing Model Development

Part II presents the development of computing models for automated argumentation.

5. Conceptual Design of Argumentative Agents

The existing pedagogical agents and argumentation systems cannot conduct argumentative dialogues with learners. To incorporate the "learning by arguing" paradigm, this study designed and developed an argumentative agent that can conduct argumentative dialogues with human users. This intervention will make a significant contribution to the practical application of argumentative learning. This chapter presents the conceptual design of the argumentative agent, including agent architecture, dialogue types and protocols, and fundamental concepts in argumentation computing modeling.

5.1 Computer Science Research Method

The main research methods in computer science include theoretical method, experimental method, and simulation method (Dodig-Crnkovic, 2002). The theoretical method adheres to the traditions of logic and mathematics, which seeks to find solutions or better solutions to complex problems through algorithms design and analysis. The experimental method develops complex software solutions and then evaluates the solutions through experiments. The simulation method simulates real world problems such as virtual reality and artificial life.

This study intends to create intelligent virtual peers to argue with humans, which involves the design of data models and algorithms to present human intelligence in argumentation. Therefore it aligns with the theoretical methods.

This thesis adopts the theoretical methods in computer science research and the key phases are:

- *Identify the key requirements and components*. The key requirements in order to hold human – computer argumentation, include possessing domain knowledge, to be able to perform inference based on the knowledge and be able to conduct interactive argumentative dialogues. Based on the requirements, key components are identified.

- *Design the argumentative agent architecture*. Intelligent agents are suitable carriers to conduct argumentation with humans. In this phase, the key components are designed into agent architecture.

- *Design argumentation dialogue types and dialogue protocols*. Unlike other types of software agents, the agent for this research needs to have abilities to conduct interactive argumentative dialogues with human learners. Thus, human understandable argumentation dialogue types and interactive argumentation dialogue protocols need to be designed.

- *Design knowledge models and develop argumentation automation algorithms*. There are different types of human knowledge. All together, four computing models were developed in this research to represent four types of widely used knowledge, and to automate the argumentation processes. For each of the computing model, the research focused on:

- human knowledge abstraction and modeling,
- knowledge based reasoning algorithms development, and
- argumentation automation algorithms development.

The development of each phase of the computing model had experienced multiple rounds of iterations on requirements identification, architecture design, dialogue design and algorithms development. The models or algorithms of each phase were revised and improved until a final mature model was established.

5.2 Agent Architecture

The architecture of an agent decides the key components of the agent. This section identifies the key requirements of argumentative agents and presents the architecture designed in this research.

The agent in this study is a human-like virtual character and acts as a peer learner. The agent should also be an argumentative agent that is able to argue with learners about the learning content. In this way, the agent should meet the following key requirements:

- *Possess domain knowledge.* To fulfill the learning peer and argumentation roles, the agent must have domain knowledge. Similar to a human learning peer, without domain knowledge, he/she could not make valid arguments on the learning topic. The domain knowledge should be at an appropriate level according to the student's knowledge level to engage argumentation. Unlike other expert systems which contain a complete set of consistent knowledge in the corresponding domain to provide expert opinions, the agent here is expected to have incomplete, inconsistent or wrong knowledge so as to present alternative opinions in argumentation processes.

- *Has ability to make inferences.* To participate in argumentation, the agent should have reasoning capability. For example, with a given problem, the agent should be able to work out a solution by making inference on the domain knowledge. Upon receiving an argument, the agent needs to decide if the argument is acceptable based on its knowledge, and/or organise counter-arguments if necessary.

- *Has ability to conduct interactive argumentative dialogues*. The agent must be able to conduct interactive argumentative dialogues automatically with learners, based on its knowledge and the context. The dialogues need to follow certain protocols to make arguments and counter-arguments.

Based on the above basic requirements, the key components of an argumentative agent are:

- *Knowledge Base (KB)*: It is a collection of knowledge of the argumentative agent.
- *Reasoning Engine*: It enables the agent to make inferences based on the KB. The KB and the reasoning engine enable the agent to manifest its domain knowledge.

- *Argumentation Module*: It is responsible for generating argumentative dialogues. This module enables the agent to argue with learners on learning content automatically.
- *Interface Module:* It facilitates the communication between the learner and the agent. It interprets the human learner's dialogue to the argumentation module, and presents the dialogue generated by the argumentation module to the human learner.
- *Knowledge Base Revision Module*: This component is responsible to update the knowledge base when new knowledge becomes available. This module ensures the agent can accept other opinions, think in other positions and possess learning capabilities.

The architecture of the key components is shown in Figure 5.1. The domain knowledge of the agent is achieved via the Reasoning Engine and Knowledge Base. In this way, the reasoning engine can be shared by different knowledge bases which may be in different domain areas such as earth science, physics and biology.

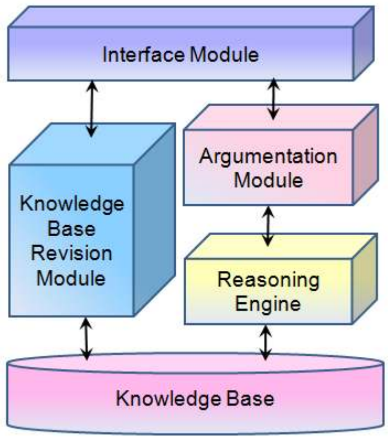


Figure 5.1 Architecture of Argumentative Agent

5.3 Agent Dialogues

In this section, argumentation dialogue types that are used by human beings or agent-agent argumentation will be reviewed first, followed by a proposal for the dialogue types and protocols that are suitable for the argumentative agents in this study.

5.3.1 Types of Argumentation

Argumentation has been widely studied in law, philosophy, and computer science. The study of argumentation started from Aristotle. He distinguished arguments of different types.

- Deductive and Inductive Argument

  Aristotle starts from the assumption that all knowledge, insights, and opinions, in so far as they arise from rational thought, are based on existing knowledge, insights and opinions; existing opinions make up the material on the basis of which we can arrive at new opinions with the help of reasoning or arguments (van Eemeren, Grootendorst & Henkemans, 1996, p. 31). Aristotle divides the arguments which may be used for this purpose into two sorts: deductive arguments and inductive arguments (van Eemeren, Grootendorst & Henkemans, 1996, p. 31).

  Deductive arguments are based on the concept of deduction, which involves starting from some general principles and concluding with particular facts that fall under the general principles. In the case of *deductive argument*, something is assumed in a number of statements (premises), and from these premises, there necessarily follows a conclusion. This means that premises establish support for the conclusion and the conclusion then follows from the premises. In a deductive argument, it is impossible for the premises to be true and the conclusion false. For example, based on the arguments of "all birds can lay eggs" and "Tweety is a bird", a conclusion that "Tweety can lay eggs" can be drawn.

  In *inductive argument*, specific cases are named in the premises, and from these premises a general conclusion is drawn. In an *inductive argument*, the premises provide reasons supporting the *probable* truth of the conclusion. For example, from "Fried potato chip is yummy" and "Fried egg is yummy", "Fried fish is generally yummy" can be concluded.

- Apodictic, Rhetorical and Dialectical Argument

Aristotle also distinguishes arguments as apodictic, rhetorical and dialectical according to the purpose the arguments are intended to serve.

Apodictic arguments seek to demonstrate absolute and reliable knowledge based on evidence that leaves no doubt about the veracity of a claim. From a naturalistic perspective, we may often state claims as apodictic truths in everyday discourse, however, those claims are rarely tested in formal educational settings (Jonassen & Kim, 2010).

Rhetorical arguments are conceived as a dialogue between an arguer and an audience. The goal of rhetorical arguments is to persuade or convince others of a claim or proposition that the arguer believes without regard to positions that others hold. A rhetorical argument is acceptable if it meets with the approval of the audience (van Eemeren & Grootendorst, 1992, p.6). Most rhetorical arguments concentrate on applying effective persuasive argumentation techniques. The most prominent model of rhetorical argumentation was developed by Toulmin (1958). He developed a structure for argumentation, including a claim (C), data (D), a warrant (W), in addition to elements such as backing (B), qualifier (Q), and rebuttal (R). In the process, an arguer justifies his or her claim by linking data (D) to the claim (C) through a warrant (W). The qualifier (Q) conveys the degree of force from data to claim, while the rebuttal contradicts the claim (R).

Toulmin's model has been very influential. However, it has some limits, such as, it is based on an informal description, and it only emphasizes the structure of the arguments without taking into account the participants and their knowledge base (Bentahar, Moulin & Bélanger, 2010). This model fails to consider both sides involved in argumentation. The model depicts only the proponent’s side, minimising the role of an opponent in the process of argumentation. The rhetorical form of argument is one-sided and has limitations in educational settings (Driver, Newton & Osborne, 2000).

Dialectical arguments represent a dialogue between proponents of alternative claims during a dialogue game or a discussion. Dialectical arguments are regarded as part of a critical discussion between two parties who are trying to resolve a difference of opinion. The goal of dialectical arguments is to resolve differences of opinions (van Eemeren & Grootendorst, 1992, p.7).

One model often mentioned is Walton's argumentation schemes for presumptive reasoning (Walton, 1996). Walton claims that argumentation is a goal-directed and interactive dialogue in which the participants reason together to advance arguments by proving or disproving presumptions. Therefore, in dialectical argumentation, counterarguments are just as important as the original argument. Walton (1996) described and analysed 25 argumentation schemes. For each argumentation scheme, a matching set of critical questions are given. The function of each argumentation scheme is to shift a weight of presumption from one side of a dialogue to the other. The opposing arguer in the dialogue can shift this weight of presumption back to the other side again by asking any of the appropriate critical questions matching that argumentation scheme. Jonassen & Kim (2010) believe that these schemes provide specific models for structuring classroom and online discussions.

In terms of argumentation logic, argumentation is often based on constructing and comparing deductive arguments (Besnard & Hunter, 2009). These are arguments that involve some premises (which refer to as the support of the argument) and a conclusion (which refer to as the claim of the argument) such that the support deductively entails the claim (Besnard & Hunter, 2009). In this study, deductive argument is selected as it fits the discussions usually held in science regarding the support, evidence and conclusion of science topics.

In terms of argumentation purpose, deciding which kind of argument to support when designing learning environments depends on the purpose of that environment. If the learning goal requires promotion or persuasion, such as designing a marketing campaign, then supporting student construction of rhetorical arguments is more appropriate. When the learning goal requires the resolution of different opinions, then dialectical argumentation should be supported, with an emphasis on generating and rebutting counterarguments (Jonassen & Kim, 2010). Therefore, dialectical arguments are more appropriate for learners to resolve learning problems.

In summary, considering the educational context, deductive dialectical arguments will be designed for agents in this study.

5.3.2 Dialogue Types in Computer Based Argumentation

Dialogues are the fundamental components in argumentation. In a computer based argumentation, the dialogues need to be formally defined so computers can generate the dialogues automatically.

There have been some dialogue types proposed in the literature. An influential model of human dialogues is the typology of primary dialogue types proposed by Walton and Krabbe (1995). The model categorise dialogues based upon the information the participants have at the commencement of a dialogue, their individual goals for the dialogue, and the goals they share. Table 5.1 lists all the dialogue types.

Table 5.1 Type of Dialogues
(Walton &Krabbe, 1995, p.66)

Type of dialogues	Initial Situation	Main Goal	Participant's Aims
Persuasion Dialogue	Conflicting points of view	Resolution of such conflicts by verbal means	Persuade the other(s)
Negotiation	Conflict of interest and need for cooperation	Making a deal	Get the best out of it for oneself
Inquiry	General ignorance	Growth of knowledge and agreement	Find a 'proof' or destroy one
Deliberation	Need for action	Reach a decision	Influence outcome
Information seeking	Personal ignorance	Spreading knowledge and revealing positions	Gain, pass on, show, or hide personal knowledge
Eristics	Conflict and Antagonism	Reaching a (provisional) accommodation in a relationship	Strike the other party and win in the eyes of onlookers

McBurney and Parsons (2009) provide a brief description for each dialogue:

- *Persuasion Dialogues* involve one participant seeking to persuade another to accept a proposition he or she does not currently endorse.

- *Negotiation Dialogues* are dialogues where the participants bargain over the division of some scarce resource. If a negotiation dialogue terminates with an agreement, then the resource has been divided in a manner acceptable to all participants.

- *Inquiry Dialogues* are dialogues where the participants collaborate to answer some question or questions whose answers are not known to any one participant.

- *Deliberation Dialogues* are dialogues where participants collaborate to decide what action or course of action should be adopted in some situation. Here, participants share a responsibility to decide the course of action, or, at least, they share a willingness to discuss whether they have such a shared responsibility. Participants may have only partial or conflicting information, and conflicting preferences. As with negotiation dialogues, if a deliberation dialogue terminates with an agreement, then the participants have decided on a mutually-acceptable course of action.

- *Information Seeking Dialogues* are those dialogues where one participant seeks the answer to some question(s) from another participant, who is believed by the first to know the answer(s).

- *Eristic Dialogues* are dialogues that participants quarrel verbally as a substitute for physical fighting, aiming to vent perceived grievances.

The eristic type of dialogue is not suitable for argumentative learning because its aim is to serve primarily as a substitute for (physical) fighting (Reed, 1998). As such, it is not expected to be an appropriate type of dialogue for the intelligent argumentative agent in this research. In our life, most actual dialogues involve mixtures of multiple dialogue types. Additionally, dialogue types are context dependent. Walton and Krabbe made no claims of comprehensiveness of the dialogue types they have proposed.

Informal descriptions of different dialogues are not enough for computers to automate the dialogue process. Formal classification and definition of the dialogues are needed. Mcburney and Parsons (2002) developed a logic-based formalism for modeling of the five atomic dialogue types in the Walton and Krabbe (1995) typology for dialogues between software agents. McBurney and Parsons (2004) defined five similar dialogue types for argumentation in software agent interaction protocols:

- *Assert*: for an agent to assert a statement (a belief, an intention, a social connection, an external commitment, etc). The agent should be able to provide justifications if required.

- *Question*: for an agent to seek justification for a prior utterance of assertion by another agent. The agent of the question creates no obligations on itself by the question utterance.

- *Challenge*: for an agent to seek justification for a prior utterance of assertion by another agent. The agent creates an obligation on itself to provide a justification against the assertion. Challenge is a stronger utterance than question.

- *Justify*: for an agent to provide justification when its prior assertion is questioned or challenged by another agent.

- *Retract*: for an agent to withdraw its prior assertion or justification.

Another dialogue protocol for software agents was proposed by Heras, Rebollo and Julian (2008). It is a dialogue game protocol for an agent to argue about recommendations in social networks. The protocol contains the following locutions:

- *Statements*: are the locutions to propose a recommendation, accept/reject proposals and assert some information.

- *Withdrawals*: for the retraction of a specific recommendation.

- *Questions*: for asking for recommendation proposals or getting more information from another agent.

- *Critical Attacks*: for posing critical questions to question the degree of expertise of the proponent, to demonstrate the proponent is not personally reliable or to demonstrate the proponent's recommendation is not consistent with others.

- *Challenges*: for requesting arguments that support a recommendation proposal or a critical attack.

Considering the dialogue types proposed in the literature, the main dialogues are those to express one's position, justify one's position and attack others' positions. Dialogue types may vary depending on the contexts. The aforementioned dialogues are not perfectly aligned for argumentative learning. The next section presents the dialogue types developed for this research.

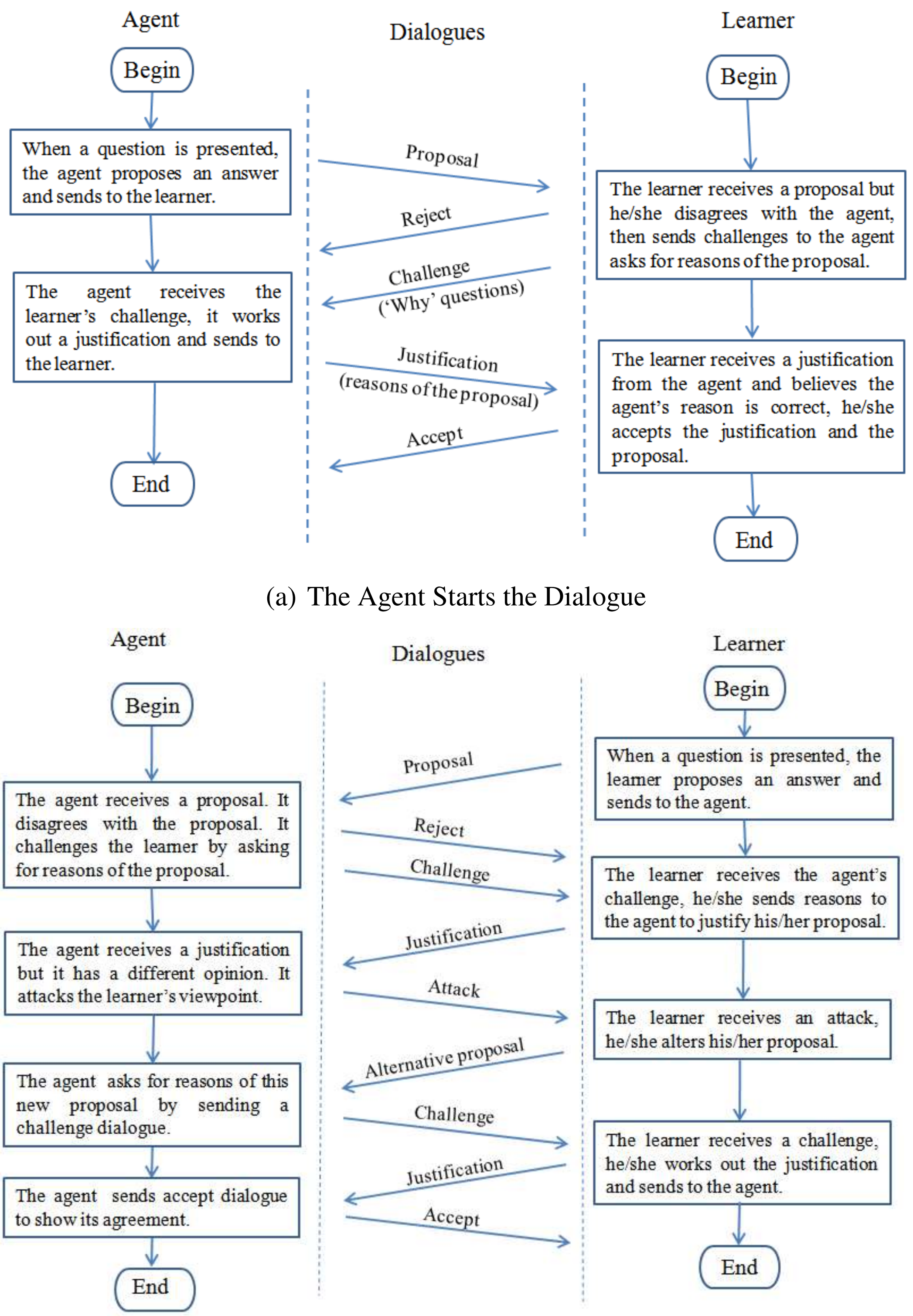
5.3.3 Dialogue Protocol for the Argumentative Agent

Considering the argumentative agent in the context of this study, the dialogue types listed in Table 5.2 have been developed.

Table 5.2 Dialogue Types of the Agent

Dialogue Type	**Description**
Proposal	Propose answers
Acceptance / Rejection	Accept or reject the other's proposal
Justification	Provide support for the opinion presented
Challenge	Ask "why-questions" to seek justification
Attack	Point out the other's mistakes
Information seeking	Ask questions of others
Information providing	Answer the other's questions or teach the others new knowledge

In a human's learning process, learners take turns to propose solutions and incorrect solutions are usually automatically ignored, so there is not a "withdraw" dialogue type to retract claims. Two typical dialogue scenarios are shown in Figure 5.2.



(a) The Agent Starts the Dialogue

(b) The Learner Starts the Dialogue
Figure 5.2 Sample Dialogue Scenarios

5.4 Collaborative Argumentation Strategy

Collaborative argumentation is desirable in educational contexts (Andriessen, 2006). Learners are expected to contribute their knowledge to the group, evaluate and critique opinions based on the shared knowledge in the group. In the argumentation process, a learner will encounter different ideas. Some of the ideas fit in with his/her existing knowledge, some of them may conflict with his/her existing knowledge. The learner has to keep on updating their knowledge when they receive new information, and make their judgment and reasoning among these inconsistent ideas.

To model human's collaborative argumentation with intelligent agents, the agents need to be able to incorporate new knowledge in its knowledge base. Otherwise, the argumentation is not collaborative as the agent cannot consider the other's knowledge. To provide the agent with human intelligence, some formalism needs to be designed for the agent to incorporate new knowledge and update its knowledge base. This involves knowledge base revision (Eiter & Gottlob, 1992), which solves the problems of how to incorporate new knowledge to an existing knowledge base and still maintain the integrity of the knowledge base.

Several approaches for revising knowledge bases have been proposed. Among these approaches, some are formula-based changes and some are model based changes (Eiter & Gottlob, 1992). In formula-based changes, the change consists of adding a new formula and retracting some formulae from the knowledge base if this is necessary for preserving consistency. In this way, a formula has to be either retracted as a whole or left in the knowledge base. Model-based changes refer only to the extensions, i.e. models of the knowledge base. These changes focus on the nature of the knowledge base, that is what can be entailed from the knowledge base, and ignore the formulae representation of the knowledge base.

After a formula-based change, some new formulae are added, and some old formulae are removed. It is easier for humans to understand the changes. After model based change, the knowledge base might be represented by some models that can be easily used by a machine but hard to be understood by human beings. For the argumentative agent where the knowledge will be presented to learners to understand, formula based approaches that keep the formulae as a whole is more appropriate.

Both of these knowledge base revision methods adhere to the principle of minimality of change which states that the knowledge base should change as little as possible if new information is incorporated (Eiter & Gottlob, 1992). This is what people usually do when they encounter new information that is proved to be correct. If the new information is not in conflict with their existing knowledge, they accept the new information. If the new information is in conflict with their existing knowledge, they accept the new information and only reject the information that conflicts with the new one. For example, if a boy has the knowledge that "tigers are mammals, horses are mammals, penguins are mammals", when he confirms that penguins are birds, he will only reject the knowledge "penguins are mammals". It is unlikely he will also reject the knowledge such as "tigers are mammals" or "horses are mammals".

When the agent receives messages from the learner, the agent will revise its knowledge base according to the knowledge that appears in the learner's message, and will then consider generating arguments to the learner. This ensures that the agent's knowledge is not so diverse with the learner's cognitive structure, as the agent keeps necessary updates of its belief based on the learner’s knowledge. Effective scaffolding happens when the agent’s knowledge is within the zone of proximal development (ZPD) of the learner (Vygotsky, 1978).

5.5 Argumentation Automation

To enable human-computer argumentative learning, argumentation automation has to be achieved for automating argumentative dialogues between intelligent agents and human beings. Some progress has been made to automate the argumentation between software agents, for autonomous agent belief revision and multi agent communication (Maudet, Parsons and Rahwan, 2007). These argumentation models for agent systems cannot be directly applied in education because they are mainly designed for machines to conduct interactions. To date, computer based argumentation can only work well in the specific contexts that they are designed for and there are no reports on automated argumentation systems in education practices.

To achieve intelligent agent-human argumentation for learning, a computing model for argumentation automation is needed. There are argumentation models proposed in the literature (for example, in the review of Chesñevar, Maguitman & Loui, 2000 and Bentahar, Moulin & Bélanger, 2010). However, the main focus of these existing models are to protect one's own position and attack the other's position. Making use of both parties' knowledge to construct more reasonable proposals is neglected in all of these models. A major difference between the argumentation model for argumentative learning and models existing in literature is that argumentation in the learning process is a collaborative discourse. This research proposes a collaborative argumentation model which is suitable in educational contexts.

A generic computational model will be proposed here, and the specific logical constructs of computing models will be following from chapter 6.

5.5.1 Fundamental Concepts

This section introduces the fundamental concepts used in argumentation modeling. The notations of the concepts and algorithms for the computing model can also be found in the literature (such as Besnard & Hunter, 2009; Parsons & McBurney, 2003).

Let letter L denote a language. The element from language L is called an atom, represented by letters a, b, c etc. In language L, formulae can be constructed from atoms using operators (for example, conjunction, disjunction and negation in classical logic). Formulae are represented by letters α, β, γ etc.

A piece of knowledge can be represented by a formula, and all the knowledge of an autonomous entity form a knowledge base which is a set of formulae. Let KB denote a knowledge base, $\models$ denote entailment relation, $\perp$ denote contradiction, then $KB \models \alpha$

denotes that the knowledge base *KB* entails a formula α (or α is a consequence of *KB*), $KB \vDash \perp$ denotes that the knowledge base *KB* is inconsistent.

An argument contains a formula and a set of formulae from which the formula can be inferred. Following the conventions in most argumentation models proposed in the literature (for example, Besnard & Hunter, 2009; Parsons & McBurney, 2003) this study defines an argument as follows:

Definition 5.1 An **argument** is a pair $A=<\Phi,\alpha>$ where α is a formula of *L* and Φ is a subset of *KB* such that

1). $\Phi \nvDash \perp$ (i.e. Φ is consistent);

2). $\Phi \vDash \alpha$; and

3). Φ is a minimal subset of *KB* satisfying1) and 2).

If $A = <\Phi, \alpha>$ is an argument, A is called an argument for α (in general α is not an element of *KB*) and Φ is called a support for α. In other words, α is the claim of the argument, and Φ is the support of the argument. The following Example 5.1 simplifies the definition for further clarification.

Example 5.1 Let *KB*= {Tweety is a bird, birds can fly, birds can lay eggs, Rabby is a rabbit, rabbits eat grass}. Here,

<{ Tweety is a bird, birds can fly }, Tweety can fly> is an argument, where “Tweety can fly” is the claim and {Tweety is a bird, birds can fly} is the support.

<{ Tweety is a bird, birds can lay eggs }, Tweety can lay eggs > is another argument, where “Tweety can lay eggs” is the claim and {Tweety is a bird, birds can lay eggs} is the support.

The need for condition 1 in Definition 5.1 is to make sure the support is consistent. A claim that comes from self contradictory support will not be trusted. In addition, contradictory premises can entail any claims in classical logic. Hence, if inconsistent supports were allowed, then an overwhelming number of useless arguments would be generated.

Condition 2 of Definition 5.1 explains that an argument is a formula together with a set of formulae from which the formula is inferred.

Condition 3 is to make sure that irrelevant information is not included as support. For example, <{ Tweety is a bird, birds can fly, rabbits eat grass }, Tweety can fly> is not an argument because the support is not the minimal subset of *KB* that entails the claim. "Rabbit eats grass" is not relevant.

It is very important to define how an argument disagrees with another in an argumentation model. An argument that disagrees with another argument is described as a counterargument. A counterargument is usually described with the notions of undercutting and rebuttal according to the literature. Some arguments directly oppose the support of others, which is called undercutting. The most direct form of a conflict between arguments is when two arguments have opposite claims. This is called a rebuttal.

Definition 5.2 Argument $<\Phi, \alpha>$ **undercuts** argument $<\Psi, \beta>$ if and only if there exists a formula ψ belongs to formula set Ψ (denoted as $\psi \in \Psi$) such that α attacks ψ .

Definition 5.3 Argument $<\Phi, \alpha>$ **rebuts** argument $<\Psi, \beta>$ if and only if α attacks β.

Here "attack" generally means opposite to each other, and it depends on the specific logic used in the implementation of the model. For example, in classical logic, α attacks β iff $\alpha \equiv \neg \beta$. It might represent for "birds can fly" attacks "birds cannot fly".

Example 5.2 Let A_1=< { Tweety is a bird, birds can fly }, Tweety can fly>,

A_2=<{ Tweety is a rabbit, a rabbit is not a bird}, Tweety is not a bird>, and

A_3=<{ Tweety is a baby bird, baby birds cannot fly }, Tweety cannot fly>. Here, A_2 undercuts $A_1$and A_3 rebuts A_1.

5.5.2 Argumentation Computing Models

Suppose the agent's knowledge base is *KB*. The automation of the agent's argumentative dialogues can be represented by the following pseudo code.

If the agent receives a question // Proposal

  If there is an argument $<\Phi, \alpha>$ on *KB* relevant to the question,

  Then propose α

If the agent receives a proposal α // Acceptance / Rejection

  If there exists an argument $<\Phi, \alpha>$ on *KB*

  Then accept α

  Else reject α

    If there is an argument $<\Phi, \neg \alpha>$ on *KB*,

    Then challenge "why α ?" // Challenge

If the agent receives a challenge "why α ?" // Justification

  If there is an argument $< \Phi, \alpha>$ on *KB*,

  Then justify with Φ // response with justification

  Else reply "I just guess so." // response without justification

If the agent receives a justification Φ for claim α // Attack

  If there is an argument $<\Psi, \beta>$ on *KB* and $\varphi \in \Phi$ such that β attacks φ

  Then attack with argument $<\Psi, \beta>$ // undercut

  Else If there is an argument $<\Psi, \beta>$ on *KB* and β attacks α

  Then attack with argument $<\Psi, \beta>$ //rebut

If the agent receives new knowledge *k* (from the other's dialogue) // Proposal

  If there is an argument $< \Phi, \beta >$ on $KB * k$ ($KB * k$ is the revised knowledge base after incorporating new knowledge *k* to *KB*) and β is different from the previous proposal α

  Then propose β

The agent dialogue automation mechanism proposed above tried to encourage learners to explain the reasoning process, and tried to think following the learner's logic. For example, when the agent receives a proposal α which is against its belief, instead of attacking the proposal, it asks "why α" to give the learner an opportunity to explain the reason. It only starts to attack when the learner cannot provide justification, or the learner provides a justification but against the agent's belief. Another example is, when attacking the learner's justifications, the agent uses "undercut" (attack the learner's reasoning logic) first, and uses "rebut" (attack the learner's conclusion) when there is no "undercut". By doing so, the agent gives the learner an opportunity to review their reasoning process.

A human being's intelligence involves different types of knowledge. Consequently, there are different types of knowledge representations in computer science. For example, chained knowledge is used to describe a food chain, or hierarchical knowledge is used to describe the decomposition relationship between a complex problem and its sub problems. This research has developed computing models for four typical types of human knowledge, which are used to enable the corresponding argumentation automation. The four computing models are:

- Argumentation computing model for chained knowledge,
- Argumentation computing model for hierarchical knowledge,
- Argumentation computing model for fuzzy dynamic knowledge, and
- Argumentation computing model for collaborative optimisation.

These models will be introduced and explained in detail in the four chapters that follow.

5.6 Summary

This chapter presented the conceptual design of an argumentative agent, including architecture, key components and the abstract level of algorithms. It is a high level design of the agent's functionalities and the computational model of argumentation. This model for argumentative learning is different from other models in the literature. Those models have been designed for machine to machine automated interaction rather than human-machine interaction for learning. Firstly, the model developed in this thesis considered the need of collaborative argumentation in an educational context. The argumentation parties use shared knowledge to draw conclusions. The existing models only use individual knowledge and the argumentations mainly focus on justifying one's own positions and attacking the others' positions. Secondly, the model developed in this thesis also considered learning related factors when generating dialogues. The goal of this argumentation model is to foster thinking and learning, while in many other models, the goal is to win the debate.

6. Argumentation Computing Model for Chained Knowledge

There is no universal argumentation computing model that is suitable for all kinds of problems. Argumentation computing models need to be designed for specific types of knowledge. Beginning with this chapter, four argumentation models will be developed in this research. This chapter introduces the first argumentation model with chained knowledge which describes the sequencing of items.

6.1 Chained Knowledge and Graph Representation

In our everyday life, a type of knowledge is widely used to describe sequences of a series of items. For example, the knowledge that describes the steps in a scientific experiment; or the knowledge that describes *eat* and *be eaten* relationships of a food web; or the knowledge that describes the proper route from city A to city B by passing a series of other cities. This type of knowledge can be modeled as chains to represent the order of the items. This type of knowledge is defined as *chained knowledge* in this thesis.

For chained knowledge, the argumentative dialogues are based around the decision of a proper sequence of a set of given items. For example, to model a food chain that contains sheep, wolf and grass; or to design a sequence for performing a series of tasks; or to find a proper route from city A to city B. This chapter presents the computing model developed in this research to automate chained knowledge based argumentative dialogues.

Chained knowledge can be formally modeled as a directed graph KB = (V, E), where

$V=\{ v_i \mid i=1,2,\ldots,n\}$, is a set of all items, and

$E=\{(v_i , v_j) \mid v_i , v_j \in V\}$ defines that item v_i precedes item v_j

If $(v_i , v_j) \in E$, v_i is termed as a parent of v_j. This chapter only considers the graphs with no loops.

Figure 6.1 depicts an example of chained knowledge on a food web, where

V= {wolf, rabbit, plant, bird, grasshopper, …}, and

E= {(wolf, rabbit), (rabbit, plant), (bird, grasshopper),
(grasshopper, plant), …}

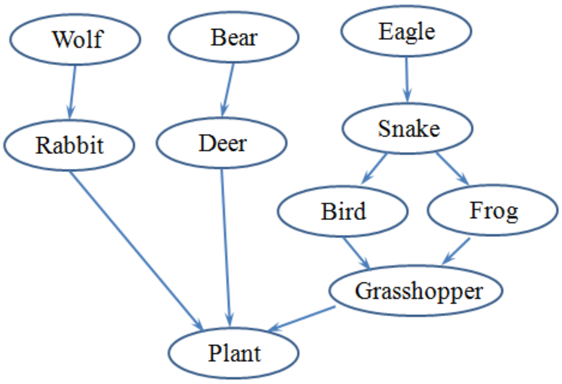


Figure 6.1 A Food Web

Since the knowledge is represented as a directed graph, graph algorithms can be applied to find a path for any two items, or to arrange a series of items in sequence if these items are in one food chain. Argumentative dialogues can be generated based on traversing graphs.

6.2 Argumentative Dialogues Automation

This section uses the food web as an example to illustrate the argumentation dialogue automation. To begin, an agent is built with food web knowledge represented as a directed graph KB. Then the agent can generate argumentative dialogues automatically by travelling through the directed graph. This agent can be applied to discuss food web topics with children. The following are the details for automation of the key argumentative dialogues:

- *Ask Questions*. The agent can generate questions automatically. For example, it can randomly choose some adjacent items in a chain, then displays these items in a random order, and asks, "Could you create a food chain for these items?"

- *Propose Answers.* For the given item set C={c_1, c_2, …, c_k }, the agent is able to construct the answer in this way: firstly find an item c_i that has no parent in C (because C has no loop, such an item must exist), put c_i as the first item in the food chain. If c_i eats c_j ($c_j \in$ C), put c_j as the next item in the food chain. This process can continue until no more items in C can be added into the food chain. This is a food chain started from c_i for only items in C. Remove the items appeared in the food chain constructed from C.

  If there are still items remaining in C, use the above method to construct another food chain started from c_i' and join it with the previous food chain(s). Continue the process until set C is empty. If the agent doesn't have the complete/correct knowledge, its answer may contain more than one sub chain combined together.

- *Proposal Acceptance / Rejection.* Upon the agent receiving an answer in the format of an array c[1], c[2], …,c[k], and if this answer is exactly the same as its own answer, it will say "I agree with you." Otherwise, it will start to attack or challenge this answer.

- *Information Seeking and Information Providing*. The agent will ask questions in the format of "Does $<v_i>$ eat $<v_j>$?" When the agent receives questions in the same format, if (v_i , v_j)$\in$KB, it will reply "Yes". Otherwise it will reply "No".

- *Challenge*. The agent will challenge others by asking questions in the format of "Why $<v_i>$ eats $<v_j>$ is wrong?" The others may think of a justification for this challenge, such as "because $<v_j>$ eats $<v_i>$" or "because $<v_j>$ eats $<v_{k1}>$ eats $<v_{k2}>$ … eats $<v_i>$" to provide a feeding relationship chain. The agent will not challenge others with questions like "Why $<v_i>$ eats $<v_j>$?" because that is the knowledge directly in or not in somebody's mind; no explanation is needed.

- *Justification*. Upon receiving a challenge in the format of "Why $<v_i>$ eats $<v_j>$ is wrong?" The agent will provide proof as follows:

  - If (v_i, v_j)$\in$KB, it will reply "$<v_i>$ eats $<v_j>$ is correct".

  - If it could find a path from v_j to v_i (which proves v_j eats v_i directly or indirectly), it will display "$<v_i>$ eats $<v_j>$ is wrong" and display the path to its counter party to prove $<v_i>$ cannot eat $<v_j>$. Because the "eat" and "be eaten" relationship cannot form a circle, so v_i eats v_j and v_j eats v_i (directly or indirectly) cannot exist at the same time.
  - If the agent cannot find proof that "$<v_i>$ eats $<v_j>$ is wrong", it will reply "Are you sure $<v_i>$ eats $<v_j>$?"

- *Attack*. For each relationship $<v_i>$ eats $<v_j>$ in the counter party's answer, if there is a path from v_j to v_i in KB, it will say "I think you are wrong. $<v_i>$ eats $<v_j>$ is not correct. Do you agree with me?"

- *Alternative Proposal Generation*. Being attacked by others, the agent will temporarily remove the knowledge being attacked and reconstruct a new answer if it can.

A typical argumentation dialogue between the agent and a learner is illustrated by an example in Figure 6.2.

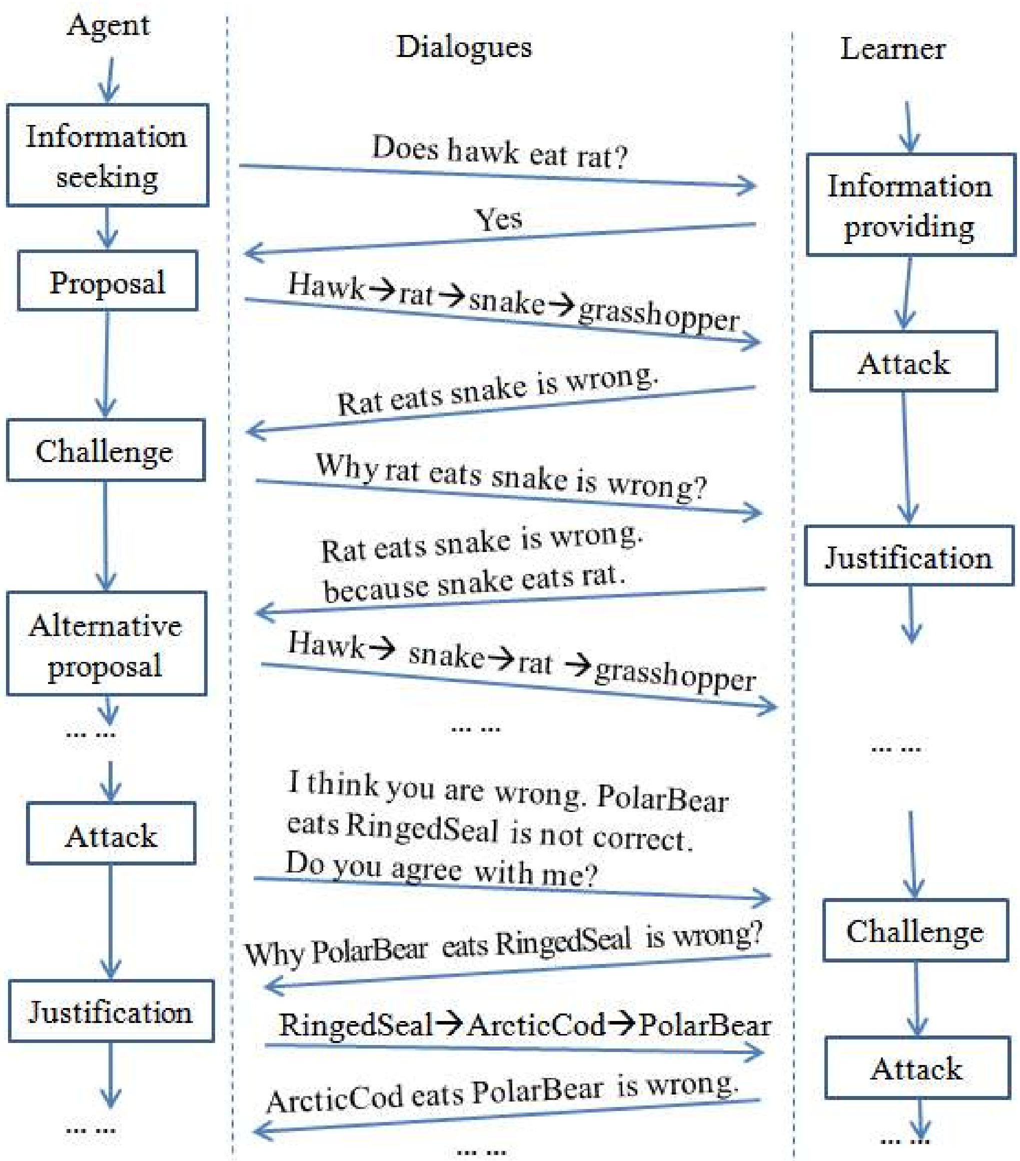


Figure 6.2 Sample Argumentative Dialogue

6.3 Remarks

This chapter presented the argumentative dialogue automation for agents with chained knowledge. The method can be used for argumentation on topics involving ordered sequences of items. Based on this model, a pilot learning system was developed and a study was carried out with children. The pilot system and the study will be presented in Part III of the thesis.

7. Argumentation Computing Model for Hierarchical Knowledge

This chapter introduces an argumentation model for hierarchical knowledge which describes the composition and decomposition relationships among components.

7.1 Hierarchical Knowledge Model

The *If…Then* alike rules represented as a_1, a_2, … $a_n \rightarrow a_0$ are widely used in expert systems. They are commonly understood as logical entailments. Such knowledge describes the statement that if a_1, a_2, … and a_n are all true, then a_0 is true. For example, *If* an animal is warm blooded, has fur, feeds young with milk, *Then* this animal is a mammal.

In addition to logical entailments, rule a_1, a_2, … $a_n \rightarrow a_0$ can also be used to represent a wide range of relationships among components, such as part and whole, or as a detailed description and abstract concept. For example, a_1, $a_2 \rightarrow a_0$ can be used to represent that if *lays eggs* and *can fly*, then this animal *is a bird*; it can be interpreted as a complex task a_0 which can be broken down to simpler sub tasks a_1 and a_2; it can also be used to represent a theory a_0 that can be decomposed to two basic elements a_1 and a_2.

One such rule shows the relationship between one component and other components. A set of such rules will show a hierarchical relationship among components. This kind of knowledge is called *Hierarchical Knowledge* in this thesis.

Hierarchical knowledge is represented by an *If…Then* alike rules. A knowledge base of hierarchical knowledge is the collection of *If…Then* rules. The knowledge base is defined as a 2-tuple $KB = <T, R>$, where

$$T = \{\ t_i \mid i = 1, 2, \ldots n.\ \}, \text{ and}$$
$$R = \{\ r_i\!:\ t_{i1}, t_{i2}, \ldots t_{ik} \rightarrow t_{i0} \mid t_{i0}, t_{i1}, \ldots t_{ik} \in T, i = 1, 2, \ldots m\}.$$

T is a component set, R is a rule set where each rule r_i describes a relationship between a component t_{i0} and other components t_{i1}, t_{i2}, … t_{ik}. Here, t_{i0} is termed as the head of a rule, t_{i1}, t_{i2}, … t_{ik} are termed as the tail of a rule. t_{i0} is also termed as the super component of t_{i1}, t_{i2}, … t_{ik}, and t_{i1}, t_{i2}, … t_{ik} are termed as the sub components of t_{i0}.A rule t_{i1}, t_{i2}, … t_{ik} → t_{i0} can have different interpretations in different contexts.

According to the super-sub component relationship, components in a knowledge base form a component hierarchy. Note that a component hierarchy is a network. It is not necessarily a tree. For example, if there is a rule set:

{ mammal, eats meat → carnivore;
mammal, has hooves → ungulate;
has fur, gives milk, warm blooded → mammal; }

The rules can be represented by a graph in Figure 7.1 to show the hierarchical relationships among the components.

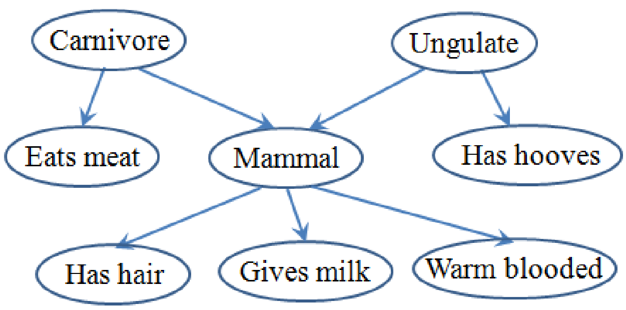


Figure 7.1 Hierarchical Structure of Rules

From the upper level of the hierarchy to the lower level, components are decomposed to sub components; and from the lower level to the upper level, components are composed to integrated components.

The following terms are defined in this chapter:

Atom Component – A component t is called an atom component if no rule exists such that it has t as the head and other components as the tail. Atom components are components that cannot be decomposed to other sub components. An atom component may describe a fundamental concept of a theory that cannot be detailed further; or a known fact that doesn't need to be proved from other components.

AtomSet – The set of atom components is noted as AtomSet.

Decomposition – Following some rules in *R*, a component *t* can be decomposed into sub components (not necessary atom components). The set of the sub components are called a decomposition of *t*. A component may have different decompositions.

For example,

$T = \{ t_1 =$ "carnivore", $t_2 =$ "mammal", $t_3 =$ "eats meat",

$t_4 =$ "has hair", $t_5 =$ "gives milk"$\}$

$R = \{ r_1: t_2, t_3 \rightarrow t_1 ; r_2: t_4, t_5 \rightarrow t_2 \}$

Here, $\{t_2, t_3\}$ and $\{t_4, t_5, t_3\}$ are all decompositions of t_1. Component t_1 can be further described by $\{t_2, t_3\}$ or $\{t_4, t_5, t_3\}$, which means that a carnivore is a mammal and eats meat, or a carnivore has hair, gives milk and eats meat.

The knowledge base is maintained periodically so that it has no loop decomposition and the decompositions are all minimal. No loop decomposition means a component's decomposition can not include the component itself. Formally, there is no decomposition Z of a component t such that $t \in Z$. Minimal decomposition means there is no decompositions Z_1 and Z_2 of a component t such that $Z_1 \subset Z_2$. i.e. the rules will not produce unnecessary sub components. For example, if $\{t_1, t_2\}$and $\{t_1, t_2, t_3\}$are two of the decompositions of a component, then it does not meet the minimal decomposition requirement, because t_3 is unnecessary.

7.2 Argumentation Automation

7.2.1 Backward Chaining and Forward Chaining

Inference over hierarchical knowledge is modeled in this research based on the forward chaining and backward chaining algorithms.

The forward chaining algorithm (Russell & Norvig, 2003) is used to determine whether a component *q* is entailed by a knowledge base. It begins from known facts in the knowledge base. If all the premises of an implication are known, then its conclusion is added to the set of known facts. For example, if an animal has hair, is warm blooded, feeds milk to its young are known and has hair, warm blooded, feeds milk→ mammal is a rule in the knowledge base, then mammal can be added. This process continues until the query *q* is added or until no further inferences can be made. The forward chaining method is useful for problems that with some known facts, one needs to find higher level components.

A forward chaining algorithm is provided below. Algorithm *Forward* can make inferences from the known components to draw conclusions. For example, if an animal is known to have fur, warm blooded and feed milk to its young, algorithm *Forward* can be used to query whether this animal is a mammal.

Algorithm. *Forward* (*Known*, *Query*)

Input: *Known*: a set of known components

Query: a set of components that need to be proved

Output: *Conclusions*: a set of components from *Query* that are proved

Justifications: a set of justifications for each component in *Conclusions*

// making inferences

Proved=*Known* // variable *Proved* records the proved components

HasChanges=*True*

// *HasChanges* indicates whether new components have been added in *Proved*

While *HasChanges* =*True*

HasChanges =*False*

For each rule r: $t_1, t_2, \ldots\ t_k \rightarrow t$ in the knowledge base

If $t_1, t_2, \ldots\ t_k$ are all in *Proved* and t is not in *Proved*

Add t in *Proved*

$t._{\mathrm{rule}}= r$ // $t._{\mathrm{rule}}$ records that conclusion t is made based on r

HasChanges =*True*

EndWhile

Conclusions=(*Proved* – *Known*)∩*Query*

// *Conclusions* is a set of new proved components that required in *Query*

// constructing justifications

Justifications = { }

For each *t* in *Conclusions*

$t_{\text{.justification}}$ ={ } // $t_{\text{.justification}}$ records the rules used to prove *t*

S={*t*} // *S* is a set records all intermediate components used to prove *t*

Do

If there is any component *t*' in *S* that some components in the tail of $t'_{\text{.rule}}$ are not in *S* and these components are not atoms, add these components in *S*

Until no more component is added

For each component *t*' in *S*, add $t'_{\text{.rule}}$ to $t_{\text{.justification}}$

Add $t_{\text{.justification}}$ to *Justifications*

End For

End of Algorithm.

The backward chaining algorithm (Russell & Norvig, 2003) works backwards from the queried component *q*. If *q* is known to be true, then no work is needed. Otherwise, the algorithm finds those implications in the knowledge base that conclude *q*. If all the premises of one of those implications can be proved true, then *q* is true. Backward chaining is a form of goal directed reasoning. It is useful for answering questions when higher level components are known and need to be broken down to low level components.

A backward chaining algorithm is provided below. This algorithm can decompose a component set *Target* to atom components. Assuming there is a knowledge base KB which contains *If … Then* alike rules. Firstly, the following variables are defined.

AtomComponents = *AtomSet* // the set of all atom components

Proved = Φ // a set used to record proved components

NotProvable = Φ // a set records the components that cannot be proved

Processing =Φ // the set of the components in decomposing process

AppliedAtoms = Φ // the set of atom components applied to decompose *Target*

AppliedRules = Φ // the set of the rules applied to decompose the *Target*

Undesired =Φ // the set of the components cannot be used in the decomposition

Algorithm *Backward* was then developed and is presented below. It can decompose variable *Target*, which is a set of components which intends to be decomposed to atom components. The rules used for the decomposition are recorded in variable *AppliedRules*, and the atom components to form the decomposition are recorded in variable *AppliedAtoms*.

Algorithm. Backward (*Target*)

For each *t* in *Target* Do

If *t* is in *Processing* or *NotProvable* , return *False*

If *t* is not in *Proved*

Add *t* in *Processing*

For each *r* with *t* as head and t $\notin$ *Undesired // r is t* $\rightarrow t_1, t_2, \dots t_k$

- If *t* is in *AtomComponents*

Remove *t* from *Processing*

Add *t* in *Proved* and *AppliedAtoms*

Goto *Next*

- ElseIf Decompose ($t_1, t_2, \dots t_k$)=*True*

Remove *t* from *Processing,*

Add *t* in *Proved*

Add *r* in *AppliedRules*

Goto *Next*

Remove *t* from *Processing*, add *t* to *NotProvable,* Return *False*

Next:

Return *True*

End of Algorithm.

Based on the *Forward* and *Backward* algorithms, argumentation dialogues can be automated. If there are some known components from a lower level in the hierarchy and there is a need to predict the higher level component, forward chaining algorithm is applied. If there is a higher level component known and this needs to be broken down to detailed lower level components, backward chaining algorithm is utilised.

7.2.2 Argumentative Dialogue Automation

Based on the forward chaining algorithm and backward chaining algorithm, argumentation dialogues of agents can be automated.

- Proposal Generation

If a problem is to break down a component *t*, use algorithm *Backward* (*t*) to obtain the decompositions. The decomposition will be the proposal, and the rules used are the justifications.

If a problem is to obtain higher level component based on the lower level components, use algorithm *Forward* to obtain the higher level component. The higher level component will be the proposal, and the rules used are the justifications.

- Proposal Acceptance or Rejection

When the agent receives a proposal, it will evaluate whether the proposal is correct based on its knowledge base. It will then decide to accept it or deny it.

- Attack

When the agent receives a rule that is different from what is in its knowledge base, it will generate attack dialogue to show its disagreement and present its rule.

- Information Seeking and Information Providing

When the agent wants to know the relationship among some components, it will generate an information seeking dialogue with the components. When the agent receives an information seeking dialogue, it will search its knowledge base and provide the corresponding rules about the components mentioned in the information seeking dialogue if the agent has such rules .

7.3 Examples

This section will provide examples to illustrate the proposed method.

7.3.1 Argumentation on Learning Activities

Learning activities negotiation is very important in creating a learner centered adaptive learning environment. Boomer (1992) stated that “if teachers set out to teach according to a planned curriculum, without engaging the interests of the students, the quality of learning will suffer. Student interest involves student investment and personal commitment. Negotiating the curriculum means deliberately planning to invite students to contribute to, and to modify, the educational program, so that they will have a real investment both in the learning journey and in the outcomes” (p. 13).

However, in current learning systems (e.g. e-learning systems or educational games), learning activities are either decided by the system (for example, the system decides the learning path even though sometimes it is based on the learners’ profile) or decided by the learner (for example, the learner selects game levels). Thus, on one hand, learners can select the levels they like to explore and systems have no control of the pedagogical direction. On the other hand, learners have to follow the systems’ learning path even if they are already very familiar with the content.

With the intelligent argumentation mechanism designed in this chapter, the system and the learner can negotiate the learning activities through argumentation. By exchanging the interests or needs of both parties and by recommendation or persuasion, learning activities that satisfy both the learner and the system are more likely to be reached.

This section will use an example to illustrate how the argumentation dialogues between the system and the learner are conducted. This example makes use of the *Backward* algorithm. Suppose the knowledge base of the agent is KB=<T, R>, where

T ={ t_1 = "have fun",
t_2 = "play games",
t_3 = "play with virtual characters",
t_4 = "play with virtual character Birdy",
t_5 = "play with virtual character Rabby",
t_6 = "have good mathematics skills",
t_7 = "have counting skills",
t_8 = "be able to do addition/subtraction",
t_9 = "have problem solving skills",
t_{10} = "play Birdy 1 2 3 Song",
t_{11} = "play Birdy Arithmetic Animation ",
t_{12} = "play How Many are They? (Story)",
t_{13} = "play Math World (Game)"
t_{14} = "play Math Chat Room" }

R= { r_1: $t_2 \rightarrow t_1$
r_2: $t_3 \rightarrow t_1$
r_3: $t_4 \rightarrow t_3$
r_4: $t_5 \rightarrow t_3$
r_5: $t_7, t_8 \rightarrow t_6$
r_6: $t_9 \rightarrow t_6$
r_7: $t_{10} \rightarrow t_7$
r_8: $t_{11} \rightarrow t_8$
r_9: $t_{12} \rightarrow t_9$
r_{10}: $t_{13}, t_{14} \rightarrow t_9$
r_{11}: $t_{13} \rightarrow t_2$
r_{12}: $t_{10} \rightarrow t_4$
r_{13}: $t_{11} \rightarrow t_4$

r_{14}: $t_{12} \rightarrow t_5$

}

The rule set *R* is depicted via a graph in Figure 7.2 for alternative understanding.

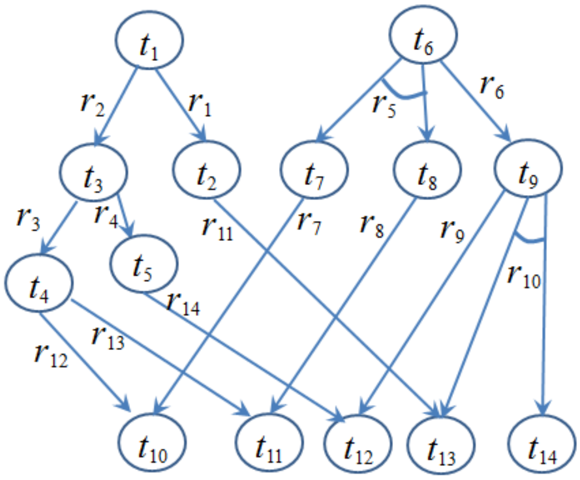


Figure 7.2 Graph Representation of the Rule Set

The sample argumentation dialogues are listed below. T stands for Tutor which is the learning system, L stands for the learner.

L: Let's play Birdy 1 2 3 Song.

(The Learner made a proposal by selecting a learning activity t_{10} in the educational game system. This selection is to be described in texts following a predefined format "Let's t_i ".)

T: Well, could you tell me why you want to play this?

(Suppose the Curriculum requirement is {t_8, t_9 }, the system hopes the learner's activity is relevant to the curriculum. System starts to ask learner's reason of the proposal).

L: Because I like to play with virtual character Birdy

(The Learner selected t_4 as the reason. The learner's selection t_i is explained by the system using a predefined format "Because I like t_i ", t_i can be any components in *T*)

T: This activity also meet your interest: play Birdy Arithmetic Animation.

(Activity t_{11} is generated by applying algorithm *Backward* ({t_4, t_8}) which combined the learner's interest of t_4 and the system's goal of t_8.)

L: OK. I accept.

(The learner selects a predefined dialogue "OK, I accept.")

7.3.2 Argumentation on Animal Classification

This example illustrates a discussion on animal classification questions. It makes use of the *Forward* algorithm.

Suppose the agent has a knowledge base KB=<T, R>, where

T ={ t_1 = "has hair",
t_2 = "warm blooded",
t_3 = "gives milk",
t_4 = "has feather",
t_5 = "lays eggs",
t_6 = "mammal",
t_7 = "bird",
t_8 = "penguin",
t_9 = "dog" }

R= { r_1: $t_1, t_2, t_3 \rightarrow t_6$,
r_2: $t_4, t_2, t_5 \rightarrow t_7$,
r_3: $t_8 \rightarrow t_4$,
r_4: $t_8 \rightarrow t_2$,
r_5: $t_8 \rightarrow t_5$,
r_6: $t_9 \rightarrow t_1$,
r_7: $t_9 \rightarrow t_2$,
r_8: $t_9 \rightarrow t_3$ }

A possible discussion between the agent and a learner could be (suppose the learner can input answers and reasons for answers by selecting some pre-defined options):

Agent: Do you know what animal class a penguin belongs to?

Learner: Mammal. Because penguin→has hair; penguin→warm blooded; has hair, warm blooded → mammal.

Agent: I don't agree with you. Penguins' bodies are covered with feathers. (The agent doesn't think penguins have hair, so it attacks the learner with its knowledge r_3.)

Learner: Bird. Because penguin→has feathers; penguin→warm blooded; has feathers, warm blooded → bird.

Agent: Your animal class is correct. But the reasons are not correct. My reason is penguin→has feathers; penguin→warm blooded; penguin→lays eggs; has feathers, warm blooded, lays eggs → bird.

Learner: Do you know what animal class a dog belongs to?

Agent: Mammal. Because dog→has hair; dog→warm blooded; dog→gives milk; has hair, warm blooded, gives milk→mammal. (The agent uses algorithm *Forward* ({dog}, {mammal, bird, fish}) proves that the animal is a mammal, hence it announces its answer and provides rule set $\{r_6, r_7, r_8, r_1\}$ used in reasoning as justification.)

7.4 Remarks

This chapter presented an argumentative dialogue automation model for agents with hierarchical knowledge. The rules in this model can be interpreted in different ways, such as logical entailment or task decomposition. As much of human knowledge is in hierarchical form, this model will have wide applications.

Based on this computing model, a learning system was developed for students to practice concepts of animal classification. An educational study was carried out with secondary school students. The system and the study are covered in Part III.

8. Argumentation Computing Model for Fuzzy Dynamic Knowledge

When a human argumentation process involves complex cognition, a more complex knowledge model is needed. In some argumentation processes there are supporting statements to prove the arguing position. For each supporting statement, there are further supporting statements. The supporting statements and the statements being supported form a causal effect network. Cognitive map is a model that represents cause and effect relationships. Although it is natural to use cognitive map as a tool to model argumentation (Yalaoui & Madjid, 2006), there is no existing cognitive map model to support argumentation automation.

Cognitive Mapping has some limitations in modeling human fuzzy concepts and dynamics. Fuzzy Cognitive Map (FCM) is an extension of cognitive map. It is effective in modeling dynamic and evolving systems. The first FCM based argumentation model was developed in this thesis.

8.1 Fuzzy Cognitive Map (FCM)

Cognitive Map (CM) was used by Axelrod (1976) for visualizing causal relationships among factors to facilitate human cognitive thinking in politics. Fuzzy Cognitive Map (FCM) (Kosko, 1986; Miao & Liu, 2000) is an extension of CM by introducing fuzzy weight to differentiate the strength of different causal relationships. There are several variations on FCM representations, the following one is used for argumentation modeling in this thesis.

Definition 8.1 Fuzzy Cognitive Map (FCM). An FCM is a tuple $< C, R >$, where

$C = \{c_i \mid i = 1,2, \ldots n\}$ is a set of vertices representing the concepts. The value of each concept $v(c_i)$ is 1, 0 or −1 to distinguish the three states of the concept.

$R = \{r_{i,j} \mid i, j = 1,2, \ldots n\}$ is a set of arcs representing the causal relationships among concepts. $r_{i,j}$ is an arc representing the causal effect from c_i to c_j.

In relationship $r_{i,j}$, c_i is the causal concept and c_j is the effect concept. The value of $r_{i\,j}$ can be a positive or negative number. A positive number represents the positive effect and a negative number represents the negative effect. The absolute value of the number represents the strength of the causal relationship.

The value of concept c_i is decided by the value of its causal concepts as shown in formula (8.1).

$$v(c_i) = \begin{cases} 1, \ if \ \sum_j v(c_j) \,.\, r_{j,i} > 0 \\ 0, \ if \ \sum_j v(c_j) \,.\, r_{j,i} = 0 \\ -1, \ if \ \sum_j v(c_j) \,.\, r_{j,i} < 0 \end{cases} \qquad \text{(Formula 8.1)}$$

"·" is arithmetic multiplication

For example, in the FCM shown in Figure 8.1, there are three concepts: grass, sheep and wolf. In this example, let the value 1, 0 and −1 of these concepts represent the status of "quantity increases", "quantity no changes" and "quantity decreases" of the concepts. So $v(c_3)$= 1 means "the sheep number increases". In this example, grass has positive effect on sheep and wolf has negative effect on sheep.

Figure 8.1 An Example of Fuzzy Cognitive Map

If $v(c_1)$=1 is known, the value of $v(c_3)$ can be obtained by applying formula (8.1):

$$v(c_3)=v(c_1).\ r_{1,3}=1\times(+2)=2>0,$$

$v(c_3)$= 1 means the increase of grass quantity will result in more sheep. If $v(c_1)$=1and $v(c_2)$=1 at the same time, then

$v(c_3)=v(c_1).\ r_{1,3}+ v(c_2).\ r_{2,3}=1\times(+2)+ 1\times(-5)= -3< 0,$

$v(c_3)= -1$ tells that the wolf 's negative effect ($r_{2,3}$) to sheep is stronger than the positive effect ($r_{1,3}$) of grass, so the overall number of sheep will decrease.

FCM inference is fast as it can be carried out through numeric calculation. Suppose all concepts' values are zero initially. If non-zero input values are given to some concepts, the values can be propagated to other concepts via the causal links. Other concepts will gradually be affected and change values through the inference. If the FCM has no circle (a circle is a closed path that starts from a concept, following some causal links and finally come back to itself) and the input values are static (i.e. a constant value not changing over times), after limited steps of inferences, the impact of the input values are fully propagated (Miao & Liu, 2000). The FCM reaches to a static status that all concepts keep a fixed value, unless different inputs emerge. FCMs with no circles are considered in this thesis.

Definition 8.2 Transitive Closure. Suppose an FCM has n concepts, the transitive closure of the FCM is an $n\times n$ matrix T, where

$$T[i,j] = \begin{cases} 1, i = j \text{ or there exists a directed path from } i \text{ to } j \\ 0, \text{otherwise} \end{cases}$$

The transitive closure is important in finding out which concept has causal effect on which concept. It can be calculated using the Floyd–Warshall algorithm (Hougardy, 2010; Floyd, 1962) by considering the FCM as a weighted directed graph with 1 as the weight of arc r_{ij} if $r_{ij}\in R$ and $+\infty$ as the weight otherwise.

Definition 8.3 Sub-FCM . Given an FCM F=<C, R>, the Sub-FCM of F is F'=<C', R'> where $C'\subseteq C$ and $R'=\{r_{ij} \mid r_{ij} \in R \text{ and } c_i, c_j \in C'\}$.

So a Sub-FCM can be identified only by concepts, as it contains all the relationships among these concepts. Inferences do not always involve the whole FCM, they might be limited in a sub-FCM.

8.2 FCM Based Argumentation

There has been no FCM based argumentation models in the literature. Computational models for argumentation are needed to generate the argumentative dialogues automatically.

The initial value of the concepts in an FCM represents the current context before the inference starts. These initial values are noted as *input* to the FCM. They are the initial facts for the inference. For example, $\{v(c_1)=1,\ v(c_2)=1\}$ is an input for the FCM in Figure 8.1.

Definition 8.4 Input. An input $\tilde{I}$ is a set of value assignment to concepts in an FCM F=<C, R>, written as

$$\tilde{I}=\{v(c_i)=x_i \mid c_i \in C' \subseteq C,\ x_i \in \{-1, +1\}\ \}.$$

For an FCM with no circle and with a given static input $\tilde{I}$, the values of other concepts can be gradually calculated. That is, if a concept belongs to $\tilde{I}$, its value is kept as what is assigned in $\tilde{I}$; otherwise, its value is calculated as based on its causal concepts following formula 8.1. After limited steps, the final values for all the concepts will be obtained (Miao & Liu, 2000).

Statements can be made on the values of concepts. In figure 8.1, "v(c_3) is 1" means "the sheep quantity increases". This kind of statement is termed a *claim*. Claims are descriptions on the status of concepts.

Definition 8.5 Claim. For an FCM F=<C, R>, a claim is a pair [c, x] where $c \in C$ is a concept, $x \in \{-1, 0, 1\}$ is the claimed value for c.

Claims can be made randomly, but only rational claims are considered as arguments. An argument is defined as a claim together with its proof.

Definition 8.6 Argument. Given an FCM F=<C, R> and an input $\tilde{I}$, an argument is a pair A=<S, α > where α is a claim and S is a Sub-FCM of F such that

1. α can be inferred from S with input $\tilde{I}$,
2. S is the minimal Sub-FCM which contains all relationships needed to obtain α from $\tilde{I}$.

If A = < S, α> is an argument, α is termed the claim and S the support of the argument. In the definition, condition 1 ensures S is the proof of α and condition 2 ensures no irrelevant relationships are involved in the proof.

Figure 8.2 is an FCM F=<C, R> about disease risk factors. The concepts and knowledge come from a research on diabetes (Giles et. al., 2007).

C= { c_1=Risk of Diabetes, c_2=Drink Alcohol,
c_3=Body Weight, c_4=Regular Exercise ,
c_5=Risk of Flu, c_6=Flu Vaccine}

R= { $r_{2,1}$= +2, $r_{3,1}$= +10, $r_{4,1}$= −2,
$r_{4,3}$= −4, $r_{4,5}$= −2, $r_{6,5}$= −10 }

Given the fact { v(c_4)=1}, <{$r_{4,3}$= −4, $r_{3,1}$= +10, $r_{4,1}$= −2}, [c_1 , −1]> is an argument, tells us that if a person does regular exercise, which will reduce the risk of diabetes and reduce the body weight; lost weight also reduces the risk of diabetes. So under the fact that the person has regular exercise, it can be claimed that his/her risk of diabetes is reduced.

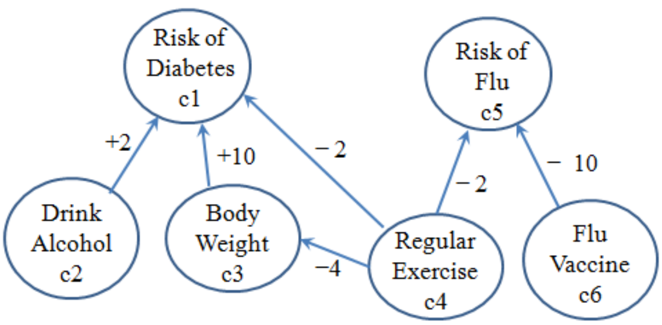


Figure 8.2 FCM on Disease Risk Factors

Suppose a claim on concept c is considered. For any concept c' in the FCM, if c' cannot be reached from concepts in $\tilde{I}$ or it cannot reach c, then it cannot be a factor to effect c. Only when c' is in a path from a concept in $\tilde{I}$ to c, does it contribute to the inference of $v(c)$. Based on this, algorithm *BuildArgument* was designed to work out $v(c)$ and its support. The algorithm makes use of the transitive closure of the FCM. For an FCM, the transitive closure is a constant matrix. It only needs to be re-calculated after adding or removing relationships.

Algorithm. BuildArgument (c)

Suppose:

F: F=< C, R> is an FCM

T: the transitive closure of F

$\tilde{I}$: input set

Parameter: c: a concept in F

Return: K: the claim about concept c

S: support for $v(c)$

$C_1=\{c' \mid c' \in C$ and there is $c_k \in \tilde{I}$ that $T[c_k, c']=1\}$

//concepts that can be reached from $\tilde{I}$

$C_2=\{c' \mid c' \in \mathrm{C}$ and $T[c', c]=1\}$

//concepts that can reach c

$C_S= C_1 \cap C_2$

If $C_S \neq \{\}$

S=<C_S,R_S> where $R_s=\{r_{ij} \mid r_{ij} \in R$ and $c_i, c_j \in C_S\}$

Calculate $v(c)$ based on S and $\tilde{I}$

K=[c, $v(c)$]

Return K and S

Else

S= ∅, K = ∅ //∅ means undefined

EndIf

End of Algorithm.

For example, in Figure 8.2, if $\tilde{I}=\{v(c_4)=1, v(c_6)=1\}$, and a claim on c_1 is to be made. The algorithm can find that c_1, c_3 and c_4 are in the path from $\tilde{I}$ to c_1. So $C_S=\{c_1, c_3, c_4\}$ and $S=<C_S, R>$ where $R=\{r_{3,1}, r_{4,1}, r_{4,3}\}$. Calculating from S and $\tilde{I}$, claim $[c_1, -1]$ is obtained. c_2 cannot be reached from $\tilde{I}$ and c_5 cannot reach c_1, so c_2 and c_5 are not in S.

It is important to define how an argument disagrees with another in an argumentation model. An argument that disagrees with another argument is described as a counterargument. Counterargument is usually captured with the notions of undercutting and rebuttal in the literatures (Parsons & McBurney, 2003; Besnard & Hunter, 2009). Some arguments directly oppose the support of others, which is called undercutting. The most direct form of a conflict between arguments is when two arguments have opposite claims. This is called rebuttal.

In the FCM based argumentation model, counterarguments can be built in three ways: disagree with the claim, disagree with the causal relationships in the support, and disagree with the values of concepts inferred from the support. Algorithm *BuildAttack* is to build attack to other's argument. Suppose both parties share the same understanding on the input set.

Algorithm. BuildAttack (F_B, $[c, x]$)

Suppose:

F: $F=< C, R>$ is own FCM

T: the transitive closure of F

$\tilde{I}$: input set

Parameter: $[c, x]$: opponent's claim

F_B: $F_B=<C_B,R_B>$, opponent's support for the claim

Return: responses to opponent with disagreements

// disagree with relationships in FCM

For each $r^B_{ij} \in R_B$

If $(r^B_{ij} \cdot r_{ij} < 0)$

Return disagreement with r^B_{ij}, show its own opinion r_{ij} to opponent

EndIf

EndFor

// disagree with values of concepts other than c,
// response with the concept value and support
Based on $\tilde{I}$ and F_{B}, calculate values for concepts in C_{B},
For each concept $c_{\mathrm{k}} \in C_{\mathrm{B}} - \{c\}$ with value v(c_{k}),
    Call BuildArgument(c_{k}) to get claim [c_{k}, x_{k}] and support S
    If ($x_{\mathrm{k}} \neq$v(c_{k}))
        Return disagreement with [c_{k}, v(c_{k})], show its own claim [c_{k}, x_{k}] and support S to opponent
    EndIf
EndFor
// disagree with the claim
Call BuildArgument(c) to get claim [c, x_{k}] and support S
If ($x_{\mathrm{k}} \neq x$)
    Return disagreement with [c, x], show its own claim [c, x_{k}] and support S to opponent
EndIf
End of Algorithm.

In the BuildAttack algorithm, the algorithm attacks the opponent's reasoning logic first. If no conflicts are found from the opponent's reasoning logic, then attack the conclusion. So the attack algorithm encourages the opponent to rethink his/her reasoning processes.

8.3 Argumentation Automation

In order for the intelligent agents to communicate with humans, descriptions are provided for all the concepts, values and relationships. For example, c_{x} is described as "grass", the status 1 of c_{x} is described as "grows well". The descriptions were noted with angle brackets. Similarly, "<c_{y}>" means "sheep", "<c_{x}> <c_{x} status 1>" means "grass grows well", "<c_{y}> <c_{y} status −1>" means "sheep number decreases". If r_{xy}= +5 then <r_{xy}> means "grass grows well which results in sheep number increases, strength 5 / grass grows badly which results in sheep number decreases, strength 5" (There are two identical descriptions for r_{xy}. If the value of c_{x} is known, only one description is used for r_{xy}). A claim [c_y , −1] can be represented as "<c_y> <c_y status −1>" which means "sheep number decreases". With these descriptions, the virtual characters can talk to learners in a way similar to natural language. The learners communicate with the system by selecting concepts from dropdown boxes and entering values.

Argumentation dialogues can be automated:

- *Question*. The agent can generate questions automatically. It will randomly choose two concepts c_i, $c_j \in C$, and two states of the concepts v_i, $v_j \in \{1,-1\}$, then generate questions which follow the template "if <c_i> < c_i status v_i>, <c_j> <c_j status v_j>, what will happen to <c_k>?" The questions will be mapped to sentences as "if grass grows well, wolf number increases, what will happen to sheep?"

- *Proposal.* To the agent, a proposal is an answer to a question. The agent can obtain the value of c_k when the input is v(c_i)= v_i and v(c_j)= v_j by calling BuildArgument (c_k).

- *Acceptance / Rejection*. If the learner's answer is the same as the agent's, the agent will say "I agree with you." Otherwise, the agent will start to challenge the learner.

- *Information Seeking and Information Providing*. The agent will ask questions in the format of "What is the relationship from <c_i> to <c_j>?" to others. For other's question in the same format, the agent will reply <$r_{i,j}$> (the description of $r_{i,j}$) if $r_{i,j}$ exists in FCM_{Peedy}. Otherwise, the agent will reply "Sorry, I have no idea."

- *Challenge*. When receiving a claim [c, v], if the agent call *BuildArgument* and obtains a different claim [c, v'], it will challenge others by asking "Why <c> < c status v>?" .

- *Justification*. When receiving a challenge in the format of "Why <c> < c status v>?", the agent will call *BuildArgument*(c) then display the support S.

- *Attack.* When receiving justification from others, the agent will call *BuildAttack* in response to others.

8.4 Examples

The agent's dialogues encourage thinking when it is applied to facilitate argumentative learning with human learners. When the agent receives a proposal that it disagrees with it will challenge the learner by asking for proof, instead of attacking the proposal directly; when the agent receives a justification, it will attack the learner's reasoning logic first, then attack the claim when it cannot find mistakes from the learner's reasoning logic. These all encourage the learner to explore more on the reasoning processes.

Example 1:

Below is an example dialogue to illustrate the automated argumentation between the agent and a learner:

Tutor: If grass grows badly, infectious disease in wolf increases, what will happen to sheep?

Learner: (Proposal) Sheep number decreases. (The learner proposes this claim by selecting "number increases" from the dropdown box containing all the possible values for sheep: number increases, number decreases, number no changes.)

Agent: (Challenge) Why would sheep numbers decrease?

Learner: (Justification) Grass──(+5)──> Sheep (The learner constructs this support by selecting concepts from the dropdown boxes and entering integer values ranging from −10 to 10. The learner can construct more than one relationship.)

Agent: (Attack) I think sheep number increases. Because infectious disease in wolf increases which results in wolf number decreases, strength 9; wolf number decreases which results in sheep number increases, strength 5; grass grows badly which results in sheep number decreases, strength 2. (the agent also displays the following text in a text area or speech balloon as references for the learner:

Infectious disease in wolf—— (−9) ——>Wolf

Wolf —— (−5) ——> Sheep

Grass —— (+2) ——> Sheep

They are the support for Peedy's claim.)

In this scenario, the agent’s challenge encourages the learner to explain the reasons for his/her claim. Generating explanations can lead to deeper understanding. Peedy's attack leads the learner to think about other indirect factors (such as wolf) that affect the quantity of sheep.

Example 2:

Tutor: If dietary fibre increases in food, what will happen to risk of diabetes?

Learner: (Proposal) Risk of diabetes increases.

Agent: (Challenge) Why does the risk of diabetes increase?

Learner:(Justification)

Dietary fibre—— (+5) ——>Body weight

Body weight —— (+9) ——> Risk of diabetes

Agent: (Attack) I disagree with you on the relationship between dietary fibre and body weight. I think "dietary fibre increases in food which results in body weight decreases, strength 5", or "dietary fibre decreases in food which results in body weight increases, strength 5". (The agent also displays the following in a text area or speech baloon:

Dietary fibre —— (−5) ——>Body weight

This is the knowledge of the agent.)

Learner:(Proposal with justification)

Risk of diabetes decreases.

Dietary fibre—— (−1) ——>Body weight

Body weight —— (+9) ——> Risk of diabetes

Agent: (Acceptance) I agree with you.

In this scenario, the learner might think that increasing food intake will increase body weight. The agent’s attack brings in the conflict idea that increasing fibre intake will decrease body weight. This conflict idea might stimulate the learner to adjust his/her existing viewpoint on fibre, or explore the impacts of different diet (e.g. sugar, fat, animal protein) to body weight. Such argumentation provides an environment rich in cognitive conflicts, and cognitive conflict is an important stimulus for learning.

8.5 Remarks

Fuzzy descriptions and dynamic causal systems widely exist in human cognition and the knowledge process. However, no such model has been developed for argumentation in the literature. This thesis developed the first FCM based argumentation model.

The FCM based argumentation model developed in this thesis has many advantages: Firstly, human's domain knowledge and the supportive structure of arguments are all represented by an FCM. Argumentation processes can be generated through numeric inferences which is faster than rule based reasoning. Secondly, this model adopts fuzzy concepts which can model the dynamic knowledge more accurately. The effects among concepts are either true (exist) or false (do not exist) in classical logic, which cannot model the real world accurately. For example, nice grass has a positive effect on sheep, and the wolf population growth has negative effect on sheep. In classical logic, it is hard to decide the effect on sheep when both factors exist. FCM can represent the strength of the effect, so it is efficient to evaluate the impacts that come from different factors and obtain an overall effect.

9. Argumentation Computing Model for Collaborative Optimisation

Collaborative argumentation is effective in problem solving. When a group of people solve a problem collaboratively, they put forth their own opinions and also consider other's opinions. This enables them to explore a wide range of possibilities. During the argumentation process, they critique and evaluate the different opinions. Therefore participants are able to exam the advantages and disadvantages of different approach and choose an optimal solution based on the collective knowledge of the group. This chapter presents a computing model to automate argumentation dialogues for optimal solution construction.

9.1 Argumentation Approaches

Collaborative argumentation in learning means to negotiate mutually accepted understanding to theories or solutions to problems. Negotiation strategies affect the outcomes of the argumentations.

- Position Based Negotiation / Non-Collaborative Argumentation

Traditional negotiation strategy is mainly *Position Based Negotiation* which focuses on positions, such as price, time, quantity, etc. In a position based negotiation, the negotiation parties are firmly committed to their arguing positions. A position tells others what a negotiation party wants, and reflects his/her point of view on a certain issue. It does not convey to others why he/she asks for the position; nor does it provide others the opportunity to take his/her interests into account. In position based negotiation, the involved parties argue only their positions. Their underlying reasons for their position may never be explicitly mentioned. If there is no agreement on the arguing position, the negotiation fails.

If one applies this negotiation strategy in argumentative learning, each party will insist on their own position. They will not exchange information with others, nor will they consider others' knowledge. This is not a collaborative argumentation process. It is more like a debate.

- Interest Based Negotiation / Collaborative Argumentation

Interest Based Negotiation (Fisher & Ury, 1983) focuses on satisfying the underlying reasons rather than meeting the stated positions. The interests of a negotiation party tell others why they want something. The interests reflect the negotiator's underlying concerns, needs or desires behind an issue. In interest based negotiation, the interests of participants are identified and explored, which helps each party to understand the others' perspectives. By discussing the reasons behind the positions and thinking of alternatives, mutually acceptable agreement is more likely to be achieved.

Negotiating certain issues is similar to multiple parties attempting to divide a pie. In position based negotiation, the primary concern is to satisfy one's own desires; meeting the needs of the other side is unimportant; and everybody wants to take as big a slice of the pie as possible. However, in interest based negotiation, one seeks an arrangement that ensures both sides a fair measure of satisfaction; everybody views negotiation as an inventive process for integrating interests and generating new opportunities; and when it comes time to slice the pie, all participants want to hold the knife together to affirm mutual trust and good faith, all wanting to achieve a win-win outcome. Negotiation with this understanding is a method for adjusting the balance to ensure both fairness and mutual gain (Marcus, Dorn & McNulty, 2011).

When applying this negotiation strategy in argumentative learning, all the parties will share knowledge and build mutual understandings or solutions. This is a collaborative argumentation process.

- Cooperative-Competitive Negotiation/Collaborative-Optimal Seeking Argumentation

Traditionally, people use negotiation as a means of compromise in order to reach agreement. In general, negotiation is defined as an interactive process which aims to achieve an agreement among multiple parties. All parties have their own goals and work for their own interests, so they are competitive among each other by nature. In some common environment, it is desirable for the parties to cooperate in order to achieve efficient, mutually beneficial, win-win solutions. That is to say, cooperation and competition are both very important in these negotiation tasks.

Cooperative-Competitive Negotiation (Tao et. al., 2009 & 2011) is a more comprehensive interest based negotiation where the negotiation parties use their knowledge jointly to create an optimal solution acceptable to all parties. During the negotiation, negotiators can share information to have a more comprehensive view, they can exchange goals to pursue mutual benefits and they can share capabilities to develop cooperative solutions. Meanwhile, each party works towards their own benefits and tries to find optimal solutions among competitive options. Hence, this is a new model of negotiation and it advances the existing interest based negotiation by introducing cooperative-competitive characteristics.

Cooperative-competitive negotiation strategy focuses on finding optimal solutions. This strategy gives negotiation parties opportunities to plan on the whole (even if they are self interested) and make full use of all parties' capabilities and knowledge to maximise the overall benefit. By applying this negotiation strategy in argumentative learning, it would enable multi parties to share knowledge and collaboratively find optimal solutions. This kind of argumentation is called collaborative – optimal seeking argumentation in this research. This chapter is to automate this kind of argumentation.

9.2 Knowledge Model

Collaborative – optimal seeking argumentation is used for finding optimal solutions through argumentation. The problem to be solved can be broken down to simpler problems. The simpler problems may be further broken down. To automate the optimal seeking argumentation, a knowledge model is needed to represent the components of problems and how complex components can be decomposed to elementary components, where the elementary components can be achieved in a more straight forward manner.

An agent that can argue for optimal solutions should have a knowledge base to store the components of problems and the decomposition relationships among the components. The argumentative agent's knowledge base is defined as a 3-tuple $KB = \langle T, R, C \rangle$, where

$$T = \{ t_i \mid i = 1, 2, \ldots n. \},$$
$$R = \{ r_i: t_{i0} \rightarrow t_{i1}, t_{i2}, \ldots t_{ik} \mid t_{i0}, t_{i1}, \ldots t_{ik} \in T, i = 1, 2, \ldots m\},$$
$$C = \{c(t) \mid t \in T\}.$$

T is a component set. R is a relationship set where each relationship r_i describes how a super component is decomposed to sub components. t_{i0} is termed as the head of a relationship, $t_{i1}, t_{i2}, \ldots t_{ik}$ are termed as the tail of a relationship. C is a criteria set which will be discussed later in this section. $c(t)$ is the criteria values that used to evaluate t, such as cost, safety, quality and etc.

According to the super-sub component relationship, components of a problem form a component hierarchy, which is a network and not necessarily a tree.

- Atom Component and Composite Component

A component t is called an atom component if there doesn't exist a decomposition relationship such that it has t as its head and other components as its tail. Atom components are components that cannot be decomposed to other sub components. An atom component may describe a fundamental concept of a theory that cannot be detailed further; or a simple task that can be finished directly, therefore doesn't need to consider different options to optimize the implementation. Except the atom components, other components in the knowledge base are termed composite components.

Since different agent has different knowledge about the world around, an atom component of one agent maybe a composite component of another agent. There are similar cases for human beings. For example, to one person, a plant is made up of flowers, leaves, stem and root. To another person, the flower can be further described in detailed parts such as petals, as well as stigma, style and ovary for female parts, and anther and filament for male parts. For another example, for a company director, obtaining a house is an atom component of his/her plan of setting up a new business in a suburb. However, it is a composite component for a builder which may contain a sub component of buying a block of land and a sub component of building a house.

- Decomposition

Following some relationship in *R*, a component *t* can be decomposed into sub components (not necessarily atom components). The set of sub components are called a decomposition of *t*. A component may have different decompositions.

A component is achievable if it can be decomposed to a set of atom components, and the atom components are all acceptable or practical.

For example, when discussing on how to take care of a plant,

T ={ t_1 = "take care of a plant",
t_2 = "sufficient water",
t_3 = "access to light",
t_4 = "watering often",
t_5 = "expose to sunlight",
t_6 = "plant near a river" }
R= { r_1: $t_1 \rightarrow t_2, t_3$, r_2: $t_2 \rightarrow t_4$, r_3: $t_3 \rightarrow t_5$, r_4: $t_2 \rightarrow t_6$ }

Here, {t_2, t_3}, {t_4, t_3}, {t_4, t_5} and {t_6, t_5} are all decompositions of t_1. Component t_1 can be achieved by { t_4 , t_5} or { t_6 , t_5} , i.e. to take care of a plant, one solution is to water it often and expose it to sunlight. Another solution is to plant it near a river and make sure it is exposed to sunlight.

- Criteria of Components

There are several criteria to describe a component, such as price, quality, benefits etc. The criteria of a component t is defined as a vector (v_1, v_2, … , v_n) from a domain vector (D_1, D_2, …, D_n).

$$c(t) = (v_1, v_2, \ldots, v_n) \in (D_1, D_2, \ldots, D_n), D_i \text{ is the domain of } v_i.$$

For example, if a component t is "build a robot". $c(t)$=($200, very light) from domain (R^+, {very light, light, heavy, very heavy}). This may mean, the price is $200 from a positive real number domain, and the body weight is very light from a set domain which contains descriptive variables regarding body weight.

The values in the criteria allow argumentation parties to make comparisons between different solutions and to choose an optimal one. Suppose agents are able to compare the preference among multi-criteria (In & Olson, 2004). For example a simple way could be by using weight to combine all dimensions in the criteria to a single value then compare this single value.

In the rest of this chapter, criterion is considered as a single value and it supposes a smaller value is better than a larger one, without loss of generality. For composite components, they have different decompositions, each having different criteria values. c(t) denotes the smallest among them, or a lower bound of them. The estimated criteria of composite components can be used as a heuristic in search algorithms. Choosing a small estimated value can make sure the component has more opportunity to be considered. For atom components, c(t) is the actual criteria value. If a component is not acceptable or practical, c(t)= $+\infty$.

- AND/OR Graph Representation of Knowledge Base

For easy presentation of algorithms, a graphical representation of the knowledge base is defined by using an AND/OR Graph. An AND/OR Graph (Nilsson, 1982) is a hyper graph. Instead of arcs connecting pairs of nodes in the graph, there are hyper arcs connecting a parent node with a set of successor nodes. These hyper arcs are called connectors. Suppose KB=<T_{KB}, R, C> and its AND/OR Graph representation is Q=(T_Q, E, C), where

$T_Q = T_{KB}$, i.e. nodes in Q are components in KB,

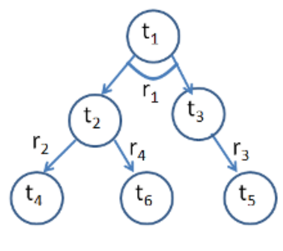
E={ (t_{i0} , { t_{i1}, t_{i2}, … t_{ik} }) | $t_{i0} \rightarrow t_{i1}, t_{i2}, \ldots t_{ik} \in R$}, i.e. connectors in Q are decomposition rules in KB.

Leaf nodes in Q are atom components in KB.

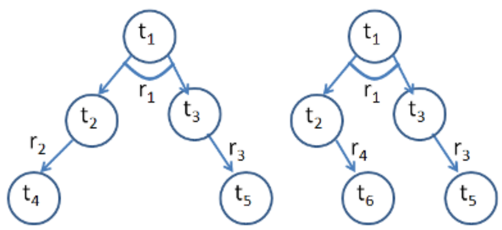
- Solution Graph and Partial Solution Graph

In an AND/OR graph Q, a node t can be expanded to its successors by following exactly one connector. Each successor node can be expanded further in the same way and a graph rooted on t will be generated. The graph is called a *Partial Solution Graph* of t. If all the leaves of the partial solution graph are the leaves of Q, the partial solution graph is a solution graph. Partial solution graph and solution graph are graph representations of component decompositions.

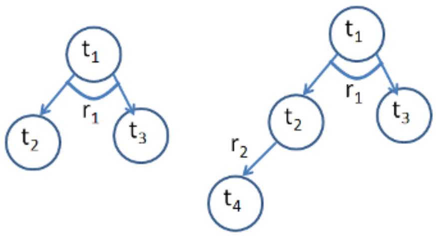
In the above plant example, the AND/OR Graph representation of the knowledge base is shown in Figure 9.1(a). Two possible solution graphs are shown in Figure 9.1(b) and two partial solution graphs are shown in Figure 9.1(c).



(a) Graph Representation of KB



(b) Possible Solution Graphs



(c) Partial Solution Graphs

Figure 9.1 Graph Representation of Knowledge

Suppose the knowledge base of an agent is maintained periodically so that it has no loop decomposition and the decompositions are all minimal. The requirement of non loop decomposition means a component's decomposition can not include the component itself. Formally, there is no decomposition Z of a component t such that $t \in Z$. Minimal decomposition means there is no decompositions Z_1 and Z_2 of a component t such that $Z_1 \subset Z_2$. i.e. the rules will not produce unnecessary sub components. For example, if $\{t_1, t_2\}$ and $\{t_1, t_2, t_3\}$ are two of the decompositions of a component, then it does not meet the minimal decomposition requirement because t_3 is unnecessary.

9.3 Argumentation Automation

Firstly, a method to decompose a component, named *t,* to atom components (which correspond to basic acceptable or practical components) is developed by using a heuristic search strategy.

Suppose there is a knowledge base KB which contains relationships about component decompositions. For an atom component, if it is acceptable or practical, c(t) is the actual criteria value. If it is not acceptable or practical, c(t)= $+\infty$. Suppose the agent is able to perform multiple criteria preference analysis (In & Olson, 2004) and find the solution with the optimal criteria. For simplicity, the smaller criteria solution is considered as the better one.

Algorithm *Decompose* listed below will decompose t to atom components based on Nilsson's AO* algorithm (Nilsson, 1982). During the process of creating a search graph and marking a partial solution graph, the algorithm is gradually approaching to the optimal solution by using the criteria of each component as heuristics. The algorithm starts from *t*, selects and marks the connector with the smallest criteria as the temporary best solution for *t*. It then continues to decompose the sub-components of *t*. Whenever new information that makes changes to the criteria of a component is encountered, the algorithm will propagate the newly discovered information up the component hierarchy, re-calculate the criteria and make a new selection among connectors.

Algorithm. Decompose (*t*)

1. Create a search graph Q, Q ={ *t* }
   If *t* is an atom component, label *t* as *Solved*. cost (*t*) = c (*t*)

2. Until *t* is labeled *Solved* , or cost (t) = +∞ do

   a. // Select node to expand
      Compute a partial solution graph H in Q by tracing down marked connectors in Q from *t* (marks will be discussed later in step 2c of this algorithm)
      Select any non terminal leaf node *n* of H

   b. // Expand node *n* by generating its successors
      If $n \rightarrow n_1, n_2 \ldots n_k \in R$, add all sub components of *n* to Q
      For successors n_j not occurring in Q, cost(n_j)= c(n_j)
      If n_j is leaf, label *Solved.*

   c. // Propagate the newly discovered information up the graph
      S={*n*}   // *S* is a set of nodes that have been labeled solved
                               //or whose cost have been changed
      Until *S* is empty do
            Remove a node *m* (*m* has no descendants in S) from S

            // Compute the cost of each *m*'s decomposition

// cost (m) is the minimum cost among all connectors

For each connector $m \rightarrow m_{i1}, m_{i2}, \ldots, m_{ik}$

$\text{Cost}_i\ (m) = \text{cost}(m_{i1})+\text{cost}(m_{i2})+\ldots+\text{cost}(m_{ik})$

$\text{Cost}(m)=\min_i\ (\text{cost}_i\ (m))$

Mark the best path out of *m* by marking the connector with minimum cost

If all nodes connected to *m* through this new marked connector has been labeled *Solved*, label *m Solved*

If *m* solved or cost of *m* just changed, add all of the ancestors of *m* to *S*

3. If *t* is labeled *Solved*, return *True*, else return *False*

End of Algorithm.

With the *Decompose* algorithm, argumentation dialogues can be automated. Suppose an argumentative agent encounters a task *t*. If algorithm Decompose (*t*) returns *True*, the partial solution graph H is the optimal decomposition for component *t*. The atom components of H form the optimal solution of *t*, and the atom components can be generated as a proposal for others. When an agent receives a proposal, it will evaluate it and then decide whether to accept or deny it.

Upon receiving new knowledge from other agent(s), the agent will carry out a temporary knowledge base revision by adding the new knowledge to its existing knowledge base. Whether to incorporate the new knowledge permanently in the knowledge base will be decided by the agent through other mechanisms. The temporary knowledge base revision can be implemented by algorithm *KBRevision* listed below.

Suppose the knowledge base of the agent is KB=<*T*, *R*, *C*>, and the agent will revise the KB to incorporate new knowledge noted as KB'=< *T*', *R'*, *C'* >.

Algorithm. KBRevision ( )

For each new component in T ', add into T

For each new relationship in R', add into R if it doesn't cause loop decomposition

For each new criteria $c_{new}(n)$

If there is no criteria of n exists in KB, add $c_{new}(n)$ into C

If there is criteria $c_{old}(n)$ exists and $c_{old}(n) \neq c_{new}(n)$,

a. $c(n) = \min(c_{old}(n), c_{new}(n))$, which makes sure the low criteria solution has the opportunity to be selected.

b. propagate the new criteria to upper lever components (details will be omitted here as it is similar as what have been done in algorithm Decompose, step 2.c.)

c. If n is an atom in KB'

Add $n \rightarrow n'$ in KB, $c(n')=c_{new}(n)$

If n is an atom in KB

Add $n \rightarrow n''$ in KB, $c(n'')=c_{old}(n)$

End of Algorithm.

After receiving new information from another agent, the agent can perform algorithm KBRevision. Based on the newly built temporary knowledge base, if Decompose (t) returns *True*, the partial solution graph H is the solution to t. This solution is a collaborative solution because it is constructed on both parties' knowledge. It is also an optimal solution because it selected the solution marked with the best criteria.

- Correctness of the Method

If no solution for t, i.e. all decompositions of t contain not acceptable or not practical atom components, according to the algorithm cost(t) will reach $+\infty$, so the algorithm returns false.

If there is a solution from t to a set of atom components, and if for all component decomposition relationship $n \rightarrow n_1, n_2 \ldots n_k$, $c(n) \leq c(n_1)+ c(n_2) \ldots + c(n_k)$, the algorithm will terminate and return True. By tracing the marks, graph H is the optimal solution. cost(t) is the cost of the solution.

Hence, with the restriction that for any composite component *t*, the estimated criteria c(*t*) is always smaller than the sum of its sub components, i.e. the estimated criteria is always smaller than the real criteria, the algorithm can find the optimal solution.

By limiting the estimated criteria of a component *t* to be not bigger than the actual criteria, the actual low criteria solution of *t* will have the opportunity to be explored. However, if the estimated criteria are much lower than the actual criteria, this will direct the algorithm to spend time exploring this seemingly optimal but actually not optimal branch. Hence a good estimation will reduce the unnecessary search and find the optimal solution.

9.4 Example

This section illustrates the argumentation computing model with an example. Let's assume a group of students want to build a robot vehicle to deliver mail within a secondary school campus. Some relevant considerations include: energy source, robot body and navigation system. The argumentation starts when students discuss the design of the robot.

- Non-collaborative Argumentation

In a non-collaborative argumentation, the students' discussion might turn into a debate, as they all insist on their own opinion. For example:

> *A: Let's design a robot together. I think we should use a petrol engine as the energy power.*
> *B: No, petrol engine is not environmentally friendly. We should use solar cells.*
> *A: I don't agree. Solar cells are not powerful enough.*
> *B: But petrol engine will cause air pollution.*

In this case, neither student A nor student B would like to give in, so no agreed solution was reached.

- Collaborative Argumentation

In a collaborative argumentation, students may discuss the reasons for their design options, and share knowledge with each other. They may use both parties' knowledge to find a solution that satisfies both parties' requirements. For example:

> *A: Let's design a robot together. I think we should use plastic to build the robot's body and use a petrol engine as the energy power.*
>
> *B: No, petrol engine is not environmentally friendly. My design is to use steel to build the robot's body and use solar cells as the energy source.*
>
> *A: I don't agree. A steel body is too heavy. Why not use plastic body and solar cells?*
>
> *B: Good idea.*

In this case, student A and student B reached an agreed solution by using shared knowledge.

- Collaborative Optimal Seeking Argumentation

In the design of a robot vehicle the group may need to consider many factors, such as cost, complexity, development time and so on. The design process is to find an optimal plan. Now let's use the proposed collaborative optimal seeking argumentation model to illustrate the argumentative design processes. Only price is considered as a criterion to evaluate different options. If many criteria need to be evaluated, they can be combined into one value by using utility functions. For simplicity of presentation, some symbols are defined to represent the components involved.

t_1 : Robot vehicle

t_2 : Energy source

t_3: Robot body

t_4 : Smart navigation system

t_5 : Petrol engine

t_6 : Steel body

t_7 : Plastic body

t_8 : Buy a commercial navigation system

t_9 : Solar cells

t_{10}: Develop a navigation system

The interpretation between computer symbols and natural language can be programmed by mapping to predefined templates. For example,

- Component t_1 can be mapped to “robot vehicle”
- Rule $t_1 \rightarrow t_2, t_3, t_4$ can be mapped to “robot vehicle *can be achieved by* energy source, robot body, smart navigation system”
- Proposal dialogue (t_5 , t_6) can be mapped to “*I propose* petrol engine, steel body”
- Proposal dialogue (t_5, t_6) with justification ($t_1 \rightarrow t_5, t_6$) can be mapped to “*I propose* petrol engine, steel body, *because* robot vehicle *can be achieved by* petrol engine, steel body”

With the interpretation, human users can easily understand the meaning of the agent’s arguments. Human users can also generate arguments by selecting components or constructing rules. For example, a user can express his/her view of using solar cells as the robot’s energy source by selecting component (t_9) as the proposal, and selecting t_2, the arrow and t_9 to form a formula ($t_2 \rightarrow t_9$) as the justification.

To focus on the mechanisms of argumentative dialogue generation, this illustration demonstrates the argumentation among four agents A, B, C and D on the design of a robot vehicle, without showing the translations between natural language and computer symbols.

The knowledge bases of the four agents are noted as KB_a, KB_b, KB_c and KB_d respectively. For simplicity, the (estimated) prices are listed with the components together.

KB_a= (T_a, R_a, C_a) where

$T_a = \{t_1(\$230), t_2(\$100), t_3(\$50), t_4(\$80), t_5(\$100), t_6(\$50), t_8(\$80)\}$

$R_a = \{t_1 \rightarrow t_2, t_3, t_4; \quad t_2 \rightarrow t_5; \quad t_3 \rightarrow t_6; \quad t_4 \rightarrow t_8\}$

The knowledge base of agent A can be represented as a directed graph as shown in Figure 9.2.

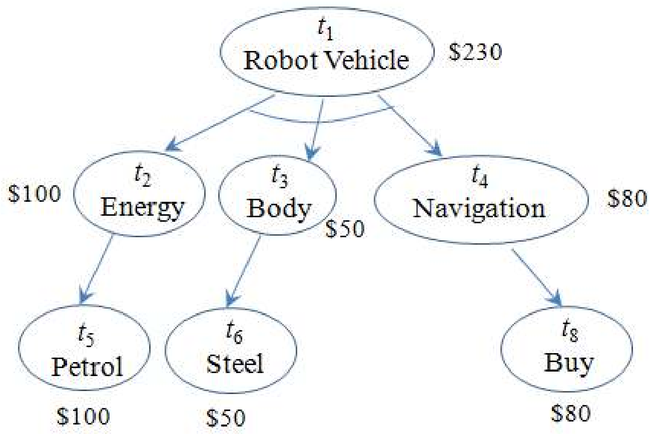


Figure 9.2 Knowledge Base of Agent A

$KB_b=(T_b, R_b, C_b)$ where

$T_b = \{t_1(\$240), t_2(\$110), t_3(\$50), t_4(\$80), t_6(\$50), t_7(\$50), t_8(\$80), t_9(\$110)\}$

$R_b = \{ t_1 \rightarrow t_2, t_3, t_4; \quad t_2 \rightarrow t_9; \quad t_3 \rightarrow t_6; t_3 \rightarrow t_7; \quad t_4 \rightarrow t_8;\}$

The knowledge base of agent B can be represented as a directed graph as shown in Figure 9.3.

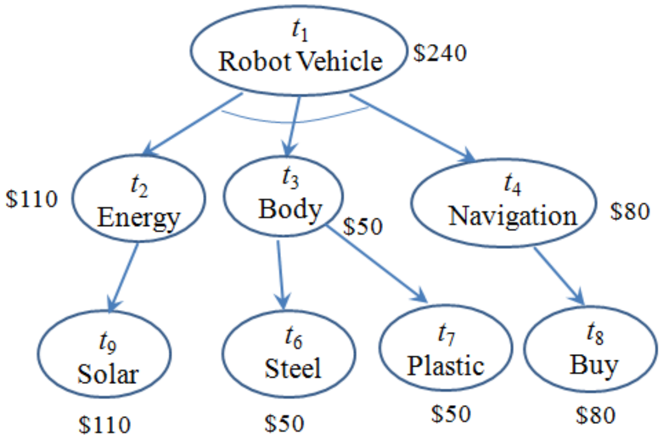


Figure 9.3 Knowledge Base of Agent B

$KB_c=(T_c, R_c, C_c)$ where

$T_c = \{ t_4(\$0), t_{10}(\$0)\}$

$R_c = \{t_4 \rightarrow t_{10}\}$

The knowledge base of agent C can be represented as a directed graph as shown in Figure 9.4.

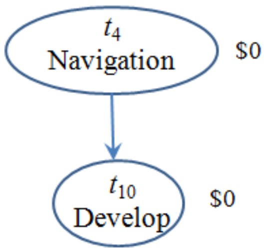


Figure 9.4 Knowledge Base of Agent C

The overall task of agent A is to build a robot vehicle. After calling *Decompose* (t_1), the solution graph (by tracing down the marks from t_1) is listed in Figure 9.5 (the price is listed beside each node). Agent A proposes to use a petrol engine (t_5), steel robot body (t_6) and buy a navigation system (t_8). The total cost is $230. The proposal on how to build a robot vehicle (t_5, t_6, t_8) together with the rules in the solution graph ($t_1 \rightarrow t_2, t_3, t_4$; $t_2 \rightarrow t_5$; $t_3 \rightarrow t_6$; $t_4 \rightarrow t_8$) are sent to other agents. The rules are knowledge supporting the proposal. Exchanging of such information can help agents to share knowledge with each other and work collaboratively.

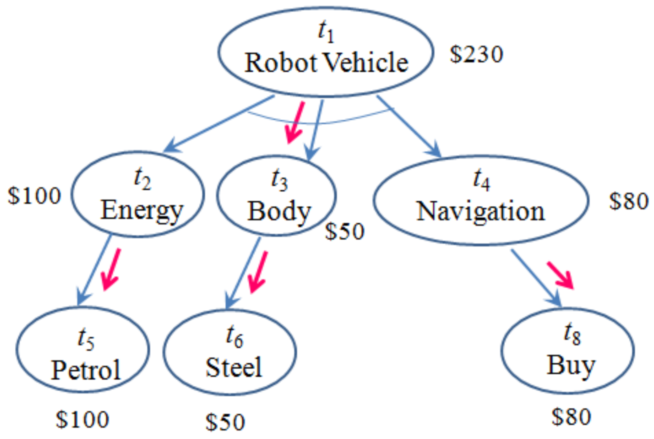


Figure 9.5 Proposal of Agent A

Considering a petrol engine is not environmentally friendly, agent B thinks a petrol engine is not acceptable so it rejects A's proposal. Agent B proposes using solar cells as the energy source. The solution graph (by tracing down the marks from t_1) is displayed in Figure 9.6, and the total cost is \$240. The proposal (t_9, t_6, t_8) together with the supporting knowledge, i.e. the rules in the solution graph ($t_1 \rightarrow t_2, t_3, t_4$; $t_2 \rightarrow t_9$; $t_3 \rightarrow t_6$; $t_4 \rightarrow t_8$) are sent to other agents.

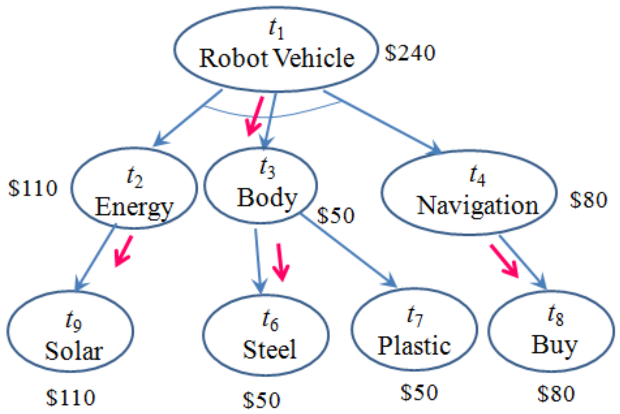


Figure 9.6 Proposal of Agent B

After agent A receiving agent B's proposal, agent A accepts the idea of using solar cells as the energy source. It adds this knowledge to its knowledge base. As a petrol engine is not acceptable, the cost is marked as + ∞ to exclude it from consideration. After the revision, agent A's knowledge base can be represented as Figure 9.7.

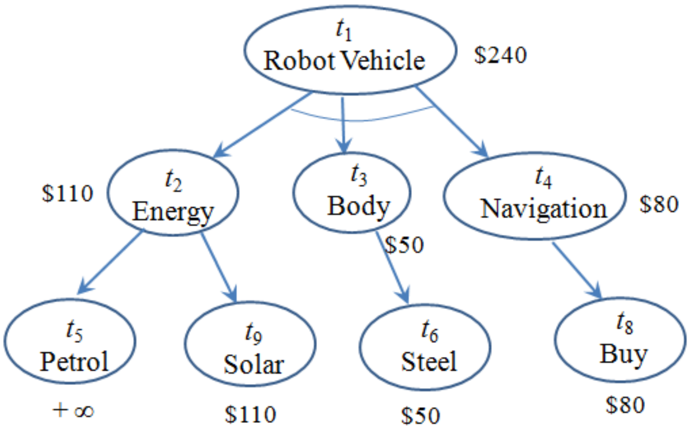


Figure 9.7 Agent A's Revised Knowledge Base

Agent D disagrees with B's proposal. It thinks a steel body would be too heavy for a robot vehicle that is simply used for mail delivery within a school campus. So a steel body is excluded from the solution. Agent B proposes an alternative solution which is to use plastic materials to build the robot's body. Agent B's alternative solution is shown in Figure 9.8.

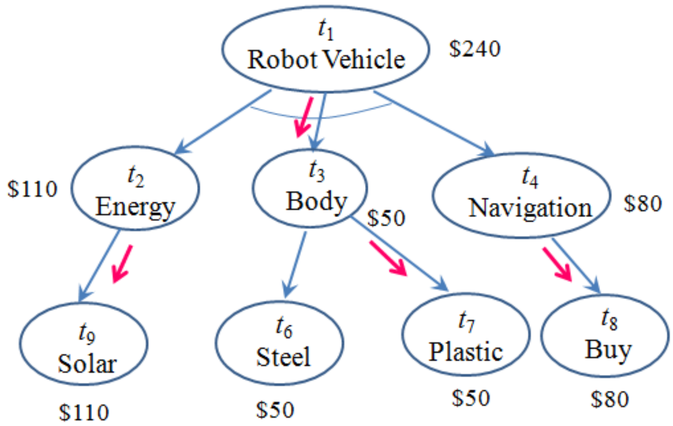


Figure 9.8 B's Alternative Solution Graph

B's alternative proposal (t_9, t_7, t_8) together with the supporting rules ($t_1 \rightarrow t_2$, t_3, t_4; $t_2 \rightarrow t_9$; $t_3 \rightarrow t_7$; $t_4 \rightarrow t_8$) are sent to other agents. If agent A believes the knowledge of using plastic materials to build robot is useful, it will add the rule in its knowledge base.

Agent C has knowledge on building navigation systems, but it doesn't have knowledge on building robots. After reviewing B's proposal, agent C believes the knowledge from B (rules in B's alternative proposal) is useful, it adds them to its knowledge base. Now, C also has knowledge on building robots. Based on the revised knowledge base, C suggests that to build a navigation system instead of spending money to buy a commercial product. C's proposal is shown in Figure 9.9. Agent C's proposal suggests that to use solar cells (t_9) as the energy source and plastic materials (t_7) as the body, to develop a software program (t_{10}) as the robot's navigation system. The total cost is $160. This proposal is accepted by the group of agents. It meets the requirements of environmentally friendly and light in weight, it is also optimal in cost.

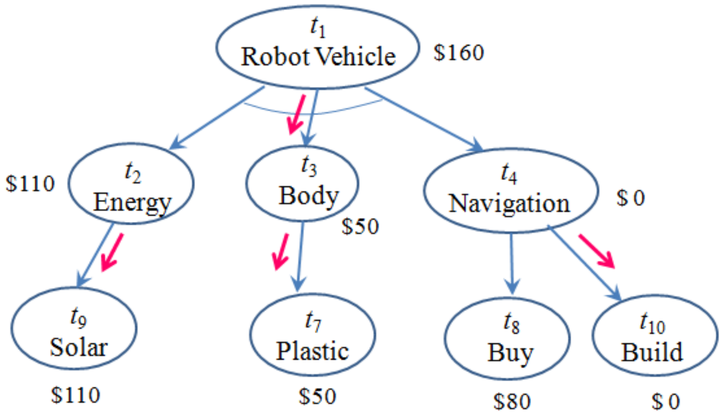


Figure 9.9 Agent C's Proposal

9.5 Remarks

This chapter presented the argumentation model developed in this research for collaborative optimisation. With this model, intelligent agents are able to find the optimal solution through collaborative argumentation with human beings and other agents. It can be applied in problems that involve multiple options with different advantages and disadvantages where optimal solutions are pursued.

Summary of Part II

This research was to fill the gap between the needs for argumentative learning and the fact that there is a lack of computer systems that are able to conduct human-computer argumentation. Four argumentation computing models have been developed in this research for the typical human knowledge, namely: chained knowledge, hierarchical knowledge, fuzzy dynamic knowledge and knowledge for collaborative optimisation.

Argumentation is a complex process which requires a high level of intelligence. The computing models provide mechanisms for computers to carry out automated argumentation. This is a significant contribution and will lay a foundation for human-computer argumentative learning and other argumentation automations between computers and human beings. It will not only enable a large range of applications in education but also many other areas such as business and legal services.

Part III. Educational Study
– Intelligent Agents as Argumentative Learning Peers

Part III presents the educational studies on argumentative learning with intelligent agents, reports the study results and discusses the research findings.

10. Educational Research Methodology

Part II of this thesis presented the four computing models developed for argumentation. These models can be applied in building intelligent agents to conduct collaborative argumentation dialogues on learning topics, and enable a wide range of innovative applications in learning and teaching. Part III of this thesis is to present the development and trialing of learning systems with intelligent agents as virtual arguing peers. The educational study focuses on learning effects, learner - agent interaction and learning experiences while interacting with an argumentative agent.

This study adopted a design based research methodology to guide the research process, and incorporated a mix of quantitative and qualitative methods to collect and analyse the data. The outline of this chapter is as follows:

- 10.1 reviews research paradigms and research methods,
- 10.2 introduces the choice of design based research,
- 10.3 introduces the choice of phenomenographic as a qualitative method,
- 10.4 introduces the choice of science as the learning topic,
- 10.5 briefs the data collection and analysis methods,
- 10.6 analyses the validity and reliability of this study,
- 10.7 identifies the limitation, and
- 10.8 summarises the chapter.

10.1 Review of Research Methodology

Research is a way of gaining knowledge or new understanding. Educational research is "the way in which people acquire dependable and useful information about the educative process" (Ary, Jacobs & Sorensen, 2010, p. 19). Educational research adopts scientific approaches to study educational problems. In this way educational research is a "process of systematic inquiry that is designed to collect, analyse, interpret and use data to understand, describe, predict, or control an educational or psychological phenomenon or to empower individuals in such contexts" (Mertens, 2005, p.2). The ultimate goal of educational research can be regarded as an attempt "to discover general principles or interpretations of behavior that people can use to explain, predict, and control events in educational situations - in other words, to formulate scientific theory" (Ary, Jacobs & Sorensen, 2010, p. 19).

In order to conduct scientific and empirically based research, the researcher needs to have a clear approach and this is considered as a methodology. In the literature, a large number of texts provided no definition for the terms methodology or research method, and some texts use the terms interchangeably (Mackenzie & Knipe, 2006). The most common definitions suggest that "methodology is the overall approach to research linked to the paradigm or theoretical framework while the method refers to systematic modes, procedures or tools used for collection and analysis of data" (Mackenzie & Knipe, 2006). This thesis adopts this definition.

Research methodology is influenced by the researcher's philosophical assumptions, and includes their rationale for using the research methods inherent to the study as well as a consideration of their justification of how the methods are used in the whole research process.

10.1.1 Research Paradigms

According to Mertens (2005), a paradigm is "a way of looking at the world. It is composed of certain philosophical assumptions that guide and direct thinking and action" (p.7). A number of theoretical paradigms are discussed in the literature such as: positivist (and postpositivist), constructivist, interpretivist, transformative, emancipatory, critical, pragmatism and deconstructivist (Mackenzie & Knipe, 2006). In different texts, there are different terms to label the paradigms and there are varied claims regarding how many research paradigms there are (Mackenzie & Knipe, 2006).

Mertens (2005) categorised the educational and psychological research into four paradigms: postpositivism, constructivist, transformative and pragmatic.

- *Positivism (and Postpositivism) Paradigm*: Positivism assumes there exists “an apprehendable reality” which is “driven by immutable natural laws and mechanisms” (Guba & Lincoln, 1994, p.109). Positivism believes that "the social world can be studied in the same way as the natural world" (Mertens, 2005, p.8). The key method is experiment. Researchers can find the truth of the reality through carefully controlled experiments, and “replicable findings are, in fact, ‘true’ ” (Guba & Lincoln, 1994, p.110). Positivism guided early educational and psychological research and later it shifted away to postpositivism. Postpositivism believes the reality is “imperfectly apprehendable because of basically flawed human intellectual mechanisms and the fundamentally intractable nature of phenomena” (Guba & Lincoln, 1994, p110). Postpositivism emphasises the importance of multiple methods of inquiry, and seeks reduction of bias through validity techniques (e.g. triangulation). As it is impossible for humans to accurately perceive the reality, “replicated findings are *probably* true (but always subject to falsification)” (Guba & Lincoln, 1994, p110).

- *Constructivist Paradigm*: Constructivists maintain that scientific knowledge is constructed by scientists. Constructivists believe that knowledge is socially constructed by people active in the research process, and that researchers should attempt to understand the complex world from the point of view of participants. The constructivist paradigm emphasizes that "research is a product of the values of researchers and cannot be independent of them" (Mertens, 2005, p.13). Constructivist researchers tend to adopt qualitative data collection and analysis methods, or a combination of both qualitative and quantitative methods. Quantitative data may be used as supports or supplements to qualitative data.

- *Transformative Paradigm:* The transformative paradigm usually relates to the study on gender, inequality and injustice in society. As Mertens (2005) stated "the transformative paradigm stresses the influence of social, political, cultural, economic, ethnic, gender, and disability values in the construction of reality" and "what is taken to be real needs to be critically examined via an ideological critique of its role in perpetuating oppressive social structures and policies." (p.

23) Transformative paradigm advocates approaches based on mixed methods and social justice.

- *Pragmatic Paradigm:* The pragmatic paradigm places the research problem as central. "Truth is what works at the time" (Creswell, 2003, p.12). Researchers are 'free' to choose any method to provide the best understanding of a research problem. Pragmatism provides theoretical foundation for multiple methods, different worldviews, and different assumptions, as well as to adopt different forms of data collection and analysis to be used in one study.

Research paradigm followed by this thesis: A pragmatic paradigm is followed in this study. The research questions are to understand the learning outcomes, learning interactions, learning activities and learning experiences, which cover many aspects of learning while students are arguing with an intelligent agent. In order to respond to the proposed research questions it was necessary to adopt a pragmatic paradigm and use a mixed methods research approach so as to capture sufficient rich data to be able to respond to the questions.

10.1.2 Qualitative, Quantitative and Mixed Methods

Research methods are the techniques used to collect, analyse and report the data and the approaches are generally classified as being quantitative, qualitative or mixed methods.

- Quantitative Methods

  Quantitative methods investigate social phenomena via statistical, mathematical or computational techniques. Quantitative researchers collect numerical data from participants and then they analyse the data with statistics. They use the numerical result to prove theories. The objective of quantitative research is to develop theories pertaining to phenomena.

Quantitative approaches usually rely on a hypothetico-deductive model of explanation. Inquiry begins with a theory of the phenomenon to be investigated. From that theory some hypotheses are deduced and tested. Based on the result of hypothesis testing, theories are refined, extended or abandoned (Ary, Jacobs & Sorensen, 2010).

- Qualitative Methods

Qualitative methods are predominant in the constructivist paradigm (Mertens, 2005). They are used in research that "is designed to provide an in-depth description of a specific program, practice, or setting" (Mertens, 2005, p. 229). The ultimate goal of qualitative research is "to portray the complex pattern of what is being studied in sufficient depth and detail so that someone who has not experienced it can understand it" (Ary, Jacobs & Sorensen, 2010, p. 421).

Qualitative method uses field work methods (interviewing, observation, and document analysis) as the principal means of collecting data. Data collected include interviews, group discussions, observation and reflection field notes, pictures and other materials. Through the analysis of the qualitative data, the research attempts to interpret the phenomena.

Qualitative methods are concerned about context and meaning. It assumes that "human behavior is context bound - that human experience takes its meaning from and, therefore, is inseparable from social, historical, political, and cultural influences" (Ary, Jacobs & Sorensen, 2010, p. 424). Unlike the quantitative research in the experimental context, "qualitative research studies behavior as it occurs naturally." (Ary, Jacobs & Sorensen, 2010, p.424). Qualitative methods often take into account a broad range of factors and influences in the context.

- Mixed Methods Research

Mixed methods research is utilized in studies because researchers believe that multiple approaches may provide better information for them to understand a particular phenomenon and they can utilize the advantages of each method and strengthen the study. Ary, Jacobs & Sorensen (2010) believed that "by mixing methods in ways that minimize weaknesses or ensure that the weaknesses of one approach do not overlap significantly with the weaknesses of another, the study is strengthened" (p.559).

Mixed methods researchers adopt both quantitative and qualitative methods in a single study for purposes of obtaining a deeper understanding of a phenomenon. They collect and analyze both quantitative and qualitative data in the study. Mixed methods research is not just combining two methods but "it incorporates and embraces blends of paradigms, philosophical assumptions, and theoretical perspectives directly driven by the purpose of the study and the intended audience" (Ary, Jacobs & Sorensen, 2010, p.561).

Mackenzie and Knipe (2006) pointed out that which research methods (qualitative/quantitative or mixed methods) are appropriate for a study is determined by the research paradigm and research questions. They further argue that it is possible for all paradigms to employ mixed methods rather than being restricted to any one method, which may potentially limit the depth and richness of a research project. Table 10.1 listed the research methods commonly used by different research paradigms.

Table 10.1 Paradigms, Methods and Tools
(Mackenzie & Knipe, 2006)

Paradigm	Methods (primarily)	Data collection tools (examples)
Positivist/ Postpositivist	Quantitative. (Qualitative methods can be used but quantitative methods tend to be predominant)	Experiments, quasi-experiments, tests, scales
Interpretivist/ Constructivist	Qualitative methods predominate although quantitative methods may also be utilised.	Interviews, observations, document reviews, visual data analysis
Transformative	Qualitative methods with quantitative and mixed methods.	Diverse range of tools - particular need to avoid discrimination. For example: sexism, racism, and homophobia.
Pragmatic	Qualitative and/or quantitative methods may be employed. Methods are matched to the specific questions and purpose of the research.	May include tools from both positivist and interpretivist paradigms. For example: interviews, observations and testing and experiments.

Research methods of this thesis: This research adopts mixed methods research for data collection and analysis. Conducting mixed methods research has several advantages compared to conducting quantitative or qualitative research alone. These advantages are particularly significant to this study:

First, using mixed methods can collect various kinds of data that ensures as many research aspects as possible is covered. For researchers that don't have much or have limited existing knowledge (such as this study), collecting a wide range of rich data is essential.

Second, mixed methods research allows the collection and analysis of both qualitative and quantitative data, thus it can generate a deeper insight compared to using only one method and therefore a more complete understanding of complex phenomena.

Third, mixed methods research allows the researcher to compensate for the weaknesses of one method with the strengths of another. The triangulation can improve the validity and reliability of research findings (Golafshani, 2003).

10.2 The Choice of Design Based Research Approach

10.2.1 Design-Based Research

This thesis adopts a design-based research approach. In educational research, design-based research methodology intends to bring together design and research in order to create a better understanding of educational phenomena. Design-based research (Design Based Research Collective, 2003) is a research methodology that encompasses different terms in the literature, including design experiments (Brown, 1992), design research (Collins, Joseph & Bielaczyc, 2004), development research (van den Akker, 1999), and developmental research (Richey, Klein, & Nelson, 2003). Although each of these methodologies has a slightly different focus, the underlying goals and approaches are similar (Wang & Hannafin, 2005).

Wang and Hannafin (2005) captured design-based research as "a systematic but flexible methodology aimed to improve educational practices through iterative analysis, design, development, and implementation, based on collaboration among researchers and practitioners in real-world settings, and leading to contextually-sensitive design principles and theories" (p. 6). This research aims to improve learning through the design and development of argumentative learning systems. Design based research is employed as the overall methodology which guides the whole research process.

10.2.2 Rationale of Design Based Research

This research is aligned with a design-based research methodology for the following reasons:

- *The intertwined theoretical and practical goals.* In design-based research "the central goals of designing learning environments and developing theories or 'prototheories' of learning are intertwined" (Design-Based Research Collective, 2003, p5). As Anderson and Shattuck (2012) pointed out, design-based research is a methodology that "seeks to increase the impact, transfer, and translation of education research into improved practice. In addition, it stresses the need for theory building and the development of design principles that guide, inform, and improve both practice and research in educational contexts" (p.16). That is, design-based research in education is driven by two broad goals - "to develop educational products (loosely defined as educational technologies, curricula, or participant structures) that work and to build a theoretical framework for future designs" (Bowler and Large, 2008, p40). This matches the needs of this research because one main purpose is to design and develop an argumentative learning system to assist students' science learning. Secondly, it is to study the argumentative learning generated by interacting with the system so as to generate theories on argumentative learning, and to discover guidelines for further argumentative system design and development. The design-based method fits the purpose of this study.

- *Mixed methods research.* Design-based research "typically involves mixed methods using a variety of research tools and techniques" (Anderson & Shattuck, 2012, p. 17). In design-based research, "researchers assume the functions of both designers and researchers, drawing on procedures and methods from both fields, in the form of a hybrid methodology" (Wang & Hannafin, 2005, p.6). This research studies argumentative learning from different perspectives, including learning outcomes, learner-agent interactions and experiences. Both quantitative and qualitative data needs to be collected and analysed, in order to cover more aspects and gain more in depth understanding of argumentative learning.

- *Multiple Iterations.* Design-based research processes are "iterative cycle of analysis, design, implementation, and redesign", because the initial plan "is usually insufficiently detailed so that designers can make deliberate changes when necessary" (Wang & Hannafin, 2005). It is hard for an educational intervention to be finished perfectly the first time. Design-based interventions are "rarely if ever designed and implemented perfectly; thus there is always room for improvements in the design and subsequent evaluation" (Anderson & Shattuck, 2012, p.17). Argumentative learning systems and argumentative learning are relatively new areas. Because there are lots of unknowns to explore it is near impossible to obtain an ideal software system on the first attempt. The system design and development has taken place through continuous cycles of design, development, testing and evaluation, and redesign. Design-based methods fit the design and redesign cycle of this study.

In summary, design-based research supports the practical and theoretical goals of this study, utilises both quantitative and qualitative methods needed to address the research questions, and aligns with the software system design, evaluation, improved design and evaluation life cycle. Hence design-based research is adopted as the overall methodology.

10.2.3 Design Based Research Phases

According to Amiel and Reeves (2008), design-based research has four phases, as illustrated in Figure 10.1. Design-based research starts from the analysis of practical problems. In this phase, the researcher establishes research questions and identifies problems that merit investigation. Then, based on the problem, develops innovation intervention. Next, the researcher applies the intervention to the problem. Data is collected, examined and reflected upon and new designs are created and implemented. This is a "continuous cycle of design-reflection-design" (Amiel and Reeves, 2008, p.35). Finally, the researcher produces theory and practical outcomes. The outcomes of design-based research are "a set of design principles or guidelines derived empirically and richly described, which can be implemented by others interested in studying similar settings and concerns" (Amiel and Reeves, 2008, p.35).

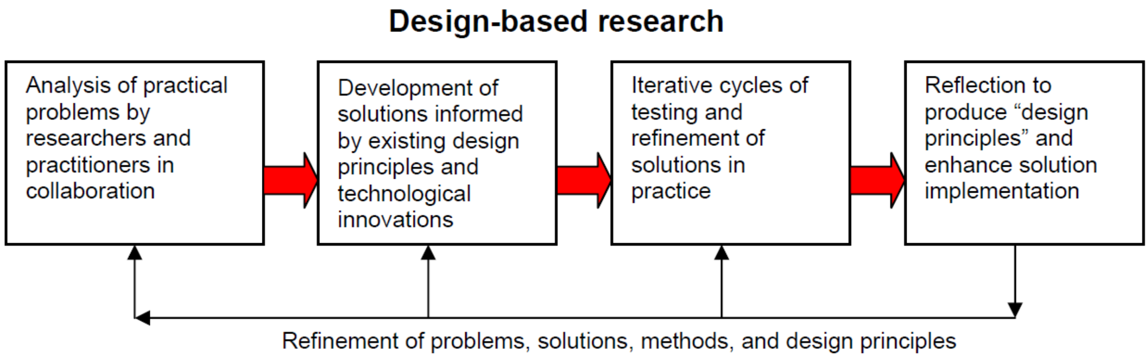


Figure 10.1 Design-based Research Phases
(Amiel & Reeves, 2008, p.34)

This study follows the phases proposed by Amiel and Reeves (2008), as well as general software engineering practice. It can be presented as the following phases:

- Review the existing work in argumentative learning and existing software systems that support argumentation, and document the requirement of an argumentative learning system.
- Design the argumentative agent.
- Implement a pilot system and evaluate with real users.
- Based on the pilot study, implement a further argumentative learning system. Conduct a study to obtain detailed understanding of the learning with an argumentative agent.
- Reflect and summarise research results, and propose or advance theories. Barab and Squire (2004) stated that "design-based research is concerned with using design in the service of developing broad models of how humans think, know, act and learn; that is, a critical component of design-based research is that the design is conceived not just to meet local needs, but to advance a theoretical agenda, to uncover, explore, and confirm theoretical relationships" (p.5).

10.3 The Choice of Phenomenography as a Qualitative Method

Phenomenography is selected in this study as the main qualitative method in analysing learners' argumentative learning experiences with intelligent agents.

10.3.1 Phenomenography

Phenomenography is a qualitative research method. It is adopted by many researchers in Australia, the Netherlands, and the United Kingdom (Richardson, 1999). Phenomenography has its roots in a set of studies on learning among university students in the University of Goteborg, Sweden, in the early 1970s. The studies investigated why some people were better at learning than others. Phenomenography was used to deal with the content aspect of learning−the different ways students understand the content of learning; and the act aspect of learning−the different ways students experience the learning situation and their act of learning (Marton, 1997). Marton (2001) described phenomenography as "a research method for mapping the qualitatively different ways in which people experience, conceptualize, perceive, and understand various aspects of, and phenomena in, the world around them" (p.144).

- Phenomenography Studies Human Experiences

In phenomenographic research, the researcher chooses to study how people experience a given phenomenon, not to study a given phenomenon. Marton (1981) described phenomenography as a kind of research which "aims at description, analysis, and understanding of experiences; that is, research which is directed towards experiential description" (p.180). Marton and Booth (1997) highlighted that "the unit of phenomenographic research is a way of experiencing something ... and the object of the research is the variation in ways of experiencing phenomena. At the root of phenomenography lies an interest in describing the phenomena in the world as others see them, and in revealing and describing the variation" (p. 111).

Phenomenography studies the way people experience something, which "is an internal relationship between the experiencer and the experienced" (Marton & Booth, 1997, p.113). Bowden (2005) demonstrates the object of a phenomenographic study using the model shown in Figure 10.2. The model highlights that the object of a phenomenographic study is not the phenomenon but rather the relations between the subjects and the phenomenon.

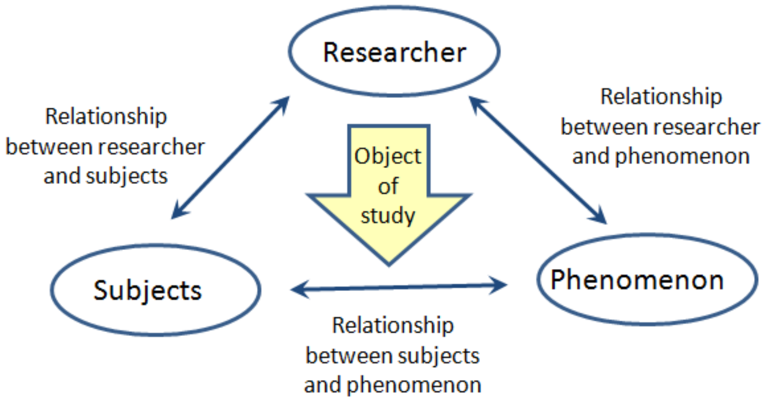


Figure 10.2 Phenomenographic Relationality
(Bowden, 2005, p.13)

Phenomenography aims for a collective analysis of individual experiences. "In phenomenography individuals are seen as the bearers of different ways of experiencing a phenomenon, and as the bearers of fragments of differing ways of experiencing that phenomenon. The description we reach is a description of variation, a description on the collective level, and in that sense individual voices are not heard. Moreover, it is a stripped description in which the structure and essential meaning of the differing ways of experiencing the phenomenon are retained, while the specific flavors, the scents, and the colors of the worlds of the individuals have been abandoned" (Marton & Booth, 1997, p.114). Thus, in a phenomenographic study, data is collected at an individual level, but the aim is to find the collective awareness and variation in how a phenomenon is experienced.

- Phenomenography is to Find Different Categories of Human Experiences

Phenomenographers aim to describe the variation in ways people experience phenomena in their world. They "seek the totality of ways in which people experience, or are capable of experiencing, the object of interest and interpret it in terms of distinctly different categories that capture the essence of the variation, a set of categories of description from the second-order perspective" (Marton & Booth, 1997, p121).

Phenomenography supports the view that there are limited ways to experience particular phenomena. The basic principle of phenomenography is that "whatever phenomenon we encounter, it is experienced in a limited number of qualitatively different ways" (Marton & Booth, 1997, P122). Marton and Booth (1997) argue that "the worlds we inhabit are recognizable and communicable at all means that the number of ways of experiencing any phenomenon in the world is limited" (p.126). Phenomenographic studies aim to find the limited categories of experiences from a given group of subjects in a given context.

- Phenomenography is Different from Phenomenology

In phenomenology, "the researcher (the philosopher) is exploring her own experience by reflecting on it"; in phenomenography, "the researcher is exploring other people's experiences by reflecting on them" (Marton & Booth, 1997, P120). Ary, Jacobs and Sorensen (2010) explained in more detail that "a phenomenological study is designed to describe and interpret an experience by determining the meaning of the experience as perceived by the people who have participated in it" (p. 471). Phenomenological research "rooted in philosophy and psychology, the assumption is that there are many ways of interpreting the same experience and that the meaning of the experience to each person is what constitutes reality" (p.471). In addition, "phenomenology makes a distinction between the appearance of something and its essence. The central research question aims to determine the essence of the experience as 'perceived by the participants'. Phenomenology moves from individual experience to a universal essence and always asks what is the nature or meaning of something" (p. 472). Ary, Jacobs and Sorensen (2010) summarised that phenomenology involves "the understanding of the essence of the phenomenon", whereas phenomenography focuses on "investigating the experience of others and their subsequent perceptions of the phenomenon - their reflections on the phenomenon"(p.474).

10.3.2 The "Outcome Space" of Phenomenography

The fundamental results of phenomenographic research are a set of second-order categories of description. The descriptions of experience are not psychological and not physical, "they are descriptions of the internal relationship between persons and phenomena: ways in which persons experience a given phenomenon and ways in which a phenomenon is experienced by persons" (Marton & Booth, 1997, p.122). The categories of description and the relations among the categories form the "outcome space". More precisely, "the outcome space is the complex of categories of description comprising distinct groupings of aspects of the phenomenon and the relationships between them" (Marton & Booth, 1997, P125).

The "outcome space" comprises both the categories and their relations. It is usually presented as a diagram showing the categories and their relationships. The relationship among categories is important. Åkerlind (2005) stated that "the phenomenographic researcher tries to make the variation in experience meaningful, by searching for structure and distinguishing aspects of variation that appear critical to distinguishing qualitatively different ways of experiencing the same phenomenon from aspects that do not. The aim is to describe variation in experience in a way that is useful and meaningful, providing insight into what would be required for individuals to move from less powerful to more powerful ways of understanding a phenomenon" (p.72).

10.3.3 Why Apply Phenomenography in this Study?

Argumentative learning with virtual characters is a new way of learning. To the best knowledge of the researcher, there is no report on the experience of argumentative learning with intelligent agents. Students' experiences and perceptions of argumentative learning is one of the main interests of this study.

Both phenomenology and phenomenography have human experience as their object. But phenomenology is different from phenomenography. In phenomenology, “the researcher (the philosopher) is exploring her own experience by reflecting on it”; in phenomenography, “the researcher is exploring other people's experiences by reflecting on them” (Marton & Booth, 1997, P120). Phenomenology “involves the understanding of the essence of the phenomenon”, whereas phenomenography “focused on investigating the experience of others and their subsequent perceptions of the phenomenon - their reflections on the phenomenon” (Ary, Jacobs & Sorensen, 2010, p.474).

Phenomenography studies human experiences which fits the research aim. The phenomenographic approach is noted as being distinctive in that it identifies different ways we experience and understand phenomena in the world around us. Phenomenographic research employs a second order perspective. Researchers report on other people's ideas about the world, rather than the first order perspective whereby researchers make statements about the world. The second order perspective is clearly useful in this study which investigates students' argumentative learning experiences with an intelligent agent. This ensures the feedback on argumentative learning is from the learners' perspective and not the researcher's interpretation.

10.4 The Choice of Science as Learning Topic

This research is to apply the developed argumentation model and argumentative learning system in facilitating science learning, but the model is not limited to science learning.

Science is chosen as the topic area, because science is one of the most common subjects at schools. Scientific knowledge is very important, for example, it helps us to understand the natural world around us, makes positive impacts on our lives, opens new ways of thinking, and provides people with essential skills and knowledge for many careers.

Another reason for choosing science as the topic is because of the perceived importance of argumentation in science education. Scientific knowledge is socially constructed, validated and communicated (Driver et al. 1994). Scientific understandings are constructed when individuals engage socially in talk and activity about shared problems or tasks (Driver et al. 1994). Students should be given the opportunity for discursive practices in general and argumentation in particular (Driver, Newton & Osborne, 2000). Therefore, this research attempts to improve the effectiveness of scientific knowledge learning by facilitating collaborative argumentation between learners and intelligent agents with regard to science topics.

10.5 Briefs on Data Collection and Analysis Methods

This study is based on design-based research and it has several phases as indicated in section 10.2. There were two educational studies conducted: a pilot study and the main study. This section briefs the data collection and analysis methods with further details introduced in chapter 11, 12 and 13.

10.5.1 Pilot Study Procedure and Methods

Participants: There were five participants in the pilot study. They were known to the researcher and volunteered to participate the study. There were 3 boys and 2 girls and their ages ranged from 6 to 9 years.

Procedures: Each child used the pilot learning system individually in one session for 20 minutes. Following this they were interviewed by the researcher in a semi structured interview with the questions provided in section 11.2.

Data Collection: The following data was collected:

- *Video recording:* The children's interactions with the learning system were captured by a usability software tool Morae, including audio, on–screen activity and facial expression. The Morae video recording was essential in capturing accurate details about the children's learning. The video provides opportunity for further review of the children's learning from the children's dialogue and actions. Capturing the data on video tape also allows retrospective analysis. The video recording was used to understand the learner's interaction with the learning system.

- *Interview:* The interviews were conducted individually which was used to understand the learners' perception to the argumentative agent. The interview questions are provided in section 11.2.

Data Analysis: The data was analysed to obtain understandings on children's interaction with the learning system and children's perception to the argumentative agent.

- *Learning Interaction:* The video recording provided detailed information on learner-system interaction. The children's activities were counted and reported by descriptive statistics.

- *Interview:* The interviews concerned learners' perceptions to the argumentative agent. The children's responses were categorised and presented.

10.5.2 Further Study Procedure and Methods

Participants: In the main study, the participants included 33 secondary school students in Henan Province of China. The students' ages ranged from 13 to 15. There were 19 girls and 14 boys. The participant selection was based on convenience sampling. The teacher of the students was known to the researcher, and he could easily organise the study as an after school program with volunteer students. This arrangement was convenient to the students as the study venue was in their familiar environment, and the students were informed that they could freely attend the study and leave the study without any negative consequences. Ethical clearance to conduct this study was obtained from the Victoria University ethics committee (HRE13-056: Study on Dialogue Agent Mediated Learning).

Procedures: There were two learning systems used in the study, one argumentative system and one non-argumentative system. Using two systems aimed to find out the effect of argumentative learning. The students were randomly divided into two groups, a control group and an experiment group. All the students took a pre-test. Initially the control group used the non-argumentative system and the experiment group used the argumentative system. After finish one learning session, all students took a post-test.

Then, the control group used the argumentative system and the experiment group used the non-argumentative system for a second learning session. After the second learning session, all students completed a questionnaire. The study procedure had two purposes: 1) after the first learning session, the pre-test and post-test of the two groups could be used to compare the learning gains of using the different learning systems; 2) after the second learning session, all the students had opportunity to use both learning systems, afterwards they could compare the two systems from the questionnaires.

The total time from the beginning of pre-test to the end of questionnaire was about one hour, and all the screen activities were captured during this period of time. Finally, 20 students were randomly selected and telephone interviewed to understand their learning experiences. The administration of pre-test, post-test and questionnaire, and the collection of screen recordings were conducted by the school teacher. The telephone interviews with students who agreed to do so were conducted by the researcher within two weeks of the learning sessions.

Data Collection: Data was collected from multiple sources which ensured the researcher was able to obtain understanding of students' learning from different aspects. The data collected include:

- Pre-test and post-test: The test data was used to compare students' learning gains when using different learning systems.
- Biology interest: A Likert scale on biology interest was administered to gain an awareness of students' interest in biology.
- Questionnaire: The questionnaire was used to understand students' self reported learning activities and students' perceptions to argumentative learning.
- Screen recording: The screen recording was used to obtain details of the learner and argumentative agent interaction, including learning activities and performance.
- Interview: The interviews were conducted individually which was used to understand the learners' learning experiences.

Data Analysis: The data was analysed to obtain understanding mainly on the following aspects:

- Learning gain: Student t-tests were performed on the pre-test and post-test to compare the learning gains between using the argumentative system and the non-argumentative system.
- Learner-agent interaction: Pearson's product moment coefficient (Pearson's *r*) was calculated to find out the correlations between the student's performance and the argumentative agent's performance in answering science questions. If the two variables were positively correlated, it is more likely that the student's knowledge affected the argumentative agent's knowledge and performance, i.e. the students seriously passed their knowledge to the agent.
- Learning experience: The interviews and some questions of the questionnaires were analysed following the phenomenographic approach. The qualitatively different learning experiences were reported.
- Impacts of argumentative activities: Relevant data was analysed to find out the relationships between argumentative activities and other factors. The analysis included: Pearson's *r* was computed to test the correlation between argumentative activities and biology interest; multiple regression analysis was carried out to find out the contribution of argumentative activities to learning gains; student t-tests were performed to compare the argumentative activities between two groups with different experiences.

10.6 Reliability and Validity

Reliability is "the extent in which the findings of a study can be replicated" (Sin, 2010, p. 310). It implies that different researchers that carry out the same study will achieve similar results. However, Fidel (1993) argued that "qualitative studies cannot be replicated because they examine a phenomenon at a certain point in time and because they are flexible, dynamic, and creative" (p. 231). That is to say, absolute replication of a study is hard to achieve because the social world is changing and the data obtained from a study only reflects the world at the time they were collected. In addition, data collected by different researchers, using differing methods and with different participants will result in different data sets which may not come to the same conclusion.

This research involves the investigation of students' learning experiences. It uses unstructured interviews to gather student's learning experiences. The data collected from different participant groups, at different times and by different researchers will be different. In addition, qualitative research is unavoidable because it involves the researcher's ideas. This study may not be replicated to obtain the same result.

However, "these different ways of approaching the same subject result in an increased understanding of complex phenomena, not in a failure of reliability" (Malterud, 2001, p. 484). Instead of focusing the study on replicability, this study focuses on collecting the accuracy and comprehensiveness of data for the selected sample, to increase the understanding of argumentative learning with intelligent agents. However, a number of steps were undertaken to enhance the reliability of this study, including

- study procedures, data collection and analysis methods were documented, which enables future researchers to repeat the work and allows readers to access its reliability;
- all interviews were recorded so as to reduce the involvement of the researcher's memory recall which might happen if the researcher attempted to remember the conversation;
- all interviewees were given the opportunity to explain their thoughts freely without comments which may create bias in the interviewee's response; and
- quotations from interviews were included as evidence which allows readers to judge its objectiveness.

Validity is defined as "the extent to which any measuring instrument measures what it is intended to measure" (Carmines & Zeller, 1979, p. 17). It is concerned with two main issues: firstly, whether the means of measurement are accurate; secondly, whether they are actually measuring what they intended to measure (Winter, 2000).

In this research, validity was achieved by adopting triangulation techniques (Denzin, 1970), that is, to employ multiple methods to investigate the phenomenon from different angles and strengthen the validity of the findings.

Triangulation is “the combination of methodologies in the study of the same phenomena” (Denzin, 1970, p. 297) and it involves “varieties of data, investigators, and theories, as well as methodologies” (Denzin, 1970, P301). Golafshani (2003) considers triangulation as “a strategy (test) for improving the validity and reliability of research or evaluation of findings” (p.603). Patton (2002) also advocates triangulation by stating “triangulation strengthens a study by combining methods. This can mean using several kinds of methods or data including using both quantitative and qualitative approaches” (p. 247).

There are four basic types of triangulation: (1) data triangulation, the use of a variety of data sources in a study; (2) investigator triangulation, the use of multiple researchers or evaluators; (3) theory triangulation, the use of multiple theoretical schemes to interpret the phenomenon; and (4) methodological triangulation, the use of multiple methods to collect data (Denzin, 1970). This research mainly employed methodological triangulation in order to collect different in-depth data. The main methods used for data collection included pre-test, post-test, questionnaire, interview and screen/video recording. The rich data collection of this study increases the extent that the research truly measures what it was intended to measure. As Golafshani (2003) believes “engaging multiple methods, such as, observation, interviews and recordings will lead to more valid, reliable and diverse construction of realities” (p.604).

10.7 Limitation

The main limitation of this study was the relatively small sample size. Therefore, the research results should be taken into consideration with this in mind before it is generalized to the broader community.

However, this research collected and analysed rich data from multiple sources. The research results contribute to greater insights about human-computer argumentative learning, and gives an in-depth insight into the learning of one specific group of students in the complex environment of argumentative learning with intelligent agents.

10.8 Summary

This chapter described the use of the design-based research approach in the development and trialling of argumentative learning systems to the learning of science topics. The research involves two iterative cycles of development and evaluation: a pilot study and a further main study. Data collection and analysis methods in the two studies were briefed in this chapter, and the resultant details are reported in the following chapters.

11. Pilot System and Study

"Learning by arguing" provides new learning opportunities. This chapter presents the pilot system, ArgPal, developed in this research and the study conducted with the system. ArgPal is an interactive learning system that can be used by children to learn knowledge on echo-systems. In ArgPal, an intelligent agent was developed as an arguing peer. A study was carried out to understand children's learning with the learning system, particularly the children's interaction with and perception toward the argumentative agent.

11.1 Overview of the Pilot System - ArgPal

ArgPal was designed for children to learn ecosystems to understand the food chain. The topic of food chains was selected because it is a practical and understandable topic to children, which does not rely on prior knowledge. ArgPal was based on the argumentative agent conceptual design (chapter 5) and the argumentation computing model of chained knowledge (chapter 6).

A food chain is an example of a typical flow of energy in an ecosystem. It indicates and represents the transfer of energy from producers through a series of organisms which feed and depend upon each other. A food web is thus a series of interrelated food chains that represent the feeding relationships in an ecosystem. A species is normally food of more than one type of consumers. A food chain is usually presented as it follows the energy flow direction, i.e. from energy producer to energy consumer. For example, Grass –>sheep –>wolf is a food chain. It represents a chain of "eaten by" relationships. In order to make it easy for children to understand the notation, in this research the direction of arrows are changed to show the relationship of "eat", and only plants and animals are included in the food chains. In ArgPal, a food chain looks like this:

$$\text{tiger} \xrightarrow{eats} \text{wolf} \xrightarrow{eats} \text{sheep} \xrightarrow{eats} \text{grass.}$$

There are two virtual characters in this system. Leo is a pink colored bee. He is modeled as a tutor, and he presents questions to the learner and evaluates the answers.

Peedy is a green parrot. He is modeled as a co-learner. He works on questions and answers and conducts argumentative dialogues with the learner. The two virtual characters have a set of animations to engage children. They can communicate with the learner via natural language. A speech balloon pops up to show the virtual character's dialogue sentences when the virtual character talks. The learner can interact with the system via mouse and keyboard inputs.

The system interface has three main areas: the question area, Peedy's answer area and the learner's answer area (Figure 11.1).

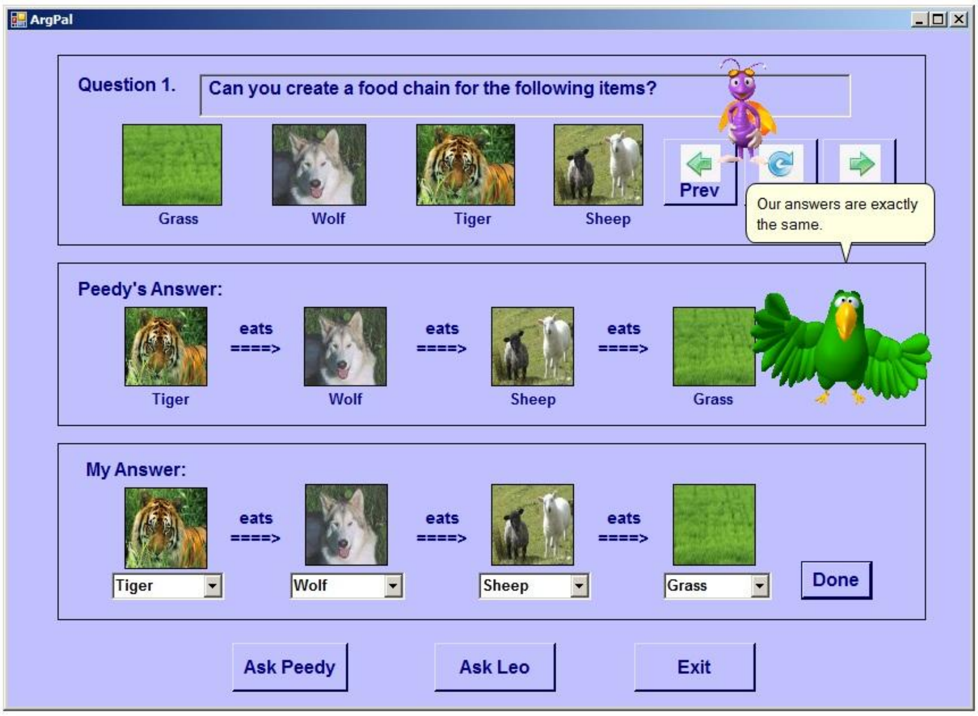


Figure 11.1 Interface of ArgPal

Each question asks the learner to arrange four items to form a food chain. At the beginning of a question, the system will display four food chain items in a random order. Leo will ask, "Can you create a food chain for the following items?", then points to each item and reads the name of the item to the learner. Then the learner and Peedy can start to work out answers. The learner can build the food chain by selecting from the dropdown boxes which contains the four items, or by moving and arranging the pictures. After finishing the answer, the learner can press the "Done" button, then Peedy's answer will be displayed in Peedy's answer area. The learner can compare his/her answer with Peedy's. If Peedy has the same answer as the learner, he will say out loud, "Our answers are exactly the same." Otherwise, he will start to argue with the learner.

In this pilot system, Peedy can conduct the following types of dialogue:

- *Proposal*: To Peedy, a proposal is the answer to a question. Upon receiving a question, Peedy will start to work out an answer. For the given four items, Peedy will order the items to form a food chain. He will them propose this solution in his answer area.

- *Acceptance / Rejection*: When the learner finishes his/her answer and presses the "Done" button, Peedy will start to evaluate the learner's answer. If the learner's answer is exactly the same as Peedy, he will say "Our answers are exactly the same." Otherwise, Peedy will start to attack or challenge the learner.

- *Information Seeking*: Peedy requests information from the learner. The dialogue is like "Does a hawk eat rats?"

- *Information Providing*: To reply, the learner questions in the format "Does <animal name> eat <animal/plant name>?" Peedy will answer "Yes" if this is true according to his knowledge. Otherwise Peedy will answer "No".

- *Attack*: Peedy shows disagreement with the learner's answer. Peedy's attack dialogue is like this: "I am afraid you are wrong. PolarBear does not eat RingedSeal. Do you agree with me?" (Figure 11.2). The learner can reply by choosing the "Agree", "Disagree", "Not Sure" or "Ignore" button.

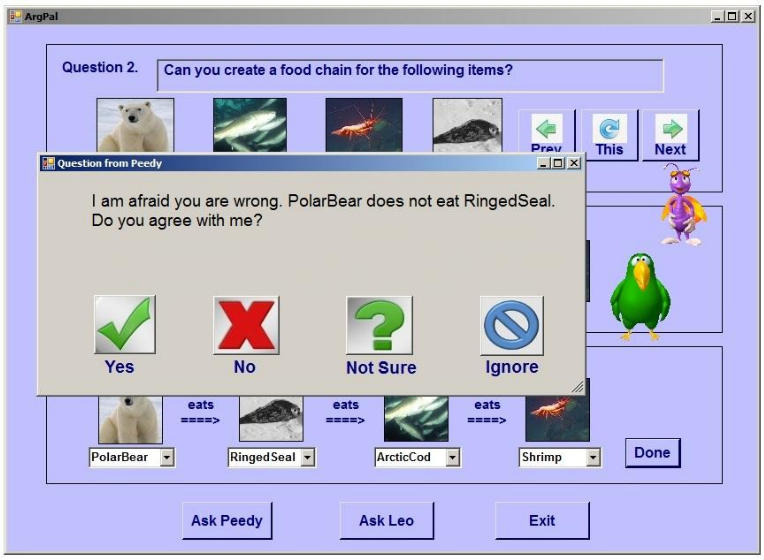


Figure 11.2 Peedy's Attack

- *Challenge*: Peedy requests the learner to rethink the answer. The question is like "Are you sure Raccoon eats Fish?"

- *Alternative Proposal*: Peedy proposes an alternative food chain when his original proposal is rejected or attacked by the learner.

- *Request Advice*: Peedy requests the learner's advice regarding his answer. The dialogue looks like "Our answers are different. Is there anything wrong in my answer?" (Figure 11.3).

Figure 11.3 Peedy Requests Advice

There are no "Justification" dialogues from Peedy, as the food chain topic doesn't involve complex reasons to explain the answer selected. The learner can initiate a dialogue by pressing the “Ask Peedy” button. A dialog box (as shown in Figure 11.4) will appear which includes four types of dialogue: information seeking (Ask Peedy), information providing (Tell Peedy), attack (Disagree with Peedy) and challenge (Challenge Peedy). Peedy will reply accordingly.

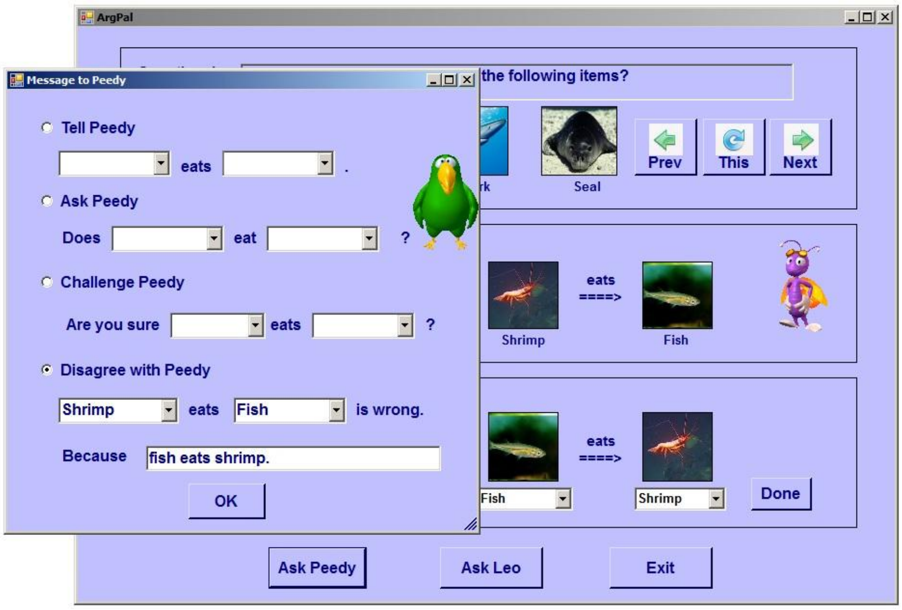


Figure 11.4 Ask Peedy Dialogue Box

Finally, Leo will evaluate the answers of the learner and Peedy, as well as present the correct answer. The learner can ask for the correct answer any time by pressing the “Ask Leo” button.

Peedy's role is to provide a virtual learning peer for the learner. Through comparing answers, pointing out each other's mistakes and exchanging information, the learners are expected to think more than playing by individuals.

Leo and Peedy have their own knowledge base respectively. A sample knowledge base is listed in Figure 11.5 (the arrows mean "eats"). Leo’s knowledge base represents the complete domain knowledge considered in this system. With the knowledge base, Leo can generate questions automatically. He will randomly choose 4 items from a food chain and display them in a random order in the question area. Then he will ask “Can you create a food chain for these items?” with animations.

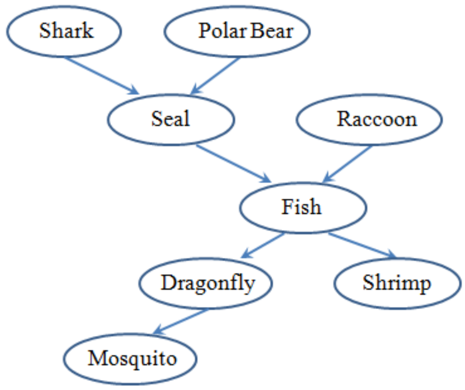


Figure 11.5 Sample Knowledge Base

Peedy has incomplete and incorrect knowledge. With the incomplete and incorrect knowledge, Peedy is able to bring in alternative thoughts to argue with the learner. By adjusting Peedy's knowledge base to include common misunderstandings in food chains, this system can be used to encourage children's thinking on the common misconceptions.

11.2 Study Procedures

The pilot study was conducted with five children, 3 boys and 2 girls. Their ages ranged from 6 to 9 years. The study was mainly designed to serve two purposes: firstly to assess the potential effectiveness and implications of argumentative learning; secondly to evaluate the system and get feedback for further improvement.

The five children were briefly introduced to the interface of the ArgPal system. Then they interacted with the system for approximately 20 minutes. They were also told that they could either respond to or ignore Peedy’s questions when the questions appeared on the screen.

The children's interaction with the system was recorded with a usability software tool Morae. Morae can capture audio, on-screen activity, and user's facial expression.

After interacting with the system, the children were interviewed individually. During the interview, the children were asked some questions regarding their perceptions to the argumentative agent. The interview questions were around agent's persona. Ryu and Baylor (2005) developed an instrument to evaluate a pedagogical agent's persona. The instrument had four categories of items to evaluate agent's persona including the agent's ability to facilitate learning, credibility, human like behavior and engagement. Similar categories of questions were asked in this study except for the human-like properties, as the agent's appearance is not the focus of this research. The interview questions were varied in order to follow each child's interest and feeling. The questions were mainly on the following topics:

- *Regarding Peedy's entertainment effect:* Is Peedy interesting? Do you like to play this (point to the learning system) with Peedy or without Peedy?

- *Regarding Peedy's intelligence*: Do you think Peedy is clever? Do you think Peedy knows about the food chain?

- *Regarding Peedy's effect on learning:* Do Peedy's questions remind you to think about other things? Do you ever change your opinion because of Peedy's question? Does Peedy help you know more about the food chain?

- *Regarding Peedy's argumentation*: Do you like Peedy to work out his answers here (point to Peedy's answering area)? Do you like Peedy to ask you questions? Do you like Peedy to have the same opinion as you or do you like it when he disagrees with you?

11.3 Results

The video and interview data revealed children's interaction with the learning system and their perception to argumentative learning. In reporting the result, pseudonyms were used for the five children. The names used were Daniel, Kylie, Michael, Emily and Alan. Format of "<child name>, Video, <question number>" is used to refer the data in video recording. For example, "Daniel, Video, Q3" refers to the video clip of Daniel, when he was answering question 3. Format of "<child name>, Interview" is used to refer the interview data. For example, "Kylie, Interview" refers to the interview data of Kylie.

11.3.1 Children's Interaction with Peedy

The video data (including children's face and screen capturing) were reviewed many times. The video data showed that children were interested in playing and discussing with the argumentative agent.

- The children enjoyed playing with Peedy

In ArgPal, Peedy has some animations (e.g. big smile, showing confused expression, eating biscuits, presenting medals). The video recording showed that the children enjoyed playing with Peedy. For example:

Kylie smiles to Peedy's congratulation. (Kylie, Video, Q1)

Michael moves Peedy around and laughs. (Michael, Video, Q4)

Emily laughs at Peedy's confusing animation (Emily, Video, Q2) and thinking animation (Emily, Video, Q5)

Alan makes faces when Peedy shows answer. (Alan, Video, Q9)

The children knew that Peedy could talk to them but he couldn't "hear" them. Although the children couldn't help talking to themselves and to Peedy as they interacted with the system. For example,

Kylie says "yes" when she sees Peedy has the same answer as hers. (Kylie, Video, Q1) When Leo presents the correct answer, Kylie says "yes" for each step of the answer. (Kylie, Video, Q1)

Emily sings "You are wrong, you are wrong, Peedy" when she finds Peedy is wrong. (Emily, Video, Q2)

Alan has the same answer with Peedy, Peedy shows a big smile with teeth, Alan says "oh, cool". (Alan, Video, Q6) When asked by Peedy "Are you sure...", Alan says "I do" and presses the "Yes" button. (Alan, Video, Q9)

- The children answered Peedy's questions

This was the first time the children used this system. They had options to ignore Peedy's questions, but they addressed most of the argumentative questions that arose from Peedy. Children's interactions with Peedy included responding to Peedy's questions and asking questions to Peedy. Children's responses to Peedy's questions were classified in three categories:

- *Addressed with thinking*: a button (except the Ignore button) is pressed after some time thinking
- *Addressed without thinking*: a button (except the Ignore button) is pressed quickly.
- *Ignored*: "Ignore" button is pressed

The children also asked Peedy questions. The questions were classified in two categories:

- *Sent*: the question is sent to Peedy
- *Cancelled*: the question is cancelled

During the software session, children's dialogues with Peedy were counted and listed in Table 11.1.

Table 11.1 Dialogues between Children and Peedy

Name	Question from Peedy			Question to Peedy	
	Addressed with thinking	Addressed without thinking	Ignored	Sent	Cancelled
Daniel	2	1		1	4
Kylie	1	3	2		2
Michael	2			1	1
Emily	4		3	3	1
Alan	6			2	

In the pilot study, Peedy generated 24 argumentation dialogues. Fifteen dialogues were addressed by the children with thinking, and nine dialogues were addressed without careful thinking or they were ignored. Among the 9 dialogues not being addressed seriously (i.e. they were either ignored or addressed without careful thinking), 4 of them were ignored by Kylie after she found Leo always had the correct answer. Following that experience she always ignored Peedy's dialogues. One dialogue had the *Ignore* button pressed by Emily, but she changed her answer according to the advice in Peedy's dialogue. So the *Ignore* button might have been incorrectly pressed by Emily. Basically, most of Peedy's dialogues were addressed seriously by the children.

The video recording evidenced the children's serious interaction with Peedy. For example:

> *Emily gets a shock when she realises that Peedy's answer is different from hers. (Emily, Video, Q2) Emily tells Peedy "hawk eats snake", then says "let's see what happened." (Emily, Video, Q3) Asked by Peedy "Are you sure dolphin eats plankton?" she presses "Ignore", then shakes her head and says "no, dolphin doesn't eat plankton. I am going to say this is big fish" and changes her answer to dolphin eats big fish. (Emily, Video, Q9)*

Emily tells Peedy "snake (eats) bird (eats) caterpillar (eats) leaf" and waits for Peedy's response. (Emily, Video, Q10)

Alan is asked by Peedy "I have no idea. Are you sure hawk eats snake?" After thinking he says "Oh yes" and presses the "Yes" button. (Alan, Video, Q3). Alan is asked by Peedy "Are you sure seal eats fish?" After thinking he says "Yes, seal eats fish" and presses the "Yes" button. (Alan, Video, Q4)

- The children initiated dialogue with Peedy

The pilot study showed that the children were willing to participate in argumentative dialogue with Peedy. They answered Peedy's questions about the food chain, and they also initiated dialogue with Peedy. The children had 15 attempts to initiate dialogue to Peedy, but 8 of them were abandoned after they had a look at the dialog box for them to "talk" to Peedy. 7 of them were successfully sent to Peedy.

From the pilot study it was discovered that the prototype system had some limitations. For example, the dialog box for children to "talk" to Peedy was text based, and the children had to choose the right English words of animals or plants which they want to argue. This increased the difficulty. But the children managed to argue with Peedy even when there were inconveniences. For example,

After 2.5 minutes of attempting Daniel asked the researcher to tell Peedy that a "Dragonfly eats mosquito." (Daniel, Video, Q5)

Emily attempts to tell Peedy something, but she doesn't know how to do it so canceled. (Emily, Video, Q2) Emily tells Peedy the same answer as hers. Peedy said "Thank you let me think about it". Emily smiled. (Emily, Video, Q8)

11.3.2 Children's Perception to Peedy's Persona

After the tasks were finished, the researcher interviewed the children about their attitudes towards Peedy. The questions mainly focused on the children's perception to agent's entertainment effect, cognition, helpfulness in facilitating learning, and their attitude to Peedy's argumentation. The children’s interviews were transcribed. Their answers to interview questions showed their attitude to the system.

- Perception to Peedy's Entertainment Effect

All of the children indicated that they thought that Peedy was interesting. For example:

> *"He has wings, he can fly. He moves and flies here and there, that is interesting." (Daniel, Interview)*
>
> *"Yes, Peedy is very interesting." (Alan, Interview)*
>
> *"He is so interesting, sometimes he goes crazy." (Emily, Interview)*

When the researcher suggested to the children to imagine a system without Peedy, and asked "Did you like to play with this (pointed to the learning system) with Peedy or without Peedy?"All of the children stated that they preferred Peedy's presence in the system. Daniel even gave suggestions about how to make Peedy more interesting and to include more birds as part of the system (Peedy is a bird).

> *"I want Peedy. If I have more birds (there) will be fun." (Daniel, Interview)*
> *"You can also let him talk more. Don’t let him always stand there." (Daniel, Interview)*

- Perception to Peedy's Intelligence

Since Peedy has both right and wrong answers, most of the children think Peedy is not clever. When asked "Do you think Peedy is clever?" the following responses were given:

"Yes, clever." (Daniel, Interview)

"Peedy is not clever, Leo is clever." (Kylie, Interview)

"Sometimes. " (Michael, Interview)

"Not really, he got a few wrong (answers). " (Alan, Interview)

"Yeah, a few wrong (answers).When he got right (points to Alan), Peedy got wrong. " (Emily, Interview)

Although the children didn't self report many of their views about Peedy's intelligence and knowledge about food chains, most of the children actually considered Peedy did have a "brain" and consequently addressed Peedy's questions seriously. When being asked "Do you think Peedy knows about the food chain", they believed Peedy had some knowledge. For example:

"He can think (about food chain questions). But his brain is wrong. So his answer can be wrong. " (Daniel, Interview)

"Yeah, some of them." (Emily, Interview)

- Perception to Peedy's Effect on Learning

To understand Peedy's effect on learning, some questions were asked to children regarding thinking and knowledge acquisition, such as "Does Peedy's questions remind you to think about more things? Does Peedy help you know more about the food chain?" All of the children reported that they felt that Peedy didn't help them with their learning, because Peedy made so many mistakes. For example:

"Peedy didn't let me know more, I let Peedy know more." (Daniel, Interview)

"He might be always wrong. Sometimes." (Emily, Interview)

"Sometimes he is wrong." (Alan, Interview)

- Perception to Peedy's Argumentation

A few simple questions were asked to see whether children enjoyed the existence of Peedy. Peedy was modeled as a peer learner. He answered questions alongside the learner. When asked, "Do you want Peedy to work out his answers here? Which one do you think is better, with or without showing Peedy's answer?" The children replied that they liked Peedy to present answers. For example,

"With answer." (Why?) "Otherwise I don't know what is his guess. I want to see his guess. Even if he has a different (answer) I still want to see." (Emily, Interview)

"Yes, I do like that." (Why?) "If he is wrong, I can see how other people are wrong." (Alan, Interview)

When asked, "Do you like Peedy to ask you questions?" The children reported that Peedy's questions were fun for them, and they could see others' opinions. They could also find the reasons for their mistakes. For example,

"Yes. I like questions from Peedy. <u>It's interesting he can ask questions</u>. If Peedy only work out answers, didn't say where I am wrong .... Yes, doing so I can see the reasons." (Alan, Interview)

(Researcher: Do you like Peedy to have the same opinion as you or to disagree with you?) "Different with me. <u>So I can see his real guess</u>, not copy me. Otherwise, I don't know what is his real guess." (Emily, Interview)

11.4 Discussion

This study provided some important results and guidelines on argumentative learning with intelligent agents, which were incorporated into the development of future argumentative agents. Most importantly, it demonstrated that the children had positive attitudes toward the argumentative agent and they did not need prior training to be able to engage in the argumentation. The children in the pilot study considered the dialogues from Peedy as fun and they took an active part in dialogue with Peedy regarding the food web questions.

The interaction between children and the system provided good learning opportunities. During the study the children were not only engaged by Peedy, but also carried topic related thinking through argumentative dialogues with Peedy. These included: when the children compared their answers with Peedy's, when they told Peedy information, and when they changed their answer after Peedy's dialogue. These examples highlight the children had active interaction with Peedy's alternative ideas. The motivation of implementing this system was that recognizing and addressing conflict between different solutions constituted good learning opportunities (Constantino-Gonzales & Suthers, 2001). In the ArgPal system, Peedy often presented alternative ideas and conducted argumentative dialogues. Thus, children's interaction with Peedy constituted good learning opportunities in the scenarios under investigation.

From the observations and interviews, additional information that guided the further design of argumentative agents became evident and that was an integral part of the process of designing and redesigning.

Firstly, the argumentative agent (Peedy) needed to have similar competency to the learner. The interview responses showed that the children didn't think Peedy was clever, and they didn't think they had learned from Peedy because Peedy made many mistakes. In the ArgPal system, all the food chain questions were easy for the children. In fact the children were more knowledgeable on this topic than Peedy. As a result they then thought Peedy was not clever. The competency of Peedy was too low for the participants. All the participants noticed that Peedy often made mistakes by the end of the study. The designed competency of Peedy should be an equal power with the learners, so that Peedy is able to promote the cognitive conflict necessary for new learning. If the learning companion's competency is too high, it might decrease a learner's self-efficacy beliefs (Kim & Baylor, 2006b). If it was too low, the different point of view from the companion may be neglected as a wrong perspective which may prevent further thinking.

Secondly the learning topic in ArgPal should not be too easy or obvious to children. The questions have to be adjusted to an appropriate level so that the children have incomplete knowledge about the answers and they are then able to build on in constructive ways. If the children can finish all questions easily they will consider Peedy as being not clever especially if Peedy makes mistakes. This might prevent the children from seriously thinking about Peedy's messages. In ArgPal, the food chain is a very easy topic and doesn't have many alternatives to discuss. To investigate argumentative learning, more complex topics should be chosen and as a consequence older participants should be invited to the study to match the more challenging and more diverse topics.

Thirdly, the interface should be easy to use. In this study, the interface for children to initiate dialogues was not very user friendly and practical. The "Ask Peedy" dialogue box was complex for the children in the study. Half of the children's intentions to talk to Peedy were cancelled after they saw the complex interface.

The pilot study was important as it demonstrated the learners' positive attitudes towards the argumentative agent and also generated suggestions for further improvement. The following chapter reports the development of an improved argumentative learning system that addresses the issues discovered from the pilot study.

12. Argumentative Learning System and Study Design

To date there have been many research projects which have described and reported on the results of incorporating intelligent agents in learning environments. Such research focused on discovering cause and effect relationships, typically measuring the impact of various virtual character features (e.g. instructional role, gender, voice,) on a number of quantitative variables (e.g. performance, engagement, credibility). However, researchers have overlooked the essential foundation of interacting with agents, that is, what learners experience when interacting with an artificial created character (Veletsianos & Miller, 2008).

Understanding the multitude of experiences that a learner encounters when interacting with virtual characters can help to expand our existing knowledge and research and enable us to (1) better understand the users' experiences; (2) more effectively comprehend what the future holds for computerised interactions, human–computer conversations, artificial intelligence and intelligent tutoring systems; (3) encourage future research endeavours on the exploratory and open-ended nature of interpretive pedagogical agent examination; and (4) evaluate previous research findings with respect to the lived experience of interacting with virtual characters (Veletsianos & Miller, 2008).

In the pilot study, a learning system was designed for a younger group of children, aged from 6 to 9 years old. As argumentation arose as the primary interest in a more focused learning study, there was a commensurate realisation that older participants would be more appropriate targeted since the learners needed to be able to generate complex argumentative dialogues and express multifaceted experiences. Hence, in this main study, an older group of students were chosen and the learning topics were also changed to relate to their relevant level of school experience.

Based on the findings from the pilot study, a new argumentative learning system was implemented. This study was conducted with 33 secondary school students to understand students' learning with the argumentative agent. In this study, the researcher not only studied the students' learning in terms of knowledge acquisition but also studied the students' learning experiences with the argumentative agent. The argumentative learning system and study design are presented in this chapter and the study results and discussions will be reported in chapter 13 and chapter 14.

12.1 Overview of the Animal Classification Learning System

Evidence from the pilot study informed the research so that:

1) The learning content should not be too simple otherwise the learners can find the obvious answer easily and hence no interest to discuss with the argumentative agent. The learning content should also encourage argumentation, such as involving logical reasoning and sufficient alternatives for learners to explore.
2) The argumentative agent's competency shouldn't be too low otherwise the learners don't believe the argumentative agent's knowledge and would tend to ignore the agent's opinions even if some opinions were valuable.

For this study, a new argumentative learning system was developed. In this new system, *animal classification* was chosen as the science topic. In this topic, the virtual agent and learners were able to discuss animal features and classification rules. Different people may have different ideas and there are alternatives to explore. In addition, in this new system the virtual character is provided with a high percentage of correct knowledge therefore it is more competent in animal classification questions. In this way, the learners are more likely to see the virtual character's intelligence and more willing to discuss with it seriously.

The main improvements of the new system are the increased knowledge of the agent and the adjusted topics of the system. There are also other efforts to make the system more engaging (e.g. awards) and easier to use. The learning system was developed based on the argumentative agent conceptual design (chapter 5) and the argumentation computing model for hierarchical knowledge (chapter 6).

There are still the same two virtual characters as in the pilot study, Leo the pink bee and Peedy the green parrot. Leo is modeled as a tutor who asks questions and announces correct answers. Peedy acts as a virtual learner. He proposes answers and discusses the answers with the learner. Peedy is the argumentative agent.

Both Peedy and Leo have knowledge bases which contain their animal classification knowledge. They generate dialogues based on their knowledge bases. Leo's knowledge base contains the complete knowledge considered in this system, so that Leo can present questions and evaluate answers based on his knowledge base. Peedy has a different knowledge base which contains errors and Peedy's opinions are not always correct. As a result, Peedy may bring conflicting ideas which is intentionally aimed at stimulating the learners to reflect their existing knowledge, explore the relevant knowledge or resolve the conflicts.

The main interface is shown in Figure 12.1. It has five main areas:

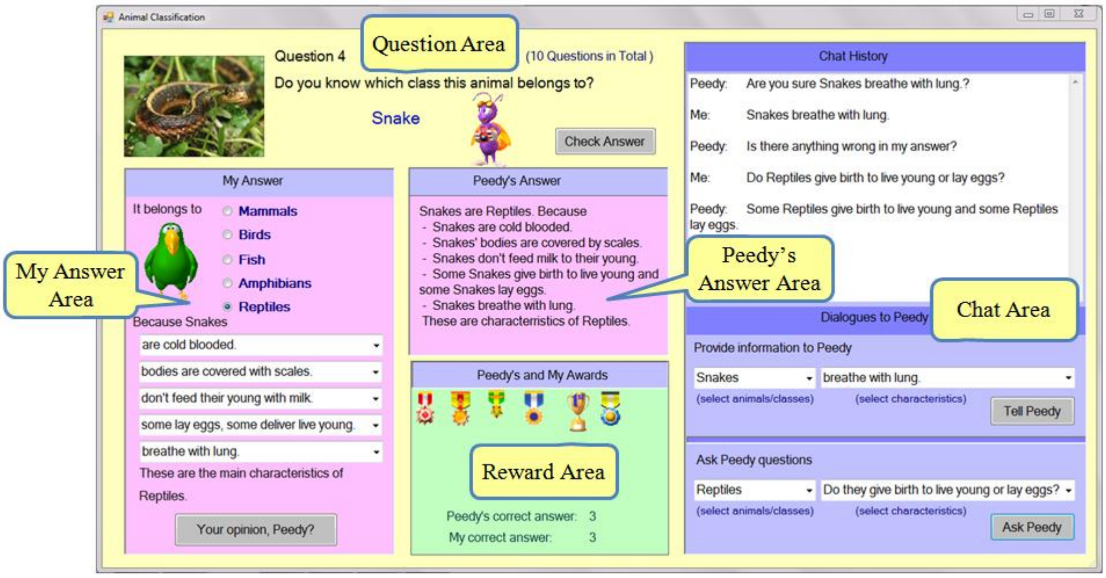


Figure 12.1 Main Interface

- *Question Area*: Leo presents questions in this area. For example, when an animal name and a picture are displayed, Leo asks "Do you know which class this animal belongs to?" In this area, there is a "Check Answer" button. When the learner presses this button, Leo will announce the class to which the animal belongs and correct the learner's mistakes regarding the animal features. In each session, there are 10 animals for the learner and Peedy to classify.

- *Learner's Answering Area*: The learner can select the animal class and describe the animal features on which the classification is based. The features include how the animal's body is covered, whether it is warm blooded or cold blooded, whether it feeds on milk or not, how it produces the next generation and how it breathes. After finishing the answer, the learner can press the "Your opinion, Peedy?" button to see Peedy's responses.

- *Peedy's Answering Area*: After the learner presses the "Your opinion, Peedy?" button, Peedy will present his answer. Peedy then starts the discussion with the learner. He may ask the learner questions, show different opinions or point out the learner's mistakes. For each question, Peedy keeps quiet before the learner presses the "Your opinion, Peedy?" button, so the learner has time to work independently before discussing with Peedy. While Peedy discusses with the learner, Peedy may update his knowledge or revise his answer.

- *Reward Area*: The medals and the number of correct answers are displayed in this area. Peedy's and the learner's medals are displayed together. By considering the learner and Peedy as being on one team, the learning system tries to encourage the learner to collaborate with Peedy to jointly receive more medals.

- *Chat Area*: The learner can select items from the dropdown boxes to form questions and answers for Peedy. The "Tell Peedy" button is for the learner to answer Peedy's questions, tell Peedy new knowledge and attack Peedy's wrong opinions. The "Ask Peedy" button is for the learner to ask Peedy questions, including the features of any animal classes or the discussed animal. The conversation history of Peedy and the learner is displayed in the "Chat History".

The aim of the system is to enhance students' learning through argumentation with Peedy. Peedy communicates with the learner verbally in English. The conversation text is displayed in the speak balloon or chat history. The learner communicates with Peedy by selecting items from the dropdown boxes to form sentences.

In addition to the dialogues for engaging and entertaining, Peedy is designed to conduct argumentative dialogues according to the computational model designed in chapter 5 and dialogue types listed earlier in Table 5.2. To reduce the interaction rounds and facilitate efficient information exchange, some adjustments are made:

1) There is no stand-alone rejection dialogue. The rejection dialogue is combined with the attack dialogue. To attack is to point out the opponent’s mistakes automatically implies the rejection of the other's proposal;
2) The justification dialogue is combined with proposal so the challenge dialogue to ask for the justification of a proposal is not needed;
3) A *Request Advice* dialogue is added for Peedy to remind the learner to check and compare his answers with Peedy’s. In this learning system, Peedy mainly conducts the following types of dialogues:

- *Proposal:* Peedy proposes his answers which are displayed in Peedy's Answering Area. During the interaction with the learner, Peedy may acquire new knowledge or modify his existing knowledge. He may generate alternative proposals based on his updated knowledge.

- *Acceptance*: If Peedy has the same idea as the learner, Peedy will say, "I agree with you." If Peedy encounters new knowledge that he didn’t know previously, he will say, "Thanks for telling me. I will remember this in my little brain." If Peedy receives new knowledge (e.g. tigers are warm blooded) which is in conflict with his existing knowledge and he decides to accept it, he will say, "I thought ....(e.g. tigers are cold blooded.) Well, you might be right. I accept your idea." Figure 12.2 shows an example where Peedy accepts the other’s opinion.

Figure 12.2 Peedy Accepts the Other's Opinion

- *Attack*: If Peedy disagrees with the learner, he discusses with the learner using the sentence "I don't agree with you. I think..... / In my opinion ......" Figure 12.3 shows an example where Peedy attacks the other's opinion.

Figure 12.3 Peedy's Attack

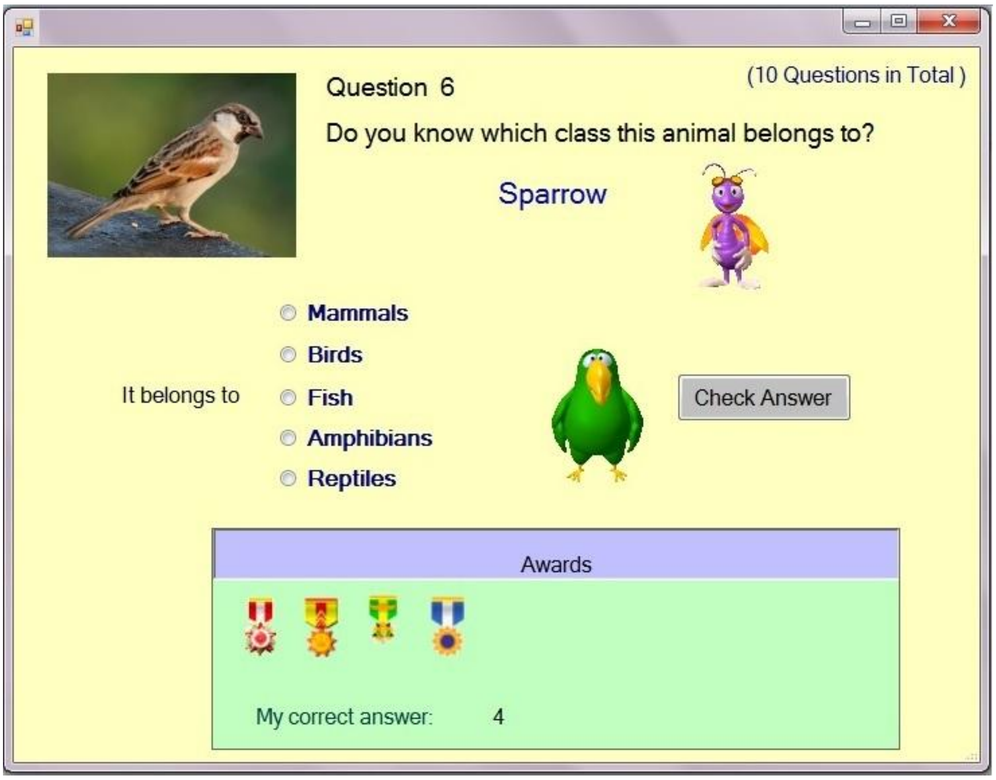
- *Information Seeking*: Peedy can ask the learner questions. For example, "I have no idea. Do you know what mammals' bodies are covered with?" or "Do you know if frogs breathe with lungs, gills or both?"

- *Information Providing*: Peedy can provide information to the learner. For example "To my knowledge, mammals' bodies are covered with fur or hair."

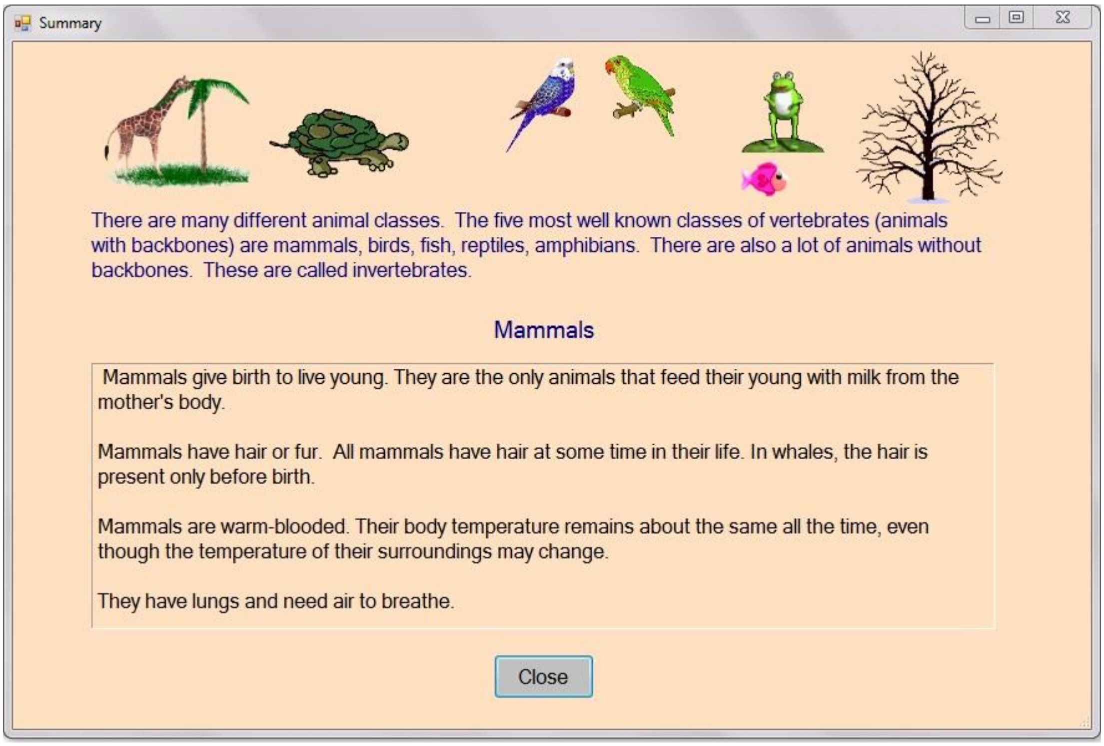
- *Request Advice*: Peedy asks "Is there anything wrong in my answers?" to prompt the learner to compare his answer with Peedy's and correct Peedy's errors, if any.

12.2 Participants and Procedures

To study the effect of argumentative learning, the researcher created two versions of the animal classification learning system, an argumentative version and a non-argumentative version. The argumentative version is as described above. The non-argumentative version uses the same characters and same questions but Peedy is not able to argue on animal classification questions with the learner. The main screen of the non-argumentative learning system is shown in Figure 12.4 (a). In the non-argumentative learning system, Peedy still keeps the dialogue to encourage learners, such as "Congratulations", "Well done" and "No worries" but he does not conduct argumentative discussions with the learner on learning content. Instead, after the first time a new animal class appears, the key features of that animal class is displayed in a page to the learner. For example, take the mammals as shown in Figure 12.4 (b). The argumentative system expects to improve students' knowledge through argumentation and the non-argumentative system intends to improve students' knowledge by providing information directly.



(a) Main Interface



(b) Information Page

Figure 12.4 The Non−argumentative Learning System

The participants were 33 secondary school students. Their ages ranged from 13 to 15, and there were 19 girls and 14 boys. They were randomly divided into two groups: 17 students in Group A (experimental group, 8 boys and 9 girls) and 16 students in Group B (control group, 6 boys and 10 girls).

All the students took a pre-test. Group A then used the argumentative system and Group B used the non-argumentative system. After finishing one learning session, all students took a post-test. Group B then used the argumentative system and Group A used the non-argumentative system for a second learning session. After the second learning session, all students completed a questionnaire. This study procedure had two purposes: 1) after the first learning session, the pre-test and post-test of the two groups were used to compare the learning gains of the different learning systems; 2) after the second learning session and after all the students had the opportunity to use both learning systems, a comparison could be made between the two systems from the questionnaires.

The total time from the beginning of the pre-test to the end of questionnaire was approximately one hour, and all the screen activities were captured during this period of time. Finally, 20 randomly selected students were interviewed to understand their learning experiences. The study procedures are listed in Table 12.1.

Table 12.1 Study Protocol

Steps	**Group A** (experimental group)	**Group B** (control group)
1. Survey 1 (Pre-test)	Pre-test on animal classification knowledge, and a biology interest questionnaire	
2. Learning Session 1	Argumentative version	Non-argumentative version
3. Survey 2 (Post-test)	Post-test on animal classification knowledge	
4. Learning Session 2	Non-argumentative version	Argumentative version
5.Survey 3 (Questionnaire)	A questionnaire on learning activities and learning experiences	
6. Interview	Discussing learning experiences	

Survey 1 (included a pre-test) and survey 2 (a post-test) were mainly used to collect students' animal classification knowledge before and after the first learning session. Students' biology interest was also collected in Survey 1. Fourteen statements were presented in the biology interest questionnaire and students were asked to express agreement or disagreement on a 5-point Likert scale.

Learning Session 1 was designed for students to learn the animal classification system. The questions were the same for Group A and Group B. The only difference was that for Group A Peedy argued with students on the learning content while in Group B Peedy did not argue. So the pre-test to post-test learning gains were used to compare the effectiveness between the two software versions.

Learning Session 2 was designed for students to learn with another version of the system. This time, Group A played with the non-argumentative version and Group B played with the argumentative version. The questions were the same for both groups but this set of questions were different from those used in learning session 1.

Survey 3 (a questionnaire) was administered after the two learning sessions. It was designed so the students were able to compare the two systems, express their perception to argumentative learning and report their learning activities and experiences. Students were encouraged to express their real feelings, and they were informed that the questionnaires were anonymous and would only be used for research purposes.

Interviews were conducted with 20 students randomly selected from the 33 participants to explore their learning experiences in more detail. The interviews were focused on the impact of argumentation on their learning.

12.3 Data Collection and Measurements

Data was collected from multiple sources, including a pre-test, post-test, questionnaire, screen recording and/or interview. This was to ensure that the study captured sufficient details from different aspects of argumentative learning in the designed settings.

Survey 1 was used to collect the students' animal classification knowledge and students' personal information (age, gender), as well as students' biology interest. The students' biology interest was assessed based on the Biology Attitude Scale of Russell and Hollander (1975). Students' biology interest was collected to identify whether there were some correlation between biology interest and argumentative activities. Survey 1 is attached in Appendix 1.

Survey 2 was a post-test which asked the same question as what was in the pre-test. It was used to test students' knowledge gain after interacting with the system. Survey 2 is attached in Appendix 2. Survey 3 (a questionnaire) was used to collect students' self-reported learning activities, learning experiences and their opinions on both learning systems. It is attached as Appendix 3.

Interviewing is a common method to collect data for phenomenographic study. Bowden (2005) and Trigwell (2000) agree that the sample size for a phenomenographic study is influenced by two factors. On one hand, the researchers should obtain enough people to ensure sufficient variation in ways of experience; while on the other hand, the sample size must also ensure that the amount of resulting data remains manageable. Bowden (2005) believes a sample size between 20 and 30 is ideal and Trigwell (2000) favours 15 to 20 interviewees. In recent studies, 15 to 20 interviews are also common (Diehm & Lupton, 2012; Paakkari, Tynjälä & Kannas, 2010; Christiansen, 2011).

In this study, 20 students were interviewed individually from the 33 students who participated in the study. Each interview lasted between 10 to 20 minutes and the interview was conducted within two weeks following the learning sessions. As the study aimed to find out students' learning experiences and perceptions to the argumentative agent, the semi-structured interview process was sufficiently open-ended to ensure a wide range of ideas were explored. The interview questions included a broad range of questions to inspire conversation, such as about what have they learned, what they have done, what were the most interesting things, and how they perceived argumentative learning. The actual interview questions and discussions had similar questions but also allowed for variance between interviews as different opinions were raised by the students. However, it remained important that all communications focused on the impact of argumentative learning to the learners. A reference interview schedule is listed in Appendix 4.

12.4 Data Analysis

Data analysis was performed to obtain understandings mainly on the following aspects:

- Learning Gain

Student t-tests were performed on the pre-test and post-test to compare the learning gains between the use of the argumentative system and non-argumentative system.

- Learner-Agent Interaction

Pearson's product moment coefficient (Pearson's r) was calculated to find out the correlations between the student's performance and the argumentative agent's performance in answering questions. If the two variables are positively correlated, it is more likely that the student's knowledge affected the argumentative agent's knowledge and performance, i.e. the students seriously passed their knowledge to the agent.

- Impacts of Argumentative Activities

Relevant data was analysed to find out the relationships between argumentative activities and other factors. The analysis includes:

- Pearson's *r* was computed to test the correlation between argumentative activities and biology interest;
- Multiple regression analysis was carried out to find out the contribution of argumentative activities to learning gains;
- Student t-tests were performed to compare the argumentative activities between two groups with different experiences.

- Learning Experience

The interviews and some questions of the questionnaires were analysed following a phenomenographic approach to understand students' learning experiences. The interviews were audio recorded and transcribed by the researcher. The questionnaires and interview transcripts were analysed iteratively to identify categories of description. The analysis was conducted according to the following steps:

- *Data relevant to the research questions were selected.* Portions of the interview or questionnaire data that were relevant to the student's experiences were selected and marked by data source (interview or questionnaire) and student number. These portions were quotations from students. All these relevant quotations were gathered together so that individual cases merge into the overall experience descriptions.

- *Transcripts were read and re-read many times in order to identify the major categories of description*. Quotations from students were assigned to broad groupings of qualitatively different ways of experiences. Grouping marks were added to each quotation. Initially each quotation was marked by data source, student number and grouping.

- *The categories were iteratively reviewed, revised and refined until all the transcripts were consistently assigned in the categories and sub-categories*. According to Marton and Booth (1997), "the individual categories should each stand in clear relation to the phenomenon of the investigation so that each category tells us something distinct about a particular way of experiencing the phenomenon"; and "as few categories should be explicated as is feasible and reasonable, for capturing the critical variation in the data" (p.125). Following this criteria, this research attempted to identify concise categories to cover the distinct qualitatively different experiences.

- *The categories were defined and presented in the outcome space*. In this step, categories were presented with meanings of the category and representative quotations from students. Diagram representation was drawn to show the relationships among the categories.

12.5 Summary

This chapter presented the improved argumentative learning system based on the findings of the pilot study. The study design was then presented followed by the data collection and analysis methods. Data was collected from multiple sources to ensure that the learning details were collected as much as possible. The results are reported in the following chapter, and findings are discussed in chapter 14.

13. Results

The aim of this study was to explore the learning effects, learner-agent interaction and learning experiences in an argumentative agent facilitated learning environment. The main study was designed and carried out with 33 students. This chapter presents the results of the study.

13.1 Test Scores

The study involved two sessions. A pre-test and post-test were taken before and after the first session for both group A and group B. In the first session, group A students used the argumentative system and group B students used the non-argumentative system. In the second session, group B students used the argumentative system and group A students used the non-argumentative system. The pre-test and post-test papers were marked based on the number of correct features they described for each animal class. Student A2 and A7 in group A misunderstood a question in the post-test. They listed some animals in each class instead of explaining the features of each class, thus their post-test scores were not able to represent their knowledge after the first learning session. So student A2 and A7 were removed from the analysis. Student B16 in group B did the post-test after finishing both software sessions which was not aligned with the study procedures. Student B16's post-test score was also not able to represent his/her knowledge after the first learning session, so student B16 was also removed from the analysis. The pre-test and post-test scores are shown in Appendix 5. The higher the score indicates that the student demonstrated greater levels of understanding and the lower score indicated that the student demonstrated less. The mean and maximum score is shown in Table 13.1.

Table 13.1 Mean and Maximum Score of Pre-test and Post-test

Group	No. of Students	Pre-test		Post-test	
		Mean	Max Score	Mean	Max Score
A	15	6.27	9	8.67	19
B	15	5.2	8	6.13	13

The result showed that both groups did better in the post-test than the pre-test in terms of the mean scores. That is to say, students' animal classification knowledge had increased after the learning session. To examine whether the knowledge increase is statistically significant, student t-tests were conducted. The results are shown in Table 13.2.

Table 13.2 T-tests Results

	t-statistics	p value
Independent t-test on pre-test between group A and B	1.42	.17
Paired t-test on group A between pre-test and post-test	2.10	**.03**
Paired t-test on group B between pre-test and post-test	1.16	.13

Student independent t-tests were performed on the pre-test of group A and group B, with two tailed p= .17 (t = 1.42). These indicate that there was no evidence (at 0.05 level of significance) to claim a difference between the two groups' mean of pre-test scores. It confirms that group A and group B had a similar level of knowledge about the content relevant to this study.

In both group A and group B, the average of the post-test scores was higher than that of pre-test scores. Paired t-tests were performed on each group to test the improvement of content knowledge from pre-test to post-test:

- A paired t-test was performed on the pre-test and post-test of group A, with p= .03 (t=2.10) for one-tailed t-test. This shows that there was sufficient evidence (at 0.05 level of significance) that the mean of the post-test score was higher than the mean of the pre-test score for group A.

- A paired t-test was performed on the pre-test and post-test of group B, with p= .13 (t=1.16) for one-tailed t-test. This shows that there was insufficient evidence (at 0.05 level of significance) that the mean of the post-test score was higher than the mean of pre-test score for group B.

In this study, group B was the control group which used the non-argumentative learning system. Group A was the experimental group which used the argumentative learning system. The t-tests results confirmed that students in the experimental group increased their animal classification knowledge significantly, while students in the control group did not have significant increase in their knowledge. Hence, the argumentative agent in this study was effective in improving the students' animal classification knowledge.

13.2 Argumentative Activities

The argumentative activities between the learner and the system were studied with the data collected from the questionnaire and the screen recording highlighting their actions while engaging with the system.

13.2.1 Self-reported Activities from Questionnaire

After the two learning sessions of the study, all students had used the argumentative learning system. Group A used it in the first session and group B used it in the second session. All the students completed a questionnaire after they finished the two learning sessions. In the questionnaire, students were asked to make selections on some pre-defined items regarding interaction activities. The self-reported argumentative activities according to the questionnaire are listed in Table 13.3.

Table 13.3 Argumentative Activities from the Questionnaire

Activities		Response	
		No. of students	Percentage
When Peedy presents different opinions, what did you do?	Ignore him	0	0
	Re-think on my idea	31	93.94%
	Consult others to find out who is correct	2	6.06%
	Correct Peedy	18	54.55%
	Other (discuss with Peedy)	4	12.12%
When Peedy needs help, what did you do?	Ignore him	0	0
	Tell him the right answer I think	31	93.94%
	Just randomly choose an answer, I don't care if the answer I provided to Peedy is correct or not.	2	6.06%

When Peedy presented different opinions, most students (93.94%) reflected on their own ideas which indicated that Peedy's opinions inspired the students' thinking. Half of the students (54.55%) started to correct Peedy's answer. Four students reported that they would also consider other actions when different opinions arose, and they all mentioned discussions with Peedy. Figure 13.1 depicted the activities when Peedy showed different opinions.

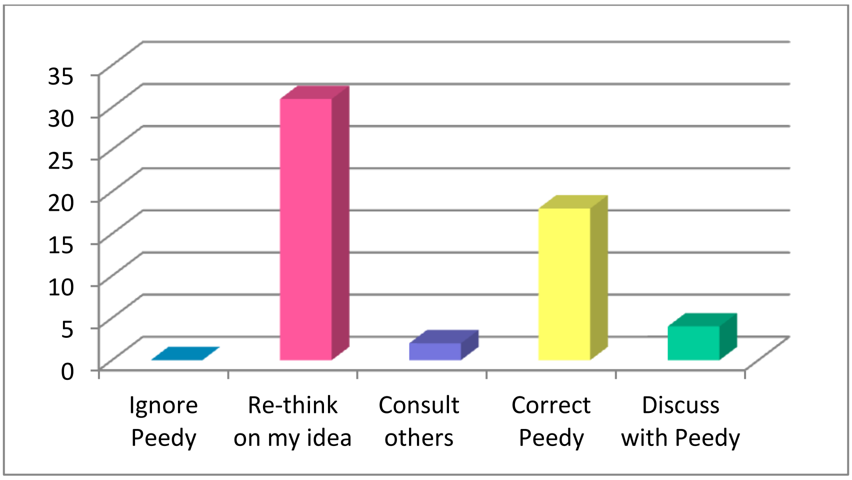


Figure 13.1 Activities When Peedy Showed Different Opinions

When Peedy needed help, most students (93.94%) tried to tell Peedy the correct answer, which indicated that the students were willing to help Peedy as well. Figure 13.2 depicted the activities when Peedy needed help.

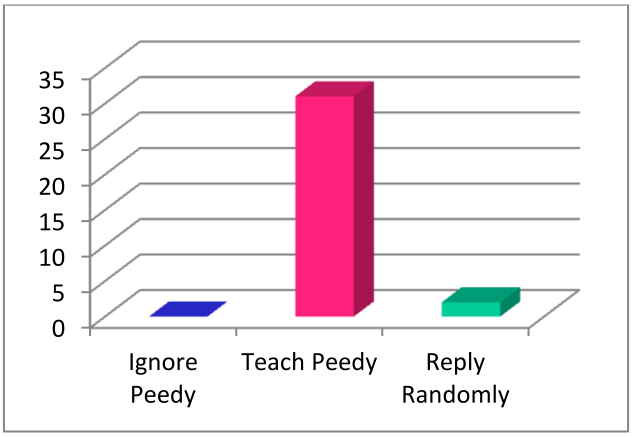


Figure 13.2 Activities When Peedy Needed Help

13.2.2 Observed Activities from Screen Recording

All the students' interactions with the learning system were recorded via screen capturing software. Students made some mistakes which might have been due to their incorrect knowledge, misunderstandings or just carelessness. The screen recording showed that the students were engaged in the interaction with Peedy. When Peedy presented his answer, the students usually compared their answers with Peedy's and made changes accordingly.

Leo: *Do you know which class this animal belongs to? (text "Penguin" and a picture of penguin are displayed on the screen)*

Student: *It belongs to Birds. Because penguins*

- *are warm blooded*
- *bodies are covered with hair or fur*
- *don't feed their young with milk*
- *give birth to live young*
- *breathe with lung and gills*

(Press the "Your opinion, Peedy?" button)

Peedy: *Penguins are birds. Because*

- *Penguins are warm blooded*
- *Penguins bodies are covered with feathers*
- *Penguins don't feed milk to their young*
- *Penguins lay eggs*
- *Penguins breathe with lungs*

Student: *(Compares with Peedy's answer. Modified 2 items in his answer.)*

It belongs to Birds. Because Penguins

- *are warm blooded*
- *bodies are covered with feathers (modified according to Peedy's answer)*
- *don't feed their young with milk*
- *give birth to live young*
- *breathe with lungs (modified according to Peedy's answer)*

Peedy: *I have a different opinion. I think birds lay eggs.*

Student: *(Change to "lays eggs")*

---from screen recording of student A4 Question 6

The students also considered Peedy's questions. After realising Peedy was correct, they adjusted their answers. For example,

The student describes a crocodile giving birth to live young. Peedy says "I don't think so. In my opinion, crocodiles lay eggs." The student changes her answer to "lay eggs".

---from screen recording of student B11 Question 2

The students argued with Peedy when they disagreed with Peedy. For example, in the following scenario of a student in one session as shown in Figure 13.3,

when talking about elephants, Peedy thinks elephants don't feed milk to their young; the student tells Peedy that elephants do feed milk. Peedy accepts the *student's opinion and adds "Elephants feed milk to their young" in his answering area.*

---from screen recording of student B10 when answering Question 4

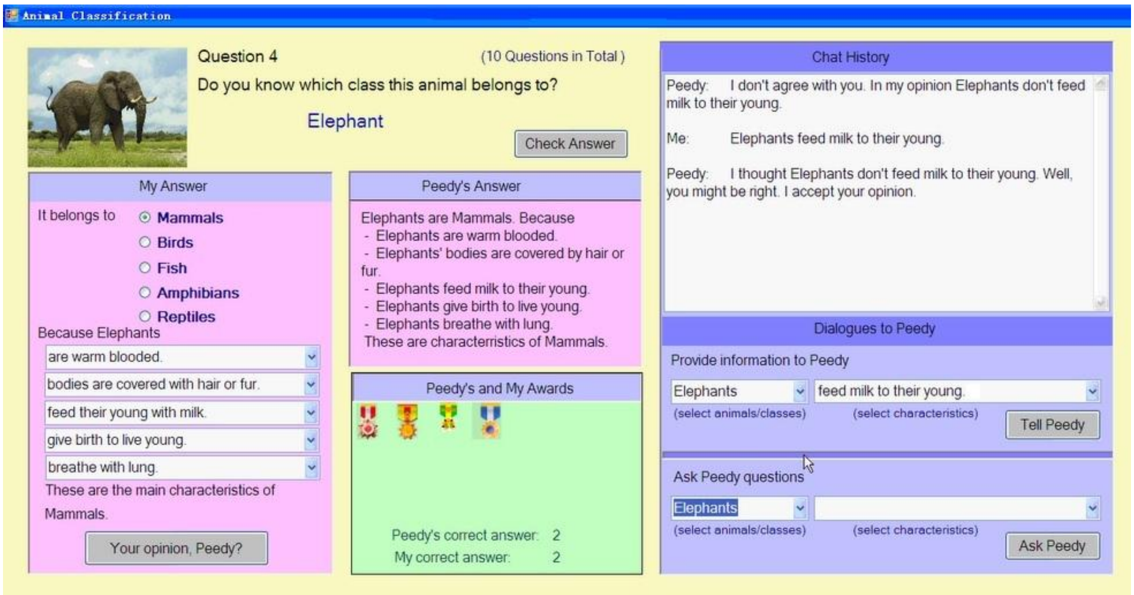


Figure 13.3 Screen Shot of a Student

The students also helped Peedy, such as in instances where they taught Peedy the correct answers based on their previous knowledge.

The student tells Peedy "frog lays eggs", "frog breathes with both lung and gills" and "frog is cold blooded". Then Peedy updates his knowledge and gets all the features of frog correct.

---from screen recording of student A10 Question 5

Peedy's questions prompt the students to re-consider their own answers and tried to find evidence from other sources, such as from their friends or the Internet. For example:

Student: (believes red eyed tree frog is cold blooded)
Peedy: Are you sure red eyed tree frog is cold blooded?
Student: (changes to warm blooded)
Do you know if frogs are cold blooded or warm blooded?
Peedy: I don't know if frogs are cold blooded or warm blooded.

Student: (goes to search from the Internet, changes to cold blooded)

---from screen recording of student A14 Question 5

In addition to the interaction scenarios, the screen recordings also showed students' argumentative activities. To complete a question, the students and the agent usually discuss with each other such as when they asked a question to each other, point out each other's mistakes, or modify their answers. The students' activities can be classified into five categories:

- *Ask*: ask Peedy questions by pressing the "Ask Peedy" button.
- *Answer*: answer Peedy's questions by pressing the "Tell Peedy" button.
- *Disagree*: show disagreement with Peedy's opinions, by pressing the "Tell Peedy" button.
- *Agree and Tell*: show agreement with Peedy's opinions, or provide new knowledge to Peedy, by pressing the "Tell Peedy" button.
- *Modify*: modify answers in the learner's answering area.

The number of activities of each category and each student is recorded in Appendix 6. There were 142 *Ask* activities, 100 *Answer* activities, 150 *Disagree* activities, 75 *Agree and Tell* activities and 197 *Modify* activities in total. The percentage of each activity is depicted in the following pie chart (Figure 13.4).

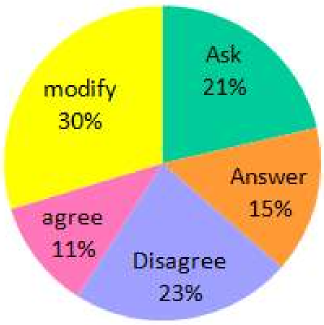


Figure 13.4 Observed Argumentative Activities

To find out whether there were any relationships among these activities, Pearson's Product Moment Correlation (Pearson's *r*) was computed to investigate the correlations between the different activities. The result is shown in Table 13.4. A negative correlation was found between the *Disagree* and *Modify* activities approaching marginal significance (r = -0.34, p= .05). This indicated that students with more *Disagree* activities tended to have less *Modify* activities. A possible explanation for this result could be related to the learners' confidence. If a student was confident at his/her knowledge, s/he might generate more *Disagree* dialogues to correct the agent's answer while perform less *Modify* activities to revise his/her own answers (details are discussed in section 14.4.1).

Table 13.4 Correlation Between Different Activities

(Pearson's *r* and *p*-value in brackets)

	Ask	Answer	Disagree	Agree
Answer	-0.05 (.78)			
Disagree	0.01 (.97)	0.13 (.46)		
Agree	-0.24 (.17)	-0.17 (.34)	-0.29 (.11)	
Modify	0.27 (.13)	-0.14 (.43)	-0.34 (**.05**)	0.27 (.14)

13.3 Learning Experiences - A Phenomenographic Study

Students' learning experiences were collected from questionnaires (e.g. question 1, 3, 5, 7, 8 of the questionnaire) and interviews. The students were asked to describe their learning using adjectives in the questionnaire. The most frequent words used were *interesting*, followed by *cheerful*, *joyful*, *delightful*, *relaxing*, *enthusiastic* and *fun*.

After the two sessions with both the argumentative and non-argumentative agent, students were asked in the questionnaire which kind of Peedy (name of the intelligent agent) they found most friendly and useful. 32 out of 33 students replied that they chose the argumentative one as being more influential and helpful. The student who chose the non-argumentative Peedy might have recorded his answer in error the first time in the questionnaire because in the follow-up interview he said he preferred the argumentative Peedy.

Learning experience data collected from the questionnaires and interviews were analysed according to the phenomenographic approach, and it revealed the qualitatively different learning experiences.

13.3.1 Overview of the Learning Experience Categories and the Outcome Space

The phenomenographic study of the data revealed three qualitatively different categories of learning experiences: argumentative learning is experienced as a way for knowledge building (Category 1), skill building (Category 2) and disposition building (Category 3). The experience categories and sub-categories from this study are listed in Table 13.5.

Table 13.5 Categories of Argumentative Learning Experience

Category		Description
1. Knowledge Building		
1.1	Knowledge Acquisition	Argumentative learning is experienced as a way for knowledge building.
1.2	Memory Retention	
1.3	Deep Understandings	
1.4	Critique and Analysis of Opinions	
1.5	Conceptual Change	
2. Skill Building		
2.1	Critical Thinking Skill	Argumentative learning is experienced as a way for skill building.
2.2	Communication Skill	
3. Disposition Building		
3.1	Active Thinking	Argumentative learning is experienced as a way for disposition building.
3.2	Confidence	
3.3	Positive Attitude	
3.3.1	Enjoyment	
3.3.2	Interest to Biology	

The categories were formed following the criteria outlined by Marton and Booth (1997): first, “the individual categories should each stand in clear relation to the phenomenon of the investigation so that each category tells us something distinct about a particular way of experiencing the phenomenon”; second, “the categories have to stand in a logical relationship with one another, a relationship that is frequently hierarchical”; third, “the system should be parsimonious, which is to say that as few categories should be explicated as is feasible and reasonable, for capturing the critical variation in the data” (p.125). In this research, each category tells us a distinct learning experience occurred while interacting with an argumentative agent, and all the categories cover the variety of participant experiences in the context of this study.

The categories can be represented as an outcome space which is the diagrammatic representation of the categories and their relationships. In this study, a cylinder is used to represent the outcome space. The whole experience is represented as a cylinder comprising three parts: knowledge, skill and disposition. It is depicted in Figure 13.5. The size of each part doesn't reflect the percentage of the students who had that experience. The divided cylinder shows the three categories that form the overall experiences, and there is no priority or order among the three categories.

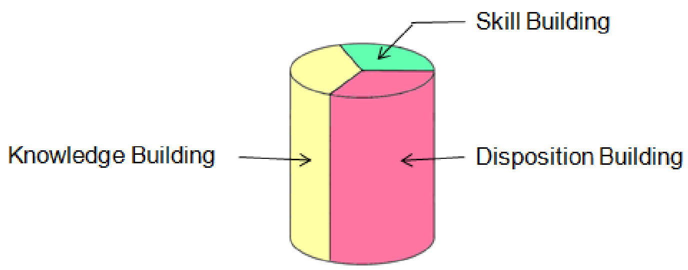


Figure 13.5 High Level Outcome Space

According to Marton (1997), “the different ways of experiencing a certain phenomenon, characterised by corresponding categories of description, represent different capabilities for dealing with (or understanding) that phenomenon. As some ways of experiencing the phenomenon are more efficient than others in relation to some given criterion, it is possible to establish a hierarchy of categories of description.”

(p. 98). In this study, the sub-categories of the knowledge category form a hierarchy. The sub-categories range from *Knowledge Acquisition* and *Memory Retention*, *Deep Understanding*, *Critique and Analysis of Opinions* to *Conceptual Change*, and the involved cognitive process range from simple to complex, from fundamental to a higher level. This is illustrated as objects from bottom to top in the outcome space with *Knowledge Acquisition* and *Memory Retention* at the lower level of the hierarchy. They involve the same level of cognitive process. The bottom object is the foundation for the upper object, and the upper object is based on the bottom object and reaches an advanced stage.

In the skill category, the sub-category of *Critical Thinking Skill* and *Communication Skill* are in parallel relationship. In the disposition category, the sub-category of *Active Thinking*, *Confidence* and *Positive Attitude* are also in parallel relationship. The sub-category Positive Attitude can be further broken down to *Enjoyment* and *Interest to Biology*, which forms a hierarchy. With enjoyment to the learning system, the interest to the learning content (interest to biology) can be gradually developed. A detailed outcome space is shown in Figure 13.6.

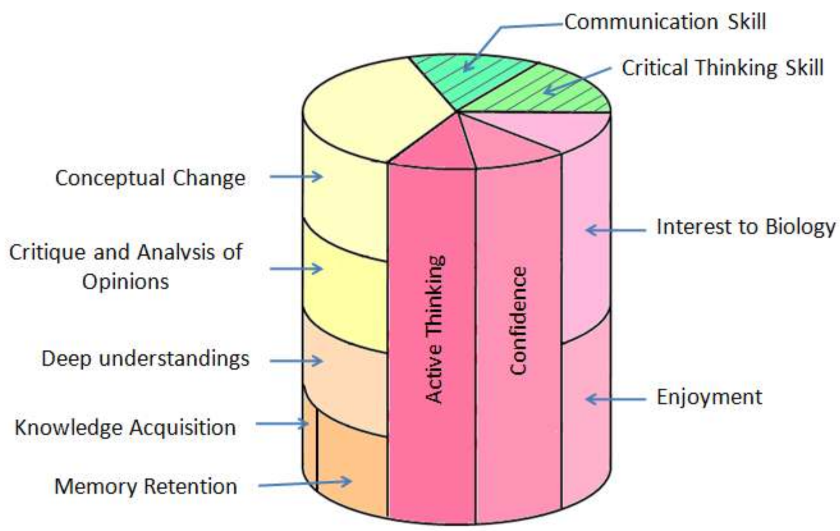


Figure 13.6 Detailed Outcome Space

The metaphor depicted in Figure 13.7 explains the connections between categories and their relationship to the whole argumentative learning phenomenon. That is, argumentative learning is equated as being fertile soil. It provides the nutrients of cognitive conflicts, explanation and elaboration opportunities, multiple viewpoints of a problem, and connections between new and existing knowledge. The soil ensures the growing of different plants including trees of knowledge, skill and disposition. The trees are all blossoming and bearing fruit. The fruits are the educational achievements.

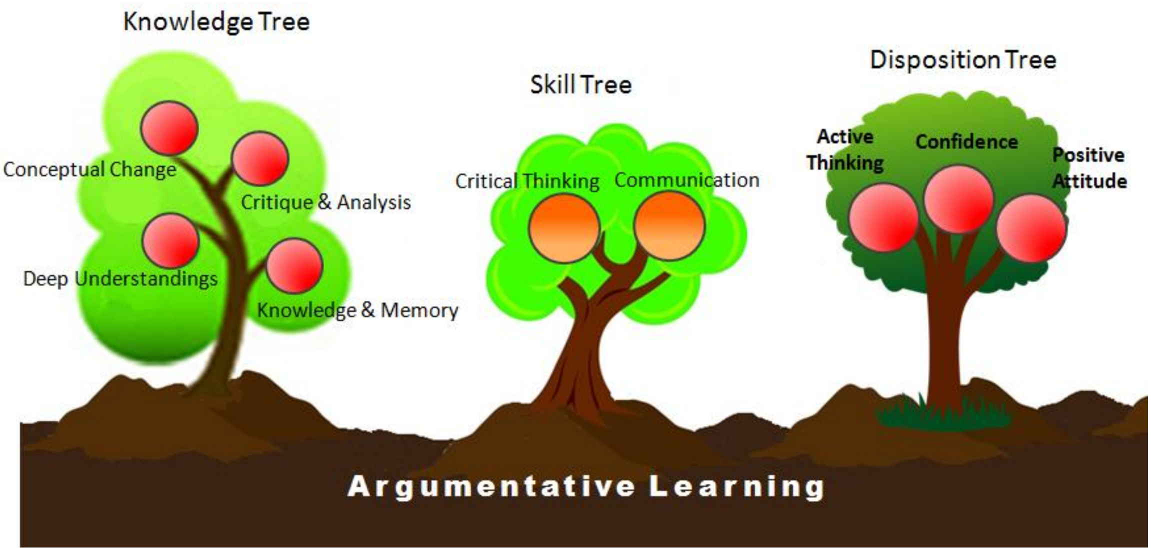


Figure 13.7 Metaphor of the Outcome Space

The meanings for each category are detailed in the following section with representative quotations from the interviews and questionnaires. This approach is a usual strategy deployed to report the findings in phenomenographic studies. Representative quotations were selected and numbered from both the questionnaire data and interview data. The reference for the quotation uses the format of "<quotation source>-<student ID>, <quotation ID>". For example, "Interview-A1, 3" refers to the quotation from interview data of student A1, and it is the 3rd representative quotation. "Questionnaire-B2, 5" refers to the quotation from the questionnaire of student B2, and it is the 5th representative quotation.

13.3.2 Category 1: Argumentative Learning is a Way for Knowledge Building

In this category, argumentative learning is experienced as a way to impact on the student's knowledge base. Through interaction with the learning system, the students felt they had either broadened their knowledge base about the topic, deepened their understandings, or changed their existing misconceptions. This category comprises five sub-categories.

Sub-Category 1.1: Knowledge Acquisition

Students felt that argumentative learning allowed them to exchange information with the argumentative agent, Peedy, so that they acquired new knowledge from the interactions. For example:

- *The discussion is always better than guessing by oneself. <u>Peedy lets me know lots of things that I didn't know before</u>. (Questionnaire-A7, 1)*

- *During the learning session with Peedy, I got to know about some animals that I knew before, and some animal knowledge that I didn't know before. It broadens my vision and enriches my knowledge. (Questionnaire-A8, 4)*

- *It allows me to know more about others' opinions, and see whether they are the same as or different to mine. (Interview-B1, 8)*

- *<u>Learning with him (Peedy) makes me know more knowledge about animals</u>. Meanwhile, we can discuss our individual thoughts, make progress together and acquire more knowledge. (Questionnaire-B1, 3)*

- *In the discussion, everybody can express opinions and ideas freely, we can learn more in this way. In the traditional way, the teacher, I feel as if the teacher poured knowledge on me. (Interview-B1, 6)*

Sub-Category 1.2: Memory Retention

In addition to acquiring new knowledge the students also felt that their interactions with Peedy were effective in highlighting new knowledge so that they retained the new information for longer periods of time. For example:

- *When I correct Peedy's answers, it reminds me to think about the question again, to think about why the answer is like this. When I tell him, it strengthens my memory of this answer. (Questionnaire-A14, 3)*

- *<u>Although he is misleading sometimes, he strengthens my impression</u> of animal classification. It is helpful to me. (Questionnaire-A2, 1)*

- *<u>He helps me remember the mistakes I made, and helps me remember the questions that I was not able to answer</u>. If he (Peedy) was wrong, I could remember it and this reinforced my memory. If I was wrong, I could realise my mistakes and this made my impression to this question even deeper. (Questionnaire-A9, 1)*

- *If my idea was wrong, Peedy would tell me his opinion and prove he was correct. This left me a deep impression of this question. If Peedy was wrong, I would tell him immediately, meanwhile it also strengthened my impression. (Questionnaire-B5, 1)*

- *We can gain a lot during the discussion, and will have more impression than telling the answers directly. (Interview-A2, 1)*

Sub-Category 1.3: Deep Understandings

Some students felt they gained a deep understanding when they pointed out each other's mistakes, found out the correct answers by themselves, or analysed different perspectives of a topic. They thought they understood the problems better and they could apply the knowledge learned as a future reference. For example:

- *<u>It deepens my understanding</u>. It prevents me from making such mistakes later. (Questionnaire-A2, 2)*

- *If he is wrong, by pointing out the mistakes to each other, we can have deeper understanding. <u>I will not make mistakes if I encounter such questions in the future</u>. (Interview-A3, 3)*

- *If arguing, if we use the argumentative method, we can understand the good and bad aspects of a thing. It is beneficial to gain deeper understanding of that thing. (Interview-A11, 4)*

- *I feel he is like a teacher to teach me when I encounter difficulties. Then I have real grasp of the thing. (Interview-A6, 2)*

- *Sometimes he tells you the correct answer. Sometimes when he is cheating on you and you find out the correct answer by yourself, this can deepen your understanding of the question. (Interview-A2, 2)*

When learners integrate new ideas into a network of relevant ideas in the learners' existing cognitive structure, deep learning occurs. In this study, argumentative learning was also a way to help students review their existing knowledge, and connect the new knowledge with the old. For example:

- *He can help me firmly remember the answers which I didn't understand before, he also told me lots of knowledge that I didn't know. Through communication with him, I reviewed what I had learned and knew a lot of new knowledge. (Questionnaire-A14, 2)*

- *It can stimulate my learning interest, and lets me recall some knowledge learned before. (Questionnaire-A3, 1)*

Category 1.3 is different from category 1.1 and 1.2. In category 1.1 and 1.2, the knowledge mentioned by the students was isolated facts. They accumulated the facts and remembered them. In category 1.3, the knowledge was learned in an integrated way. Students connected the knowledge with their existing knowledge structure and subsequently knew how to apply the knowledge at a later date.

Sub-Category 1.4 Critique and Analysis of Opinions

In argumentative learning, the students and Peedy critique each other's opinions to approach the correct answers. Students considered Peedy a character that helped to point out or discover mistakes. For example:

- *Peedy can point out my mistakes and remind me. (Questionnaire-A13, 2)*

- <u>*It enables me to find my mistakes. My answer is not always correct.*</u> *(Questionnaire-B16, 2)*

- *When my answer and Peedy's answer are different, of course, I may find mine has errors. (Interview-A11, 2)*

According to some students, Peedy encouraged self-checking, one essential aspect to critiquing and analysing one's own opinion. For example:

- *He lets me check by myself more frequently and I don't always believe myself to be right. (Questionnaire-A6, 1)*

- <u>*When he posts questions to me, it reminds me to check my answer again and see if I am correct.*</u> *If he is wrong, this allows me to point out his problem. This enables me to remember the knowledge again. (Questionnaire-B10, 1)*

- *After he speaks, I will have a look, and see whether I am really wrong. I will check through.* <u>*I developed the habit of checking*</u>*. (Interview-A6, 3)*

- *I will reflect on whether my answer contains mistakes. If there are no mistakes, I will tell Peedy. (Interview-B15, 3)*

Argumentative learning does not merely involve critiquing answers, it analyses the reasons behind the answers. The study has shown that the agent had the power to motivate students to analyse the reasons behind the answers. For example, some students noted:

- *When answering questions, if I was wrong, he would help me enthusiastically. He let me amend the mistake and then explained to me and let me know why it was this answer. He also let me know other knowledge about this animal. (Questionnaire-A11, 2)*

- *He helped me understand why I was wrong. This enabled me know the reasons for the mistake and to corrected it immediately. (Questionnaire-A8, 2)*

Experience in category 1.4 describes an active reaction to the knowledge encountered. In the previous categories 1.1, 1.2 and 1.3, the student acquired and extended their knowledge about concepts. However, they were passive in initiating dialogue with the argumentative agent. In category1.4, the students actively interacted with the argumentative agent, such as analysing and critiquing different opinions, in order to reach acceptable answers.

Sub-Category 1.5: Conceptual Change

A few students thought argumentation could change existing misconceptions. For example:

- *Surprisingly, a penguin is a bird. (Questionnaire-B8, 4)*
- *Peedy can answer my questions. If I am wrong, he will propose different views which give me a deeper impression. He can also change my long-held existing views. (Questionnaire-A13, 3)*
- *When discussing with him, sometimes we argue over our different opinions. Then it becomes clear to me, and I realize that what I believed before was wrong. (Interview-A13, 3)*

The students' experiences classified in category 1.5 revealed that the students were active in initiating dialogues with the agent, similar to that in category 1.4. Category 1.4 highlights the critique and analysis process, and misunderstandings may still exist. Category 1.5 highlights the outcomes when some misconceptions are changed. The five sub-categories are compared in Table 13.6, regarding the learners’ learning outcomes, initiative in dialogue, and undertaking some main activities with Peedy.

Table 13.6 Comparison of the Sub Categories

Sub Category	Outcome	Dialogue Initiative	Activity
1.1 Knowledge Acquisition 1.2 Memory Retention	Isolated knowledge, longer memory	Passive	Exchange and highlight information
1.3 Deep Understandings	Integrated knowledge	Passive	Connect relevant knowledge together
1.4 Critique and Analysis of Opinions	Better answers	Active	Analyse and critique different opinions
1.5 Conceptual Change	Corrected concepts	Active	Resolve conflicts

13.3.3 Category 2: Argumentative Learning is a Way for Skill Building

Argumentative learning is a way to build skills that are inherent to effective learning. In this study, students believed that they had developed skills in critical thinking and communication

In this research, Peedy was designed to have both correct knowledge and incorrect knowledge. Peedy conducted dialogue with the learners based on his knowledge. The learners themselves had to judge which knowledge was correct. This mechanism of the agent helped the students to develop their critical thinking skills. The following examples are students' acknowledgements to this aspect gathered from their questionnaire or from their interview:

- *It deepens my grasp of knowledge, developed my judgment.* *(Questionnaire-B2, 2)*
- *He sometimes makes me unsure that this answer is correct or that answer is correct. (Interview-B1, 2) I usually ask him, and then have a look at his opinion. I then think about it, to decide if I should choose his (answer) or mine. (Interview-B1, 5)*
- *Sometimes I was misled by him, sometimes I insisted on my own correct opinion. (Interview-A2, 3)*

To argue with others, one has to organise one's own ideas and explain these to others. Argumentation is an activity which forces people to put their thoughts in order and to communicate them clearly. This study received confirmation from students who felt that argumentative learning developed their communication skills. For example, some students stated:

- *Argumentation topics have two sides. We cannot say which side is correct and which side is wrong. <u>(Argumentation) can improve our presentation skills,</u> and (ability) to switch position to consider the opponent's opinions. (Interview-B2, 4)*

- *(Argumentative learning) can make me better organise my language and deepen my understanding. (Interview-A8, 2)*

- *(Argumentative learning) can develop divergent thinking, develop my explanation skills and also develop my ability to respond. (Interview-A6, 4)*

13.3.4 Category 3: Argumentative Learning is a Way for Disposition Building

In addition to knowledge and skill building, Peedy also changed the students' dispositions and attitude towards science.

Sub-Category 3.1: Active Thinking

During the interaction with the learner, Peedy sought information from the learner, expressed disagreement with the learner's opinions and questioned the learner's answers. These all encouraged the learner to think about the inter-related knowledge in the given scenarios. Some students pointed out:

1. *To learn with Peedy, I must think carefully. (Questionnaire-A14, 4)*
2. *He (Peedy) makes me able to deeply remember which answers are incorrect. And he makes me think every time which benefits my learning. (Questionnaire-A5, 1)*

3. *He can post questions and let me think, and correct my mistakes. (Questionnaire-B10, 2)*

4. *He makes me think. If you are correct, he will use a wrong answer to disturb you. But in this way you can remember the answer better. (Questionnaire-B14, 1)*

5. *He lets me learn how to think. This is what I love the most. (Questionnaire-B9, 3)*

Sub-Category 3.2: Confidence

By correcting their own errors and also helping Peedy to arrive at correct answers, the students felt they had gained in their own confidence. For example:

- *"It (Peedy) enables me to correct my errors in time, and lets me become more confident." (Questionnaire-B9, 2)*
- *"Argumentative learning can help people answer questions confidently." (Interview-B10, 4)*

Sub-Category 3.3: Positive Attitude

When students were asked to describe their learning experiences using adjectives, the most frequent words used were *interesting*, followed by *cheerful*, *joyful*, *delightful*, *relaxing*, *enthusiastic* and *fun*. Students felt that they had developed a positive attitude toward their science learning. The positive attitude they developed is evidenced by the enjoyment to Peedy and the learning system (Category 3.3.1: Enjoyment), and being interested in learning about biology (Category 3.3.2: Interest to Biology).

Peedy has emotions and animations which are fun factors according to students as described below:

- *My favorite thing is that Peedy shows very lovely expressions when I answer the questions, which makes me laugh. (Questionnaire-A13, 5)*

- *My favorite thing is that he discusses questions with me. If there are things I don't understand, I can discuss these with him. When I gave him a correct answer, he showed me a very happy smile. (Questionnaire-B11, 2)*

- *When my answer is different to his, we discuss the issue actively, which is very enjoyable. He is cute when flying! (Questionnaire-B3, 3)*

To students, discussions and argumentations with Peedy were enjoyable. Argumentative learning is a way that has given them a learning opportunity that supports an appropriate challenge in an enjoyable way. For example, some students noted:

- *I have some questions that don't understand. We always discuss together. He is not that clever, but he is very warm-hearted to help me. It is very interesting. (Survery-A16, 2)*

- *When I discuss with Peedy, I think of the discussions I have had with classmates in class. I keep looking at Peedy's expressions when I discuss with him. That's interesting. (Questionnaire-B12, 1)*

- *When I answer questions, I can ask him if I don't know. He accepts my opinions sometimes. It's interesting to discuss questions with him. He is expressive, that's very amusing. (Interview-A13, 1)*

- *I am a person who loves to talk and loves to discuss. In the discussion, if you have problems you can communicate these to others. That's really good. (Interview-B15, 1)*

- *I feel happy about arguing with others. (Interview-B3, 3)*

In addition to the enjoyable interactions with the system, the students also developed an interest in learning about the science content, biology. For example,

- *Through learning with Peedy, I acquired lots of knowledge that I didn't know before. It allowed me to have fun from learning. We helped each* *other. It (Peedy) enabled me to have an active attitude in biology learning. (Questionnaire-A15, 5)*

- *Peedy can help me learn biology, and <u>make me more interested in biology.</u> (Questionnaire-B2, 1)*

- *When discussing with him, I have a friendly feeling. This can inspire my eagerness to learn. (Interview-A3, 1)*

- *<u>Peedy can inspire my interest, I love biology more</u>. (Interview-A13, 2)*

13.3.5 The Response Distribution

Different students had different learning experiences. Table 13.7 summarises the students' responses regarding learning experience categories, (further details are recorded in Appendix 7). The most common responses of the students were about memory retention (21 students or 63.64% of the participants), critique and analysis of opinions, knowledge acquisition and having a positive attitude.

Table 13.7 Learning Experience Response

Category		Response	
		Number	Percentage
1. Knowledge Building			
1.1	Knowledge Acquisition	14	42.42%
1.2	Memory Retention	21	63.64%
1.3	Deep Understandings	7	21.21%
1.4	Critique and Analysis of Opinions	18	54.55%
1.5	Conceptual Change	2	6.06%
2. Skill Building			
2.1	Critical Thinking Skill	3	9.09%
2.2	Communication Skill	6	18.18%
3. Disposition Building			
3.1	Active Thinking	7	21.21%
3.2	Confidence	2	6.06%
3.3	Positive Attitude	14	42.42%

The result is depicted in Figure 13.8. It shows that students have experienced a variety of learning attributes. Some categories are reported by participants more than others.

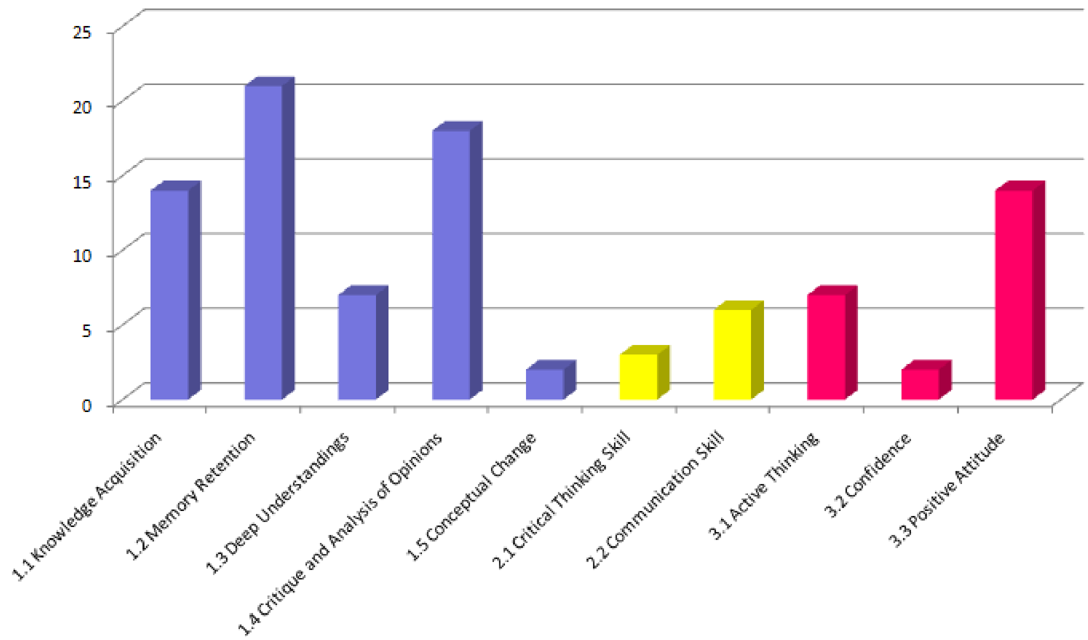


Figure 13.8 Response Distribution

13.4 Relationships Discovered

13.4.1 Peedy and Students' Performance

In general, the study showed that students were willing to enter into discussions with Peedy. They answered Peedy's questions, countered Peedy's different opinions and also provided Peedy new knowledge.

Peedy was provided with initial knowledge. Without providing new knowledge, Peedy could achieve 7 correct answers out of the 10 questions, as designed in the system. During Peedy's interaction with the peer students, new knowledge was conveyed from the peer student to Peedy, which enabled Peedy to update his knowledge and modify his answers. If Peedy received more correct knowledge from the peer student, he was more likely to achieve a higher score and present more correct features. The learning system recorded the number of correct answers Peedy and the student got respectively. The system also recorded the number of correct animal features presented by Peedy and the learner respectively (Appendix 8). The information is summarised in Table 13.8.

Table 13.8 Peedy and Student's Correct Answers and Correct Features

	Learner's		Peedy's	
	Answer	Feature	Answer	Feature
Mean	8.45	40.30	8.36	40.70
Standard Deviation	1.25	4.91	1.03	2.87

Table 13.8 shows that the average number of correct answer from the learners (8.45) is similar to that of Peedy’s (8.36). The average number of correct features fromthe learners (40.30) is similar to that of Peedy’s (40.70). To assess whether the students’ performance was related to Peedy’s performance, the corresponding correlations were analysed.

Pearson’s *r* was computed to assess the relationship between Peedy's answer and the student's correct answers, as shown in Table 13.9. There was a positive correlation between the two variables with marginal significance (two tailed $p = 0.08 < 0.1$). Pearson’s *r* was also computed to assess the relationship between Peedy's and the student's correct features. There was a significant positive correlation between the two variables (two tailed $p = .008 < .05$).

Table 13.9 Correlation Between Peedy and Students’ Performance

	r	p-value
Between student's and Peedy's correct answers	0.31	.08
Between student's and Peedy's correct features	0.46	.008

In conclusion, Peedy's performance in the learning system was positively correlated with that of the students. This result shows that the students interacted with Peedy seriously and they helped Peedy with the knowledge they possessed. If the students simply interacted with Peedy for fun, or randomly chose items to reply to Peedy’s questions, there would not have been a positive correlation.

This result clearly indicates that intelligent agents can be employed to facilitate human-agent argumentative learning, as the learners argued with the agent simulated peers seriously.

13.4.2 Argumentative Activity and Learning Experience

The phenomenographic study in this research revealed students' learning experiences while arguing with virtual characters (section 13.3). Knowledge acquisition (category 1.1), memory retention (category 1.2) and deep understanding (category 1.3) pertain to "absorbing knowledge" where the students collected and remembered the knowledge they encountered. Critique and analysis of opinions (category 1.4) and conceptual change (category 1.5) pertain to "constructing knowledge" where the students critiqued and analysed the different viewpoints raised in the argumentation and consequently constructed new knowledge. Category 1.4 and 1.5 involve higher level cognitive processes more than category 1.1, 1.2 and 1.3.

Students can be grouped according to whether they had experience of "constructing knowledge", or whether they had experienced higher level cognitive processes.Taking this into account the students were labeled into two groups, X and Y, with Group X being the students who experienced the higher levels of cognitive processes (as defined in category 1.4 and 1.5), and Group Y being those who did not experience higher levels of cognitive processes. Group X totaled 18 students, and group Y totaled 15 students (details are recorded in Appendix 7).

The average activities of the two groups are displayed in Table 13.10, which shows on average that students in group X had more *Ask*, *Disagree* and *Modify* activities, and students in group Y had more *Answer* and *Agree* activities.

Table 13.10 Average Activities of Group X and Y

Group	Number of Students	Ask	Answer	Disagree	Agree	Modify	Total Activities
X	18	4.78	2.89	4.78	2.11	7.22	21.78
Y	15	3.73	3.20	4.27	2.47	4.47	18.13

T-tests were performed to investigate whether the difference between the two groups was significant. Two tailed t-test assuming equal variance were performed on the two groups regarding the different activities. The result is listed in Table 13.11. T-test results showed the significance difference for the *Modify* activity between Group X and Group Y (two tailed $p = .03 < .05$). There was sufficient evidence (at 0.05 level of significance) to show that the mean of the *Modify* activity of group X (average 7.22) was higher than that of group Y (average 4.47). This result indicated that students who reported experience of higher level cognitive processes had more *Modify* activities during the study. The average total activities in group X was also more than that of group Y but it is not statistically significant ($p=.10> .05$).

Table 13.11 T-test Between Group X and Group Y

	T statistics	p-value (two tailed)
Ask	0.79	.44
Answer	-0.51	.61
Disagree	0.41	.68
Agree	-0.52	.61
Modify	2.24	**.03**
Total Activities	1.69	.10

13.4.3 Argumentative Activity, Biology Interest and Knowledge Acquisition

When students are interested in a subject, they may pay special attention to it, observe carefully and explore actively. It was expected that students who had more interest in biology would have more argumentative activities. Pearson's product moment correlation coefficient (r) was computed to assess the relationship between the total argumentative activities and the biology interest. The total argumentative activities were listed in Appendix 6 and the students' biology interests were listed in Appendix 5. There was no significant correlation between the two variables ($r = -0.25$, two tailed $p = .15$). This indicates that in this study there is no evidence to show that students who had more interest in biology would have more argumentative activities. One possible explanation could be that the learning system didn't provide enough space for students with an interest in biology to explore further (details are discussed in section 14.4.1).

The purpose of introducing the argumentative learning system was to improve the learners' scientific knowledge. Therefore, the argumentative activities were expected to be positively related to the learners' achievement. Students' achievement couldn't be measured by a post-test as group B students did the post-test before using the argumentative system. Students' achievements however, can be measured by the number of correct answers scored by the learning system; or the number of correct animal features they presented during the interaction with the system. This was tallied by the researcher based on the screen recording. In the regression analysis, the correct features were used as an indicator of the students' achievement as it contained more information than the correct answers. Pearson's r was computed to assess the relationship between the total activities and students' correct features. The study found that there was a significant positive correlation between the two variables ($r= 0.40$, two tailed $p =.02 < .05$). This result confirms that students who had more argumentative activities also had more achievements.

Are argumentative activities a main contributor for students' achievements? A multiple regression analysis was carried out to examine the relationship between students' achievement and other influential factors including argumentative activities. In the study, since achievement was likely to be affected by previous knowledge, it was necessary to take into account the influence of the previous animal classification knowledge of each student. For group A students, their prior knowledge was indicated by their pre-test scores. For group B students, their prior knowledge before the argumentative activity was the post-test scores, as they used the argumentative system after the post-test. Student B16 did her post test after the two sessions so her post test score couldn't be considered as prior knowledge. Student B16 was removed from the regression analysis. The model of multiple linear regression is as follows:

$$Achievement_{\text{i}} = b_0 + b_1 * TotalActivity_{\text{i}} + b_2 * PriorKnowledge_{\text{i}} + \text{e}_{\text{i}}$$

where e was the error term (assumed to be normally distributed with zero mean). b_0, b_1 and b_2 were coefficients to be estimated. i was an index for each student.

In the regression model, *Achievement* was a dependent variable (criterion variable) which is indicated by the correct features students presented during the interaction (Appendix 8). *TotalActivity* and *PriorKnowledge* were entered as independent variables (predictor variables) to predict the dependent variable (total activity can be obtained from Appendix 6 and prior knowledge can be obtained from Appendix 5).
Variable *Achievement*, *TotalActivity* and *PriorKnowledge* were obtained from appendixes as follows:

Achievement: from Appendix 8, column *Learner's Feature*,
TotalActivity: from Appendix 6, column *Total Activities*,
PriorKnowledge: from Appendix 5, column *Pre-test* for Group A students and *Post-test* for Group B students.

Descriptive statistics of independent variables are listed in table 13.12.

Table 13.12 Descriptive Statistics of Variables

Variable	Mean	Standard Deviation
Achievement	40.19	4.94
TotalActivity	19.94	6.36
PriorKnowledge	6.16	2.63

The regression analysis was presented in Table 13.13. It indicated a significant model ($p= .002$). R^2 indicates the overall model fit is 0.34, which means that 34% of the variation in *Achievement* can be explained by the variation of *TotalActivity* and *PriorKnowledge*.

Table 13.13 Regression Result

The regression analysis models the *Achievement* as a linear function of *TotalActivity* and *PriorKnowledge* (R^2=0.34, p= .002)			
Item	coefficient	t-statistic	p-value
Intercept	31.70	12.20	6.06E-13
TotalActivity	0.15	1.14	0.27
PriorKnowledge	0.91	2.94	0.01

The regression coefficients describe the relation between a predictor and a criterion variable after the effects of other predictor variables have been removed. They range from -1 to 1 (0 means no relation at all, 1 or -1 mean that variations in one variable can be explained completely by variations in another). In this study, a significant predictor variable, as might be expected, was the students' prior knowledge (b_2=0.91, p= .01< .05). Total Activity was not a significant predictor variable (b_1=0.15, p= .27> .05). This regression analysis showed that the students' prior knowledge was a predominant predictor variable of their achievement, while the argumentative activities was not found to have significant impact on students' achievement.

In the design of the study, it was expected that the argumentative activities would have a significant impact on student learning outcomes. However, the regression analysis did not support this viewpoint. The regression analysis showed that students' prior knowledge had a significant impact on the students' learning outcomes yet argumentative activities did not have significant impact on learning outcomes. This might because that the argumentation opportunities in the learning system were not sufficient to make a difference in learning outcomes. This finding will be further discussed in section 14.4.1.

13.5 Summary

This chapter analysed the collected data and presented the key results which can be summarised as follows:

- *Learning gain*: The argumentative agent improved the students' animal classification knowledge at a greater rate than the non-argumentative agent.
- *Learner-agent interaction*: Students' performance was positively correlated with his/her virtual peer's performance.
- *Learning experience*: The students' learning experiences were categorised into three areas concerned with knowledge, skills and dispositions.
- *Learning Activity*: Students who were more engaged in *Modify* activities throughout the learning experienced greater instances of high level cognitive process; argumentative activities were not proved to be a main contributor to knowledge acquisition.

14. Discussions

To date no studies have been reported on argumentative learning between human learners and computer virtual characters. This research designed and implemented an intelligent agent that is able to conduct argumentation with human learners, and studied the learners' argumentative learning with the intelligent agent. In this study, data collection and analyses concentrated on answering four research questions involving the following elements: academic achievement, learner – agent interactions, learning experiences and argumentative activities. Overall, the results from the study revealed that argumentative learning with an intelligent agent has positive impacts on learning. This chapter discusses the main findings from the study, and proposes possible improvements to learning environments that incorporate argumentative agents.

14.1 Academic Achievement

The first research question from this study asks, "Is learning with argumentative agents effective in improving learners' knowledge?" This research question is to investigate the learning effects, specifically, whether learning with the argumentative agent had the capacity to improve the scores in a pre-test post-test context compared to learning with a non-argumentative agent. This question helped to focus the study on the investigation of the role of the argumentative agent as a means to support student learning. The result of the study indicates that an argumentative agent does have a positive effect to help students improve their scientific knowledge.

14.1.1 The Argumentative Agent Led to Better Learning Gain

The study was carried out with two groups. One group learned with an argumentative agent which was able to conduct argumentative dialogue with the students. The other group learned with a non-argumentative agent. As reported in section 13.1, the analysis of the pre-test to post-test scores revealed that the students who learned with the argumentative agent had a significant improvement from the pre-test to post-test score (one tailed $p = .03 < .05$), while the improvement of the non-argumentative group was not significant (one tailed $p = .13 > .05$). The only difference between the two groups was the presence of the argumentative agent or non-argumentative agent. The result demonstrates that the argumentative agent was beneficial to learning.

This is consistent with existing research. A study conducted by Asterhan and Schwarz (2007) showed that students who participated in argumentation conditions achieved greater gains in concept understanding compared with the participants in the control group, and students in argumentative conditions were able to retain the gains longer than the participants in the control group. Researchers also investigated the argumentative learning effects through scaffolding the argumentation process. It was found that the group with argumentation scaffolding performed significantly better in problem solving processes than the group without argumentation scaffolding (Cho & Jonassen, 2002;Oh & Jonassen, 2007), and the groups with argumentation scaffolding had significantly more correct answers (Nussbaum, Sinatra & Poliquin, 2008).

14.1.2 Learning Opportunities Fostered by Argumentative Learning

In this study, the argumentative agent was proven effective in improving students' scientific knowledge. The effectiveness came from the learning opportunities which eventuate through the argumentative learning.

Firstly, argumentation highlights knowledge points which result in a longer retention of specific facts. Besides the motivation factors that facilitate learning when interacting with an artificial animated peer, key knowledge points are highlighted and discussed repeatedly during the argumentative activities. For example, the students discussed animal features and classification rules with the agent, compared their answers with the agent, pointed out the agent's errors, asked agents questions, answered questions from the agent, and modified their answers throughout the discussion. The rounds of interaction gave students a variety of opportunities with the knowledge they discussed, which therefore enabled them to retain the content for a longer time.

Secondly, argumentation involves explanation and elaboration which leads to deep learning. In this study, the designed argumentative learning system provided multiple opportunities for explanations to occur. During the argumentation, students sorted out their own thinking and explained their organised thoughts to the agent. This process clarified their understanding. In the interactions between the students and agents, the students discussed not only in which class the animals belonged to but also explained why the animals belonged to that particular class, indicating that they not only knew the facts but also the rationale behind the fact. They integrated the relevant knowledge, which is an important aspect of deep learning. By the 1980s, cognitive scientists had discovered that children retain material better and are able to generalise it to a broader range of contexts when they acquire deep knowledge rather than surface knowledge, and when they learn how to use that knowledge in real world social and practical settings (Sawyer, 2006). Deep learning requires that learners relate new ideas and concepts to their previous knowledge and experience, integrate their knowledge into an interrelated conceptual system, look for patterns and underlying principles, evaluate new ideas and relate them to conclusions, understand the process of dialogue through which knowledge is created, and reflect on their own understanding and their own process of learning (Sawyer, 2006). The argumentative agent provided such opportunities and enabled students to integrate their knowledge, evaluate their partners' ideas, conduct dialogue to construct answers and explore underlying principles to problems. In this way, argumentative dialogues fostered deep learning. Additionally, 21.21% students self-reported that they believed that through argumentative learning, they could gain deeper understanding (as shown in Table 13.7).

Third, argumentation promotes conceptual change. Argumentation introduces cognitive conflicts that motivate learners to seek equilibrium. In this study, the argumentative agent often presented different opinions to the learners. The learners were immersed in an environment with many conflicting ideas which stimulated them to adjust their existing knowledge and adopt new knowledge. For example, during the process of arguing with the agent, students evaluated the agent's different opinions or changed their opinions based upon the extent to which they were persuaded by the agent. This gave them the opportunity to discover more about what others knew and change their own incorrect ideas accordingly. As Driver, Newton & Osborne (2000) highlighted, conceptual change occurs when students are given the opportunity to tackle a problem in a discussion to identify different thoughts, to evaluate these thoughts and move toward an agreed opinion. Asterhan and Schwarz (2007) also demonstrated that argumentation enabled students to achieve greater gains in understanding concepts. In this study, conceptual change was supported when the agent raised different opinions and when the students checked and analysed the different answers.

Fourth, argumentation encouraged collaborative learning and knowledge co-construction. Students and the argumentative agent could communicate with each other to ask questions, explain and justify their reasons, and reflect upon their knowledge, thereby motivating and improving learning. Students also negotiate with the agent by checking and countering the agent's opinions. An important issue in research on learning is the construction of knowledge through negotiation. Some of the ways in which students negotiated the meaning or interpretation of knowledge have been found to enhance their learning. As the student and the agent bring different opinions to bear and negotiate, they co-construct the knowledge.

The effectiveness of argumentative learning comes from the combined action of the many opportunities embedded in argumentative learning, while not from the effect of a single opportunity. For example, simply providing learners with an environment which includes cognitive conflicts cannot ensure effective learning. Brown and Palincsar (1989) noted "change is not the automatic outcome of group problem solving...... it is the result of certain social settings that force the elaboration and justification of various positions…...experienced learners can cause change on their own by adopting these process roles in thought experiments, or by 'internalizing' role models from their experiences of group discussion in later intrapersonal dialogues." (p.408). Rogoff (1998) also stated, "although conflict has been repeatedly pointed to as an impetus for cognitive change, it may not be the conflict but the processes of co-elaboration which support cognitive progress, as several points of view are examined and modified to produce a new idea that takes into account the differing standpoints" (p.717). Argumentative learning leads the learners towards collectively valid objective and coherent ideas which contribute to learning. The system designed in this study is a holistic environment that includes opportunities for knowledge highlighting, deep understanding, conceptual change, knowledge co-construction which together contribute to effective learning.

In this study, argumentative learning with virtual characters is shown to be effective in science learning. For the students who learned with the non-argumentative system in the first session, they worked on animal classification questions, and read the information pages regarding animal classification knowledge provided by the system. They acquired knowledge mainly from the information pages. For the students who learned with the argumentative system in the first session, they worked on animal classification questions and argued with the agent. They acquired knowledge mainly from the interaction with the argumentative agent. During the argumentation with the agent, all the above mentioned opportunities are encouraged. Thus the group who learned with the argumentative system had more improvement of pre-test to post-test scores than the group who learned with the non-argumentative system.

14.2 Learner-Agent Interaction

The second research question was "are learners interested in arguing with the argumentative agent and do they argue with the agent seriously?" It investigated whether students were engaged in the learning system and whether they seriously interacted with the system. This question focused the study on the investigation of the learner-agent relationship. The data supported that the students didn't simply interact with Peedy, the agent, for fun, but they actually discussed learning content with Peedy seriously as if Peedy was a human learner.

14.2.1 The Argumentative Agent Engaged Serious Interaction

One of the most compelling features of intelligent agents is that they can demonstrate much more than simple instructions or advice. By their very nature, intelligent agents have the ability to possess personalities and to exhibit specific behaviors. These motivational factors have the ability to attract the students' attention. All students in this study reported that they loved to interact with the argumentative agent. They described the learning session with the argumentative agent as “interesting”, “cheerful”, “joyful”, “delightful”, “relaxing”, “enthusiastic” and “fun”.

During the study, students were simply told that there would be an animated character in the software. They were not given instructions regarding how to interact with it. All students in the study were able to readily and regularly conduct dialogue with this agent without any need to request help or guidance from the teacher. Screen recording data revealed that all students interacted with Peedy, the intelligent agent. Nobody worked individually on their own answers and left Peedy out. This showed the intuitive appeal of these kinds of software agents to students, and also shows that the students knew how to naturally interact with the argumentative agent.

Arguing with a human partner is different from arguing with a virtual agent. A human partner is expressive, understanding and has recognised intelligence during the communication, so students tend to communicate seriously with their human partners. However, when faced with a virtual character, will the students interact with a similar degree of seriousness, or will they simply talk to the agent for fun without really considering the knowledge aspect in the communication? This was an important question regarding argumentative learning with an intelligent agent. If there was no serious interaction between the learner and the agent, it would be impossible to use an intelligent agent to stimulate argumentative learning in schools or other educational contexts.

Although there have been few reports on designing argumentative agents in learning, there do exist a number of studies using software agents to accompany learners. Several such studies have shown that learners did not interact seriously with an agent. For example, in the study by Holmes (2007), the students left their agent advisor behind or essentially ignored the agent’s advice, or they responded to the agent but did not actually follow its instructions.

Encouragingly, the results from this study (section 13.4.1) showed that the correct animal features presented by Peedy had a significant positive correlation with that of the students (two tailed $p = .008 < .05$). This revealed that Peedy's score was influenced by the students with whom it interacted. If the student's score was high, most likely Peedy's score was also high. So the students were not likely to engage in randomly chosen dialogue with Peedy, rather, they were genuinely and seriously collaborating with Peedy, based on their own knowledge on animal classification. The serious learner-agent interaction confirms the reliability of using intelligent agents to facilitate argumentative learning.

14.2.2 "The Media Equation"

Before the empirical study with students, there were many uncertainties regarding the interaction between a human learner and a computer simulated virtual character. Do learners engage in the argumentation with a virtual character? Do learners simply interact with the virtual character for fun while not seriously consider the virtual character's knowledge related arguments? If the human learners didn't argue with the virtual character seriously, there wouldn't be meaningful argumentative learning.

The research results from this study showed that the students communicated with the virtual peer seriously on knowledge related topics. The students reacted to virtual peers in a similar way as they towards human peers.

In the literature, extensive studies have been conducted on investigating whether people generally react towards computers and artificial entities in the same way that they would towards humans. Reeves and Nass (1996) raised the viewpoint of "the media equation" where they believe that the "media equal real life". They stated that "equating mediated and real life is neither rare nor unreasonable. It is very common, it is easy to foster, it does not depend on fancy media equipment, and thinking will not make it go away. The media equation – media equal real life – applies to everyone, it applies often, and it is highly consequential" (p. 5). They conducted numerous studies and concluded that "individuals' interactions with computers, television, and new media are fundamentally social and natural, just like interactions in real life" (p. 5). Reeves and Nass (1996) also believed human-media interactions are social and natural. They stated "when media conform to social and natural rules, however, no instruction is necessary. People will automatically become experts in how computers, television, interfaces, and new media work." (p. 8).

The media equation is relevant to human psychological tendency. In human cognitive functioning, there is a strong tendency to accept any incoming information as true, as "unacceptance is a more difficult operation than is acceptance" (Gilbert, 1991, p. 111). Lee (2004) stated that "this natural preference for acceptance over rejection is a manifestation of the fundamental psychological tendency shaped through the course of human evolution." Mantovani (1995) explained this in evolutionary terms, "we act in a world in which it is important to respond promptly to situations, while accuracy usually is not the top priority. The result is that human cognitive systems have developed adaptively the tendency to treat all representations as if they were true, except when there is proof to the contrary" (p.680). So when human beings encounter media or simulation technologies, they have the default readiness to accept the virtual as real.

Veletsianos and Miller (2008) pointed out that, "If we treat media and computers as humans, and we perceive our interactions with them to be inherently social, we will treat virtual characters as being human counterparts" (p. 972). This study provided evidence to support this viewpoint. In this study, the learners were ready to use the system without training and they also viewed the agent's knowledge as credible and appropriate, and discussed the topics seriously with the agent.

The media equation can bring many benefits to the design of learning environments, especially for those learning environments which require human interaction with people and places. As pointed out by Resnick (1997), "the potential applications of the media equation include such diverse tasks as designing simple online messages, creating software agents, and designing political advertising. Accepting the generalizability of the media equation to all kinds of media will allow designers to create more powerful and effective interfaces, but at the same time keep them simple" (p. 461).

The media equation provides foundation for using intelligent virtual characters to facilitate argumentative learning.

14.3 Learning Experiences

The third research question was “what are the learners' learning experiences?” and supported the research to investigate the students’ learning experiences. The phenomenographic approach is noted as being distinctive in that it identifies similarities and differences in the way we experience and understand phenomena in the world around us. This study identified the qualitatively different experiences in the context of this study using the phenomenographic approach. The phenomenographic results particularly contributed to the understanding of how students think about learning through argumentation with an intelligent agent. Identifying the different ways students experience learning will help educators to improve student learning outcomes and provide a foundation for developing more appropriate curricula or instructional approaches in their learning programs.

14.3.1 The Learning Experiences are Multi-Dimensional

The phenomenographic study showed that the students’ experiences were multi-dimensional, including the dimension in knowledge, skill and disposition. Multi-dimensional experiences are very important in the field of science. Students should not only learn the factual knowledge in science, but also develop the skills which are essential for scientists, such as complex communication/social skills, problem solving skills, and critical thinking skills, as well as cultivate positive dispositions in science.

A) The Knowledge Dimension

In the knowledge dimension, the students reported five types of experiences. These learning experiences gradually move from simple to complex.

- *Knowledge Acquisition and Memory Retention* (identified in Category 1.1 and 1.2): To obtain knowledge is a fundamental aspect of learning. In this study, the students acquired information from their dialogue with an argumentative agent. The agent brought new things to light which the students didn't know previously. Through the dialogue, information was highlighted and discussed, which left students with better memory recall hence the ability to remember for a longer time.

- *Deep Understandings (identified in Category 1.3)*: Deep understanding is one of the goals of science education. Tanner and Allen (2005) pointed that "underpinning science education reform movements in the last 20 years—at all levels and within all disciplines—is an explicit shift in the goals of science teaching from students simply creating a knowledge base of scientific facts to students developing deeper understandings of major concepts within a scientific discipline" (p. 112). A scientist does not just have more knowledge, but the knowledge he has is connected in a logical and meaningful manner, and he can apply his knowledge appropriately. In this study, the learner and the agent discussed answers and analysed reasons during the study. These activities related the relevant information together. To intend to understand, relate new ideas to previous knowledge, relate evidence to conclusions, and examine the logic of the argument are all attributes of deep learning (Neal, 2005).

- *Critique and Analysis of Opinions (Category 1.4):* Critical thinking is important for learning in the field of science. Students should actively access the scientific contents around them, critique and analyse them and make them their own knowledge. The argumentative agent provided such an environment to confront the students with alternative ideas. As students worked with the agent, they compared their answers with the agent, made judgments on different opinions, and self-checked their answers. The students practiced critical thinking when they checked and analysed answers.

- *Conceptual Change (Category 1.5)*: The argumentative agent's different opinions stimulated the students to re-think their answers and seek additional information to solve the conflict. This resulted in conceptual changes. Conceptual change is a desired status in science learning. Learners have many misunderstandings about how the world really works. Science education researchers have found that individuals whose ideas conflict with new information might disregard the new information in favor of their existing beliefs, and they hold onto these misconceptions until they have the opportunity to build alternative explanations based on experience. Tanner and Allen

(2005) point out that "learning that accompanies conceptual change stands in contrast to learning that is associated with the accrual of new ideas put forward by others. … Teaching toward conceptual change, however, requires that students consider new information in the context of their prior knowledge and their own worldviews, and often a confrontation between these existing and new ideas must occur and be resolved for understanding to be achieved" (p.113). To overcome misconceptions, learners need to actively construct new understandings. The agent continuously provided conflict to the learners' existing knowledge structure to promote conceptual change.

There are studies in the literature reported that argumentation enhances learning. Oh and Jonassen (2007) investigated the argumentative learning effects by scaffolding the argumentation process. It was found that the groups with argumentation scaffolding performed significantly better in problem solving processes than groups without argumentation scaffolding. Nussbaum, Sinatra and Poliquin (2008) found that the groups with argumentation scaffolding had significantly more correct answers. Ravenscroft, McAlister and Sagar (2010) studied the learners' collaborative argumentation supported by a web-based tool and found that the tool succeeded in stimulating critical and collaborative thinking.

This research is different from the aforementioned research in two ways. First, they studied the learning of computer supported human-human argumentation. This study focused on the learning during human-agent argumentation. Second, this research studied learner's self-reported learning experiences which was not covered in the aforementioned research. In this study, the benefits of argumentative learning are not only measured in pre-test and post-test scenarios, but were also reported by learners as they articulated the enhancement in their learning experiences.

B) The Skill Dimension

Instead of the traditional way of passing knowledge to learners, researchers believe learning science content through argumentation is another important way. Driver, Newton and Osborne (2000) stated that "science in schools is commonly portrayed from a ‘positivist perspective’ as a subject in which there are clear ‘right answers’ and where data lead uncontroversially to agreed conclusions” (p. 288). That is, the main practice of science education is to pass knowledge to the learners. However, “current research into the activities of scientists, however, points to a different picture of science: here, in contrast, the contribution of discursive practices to the construction of scientific knowledge is portrayed as important” (Driver, Newton & Osborne, 2000, p.288). Yelland (2011) has a similar view and she suggests that “moving beyond simple recall of knowledge is essential if we are to engage with meaningful curricula in the 21st century” (p. 33).

Science is socially constructed. The work of scientists includes assessing alternative opinions, interpreting texts, communicating the study to others, evaluating the potential viability of scientific claims, as well as argument in the public domain through journals, conferences and other forms of media. Through these processes, scientific ideas are checked and criticized and scientific theories are established.

Science education should also teach students the necessary skills for being a scientist and for future life, including communication skills, presentation skills, problem solving skills and critical thinking skills. Driver, Newton and Osborne (2000) contend that “if science education is to help young people engage with the claims produced by science-in-the-making, science education must give access to these forms of argument through promoting appropriate classroom activities and their associated discursive practices. Such practices, and only such practices, are the means of socialising young people into the norms of scientific argument from which they may gain confidence in their use, and a deeper understanding of their function and value” (p.288). They also highlight that “it is necessary to reconceptualise the practices of science teaching so as to portray scientific knowledge as socially constructed. This change in perspective has major implications for pedagogy, requiring discursive activities, especially argument, to be given a greater prominence.” (p. 289)

The argumentative learning system developed in this research created an environment for students to present their answers, argue with Peedy, and make judgment on different opinions. The students reported that they have practiced their critical thinking skills and communication skills. This shows that the argumentative agent has the potential to engage students in meaningful scientific argumentation, and supported students to develop the potential skills and knowledge base to become scientists in the future.

C) The Disposition Dimension

A student's attitude towards science is an important factor in science education. Osborne, Simon and Collins (2003) consider science attitudes as "the feelings, beliefs and values held about an object that may be the enterprise of science, school science, the impact of science on society or scientists themselves" (p.1053). Parker and Gerber (2000) also point out that the learning outcomes for science curricula should consider science achievement and positive attitudes toward science, as "attitudes, feelings, or perceptions of science are recognized as important for science achievement and for selection of science related careers by students" (p. 237).

Hence, in addition to increase the learners' knowledge and skills, learning systems should also help learners' disposition building. In this study, the students reported their experience in the disposition dimension. They believed that the system built their confidence, promoted their thinking and raised their interest.

Students' attitudes toward science may alter their achievement in science. Papanastasiou and Zembylas (2004) stated that "intuitively, one may assume that attitude and achievement should be positively related (i.e. higher achievement would lead to more positive attitudes and vice versa)" (p. 260). Researchers have conducted different studies which cover the relationship between attitude towards science and achievement in science. Although the relationships differs from one country to another (Papanastasiou & Zembylas, 2004), several studies found that attitudes toward science were positively correlated with science achievement (Nasr & Soltani, 2011; Freedman, 1997).

Since attitude towards science is very important, it has therefore become the responsibility of educators to cultivate the students' scientific dispositions. Animated intelligent agent's positive impacts on students' motivation have long been recognised by researchers. The agents' appearance, animation and emotion are fun factors to students. In this study, the agent was modeled as a peer learner. The evidence clearly showed that discussing with a virtual peer was interesting to the students further highlighted by comments such as, "I am a person who loves to talk and loves to discuss" (Interview-B15, 1), "when I am discussing with Peedy, I think of the discussion with classmates in class" (Questionnaire-B12, 1), "I feel cheerful to argue with others" (Interview-B3, 3). The interesting experience motivated the students to enjoy their learning.

Interest is a kind of awareness inclination for understanding the world and acquiring cultural and scientific knowledge. When students are interested in a certain field, they may pay special attention to it, observing carefully, memorising well and actively thinking. In this study, students reported that they were encouraged to think and gain confidence and interest in the learning topic. The results of this study inform us that argumentative agents have the potential to not only enhance scientific knowledge and skills learning, but also cultivate scientific dispositions.

14.3.2 Relationships between the Learning Experiences and Educational Objectives

The multi-dimensional learning experience is related to the taxonomy of educational objectives proposed in the literature.

The taxonomy of educational objectives is a framework for classifying statements of what we expect or intend students to learn as a result of instruction (Krathwohl, 2002). Bloom's Taxonomy has been widely used as an aid to define objectives in education (Carter, 1985). Bloom's Taxonomy (Bloom et al., 1956) classifies objectives of learning into three domains: cognitive, affective and psychomotor. The cognitive domain includes "those objectives which deal with the recall or recognition of knowledge and the development of intellectual abilities and skills" (Bloom et al., 1956, p.7). The affective domain includes "objectives which describe changes in interest, attitudes, and values, and the development of appreciations and adequate adjustment” (p.7). The psychomotor domain is the “manipulative or motor-skill area” (p.7).

Bloom’s Taxonomy does not distinguish between knowledge and skill. Carter (1985) provided an alternative taxonomy that divided educational objectives into the following domains:

- *Knowledge* (what the student knows): including factual knowledge and experiential knowledge;
- *Skill* (what the student can do): including mental skills, information skills, action skills and social skills;
- *Personal qualities* (what the student is): including mental characteristics, attitudes and values, personality characteristics and spiritual qualities.

The learning experienced by the students fell into similar categories as those in Bloom's Taxonomy and Carter's Taxonomy. The corresponding relationship is depicted in Figure 14.1.

Bloom's Taxonomy		**Student Experience**		**Carter's Taxonomy**
Cognitive Domain	<----->	Knowledge Building	<----->	Knowledge
Psychomotor Domain	<----->	Skill Building	<----->	Skill
Affective Domain	<----->	Disposition Building	<----->	Personal Qualities

Figure 14.1 Student Experience and Educational Objective Taxonomy

In Bloom's Taxonomy, the cognitive domain has six categories: knowledge, comprehension, application, analysis, synthesis and evaluation, which are ordered from simple to complex and from concrete to abstract (Krathwohl, 2002). Later, the cognitive domain was extended to two dimensions: the knowledge dimension and the cognitive process dimension (Krathwohl, 2002). This is referred to as the revised Bloom’s Taxonomy. The knowledge dimension involves the subject matter, including factual knowledge, conceptual knowledge, procedural knowledge and metacognitive knowledge (Krathwohl, 2002). The cognitive process dimension of the revised

Bloom’s Taxonomy is further divided into six categories (Anderson et al., 2001, p. 67-68):

- *Remember*: Retrieve relevant knowledge from long-term memory
- *Understand*: Construct meaning from instructional messages, including oral, written, and graphic communication
- *Apply*: Carry out or use a procedure in a given situation
- *Analyze*: Break material into its constituent parts and determine how the parts relate to one another and to an overall structure or purpose
- *Evaluate*: Make judgments based on criteria and standards
- *Create*: Put elements together to form a coherent or functional whole; reorganise elements into a new pattern or structure

In the students' Category 1 experience, argumentative learning is a way for knowledge building. There are five sub-categories. These sub-categories also have some resemblance to the revised Bloom’s Taxonomy regarding cognitive processes, as illustrated in Figure 14.2.

Cognitive Processes of the revised Bloom’s Taxonomy		**Students' Experience Regarding Knowledge Development**
Remember	<——>	Category 1.1 and 1.2: Knowledge Acquisition and Memory Retention
Understand Apply	<——>	Category 1.3: Deep Understandings
Analyze Evaluate	<——>	Category 1.4: Critique and Analysis of Opinions
Create	<——>	Category 1.5: Conceptual Change

Figure 14.2 Student Experiences and Cognitive Processes

The educational objectives emphasised what educators expect or intend students to learn as a result of education, but the learning experiences represent the students’ view of learning. The result of this study can be used to evaluate students’ learning and plan argumentative learning systems that are aligned with the education objectives. In this study, the outcome space and categories of description presented the students' view on argumentative learning with virtual peer learners. From this result, some suggestions can be generated on how to support effective argumentative learning, especially on scientific knowledge and skills learning. These suggestions are presented in section 14.5.3.

14.4 Argumentative Activities

The fourth research question investigated the argumentative activities by asking, "Do different activities have different impacts on learning?" The research questions tried to identify the influences of argumentative activities on academic achievement and learning experiences. The study did not find a positive association between argumentative activities and academic achievement (i.e. there was no evidence shown that students who had more argumentative activities obtained better academic achievement scores), but the results indicate a positive association between the *Modify* activity and the high level cognitive process experience (i.e. students who had more *Modify* activities during the study also self-reported experiences that contained higher level cognitive processes).

14.4.1 Argumentative Activities are Affected by the Nature of Problems

It is expected that students who had a more interest in biology would be more engaged in exploring a system containing biology questions, and would complete more argumentative activities, and as a consequence would result in better academic achievement. However, the study results did not support this idea (section 13.4.3). The results did not show a positive association between argumentative activity and an associated interest in biology. The argumentative activities were also found not to have a significant impact on students' academic achievement.

An explanation could come from the nature of the problem space. Argumentative activities are affected by the nature of the problem. In the designed learning system, the interaction between the students and the system was guided by animal classification questions. Although there were plenty of alternatives to discuss the different animals, animal features and classification rules, the answer to the question was fixed. Once the student and the agent reached an agreement on the answer to a particular question, they naturally stopped the argumentation and moved on to the next question. In addition, on each question page, there was a text label to indicate the current question number and the total number of questions. This quiz style presentation suggested to students that their tasks were to finish the questions. Being familiar with traditional school education, it is easy for students to interpret the learning tasks as a problem which needs to be solved quickly to attain a better grade, instead of activities designed to enhance the understanding of the problem. Therefore students may not want to spend extra time in argumentation when the answer is already settled. So the number of argumentation activities a student completed was determined by how quickly they could reach an agreement with the agent, not determined by the interest of biology or other personal attributes.

This finding suggests a design of the system needs to be as an open-end environment for students to explore and not give them the impression that they have to finish certain tasks. Students may then feel able to explore in the space more freely. In such cases, students with a stronger interest in biology are more likely to complete more activities. The argumentative activities are related to knowledge exchange, evaluation and analysis. More activities will provide more learning opportunities and thereby students should obtain more knowledge and skills.

The study also revealed that different argumentative activities are affected by each other. For example, in this study, students with more *Modify* activities had less *Disagree* activities (section 13.2.2). One reason for this was because of the time allocation. When students excessively focused on pointing out the agent's mistakes (disagree activity), they may not have enough time or effort left to seriously consider the value of the agent's position and accordingly modify their own opinions. When students concentrated on modifying their own answers, they may have forgotten to show disagreement with the agent's opinion. Another reason relates to the students' existing knowledge and confidence. When students were confident of their knowledge, they tended to criticise the agent's opinions; but when students were less confident of their own knowledge, they tended to observe the agent's opinion and modify their own answers accordingly.

14.4.2 Learning Activities Influence Learning Experiences

In the knowledge dimension, the students reported five types of experiences which constitute the five sub-categories: knowledge acquisition, memory retention, deep understanding, critique and analysis of opinions, and conceptual change. These learning experiences gradually move from simple to complex. Learners who only experienced the categories of 1.1, 1.2 and 1.3 focused on “absorbing knowledge” (refer to this experience as the “lower lever experience” and name the corresponding learners Group Y). Learners who experienced the higher two level categories focused on “constructing knowledge” (refer to this experience as the “higher level experience” and name the corresponding learners Group X).

Of the five argumentative activities identified in section 13.2.2, *Ask*, *Answer*, *Modify*, *Disagree*, *Agree −Tell,* Group X had significantly more *Modify* activities than Group Y (section 13.4.2).

Therefore it can be concluded that learning activities influence students’ experience. Phynomenography studies the way people experiencing something, which "is an internal relationship between the experiencer and the experienced" (Marton & Booth, 1997, p.113). In this study, this is the relationship between the students and the argumentative learning phenomenon. The way to an understanding of a phenomenon is always by awareness, and thus a phenomenon is understood in terms of the subject’s relevant experiences present in awareness. It is not possible to have an experience without being exposed to it.

Of the five activities, the *Modify* activity occurred when the learner changed their answers, hence it was apparent that the modify activity was relevant to the experience of *Conceptual Change*. Students who had conducted more modify activities were more likely to have had the higher level experience.

The *Ask* and *Answer* activities were more relevant to information exchange between the learner and the agent. They were less relevant to higher level experience, so there is no significant difference in relation to these two activities between Group X and Y.

The *Agree* and *Disagree* activities should be relevant to the *Critique and Analysis of Opinions* experience, however no significant difference was found on the number of activities completed by Group X and Y. This is probably because some *Agree* and *Disagree* activities were mostly used to help the agent obtain the correct answers, so the learners were not aware these activities were also of benefit to their own learning. Thus, these activities did not bring much awareness to their *Knowledge Building* experience.

Since learning activities can influence learning experiences, educators can design learning environments to incorporate certain activities to promote positive learning experiences.

14.5 Suggestions

The study gave positive supports to the view that argumentative learning with an intelligent agent could be a promising learning strategy. In addition, some possible improvements emerged from the study, which are reported in the following.

14.5.1 Personalised Argumentation

It was noticed in the study that there were variations between students' knowledge. For example, some students had sound knowledge on all kinds of animals, but others were not familiar with species like reptiles or amphibians. However, the agent was designed following a fixed mechanism to generate argumentative dialogues. It was able to respond to the students' questions. The response dialogues from the agent fitted the student, as these dialogues followed the students' enquiries. But the dialogues which the agent initiated did not always meet the students' needs. Sometimes, the students have already been very familiar with the topic and would rather have discussed something else, or the questions were beyond the capability of the students and they had no idea what to do.

The diversity of learners' prior knowledge required the intelligent agent to understand the learner's levels of competency so as to conduct personalised argumentation. If the agent's dialogues do not fit the learner, it will not provide the preferred stimuli to promote thinking and learning. Dialogues need to be adapted to learners' knowledge levels. Questions that are too simple can lead to less motivation among students, and questions that are too difficult yield less discussion and a lower level of knowledge co-construction. According to Vygotsky's social constructivism view of learning, the argumentative agents should provide supports within the learners' Zone of Proximal Development (Vygotsky, 1978) and scaffold the learners to higher levels of cognitive development.

14.5.2 Open-ended Problem Solving Learning Tasks

The topic in this study was animal classification. These types of questions have correct answers. When the tasks were organised in a structured way, the students focused more on answering the question promptly, rather than attempting to convey meanings. Argumentative activities should be organised in open learning environments to foster the acquisition of knowledge. In open learning environments, learners are encouraged to look at problems from different perspectives in order to reach an adequate solution.

Ill-structured problems (Voss, 2005) can offer learners the chance to explore the problems in an extensive and broad way. Ill-structured tasks require more interaction processes to establish common ground than well-structured tasks with a pre-defined solution path. Learners are more likely to engage in the discussion and complete more argumentative activities with tasks that require them to discuss their findings and to exchange arguments rather than with learning tasks that do not explicitly call for argumentation. This is confirmed by the study of Cho and Jonassen (2002) who found that the groups who solved ill-structured problems produced more arguments than the groups who solved well-structured problems. They also found that ill-structured problems are more affected by argumentation than well-structured problems. When solving an ill-structured problem, students are required to choose a preferred solution and reject alternative ones, develop their own argument and defend their own solution. As no single correct convergent solution exists in an ill-structured problem, a student in a group must argue to persuade others that his or her ideas are more reasonable and valid than others. Hence, ill-structured problems provide students with more opportunities to make arguments than well-structured problems.

The target problems for argumentative learning could be ill-structured problems for which no single solution exists, but that have to be looked at from different perspectives in order to reach an adequate solution. Tasks should be designed to produce a diversity of outcomes and to require the consideration of a plurality of explanations.

14.5.3 Variety of Learning Content

This study has revealed a clear potential for using argumentative agent to facilitate students' learning experiences.

The outcome space in the knowledge dimension revealed that the hierarchical experiences move from simple cognitive process to complex cognitive process, through Category 1.1 and 1.2 to Category 1.5. Students who only experience categories 1.1, 1.2 and 1.3 were more focused on "absorbing knowledge". They collected and remembered facts and tried to understand the facts. Students who experienced categories 1.4 and 1.5 were more focused on "constructing knowledge". They critiqued, analysed and argued on different ideas to form new understandings.

In the absorbing knowledge stage, students accumulated knowledge. It provides the foundation for the advanced stage where students construct new knowledge. It would appear that the learning is likely to be less successful when students don't move beyond the learning experiences of category 1.1, 1.2 or 1.3. Therefore, educators should design learning programs that orient students towards the full range of possible ways to experience learning. The argumentative agent should focus on knowledge exchange in the earlier stage of a new topic, such as, ask questions and provide information. This will provide the learners some basic understanding to a topic. Then in the later stage, the argumentative agent can focus on dialogues, such as attack dialogue, to bring in cognitive conflicts to encourage critical thinking and promote conceptual change.

The outcome space in the skill dimension showed that the system designed in this research supported students' skill development, according to the students' self-reported experiences. The students felt that they practiced critical thinking skills (9.09%) and communication skills (18.18%). This is a small proportion among all the participants. However, due to the growing role of science and technology in everyday life, science skills become more and more important to all students, not just to students who are aspiring to become future scientists. Thus, systems designed for science learning should put more focus on skills development than previously. Virtual characters facilitated learning systems can be designed to contain multiple activities for students to practice critical thinking, communication, argumentation and/or complex problem solving skills. The skills obtained from the learning systems should have impacts in their future life or career.

14.6 Summary

This chapter discussed the findings discovered from the data collection and analysis, and answered the four research questions stated in chapter 1. The following statements can be made on the basis of the analyses:

- argumentative learning with an intelligent agent leads to effective learning gains;
- the learners and the intelligent agent do engage in serious argumentation;
- the argumentative learning experiences are multi-dimensional, including knowledge building, skill building and disposition building;
- argumentative activities influence learning experiences; and argumentative activities are influenced by the nature of problems, open-ended problem solving questions are more suitable for argumentative learning.

Summary of Part III

The literature indicated that argumentative learning had the potential to act as a promising learning strategy. However, prior to the study reported here there was no learning system that was able to conduct argumentation with learners to facilitate this new way of learning, especially on school science topics. This research developed two science learning systems, where virtual peers can conduct argumentative dialogue with learners. Studies were carried out to investigate students' learning while interacting with the systems.

The studies covered a wide range of investigations including: knowledge acquisition, learner–virtual peer interaction, learning activities and learning experiences. The results of the study showed that the designed argumentative virtual peer can significantly improve the pre-test to post-test scores. The study also evidenced that learners engaged in serious argumentation with the argumentative virtual peer, which confirmed the prospects of using virtual peers to facilitate argumentative learning. The phenomenographic analysis revealed students' multi dimensional learning experiences which provided understanding of learning with argumentative agents from the learners' perspectives.

As a pioneer study on argumentative learning with intelligent agents, this study contributes knowledge to the understanding of human-computer argumentative learning and the design and development of future argumentative learning systems.

Part IV. Conclusions

Part IV concludes this thesis by highlighting the main contributions and suggesting future works.

15. Conclusions and Future Works

Collaborative argumentation becomes an essential element in science education. It plays an important role in leading to deep learning, fostering conceptual change, promoting knowledge co-construction and supporting problem solving. However, collaborative argumentation has so far not been widely adopted in schools, primarily due to the availability of qualified human argumentation facilitators. This research presents a unique approach which uses computer based virtual peers to facilitate argumentative learning. Prior to this study, there is no computer system had been designed that could conduct human-computer argumentation successfully.

This research set out to design computing models for argumentation automation and to develop learning systems with intelligent agents to facilitate argumentative learning. The research also investigated students' argumentative learning while interacting with an intelligent agent in computer based tasks. The study results demonstrate the huge potential benefits of argumentative learning with intelligent agents. This chapter highlights the main contributions of the research and suggests future research explorations.

15.1 Main Contributions

First, this research developed four argumentation computing models. It laid a foundation for practical argumentative learning.

Argumentation has an essential role to play in learning. It provides a context that stimulates cognitive conflicts and the cognitive conflicts encourage learners' cognition to advance. The argumentative dialogues can verify ideas or generate new ideas, and help the learners reach their potential. It has been recognised that argumentation has many benefits in learning, such as it promotes scientific thinking (Duschl & Osborne, 2002; Driver, Newton & Osborne, 2000); leads to deep understanding and knowledge co-construction (Newton, Driver & Osborne, 1999); fosters conceptual change (Asterhan & Schwarz, 2007); and supports problem solving (Oh & Jonassen, 2007).

However, there are major barriers that prevent argumentative learning from being widely applied in schools. Argumentative learning requires qualified peers to facilitate and closely supervise the argumentation process. Student peers are applied in some context but has many limitations. For example, student peers might wander off the learning topic and turn to discuss other irrelevant topics; student peers may not have the proper knowledge to provide the right scaffolding to each other, or might lead to wrong conclusions. Teachers are ideal arguing peers. However, with the current high student-teacher ratio in classrooms, it is impossible to have one teacher closely supervise one student or a very small group of students. Therefore, although argumentative learning has many desirable benefits, it has not been widely applied in schools.

The advance of computer science and information technology brings innovations to learning systems. Lifelike virtual characters have been developed to enable new learning. The lifelike characters that facilitate learning are termed as pedagogical agents. The pedagogical agents have brought advantages to learning systems that have not been available before. However, no pedagogical agent is able to conduct automated argumentation with human learners. Argumentation support systems have also been developed to support human-human argumentation. These systems also cannot conduct automated argumentations with human learners.

This research was to fill the gap between the needs for argumentative learning and the fact that there is a lack of computer systems that are able to conduct human-computer argumentation. Four argumentation computing models have been developed in this research for the typical human knowledge, namely:

- chained knowledge,
- hierarchical knowledge,
- fuzzy dynamic knowledge, and
- knowledge for optimal solutions.

The computing models provide mechanisms for computers to carry out automated argumentation. This is a significant contribution and will lay a foundation for human-computer argumentative learning and other argumentation automation between computers and human beings. It will not only enable a large range of applications in education but also many other areas such as business and legal services.

Second, for the first time, this research studied argumentative learning with intelligent agents. It contributes knowledge to argumentative learning between human learners and intelligent virtual characters.

The development of the computing models made argumentative learning with virtual peers possible and practical. This research developed two learning systems with argumentative agents. The argumentative agents were modeled as virtual peers and they could conduct argumentation with human learners on science topics. Prior to this study there was no existing learning system that was able to conduct human-computer argumentation related to school science topics.

For the first time, this research studied argumentative learning with intelligent agents. It investigated a wide range of learning aspects, including academic achievements, learner – agent interactions and learning experiences. The results are encouraging and they are summarised as follows:

Academic achievement: The analysis of the pre-test to post-test scores revealed that the argumentative agent can significantly improve the learning outcomes compared with a non-argumentative agent. The effectiveness of the argumentative agent came from the learning opportunities which arose during the learning processes, such as, collaborative argumentation, elaboration, clarification, negotiation and co-construction.

Learner – agent interaction: Arguing with a human partner is different from arguing with a virtual peer. A human partner is expressive, shows their understanding and has recognised intelligence during the communication. In this way students are able to communicate seriously with their human partners. Encouragingly, the results showed that the students communicated with the virtual character seriously on knowledge related topics, and they reacted to the virtual peer in a similar way as they towards a human peer. The serious learner – virtual character interaction confirms the practicability of using virtual characters to facilitate argumentative learning.

Learning experiences: In this phenomenographic study the questionnaires and interview data revealed three qualitatively different categories of learning experiences: knowledge building, skill building and disposition building. The students' multi-dimensional experience provides understandings on argumentative learning with intelligent agents from the learners' perspectives.

The findings of this research are of major significance since they demonstrate the potential of applying argumentative agents in science education, and provide insights into human–computer argumentative learning and guidance regarding future argumentative learning environment development.

15.2 Future Research

The work in this thesis presents a stepping stone towards further research on human-computer argumentation modeling, argumentative learning system development and educational study on argumentative learning with intelligent agents. This work can be extended and further explored and now a new area of argumentative learning with intelligent agents presents itself. The following are some example research topics:

Argumentation modeling: It is recognised that diverse forms of knowledge exist. In this way it will become valuable to explore other argumentation computing models in subsequent research to accommodate the various argumentation needs in different knowledge formats and in various applications.

Argumentative learning systems development: The argumentation between the learner and the agent in this study is not as convenient as human−human argumentation. The agent can talk to learners verbally in a natural language through a text to speech engine. However, the learners can only communicate with the agent by selecting options with mouse and keyboard. This inconvenience was mainly caused by the immature natural language recognition technology and the complexity of natural language processing. Therefore, technologies are not ready for an agent to recognise the learner's speech and understand the learner's thought. It is worthy to explore new ways for human learners to express their ideas efficiently.

Argumentative learning study: In this research, only the interaction between an individual user and an intelligent agent was studied. The agent was proven beneficial to individual's learning. The argumentative agent may also play an important role in support collaborative argumentation among multiple human users. It warrants further studies that might investigate the learning interactions among an intelligent agent and multiple users, or among multiple intelligent agents and multiple users. Conducting large scale studies to investigate the influence of argumentative learning on students' academic achievements, as well as to identify what type of learners might benefit from argumentative learning scenarios could also be accommodated in future studies.

Argumentative learning is a promising educational approach. It is hoped that the work presented in this thesis will provide insights for future research on argumentative learning with virtual peers.

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Appendix

Appendix 1. Survey 1 on Animal Classification System

Group _________ Student No. _____________

Welcome to the study of Animal Classification System.

Part I. Personal Information

1. Age: ____________

2. Gender: □ Male □ Female

Part II. Biology Interest

Please indicate the extent of your agreement or disagreement with each statement by circling the relevant number, from 1 (strongly disagree) to 5 (strongly agree).

1.	Biology is very interesting to me.	1	2	3	4	5
2.	I don’t like biology, and it scares me to have to take it.	1	2	3	4	5
3.	I am always under a terrible strain in a biology class.	1	2	3	4	5
4.	Biology is fascinating and fun.	1	2	3	4	5
5.	Biology makes me feel secure, and at the same time it is stimulating.	1	2	3	4	5
6.	Biology makes me feel uncomfortable, restless, irritable, and impatient.	1	2	3	4	5
7.	In general, I have a good feeling toward biology.	1	2	3	4	5
8.	When I hear the world “biology,” I have a feeling of dislike.	1	2	3	4	5
9.	I approach biology with a feeling of hesitation.	1	2	3	4	5
10.	I really like biology.	1	2	3	4	5
11.	I have always enjoyed studying biology in school.	1	2	3	4	5

12. It makes me nervous to even think about doing a biology experiment.	1	2	3	4	5
13. I feel at ease in biology and like it very much.	1	2	3	4	5
14. I feel a definite positive reaction to biology; it's enjoyable.					

Part III. Animal Classification Knowledge

1. What kinds of animals do you think are mammals?

2. What kinds of animals do you think are birds?

3. What kinds of animals do you think are fish?

4. What kinds of animals do you think are reptiles?

5. What kinds of animals do you think are amphibians?

~ Thank you. ~

Appendix 2. Survey 2 on Animal Classification System

Group _________ Student No. _____________

Now you have used the animal classification learning system. You may have some different understanding. Please answer the following questions again (same as that in Survey 1).

1. What kinds of animals do you think are mammals?

2. What kinds of animals do you think are birds?

3. What kinds of animals you think are fish?

4. What kinds of animals you think are reptiles?

5. What kinds of animals you think are amphibians?

~ Thank you. ~

Appendix 3. Survey 3 on Animal Classification System

Group _________ Student No. _____________

(Please answer the following questions and tick when appropriate)

1. Now you have used the two types of animal classification systems. In one system, Peedy encourages you but he doesn't discuss with you on animal classification questions, we call him "**encouraging Peedy**". In another system, Peedy discusses with you on the animal classification questions, we call him "talkative **Peedy**". Which one do you like better?

   □ the encouraging Peedy □ the talkative Peedy

   Why?

____

____

____

____

____

2. When you find the talkative Peedy's idea is different from you, what do you often do?

   □ ignore him

   □ re-think on my idea

   □ ask others to find out who is correct

   □ tell Peedy that he is wrong

   □ Other, please specify ______________________

3. Do you think Peedy's different opinions help you in your learning?

   □ yes □ no

   If you answered "yes", how do you think this helps your learning?

____

____

____

____
____

If you answered "no" , do you think you are distracted by peedy? How?

____
____
____
____
_____

4. When Peedy needs help, such as he comes up with wrong answers, or he asks you questions, what do you often do?
   - □ ignore him
   - □ tell him the right answer I think
   - □ just randomly choose an answer, I don't care if the answer I provide to Peedy is correct or not
   - □ Other, please specify ______________________

5. Do you think it would help your learning when you help Peedy to get his correct answers?

   □ yes □ no

If you answered "yes", how do you think this helped your learning?
____
____
____
____
____

If you answered "no", do you think this distracted your learning? How?

____
____
____
____
____

6. What are the adjectives you would like to use to describe your learning with the **talkative** Peedy?

____

____

____

____

____

7. For the **talkative** Peedy, what are the things you love the most and what are the things you love the least?

   Things love the most:

____

____

____

____

____

   Things love the least:

____

____

____

____

____

8. Describe your overall learning experience with the talkative Peedy. Was it an enjoyable experience?

____

____

____

____

____

____

~ Thank you. ~

Appendix 4. Reference Interview Schedule

My name is ______. I am very interested to know how do you feel about Peedy. I would like to ask you some questions regarding Peedy. It should take about 10 to 20 minutes. Are you willing to answer some questions?

(Subjects in school) How many subjects you are learning in school? Which subject you love the best? How do you like science?

(Perception to the discussion with the agent) Do you like to discuss with the virtual character? Do you think the virtual character has science knowledge? Does the virtual character helps you with your learning? How? What is your overall experience?

(Impact of argumentative learning) How do you think of the argumentation between you and the virtual character? Do you think the argumentation is helpful to your learning and how? Did you benefited from the argumentation and what are the benefits?

(Differences of discussing with a virtual character and a classmate) Do you think there are any differences between discussing with the virtual character and your classmate? What are the advantages and disadvantages? Which kinds of discussion you prefer? Why?

(Ideal virtual characters) If you are going to design a virtual character for your science learning, what will it look like?

Is there anything else you would like say? Thanks for sharing your ideas. That is wonderful.

Appendix 5. Pre-test and Post-test Scores

Student ID	Pre-test	Post-test	Biology Interest
A1	4	4	56
A2	--	--	54
A3	6	7	52
A4	3	2	54
A5	5	5	62
A6	9	11	62
A7	--	--	58
A8	7	18	51
A9	6	13	56
A10	7	8	44
A11	9	5	52
A12	7	7	48
A13	9	19	67
A14	5	13	52
A15	7	9	58
A16	6	6	49
A17	4	3	49
B1	5	3	42
B2	8	7	56
B3	8	8	70
B4	6	6	48
B5	7	8	62
B6	1	2	42
B7	2	2	46
B8	3	7	46
B9	5	13	56
B10	6	7	50
B11	7	11	55
B12	3	2	47
B13	4	9	51
B14	8	4	68
B15	5	3	64
B16	--	--	62

Appendix 6. Argumentative Activities from Video Recording

ID	Ask	Answer	Disagree	Agree+Tell	Modify	Total Activities
A1	0	6	2	2	1	11
A2	0	3	9	4	3	19
A3	0	2	0	7	11	20
A4	1	2	3	1	13	20
A5	1	1	9	0	2	13
A6	0	3	1	1	7	12
A7	10	0	4	5	9	28
A8	5	2	14	0	2	23
A9	6	4	4	2	5	21
A10	2	6	12	3	4	27
A11	3	4	7	2	4	20
A12	5	5	7	0	2	19
A13	9	3	3	1	5	21
A14	8	2	4	1	9	24
A15	10	4	3	3	3	23
A16	10	5	10	0	6	31
A17	5	5	4	1	4	19
B1	1	1	5	2	5	14
B2	3	5	1	2	4	15
B3	0	2	6	4	2	14
B4	0	3	1	5	9	18
B5	5	4	4	1	7	21
B6	7	2	3	1	1	14
B7	2	3	5	3	1	14
B8	14	3	1	3	13	34
B9	9	2	3	1	12	27
B10	4	5	8	4	10	31
B11	8	0	7	3	10	28
B12	1	2	0	8	8	19
B13	4	3	2	1	5	15
B14	4	0	0	1	4	9
B15	1	2	5	2	4	14
B16	4	6	3	1	12	26

Appendix 7. Learning Experience Response

ID	Learning Experience Category									
	1.1	1.2	1.3	1.4	1.5	2.1	2.2	3.1	3.2	3.3
A1	y	y		y						y
A2		y	y			y				
A3		y	y							y
A4	y			y						
A5	y	y						y		y
A6		y	y	y			y			
A7	y			y			y	y		
A8	y	y		y			y			
A9		y								
A10	y			y						y
A11		y	y	y						
A12		y								
A13		y		y	y					y
A14		y	y	y				y		
A15		y	y							y
A16										y
A17		y								
B1	y			y		y				
B2	y	y				y	y			y
B3	y	y					y			y
B4		y		y				y		
B5		y								
B6	y			y						
B7	y									y
B8	y	y		y	y					
B9		y		y				y	y	
B10	y		y	y				y	y	
B11				y						y
B12										y
B13		y								y
B14								Y		
B15	y			y			y			y
B16		y		y						

"y" indicates that the student has the experience.

Appendix 8. The Learning System Recorded Correct Answers and Correct Features

ID	Learner's		Peedy's	
	Answer	Feature	Answer	Feature
A1	9	35	9	42
A2	9	28	9	37
A3	9	44	9	40
A4	10	45	8	41
A5	8	40	6	34
A6	9	40	9	41
A7	9	39	8	37
A8	10	44	7	38
A9	10	44	9	44
A10	8	45	8	42
A11	9	46	10	46
A12	9	39	7	39
A13	10	48	9	44
A14	9	42	9	43
A15	10	43	9	45
A16	8	40	7	40
A17	8	42	8	42
B1	6	36	6	37
B2	8	43	9	45
B3	9	43	8	38
B4	8	42	9	42
B5	10	46	10	44
B6	6	36	9	40
B7	8	33	7	37
B8	9	41	9	41
B9	9	44	8	38
B10	7	40	8	40
B11	8	42	9	38
B12	8	29	9	40
B13	7	37	9	41
B14	6	31	9	41
B15	6	39	7	41
B16	10	44	9	45