FAKULTÄT FÜR INFORMATIK

TECHNISCHE UNIVERSITÄT MÜNCHEN

Master's Thesis in Informatics

Implementation and Evaluation of a Persuasive Mobile Food Recommendation System

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Acknowledgments

Abstract

Contents

1 Introduction

The motivation behind this Master Thesis is to implement and evaluate a Healthy Food Recommendation System for Mobile. In the beginning, it provides overview and give the reasoning about the selection of system. Relevant background and related work is presented, Followed by the development and design process together with the evaluation process will be presented.
This chapter will enlighten the motivation behind developed system in Section 1.1. Followed by goals in Section 1.2. Whereas Section 1.3 will provide a brief outline on structure of thesis.

1.1 Motivation

Rapid innovation and significant advancement in the field of technology and scientific research has made smartphone a primary computing and communication device. Smartphone is now become a necessity of life and people use it as an assistant for their day to day work. According to latest survey more than half of Internet traffic is accounted by mobile device. Enhancement in communication technology and flexible data option provided by network operators has increase relevance of interactive mobile applications. Packed with hundreds of features smartphone use different applications for variety of functionalities which required internet connectivity. Furthermore, smartphone support touch screen and rich support of multimedia and other application take the user experience to the next level.

Suggestions are the important factor of our day-to-day life. From watching a movie, to cooking and to on shopping. We need valuable advice. Recommendations are always helpful in choosing a better alternative. It not only save time but also minimize the individual's effort.

Recommender system are increasingly popular now are days. Form e-comers to movie websites, they not only help to increase business but also behave an personalize user preference assistance. Another aspect of describing Recommend system is filtering technology that user to filter suggests the information to user according to his taste. In order words we can also say that Recommender systems are the smart search engine, which suggest result by, compare different items with each other. Research and advancement are going on this domain in order to improve the quality of recommendations. The most important goal for recommendation system designers is user willingness to peruse recommendation provided by the system. Fundamental process of recommendation is finding and conceptualizing relationship of item, current context and how the message is communicated, opens up the way of persuasiveness in recommendations.

Services provided by recommendation system through e-commerce to cooking are numerous in nature. Searching of products returns an overwhelming set of options. For instance, Comparing and Filtering of products among irrelevant set and find the suitable product. Such techniques work fine with web interface, whereas, smartphones they are not very useful due to hardware limitations. Critique-based recommendation helps in revision and acquisition of user preference, in order to improve quality of recommendations.

One the basic need is Food among human. Good health represents proper dietary habit. However, diet plan is always based on person's physical conditions like gender, weight, age and health status. Furthermore, taste and food preference is differ among individuals. Therefore, creating balance dietary plan based on individuals taste and health preference is always challenging.

The World Health Organization [39] is predicting that the number of obese adults worldwide will reach 2.3 billion by 2015 and the issue is attracting increased attention. Therefore, electronic food management systems have become a hot topic and, are under consideration to replace traditional paper based program. Idea of using electronic devices for health related matter is not new; similar devices are in use by patients for medical reasons e.g. Glucometer, and blood pressure monitor. People want, to carry better life style and to live healthy. Therefore popularity of food monitoring systems is getting popular. These systems are not only providing valuable services but hold user preferences and keeps history to provide more personalize recommendations. Recommendations are based on food ratings and browsing histories.

Food recommendations have gotten a tremendous amount of success and still in research phase for further improvement. Along with significant advancement and feature set like similar recipes, recipe nutrition detail, where to buy ingredients from some research, some wholes are still remaining. Indeed recommendation techniques like collaborative, content and knowledge based filtering are good for job done. But food domain is not quite simple. User preference and taste not only change by their mood but much more depend upon their health. Therefore, Active learning and critiquing techniques are required to improve better recommendation. So that user can give their feed back and get what ever his preferences are. Mostly approaches are done critiquing by using rating of recipes and generate their result by using celebrative or content based filtering. Similarly, knowledge based filter digs some more; here rating is based on ingredients. Furthermore, persuasion of recommendation is always not guarantied in all cases. Clearly the system is not able to provide the best recommendations due to its detachment from the current situation; what is lacking in these approaches are intersection of persuasiveness, active learning and critiquing and last but not the least user preference context.

This work focuses on generation of health food recommendation on a mobile platform. Recommendation relies on user context, which allow user to critique, based on ingredients and recipes depends on his health and taste through which system will perform active learning. Lastly all recommendations should be persuasive in nature. in order to achieve persuasiveness in recommendations, we focus on user interface and the explanation of recommendation. Which helps user to get an idea why system generates this recommendation to me.

The following short description of the target scenario will illustrate the driving idea behind this research project.

John is a software engineer and very health conscious. He has a tight schedule due to work and gym but loves to cook. He wants to keep track of his diet depends on his taste and preferences. Furthermore, he wants try out some new food base on his time schedule

1.2 Goals

On the basis of scenario, describes in last section, this work reflects the goals which are stated below:

A recommendation is valuable if it interests the user. To determine the generated recommendation is according to user interest entails to our first primary goal, which is offering Persuasive recommendations. Major factors should be considered before given suggestion is Message and Source. Therefore our Second goal is to implement Active Learning and Critiquing approach to justify our suggestion. Since Critiquing relies on context that’s why it is important to understand the Consumption and Accessibility context which infers our third goals. Similarly understanding the food ontology refers in scenario helps us to understand forth goal of system. Finally how the user will interact with his device conveys our last goals, which is Mobile user interface.

To achieve primary goals there are several other interesting secondary goals, which facilitate, how our primary goals should be achieved. Starting with the research phase, which includes question and answers to user how they want to use such system in order to achieve better usability. Next focus on existing search work how the other system implements food recommendation scenarios, finding out what are their weakness and strengths. Food ontologies understanding how they are interrelate with other. What factor in which recipes are dependent on in order to develop strong system. Understanding user context which time he prefers which recipe. Furthermore, it is important to research on what researches and related work are out there under Persuasive and Active learning and Critiquing system to grab the understanding, how we can get inspiration from their valuable approaches and work. Finally focus on user experience of such application is one of challenging task, how and where to show the important aspects of recipe in our interface, so that it is easy to learn and has improved usability in comparison with current market applications.
Once the research phase has done next step to collect the functional and non-functional requirement of the system, which is collected by interviewing friends and family voluntaries. Once the system is build it has been tested with gathered functional and non-functional requirement and find out the limitation or boundary conditions of system. More over iOS client needs to be test with given requirement additionally user satisfaction should be required for usability test.

Finally, evaluation of developed prototype by user study. In order to clarified the methodologies and processes followed by our selected approaches. After finishing the evaluation reflected results leads to potential improvements and opens up the new direction of research.

1.3 Outline

Division of this thesis is split up into six chapters. *Chapter1* contains introduced the ideas, motivations and goals.

Chapter2 starts with background in which some definitions and classification of recommendation systems, Followed by different types of profiling and contexts that impact on recommendations. Furthermore, in related work section, pervious work of

Persuasiveness, Critiquing and Personalized food recommendation techniques have been discussed.

Chapter3 explains the Profiling and Context in details along with factors of recommendations. Moreover it covers algorithms that are used to develop the system.

Chapter4 discuss the System design and architecture phase, which hold the all ERD, components view, servers on which system depend. In the end of the chapter API calls are mentioned which are provided by server.

Chapter5 elaborates how the user study has been conducted by mentioning the goals, methods, and testing framework along with the dataset. In the end of this chapter measured results and discussion is mention.

Chapter6 will summarizes the achievements and gives clues about further development and research.

2 Background and Related Work

This chapter will establish the foundation of Persuasive recommendation system along with active learning and critiquing approach. Prior to in depth analysis, it will provide important background information along with some required definitions. Additionally, related work will presented, as the chapter proceed further to the end.

2.1 Definitions

2.1.1 Recommender System

Recommender Systems (RS) are search tools, which supports user decision-making by providing the suggestion that, are according to their interests. Such systems are in widely use from social networking to e-commerce sites in order to achieve different purposes. In e-commerce site, they help not only to serve the customer by suggesting items according to their preferences but also support business to improve in its sale. On the other hand in social network site, to suggest friends or pages like according to user preferences. According to Ricci [22] "RS are information search tools that have been recently proposed to cope with the "information overload" problem, i.e., the typical state of a web user, of having too much information to make a decision". Proposed solution [21] is an intelligent system that suggests the product or service that fulfill the user's preference in given context or situation. Suggestions provided by such systems are depended on the model how they are keeping information. Majority of RS are typically community based. In this kind of modeling suggestions are depend about item popularity among the user. Where popularity is calculated by ratings. Important question that arise in such systems are to find item accuracy according user preferences. On the other hand Personalized models are used that depends on the various factors which includes user's preferences, history of bought/liked items, or the items the user has ranked in the past. Various techniques are use in the developing of recommender system. Classification of recommendation systems [24] will be discussed as follows.

Content-based filtering

In this technique recommendations are based on user preferences. System recommend items that similar to once's liked by user. Item similarity is calculated by features associated with the compared items [24]. For example, if a user has rated positively, recipe A under the category of sweets then next suggestion that is provided by the system is one which is similar to one user has liked before.

Collaborative-based

Collaborative filtering is a technique in which system find the correlation between item and user, based on other user's feedback having a similar taste in past [24]. Initially system calculates all similar taste users for the current user and calculate the recommended item that contains either rated or liked by other users having similar taste. Importantly in this approach item speciation will not be considered. For instance, if user like recipe A then next recommendation would be recipe that there are other users who liked recipe A also liked recipe B.

Demographic

Recommendations are generated according to user demographic profile. Recommendations can be produced for different demographic niches by combining the ratings of users in demographic clusters [13]. For example, suggestion provided by the systems are shown according to user's age.

Knowledge-based

In knowledge-based systems item recommendation is based on domain specific knowledge, which justifies how certain item features meet according to user's preferences [24]. Importantly, it uses predication techniques namely Case-based reasoning which reuses the cases past cases that are similar to current case in order to identify item set of recommendation.

Community-based

Type of recommendations provided by this kind of system based on preference of user friends. According to Ricci research [24], People tend to rely more on recommendations provided by friends rather than on recommendations from anonymous individual having similar taste. Such type of RS model relies on user's social relations including preference of user's friends. Suggestions depend on rating that is provided by user's friends.

Hybrid Recommender Systems

Hybrid system is a fusion of any two or more techniques motioned above. Ricci [24] explains the motivation behind such system to avoid the limitation of one technique. For instance, Collaborative filtering have cold startup problem i.e. they are unable to suggest those items, which have no ratings. On the other hand Content-based doesn't have such limitation by combination of both approach new hybrid system can be formed. Similarly, Burke and Robin [3] proposed the combination techniques to create a new hybrid system.

2.1.2 Contexts

Recommendation techniques used by traditional system relies on vector of item rating and user preferences. According to Suchman [30] these approaches ignores the notion of "situated actions" which infers that user have particular context and item preference within one context may be different from another context[1]. Absence of context may lose information predictive power because of aggregation of multiple contexts. For instance user wants to buy cloths for his child. Instead of given him child dress system suggests dresses according to user choice because of incomplete contextual information.

Since context is a multi dimension topic therefore vast amount of research has been done in area, narrowing down role of context in recommender system, context can be defined as all information according to given situation. One of the early definitions of context in terms of operation [27] defined as where you are, who you are with, and what resources are nearby. As research further increases, new and most sited definition of context according to Adomavicius [1] "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". Also, Dourish, P. et al., [6] while observing the uses of context they classified into two views namely *representation* and *interaction* views. They assumed four key assumptions for describing representational view. Context is independent from underlying activity, delineable, stable and in a form of information. According to this view, context can be known prior as it is a set of observable attributes and structure of these attributes does not change with respect to time. Futhermore, [6] while observing the uses of context they classify into two views namely *representation* and *interaction* views. They assume four key assumptions for describing representational view context is independent from underlying activity, delineable, stable and in a form of information. According to this view, context can be known prior, as it is a set of observable attributes and structure of these attributes does not change with respect to time. On the other hand interactional view features are dynamic. It assumes that context and activity have a relationship.

Adomavicius [1] ascertain [6] claims on categories and explains 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. He classifies the knowledge of a recommender system about the contextual factors into three categories;

Fully observable: refers to explicit knowledge of structure and values of contextual factors of application at the time when recommendations are made. These factors refer as Purchasing Purpose, Shopping Companion and time. For example, User wants to buy shirt, besides having information of selling point and item. Theses may include information about the time, for whom. *Partially observable*: application has some of information about the context explicitly. For instances, Purchasing Purpose, Shopping Companion and time, all information given but the structure is missing. *Unobservable*: no information regarding contextual information is provided explicitly. Utilizing only the latent knowledge of context in an implicit manner makes recommendations. 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.

Furthermore, Adomavicius [1] find out the dependency of contextual factors over time and classify them into categories. *Static*: The relevant contextual factors and their structure remains the same (stable) over time. *Dynamic*: contextual factors change in some way.

How Contextual Factors Change	Knowledge of the RS about the Contextual Factors		
	Fully Observable	Partially Observable	Unobservable
Static	Everything Known about Context	Partial and Static Context Knowledge	Latent Knowledge of Context
Dynamic	Context Relevance Is Dynamic	Partial and Dynamic Context Knowledge	Nothing Is Known about Context

Figure 2.1: Contextual Information Dimensions.
[1]

Representing and Modeling Context

Classical recommendation system has the prediction problem in which user's rating for item reflects the degree of user preferences. Therefore, a recommender system tries to estimate a rating function.

$$R : UsersxItems \rightarrow Ratings \tag{2.1}$$

It's a 2D matrix of user-item to an ordered set of rating values. Where "R" a general-purpose *utility* (or preference). Since the value of "R" is partial function therefore rating of all user-item are not known which invokes the predication problem.

$$R : UsersxItemsxContexts \rightarrow Ratings \tag{2.2}$$

In contrast, context aware recommenders have additional evidence to estimate user preference on unseen item. Contextual evidence can be applies to input function and viewed as "multidimensional". Where, any information related to data and user can be refer as Contextual information

Paradigms for Using Contextual Information

According on algorithm approaches of context aware recommendation, represents in form of *U x I x C x R*, Where "U" is for User, "R" denotes rating, "C" is contextual dimension, and produce contextual recommendations list i1, i2, i3 ... for each user "U". Figure 2.2 illustrates the paradigms used in processing Contextual Information. These are categorize as follows:

Contextual prefiltering: In this filtering Context is applied an input. With the help of any classical 2D recommendation data selection approach, applies current context which is used for selection of relevant ratings and dataset.

Contextual postfiltering: Prediction of rating is applied with the help of traditional 2D recommender system technique. On the resultant set of recommendation applies the context for each user.

Contextual modeling: Directly integrates the contextual information in the modeling technique as part of the rating estimation. .

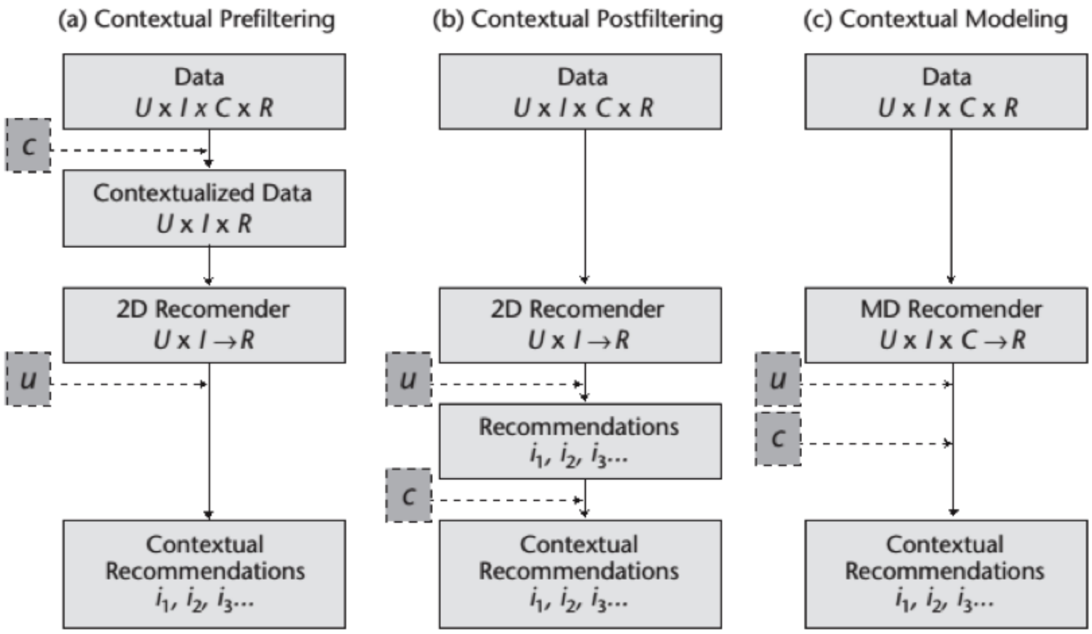


Figure 2.2: Paradigms for Incorporating Context in Recommender Systems. [1]

2.1.3 User Profiling

User profiling is process of acquiring information about the user, which helps in constructing the user model. Rate of acceptance and effectiveness of recommendation will effect how much system has information about the user. Tang [33] explained, In the context of software applications, a user profile or user model comprehends essential information about the user. It also refers to digital representation of person in a system and hold the person's preferences. Variations in user profile content depend on application. Some applications depend on demographic information of user while other relies on rating, liking, disliking or other preferences. Also, consideration of user interaction and behavior take plays an important role for providing precise recommendations.

Schiaffino [26] stated that discovery of differences and similarities in interests among users is a key to provide personalized recommendations. Which implies that application users have different preferences and interests to achieve their goals which leads to importance of creation of user profile in order to find out relationship between users according to their interests. Content of user profile depends on application domain and variations are presents in application. Categorically there are two methods to gather content of user profile. First method is manually, in this technique users are being interviewed, fill some forms or questionnaires. For instance asking about his demographic profile like where he is from, which dishes he likes or rating based questions like how frequently he eat junk food? On the other hand by mean of implicit learning about user preference which requires artificial intelligence (AI) technique like Case-based reasoning, Bayesian Networks, Artificial neural networks. Most of these techniques are beyond the scope of this work so they will not be described in more details. Fundamentally there are two different alternatives to build a user profile; either the information is obtained explicitly from user or implicitly through the observation of user's actions. The next section describes these alternatives.

Explicit Profiling

Explicit profiling often known as explicit user feedback is the simplest way of gathering information about users. In this technique, user has to fill questioners in order to develop profiles. Profiles developed by this techniques are totally depends on the questioner. Normally, data contains demographic information regarding the user like name, age, location and other preferences. Gauch [26] suggests input methods that allows user to rate item according to their interest. Alternatively system can provide check box and text field in order to get preference of user. *HTML forms, Questionnaires, Rating, User preference and Touch sensors* are some techniques user to obtain explicit profile. Whereas, the limitation of this technique is that it requires user time and willingness to provide their data. Some user has reservation in regards to provide their personal information because of potential privacy concern. However user's preference can always be determine via this technique.

Implict Profiling

Implicit profiling is also known, as implicit user feedback is another approach for building user profile. It is popular and widely used methodology to develop user profile based on user 's acquired information. Mostly profiles are derived form monitoring or observing user activities. Information acquires by the system helps them to ensure the given recommendation is according to user interest. For example popular website for watching videos, "YouTube". It's recommendations are made on similar to those videos that were watched by user in the past. Single-sign-on (SSO) [**hursti1997single**] one the most common methodology for user registration. Since the information is implicit, they may contains user demographic information. Similarly user preference likes, dislikes, locations can be fetch by integration of related third party services. Information obtain from this mechanism plays an important role in personalized recommendation system. *Search logs, Browser cache and User monitoring agents* are some techniques used to generate implicit profile. Main advantage of this technique is user doesn't have to fill the forms and provide their information. Kelly [26] provides an overview of standard techniques that helps to build user profile and information types about the user that can be inferred from user's behavior.

2.1.4 Conversation-based Critiquing Recommenders

Recommender systems may also vary in the function to the extent that user can get engage in the dialogues. In traditional techniques data was collected once and terminate after recommendations are made. Assumption of these approaches are user know all his preferences at the beginning, which was not the case. Whereas, user taste may change over time and he want to interact with different option. Smyth [14] handles this problem and called "Conversational recommendation system" (CRS). He states that CRS have their origins in conversational case-based reasoning (CCBR) which apply similar techniques to elicit query information in problem solving domains and diagnostic tasks." It is an interactive approach in which user preferences are establish through conversation session. At first initial set of recommendations are given to the user. System adapts the user feedback to further enhance the recommendations. Smyth [14] distributed feedback into three categories. *Rating-based* in this approach user provides rating for an specific item. *Critique-based* where user add constrain over item features. *Preference-based* in which user indicates its preference for one particular item over the others.

2.1.5 Active Learning

Active learning (AL) is a methodology to learn about user's preference by asking him/her to rate a number of item known as training point [25]. Data is formed by model that approximates user's preference. It is useful where user's preferences are change with respect to context. Rashid [20] explains that objective of AL may varies according to objectives of recommendation systems. For example, what is important in the recommender system being built? The difficulty of signing-up (user effort)? If the user is happy with the service (user satisfaction)? How well the system can predict a user's preferences (accuracy)? Furthermore, this approach can solve cold startup problem in an effective manner. Figure 2.3 explains how interactive process works in order to obtain training data, unlike passive learning, where data is simply given to system in a linear fashion. Rubens [25] categorized AL method according to their primary goal.

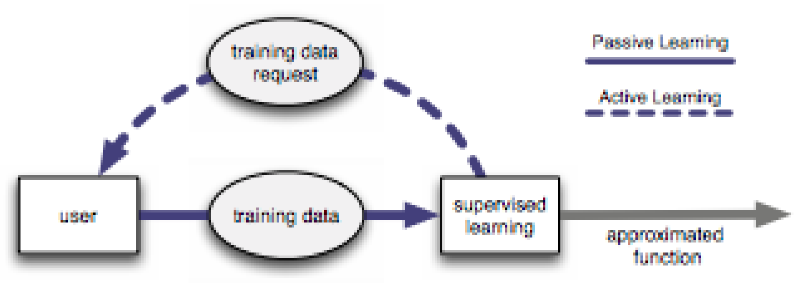


Figure 2.3: Active vs Passive Learning
[25]

Instance-based Methods

In this kind of approach points selection relies on their properties in an attempt to predict user's rating by the closest match to other user, without have explicit knowledge about underlying model [2]. Whereas, it assumes that under considered model, any data and rating predictions are accessible.

Model-based Methods

In this methodology point selection is based on best construct model that explains data supplied by the user to predict user ratings [2]. Similarly, select point are used to maximize the reduction of expected error of the model. Whereas, it assumes that in addition to any data available to instance-based methods, the model and its parameters are also available.

Modes of Active Learning: Batch and Sequential

Since the expectation of user is to high for the system while they are performing interaction. They expect immediate output from the system. One common approach is to recalculate the rating of item once user rated that specific item, known as sequential mode. However another possibility is that to allow user to rate several features of items or rate several item before model readjustment, known as batch mode. As immediate reflection of data in sequential mode is an advantage but cost of interaction will always effect. Therefore, trade-off exists between Batch and Sequential AL; the usefulness of the data vs. the number of interactions with the user.

2.1.6 Persuasive Recommedations

Traditionally, prevalent research in recommender systems has been focused on algorithms development and evaluation that provide precise recommendations[40]. The presumption behind the algorithm that its accuracy contribute to the quality and acceptance of the recommender systems has been changed lately[17]. Context and profiling techniques are also emerged as an important pillars. Additional factors which are important and should be focused on is presentation of recommendation so that user can interact with the system in more convenient fashion[17], transparency of system or explain working of system to the end user[29], persuasion[19] and recommendation's novelty[5]. Fogg [8] defines persuasion as *the attempt of changing people's attitudes or behaviors or both*.However, explanation of recommendation also have influence on user [16] [10].

Persuasion factors

Aristotle [9] was the first one who talked about persuasion. He claims *ethos/character of the speaker*, *message's receiver pathos/emotions* and textitlogos/argument are the main elements that plays an important role in persuasion. Since, difference of opinion exists in factor of recommendation. The most cited one is Cialdini's [4] known as "6 Influence Principles (also known as Six Weapons of Influence)". If they implemented in a system then effect of persuasion increase. Theses principle include; *Reciprocity* (humans have the tendency to return favours), *Commitment* (or consistency: people's tendency to be consistent with their first opinion), *Social proof* (people tend to do what others do), *Scarcity* (people are inclined to consider more valuable whatever is scarce), textit Liking (people are influenced more by persons they like) and *Authority* (people have a sense of duty or obligation to people who are in positions of authority). Where Figure2.4 indicates effect of Communication Persuasion Paradigm[41].

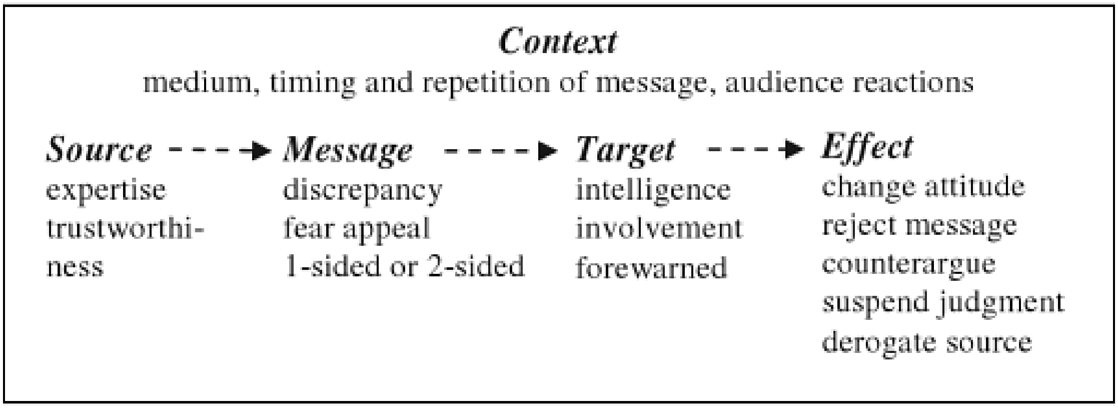


Figure 2.4: Communication Persuasion Paradigm
[41]

Explanations in Recommender Systems

An explanation consider an additional information provided by system output to achieve certain goals [36]. Explanation persuade user to try or buy recommended item[37]. Several aspects should be considered in order to introduce explanation into the system. Following are the seven goals for explanation in recommendation system[35].

1. **Transparency** in recommendation system helps to understand how the recommendations are generated and how overall system mechanics[35]. Furthermore, it allow user to check the quality of system and in case of anomalies user have an idea why system has given this result. Let's consider an example, suppose system recommends a movie in comedy genre for a particular actor although user is not interested in it. System will provide an explanation you like some movies of this actor that's why it is in your recommendation.

2. **Scrutability** allows user to correct misguided assumptions made by system. Since user preferences may always change due to contextual factors. Therefore, it is important that explanations enable the user to understand what is going on in the system and let them exert control over the type of recommendations. Scrutability is related to the established usability principle of User Control[18].

3. **Trust** increases user's confidence in the system[35]. Trust could also relies on recommendation algorithm[15]. Studies suggested that trust is related to transparency and increase the possibility of interaction with the system.[7]. If users find system trustworthy then they are intent to return back to the system[7].

4. **Persuasiveness** convince users to try or buy [35], where as it may increase user evolution of the system. It allow user to gain benefits form the system rather than relied on other individuals.

5. **Effectiveness** helps user to make good decision [35]. Effectiveness is totally depends on recommendation algorithm. It also helps user to evaluate the quality of recommendation according to their preferences and also discard those item, which are not related to taste.

6. **Efficiency** help users make decisions faster [35]. Nielsen describe efficiency is an establish usability principle and explain it is ability of system to help user in fast decision making while selection of best suited item[18].

7. **Satisfaction** is the ability to make system fun while user is interacting with the system [35]. Similarly, providing poor recommendation tends to decrease a user's interest [32] or acceptance of a system[10].

2.1.7 Mobile Recommender Systems

With the technical advancement and features like computers, mobile phones have become a primary platform. By Combining with recommendation system it become a key tool for business and users. Due to this trend personalization in recommendation become more focused. Hence, it is important to understand the capabilities of mobile and how the information will access and displayed on mobile phone for usability prospective[18]. Schiller [28] describe the mobile recommendation system in three dimensions. According to him each one has its own impact on system usage and functionality. Furthermore, these dimensions are independent but there are examples for all the possible combinations of these dimensions, are stated as follows:

1. **Device portability** describes as information can be access from any location without bounding it to any specific location. Furthermore, user experience will be the same regardless of the location it is being accessed from.

2. **User mobility** refers to information is access from mobile device, like smartphone and tablets. On the other hand there are some constrains regarding the screen sizes and how information will be displayed on such devices.

3. **Wireless connectivity** refers to all the information, which is access by the mobile, is via wireless technology such as wifi, 3G and LTE.

General Issues

Besides, all the advancements and opportunities provided by mobile devices. Some limitations are exists and stated as follows:

1. **Resource limitation**
   Mobile devices offer less memory and power consumption as computer to standard computing machine for example desktop computers.[22].

2. **Connectivity**
   Since the communication in mobile system is depends on wireless connectivity therefore, high level interruption and noise occured. Additionally, data rate is also very low as compare to standard wire communication.[22].

3. **Battery life**
   Although significant research and improvement has been performed in battery life of mobile device but a lot needs to be done for providing longer battery life.[22].

4. **Fragmentation**
   Fragmentation refers to different screen sizes of devices. Since there are more than thousands of devices that exist having different screen size and resolutions. It is a challenge for developer to support all of them.[22].

2.2 Related Work

This section gives an overview of previous work and related papers on the respective domain.

2.2.1 User's Food Preference Extraction for Personalised Cooking Recipe Recommendation

Mayumi, M. et al., [38] design system to enlighten importance of personalized recipe recommendation system which is based on user's food preferences. In this research user's preferences are gathered by his browsing and cooking history. Recommendations provided by this system is not depends on what user ate in past. Moreover, system does not require particular action of user to collect his preferences. Figure 2.5 illustrate the idea estimating user's favorite ingredients. Their approach breakdowns the recipes into like and dislike ingredients set. It calculate ingredient the score by incorporating the frequency of that ingredient in the dishes that has eaten by user and consider them in like ingredient. Whereas, ingredient is consider as dislike by user if he never browsed the recipe details or never cooked. Since system is working on implicit profiling therefore unable to consider addition context and preference of user while generating recommendations.

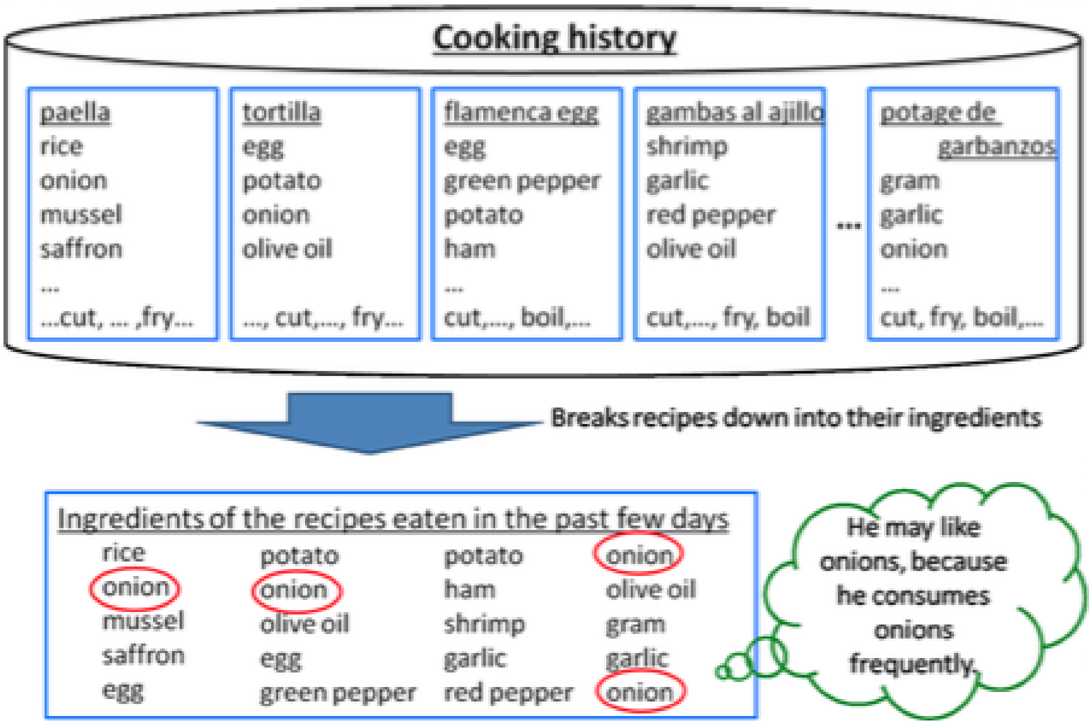


Figure 2.5: Extracting the favorite ingredients using cooking history [38]

2.2.2 Knowledge Base Framework for Development of Personalised Food Recommendation System

Suksom, N. et al., [31] focus on personalized food recommendation system aims to provide dietary recommendation based on individual diet and preferences by using knowledge base recommendation technique. Where as, knowledge based depends on ontology and rule-based knowledge development. Figure 2.6 gives an overview of system. All user preferences are set initially and recommendations are based on his heath preference infers system not supports critiquing approach.

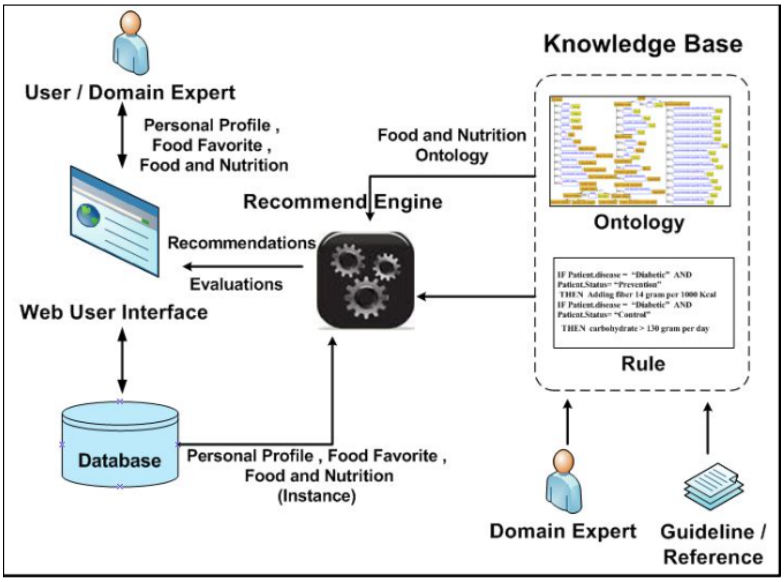


Figure 2.6: Knowledge-based framework for the food recommender system [31]

2.2.3 Recommending Food: Reasoning on Recipes and Ingredients

Focus of the research is to investigate recipe recommendation system techniques by applying different recommendation techniques [**freyne2010recommending**]. Initially with collaborative filter approach with simple break down to relate recipe and ingredients result were not so good but by applying content based approach there were significant improvements in result. For optimal solution they used hybrid approach of content-based and collaborative filter. Summary of their work is stated as after breaking down the recipes into ingredients, give and compute score ingredient score, applying collaborative filter to narrow down the ingredient score and finally applying content based approach in which prediction of recipe rating is examine by the score of individual ingredients. This approach conveys the basic idea recipe recommendation system. With the addition of user preference and their feedback it could achieve more.

2.2.4 Recipe recommendation using ingredient networks

Teng, C. et al.,[34] research permits collaborative recipe generation and modification. Recipes data are gathered according to regional preferences and modification is done by individual ingredient preferences. By this approach two kinds of networks are created one is ingredient complement and other is ingredients substitution. The network suggests which substitution of ingredient increases the taste of the recipe and gives those recipes, which is high rated by user. System uses collaborative filter approach along with data mining techniques. System does not have diet specific recipes according to user preference nor consider any user context.

2.2.5 Critique-Based Mobile Recommender Systems

Ricci [23] illustrates the critique based mobile base recommendation in the domain of travel. Motivation behind this research to collect collects user preferences via critique with low amount of user effort. According to this research it is an advantage to collect user preference via critiquing and it is relatively fast. Figure **??** shows how the critiquing is perform. On the other hand it does not support reactiveness if use preferences has changed. It gives the basic idea how to gather information regarding user preferences in our system.

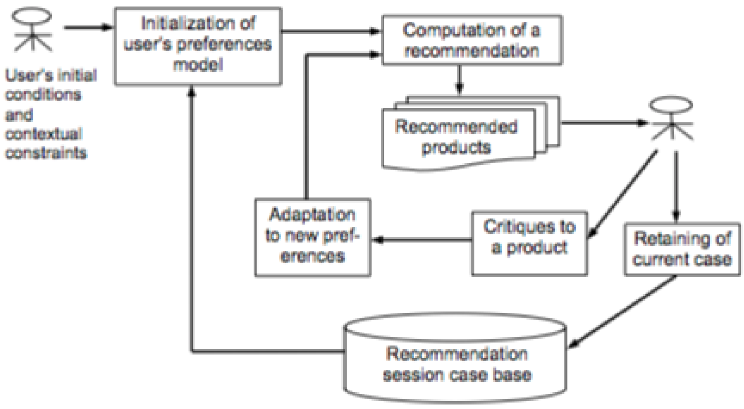
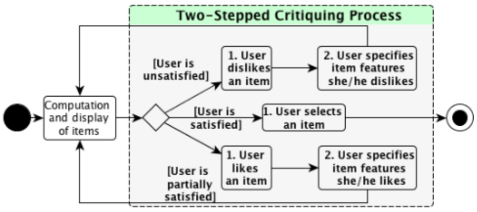


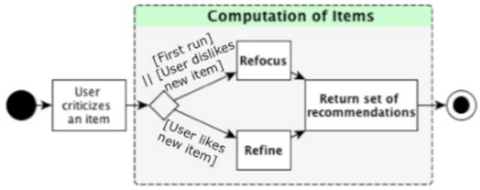
Figure 2.7: Critique-Based recommendation model
[23]

2.2.6 Active Learning Strategies for Exploratory Mobile Recommender Systems Interactive Explanations in Mobile Shopping Recommender Systems

Motivation behind this approach to developed a explorative shopping mobile recommendation system by using conversation-based active learning approach [12]. It uses the utility-based context and critiquing for feedback. Recommendations improvements are done by two-step critiquing process which illustrating in at Figure 2.8a. Critiquing process is relies on either positive or negative feedback. Figure 2.8b show the refine model of recommendation in a system. On the other hand it does not deals with the context and tell user why this recommendation is given to him.



(a) The two-stepped critiquing process [12]



(b) Active Learning recommenation model [12]

Figure 2.8: Active Learning Strategies

2.2.7 The Persuasive role of Explanations in Recommender Systems

Ricci, F. et al.,[9] design and analyze a movie recommendation system in which they tried to recommend those movies that are according user's interest. It helps them to understand the persuasion effect that users are willing to accept recommendation or not. System is design to suggest persuasion recommendation based on Kaptein's [11] methodology and follows the approach of six(6) best-matching explanation **??** to provide Persuasion Principle. This approach is does not support active learning and critiquing approach not handling of current context.

Influence Strategy	Explanations
Reciprocity	A Facebook friend, who saw the movie that you suggested him/her in past, recommends you this movie
Scarcity	The recommended movie will be available to view from 15/1/2014 to 31/1/2014 on cinemas
Authority	The recommended movie won 3 Oscars
Social Proof	76"%" users rated this movie with 4 to 5 stars
Liking	Your Facebook friends like this movie
Commitment	Watch this movie and you may change your mind about this kind of movies

Table 2.1: Best-matching Explanations on each Influence Strategy

3 System Components

This chapter will provide the explanation about the components of the system it and their attributes. It will also highlight how they intereact with each other in order to achieve the goals of this thesis. The chapter begins with explanation of profiling approaches, followed by impacts of context, critiquing and persuasion.

3.0.8 User Profile

One the core component of a system is to recommend user food that suits to his preferences, which can be gathered by profiling a user. In our system we followed a hybrid approach to build a user profile. Demographic information of a user is implicitly fetched from his Facebook account. The reason behind following implicit profiling approaches is to get user information without bothering them. This allows system to have up to date information about them. However, it has been noticed that people are reluctant to those systems that request permission to access their social network activity information. Knowing these concerns, we only ask users to permit access to their basic information. Following are the acquired attributes from Facebook profile.

1. Birthday
2. Email
3. FirstName
4. LastName
5. Gender
6. Name
7. Profile Link
8. UserId

Moreover, explicit profiling techniques are used to gather users' contextual information and their preferences. While explicit profiling reveals accurate information, there however exist shortcomings in this technique. It demands user's time and willingness to provide the data by filling the long forms, which seems to be tedious to the users. As the system is Knowledge based Personalized recommender, this problem has to be dealt efficiently because the recommendations produced by the system are highly influenced by user feedback. Therefore instead of making a user to provide all the information, we collect this data by using interactive forms based, which includes simple toggling, rating and selection mechanism that also increase the usability of the system.

3.0.9 Food Profile

Food recommendation is the basic research area of this thesis. Based on this approach our research is to provide recommendation according to both individual's dietary needs and preferences. Understanding food domain is very complex and challenging task when its come to recommender domain. User's selection of a recipe is highly depends on it's ingredients. Also there are some other factors which includes cooking methods, ingredient costs and availability, complexity of cooking, preparation time, nutritional breakdown, ingredient combination effects, as well as cultural and social factors [**freyne2010recommending**]. Our research starts with in finding out how popular websites are dealing in this domain and structuring the recipes. So that we can get inspiration about the important features that user are looking for while he interacts with such system. Next chore of our research is to build a recipe database therefore we need a provider-API that ensures a large number of recipes. Among these APIs two notables with impressive meta-data about recipes are:

1. Yummly API.
2. Big-Oven API.

Both services are crowd-source driven, highly recommended in food domain and are offering almost the same data set. Next step to find the best suited API for our research therefore we preformed some experiments targeted to comparison between both selected API. Result of this experiment showed that Yummly API is not providing cooking description. On the other hand Big-Oven API doesn't support recipe's nutritional information and have limited number of calls per hour for student account. Regarding selection of API our focus was, it should provide all the relevant information about the recipes required by our research, in order to avoid any dependency. Considering mentioned fact we decided to choose Big-Oven API.

Concerning about the attributes of food profile we followed the common approach that recipe have some important key attributes like cooking methods, ingredient preparation time, nutritional breakdown [**freyne2010recommending**]. However we are unable to get nutritional information due to API's constrain, as discussed early, but in our data model we are considering it for future research purpose. Figure 3.1 illustrates the key attributes of food profile which is a common fashion for representing a recipe. We followed an hybrid approach [31] [34] [**freyne2010recommending**] for our personalize knowledge bases food recommendation system. Recipe's ingredients are the primary factor on which recommendations are relied.

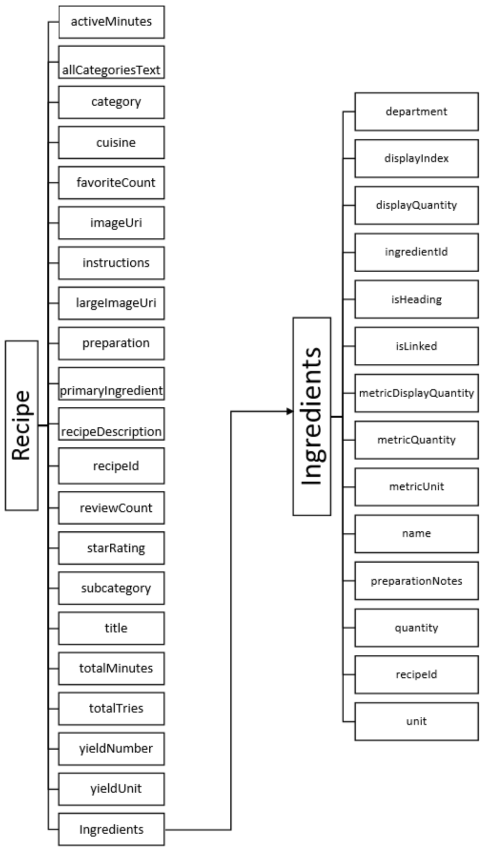


Figure 3.1: Attributes in Food Profile

Assumption

In order to simplify evaluation of recipe recommendation, System assumed that liking and disliking of ingredients by user is based on his dietary needs and health preferences. Suppose user does not like a particular ingredient let's say "X", therefore system learns from user's critique and eventually avoids such recipes, which have "X" as an ingredient in it.

Big-oven API

Big-oven API provides all the information about the recipe in a well-structured and well documented manner. Along with the high number of recipes, they offer functionalities including *Search, Display Recipes, Recipe review, Grocery List and Rest-based API support* . For this thesis we focus only few of them to develop a database of your system. Following are some API calls that are implemented in our system.

1. Reading a Recipe.
   URL request:
   GET http://api.bigoven.com/recipe/id

Parameter	Description	Required
id	Primary key(ID) of recipe	Yes

Table 3.1: Bigoven- Reading a Recipe.

2. Big-Oven API.

3.1 Contexts

3.1.1 Consumption Context

3.1.2 Accessibility Context

3.2 Critiquing

3.3 Persuasion

3.4 Approaches

4 System Design and Implementation

4.1 System Architecture

4.1.1 Overview

4.1.2 Working

4.1.3 Class Drigram

4.1.4 ERD

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4.2.1 Service 1

5 Evaluation And Conclusion

6 Summary and Future Work

6.1 Summary

6.2 Future Work

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