Fuzzy Logic Based Recommender System

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***Abstract*— with current projections regarding the growth of Internet sales, online retailing raises many questions about how to market on the Net. A Recommender System (RS) is a composition of software tools that provides valuable piece of advice for items or services chosen by a user. Recommender systems are currently useful in both the research and in the commercial areas. Recommender systems are a means of personalizing a site and a solution to the customer's information overload problem. Recommender Systems (RS) are software tools and techniques providing suggestions for items and/or services to be of use to a user. These systems are achieving widespread success in ecommerce applications now a days, with the advent of internet. This paper presents a categorical review of the field of recommender systems and describes the state-of-the-art of the recommendation methods that are usually classified into four categories: Content based Collaborative, Demographic and Hybrid systems. To build our recommender system we will use fuzzy logic and Markov chain algorithm.**

Keywords: **Recommender System, Information Filtering, Prediction, Classification, User based, Item base, Fuzzy Logic.**

I. INTRODUCTION

Web discovery applications like Stumble Upon, Reddit, Digg, Dice (Google Toolbar) etc to name a few are becoming increasingly popular on the World Wide Web. Information on the Internet grows rapidly and users should be directed to high quality Websites those are relevant to their personal interests. However, there is no way to Judge these web pages. Displaying quality content to users based on ratings or past Search results are not adequate. There's a lacking of powerful automated process combining human opinions with machine learning of personal preference.

The goal of this project is to study recommendation engines and identify the shortcomings of traditional recommendation engines and to develop a web based recommendation engine by making use of user based collaborative filtering (CF) engine and combining context based results along with it using fuzzy logic and markov chain algorithm.

The system makes use of numerical ratings of similar items between the active user and other users of the system to assess the similarity between users' profiles to predict recommendations of unseen items to active user. The system makes use of Pearson's correlation to evaluate the similarity between users.

The results show that the system rests in its assumption that active users will always react constructively to items rated highly by similar users, shortage of ratings of some items, adapt quickly to change of user's interest, and identification of potential features of an item which could be of interest to the user. The System would benefit those users who have to scroll through pages of results to find relevant content.

II. PROBLEM STATEMENT

While studying recommender system, there were some hints at the problems that these companies have to overcome to build an effective recommender system.

1. Lack of Data

Perhaps the biggest issue facing recommender systems is that they need a lot of data to effectively make recommendations. It's no coincidence that the companies most identified with having excellent recommendations are those with a lot of consumer user data: Google, Amazon, and Netflix. A good recommender system firstly needs item data (from a catalog or other form), then it must capture and analyze user data (behavioral events), and then the magic algorithm does its work. The more item and user data a recommender system has to work with, the stronger the chances of getting good recommendations.

Figure 1: Data Gathering for Recommender System

2. Changing User Preferences

Again suggested by Paul Edmunds, the issue here is that while today I have a particular intention when browsing e.g. Amazon – tomorrow I might have a different intention. A classic example is that one day I will be browsing Amazon for new books for myself, but the next day I'll be on Amazon searching for a birthday present for my sister. On the topic of user preferences, recommender systems may also incorrectly label users.

3. This Stuff is Complex!

Below slide illustrates that it takes a lot of variables to do even the simplest recommendations. So far only a handful of companies have really gotten recommendations to a high level of user satisfaction – Amazon, Netflix (although of course they are looking for a 10% improvement on their algorithm), Google are some names that spring to mind. But for those select few success stories, there are hundreds of other websites and apps that are still struggling to find the magic formula for recommending new products or content to their users.

Figure 2: Variables needed for Recommendation

III. Objective

Current recommender systems have a clear main objective: to guide the user to useful/interesting objects. It is very noticeable that this objective is composed of two different tasks:

1. To generate suggestions to be accepted by the user.
2. To filter useful/interesting objects. The first task has to do with the most external and interactive behaviour that any recommender directly reveals to the user. The second task is related to the known task ''find good items'', with a more internal and less inter metrics published to date, it is difficult to identify these two tasks together, as a whole objective, on them. Moreover, a certain research bias towards the second part of the objective could be noticed, while frequently losing the first part.

IV. Scope of Reccomender System

Recommender System are the software engines and approaches for providing suggestion of products to the user which might be most probably matched to the user's choice. Usually the recommender system is a technology which filters out the information to envision in case a particular user will like a specific item; this is usually called as prediction problem, or to identify N set of items that will be of certain users interest called as Top N recommendation problem. From past few years the use of recommender System is being gradually increasing in various different applications, for instance application for recommending books, CDs and other products at different search engines like amazon.com , Netflix.com, ebay.com and so on. Even the Microsoft suggests many additional software's to user, to fix the bugs and so forth. When a user downloads some software, a list of software is provided by the system. All the above examples would be result of diverse service, but all of them are categorized into a recommendation System, Identifying web-pages that will be of interest, or even implying backup ways of searching for information's.

V. Literature Survey

In the last sixteen years, more than 200 research articles were published about research-paper recommender systems. I found that more than half of the recommendation approaches applied content-based filtering (55%). Collaborative filtering was applied by only 18% of the reviewed approaches, and graph-based recommendations by 16%.The use of efficient and accurate recommendation techniques is very important for a system that will provide good and useful recommendation to its users.

Serial No.	Year Of Pub & Journal Info	Paper Info	Technology Used	Conclusion
1.	IRACST - International Journal of Computer Science and Information Technology & Security (IJCSITS), ISSN: 2249-9555 Vol. 2, No.5, October 2012	A Fuzzy Logic Based Personalized Recommender System	Fuzzy Near Compactness (FNC) concept	Personalized attribute-based recommender system as a solution to less frequently purchased products. The system also has the potential of increasing sales for online businesses.

Table 1- Literature survey-1

Serial No.	Year Of Pub & Journal Info	Paper Info	Technology Used	Conclusion
2.	February 9–12, 2011, Hong Kong, China. Copyright 2011 ACM 978-1-4503-0493-1/11/02	Recommender Systems with Social Regularization	Low-Rank Matrix Factorization	Design an effective algorithm to identify the most suitable group of friends for different recommendation tasks.
3.	IJCSI International Journal of Computer Science Issues, Vol. 8, Issue 1, January 2011	FARS: Fuzzy Ant based Recommender System for Web Users	fuzzy recommender system based on collaborative behavior of ants (FARS)	By applying FCM and ant based clustering algorithms users are grouped in appropriate clusters.

Table 2- Literature survey-2

VI. RECCOMENDATION SYSTEM

Recommendation system is an information filtering technique, which provides users with information, which he/she may be interested in.

1. Classification of Recommendation Systems:

Most of the recommendation systems can be classified into either User based collaborative filtering systems or Item based collaborative filtering systems. In user based collaborative filtering a social network of users sharing same rating patterns is created. Then the most similar user is selected and a recommendation is provided to the user based on an item rated by most similar user. In item based collaborative filtering relationship between different items is established then making use of the active user's data and the relationship between items a prediction is made for the active user. [25]

2. Methodologies

The proposed system makes use of Pearson's correlation to implement User based collaborative filtering, and context, Synonym Finder to implement Context based filtering techniques to generate recommendations for the active user.

Following are the methodologies used/researched so far:

- *Taste:*

  Taste is a flexible, fast collaborative filtering engine for Java. It takes the users' preferences for items and The engine takes users' preferences for items ("tastes") and recommends other similar items [25]

- *Vogoo:*

  Vogoo is a php based collaborative filtering and recommendation library. It recommends items to users, which matches their tastes. It calculates similarities between users and creates communities based on them. The figure below shows the results of using vogoo to generate similar taste sharing users and recommendations made by the most similar users [25]

- *Fuzzy Logic:*

  Here I tried to make use of fuzzy logic to calculate similar users.

Following is the currently used approach:

User Request:

User makes a request for recommendation by clicking on the recommendation menu. User is asked to provide contextual information.

Server:

The information provided by the user is send to the server. The server is composed on 2 sub engines: user based collaborative filtering engine, and context based engine. The server sends users request to both the sub engines.

User based collaborative filtering engine: - calculates similar users based on the numerical ratings of common items rated by the active users and other users of the system. The system achieves this by making user of the Pearson's correlation

Pearson's Correlation:

It is a way to find out similar users. The correlation is a way to represent data sets on graph. Pearson's correlation is x-y axis graph where we have a straight line known as the best fit as it comes as close to all the items on the chart as possible. If two users rated the books identically then this would result as a straight line (diagonal) and would pass through every books rated by the users. The resultant score is this case is 1. The more the users disagree from each other the lower their similarity score would be from 1. Pearson's Correlation helps correct grade inflation. Suppose a user 'A' tends to give high scores than user 'B' but both tend to like the book they rated. The correlation could still give perfect score if the differences between their scores are consistent.

Inaccurate queries: We have user typically domain specific knowledge. And users don't include all potential Synonyms and variations in the query, actually user have a problem but aren't sure how to phrase.

VII. PROPOSED ARCHITECTURE

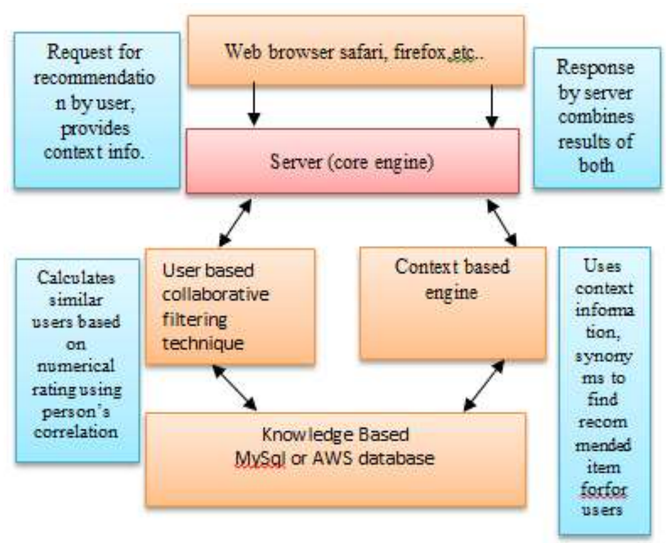

Figure 3: Proposed Architecture

Description:

1. User types in the URL for the system on a Web Browser.
2. User logs into the system using his `userid`.
3. The user chooses from amongst the type 2 different types of recommendation systems available.
4. If the user chose 'Collaborative Filtering' option, the system calculates similar users making use of

engineering algorithms, and then recommends items to the users based on the most similar user.

5. If the user chose 'Context based Filtering' option, the system then makes use of the context information, and Synonym Finder to make predictions.

VIII. PROPOSED METHOD

- *Fuzzy Set and Fuzzy Logic*

Fuzzy set theory consists of mathematical approaches that are flexible and well-suited to handle incomplete information, the un-sharpness of classes of objects or situations, or the gradualness of preference profiles. Fuzzy set theory and logic provide a way to quantify the uncertainty due to vagueness and imprecision. Membership functions, a building block of fuzzy sets, have possibilistic interpretation, which assumes the presence of a property and compares its strength in relation to other members of the set. A fuzzy set A in X is characterized by its membership, which is defined as: (x) : x X [0,1] μ A , where X is a domain space or universe of discourse. Alternatively, A can be characterized by a set of pairs:

$$A = \{(x, \mu A(x)), Xx\} \ldots\ldots\ldots\ldots (1)$$

According to the context in which X is used and the concept to be represented, the fuzzy membership function, (x μ A), can have different interpretations. As a degree of similarity, it represents the proximity between different pieces of information. For example, movie x in the fuzzy set of "electronics" can be estimated by the degree of similarity. As degree of preference, it represents the intensity of preference in favor of x, or the feasibility of selecting x as a value of X. For instance, a product rating of 4 out of 5 indicates the degree of a user's satisfaction or liking with x based on certain criteria.

Formalism of the Representation and Inference Methods

The proposed fuzzy theoretic content-based approach is based on a user's previous feedbacks, and features of the new items and features of the set of items for which the user has provided feedback. The rationale of this method is users are more likely to have interest in item like movie that is similar to the items like movies they have experienced and liked. This approach is useful for new item like movie with no or few user ratings and purchase. It is solely based on one user's previous interest expressed by ratings. The representation scheme, inference engine consisting of recommendation strategies and similarity measures, and the algorithm of the proposed method are presented in this section.

- *Items Representation Using Fuzzy Set*

For an item described with multiple attributes, more than one attribute can be used for recommendation. Moreover, some attributes can be multi-valued involving overlapping or not mutually exclusive possible values. For example, products are multi-categorized and multi-functional. These values of multi-valued attributes in an item can be represented more accurately with in a fuzzy set framework than with in a crisp set framework. Let an item Ij (j = 1 … M) be defined in the space of an attribute X ={x1, x2, x3, …. xL}, then Ij can take multiple values such as x1, x2, …, and xL. If these values of X can be sorted in the decreasing order of their presence in the item Ij expressed by degrees of membership, then the membership function of item Ij to value xk (k = 1 …L), denoted byμ (I) x j k , can be obtained heuristically. Hence, a vector formed for Ij:

$$xj = \{(xk, \mu(I)x\ j\ k), k = 1 \ldots l\} \ldots\ldots\ldots (2)$$

μ (I) xj k can be interpreted as the degree of similarity of Ij to a hypothetical (or prototype) pure xk type of the item; or as the degree of presence of value xk in item Ij.

- *Fuzzy Theoretic Similarity Measures*

One of the most important issues in recommender systems research is computing similarity between users, and between objects (items, events, etc.). This in turns highly depends on the appropriateness and accuracy of the methods of representation. In fuzzy set and possibility framework, similarity of users or items is computed based on the membership functions of the fuzzy sets associated to the users or items features. Similarity is studied and applied in taxonomy, psychology and statistics. Similarity is subjective and context dependent. The set-theoretic, proximity-based and logic-based are the three classes of measures of similarity. Based on the results of the study those measures that are relevant for items recommendation application are adapted.

IX. ANALYSIS

In below table essential parameters are discussed below along with their respective meanings and possible values i.e Yes: Y, No: N, Not Discussed: ND.

Serial No	Parameters	Meaning of Parameter	Possible Values
1	***Efficiency***	A level of performance that describes a process that uses the lowest amount of inputs to create the greatest amount of outputs in minimum time & memory	Yes, No, Not Discussed
2	***Accuracy in terms of prediction***	Accuracy of algorithms should be Maintained. Error rate should be Minimized.	Yes, No, Not Discussed

3	***User stratification***	User specifications and needs must be satisfied	Yes, No, Not Discussed
4	***Automatable***	Methods describes are automatable which reduces manual work	Yes, No, Not Discussed
5	***Robustness***	Specification are may not be covered and but appropriate performance of a system	Yes, No, Not Discussed
6	***Integration***	Integration of system allows combination of 2 concepts such that system is capable of producing better results.	Yes, No, Not Discussed
7	***Flexible***	Flexibility refers to designs that can adapt when external changes occur.	Yes, No, Not Discussed
8	***Performance***	Backtracking or recovery process defines the performance of the system	Yes, No, Not Discussed
9	***Satisfaction of the Recommendation Provider***	User should be satisfied with recommended results. Relevant information should be provided in order to win out user satisfaction.	Yes, No, Not Discussed
10	***Diversity***	The concept of diversity encompasses acceptance and unique.	Yes, No, Not Discussed
11	***Timing constraint***	Appropriate timing is associated with every algorithm	Yes, No, Not Discussed
12	***Effortless***	The quality of a system that makes the user to use it easily	Yes, No, Not Discussed
13	***Optimization***	Optimization is the process of modifying a system to make some features of it work more efficiently or use fewer resources	Yes, No, Not Discussed
14	***Error rate***	It measures the total number of incorrect predictions against the total number of predictions	Yes, No, Not Discussed
15	***Precision***	It is defined where datasets are much unbalanced.	Yes, No, Not Discussed
16	***Recall***	It is the proportion of the number of data items that system selected as the positive	Yes, No, Not Discussed
17	***F1-Score***	For optimization F1 score combines both recall and precision with equal importance into a one parameter.	Yes, No, Not Discussed
18	***Receiver Operating Characteristic (ROC) graph***	It is technique to organize, visualize, and select classifiers that depend on their performance in 2D space.	Yes, No, Not Discussed

Table-3 Evaluation parameters for product recommendations

X. PRIOR AND RELATED WORK

As merchandisers gained the ability to record transaction data, they started collecting and analyzing data about consumer behavior. The term *data mining* is used to describe the collection of analysis techniques used to infer rules from or build models from large data sets. One of the best-known examples of data mining in commerce is the discovery of association rules—relationships between items that indicate a relationship between the purchase of one item and the purchase of another. These rules can help a merchandiser arrange products so that, for example, consumer purchasing ketchup sees relish nearby.

More sophisticated temporal data mining may suggest that a consumer who buys a new charcoal grill today is likely to buy a fire extinguisher in the next month. More generally, data mining has two phases. In the learning phase, the data mining system analyzes the data and builds a model of consumer behavior (e.g., association rules). This phase is often very time-consuming and may require the assistance of human analysts. After the model is built, the system enters a use phase where the model can be rapidly and easily applied to consumer situations. One of the challenges in implementing data mining within organizations is creating the organizational processes that successfully transfer the knowledge from the learning phase into practice in the use phase. Automatic recommender systems are machine learning systems specialized to recommend products in commerce applications.

XI. POPOSED ALGORITHM

Fuzzy Preference Tree-Based Recommendation Approach

In this algorithm it intends to cover both the user's intentionally expressed preference and their extensionally expressed preference from the user items. It form the structure based on two factors such as matching the corresponding the parts and rating by prediction on user targeted item using user preference aggregations. Next the two trees are mapped using conceptual similarities between the corresponding parts of two trees with fuzzy preference.

- Here the user's fuzzy preference tree is mentioned as and the item tree
- The maximum conceptual similarity tree mapping between and
- Then both trees are weighed equally and constructed by merging into
- The tree operation is done and the merging is defined by Next the function pr (), that takes the fuzzy preference tree and similarity tree mapping as input

Then it works as follows:

Algorithm: Rating prediction algorithm. [19]

$\mathrm{Pr}(t_u[\mathrm{j}], \mathrm{M}_{\mathrm{u,j}})$

Input: Fuzzy preference tree node
Output: the predicted rating

1. $mc \leftarrow MatchedChildren(t_u[j], \mathrm{M}_{\mathrm{u,j}})$
2. $if\ v(t_u[j]) = null\ and\ mc = null$
3. Return 0;
4. Else if $v(t_u[j]) \neq null\ andmc = null$
5. Let the preference value be $\sim_{p_{uj}=\{F_{1,uj},F_{2,uj},......\}}$
6. Return $\sum_{k=1}^{r} k * f_{k,uj}$
7. Else if $v(t_u[j]) = nulland\ mc = null$
8. Return $\sum_{t_n[j_x] \in mc} w_x * pr(t_u[j_x], M_{u,j})$
9. Else if $v(t_u[j] \neq null\ and\ mc(t_u[j]) \neq null)$
10. Return $\beta_j * \sum_{k=1}^{r} k * f_{k,uj} + (1 - \beta_j) * \sum_{t_n[j_x] \in mc} w_x * pr(t_u[j_x], M_{u,j})$

Hybrid Filtering

Both content-based filtering and collaborative filtering have their strengths and weaknesses. Three specific problems can be distinguished for content-based filtering:

- *Content description*. In some domains generating a useful description of the content can be very difficult. In domains where the items consist of music or video for example a representation of the content is not always possible with today's technology.
- *Over-specialization*. A content-based filtering system will not select items if the previous user behaviour does not provide evidence for this. Additional techniques have to be added to give the system the capability to make suggestion outside the scope of what the user has already shown interest in.
- *Subjective domain problem*. Content-based filtering techniques have difficulty in distinguishing between subjective information such as points of views and humour. [13]

A collaborative filtering system doesn't have these shortcomings. Because there is no need for a description of the items being recommended, the system can deal with any kind of information. Furthermore, the system is able to recommend items to the user which may have a very different content from what the user has indicated to be interested in before. Finally, because recommendations are based on the opinions of others it is well suited for subjective domains like art. However, collaborative filtering does introduce certain problems of its own:

- *Early ratter problem*. Collaborative filtering systems cannot provide recommendations for new items since there are no user ratings on which to base a prediction. Even if users start rating the item it will take some time before the item has received enough ratings in order to make accurate recommendations. Similarly, recommendations will also be inaccurate for new users who have rated few items.
- *Scarsity problem*. In many information domains the existing number of items exceeds the amount a person is able (and willing) to explore by far. This makes it hard to find items that are rated by enough people on which to base predictions.
- *Grey sheep*. Groups of users are needed with overlapping characteristics. Even if such groups exist, individuals who do not consistently agree or disagree with any group of people will receive inaccurate recommendations.

A system that combines content-based filtering and collaborative filtering could take advantage from both the representation of the content as well as the similarities among users. Although there are several ways in which to combine the two techniques a distinction can be made between two basis approaches. A hybrid approach combines the two types of information while it is also possible to use the recommendations of the two filtering techniques independently. [13]

We used MovieLens10k dataset using hybrid filtering technique and Pearson correlation similarity.

XII. COMPARATIVE ANALYSIS OF ALGORITHAM

These algorithms show varied performance under different training sets. The dimensionality-reduction algorithm requires the highest runtime. The item-based algorithm works slowly for the large number of products. The spreading-activation and link-analysis algorithms require less number of iterations to achieve acceptable recommendation quality. The generative model algorithm is very efficient as it needs a small number of hidden classes for quality recommendations. The spreading-activation algorithm is especially fast. The link-analysis algorithm usually performs the best

Collaborative Filtering Recommendation Algorithm	Advantages	Disadvantages
User-based Algorithm[27].	Simple to implement	Suffer serious Scalability problems Due to sparsity accuracy is low.
Item-based Algorithm [27].	Better performance & quality than user based algorithm. Less computation. Provides higher efficiency. Faster than user based algorithm	Slow for large number of items.
Dimensionality-reduction Algorithm. [27]	Simplifies the sparsity problem.	Requires the highest runtime.
Generative-model Algorithm [27]	Scalable Flexible	Expensive due model building One can lose useful information due to reduction models.
Spreading-activation Algorithm[27]	Relaxes the sparsity & cold start Problem Fast as it computes Recommendation only for target consumers	Works only when sufficient data is not available
Link-analysis Algorithm [27]	Better performance than user based & Item based algorithm. Useful when sparse data is available.	Works only when sparse data is available

Table-4 Comparative Analysis of Collaborative Filtering Recommendation Algorithm [27]

Recommendation Strategy	Advantages	Disadvantages/Limitations
Content Based Recommendation	User Independence Transparency	Limited content analysis Over-specialization
Collaborative Filtering	Easy to create and use Explain-ability of the Results New data can be added Easily More applicable in the reality	It totally depends on human ratings Sparsity(Insufficient data) Scalability Ignore the social relationships. Cold start problem (Low Accuracy)
Trust Based Recommendations	Avoid cold start problem. Alleviate the sparsity problem	Difficult to develop a trust network

Table 5-Comparative Analysis of Recommendation Strategies [27]

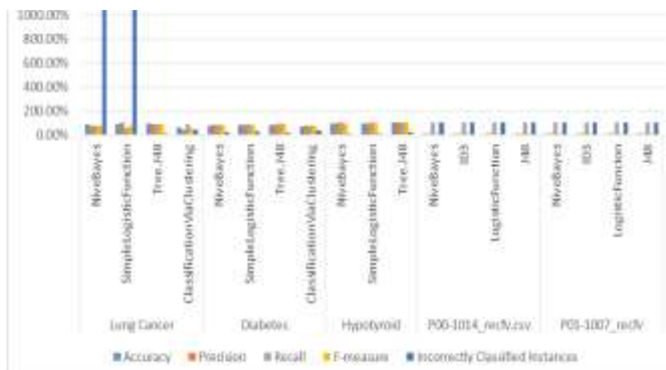

Figure 4. Comparative analysis of algorithm

XIII. IMPLEMENTATION

There are various level of implementation took part to build this system some important of them is listed below:

A. *Dataset and Preprocessing.*

The benchmark dataset from MovieLens at the University of Minnesota (http://movielens.umn.edu), which has been widely used in recommendation research, is employed in this study. The dataset includes movie attributes, user ratings, and simple user demographic information. The dataset consists of 100,000 ratings (1-5) from 943 users on 1682 movies; and each user has rated at least 20 and at most 737 movies.

Genres in the MovieLens dataset are represented with binary values, which do not reflect the true content of movies in the genre space. Therefore, we use the proposed representation scheme by incorporating information about movie genres from the Internet Movie Database (imdb.com), which is a large database consisting of comprehensive information about past, present and upcoming movies.

B. Implement similarity model

After data cleaning process, actual implementation process started. In this phase I build recommender system based on user-user similarity and item-item similarity as well. I used Pearson correlation similarity and used mahout for this system.

Recommender systems for movies are designed and developed to assess the effectiveness of the proposed methods. The system works as follows:

a) For each user, it randomly splits the ratings dataset into a training set and a test set.
b) Using the training set, it computes recommendation confidence score for each item in the test set using the different similarity measures and recommendation strategies.
c) For each user, using the movies in the testing set, it computes Top-N recommendations and the recommendation accuracy– precision, recall, and F1–measure. Moreover, computational time for learning user preference and presenting the recommendation are recorded.
d) Using different random selection of the movies into testing and training sets, 10 different runs are executed to avoid sensitivity to sampling bias, and the average results are reported

C. Evaluation metrics

Accuracy is a commonly used metric for a recommender system based on user tasks or goals. The accuracy metrics includes predictive and recommendation accuracy measures. Predictive accuracy measures such as mean absolute error, mean square error and percentage of correct predictions are found to be less appropriate when the user task is to find 'good' items and when the granularity of true value is small because predicting a 4 as 5 or a 3 as 2 makes no difference to the user. Instead, recommendation accuracy metrics including recall, precision and F1-measures are more appropriate. Approximations to the true precision and recall are computed using movies for which ratings are provided and held for testing. This approach of measuring performance is widely used in recommender systems research.

Precision measures the ratio of correct recommendations being made. Recall reflects the coverage or hit rate of recommendations.

F1-Measure = (2*precision*recall)/(precision + recall)

is a single metric that combines precision and recall. They are defined as:

Precision = (no of movies in the TOP-N movies with rating b4) / N

Recall = (no of movies in the TOP-N with rating) / M

Where M is total number of movies rated as interesting in the test cases; and N is total number of movies recommended.

XIV. RESULTS

Mean of recommendation accuracies by recommendation strategy and similarity measure are presented in Figure 5. The maximum mean precision, recall and F1 measure are around 53%, 27%, 36% for FLRS compared to the 55%, 38%, and 38% for FTM and 49%, 39% and 38% obtained for the CSM (Crisp Set Similarity based) approach, respectively.

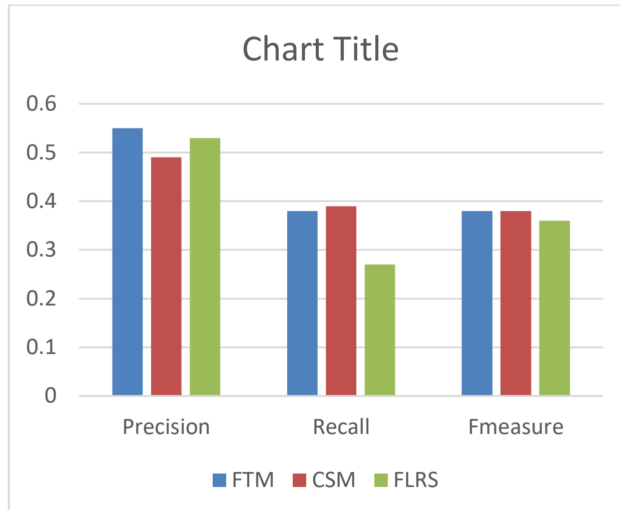

Figure: 5 Average/Mean recommendation accuracies by similarity measure

The Figure 6 and 7 indicates the proposed approach improves the performance of user-based CF method. Based on evaluated results our approach has more accurate results and therefore our approach shows more qualified recommendations compared to fig 8 which is results of user based CF system. [25]

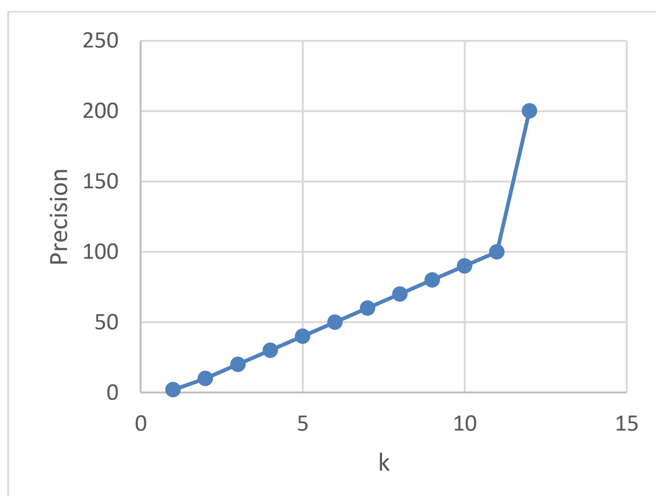

Figure: 6 Precision measures for top N recommendations

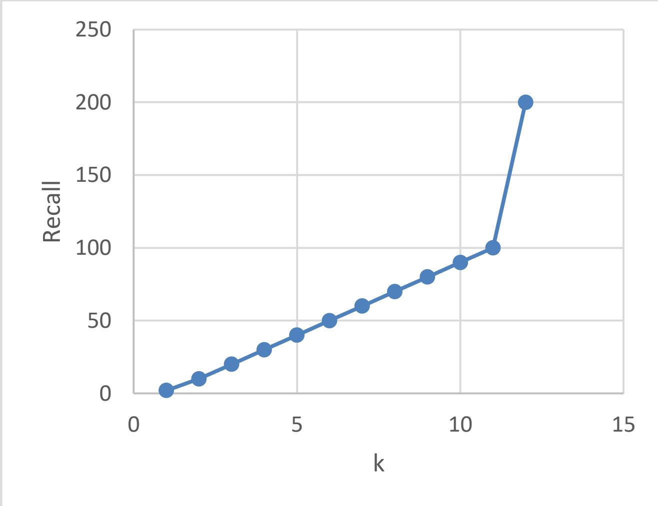

Figure: 7 Recall measures for top N recommendations

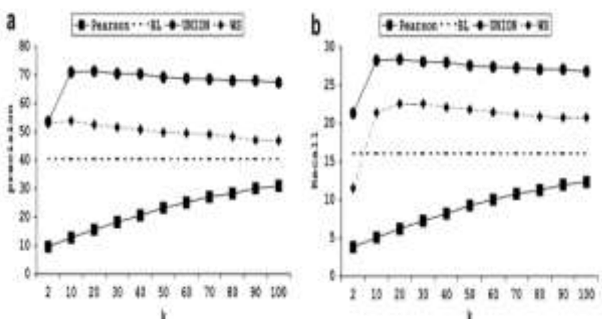

Figure: 8 Precision and recall of user based CF.

The Figure 9 and 10 indicates the proposed approach improves the performance of FARS method. Based on evaluated results our approach has more accurate results and therefore our approach shows more qualified recommendations. [23]

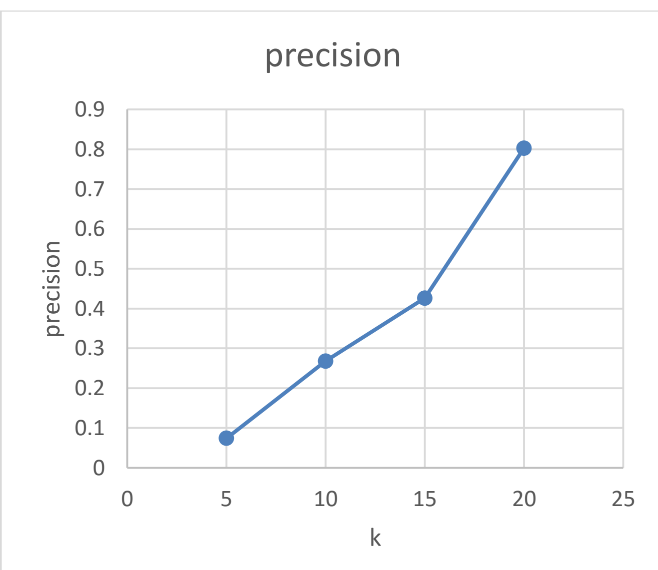

Figure: 9 Precision measures for top N recommendations

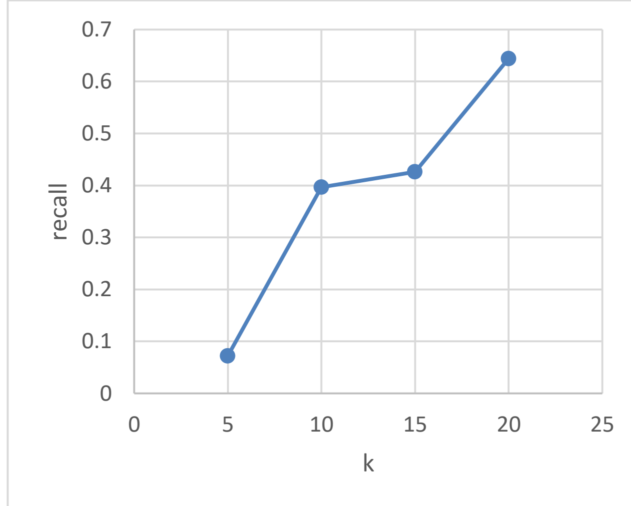

Figure: 10 Recall measures for top N recommendations

Figure 11 and 12 indicates the proposed approach improves the performance of FARS.

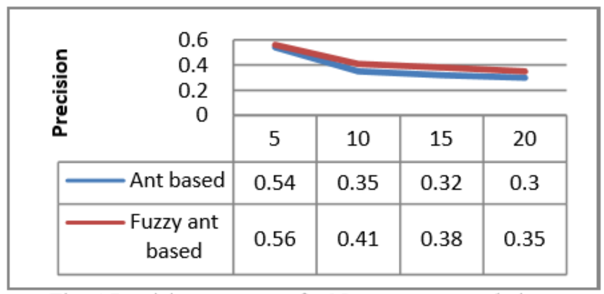

Figure: 11 Precision measures for N top recommendations

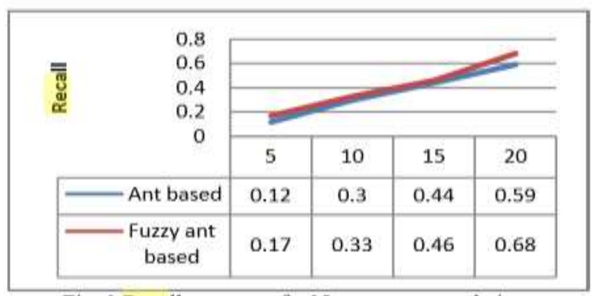

Figure: 12 Recall measures for N top recommendations

XV. CONCLUSION AND FUTURE WORK

Recommender systems are tools which provide a personalized environment for the users of a web site by investigating their navigational behavior in a period of time. In this paper a fuzzy logic based recommender system (FLRS) was proposed. This research develops a fuzzy logic methodology for recommender systems. Using actual data on movies, the results of the research integrating user and item features, and using fuzzy and possibility theories as the foundation for representing and reasoning about uncertainty contribute to the effectiveness and efficiency of the proposed method for recommender systems.

We performed experimental comparison of our proposed method against well-known user based CF, FARS, FTM and CSM approach.

Further studies are planned to extend this approach in several directions. First, inclusion of additional attributes for movies expected to improve the performance of the system. Second, test the FTM approach with additional dynamic datasets and domain applications to see the generalization of the results.

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