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Resumen

Un sistema de recomendación sensible al contexto analiza las necesidades y preferencias de los usuarios con el propósito de recomendar items utilizando la información contextual que describe la situación actual del usuario. En esta tesis se propone un método para sistemas de recomendación sensible al contexto que puede ser aplicado en diferentes dominios para mejorar las recomendaciones utilizando la información contextual en un método de recomendación híbrido. El método involucra diferentes técnicas que trabajan simultáneamente para obtener las recomendaciones: filtrado colaborativo, basado en contenido y un Sistema de Inferencia Difuso para procesar reglas y atributos difusos. Posteriormente, las recomendaciones son filtradas por los factores de contexto que representan la situación actual del usuario. En esta tesis se analiza el trabajo relacionado y destaca las principales contribuciones del método, presentando resultados de un extensivo conjunto de experimentos que validan el método propuesto.

Abstract

The context-aware recommender system analyzes the needs and preferences of users in order to recommend items using contextual information that describes the current situation of the user. In this thesis a method for context-aware recommender system was proposed, this method can be applied in different domains to improve the recommendations using contextual information in a hybrid recommender method. The proposed method involves several techniques that working simultaneously to get recommendations: collaborative filtering, content-based and Fuzzy Inference System to process rules and fuzzy attributes. Subsequently, recommendations are filtered by contextual factors that represent the current situation of the user. This thesis presents an analysis of related works and highlight the main contributions of the method, presenting results of an extensive set of experiments that validate the proposed method.

Contents

List of Figures

List of Tables

Chapter 1

Introduction

The purpose of this research is to make a contribution in the application of contextual information in recommender systems by proposing a methodology for the development of context aware recommender systems. The method follows an hybrid approach by using integrating several recommendation techniques through a fuzzy inference system. The proposed method was validated by by the execution of several experiments, and the immplemantion of a case study and the collection of contextual information through questionnaires. The results presented are favorable indicating the strnghts of the hybrid method.

1.1 Motivation

Often people need take decisions, even when they do not have enought experience or information to decide among the possible alternatives. For this, is common for people to seek help by asking friends or people which they have certain level of affinity for recommendations.

This problem is aggravated by the large amount of information generated by society resulting in an information overload where users are not capable of identifing the relevant information from the irrelevant. This lack of experience, time and other resources highlights the need of automatic or semi-automatic methods to filter relevant information. Currently information filters are an integral component of the Web where for instance automatic search engines help users to find or make decisions through (some times) personalized recommendations of products and services. On the other hand, in recent years mobile computing has drasticaly incremented its importance, because of the impact of its use in daily life, if an application is available in a smartphone it can be used allmost anywhere, and thanks to sensors and GPS technology location aware applications are common. New technologies also consider information about the current situation of the user in mobile applications as intelligent systems can take advantage of the benefits that this technology provides to manage the context that changing constantly. Mobile and ubiquitous computing[55]

[23] are proposing a wide variety of applications that need recommendation engines using context to meet their purpose. But still there is a need to model the information available in the system in order to provide context awareness. Information regarding context can also be described in natural language in a fuzzy manner. For instance when describing her currgitent situation a user could say: “Is early in the morning and I am currently near my work and I need to find a coffe shop that expensive, is open and not very far”. This sentence uses many words to describe the situation that are not crisp and instead the description uses fuzzy variables to describe context.

1.2 Context of use

Context is an important concept in everyday life. People often provide context when writing postcards referring to the weather or the holiday atmosphere. A knowledge of context can also help to explain why certain object was produced or designed the way it is.

When a product (or system) is developed, it will be used within a particular context. It will be used by a user population with certain characteristics. The user will have certain goals and wish to perform various tasks. The product will also be used within a certain range of technical, physical and social or organizational environments[50] that may affect its use.

We can refer to these environments as the *context of use*(see figure 1.1), this concept has been formally defined by ISO standard 9241-11[32] as *"users, tasks and equipment(hardware, software and materials), and the physical and social environments in which a product is used"*. In daily life we often find products that are difficult to use or understand. This type of difficulties are *usability problems* that arise from diverse issues that have not been addressed in the design of the product's *user-artifact interaction*. The *user-artifact interaction* refers the way that the user interacts with a product and vice versa, this term has been studied in Human Computer Interaction.

As emerging technologies constantly change the way people interact with products and their physical environment, recent studies have started looking at *human experience* as a source to generate products or systems that *engage* the user.

The *user experience*, *context of use* and *product usability* have been associated in computer sciences field. The *Usability* is became a well-established concept in the IT world to represent the user-friendliness of a system. However, there was a need to establish the concept more clearly and to determine how to measure it. Probably the best known definition of usability is by Nielsen[54]: *"usability is about learnability, efficiency, memorability, errors, and satisfaction"*. However, the definition of usability from ISO 9241-11[32]: *"the extent to which a product can be used by speci-*

fied users to achieve specified goals with effectiveness, efficiency and satisfaction in a specified context of use", is becoming the main reference of usability.

Thus, taking in account these definitions we can say that designing for *usability* involves establishing user requirements for a new *system* or *product*, developing design solutions, prototyping the system and the user interface, and testing it with representative users.

In the study of Sato[66] that brings *context issues* into design practice, addressed the concept of *context* as a critical component of the design information in order to enhance the *human-centred design practice*. After a literature's revision for definitions of *context* in diverse fields, Sato explains that there are external and internal conditions into the definitions and suggest that it has four characteristics:

1. Aspects of context are based on the nature of actions and conditions.

2. Descriptions depends on the focus of the viewpoints.

3. Contextual changes are triggered from differents elements of the domain.

4. Context evolves over the time, some aspects change fast and others change slow.

From this, Sato defined *context* as a *mental model* or a *pattern of one's memory* triggered by *elements in the situation*, where situation is a collective condition at the scene of interaction composed of relations among *variables of conditions*. Sato employed this concept to describe the *influence of contexts* in *people's interactions* and *system performance* and vice versa.

In this thesis we present first a *logical model* that explains the relationship between *context*, *contextual information* and *contextual factors*. Figure 1.1 gives a graphical representation of these relations. The goal is to facilitate the use and implementation of fuzzy context in recommender systems for different domains.

In the figure 1.1, the first box shows different real life situations of the user (contexts), the user can changes from situation to situation in a little time or a long time, this situational or contextual information in the real world provides the abstract knowledge that the system will use to determine the *"contextual information"* that will be used. From the real world specific data will be extracted by different means as sensors, user interaction or even manual input. In this work we call this data *"contextual factors"*(for instance, place and orientation, preferences, date and time, etc.) and represents the information that affects the recommendation process. The information could be represented as fuzzy variables or crisp variables depending of its domain values. Later, contextual factors are implemented as data structures that define the domain proposed for each one. The number of possible values varies for each application and is in this point where the designers take decisions about

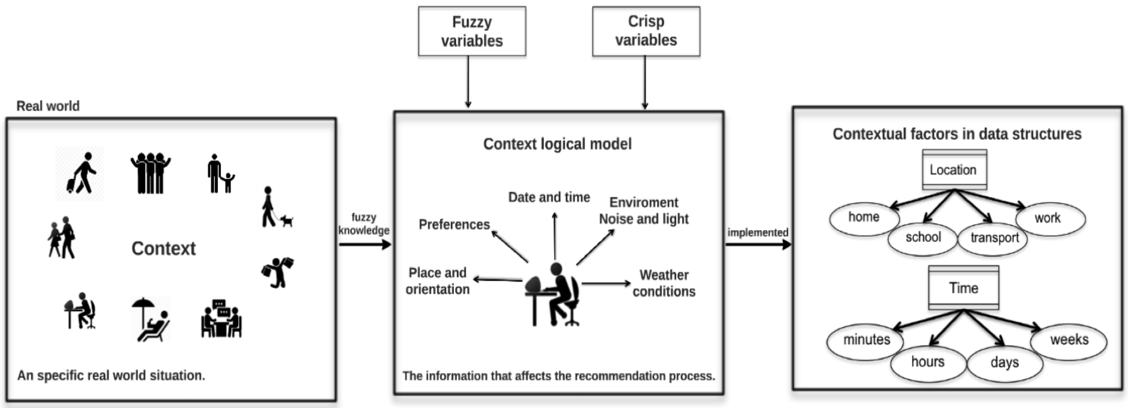

Figure 1.1: Logical data model of context for an application.

the properly data structure that it will be implemented.

1.3 Context-awareness

Traditional recommender systems provides suggestions of useful items for a certain user. The suggestion relates to various decision-making processes, for instance, what items to buy, what music to listen to or what on-line news to read. *Item* is the general term to denote what product or service the system recommends for each user. A recommender system normally focuses only on a single type of item [64]. The improvement efforts for previous recommender systems have been mainly focused on the *integration of context* in the recommendation process. The idea behind *context-aware computing* is to provide information or services for the user based in the user's situation [26]. In order to do that, the application needs to obtain situational data, process it and make use of it in a manner that benefits the user.

Context is a concept that is not easy to define, as it is related with several disciplines that propose different definitions. For example, the authors Bazire et.al.[15] compare the notion of context in different fields and conclude that is complicated to make a unifying definition of context because of the nature of the concept in many disciplines. In computer science Fischer[30] defines context as *"the interaction between humans and computers in socio-technical systems that takes place in a certain context referring to the physical and social situation in which computational devices and environments are embedded"*. Fischer also identifies the important aspects to consider when the context is used: how it is the contextual data obtained, how the context is represented and what goals and purposes the context has when is used in a particular application.

Probably the definition most used in the field of recommender systems to define *context* is proposed by Dey[26]: *"Context is any information that can be used to characterize the situation of an entity. An entity is a person, place or object that is considered relevant to the interaction between a user and an application, including the user and applications themselves."* This definition makes it easier to define the contextual factors in a specific application. For instance, in a tourist guide application the entities can be companion(friends, family, couple), place of interest, season and weather, these could be considered as relevant contextual factors that help the

recommender system to provide items adjusted the situational data of the user.
Context-aware recommender systems are gaining even more attention because of their performance and implementation for different domains, the way to improve personalized recommendations based in contextual factors is an important technique to increase the benefits in many domains. For instance, taking in account the *hour of the day*, or the *day of the week* when recommending restaurants could filter out restaurants that are currently closed or near closing time, when the user receives this information in real time, the user has the way for taking alternatives of restaurants that provide services. Nowadays, many companies are incorporating some type of context (as time, location or companion) in their recommendation engines, the application can be found in fields such as e-commerce[68] [18], music[65] [12] [41], places of interest[14], movies[29], vacation packages[48] [49], travel guides[67], e-learning[56] and restaurants[24].
Plus, context can be used to improve the user satisfaction in recommender systems, thus the quality and accuracy of predictions is improved too.

The method proposed in this thesis uses three recommendations techniques, applied as a Case Study in a restarant domian:

1. *Expert's Fuzzy Inference System*, this is a rule based recommender defined by an expert in the domain, in the case of a restaurant recommender it consid-

ers the following variables: *ratings average: low,medium and high*, *price of restaurant: cheap, average and expensive*, and *number of ratings of item: few, several and many*, these variables are used to infer how relevant a restaurant is for the user. This recommendation is based on the popularity of each item in the user community.

2. *Content-based technique* utilizes the item profiles to compare how *similar* is an item with respect to another, i.e. restaurants that are *similar* (same cuisine, ambient, price range) to others that the user has rated high. The idea is to find items with similar features.

3. *Collaborative filtering technique* is based on the user profile to identify user's preferences and to find neighbors that have the same tastes. The recommendation consist in the suggestions of other users with similar tastes that rated restaurants again in a similar way but where have not been rated by the current user. A Top-N list of restaurants is obtained to recommend for the user.

The results of the three techniques are a list of recommendations for the user, later, these recommendations are adjusted for the current context. This is the last step and is represented as a *context filter* in the method, as a result a list of contextualized recommendations is obtained.

In the method, each technique works simultaneously to obtain recommendations, the hybrid method allows to generate suggestions even without user information, i.e., using content-based technique or the fuzzy inference system, so the system faces the cold-start or the overspecialization problem using these thechniques, these problems are described in section 3.3.1 and 3.3.2, respectively.

To evaluate the performance of the proposed recommender several experiments were maded, the algorithms were tested using contextual datasets and the number of contextual factors used varied according to the information provided by the dataset. The goal of the experiments were to observe the role of contextual data in the performance of the algorithms and to have a better understanding of what contextual factors are more important for users in a specific situation, how recommendations are improved using context and, the accuracy in recommendations.

Chapter 5 shows the results while discussion about results are explained in each section.

As a user-cenetered system another important aspect to consider and measure is the *user satisfaction*, for this two metrics were used: *task-success* and *time-on-task*. These usability metrics allow designers to measure the user experience.

Usability metrics can help reveal patterns that are hard or even impossible to see. Evaluating software applications with a small sample size (between 5 and 8 tests) usually reveals the most obvious usability problems[6].

Then, as a general rule of thumb, during the early stages of design, it needs fewer participants to identify the major usability issues. As the design gets closer to completion, the tests should include more participants to identify the remaining issues[6].

Following this precept, ten representative users were selected to test the system, subsequently, it was realized an analysis about the system performance and issues presented in the user interaction. The chapter 6 explains the process to evaluate the system and the results obtained.

1.4 Aims

The contribution is to propose a method for context-aware recommender systems using different techniques of recommendation, another aim is to provide a *useful knowledge* to utilize a hybrid method that is easily implemented in different domains such as e-learning, movies, music, tourism, etc. In this particular case, the restaurants domain is used as a case of study to test the method.

Another important contribution is the use of fuzzy rules in the proposed method, this allows the use of linguistic information closer to the real context of the people, i.e., the method uses this technique to analyze the user preferences and get recommendations based in that information. For instance, the system provides a list of range of prices, this allows the user to select a specific range of price to get recommendations adjusted for the tag selected.

In order to support the achievement of contributions, the particular aims of this thesis are the following:

- Elaborate an analysis about the state of the art in the field of context-aware recommender systems through the revision of the relevant literature.
- Selection of algorithms that representative of the alternatives for this problem domain in order to compare their perfomance.
- Design and cunduct several experiments with the proposed algorithms.
- Based on the previous experiments and results, propose a hybrid method and apply it in a case of study.
- Define the fuzzy inference system that serves as recommender technique in the proposed method, as well as the variables and fuzzy rules involved.
- Develop a prototype of a context-aware recommender system using the proposed method.
- Evaluate the proposed method using usability metrics.

1.5 Outline

The rest of this thesis is organized as follows:

- **Chapter 2** describes an in-depth study and background of current and related work, presenting a general overview of recommender systems and their evolution in recent years. This study includes traditional recommender systems, their methods and techniques to improve recommendations, aswall as the challenges of these systems. Subsequently, hybrid methods used in different applications, their limitations and advantages for each hibridation and the domains of application. Finally, context-aware recommender systems are disscussed, in the same way, with an analysis of the advantages and disadvantages of the use of context in recommender systems.

- **Chapter 3** describes the fundamental concepts that form the basis of the proposed method.

- **Chapter 4** presents a model of context-aware recommender system, the proposed method involves the paradigm of post-filtering in a restaurants domain. This chapter includes the overall explanation of data models and the functionality, as well as its components for this case of study.

- **Chapter 5**, the general results of different projects involved are presented along with the validation of every experimentation. The experiments were realized using different datasets and different algorithms in order to find an optimal manner to reduce the error level. This chapter also details the results for each experiment from a point of view of scientific results.

- **Chapter 6**, after the development of context-aware recommender system, the impact of context in recommendation process was evaluated. This chapter describes the usability tests that were applied on-line in order to evaluate the satisfaction of users. Details of the environment and the characteristics of the tests are described, as well as the results of each one.

- **Chapter 7**, this chapter concludes with a summary of its contributions and limitations. Final conclusions are drawn and also proposals for future work are presented.

At the end, this thesis includes several appendices describing detailed technical aspects of the context-aware recommender system *(appendix C)*, the pseudocode of algorithms *(appendix A)*, interfaces of the prototype of context-aware recommender system *(appendix D)* and experiment study materials *(appendix B)*.

Chapter 2

State of the art

In this section the state of the art in conventional and context aware recommender systems is presented.

As a technology recommender systems have beem applied in many domains, and sometimes they represent the key technology for the success of web and mobile applications.

Some works utilize social information to recommend such as Manca et.al.[51] where the friend recommender system is applied in the social bookmarking domain, its goal was to infer the interest of users from content selecting the available information of the user behavior and analyzing the resources and the tags bookmarked for each user, therefore the recommendations are through mining user behavior in a tagging system, analyzing the bookmarks tagged of the user and the frecuency for each used tag. J.Yao et.al.[76] proposes a new product recommendation approach for new users based on the implicit relationships between search keywords and products. The relationships between keywords and products are represented in a graph and relevance of keywords to products is derived from attributes of the graph. The relevance information is utilized to predict preferences of new users. J. Golbeck et.al.[35] presents FilmTrust, a website that integrates Semantic Web-based social networks, augmented with trust, to create prediction movie recommendations. Trust takes on the role of a recommender system forming the core of an algorithm to predict a rating for recommendations of movies. This is an example of how the Semantic Web, and Semantic trust networks in particular, can be exploited to refine the user experience.

Traditional recommender techniques has its pros and cons, for instance, the ability to handle data sparsity and cold-start problems or considerable ramp-up efforts for knowledge acquisition and engineering. Establish hybrid systems that combine the strengths of algorithms and models to overcome some of the shortcomings and problems has become the properly manner to improve the difficults for each algorithm. An example is presented by L.Castro et.al.[21] a hybrid recommender system for the province of San Juan, Argentina, to recommend tourist packages based on preferences and interest of each user, artificial intelligence techniques are used to filter and customize the information. The prototype of recommender system utilizes three techniques to recommend: demographic, collaborative and content-based. The goal is to recommend tourist packages that matches with the user profile. L. Martinez et al.[52] presents REJA, a hybrid recommender system that involves collaborative filtering and knowledge-based model, that is able to provide recommendations in some situation for user; besides it provides georeferenced information about the recommended restaurants. Balabanovic et.al.[9] presents Fab, a hybrid recommender system for automatic recognition of emergent issues relevant to various groups of users. It also enables two scaling problems, pertaining to the rising number of users and documents, to be addressed. Claypool et.al.[25] presents P-Tango system that utilizes content-based and collaborative filtering techniques, it makes a prediction through the weighted average that includes content-based prediction and collaborative filtering prediction. The weights of predictions are determined on a per-user basis, allowing the system to determine the optimum mixture of content-based and collaborative recommendation for each user. Pazzani M.[60] presents Entree as a hybrid recommender system that it does not use numeric scores, but rather treats the output of each recommender (collaborative, content-based and demographic) as a set of votes, which are then combined in a consensus scheme. The recommender system includes information such as the content of the page, ratings of users and demographic data about users. Others works with hybrid recommender systems are ProfBuilder [5], PickAFlick[20] and [72], where are presented multiple recommendation techniques. Usually, recommendation requires ranking of items or selection of a single best recommendation, at this point some technique must be employed to recommend.

Traditional recommender systems such as above mentioned, tend to use simple user models. For example, user-based collaborative filtering generally models the user as a vector of item ratings. As additional observations are made about users preferences, the user models are extended, and the user preferences is used to generate recommendations. This approach, therefore, ignores the notion of any specific situation, the fact that users interact with the system within a particular context and that preferences of items might change in another context. Overall, the context is able to make the recommender system be powerful that is adaptable to the changing user's situation.

The context is defined in the domain of the application and the system has a context model that provides the information for the recommender system. For instance Ricci et.al. [12] uses the context in music domain using a model-based paradigm, in this context-aware recommender system the context was defined as a set of independent contextual factors(independent in order to get a mathematical model) such as *driving style, road type, landscape, sleepiness, traffic conditions, mood weather and natural phenomena* to specifies the relevant context for the music recommendation. In order to estimate the relevance of selected contextual factor, the users were requested to evaluate music tracks in different contextual situations for each genre. The prediction takes in account this relevance to recommend music tracks prefered by the user according the genre and the contexts mentioned.In restaurant domain Chung-Hua et al.[24] presents a context-aware recommender system for mobiles using a post-filtering paradigm, the architecture involves a model client-server that works with a request of data in the client side for the server side. Subsequently, taking in account the contextual factors to filter the properly restaurants to recommend. The context-aware recommender system uses such as contextual factors *location and season*, also utilize the user preferences to personalize the recommendations in the user context. Baltrunas et.al.[13] presents ReRex for tourism, a context-aware recommender system based in a model-based paradigm, the system recommends and provides explanations about the why the places of interest(PoI) are recommended. The proposed model computes a personalized context dependent rating estimation. Subsequently, in order to generates the explanation of recommendation the system uses the factor that in the predictive model has the lasgest positive effect on the rating prediction for the point of interest. The set of contextual factors considered in ReRex are *distance*, temperature, weather, season, companion, time day, weekday, crowdedness, familiarity, mood, budget, travel length, transport and travel goal. The main issue in ReRex system is the low user satisfaction because of the explanations not able to be understood, however the users recognize that the explanation is a very important component that it influence the system acceptance. Noguera et. al. [55] presents a context-aware recommender system for tourism based in REJA that utilizes the location through a 3D-GIS system, the application uses progressive downloading and rendering of 3D maps over mobiles networks. It is also in charge of tracking the users location and speed based on GPS and the requesting. The system utilizes pre-filtering and post-filtering paradigm. Pre-filtering is used to reduce the number of items considered for the recommendation according to the users location, and post-filtering is applied to re-rank the previous top-N list according to the physical distance from the user for each recommended restaurant. The disadvantage in this system is the lack of user reviews, because the recommendations are based only in the location point without consider the experience of other diners concerning the recommended restaurant. Cena et al.[22] presents a tourist guide for context in intelligent content adaptation. UbiquiTO system is a tourist guide that integrates different forms of context-related adaptation: for media device type, for user characteristics and preferences, for the physical context of the interaction. UbiquiTO uses a rule-based modeling approach to adapt the content of the provided recommendation, such as the amount, type of information and features associated with each recommendation. Bulander et.al[19] presents the MoMa-system that offers proactive recommendations using a post-filtering approach for matching order specifications with offers. When creating an order, the client application will automatically fill in the appropriate physical context and profile parameters, for example, *location* and *weather*, then, for example, the facility should not be too far away from the current location of the user and beer should not be recommended if it is raining. On the other side, advertisers suppliers put offers into the MoMa-system. These offers are also formulated according to the catalogue. When the system detects a pair of context matching order and offer, the end user is notified, in the preferred manner (for example, SMS, email). At this point, the user must decide whether to contact the advertiser to accept the offer. Finally, Schifanella et al.[69] develops Mob-Hinter, a *context-dependent* distributed model,where a user device can directly connect to other mobile devices that are in *physical proximity* through ad-hoc connections, hence relying on a very limited portion of the users community and just on a subset of all available data (pre-filtering). The relationships between users are modeled with a similarity graph. MobHinter allows a mobile device to identify the affinity network neighbors from random ad-hoc communications. The collected information is then used to incrementally refine locally calculated predictions, with no need of interacting with a remote server or accessing the Internet. The Recommendations are computed using the availables rating of the user neighbors. Abowd et. al. presents Cyberguide project [1], which encompassed several tour guide prototypes for different handheld platforms. Cyberguide provided tour guide services to mobile users, exploiting the contextual knowledge of the users current and past locations in the recommendation process. The PECITAS system [73] presented by Thumas offers location-aware recommendations for personalized point-to-point paths. The paths are illustrated by listing the various connections that the user must take to reach the destination using public transportation and walking. An interesting aspect of PECITAS is that, although an optimal shortest path facility is incorporated, users may be recommended alternative routes that pass through several attractions, given that their specified constraints (e.g. latest arrival time) and travel-related preferences (maximum walking time, maximal number of transport transfers, sightseeing preferences, etc) are satisfied. Yu and Chang presents LARS [77] which supports personalized tour planning using a rule-based recommendation process. This system packages where to stay and where to eat features together with typical tourist recommendations for sightseeing and activities. For instance, recommended restaurants (selected based on their location, menu, prices, customer rating score, etc) are integral part of the tour and the time spent for lunch/dinner is taken into account to schedule visits to attractions or to plan other activities. Savage et. al. presents "I'm feeling LoCo" system [67] that proposes a ubiquitous location based recommendation algorithm that focuses on user experience by considering user preferences, time, location and similarity measures automatically, having Foursquare as a dataset. We also focus on user experience and aim that user input is minimal. The information om the user's social network, form of transportation and phone's sensors is inferred to provide recommendation of places om the dataset. Reddy et.al[63] presents Life-Track system that incorporates sensor information into song selection. The songs are represented in terms of tags that the user assigns in order to link the songs to the appropriate contexts in which they should be played. User feedback is incorporated to make a song more or less likely to play in a given context. Context considered relevant to song selection includes location, time of operation, velocity of the user, weather, traffic and sound. User locations and velocity are determined by GPS. Location information includes tags based on zip code and whether the user is inside or outside (inferred by the presence or absence of a GPS signal). The times of the day are divided out into configurable parts of the day (morning, evening, etc). The velocity is abstracted into one of four states: static, walking, running and driving. Use of accelerometers are planned to enable indoor velocity information. If the user is driving, an RSS feed on traffic information is used to typify the state as calm, moderate or chaotic. If the user is not driving, a microphone reading is used for the same purpose. Additionally, an RSS feed provides a meteorological condition (frigid, cold, temperate, warm or hot).

The table 2.1 describes examples of contextual factors in different domains of application, specifies the contextual factors considered such as part of the context, the methodology for each application and kind of devices.

Table 2.1: Comparison of context-aware recommender systems.

Application	Contextual Factor	Domain	Paradigm	Device
CoMoLE	**Time, available time, place, device, level of knowledge, learning style.**	**E-learning**	**Pre-filtering**	**Mobiles, PC, laptop.**
Moma-System	**Location, time.**	**E-commerce**	**Post-filtering**	**PC, laptop.**
UbiquITO	**Season, time, temperature.**	**Tourism**	**Post-filtering**	**Mobiles**
ReRex	**Distance of the point of interest, temperature, weather, season, weekend, companion, travel goal, transport.**	**Tourism**	**Model-based**	**Mobiles**
LifeTrack	**Location, time, day of the week, traifc noise(level), temperature, weather.**	**Music**	**Post-filtering**	**PC, Mobiles.**
CARS	**Location and season.**	**Restaurants**	**Post-filtering**	**PC, laptop.**
InCarMusic	**Driving style, road type, landscape, sleepiness, traffic conditions, mood weather and natural phenomena.**	**Music**	**Model-based**	**Mobiles**
REJA	**Location.**	**Restaurants**	**Pre-filtering and Post-filtering**	**PC, laptop, mobiles.**
CiberGuide	**Location, time, weather.**	**Tourism**	**Post-filtering**	**Mobiles**
PECITAS	**Location, routes.**	**Transport**	**Post-filtering**	**Mobiles**
LARS	**Tourists location and time.**	**Tourist packages**	**Post-filtering**	**Mobiles**
I'm feeling LoCo	**Location, transportation.**	**Tourism**	**Model-based**	**Mobiles**
MOPSI	**Location**	**Tourism and transport**	**Post-filtering**	**Mobiles**

Chapter 3

Background

In this chapter the fundamental concepts related this work are presented: Formal definitions referring to fuzzy systems, contextual factors and recommender system techniques used by the proposed method.

3.1 Production systems and fuzzy models

A central aspect of the proposed method is the use of both fuzzy logic and fuzzy inference systems, in this section formal definitions of these models of knowledge representation are presented.

3.1.1 Traditional Production Systems

Production Systems represent knowledge in form of rules, which specify actions that will be executed when certain conditions are met. In these systems Experts in a certain domain identify a set of rules based on their experience to resolve different kinds of problems. Also known as rule based systems, many implementations consist of mainly these three components [17] [45]:

1. **Production Rules (PR)**. A set of production rules (also known as *IF-THEN* rules) having a two part structure; the antecedent, conformed by a set of conditions and a consequent set of actions.

2. **Working Memory (WM)**. Represents the current knowledge or facts that are known to be true so far. These facts are tested by the antecedent conditions of the rules and the consequent part can change them.

3. **Inference Engine (IE)**. This interpreter matches the conditions in the production rules with the data/instantiations found in the WM, deriving new consequences.

The basic operation of these systems is described as a cycle of three steps [17]:

1. **Recognize**: Find which rules are satisfied by the current WM. The antecedent part of the productions consists of a set of clauses connected by AND operators,

when all these clauses have matching data on the WM the production has a chance of firing.

2. **Conflict Resolution**: Only one production can be fired at a time, so when two or more rules can be fired concurrently a conflict occurs. Among the production rules found in the first step, choose which rules should fire.

3. **Actions**: Change the working memory by performing the actions specified in the consequent part of all the rules selected in the second step. Changes occur by adding or deleting elements of the WM.

This cycle continues until no further production rules can be fired. This control strategy is data driven because whenever the antecedent part is satisfied the rule is recognized, this strategy is also named chain-forward. Other strategy is chain-backward in which case the work is done from the conclusion to the facts, to chain-backward, goals in the WM are matched against consequents of the production rules. A drawback that has been recognized in these traditional productions systems, is that some times rules are not fired in the Recognize step because no appropriate match exists in the WM. Partial matching of rules is not possible and this can be a limitation in some systems because premature termination of the cycle is not desired. An approach to handle partial matching is using fuzzy logic [45]. In the next section a review of the extension of production systems with fuzzy logic is presented.

3.1.2 Fuzzy Production Rules

Fuzzy production rules use fuzzy logic sets to characterize the variables and terms used in the propositions of the rules. Fuzzy production rules or fuzzy *IF-THEN* rules are expressions of the form *IF* antecedent *THEN* consequent, where the antecedent is a proposition of the form *"x is A"* where x is a linguistic variable and A is a linguistic term. The truth value of this proposition is based on the matching degree between x and A. Propositions are connected by *AND*, *OR* and *NOT* operators. Some implementations of fuzzy rule-based systems also include other kinds of data types in their propositions, for example the FLOPS system includes fuzzy numbers, hedges, and non fuzzy data types (integers, strings and float) [71]. Depending on the form of the consequent, two main types of fuzzy production systems are distinguished [8]:

- **Linguistic fuzzy model**: where both the antecedent and consequent are fuzzy propositions.
- **Takagi-Sugeno fuzzy model**: the antecedent is a fuzzy proposition; the consequent is a crisp function.

As before, other non-fuzzy consequents can also be implemented, like the execution of commands or the addition of new data.

Linguistic Variables (LV) are variables that can be assigned linguistic terms as values, i.e. if we define a linguistic variable *SPEED* we can assign it the linguistic terms *SLOW*, *MEDIUM* or *FAST*. The meaning of these linguistic terms is defined by their membership functions (MF). *LV* can be defined as a *5-tuple* *LV*=$< v, T, X, g, m >$ where v is the name of the variable, T is the set of linguistic terms of v, X is the domain (universe) of v,g is a syntactic rule to generate linguistic terms, m is a semantic rule that assigns to each term t its meaning *m(t)*, which is a fuzzy set defined in X.

3.1.3 Fuzzy Inference Systems

Fuzzy Inference Systems (FISs) also called *Fuzzy Models* are fuzzy production systems used for modeling input-output relationships. From this input-output view, Babuka [8] describes these systems as *"flexible mathematical functions which can approximate other functions or just data (measurements) with a desired accuracy"*. Fuzzy Productions Rules define the relationship between input and output variables. Input variables are defined in the antecedent part of the rule and the consequent part defines the output variables. These FISs are used mainly in control systems, and are basically composed of five modules[8]:

1. **Rule Base.** The set of fuzzy production rules.

2. **Database.** Where the membership functions are defined.

3. **Fuzzy Inference Engine.** This module executes the fuzzy inference operations.

4. **Fuzzifier.** This interface transforms the inputs of the systems (numerical data) into linguistic values.

5. **Defuzzifier.** This interface transforms the fuzzy results into numerical data.

Usually the Rule Base and Data Base modules are collectively called the Knowledge Base module. The steps involved in fuzzy inference in a FIS are [28]:

1. Compare the input variables with the membership functions in the antecedent, to obtain the membership values of each linguistic term. This step is frequently called fuzzification.

2. Compose through a specific T-Norm operator (mainly max-min or max-product) the membership values to obtain the degree of support of each rule.

3. Generate the qualified consequence (fuzzy or numeric) of each rule depending on the degrees of support. These outputs are then aggregated to form a unified output.

4. Then the output fuzzy set is resolved or defuzzified to a single numeric value.

Three main inference systems can be described:

- **Tsakumoto**: The output is the average of the weights of each rule numeric output, induced by the degree of support of each rule, the min-max or min-product with the antecedent and the membership functions of the output. The membership functions used in this method must be non-decrease monotonic.

- **Mamdani**: The output is calculated by applying the min-max operator to the fuzzy output (each equal to the minimum support degree and the membership function of the rule). Several schemes have been proposed to choose the numeric output based on the fuzzy output; these include the centroid area, area bisection, maximum mean, maximum criteria.

- **Sugeno**: The fuzzy production rules are used. The output of each rule is a linear combination of the input variables plus a constant term, and the output is the average of the support degree of each rule.

3.2 Context

People transmit ideas to each in a complex way. This is due to many factors such as: the richness of the language shared, the common understanding of how the world works, and an implicit understanding of situations in daily life. When people talk, they are able to use implicit situational information (contextual information), to increase the conversational bandwidth.

Unfortunately, this ability to transmit ideas does not transfer well to persons interacting with computers. In traditional interactive computing, users have poor mechanisms for providing input to computers. Consequently, computers are not currently enabled to take full advantage of the context of the human-computer dialogue. By improving the computer's access to context, we increase the richness of communication in a human-computer interaction enabling the development of more useful computational services.

In order to use context effectively, we must define what context is and how it can be used. An understanding of *how context can be used* will help application designers to determine what context-aware behaviours to use in applications[26].

To stablish a specific definition of *context* that can be used in the *context-aware* computing field, is necessary to review how researchers define the context in their own work. Schilit and Theimer[2] refer to context as *location*, *identities of nearby people and objects*, and *changes to those objects*.

This type of definitions that define context by example are difficult to apply when developers try to determine whether a type of information not listed in the definition is part of the context or not, as it is not clear how it can be used by the definition. Schilit et al.[70] affirms that the most important aspects of context are: *where you* *are*, *who you are with*, and *what resources are nearby*. Pascoe[58] defines context to be the *"subset of physical and conceptual states of interest to a particular entity"*. These definitions are too general, context is all about the whole situation relevant to an application and its set of users. It is complicated enumerate which aspects of all situations are important, as this will change from situation to situation. For this reason and for the purpose of this thesis, the definition of context proposed by Dey[26] has been adopted (see section 1.3).

However, another important aspect is to stablish a meaningful classification that covers the characteristics that describe the contextual factor.

Dourish[27] has distinguished between two different views of context: the *representational view* and the *interactional view*. The *representational view* makes four key assumptions: context is a *form of information*, it is *delineable*, it is *stable*, and it is *independent* from the underlying activity. In this view, context can be described using a set of observable attributes that are known a priori. Furthermore, the structure of these contextual attributes does not change over time. The *interactional view*, takes a different stance on the key assumptions made by the representational view. In the interactional view, the scope of contextual features is defined dynamically, and it is occasioned rather than static. Rather than assuming that context acts as a set of conditions under which an activity occurs, this view assumes a cyclical relationship between context and activity, where the activity gives rise to context and the context influences activities.

Context should include information to allow systems to use contextual information about users and their situation, enabling the system to provide users personalised and contextual services. The importance of context lies in the assumption of the influence of *contextual factors* that matter for users when they decide, choose or discard an item.

In the real world, the context in a situation is involved in the *environment* of the people, the *entities* belong at the *situational information*, but an entity becomes in a *contextual factor* when its information *affects* the recommendation process, therefore, the entity and its values of domain will be involved in the process such as a contextual factor.

The domain values of a contextual factor change over time, in real life the situation occurs when we decide that, for instance, we like a kind of clothes and the next day, for a any reason we don't like it anymore. As for the representation of the *"change of time"* , a data model of *time* should be specified in a way that the system *interprets* time as a data structure (for instance weeks, days, hours, minutes, seconds, etc.).

Assuming the existence of certain contextual factors such as *time*, *location* and *purchasing purpose* that are identified in the context of recommendations, Adomavicious[4] proposes two important aspects that highligh when different kinds of context are defined: *what a recommender system may know about these contextual factors* and, *how contextual factors change over time.*

A recommender system can have different types of knowledge, which may include the exact list of all the relevant factors, their structure, and their values, about the contextual factors. Depending on what exactly the system knows (that is, what is being observed), Adomavicious categorizes the knowledge of a recommender system about the context as the following:

- **Fully observable**: The contextual factors relevant to the application, as well as their structure and their values at the time when recommendations are made, are known explicitly. For example, when recommending the purchase of a certain product, like a shirt, the recommender system may know that only the *Time*, *PurchasingPurpose*, and *ShoppingCompanion* factors matter in this application. Further more, the recommender system may know the structure of all three contextual factors, such as having categories of *weekday*, *weekend*, and *holiday* for *Time*. Further, the recommender system may also know the values of the contextual factors at the recommendation time, for instance, *when this purchase is been made*, *with whom*, and *for whom*.

- **Partially observable**: Only some of the information about the contextual factors described above, is explicitly known. For example, the recommender system may know all the contextual factors, such as Time, PurchasingPurpose, and ShoppingCompanion, but not their structure. Note that there can possibly be different levels of *"partial observability"*.

- **Unobservable**: No information about contextual factors is explicitly available to the recommender system, and it makes recommendations by utilizing only the latent knowledge of context in an implicit manner. For example, the recommender system may build a latent predictive model, such as hierarchical linear or hidden Markov models, to estimate unknown ratings, where unobservable context is modeled using latent variables.

How contextual factors change over time. Depending on whether contextual factors change over time or not, two categories are proposed:

- **Static**: The relevant contextual factors and their structure remain the same (stable) over time. For example, when recommending the purchase of a certain product, such as a shirt, we can include the contextual factors of Time, PurchasingPurpose and ShoppingCompanion without change during the entire lifespan of the purchasing recommendation application.

- **Dynamic**: This is the case when the contextual factors change in some way. For example, the recommender system (or the system designer) may realize over time that the *ShoppingCompanion* factor is no longer relevant for purchasing recommendations and may decide to drop it. Furthermore, the structure of some of the contextual factors can change over time, for instance, new categories can be added to the *PurchasingPurpose* contextual factor over time.

On the other hand, Fling[31] generalizes four types of contexts that can be used in different applications:

- **Physical context**: representing the time, position, and activity of the user, but also the weather, light, and temperature when the recommendation is supposed to be used.

- **Social context**: representing the presence and role of other people (either using or not using the application) around the user and whether the user is alone or in a group when using the application.

- **Interaction media context**: describing the device used to access the system (for example, a mobile phone or a kiosk) as well as the type of media that are browsed and personalized. The latter can be ordinary text, music, images, movies, or queries made to the recommender system.

- **Modal context**: representing the current state of mind of the user, the user's goals, mood, experience, and cognitive capabilities.

Subsequently the revision of the literature of context, it is important to mention a formal definition that describes what features it has a context-aware system, this definition is proposed by Dey[26]: *"a system is context-aware if it uses context to provide relevant information and/or services for the user, where relevancy depends on the user's task."*

This definition is closer to the reality about behaviour of *context-aware recommender system* when incorporates contextual information.

Based in this definition, Dey proposes some characteristics that a context-aware application should be support:

- **Presentation of information** and services to a user.
- **Automatic execution** of a service for a user.
- **Tagging of context** to information to support later retrieval.

An example to explain the context in a context-aware application, for instance, it can be an indoor mobile tour guide. Here, the entities are the user, the application and the tour sites. We will look at two pieces of information (weather and the presence of other people) and use the definition to determine if either one is context. The weather does not affect the application because it is being used for indoor activities. Therefore, it is not context. The presence of other people, however, can be used to characterize the users situation. If a user is traveling with other people, then the sites that they visit may are the points of interest for the user. Therefore, the presence of other people is context because it can be used to characterize the user's situation.

3.3 Recommender systems

3.3.1 Collaborative Filtering

The idea behind collaborative recommendation approaches is to exploit information about past behavior or opinions of an exisiting user community for predicting which items certain user of the system will most probably like or be interested in[43]. Recommender systems are useful in several types of applications, however, their biggest impact has been mainly in ecommerce web sites in order to personalize the information for a particular user as the system can help to promote several items of his or her interest, thus increasing the sales of the on-line store. In traditional implementations a collaborative filtering algorithm (CF) takes as input a given *user-item* sparse matrix of ratings to generate a prediction for each user-item pair indicating to what degree the current user will like or dislike an item. Subsequently with that information a list of the top n recommended items for the user can be generated. The generated list contains only those items that have not been reviewed by the user. Different approaches are utilized for CF such as: a) User-based nearest neighbor recommendation, b) Item-based nearest neighbor recommendation and c) Model-based recommendation.

a) User-based nearest neighbor is an approach that only uses the rating matrix to obtain recommendations. The neighborhood selection consists in taking the k nearest (similar) neighbors into account usind the k threshold to define the size of the neighborhood. A small neigborhood can not make accurate predictions, and on the other hand if the neighborhood is too large the information about certain nighbours could not be significant.

To obtain the similarity value between a user and his neighbors, the Pearson correlation is commonly used, taking the values from $+1$ (strong positive correlation) to -1 (strong negative correlation) to define how similar a neighbor is. The similarity $sim(a, b)$ of users a and b, given the rating matrix R is denoted by the following equation:

$$sim(a,b) = \frac{\sum_{p \in P}(r_{a,p} - \bar{r_a})(r_{b,p} - \bar{r_b})}{\sqrt{\sum_{p \in P}(r_{a,p} - \bar{r_a})^2}\sqrt{\sum_{p \in P}(r_{b,p} - \bar{r_b})^2}} \tag{3.1}$$

Where the symbol $\bar{r_a}$ corresponds to the average rating of user a. Subsequently, a formula to calculate the prediction of the user a for item p that also factors the relative proximity of the nearest neighbors N and $a's$ average rating $\bar{r_a}$ is denoted by the following equation:

$$pred(a,b) = \bar{r_a} + \frac{\sum_{b \in N} sim(a,b) * (r_{b,p} - \bar{r_b})}{\sum_{b \in N} sim(a,b)} \tag{3.2}$$

b) Item-based nearest neighbor is the same idea as the *User-based* recommendation, the difference is that this approach tries to find similar items instead of similar users to make a prediction using again only the rating matrix as input. Then, in an *item-based* recommendation is to compute predictions using the similarity between items and not the similarity between users. To find similar items a Cosine similarity measure is often used, this metric measures the similarity between two *n-dimensional* vectors based on the cosine of the angle between them. Therefore, the similarity between two items a and b viewed as the corresponding rating vectors a and b, is formally defined as follows:

$$sim(\overrightarrow{a}, \overrightarrow{b}) = \frac{\overrightarrow{a} * \overrightarrow{b}}{|\overrightarrow{a}| * |\overrightarrow{b}|} \tag{3.3}$$

Where the * symbol is the dot product of vectors and $|a|$ is the Euclidian length of the vector, which is defined as the square root of the dot product of the vector with itself.

c) Model-based approach, in this technique the raw data is first processed off-line, as described for *item-based* filtering or also using some dimensionality reduction technique. At run time, only the learned model is required to make predictions. Although a *memory-based approach* is theoretically more precise because the full data is available for generating recommendations, such systems face problems of scalability when for instance a database of tens of millions of users and items are used. An example of this approach is *matrix factorization* or *latent factors model*, normally used to fill a rating matrix to calculate predictions taking in account the *latent factors*.

Data sparsity and cold-start problem

In real-world applications, the ratings matrix tend to be *very sparse*(sparcity problem), as customers typically provide ratings for (or have bought) only a small fraction of the catalog items. In general, the challenge in that context is thus to compute good predictions when there are relatively few ratings available. One straightforward option for dealing with this problem is to exploit additional information about the users, such as gender, age, education, interests, or other information available that can help to classify the user. The set of similar users (neighbors) is thus based not only on the analysis of the explicit and implicit ratings, but also on information external to the ratings matrix. These hybrid systems [61], however, are no longer *purely* collaborative, and also bring new questions on how to acquire the additional information and how to combine the different classifiers. Still, to reach the critical mass of users needed in a collaborative approach, such techniques might be helpful in the *ramp-up phase* of a newly installed recommendation service.

The *cold-start problem* can be viewed as a special case of sparsity [40]. The questions here are (a)*how to make recommendations to new users that have not rated any item yet* and (b)*how to deal with items that have not been rated or bought yet.* Both problems can be addressed with the help of hybrid approaches [3]. To face the *new-users problem*, one option could be to ask the user for a minimum number of ratings before the service can be used. In this situation the system could intelligently ask for ratings for items that, from the view point of information theory, carry the most information[62]. A similar strategy of asking the user for a gauge set of ratings is used for instance in the Eigentaste algorithm presented in [36].

3.3.2 Content-based algorithm

In a content-based recommendation (CB), the task consists of determining those items that best match the active users preferences. Although such an approach must rely on additional information about items and user preferences, it does not require the existence of a large user community or a rating history, i.e., recommendation lists can be generated even if there is only one single user.

In practical settings, technical descriptions of the features and characteristics of an item (such as the genre of a book or the list of actors in a movie) are more often available in electronic form, as they are partially already provided by the providers or manufacturers of the goods. What remains challenging, however, is the acquisition of subjective, qualitative features.

In domains of quality and taste, for example, the reasons that someone likes something are not always related to certain product characteristics and may be based on a subjective impression of the items exterior design [43].

Content representation

The simplest way to describe catalog items is to maintain an explicit list of features for each item (also often called attributes, characteristics, or item profiles). For a book recommender, one could, for instance, use the genre, the authors name, the publisher, or anything else that describes the item and store his information in a relational database system. When the users preferences are described in terms of his or her interests using exactly this set of features, the recommendation task consists of matching item characteristics and user preferences [43].

Vector space model

CB systems have historically been developed to filter and recommend text-based items such as e-mail messages or news. The standard approach in CB recommendation is, therefore, not to maintain a list of *meta-data features*, but to use a list of relevant keywords that appear within the document. The main idea, of course, is that such a list can be generated automatically from the document content itself or from a free-text description thereof [43].

Overspecialization and cold-start problem

Learning-based methods quickly tend to propose more of the same, that is, such recommenders can propose only items that are somehow similar to the ones the current user has already (positively) rated. This can lead to the undesirable effect that obvious recommendations are made and the system, for instance, recommends items that are *too similar to those the user already knows.*

A typical example is a news filtering recommender that proposes a newspaper article that covers the same story that the user has already seen *in another context.* The system in [16] defines a threshold to filter out not only items that are *too different* from the profile but also those that are *too similar.* A general goal is to avoid the *overspecialization*, therefore increasing the serendipity of the recommendation lists that now includes unexpected items in which the user might be interested, because sometimes expected items are of little value for the user.

The *cold-start problem*, which we discussed for collaborative systems, also exists in a slightly different form for content-based recommendation methods. Although CB techniques do not require a large user community, they require at least an initial set of ratings from the user.

In all described filtering techniques, recommendation accuracy improves along with the number of ratings; significant performance increases for the learning algorithms were reported in [59] when the number of ratings was between twenty and fifty.

However, in many domains, users might not be willing (or is not feasible) to rate that many items before the recommender service can be used. In the initial phase, it could be an option to ask the user to provide a list of keywords, either by selecting from a list of topics or by entering a free-text input.

3.3.3 Hybrid recommender systems

Each recommender system technique has its pros and cons, for instance, the ability to handle data sparsity and cold-start problems or considerable efforts for knowledge acquisition and engineering.

User models and contextual information, community and product data, and knowledge models constitute the potential types of recommendation input. However, none of the basic approaches are able to fully exploit all of these. Consequently, building hybrid systems that combine the strengths of different algorithms and models to overcome some of the afore mentioned shortcomings and problems has become the target of recent research. Hybrid recommender systems are technical approaches that combine several algorithms or recommendation components [43].

3.3.4 Context-aware recommender systems

Traditionally, the recommendation problem has been viewed as a prediction problem in which, given a user profile and a target item, the recommender system's task is to predict that user's rating or that item, reflecting the degree of user's preference for that item[43].

Specifically, a recommender system tries to estimate a rating function: $R : Users * Items \rightarrow Ratings$, that maps *user-item* pairs to an ordered set of rating values.

In contrast to the traditional model, context-aware recommender system tries to incorporate or utilize additional evidence (beyond information about users and items) to estimate user preferences on unseen items.

When such contextual evidence can be incorporated as part of the input to the recommender systems, the rating function can be viewed as *multidimensional*: $R : Users * Items * Contexts \rightarrow Ratings$, where **Contexts** represents a **set of factors** that further delineate the conditions under which the *user-item* pair is assigned a particular rating.

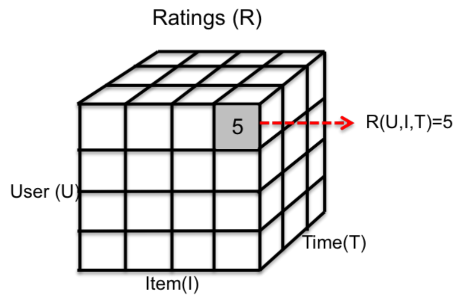

Figure 3.1: Multidimensional model of context.

The underlying assumption of this extended model is that user preferences for items are not only a function of items themselves, but also a function of the context in which items are being considered[47].

A multidimensional model as those found in data warehousing systems[44] is used to depict the context dimensions, in figure 3.1 the time dimension belongs to the **set of contextual factors** and, is described as a **set of attributes**, for instance it may consist of attributes such as *morning*, *evening*, *nigth*, etc., as it was mentioned in section 1.2.

3.3.5 Paradigms for using of contextual information

When recommender system uses contextual information, it starts with the data having the form $U * I * C * R$, where C is additional contextual dimension and end up with a list of contextual recommendations i_1,i_2,i_3...i_n for each user. However, when the recommendation process does not take into account contextual information, is posible to apply the information about the current (or desired) context c in various stages of the recommendation process. Adomavicious[4] defines three paradigms for the context-aware recommendation process that is based on contextual user preference:

- **Contextual pre-filtering (or contextualization of recommendation input).** The approach uses contextual information to select the most relevant 2D (Users x Items) data for generating recommendations. One major advantage of this approach is that it allows deployment of any of the numerous traditional recommendation techniques previously proposed in the literature[3]. In particular, when using this approach, context c essentially serves as a query (or a filter) for selecting relevant rating data. An example of a contextual data filter for a movie recommender system would be: if a person wants to see a movie on Saturday, only the Saturday rating data is used to recommend movies. Note that this example represents a crisp pre-filter because the data was filtered using exactly the specified context (figure 3.2.a).

- **Contextual post-filtering (or contextualization of recommendation output).** In this approach context information in the input data is ignored when generating recommendations, that is, when generating the ranked list of all candidate items from which any number of *top-N* recommendations can be made. Instead, the contextual post-filtering approach uses contextual information to adjust the obtained recommendation list for each user. The recommendation list adjustments can be made by: (1) filtering out recommendations that are irrelevant in a given context, or (2) adjusting the ranking of recommendations in the list. For example, in a movie recommendation application, if a person wants to see a movie on a weekend, and if on weekends he or she only watches comedies, the system can filter out all noncomedies from the recommended list (figure 3.2.b).

- **Contextual modeling (or contextualization of recommendation function).** This approach uses contextual information directly in the recommendation function as an explicit predictor of a user's rating for an item and, thus, gives rise to truly multidimensional recommendation functions representing either predictive models (such as decision trees, regression, and so on) or heuristic approaches that incorporate contextual information in addition to the user and item data (figure 3.2.c).

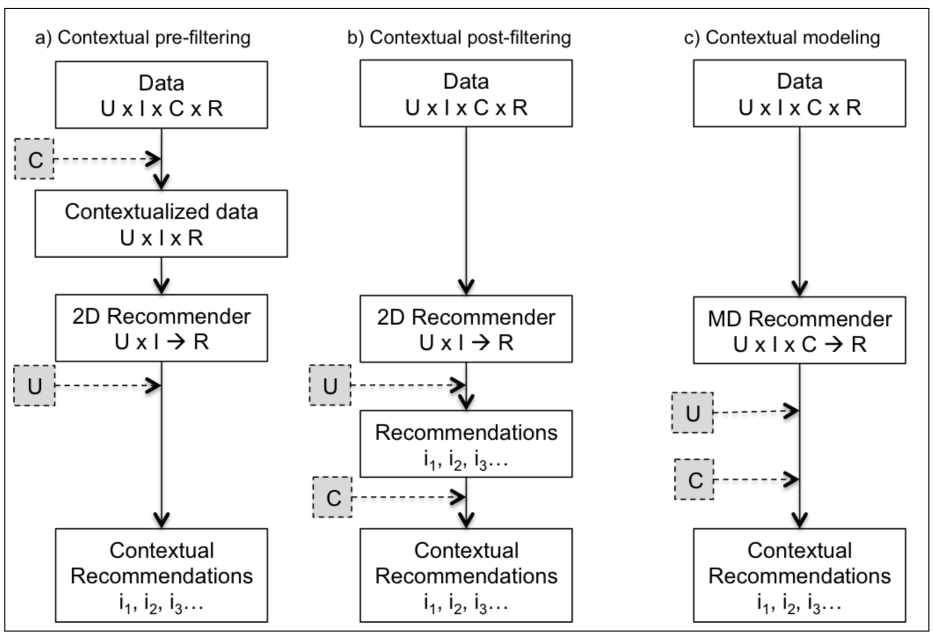

Figure 3.2: Paradigms for incorporating context in recommender systems[4].

Chapter 4

Proposed method

¡¡¡¡¡¡¡ HEAD This chapter presents the proposed method, the recommender system uses user's context to infer the predictions of items. First, the data models are defined in order to explain what characteristics (or information) was used from each model.

Overall, the post-filtering approach is applied in order to cover the user's needs in a wider range of satisfaction and, it is based in the information that users provide to the recommender system. This chapter describes each component in the method, as well as its functionality and how is connected with another components of the method.

4.1 Data models

=======

The method proposed in this thesis uses three recommendations techniques. In order to explain the method, a Case Study in a restarant domian will be used. The techniques are the following:

1. *Expert's Fuzzy Inference System*, this is a rule based recommender defined by an expert in the domain, in the case of a restaurant recommender it considers the following variables: *ratings average: low,medium and high*, *price of restaurant: cheap, average and expensive*, and *number of ratings of item: few, several and many*, these variables are used to infer how relevant a restaurant is for the user. This recommendation is based on the popularity of each item in the user community.

2. *Content-based technique* utilizes the item profiles to compare how *similar* is an item with respect to another, i.e. restaurants that are *similar* (same cuisine, ambient, price range) to others that the user has rated high. The idea is to find items with similar features.

3. *Collaborative filtering technique* is based on the user profile to identify user's preferences and to find neighbors that have the same tastes. The recommendation consist in the suggestions of other users with similar tastes that rated

restaurants again in a similar way but where have not been rated by the current user. A Top-N list of restaurants is obtained to recommend for the user.

The results of the three techniques are a list of recommendations for the user, later, these recommendations are adjusted for the current context. This is the last step and is represented as a *context filter* in the method, as a result a list of contextualized recommendations is obtained.

In the method, each technique works simultaneously to obtain recommendations, the hybrid method allows to generate suggestions even without user information, i.e., using content-based technique or the fuzzy inference system, so the system faces the cold-start or the overspecialization problem using these thechniques, these problems are described in section 3.3.1 and 3.3.2, respectively.

To evaluate the performance of the proposed recommender several experiments were conducted, the algorithms were tested using contextual datasets and the number of contextual factors used varied according to the information provided by each of the datasets. The goal of the experiments were to observe the role of contextual data in the performance of the algorithms and to have a better understanding of what contextual factors are more important for users in a specific situation, how recommendations are improved using context and, the accuracy in recommendations.

¿¿¿¿¿¿¿ origin/master

4.2 Data models

4.2.1 Data Model

The first step of the method is to define a Data Model, defining an abstraction of the context. An effective on-line recommender system must be based upon an understanding of consumerś preferences and successfully mapping potential products into these preferences[4]. Pan and Fesenmaier[57] argued that this can be achieved through the understanding of how consumers describe in their own language a product, a place, and the overall experience when they are consuming the product or visiting the place. It is observed that the language of the consumers is often imprecise, with values of attributes values often expressed in fuzzy terms. In order to create the data model the designer must first consider those atributes that customers take into consideration when choosing an item. Then situational and contextual factors must also be considered.

4.2.2 Restaurant model

As an exemple a case study will be used, a Restaurant context-aware recommender system.

Traditionally, choosing a restaurant has been considered as rational behavior where a number of attributes contribute to the overall usefulness of a restaurant. For example: food type, service quality, atmosphere of the restaurant, and availability of information about a restaurant, plays an important role at different stages in consumer's desition making[7]. While food quality and food type have been perceived as the most important variables for consumers' restaurant selection, situational and contextual factors have been found to be important also. Due to this Kivela[42] identifies four types of restaurants: 1) *fine dining/gourmet*, 2) *theme/atmosphere*, 3) *family/popular*, and 4) *convenience/fast-food*; on the other hande Auty[7] identifies four types of dining out occasions: 1) *celebration*, 2) *social occasion*, 3) *convenience/quick meal*, and 4) *business meal*.

Taking in to account the context, the model proposed was definded with 55 attributes about restaurants. An exploration about contents of models of others works were compared to define the suitable information into the model. Therefore, the restaurant model is a binary vector with the following contextual attributes: 1) *price range*, 2) *payment type*, 3) *alcohol type*, 4) *smoking area*, 5) *dress code*, 6) *parking type*, 7) *installations type*, 8) *atmosphere type*, and 9) *cuisine type*. An example of a restaurant model is depicted in figure 4.1 with some domain values of the context represented by a binary vector where *1* means that the restaurant has the property that corresponds to the position value. Additionally, the restaurant model contains other information such as *users's reviews*, *ratings average*, and *geographycal location.*

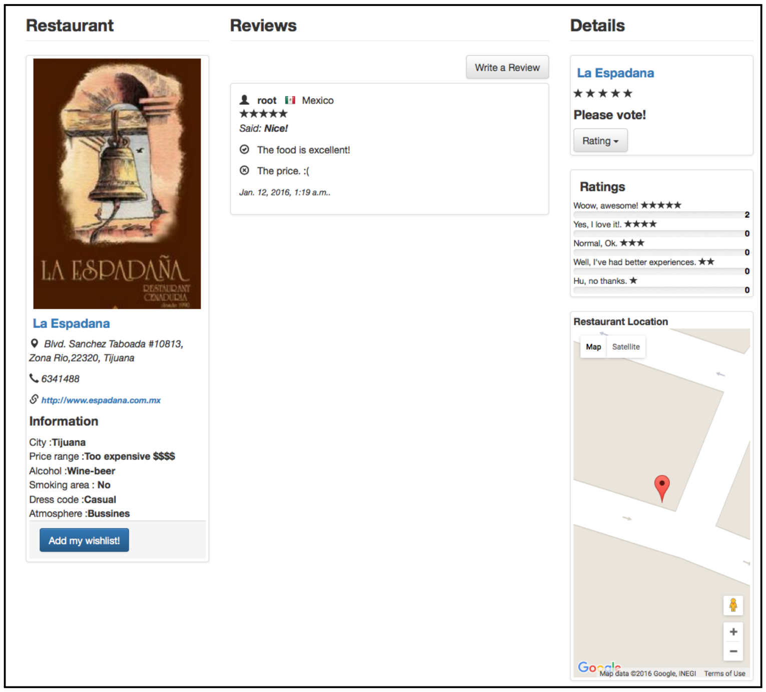

Figure 4.1: User interface of the restaurant model.

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Restuarant data model

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Contextual Factors Data model

The data model was implemented in a PostgreSQL database system, while the information in th context-aware recommender system was managed in a schema of a relational database. Technical support about installations of dependencies and the application are described in appendix C. ¿¿¿¿¿¿ origin/master

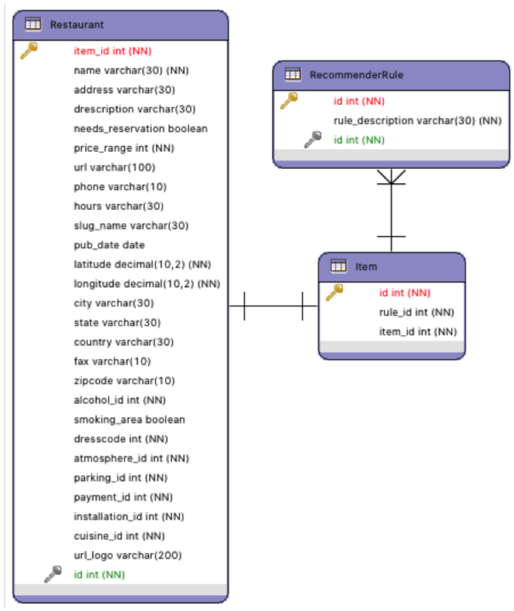

Figure 4.2: The restaurant data model.

The data model in postgreSQL is depicted in the figure 4.2, the model contains the restaurant entity and its attributes. The restaurant entity is related to *Item entity* in a *"one-to-one"* relation that at the same time is related to the *RecommenderRule entity* which specifies some restrictions for item recommendations. A large view of all the entities related is depicted in the whole scheme refered in figure 4.5. Some related entities corresponding to the proposed contextual factors, are defined as follows:

- **Price:** *cheap, regular, expensive, too expensive.*
- **Payment:** *credit/debit card, cash.*
- **Alcohol:** *no alcohol, wine-beer.*

- **Smoking area:** *yes, no.*
- **Dresscode:** *casual, informal, formal.*
- **Installations:** *garden, terrace, indoor, outdoor.*
- **Atmosphere:** *relaxed, familiar, friends, bussines, romantic.*
- **Parking:** *no parking, free parking, valet parking.*
- **Cuisine:** *japanese, chinese, italian, argentinean, cantonese, mandarin, mongolian, arabic, greek, spanish, brasilian, swiss, szechuan, asian, international, steak grill,vegetarian, natural/healthy/light, traditional mexican, tacos, mediterranean, middle eastern, american/fast food, gourmet, pizza, bar/beer, tapas cafe/bar, french, birds, seafood.*

The cuisines were defined according the food variety of restaurants in Tijuana, there are 30 types of cuisines defined in the system.

The smoking area is an attribute with boolean value, it defines if a restaurant has a smoking area in its installation. A fuzzy contextual factor found in this case study is the **Price**.

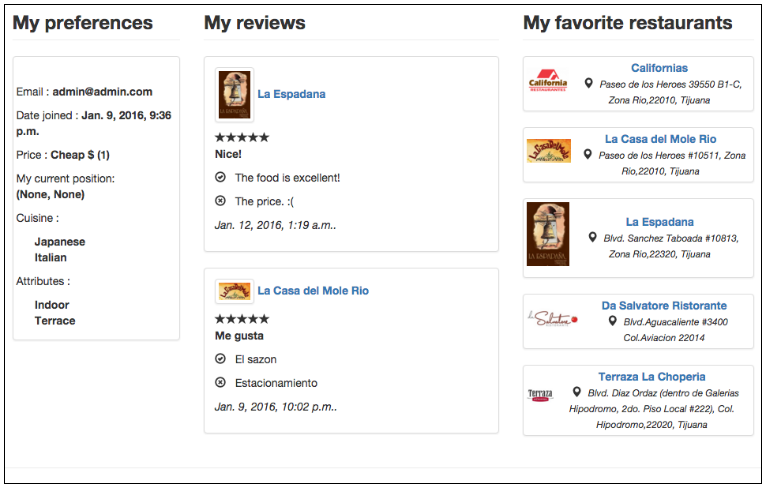

Figure 4.3: Example of user interface for user profile.

4.2.3 User model

The user's profile is derived from the ratings matrix. Let $U = [u_1, u_2, ...u_n]$ the set of all users and $I = [i_1, i_2,...i_n]$ the set of all items, if R represent the ratings matrix, an element $R_{u,i}$ represents a users rating $u \in U$ in a item $i \in I$. The unknown ratings are denoted as $\neq$. The matrix R can be decomposed into rows vectors, the row vector is denoted as $\overrightarrow{r_u}$=$[R_{u,1}...R_{u,|I|}]$ for every $u \in U$. Therefore, each row vector represents the ratings of a particular user over the items. Also denote a set of items rated by a certain user u is denoted as $I_u = i \in I | \forall i : R_{u,i} \neq \emptyset$. This set of items rated represents the user preferences where for each domain element $R_{u,i} \in [1 - 5]$ represents the intensity of the user interest for the item.

In context-aware recommender systems, user profiles have contextual information such as: 1) price range, 2) current location, 3) cuisine types, 4) attributes or features of restaurants that the user want, 5) the reviews posted, and 6) a list of favorite restaurants. The user profile is stored in database and it is available for queries upon request, and it can be changed by users many times in a session. The information used to make recommendations is the most recent. The user interface is represented in figure 4.3.

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User data model

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User Data Model Implementation

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The user's data model in postgreSQL is represented in the figure 4.4, the model involves the entities: *User, UserProfile, and Friends. UserProfile entity* provides the contextual information of user, *User entity* is the default model defined in the system and is related to userProfile for suplies valuable information. The *Friends entity* represents the social aspect into the userProfile, Friends involves the users related to the current user taking in account the preferences of each other.

The user profile entity is related with: price and cuisine are the same that in restau-

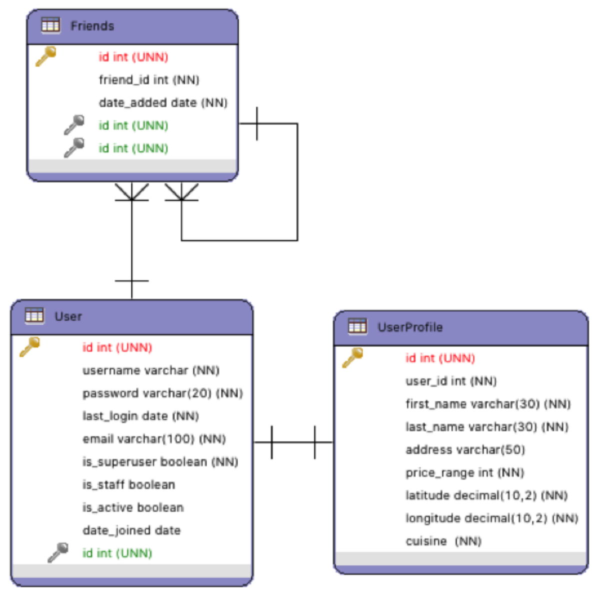


Figure 4.4: The user data model.

rant model, attribute groups corresponds to restaurant model mentioned (section 4.2.2). A total of 55 attributes(or characteristics) could be contained in user profile, this information is used such as contextual information also. The domain values are following:

- **Price:** cheap, regular, expensive, too expensive.

- **Cuisine:** japanese, chinese, italian, argentinean, cantonese, mandarin, mongolian, arabic, greek, spanish, brasilian, swiss, szechuan, asian, international, steak grill,vegetarian, natural/healthy/light, traditional mexican, tacos, mediterranean, middle eastern, american/fast food, gourmet, pizza, bar/beer, tapas cafe/bar, french, birds, seafood.

- **Attribute groups:** Installations, atmosphere, parking, payment, smoking area, dresscode, alcohol.

4.2.4 Relational data model

A complete database relational scheme is represented in the figure 4.5. This model involves the whole database for context-aware recommender system, as well as the entities and ¡¡¡¡¡¡¡ HEAD relations among them.

The context is modeled as a relational database, each user context is a new register into data table to store user contexts.

Contextual information is also stored in the entities: ======= relations among them.

Contextual information is also stored in the following entities: ¿¿¿¿¿¿¿ origin/master *Reviews, CurrentLocation, DistancePoi and Ratings.* For instance, *Reviews entity* describes the user's opinion about visited restaurants, this information contributes to have additional information about recent preferences of diners.

CurrentLocation entity stores the geographical position of user to get a *"nearby recommendation"*, the system locates restaurants around 2 kilometers from the user position, for instance the system can takes a user position as *latitude:32.529865* and *longitude: -116.986605*, this information is stored to calculate distances from this point. The geographical position is changed frequently, in this manner, it allows the adaptation for each particular situation of user. *Distance Poi entity* stores the distances (kilometers) between the user and restaurants, this information is used to calculate *"nearby recommendation"*, each recommended restaurant ought be over the threshold defined.

Finally, *Rating entity* represents the user preferences in a vector of ratings that could be increased in time and the user's preferences patterns could be changed in time also.

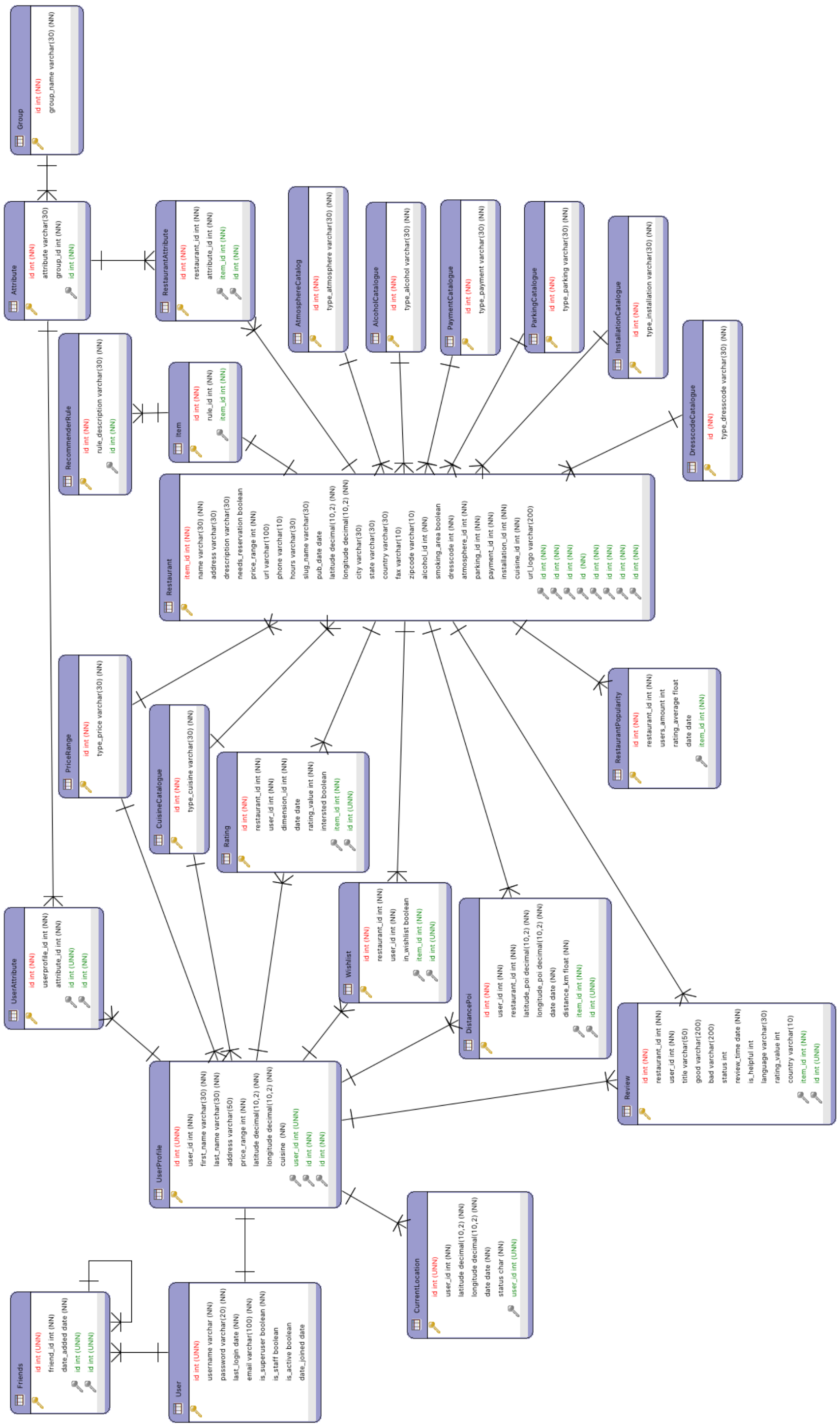


Figure 4.5: The data model of context-aware recommender system.

4.3 Expert recomendation

Fuzzy logic is a methodology that provides a simple way to obtain conclusions of linguistic data. Is based on the traditional process of how a person makes decisions based in linguistic information.

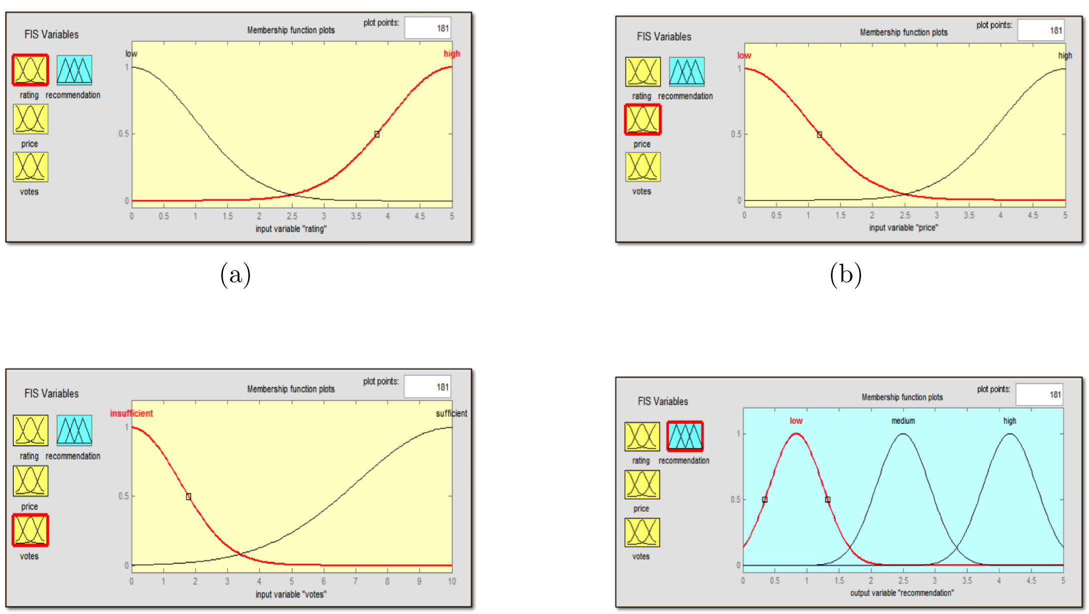
Fuzzy logic is a computational intelligence technique that allows to use information with a high degree of inaccuracy; this is the difference with the conventional logic that only uses concrete and accurately information [78].

In this work, fuzzy logic is used to model fuzzy variables that highligh in the popularity of a restaurant. The context-aware recommender system has implemented a fuzzy inference system that represents the expert recommendation.

The expert(fuzzy inference system) generates recommendations when the recommendation techniques (collaborative filtering, content-based) are not getting results because of the cold start problem.

The fuzzy inference system proposed has 3 **input variables** (such as in previous work realized[34]): 1)*rating* is an average of ratings that has a particular restaurant inside the user community; the domain of variable is 0 to 5 and contains 2 membership functions labeled as *low* and *high*(figure D.2a), 2)*price* represents the kind of price that has a particular restaurant; the domain of variable is 0 to 5 and contains 2 membership functions labeled as *low* and *high* (figure D.2b), and 3)*votes* is used to measure how many items have been rated by the current user, i.e., the participation of the user, if the user has rated few items (less than 10) is not sufficient to make accurate predictions(figure 4.9c), the domain of variable is 0 to 10 and contains 2 membership functions labeled as *insufficient* and *sufficient*.

The **output variable** is *recommendation*, represents a weight for each restaurant proposed by the expert considering the inputs mentioned above, the domain of variable is 0 to 5 and contains 3 membership functions labeled as *low*, *medium* and *high* (figure 4.10c).



(a) (b)

(c) (d)

Figure 4.6: The Gaussian membership functions of the expert system.

The proposed fuzzy inference system(figure 4.7) represents the users experience and their knowledge about restaurants. This factors are considered important for users that visiting a restaurant. This information is recovered of user profile and restaurant profile; and the system uses this information to get weights that influence in the final recommendations. The fuzzy inference system uses 5 inference rules that involve the variables of inputs and output. The input variables determine the recommendation activation; each input variable contains labels as *low* and *high* that also correspond to memberships functions of Gaussian type. For the output variable *recommendation* the labels *low*, *medium*, and *high* are used with membership functions Gaussian type also. The rules are:

1. *If* ***rating*** *is high and* ***price*** *is low then* ***recommendation*** *is high.*

2. *If* ***rating*** *is high and* ***votes*** *is sufficient then* ***recommendation*** *is high.*

3. *If* ***rating*** *is high and* ***votes*** *is insufficient then* ***recommendation*** *is medium.*

4. *If* ***rating*** *is low and* ***price*** *is high and then* ***recommendation*** *is low.*

5. *If* ***rating*** *is low and* ***votes*** *is insufficient then* ***recommendation*** *is low.*

4.4 Fuzzy Weighted Average

The main goal of this fuzzy inference system is to assign weights for each recommendation list. The recommendation technique is based in the amount of available

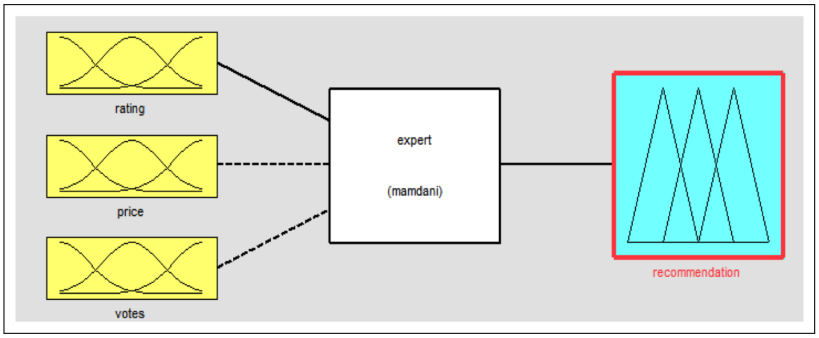


Figure 4.7: Fuzzy Inference System of expert.

information stored, so each technique utilizes this information to provide a list of restaurants as well as a weight for each one, therefore, these are used for recommendations if its weight is upper the threshold. The fuzzy inference system has inputs and outputs to infer each list's weight, its variables are depicted in figure 4.8. There are 3 membership functions for inputs and 3 for outputs. The input variables are: *userSimilarity, restaurantSimilarity and Participation* and are depicted in figure 4.9. The (4.9.a) and(4.9.b) are in a range from 0 to 1 to define the similarity average among users and restaurants, respectively. The figure (4.9.c) has a range from 0 to 15 to represent the ratings of the user(participation). This information is stored in the Popularity entity (see figure 4.5).

By other side, the output variables are: *Expert, RestaurantProfile and Correlation*, these are depicted in figure 4.10. The figure (4.10.a) represents the weight for expert recommendation list, figure (4.10.b) represents the weight of the content-based list and figure (4.10.c) represents the weight of collaborative recommendation list, their

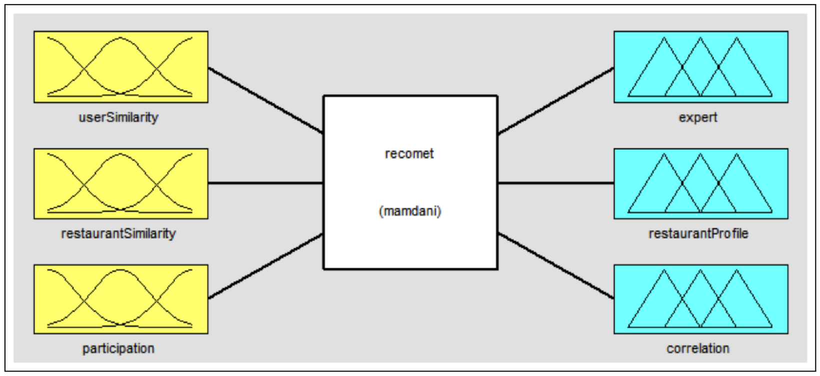
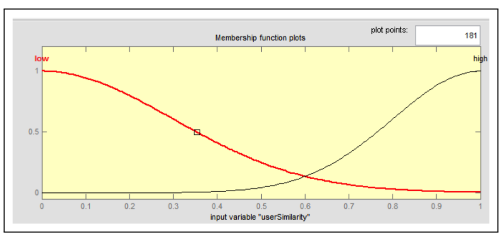
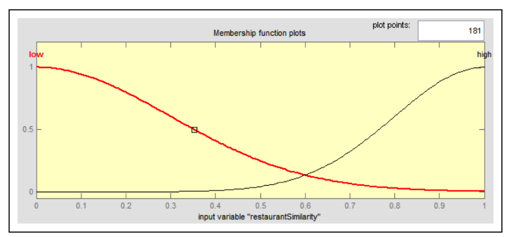


Figure 4.8: Fuzzy Inference System to assign weights.

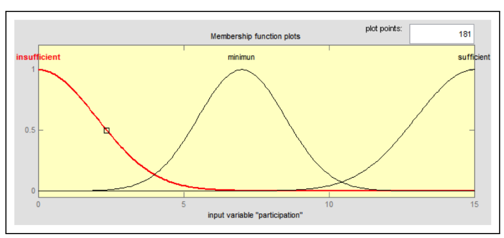
membership functions are in a range from 0 to 1 to get the value. Taking in account



(a)



(b)

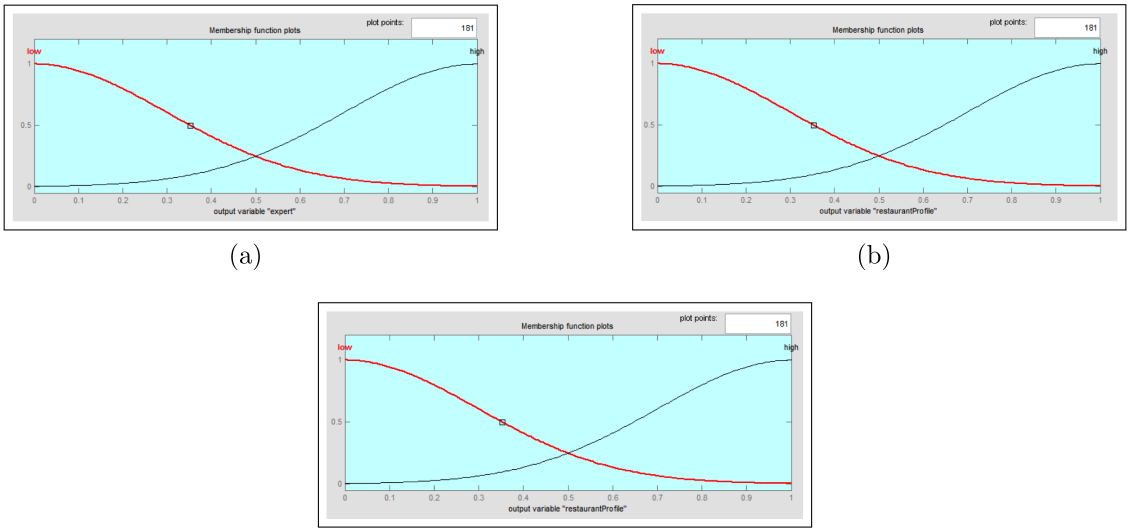


(c)

Figure 4.9: The Gaussian membership functions of input variables.

the input variables, the rules utilized to infer the output values are following:

1. *If* ***userSimilarity*** *is low and* ***restaurantSimilarity*** *is low and* ***participation*** *is insufficient then* ***expert*** *is high,* ***restaurantProfile*** *is low,* ***correla-***



(a) (b) (c)

Figure 4.10: The Gaussian membership functions of output variables.

tion *is low.*

2. *If* ***userSimilarity*** *is low and* ***restaurantSimilarity*** *is low and* ***participation*** *is sufficient then* ***expert*** *is low,* ***restaurantProfile*** *is low,* ***correlation*** *is high.*

3. *If* ***userSimilarity*** *is low and* ***restaurantSimilarity*** *is low and* ***participation*** *is minimun then* ***expert*** *is low,* ***restaurantProfile*** *is low,* ***correlation*** *is high.*

4. *If* ***userSimilarity*** *is low and* ***restaurantSimilarity*** *is high and* ***participation*** *is insufficient then* ***expert*** *is low,* ***restaurantProfile*** *is high,* ***correlation*** *is low.*

5. *If* ***userSimilarity*** *is low and* ***restaurantSimilarity*** *is high and* ***participation*** *is minimun then* ***expert*** *is low,* ***restaurantProfile*** *i s high,* ***correlation*** *is low.*

6. *If* ***userSimilarity*** *is low and* ***restaurantSimilarity*** *is high and* ***participation*** *is sufficient then* ***expert*** *is low,* ***restaurantProfile*** *is high,* ***correlation*** *is low.*

7. *If* ***userSimilarity*** *is high and* ***restaurantSimilarity*** *is low and* ***participation*** *is insufficient then* ***expert*** *is low,* ***restaurantProfile*** *is low,* ***correlation*** *is high.*

8. *If* ***userSimilarity*** *is high and* ***restaurantSimilarity*** *is low and* ***participation*** *is minimun then* ***expert*** *is low,* ***restaurantProfile*** *is low,* ***correlation*** *is high.*

9. *If* ***userSimilarity*** *is high and* ***restaurantSimilarity*** *is low and* ***participation*** *is sufficient then* ***expert*** *is low,* ***restaurantProfile*** *is low,* ***correlation*** *is high.*

10. *If* ***userSimilarity*** *is high and* ***restaurantSimilarity*** *is high and* ***participation*** *is insufficient then* ***expert*** *is low,* ***restaurantProfile*** *is low,* ***correlation*** *is high.*

11. *If **userSimilarity** is high and **restaurantSimilarity** is high and **participation** is sufficient then **expert** is low, **restaurantProfile** is low, **correlation** is high.*

12. *If **userSimilarity** is high and **restaurantSimilarity** is high and **participation** is minimun then **expert** is low, **restaurantProfile** is low, **correlation** is high.*

At the end, a *weighted average* allows to get predictions for each restaurant in the list of recommendations. In this way, for instance if the **expert** has a weight of **0.5**, the **restaurantProfile** is **0.8** and the **correlation** is **0.6**, the system uses these weights to calculate the final prediction for a particular restaurant using the formula of the weighted average:

$$prediction_i = \frac{(0.5 * 4.0) + (0.8 * 5) + (0.6 * 4.5)}{(0.5 + 0.8 + 0.6)} \tag{4.1}$$

The prediction corresponds the final value of recommendation for the item, and is used to include it or exclude it of the list of recommendation if is not over the threshold. So, for this case, the prediction is **4.57**, it means that this restaurant will be in the recommendation list of the user, subsequently, the recommendations list will be contextualized.

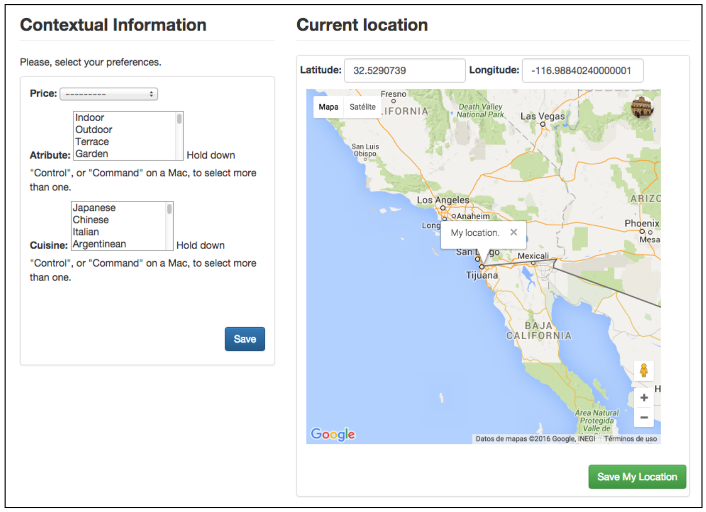


Figure 4.11: System interface to collect contextual information.

4.5 Contextual recommendation

The interface of the system(figure 4.11) allows to collect contextual information such as type of price, restaurant's attributes, type of cuisine and geographical location. The context-aware recommender system uses post-filtering paradigm, then the contextual information is used for adjust the final recommendations list. For example, geographical location is used to get restaurants around 2 kilometers of distance, next, the list of nearby restaurants is displayed for the user.

If context-aware recommender system considers another attributes as type of price and type of cuisine preferred by the user, the system gets restaurants matched in the context especified by the user in this time. In the attributes box, the user can chose any preference about what things are importants to select a restaurant. The

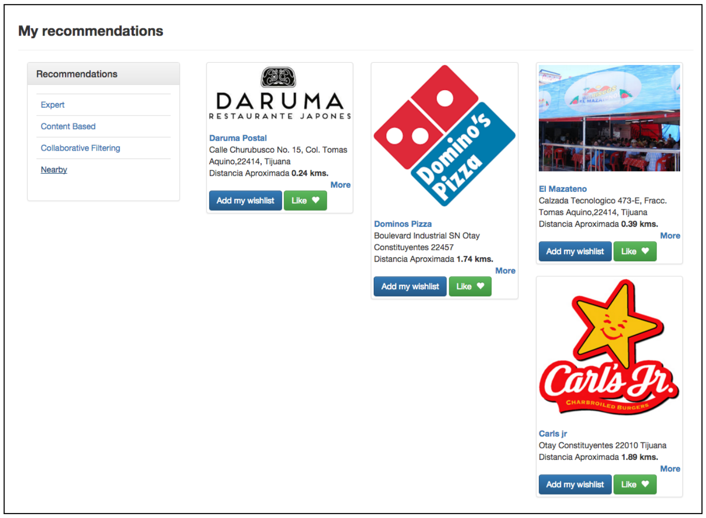


Figure 4.12: System inferface of recommendations for the user.

features are collected from the dataset of Tijuana restaurants. In the cuisine box, the user choosen his/her favorite cuisine, it can be one or more cuisines such as in attributes also. The context changes constantly, indeed, the users migh change it many times such as them wish.

After the post-filtering, the system displays the recommended restaurants according the information provides by the user. The context-aware recommender system contains four techniques to display recommendations. The interface in figure 4.12 shows recommendations: *1) Expert, 2) Content-based, 3) Collaborative filtering and 4) Nearby.* Each one was explained above, except the nearby recommendations. For nearby recommendations the system calculates the approximate distance between the current geographical location of the user and the available restaurants in the area. The threshold is 2 kilometers around the user position to determine what

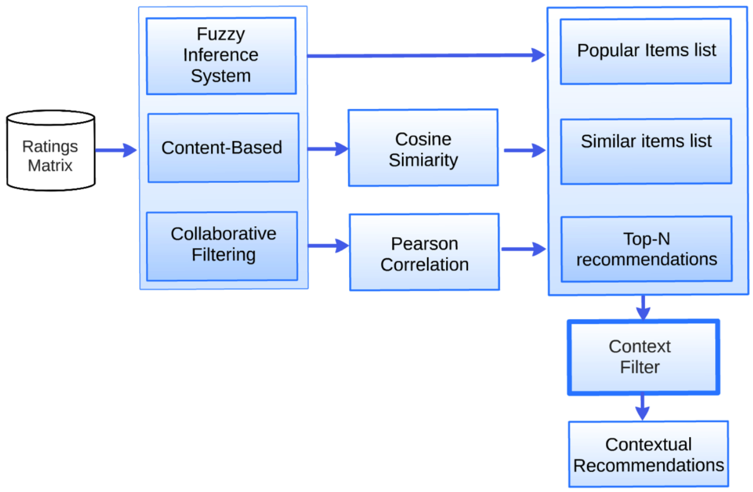


Figure 4.13: Scheme of the proposed method.

restaurants will be recommended. The geographical position is obtained throught Google maps services.

4.6 Methodology

The scheme of proposed method is depicted in the figure 4.13. In the first part, the three techniques of recommendations are suplied by the rating matrix.

Ratings matrix makes that **fuzzy inference system** can obtain the inputs values to calculate the output value. **Content-based** utilizes the rating matrix and user profiles to compare the similarity among the restaurants through cosine similarity measure. **Collaborative filtering** is based in user profiles content in ratings matrix, using Pearson correlation calculates the similarity among the users, subsequently, a list of neighbors is obtained to use their preferences to calculate predictions.

Ratings matrix makes that **fuzzy inference system** can obtain the inputs values to calculate the output value. **Content-based** uses the rating matrix and restaurant profiles to compare the similarity among restaurants through a cosine similarity measure. **Collaborative filtering** is based on user profiles contained in the ratings matrix, using a Pearson correlation to calculate the similarity among users, subsequently, a list of neighbors is obtained to use their preferences to calculate the predictions.

The second part shows the recommendation lists for the user. Later, the recommendation lists are reduced when the context filter is applied, i.e., the recommendations are adjusted for the user current context. Finally, the contextual recommendations list is displayed in the user interface (figure 4.12).

Chapter 5

Experiments and Results

5.1 Experimental settings

This chapter describes the experiments that were used in order to compare several recommender techniques. In this particular experimental scenario, the basic guidelines proposed in Adomavicius [4] are followed, and they are briefly explained next.

- **Hypothesis:** before running the experiment we must form an *hypothesis*. It is important to be concise and restrictive about this hypothesis, and design an experiment that tests the hypothesis. For example, an hypothesis can be that algorithm **A** better predicts user ratings than algorithm **B**. In that case, the experiment should test the prediction accuracy, and not other factors.

- **Controlling variables:** when comparing a few candidate algorithms on a certain hypothesis, it is important that all *variables* that are not tested will stay fixed. For example, suppose that we wish to compare the prediction accuracy of movie ratings of algorithm **A** and algorithm **B**, that both use different collaborative filtering models.

- **Generalization power:** when drawing conclusions from experiments, we may desire that our conclusions generalize beyond the immediate context of the experiments. When choosing an algorithm for a real application, we may want our conclusions to hold on the deployed system, and generalize beyond our experimental data set. Similarly, when developing new algorithms, we want our conclusions to hold beyond the scope of the specific application or data set that we experimented with. It is important to understand the properties of the various data sets that are used. Generally speaking, *the more diverse the data used, the more it can generalize the results.*

5.1.1 Off-line experiments

An off-line experiment is performed by using a pre-collected dataset of users choosing or ratings. Using this data set tries to simulate the behavior of users that interact with a recommender system. In doing so, it assume that the user behavior when the data was collected will be similar enough to the user behavior when the recommender system is deployed, so that we can make reliable decisions based on the simulation. Off-line experiments are attractive because they require no interaction with real users, and thus it allows to compare a wide range of candidate algorithms at a low cost.

The downside is that it can answer a very narrow set of questions, typically questions about the prediction of an algorithm. The goal of the offline experiments is to filter out inappropriate approaches, leaving a relatively small set of alternatives algorithms for subsequently to be tested for the more costly user studies or online experiments[4].

5.2 Datasets

5.2.1 Tijuana Restaurants

The method uses collaborative filtering to find restaurants for the user[75]. The ratings of user profiles are used to determine the similarity among users using Pearson correlation.

The similarity between the user and neighbors is used to calculate a weighted average of ratings for each particular item; the top-N ratings are used as a list of recommended restaurants for the active user. The output of the collaborative filter-

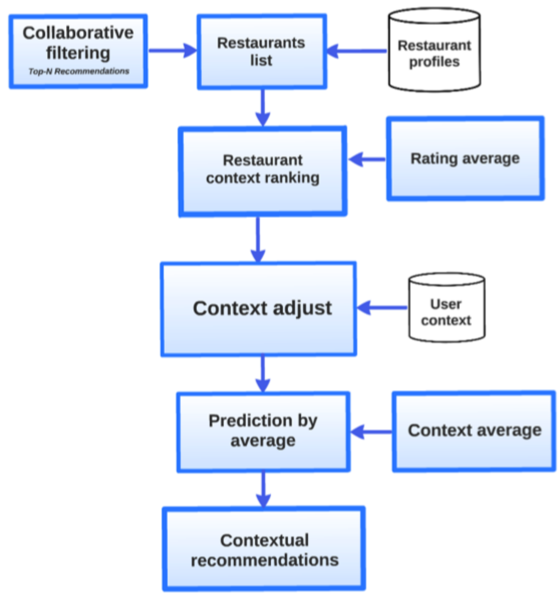


Figure 5.1: The post-filtering approach for Tijuana restaurants.

ing algorithm (top-N list) is supplied to the next step of the post-filtering process. The restaurants are adjusted to the context in the next step in order to make ranking of restaurants in the current context. Post-filtering is based on the average of ratings in a specific context, so prediction is made with: 1) the average post- filtering a restaurant has in the current context (that is the mean of user ratings) and 2) the rating predicted by the collaborative filtering algorithm. The top-N list contains the restaurants with highest predictions, so each restaurant is adjusted for the users context and listed in contextual recommendations; the process is depicted in figure 5.1.

In order to validate the proposed approach , data about restaurant preferences of users in different contexts was collected. The study subjects were students with a major in engineering, masters program and professors of the Tijuana Institute of Technology. A total of *50 users* answered a questionnaire; the questions were about their preferences for nearby restaurants and the technology most often used by them. The *questionnaire* consisted of *8 questions* and also they were asked to rate any number of restaurants from a list of 40 restaurants. Each of the restaurants chosen, was rated 6 times one per proposed context, a matrix rating with *1,422 ratings* was collected. The questions are shown in table 5.1. The reason for allowing users to chose what restaurants to rate it to give them the same liberty they have when visiting a web or mobile application.

The user's answers from question 1 to question 6 are represented in the figure 5.2. *Figure 5.2a* represents the percentage of surveyed students and teachers; *figure 5.2b* the percentage of the element that users consider the most important to visit a restaurant; *figure 5.2c* represents the preferences of devices when are using Internet for restaurant recommendations; *figure 5.2d* represents the percentage of operating system that often used, *figure 5.2e* shows the percentage of users that use the Internet to search restaurants in Tijuana; and *figure 5.2f*, shows the percentage of users that would like using a restaurant recommender system of Tijuana. For questions 7 and 8 only the top-ten restaurants are shown, without/with the contextual situation. In figure 5.3a, the favorite restaurant is **Daruma**(178 votes), whereas in figure 5.3b,

Table 5.1: Questionnaire applied to collect contextual dataset.

Question	Answers
1.What is your occupation?	1. Student 2.Employee
2.According your priority, order by importance the features you consider when you choose to visit a restaurant.	1.Installation/decoration 2.Prices 3.Service 4.Dishes 5.Atmosphere 6.Location
3.What are the devices that you used utilizes?	1.Smartphone 2.Tablet 3.Laptop 4.PC
4.What Operating System do you used?	1.Android 2.Windows 3.iOS 4.Symbian 5.Blackberry 6.Other
5.Did you use an application to search restaurants in Tijuana?	1.Yes 2.No 3.Which one?
6.Would you like to use an application of recommender systems of Tijuana?	1.Yes 2.No
7.Please, rates your favorites restaurants(without context).	Restaurant list
8.Please, rates your favorites restaurants in contextual situations.	Restaurant list

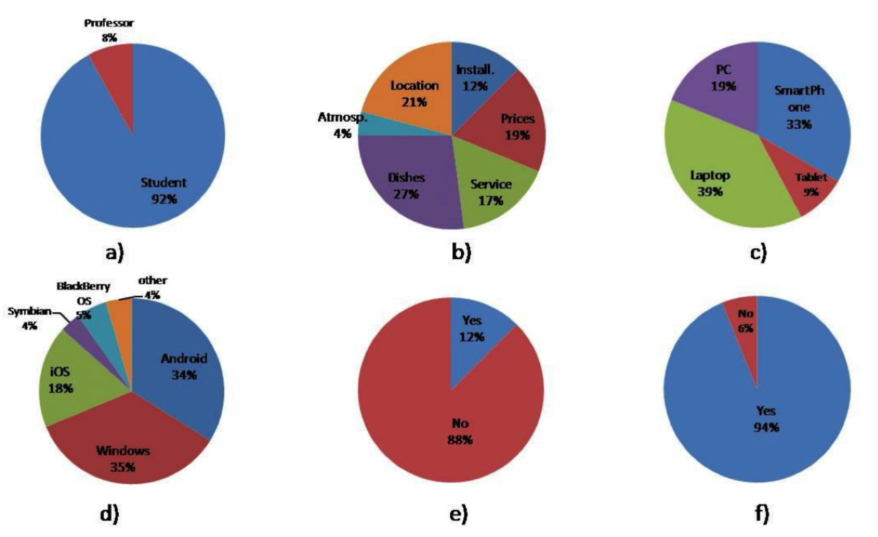


Figure 5.2: The chart cakes show the users preferences for questions from 1 to 6.

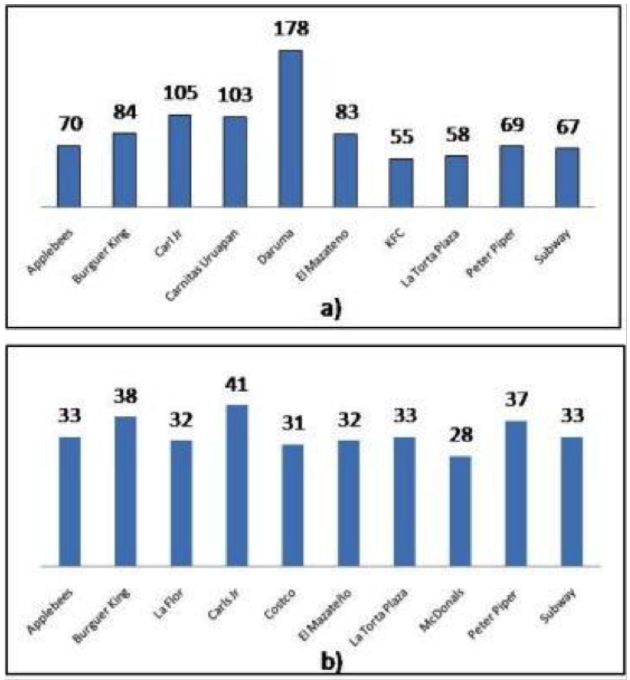


Figure 5.3: The chart shows the users preferences for questions 7 and 8.

Daruma does not appear in the top-ten. When considering the context *midweek*, the favorite restaurant was **Carlś Jr.**, which appears in both graphs; this restaurant was also the most voted in the different contexts. Contextual recommendations of post-filtering approach depends of context *midweek* or *weekend*, which is the day when the restaurants were rated. Subsequently, the result of the query is refined according to the user context; the 6 contexts mentioned correspond to combinations of contextual factors shown in table 5.2. The dataset was explicitly collected from **50 users** whom answered questionnaire (see table 5.1). A total of 172 predictions was made for different users and the mean absolute error **MAE=0.5859** when the

Table 5.2: Contextual factors considered in the questionnaire.

Contextual Factor	Context
Day	1.Midweek(Monday, Thuesday,Wednesday and Thursday) 2.Weekend(Friday,Saturday and Sunday)
Place	1.School 2. Home 3.Work

context **midweek** for the current user was considered. The observation for this result is that using a small dataset the performance of the method proposed is limited. On the other hand, having only one contextual factor does not improve the accuracy of the recommendations in this domain.

5.2.2 MovieLens collection

GroupLens Research has collected and made available rating data sets from the MovieLens web site (http://movielens.org).

The data sets were collected over various periods of time, depending on the size of the set.

- *MovieLens 1M*: Stable benchmark dataset, 1 million ratings from 6000 users on 4000 movies. Released 2/2003.

  Downloaded from http://grouplens.org/datasets/movielens/1m/.

- *MovieLens 10M*: Stable benchmark dataset, 10 million ratings and 100,000 tag applications applied to 10,000 movies by 72,000 users. Released 1/2009.

Downloaded from http://grouplens.org/datasets/movielens/10m/.

The proposed method for MovieLens uses post-filtering and time segmentation. Time in recommender systems is used as a contextual factor in the research reviewed [11], [10], [46], and [39], results vary according the techniques that were done.

In [39] the pre-filtering approach was used, time was divided in time intervals and the size of time intervals is directly proportional to the distance from initiating the historical information to the current user context. In [46] a tracking model of user behavior over the life-time of data is proposed, in order to exploit the relevant components of all data instances, while discarding only what is modeled as being irrelevant.

In [11] it is shown that the time division is beneficial and its performance depends on the items selection method and influence of contextual variables in item ratings. In [10] the user profile is segmented into micro-profiles corresponding to a particular context, each context represents a time span in which recommendations for users are derived.

This experiment implements fuzzy logic on time segmentation, in order to improve user satisfaction by providing recommendations based to context and recents user preferences without discarding tastes in the past, as they include important information for the recommender system proposed.

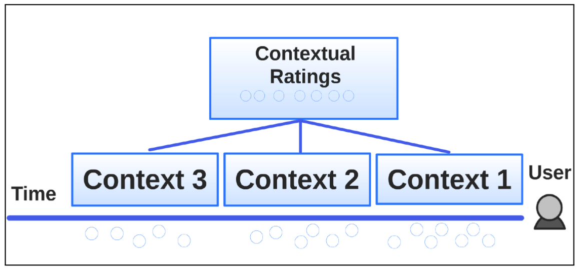


Figure 5.4: Time segmentation of contexts based on current user context.

The first phase is division of three time segments based on the current context of the user is performed such as in is depicted in figure 5.4. In recommender system, the first step is to obtain the user context, from this information three contexts (figure 5.4) will be obtained that representing a time segment of three months each one, in total the algorithm considers all the ratings users did during nine months prior the current context. Subsequently, ratings are classified by contexts and reused as contextual rating matrix being, a ratings matrix for each context.

The size of matrix depends of users' participation during the last nine months. One of the aims is to identify the user behavior through recent information, in order to, for instance, know whether the user changes ratings constantly; whether usually assign high, low or mixed ratings; whether user likes to see different items or whether have a favorite category.

Recommender systems use the collaborative filtering algorithm in order to find relevant items for the user [75]. User's profiles are used for determine the similarity between users calculated with Pearson correlation. The similarity between users can provide valuable information as long as user participation is enough (less than 10 ratings). The next step is to obtain recommendations list (Top-N), three contextual lists are the outputs of collaborative filtering algorithm and contain items with user's predictions for each context.

Popularity's prediction considers other variables: 1) users participation in respect of an item in the context and, 2) the rating's average that users have given for item in the same context.

A Fuzzy Inference System (FIS) uses these parameters to assign a weight within a scale from 1 to 5 (prediction value). These recommendations are used when the ratings matrix is sparse, a popularity prediction is done.

Finally, the system gets the recommendations list for each user in different contexts. The recommendation process for pre-filtering approach is depicted in figure 5.5. The dataset used to test the algorithm was MovieLens(100000 ratings) with 943 users and 1,682 movies. The ratings were collected in a period of 2 years.

MovieLens is not a contextual dataset, however, the timestamp was used to determine the rating time, i.e., in this way it was noted the day to know whether the rating time was in weekday or weekend. In this terms, the context was used. Then, the time for each context was divided in 3 months each one, this span covers 9 months before the user's current context.

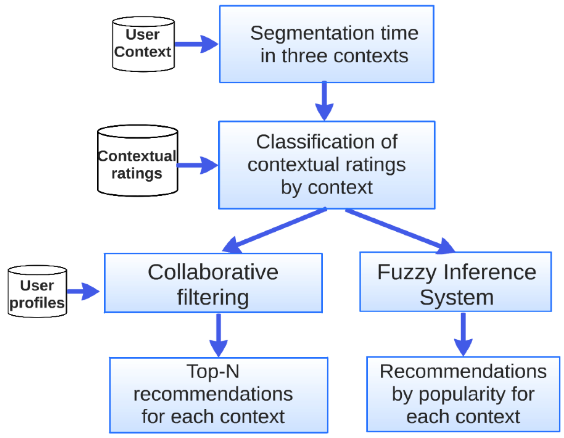


Figure 5.5: Pre-filtering approach used for Movielens dataset.

Table 5.3: Results of comparison by contexts in MovieLens dataset.

Context	# Preditions	MAE
1	12235	0.28
2	21049	0.24
3	1075	0.38

The neighbors in each context are considered to recommend movies in that context only. An average of predictions are considered for add a movie to the top-N list of contextualized recommendations.

The result in table 5.3 shows the error in three contexts. The error increase in context 3, in this context the ratings matrix is a little bit sparse; the error is justifiable because user has less participations.

5.2.3 TripAdvisor collection

The dataset used to evaluate the algorithm was TripAdvisor in two versions downloaded[79], this datasets was used in [81] and [80] to evaluate the performance of context-aware recommender systems.

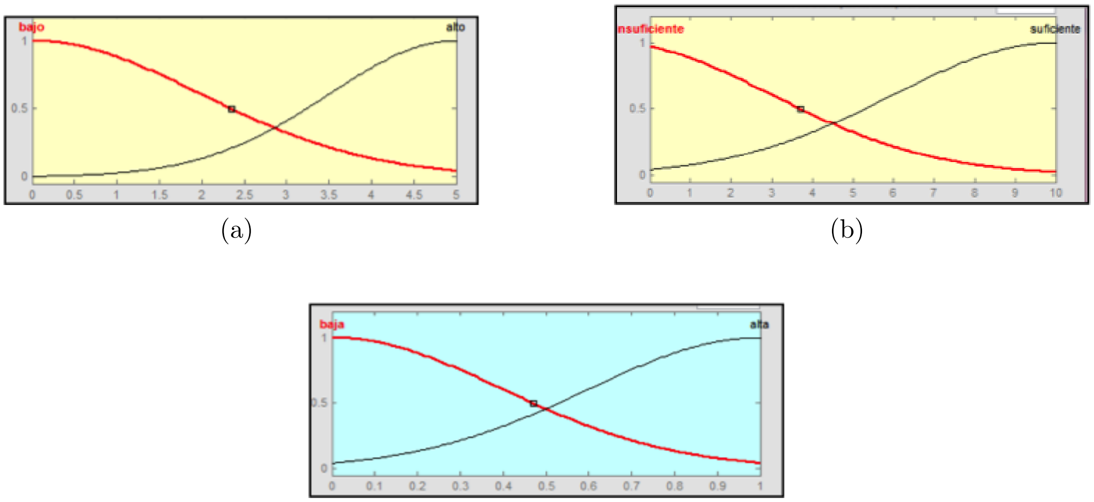
The first dataset contains 4669 contextual ratings, 1202 users and 1890 hotels; the second dataset contains 14175 contextual ratings, 2731 users and 2269 hotels. Data were collected of reviews online in tripadvisor.com. There is only one context: type of trip (family, friends, bussines, romantic and relax).

The proposed method consists of three algorithms to recommend: Fuzzy Inference System, collaborative filtering and content-based. Each one uses rating matrix to get recommendations.

The context-aware recommender system uses the post-filtering paradigm[4] for adjust recommendations in context. The recommendation by popularity is through the Fuzzy Inference System depicted in figure 5.7, the Fuzzy Inference System contains the variables that are involved in the process to recommend in a human interaction, this process is the same that the recommender system does.

The output represents how matter each item into the users community, i.e. if it was a popular item for users.

The FIS has Gaussians membership functions and are depicted in figure 5.6. The



(a) (b) (c)

Figure 5.6: Gaussian Membership functions in the input are: a) RatingAverage, b) UserParticipation, and an output: c) Recommendation.

fuzzy inference system uses fuzzy rules to infer the inputs and output(a crisp value) that represents the weight of the recommendation. The rules are following:

1. *If* ***RatingAverage*** *is low and* ***UserParticipation*** *is insufficient then* ***recommendation*** *is low.*

2. *If* ***RatingAverage*** *is low and* ***UserParticipation*** *is sufficient then* ***recommendation*** *is high.*

3. *If* ***RatingAverage*** *is high and* ***UserParticipation*** *is insufficient then* ***recommendation*** *is low.*

4. *If* ***RatingAverage*** *is high and* ***UserParticipation*** *is sufficient then* ***recommendation*** *is high.*

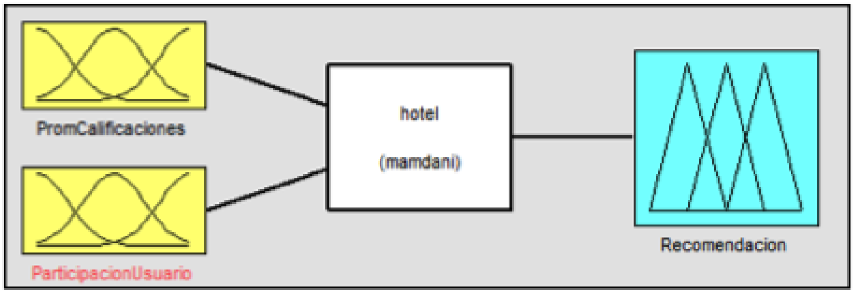


Figure 5.7: Fuzzy Inference System.

Content-based uses cosine similarity to compare the binary vectors representing the profile of each item, thereby obtaining a numerical value that determines similarity, based on a threshold.

In other words, it makes a comparison of profiles of each item to determine the most similar to items the user has rated with highest score, context-aware recommender system proposed has a scale from 1 to 5. In the next step the outputs

Table 5.4: Example of contextual ratings in the user profile.

User profile		
Item	Rating	Context
La Casa del Mole	5.0	Midweek
Daruma	4.0	Weekend
Daruma	5.0	Midweek
Carl's Jr.	3.0	Weekend

of every recommender algorithm is represented by a list of recommended items. Subsequently applies the context filter and context-aware recommender system gets the final contextual recommendations. Context-aware recommender system identifies contextual data of the user profile (see table 5.4), and compares recommended

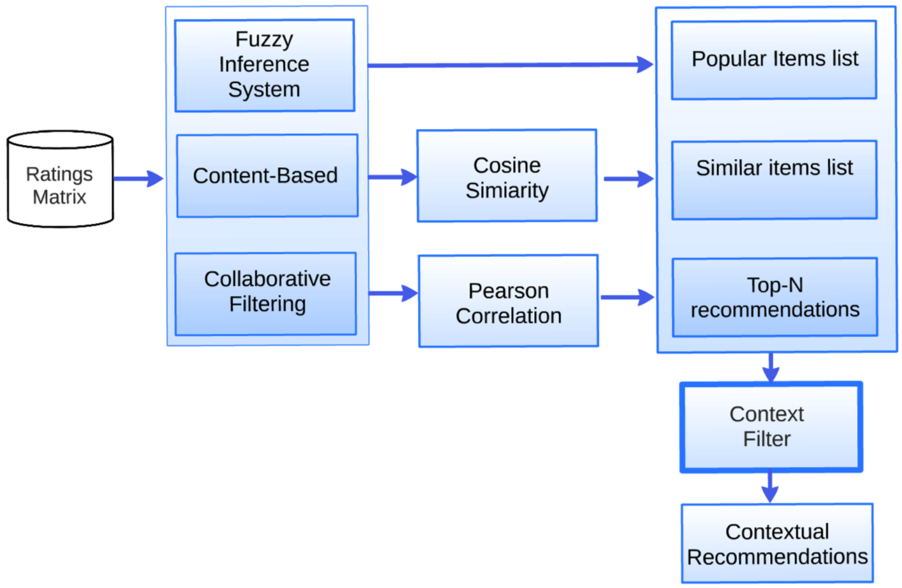


Figure 5.8: Recommender system methodology.

items to filter those items that are adjusted to the user context. The context filtering is the last step before to get the recommended items. The schema of architecture for context-aware recommender system is depicted in figure 5.8. Two experiments were performed using TripAdvisor dataset, table 5.5 describes the data sets and the scarcity percentage of the specified data. Scarcity of 99% mean that there are problems to recommend items because the information is not enought to get good recommendations.

By other side, in table 5.6 the comparison shows that the algorithm has a acceptable performance, i.e., the error falls into the range of results obtained with others algorithms. Then, contextual recommendations were evaluated with the Root Mean

Table 5.5: Datasets description.

Dataset	Users	Items	Ratings	Scarcity (percent)
TripAdvisor v1	1202	1890	4669	99.79
TripAdvisor v2	2731	2269	14175	99.77

Table 5.6: Comparison of RMSE.

Dataset	Algorithm	RMSE
TripAdvisor v2	FC + Post-filtering	0.504
	FC	0.994
	Pre-filtering + Relaxation	0.985

Square Error in order to compare the results with context relaxation algorithm[80] that is evaluated with the same dataset.

The cosine similarity plays an important role in content-based because if similarity value among items is high, the recommendations will improve the degree of user satisfaction.

This is observed when calculating the similarity average in each dataset as shown in table 5.7. FIS can provides a list of popular items for each dataset, recommendations through averages are obtained, and recommendations are conditioned to show it when the collaborative filtering and content- based are not delivering recommendations because of data scarcity.

Table 5.7: Level of similarity among items in datasets.

Dataset	Similarity	Avg.votes per user.
TripAdvisor v1	0.448	5
TripAdvisor v2	0.508	8

However, the majority of popular items of dataset were rated in contexts: romantic, family and bussines, that means that the dataset has biases.

In this experiment the context-aware recommender system proposed involves the paradigm of post-filtering for contextual recommendations. The structure of the datasets facilitated the evaluation of recommendations although the rating matrix has been scarce in both cases. Anyway, information of items and users was used to test the system and a good performance of the system was done.

With respect the performance, post-filtering allows select relevant items that are adjusted into the context, indeed, post-filtering and implementation of different recommendation techniques the system has suitable performance and the datasets help the processes performed.

5.2.4 Filmtrust and InCarMusic

FilmTrust is a small dataset crawled from the entire FilmTrust website in June, 2011. Filmtrust contains a ratings matrix of 35498 ratings, 1504 users and 2071 movies.

The dataset has a density of 1.14% and was used in [38] using the trust level such as context. The web page is `http://www.librec.net/datasets.html`.

InCarMusic dataset[12] has 8 contextual factors and the possible values for contextual conditions are explained in table 5.8.

Table 5.8: Contexts in InCarMusic dataset.

Context	Values
Driving style	elaxed, driving, sport driving.
Road type	city, highway, serpentine.
Landscape	coast line, country side, mountains/hills, urban.
Sleepiness	awake, sleepy.
Traffic conditions	free road, many cars, traffic jam.
Mood	active, happy, lazy, sad.
Weather	cloudy, snowing, sunny, rainy.
Natural phenomena	day time, morning, night, afternoon.

Music tracks were ten different genres. There is not unified music genre taxonomy, for this reason the recommender system uses the genres defined in [74]: classical, country, disco, hip hop, jazz, rock, blues, reggae, pop and metal, 50 music tracks and 42 users in dataset.

Results

For experiments with matrix factorization technique the *Graphlab toolbox* was used. FilmTrust, InCarMusic and Movielens (1 millon and 10 millions) were used to test the algoritmh. The test involves *K factors* that are increasing for *50 iterations.* Previously, was done a test to identify what number of iterations are enough to get a good result with no overload of process in the algorithm.

Results are depicted in the chart 5.9 where the *axis (x, y)* represent the *K value* and the *error value*, respectively. The observations deal to small differences among the datasets, in a range of *0.80-0.90*, and the high variability is in *MovieLens* 10

Table 5.9: RMSE of datasets using matrix factorization.

Dataset	Ratings	Cosine Sim.	RMSE
Tijuana Rest.	896	0.67	0.60
Mexico Rest.	1161	0.25	0.54
InCarMusic	4012	0.45	0.93
TripAdvisor	4669	0.17	0.85
MovieLens	10000	0.46	0.51
Movielens	100000	0.94	0.42

millions. Thus, the large dataset implies more unstable behaviour, while in a small dataset(Filmtrust) the error is less variable. A comparison among MovieLens 1 million and 10 millions shows that there's not a significant difference.

By other side, another datasets were used to test matrix factorization under the same parameters to calculate the RMSE for each one.

Table 5.9 presents the total of ratings of each dataset, the cosine similarity that means how similar are the items into the dataset, and the RMSE error obtained in the test with matrix factorization technique, the datasets contain less number of ratings than the presented in the chart 5.9. Making a comparison and according the table 5.9 is not possible to affirm that matrix factorization has a better performance with small datasets, because TripAdvisor and InCarMusic datasets obtain a similar error in the same range that the large datasets.

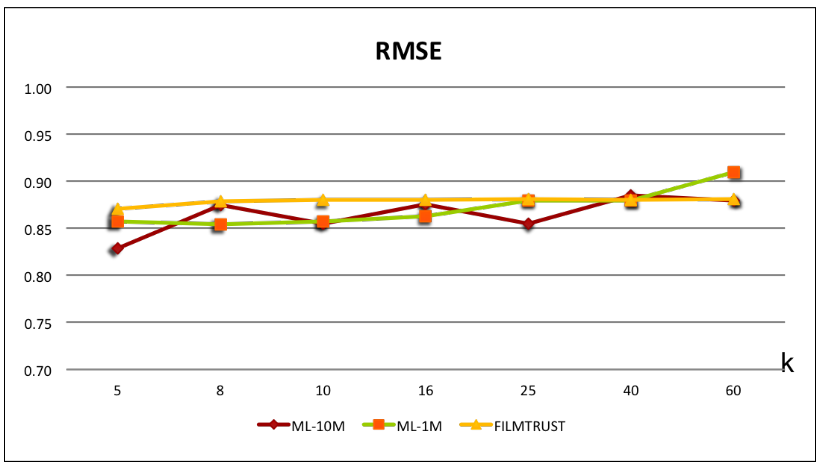


Figure 5.9: RMSE results of matrix factorization.

Chapter 6

System evaluation

Initially most recommenders have been evaluated and ranked on their prediction power, i.e, their ability to accurately predict the user's choices. However, it is now widely agreed that accurate predictions are crucial but insufficient to deploy a good recommendation engine. In many applications people use a recommendation system for more than an exact anticipation of their tastes.

Users may also be interested in discovering new items, in rapidly exploring diverse items, in preserving their privacy, in the fast responses of the system, and many more properties of the interaction with the recommendation engine. We must hence identify the set of properties that may influence the success of a recommender system in the context of a specific application. Then, we can evaluate how the system performs on the relevant properties[4].

In this thesis it performs the **on-line experiments**, this is maybe the most trustworthy experiment because is when the system is used with **real users**, typically **unaware** of the experiment. In this type of experiment it is possible to collect only certain types of data but this experimental design is closest to reality.

6.1 Metrics

For purposes to get real data from user experience, usability was used as evaluation metric of the prototype, then, two test were proposed: the **task-success** and **time-on-task** metrics.

The **task-success metric** is perhaps the most widely used performance metric. It measures how effectively users are able to complete a given set of tasks. The **time-on-task metric** is a common performance metric that measures how much time is required to complete a task[6].

The **task-success** is something that almost anyone can do. If the users can't complete their tasks, then something is wrong. When the users fail to complete a simple task can be an evidence that something needs to be fixed in the recommender system. The tests consist of a list of thirteen simple tasks that users shall perform in the system prototype. Before to start, a brief description about the system functionalities and instructions to perform the test was explained. The tasks list are the following:

1. *Rated a restaurant without context.*
2. *Add context to the user profile.*
3. *Filter restaurants by favorite context.*
4. *Find information of a specific restaurant.*
5. *Find all the reviews of a specific restaurant.*
6. *Find section "my favorite restaurants".*
7. *Add a review for a restaurant.*
8. *Find the most popular restaurants.*
9. *Add a restaurant to your wishlist.*
10. *Get recommendations based on expert opinion.*
11. *Get the recommendations content-based.*
12. *Get the collaborative recommendations.*
13. *Get recommendations of the nearby restaurants.*

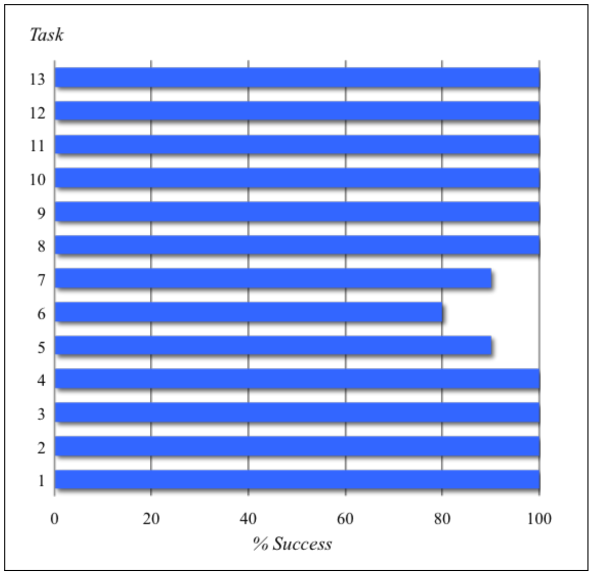


Figure 6.1: Chart of the percent of success for each task.

6.2 Enviroment set up

Each user makes the list tasks, the average time that each user used to finished the list was around 10 minutes. The data was collected in every session and concentred in a chart in order to observe the users behaviour for each task.

In the figure 6.1 the axis *(x, y)* represent the *task number* and *percent of success*, respectively. The chart shows that only three tasks weren't accomplished successfully, the task 5, 6 and 7.

The issue in task 5 was that users can not found easily the reviews section in the screen because the reviews are in the restaurant's profile and not in the *Home page*. The issue in task 7 is related of task 5 because the user couldn't find the manner to add a review, the user needs to click the restaurant profile to add the review. The task 6 correspond to the favorites restaurants section that it is in the main screen, but the issue is that the user was confused to choose "wishlist container" (see appendix D) instead "favorites restaurants", both were showed in the *Home page*. Overall, these results mean a redisign in the prototype system to facilitate the performance of the tasks and create a more friendly interface.

By other side, the time that takes a participant to perform a task says a lot about the usability of the application. In almost every situation, the faster a participant can complete a task, the better the experience. In fact, it would be pretty unusual for a user to complain that a task took less time than expected[6].

The next test *task-on- time* is applied to measure time that an user uses to make each task. The time of task that each user used for each task is in table 6.1. The time depends of the user capabilities and the complexity of the task. Some users perform and understand the task easily(as the user 9) but others take more time to perform the task(as the user 3). The "Null" value in table 6.1 means that the user don't perform the task. After an analysis the user's feedback, it concludes that the problem is that task is not explained correctly, then, it needs to be more specific.

Table 6.1: Time-on-task data for 10 users and 13 tasks.

Task	Us1	Us2	Us3	Us4	Us5	Us6	Us7	Us8	Us9	Us10
1	12	28	24	30	19	33	23	16	5	7
2	3	4	17	5	17	134	9	16	12	11
3	123	69	159	53	69	113	44	41	70	98
4	20	4	86	40	13	4	17	3	20	3
5	50	10	63	50	7	11	10	5	20	Null
6	10	30	28	27	5	46	Null	7	Null	34
7	10	20	16	8	15	Null	9	24	16	28
8	18	24	10	10	5	3	27	4	5	6
9	5	6	31	4	45	9	12	5	3	8
10	15	17	15	11	10	19	13	10	20	20
11	30	15	20	16	20	22	15	13	18	20
12	12	14	19	14	40	10	17	17	15	15
13	25	15	15	14	10	10	11	10	10	25

6.3 Results

To measure the efficiency of the metric, it choose a confidence interval. In this way, it is observed the time variability within the same task and also helps visualize the difference among the tasks to determine whether exists a statistically significant difference between these. Figure 6.2, shows the confidence interval for each task. The median was used to calculate the lower bound and upper bound of the confidence interval. In order to have more precision in the confidence interval, it used the median instead the mean, the median corresponds the red numbers of the chart. Figure 6.2 also shows that task 2 and 3 show large confidence interval because of the delay of users to accomplish these task.

After tests, the USE *(Usefulnes*, *Satisfaction*, and *Ease of Use)* questionnaire [53]

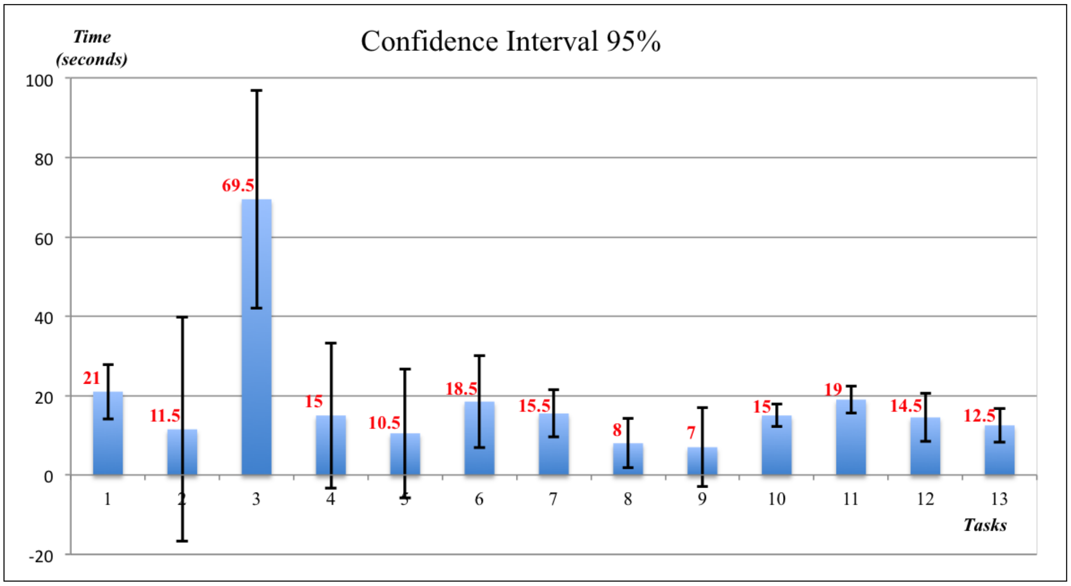


Figure 6.2: Confidence interval per task with a confidence level of 95%.

was applied in order to get the user's feedback and comments to know about the difficults in the test. Finally, it applied a questionnaire that measure the satisfaction level of users, this questionnaire serves to evaluate the experience that they had in the system interaction. The *USE questionnaire*(see appendix B) consists of 30 rating scales divided into 4 categories: *Usefulness*, *Satisfaction*, *Ease of Use*, and *Ease of Learning*. Each is a positive statement to which the user rates level of agreement on a Likert scale.

The USE questionnaire allows to get values for *Usefulness*, *Satisfaction*, *Ease of Use*, and *Ease of Learning*. The visualizing of the results is in the figure 6.3, where the four axis of the chart represent the values of percent which users rated positively this factors with respect to their experience with the system prototype. The values

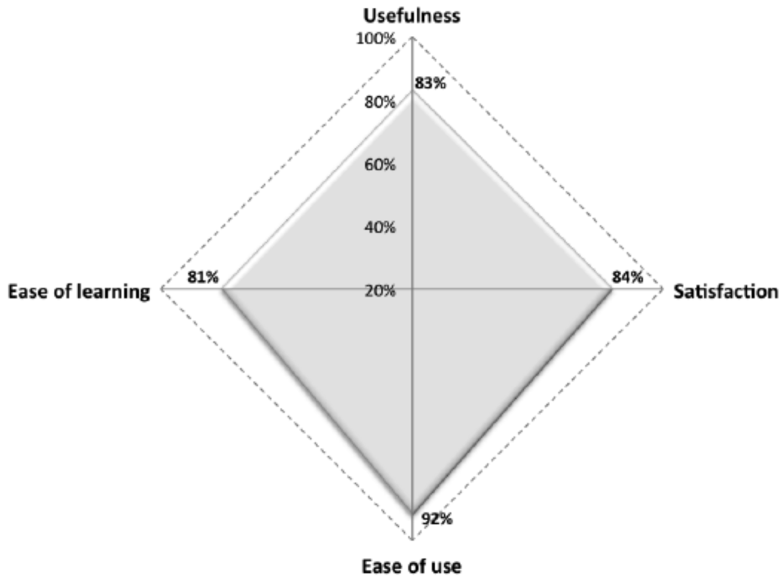


Figure 6.3: The radar chart that depicts the four axis evaluated.

are *Usability 83%*, *Satisfaction 84%*, *Easy of use 92%*, and *Easy of Learning 81%*, it means that the test was success, subsequently, as future work a second test will be make to compare the improves.

Chapter 7

Conclusions and future work

In the past, computer software was designed with little regard for the user, so the user had to somehow adapt to the system. This approach to system design is not at all appropriate today, the system must adapt to the user. This is why design principles[37] are so important. The principles represent high-level concepts applied to the systems for the better design of user interfaces. We took this principles as a guideline to design the first prototype, however when the system is in a pilot test, we hope find the common problems that the users face normally. So, it was observed the user behaviour in the test, in order to identify the most frecuently difficults and doubts about proposed tasks.

Later, it was done a brief interview with the users in order to understand their feelings or mood, their experience, and overall, their opinion about the system prototype. The conclusions are based in user's comments, then the common errors in the system interface are summarized in three points:

1. Incomplete information for user, i.e., the system doesn't had enough and clear information to be a friendly interface, and therefore the user couldn't do easily a task.

2. Fails in design, because of unordered elements in the screen, in other words, the elements are not in the correct site into the screen to be easily identified per users.

3. Fails in the language and confusion, because of the english language is not the native language of the users.

The three points mentioned represent the null values in data table (see Table 6.1), some users don't perform the task because they were confused, so they decided to omit the task. The null values weren't took in account when the median was calculated to obtain the confidence interval(see figure 6.2).

By other hand, the USE questionnaire was useful to identify the weaknesses in the system prototype. The percent in the factors is in acceptable level (80%), it allows to say that the system has a good performance in the first test, but an increment in the number of users to perform the next possible test could get more real information.

For the future work we proposed to improve the problems found in the user interface, so the proposals are the following:

1. Redesign the user interface could helps to be more friendly for users. The redesign involves:
   (a) Analyze the amount of information enough for a easy understanding, i.e., how much information the user needs seeing without overload it.
   (b) Modify the tasks descriptions in the most simple way to avoid confusion.
   (c) Add more language functionalities for to facilitate the tasks for users.
2. To apply the usability test again with the changes in the interface in order to observe the level of improves and to compare the results.
3. Apply an statistical test to analize the results.
4. Add collaborative filtering based on model (matrix factorization technique) in the system prototype in order to improve the level of user satisfaction in the context.
5. Add any contextual factors(such as companion, time of day, budget, etc.) in order to include more context information that contributes to improve the recommendations.

The proposed method was used in the system prototype in order to validate its performance, the case of study shows acceptable results but we consider that the method could be efficient in others domains. The challenge is to apply the method in a e-learning environment because the context involves more precise factors (for instance the level of noise, the level of light, the level of knowledge, the location of the users, etc.) and the recommendation process considers more conditions(or fuzzy rules) to make a recommendations, as well as the information of the user profile that contains more characteristics of the user preferences(as goals, level, learning style, activities, homework, score, average, etc.) The base of this future work is the Protoboard system[33] that is a e-learning platform for students of Tijuana Institute of Technology.

Publications

1. *Restaurant Recommendations based on a Domain Model and Fuzzy Rules. Xochilt Ramírez-García, Mario García-Valdéz. International Seminar on Computational Intelligence. Tijuana Institute of Technology. Tijuana Mexico. (2012).*

2. *Post-filtering for a Context-Aware Recommender System. Xochilt Ramírez-García, Mario García-Valdéz. Recent Advances on Hybrid Approaches for Designing Intelligent Systems . Springer International Publishing Switzerland. (2013).*

3. *Recomendaciones contextuales basadas en el enfoque de post-filtrado. Xochilt Ramírez-García, Mario García-Valdéz. Modelado computacional de Habilidades Linguisticas y Visuales. Vol.74. Research in Computer Sciences, IPN. 2014.*

4. *Context-aware Recommender System Based in Pre-filtering Approach and Fuzzy*

Rules. Xochilt Ramírez-García, Mario García-Valdéz. Recent Advances on Hybrid Approaches for Designing Intelligent Systems . Springer International Publishing Switzerland. (2014).

5. *Context-Aware Recommender System Using Collaborative Filtering, Content-Based Algorithm and Fuzzy Rules. Xochilt Ramírez-García, Mario García-Valdéz, 2016.*

6. *A Hybrid Context-aware Recommender System for Restaurants. Xochilt Ramírez-García, Mario García-Valdéz, 2016.*

Appendix A

Pseudocode

Algorithm 1 Get Cosine similarity values

Require: The list of itemProfilesUser and itemProfilesAll in binary format.
Ensure: The list of cosine similairty value for each item of the itemProfilesUser with each element of itemProfilesAll.

```
allProfiles ←[ ]
for itemu to size of itemProfilesUser do
  for itema to size of itemProfilesAll do
    if itemu = itema then
      jump next item
    else
      cosineSimilarityValue ← among itemu and itema
      itemProfiles ← itemu, itema, cosineSimilarityValue
    end if
  end for
end for
return allProfiles
```

Algorithm 2 Collaborative filtering algorithm

Require: The userId.
Ensure: The Top-N list of recommendations for the current user.

```
ratingMatrix ← allRatings
Call Recommendations ← getRecommendations() module
return Recommendations
```

Algorithm 3 Content-Based Algorithm

Require: The user id.
Ensure: The Top-N list of recommendations.

```
RV ← All items that user rated with 5
for item to size of RV do
    if item is not in RV then
        UV ← itemid
    end if
end for
allItems ← [ ]
getItemsProfilesUser ← Binary vectors of RV
allRatings ← Rating matrix
for item to size of allRatings do
    if itemid is not in allItems then
        allItems ← item
    end if
end for
getAllItemsProfiles ← Binary vectors of allItems
getCosineSim ← getItemsProfilesUser,getAllItemsProfiles
for item to size of highCosineSim do
    if itemsimilarity ≥ 0.8 then
        highCosineSim ← item
    end if
end for
Sort highCosineSim list
return itemProfiles
```

Algorithm 4 Get item profiles

Require: The UV vector, allItems vector and boolean value of userProfile.
Ensure: The list of temProfiles in binary vectors.

```
if userProfile true then
    getItemsProfilesUser ← UV
    for itemp to size of UV do
        get binary vector of itemp
        itemProfiles ← itemp
    end for
else
    allItemProfiles ← allItems
    for itemp to size of allItems do
        get binary vector of itemp
        itemProfiles ← itemp
    end for
end if
return itemProfiles
```

Algorithm 5 Calculate Cosine similarity

Require: The itemProfileUser and itemProfileAll, both vectors in binary format.
Ensure: The cosine similarity value.

```
sum ← 0
normaItemUser ← 0
normaItemAll ← 0
for position to size of itemProfileUser do
    sumProduct ← sumProduct + (itemProfileUser[position] * itemProfileAll[position])
end for
for item to size of itemProfileUser do
    normaItemUser ← normaItemUser + itemProfileUser[item]^2
end for
for item to size of itemProfileAll do
    normaItemAll ← normaItemAll + itemProfileAll[item]^2
end for
squareRootUser ← squareroot(normaItemUser)
squareRootAll ← squareroot(normaItemAll)
cosineSimilarity ← sumProduct/(squareRootUser * squareRootAll)
return cosineSimilarity
```

Algorithm 6 Create a binary vector of item profile

Require: The tem profile content in r.
Ensure: The temProfile of r in a binary vector.

$price \leftarrow [4]$
$payment \leftarrow [2]$
$alcohol \leftarrow [2]$
$smokingarea \leftarrow [2]$
$dresscode \leftarrow [3]$
$parking \leftarrow [3]$
$installation \leftarrow [4]$
$atmosphere \leftarrow [5]$
$cuisine \leftarrow [30]$
$price[positionPriceId - 1] \leftarrow 1$
$payment[positionPriceId - 1] \leftarrow 1$
$alcohol[positionPriceId - 1] \leftarrow 1$
$smokingarea[positionPriceId - 1] \leftarrow 1$
$dresscode[positionPriceId - 1] \leftarrow 1$
$parking[positionPriceId - 1] \leftarrow 1$
$installation[positionPriceId - 1] \leftarrow 1$
$atmosphere[positionPriceId - 1] \leftarrow 1$
$cuisine[positionPriceId - 1] \leftarrow 1$
$itemProfile \leftarrow price+payment+alcohol+smookingarea+dresscode+parking+ installation + atmosphere + cuisine$
return $itemProfile$

Algorithm 7 Get recommendations

Require: The currentUser and ratingMatrix.
Ensure: The Top-N list of recommendations for the current user.

```
Dictionaries totals ← {}, sumSimilarity ← {}
predictions ←[ ]
for otherUser to size of ratingMatrix do
    if otherUser = currentUser then
        jump next otherUser
    end if
    similarityValue ← get pearsonSimilarity
    if similarityValue ≤ 0 then
        jump next otherUser
    end if
    for item to size of profileOther do
        if item is not in profileUser then
            if profileUser[item] = 0 then
                Set in totals ← item
                totals[item] Add ratingMatrix[otherUser][item] * similarityValue
                Set in sunSimilarity ← item
                sumSimilarity Add similarityValue
            end if
        end if
    end for
end for
for each (item, total) in totals do
    predictions ← [(total/sumSimilarity[item], item)]
end for
Ranking of predictions
return predictions
```

Algorithm 8 Get Pearson correlation

Require: The currentUser, otherUser and preferences.
Ensure: The pearsonCorrelation score.
  Dictionaries $itemsRatedMutually \leftarrow \{\}$
  for each $item$ in preferences of $currentUser$ **do**
    if $item$ is in preferences of $currentUser$ **then**
      jump next $itemsRatedMutually[item] \leftarrow 1$
    end if
  end for
  $numberElements \leftarrow$ size of $itemsRatedMutually$
  if $itemsRatedMutually = 0$ **then**
    return 0
  end if
  for $item$ to size of $itemsRatedManually$ to get all preferences **do**
    $sumCurrentUser \leftarrow preferences[currentUser][item]$
    $sumOtherUser \leftarrow preferences[otherUser][item]$
  end for
  for $item$ to size of $itemsRatedManually$ to get squares **do**
    $squareCurrentUser \leftarrow square(preferences[currentUser][item])^2$
    $squareOtherUser \leftarrow square(preferences[otherUser][item])^2$
  end for
  for $item$ to size of $itemsRatedManually$ to get sum of products **do**
    $sumProduct \leftarrow preferences[currentUser][item] * preferences[otherUser][item]$
  end for
  $pearsonNumerator \leftarrow sumProduct - ((sumCurrentUser * sumOtherUser)/numberElements)$
  $pearsonDenominator \leftarrow square(squareCurrentUser - ((sumCurrentUser)^2/numberElements) * squareOtherUser - ((sumOtherUser)^2/numberElements))$
  $pearsonCorrelation \leftarrow pearsonNumerator/pearsonDenominator$
  return $pearsonCorrelation$ among two users

Algorithm 9 Matrix factorization

Require: R is a matrix to be factorized, dimension N * M, P an initial matrix of dimension N * K, Q an initial matrix of dimension M * K, K is the number of latent features, steps for the maximum number of steps to perform the optimization, alpha is the learning rate and beta is the regularization parameter.
Ensure: The factorized matrix P and Q.

$alpha \leftarrow 0.0001, beta \leftarrow 0.001$
$QMatrix \leftarrow QMatrix * T$
for $step$ to $rangeSteps$ **do**
  for i to size of $RMatrix$ **do**
    for j to size of $RMatrix[i]$ **do**
      if $RMatrix[i][j] > 0$ **then**
        $e_{i,j} \leftarrow RMatrix[i][j] - dotProduct(PMatrix[itoend], QMatrix[inittoj])$
      end if
      for k to range of $KFactors$ **do**
        $PMatrix[i][k] \leftarrow PMatrix[i][k] + alpha * (2 * e_{i,j} * QMatrix[k][j] - beta * PMatrix[i][k])$
        $QMatrix[k][j] \leftarrow QMatrix[k][j] + alpha * (2 * e_{i,j} * PMatrix[i][k] - beta * QMatrix[k][j])$
      end for
    end for
  end for
  $eR \leftarrow dotProduct(PMatrix * QMatrix)$
  for i to range of $RMatrix$ **do**
    for j to size of $RMatrix[i]$ **do**
      if $RMatrix[i][j] > 0$ **then**
        $e \leftarrow e + (beta/2) * PMatrix[i][k]^2 + QMatrix[i][j]^2$
      end if
    end for
  end for
  if $e < 0$ **then**
    $break$
  end if
end for
return $PMatrix, QMatrix * T$

Appendix B

USE Questionnaire

Usefulness

- It helps me be more effective.
- It helps me be more productive.
- It is useful.
- It gives me more control over the activities in my life.
- It makes the things I want to accomplish easier to get done.
- It saves me time when I use it.
- It meets my needs.
- It does everything I would expect it to do.

Ease of Use

- It is easy to use.
- It is simple to use.
- It is user friendly.
- It requires the fewest steps possible to accomplish what I want to do with it.

- It is flexible.
- Using it is effortless.
- I can use it without written instructions.
- I don't notice any inconsistencies as I use it.
- Both occasional and regular users would like it.
- I can recover from mistakes quickly and easily.
- I can use it successfully every time.

Ease of Learning

- I learned to use it quickly.
- I easily remember how to use it. It is easy to learn to use it.
- I quickly became skillful with it.

Satisfaction

- I am satisfied with it.
- I would recommend it to a friend.
- It is fun to use.
- It works the way I want it to work.
- It is wonderful.
- I feel I need to have it.
- It is pleasant to use.

Source: From the work of Lund (2001). Users rate agreement with these statements on a 5-point Likert scale, ranging from strongly disagree to strongly agree. Statements in italics were found to weight less heavily than the others.

The on-line questionnaire is in the next link: http://goo.gl/forms/LXQAerSKi4r0mTa33.

Appendix C

Technical support of installation

Dependencies of the application

- Django framework 1.7.

  Url: https://www.djangoproject.com/download/

- Django-registration library.

  Url: https://pypi.python.org/pypi/django-registration

- Django-countries library.

  Url: https://pypi.python.org/pypi/django-countries

- Django-geoposition library.

  Url: https://pypi.python.org/pypi/django-geoposition

- Python-dateutil library.

  Url: https://pypi.python.org/pypi/python-dateutil/2.4.1

- Pyproj library.

  Url: https://pypi.python.org/pypi/pyproj?

- Numpy library.

  Url: https://pypi.python.org/pypi/numpy

- PostgreSQL database.

  Url: http://www.postgresql.org/

- Psycopg2 connection to database.

  Url: http://initd.org/psycopg/docs/install.html

- System prototype programmed in Python language Url:https://github.com/xochilt/recomet.

Tijuana Restaurants dataset

Table C.1 shows a sample of dataset where the domain of contextual factors is depicted as numeric values, from column 5 to 12 are the contextual factors used in the system and each column contains the domain values. The column names are: *payment type*, *alcohol type*, *smoking area*, *atmosphere type*, *dress code*, *installations type*,*parking type*, and *cuisine type*. The complete dataset is available to download

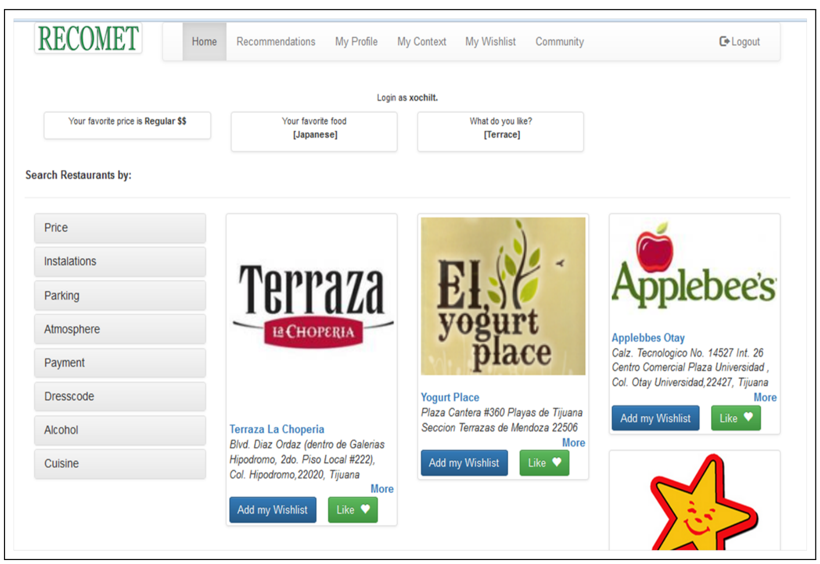
Table C.1: Sample of Tijuana dataset and contextual factors.

Id	Restaurant	Price	Latitude	Longitude	5	6	7	8	9	10	11	12
1	Californias	3	32.52837	-117.02001	2	0	1	2	2	1	1	20
2	Yogurt Place	2	32.53404	-117.12053	1	0	1	2	2	1	1	19
3	Los Arcos	1	32.51582	-117.01032	2	0	1	2	2	1	1	24
4	La Casa del Mole	2	32.51995	-117.01001	2	0	1	2	2	1	1	20
5	Cafe de la Flor	2	32.53198	-116.94801	2	0	1	3	2	1	1	16
6	Casa Plascencia	3	32.5137	-117.00712	2	0	1	4	2	1	1	22
7	La Lena	3	32.51238	-117.00417	2	0	1	4	2	1	1	17
8	La Querencia	3	32.51678	-117.00961	2	0	1	4	2	1	1	22
9	Big Boy	2	32.51957	-117.01942	1	0	2	2	2	1	1	26
10	Burger King	1	32.53387	-116.95086	1	0	2	2	2	1	1	26
11	Cheripan Otay	4	32.51987	-117.01253	2	0	1	2	2	1	1	4
12	Costco	1	32.50826	-116.96436	1	0	2	2	2	1	1	26
13	Daruma Postal	2	32.52874	-116.98579	1	0	2	3	1	1	2	1
14	Dominos Pizza	1	32.53481	-116.97108	1	0	2	2	2	1	1	27
15	El Mazateno	1	32.52836	-116.99242	2	0	2	3	1	1	2	24
16	El Porton	2	32.47732	-117.02924	2	0	1	4	2	1	1	20
17	El Rodeo	1	32.54961	-116.90429	2	0	1	2	2	1	1	17
18	Giuseppis Rio	4	32.53135	-116.94833	2	0	1	4	2	1	1	3
19	KFC	1	32.52821	-117.02397	1	0	2	2	2	1	1	26
20	La Torta Plaza	1	32.53434	-117.01821	1	0	2	3	2	1	1	26
21	Landini Ristorante	3	32.51483	-117.01069	2	0	1	4	3	1	1	3
22	Carls jr	1	32.52973	-116.9682	1	1	2	2	2	1	1	26
23	Carnitas Uruapan	1	32.50907	-116.98759	2	1	1	3	2	1	1	20
24	Fonda Argentina	3	32.51339	-117.00743	2	1	1	3	2	1	1	4
25	La Espadana	4	32.51786	-117.00954	2	1	1	4	3	1	1	20

in the url: http://www.xochilt.wix.com/ittresearch.

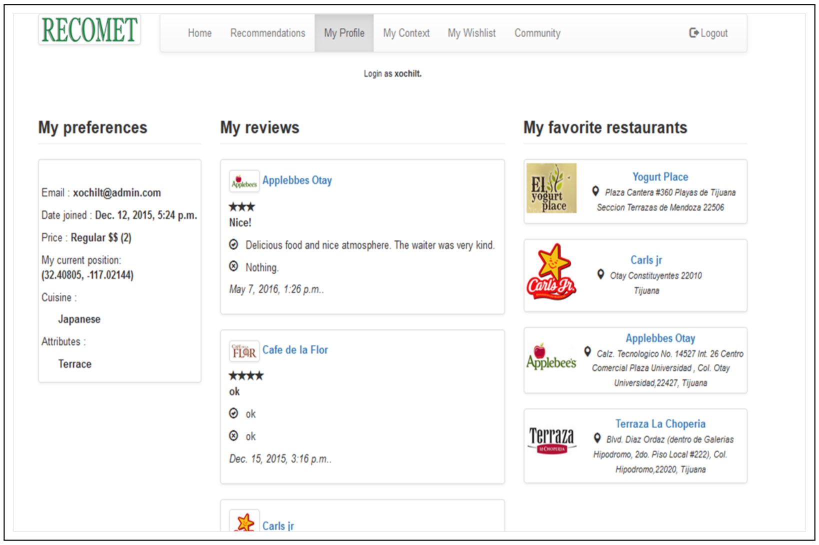
Appendix D

System interfaces

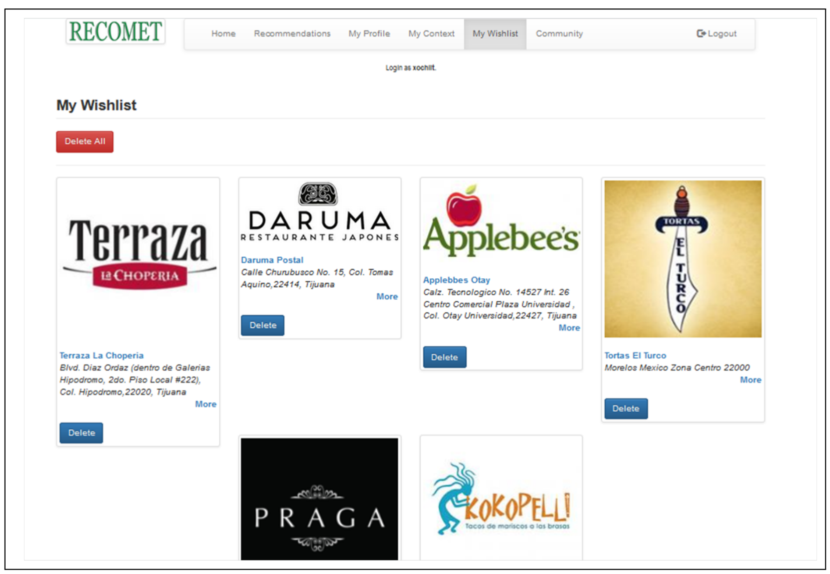


(a)

Figure D.1: Home page of the system prototype.



(a)



(b)

Figure D.2: **a)** *My profile*(user profile) and **b)** *My wishlist*(the user whishlist) interfaces of the system.

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