An Interactive Interface for Instilling Trust and providing Diverse Recommendations

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Submitted By

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CERTIFICATE

This is to certify that **Ms. Ivy Jain** (2k12/ISY/13) has carried out the major project titled "An Interactive Interface for Instilling Trust and Providing Diverse Recommendations" as a partial requirement for the award of Master of Technology degree in Information Systems by Delhi Technological University.

The major project is a bonafide piece of work carried out and completed under my supervision and guidance during the academic session 2012-2014. The matter contained in this report has not been submitted elsewhere for the award of any other degree.

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Abstract

Recommendation systems are software tools that provide suggestion of items that a user may like. In the thesis, we basically work under two disciplines of the recommender system- context aware recommender system and providing explanations in recommender approach.

The incorporation of context in recommendation systems is important for providing good recommendations as it improves the performance. Context awareness is an important concept in many disciplines. There are various methods that have already been proposed for context aware recommendation systems and can be classified into pre-filter, post-filter and contextual generalization. However, we found that there are some problems in using a single approach. So, in the first phase of our thesis work, we propose a new approach by combining pre-filter and post-filter methods based on the importance of contextual attribute. We believe that the contextual attribute should be dynamically selected for every user, as we found that it varies according to the user behaviour. In our approach, in case of a few rating scenario a simple method is used to provide a solution. The strategy adopted is advantageous over the single approach and is effective in improving the accuracy for the context aware recommender system.

In the second phase of our work we found that recommendation system ability to instill trust in its users and convince them about the recommendations provided is effective using suitable explanations. Although majority of existing research focus on the algorithm used to provide explanation, our algorithm focuses on the presentation of explanation interface for making the user understand the recommendations and its explanation better. The major contribution of our work is that it designs a complete model consisting of various visualization styles, where by each style is used for a specific purpose only. The explanation interface designed is for a hybrid recommender system where the explanation interface of individual recommender is re-used in a form that describes it best. In this model the user is held at an important position and using the explanations can incorporate diversity in the recommendations provided by the system. Results obtained shows that users found the system developed very interactive, appealing, assisting them to better understand the recommendations using various styles, low disappointment level and capable of accounting for diverse recommendations thus leading to overall satisfaction.

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Chapter 1

Recommendation system

1.1 Introduction

Recommendations systems are gaining popularity as it is a useful means for user to evaluate a large number of choices available on the internet. The output provided by these recommendation system help In decision making such as what book to read, which movie to watch, what music to listen to etc.

A RS is basically designed for only a single type of item (e.g. books) and there are various recommendation techniques to provide them with a list of suggestions. There are basically to help those individuals who lack experience to distinguish between various options available. One popular example of this is amazon.com [1] that provides different suggestions for different users.

Another simpler variant of the personalized approach of recommender system is the non-personalized recommendation techniques that suggest items to user ignoring the person in context. These recommendations are very common e.g. top ten selections of books, top 10 popular movies. Although it is a simple approach it is not as useful as the personalized recommender as they are not based on different individual taste and thus suggestions remain the same for every individual.

The study of recommender system is a relatively new field and gained popularity around mid 1990s [2]. Recommendations system today have been employed in various fields-

a. Recommendation system plays a very important role in popular sites such as amazon, IMDb, Netflix, Yahoo.
b. There are many dedicated conferences held on recommender system like the ACM RecSys that is an annual conference discussing the growth and new ideas in recommender system technology

c. Many books are published solely on the recommendation system techniques and future aspects and have special issues in journals

1.2 Recommendation System Function

The recommendation system function is different both from the service provider and the customer point of view. For e.g. we have an online shopping website, from the customer point of view the recommendation system function is to help him find a suitable item he/she is looking for with minimum delay possible. Whereas, from the service provider point of view the main goal is to increase the person viewing and then buying from this website.

Basically the major reason why a service provider would like to implement this technology-

- *Increase the number of items sold*- this is obvious the main aim of any service provider will be to increase his overall sales. This aim can be achieved by employing good recommendation techniques since if a user is able to find a suitable item, he/she is more likely to buy that. Although non- commercial items though do not have any cost associated with items have such goals for e.g. increasing the viewing of news item.
- *Sell more diverse items*- this aim is becoming more popular now a days as the aim of a service provider is not only to increase the overall sales but also to sell products that are not just the popular ones. A recommendation technique that is able to sell product that a user may not find without having recommendations is considered valuable.
- *Increase user satisfaction*- by user satisfaction the provider needs to make the system enjoyable for the user. Obviously, making the user enjoy the system will result in user repeated returns to the same web-site
- *Increase user loyalty*- a RS should recognize repeated return of user and should treat the same as a valuable customer

So basically it is very clear from the above mentioned points that employing recommendation system is very important from the service provider point of view and improving the overall business. But the RSs should have a balance between the needs of both the service-provider and the user. Each of the component is important for improving the overall business.

[3] is a popular reference that mentions 11 popular RS aims. Some popular among them are mentioned below-

- *Find some good items*- the main aim of a RS is to provide the user with a ranked list of items that he/she may like.
- *Find all good items*- sometimes it is better to find all the items that a user may need. This is useful if the number of items available in the system is very small or to know the initial preference of a relatively new user.
- *Recommend a sequence*- instead of recommending a single item, the RS can focus on series of items that may as a whole be beneficial. For e.g. recommending an entire playlist of songs sung by Arijit Singh.
- *Recommend a bundle*- another possible aim of a RS technique can be to recommend a group of related items, for e.g. an Ipod with beat headphone or other accessories.
- *Express self*- some user does not wish to see the recommendation but what is important for them is just to give their opinion about something. This may not increase the sales but still can hold the user together with the web-sites and can be beneficial in other ways
- *Help others*- user may also provide their opinions about an item as they know that it might affect the community as a whole. Providing opinion may also change their view point. For e.g. providing review about a movie released on Friday
- *Influence other*- the user may also wish to force others to buy a particular item by providing their comments. This may be even dangerous as there are some users whose ultimate aim will be the promotion of their item and not the benefit of that user.
- *Just browsing*- user may browse through the catalog without the intention of buying just like window shopping. But such users should be treated well as they are potential customers.

- *Find credible recommender*- users have a tendency of not trusting the recommendations provided by the user. So, sometimes they just keep on using the system with the aim of verifying the suggestions and not actually buying that item. Employing various techniques to help improve the trust of the user is one of the major research areas today.

1.3 Recommendation System Techniques

To be able to recommend a rank list of items to a user it is important to use a technique that is able to predict useful items by learning some attribute of a user or other users. Various categories of recommendation systems have been proposed [4]-

- *Content based*- [5] the system recommends items that are similar to those items that a user liked in the past. A feature vector of the previous rated movies is constructed and then is compared with the unknown items to the user. For e.g. in a movie recommender system if a user have a positive rating for the movies of romantic genre then the system will recommend movies of the genre in future.
- *Collaborative filtering*- [6] the system recommend items to a user based on items consumed by similar minded people. By similar minded we mean that those person that have taste similar to the target user. A profile of every user is created based on the past ratings and then similar neighbors are found out using a distance measure such as pearson coefficient.

  Collaborative recommender is further classified into model and memory based approaches [7]. In memory based approach the rating is based on aggregate of similar user ratings for the same item while in model approach ratings are used to learn a model that is further used to provide ratings.

- *Demographic*: [8] a RS may suggest items to a user based on the demographic e.g. country, language of a user. Many web sites use this simple method. For e.g. a web site transfer to a particular web site based on the country of the user
- *Knowledge*-[9] These RS system recommend items by knowing how an item can fulfill the need of the user. This can be achieved only with the help of a domain expert in the

area of interest. One of the distinguished type of knowledge based recommender is case-based recommender system.

- *Hybrid recommendation systems*- [10, 11, 12, and 13] these type of recommendation techniques are basically a combination of the one or more traditional recommendation techniques mentioned above. For e.g. content based and collaborative recommender can be combined together as they complement the advantages and disadvantages of each other.

Traditional recommendation systems do not consider the contextual information such as companion, mood etc but several studies have shown that including contextual information helps in improving prediction of users preferences. So after all these traditional recommendation system techniques context aware recommendation system (CARS) gained a lot of popularity and is described in chapter 2 of the thesis.

1.4 Recommendation System and the Human Involvement

As a lot of research was going on in this area, earlier researches thought that providing just the correct recommendations would be enough for user to accept the system. But later on different factors [14] was seen to be important for the user satisfaction, one being the qualitative aspect of the items suggested as well the way the recommendations were provided.

It was proved that the interaction of the user with the system, its involvement, the way recommendations are presented or compared all are important for designing a complete system. An important result of such studies was using explanations in recommender system. Using explanations help the user to trust the system and make the system use enjoyable. For e.g. in collaborative filtering style explanations are used as a popular statement “User who have taste similar to you have also liked the item”. Content style explanations are quoted as “this items contains following attributes that you have liked in the past”. Consider a movie recommender system here the explanation will be of the form “this movie was recommended to you as it has actor shahrukh khan who is your preferred actor as shown in your past history”. Explanations in recommender system are discussed in detail in chapter 3 of the thesis.

1.5 Organization of the Thesis

The remaining thesis is described as follows: chapter 2 provides an introduction to the context aware recommender system. Chapter 3 introduces using explanations in recommender system. Chapter 4 presents the literature survey on context aware recommendation system as well as the explanations. Chapter 5 presents the architectural details of proposed system. Chapter 6 explains the experimental setup and the results. Chapter 7 concludes the thesis with some possible enhancements.

Chapter 2

Context aware Recommender System

2.1 Introduction

The information content available on the internet is increasing and so is the importance for the recommendation systems (RSs) as it provides the user with valuable information. Nowadays, RSs are being employed in almost every application. These are very helpful for those people who get confused because of the various alternatives that are available on the Internet. It is very important for the recommender systems to not only suggest users with option that they may find useful but also provide them with diverse suggestions that may even help them discover their own preferences. Online recommendation systems are widely used in many applications such as recommendation system for books at amazon.com, for movies at Netflix, for music at Pandora Radio, search engines like Google and social network sites [15, 16, 17, 18].

Which movie should be watched today? With the large number of movies available on the internet, this question becomes difficult to answer. Personalized recommendation systems help people by narrowing the various options of films available according to the unique taste of every user as shown in figure 1.

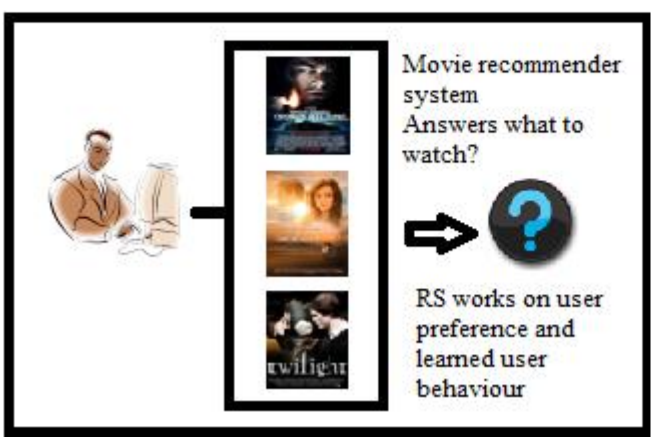

Figure 1 Traditional Recommendation System

Traditional recommendation systems do not consider the contextual information such as companion, mood etc but several studies have shown that including contextual information helps in improving prediction of users preferences. At the same time, context is also important for many applications like in making choice about a movie as shown in figure 2.

Figure 2 Context aware Recommendation Systems

2.2 What is Context?

Context is defined by [19] as "any piece of information that describes the situational characteristic of an entity, which refer to a person, place or object. The entity under question is considered important to the communication between user and application including both of them."

Context is basically a complex term that is used in various disciplines like computer science, philosophy, psychology, linguistic sciences. Context as a term is used in various disciplines, each of the disciplines being different from each other have its own view of how context is defined for that discipline. According to a popular dictionary context is described as "conditions/circumstances that affect behavior". Context is not only defined differently across the many disciplines but also in the subfields of those disciplines. The concept of context is huge and that's why here we would only like to define it in fields that are related to recommender systems, such as e-commerce personalization, management and marketing, data mining, information retrieval, databases and ubiquitous and mobile context-aware systems [20]

a. *Data Mining*- Context here is considered to be the various life stages of the customer. The life stages considered should determine a significant change in preferences of the customer or to the status and value for the company. Example of such context includes major event of customer life like his/her new job, birth of a child, divorce or retirement.
b. *E-commerce Personalization*- [20] In e-commerce web site while making the purchases the intent of purchase is consider as a contextual information. The behavior of the customer depends on his intent. For e.g. a customer from his account may buy different products for different reasons: a branded clothing for own use, a non branded clothing for gifting purpose or a gadget for her hubby
c. *Ubiquitous and mobile context-aware systems*- In this field, context-aware systems, context was initially defined as the location of the user, the identity of people near the user, the objects around, and the changes in these elements
d. *Information Retrieval*- Another important usage of context is in the field of information retrieval and access. The major problems with such type of systems are that they cater to only short term problems or instant request (for e.g. "find all meetings held during spring on a hot day inside a Chinese restaurant in Europe"), and are not to model trends that sustain for long to know the long-time user preferences.
e. *Marketing and Management*- In the field of marketing research, it has been proven that context plays a very important role in making different business strategies as the behavior of the customer is dependent on the situation in which the complete transaction take place. By, analyzing and understanding such behavior useful decisions can be made that will be beneficial for both the customer and service-provider. The decision making rules of the customer vary based on the usage situation, the use of the good (for gift or self) and purchase initiator (catalog based, shelf in store, helped by sales person). So for accurately predicting the preferences of the customer it is important to implement the relevant contextual information.

2.3 Using the Contextual Information in Recommender System

Context aware recommender system (CARS) rely on ratings as a way to for the user to specify its preferences for the various items. For e.g. in case of a movie recommender, Arun may assign a rating of 3 (out of 5) for the movie “Inception” that is specified as R_{movie} (Arun, Inception) =3. At the start of the recommender process we have initial set of ratings. Ratings can either be given directly by the user of can be inferred by the system itself. Once an initial set of ratings is prepared the system estimate the rating function R by using equation1

$$R: User \times Item \rightarrow Rating \ldots (1)$$

The above equation is applied for those users, item pair that the users have not rated in its initial set. Context aware recommender system thus functions by prediction the user preferences by using in addition to above equation 1 contextual information as an explicit additional category of data. Now the rating function that models the preferences is a function of a triplet of user, tem and the contextual information. In other words, ratings are defined with the rating function as equation 2:

$$R: User \times Item \times Context \rightarrow Rating \ldots (2)$$

where User, Item and Rating is in the domains of users, items and ratings respectively. Context specifies the contextual information associated with the application.

The contextual information can be obtained in a number of ways, including:

- *Explicitly,* This is a simple method in which the relevant people are approached directly and contextual information is found out by asking direct questions of finding this information by other possible methods. For e.g. before providing access to a website, a user may be asked to fill a form.
- *Implicitly,* In implicit way of gathering the contextual information the users need not to give their input rather it is taken from the data in the system or environment such as in cellular system the change in location can be used to describe the contextual information

of location. Another important contextual information i.e. time can be obtained through the timestamp of the transaction.

Here there is no interaction with the user directly, only the information is accessed and data is extracted from that.

- *Inferring-* The context is inferred from data mining or statistical methods. For e.g. a system would like to know the identity of the person holding the remote of TV (husband, wife, son, daughter, etc.). This being unknown to the television company may be inferred by observing the various TV channels watched and the duration they are visited by using the data mining methods.

2.4 Paradigm for Incorporating Context

When we have the contextual information available in the system, as shown in figure 3, the process starts with data in the form of $U \times I \times C \times R$ where U, I, R have their regular meanings and C is the additional contextual information. After the entire process is completed we get a list of recommendations i1, i2, i3 … for every user. However, in CARS the contextual information can be applied at various stages of the recommendation process. Thus the context aware recommender system can take up three forms based on the stage in which the context is used in-

a. *Contextual pre-filtering-* In this paradigm, the context is used to drive the data construction. The current context c information is used for selecting the relevant set of data that comprise of ratings. Then the system works as a 2D recommender system and any of its method can be used for predicting ratings of unknown movies for that particular user. This method is fast and efficient.

b. *Contextual post-filtering-* In oppose to pre-filtering, contextual post-filtering initially ignores the contextual information completely while generating recommendations in the form of a ranked list of all preferred items used to generate the top-N recommendations, depending on the values of N. Here also the 2D recommender can be applied directly as in the case of contextual pre-filter. Then after the list is obtained the post-filter adjusts it by using one of the following technique:

• Filtering the recommendations that are irrelevant with respect to a context

• Adjusting the recommendation list based on the context

c. *Contextual modeling* - In this paradigm, as a part of rating estimation context is used directly. The contextual information is an explicit indicator of a user's rating for an item. While contextual pre-filtering and contextual post-filtering approaches can use 2D recommendation functions, the contextual modeling approach uses multidimensional recommendation functions

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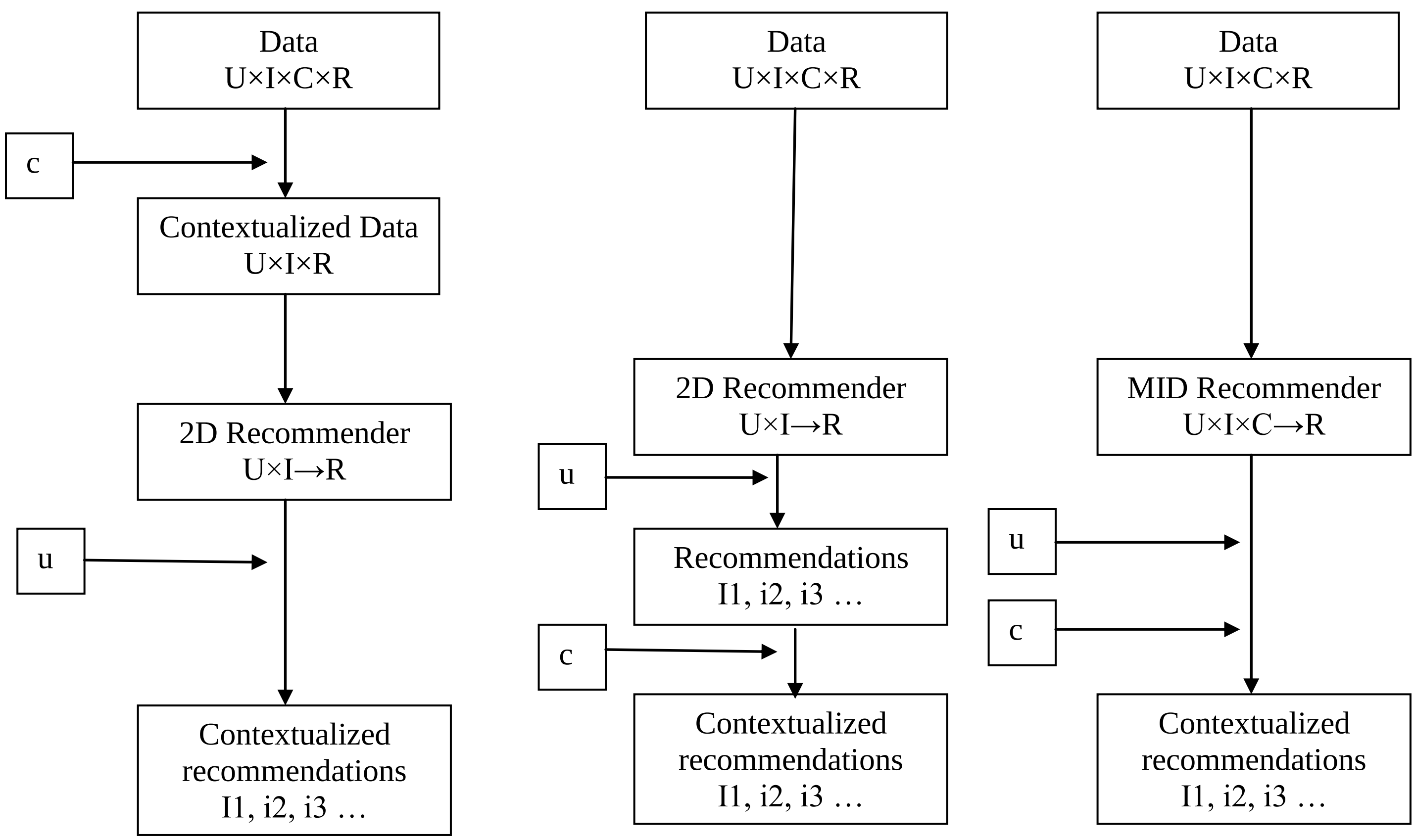

Figure 3. Paradigm for Incorporating Context

Chapter 3

Explanation in recommender system

3.1 Introduction to using Explanations

Recommender system is used to suggest items that a user may like based on various algorithms as described in chapter 1. Earlier works on recommender system used precision and recall [21] as the basic metrics to evaluate a recommender system but further studies proved that the most important measure for the recommender system is user satisfaction [22] that includes serendipity [23], diversity [24], trust [25] and loyalty.

To achieve these goals, it is very important to provide the recommended list of items with explanations. Explanation is used to affect the opinion of an item in a recommended list positively for a user. An explanation is defined by [26] as “a piece of information as to why an item was recommended and how to develop a better communication in commercial systems”. [27] define explanation as “a way to make user better understand how an item satisfy their needs”.

3.2 Goals of using Explanation in Recommender System

The seven main aims of explanation facility as described in [28] as follows-

a. *Transparency*- An explanation is considered to be transparent if it clearly describes how a recommendation was chosen for a particular user. It is very important specially in case of a medical application.

Transparency is not same as justification- transparency is usually an account of how the system works justification can basically describe the recommendation algorithm. However in recommendations system the transparency may sometimes refer to as providing justification in real sense.

Transparency has effect on other evaluation criteria like trust, acceptance [27]. Transparency is also linked to scrutanabilty but generally scrutanability is considered as altogether separate criteria.

b. *Scrutanability*- An explanation can be considered as scrutanable if it makes the system capable of correcting the reasoning behind providing recommendations.

It helps correct the wrong assumption made by the system. That's why, as mentioned above it is often related to transparency. Providing user transparency about the insight of the system help them understand the working as well as change if necessary.

But scrutanabailty is a complex criterion. Users may not like to scrutinize all by self and put in extra efforts for the system. In addition to providing the users with the option of scrutinizing they should also be made clear the negative effects their changes will have on the system.

c. *Trust*- an explanation that increases user confidence in the system is trustworthy. [29] Showed that transparency and user interaction with the recommender system increases the trust.

   Trust can also be dependent on the accuracy of the underlying algorithm used. It is obvious that if the user considers the system trustworthy, the chances are more that the user will return to the system.

   Trust may also be affected by the interface design of the system. [30] provides a study where in maximum portion of comments around 50%, the users were affected by the overall visual design of the system and hence measured the credibility of the web pages.

d. *Effectiveness*- an effective explanation help a user to make better decisions that would not have been possible without explanation facility.

   This criterion is highly dependent on the accuracy of the underlying algorithm used. If the algorithm used is not correct for the particular application that even with the explanation interface being designed effectively, it cannot help the user to make better decisions.

Basically an effective application presents arguments on the quality of the suggested items. This increases the chances that the user will discard the irrelevant items. A very simple measurement of this criterion would be a difference of rating before and after the consumption of an item.

e. *Efficiency*- an explanation is used to help user choose an item quicker.

Efficiency can be improved by providing the user with a comparison of the various competiting options [31]. By providing a well defined and concise comparison of items available the user will have easy choice of the options available.

Efficiency is an important measure for the conversational systems, where the users keep on interacting with the recommender system. Efficiency as an objective measure can be found out by the total time taken for the interaction between the computer and the user as well as the number of interactions needed.

f. *Persuasiveness*- explanations are also used by some commercial expert systems to change the buying behavior of the user.

It can however be measured by so many ways. For e.g. first we may ask a user to provide a rating for an item without explanation then we may again ask to re-rate the movie but with the explanation interface. Here the difference between the two ratings will measure for persuasiveness.

Although persuading a user to buy a product may be beneficial for the application but it should also be clear that too much persuasion can also be bad for the system.

g. *Satisfaction*- The ultimate goal of recommender system is to improve user satisfaction by making the system enjoyable.

To basically measure satisfaction, a user may directly ask whether the system is enjoyable to use or whether they like the explanations provided. However there may be indirect measurement for the same like measuring the loyalty of the system.

The criteria’s are often contradicting to each other. As providing effective explanations may be considered good for satisfaction of the system but at the same time in effort to increase the efficiency we may have other disadvantage like having the user put in more efforts that may decrease the satisfaction for the user.

Other possible aims as described in [32] include-

h. Validity- an explanation facility can allow the user to validate the items recommended by providing a comparison of required item and recommended item.

i. Comprehensibility- the explanation interface may support user by relating his known concepts to those implemented by recommender system.

j. Education- an explanation is used to educate user about the product in case the system is not able to have a satisfactory outcome.

3.3 Presentation and Interaction with Recommendations

The interaction model that is used to gather the user preferences is affected by the presentation of the recommendations. The presentation and interaction both can in turn affect the type of explanations that can be generated.

3.3.1 Presenting Recommendations

The categories for structuring the recommendations presentation are:

• *Top item*- This is the simplest method of all. In this the recommendation is presented by just showing the best item for the users. For e.g. “You have been watching a lot of TV, and star plus in particular. This is the recent and most popular serial from the star plus”

• *Top N-item*- The top item is simple but do not give many options to the user so a system may present a list of items at once. “You have watched a lot of cricket and apparels. You might be interested in the cricket world cup results and the popular apparels brand.” The systems can also explain the relation between the items suggested and also the reason behind the relation and recommendation.

• *Similar to top item*- After the user provide his/her preferences as ratings the recommender system can suggest items that are similar to items that he/she have already rated. E.g. “You might also like to watch Titanic”

• *Predicted ratings for all items*- The system may also allow the user to search for all the available option instead of forcing the selection on the user. Generally recommendations are presented as a predicted store that ranges between 0 and 5 for every item. A user can always have a question that why a particular item is rated so low. To satisfy the user the system is accompanied with an explanation such as “ this movie contains horror genre that you do not seem to like.”

• *Structured overview*- A complex but an efficient way to present recommendations is in the form of structure overview where the structure contains a comparison between items. The user thus can easily distinguish between available options and what all options can be considered as an alternative if the chosen option fails to meet the user demand.

3.3.2 Interacting with the Recommender System

Interaction with the recommender system is a way to provide input which is in the form-

• *The user specifies their requirements*- The user can simply specify their preferences in simple language like English. This system do not require user past history. Since the preferences are specified directly there is no need of explanations to be specified directly. The explanations may be given indirectly by satisfying the stated requirements.

• *The user asks for an alternation*-. A direct way is to let the user communicate with the recommender explicitly and then the user can ask for a change. For e.g. a structured overview can explain the difference between the selected item and remaining items.

• *The user rates items*- To alter the recommendations type that a user receive, the user may even modify a rating they made in the past to correct the predicted score.

• *The user gives their opinion*- Instead of describing everything technically, a user can specify after consuming an item that whether the item is interesting or not, if they would like to see items similar to the recommended items or if the recommended items are not novel or serendipitious.

• *Mixed interaction interfaces*- The above type of interaction interfaces can be combined to form a mixed interaction interfaces [33].

Chapter 4

Literature survey

4.1 Methods of incorporating context

A lot of research has been done on context aware recommendation system (CARS). These are widely used in online shopping, websites and now gaining popularity in other fields like social web [34] and mobile [35, 36]. As mentioned in [37] the basic classification of CARS are as follows-

4.1.1 Pre-filter method

The pre-filtering method uses the most relevant contextual attributes to construct a relevant 2D ($user \times item$) data. For e.g. [23] presents a reduction based approach in this, a 3D rating prediction function supporting the context companion is given by $R^{D}_{user \times item \times companion}: U \times I \times C \to Rating$, where D contains the records of <user, item, companion, rating> where ratings are provided by the user. Then, the 3D prediction function can be specified in 2D prediction function as given in (3)-

$$\forall (u,i,c) \in U \times I \times C, R^{D}_{user \times item \times companion}(u,i,c) = R^{D[companion=c](user,item,rating)}_{user \times item}(u,i)$$

(3)

Here, [companion=c] is a contextual pre-filter taking c as the selected companion attribute and D [companion=c] (User, Item, Rating) denotes a reduced dataset obtained using the pre-filter. A number of variant of the pre-filter method have been proposed [38,39] and have found to improve the recommendation provided for the selected application.

The pre-filtering method leads to sparsity of $user \times item$ matrix when the context is granular [40] or there are large numbers of context in the system.

4.1.2 Post-filter method

The post filtering method ignores the contextual attribute first and applies traditional recommendation approach to get recommendation list. Then after that, the recommendation list is obtained by making adjustments as shown in figure 4. For adjustments we can use either of the two approach [40]-

- Filtering- remove recommended items that have less chance of relevance
- Weight- reorders the recommendation list obtained by predicted rating

Both of these approaches are used on the recommended items obtained after applying traditional recommendations. Post-filtering method although is a better alternative than pre-filter but is expensive. In most cases, pre-filter provide a quick and reasonable solution [40].

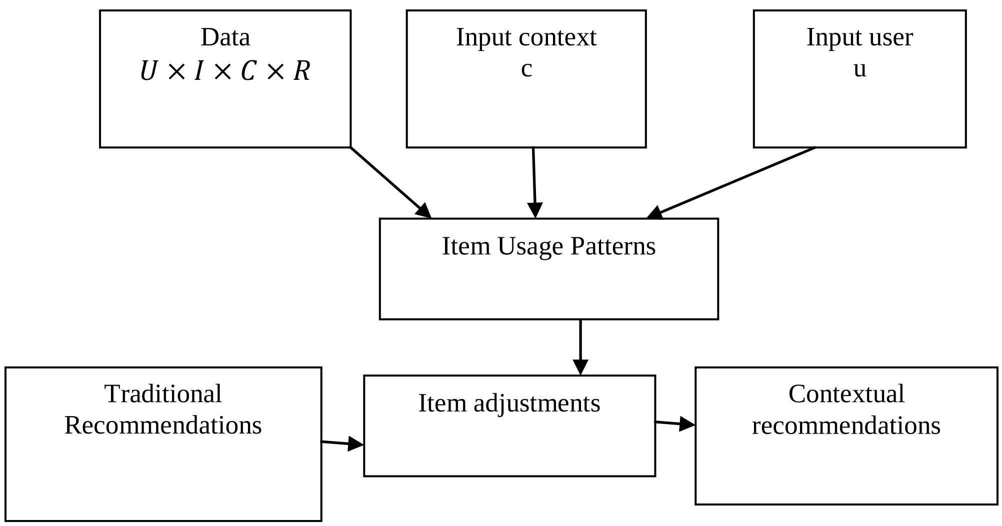

Figure4. Post-filter part of the Design

The contextual post-filtering technique can be divided into heuristic and model-based techniques. Heuristic post-filtering method first finds a common item characteristic (referred to as attributes) for a particular user and a context e.g. preferred sport to watch in a given context. The attributes are then used to make adjustments in the recommendations by one of the following-

- *Filtering* out those items that do not have a significant amount of the common item characteristics (e.g. the recommended movie should have John as actor and comedy as genre)

- *Ranking* the recommended items in the list on the basis of number of relevant characteristics the have (e.g. the movie that have genre as comedy will be ranked higher in the list)

Whereas, model-based post-filtering approaches can build predictive models that describe the probability with which the user prefers a particular item for a specific context. Theses probabilities are then used for making adjustments in the following manner:

- *Filtering* out recommended items that have the probability of relevance smaller than a pre-defined minimal threshold
- *Ranking* recommended items by ranking the predicted scores with the probability of relevance.

4.1.3 **Contextual modelling**

In this method contextual information is used directly as a part of the rating estimates.

4.2 Explanation styles in Recommender System

Using explanations in recommender system has a positive effect on the usability and accuracy of the overall system. [41] Is the first work done to tell about the importance of explanations, after that there have been a series of work done in this area.

Recommendation system works on different algorithm and explanation may follow one of those styles irrespective of whether or not is the underlying algorithm used to compute the recommendations. An example of explanations in system by their explanation style is shown in table 1 as in [23]

System	Example	Explanation style
LibraryThing.com	"Recommended by user X for book A"	Case- based
Netflix.com	"A list of similar movies user have highly rated in the past"	Case- based
Amazon.com	"Customers Who Bought This Item Also Bought . . ."	Collaborative style
***LIBRA* [42]**	Keyword style Neighbor style Influence style	Collaborative
MovieLens [41]	Histogram of neighbors	Collaborative
Amazon.com	"Recommended because you said you owned Book A"	Content- based
News Dude	"This story received a [high/low] relevance score,	Content-based

	because it contains the words f1, f2, and f3.”	
OkCupid.com	Graphs comparing two users according to dimensions such as comparison of how users have answered different questions	Content-based
Adaptive place Advisor [43]	Dialog e.g. “Where would you like to eat?” “Oh, maybe a cheap Indian place.”	Conversational
ACORN [44]	Dialog e.g. “What kind of movie do you feel like?” “I feel like watching a thriller.”	Conversational
INTRIGUE	“For children it is much eye catching, it requires low background knowledge and the visit is quite short. For you it is much eye catching and it has high historical value. “	Demographic
SASY [45]	“. . . because your profile has: *You are single; *You have a high budget”	Knowledge/utilitybased
”Organizational	Structured overview: “We also recommend the following	Knowledge/utilitybased

Structure" [31]	products because- they are cheaper and lighter, but have lower processor speed.	

Table 1. Examples of various Explanation Styles

The various explanation style include-

A. Collaborative based explanation style

The input for this is the users and their ratings. Based on the ratings given by various users, the system calculates neighbors of a user u. Then the ratings of the nearest neighbors are used to compute the recommendation items for u. The most common example of this is Amazon.com that uses the explanation "customers who bought this also bought"

[45] Showed that best way to present this style is using bar-chart

B. Content based explanation style

The input for this style is the past ratings given by a particular user. Further items are recommended to a user if that item is similar to highly rated items. [46] presents an example of content based explanation style that finds out the favorite actor based on highest rated movie by the user in past.

Other explanation style includes case-based explanation style [47] and present arguments like: "case X differ from what you asked in attribute A and is still the highest rated item ". [46] Presents an explanation that uses the demographics of user, as an input. [48] Present a social network style explanation and its affect on a music recommender system.

Not only the style of explanation but even the visualization of information plays a very important role for user to enjoy and continue using the recommender system. Many commercial sites are using different visualization techniques like IMDb.com uses a ten scale rating whereas Lastfm.com uses tagging for explanations. Advance visualization techniques like the tree map are also used for interactive explanations. [41] Presents a study on how visualization techniques affect explanations. Studies are also done to know which presentation format user prefer [26] and it has been seen that sometimes a user do not have any clear preferences like in case of textual and graphical representation

C. Case based reasoning (CBR) explanations

Explanation may ignore completely everything and just focus on the similar items for recommendations. These items are called cases. For example, the FINDME recommender as shown in table1.

One of the classes of case based explanation is an influenced based explanation that is found out by the difference in the scores of items before and after an explanation.

D. Knowledge and utility based explanations

In these type of explanations the input to the system is the need of the user or description of his/her interests. The system then matches every item with the need of the user.

For e.g. a knowledge recommender system take input need of user in terms of camera properties such as memory, resolution and price. Based on this, the various items were analyzed. One of the way to explain the recommendation can be "high in memory and low price". The best way to present such recommendations is as a structure overview of the various available items.

E. Demographic style explanations

For a demographic style recommender, the demographic profile of the user is input to the system. Then the algorithm compares the demographic profile for various users and identifies similar users. Then a prediction is made about an item i based on how similar user rated that item and the degree of their similarity.

A lot of systems are seen but only one could be found that offers demographic style explanations. One of the possible reason can be the demographic information is very sensitive for e.g. “we recommend a romantic movie as you are a girl aged 18-20”

Chapter 5

Proposed Solution

Phase 1- In the first phase of our work we propose a hybrid approach that combines the pre- and post-filter methodology described in chapter 2. Our approach is based on the fact that different contextual information holds varying importance to users for e.g. while selecting a movie to watch, companion may be important for a user while weather may not be important depending on which it can be pre- or post-filtered. Intuition and experience tell us that even the importance of contextual information is also different for different users as for an unemployed person the day (weekend or weekday) may not be important while selecting a movie. On the other hand, for an office going person day may be important as in weekday he may watch only comedies to relax himself. We therefore, by using our hybrid approach are able to generate recommendations more appropriate for a user.

Movie Recommender Design

Our algorithm is a hybrid combination of the pre and post filter method discussed in chapter 2.

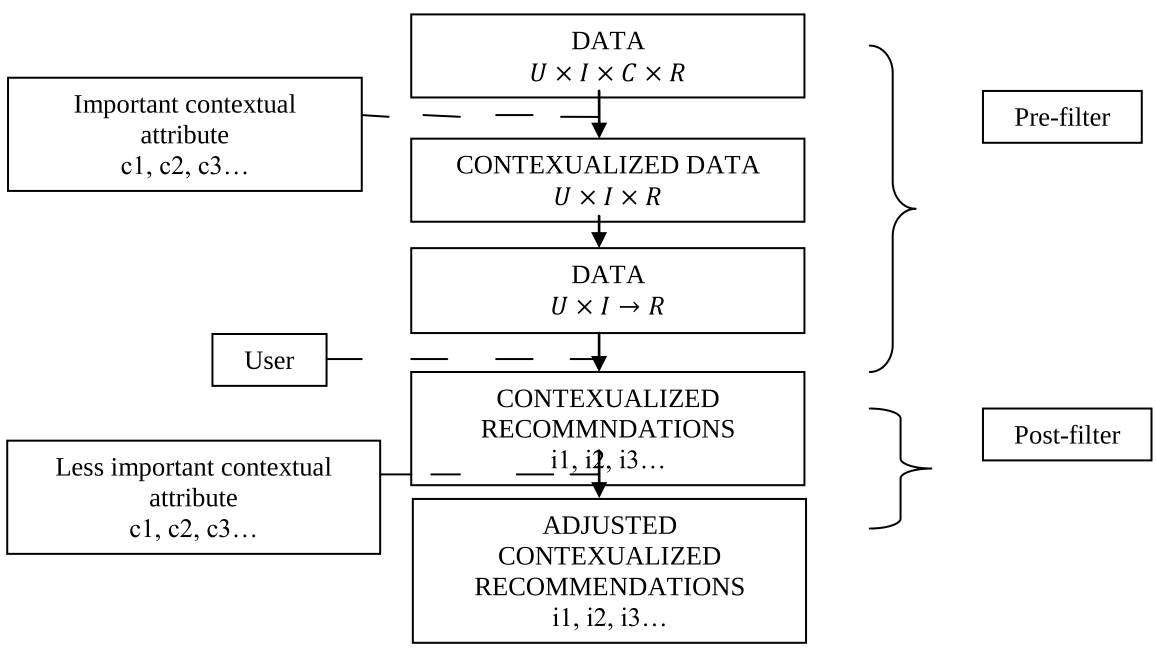

Figure 5 Design of the System

Expected advantage of our method

By, using only the most important contextual attribute as a pre-filter it reduces the sparsity problem in the pre-filter method. At the same time, since the dataset is reduced according to the contextual attribute and recommendation list is obtained on the basis of the reduced dataset before applying post-filter it is quicker than the post-filter method.

5.1.1 Design overview

In this section, we present a movie recommender system that deals with the users past ratings and the dynamic selection of importance of context for them. We have few ratings of users along with their context stored in a database. So, we adopt the most popular approach of RS that is collaborative filtering.

Our approach is divided into various phases as shown in figure 4.

Analyzing context importance to user

We have used, three contextual information in our model-

- Time (day of week)- weekday, weekend
- Companion (type)- gf/bf, friends and family
- Weather- hot, mild and cold

Then after collecting rating and contextual data for the movies seen by users, we applied a test on the data available of every user to find significant contextual attributes that affect movie watching experience as shown by difference in the type (genre) of movies as well as rating distribution of movies seen by a user in particular context. As we believe that, if a user Sam watches same genre of movies with companion “gf/bf”, “family” and “friends”, with a similar rating distribution the contextual attribute “companion” do not affect his movies watching experience. While for any other user Sara with companion “family”, she do not watch romantic movies but with companion “gf/bf” she watches only romantic movies, there is no point recommending her romantic movies next time she selects the contextual attribute as “family”. Then after selecting the most relevant and less relevant contextual attributes next according to the most relevant contextual attribute we applied pre-filter approach and according to the less relevant attribute we applied post filter approach.

Pre-filter approach

The pre-filtering approach uses the most relevant contextual attributes to construct a relevant 2D ($user \times item$) data as in chapter 2. For e.g. if for a user the most important contextual attribute is weather then for a selected value c, [weather=c] is a contextual pre-filter taking c as the selected companion attribute and thus will keep only those records in the data set that has the value for contextual attribute as c and all the values of user, item, rating are kept unchanged. Now on this reduced data set collaborative filtering is applied.

Collaborative filtering

Collaborative filtering uses the opinion of people that have interest like you as seen in the past, to predict the items that may interest you now. For our work, we use Pearson coefficient [c22] to find the similarity of a user with other users.

In this way, we get the contextualized recommendation as per the attribute selected to be most important for the user.

After getting these recommendations the next step is to apply post-filter.

Post-filter approach

Generally, the post filtering approach ignores the contextual attribute first and applies any 2D recommender method to get the traditional recommendations. Then after that, the final recommendation list is obtained by either filtering or adjusting according to the contextual attribute as discussed in chapter 2. In our approach, we do not apply CF on entire data to get traditional recommendations instead we take the recommendations directly, as the recommendations obtained from the pre-filtering approach. Then further using the less relevant attribute, we apply post filtering approach to adjust recommendations obtained from pre-filtering approach based on the item usage pattern of the user. To obtain the less relevant attribute we use the see whether the attribute is affecting the choice of movie for a user that is, we check for the variance as discussed above

5.1.2 Formal Description of Algorithm

Goal- Movie recommendations for a user based on his previous ratings, behaviour and context

Input- current user, current context and user's history database stored as records

Output- Top N recommendations for user based on the selected contexts

Pre-condition:

The information about user, movies and ratings for the movies by the various users are stored in the database. If the user is new, then non-personalized recommender approach is followed. For each of the context selected top 10 rated movies are found and further their combined rank is generated to have the top 10 movie recommender list. Addition of new user is further made to the database.

Algorithm

1. User u is identified.
2. Value for context companion (c1), weather (c2) and day of week (c3) is identified.
3. For selected user u :

For each of the context attribute

- 3.1 for each value v of contextual attribute
  - 3.1.1 Store the different genres appearing for a value v in an array
  - 3.1.2 Calculate the percentage match in the array for particular values to get the variance for a contextual attribute.
- 3.2 compare the variance of the various attributes
- 3.3 The attribute with largest variance is selected as the most important attribute and accordingly less and least important attribute.

4. Then for the most important contextual attribute identified-
   4.1 take that selected value for that attribute as c_i where i=1,2,3 depending on the most important attribute found
   4.2 Based on $c_{i,}$ reduce the dataset to contain only those entries that have value of most important attribute as c_i keeping all the other attribute value to be the same
   4.3 Now for the reduced dataset apply the collaborative filtering algorithm mentioned in section 1.2 to get the predicted item i1, i2, i3….

5. For the less important attribute identified-
   5.1 take the selected value for that attribute as c_j where j=1,2,3 and j!=i depending on the less important attribute identified
   5.2 for the value c_j learn the behaviour of user u, as to what genre of movie the user watched in past with value c_j
   5.3 Now filter the predicted items i1, i2, i3…. According the genres identified to be less relevant in the previous step 6.2

6. Ignore the least important attribute as it do not affect the movie watching experience of the user

Post condition:

The user now sees movie recommendations which is the result of top P selected from pre-filter and adjusted using post-filter.

Phase 2- In the second phase of our work we designed an explanation interface for a hybrid recommender system that re-uses the explanation style of the individual recommender. The explanation interface uses a combination of all the visualization style with each style having a specific purpose making it interactive and appealing. We therefore by using our framework are not only able to make the system visually more attractive for the user (subjective aspects of the system) but also provide high efficiency and low disappointment for user (objective aspects of the system).

The main aim of our framework is to design an interactive and appealing interface to its users so that he/she better understand the recommendations provided and is more likely to return to the system.

5.2.1 Major Design Principle

As in [49] there are three dimensions that determine the category of explanation approach taken by the recommender system.

1. *Reasoning model*- our framework follows white-box explanation approach as it partially disclose the recommendation model and the content to its user while providing explanations

2. *Recommendation paradigm*- For providing recommendations, a hybrid algorithm [50] [51] [52] of content and collaborative filtering is used having the parallel, cascade and switched combination.

3. *Information categories*- the system caters to all the three aspects of information i.e. user, recommended item, alternatives. The system give explanations based on user's known ratings as well as the characteristics of the recommended item. Since the system presents the items based on the difference in color and size, it helps an easy comparison of the alternatives by the given user.

5.2.2 Explanation interface

The interface of the system is designed as

1. *Explanation style*- For our system it follows a hybrid combination of both the collaborative and content based explanation style as described in chapter 4. Clicking on the title of the movie poster gives collaborative style explanation while clicking on the sides of the movie poster gives the content based explanation style.

2. *Presentation*- In our system the recommendations are presented as a tree-map of top N recommended items. Here all the visualizing elements have their own purpose. A movie is recommended by displaying its poster having various attributes-

2.1 Color basically gives the result of the content recommender that is, if the number of features (liked by the user) that the recommended movie has is more than the threshold, the movie poster is displayed in color otherwise black and white. A colored poster attracting eye of the user will contain higher number of liked features.

2.2 Size of the movie poster is determined by the result of the collaborative recommender. If the poster is bigger in size then the movie is rated higher by its neighbor. (So, the poster that is both colored as well as biggest in size will first catch the eye of the user and will top the list)

2.3 Graphs are used to show the rating of the neighbors by clicking on the title of the movie, as it best describes the collaborative filtering result [53].

2.4 Text is used to explain the features liked by the user in the past where '+' represents liked and '-'represents disliked feature in that movie.

2.5 Animation- whenever the top N list includes a new movie (that was not a part of the recommended list previous time user asked for the recommendations) then that movie's border is animated. This is done so that those movies get instant user attention.

3. *Interaction*- Our system is a type of mixed interaction interface as in this the user can interact with the system in a variety of ways-

3.1 The user rates an item- the user can give their opinion by giving the movie a rating out of 5, where 1-2 means a negative opinion and 3-5 is considered a positive opinion.

3.2 The user can ask for an alteration- the user can scrutinize the recommendations provided to him\her. In our algorithm the user can alter the feature the system thinks the user like, the mixing ratio of the collaborative and content recommender and can even tag their friends. Tagging their friends will give those users a higher credibility while deciding for that user.

3.3 The user can ask for new recommendations- if there are no new recommendations (animated border) then the user can alter the hybrid combination of both the algorithms. In case a particular combination is not recommended to a user that will be dimmed and not available to that user.

5.2.3 Options available to user

a. Hybrid style of explanation- clicking on the title gives the collaborative style explanation using a screen as shown in figure 6

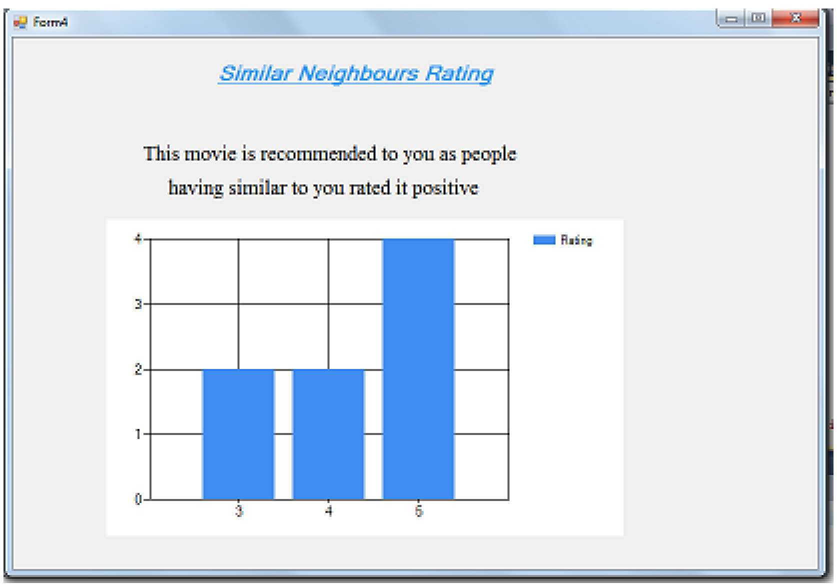

Figure6. Interface of Similar Neighbor ratings

b. While clicking on the sides gives content style explanation as in figure 7

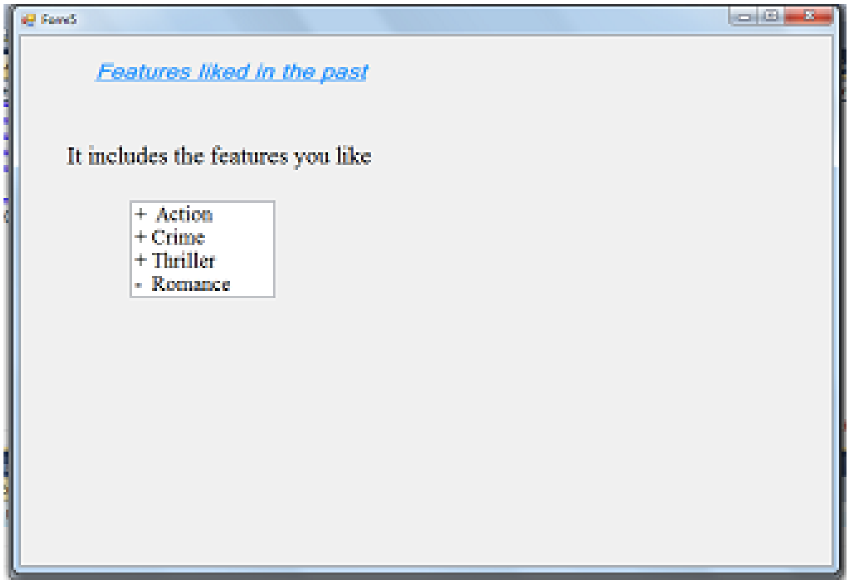

Figure 7 Interface of Features liked in the Past

c. Scrutanability- user can alter the recommendations by providing their input as shown in figure 8

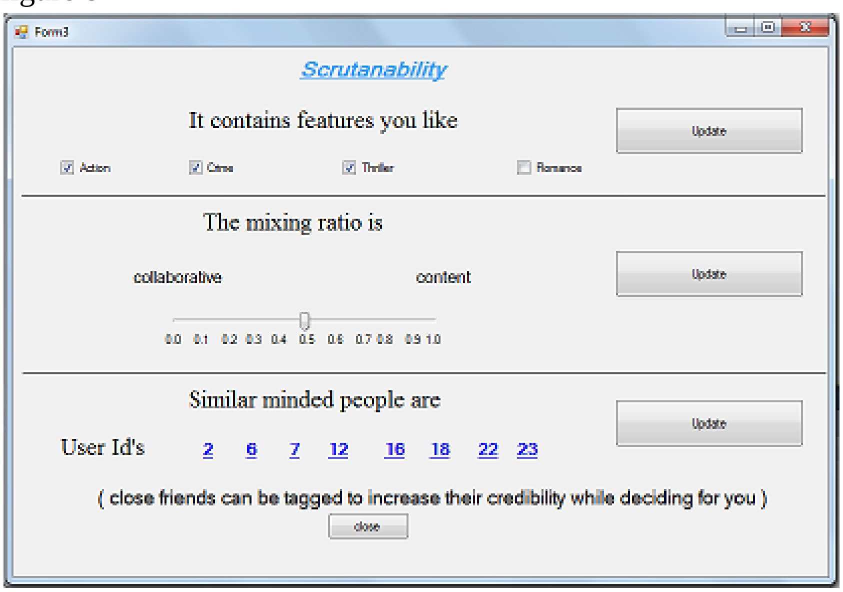

Figure8. Interface of Scrutanability

d. Validate- user can validate the new recommendations provided by making a comparison of the recommended item and previously rated movies as shown in figure 9

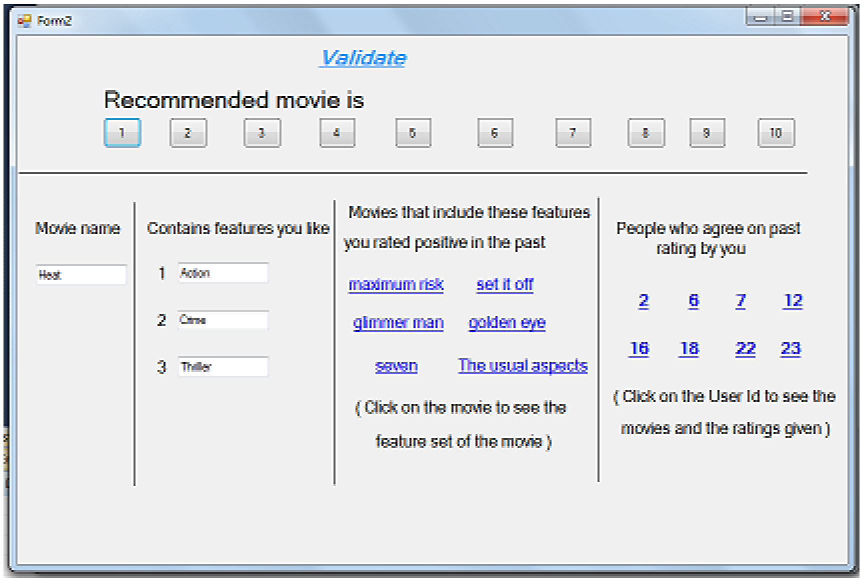

Figure9. Interface for Validate

e. Different algorithms- user can change the recommended list of movies by choosing a different combination of the content and collaborative algorithms as shown in figure 10

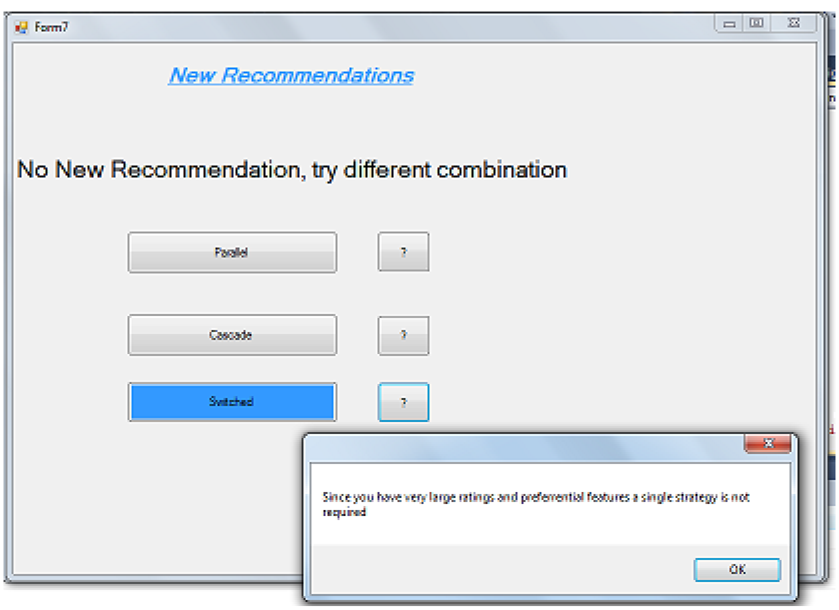

Figure10. Interface of New Recommendations

*5.2.*4 Expected Benefits of our framework-

The framework takes care of the subjective aspects of the recommender system [54]- interaction usability and appeal. Unlike other recommender system, our framework not only suggests the items to user but also provide a comparison between the alternatives using a differentiation of color and size. While displaying the recommendations the system follows the principle as in [55]- (a) categorizing the remaining recommendation as a tradeoff to the top candidates (b) eliminate dominated categories to be shown next to each other.

Another benefit is that the user is allowed to interact with the system in a variety of ways. Explanations are provided on a separate window thus, even if a user does not wish to see the explanation can skip that. The framework other benefit is that the GUI has a textual counterpart for those who find evaluating recommendation using GUI very difficult. This feature is provided to support those users that do not have clear preference of text or image[30].

Another major contribution is that it includes explanation based diversity [56] that is the user can get diverse recommendation by making an alteration in what the system thinks the user likes or tagging their friends or changing the hybrid combination of the recommender by explaining the system. As presentation of explanation affect system effectiveness [57] [22] [58], the explanation interface designed is expected to provide good results.

Chapter 6

Experiment and Evaluation

Phase 1-

User study

In order to evaluate the performance of our system we conducted a study of 20 users in our laboratory for a period of 4 weeks. The group selected included IT professionals of age 22-28years. Basically, browser based software was made to stimulate a movie recommender system that recommends some movies from the set of movie available in the system. A screenshot of the software is shown in figure 11.

For the system 50 movies were selected equally distributed in popular movie genre form movie lens [59] database. We used three contexts {companion, day, weather}. The systems train for first 10 instances for each context without showing any recommendations. Then the process started recommending movie obtained by pre-filter and then filtered by post-filter.

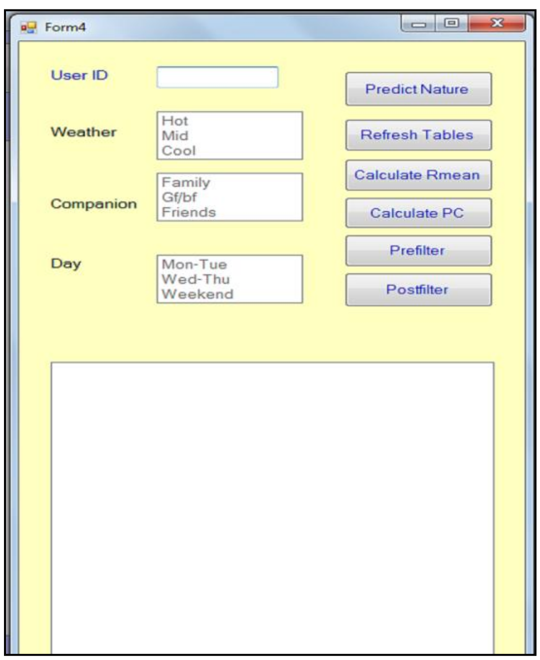

Figure 11 Screenshot of our System-I

a. Then the user is asked to enter his user id. After the user enters his user id and click on predict nature tab- the contextual attribute that is green e.g. weather in a case is the most important attribute for the user while the attribute that is red is less important for the user. The attribute that is dimmed comes out to be the least important for the user.

b. After the user click on the pre-filter and the post-filter tab the recommendations are provided to the user, which may then be selected and watched by the user.

c. After the user watches a movie he is provided with a feedback from as shown in figure 12 asking-

- User id
- Movie id of the movie watched
- Rating (out of 5)
- Did the system recommend you something that you didn't know?

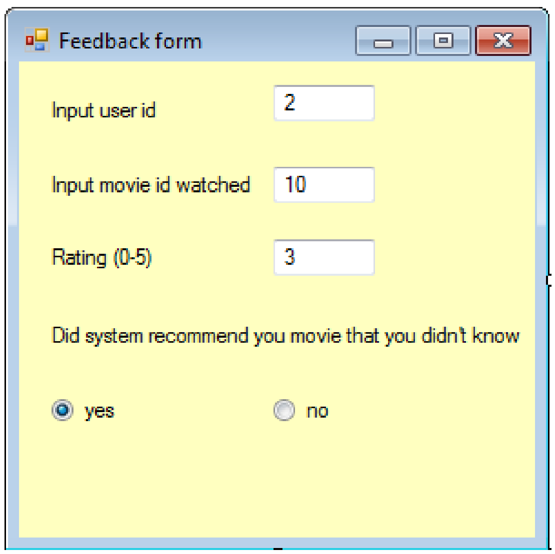

Figure12. Feedback form

Performance

To evaluate the performance of the system we use the following metrics and modified their definition as per our system-

1.1 Accuracy/Precision- As in [60] precision is the probability that recommended movie is liked by a user. It is taken to be the ratio of movies rated (above 3) by the user in the recommendation list to the total number of movies in the recommendation list. We used precision so as to determine the accuracy of the system.

1.2 Diversity- It is the ability of the recommendation system to recommend something new to the user. For evaluating the diversity of the system as in [61] we used the answer to question-“Did system recommend u movie that you didn’t know” in the feedback form (figure 12)

1.3 Rank- as in [62] we use $rank_{u,m}$ the percentile-ranking of movie m within the ordered list of all movies in the recommended list for user u. in this way, $rank_{u,m}$= 0% mean that movie m is predicted to be most liked by the user u in the recommendation list. On the other hand, $rank_{u,m}$=100% means that movie m is predicted to be least liked by user u as is therefore at the end of the recommendation list. So for measuring the quality for the system we use expected percentile ranking in the test period given by equation (4) below-

$$\overline{rank} = \frac{\sum_{u,m} r_{u,m} \times rank_{u,m}}{\sum_{u,m} r_{u,m}} \qquad (4)$$

Lower rank values are desirable as it means that the movie rated positive is close to the top of the recommendation list.

Results

The testing of our system for the above metric is performed for 50 movies in the system. Period of watching movie was kept to be 4 weeks. The user rating for the watched movie and the relative position of the movie rated positive was stored in the system. With the above parameters the system is tested for 5 users. The window size of the recommended list varies from 4-12

The results shows good performance in terms of precision and a maximum precision is achieved in the system when the number of movies in the list is 7 (as shown in figure 13)

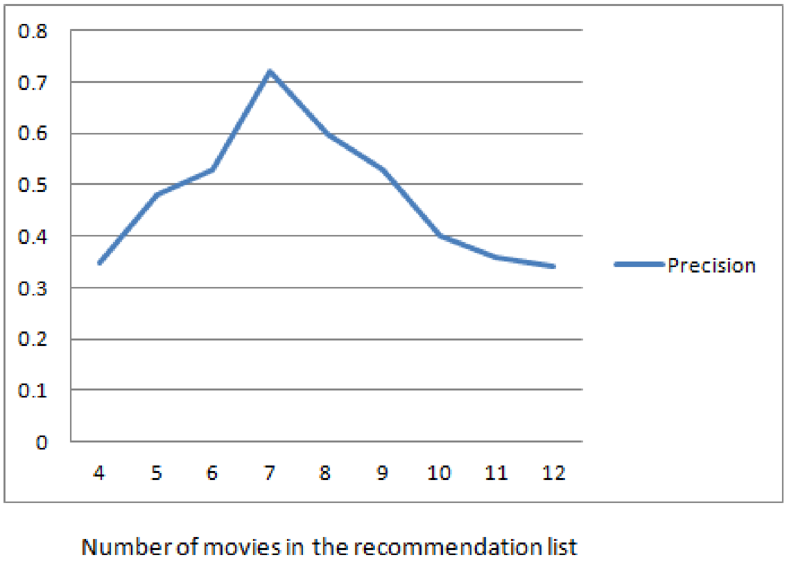

Figure 13 Precision metric

For diversity we found the number of users that have selected yes for the answer to the question "Did system recommend u movie that you didn't know" in the feedback form. While testing of the system by the 5 user, 3 of them selected "yes" for the particular question so diversity of the system was found to be good.

The expected percentile rank of our system is found to be as low as 15%. It was found that the percentile rank decreases with the increase in the number of relevant images for a user. The rank obtained is better than that of a single approach due to the filtering of movies obtained after pre-filtering by the post-filter method (according to the relevance for a user) in our method.

Phase 2-

A. User study

To analyze the effect of our explanation interface on users we adopted a two-stage approach. In the first stage, we did a user study in laboratory with 25 users. The users interacted with the movie recommender system and the explanation interface designed. The user's evaluation was used to find the effectiveness of the explanation interface designed and the disappointing level [62] of the users. In the second stage the users were given a questionnaire to be filled out to assess the qualitative aspects of the system.

The group of participants includes 45 IT professionals of age 24-29years. In the initial phase of training, the users were asked to rate some of the movies before providing them recommendations. They rated 9 movies on average in their initial stage.

The study was conducted in the laboratory of our university where the students interacted with browser based software shown in figure 14. The experiment was accompanied by an assistant to answer all the technical questions of the user.

We have chosen movie as the domain for our experiments as its data set is publically available. For the description of movies and other information we used a subset of movielens dataset [30] containing 315 movies.

B. Performance

Objective evaluation

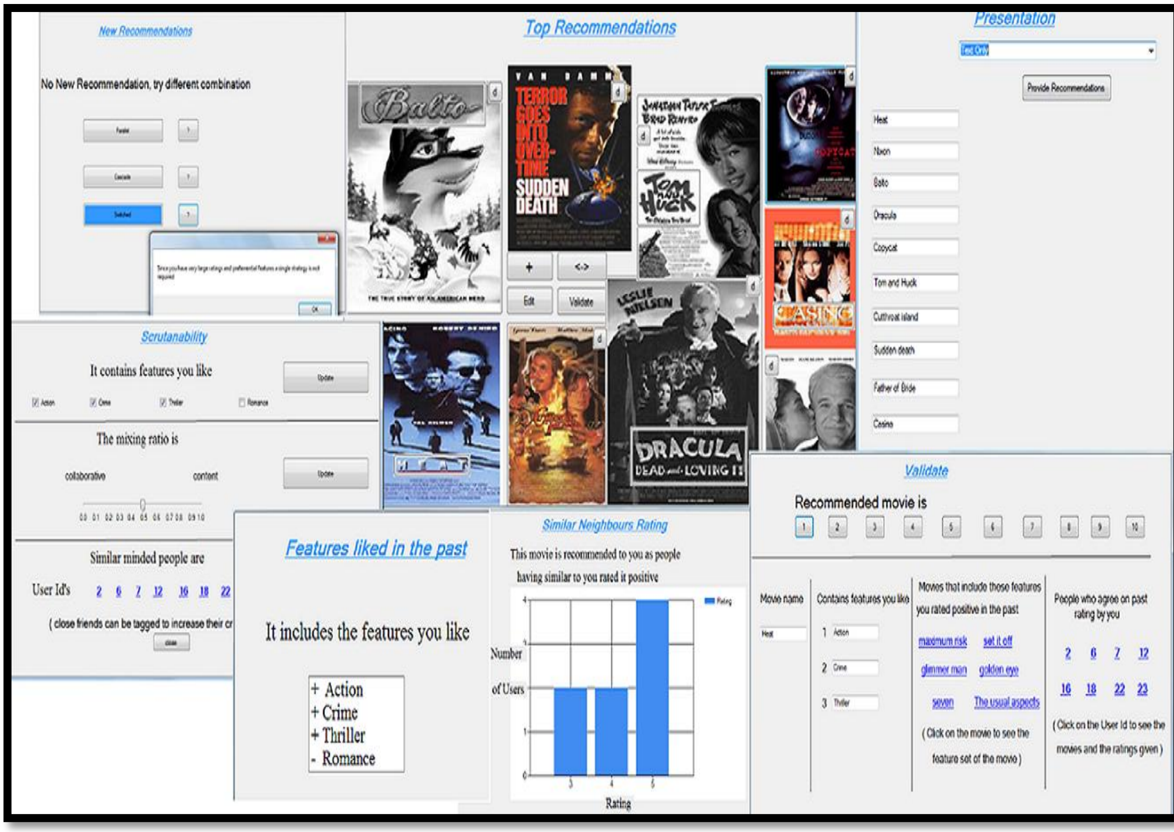

Figure14. Complete Screenshot of the System designed in phase 2

Procedure

The procedure we used is same as described in [64]

1. Ask user to rate some movies
2. Let R be the recommended list of items
3. Let e be the explanation interface
4. For a recommended movie r in R do
5. Present explanations of r using the interface e to the user
6. Ask for rating of user
7. Ask the user to re-rate the recommended movie r after watching it.
8. End for.
9. Ask the user to rate the explanation interface designed.

For measurement, we define a term interactive-rating as the rating given by the user to a movie after being provided the explanations by our interactive system and actual-rating as the rating given by the user to an item after watching it.

So, the interface is said to provide satisfactory result to the user if the mean of the difference between actual and interactive rating is centered near zero value. For the measurement purpose we find out the correlation [64] between interactive-rating and actual-rating given by equation (5)

$$corr(x,y) = \frac{\left(\sum_{i=1}^{n}(x_i-\bar{x})(y_i-\bar{y})\right)}{\sqrt{\sum_{i=1}^{n}(x_i-\bar{x})^2 \sum_{i=1}^{n}(y_i-\bar{y})^2}} \qquad \ldots (5)$$

A high positive value of corr(x,y) is desired as it shows that the system designed is able to estimate the actual rating given by the user using explanations.

To calculate the disappointing level for the user we calculate the mean difference of interactive-ratings (of items rated 3 and above) and those items actual rating. This is so as the items rated below 3 by the user after seeing the explanation given by the system will not be consumed by the user and hence cannot result in disappointment to the user. A low disappointment level for the user is desired for good performance of the system.

Subjective evaluation

Design of questionnaire based study

The analysis of the laboratory study will provide how effective the explanation interface is for the users. For other possible aims of the system we conducted a questionnaire based study. We present the user a questionnaire with 5 questions related to the quality of the interface designed. The user were asked to rate them on a scale of 1(strongly disagree)-5(strongly agree).

C. Results

Each measured variable was analyzed by running paired sample t-test. The evaluation procedure was completed by 12 users and since the system allowed viewing explanations for different recommendations by a user we get data about 26 recommendations.

The results of stage 1 are shown in table 2. The mean and standard deviation of the interactive-rating is given in the second and the third column. However the mean and the standard deviation of actual-rating is 3.75 and 1.02 respectively. We calculated Pearson correlation coefficient to show the similarity in patterns of both the ratings and is given in fourth column. The fifth column shows the mean rating given for the presentation of the interface

Explanation type	Mean-rating μ_r	Std.deviation σ_r	Corr(x,y)	Mean-rating for presentation μ_p
Interactive-rating	3.80	0.56	0.516	4.15

Table2. Results of Objective Evaluation

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The result of objective evaluation shows a high correlation between the mean rating of the explanation interface and the actual ratings given by the user. Also the user provided a very high average rating for the overall presentation of the interface designed.

The disappointment level for the system was found to be 28% whereas the absolute disappointment level was 17% considering only the cases where a positive interactive-rating(3-5) lead to a negative actual-rating(1-2). The results for the subjective evaluation are shown in table 3. It shows the mean responses and standard deviation given by user for each question in the questionnaire.

Items of Questionnaire	**Mean(std)**
This interface enable me to compare movies efficiently	3.38(1.09)
I would like to use this interface for selecting a movie to watch in future	3.04(1.34)
The explanation clearly describes how recommendation was chosen	3.56(1.24)
I enjoyed using the system and my chosen movies	3.21(1.09)
Rate interface in terms of interface label, layout, clarity of information and appeal	4.11(0.35)
It gives me more control for searching movies	2.47(1.08)

Table3. Result of Subjective Evaluation

For subjective evaluation, the participants on an average provided a high rating for each of the qualitative aspects of the explanation interface.

Chapter 7

Conclusion and Future Work

In this thesis work we have discussed an algorithm for CARS for the movie recommender application. The algorithm is a hybrid method that combines the post and pre-filter methods on the basis of the importance of contextual attribute. Due to this hybrid combination, it reduces the sparsity problem in the pre-filter method and at the same time it is quicker than the post-filter method. The algorithm additionally finds context to be of varying importance for the different users and thus computes recommendation accordingly.

The results obtained in this study were conducted as a laboratory experiment. We considered accuracy, diversity and rank to be used as a metric for performance evaluation of our system. The results obtained in section 5 are efficient having an edge over a single pre or post-filter method used.

As a part of future work we would like to see the effect of the different context generalization level on our system. Also, we would like to study the performance of pre-filter, post-filter and contextual modelling approach on different application and find various ways to combine them that would be advantageous over the available methods in literature.

Later on our work focused on the presentation of recommendation and explanation rather than the algorithm used to compute accurate recommendations for the user. The prototype developed is the first attempt to build a complete model which uses all the visualizing styles where each style is used for a specific purpose only.

The major contribution of this work is that it builds an explanation interface for a hybrid recommender in such a way that individual explanation interface can be reused for developing interface for the hybrid recommender. Displaying recommendation as movie poster and varying their size, color based on the content and collaborative value not only increases the interface hedonic characteristic but also helps in an easy comparison on the movies recommended to the user.

The study provided both the objective and the subjective assessment of the interface by the user. The result section showed a high efficiency and low disappointment level based on rating before and after user watches the movie as a result of objective evaluation. The subjective result showed that the interactive design helped in improved perceived quality of the system by its users.

As a part of future work, we would like to perform an online experiment comparing the interface developed and other interfaces in literature on a real world platform among users of different demographics. Another future aspect can understand why a specific user prefers a specific style and whether any particular context/situation governs his choice made. Personalizing the interface based on the user and the context can provide improved results. Also, a long term future aspect can be to educate the users on how can the controls provided to them can lead to wrong results and helping them to improve the condition while exercising their control

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A. Appendix

The work presented in the thesis resulted in the following publications:

[1] Rahul Katarya, Dr. O.P Verma, Ivy Jain "User Behaviour Analysis in Context-aware Recommender System using Hybrid Filtering Approach", in the proceedings of fourth International Conference on Computer and Communication Technology (ICCCT-2013)

[2] Rahul Katarya, Ivy Jain "An Interactive Interface for Instilling Trust and providing Diverse Recommendations", communicated in the proceedings of Third International Conference on Advances in Computing, Communications and Informatics (ICACCI-2014)