TWIN: Personality-based Recommender System

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Abstract

One of the important issues arising in the modern world is the information overload problem. In order to help the person navigate through the sea of all possible choices available online, Recommender Systems have started to appear. They collect preferences of people based on explicit ratings of various products or on the analysis of behaviours of the users working within the system. Therefore Recommender Systems become able to suggest new items to their users taking into account things liked by people with similar tastes.

The process of preferences retrieval and the choice of the recommendation algorithm are key parts of the Recommender System construction. There are a number of classical approaches available: content-based, collaborative filtering, etc. with the tendency to choose the combination of them to create a hybrid system. But recently a new type of Recommender System has appeared that utilises personality information about the users. It provides a more personalised approach to user representation aimed at improving the quality of the recommendations.

In this thesis we propose the TWIN Personality-based Recommender System. In order to produce recommendations it applies the results achieved in the personality from the text recognition research field to Personality-based Recommender System user profile modelling. In this way it creates a bridge between the efforts of automatic personality score estimation from plain text and the field of Recommender Systems. TWIN also serves as a tool for visualizing the resulting scores to perform personality analysis. We show that the application of the TWIN in online tourism domain produces valuable results in recommending tourist facilities to "like-minded" people. We describe the components of the TWIN system, the experiments conducted on the system, and we present an analysis of the very promising results obtained.

Declaration

I hereby certify that the material, which I now submit for assessment on the programmes of study leading to the award of a Master of Science (research), is entirely my own work and has not been taken from the work of others except to the extent that such work has been cited and acknowledged within the text of my own work. No portion of the work contained in this thesis has been submitted in support of an application for another degree or qualification to this or any other institution.

_____ _____

Signature of candidate Date

I hereby certify that to the best of my knowledge all the unreferenced work described in this thesis and submitted for the award of a Master of Science (research) is entirely the work of Alexandra Roshchina. No portion of the work contained in this thesis has been submitted in support of an application for another degree or qualification to this or any other institution.

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Signature of supervisor Date

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List of publications based on this thesis

1. Sánchez García, J., Callarisa, L., Cardiff, J., Roshchina, A. (2012). Harnessing Social Media Platforms to Measure Customer-based Hotel Brand Equity, International Journal of Tourism Management Perspectives, Elsevier, accepted for publication.
2. Roshchina A., Cardiff J., Rosso P. (2012). Evaluating the Similarity Estimator Component of the TWIN Personality-based Recommender System. in LREC 2012 - 8th International Conference on Language Resources and Evaluation, Istanbul.
3. Sánchez García, J., Callarisa, L., Cardiff, J., Roshchina, A. (2011). Análisis del valor de marca de las top 10 cadenas hoteleras en las top 10 ciudades a través de las comunidades virtuales, in Estrategias Competitivas en Canales de Distribución Comercial Tradicional Versus On-Line, pp. 381-407, Casielles,Trespalacios Gutiérrez, Estrada Alonso, González Mieres (coordinadores), Cátedra Fundación Ramón Areces de Distribución Comercial, ISBN 978-84-8367-357-7 (book chapter, in Spanish).
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Chapter 1: Introduction

During the years of its existence the Web has changed the way people think of the processes of getting appropriate information and the way they communicate with each other. With the transformation of the Web from the provision of "brochure-like" access to the information owned and edited by companies and authorities, global net developers have realised the importance of the previously unnoticed individual opinions of Web content readers and the impact they could make on the process of information dissemination. Due to the appearance of the more intuitive tools of content manipulation and administration, the model of a person's interaction with the Web has changed. The user and her interests and needs have become the main starting point of all actions held by online intelligent applications. By exploiting the "wisdom of the crowds" (Surowiecki, 2005) such applications make use of the collective intelligence to get a broader view over the particular area of knowledge.

The availability of billions of words collected together in billions of documents has become one of the greatest opportunities for a person and at the same time one of his deepest fears. Web users have started experiencing the huge overload of the multitude of information that is appearing online with the development of Web 2.0 facilities providing the user-generated content (e.g., Wikis, blogs, file sharing tools, etc.). As the volume of such products and services has grown tremendously, it has become necessary to help the user choosing from the broad set of options. When considering situations with high uncertainty (for example, searching for a hotel in a place to which the user has never been) people tend to avoid rational decision making procedures (Oliveira, 2007). Formal attributes of the various objects under evaluation (for example, the number of hotel stars, ratings of hotel facilities, etc.) can be interpreted differently by different people and sometimes do not provide sufficient information to make a particular decision. Thus there appears a necessity to find an expert's advice to follow. The common practice has become to write expert or user-generated reviews to describe and rate all the parameters of the particular product or service.

As the volume of the available reviews itself grows, the possibility of manual processing and analysing of each individual review becomes extremely tedious for most of the users leading to

the tendency to go only through the first page of search results and rarely further than the second or third one (Viney, 2008). The solution to the information overload problem was found in the development of the so-called Recommender System, the main aim of which is to provide automatic suggestions of items (or even other people) that have specific characteristics similar to the preferences of the target user.

1.1 Motivation

Traditional Recommender Systems collect information from the user explicitly by asking the user to fill in the fields in the user profile (usually demographic data or products ratings) or implicitly by studying user behaviour (logs of purchases, content analysis, etc.) (Tuzhilin, 2005). With the growing interest in the connection between the consumer personality and specific characteristics of the products (e.g. brands) the person is more likely to purchase (Mulyanegara et al., 2007) the challenging task of introducing the personality dimension into Recommender Systems has arisen.

Only a few approaches of personality-based user model construction exist in the field of Recommender Systems. One of them retrieves personality information through asking the user to manually fill in questionnaires (Nunes, 2008). However it seems to be at least problematic to require each user to go through this procedure during the profile construction step. Furthermore, people do not always provide sincere answers and incorrect data can produce a negative impact on the quality of the recommendation.

One of the alternatives to questionnaires could be the estimation of the personality from the user generated content that is freely available in many online communities. Much work has been done in the field of psychology to extract specific features from the text to establish the connection between the way the person writes and her personality (Tausczik and Pennebaker, 2009). Thus, the unique approach we follow here is the challenging task of adding the personality dimension to the Recommender System through the automatic personality recognition from linguistic cues from the texts of the users (Mairesse, 2007).

1.2 Aim

We propose the “Tell me What I Need” (TWIN) Personality-based Recommender System to implement the possibility of recommending items chosen by the like-minded (or “twin”) people with similar personality types estimated from the plain text.

In order to evaluate the performance of the TWIN system we have chosen to apply it to the online travelling domain. We experiment with datasets collected from the tourist's reviews managing website and create a web application to produce the recommendations of the hotels.

Below we provide the main hypotheses of the thesis.

Hypothesis 1

The pattern of personality scores *automatically* estimated from the texts written by authors in the online travelling domain calculated by means of algorithms available from psychological research may vary from one person to another.

Hypothesis 2

Personality-based user model constructed from such personality scores may be used as a personality profile for the proposed TWIN Recommender System.

Hypothesis 3

TWIN Recommender System with such personality profile may provide accurate recommendations.

1.3 Thesis organization

This thesis is organized as follows. In Chapter 2 we provide the background information about Recommender Systems, existing personality theories, practical ways of personality estimation and we present an overview of the emerging field of Personality-based Recommender Systems. In Chapter 3 we describe the components of the TWIN system and their functionality. Chapter 4 presents the experiments conducted in order to validate the TWIN system. The possible ways of evaluating the TWIN system are described in Chapter 5. The details of the system implementation are given in Chapter 6. Finally, in Chapter 7 we summarise the outcomes of our work and describe possible directions for the future research.

Chapter 2: Background

This chapter provides the background information about the field of our research. In Section 2.1 we give an overview of Recommender Systems, their types, characteristics and areas of application. Section 2.2 describes the approaches to personality estimation, focusing in particular on the Big Five classification scheme. We also describe the means by which personality can be estimated from plain text and online social media sources. In Section 2.3 we talk about Personality-based Recommender Systems and describe the work undertaken in the field. Section 2.4 summarises the advantages and drawbacks of existing approaches of Personality-based Systems construction and we explain our visions of possible improvement.

2.1 Recommender Systems

In the real world the person is surrounded by other people almost all the time so there is always the possibility to obtain help through word-of-mouth. When we are online, the process is mirrored by special types of intelligent Web services known as Recommender Systems. Ricci et al. (2010) define Recommender Systems (RSs) as "*software tools and techniques providing suggestions for items to be of use to a user*".

Recommender Systems have become an important part of the everyday life in the online world (Schafer, 1999), as the ever increasing amount of information produces a serious challenge to the user. RSs help the person to make the right decision about choosing a particular piece of content (among a large number of alternatives: books, music, documents, web pages, jokes, etc.). RSs are applied as a part of successful marketing strategies by E-commerce firms (Bodapati, 2008). Analysing the history of product purchases, RSs help to make predictions of items that the user could find interesting in the future. Thus, such systems become beneficial not only for customers but for businesses also, increasing the amount of successful sales. Some of these systems are being built for commercial reasons (to sell more diverse goods, etc.), some are purely for research needs (to improve recommendation algorithms, study users' needs more precisely, etc.) and some are built for leisure (Park et al., 2011).

An intuitive visualization of the recommendation process is presented on Figure 2.1 (Pu et al., 2011). It shows that the essence of the recommendation task is that it produces the filter constructed over all the available options the user can choose from. Instead of considering thousands of alternatives the user now takes only a limited number of items into account. It should be noted that Step 3 is not obligatory as in some Recommender Systems the user does not have access to the profile and cannot make manual changes to it. According to the quality of the received recommendations the user can alter the preferences to improve the future performance of the system.

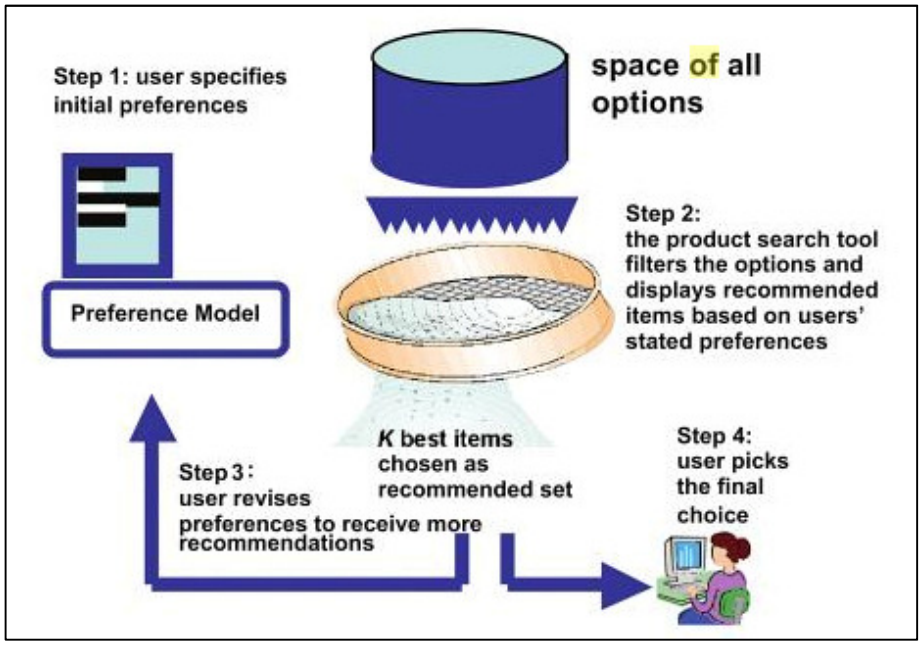


Figure 2.1: Recommending K best items

Recently with the appearance of the various mobile devices and services such as GPS and Wi-Fi, a new dimension is being introduced to the Recommender Systems area. It provides a number of challenges due to the limitations of the mobile devices compared to PCs. Nevertheless it also brings new characteristics: *location-awareness* (the physical location of the person is known at any particular moment) and *ubiquity* (the information can be delivered at any time when it is required) (Ricci, 2010). Mobile Recommender Systems are appearing to serve a number of tasks including search for tourist attractions (services, places, etc.), route recommendations, news and multimedia recommendations, etc.

There exist a number of main types of Recommender Systems: *collaborative filtering*, *content-based* and a number of others. They are described in more details below.

2.1.1 Collaborative filtering Recommender Systems

This of the most popular type of Recommender System and is widely used nowadays (Gemmell et al., 2009). Collaborative filtering systems rely on users' ratings in order to provide recommendations. This approach allows the recommendation of items highly rated by similar individuals and does not require extensive knowledge about items themselves. This is especially valuable when considering multimedia items for which content analysis and comparison is at least challenging. Furthermore, items with totally different content types could also be compared and recommended (which is not possible in content-based systems). One of the important features is the quality-based approach that relies on opinions of other individuals and not on the properties of items.

The main underlying task of collaborative filtering RSs is the choice of the appropriate similarity measure. The most popular measures are described below:

1. *Cosine similarity* (each item's attributes are seen as a multidimensional vector and to assess the similarity between two such vectors the cosine of the angle between them is considered)
2. *Pearson correlation similarity* (based on the correlation between two items)
3. *Probability-based similarity* (if the user purchased one item after another then the probability of the similarity of those items increases)

The classical example of a collaborative-filtering RS is Amazon[1] that recommends books and other goods based on the user's purchase behaviour and its similarity with what other people prefer to buy. Among the other examples is MovieLens[2]. Users provide information about the movies they love or hate and the system is recommending new movies to watch based on the preferences of the people with the same taste. Another example is Netflix[3] that recommends movies and TV shows that are rated by its users.

Table 1.1 shows the problems that exist in the field of collaborative filtering RSs and their possible solutions (Su and Khoshgoftaar, 2009). As the amount of products and people involved is huge, the user-item matrix is usually very sparse that produces three main problems: *cold start* (new users will not receive proper recommendations if there are no other people's ratings yet), *reduced coverage* (not all the items in the system are rated) and *neighbour transitivity* (users may have similar interests but they haven't rated the same items yet and therefore the connection

[1] http://www.amazon.com
[2] http://movielens.umn.edu
[3] https://signup.netflix.com

between them could not be established). Dimensionality reduction techniques, including *singular value decomposition*, *latent semantic indexing* and *principal component analysis,* can be applied to address data sparsity problems (Su and Khoshgoftaar, 2009). Problems with synonymy occur when the same items have different names and are treated as separate entries. In this case Latent Semantic Analysis can be applied to construct the semantic space to show the connections between the items. The *Gray sheep* limitation appears when a user does not have interests that follow those of a particular group and therefore is not able to receive valuable recommendations.

Problems	**Possible solutions**
Data sparsity • Cold start • Reduced coverage • Neighbor transitivity	Dimensionality reduction • Singular value decomposition • Latent semantic indexing • Principal component analysis
Synonymy	Latent Semantic Indexing
Gray sheep	Combining content-based and collaborative filtering techniques

Table 1.1 Collaborative filtering RSs: problems and possible solutions

There are two main approaches to construct the collaborative filtering system: *user-based* and *item-based*.

User-based approach

The crucial point of this approach is the careful construction of the user profile that could reveal the behavioural pattern of the individual (expressed by the ratings of the specific items). The next step involves the construction of the circle of people with similar patterns and the selection of the items (with assigned weights) that they had rated. The items with the highest weights are then recommended to the target user (Almazro, 2010).

The concept of preferences of the user can be expanded to include not only the ratings information but also the features available in various online social services. Sen at al. (2009) propose the exploitation of tagging patterns (the "tagomenders" approach) to establish similarity between users by comparing the individual tag usage. Gedikli and Jannach (2010) analyse the approach of rating users' tags to produce the tag-based recommender. Al-Sharawneh and Williams (2010) examine social networking sites to incorporate information about the trustworthiness of the calculated circle of similar people (to distinguish between friends and strangers).

Item-based approach

The Item-based approach relies on the similarity between items instead of similarity between users. The recommendation of the new items is based on the computation of the current user ratings history to identify the ratings pattern. Item-based methods are more preferable when the number of users is considerably higher than the number of items and when the changes in the item sets are not very frequent compared to the changes in the users (Ricci et al., 2010).

An example of a collaborative filtering system is Movies2Go[4] which is aimed at recommending movies and TV programs. It provides results based on user voting data (Mukherjee et al., 2001). Another popular music listening website is Last.fm[5]. By analysing the history of user's preferences, the Scrobbler[6] application updates the library of tracks on the user's computer or iPod. The implemented Recommender System produces a list of recommendations of new musical compositions.

2.1.2 Content-based Recommender Systems

Content-based filtering is the oldest type of recommendation approach (Olsson, 2003). The user is supposed to feed the system with his initial ratings on a number of items for the system to be able to recommend pieces of content that have similar attributes to those that the user had already seen.

Recommender Systems of this type do not take other users' ratings into account. Therefore one of the main advantages of content-based RSs is that the user's unique taste is not smoothed by preferences of people from like-minded groups *(*Nageswara and Talwar, 2008). Thus, people with extreme likes will still receive appropriate recommendations. However, sometimes this advantage turns into drawback due to the overspecialization problem discussed below. Content-based RSs try to provide recommendations based only on the attributes (author, title and other metadata) of the item or its content. This leads to one of the drawbacks: if items do not contain any metadata initially (music, video) it is necessary to explicitly define it (Nageswara and Talwar, 2008). Recently the elegant solution to the above mentioned problem has been found with the appearance of social tagging facilities allowing people to explicitly annotate the content they are uploading to the system (as well as associating the existing item with the concept represented by the tag). The resulting structure provides a simple self-organizing classification approach known as *folksonomy* (Mathes, 2004). Folksonomy can be utilised for the

[4] http://www.movies2go.net
[5] http://www.last.fm
[6] http://www.last.fm/download

construction of content-based Recommender System profiles describing items by the tags attached to them (Cantador et al., 2010).

Some of the challenging opportunities for the development of the content-based RSs as well as the main problems are presented in Figure 2.2 (Semeraro, 2010). The first drawback is the limitation of the content analysis. Due to polysemy, multi-word concepts and synonymy, the keyword representation of items and profiles is not always accurate. Semantic analysis of the extracted keywords could be performed to choose the most appropriate ones. The second drawback is the overspecialization that brings the emergence of the unbreakable circle of the very similar recommendations based on the unchanging interests of the person. Such limitation can be overcome by introducing serendipity into the results produced by the RS for the user to discover some unusual items that would not be normally considered as interesting.

PROBLEMS	CHALLENGES	RESEARCH DIRECTIONS
Limited Content Analysis	Beyond keywords: novel strategies for the representation of items and profiles	▪ Semantic analysis of content by means of external knowledge sources ▪ Language-independent CBRS
	Taking advantage of Web 2.0 for collecting User Generated Content	Folksonomy-based CBRS
Overspecialization	Defeating homophily: recommendation diversification	▪ "computational" serendipity → programming for serendipity ▪ Knowledge Infusion

Figure 2.2: Content-based RSs: challenges and research directions

To create a valuable representation of the item the traditional content analysis techniques, such as keyword extraction approach, are becoming out-of-date (due to polysemy, synonymy, etc.). Social media services are recognised now as a valuable source of information that could be integrated within the system from external sources (ontologies, folksonomies, etc.) (Agichtein, 2009).

Content-based RSs are in some way "easier" than collaborative filtering systems as they do not depend on other users' preferences. But in some cases this advantage turns into a drawback. It

introduces overspecialisation when the user is recommended only the same types of the items he used to like in the past (*homophily problem*). If other people's tastes were taken into account the user would receive recommendations of completely new items not necessarily similar to those already positively validated by him (Nageswara and Talwar, 2008). The solution to this problem could be found in the development of new algorithms that would encourage serendipity – "recommendation of surprisingly new items" (Semeraro, 2010).

It is quite straightforward to provide explanations of the recommendations in the RSs of this type as it could be represented as a list of content attributes similar to the user preferences (Semeraro, 2010). Another advantage of content-based RSs is that they are able to recommend new items and do not require a person to rate the new content in order to start providing recommendations (*first-rater problem*).

One example of content-based RSs is the ACR News[7]. The site serves as an entry point for air conditioning and refrigeration professionals. The system provides daily news in the field by means of the Usenet news Recommender System and utilises the content-based filtering algorithm.

There are many examples of content-based RSs in the field of music and films recommendations. The example of the music RS is Pandora Radio[8] that suggest the music composition similar to the one the user already likes.

2.1.3 Other types of Recommender Systems

Other types of Recommender Systems include *demographic* Recommender Systems (based on the age, country or language of the user), *knowledge-based* Recommenders (specialising in recommending data from a particular domain of knowledge by estimating a person's needs in that field*), community-based* (recommendations are based on the items that are favourable for user's friends), *hybrid* Recommender Systems (which utilise a combination of the above mentioned approaches) and the emerging type of *personality-based* Recommenders (which use personality characteristics to find matching people). We discuss Personality-based RSs in more detail in Section 2.3.

2.1.4 Data mining methods for Recommender Systems

Most data is stored in electronic formats nowadays. This leads to the possibility of automatically or semi-automatically processing of the information. The efficiency of the analysis is studied in the data mining discipline (Witten and Frank, 2005). The main purpose of practical data mining

[7] http://www.acr-news.com
[8] http://www.pandora.com

is to find hidden patterns in the training set (usually labelled with correct answers manually by human experts) and describe them explicitly in a specific structural format, which will allow the assignment of the previously unseen instances to a particular class.

Data mining methods can be broadly classified into two categories: *supervised* and *unsupervised* approaches. Supervised algorithms at the learning stage make use of the data annotated with correctly assigned classes while unsupervised algorithms try to learn the structure from the unlabelled data by grouping similar objects together according to the specific distance function (Witten and Frank, 2005). Recommender Systems make use of the algorithms and techniques available from the data mining field for the information extraction purposes (Sharma and Suman, 2011). The most widely used approaches are discussed below.

Classification

Classification is a "mapping from unlabelled instances to classes" (Kotsiantis, 2007). One of the most popular classifiers applied for the RSs is the *k-nearest-neighbours* (kNN) (Almazro et al., 2010) which is based on the idea that if the current user or item is close (or similar) to one of the groups in the training set then it should be assigned to the same class as the set of "neighbours". kNN is a *lazy learner* as it makes decisions only at the classification step and it is frequently used as a baseline algorithm to be implemented and further extended for the Recommender System (Bogers, 2009). It represents an unsupervised data mining method. Other examples of classifiers are *decision trees* (which construct a set of rules based on the training set data), *Bayesian classifiers* (which introduce the probability-based set of rules to deal with uncertainty), and neural networks (in which the structures of nodes and weighted links based on the analogy with the way the neurons wok in the biological brain).

Association rules

Association rules are computed by analysing the patterns of co-occurrence of items during the same transaction performed by the user (Park et al., 2011). The larger the frequency of the set (*support count*) of items (the more often they occur together) the higher the *confidence* of the underlying rule (Ricci, 2010). The Association rules approach is normally utilised to process large datasets as it produces a compact representation of their content (Nunes, 2010).

Clustering

Clustering is a technique used to create the partitioning of the data into "natural" groups where all the members are "similar" (applying a specific distance measure) to each other. Clustering for the RSs is less accurate than, for example, kNN classifiers as the recommendations produced are

based on the average of the opinions of other people in the same cluster. Therefore, for efficiency reasons, the combination of clustering and kNN is usually utilised (Nunes, 2010). User data is pre-clustered offline and kNN is applied only within the appropriate cluster (Alag, 2009).

2.1.5 User profile construction for Recommender Systems

One of the most important parts of the Recommender System development is the construction of the user model, that would be best processed by the application, and providing its proper visual representation that would be convenient and intuitive for the user.

User model

Recommender Systems collect the information about a particular user either explicitly (asking individuals to provide their preferences) or implicitly (automatically analysing the data or the activity of the user) and store it in the Preference Provider (or simply, the user profile). The appearance of various social services on the web brings about the possibility of gathering a large amount of "outside world" information in order to describe the user from different points of view. For example, Ghosh and Dekhil (2008) propose the description of the user through gathering the data from a number of sources: Google Calendar[9], FOAF[10] (the Friend Of a Friend project), etc. and to cover the diversity of formats in the data through the construction of a Retail User Profile Ontology to store semantically enriched profile entries. The user profile thus is described using RDF triples and is accessible via SPARQL queries, creating an easily extensible approach to effectively deal with semi-structured and sparse data. Diederich and Iofciu (2006) describe the user based on the keywords (viewed as tags) crawled from the DBLP[11] data set publications. More recently there has appeared an interest in the personality-based user profile. Nunes (2008) proposes to construct it by means of personality questionnaires to explicitly retrieve the information about the user.

Visual user profile

The development of the graphical user interface is a challenging task that involves the analysis of the tastes and preferences of the target audience as most of the users evaluate the general performance of the application based on the usability of its interface (Gribova, 2007). Usability reflects the quality and the satisfaction of users' interactions with the system.

[9] https://www.google.com/calendar
[10] http://www.foaf-project.org/
[11] http://www.informatik.uni-trier.de/~ley/db/

As one of the main purposes of the Recommender System is to assist the user in the process of decision making, the transparency of the interface plays one of the major roles. An example of an attempt to find the sufficient design requirements for the Recommender System is the ACE (Accuracy, Confidence, Effort) framework that also includes the means of measuring of its variables (Pu et al. 2011).

The design of the RS should follow the same guidelines as any other web application. Below is the list of the main usability principles defined by Jakob Nielsen (Leventhal and Barnes, 2010):

1. Learnability (the intuitiveness of the design for the new user)
2. Efficiency (the extent to which the user is able to complete the new tasks after he gets familiar with the interface)
3. Memorability (how fast the user is able to perform the same tasks after a period of not using a system)
4. Errors (the amount and the type of errors the user makes when interacting with the system)
5. Satisfaction (how much the interface is favored and accepted by the user, follows his tastes)

2.2 Personality estimation

The classification of personality types has always been among the widely addressed philosophical questions. The notion of personality traits' variance and its influence on people's behaviour was being discussed in works of Aristotle and his student Theophrastus in the fourth century BC (Matthews et al., 2009). It was claimed that each particular trait could be studied separately.

Contemporary trait theory was developed having roots in a number of fields (Matthews et al., 2009): natural language (there are over 18,000 English words associated with personality), medicine (the Hippocratic theory of humours as the basis of the Galen's temperament classification of characters known as melancholic, choleric, phlegmatic and sanguine; the notion of humours then reappeared in the works of Kant and Wundt who utilised them to produce the humoral schemes of temperament), folk psychology (classification of personalities according to twelve sun signs or the Chinese system that predicts certain personality traits of people born in a specific year).

The appearance of the scientific trait theory became possible from the beginning of the 20th century through systematic data collection and the development of statistical methods such as data correlation techniques and factor analysis.

The process of personality modelling includes the construction of the basic classification dimensions and the questionnaire for measuring them. This is the primary concern of the *psychometrics* field of study that develops "theory and technique of educational and psychological measurement, which includes the measurement of knowledge, abilities, attitudes, and personality traits"[12].

In the era of virtual communities and electronic data exchange, the personality dimension is supporting a number of tasks in such areas as e-learning and training (e.g. to construct learners' psychological profiles in order to choose a better educational approach), entertainment (to build highly intellectual gaming environments), etc. Depending on the data available, personality traits can be estimated explicitly through questionnaires (John, 1991) or implicitly. The implicit scenario involves the extraction of specific features from texts written by the particular person (Mairesse et al., 2007) or the construction of special learning environments where the behaviour, emotions and conversational parameters of the person can be observed (Robison et al., 2009).

2.2.1 Psychometrics and questionnaire construction

Gustav Fechner in his "Elemente der Psychophysics" defined psychophysics (the precursor of psychometrics) as "an exact science of the fundamental relations of dependency between body and mind" (Jones and Thissen, 2007). The modern discipline of psychometrics was formalised with the appearance of the Psychometric society in the University of Chicago in 1935 and in 1936 the book "Psychometric Methods" was published by J. P. Guilford (Jones and Thissen, 2007).

Psychometrics applies statistical methods and models to process data for psychological research. In order to calculate the personality representation the researcher should carefully construct the questionnaire, reflecting the number of hypothesised trait categories. There are three formal quality characteristics of the questionnaire defined and estimated by psychometrics (Matthews et al., 2009):

1. Reliability

   This step is used to test the internal consistency of the questionnaire. The most common measure here is the Cronbach alpha[13] statistic which compares the variance of answers to each particular question with the variance of whole test results.

[12] http://en.wikipedia.org/wiki/Psychometrics
[13] http://en.wikipedia.org/wiki/Cronbach's_alpha

2. Stability

   The questionnaire should pass the test-retest step: initial test results should correlate highly with the repeated measurement over a period of time.

3. Validity

   Obtained results should be checked for correlation with some independent quality index or proved experimentally.

The development of the modern psychometrics is associated with the changes in measurements of the psychological data and its analysis through the creation of improved personality scales with extended administrative capabilities (e.g. *item response theory* (Morizot et al., 2007)).

2.2.2 Personality traits classification

A number of statistical approaches are used to find correlations between various traits, following which factor analysis techniques are applied to group positively correlated traits into larger groups. Each dimension consists of a number of traits that are related to each other and thus if a person has one of the traits in a particular dimension he is likely to have other traits from the same group.

A number of traits' classifications exist (Matthews et al., 2009):

1. 16PF[14] (Sixteen Personality Factor Questionnaire) by Cattell, Eber and Tatsuoka. It measures 16 traits (Warmth, Reasoning, Emotional Stability, Dominance, etc.);
2. CPI[15] (California Psychological Inventory). It measures the data on 18 scales and consists of 434 true-false questions. CPI is widely used in industry as a way to estimate the leadership and coaching abilities to improve the personal performance;
3. OPQ[16] (Occupational Personality Questionnaire). It estimates 31 traits and is used for personnel recruitment purposes (to assess the preferred style of behaviour at work);
4. EPQ-R[17] (Eysenck Personality Questionnaire-Revised). It measures three factors (Extroversion, Neuroticism and Psychoticism). It has been applied in human resources management, clinical research and career counselling;
5. NEO-PI-R[18] (NEO-Personality Inventory-Revised) by McCrae and Costa (1996) known as "The Big Five". It consists of 240 questions, and has used for occupational assessment, counselling and research.

[14] http://www.ipat.com
[15] https://www.cpp.com/products/cpi/index.aspx
[16] http://www.psychtesting.org.uk/test-registration-and-test-reviews/test-reviews.cfm?page=summary&Test_ID=185
[17] http://www.edits.net/products/41-epqrepqr-shortjepq.html
[18] http://www4.parinc.com/Products/Product.aspx?ProductID=NEO-PI-R

Slight variations present in the naming of the five factors in "The Big Five" and some critics argue (Matthews et al., 2009) that the above mentioned number of traits is not sufficient to reflect all the diversity of existing traits while others suppose that five could be further reduced to a smaller amount of traits. Nevertheless, "The Big Five" personality traits classification is one of the most widely used and recognised (Matthews et al., 2009). It covers most of the traits' classification schemes.

2.2.3 The Big Five

The short version of the NEO-PI-R – Big Five Inventory (BFI)[19] – consists of 44 questions and is widely used in research as it requires less time to be filled in and prevents the participants from becoming bored (John et al., 2008). Thus we have chosen BFI for the purposes of personality modelling in the TWIN Recommender System.

The Big Five model includes the dimensions of Openness to experience, Consciousness, Extraversion, Agreeableness and Neuroticism (abbreviated as OCEAN). The brief description of each of the categories is provided below.

Extraversion

Extraversion refers to the desire of active and energetic participation in the world around. Such people are open to communications, talkative and tend to experience positive emotions. Introverts on the contrary are more focused on their own feelings and do not need so much external stimulation which lead to the comfortableness of being alone.

Agreeableness

Agreeable people tend to eagerly cooperate with others and are generally seen as helpful and generous compared to people with disagreeable behaviour that includes self-interest and sometimes even unfriendliness. More generally, agreeable people are often unable to make tough decisions because they tend to care about other people's interests more.

Conscientiousness

Conscientiousness is seen as the ability to control impulses and to hold to long-term plans as well as being able to foresee the consequences of one's behaviour. Such people are usually perceived as intelligent and wise. In extreme cases it could lead to perfectionism and tendency to become a workaholic. Unconscientious people tend to enjoy things that bring immediate satisfaction and perceived as are spontaneous, joyful, impulsive and unreliable.

[19] http://www.ocf.berkeley.edu/~johnlab/bfi.htm

Neuroticism

Neuroticism is positively correlated with the susceptibility to experiencing negative feelings such as anxiety, anger and depression. Neurotics respond very emotionally and tend to perceive each situation as threatening which causes an inability to think clearly and make right decisions under stress. Low levels of neuroticism usually mean emotional stability and calmness as well as low exposure to negative thoughts.

Openness to experience

This trait represents the tendency of the person to be sensitive to new ideas, non-conventional thinking and to being intellectually curious. It also includes the ability of symbolic thinking on the high level of abstraction. When scored low on this trait, people tend to have more common interests with which they are more familiar and do not like complex ambiguous things.

2.2.4 Psycholinguistics and Social Media

Psycholinguistics is the discipline that makes an attempt to "uncover the mental processes that are implicated in the acquisition, production, and comprehension of language" (Altmann, 2006). The first studies in psycholinguistics go back to Freud's slips of the tongue that were claimed to reveal the person's real intentions leading to unconsciously made speech mistakes. Further research tried to linguistically detect a person's anxiety level and to diagnose psychological deviations by analysing transcribed speech.

With the appearance of social data on the Internet, linguists and psychologists have gained access to large corpora of texts reflecting the way people talk naturally (which typically also include information about the author such as age, gender, social status, interests, etc.). From the 1970's computerised text analysis tools have started to appear. While the first programs used to implement sophisticated algorithms were based on language variables not directly visible to users, subsequently created tools became more and more transparent.

The volume of social services on the Web is constantly growing, including *blogs* (a resource to express private, scientific or other means of opinions, posing questions, discussing problems, etc.), *wikis* (online text collections that allow users to write their own articles as well as edit other authors' articles; these are used for setting up digital libraries, knowledge repositories of large companies and institutions, and for developing technical documentation), *file sharing tools* (services to share things such as photos (Flickr[20]) and bookmarks (del.icio.us[21]) and to

[20] http://flickr.com/
[21] http://delicious.com/

conveniently organise them) and *Social Networks* (services such as Facebook[22], Bebo[23], Twitter[24], etc. that offer a space for the user to organise personal information, maintain existing relationships and find new friends). The data available from the above mentioned services combined with data collected through thoroughly organised laboratory studies provides a broader view of the interconnection between language and human behaviour.

Research has shown that there is a correlation between the Big Five dimensions and linguistic features found in texts. Tausczik and Pennebaker (2009) have discovered that the use of first-person singular pronouns correlates with depression levels, while the volume of positive emotions words reveals extraversion. Mairesse et al. (2007) has shown that emotional stability (the opposite of neuroticism) is correlated with the amount of swearing and anger words used by the person while agreeableness is associated with back-channelling (personality types were estimated from self-reports and observers' reports). Some of the traits were studied more thoroughly (for example, extraversion) which could be caused by a higher level of representativeness of the particular trait related linguistic cues (Mairesse et al., 2007).

Quercia et al. (2011) conduct their research in the area of social media (Twitter posts in particular) to study the personality of the users. They have established connections between Twitter users and their Facebook profiles working with the Facebook application myPersonality (some of the users provided the links to their Twitter accounts) developed by the "myPersonality Research" project[25]. An example of the application's user interface is shown in Figure 2.3.

The authors have classified Twitter users into 5 categories: *listeners* (who mainly follow others and do not provide a lot of content themselves; correlations were found with extraversion (positive) and neuroticism (negative) traits and between the age of the individual and the amount of users to follow), *popular* (who have many followers; there is a positive correlation between the popularity of the user and his age), *highly-read* (who are highly cited in other people's reading lists and their personality type shows high scores in openness to experience) and *influential* (described below).

To estimate the amount of influence of the people in the last group two measures are used: the Klout score[26] (depends on the number of times the tweet was clicked, replied and retweeted) and the measure introduced by the TIME magazine (based on the Twitter and Facebook popularity)

[22] http://facebook.com/
[23] http://bebo.com/
[24] http://twitter.com/
[25] http://mypersonality.org/research/
[26] http://klout.com

(Silver, 2010). The Influential trait positively correlates with extraversion and additionally individuals with high scores in the TIME measure also have scored highly on conscientiousness.

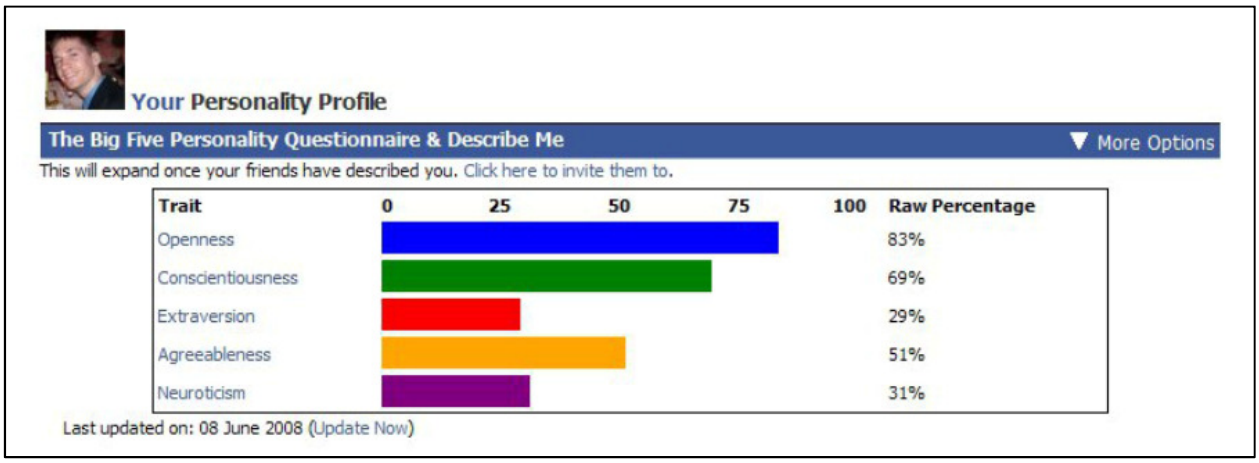


Figure 2.3: Fragment of the myPersonality application user interface

Oberlander and Nowson (2006) have focused on classifying the personality of the authors of weblogs, based on the ideolects (individual words usage) of the people. They have been using bi- and tri-grams to extract the personality from the text (all nouns were tagged via CLAWS). The authors have found that even the small set of extracted features shows the correlation between the features and particular personality traits.

Minamikawa and Yokoyama (2011) have made an attempt to estimate Egogram (the personality parameter introduced in Transactional Analysis) from the texts of Japanese weblogs. Figure 2.4 shows the 5 ego states included in Egogram (Minamikawa and Yokoyama, 2011). The selection of appropriate items from the bag-of-words representation of the texts was based on the information gain calculation. The feature set included adjectives, adverbs, conjunctions, exclamations and emoticons. Multiniomial Naïve Bayes classifiers were built for each of the ego states that were modelled separately.

Ego States	Features
CP (Critical Parent)	paternal, idealism, responsible, conservative, critical
NP (Nurturing Parent)	maternal, nurturing, pampering, sympathetic
A (Adults)	objective, rational, logical, cold
FC (Free Child)	creative, active, selfish, abandon
AC (Adapted Child)	adaptable, obedient, cooperative, passive

Figure 2.4: Egogram. Traits of five ego states

Celli (2012) has proposed an unsupervised approach to personality estimation based on linguistic cues. He analysed FriendFeed[27] (the popular Italian social network) data in order to construct the personality model of the authors, selecting 22 features mentioned in Mairesse et al. (2007). The evaluation procedure involved the comparison of the scores produced for various posts of the same user. Two measures are introduced – accuracy (showing the reliability of the model) and validity (the variability of the personality type among the posts of the same author) - which are calculated in an unsupervised way. The author has found that the most common personality type on FriendFeed is an *extrovert*, *insecure*, *agreeable*, *organised* and *unimaginative* person. The average accuracy of the results is 0.631 and the average validity is 0.729 (Celli, 2012).

Golbeck et al. (2011) estimated the personality of Facebook users. Each Facebook profile provides a lot of valuable information (birthday, location, the number of education places and job positions, last profile update, the date the user joined the Facebook, etc.). One of the features of the profile is the availability of "About Me" and status updates texts. These were used as a source of estimating the personality based on linguistic cues. The authors found that the Conscientiousness factor has the largest number of correlations with linguistic categories. To predict the personality, the authors considered three groups of features apart from linguistic ones. The correlations between the features scores and personality scores (estimated from questionnaires of the users) are shown in Figure 2.5. In order to predict the personality score, the M5'Rules and Gaussian Processes algorithms of the WEKA (Hall et al., 2009) tool were applied. Results have shown that the personality type based on the Facebook profile features can be predicted to within the 11% of its actual value.

[27] http://friendfeed.com

	Open.	Consc.	Extra.	Agree.	Neuro.
Linguistic Features					
Swear Words	0.006	**-0.171**	0.032	-0.084	-0.120
Social Processes (e.g. Mate, talk, they, child)	0.010	**0.264**	0.091	-0.022	-0.142
Human Words (e.g. baby, man)	0.078	**0.203**	0.070	-0.050	-0.062
Affective Processes (e.g. Happy, cried, abandon)	0.105	-0.009	0.136	**0.203**	0.038
Positive Emotions (e.g. Love, nice, sweet)	0.052	0.045	0.117	**0.167**	-0.013
Anxiety Words (e.g. Worried, fearful, nervous)	0.044	-0.150	0.008	0.101	**0.192**
Perceptual Processes (e.g. Observing, heard, feeling)	-0.040	**-0.195**	**-0.163**	-0.027	0.096
Seeing Words (e.g. View, saw, seen)	0.060	**-0.227**	-0.112	0.013	0.067
Biological Processes (e.g. Eat, blood, pain)	-0.014	0.042	0.038	**0.154**	0.067
Ingestion Words (e.g. Dish, eat, pizza)	-0.098	-0.050	0.029	0.031	**0.207**
Work Words (e.g. Job, majors, xerox)	0.134	0.096	**0.154**	0.048	-0.044
Money Words(e.g. Audit, cash, owe)	**-0.161**	0.024	0.012	-0.006	0.029
Structural Features					
Number of Friends	-0.094	-0.078	**0.186**	0.013	-0.069
Egocentric Network Density	**-0.152**	0.050	**-0.224**	0.059	0.032
Activities and Preferences					
Activities (char length)	0.115	0.095	**0.188**	0.066	-0.145
Favorite Books (char length)	**0.158**	-0.093	0.019	0.082	0.028
Personal Information					
Relationship Status (none listed,single, not single)	0.093	0.071	**0.194**	0.040	-0.036
Last Name length in characters	0.012	-0.111	0.000	-0.044	**0.184**

Figure 2.5: Pearson correlations between various features scores and personality scores

Another work that involves the personality-based user profile construction was proposed by Brockmann (2009), in his attempt to produce personality rich dialogs between computer characters. In the experiment, 10 pairs of people went to see 3 movies of different genres. Afterwards they had a chat about the movie they had just seen and their dialogs were transcribed to construct the corpus (CrAg corpus) of utterances. Each participant had also previously filled in a personality questionnaire. Each utterance was assigned a topic according to the content semantics (e.g. characters, music, special effects, etc.). A personality mapping was then calculated (following the Three-Factor Model) and represented using additive multiattribute value functions (AMVFs) (Dyer and Sarin, 1979). Finally, utterances were recombined to construct dialogs between computer personages according to their personality characteristics. The results were estimated by human judges (both native English speakers and non-native English speakers). The hardest dimension to recognise was neuroticism and the most visible was extraversion.

To assign a personality characteristic to the specific utterance a number of features are taken into account:

1. Linguistic Inquiry and Word Count (will be described in detail below) category (certainty words, negative emotion words, social process words, etc.)
2. Medical Research Council (MRC[28]) Psycholinguistic database dictionary category (age of acquisition, familiarity, part of speech, etc.) (Coltheart, 1981)
3. Utterance type (presence of questions, prompts, etc.)
4. Prosodic features (speech rate, etc.)
5. Formality measure F, defined as:

$$F = (\text{noun freq.} + \text{adjective freq.} + \text{preposition freq.} + \text{article freq.} - \text{pronoun freq.} - \text{verb freq.} - \text{adverb freq.} - \text{interjection freq.} + 100) / 2$$

To calculate the utterance personality score AMVFs are utilised. Figure 2.6 shows an example of the AMVF calculation for extravert language.

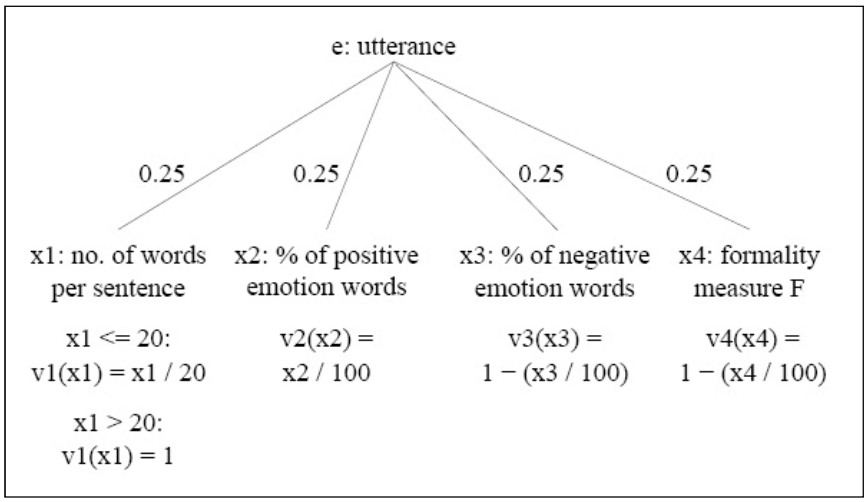


Figure 2.6: Assigning the personality characteristic of the utterance using AMVFs

The value (v) of the utterance e is calculated as:

$$v(e) = v(x_1, \ldots, x_n) = \sum_{i=1}^{n} w_i v_i(x_i)$$

where

w_i – weight of the leaf (product of weights from the root to the leaf)

v_i - function to calculate the value x_i.

[28] http://www.psy.uwa.edu.au/mrcdatabase/uwa_mrc.htm

The Linguistic Inquiry and Word Count (LIWC) Program

One of the most widely used tools in the personality research is the Linguistic Inquiry and Word Count[29] program (Tausczik and Pennebaker, 2009) which was exploited in many projects described above. LIWC is a text analysis tool that counts and sorts words according to their psychological categories defined in the program dictionaries. The program processes the text word by word, establishing the category of each word and calculating the overall percentage of each of the discovered categories.

The LIWC categories are linked to various psychological processes in order to find the correlations between them:

1. Attentional Focus

   The usage of personal pronouns is related to the focus of attention. The more people are involved in a painful experience and focus on themselves, the higher the number of personal pronouns. The tense of the verbs reflects the temporal state of the focus of attention. For example, the study of political advertisements has shown that positive advertisements use present and future tenses of the verb to talk about acts of the candidate while negative ones focus on the past actions of the opponent.

2. Emotionality

   LIWC is able to identify the usage rates of positive and negative emotions. The research shows that the higher the number of emotion words, the more involved the person is in the traumatic experience.

3. Social relationships

   The language can give insight into the status of the people involved in the conversation. The lower the status, the more the first-person singular is used and the higher the rate of questions asked.

   Word count shows the intensity of the communication within the group and assents (agree, ok, etc.), question marks and first-person plural can reveal the level of cohesion within the group. However when assents appear at the very beginning of the discussion they could signal blind agreement.

   Word usage can also indicate deception and honesty. A high percentage of negative emotion words, motion words, sense words, fewer exclusion words and less first-singular could detect that the person is lying.

[29] http://www.liwc.net

The analysis of pronouns reflects the closeness of the relationship. The greater the number of second person, the lower the satisfaction with the relationship and the higher the tendency to criticism and confrontation.

4. Thinking styles

   Exclusive words usually signal the attempt to make a distinction between a number of possible solutions and conjunctions are used to group thoughts together. The use of causal and insight words can mean the process of the reevaluation of the past event and often the improvement of the physical health.

5. Individual differences

   LIWC categories can be used to relate the language usage to the personality traits. For example, extraversion could be expressed by the higher words count, higher percentage of social words and positive emotion words.

At the moment the dictionary contains more than 80 predefined categories including:

1. General descriptor categories (word count, words per sentence, etc.)
2. Standard linguistic dimensions (pronouns, adverbs, prepositions, etc.)
3. Words reflecting psychological processes (social processes, cognitive processes, etc.)
4. Personal concern categories (work, leisure, money, etc.)
5. Paralinguistic dimensions (assents, fillers, etc.)
6. Punctuation categories

The list of categories and their abbreviations is shown in Figure 2.7.

LIWC FEATURES (Pennebaker et al., 2001):

· **Standard counts:**
- Word count (WC), words per sentence (WPS), type/token ratio (Unique), words captured (Dic), words longer than 6 letters (Sixltr), negations (Negate), assents (Assent), articles (Article), prepositions (Preps), numbers (Number)
- Pronouns (Pronoun): 1st person singular (I), 1st person plural (We), total 1st person (Self), total 2nd person (You), total 3rd person (Other)

· **Psychological processes:**
- Affective or emotional processes (Affect): positive emotions (Posemo), positive feelings (Posfeel), optimism and energy (Optim), negative emotions (Negemo), anxiety or fear (Anx), anger (Anger), sadness (Sad)
- Cognitive Processes (Cogmech): causation (Cause), insight (Insight), discrepancy (Discrep), inhibition (Inhib), tentative (Tentat), certainty (Certain)
- Sensory and perceptual processes (Senses): seeing (See), hearing (Hear), feeling (Feel)
- Social processes (Social): communication (Comm), other references to people (Othref), friends (Friends), family (Family), humans (Humans)

· **Relativity:**
- Time (Time), past tense verb (Past), present tense verb (Present), future tense verb (Future)
- Space (Space): up (Up), down (Down), inclusive (Incl), exclusive (Excl)
- Motion (Motion)

· **Personal concerns:**
- Occupation (Occup): school (School), work and job (Job), achievement (Achieve)
- Leisure activity (Leisure): home (Home), sports (Sports), television and movies (TV), music (Music)
- Money and financial issues (Money)
- Metaphysical issues (Metaph): religion (Relig), death (Death), physical states and functions (Physcal), body states and symptoms (Body), sexuality (Sexual), eating and drinking (Eating), sleeping (Sleep), Grooming (Groom)

· **Other dimensions:**
- Punctuation (Allpct): period (Period), comma (Comma), colon (Colon), semi-colon (Semic), question (Qmark), exclamation (Exclam), dash (Dash), quote (Quote), apostrophe (Apostro), parenthesis (Parenth), other (Otherp)
- Swear words (Swear), nonfluencies (Nonfl), fillers (Fillers)

Figure 2.7: LIWC categories

2.3 Personality-based Recommender Systems

Recent research shows that users tend to appreciate Personality-based Recommender Systems more than classical ratings-based systems, and return to sites that implement them more often (Hu and Pu, 2009), as such approach is relatively new and systems can match people's interests at a deeper level. This type of RS can be used to recommend very different products from movies to research papers as personality will serve as a linking factor (Hu, 2010) and similarity measures for RSs based on personality features produce promising results (Tkalčič et al., 2009). As the idea itself is still an emerging trend, the variety of proposed systems of this type is not extensive.

Nunes (2010) in her research provides an overview of the state of the art of Personality-based RSs. She mentions three pioneering works in the field. The concept of the emotional intelligence was incorporated into the user profile by Gonzalez et al (2007) to create the Smart User Profile (which includes feelings, impressions and emotional states of the users as well as their moods retrieved by means of machine learning techniques). Masthoff and Gatt (2006) experiment with predicting group satisfaction based on the individual user satisfaction (the more satisfaction and

positive emotions the first purchase brings to the user, the more likely he will return to make another purchase). Saari et al. (2005) have introduced the concept of psychological customization to extract the user's emotional state, attention, learning abilities, etc. at the particular moment of working with the system.

"What to rent" [30] is an example of an implementation of a Personality-based Recommender System. It utilises the LaBarrie[31] theory in order to produce suggestions of films to watch depending not only on the personality but also on the current mood of the user. The personality construction procedure involves filling in the questionnaire to assess the main features of the character of the individual for movies recommendation.

It the following subsections, we survey the principal works in Personality-based Recommender Systems.

2.3.1 Tkalčič approach

Tkalčič et al. (2009) proposed a personality-based approach for collaborative filtering RSs that follows the Big Five model. They make an assumption that the personality of the user doesn't change significantly over time and thus the neighborhood of the user can be calculated in advance (lower real-time computational effort). The personality scores were calculated by means of the questionnaire. The authors applied and tested three similarity measures for the offline collaborative filtering experiment: ratings-based, using Euclidian distance with the Big Five data and weighted Euclidian distance with the Big Five data. The approaches using the Big Five data have performed statistically equivalent or better than ratings-based.

2.3.2 Hu and Pu approach

A Personality-based music Recommender System was introduced by Hu and Pu (2010). The authors base their system on the correlations between musical preferences and personality types that follow the finding of Rentfrow (2003). Rentfrow found four preference groups according to various styles of music compositions that people are fond of. For example, the "reflective and complex" group (which prefers jazz, blues and classical music) has correlations with openness to new experience Big Five dimension and "energetic and rhythmic" group (which tends to appreciate rap, hip-hop, funk and electronic music) correlates positively with extraversion and agreeableness.

The personality data of the music RS has been calculated by means of the Big Five questionnaire. The similarity between the two users has been estimated based on the Pearson

[30] http://whattorent.com
[31] http://whattorent.com/theory.php

correlation coefficient with the personality scores. The authors have also tested the combined similarity measure that incorporates ratings data. They have shown that the personality-based approach achieves a significant improvement over the baseline of considering only ratings data.

2.3.3 Nunes approach

In her research, Nunes (2008) proposes the personality-based Recommender System to provide a better personalised environment for the customer. She claims that one interesting outcome of introducing a psychological dimension into the recommender system could be the possibility of products categorization based not only on their attributes (price, physical parameters, etc.) but also on the effect they may have on the consumer.

To construct the user profile, Nunes (2008) proposes the following model. $C_{user\text{-}i}$ is represented by the list of pairs (personality trait and its value) of the following format:

$$C_{user-i} = [((i, d, f)_1 , v_1), ((i, d, f)_2 , v_2), \ldots , ((i, d, f)n , vn)],$$

where

i – one of the items in NEO-IPIP inventory (“have a vivid imagination”, “get angry easily”, “trust others”, etc.),

d – Big Five categories,

f – Big Five category facet,

v – personality trait value expressed by valence taken from the list of 5 possible options (very-inaccurate, moderately-inaccurate, neither-accurate-nor-inaccurate, moderately-accurate, very-accurate).

In order to fill in the user profile an online tool is utilised which has a number of questionnaires for the user to complete. It is organised as a list of statements from NEO-IPIP inventory. Each of the statements should be evaluated by the user (choosing from the five possible options mentioned above). After completion, results are calculated based on the NEO-IPIP Norms developed by Johnson (list of mean values and standard deviations (SD) for each of the Big Five categories and each of 6 facets in those categories) using the following formulas:

$$\text{Score}_{\text{BigFive-facet user-i}} = 50 + (10 * (\text{score}_{\text{facet user-i}}) - \text{mean}_{\text{facet}}) / \text{SD}_{\text{facet}})$$

$$\text{Score}_{\text{BigFive-domain user-i}} = 50 + (10 * (\text{score}_{\text{domain user-i}}) - \text{mean}_{\text{domain}}) / \text{SD}_{\text{domain}})$$

Finally, the user is presented with the detailed description of his personality organised in the prognostic report.

Nunes (2008) conducted a number of experiments to evaluate the constructed Recommender System. In the first experiment 100 participants were asked to complete the NEO-IPIP Inventory (300 statements) to describe the personality of an ideal president and the personality of two real candidates using the online tool. Only 10% of people were able to complete the whole task (900 statements in total). To assess the validity of the experiment the results of the recommendation of one of the candidates (based on the profile of the ideal president) were compared to the actual voting option participants chose. If only the 5 main categories of the Big Five model were taken into account the accuracy of the recommendation was 80%. With the decomposition of the main categories down to 30 facets the accuracy reached 100%. In the second experiment the Social Matching system was imitated. 280 participants were asked to intuitively form groups to work on a project. The choice they made was then compared to the predictions of the Recommender System. As only a small percentage of participants were able to complete the whole questionnaire from the NEO-IPIP Inventory, the experiment was repeated with the new questionnaire based on TIPI Inventory with only 10 statements to evaluate. As a result 4, out of 19 intuitively formed groups were predicted with 100% accuracy.

2.4 Summary

In this chapter we have described the emerging research area of Personality-based Recommender Systems. We have studied the existing approaches and algorithms of building an RS and presented an overview of the personality estimation task.

It was found that existing Personality-based RSs utilise questionnaires (mostly following the Big Five model) in order to construct the personality profile of the user. One of the drawbacks of this method is the amount of time required to complete the task. The other important factor is the correctness of the information provided by the user as questionnaire statements may be misinterpreted or answered inaccurately.

In our research, we introduce an alternative way of constructing a Personality Based RS, which provides an automatic calculation of the user's personality scores from text that they write, which is freely accessible from online accounts on social media services. We apply the tools of personality from the text estimation available from previous research. The advantage of the proposed approach is that it does not require any special effort (e.g. filling in the questionnaire, etc.) from the user to estimate his personality (other than the user profile name from the appropriate social media resource) to receive appropriate recommendations.

Chapter 3: The TWIN System

The number of available Recommender Systems is constantly growing nowadays in order to improve the quality of the user's time spent online and to provide a convenient shortcut to the most valuable and personalised information. Recommender Systems trace the behaviour of people and automatically process the artefacts they create in order to learn the users' preferences. Such information leads to the possibility of recommending newly appearing items based on a person's likes and dislikes.

As one of the main contributions of online communities (such as Facebook, TripAdvisor, etc.) is the exchange of pure text messages, the most beneficial way of gathering implicit information about the authors involves the application of natural language processing tools and techniques. Such text analysis could be more efficient compared to the standard voting procedures and extraction of the attributes of an item utilised in traditional Recommender Systems (Fleischman and Hovy, 2003).

Recent research in psychology has developed tools that allow the estimation of the author's personality from the context of the words that are used in the text (Tausczik and Pennebaker, 2009). We have decided to apply those findings to introduce the personality dimension in the Recommender Systems field. One of the main advantages of the approach is that the user is not required to perform any additional steps (such as filling in questionnaires, voting, or providing descriptions of the content) to get appropriate recommendations. The personality is constructed automatically from the text of the users through the analysis of their natural style of writing. Furthermore, this eliminates the subjectivity and interference that could be introduced by the user evaluating or describing content.

In this research work, we propose the TWIN ("Tell me What I Need") Personality-based Recommender system, which follows a combination of the content-based and user-based collaborative filtering approaches. We make an assumption that the "similarity" between people can be established by analysing the context of the words they are using. Accordingly, the occurrence of the particular words in the particular text reflects the personality of the author.

This suggestion leads to the possibility of the text-based detection of a circle of "twin-minded" authors whose choices could be quite similar and thus could be recommended to each other.

3.1 Task description

Facing the uncertainty arising from the high amount of options available in online communities, the user needs a tool (a Recommender System) that would help him to navigate through the content in the most effective way. Therefore such a tool should become the bridge between the user (his characteristics) and other people and their contributions.

The ideal situation for the individual working with the Recommender System is the implicit gathering of his preferences, their automatic analysis and the provision of the list of most relevant items based on those characteristics. As the crucial part of the process is choosing the right type of information that would describe the user most precisely, the personality assessment could be more effective than the description provided by purely demographic or behavioral data ("traces" of the user behavior within the system, such as pages viewed, items purchased, etc.). As the automatic and effortless approach is the preferred one, the personality should be estimated from online sources that already have some of the user contributions available for analysis. Existing online communities (Facebook, TripAdvisor, Twitter, etc.) provide a large amount of such freely accessible information that can be collected and processed to produce personality scores for the individual.

In the TWIN system we follow the personality-based approach described in Chapter 2 to represent the user (following the Big Five model). Thus the first step the system performs when the user logs in is the crawling of resources already created by the person. As mentioned previously, we are estimating the personality from the textual content automatically using the tool created in previous research (Mairesse, 2007). In this way, the individual is not obliged to explicitly provide his personal information, ratings, answer any questions, etc., which saves him time and minimises the effort.

When the personality analysis is over, the information is stored in the database and used to construct and visualise the user profile. To generate the precise description of the user information an ontology is constructed based on the general vocabularies freely available on the Semantic Web (Berners-Lee, 2001).

The TWIN system can be utilised in two different ways: as a RS or as a personality visualiser.

The main approach is to use TWIN as a Recommender System (asking to actually perform the recommendations). In order to produce recommendations, TWIN searches for the profiles of

people with personality types similar to that of the target user, and creates a list of items most favored by them. The list of recommendations is further visualised for the user at the final stage of the process.

The second manner of usage of the TWIN system application involves only the analysis of the calculated personality scores (through the visual interface). The main advantage of this approach is that it can be utilised to tune and improve the performance of the underlying personality estimation algorithm (providing a the visual representation of the resulting scores).

3.2 TWIN system components

In this Section we provide a more detailed introduction to the structure of TWIN. The main components of the TWIN Recommender System are presented in Figure 3.1.

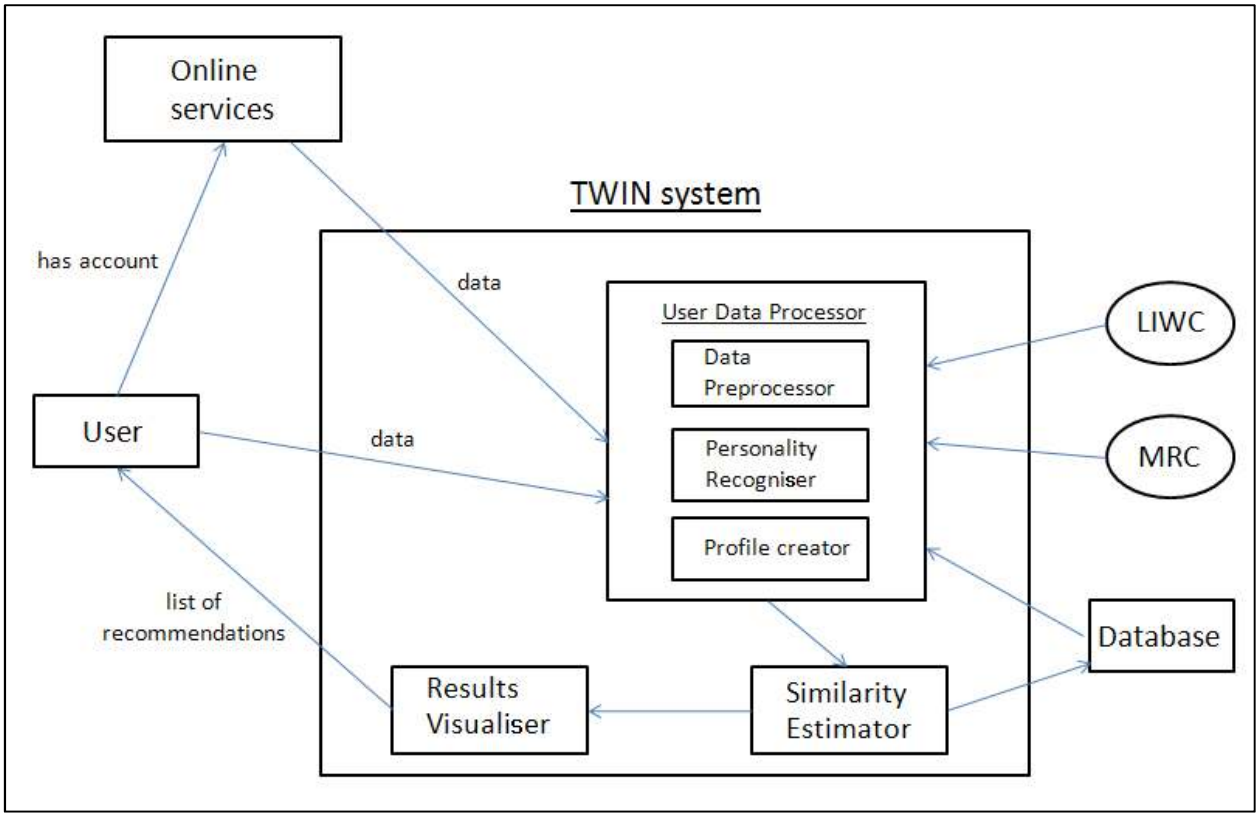


Figure 3.1: TWIN system: architecture

3.2.1 User Data Processor

This component includes the Data Preprocessor, the Personality Recogniser and the Profile creator modules, which are described in detail below.

3.2.1.1 Data Preprocessor

The Data Preprocessor component retrieves the textual data written by the user from the online community service (Facebook, TripAdvisor, etc.) by the provided username. This raw data contains special characters (e.g. apostrophes, semicolons) that should be represented properly when being saved in the database and we do not take synonyms, acronyms and similar issues into account. Therefore the Data Preprocessor performs the task of replacing the above mentioned symbols with the corresponding html characters (e.g. single quote is replaced with "´").

3.2.1.2 Personality Recogniser

To calculate the personality scores from the data provided by the user the User Data Processor utilises the Personality Recogniser tool (Mairesse et al., 2007). This is based on the dictionary created for the LIWC tool (described in detail in Section 2.2.4) and on the Medical Research Council (MRC) categories dictionary. The list of the MRC categories is shown in Figure 3.2. Parameters in the list refer to the norms of the frequency characteristics of the particular word (defined, for example, in works of (Kucera and Francis, 1967) and (Thorndike and Lorge, 1944), its familiarity, etc.

MRC FEATURES (Coltheart, 1981):

Number of letters (Nlet), phonemes (Nphon), syllables (Nsyl), Kucera-Francis written frequency (K-F-freq), Kucera-Francis number of categories (K-F-ncats), Kucera-Francis number of samples (K-F-nsamp), Thorndike-Lorge written frequency (T-L-freq), Brown verbal frequency (Brown-freq), familiarity rating (Fam), concreteness rating (Conc), imageability rating (Imag), meaningfulness Colorado Norms (Meanc), meaningfulness Paivio Norms (Meanp), age of acquisition (AOA)

Figure 3.2: The list of MRC categories

The Personality Recogniser processes the text word by word getting the category of each word and calculating the overall percentage of each of the discovered categories. In order to establish the personality of the author the Personality Recogniser applies WEKA models trained on the Psychology Essays corpora (Pennebaker and King, 1999), which is comprised of texts, associated LIWC categories scores and the real personality scores of the authors collected through the Big Five questionnaire. Finally 5 scores (corresponding to each of the Big Five dimensions) are produced for the processed text - each of them ranging from 1 to 7 (where 1 means that the trait is weekly expressed and 7 means strong expressiveness). Each of the Big Five dimensions of the Personality Recogniser has four models associated with it based on four data mining algorithms: linear regression, M5' model tree, M5' regression tree and support vector machines for regression. The details of each of these are provided below.

Linear Regression

Linear regression is one of the basic algorithms for mining the data with numeric attributes. It provides the linear combination of all the attribute values with their weights estimated from the training data in order to represent a particular class (Witten and Frank, 2005):

$$x = w_0 + w_1a_1 + w_2a_2 + ... + w_ka_k,$$

where w_k is a weight, a_k is the value of the attribute and x is a class.

Below is an example of the fragment of the openness to experience WEKA model with linear regression algorithm:

*ZOPEN = 0.0008 * BROWN-FREQ + -0.009 * CONC + -0.0212 * FAM + 0 * K-F-FREQ + 0.1653 * K-F-NCATS + 0.0076 * MEANC + 0.2425 * NLET + 0.9659 * NPHON + -0.917 * NSYL + 0 * T-L-FREQ + 0.0007 * WPS + 0.1557 * Qmarks + 0.0127 * Unique + -0.0377 * Dic + -0.0168 * Sixltr + 0.0546 * Pronoun + 0.1225 * We + -0.0434 * Self + 0.0792 * You + 0.0747 * Other + 0.0668 * Article + 0.0219 * Preps + -0.0636 * Number + 0.1443 * Affect + -0.1315 * Posemo + 0.1275 * Posfeel + -0.1593 * Optim + -0.1151 * Negemo + -0.0821 * Anger + -0.0365 * Cogmech + 0.0606 * Insight + 0.0664 * Discrep + 0.1525 * Inhib + 0.0343 * Tentat + 0.0741 * Certain + 0.0564 * Senses + 0.0671 * Hear + -0.0928 * Feel + -0.066 * Social + 0.0739 * Humans + -0.0291 * Time + -0.0177 * Present + 0.0319 * Excl + -0.0701 * Achieve + 0.2034 * Swear + 0.0541 * Period + 0.0557 * Comma + 0.2532 * Colon + 0.1957 * SemiC + 0.0475 * Dash + 0.0599 * Apostro + 0.3377 * Parenth + -0.0443 * AllPct + 13.0094*

where attribute values (*BROWN-FREQ, CONC,* etc.) are the percentage of words found under each of the LIWC and MRC categories (see Section 2.2.4 for the explanations of the abbreviations). The choice of the specific categories for modelling of each of the Big Five dimensions is learned from the training data.

Decision Trees

Regression and model trees are types of general decision trees (Witten and Frank, 2005) that deal with numeric prediction (rather than category prediction). A decision tree is a structure learned from the training data. Each node of the tree represents a function to compare specific attributes

of the unseen instance that needs to be classified. Each leaf assigns a class (or the probability of the specific class) to the instance after all the comparisons have been made while traversing all the nodes of the tree down to the particular leaf. The specific types of decision trees used by Personality Recogniser are regression and model trees structures.

Regression trees differ from ordinary decision trees in the fact that their leaves contain the average value assigned to the instances that reach that leaf. Below is an example of a fragment of the WEKA extraversion model using the M5' Regression tree algorithm (only the first of the leaves with linear regression model - *LM1* - is shown):

Sexual <= 0.125 :
| Period <= 6.275 : LM1 (409/116.28%)
| Period > 6.275 :
| | Social <= 5.785 : LM2 (280/109.868%)
| | Social > 5.785 :
| | | Hear <= 1.365 : LM3 (253/120.444%)
| | | Hear > 1.365 : LM4 (86/123.519%)
Sexual > 0.125 :
| Negate <= 2.955 :
| | FAM <= 601.589 :
| | | Article <= 4.495 : LM5 (259/114.439%)
| | | Article > 4.495 : LM6 (326/121.763%)
| | FAM > 601.589 :
| | | Tentat <= 2.865 : LM7 (253/106.73%)
| | | Tentat > 2.865 :
| | | | Assent <= 0.125 : LM8 (157/105.593%)
| | | | Assent > 0.125 :
| | | | | T-L-FREQ <= 30894.95 : LM9 (108/117.678%)
| | | | | T-L-FREQ > 30894.95 : LM10 (40/117.341%)
| Negate > 2.955 : LM11 (305/134.66%)

LM num: 1
ZEXTRA =
+ 4.7964

LM num: 2
ZEXTRA =
+ 4.3708

where attribute values (Assent, Article, Negate, etc.) are the percentage of words found under each of the LIWC and MRC categories. Only two examples of leaves are shown ("LM num: 1" and "LM num: 2").

Model trees have linear regression models in their leaves. Below is an example of a fragment of the WEKA Consciousness model using the M5' Model tree algorithm (only the first of the leaves with linear regression model – "LM num: 1*"* - is shown):

Swear <= 0.925 :
| Pronoun <= 16.71 : LM1 (22/49.343%)
| Pronoun > 16.71 : LM2 (46/77.164%)
Swear > 0.925 :
| Sexual <= 0.615 : LM3 (14/68.303%)
| Sexual > 0.615 :
| | NSYL <= 1.137 : LM4 (4/34.268%)
| | NSYL > 1.137 : LM5 (10/52.965%)

LM num: 1
CON.J =
*0.0133 * CONC*
*- 0.0222 * IMAG*
*- 0.0572 * Pronoun*
*+ 0.0658 * Posemo*
*- 0.5933 * Sad*
*+ 0.0386 * Insight*
*- 0.0387 * Senses*
*+ 0.0437 * Comm*
*- 0.1082 * Swear*
+ 8.2099

where attribute values (Pronoun, Swear, etc.) are the percentage of words found under each of the LIWC and MRC categories.

Support Vector Machines for Regression

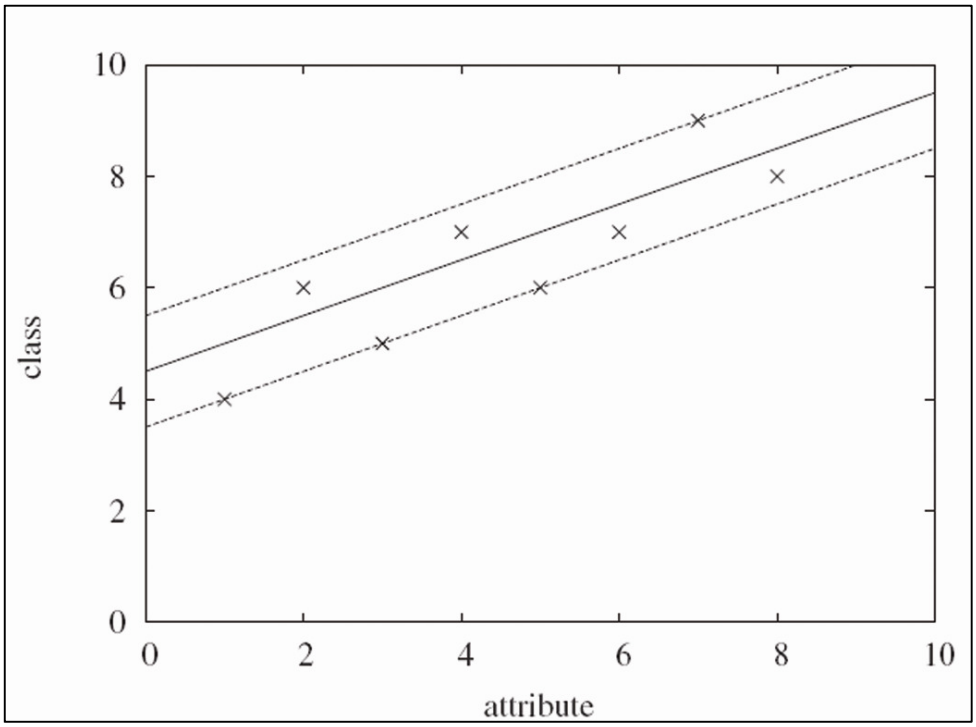


Figure 3.3: Support vector regression. ε = 1. Regression line for 8 data points, one attribute considered

As with linear regression, the main aim of the support vector machines algorithm is to find a function to approximate the training data points and minimise the prediction error (Witten and Frank, 2005). The difference lies in the fact that the user can specify the ε parameter in order to draw a tube around the regression line (see Figure 3.3).

The ε parameter represents how close the line will fit the training set. All errors (the deviations from the regression line) within the tube are ignored and only support vectors (those lying on the tube border or outside) will have an influence on the prediction error. The task of the algorithm is to find a balanced solution between a minimum prediction error and the maximum flatness of the tube.

Below is a fragment of the SVM model for the Consciousness parameter. Only attribute weights are shown, not support vectors.

(normalised) ZCONSC =

*0.0724 * (normalised) AOA*

*+ -0.3523 * (normalised) BROWN-FREQ*

*+ 0.0705 * (normalised) CONC*

*+ 0.0243 * (normalised) FAM*

*+ -0.0827 * (normalised) IMAG*

*+ 0.0326 * (normalised) K-F-FREQ*

*+ 0.0509 * (normalised) K-F-NCATS*

*+ -0.0581 * (normalised) K-F-NSAMP*

*+ 0.0543 * (normalised) MEANC*

*+ -0.0203 * (normalised) MEANP*

*+ -0.1685 * (normalised) NLET*

*+ -0.0056 * (normalised) NPHON*

*+ 0.1571 * (normalised) NSYL*

*+ 0.2616 * (normalised) T-L-FREQ*

*+ 0.022 * (normalised) WPS*

*+ 0.0258 * (normalised) Qmarks*

*+ -0.1017 * (normalised) Unique*

...

3.2.1.3 Profile creator

The common way to save information about people and to model their identity within Recommender Systems is to create User Profiles. These profiles can be knowledge-based (if person's details are acquired through questionnaires) or behaviour-based (extracted by means of various natural language processing techniques) (Nunes, 2008). Here we follow the behaviour-based approach, retrieving the profile data implicitly through the analysis of the text written by the particular person.

We have decided to apply the principles of the Semantic Web and reuse existing ontologies to construct the user model of the TWIN system. This format allows the sharing of the information in a meaningful way between various applications (Roshchina et al., 2008) and such a choice is a step towards a RS in that applies the ontology-based knowledge representation approach proposed in recent research (Cantador, 2008). In order to represent the TWIN user we have built an ontology based on the GUMO (Heckmann, 2005), Dublin Core[32] and FOAF[33] vocabularies. Figure 3.4 shows the relationship between the classes in the constructed user ontology. A more detailed description of the classes can be found in Appendix A.

[32] http://dublincore.org
[33] http://www.foaf-project.org

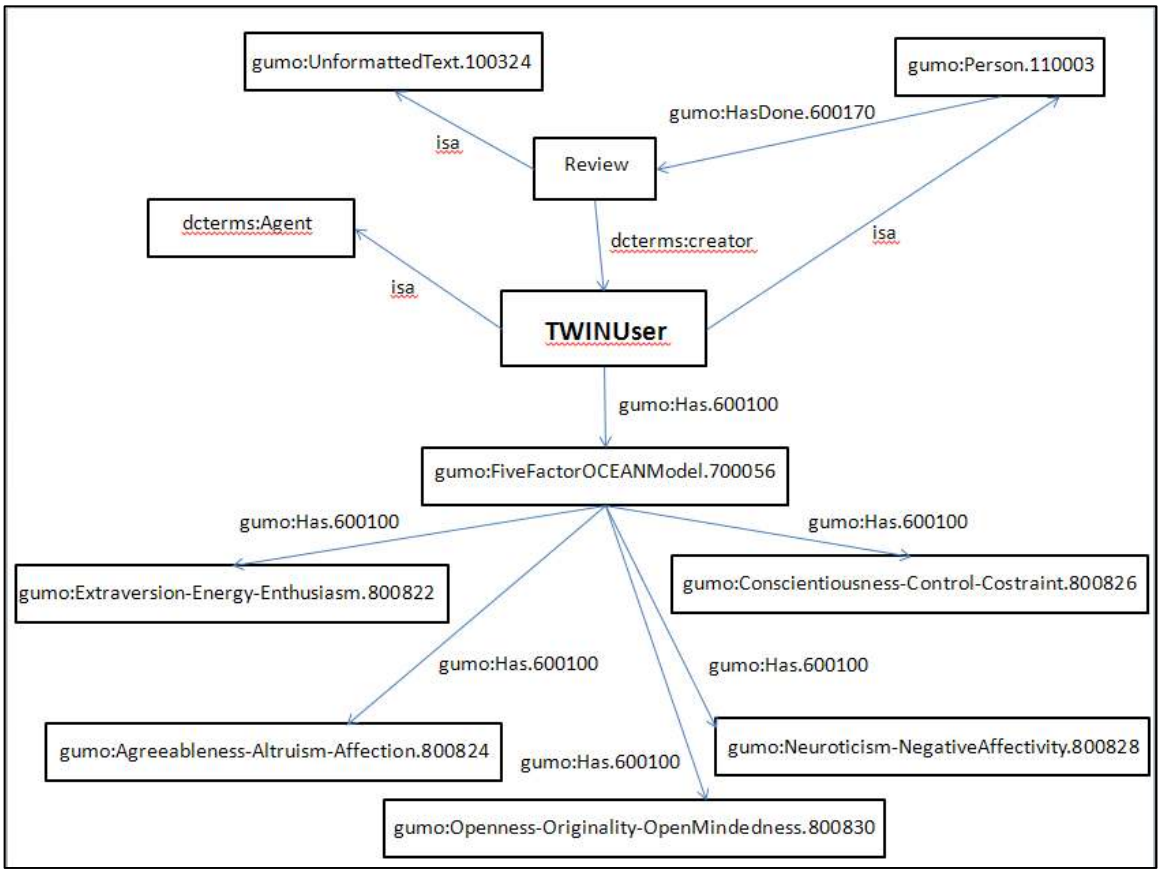


Figure 3.4: TWIN user ontology

The Friend of a Friend (FOAF) vocabulary, originally created by Dan Brickley and Libby Miller, is aimed at describing people, relations between them, their interests (Mika, 2004). FOAF has become very popular with the emergence and fast spreading of social on-line networking services.

Dublin Core vocabulary is aimed at bringing semantics to the discovery and managment of resources promoting interoperability and co-operation. It provides a way of extensively describing multipurpose metadata.

The GUMO ontology provides a way of extensively describing the user and is a part of the framework that realises the concept of ubiquitous user modelling (Heckmann, 2005). It includes demographic information, psychological state, among other aspects. It has appropriate classes to represent the Big Five model personality parameters as well as general user data (age, gender, etc.).

The GUMO vocabulary defines two classes that we have utilised the purpose of the TWIN user profile construction: gumo:UnformattedText.100324 (to describe any text with no specific

structure) and gumo:Person.110003 (to represent the general user). The main classes introduced in the TWIN ontology are the Review class, implemented as a subclass of gumo:UnformattedText.100324, and the TWINUser class, being a subclass of the gumo:Person.110003 and the corresponding GUMO classes to model the personality of the user.

Figure 3.5 shows an instance of the user ontology describing one of the users of the TWIN system (Cheryl63) exported to and visualised by Protégé ontology editor. It can be seen that Cheryl63 (an instance of the TWINUser class) has written five reviews (instances of the Review class) and has personality scores that are instances of the corresponding GUMO Big Five model classes.

The profile of each of the users is constructed as a mean of the scores produced by the Personality Recogniser for each of the pieces of textual information created by the individual and crawled from the corresponding online community. Thus, each user profile is seen as the following structure:

$$Profile_{user\text{-}i} = [\ (bfi\text{-}open, v_{i,1}), (bfi\text{-}cons, v_{i,2}), (bfi\text{-}extra, v_{i,3}), (bfi\text{-}agree, v_{i,4}), (bfi\text{-}neuro, v_{i,5})\ ],$$

where

user-i is the profile of the current user,

bfi-open is the Big Five Openness to Experience parameter,

bfi-cons is the Big Five Consciousness parameter,

bfi-extra is the Big Five Extraversion parameter,

bfi-agree is the Big Five Agreeableness parameter,

bfi-neuro is the Big Five Neuroticism parameter

and $v_{i,j}$ are the values of the corresponding Big Five parameter.

3.2.2 The Similarity Estimator

The goal of the Similarity Estimator is to search for similar-typed people among all of the users profiles within the system, based on the assigned personality scores. The final recommendations are calculated considering the items liked by the community of discovered people.

As the k-nearest neighbour approach (kNN) shows high performance (Islam et al., 2007) and is relatively easy to apply for the RS, we have chosen to implement it for the Similarity Estimator

component. The kNN algorithm calculates the value of the distance function in order to select k-nearest points from the current one and assign the majority class of the found circle of neighbours. To estimate the similarity of user profiles, we have chosen the most commonly used Euclidian distance (Witten and Frank, 2005):

$$\sqrt{\left(a_1^{(1)} - a_1^{(2)}\right)^2 + \left(a_2^{(1)} - a_2^{(2)}\right)^2 + \ldots + \left(a_k^{(1)} - a_k^{(2)}\right)^2},$$

where k is the number of attributes (in our case the maximum was 5) and a_k are attribute values.

The typical values for the k parameter (the number of neighbours) are 1, 3 and 5 (Islam et al., 2007). We have chosen the value 5 so that the number of recommendations will not be too large and at the same time will be sufficient to produce meaningful results.

3.2.3 The Results Visualiser

The Results Visualiser is constructed as a Flash application to represent the results of the recommendation for the user. It requires the user profile name of the particular social media site to retrieve the textual information written by the user. After the calculation of the personality performed by the Profile creator, its visual representation is provided by the Results Visualiser. Therefore the user can analyse his personality scores and compare them to other users' scores.

3.3 Summary

In this chapter we have provided a description of the TWIN system and its components. We have introduced the means by which it applies personality from the text recognition (the Personality Recogniser tool available from the previous research) to form the basis of the underlying recommendation algorithm for the RS.

The main components of the TWIN system were discussed in detail: the *User Data Processor* (which collects the data written by the user from the social media online resource, analyses it, calculates personality scores and stores the results in the user profile following the constructed user ontology), the *Similarity Estimator* (which performs the general functionality of the RS by applying the kNN algorithm to find the circle of people with similar personality) and the *Results Visualiser* (the Flash user interface that visualises the calculated personality of the user and presents the list of found recommendations).

In the following Chapter, we proceed to describe the experiments conducted with the TWIN system, and discuss their outcomes.

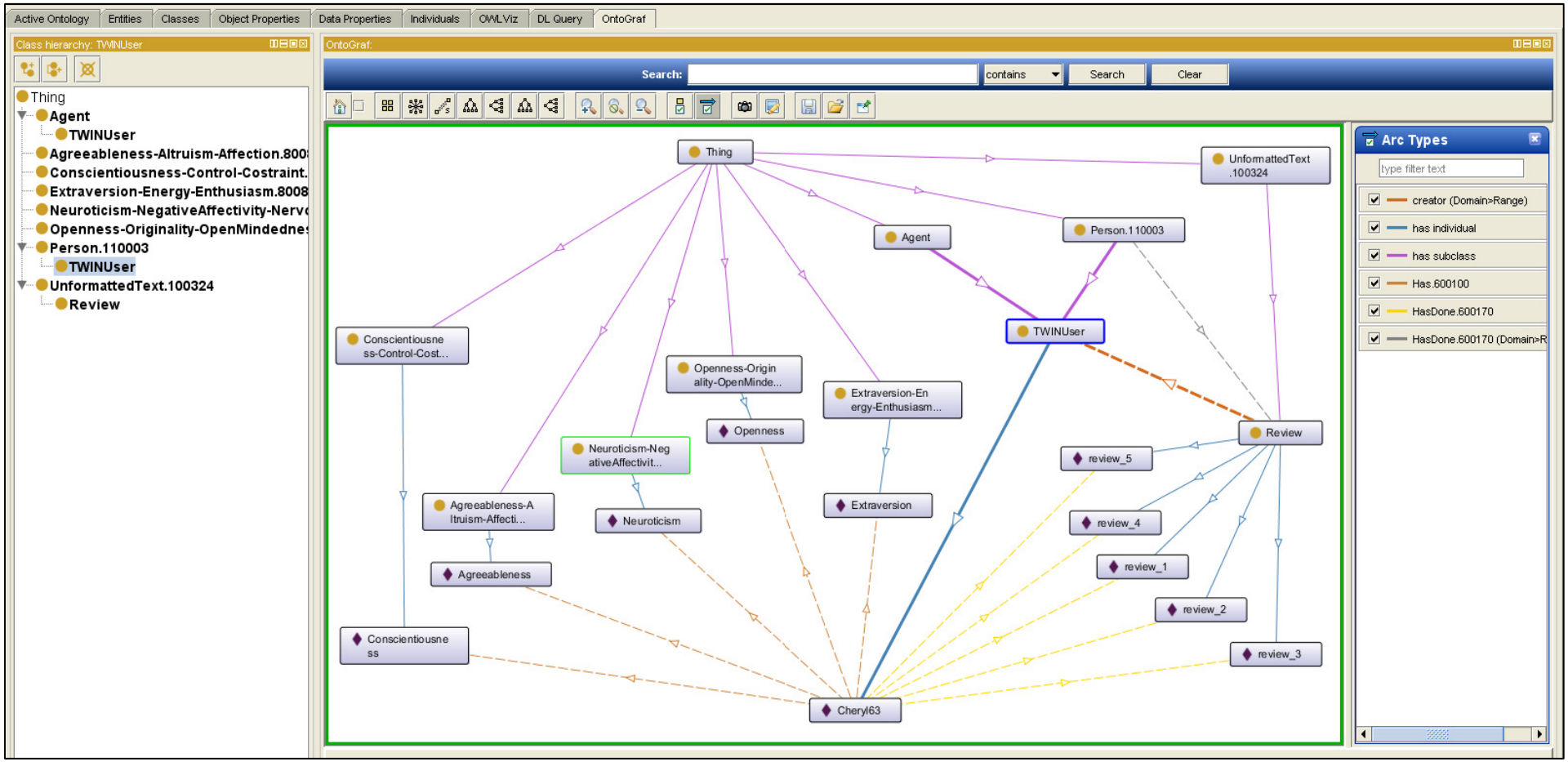


Figure 3.5: TWIN user (Cheryl63) profile ontology

Chapter 4: Experiments and Results

In this chapter we provide the description of the experiments performed in order to evaluate the possibility of the TWIN system construction as well as the structure of the dataset crawled from the TripAdvisor website.

4.1 Online travelling domain and Recommender Systems

One of the fastest developing online domains is the travelling sector. Travellers trying to find a suitable accommodation tend to rely on a number of factors. In particular their choice depends on the hotel awareness (the place is somehow more familiar to the person, for example as a result of advertising) and hotel attitude based on the attributes of the hotel that are pivotal to the person (for example location, cleanliness, service, etc.) (Vermeulen and Seegers, 2008; Sánchez García et al., 2011). Thus the choice the traveller makes can become highly influenced by the market games, advertising, popularity of some locations, etc. For this reason many people tend to trust more the opinions of other travellers when making a decision about a particular place to go (O'Connor, 2010).

Research shows that the role of social media in the online travelling domain, which allows experience sharing, is significant and a high percentage of search engine results are links to the social media sites belonging to a number of major categories like virtual community sites, review sites, personal blog sites and social networking tools (Xiang and Gretzel, 2010).

Recently social sites such as TripAdvisor[34] have started to emerge to allow their users to publish reviews of the places to which they have travelled. TripAdvisor provides the interface to search through the travel facilities (hotels, restaurants, etc.), check their availability for a specific date and read the reviews associated with them. Most of the users of TripAdvisor (97%) return to the site and utilise its content to plan their next trip (O'Connor, 2010). But as the volume of the available reviews is growing in size every day, it is impractical for users to manually retrieve and consider each review. This is where the necessity of constructing a Recommender System

[34] http://www.tripadvisor.com

appears to provide automatic filtering of relevant touristic places through the analysis of reviews texts and travellers profiles.

4.2 TripAdvisor data collection

In order to evaluate the performance of the TWIN system, we apply it in the travelling domain, to suggest hotels from the TripAdvisor site by filtering out reviews produced by people with like-minded views to those of the user. In order to establish the similarity between people we construct a user profile by modelling the user's personality (according to the Big Five model) based on linguistic cues collected from the user-generated text of the reviews. This approach provides recommendations that rely on factors independent in many ways from the user's pre-existing attitudes in the hotel market. It also avoids the subjective step of specifying explicit preferences.

Our perspective of text oriented investigation of interests was chosen according to the following principles:

- Sites such as tripadvisor.com allow the user to provide a broad description of the hotel based on their evaluation of its location, quality, service and many other factors as well as on the availability of photo uploading facilities. However many users ignore these options and fill in only the main section of the review – the text itself. Therefore it is useful to have a tool that would be able to make recommendations inferred from texts of the reviews.
- In many cases, factors such as gender, age and marital status do not play a significant role when talking about people's preferences and general interests.
- This approach can be used in addition to the more classical search based on the predefined fields mentioned earlier.

The diagram in Figure 4.1 describes the experiment with the TripAdvisor dataset:

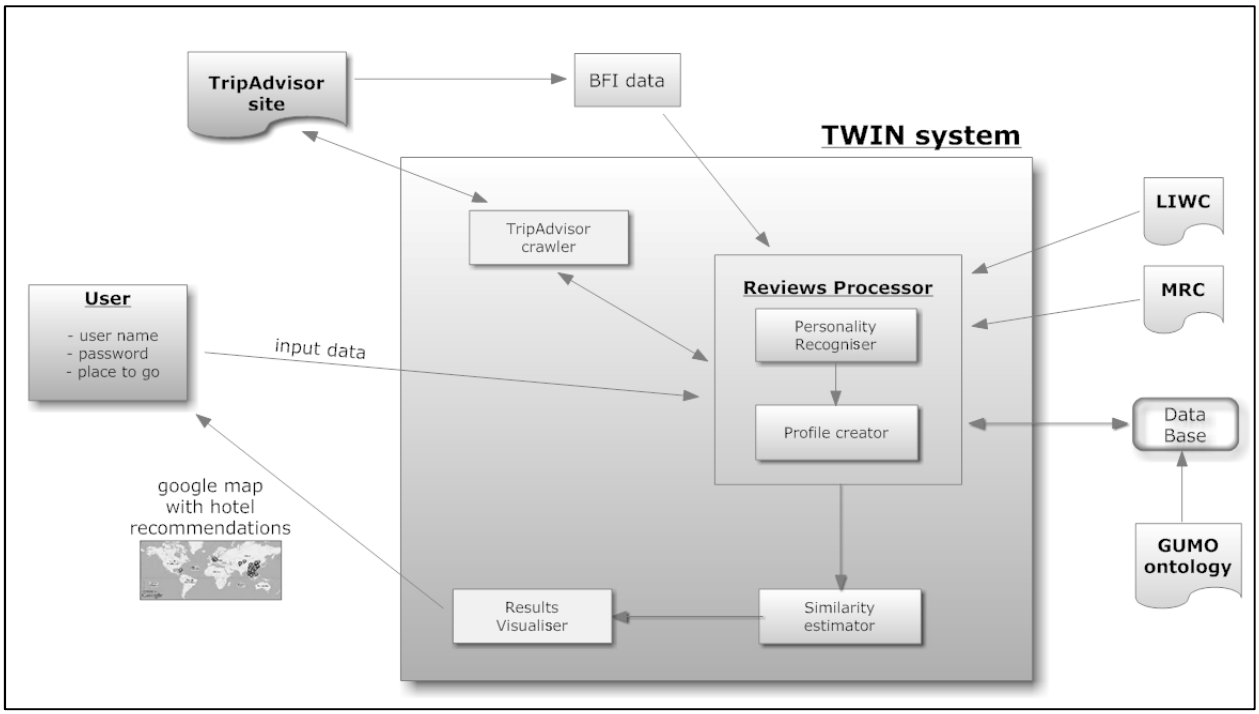


Figure 4.1: TripAdvisor data experiment using TWIN system

The diagram presents the TripAdvisor hotels recommender. The TWIN system is utilised to visualize a list of hotels for the user on the GoogleMap based on the destination he is interested in and the personality similarity between the particular user and other users of the system. The user profile is constructed to reflect the personality calculated from the reviews the user has written, crawled from the TripAdvisor site, and personality scores are stored in the database following the constructed user ontology.

4.2.1 TripAdvisor data

We built a Java crawler and constructed a dataset based on reviews submitted to the TripAdvisor website. The TripAdvisor site provides a large variety of user-generated content. For the purposes of our research we have utilised the information about hotels, reviews and people (Sánchez García et al., 2011). From all the available information, we extracted the parameters listed in Table 4.1. An example of the TripAdvisor hotel data is shown in Figure 4.2.

Parameter
Name of the hotel
Number of stars
TripAdvisor index
Rating by reviewers
City and brand name

Table 4.1: TripAdvisor hotels' fields crawled

Figure 4.2. TripAdvisor hotel information

All the available fields included in the TripAdvisor dataset are shown in Table 4.2. The typical review information is shown in Figure 4.3.

Parameter
Review title
Hotel rating
Text of the review
Detailed hotel ratings (value, rooms, location, cleanliness, service, sleep quality)
Date of stay
The purpose of the hotel visit
People the reviewer were travelling with
The field states whether the reviewer would recommend the hotel to others
The author of the review

Table 4.2: TripAdvisor reviews' fields crawled

Finally, Figure 4.4 shows a standard user profile. As most of the profiles are incomplete (especially the "Travel preferences" section) the most important information to be gathered was the number of contributions (reviews, photos, blog posts) made by each person.

Figure 4.3: TripAdvisor hotel review[35]

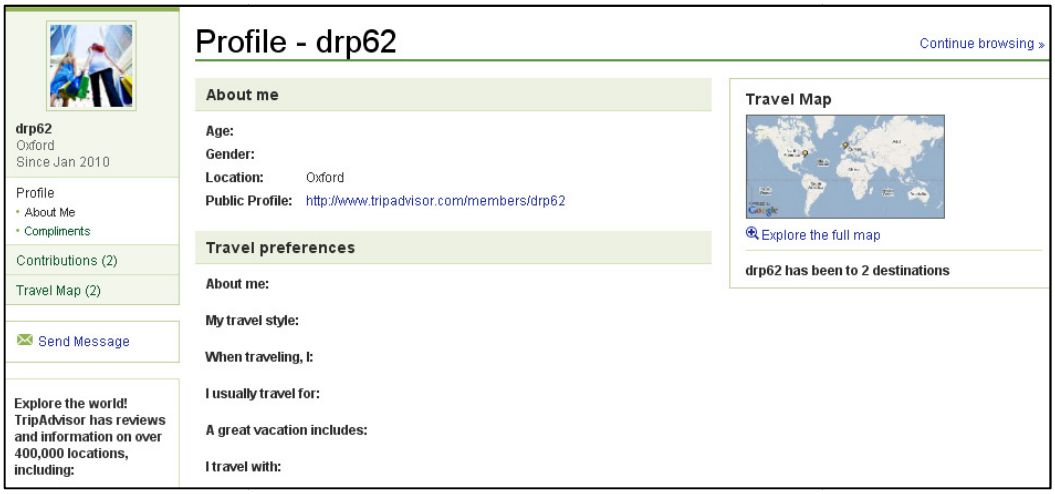


Figure 4.4: Example TripAdvisor user profile[36]

[35] http://www.tripadvisor.ie/ShowUserReviews-g60763-d1776857-r105393078-The_Setai_Fifth_Avenue_a_Capella_managed_Hotel-New_York_City_New_York.html
[36] http://www.tripadvisor.ie/members/drp62

4.3 Calculating personality from the text

As mentioned above, there are two main ways of estimating the personality of an individual. The most widely used is questionnaire completion, while the more challenging way is to estimate the personality based on linguistic cues.

We investigated the questionnaire approach for the TWIN system construction and have built a web page with the Big Five questionnaire[37] (John, 2008). As the time required to fill in the questionnaire is approximately 15 minutes and most users are not sufficiently motivated to complete it, we decided to implement the personality from the text estimation only.

We processed reviews data with the Personality Recogniser tool to produce the Big Five scores for each of the reviews texts. The overview of the dataset is presented in Table 4.3.

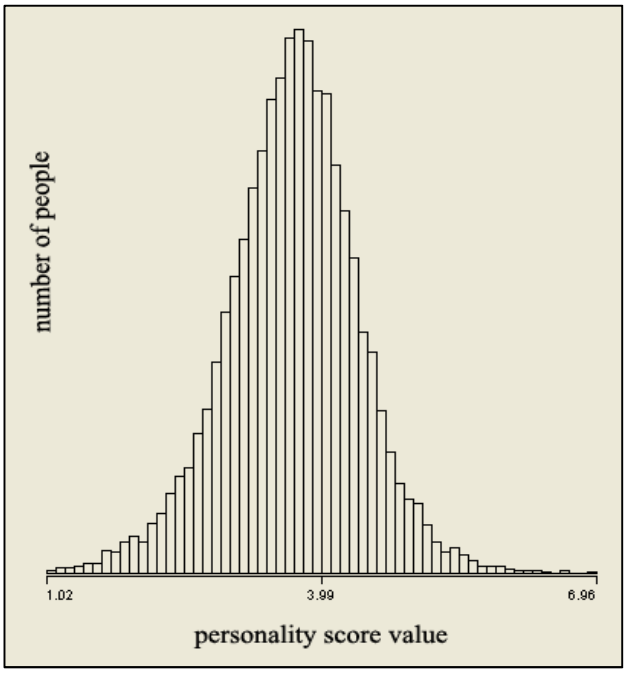
Parameter	Value
Number of reviews	14,000
Number of people	1,030
Average number of reviews per person	13.8
Minimum number of reviews per person	5
Maximum number of reviews per person	40
Number of words in all reviews	2.9 million
Average number of words per review	210.8
Average number of words per sentence	16.6
Minimum number of words per sentence	3
Maximum number of words per sentence	39.7

Table 4.3: TripAdvisor dataset parameters

At the pre-processing stage we filtered out the small percentage of those (approximately 1.2%) for which the scores were incorrectly calculated (i.e., those which were outside the expected range of 1 to 7). As each score is calculated from the text of the review independently (for more details see Section 3.2.1.2), we have analysed each of them separately. The results per each dimension are summarised in Tables 4.4-4.8 and Figures 4.5-4.9.

[37] http://www.ocf.berkeley.edu/~johnlab/bfi.php

Extraversion

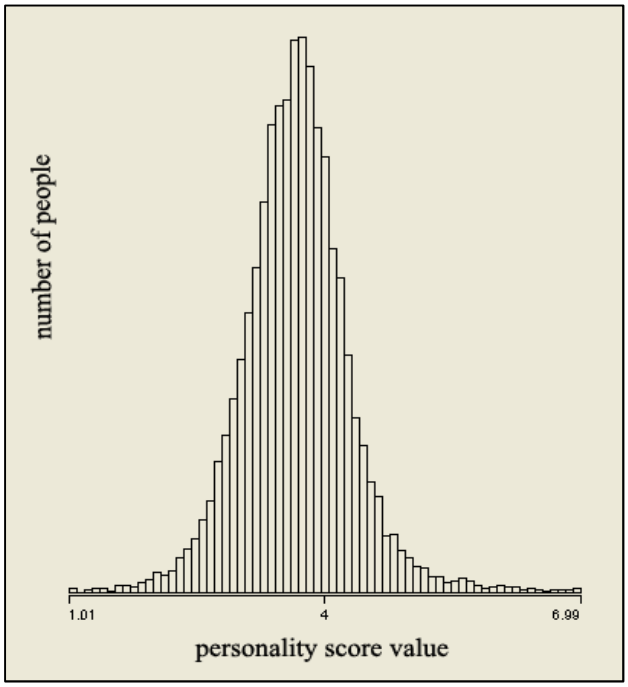


Parameter	Value
Minimum	1.01
Maximum	6.988
Mean	3.665
Standard deviation	0.634

Table 4.4: Extraversion scores parameters

Figure 4.5. Extraversion scores distribution

Agreeableness

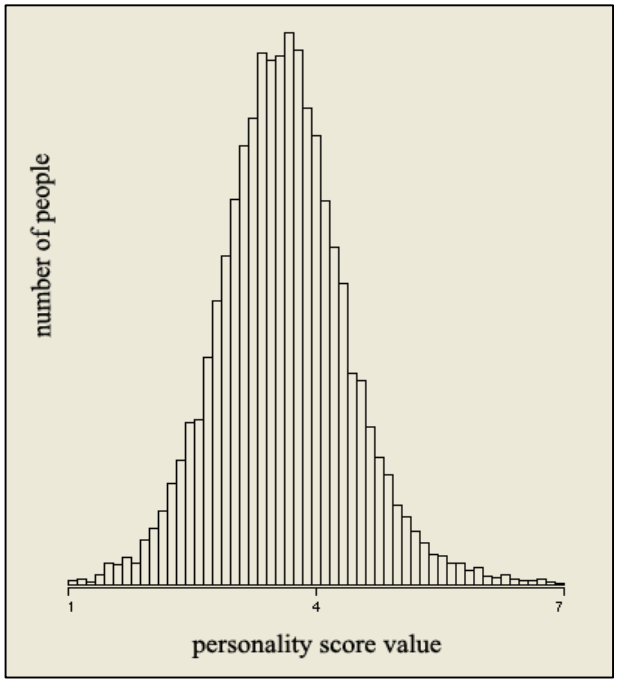


Parameter	Value
Minimum	1.024
Maximum	6.964
Mean	3.675
Standard deviation	0.708

Table 4.5: Agreeableness scores parameters

Figure 4.6: Agreeableness scores distribution

Consciousness

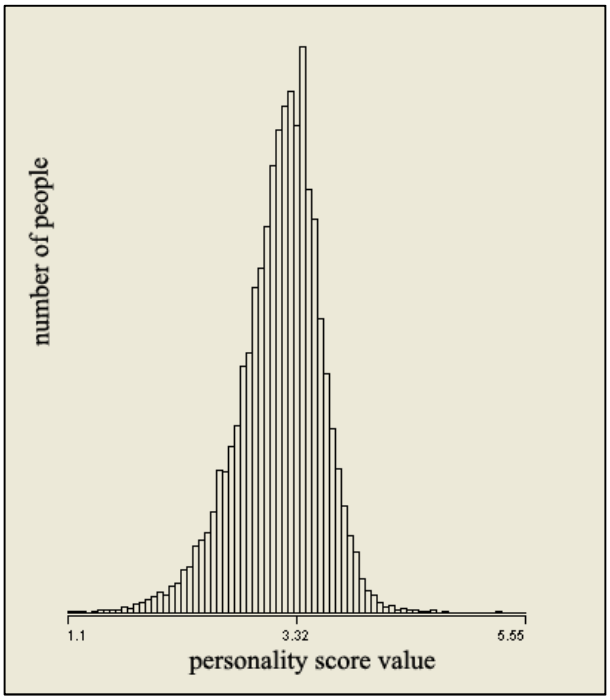


Parameter	Value
Minimum	1.001
Maximum	6.998
Mean	3.605
Standard deviation	0.782

Table 4.6: Consciousness scores parameters

Figure 4.7: Consciousness scores distribution

Neuroticism

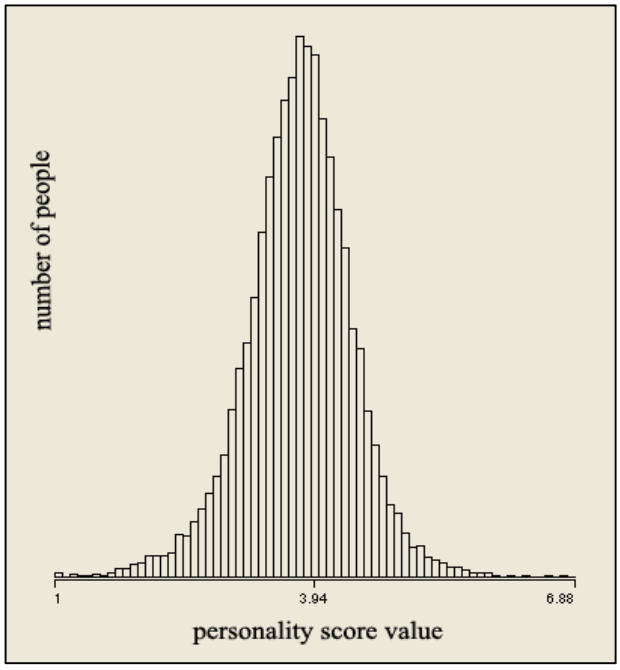


Parameter	Value
Minimum	1.099
Maximum	5.548
Mean	3.158
Standard deviation	0.411

Table 4.7: Neuroticism scores parameters

Figure 4.8: Neuroticism scores distribution

Openness to experience



Parameter	Value
Minimum	1.001
Maximum	6.876
Mean	3.761
Standard deviation	0.603

Table 4.8: Openness to experience scores parameters

Figure 4.9: Openness to experience scores distribution

As can be seen from the results obtained, scores for each of the Big Five dimensions have close to normal distributions with the highest standard deviation for the Consciousness trait and the lowest for the Neuroticism trait. This shows that people in the constructed dataset differ by Consciousness parameter more compared to the differences in the other four traits while Neuroticism scores are less variable across the dataset. Neuroticism scores also have the smallest maximum and mean values comparing to scores per other traits. Openness to experience trait has the largest mean value – this fact is interesting considering that the processed dataset consists of travellers' reviews showing the tendency for those people to be more open-minded and curious to have more diverse life experiences.

4.4 User profile construction

To model the personality, we store the mean score of each of the Big Five parameters calculated from the text of each of the reviews (Roshchina et al., 2011). We randomly selected 15 people from our dataset who contributed more than 30 reviews. Using the Personality Recogniser (with a linear regression algorithm) we obtained personality scores for each of the texts written by each individual. As each score is calculated from the text of the review independently we analysed them separately. The visualised scores per each of the Big Five dimensions are presented in Figures 4.10 – 4.14. Each grey dot represents a value of the particular trait score per each review

of the current person. Dots with a "+" symbol in the middle show the mean score of all the reviews of the person. Line that joins all of such dots helps to see more clearly the variability in the mean scores.

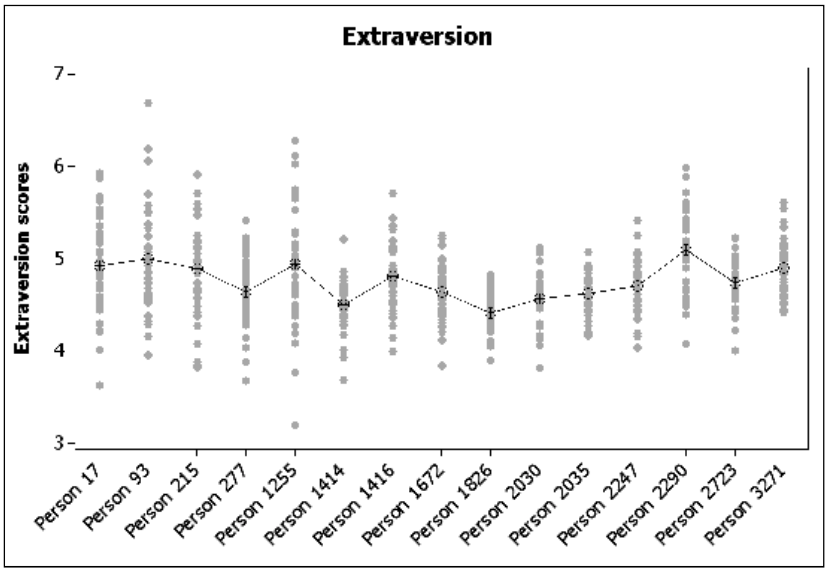


Figure 4.10: Extraversion scores distribution with means for each review set

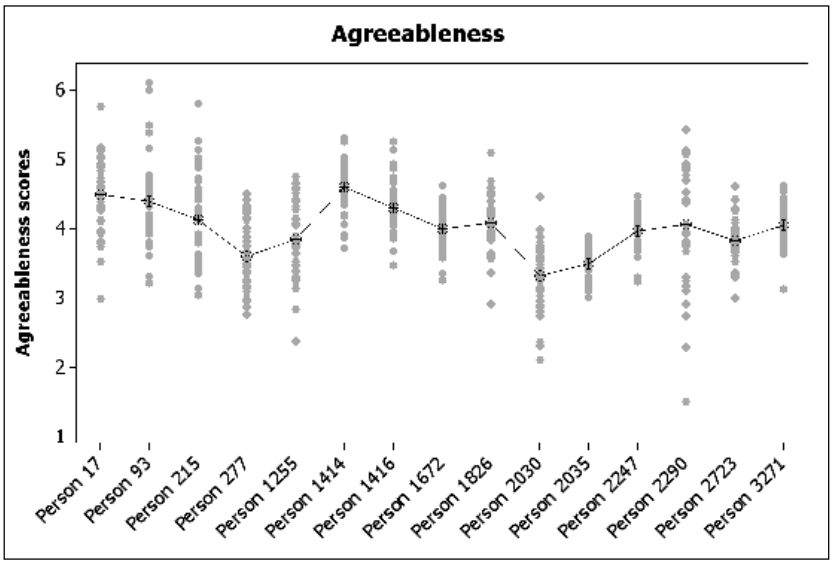


Figure 4.11: Agreeableness scores distribution with means for each review set

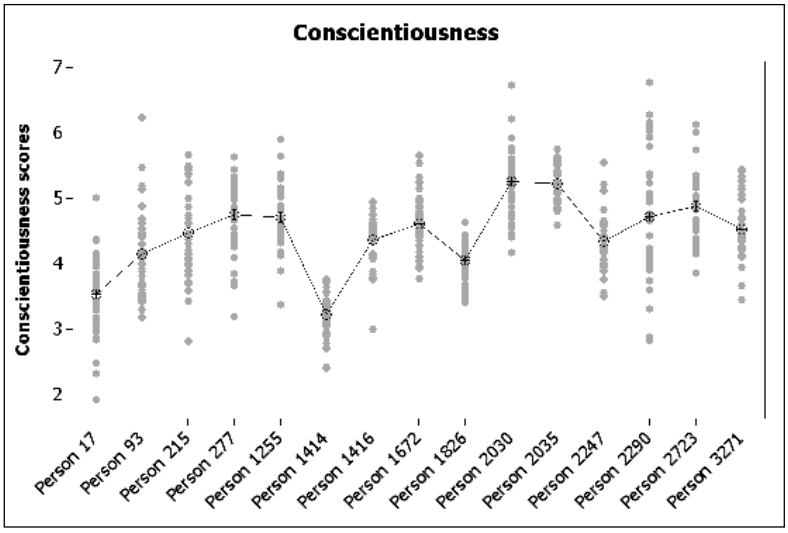


Figure 4.12: Conscientiousness scores distribution with means for each review set

In order to check whether the means of personality scores per person differ from each other we have performed the ANOVA test (Analysis Of Variance) (Meloun and Militky, 2011). Normally when there are only two samples the standard t-test is applied but here we were comparing the variance of mean values of 15 samples representing 15 different people. The test has shown significant differences ($p < 0.001$) between persons in each of the Big Five categories. Thus it can be concluded that mean scores vary sufficiently from one person to another showing different personality patterns for each person which results in the correctness of the Hypothesis 1. This fact enables us to use the mean score as the estimation of the personality in each of the 5 dimensions. Therefore we can accept that the Hypothesis 2 is also correct.

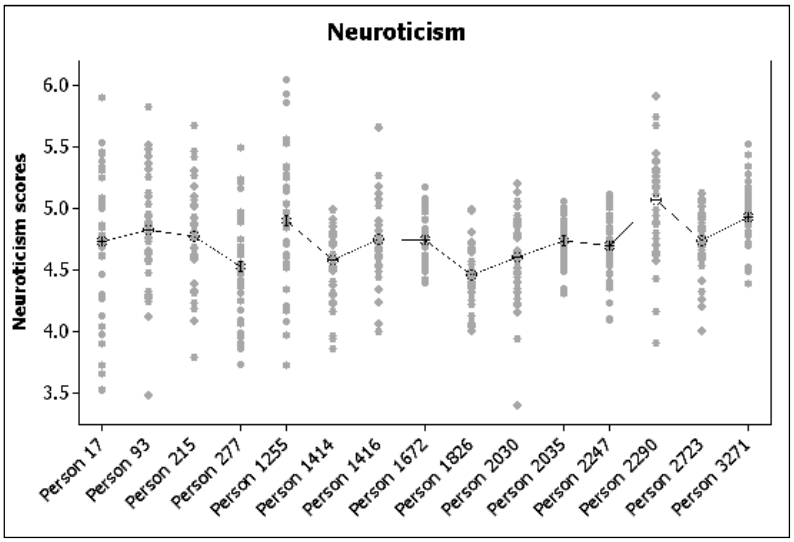


Figure 4.13: Neuroticism scores distribution with means for each review set

It can be seen that openness to experience scores have the highest variability in means which suggests that this trait may be the easiest to detect. This result is in agreement with Mairesse et al. (2007) who had also found that openness to experience is the easiest trait to model.

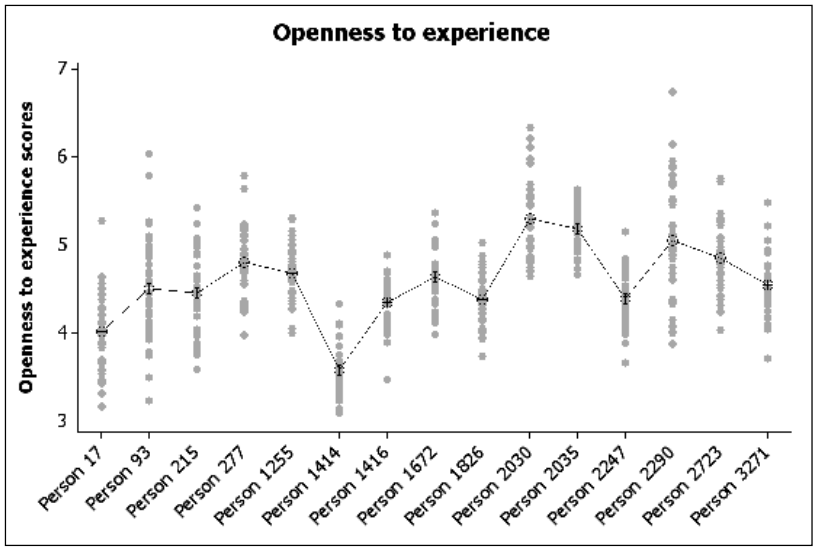


Figure 4.14: Openness to experience scores distribution with mean scores for each review set

4.5 Comparison of the performance of Personality Recogniser Algorithms

To evaluate the performance of the 4 algorithms available in the Personality Recogniser we selected 15 people who contributed more than 30 reviews from our dataset (Roshchina et al., 2011). We calculated the scores of each of the Big Five parameters for each review separately applying all the 4 algorithms. To compare the performance of the algorithms we analysed the standard deviations of the scores of reviews written by the same person. The hypothesis under consideration is that the algorithm producing scores that differ the least for the reviews of the same author will be the best to apply for the personality recognition task in the TWIN system.

We studied the performance of the algorithms separately for each dimension as the Big Five scores are estimated independently from the text of the review. For each personality trait we have constructed 4 samples (representing each of the 4 algorithms) of standard deviations of the reviews scores of the 15 individuals. The ANOVA test (Meloun and Militky, 2011) results have shown significant differences between the samples for almost all of the Big Five parameters. Therefore, the performance of the algorithms differs for all of the traits (see Table 4.9).

Big Five trait	Algorithms results
Openness to experience	Differ at $p < 0.05$
Consciousness	Differ at $p < 0.001$
Extraversion	Differ at $p < 0.001$
Agreeableness	Differ at $p < 0.001$
Neuroticism	Differ at $p < 0.001$

Table 4.9: ANOVA test for the algorithms comparison

It can be conjectured that openness to experience is the easiest trait to model as the difference between the algorithms results is less significant than in the rest of the traits. This result is in agreement with the previous research (Mairesse, 2007). On the other hand, the Consciousness trait (see Figure 4.15) is likely to be the hardest to model (this was also shown in Mairesse's (2007) work) as each algorithm shows highly significant differences in the results variation.

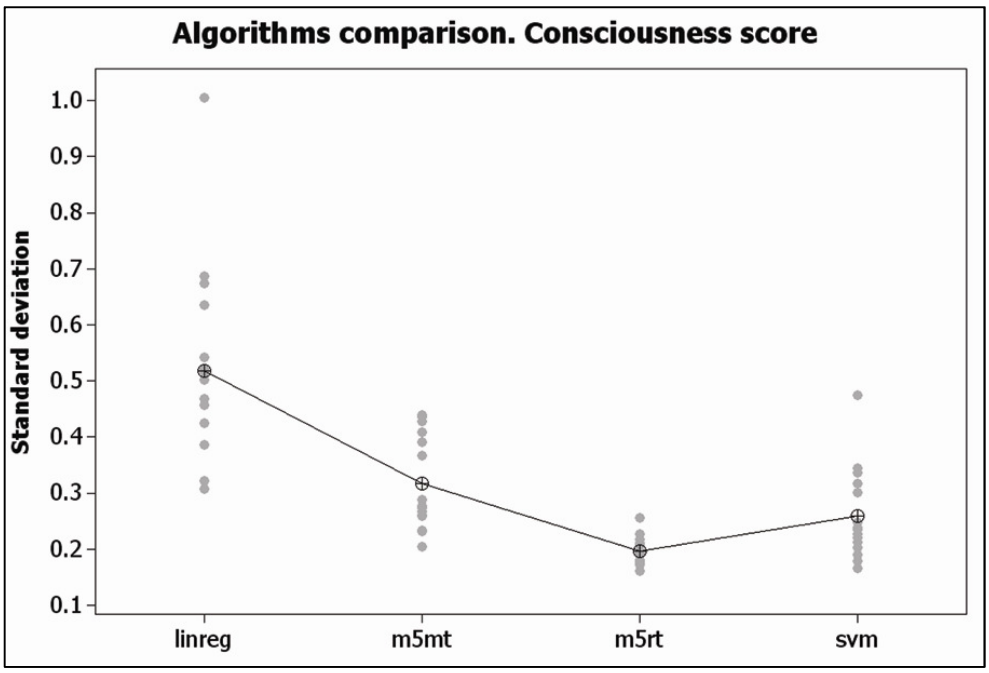


Figure 4.15: Algorithms results comparison. Consciousness score. (linreg - linear regression, m5mt - M5' model tree, m5rt- M5' regression tree, svm - support vector machines)

In order to find the algorithm that shows the best results for each of the traits, we performed Fisher's Least Significant Difference (Fisher's LSD) test to carry out all pairwise t-tests (Westfall et al., 1999). The results are shown in Table 4.10.

Big Five trait	Algorithm that differs significantly	Performance
Openness to experience	M5' regression tree	slightly significantly better
Consciousness	Linear regression	significantly worse
Extraversion	M5' regression tree	significantly better
Agreeableness	M5' regression tree	slightly significantly better
Neuroticism	M5' regression tree	significantly better

Table 4.10: Algorithms that differ significantly

We have hypothesised that the algorithm to be considered the best would produce scores that differ the least for the reviews of the same author. We compared results separately for each of the Big Five traits as the estimation of the personality scores from the review text is performed independently for each dimension.

We found that the M5' regression tree algorithm of the Personality Recogniser tool performs better on the reviews data than the other 3 algorithms available. We have decided to utilise it for the personality profile construction task in the TWIN system.

4.6 Summary

In this chapter we described the experiments we performed in order to select the best design options for the TWIN system. We created a TripAdvisor reviews dataset to test the performance of the TWIN system components. We calculated the text-based personality scores of each of the reviews of all the authors in the dataset and designed the experiment to select the best option of user profile representation. According to the results, we have chosen to set the mean of reviews scores per author as the overall user personality estimator. We have proved the correctness of the first two hypotheses provided in the Introduction Chapter. We also performed a comparison of the four algorithms available in the Personality Recogniser tool and selected the one showing better results on our test dataset.

Chapter 5: Evaluation

The effectiveness and usefulness of the TWIN system depends on the accuracy of the personality match. The evaluation therefore requires a separate independent experiment to evaluate the correctness of the estimation of the author's personality. Two approaches can be considered here: contacting people directly and asking them to fill in a questionnaire in order to establish their actual personality scores (ideal situation) or (if this is not possible) trying to compare the scores of different pieces of textual information produced by the same author.

In this Chapter we provide a description of the two approaches mentioned above. After completing this task, we should be able to compute the performance of the personality recognition algorithm. This would allow us to experiment with and compare other models apart from the one implemented in the Personality Recogniser. As the main contribution of this work is the constructed TWIN application, we provide in this Chapter the TWIN system evaluation guidelines for future work as well as one of the first attempts in this direction.

5.1 Questionnaire-based evaluation

The first approach we could follow in order to evaluate the TWIN system is to consider the actual personality scores and comparing them to the scores computed from the text. As mentioned in Section 2.3, the standard approach taken by Personality-based RSs is the use of the questionnaire. The TWIN system, built as a web-based application, includes a link to the questionnaire page mentioned in Section 4.2.1 that has an instance of the Big Five Inventory (John, 2008). Although the brevity of the questionnaire results in a lower accuracy than the standard Big Five questionnaire NEO-PI-R (NEO-Personality Inventory-Revised) by McCrae and Costa (1996) and contains only 44 questions, it has been successfully applied in many research projects (some of which were mentioned in Chapter 2). It allows "efficient and flexible assessment of the five dimensions" and is widely used in the personality from the text recognition (Golbeck et al., 2011). The fragment of the web page with the questionnaire is presented in Figure 5.1.

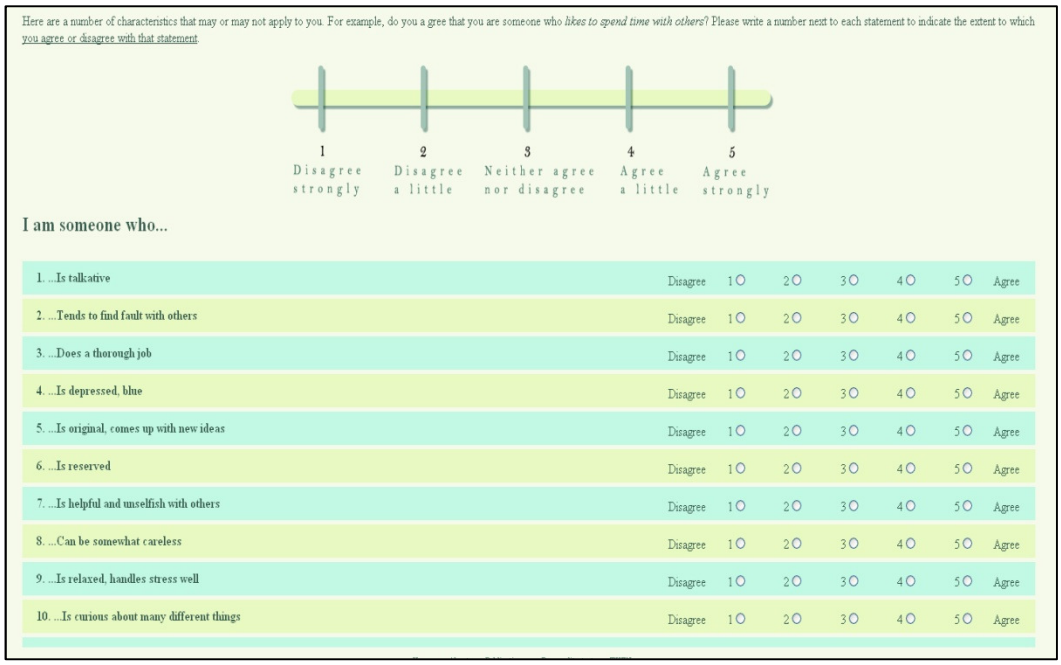


Figure 5.1: Big Five questionnaire web page

5.1.1 Obtaining personality data

We considered two approaches of obtaining the personality scores through the questionnaire: constructing the sample of people who would like to take part in the experiment or using online social media services to contact people.

Constructing the set of users

We could consider the traditional approach of creating a circle of volunteers (at least 35 people) who could contribute between 5 and 13 pieces of textual information (with the preference of 7) they had written and fill in the personality questionnaire. We have chosen 5-13 items in order to have a similar number of textual pieces to analyse as in the constructed TripAdvisor dataset for comparison reasons (5 was the minimum number of reviews per person and 13 was the mean number of reviews). The chosen length of the review is the standard 250 words (which is also close to 210.8 - the average number of words per review in the collected TripAdvisor dataset).

Using social media services

Social media services provide a convenient way of contacting a large number of people and receiving a fast response. In particular the personality information could be extracted from services such as TripAdvisor or Facebook by crawling the texts written by people or other information such as age, location, etc.

In order to contact the authors of reviews from the TripAdvisor site, we constructed a small tool to automatically send the request to complete the Big Five questionnaire from the web page mentioned above. The program applies the Java API of the Selenium web browsers automation tool[38] to open the TripAdvisor user profile and send a message with the link and the description of the TWIN project to the target user. We rejected this approach as the policy of the TripAdvisor site does not allow us to send messages to its users with links to external web sites.

A lot of textual information are available on Facebook in the form of users' comments and discussions. As mentioned in Section 2.2.4, the personality user profile was constructed under the "myPersonality Research" project containing the Big Five scores. This information could be utilised in order to compare the scores calculated from the text of users' comments with the scores available from the "myPersonality" profile.

5.1.2 Convergence analysis

In order to evaluate the performance of the personality from the text recognition algorithm we could use convergence analysis. It estimates how fast one value is approaching to the other, or one distribution to another (Robu et al., 2009). In our case, it could be used to reflect the dynamics of the personality estimation.

A similar task arises in the work of Robison et al. (2009), in which the authors predicted the personality of people from their interaction with the constructed educational environment Crystal Island based on three factors: *situational attributes* (location of the person, actions, etc.), *affective attributes* (responses to virtual agents, frequency of emotions, etc.) and *conversational attributes* (frequency and duration of communication with virtual agents). As each of the participants is required to fill in the personality questionnaire before taking part in the experiment, the real personality scores are known. The convergence analysis is applied to estimate how fast the induced scores approach the real scores in real time.

For our purposes we could apply convergence analysis in order to track how fast the computation of the personality values approaches the real scores gathered from the questionnaire. The dimension of time could be introduced by adding one piece of text of the same author at each step. Therefore we could compare the number of algorithms based on this evaluation procedure measuring their speed and accuracy.

[38] http://seleniumhq.org/

5.2 Text-based evaluation

For the second evaluation approach we assume that no actual personality values are known for people whose pieces of text are analysed to construct user profiles. The performance of the personality recognition algorithm could be estimated from the hypothesis that texts of the same author should belong to the same cluster when performing clustering of all the available texts. We have tested this approach on our TripAdvisor dataset, as described below.

5.2.1 TripAdvisor experiment

In order to evaluate the performance of the kNN algorithm that forms the basis of the Similarity Estimator component (Roshchina et al., 2012), we have designed the following experiment.

We selected 26 people from the TripAdvisor dataset who have contributed more than 35 reviews. We split the data into two parts: training and test sets. For the test set, we selected 5 reviews from the list of reviews of each person in the training set (at the same time deleting those reviews from the training set). We experimented with two types of training sets: with reviews' scores per person (821 instances) and with mean vectors of reviews' scores per person (26 instances).

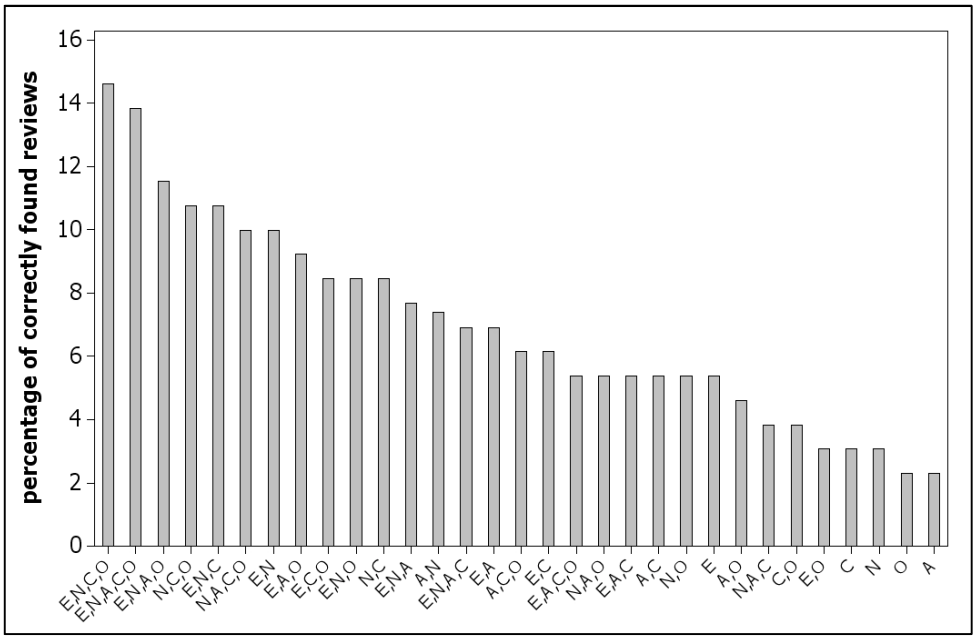


Figure 5.2: The percentage of correctly found reviews considering plain personality scores. Each Y value represents a combination of the Big Five parameters (E – Extraversion, A – Agreeableness, N – Neuroticism, C – Consciousness, O – Openness to Experience)

As we found that different traits of the Big Five have different levels of estimation complexity (see Section 4.3), we experimented with all 31 combinations of the Big Five parameters to feed the WEKA (Hall et al., 2009) kNN algorithm in order to select the combination that would

produce better results. The results are summarised in Figure 5.2 (training set with plain scores of reviews per person) and Figure 5.3 (training set with mean scores of reviews per person).

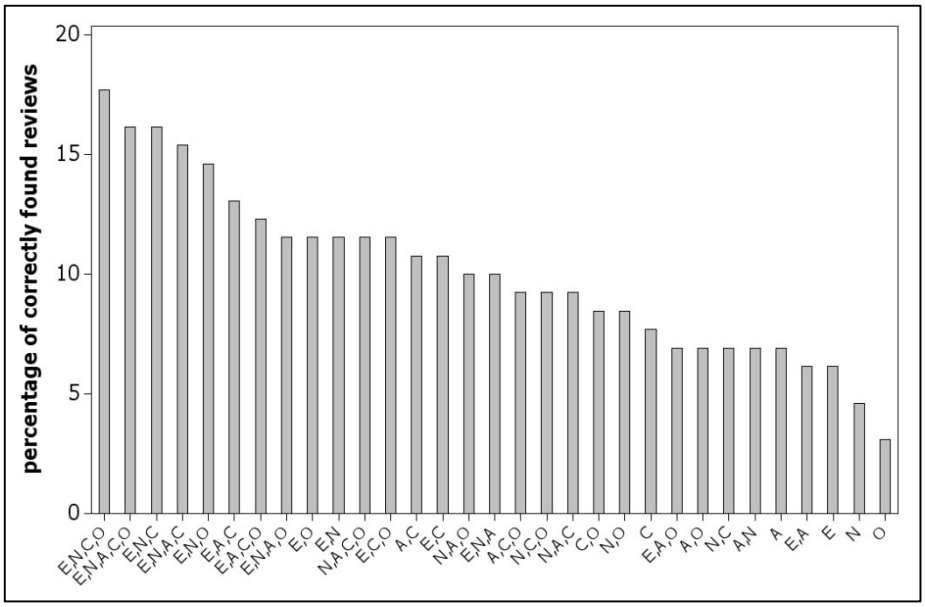


Figure 5.3: The percentage of correctly found reviews considering mean personality scores vectors per person as the training set.

It can be seen that results of the classification are not very optimistic, although similar results were obtained by Mairesse (2007) for the regression classification task. He stated that "the improvements seem relatively small" (over the baseline) explaining that the essence of the regression algorithm requires "the association of an exact scalar value with each individual". The results we obtained can be considered promising taking into account the difficulty of the personality from the text estimation on real-world data. One of the key points in personality score calculation is the recognition of sentence and word boundaries which are not always defined strictly in reviews dataset (missing punctuation marks, misspelled words, etc.). Thus, one of the approaches to improve the results is to incorporate additional information available in the TripAdvisor user profile, e.g. age, gender, location, etc., as well as the experimentation with the personality from the text recognition algorithm itself. Therefore we cannot totally reject the correctness of the Hypothesis 3 as the underlying personality calculation algorithm needs further improvement.

It can be concluded that the kNN algorithm performs better when considering the mean vectors of reviews' scores that represent the overall personality of the author. Therefore it was reasonable to select these mean vectors to be saved as the user profile information in the TWIN system (see Section 4.3).

It can be seen that not all combinations of the Big Five parameters produce the same results. Figure 5.3 shows that the combination "Extraversion-Neuroticism-Consciousness-Openness to Experience" performs better than any other combination, with the combination of all the five traits occupying second place. Therefore, in future work we could optimise the TWIN system constructing the user profile considering only four dimensions of the Big Five.

Polarity of the reviews

In the experiment described above, we did not take the polarity of the reviews into account when performing the kNN search. TripAdvisor allows its users to rate the hotel from 1 to 5 when contributing the review. Reviews that give a negative assessment to the hotel intuitively would contain more negative words, and this fact could influence the calculation of the specific personality score (e.g., neuroticism). Additionally, the amount of negative and positive reviews itself could provide some interesting insights in the type of the personality of the author.

We considered 3 classes of reviews: negative (hotel rating is less than 2), neutral (hotel rating of 3) and positive (hotel rating greater than 4). This data has been incorporated in the feature vectors to perform the kNN algorithm. Figure 5.4 and Figure 5.5 show the results of the kNN classification considering the polarity of the reviews.

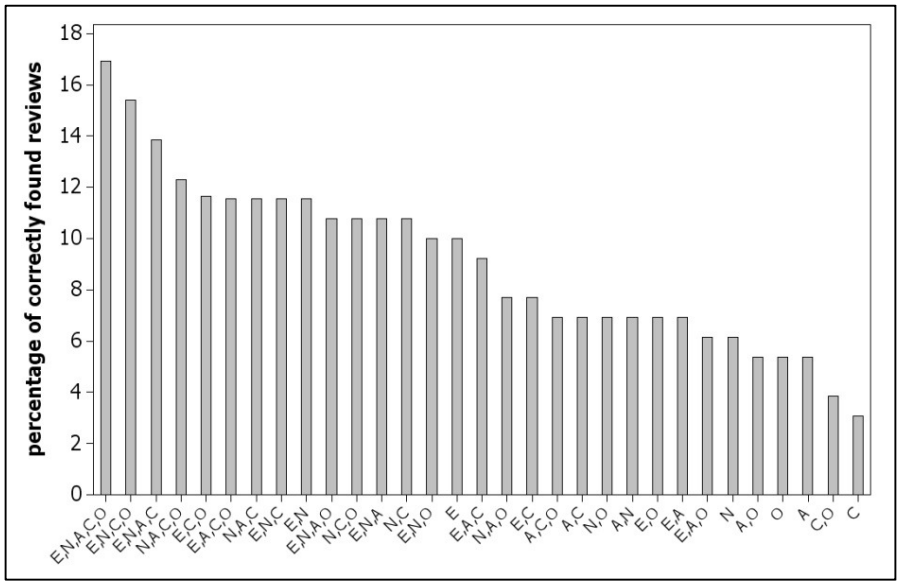


Figure 5.4: The percentage of correctly found reviews considering the polarity of the reviews and using plain personality scores as the training set.

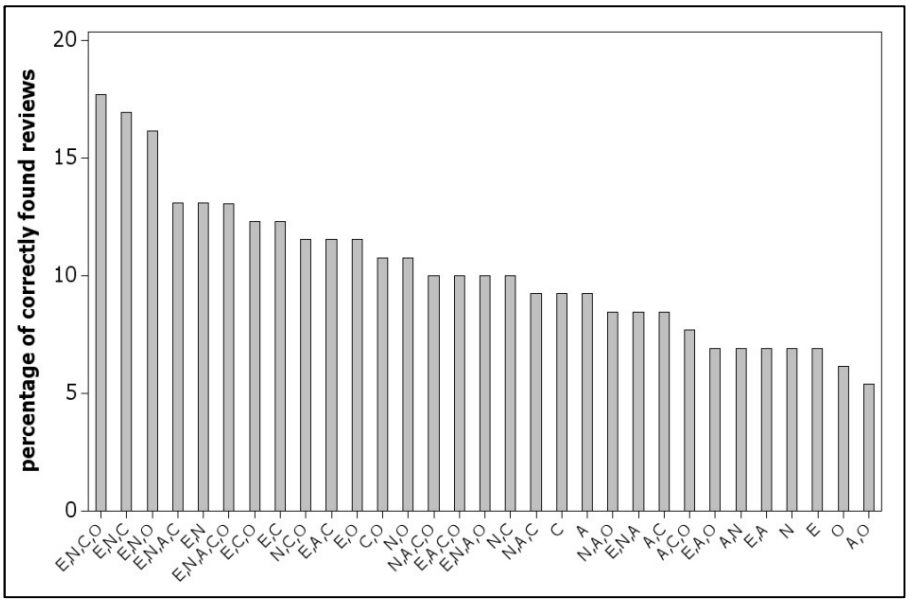


Figure 5.5: The percentage of correctly found reviews considering the polarity of the reviews and using mean personality scores vectors per person as the training set.

We performed the ANOVA test to see whether differences exist between the above mentioned methods of constructing the user profile vector. We considered four variants of the training sets: with plain reviews scores (1), with means of reviews scores per person (2), with plain reviews scores and the polarity of the reviews (3) and with means of reviews scores per person and the polarity of the reviews (4). The ANOVA test showed significant differences ($p < 0.001$) between the approaches.

In order to choose the best approach we performed Fisher's test and found that variant (1) is significantly worse compared to all the rest methods of the population of the training set. The best two approaches are (2) and (4). As the difference between them is not significant we have decided not to implement the polarity of the review calculation in the Similarity Estimator component.

Other reviews' fields

As we were working with the text of the reviews only, we did not consider other fields such as the information about the number of the hotel stars, age, gender and location of the user. All of these factors could add to the picture of the user's personality.

5.3 Summary

In this chapter we have described the possible ways of the TWIN system evaluation. We have discussed the two alternative approaches we could follow: text-based and questionnaire-based.

The Questionnaire-based approach requires constructing the circle of people who would be able to fill in the Big Five questionnaire in order to compare the real personality scores to the scores calculated from the text provided by the volunteers. We mentioned that the comparison could be made by means of the convergence analysis to reflect the dynamics of the personality estimation.

Following the text-based approach we experimented with the WEKA kNN algorithm implementation to estimate the performance of the Similarity Estimator component. We found that taking into account various combinations of Big Five traits scores produces different percentage of correctly found reviews per person. The combination of Extraversion, Neuroticism, Consciousness and Openness to Experience gives the largest percentage followed by the combination of all five traits. The overall results could not be considered very satisfactory but they are still promising and are mostly in line with the previous research. We have suggested a number of improvements to the current algorithm (considering the polarity of the reviews, etc.).

The results of the evaluation procedures do not show the correctness of the Hypothesis 3 but they do not either give sufficient evidence to reject it. It can be concluded that the suggested improvements to the current personality estimation algorithm could provide more support to the Hypothesis 3.

Chapter 6: Conclusions and further work

In this research we have developed, presented, and conducted experiments on the TWIN Personality-based Recommender System. We have investigated the challenging task of the personality from the text estimation and applied it to the TWIN Recommender System in the online travelling domain.

The main issues addressed in this work are:

1. The study of the methods and algorithms for the Recommender System construction
2. The study of the tools and techniques for personality from the text recognition
3. The collection of a TripAdvisor reviews dataset
4. The construction of the TWIN system user profile
5. The building of the Apache Tomcat-based TWIN Server
6. The development of the Flash user interface for the TWIN system
7. The implementation of the TWIN system in the online travelling domain

In order to validate the methods forming the base of the TWIN system we have performed a number of experiments. We constructed a TripAdvisor dataset consisting of 14,000 reviews written by 1,030 people. We calculated the personality scores using the Personality Recogniser tool. We have processed the results and calculated the main statistics (minimum, maximum, mean and standard deviation) for each of the Big Five traits (Extraversion, Agreeableness, Consciousness, Neuroticism and Openness to experience). For each dimension the distribution of the resulting scores has appeared to be normal.

One of the major tasks of the Recommender System construction is the development of the user profile. In order to find the appropriate structure for the profile we chose 15 people from the TripAdvisor dataset who contributed more than 35 reviews. We performed the ANOVA test to see whether the personality scores pattern varies sufficiently from one person to another. As the answer was positive we decided to use the mean score of all the reviews (for each of the Big Five parameters) written by the particular person as the estimator of his personality. The experiment allowed us to accept the correctness of the Hypothesis 1 and the Hypothesis 2.

The Personality Recogniser tool has 4 algorithms (Linear regression, M5' model tree, M5' regression tree and SVM) and we have utilised the same set of reviews as in the previous experiment to compare the performance of each of them. The hypothesis we considered is that the algorithm producing scores that differ the least for the reviews of the same author will be the best to apply for the personality recognition task in the TWIN system. We applied the ANOVA test and the Fisher's LSD test to conclude that M5' regression tree performs sufficiently better for the 4 of Big Five parameters. Therefore we have chosen it as the main personality from the text estimation algorithm for the TWIN system.

This experiment was held in order to evaluate the Similarity Estimator – the main component of the TWIN system that provides the Recommender System functionality. We were focusing on the scores of each individual review here. With the 26 people chosen, we found that the percentage of the correctly identified reviews was 10% on average. Considering the difficulty of the task of the personality from the text recognition and especially the fact that the research was based on the real world data from the TripAdvisor, we concluded that the results are satisfactory. The results of the experiment do not provide sufficient support to the Hypothesis 3 and the modification of the personality estimation algorithm is needed in order to prove the correctness of the Hypothesis 3.

The TWIN system was developed as a client-server application and applied in the online travelling domain. Its functionality was used to provide recommendations of hotels to the TripAdvisor website users with similar personality types. The estimation of the personality was based on the texts of the TripAdvisor reviews crawled and analysed for each of the TWIN system users.

6.1 Major contributions

The major contributions of this research work are as follows:

1. The application of the automatic personality from the text recognition methods to the construction of the user profile of the Personality-based Recommender System.
   In this thesis we have made an attempt to create a bridge between the personality of the person estimated from the text and personalities of other people implemented as a Recommender System. One of the main features of the resulting Personality-based RS is the absence of the need to fill in the questionnaire that is a time consuming step.
2. Generating TripAdvisor reviews datasets and experimenting with them.
   The Java crawler was constructed to collect 14,000 reviews written by 1,030 people. We have discussed a number of experiments that were performed over the subset of the

above mentioned dataset in order to develop the TWIN system. Among the outcomes of the experiments is the conclusion that Openness to experience trait is the easiest to detect while Consciousness trait is the hardest to model.

3. The development of the TWIN system

   We have provided the detailed description of the Recommender System that was proposed in this thesis, including the *Server* and *Client* parts of the application.

6.2 Further work

There are a number of experiments that could be performed in future research that we would consider to be of great interest. The following tasks are the list of the issues left for the future work:

1. Convergence analysis of the reviews' personality scores estimated from the text and from the Big Five questionnaire filled in by the corresponding author.

   In order to evaluate the performance of the currently implemented algorithm of the Similarity Estimation component we are planning to perform the convergence analysis that will show how fast the real personality scores are approaching the scores that are estimated from the text. That would give us the tool of comparing the performance of the current implementation of the Similarity Estimator and the other algorithms that we plan to evaluate.

2. The development of the improved algorithm for the personality from the text recognition.

   As the algorithm implemented in the Personality Recogniser did not show the desired results, one of the tasks for the future work is its improvement (e.g. considering other fields of TripAdvisor reviews and different linguistic cues apart from those stored in LIWC and MRC dictionaries, etc.).

3. The improvement of the user interface according to the usability recommendations.

   This step will involve changes in the user graphical interface of the *Client*: the implementation of the more efficient and optimised algorithm for the construction of the circle of nearest neighbors in the Similarity Estimator component (decreasing the response time of the recommendations calculation step), providing a more intuitive visualization of the personality in the user profile window, etc.

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Appendix A: Detailed representation of the TWIN user profile ontology

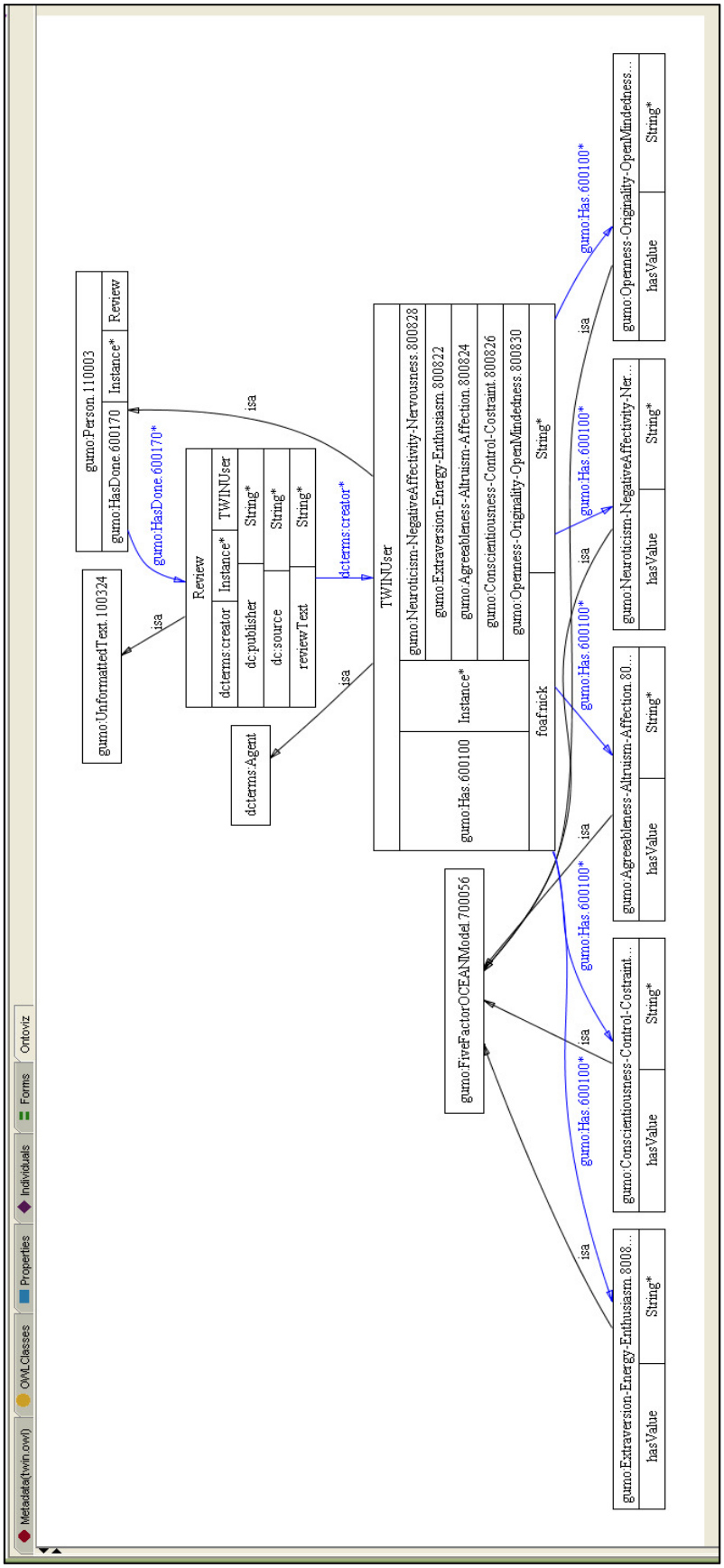


Figure A.1: TWIN user profile ontology

Appendix B: TWIN system implementation

B.1 TWIN system development

During the process of application development we have built a JSP-based website[39] with the summary of the TWIN system description. The main page of the website is represented on Figure B.2.

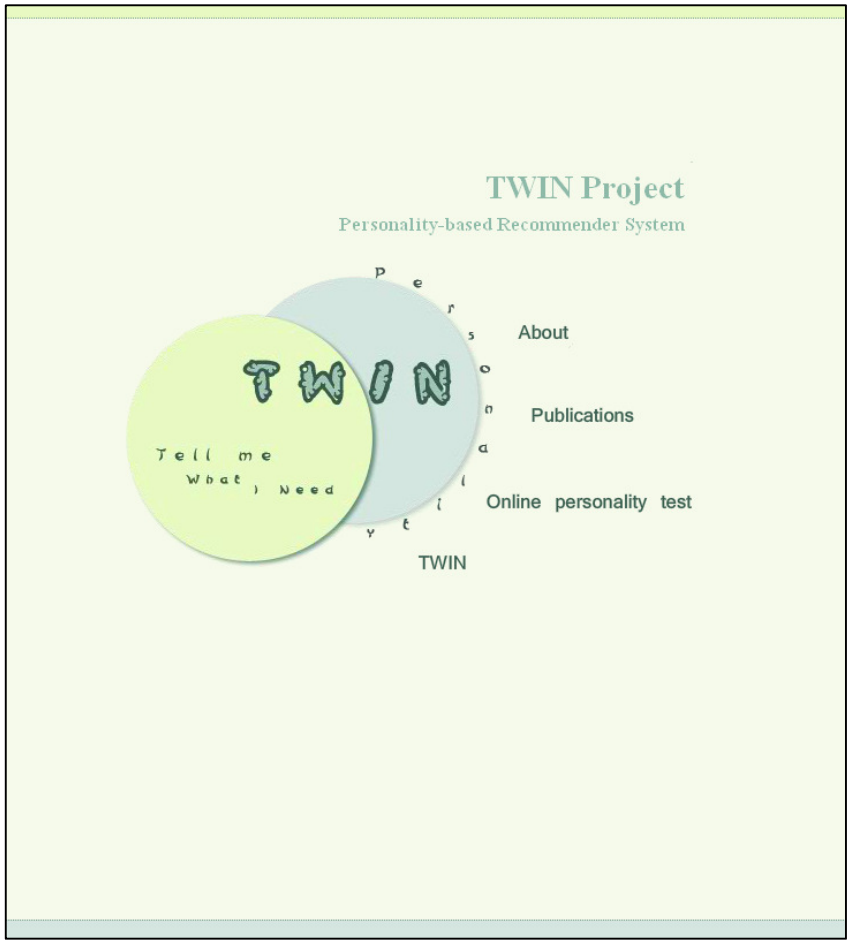


Figure B.2: TWIN system website

The structural components of the TWIN system are shown on Figure B.3. The TWIN system is built as a client-server web application. The Server part is written in Java under the Apache Tomcat server[40] and utilises the MySQL[41] database for data storage. The Client part utilises the Flash technology and is written in ActionScript3[42].

[39] http://twin-persona.org
[40] http://tomcat.apache.org
[41] http://www.mysql.com
[42] http://www.adobe.com/devnet/actionscript.html

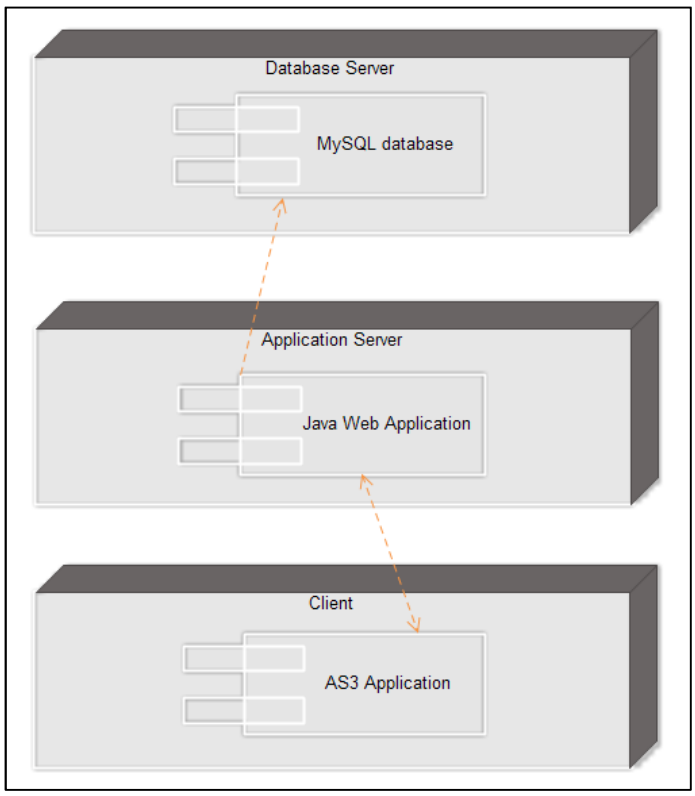


Figure B.3: TWIN system: main structural components

B.2 Architecture of the TWIN application

The detailed representation of the contents of the implemented Client and Server parts of the TWIN system are shown on Figure B.4.

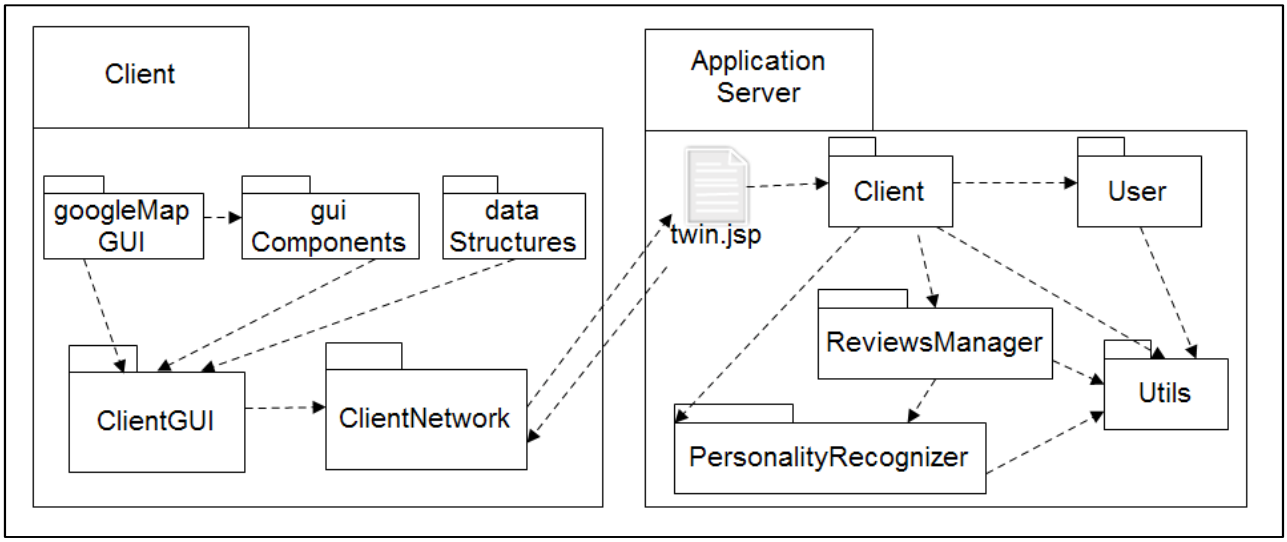


Figure B.4: TWIN system: structure of the Client and Server components

The communication between the parts is performed via http. The main functionality of the application is realised on the Server and is available to the Client through the twin.jsp web page. The page provides an interface to save the new user data, to get hotels recommendations, get the user RDF profile description and a number of additional functions (such as caching the latitude and longitude returned by the Google Maps flash API, etc.).

Figure B.5 shows the structure of the classes of the Client graphical user interface. The ClientGUI.MainWindow class is the entry point and it includes all the main functionality. It loads the rest of the windows on request.

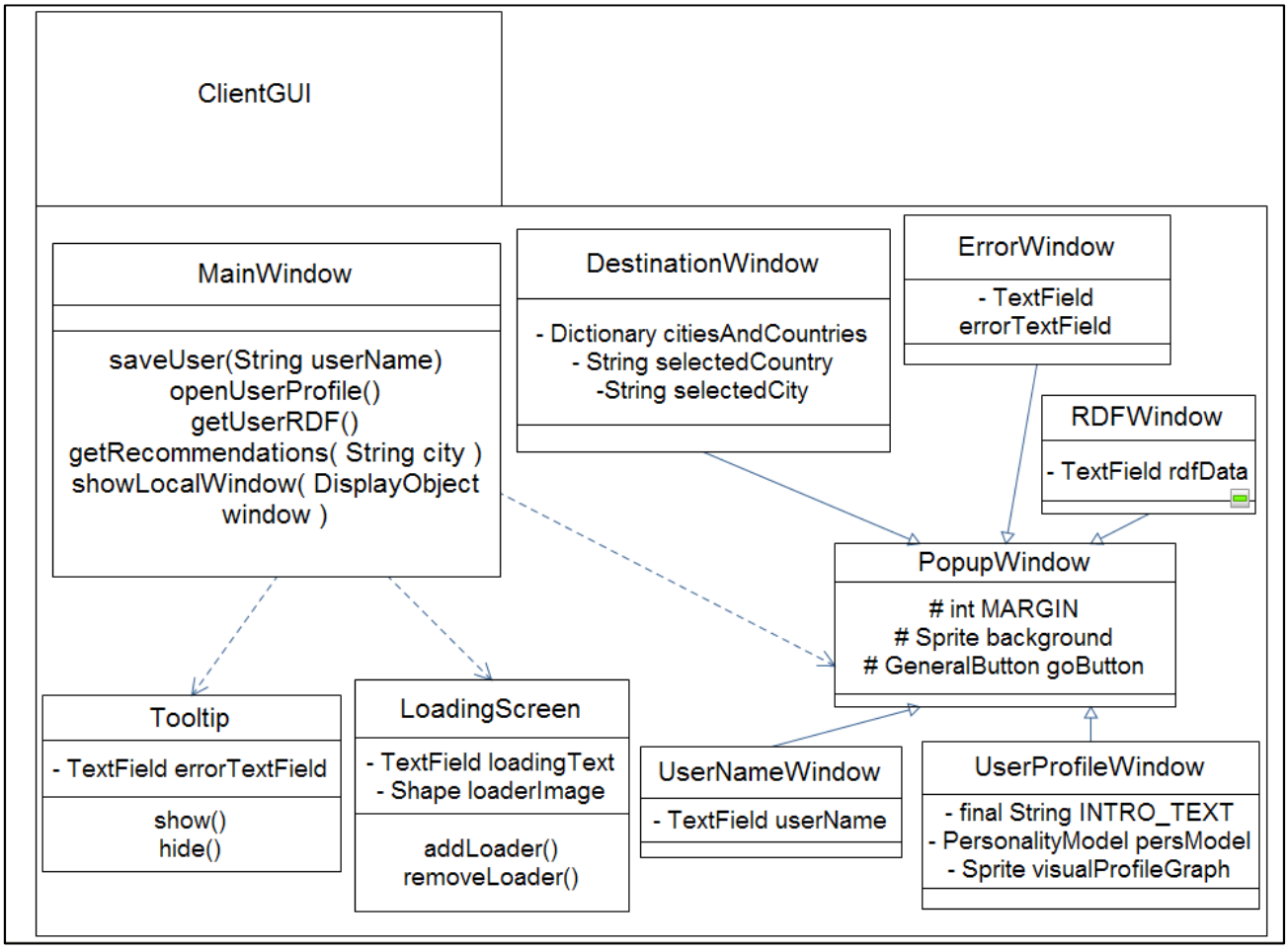


Figure B.5: Client. ClientGUI package contents

The other GUI windows are inherited from the ClientGUI.PopupWindow class which sets the dimensions of the window, adds the closing button and the drag&drop effects. ClientGUI.UserNameWindow is the first window that the user is presented with. It simply requests the existing TripAdvisor name from the individual and sends it to the Server in order to crawl the reviews from the TripAdvisor user profile. ClientGUI.ErrorWindow displays the errors

that could occur in the process of connecting to the server, opening the database connection, reviews crawling, personality calculation, etc. ClientGUI.RDFWindow shows the user profile data exported in the RDF format following the TWIN user profile ontology mentioned above. ClientGUI.UserProfileWindow shows the main representation of the calculated personality and will be discussed in details in the following Section. ClientGUI.Tooltip and ClientGUI.LoadingScreen are additional classes utilised to provide broader descriptions of the Big Five traits and to indicate the loading process accordingly.

ClientGUI.MainWindow communicates with the Server via the ClientNetwork.ServerConnection class shown on Figure B.6 and stores the response in the serverResponse variable. The response in the String format is further parsed and its components are passed to the appropriate handlers.

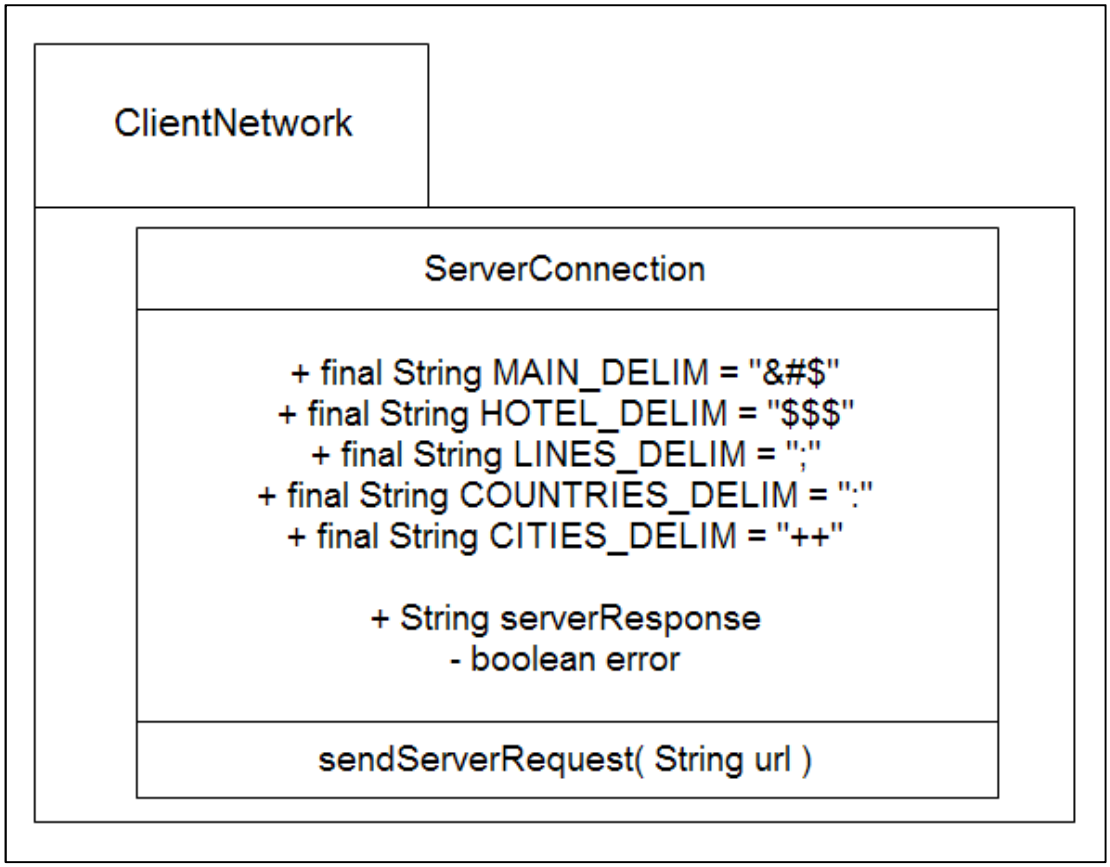


Figure B.6: Client. ClientNetwork package contents

The Server utilises Client (see Figure B.7) and User (see Figure B.8) packages to process the data sent by the Client application. It stores the main user parameters (name, review information and Big Five personality scores) in the database. It calculates the recommendations of the hotels

applying the kNN algorithm to the users' personality vectors. Additionally the Server performs the conversion of the user data to RDF format in User.UserProfileManager class.

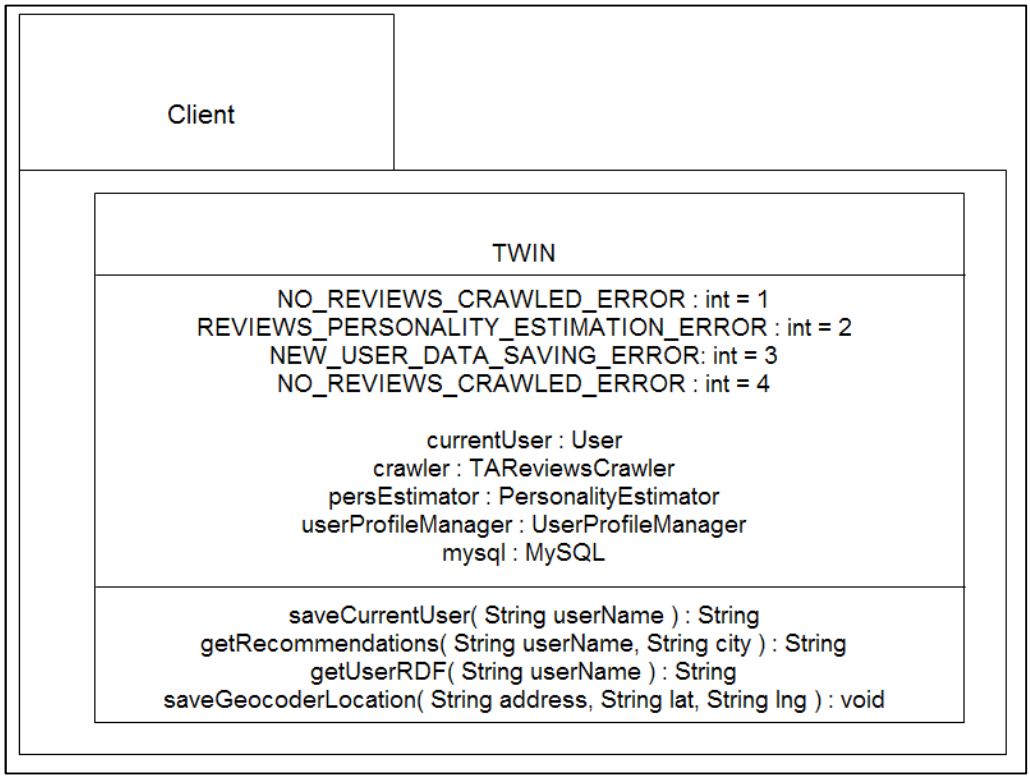


Figure B.7: Client package of the Server

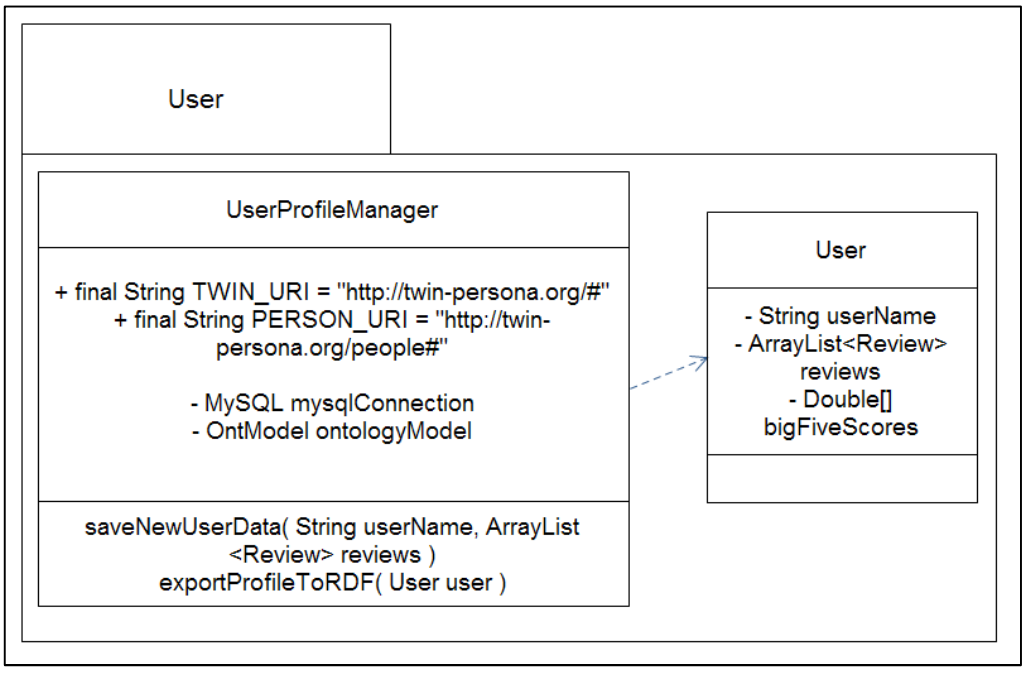


Figure B.8: User package of the Server

In order to crawl and process (calculate the personality scores) the reviews of the user the ReviewsManager package is used (see Figure B.9). It utilises the PersonalityRecogniser classes and the ReviewsManager.TripAdvisorReviewsCrawler. The retrieval and the processing of the TripAdvisor HTML pages are performed through the Java API of the Selenium web browsers automation tool by means of XPath language[43]. This class saves the text of the review with the information about the hotel (name, address, region, country and city).

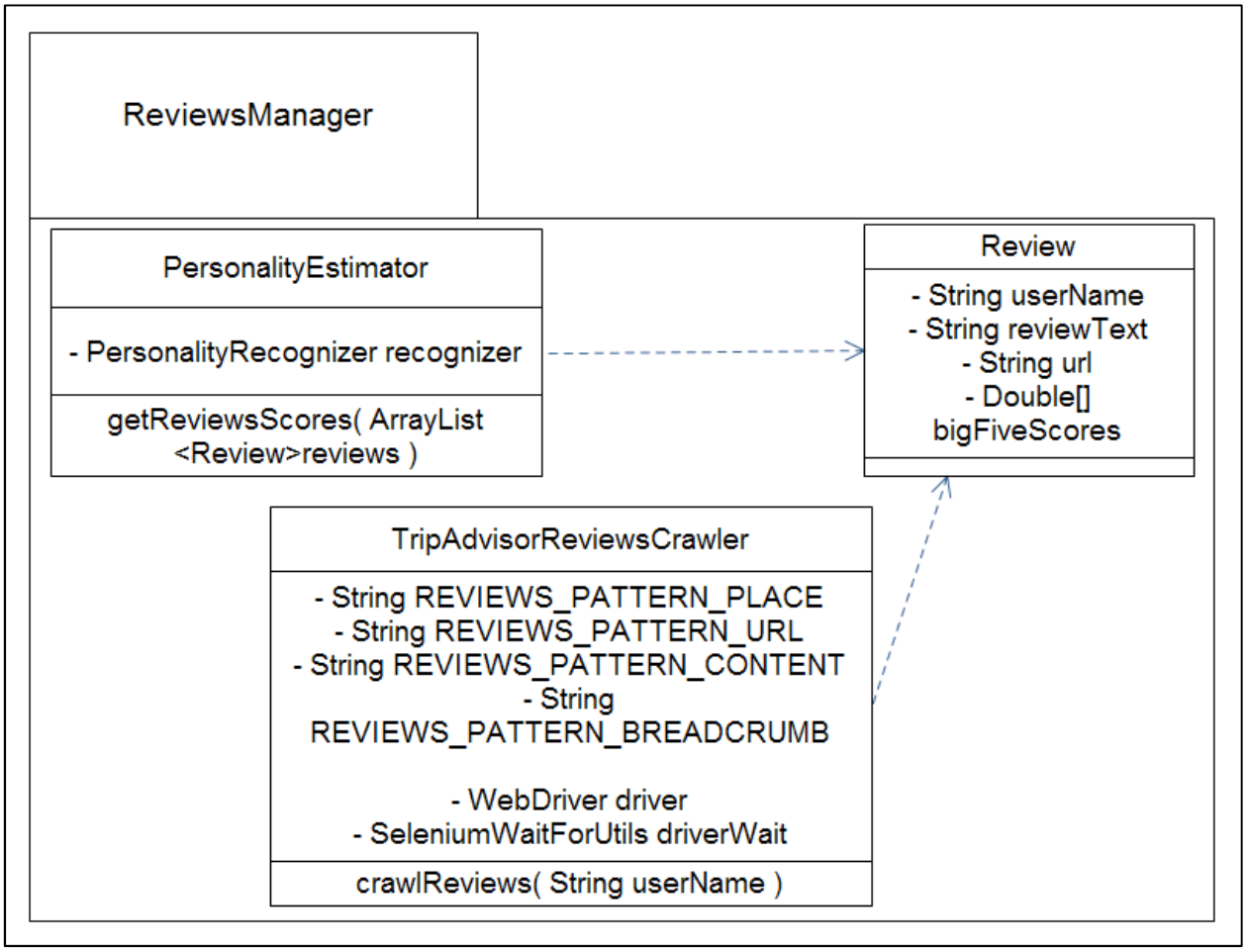


Figure B.9: ReviewsManager package of the Server

The results of the recommendation procedure (kNN LinearSearch among other user profiles) are sent to the Client and visualised on the Google Map. The contents of the Client GoogleMapGUI package are shown on Figure B.10.

[43] http://www.w3.org/TR/xpath/

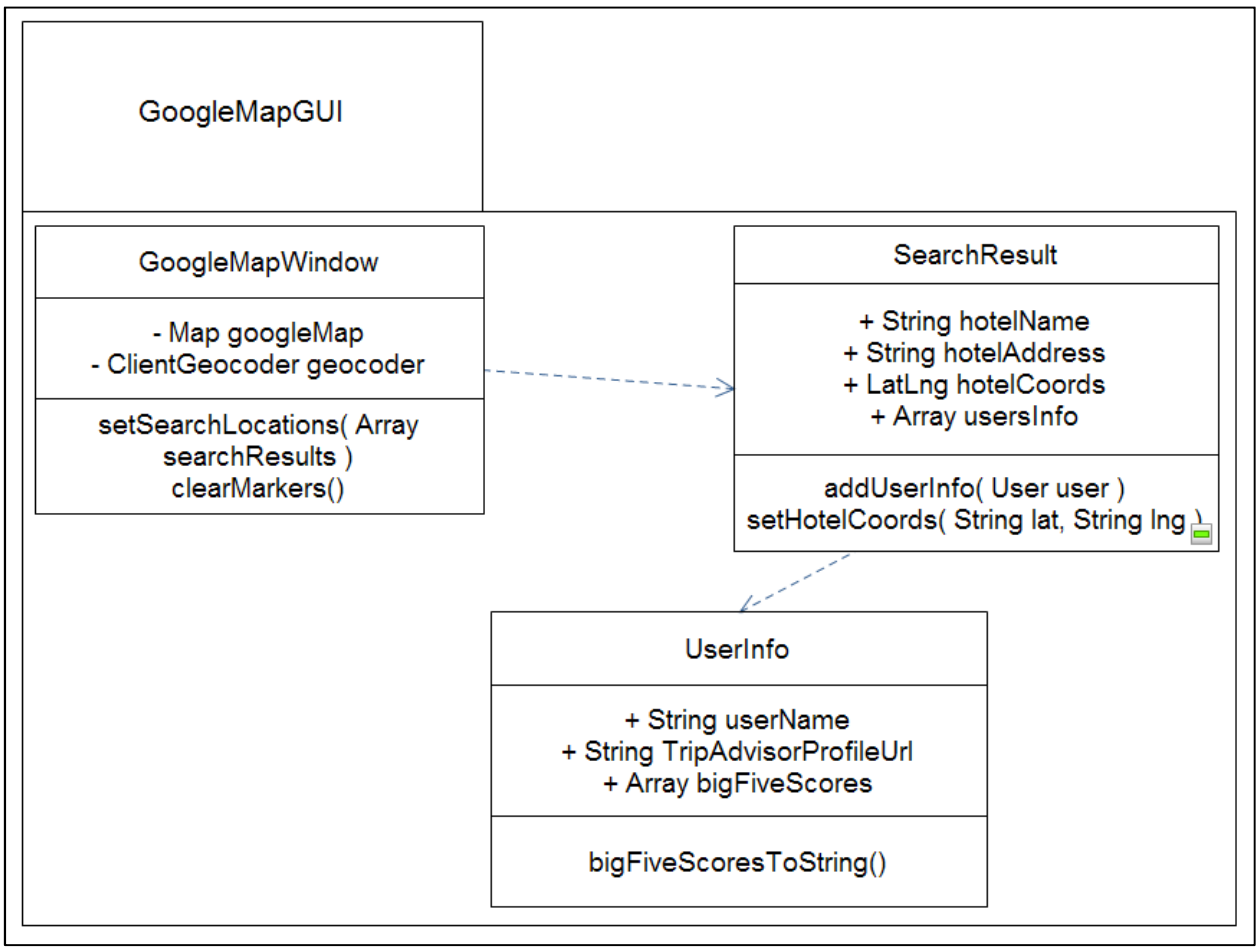
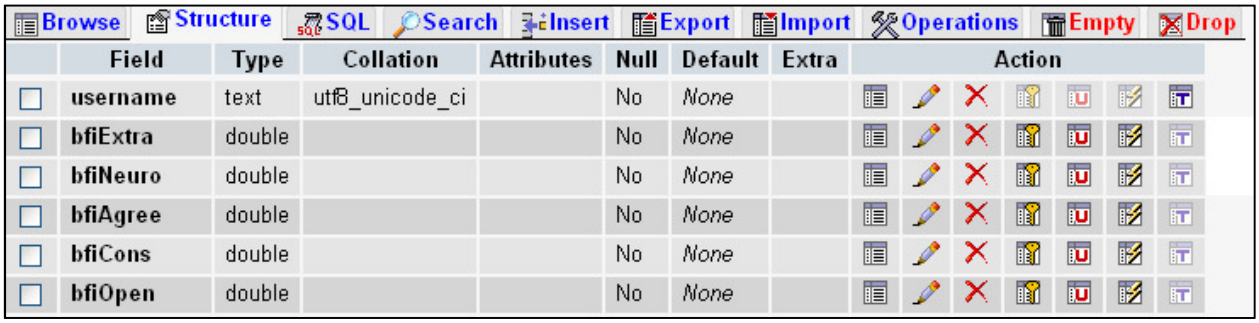


Figure B.10: GoogleMapGUI package of the Client

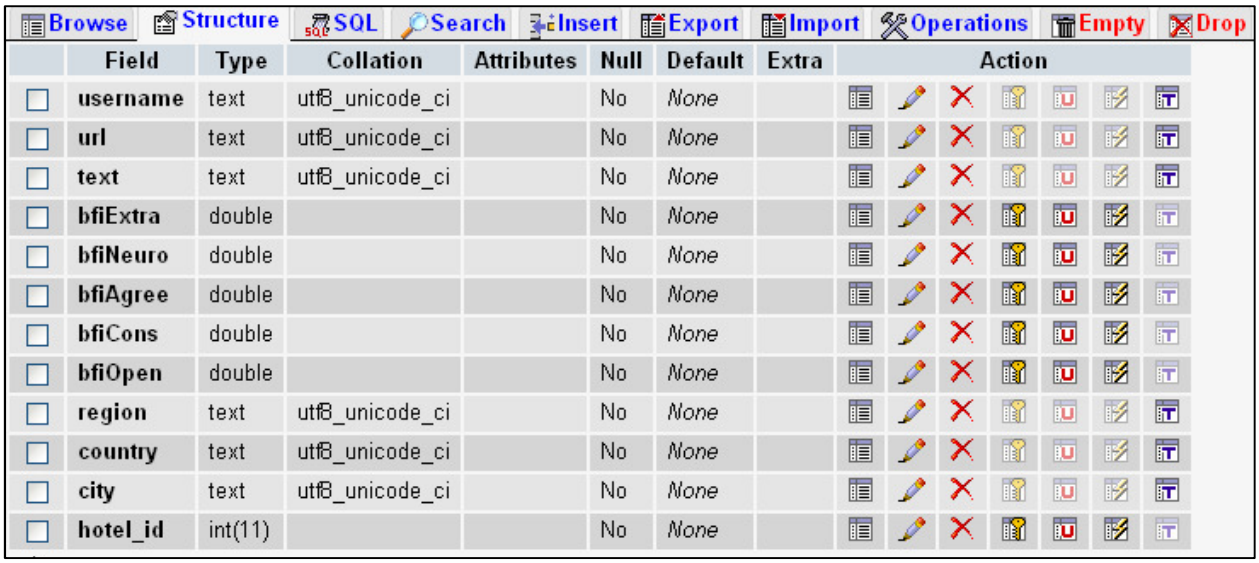
B.3 Data structures

All information required for the TWIN system is stored in three MySQL tables: “twin_users”, “twin_reviews” and “twin_hotels”. The user profile information is saved in the “twin_users” table that has the structure shown in Figure B.11. Reviews of each of the people are saved in the “twin_reviews” table that has a structure shown in Figure B.12. Each review has the author, the url, the text of the review itself, the values of the Big Five scores and the information about the hotel (region, country, city and hotel_id). The structure of the “twin_hotels” table is shown in Figure B.13 including the name of the hotel, its address, its latitude and longitude (the last fields are used to visualise the hotel on the GoogleMap).



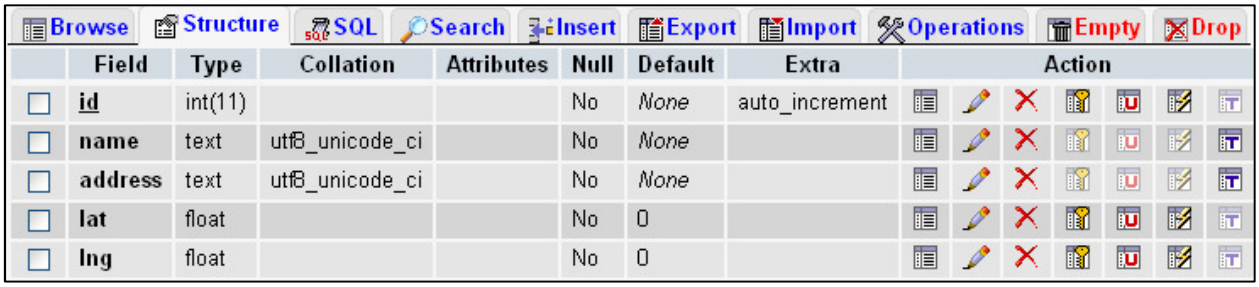
	Field	Type	Collation	Attributes	Null	Default	Extra	Action
☐	username	text	utf8_unicode_ci		No	None		
☐	bfiExtra	double			No	None		
☐	bfiNeuro	double			No	None		
☐	bfiAgree	double			No	None		
☐	bfiCons	double			No	None		
☐	bfiOpen	double			No	None		

Figure B.11: The structure of the twin-users table



	Field	Type	Collation	Attributes	Null	Default	Extra	Action
☐	username	text	utf8_unicode_ci		No	None		
☐	url	text	utf8_unicode_ci		No	None		
☐	text	text	utf8_unicode_ci		No	None		
☐	bfiExtra	double			No	None		
☐	bfiNeuro	double			No	None		
☐	bfiAgree	double			No	None		
☐	bfiCons	double			No	None		
☐	bfiOpen	double			No	None		
☐	region	text	utf8_unicode_ci		No	None		
☐	country	text	utf8_unicode_ci		No	None		
☐	city	text	utf8_unicode_ci		No	None		
☐	hotel_id	int(11)			No	None		

Figure B.12: The structure of the twin_reviews table



	Field	Type	Collation	Attributes	Null	Default	Extra	Action
☐	id	int(11)			No	None	auto_increment	
☐	name	text	utf8_unicode_ci		No	None		
☐	address	text	utf8_unicode_ci		No	None		
☐	lat	float			No	0		
☐	lng	float			No	0		

Figure B.13: The structure of the twin_hotels table

B.4 Graphical user interface of the TWIN application

This Section provides the screenshots and the descriptions of the windows of the graphical user interface.

The first screen that the user is presented with is a Log in window that requires the existing TripAdvisor user name to start the process of calculating recommendations (see Figure B.14).

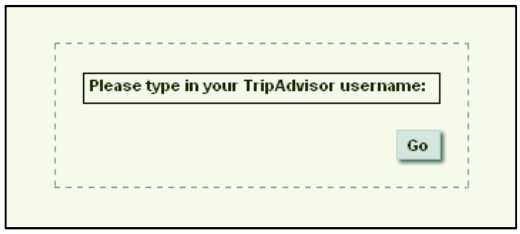


Figure B.14: Logging in into TWIN

Figure B.15 shows the loading screen and a semi-transparent error window that appears whenever the Server experiences a problem with the connection to the database or any other error happens.

Figure B.15: The semi-transparent error window and the loading screen beneath

The visual representation of the main window with all the interface elements is shown on Figure B.16. The name of the current user is displayed in the top left corner of the window with the Log out button. The navigation buttons ("View profile" and "Please, fill in the questionnaire") are in the right top corner. The questionnaire link leads to the webpage with the Big Five inventory.

In the middle of the main window there is the ClientGUI.DestinationWindow which allows the user to choose the destination country and city to search for the hotel. Currently there are 3,000 test profiles loaded into the system. Therefore, the number of countries and cities available for

searching depends on the countries and cities of the hotels that were described in the reviews of the above mentioned people. Obviously, each new user adds new possible destinations to the list.

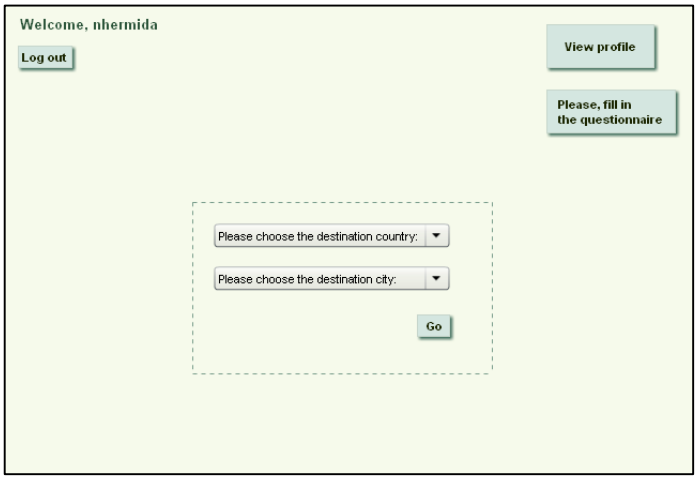


Figure B.16: Main GUI elements of the TWIN interface

The profile of the user is shown on Figure B.17. The personality data is depicted on the polar graph. Each of the Big Five dimensions is represented by its own color and the ClientGUI.Tooltip is used to show the values of the personality scores (using the 1 to 7 scale) on the mouseOver event as well as the description of each of the personality traits. The profile also includes links to the real TripAdvisor user profile ("TripAdvisor profile link") and the ClientGUI.RDFWindow ("Show user RDF"). The example of the ClientGUI.RDFWindow is shown on Figure B.18.

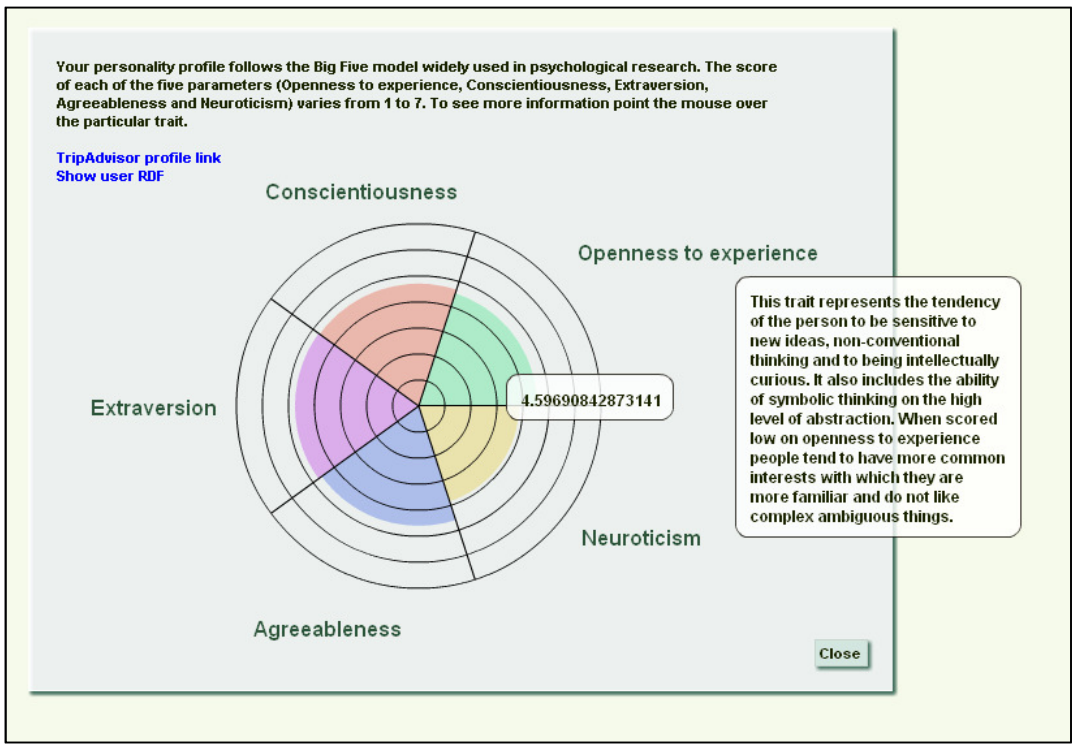


Figure B.17: TWIN user profile window

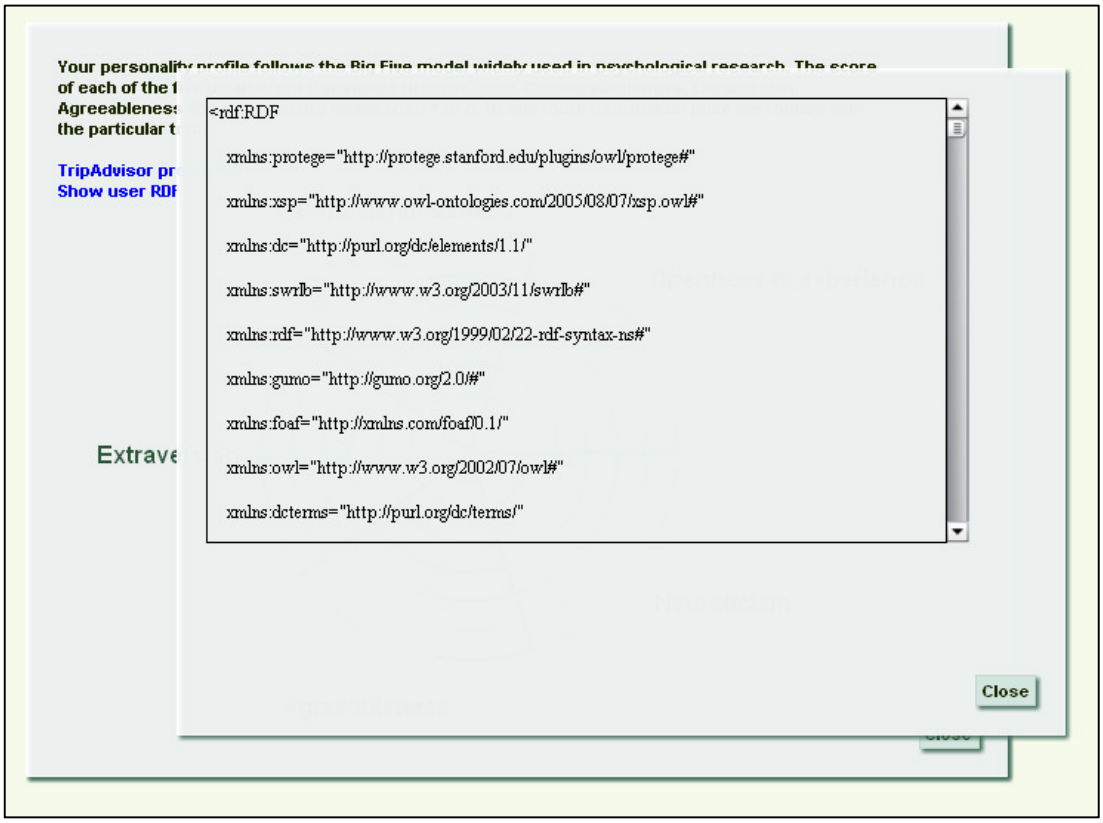


Figure B.18: RDF representation of the user profile data

The results of the recommendation algorithm are visualised and each found hotel is represented as the marker on the Google Map based on the address of the hotel. The address is saved during the reviews crawling stage and the latitude and longitude are requested via the Google Geocoding service[44]. The window with the search results is shown on Figure B.19. For each of the found hotels the name of the hotel, its address and the list of users' reviews (with the link to the user profile and the link to the review on the TripAdvisor website) are displayed.

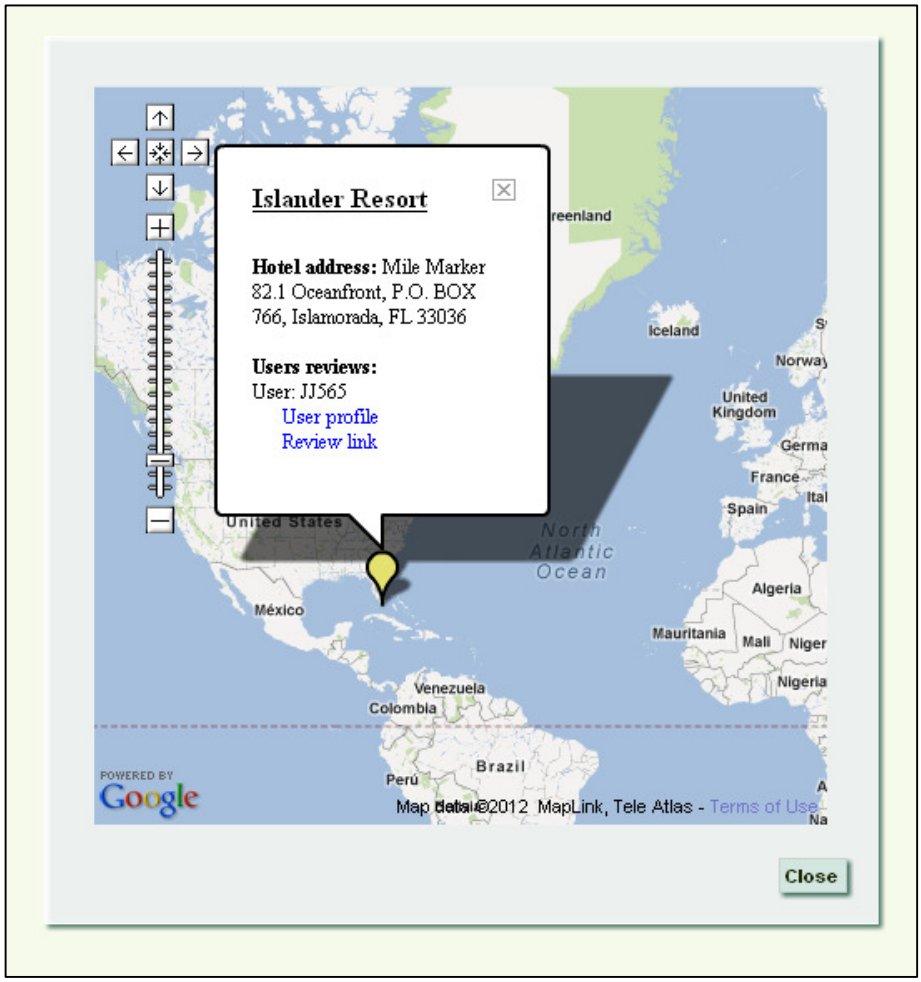


Figure B.19: Results of the recommendation on the Google Map

B.5 Summary

In this chapter we have provided the detailed description of the TWIN system components: the *Server* (written in Java) and the *Client* (Flash-based GUI). We gave the link to the deployed TWIN system that is currently available online in demo mode.

[44] http://code.google.com/apis/maps/documentation/flash/services.html#Geocoding

We described in detail the contents of the Java and ActionScript packages of the *Server* and the *Client* and the relationships between constructed classes. We have shown the structure of the MySQL tables that contain the data required for the application to work.

In the last Section we have provided the overview of the graphical interface with the screenshots of the deployed TWIN application: *log in window* to provide a TripAdvisor username, *main interface window* with the selection of available destinations, *user profile window* with the visualization of the user personality data (Big Five traits with corresponding scores), *RDF user data window* showing the RDF representation of the information about the user and the *results window* with the sample recommendation result set.