ISSN 2347-4289

Exploring Approaches Of Recommendation System In Support Of Verdict And Comparison: A Personalized Prospect

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ABSTRACT: In recent years, the WWW has seen rapid expansion in several web fields. It lead to large volume of Information on web and because of which the Information Overloading delimma arisen in various domains of web. Besides that, just bulky assortment of data lacking knowledge, its of no use. So Recommendation Systems came for rescue with Personalization which permit to present contents to user founded on explored patterns using data mining techniques. At begin of Work, the surroundings of Recommendation Systems and Personalization is presented. With this, subsequently the comprehensive outline of Recommendation System approaches like Collaborative Filtering, Content Based Filtering and Hybrid Filtering with other approaches described. So while prefering specific, one must be capable to differtiate among them using diverse parameters like advantages, disadvantages, underlying principle etc. so this work is for presenting the comparison and verdict of various approaches.

Keywords : Recommendation System, Collaborative Filtering, Content Based Filtering, Hybrid Filtering, Personalization, Information Overloading

1 Introduction

In Recent year WWW has sprung up and developed with exceedingly agile hasten and it made feasible for one and all to share-out their contents in digital form effortlessly. Also, because of superior gadgets it's beneath of everyone's fingerprint. Every day Internet is overloaded with massive amount of information. A vast amount of information brings forth every day, even every moment [1]. As an internet facing crisis of Information Overloading, obtaining precise information is really intricate [2]. At the present, users having choices ubiquitously like, what to read, what to watch, what to listen etc. Also concerning information overload, user for all time selects information like image, text, videos, and product etc. from a number of other possibilities [2]. The accessing of internet basically leads to creation of data [5]. As the amount of data on internet escalating and leading to Information overload dilemma, the Recommendation Systems (RS) came for salvage. Recommendation systems are basically cooperative with user to strain out the necessary information and also give useful solutions to user [2]. As bulky number of items publishing each day, the most relevant items are difficult to discover [3]. Several time users get results containing ambiguity [4]. So this overload can be abridged by employing Recommendation Systems (RS). Basically the information overloaded problem can be solved with personalization which allows showing only content in which user interested [2]. The significance of RS is enormously amplified as it used by sites like amazon.com and many other eCommerce portals [4]. To serve user superior way, it records users data either in explicit (usually ratings) form or implicit form (frequently clicks and Web Page views). The RS collects data as much as it can for supplementary precise recommendation of items [7]. The most important intention of presenting work is to judge against the variety of existing approaches. The paper is arranged in majorly IV sections. Section II presents the related work regarding this work. Section III presents the broad appraisal of RS approaches. Section IV presents the comparison of various approaches. Section V presents the Experiment and analysis of the Movie lens data set.

2 Related Work

As Recommendation System is a vital and primary area, there are many authors done various works. The majority of the authors considered Collaborative Filtering and Content Based Filtering as a main approach to research. Also many others tried to combine both former approaches for more effective recommendations. Content Based Filtering is one the major approach for generating predictions. Billsus & Pazzani reported a content based Newsdude system for news recommendations. Various Machine Learning methods were employed for generating user models [3]. Grady et proposed YourNews which increases transparency of personalized news system. It measures similarity between documents based on Cosine Similarity Measure [3]. Middleton et al. proposed Quickstep system for recommendation of research papers. Here, the papers are arranged based on ontology and used for modeling user's interest. Collaborative Filtering is interest of many people for research and as result majority of commercial systems are based on CF approach. Pazzani et al. Proposed web page recommender system where the rating of webpage link is considered [7]. Chen et al. proposed model for Short Term and Long Term interest of user [3]. Das et al. proposed google news for clustering news items and recommendations based on collaborative filtering [26]. Tan and Teo proposed a system PIN for retrieving and ranking news items based on user profile. Miller et al presented a special approach for recommendations on a PDA in moveilense project [31]. As former two approaches having shortcoming, so to produce more effective recommendations, researchers combined more than one technique and offered as hybrid systems. Gokhale A. et al. proposed P-Tango system which was calculated similarity between users based on Pearson Correlation Coefficient (PCC) for news recommendations [30]. In this, the offline training models are used for online recommendations. There is also work done in IR for implementing the recommendation system. In this the user's implicit data recorded for building profiles.

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Also, many authors like Banos et al. and Goossen et al. approaches for semantic filtering, which also carry significance [3].

3 Reviews of Background

3.1 What are Recommendation Systems?

Recommendation System (RS) provides definite techniques which are intended to present content to the user according to interest [8]. Basically RS automates the undertaking of predicting contents. Now a day's RS are very common taking place web as they show their existence ubiquitously from shopping portals to eCommerce sites. The RS is reasonably popular on the web as they have an aspiration like escalating selling of items, selling more varied items, gratify user according to interest, increase cross selling, understating what user precisely desires etc. [9][16]. The goal and structure of RS is varies according to the domain where it used.

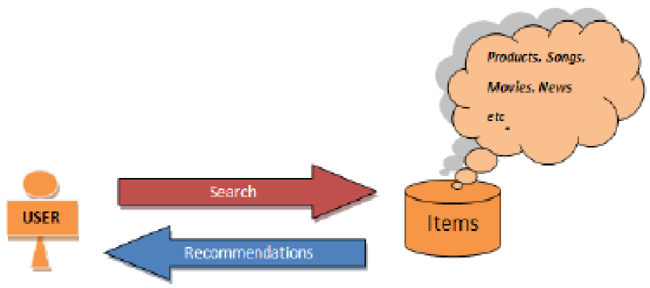

Fig.1. *Basic Recommendation System concepts*

As shown within Figure 1, the fundamental concept of Recommendation System where user interacts with items stored in sytem which may be product, movie, news, etc. As shown in the Figure 2, RS truly use several assorted. RS is fundamentally part of web application with which user interacts and it recommends most relevant items to user curiosity [10]. As both, users and online stores confronting the dilemma of information overload, the RS can unriddle it by presenting contents according to the user's interests. What Recommendations it spawn is extremely essential as it influences shopper upcoming behavior [4]. Primarily RS is

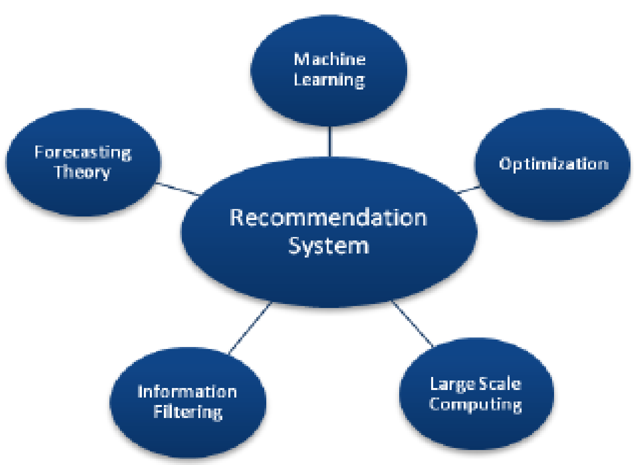

Fig.2. *Recommendation System interrelated fields*

Having intention to show items which user has not seen before [7]. For instance, items like movies (Netflix.com), songs (Pandora.com), books (amazon.com), jokes (jester.com), news (GoogleNews.com), Videos (Youtube.com) etc, can be recommended. Traditional Recommendation Systems were not using private data of users, however, while necessitate of personalization were greater than before, numerous modern RS also uses private data of user [11]. For making a variety of recommendations, the system must have data collection. The user may provide feedback in two formats like Implicit or Explicit as Table 1 depicting [7]. Subsequent to collecting data the predictions can be generated by means of filtering. Here are two types of filtering- first is Passive Filtering and Active Filtering. As on internet immense and bulky of data existing, but short of knowledge is there so data mining is answer. Devoid of knowledge, the stored data is of no use [14]. As the major rationale of RS is recommending items to user relevant to user's interest, the RS must understand the structure of an item. The items may be intricate or simple in formation. The implicit recommendation systems suggest recommendation while user searching on the site where the explicit recommendation systems generates recommendations based on user submitted query [4]. As Shown in the above Table 2, there are different challenges RS face [16]. The major challenges like scalability which express crisis with reference to how RS deals with the immense amount of data like intricate catalogs of products. The Recommendation Systems are helpful in an extensive assortment of domains like movie, news, books, research articles, search queries, social tags, and products. Also for jokes, financial services, insurance etc.

3.2 Personalization: Significant as well as Disputes

Personalization is a process in which the data related to user's preferences, behavior is stored and used for exploring user's precedent and prospect interest for endow with better-quality contents. Personalization is whichever kind of action which helps to represent content to the user according to his flavor [19]. Personalization permit evades one size fits all approach [17]. As substitute, according to their interest show contents.

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TABLE 1
USER FEEDBACK TYPES

User Feedback	Description	Example
▪ **Implicit**	▪ Users actions are supervised and analyzed	▪ For instance, Browsing history, Purchase history etc
▪ **Explicit**	▪ User explicitly provide feedback	▪ For instance, rate particular item

TABLE 2
ASSORTED CHALLENGES OF RECOMMENDATION SYSTEM

Challenges	Description
Scalability	In real time web application, the enormous amount of data exists. For example, Movielense having surplus 10 M users and ratings.
Privacy	RS records data in so far as possible and exploits the user's private data for more precise recommendation.
Diversity	Huge collection of items existing, so recommend precise items are hard.
Identify interest	As novel items existing, the user's interest may fluctuate. The interest may be short term or long term.
Accuracy	Denote the dissimilarity between the predicted items and genuine viewed items
Cost	As RS records bulky amount of information, the storage, upholding cost is high.
Sparse Data	Available data is deficient or noisy
Helpfulness	Whether the recommendations are of use or not.

The users who are logged in and explicitly enabled history; the system builds users profiles for personalized recommendation [4]. Personalization should be capable to recognize and apply the change of user's interest [4]. A personalized product recommendation is mechanism to overcome information overload take place while shopping on internet [18]. In personalization, the web usage mining plays vital responsibility and it permits analysis of log data acquired from the web server, proxy server etc.[19] Also it helps to explore the user profile for improved recommendation. Personalization can be one to one or segmentation based. If segmentation based approach is utilized, then dissimilar clusters will get assorted recommendations. The notion of personalization is primarily based on adapting to the individual needs, preferences etc.

4 ASSORTED APPROACHES OF RECOMMENDATION SYSTEMS

As primarly RS applied on web portals having large collection of items with greater complexity, so RS employs the various approacehs as shown in Figure 3. Majorly Content Based Filtering (CBF)[1], [3], [10] and Collaborative Filtering (CF) [2], [4], [6] are used for Recommendation Systems (RS) [11] and user Preference Predictions. The traditional recommendation system uses approaches like CF, CBF and Hybrid system [5] to produce more relevant recommendations by identifying individual's interest by using past activities.

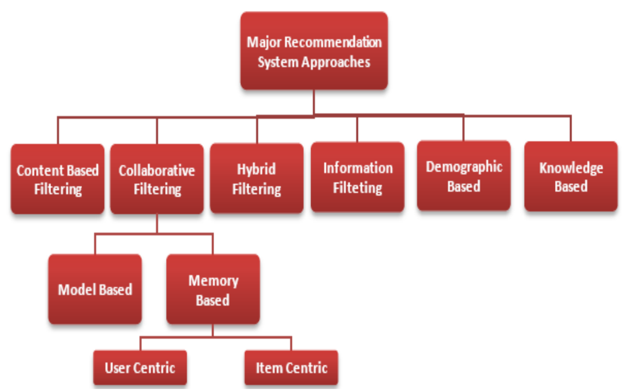

Fig.3. *Various Recommendation System Approaches*

4.1 Content Based Filtering

In Content Based Filtering (CBF) an item is recommended based on the item description and user profile of interest [10]. Basically the content information is exploited to form a profile of user's interest and these profiles used to recommend unnoticed items or information to user [1]. Basically, CBF has its origin in Information Retrieval (IR) and Information Filtering (IF) [13]. CBF generates profile for user by monitoring the description of content rated by a user before [1]. Content based filtering analyzes item description to classify items that are of scrupulous interests to user [10]. There are two major perceptions in CBF- Item Profile and User Profile [16].

Fig.4. *Content Based Filtering*

Item corresponds to items that can be recommended for user and frequently stored in the database. User Profiles assist to recommend items based on interest, the interest can be determined based on the items previously viewed as Figure 4 depicting. Furthermore profiles have information about the user and his taste [20]. Profiles are merely set of features that portray user's interest [21]. User profiles can be builded statically or dynamically. Item corresponds to items that can be recommended for user and frequently stored in the database. User Profiles assist to recommend items based on interest, the interest can be determined based on the items previously viewed as Figure 4 depicting. Furthermore profiles have information about the user and his taste [20]. Profiles are merely set of features that portray user's interest [21]. User profiles can be builded statically or dynamically. CBF uses a variety of classification learning techniques like Rule induction, Decision tree, Nearest Neighbor method, Probabilistic methods [22]. The importance of document for a specific user is determined by term weighting technique like TF-IDF (Term Frequency-Inverse Document Frequency).

TABLE 3
VARIOUS CONTENT BASED FILTERING APPROACHES

Content Based Filtering Approaches	
Task	**Techniques**
The Vector Creation	N grams
	TF-IDF method
	Stop words list
Classification Component	Decision tree and Rule Induction
	Naïve Bayes
	Linear Classification Method

As Table 3 depicts, there are two major undertakings in CBF like the Vector Creation and Classification of components. For vector creation various approaches like N-grams, TF-IDF and Stop-Word list can be employed. In addition for classification majorly Decision Trees and Rule Induction are used. Also Naïve Bayes, Linear Classification methods can be used. Basically Contents are represented using the Vector Space Model like TF-IDF or topics can be distributed by PLSI (Probabilistic Latent Semantic Indexing) model.

4.2 Collaborative Filtering

Collaborative Filtering (CF) is one the most flourishing arecognized method for accomplishment of Recommendation Systems and predicting users preferences [2]. Basically, in 1990 the CF came in the picture as a solution of Information overload dilemma [23]. At this point, in this approach, the information is recommended for the individual user that has been rated highly by other users who have pattern of ratings alike to that of the user [1] as shown in Figure 5. So here, the recommendations are generated by exploiting data like ratings transversely population of similar users [24]. CF is incredibly helpful where the content analysis is tough like multimedia contents [25]. CF helps people to make choices based on the opinion of other similar users.

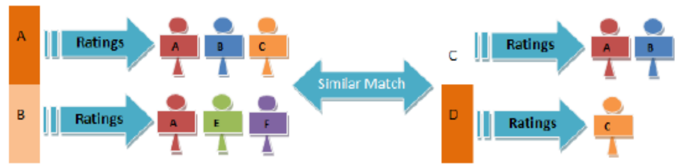

Fig.5. *Collaborative Filtering Appraoch*

CF discovers other users whose past rating behavior is alike to current user and utilized their ratings to predict what the current user like. Here the correlation amid users taken into account while recommending items. CF provides either predictions or top N recommendations for user [19]. CF is basically about the collecting and analyzing the large amount of information on user's behavior, preferences, browsing activities and predicting what the user will like based on their similarity to other users. As shown in Figure 6, CF is basically a user-item matrix in which the challenge is to forecast what value user will rate for a specific item by using ratings of other similar users. As CF represent in form of user-item matrix, the user basically shows off his interest by rating item he liked. Basically, in Collaborative filtering there are two foremost undertakings: one is to predict what the user may like based on his ratings and one more is to recommend best top N items to the user.

	Item *1*	Item *2*	……	Item *m*
User *1*	R *1,1*	R *1,2*	……	R *1,m*
User *2*	R *2,1*	R *2,2*	……	R *2,m*
.....				
User *n*	R *n,1*	R *n,2*	……	R *n, m*

Fig.6. *Fundamental Structure of User-Item matrix*

As shown in the Figure 7, the table structure matrix where each row presents user and each column presents movies.

	Movie 1	Movie 2	Movie 3	Movie 4
User 1	9	5	1	4
User 2	4		4	2
User 3				1
User 4	8	5	2	**?**
User 5	7	4		4

Fig.7. *Example of User-Item rating matrix*

There are five different users and four movies for which users rated. At this instant predicament is to decide what will be rating of user4 for movie 4? In CF, the concept of similarity measure or distance metric is exploited to guide the clustering process. There are a variety of modes for evaluating similarity amid users like Cosine Based Similarity, Pearson Correlation Coefficient (PCC), Spearman Rank Correlation, Kendall's Correlation, Mean Squared Difference and Entropy Cosine Similarity [22]. The CF brings into play idea of clustering, which cluster comparable users described as neighborhood [26]. There are two algorithmic approaches [13], [26]-

- **Memory based**

Within Memory Based approach all the collected data utilized for building predictions. All data reside in the memory for generating predictions. Here the votes or ratings of users are directly used for making predictions. Basically, it may use all users or only user's who are in the neighborhood to the active user. Over again, there are two variations in Memory Based Approach like User Centric and Item Centric.

- **Model based**

Here, the models are constructed and trained based on existing data. Merely models are used for making predictions. As compared to memory based, model based makes faster recommendations and predictions. In a model based the ratings are not straightforwardly used, as a substitute the models are created first of all for making predictions. Models necessitate to train using data sets. The models can be constructed using a range of techniques like Bayesian Networks [10], Clustering Methods [27], Association Rule Mining [14], Latent Semantic [23] etc.

4.3 Hybrid Filtering
The hybrid Filtering [5], [13], [23], [28] are based on Combination of two (or more) above revealed approaches as shown in Figure 8. In Hybrid filtering the various Recommendations system approaches like Collaborative Filtering, Content Based Filtering are combined for more effective recommendation.

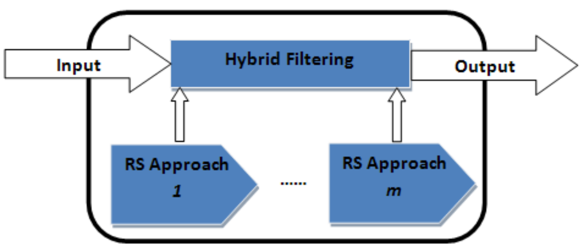

Fig.8. *Hybrid Filtering Appraoch*

As RS approaches became more established [23], the Hybrid recommendation system is emerged more. The fundamental inspiration behind the hybrid system is to use benefit of one approach to surmount disadvantage of another approach. Hybrid system combines several techniques collectively to discover more pertinent recommendations. The previous review of hybrids recognized diverse classes [23] like Feature Augmentation, Weighted, Switching, Meta-level, Feature Combination, Cascade, Mixed etc.

4.4 Information Filtering
Basically information helps to produce knowledge. As we recognized the WWW is having immense of data and for the reason that WWW facing information overload predicament. So accessing necessary information particularly is in fact challenge. Information Filtering (IF) and Information Retrieval (IR) are supportive for dealing with illustrated problem. Principally Information Filtering is a key component of IR system which contained bulky volume of documents. IF deals with retrieving information which gratify interest. The user specifies his need of information in the form of a query which specifies single instant necessitate of information. In IF the documents are fundamentally classified as relevant or non relevant. Both Information Retrieval and Information Filtering deals with textual information. The IF basically requires specifying representation of information, documents and degree of resemblance amid them.

4.5 Demographic Based Filtering
In demographic filtering, the variety of demographic features of user utilized for making recommendations. The data of users having similar demographic features like age, gender, occupation, zip code etc. is considered for forecasting recommendations as illustrated in the subsequent Table 4. In Demographic Filtering, the preferences for an item by a particular user are recognized and too the demographic information like age, gender or location is used. It recommends items to users based on demographically other related users. Demographic systems are very simple to put into practice.

TABLE 3
DEMOGRAPHIC INFORMATION FROM DATASET MOVIELENSE

Userid	Age	Gender	Occupation	Zip code
1	24	M	Technician	85711
2	53	F	Other	94043
3	23	M	Writer	32067
4	24	M	Technician	43537
5	33	F	Other	15213

As it necessitates demographic features, it does not require any feedback from users and not endure cold-start dilemma. Acquire accuracy with demographic filtering is challenging.

4.6 Knowledge Based Filtering
In this approach, the Knowledge concerning the user and item is utilized for predicting recommendations. Here the conversational interactions used to set up the active user preference. Since in previous approaches, the profile models have been used for gaining preferences, but here the preferences are recorded through the interaction with the system. In this the interest of the user is determined based on their information requirement. It recommends those items that found very similar to users needs and preferences. Its quality of recommendation is depending on knowledge that has been captured.

5 COMPARISON OF VARIOUS RECOMMENDATION SYSTEM APPROACHES
As this paper be set to carry out comparison of a range of RS approaches, this segment will condense on same. The subsequent Table 5 illustrates a comparison between various approaches [1], [2], [3], [4], [6] like Content Based Filtering, Collaborative Filtering. Collaborative filtering is more successful than the Content Based Filtering [13], [28], [29], [30].

TABLE 5
COMPARISION OF VARIOUS MAJOR APPRAOCHS

Approach	Advantages	Shortcoming

Content Based Filtering	▪ No first rater dilemma
	▪ User liberty
	▪ Transparency
	▪ No cold start affection
	▪ New item does not require ratings to be recommended.
	▪ No emerge of Scarcity
	▪ Not as much of affected from crisis of CF like sparsity, cold-start dilemma
	▪ May Recommend with a distinctive feel
		▪ Restricted content analysis
		▪ Overspecialization
		▪ Can't astonish User i.e. Serendipity crisis
		▪ Could not demonstrate too differ or alike items
		▪ Unable to interpret complex relationships
		▪ Computationally costly
		▪ Can't make a distinction amid superiority of contents
		▪ Items must be machine recognizable
		▪ Faces crisis because of-
		  ▪ Synonymy
		  ▪ Homonyms

Collaborative Filtering	▪ Don't necessitate content information
	▪ Can astonish user
	▪ Domain of knowledge not requisite
	▪ Adaptive: Quality enhanced in excess of time
	▪ Implicit feedback is adequate
		▪ Requires rating data
		▪ May deprived recommendations as sparse data
		▪ Scalability issue
		▪ Cold-Start dilemma
		  ▪ Novelty of Item
		  ▪ Novelty of Users
		  ▪ Novelty of Community
		▪ Deprived Performance with incredibly huge item set and a small number of users
		▪ Quality depends on a large collection of data
		▪ First Rater crisis
		▪ Recommendation is community based instead unique taste
		▪ Gray Sheep
		▪ Shilling attacks

Hybrid Filtering	▪ Surmount the dilemma of CF or CBF ▪ Superior Prediction	▪ Intricate implementation ▪ Expensive ▪ Depend on External data

TABLE 6
COMPARISION OF CF AND CBF BASED ON VARIOUS PARAMETERS

Technique	Background	Similarity Measure	Input	Process
Collaborative Filtering	Rating from user for the item	1. Set of items 2. Set of users	Ratings from various other alike user's	Discover other alike users to active user and their ratings for item are employed
Content-Based Filtering	Genuine features of item that depict it	1.Actual contents 2. Text files	Active users Rating for Item	Based on ratings of active user the items are predicted
Hybrid Filtering	May use both profile and data	Depends on combined techniques	Ratings, profiles of active user with other similar user	The profiles, ratings of active and other alike user can be employed

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Information Filtering	Receives a user's query for IR	1. TF-IDF 2. PLSI 3. LSA	Text that represents the user query	Information filtered according to user interest
Demographic Filtering	Demographic feature of active user	Based on demographic attributes	Ratings of active user with demographic features	The stored data regarding user with similar demographic feature is used.
Knowledge Based Filtering	Conversational interaction with system for gaining knowledge	- -	Knowledge concerning users and items	Gained knowledge used for making predictions

TABLE 7
CF ALGORITHMS WITH ADVANTAGES AND DISADVANTAGES

CF Algorithm	Fundamental Techniques	Advantages	Disadvantages
Memory Based	▪ Neighborhood based 1. Pearson Correlation Coefficient (PCC) 2. Cosine similarity ▪ Top N recommendation 1. User based 2. Item based	▪ Easy implementation ▪ Adaptive ▪ The Contents can be added without difficulty	▪ Depend on ratings ▪ Poor performance because of sparse data ▪ New item and user predicament ▪ Issue with scalability
Model Based	▪ Clustering ▪ Latent Semantic Models ▪ Association Rule Mining ▪ Decision trees ▪ Naïve Bayes classifiers	▪ Help with issue like ▪ Scalability ▪ Sparsity ▪ Improve prediction performance	▪ Model building expensive ▪ May loose information in reduction techniques

TABLE 8
COMPARISION OF MODEL BASED TECHNIQUES

Technique	Pre-Computing Similarity	Description	Similarity	Advantages	Disadvantages	Clustering
Item Centric	Yes	Similar items to earlier rated	Based on Items Techniques ▪ Cosine ▪ PCC	▪ Better Predictions ▪ Static Similarity	--	Yes
User Centric	No	Alike users to Active user	Based on Users Technique ▪ Cosine	--	▪ Deprived Predictions ▪ Dynamic Similarity ▪ Data Sparsness	Yes

As CF and CBF are major approaches for RS, the above Table 6 differentiates them on various parameters like idea, input, output etc. The above Table 7 showing differtiation between CF approaches like model based and memory based. The major difference is lies between their underlying principles of processing. Also Table 8 depicting the model based approaches like item centric and user centric. Here as various approaches are exists, the user must have proper knowledge of problem domain.

6 EXPERIMENTS AND ANALYSIS

6.1 Data Set

In this paper, data set from Movielesne is considered for experiments and analysis. The data was collected through the MovieLens website (movielens.umn.edu) during the seven-month period from September 19th, 1997 through April 22nd, 1998. The dataset consists of 100,000 ratings (1-5) from 943 users on 1682 different movies. Every user has rated at least 20 movies. Simple demographic information of users like age, gender, occupation, zip is available. The users having below 20 ratings are eliminated as a data cleaning process.

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6.2 Experiments and Analysis

Here, the similarity between users and items measured with Pearson Correlation Coefficeient (PCC), Cosine Similarity Measure, Slope, Intercept and Coefficient of Regression computed which are major techniques to determine similarity. As shown in the Figure 9, the user id with number of ratings given. In the Figure 10 shown, the number of ratings with level 1 to 5. The rating level 2 gets the maximum value among all. The Figure 11 shows first ten users with their average rating. Each user has given rating averagely above value 3. A Figure 12 depicting the Movielense dataset characteristics in the form of a percentage. The Figure 13 shows the total number of users ie. 10000, items with value 1682 and ratings with value 943 from Movielense dataset. In Figure 14, the user id and average ratings are shown. The Figure 15 showing total percent of males (71.05 %) and female (28.94) users. As well Figure 16 showing user ids and their average rating.

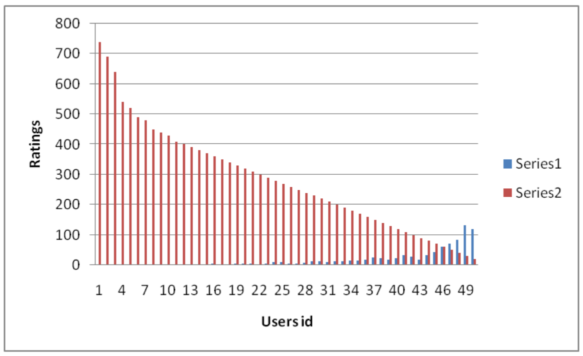

Fig.9. *The userid against number of Ratings*

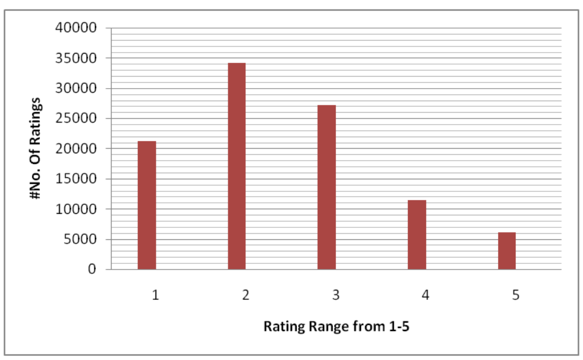

Fig.10. *Rating Range (1-5) and Number of Ratings*

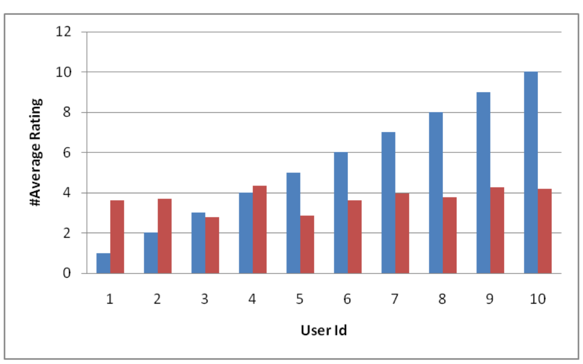

Fig.11. *First Ten Users with Average ratings*

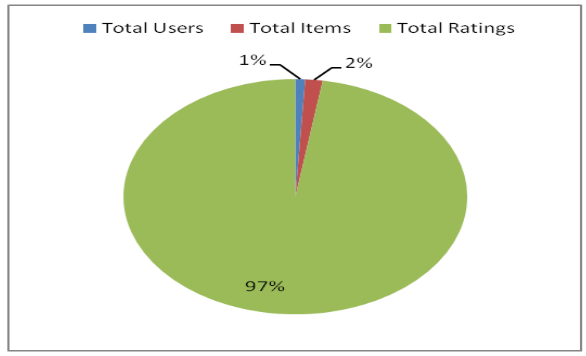

Fig.12. *Movielense Dataset Characteristics*

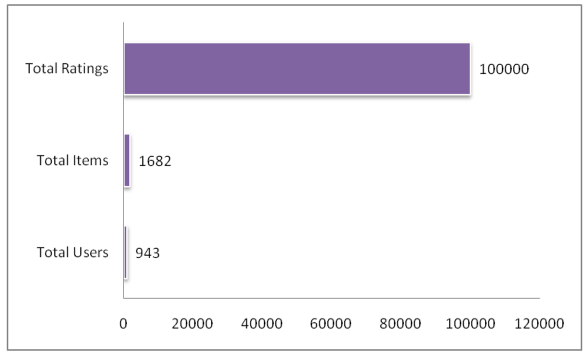

Fig.13. *Total Ratings, Items, Users from Movielense Dataset*

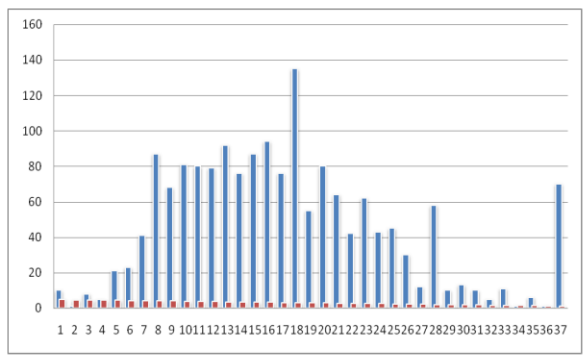

Fig.14. *User Id against Average Ratings*

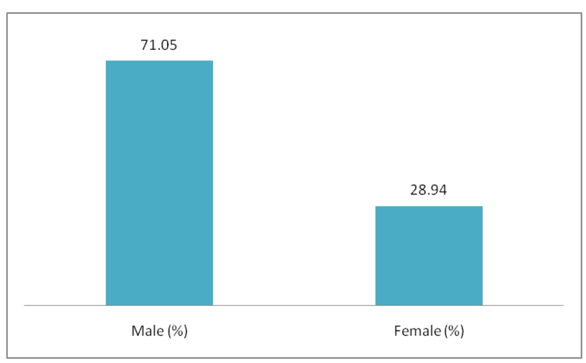

Fig.15. *Total percentage of Male and Female Gender*

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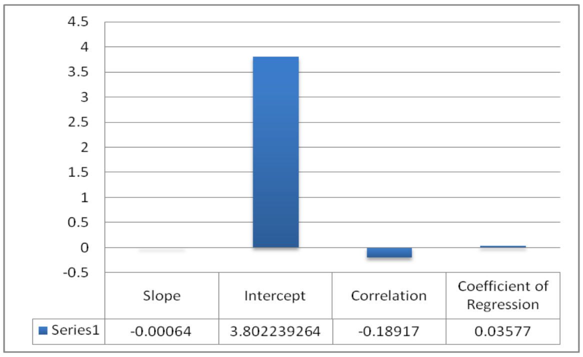

Fig.16. *Slope, Intercept, Correlation, Coefficient of Regression of Movielense Dataset*

As shown in the figure, the intercept, slope, correlation and coefficient of Regression is calculated. Here the PCC is used for measuring similarity between users instead of Cosine Similarity measure. During the experiment, the PCC value -0.1891 is obtained for 10,000 users. Also, other approaches like slope obtained with value -0.064, intercept with value 3.80 and coefficient of Regression with value 0.035 obtained.

6 Conclusion

This presented work represent attention to the foremost approaches of Recommendation system (RS) like Content Based Filtering, Collaborative Filtering, and Hybrid Filtering with other approaches like Demographic Filtering, Knowledge Based Filtering with their evaluation. Preliminary of paper focus on the basics and necessitate of Recommendation Systems and Personalization with their disputes. Subsequent to that, extensive description of assorted approaches obtainable. As there are numerous approaches, for prefering specific one the comparison assists. The comparison is mainly based on advantaged, shortcoming, input parameter, processing, output, etc. so to prefer precise approach the acquaintance of problem field is significant. Also a variety of experiments performed on Movielense dataset with 10,000 ratings and it granted to address scalability issue. It required extremely elevated computing in order to perform it in efficient time. As internet is facing information overload dilemma, the presented topic surely bears more glare of publicity in the future. With this, we anticipated to work on an assortment of models of Information retrieval and Information filtering.

Acknowledgment

I am enormously grateful to Prof. K.V. Bhosale, Prof. V. Kala, Prof. R.B. Mapari, Prof. B. Sonawane, Prof. S. Kankal, Prof. J. Dhage, Prof. B. Chaudhari, Prof. S. Bangar, Prof. Gurav of Computer Science and Technology Department, MIT, Aurangabad for their kind support, guidance and remarks. Also deeper sense of appreciation for Prof. J. Gorane, Prof. N. Anwat for their significant guidance and comments. Also thankful to Prof. M. M. Goswami, Prof. P. Ghotkar, Prof. N. S. Nikale, Prof. R.D. Kalambe, Prof.M.S. Arade, Prof. S. P. Dudhe, Prof. P. Pingate, Prof. V. Dhokane, Prof. R. Mojad, Prof. J. Borase, Prof. N. Mahajan, Prof. P. Agarwal, Prof. N. Parekh of Government Polytechnic, Nashik for their precious support and kind cooperation.

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