Trust-Based User Profiling

NIMA DOKOOHAKI

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KTH School of Information and
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SE-164 40 Kista
SWEDEN

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Abstract

We have introduced the notion of user profiling with trust, as a solution to the problem of uncertainty and unmanageable exposure of personal data during access, retrieval and consumption by web applications. Our solution suggests explicit modeling of trust and embedding trust metrics and mechanisms within very fabric of user profiles. This has in turn allowed information systems to consume and understand this extra knowledge in order to improve interaction and collaboration among individuals and system. When formalizing such profiles, another challenge is to realize increasingly important notion of privacy preferences of users. Thus, the profiles are designed in a way to incorporate preferences of users allowing target systems to understand privacy concerns of users during their interaction. A majority of contributions of this work had impact on profiling and recommendation in digital libraries context, and was implemented in the framework of EU FP7 Smartmuseum project. Highlighted results start from modeling of adaptive user profiles incorporating users taste, trust and privacy preferences. This in turn led to proposal of several ontologies for user and content characteristics modeling for improving indexing and retrieval of user content and profiles across the platform. Sparsity and uncertainty of profiles were studied through frameworks of data mining and machine learning of profile data taken from on-line social networks. Results of mining and population of data from social networks along with profile data increased the accuracy of intelligent suggestions made by system to improving navigation of users in on-line and off-line museum interfaces. We also introduced several trust-based recommendation techniques and frameworks capable of mining implicit and explicit trust across ratings networks taken from social and opinion web. Resulting recommendation algorithms have shown to increase accuracy of profiles, through incorporation of knowledge of items and users and diffusing them along the trust networks. At the same time focusing on automated distributed management of profiles, we showed that coverage of system can be increased effectively, surpassing comparable state of art techniques. We have clearly shown that trust clearly elevates accuracy of suggestions predicted by system. To assure overall privacy of such value-laden systems, privacy was given a direct focus when architectures and metrics were proposed and shown that a joint optimal setting for accuracy and perturbation techniques can maintain accurate output. Finally, focusing on hybrid models of web data and recommendations motivated us to study impact of trust in the context of topic-driven recommendation in social and opinion media, which in turn helped us to show that leveraging content-driven and tie-strength networks can improve systems accuracy for several important web computing tasks.

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Dedicated to Shahram and Parichehr

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Paper(A1) N. Dokoohaki and M. Matskin, Structural Determination of Ontology-Driven Trust Networks in Semantic Social Institutions and Ecosystems, *International Conference on Mobile Ubiquitous Computing, Systems, Services and Technologies (UBICOMM '07)*, IEEE Computer Society, pp. 263-268, Nov. 2007.

Paper(A2) N. Dokoohaki and M. Matskin, Effective Design of Trust Ontologies for Improvement in the Structure of Socio-Semantic Trust Networks, *International Journal On Advances in Intelligent Systems*, vol. 1, no. 1942 - 2679, pp. 23-42, 2008.

Paper(B1) N. Dokoohaki and M. Matskin, Personalizing Human Interaction through Hybrid Ontological Profiling: Cultural Heritage Case Study, *1st International Workshop on Semantic Web Applications and Human Aspects (SWAHA), Collocated with 3rd Asian Semantic Web Conference 2008 (ASWC '08)*, 2008, pp. 133-140.

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Paper(F2) N. Dokoohaki and M. Matskin, Mining Divergent Opinion Trust Networks through Latent Dirichlet Allocation, *International Symposium on Foundations of Open Source Intelligence and Security Informatics (FOSINT-SI2012), 2012 IEEE/ACM International Conference on Social Network Analysis and Mining (ASONAM '12)*, IEEE Computer Society. August 2012.

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1. N. Dokoohaki, "Deliverable D2.1 - Report of User Profile Formal Representation and Metadata Keyword Extension", EU FP7 Smartmuseum project, 2008.

2. N. Dokoohaki, T. Ruotsalo, T. Kauppinen, and E. Mäkelä, "Deliverable 2.2 - Report describing methods for dynamic user profile creation", EU FP7 Smartmuseum project, 2009.

3. A. Zarghami, S. Fazeli, N. Dokoohaki, and M. Matskin, Social Trust-Aware Recommendation System: A T-Index Approach, *IEEE/WIC/ACM International Conference on Web Intelligence and Intelligent Agent Technology (WI-IAT '09)*, 2009, vol. 3, pp. 85-90.

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Part I

Introduction

Chapter 1

Introduction

> In a networked world, **trust** is the most important currency.
>
> Eric Schmidt, *University of Pennsylvania Commencement Address, 2009*

Personalization and recommendation are the most popular intelligent techniques used over the web today. Introduced by research over a decade ago, and widely adopted by web enterprises today, personalization aims at exploiting the differences among users it allows data to adapt in both quantity and quality to the individual, based on interactions with the web. To implement personalization, the notion of product suggestion was born and coined as *Recommendation Systems*. Such systems use a range of algorithms which return a collection of items to users, based on a derived knowledge of their tastes or from previous interactions. This gathered knowledge constitutes models of user which are collectively constructs a user model, referred to as *user profiles*. The process of gathering and enriching this knowledge is referred to as *user profiling*. Personalized interaction and system-derived recommendations have been so widely adopted that these techniques have effectively altered the way we receive and perceive consume.

Taking into account dynamic nature of these technologies, two main concerns have been raised. The first deals with privacy nature of existing implementations of personalization across the web, due to lack of transparency on what sort of information is actually gathered about users and how users are profiled. The second concern is the filtering of personalization and recommendation. Filtered information may shield users from consuming data that does not correspond with what the systems has calculated as relevant. This restricts the user to their own cultural or ideological *filter bubble* [131].One explanation for a lack of transparency is due to large amount of uncertainty in profiles and profiled elements. The reason could be the constraints to the quality of solutions based on profiles. Another explanation for is the possibility that the data used in user profiling is outdated and is based on information gathered by the system in the past. People change as do their tastes and preferences. Despite the awareness that such absence of transparency detracts from the quality of system recommendations, little effort has been placed in remediation. To address this problem, uncertainty should be measured and be processed in the profiles.

Trust is a fundamental notion affecting daily human encounters. People rely on their perceptions of trust for being able to thrive and survive in human societies. With the extended usage of web technologies in daily life, it is reasonable that software designers seek ways to accommodate human trust in their systems. Capturing and presenting trust as a computational concept has several benefits. Trust can be used to measure and improve the reliability of user profiles and user profiling technologies. Presenting trust can also help in dealing with uncertainty in user profiling and increase the transparency of overall system.

User profiles and profiling technologies have become the most important commodity for social enterprise. All major stakeholders on the net now offer users the ability to create, maintain and manage their personal data, activities and content on-line via their respective profiles. As user profiling on the web is relied upon so heavily, integrating trust within the user model becomes an intrinsic challenge. While the research community has invested immense effort into defining trust, its application into the web has been less successful. This has been due to the fact that database and information retrieval communities have been slower in realizing the value and the impact of trust in their applications. We must understand what is the correct model and implementation of trust at the profile-level, and introduce the concept of trust-aware user profiling. Although there has been much investment on analyzing, capturing and managing trust in web applications, there exist substantial challenges that hinder effective adoption and utilization of trust-based methodologies and technologies. In this work we present state of the art concepts, technologies and methodologies proposed by author on modeling, capturing and enhancing web profiles for trust-based computation and utilization.

The thesis is organized into several parts, starting by introductory part which presents the main theme of the research, followed by challenges motivating the research, and research questions pursued. Then we consolidate methodologies and results obtained. We continue by giving a background part with respect to subtopics of various proposed contributions. It includes a state of the art in trust on the web, user profiling on the web, in trust and recommender systems, in privacy in recommender systems and in hybrid recommender systems. Each background section results are concluded by research gaps identified which justifies the aim for works. The next part explains in detail the contributions of the work followed by conclusions and future work. The manuscripts of the published work and the detailed content of the dissertation are presented in the final part of the work.

Challenges

Difficulty of positioning Trust on the Web of Profiles, Personalization and Recommendation

Implementing trust research into user profiles and personalization is a distinct challenge. In order to overcome this challenge, let us first identify the current state of trust-research. Golbeck [73] categorizes existing trust on the web onto three subcategories: trust in *content*, trust in *services* and trust in *people*. The focus of user profiling solutions is on either content or people. The research on understanding trust in any of these contexts resides in two fields: web science and e-commerce.

O'Hara and Hall [128] formulate existing problems associated with trust by identifying which languages and ontologies are relevant for presenting the requirements of on-line trust, How transparency can be embedded into daily usage of information on the web, and finally, how trust and the web of data can be fused to create a ubiquitous interaction for the user. O'Hara and Hall [128], study several key perceptions of trust including risk, confidence, credibility and reputation. There is also still no clear means to allow a balanced of utilization and sharing of personal data in a trustworthy manner.

Focusing on e-commerce web, Gefen and colleagues present extensive research on finding the impact of user trust and e-commerce has related several important perceptions of trust [66]. They have observed that the perceptions of trust can influence one's adoption of a certain information technology product [10]. Although conceptual frameworks, taxonomies and vocabularies are required to guide such research by proposing relevant propositions and ideas, the authors suggest that a research methodology needs to be devised to identify a technology that builds trust. This methodology must also emphasize how such frameworks can be combined with existing ideas to build upon similar models.

Both perspectives are subjective to their respective contexts. What is shared between is the requirements of clear *semantics* and *tools* for modeling trust and trust-based products. Thus to be able to position trust effectively on the web of personalization, we have proposed clear web semantics and ontological tools.

Limited Work on Correlating Trust to Information Privacy

While research on identifying and recognizing notions or perceptions of trust has been considerable, less attention has been given to finding correlations between trust and information privacy. This becomes specially important in the context of personal web like social networking or e-commerce. Specifically finding correlation between trust and privacy is increasingly vital. Among the first works on correlating trust and privacy, particularly in the context of social networks is Dwyer et al. [53]. In their Privacy Trust model, statistical variables examine the correlations among the constructs of Internet privacy, trust in networking sites, trust in members of network, information sharing and development of new relationships. For each independent variable, results for Facebook [56] and MySpace [119] are presented separately, and also combined. Resulting correlations have been inconsistent. They state that although the privacy metric has strong reliability, there is little evidence of influence of privacy on information sharing. Such study is widely regarded as an effective empirical survey as It points out the impact of trust and privacy in social web. Although this survey concludes without pointing out a clear relation between trust and privacy. Bèlanger and Crossler [9] provide a comprehensive review of information privacy research.

Smith et al. [149], complement this survey with an interdisciplinary review of information privacy research. They identify three major areas in which previous research contributions have been made.These are the conceptualization of information privacy, the relationship between information privacy and other constructs, and the contextual nature of these relationships. Elaborating on second contribution, they present a correlation of privacy with other constructs as a measurable commodity, dependent and independent variables. Focusing on studying privacy concerns as a metric, they state that since it is almost impossible to measure privacy itself, and also almost all empirical privacy research relies on measurement of a privacy-related construct rather than looking at privacy as an integral concept. This is to mention that the focus of privacy concerns as a measurable construct, is personal rather than group-based. Dinev and colleagues [41] follow up on their proposal by an empirical study on measuring statistical relationships between privacy and other constructs by surveying users of Web 2.0 sites. Relevant correlations to information privacy are found on anonymity, secrecy, confidentiality and control. As observed, trust is still not a construct that has been surveyed empirically in their work.

Trust and privacy constructs are context dependent notions and modeling them within the context of user profiles demands an extensive study. Namely, it must be clearly defined how these constructs affect the profiling and personalization systems. Through this research we will show that providing users knowledge that the system understands and respects their preferences accurately can boost their confidence towards the system. At the same time, by finding correct synergy between trust and privacy measures, we can maintain system performance at acceptable levels, while protecting user data.

Research Questions

The problem that we consider in this work is the notion of trust-based user profiling. The idea of combining web profiles with trust and mechanisms allowing information systems to consume and understand such statements and preferences. This improves interaction and communication between individuals and system which in turn boosts the system performances. Following this formulation of problem, the thesis aims at answering the following questions:

- **Q1**: With increasing importance of trust computing, which languages and methods shall be used to model notions of trust in user profiles ?
- **Q2**: How can we manage trust-enabled user profiles for web computing ?
- **Q3**: What are effective techniques to discover, aggregate and mine trust-based profiles ? How can we maximize the impact of trust-based user profiles in the context of information retrieval and personalization on the web ?
- **Q4**: How can we correlate notions of trust and privacy in an effective manner and exploit this correlation to benefit the applications and systems implementing these crucial concepts ?
- **Q5**: How can modern web applications be designed to incorporate trust metrics and trust-embedded user profiles in their very fabric ?

Proposed Approaches

A majority of proposed solutions by this thesis had impact on profiling and recommendation systems in digital libraries, i.e. EU FP7 Smartmuseum project [137]. Highlighted solution starts by modeling adaptive user profiles incorporating users taste, trust and privacy preferences. This led to proposal of several ontologies describing characteristics and attributes of users and their on-line content, which in turn was used for improving indexing and retrieval of items and profiles across the platform. To address important obstacles of sparsity and uncertainty of on-line profiles, frameworks for data mining and machine learning of profile contents from social networks were proposed. Results of mining populating data from social web together with profiles were shown to increase the accuracy of intelligent suggestions made by system were shown to increase the accuracy of intelligent suggestions made by the system to improve navigation of users in on-line and off-line museum interfaces.

With an ever increasing variety of data on the web, techniques are needed to be able to mine and use such content. This motivates us to take notion of trust-based profiles beyond the boundaries of digital libraries and into the social web domain. This is done by augmenting the mechanisms of discovery and recommendation of popular social recommender systems, e.g. collaborative filtering. This has led us to propose several trust-based recommendation frameworks capable of mining implicit and explicit trust across ratings networks taken from social as well as e-commerce web.

We focused both on ontological issues as well as management of profiles. Resulting recommendation techniques have shown to increase accuracy of profiles, by incorporating knowledge of items and users and diffusing them along the trust network. Leveraging on automated distributed management of profiles we showed that coverage of system can be increased effectively. Our results surpassed comparable state of art techniques, which in turn shows that trust can clearly elevate accuracy of suggestions predicted by system. To assure overall privacy of similar systems, privacy was given a direct focus. Focusing on architectures and metrics for secure trust-based recommendations were proposed. In turn it was shown that a balance between accuracy and changes of trust data passed between parties can maintain accurate output.

Finally focusing on hybrid models of web contents and recommendations led us to study the impact of trust in the context of topic-driven recommendation in social and opinion media. This helped us show that content-driven and tie-strength networks can improve systems accuracy for several computing tasks. The following main contributions will be discussed in contributions part and detailed out in included papers:

- **C1**: Modeling and Analyzing Ontology-Based Trust Networks;

  [C1.1] **Proposing a generic trust vocabulary** for modeling interactions and cooperations of agents, applications, organizations and people on the social web and a functional ontology for documenting these interactions and proposing resulting trust networks.

  [C1.2] **Introducing a benchmarking framework** for qualitative and quantitative analytics of ontological trust models and their generative trust networks.

- **C2**: Modeling and Learning Trust-Aware User Profiles;

  [C2.1] **Novel formalization of trust-aware user profiles.** Such formalization allows encapsulation of structured knowledge representation of a system with respect to collective behavior of a user across the system. The user attributes encompass individual and collective knowledge of system about the user. This together allows system to build a behavioral knowledge of applications with respect to profiled data about the user, including important notions of trust and privacy with respect to context that user is being profiled within.

[C2.2] **Proposing a greedy heuristic for mining and normalizing uncertainty semantic user profiles** where a custom fuzzy reasoner can mine, interpret and map the raw values into normalized values that can later on be used for recommendation and adaptation tasks.

- **C3**: Discovering and Aggregating Trust-Aware User Profiling;

[C3.1] **Augmenting trust-aware user profile modeling for cross-domain personalization**. We have proposed for an ontology-based generic user model, which imports a generic user model to captures the basic concepts of user. This in turn was extended with a social user model containing concepts needed to capture knowledge about on-line users.

[C3.2] **Proposing a semi-supervised profile importing architecture which can adaptively discover, aggregate and learn topic-based user profiles to support the task of personalization**. Framework supports two aims; helps for harvesting the profiles from the network and learning groupings of profiles according to their shared interest topics via a combined clustering through classification scheme.

- **C4**: Architectures and Analytics of Decentralized Trust-Based Recommender Systems;

[C4.1] **Proposing architecture for an ontology-based recommendation framework**. A generic recommendation framework allows content and profiles from the web to be imported, mined and used for generating recommendations of items and people of interest.

[C4.2] **Proposing for metrics and automated management in trust-recommender systems**. Leveraging on a social network overlay allowing trustworthy neighborhood to be found more effectively using epidemic heuristics for improved recommendation generation.

- **C5**: Modeling and Evaluating Privacy in Trust-Based Recommendation Systems;

[C5.1] **Introduction of a privacy-by-architecture framework for enabling privacy-preserving trust recommendation system**. This allows for taking measures for preserving privacy during trust calculation and computation.

[C5.2] **Analyzing balance between accuracy and privacy in privacy-by-architecture design of a trust recommender system**. We have shown that privacy and trust mechanisms, each with their respective configurations jointly form configurations of the overall framework.

- **C6**: Modeling and Measuring Trust in Hybrid Recommender Systems;

[C6.1] **Proposing a topic-based framework for review mining and summarization**. In this framework we focus on proposing algorithms to model reviews using latent topics and star ratings, ranking of reviews to summarize all reviews for a product within the top-k results.

[C6.2] **Proposing a topic-based framework for social network mining and analysis of micro-bloggers**. Within which a trend corpora can be mined . By using a probabilistic latent topic technique, both collective, and individual models can be defined.

Chapter 2

State of the Art

Trust Ontologies

An ontology [111] can serve as a tool to model and generate a network of users. This is done ultimately by describing personal information about each person (realizing the ego node), and by describing personal information regarding a set of users whom the user knows or is eager to connect to (realizing the neighbors on the network). Nodes on such a network are identified by their unique identification. We have surveyed several widely-known ontologies of trust briefly in paper 5. Table 2.1 visualizes a qualitative summary of several ontologies of trust under focus in our work.

Jennifer Golbeck [76], introduces an ontology, that creates an important schema which extends FOAF [17] giving the users this possibility to state and represent their trust in individuals they know. Context was introduced as a property of trust. Trust is context-sensitive, as a result meaning and semantics of trust can change depending on the context. This notion is represented in this ontology under general trust or specific trust or topical trust [76]. Toivonen and Denker [156], study the trust in the context of communication and messaging. They state that there are many factors which can have immense impact on the honesty and trustworthiness of the messages we send and receive. The context-sensitivity of trust has been realized and taken into account in their work.Inference web [97] at Stanford University, has built a semantic web-enabled knowledge platform and infrastructure. This platform is designated to help users on the network to exploit the value of semantic web technologies in order to give and get trust ratings to and from resources on the web. This process is referred to as justification of resources. To this end, a language called PML is used. With respect to metrics used for presenting the trust computational values and modeling the mathematical notion of trust, there exist two approaches: presenting a trust metric with discrete values and metrics with continuous values. Brondsema and Schamp [18] model and represent trust and distrust in a similar fashion using continuous values. Having continuous range

Table 2.1: Comparison among trust ontologies based on ontology component structure

Trust Ontologies	*Concept(s)*	*Relationship(s)*	*Instance(s)*	*Axiom(s)*
Golbeck	Topical trust, Agent, Person	trustRegarding, (between agent and Topical trust)	trust0...trust10 (range of trust metric), trustSubject, trustValue, trustedAgent, (subproperty of trustedAgent), trustRegarding	"A Person or Agent (e.g. Alice) trustsHighlyRe (trust10) trustRegarding a trustedPerson or trustedAgent (e.g. Bob) On trustSubject (e.g. Driving)"
Toivonen Denker	Person, Topic, Receiver, Message	Trusts (between Persons), ctxTRUSTS (between receiver and message), trustsRegarding (between Person and Topic)	trustRegarding, reTopic, (trustsAboslutelyRe ... distrustsAbsolutelyRe), ctxTRUSTS, (ctxtrustsAbosolutely ... ctxdistrustsAboslutely), trustsRegarding, Trusts, rePerson, (trustsAboslutely ... distrustsAboslutely)	Multiple axioms are inferable, for instance; 1) Stating topical trust; "A Person (Alice) trustsAboslutelyRe trustsRegarding (relationship) the Topic (Driving)", 2) Stating trust between two persons; "a Person (Alice) trusts another Person (Bob) trustsAboslutely"
PML	Belief, Element, Trust,Element, FloatMetric	Belief Relation (using hasBelievedInformation and hasBelievingAgent between Agent, information and source), Trust Relation (using hasTrustee and hasTrustor between Agent, information and source)	Agent, Source, Information, hasBelievedInformation, hasBelievingAgent, hasTrustee, hasTrustor, hasFloatValue	Two kinds of Axioms regarding the trust and belief of agent in an information from a source can be inferred, for instance; Stating trust; "FloatTrust, hasTrustee and hasTrustor (agent: userâs browser) And hasFloatValue with FloatMetric (0.55). "
Konfidi	Relationship, Item	About (Between Item and Relationship)	About, Truster, Trusted, Rating, Topic,	Trust Relationships can be stated like the following axiom; "A (trust) Relationship between truster (Alice) and trusted (Bob) exists, which is about trust topic (Cooking) with trust rating (0.95)."

of values allows easier propagation of trust values, along the edges on the networks, using inference mechanisms.

Need for an Extended Trust Ontology

Following the state of art on web ontologies for trust modeling, we have identified these shortcomings in existing work:

- Existing models do not focus on modeling multi-faceted trust [153]. Multi-faceted trust enables presentation of weighted trust in separate relationships, while we have inherently modeled this notion through the concept of relationship and its sub-concepts and properties in our proposed ontology.
- There has been less focus on analyzing trust ontologies from structural perspective. However, structural understanding of inherent network could guide design of more fine-grained relations or meta-data describing interrelations of users, items and their interest.

Our corresponding contributions to this part of the work can be found in 5.

Ontology-Based User Profiling for Personalization and Recommendation Systems

Information about the user is usually collected in a so-called *user model* and administrated by a user modeling system, server or component [165]. Whalster et al, [165] define the following two fundamental concepts: *A user model is a knowledge source in a system which contains explicit assumptions on all aspects of the user that may be relevant to the behavior of the system.* User profiling is either knowledge-based or behavior-based [115]. Knowledge-based approaches engineer static models of users and dynamically match users to the closest model. Behavior-based approaches use the user's behavior as a model, machine-learning techniques to discover useful patterns in the behavior. The difference between user profiling and user modeling relies in different levels of sophistication [63]. Web ontologies, are used to formalize domain concepts allowing description of constraints for generation or selection of contents which are similar to the interest domain of user. Web technologies are also used for formalizing the user model or profile ontology. Such models help with deciding on which resources to be adapted to the user. Web ontologies along with reasoning create formalization that boosts personalization decision making mechanisms [50, 51].

Web ontologies play a crucial role in profiling and modeling of usage-driven personalized software systems. Ontologies have been used extensively in personalization and recommendation research [60, 65, 147, 182]. Standardizing user profile syntax and semantics allows for the implementation of inter-operable personalized systems to share information about their respective users and their knowledge. Ontology-based user profiling is thus crucial to systems that can reason across multiple profiles (social semantic systems) or systems that can take advantage of complex inference on multiple ontologies representing different knowledge (e.g. Digital Libraries). Thus bringing us to the notion of hybrid models that can combine both notions.

Need for Hybrid User Profiles and Ontologies in Knowledge Services and Databases

Hybrid modeling and profiling have been widely discussed in the literature [19]. Hybrid user modeling can be defined as combining user attributes and content attributes for improving personalization effect. Hybrid approaches to user modeling and profiling, are either focused on combining strategies for profiling and user modeling [14, 136]. In addition to modeling semantics in profiles, we also need to consider the structure of profiles [30, 62]. Existing shortcomings were observed in research on ontology-based user profiling are listed as follows.

- Existing models do not consider trust and privacy or similar notions are profile-level knowledge that can be embedded into profiles for presenting user's security and privacy preferences across devices, databases or domains.

For our respective contributions to this part of work you can refer to paper 6.

Modeling Trust and Privacy in Ontology-Based User Profiles

In the user modeling field, there are several attempts to define a generic user model which contains the definition of user features and of his/her physical and social context, expressed with semantic web language and made available for all user-adaptive systems via Internet. Figure 2.1 visualizes the distribution of projects utilizing semantics for adaptation and personalization, while collocating them by their semantic qualities and knowledge types.

Ontology-based user profiles are becoming widely adopted. Museum and tour guide applications were influential ones [11, 26, 94, 168]. For instance, within the domain of digital cultural heritage, the CHIP project is definitely a significant stake holder. Considerable amount of research attention has been paid to semantically formalizing the user domain [168], as well as personalization of information retrieval.

Smartmuseum project aimed at building an on-site and off-site distributed information dissemination and retrieval platform for accessing the cultural heritage digital artifacts [11]. While profiles play important roles in capturing and storing the understanding of users in such environments, using knowledge modeling techniques such as semantic web technologies seem to be a justified approach. Figure 2.1 has

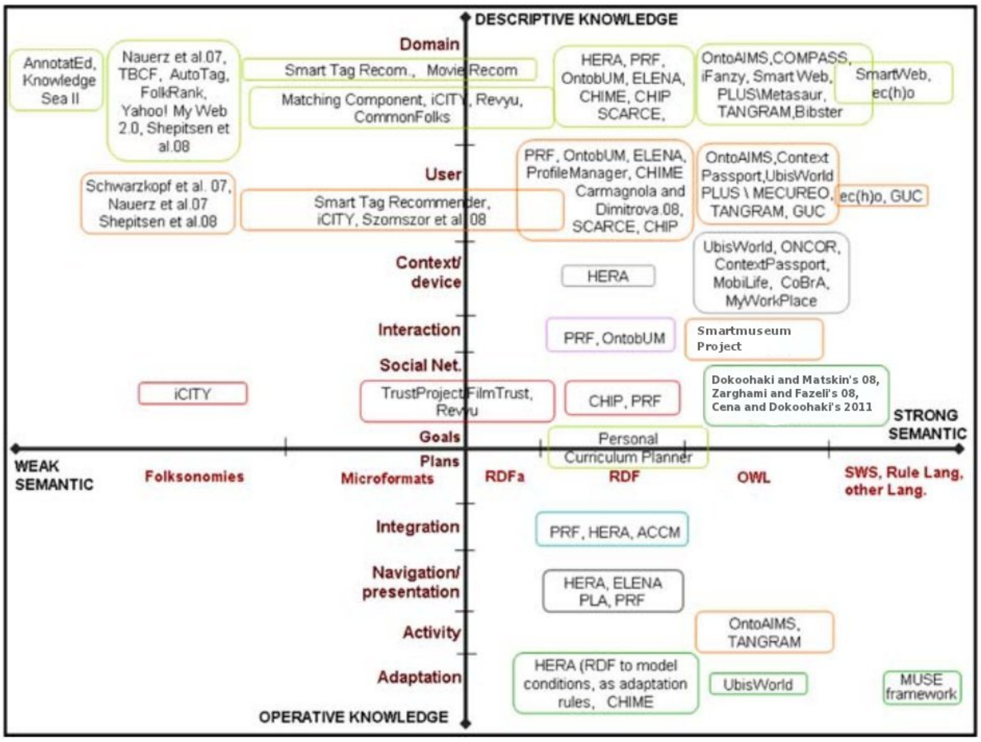

Figure 2.1: Modified visualization of works and projects using semantic technologies plotted with respect to different types of knowledge used (e.g. domain model, user model, personalization model, etc.). Original plot by Ilaria Torre [158]

been modified to incorporate several contributions of this work, including Smartmuseum project [137]. Smartmuseum project is plotted along moderate semantics as well as bordering along side interaction and social networking, similar to CHIP project. Our trust ontology [45], alongside recommendation systems using it [58,59], and social user and cross-context ontology [32], is leveled with social network with respect to use of strong semantics (i.e. OWL statements in our trust ontology [44] and SWRL [124] rules in privacy sub-ontology in our social user model [32]), similar to FilmTrust project [70].

Need for Emphasizing and Proposing Federated Ontologies of Trust and Privacy

To the best of our knowledge, there are no attempts to integrate privacy model in a generic user model. Little attention has been paid to effective incorporation of trust into user models. Among adaptive Web applications, recommender systems have been quite successful in utilizing and leveraging social trust and reputation. Golbeck first introduced the notion of ontological modeling of trust in semantic social Web [74, 76]. Examples of adoption of reputation and trust in user models as pointed out earlier have been limited. Grapple project [1] investigates capturing and utilization of reputation to model the trust between users, by allowing the users to rate each other's opinions and statements, following the eBay model [139].

Adoption of such a plain model of reputation is neither successful, nor sufficient in computational generic models of users. This is due to several reasons. The first of which is rating is an implicit model of reputation, and representing it as a simple form of property-rating or a vector of ratings strips it from its original notion. On the other hand, many systems are already using explicit trust statements to evaluate users opinions, (such as Epinions or Ciao [39, 55]). Second, since trust and reputation convey different semantics on Social Web, frameworks for modeling users should be capable of describing trust and reputation separately. This difference is pointed out when we introduce a trust model capable of describing trusted peers of a user on a social network and a reputation model capable of storing and presenting the reputation of user across different communities on-line. Existing shortcomings were observed in current research on modeling privacy ontologies in projects utilizing semantic technologies:

- Limited work on introducing models for social user profiles and cross-context personalization. There is a need to propose a more unified user ontologies for social web, specially in the context of personalization and recommendation systems.

- Existing models of users in the social web, fail to model important dimensions of social connectivity: privacy, trust and reputation. *Since trust and reputation convey different semantics in the Social Web, frameworks for user modeling should be capable of describing trust and reputation separately.* There has been limited attention to integration of privacy models in a generic user model. With ever increasing importance of privacy and security in social networks [2], it is important that explicit semantics be used to model privacy preferences in social applications.

- There is a lack of clear semantics of topic-based relationship presentations in user ontologies: Explicit and implicit models of reputation are presented in simple form of property-rating or a vector of ratings strips it from its original notion and postulation. On the other hand, many systems are already using explicit trust statements to evaluate users.

For our respective contributions to this part of our work please refer to paper 8.

Discovery and Mining of Ontology-Based User Profiles for Personalization and Recommendation

Since user profiles play a crucial role in the context of web personalization and adaptation, availability of rich and populated profiles is crucial for personalized systems. Discovering and sharing interest profiles across domains and systems have been focus of many researchers. Availability of profiles in information retrieval and personalization are subject to two important tasks: discovery and mining. Ghosh and Dekhil [68] argue that profile construction and discovery on the web can be augmented to address the sparseness of the profile data, as well as improving the content of the profiles. Teevan et al [154], study heuristics for discovering and processing the prior interactions (profiles) of users for the task of search personalization on behalf of the users. Gauch et al [64], give a complete overview of different models of discovery and retrieval for ontology-based user profiling. One problems is that most of models are either focused on modeling the user profiles rather than discovery or harvesting them, or they are very general for specific and subjective tasks of recommendation or retrieval.

Gauch and Trajkova have proposed for user ontologies in cross-domain user profiling [65, 159]. Issue of discovering and retrieving profiles across multiple domains with semantic user profiles has been discussed also in [60, 148]. This has been emphasized in the Smartmuseum profiling and recommendation architecture [142]. Figure 2.2 depicts the interface of smartmuseum artifact recommendation interface. Discovery problem aside, dealing with sparsity in such data becomes an important issue under focus. Researchers approach different methodologies to gather, analyze and generate user profiles. This is usually done through applying machine learning techniques to web data. Using these techniques has been very appealing for personalization tasks [117]. Mining web content for personalization has been attractive to addressing inherent problems of recommender systems [115]. More specifically two types of recommenders have been dependent on large number of machine learning techniques, namely content-based [133] and collaborative filtering recommenders [144].

Need for Automated Discovery of Ontology-Based User Profiles

Similar to our framework is the work by Liu and Maes [104, 161]. The focus on automation of profile and taste discovery has been pointed out in literature as well through either profile learning [114, 152, 154] or ontology-driven mining [40, 102, 130, 180]. First and foremost problem in personalization systems is dealing with sparsity in profiles and Cold Start problem. This problem has been the main focus of the semantics user profiles [5], the ontology-based user profiles [3, 113, 148] and the user models [33]. Cold start problem refers to incapability of system to cope with lack of sufficient data to reason about users. Cold start has been a

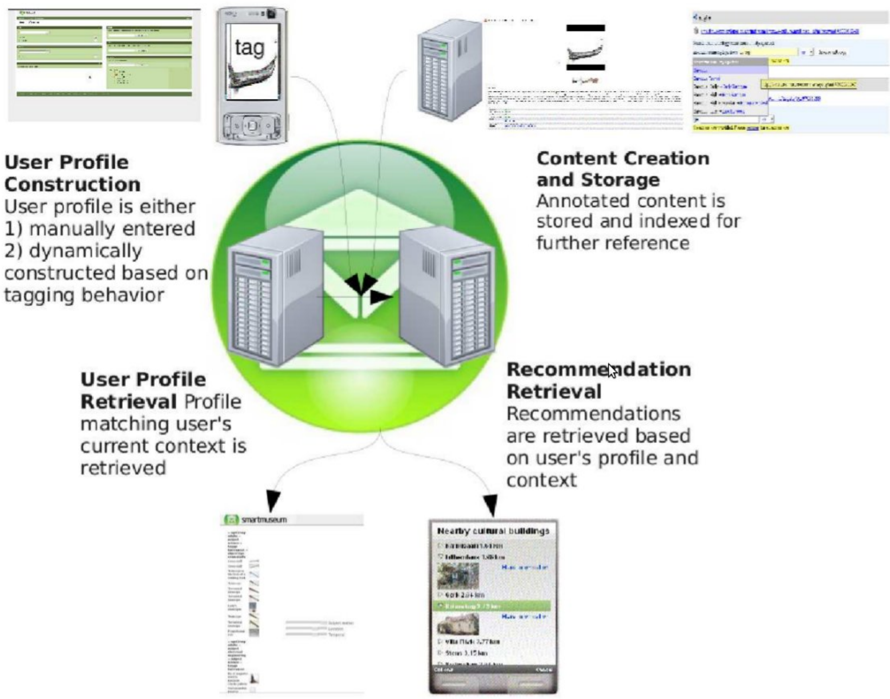

Figure 2.2: Architecture of Smartmusuem recommendation system, visualized by Rutosalo et al [142].

strong hurdle in performance of web personalization systems, and has remained until recently. Amongst the approaches proposed in dealing with such this issue user modeling [33], trust [164] and collaborative filtering remain the most successful techniques. Existing shortcomings that we have identified in this area of research are as follows:

- Limited attention to automation in profile discovery frameworks; With increasing need for back-end data mining and machine learning for decision support and intelligence, solutions are needed for processing imported or aggregated data from social networks or web in general. Emphasis on automation of such process is of benefit to resulting platform where profiles are imported and digested for recommendation in a dynamic fashion.

- There is no completely satisfactory solution to deal with increasingly important Cold-Start problem; Cold start will degrade the performance of web profiling, a new importation and mining frameworks are proposed that combine the power of data mining and machine learning with least effort on supervision of processing of data.

For respective contributions to this part of please refer to our paper 9.

Need for Mining Ontology-Based User Profiles

Focusing on weighted user profiling methodologies, an important problem to consider is *uncertainty* associated with these profiles. In modern web systems dealing with uncertainty reasoning in user profiling has become a major problem [157]. Uncertainty evaluation has been subject to inferring individual attributes from group attributes in profiles [132]. Uncertainty evaluation in Facebook for instance, has been objective to find relationship between Number of Friends and Interpersonal Impressions [157]. Thus, uncertainty reasoning has been proposed, leveraging fuzzy reasoning specifically, for dealing with cold start problem [164]. There are works on fuzzification of each weighted notion, namely trust [6,12,106,120], privacy [122,178] and ranking [77]. However not so many approaches and frameworks consider approaching collective models of afore mentioned fuzzy notions altogether. Subjective Logic [103] is one unified framework that allows for collective analysis of trust and its atomic factors such as risk. Closest proposal to our approach is Schmidt et al [35,145] that collectively model trust and reputation in a multi-agent setting. In this part of research we summarize the gaps observed as follows:

- Dealing with uncertainty inherent in profile data through explicit reasoning techniques. By associating profiles with weights we can introduce clear semantics and interpretation capabilities to address uncertainty associated with profiled user data. This is specially the case if such content is user generated and taken from multiple on-line sources of data. In modern web systems dealing with uncertainty reasoning in user profiles remains a major problem.

For respective contributions to this part please refer to our paper 7.

Trust Metrics and Ontologies for Recommender Systems

Social recommender systems are suitable candidates for adopting notion of trust-aware user profiling due to several reasons. One of the most important factors emphasized earlier in introductory part of thesis 1, is the fact that consumers increasingly and visibly express and leverage their trust and privacy for the utility they may gain through on-line services, specially recommender systems [10, 160, 171]. Trust has been shown to be an effective notion in elevating performance of recommendation systems [70, 82, 126, 134, 164]. Examples of adoption of trust-recommendation systems have been increasing both in literature and commerce. Fazeli proposes a trust recommender system for learning and teaching [57, 79].

Trust has been the focus of much research since it emerged as a reliable means for improving recommendation accuracy. Zhou et al, [181] presents a rather thorough survey of approaches to trust-aware recommender systems. Within the context of recommender system, we perceive the term trust to denote the confidence a user has in the recommendations of another. Trust complements social recommenders by addressing such problems as the reduced computability of similarity between users and improving accuracy of prediction. Yuan et al. [174], describe trust networks as being social networks with user defined trust networks. The authors determine that this type of networks hold the property of small-worldliness, which involves having closely clustered users and small average path lengths between any two users. They then use this finding to define a model for recommender systems that takes advantage of the small-worldliness of social networks in order to increase both accuracy and item coverage. In addition to trust, distrust has also been a focus of research in recommenders. Victor et al. [163] propose a model that uses distrust to complement trust. This approach helps deal more effectively with users that have undesired behavior. The concept of distrust is also used by Verbiest et al. [162]. They analyze the effect of path length on trust and accuracy. This is particularly interesting to our work since we also observe the effects of using neighbors on the accuracy and item coverage of our recommender system.

Several approaches, such as Golbeck [73], Kuter et al. [96], Avesani et al. [8], DuBois et al. [52] also exploit underlying mechanism in a network that allows for explicitly stated trust statements between users. However, not all systems support such features. The ability of users to express their confidence in others is limited due to the time and effort required to evaluate other members of the network in order to form an opinion. Therefore, the ability of recommender systems to infer trusts from limited knowledge is still a desired feature. The technique used to infer trust between users is critical to the accuracy of a trust-based recommenders.

Need for Focus on Ontology and Architecture in Trust Recommenders

Semantic technologies have become effective notions in modeling data utilized by on-line services ranging from books, movies to music recommendation platforms [31, 70, 140]. Golbeck utilizes ontological structures of profiles [70, 74] which are later on used for recommendation generation in FilmTrust framework [70]. While using adjacency matrices for storing trust values have been in favor in a number of works [108], there is an increasing focus on using semantics for describing users, items and their relationships in recommender systems [61], specially considering improved resulting accuracy for recommendation and retrieval [147]. A focus on modeling trust on item and user level was studied by O'Donovovan and Smyth [126]. They model item level trust which is similar to user level trust. Both trust models can be used concurrently to offer better results.

In addition, to cope with sparsity, decentralization and data mining can be put in focus. Han et al [78] propose a DHT-based (Distributed Hash Table) approach, where the central dataset is organized into "buckets" of users which can be saved on individual nodes, each user utilizes his most suitable "bucket" to choose neighbors with which to generate predictions. User clustering is suggested as a solution for solving scalability problems as well as a means of improving accuracy [143]. Sarwar et al. [143] present clusters as groups of users where all the users in a cluster are each other's neighbors, whereas in our case, the neighbor relation is directional. A directional neighbor relation is desirable since, while a user's neighbors will be the most similar users to it, there might be other users that are more similar to a neighbor.

Similar to the metric considered in our work, is the metric studied and discussed by Lathia et al. [99]. Lathia et al. [99] argue that dependence of CF approaches on similarity measures hides a number of pitfalls, which originate from the fact that user profiles are very empty and limited in breadth. He proposes for trusted k-nearest recommenders (kNR) [99], a trust-learning heuristic that mainly suggests the idea that recommenders, who provide useful information, should be rewarded and those who have no information available, should be downgraded. The trust-based collaborative filtering algorithm used in their method requires a centralized user-item matrix which might lead to scalability problem as the number of users increases. We summarize the gaps identified in the existing research related to this part of the work as follows:

- There is limited attention to using ontological trust models, specially trust-based profiles in recommender systems. With increasing attention to recommenders in various fields of commerce and science, need for ontological models describing various information items of interest, user profiles and their inter-relations is increasing. Thus in order to maximize adoption of trust-based profiles fully functional semantics models of recommenders can be proposed.
- There is need for studying correlative and bilateral effects of networks and metrics of trust; While values of structural studies of resulting trust networks have been pointed out, it is vital to study how mined networks of trust reshape and evolve in the face of suggestions generated by networks.

You can read further detailed contributions in paper 10 with respect to this part of the work.

Need for Focus on Metrics and Profile Network Management in Trust Recommenders

After considering data structure and architecture in trust recommenders, we gave focus to metrics and profile network management in trust recommenders. Pearson similarity is a popular weight metric, however using a more complex weighing measure than just similarity has the potential to offer more accurate results, especially in sparse datasets [108]. Approaches such as those proposed by Golbeck et al. [70–72] take advantage of trust ratings explicitly stated by the users themselves to infer trusts between nearby members of the network through trust propagation. Focusing on metrics, O'Donovan and Smyth [126] argue that similarity is not sufficient in recommenders. They propose trust metrics that measure the degree which one might trust a specific profile when it comes to making a specific rating prediction. O'Donovan uses the known ratings to create an artificial history of predictions for each user. By predicting the known ratings of users using all the other users and counting the amount of correct predictions that each user makes, O'Donovan establishes a global trust [101] for each user as the ratio of correct predictions to total predictions of a user [126].

In addition to metrics focus, we have also studied how leveraging profile management could lead to increasing decentralization of recommendation generation. Several works focus on studying decentralization techniques on recommender systems, specially trust-aware ones [108, 116, 146]. Miller [116] proposes a peer-to-peer recommender system in which nodes exchange ratings with a neighbor at each step in order to construct an item to item similarity matrix which can then be used to make offline predictions. The choice of neighbors as well as determining the neighbors of a user are implementation dependent in this approach. Unlike our approach, Miller does not maintain a profile network. This is understandable since his proposed system does not need to keep similar profiles easily accessible and only needs a profile for a one-time computation, after which it can be discarded. Ormandi et. al. [129] determine that using gossip based algorithms to cluster a network in the context of recommender systems offers potential for increasing accuracy of prediction. However, the aforementioned work does not analyze item coverage and does not cover trust-awareness in recommender systems instead focuses on load-balancing. We summarize the gaps identified in the existing research related to this part of the work as follows:

- There is a need for further studies of interrelations of effect of decentralization mechanisms on performance factors in recommender systems; Since existing work on applying decentralization heuristics to recommenders has been widely focused on addressing problems such as load balancing [129], more connection-centric focus is needed to correlate the positive impacts of decentralization to overall performance of recommendation generation process.

- There is a need for studying effect on profile (overlay) management on performance factors in recommender systems; This is also due to the fact that majority of recommenders use matrices to store and retrieve items and profiles similarity [116] and trust scores [108] indices. This is why by leveraging decentralized networks or overlays (e.g. DHTs), we can improve speed and coverage of access to profiles across the network of users.

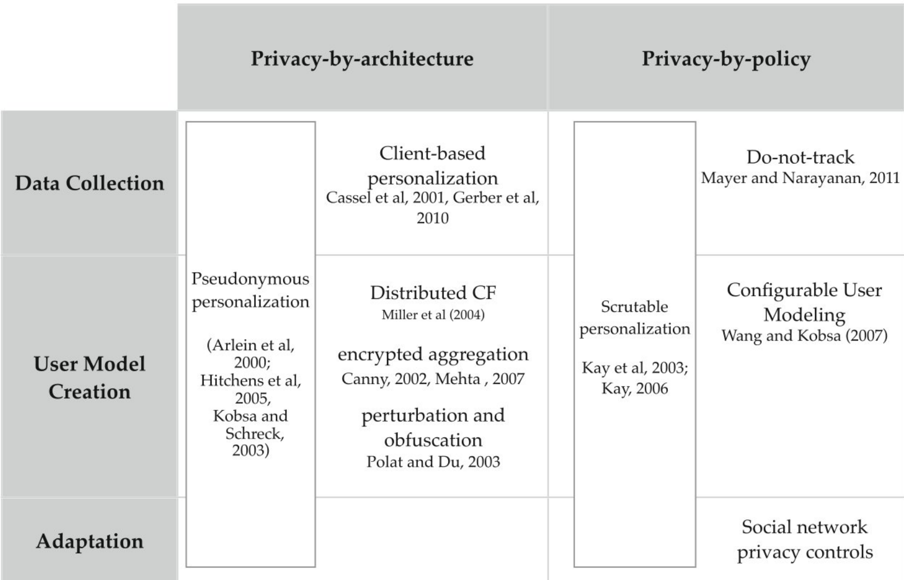

Figure 2.3: Privacy alleviating techniques in personalization systems categorized according to stages of personalization and approaches, taken from Toch et al [155].

See paper 11 for our respective contributions to this part of the work.

Privacy in Recommender Systems

Toch et al [155] provide a survey of user attitudes towards privacy and personalization as well as technologies that can help reduce privacy risks. They identify three trend categories to personalization: social-based personalization, behavioral-based personalization and location-based personalization. Three steps are identified by authors in a personalization process. According to diagram the further you move towards the lesser capabilities of user to control their information. These steps are visualized on vertical axis in figure 2.3. This collection also categorizes existing methods to addressing privacy along two horizontal axes namely privacy-by-policy and privacy-by-architecture. While former focuses on adopting and putting into action the so called "notice and choice" principles of fair and sound information practices [7,24,25,28,67,91,116,135], the latter addresses creation of systems that minimize the aggregation and consumption of identifiable and traceable personal data [86, 87, 90, 109, 167]. Privacy techniques that focus on user model creation step allow user data to be hidden from central services [24,25,135], by leveraging technologies such as distributed collaborative filtering [20,116], or to be customized by the user using configurable user modeling [167]. Techniques subject to the data collection phase block the system from rendering fine grained profiles of users by tracking their behavior across their domain. Solutions such as client-based personalization provide privacy-by-architecture solutions by not allowing systems to access user information directly. The adaptation phase and it's respective privacy solutions are subject to research.

Need for Privacy-Preserving Trust Recommender Systems

Taking measures for preserving privacy during trust calculation and computation has been of great importance. An absence of privacy protection within the context of systems dealing with trust and reputation, can ease attacks by malicious insiders, as they might infest the existing trust establishments or alter the trust computation results. In the context of recommender systems, Lam et al. [98] give an overview of privacy and security problems with recommenders. These problems are twofold: the personal information collected by recommenders raises the risk of unwanted exposure and malicious users can bias or sabotage the recommendations that are provided to other users. The latter notion is recognized as an attack on recommender systems, namely Shilling attacks [23,118]. Attacks on recommenders remain a significant security hole in these systems [37, 127, 138]. O'Donovan and Smyth elaborate on robustness of trust in recommenders and state that various attack sizes cause prediction shift for a "pushed" item [127]. This is based on an adversarial model that malicious users might find a way to penetrate a recommender system using a maximum rating for the pushed item. In such situation, where we are estimating our trust values, attack profile will reinforce the ratings of each other profile. This is called the Reinforcement problem [127]. The authors conclude that trust models can not be used to increase recommendation accuracy, but they can be used to increase the overall robustness of social systems. Zhang [177] focuses on the same problem and executes various sizes of average Shilling Attacks on a trust-aware recommender system. He demonstrates that trust-recommender exhibits more stability over a traditional kNN-based recommender. Thus, the research gaps identified with respect to the work presented can be summarized as follows:

- There is a need for proposing architectures for enabling and sustaining privacy of trust-aware recommender systems. There has been least emphasis on investigating the notion of privacy surrounding the disclosure of individual ratings and the protection of trust computation in recommender systems.

- There is a need for more empirical and experimental evaluation of stated balances [90] between perceived usefulness of system (performance and adoption) and measurable and feasible privacy utilities.

Our respective contributions to this part of work can be found in paper 12.

Trust and Topic Models in Hybrid Recommender Systems

Topic Models and Hybrid Recommender Systems

While both content and collaborative filtering recommender are dominant techniques to building recommendation systems on social web [151], it is important that one can use social and semantic information for generating informed recommendation [95]. Such systems are considered as hybrid recommender systems [21, 22]. Burke defines the term hybrid recommender system as any recommender system that combines multiple recommendation techniques together to produce its output. A new breed of such approaches are leveraging latent topic models [38,107,172,173]. Latent topic models have a wide range of application from intelligence and knowledge extraction from the text for opinion mining [15] or review recommendation [92], to sentiment analysis on micro-blogging sites like Twitter [13,36,123]. Topic models are generative probabilistic models which utilize vocabulary distillations to spot topics within text corpora. Most widely utilized topic modeling techniques include Probabilistic Latent Semantic Analysis (PLSA) [80] and Latent Dirichlet Analysis (LDA) [16].

Applications of topic models and hybrid recommenders is presented in the literature [110, 150]. McCallum et al. [110] propose Author Topic model (AT), as three Bayesian hierarchical models to deal with roles with email datasets. The Author Recipient Topic model (ART) is a directed graphical one which models social role as an explicit graphical model through a latent random variable. Argument on non-topic models being able to handle graph structure has led to an increasing level of work on embedding graph and network structure analysis into very fabric of LDA models [34, 166, 176]. Wang et al [166] propose a probabilistic framework for joint analysis of text and links between nodes (e.g., people) in a time-evolving social network. They show how their model is resilient against noisy links on an academic (co)authorship network.

Correlating Trust and Topic Models in Hybrid Recommendation Systems

As trust has been the sole focus of artificial intelligence domain, multi- or even inter-disciplinary models of trust are very recent [29]. Models of opinionated trust has been put forth in two different techniques. More recently, using natural language processing techniques have been leveraged to summarize, integrate or recommend opinion summaries in form of trustworthy topic sets. Golbeck and Hendler first set forth the concept of topical trust on the web [75], for applications in trust network building and inference [69] and social recommender systems [175]. Topical trust [75, 89] originally sets forth the idea of using topic labels as edge labels on a social network exemplifying context or nature of a trustworthy relation. With increasing popularity of tag-based systems on the web, tag models of trust have been recently proposed in the context of multimedia. Such trust metrics are mainly proposed for filtering noisy and unwanted content (here tags). This has led researchers to to differentiate between content models and user models of trust [81]. For social scientist to be able to leverage topical models for network mining, new models and new metrics need to be proposed [105]. Cha and Cho [34] extend probabilistic topic models to analyze the relationship graph of popular social-network data, so they can group the edges and nodes in the graph based on their topical similarity. To do so, they first apply the Latent Dirichlet Allocation (LDA) model and its existing variants to the graph-labeling task. Several variants of LDA are proposed and tested along with their hypothesis.

Need for Studying Trust in the Context of Modern Hybrid Recommendation Models

The existing work focuses on two types of systems: First, content trust models leveraging trust graphs for improved accuracy of recommendations generated [105, 169]. Second, frameworks proposing trust metrics that can either propagate, aggregate [83] or rank [170] people and their respective resources [29, 85] for improved recommendations. Weng et al. [170], propose a heuristic to measure the influence of individual Twitter users taking both the topical similarity and the link structure into account. They utilize an LDA algorithm to distillate and acquire topic sets from Twitter users. This is followed by constructing links between Twitter users. They show that through existing homophily in Twitter, a notion of reciprocity can be observed. Caverlee et al [29], have proposed SocialTrust++ within which they develop and analyze algorithms for and leveraging community-based notion of trust. While they place much emphasis on a community model of trust, in order to model and mine implicit communities they emphasize on usefulness of probabilistic topic modeling techniques. They also report that by leveraging LDA-based retrieval, community oriented ranking model results in a significant improvement over other alternatives [85]. We summarize the gaps identified in the existing research related to this part of the work:

- There is a need for increased attention to topical/tag-based models of trust in the context of heterogeneous and mixed-mode content for web computing. Limited attention has been paid on exploiting graph and link structures among resources and people especially in the context of on-line social media.

- There should be possibility of leveraging collective feature attributes for user/resources interlinking and trustworthiness evaluation; While topical models can measure feature notions such as saliency, relevancy and polarity, there is also room for exploiting such notions to model distrust, mistrust links between users and their resources on-line.

For our respective contribution to this part of the work please refer to papers 13 and 14.

Chapter 3

Detailed Contributions

Modeling and Analyzing Ontology-Based Trust Networks

While social networks have become the most dominant forums on the web, attracting a large number of users with diverse background, trust networks formed within and across these networks create an extraordinary test-bed to study relation dependent notions such as trust, reputation and belief. Successful adoption of trust networking across e-commerce web and web applications such as recommender systems have helped web crowd to realize the importance of networking.

Summary of Contributions

In order to successfully capture, model and present these networks web applications and users' need to understand and agree upon the meaning of trust, we present semantics of trust in a fashion that captures the meaning of relationships among agents on a social network which becomes the first aim and contribution of this work. To model semantics of relationships forming the backbone of trust networks, main components of relationships are represented and described using web ontologies [42]. Resulting models of such ontologies are thus referred to as ontology-based trust models and their generated instances are called ontology-based trust networks.

While most of the attention that researchers have paid are to modeling semantics of trust and how to leverage these models for their respective applications, less attention has been paid to analyzing and studying the structure of these networks. With increasing importance of computational social science [88, 100], more trust scientists are emphasizing the importance of analyzing and studying links and ties on a trust network, thus emphasizing the importance of trust network analysis [29, 84, 179]. Since ontology-based trust models and their resulting networks follow their own syntax, structure and semantics, a framework is needed to benchmark the ontological trust models. Thus, secondary contribution of this work proposes a framework for benching ontological trust models, both through quantitative and qualitative metrics. Quantitative aspect of such framework relies on studying the lexicon and logic of underlying vocabulary presented by trust vocabulary. This is while quantitative framework aims at benchmarking the structure of generated network instances through corresponding ontologies. We can summarize respective contributions by papers [44, 45] corresponding to content of paper 5, as follows:

C1.1 **Proposing a generic trust vocabulary** for modeling interactions and co-operations of agents, applications, organizations and people on the social web and a functional ontology for documenting these interactions and modeling resulting trust networks.

C1.2 **Introducing a benchmarking framework** for qualitative and quantitative analytics of ontological trust models and their generative trust networks.

Contributions Statement

As the main contributor of papers [44, 45] I have proposed a generic trust vocabulary, and introduced a benchmarking framework for qualitative and quantitative analytics of web ontological trust models.

Modeling, Discovering and Learning Trust-Aware User Profiles for Knowledge Platforms

User profiling remains the most dominant and pivotal methodology in web applications to collect, present personal usage data. While prying any sort of data from various sources and databases requires explicit agreement from the users side, analyzing and processing their data is even more invasive to privacy. Increasing attention is paid to capture trust while maintaining a decent privacy guarantee of exposure and consumption of this data. This creates the possibility of proposing the concept of combining trust and privacy factors at profile level with usage data gathered.

Summary of Contributions

We have introduced a user profile formalization capable of encapsulating structured knowledge of collective behavior of a user across the system, including important notions of trust and privacy with respect to context that user is being profiled within. [46]. By introducing this idea within the context of knowledge-intensive systems, methods are required to evaluate this approach. Our profiles are made up of semantic user profiles and weighted values for trust and privacy. To be able to analyze these profiles fuzzy reasoning is adopted where a unified fuzzy reasoning can learn and explain the raw values that can later on be used for recommendation and adaptation. The developed solution was specialized to context of Smartmuseum project, but we believe that our solution can be extended and reused in similar domains and contexts. We summarize the contributions by papers [46, 48] shaping content of papers 6 and 7, as follows:

C2.1 **Formalization of trust-aware user profiles** capable of storing knowledge of a system about collective behavior of a user and incorporating trust and privacy with respect to context that user is being profiled within. This allows for effective expression and insertion of trust, privacy and ranking statements within the profiled items.

C2.2 **Proposing a greedy heuristic for mining and normalizing weighted uncertain trust weights of semantic user profiles** where a unified fuzzy reasoning can mine, interpret and map the raw values into normalized values that can later on be used for recommendation and adaptation. Using proposed approach allows for Cold Start problem to be addressed to an extent where system can be bootstrapped and function uniformly in the face of new users or sparse profiles that might hinder performance.

Contributions Statement

I am the main contributor of papers [46,48] and contributions of novel formalization of trust-aware user profiles as well as greedy heuristic for mining trust weights of user profiles, presented in 3.

Discovering and Aggregating Trust-Aware User Profiling

So far trust-aware user profiles [46, 48] were modeled and described for centralized knowledge platforms, especially digital libraries. With increasing importance of social web further proposed models are needed. Such proposal can allow us to present and capture generic characteristics of users in social contexts. Such proposal also enables profiles access from multiple knowledge platforms on the web. This is based on the concept of cross system personalization which represents the idea of modeling users and keeping them personalized across multiple knowledge platforms [112, 121].

Summary of Contributions

We emphasize importance of using the concept of trust-aware user profile modeling over the web. To successfully leverage current proposed model [44], we need to align our model with a social user model [26, 27]. To do so we have proposed an ontological model of social user, composed by a generic user model component, which imports existing well-known user model structures and captures the basic concepts regarding the user; and a social model, which contains social dimensions. In such social user model that trust, reputation and privacy are pivotal concepts gluing the whole ontological knowledge models together. Existing models of users on the social web, fail to model important dimensions of social connectivity: privacy, trust and reputation.

Social web is possibly the largest repository for user created, tailored or maintained content [93]. Importing existing user data from social web can be of benefit to both users and application. On the application side, existing profiles can be populated with content that can hopefully address problems such as sparsity and Cold Start. As a matter of fact, we can benefit from an automated framework that can enable discovering [68], aggregating [4,117] and reusing user data from social web repositories for personalization services. We have proposed a framework [47] for harvesting and mining topic-based interest profiles from on-line social networks. This framework combines web mining architecture and profile generation techniques, but we put more emphasis on the actual profile generation process. While the former part helps for harvesting the profiles from the network, the latter part learns groupings of profiles according to their shared interest topics via a combined clustering through classification scheme. For clustering step we have used a kNN clustering approach, while for the classification tasks three sets of Bayesian, kNN and a tree classifiers are tested. To generate adaptive recommendation results with respect to tasks of relevancy and accuracy, we use a probabilistic topic distribution that balances between both tasks. Thus, our contribution is *proposing a semi-supervised profile importing architecture which can adaptively discover, acquire and learn topic-based user profiles to support the task of mining for personalization.* We summarize the contributions shaping content of papers 8 and 9, as follows:

C3.1 **Augmenting trust-aware user profile modeling for cross-domain personalization**. We propose an ontological user model composed of a generic user model component. The model imports existing well-known user model structures and captures the basic concepts regarding the user. The social sub-model, which contains social dimensions of users. This model allows information of users existing in social data and meta-data to be importable to our proposed framework and overall model to be reusable for social web applications in turn.

C3.2 **Automated mechanisms for mining web content for predictive profile generation**. This framework uses automated discovery techniques to gather and pre-process the data. However, machine learning allows for processed input to be rigorously analyzed through and create effective predictive topic profiles that can be used for recommendation tasks.

Contributions Statement

As the main contributor of paper 8 and secondary contributor of paper 9, my contribution to former has been ontologies of trust and reputation, while my contributions to the latter have been design and implementation of the framework described.

Ontologies and Management of Profiles in Trust Recommender Systems

Most of the existing frameworks for analyzing trust networks scrutinize the resulting qualities and quantities with respect to trust metrics chosen by system. Realizing how architectural,e.g. functional and non-functional components of system, can be developed to take advantage of such user profiles becomes one of the aims of our work. While knowledge-based recommender systems, e.g. Smartmuseum recommendation framework [141], are mainly leveraging digital library content and consumers, their domain of application becomes focal thus, limited to just digital libraries. Modeling ontology-based trust profiles for generic web architectures and services including recommendation system becomes an attractive task.

Summary of Contributions

The main contribution of this part is proposing an architecture for an ontology-based recommendation framework, allowing both content and profiles from the web to be imported, mined and used for generating recommendations of items and people of interest. The secondary contribution to develop an extended item and profile ontologies for recommender systems, that allows items and user profiles to be imported and be modeled for the task of recommendation. An empirical evaluation demonstrates how trust metric improves the trust network structure by generating connections to more trustworthy users.

In another contribution, we proposed a decentralized mechanism technique to augment recommender systems. By using a social network overlay the gossip algorithm along with an augmented distance function we cluster the users and shape a user's neighborhood with its most similar neighbors which allows us to find most trustworthy users most effectively. We showed that our decentralized approach achieves better accuracy than two popular centralized models while maintaining comparable item coverage. Also, the trust computation method in the context of the proposed decentralized approach performs better than using Pearson similarity and is comparable to the popular trust metrics [125]. We summarize the contributions with respect to papers 10 and 11, as follows:

C4.1 **Proposing architecture for an ontology-based recommendation framework**, a generic recommendation framework allows content and profiles from the web to be imported, mined and used for generating recommendations of items and people. Two components are under focus in this architecture which are semantic profile manager, capable of managing user models for both items and users. **Developing ontologies for recommender systems** allows an extended item and profile domain ontology to be developed for items and user profiles to be imported and be modelled according to any recommender system taking advantage of ontological models in their architecture.

C4.2 **Proposing metrics and automated management in trust-recommender systems**: leveraging on a social network overlay allows trustworthy neighborhood to be found more effectively using epidemic heuristics for improved recommendation generation. Resulting gossip-based recommender systems relies on epidemic network overlay algorithms to create and maintain a distributed network in which nodes can use local information to generate recommendations.

Contributions Statement

I am the secondary contributor of both papers 10 and 11. My contributions to paper 10 were ontological framework for recommendation system as well as social network analysis of resulting trust networks. My interest and contributions to paper 11 were analyzing automated management of profiles and networks with respect to variations of trust metrics. This covers a majority of the contributions presented.

Modeling and Evaluating Privacy in Trust-Based Recommendation Systems

Summary of Contributions

Within this work we extend the architectural landscape of traditional collaborative filtering techniques and trust-aware recommenders to include building blocks required for realizing a privacy-preserving trust-aware recommender system. As an example of such architecture, we implement a framework for applying data perturbation techniques to user rating profiles. We conceptualize this balance between accuracy and privacy as a Pareto notion. We show that privacy and trust mechanisms, each with their respective configurations jointly form configurations of the overall framework. According to Pareto optimality perspective, at least a joint setting of both configurations exists when utilized results in privacy of user data being maintained, while keeping accuracy decent at the same time. We have extended the architectural landscape of traditional collaborative filtering techniques and trust-aware recommenders to include building blocks required for realizing a privacy-preserving trust-aware recommender system. As an example of such architecture, we implement a framework for applying data perturbation techniques to user rating profiles. Thus, we introduced a private trust computation process. Then, accordingly, we propose methods for producing private recommendations based on trust-based collaborative filtering recommender systems. We ground this framework at the top of a trust recommender [175]. We have shown how the overall trust computation can be augmented to accommodate the private trust estimation and prediction generation. We design this framework, having protection and preserving users privacy in mind, while still providing accurate recommendations on masked data using trust-enabled collaborative filtering schemes. We conceptualize this balance between accuracy and privacy as a Pareto notion. We summarize the contributions by papers [43] shaping content of paper 12, as follows:

C5.1 **Introduction of a framework for enabling privacy-preserving trust recommendation system**. This allows us to take measures for preserving privacy during trust calculation and computation.

C5.2 **Analyzing balance between accuracy and privacy in privacy-by-architecture design of a trust recommender system**. We have shown that privacy and trust mechanisms, each with their respective configurations jointly form configurations of the overall framework.

Contributions Statement

I am the secondary contributor of paper [43]. My contributions to paper [43] have been a proposal of privacy-by-architectural design of trust recommender system as well as Pareto optimization proposal for establishing balance between privacy and trust. Thus, contributions presented in list 3 summarize my respective contributions.

Modeling and Measuring Trust in Topical Recommender Systems

An increasing number of works are focused on analyzing natural language content from social services for the benefit of users and services. While computational techniques are being proposed for analyzing spoken text on social networks, opinion mining techniques are increasingly attractive to analyze networks of users informing other like minded ones across the social media. Topic modeling mechanisms [16] are increasingly attractive, due to the success in mining diverse opinions. Thus, an increasing number of researchers are proposing their adoption within social web domain. Due to their probabilistic nature, it's possible to build social networks out of resulting mixture of topics and their associated distributions. While these networks have been limited to associating terms and authors, or communities and tags, modeling trust networks have not been of significant attention. Moreover, due to the probabilistic learning approach, we propose divergence metric as a distance measure between nodes on the network, which is novel. Since topic model can capture diverse relations among users, it can allow for aspects like saliency, relevancy and even polarity to be measured amongst networked opinions.

Summary of Contributions

To improve existing review recommendation techniques and at the same time improve the ranking used for evaluating helpfulness merits of existing reviews, we propose a novel approach to model and rank reviews. The two main components of our system rely on Latent Dirichlet Allocation (LDA) to model the reviews and on Kullback-Leibler divergence to generate an adequate ranking. We make use of the assigned star rating for the product as an indicator of the polarity expressed in the review towards the latent topics. Our framework covers different ranking strategies based on users' needs to adapt to various user scenarios. We evaluated the system using manually annotated review data gathered from a popular review site [54].

Following the experiment with review mining and recommendations, we proposed to apply opinion mining techniques to analyze networks of users discovering and connecting other similar users across the social media. Topic modeling mechanisms are increasingly attractive, due to their success in mining diverse opinions. Thus, an increasing number of researchers are proposing their adoption within social web domain. Due to their probabilistic nature, it is possible to build social networks out of resulting mixture of topics and their associated distributions. While these networks have been limited to associating terms and authors, or communities and tags, modeling trust networks have not been of significant attention. Moreover, due to their probabilistic learning approach, proposing divergence metrics as distances between nodes on the network is of novelty. Thus, in this work we are proposing a topic modeling framework, within which a trend corpora can be mined and by using a Latent Dirichlet Allocation (LDA) technique, both collective, and individual models can be defined. Resulting models are eventually used to generate social networks which reflect divergences of collective and individual opinions. We tested this hypothesis using a Twitter dataset. We summarize the contributions by papers [49, 92] shaping content of papers 13 and 14, as follows:

C6.1 **Proposing a topic-based framework for review mining and summarization**, in this framework we have focused on proposing algorithms to model reviews using latent topics and star ratings and ranking of reviews to summarize all reviews for a product within the top-k results. In addition a focus was also given on proposing methods and metrics for annotation of common features and aspects of review texts.

C6.2 **Proposing a topic-based framework for social network mining and analysis of micro-bloggers** within which a trend corpora can be mined and by using a probabilistic latent topic technique, both collective, and individual models can be defined. Resulting models are eventually used to generate social networks which reflect divergences of collective and individual opinions **Modeling a metric for measuring trust in a latent topical network**, this metric allows for group and individual links on a social graph be leveled according to divergence levels of corresponding distributions between the opinions of individuals. Measuring distances of collective opinion of groups, or individuals on a trending ground, can be modeled through information divergence.

Contributions Statement

I am a secondary contributor of paper [92] and a main contributor to paper [49]. My contributions to paper [92] have been annotation mechanism proposal for automated feature detection and extraction from reviews as well as understanding usage of latent topic models for web content mining. My contributions to paper [49] have been proposing the architecture of the framework, metric of trust and analyzing the resulting generated trust networks. Thus, the summary of my respective contributions is presented in list 3.

Chapter 4

Discussions and Conclusions

Discussions

Here we summarize contributions of the work and discuss them with respect to our research questions. The list of contribution are as follows:

- **C1**: Modeling and Analyzing Ontology-Based Trust Networks

  We proposed and developed reasoning frameworks capable of modeling and most importantly capturing trust-networks of interactions and cooperations of agents, applications, organizations and people on the social web.

- **C2**: Modeling and Learning Trust-Aware User Profiles

  We proposed and developed modeling and Learning profile techniques capable of encapsulating structured knowledge representation of a system with respect to collective behavior of a user across the system, user attributes encompassing individual and collective knowledge of system about the user as well as capturing and storing notions of trust and privacy.

- **C3**: Discovering and Aggregating Trust-Aware User Profiling

  We propose a semi-supervised profile management architecture which can adaptively discover, acquire and mine topic-based user profiles. This architecture encompasses both user modeling and profile mining, within which a generic user model is proposed for modeling social web users for task of cross-system personalization, as well as techniques for clustering and classification of social web profiles for recommendation tasks.

- **C4**: Architectures and Analytics of Decentralized Trust-Based Recommender Systems

  We have developed architecture for an ontology-based recommendation framework, a generic recommendation framework allows content and profiles from the web to be imported, mined and used for generating recommendations of items and people of interest. We also proposed for metrics and management of decentralized trust-recommender systems leveraging on a social network overlay allows trustworthy neighborhood to be found more effectively using epidemic heuristics for improved recommendation generation.

- **C5**: Modeling and Evaluating Privacy in Trust-Based Recommendation Systems

  We develop a privacy-by-architecture framework for enabling privacy-preserving trust recommendation system. This allows for taking measures for preserving privacy during trust calculation and computation.

- **C6**: Modeling and Measuring Trust in Hybrid Recommender Systems

  We propose and develop a topic-based framework for review mining and summarization, in this framework we have focused on proposing algorithms to model reviews using latent topics and star ratings, ranking of reviews. In another work we developed a topic-based framework for social network mining and analysis of micro-bloggers within which a trend corpora can be mined and by using a probabilistic latent topic technique, both collective, and individual models can be defined.

Following summarized list of all contributions in this section, we analyze how respective contributions 3 of this work map onto the proposed research questions 1. Table 4.1 visualizes mapping between proposed questions and respective contributions.

As we can see the contributions give answer to all questions stated. Two contributions, (C2 and C4) provide answers to more than at least two questions. This can be explained due to the sensitivity of the aim as well as amount of contributions. To justify the former, tasks of modeling, learning and populating the profiles are more time-consuming thus resulting contributions become larger in content and number of publications. In the case of proposing recommenders, this can be explained due to fact that recommender systems are a full-fledged software components and with availability of sufficient and sound data experiments can be tailored, which in turn can result in variety of publications and results. To justify the latter, for instance contribution C2 has been a large aim of Smartmuseum project which spanned beyond the boundary of project in terms of resource and research, thus resulting in several contributions that could give answer to several questions that this research was thriving to answer to.

Leaving the frequency of mapping questions and respective contributions asides, to understand where this research has given less focus to, we need to observe those questions that are less frequent. As it is observable this dissertation has made several contributions to questions Q3 and Q4 1, which are respectively aiming to

Table 4.1: Correlating research questions and contributions

Approach	*Questions*	*Contributions*
C1. Modeling and Analyzing Ontology-Based Trust Networks	**Q1**. what language and methods shall be used to model notions of trust for various tasks of web computing?	**C1.1**. Generic trust vocabulary and ontology, **C1.2**. Benchmarking framework for analyzing of trust models and their trust networks.
C2. Modeling, Discovering and Learning Trust-Aware User Profiles	**Q1**. With increasing importance of trust computing, which languages and methods shall be used to model notions of trust in user profiles ?, **Q2**. How can we manage trust enabled user profiles for web computing?	**C2.1**. Ontologies of trust-aware user profiles in Knowledge Applications, **C2.2**. Greedy heuristic for mining and normalizing weighted uncertain trust weights of user profiles
C3. Discovering and Aggregating Trust-Aware User Profiling	**Q3**. What are effective techniques to discover, aggregate and mine trust-based profiles ? **Q3**. How can we maximize the impact of trust-based user profiles in the context of information access, retrieval and personalization on the web	**C3.1**. Ontologies for trust-aware user profiles for cross-domain personalization, **C3.2**. Semi-supervised profile aggregation and mining architecture
C4. Architectures and Analytics of Decentralized Trust-Based Recommender Systems	**Q3**. What are effective techniques to discover, aggregate and mine trust-based profiles?, **Q3**. How can we maximize the impact of trust-based user profiles in the context of information access, retrieval and personalization on the web?, **Q4**. How can we correlate notions of trust and privacy in an effective manner and exploit this correlation to benefit the applications and systems implementing these crucial concepts?	**C4.1**. Architecture for ontology-based trust recommendation framework, **C4.2**. Decentralized trust-recommender systems architectures
C5. Modeling and Evaluating Privacy in Trust-Based Recommendation Systems	**Q4**. How can we correlate notions of trust and privacy in an effective manner and exploit this correlation to benefit the applications and systems implementing these crucial concepts?	**C5.1**. Privacy-by-architecture framework for privacy-preserving trust recommendation system., **C5.2**. Analyzing trade-off between accuracy and privacy in privacy-by-architecture design of a trust recommender system.
C6. Modeling and Measuring Trust in Hybrid Recommender Systems	**Q3**. How can we maximize the impact of trust-based user profiles in the context of information access, retrieval and personalization on the web?, **Q5**. How can modern web applications be designed to incorporate trust metrics and trust-embedded user profiles in their very fabric?	**C6.1**. Topic-based framework for review mining and summarization, recommendation, **C6.2**. Topic-based framework for social network mining and analysis

answer:

Which web applications can benefit from trust-based user profiles ? how can we maximize the impact of this technology in the context of information access and retrieval,e.g. recommendation and personalization systems, on the web ? and *while personalization systems evolve and expand onto various components of web information systems, how can modern web retrieval and personalization systems be designed to incorporate trustworthiness and trustworthiness metrics in their very fabric ?*

This is while the question Q2 and Q5 1 which seek to answer following questions, seem to have paid less attention to:

how can modern web retrieval and personalization systems be designed to incorporate trustworthiness and trustworthiness metrics in their very fabric ? how does one also manage such profiles for web computing ? what are effective techniques to discover, aggregate and mine such profiles?

Finally with studying the current importance as well as impact of some contributions proposed we believe that following questions demand more attention:

Is there a coherent niche between surrounding notions of trust such as context, reputation, interest and privacy ? how can we correlate these notions in an effective manner to benefit the applications and system leveraging such notions ?

Conclusions

Following the course of this dissertation you were provided with a collection of manuscripts summarizing the research behind establishing notion of trust-based user profiling.

Within the course of this dissertation we have introduced and elaborated on the notion of trust-based user profiling, the concept of embedding web profiles with trustworthiness metrics and mechanisms allow information systems to consume and understand such statements and preferences in order to improve interaction and communication among individuals and system which in turn boosts the system performances in various stages. To approach the formalization of profiles, we started by evaluating existing semantics and vocabularies for modeling trust on the web, which in turned allowed us to present and reason upon generated trust-networks. While formalizing such profiles at one hand, another challenge is realizing important and closely related notions such as privacy preferences of users. Thus, such profiles are designed in a way to incorporate preferences of users allowing target systems to understand privacy concerns of users during their interaction as well. Since the aim of profiling is understanding, analyzing and improving user interactive systems, an effort was invested across multiple works and projects to incorporate trust profiles within information retrieval, access and personalization systems. A majority of contributions of this work had impact on profiling and recommendation systems in digital libraries, i.e. EU FP7 Smartmuseum project. Highlighted contributions start from modeling of adaptive user profiles incorporating users taste, trust and privacy preferences. This in turn led to proposal of several ontologies for user and item domain, which in turn was leveraged for improving indexing and retrieval of items and profiles across the platform. In order to address important obstacles of sparsity and uncertainty of profiles hindering any profile processing system, frameworks for data mining and machine learning of profile contents from social networks were proposed. Results of mining and population of data from social web together with profiles were shown to increase the accuracy of intelligent suggestions made by system to improving navigation of users in on-line and off-line museum interfaces.

With ever increasing amount and variety of data on the web, mechanisms and techniques are needed to be able to mine and utilize such novel content. This in turn motivated us to take notion of trust-based profiles beyond the boundaries of digital libraries onto social web domain by augmenting the mechanisms of discovery and recommendation of popular social recommender systems, e.g. collaborative filtering. This has led us to propose several trust-based recommendation techniques and frameworks capable of mining implicit and explicit trust across ratings networks taken from social and opinion web. We researched ontological issues and management of profiles. Resulting recommendation techniques have shown to increase accuracy of profiles, by incorporating knowledge of items and users and diffusing them along the trust network, while leveraging on automated distributed management of profiles. We showed that coverage of system can be increased effectively, surpassing comparable state of art techniques. In both cases, trust has shown to clearly elevate accuracy of suggestions predicted by system. To assure overall privacy of such value-laden systems, privacy was given a direct focus where architectures and metrics were proposed and it was shown that a balance between accuracy and perturbation techniques can maintain accurate output. Finally, focusing on hybrid models of web contents and recommendations brought us to study impact of trust in the context of topic-driven recommendation in social and opinion media, which in turn helped us to show leveraging content-driven and tie-strength networks can improve systems accuracy for several computing tasks.

Future Directions

Taking into account the study of mapping between resulting contributions of this thesis and questions we aimed at answering, we believe the following future contributions can be of interest:

- Proposing research and development of other information retrieval and personalization systems that can incorporate trustworthiness.
- Proposing effective management frameworks for trust profiles and in general how trust management and its antecedents can be applied to trust profiling notions.
- Proposing and analyzing empirical and experimental studies of correlation between trust and closely related notions such as privacy and risk.
- Introducing more examples of research and development on applications that can leverage the synergy of trustworthy computing notions.

Part II

Included Papers

Chapter 5

Methods and Metrics for Modeling Ontology-Based Trust

(original version)
N. Dokoohaki and M. Matskin
Structural Determination of Ontology-Driven Trust Networks in Semantic Social Institutions and Ecosystems, *International Conference on Mobile Ubiquitous Computing, Systems, Services and Technologies (UBICOMM '07)*, IEEE Computer Society, pp. 263-268, Nov. 2007.

(extended version)
N. Dokoohaki and M. Matskin, Effective Design of Trust Ontologies for Improvement in the Structure of Socio-Semantic Trust Networks, *International Journal On Advances in Intelligent Systems*, vol. 1, no. 1942 - 2679, pp. 23-42, 2008.

Chapter 6

Trust-Aware User Profiling: Modeling and Learning

N. Dokoohaki and M. Matskin
Personalizing Human Interaction through Hybrid Ontological Profiling: Cultural Heritage Case Study, *1st International Workshop on Semantic Web Applications and Human Aspects (SWAHA), Collocated with 3rd Asian Semantic Web Conference 2008 (ASWC '08)*, 2008, pp. 133-140.

Chapter 7

Trust-Aware User Profiling: Modeling and Learning

N. Dokoohaki and M. Matskin,
Reasoning about Weighted Semantic User Profiles through Collective Confidence Analysis: A Fuzzy Evaluation, *Atlantic Web Intelligence Conference (AWIC '10), in Advances in Intelligent Web Mastering 2,* vol. 67, no. 5, V. Snášel, P. S. Szczepaniak, A. Abraham, and J. Kacprzyk, Eds. Springer Berlin Heidelberg, 2010, pp. 71-81.

Chapter 8

Trust-Aware User Profiling: Discovery and Aggregation

F. Cena, N. Dokoohaki, and M. Matskin,
Forging Trust and Privacy with User Modeling Frameworks: An Ontological Analysis, First International Conference on Social Eco-Informatics (SOTICS '2011), 2011, pp. 43-48.

Chapter 9

Trust-Aware User Profiling: Discovery and Aggregation

(original version)
N. Dokoohaki and M. Matskin,
Quest: An Adaptive Framework for User Profile Acquisition from Social Communities of Interest, *2nd IEEE International Conference on Advances in Social Network Analysis and Mining (ASONAM '10)*, vol. 0, pp. 360-364, 2010.

(extended version)
N. Dokoohaki and M. Matskin, An Adaptive Framework for Discovery and Mining of User Profiles from Social Web-based Interest Communities, *Chapter in The Influence of Technology on Social Network Analysis and Mining Book*, T. Özyer, Ed. Springer Wien, 2012.

Chapter 10

Ontologies in Trust Recommender Systems

S. Fazeli, A. Zarghami, N. Dokoohaki, and M. Matskin,
Mechanizing Social Trust-Aware Recommenders with T-Index Augmented Trustworthiness,*the 7th international conference on Trust, privacy and security in digital business (TrustBus '10)*, vol. 6264, M. S. Sokratis Katsikas, Javier López, Ed. Springer Berlin / Heidelberg, 2010, pp. 202-213-213.

Chapter 11

Management of Profiles in Trust Recommender Systems

S. Magureanu, N. Dokoohaki, S. Mokarizadeh, and M. Matskin,
Epidemic Trust-based Recommender Systems,
IEEE international conference on Social Computing 2012 (SocialCom '12), 2012.

Chapter 12

Modeling and Evaluating Privacy in Trust-Based Recommendation Systems

N. Dokoohaki, C. Kaleli, H. Polat, and M. Matskin,
Achieving Optimal Privacy in Trust-Aware Collaborative Filtering Recommender Systems, *2nd International Conference on Social Informatics (SocInfo '10)*, LNCS 6430, pp. 62-79, Springer, Heidelberg, 2010.

Chapter 13

Modeling and Measuring Trust in Topical Recommender Systems

(original version)
R. Krestel and N. Dokoohaki,
Diversifying Product Review Rankings: Getting the Full Picture, *2011 IEEE/WIC/ACM International Conferences on Web Intelligence and Intelligent Agent Technology (WI-IAT '11)*, IEEE Computer Society, pp. 138-145, Aug. 2011.

(extended version)
R. Krestel and N. Dokoohaki,
Ranking Product Reviews, *Regular Issue of ACM Transactions on Intelligent Systems (TIST)*, ACM Digital Library, Sep. 2012 (Submitted for Review).

Chapter 14

Modeling and Measuring Trust in Topical Recommender Systems

N. Dokoohaki and M. Matskin,
Mining Divergent Opinion Trust Networks through Latent Dirichlet Allocation, *International Symposium on Foundations of Open Source Intelligence and Security Informatics (FOSINT-SI2012), 2012 IEEE/ACM International Conference on Social Network Analysis and Mining (ASONAM '12)*, IEEE Computer Society. August 2012.

Part III

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