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Comparative Analysis of Various Collaborative Filtering Algorithms

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Abstract— To keep pace with increased applications of recommender systems, collaborative filtering algorithms have played a major role in providing better and accurate recommendations to the users. Their performance in providing the top results, that actually help the users, has also improved over the previous years. Collaborative Filtering (CF) algorithms are used in the social media sites as well as in the personalized recommender systems for the users and deal with problems like cold start, data sparsity, information overload, synonymy etc. Here, the recommendation is based on the preferences of user's friends or the user's own past preferences. This paper gives a detailed review of the algorithms used by various recommender system that are based on collaborative filtering. It investigates the algorithms based on their input parameters, their performance and various other factors of importance.

Keywords— Collaborative Filtering, Social Media, Folksonomy, Personalized Ranking, Data Sparsity, Tagging, User Similarity

I. INTRODUCTION

With the increased dissemination of online content as well as increase in the content and the consumers, there is a need for a system that would provide the accurate results to the users. Recommender systems (RS) [1] provide us with different tools and techniques that help the users in getting better results whether on social media sites or the e-commerce sites. Recommender systems are used almost in every sphere where suggestions are required during searching or browsing. One of the major techniques used in the recommender systems is Collaborative Filtering (CF) [2] which is based on user's ratings for the items. Collaborative Filtering is the process where the opinions of others matter . It takes the decisions based on the choices of the user's friends [3] or the ones which like the similar items as the user.

Model Based CF and Memory Based CF [4] are two basic types of collaborative filtering. Memory based CF [5] considers various similarities among the users and the items in the form of Pearson Similarity or the Cosine Similarity [6]. On the other hand, Model based CF considers various models of algorithms like Bayesian Networks or the dimensionality reduction of matrices using Principal Component Analysis (PCA) [7], etc. Memory based CF [8] and Model based CF are combined are combined together to form Hybrid CF.

Hybrid CF is used by various commercial sites for recommending purposes. There are several problems in the recommender systems that the authors deal with and these problems affect the accuracy of the recommender systems. Some of these problems are given as *cold start* problem [9], *data sparsity* problem [10], *synonymy* [3], etc. In cold start problem, the system is not able to draw inferences from the data as the data is insufficient while in data sparsity, datasets are very large containing sparse information. When similar items have different names or tags then synonymy problem occurs. To deal with these problems, CF uses a basic user-item matrix in which the users rate the items that they like or dislike and then similar users are considered for the further usage based on their ratings.

To overcome these problems several CF algorithms are given by the authors over the past years. Some of them are UICCF (User Interesting Based CF User-Item-User Activity Matrix) [10], SoMu (Social Multi-Attribute CF) [12], Hete-CF (Heterogeneous CF) [13], SaND (Social Network and Discovery in the enterprise) [14], Random Walk with Restarts (RWR) [15], Social Bayesian Personalized Ranking (SBPR) [16] and Semantic Collaborative Filtering (SCF) [17]. These algorithms use different parameters, datasets and work differently from each other.

The main aim of this paper is to discuss some of the prevalent algorithms given by the authors in the recent past and compare them based on various parameters. Paper also discusses the problems that still occur in these algorithms and their probable solutions. The rest of paper is as follows: Section I contains the introduction of this paper, Section II includes the research work done so far in this field, Section III gives a brief description of the algorithms in a tabular format, Section IV compares these algorithms based on some parameters like input parameters, performance and their future work. Section V concludes the review with the future research scope in the field of Collaborative Filtering.

II. RELATED WORK

A lot of research has been done in the field of collaborative filtering to address the problems of data sparsity, cold start problem etc. This section provides a detailed review of works carried out by different authors that have researched in this field. Every CF algorithm described, has its own set of parameters and follow a different approach compared to others in order to enhance the quality of the recommendation results. Some of the prevalent algorithms in the recent past have been discussed below.

$$sim(u,v)=\frac{\sum_{i\in I(u)\cap I(v)}\left(R_{(u,i)}-\overline{R_u}\right)\left(R_{(v,i)}-\overline{R_v}\right)}{\sqrt{\sum_{i\in I(u)\cap I(v)}\left(R_{(u,i)}-\overline{R_u}\right)^2}\sqrt{\sum_{i\in I(u)\cap I(v)}\left(R_{(v,i)}-\overline{R_v}\right)^2}} \quad (1)$$

where $R_{(u,i)}$, $R_{(v,i)}$ are the ratings of user u and v for the items $i \in I(u) \cap I(v)$, $\overline{R_u}$ and $\overline{R_v}$ are their respective average ratings.

$$\rho_{a,t} = \overline{R_a} + \frac{\sum_{i\in U_a} sim(a,i) * (R_{i,t} - \overline{R_t})}{\sum_{i\in U_a} sim(a,i)} \quad (2)$$

where U_a is the nearest neighbor of the target user a and $\rho_{a,t}$

$$dif_{(u,v)} = \frac{\sum_{i=1}^{C_1}|G_{u,i}-G_{v,i}|}{\sum_{i=1}^{C_1}|G_{u,i}+G_{v,i}|} \quad (3)$$

where C_1 is the number of item categories while $G_{u,i}$ and $G_{v,i}$ are the number of items in category i (i=1,2,3…,C_1) rated by user u and v.

$$sim'_{(u,v)} = \alpha sim(u,v) + (1-\alpha)(1-dif_{(u,v)}) \quad (4)$$

where α is the parameter to adjust the weight of user activity.

2. SoMu (Social Multi-Attribute CF) [12] calculates attraction similarity and interaction similarity parameters [19] based on users and items which improve the accuracy of the recommender systems. Attraction similarity [20] includes the likes and dislikes of the users given in eq. 5, the ones they are attracted to. Interaction similarity is given in includes the followers of the user and the ones he is following. Comprehensive similarity model is given by combining interaction similarity and attraction similarity that helps in determining the neighbors set and top-N item list recommended to the target user given in eq. 7.

$$W_1(u,v)=\gamma\frac{\sum_{i\in N(u)\cap N(v)}\frac{1}{\log(1+|M(i)|)}}{R(u,v)^2} \quad (5)$$

where $N(u)$ is the number of items be the set of items which are selected by u and $M(i)$ is the set of users who have rated item i. Let's r_{max} and r_{min} be the maximum and minimum ratings of the users and their normalized factor is given by γ.

$$W_2(u,v)=\frac{|out(u)-in(v)|}{\sqrt{|out(u)||in(v)|}} \quad (6)$$

where out(u) is the number of outlinks while in(u) is the number of the inlinks in the graph.

$$\rho_{vi}=\sum_{v\in N(i)\cap S(u,k)} W(u,v) * r_{vi} \quad (7)$$

where $S(u,k)$ is the set of nearest neighbors of user u that is decided by integrated similarity of u to other users and then the items are ranked according to the scores.

3. Hete-CF (Heterogeneous CF) [13] algorithm has a network structured based model that works on Heterogeneous Social Networks (HSN) [20], Heterogeneous Information Networks (HINs) [21], Event Based Social Networks(EBSN) [22], Location Based Social Networks (LBSNs) [23]. Hete-CF provides the information for HIN (Heterogeneous Information Networks) that models the relations between users in first term, items in second term and between users and items relations in 3rd term It works on social media information as well as social networks.

4. SaND (Social Network and Discovery in the enterprise) [14] is an algorithm that works on people and tag relations. It mainly considers five recommender systems which are given as People Based Recommender (PBR), tag Based Recommender (TBR) , combing these two People and Tag Based Recommender (PTBR) as or-PTBR, and-PTBR and Popularity Base Recommender (POPBR) . Users are not required to give any explicit inputs to the system. SaND can also be used as a personalized recommender for the users. Also, it does not work on the content or the popularity of the tags or relations. The algorithm of Recommender Score (RS) (8) is given. Here, α is the decay factor and β is the parameter control weights between users and tags.

$$RS(u,i)=e^{-\alpha d(i)}.\left[\beta\sum_{v\in N(u)} w(u,v).w(v,i) + (1-\beta)\sum_{t\in T(u)} w(u,t).w(t,i)\right] \quad (8)$$

where d(i) is the number of days since the creation date of i, w(u,v) and w(u,t) are relationship strengths of user u and v with item t and w(u,i) and w(t,i) are the relationship strengths between a and t with item i.

5. RWR (Random Walk with Restarts) [15] along with collaborative filtering presents a very unified approach. It uses the additional relationships for developing recommendation systems by considering social annotations and the friendships established among users, items and tags. It evaluates the datasets in the form of user and item graphs [24] and show the bonds of friendships among users by social tagging. A random walk [25] is done on a graph of the dataset and it shows that the friendship and the social tagging can improve performance of an item's recommendations. The formula for the relational matrix of users and items (9) is given. S is the transition probability and q is the column vector of zeroes.

$$p^{(t+1)} = (1-a)Sp^{(t)} + aq \quad (9)$$

6. SBPR (Social Bayesian Personalized Ranking) [16] leverages the social connections of the users in order to build better models of user's preferences. It follows the idea that users tend to assign the higher ranks to the items that their

friends prefer. It works on one class collaborative filtering which has pointwise methods and pairwise methods. Here, the probability that the user selects an item increases monotonically as a function of no. of friends that have selected the item.

7. SCF (Semantic Collaborative Filtering) [17] consists of SSR (Semantic Social Ranking) and Collaborative Filtering (CF). It solves the problem of data sparseness and the cold start problems in recommender systems. This approach determines semantically similar users by social tagging and discovers semantically relevant items for each other. It captures the semantics of user-generated tags and then recommend them in trustworthy items that are semantically relevant to a user's needs. Main criteria is based on folksonomy [26]. The tags which has used u has used are represented as the union of USLs (10). The semantic user similarity is given measure (11) while the Semantic Social Ranking score is being generated in (12).

$$USL_u^* = \bigcup_{i=0}^{n} USL_u^i = \bigcup_{l=0}^{6} USL_u^i(l)$$

where $USL_u^* = \bigcup_{l(c)=l, c\in v, v\in N_u^*} c_n$ (10)

semUSim(u,v)=ω$\sum_{l=0}^{6} simUSL^l(u,v)$ (11)

where ω is the normalizing factor

SSR(u,h)=$\sum_{v\in SSN_k} \frac{|USL_u^* \cap USL_v^h|}{|USL_v^h|} \times semUSim(u,v)$ (12)

where SSN_k is a set of k nearest neighbors of the user u and USL_v^h is the union of USLs connected to tags that user v has assigned item h.

III. COMPARISON OF THE ALGORITHMS

A comparative analysis of various algorithms is done here. Table 1 provides with the basic knowledge of the algorithms, their basic criteria, issues addressed by them, their advantages as well as their disadvantages.

Table 1. Comparison of algorithms on basic principles

Algorithm	**Full Form**	**Basic Criteria**	**Problems Addressed**	**Advantages**	**Disadvantages**
UICCF [10]	User Interesting Clustering Collaborative Filtering Algorithm	Improves the user-item rating matrix by using k means clustering of the users	Data sparseness problem	User similarity calculation method is improved as compared to the traditional method.	Did not consider the cold start problem and user-interest is shifted with time.
SoMu [12]	Social Multi- Attribute Collaborative Filtering Algorithm	Makes comprehensive similarity model to determine neighbor set and determine top N recommendations	Data Sparsity Problem	Improves the accuracy of the RS.	Works only on users and user related items and tags.
Hete-CF [13]	Heterogeneous Collaborative Filtering Algorithm	Uses all the relations between users and items i.e. user-user, item-item and user-item in a network structured model.	Increasing Heterogeneous Information	Can be used for recommending offline events in Event based Social Networks(EBSNs) [21], Location Based Networks (LBSNs) [22], Heterogeneous Information Networks (HINs), [20] etc.	Did not consider big data problems and information overload.
SaND [14]	Social Network And Discovery Algorithm	Combines outputs of various RS like Popularity based RS, Tag based RS, People based RS and combining the two People & Tag based RS; and these relations are shown in the graphs.	Cold Start Problem	Users are not required to give any explicit information about themselves to the system.	Did not work on the content or the popularity of people and tags.
CF+RWR [15] [25]	Collaborative Filtering Algorithm with Random Walks with Restarts	Evaluate RWR on the dataset to capture the bonds of friendships among people, tags and items.	Data Sparsity and Information Overload Problem	Additional relations among people, tags and items are used to enhance the results.	Online response time is not accepted in the real life situations.
SBPR [16]	Social Bayesian Personalized Ranking	One Class CF is used that leverages the social connections and build better models of user's preferences.	Warm Start and Cold Start Problem	Preferences of the user's friends is considered which enhances the overall results.	Social feedback of user all friends is required which is time consuming.
SCF [16]	Semantic Collaborative Filtering	Determines semantically similar users by social tagging and discovers relevant items for the users.	Data Sparseness and Cold Start Problems	Ambiguity, Synonymy issues are resolved of the traditional CF.	Main focus is on the user similarity and not on the items.

IV. COMPARISON OF SOME SPECIFIC PARAMETERS

Table 2 gives us the comparison of these algorithms on some specific parameters like source datasets, the input parameters, technique used, performance metric considered as well as their future works.

Table 2. Survey on Specific Parameters

Algorithm	Datasets	Input Parameters	Technique Used	Performance Metric Used	Future Focus
UICCF	MovieLens [27]	User-item rating matrix	K-means clustering [17]	Mean Absolute Error (MAE)	Select neighbors by structural characteristics of the social networks.
SoMu	Douban [28], MovieLens	Attraction Similarity and Interaction Similarity	Friend-user-item comprehensive similarity model.	Precision, Recall, Popularity and Coverage.	Correlation among RS and Social network can be studied.
Hete-CF	DBLP [29]	User-user, item-item and item-user relations.	Stochastic Gradient Method (SGM)is applied on users and items.	MAE and RMSE (Root Mean Square Error)	Can be implemented on the real world problems and explore big data also.
SaND	Lotus Connections (LC) [30]	People and tag relations in the form of graphs.	Direct and indirect tags are considered in RS.	Accuracy and Expectedness	Execution of more. sophisticated algorithms and optimization of parameters.
CF+RWR	Last.fm [31]	Friendship bonds of users and tags in graphical format.	Random Walk with Restarts (RWR) [24]	Precision and Recall	Implement the algorithms on large scale companies like Amazon, Netflix, etc.
SBPR	Ciao, Delicious [32], Lthing, Epinions [33]	Social feedback of user's friends as positive and negative	Bayesian Personalized Ranking (BPR)	Recall, AUC (Area Under Curve) and NDCG (Normalized Discounted Cumulative Gain)	Adding rating information, user's preference into the model and an active learning framework
SCF	Bibsonomy [34]	Semantic oriented tags and semantically relevant resources are considered	Folksonomy [25]	Precision and Recall.	Use semantic similarity on item based approach on large datasets.

V. CONCLUSION

This paper discusses various collaborative filtering algorithms such as UICCF, SOMU, HETE-CF, SAND etc and compares these algorithms on parameters like input parameters, main technique used, performance metric used etc. The main technique used by most of these algorithms is to rank the user-item matrix for the recommendations. Several new algorithms are coming up to help improve the results of the recommender systems. The disadvantages of these algorithms reveal the scope where the work needs to be done further. Various parameters can be combined in order to get better results. These parameters can be changed also for a particular dataset in order to get better results. One can see that the user's likes, dislikes as well as their friends preferences play an important role in recommending the items to these users. Hence, in the future work, the authors of this paper will try to work on some of the challenges like cold start problem and data sparseness problem in order to generate a better approach for the recommendations.

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