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A Hybrid Cluster Based Collaborative Filtering with Tensor Factorization Approach for Recommendation System in Big Data

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ABSTRACT: Nowadays, Collaborative Filtering (CF) is the most accepted recommendation technique, however many CF systems suffer from issues like data rating availableness and space dimensionality for neighborhood choice. Therefore, using clustering techniques is a way to reduce time needed for processing these correlations. In this work, a hybrid Agglomerative Hierarchical Cluster based CF approach with Tensor factorization (AHC-CF-TF) is projected to solve these issues, which exploits context variables to factorize users, items and domains into latent feature vectors. This approach hybrids clustering and a new tensor factoring based technique to reinforce the effectiveness of CF. Further, operational on the tensor composed of the overall and aspect ratings and this approach is in a position to capture the intrinsic relationships between users, items, and aspects, and provide correct predictions on unknown ratings. The experimental results on a big dataset show that the proposal improves the prediction accuracy when compared to baseline strategies.

KEYWORDS: Collaborative Filtering, Recommendation System, Tensor Factorization, Agglomerative Hierarchical Clustering, Big data application

I. INTRODUCTION

Recommendation systems found their application within the field of e-commerce and web wherever things recommend to a group of user on the idea of their demand based on their area of interest. A recommendation system is an info filtering system that designed a model from the characteristic of an item consistent with the rating or prediction, given by a user to an item. Recommendation system has a very important part in social media sites (such as Amazon, IMDB, movie Lens), social sites giants like Amazon are greatly gained from the potential of their recommenders in accurately delivering the right item to the right user [1]. Collaborative filtering (CF) is a very important and well-liked technology for recommender system. CF strategies are classified into user based mostly CF and item-based CF. the fundamental plan of user-based CF approach is to find out a collection of users who have similar favour patterns or interest to a given user and also the basic plan of item-based CF approach is to find out a collection of items having highest correlation with the given item.

In reality, people might prefer to cluster items into classes, and for every class there is a corresponding cluster of individuals who like things within the class [2]. Cognitive psychologists realize that objects (items) have totally different normalcy degrees in classes in reality [3-5]. However these collaborative filtering strategies have facing some issues like data sparseness, measurability and Cold-start etc. The challenge of those two CF as following [6, 7]: Sparsity: when users are terribly active, there are rating of the overall number of items offered in an exceedingly user item ratings database. Because the main of the collaborative filtering algorithms are supported similarity measures computed over the co-rated set of items and on the other hand massive levels of sparseness will cause less accuracy. Scalability: collaborative filtering algorithms appear to be efficient in filtering in items that are fascinating to users. However, they need computations that are very costly and grow non-linearly with the amount of users and items in an exceedingly database. Cold-start: an item cannot be suggested unless it has been rated by variety of users.

This drawback applies to new items and is especially detrimental to users with eclectic interest. Likewise, a new user needs to rate a comfortable range of items before the CF algorithm be ready to provide accurate recommendations. To solve these issues, in this work, a hybrid recommendation approach is planned that is the integration of collaborative Filtering, clustering and tensor factorization. Users are clustered based on users' ratings on items, and every users cluster contains a cluster center. The nearest neighbors of target user are often found and sleek the prediction wherever necessary based on the similarity between target user and cluster centers. Then, the projected approach utilizes collaborative filtering to provide the recommendations. Tensor resolution (TF) are often accustomed add any range of variables to a recommender system. Especially, it may be wont to hybridize content and CF in an approach like the approach proposed in [8].

In addition, this work concentrate on the employment of TF for adding contextual information. This approach is additionally named as contextual recommendation via clustering based CF-TF Recommendation as a result of it may be accustomed with efficiency bridge hidden "worlds" separated by totally different contexts and so collapse parallel dimensions into a coherent model. The recommendation joining clustering and collaborative filtering with TF is a lot of scalable and a lot of accurate than the normal one. The structure of this paper is organized as follows: Section 2 can review the literature of collaborative filtering recommender systems, describe the ratings sparsity issue and additionally justify the motivation behind this research. Section 3 explains the planned recommender system design. Section 4 describes the experimental results and discussion. Section 5 are going to be the conclusion and future work.

II. RELATED WORK

Existing recommendation system recommends books to the user supported the book name and therefore the ratings given by that user to the book or supported the quantity of views for that book. In [9], projected a two-stage algorithm that uses location of the users to predict the interest. K-means algorithm is employed to cluster the users supported the profile that is collected throughout the user check in. however predicting the conception of a book solely with the book name reduces the accuracy of the system. In [10] uses the conception of metaphysics to predict the interest of the user and the system was self-adaptive and foretold the longer term browsing pattern of the user.

Ozguret al [11] established a recommendation system exploitation association rules. In this, Apriori algorithm is employed to get the principles for recommendation with high success rate. The basket ratio that is that the ratio between the number of items viewed and during this technique the cart is enlarged to the number of items. In [12] advanced a recommendation system termed as PROTUS (PRogrammingTUtoring System), which suggested courses to the students. Their age and domain of study are considered while the course suggestion process however during this system semantic internet technology ideas are used. Navigation patterns are obtained from the past history and from that pattern, future recommendations are created effectively.

Konstantin et al [13] produced a study on the Hadoop distributed file system and that is expressed by distributing the storage and computation across the machines of a cluster, the process time will be reduced for analysing big data when compared to single node process. In [14] made an analysis on the kinds of recommendation algorithms that are existing from the earlier times. Item-based recommendation could be a technique during which two users who have rated an item are separated. Therefore the similarity index is computed among them. Then similar things are suggested to them when the similarity index is bigger than the threshold.

A model that uses collaborative filtering algorithm for supervised learning was developed and this model classifies even the new unseen item. In step with this model, there are solely two categories C1: like C2: dislike. Content-Boosted collaborative Filtering utilized content primarily to fill within the missing ratings from the initial user-item matrix. Then it employs classic collaborative Filtering techniques to achieve a final prediction. In [15] projected a recommendation system that considers a plan known as topic diversification. The list of prime n recommendation are balanced because the users' extended interest also will be taken into consideration in step with this idea. So the user will not be bored upon the similar reasonably recommendations usually created with an effective manner.

The conception of user-based collaborative filtering and Item-based collaborative filtering are combined and therefore the recommendations are created in an efficient manner. In [16] established a recommendation system for

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music by learning the content similarity. Consequently, it was used content primarily based similarity technique at first then collaborative similarity technique is obligatory on the results. The cold start drawback and the overhead of query-to-answer technique was avoided effectively. In [17] focused their study on implicit-multicriteria combined recommendation approach for music recommendation whereby they experiment is done with each user mostly and item based collaborative filtering. An alternative CF approaches [18-20] to suggest movies to users have conjointly been projected within the movie domain.

The neighborhood approach and latent issue models are delineated in [20] because the two main disciplines of CF. Model-based approaches appear to work quite well on the movie knowledge, however a majority of the made approaches on the movie knowledge are ensemble models that mix quite a few approaches (both memory-based and model-based) in quite novel ways in which. In [21] provided a comparative study on collaborative filtering recommendation algorithms for e-commerce. Recommender systems are evaluated for the standard of the recommendations provided by them in many various ways in which and by exploitation many various forms of metrics that represent three main classes: predictive accuracy metrics, classification accuracy metrics, and rank accuracy metrics. A survey of the several analysis methods for recommender systems was found in [22]. In [23] projected a knowledge-driven framework for systematic analysis of personalization strategies.

Although collaborative filtering has been terribly made in each analysis and follow, it cannot recommend new things to users with none history within the system and completely denies any info that may be extracted from contents of things, like cast list, movie genre and abstract of movie etc. Additionally the standard of recommendation is totally supported the user rating, rather than the data content. For these reasons, an efficient recommendation system is required further with high success rate.

III. Proposed Hybrid Recommendation System

In this section, a new hybrid recommendation system framework is explained that is initially based on cluster of users based on similarity matrix of users and it allows dimensionality reduction. Next, it uses the tensor factorization to refine the clustering results and produce recommendations to the end user. The architecture diagram for proposed hybrid recommendation system is illustrated in Fig.1.

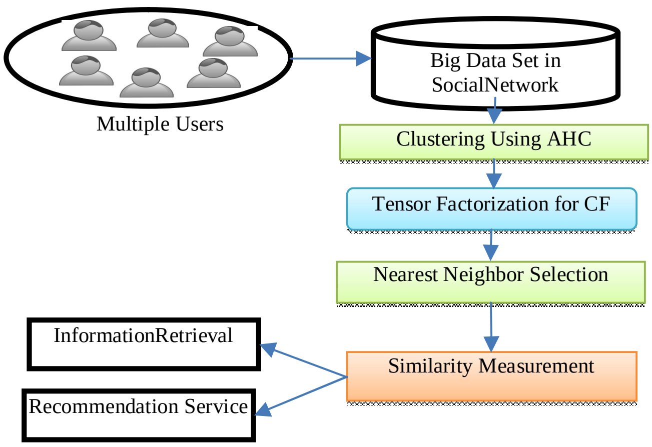

Fig.1. Proposed Hybrid Recommendation System

In that figure, after the collection of input dataset the users are grouped into some clusters using an AHC algorithm before applying CF technique. Then the rating similarities between users within the same clusters are determined where the costs of online computation time is less although the number of services in a clusters is less than that of in the whole system. Furthermore, prediction based on the ratings of the services in the same cluster will be more accurate than based on the ratings of all similar or dissimilar services in all clusters as the ratings of services in the same cluster

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are more relevant with each other with the ones in other clusters. Then the clustering results are refined by tensor factorization to produce the recommendation.

A. *User Item Rating Content*

The method of the traditional collaborative filtering recommendation algorithm involves the determination of the target user's rating for the target item that the user has not given the rating, depends on the users' ratings on observed items. As well as the user-item rating database is in the main where every user is characterised by item-rating pairs, and can be shortened in a user-item table, which contains the ratings R_{ij} that have been delivered by the ith user for the jth item, which is described the table 1 as following [24, 25].

Table 1.User-Item Ratings Table

Item / User	Item 1	Item 2	…	Item n
User 1	R11	R12	…	R1n
User 2	R21	R22	…	R2n
…	…	…	…	…
User m	Rm1	Rm2	…	Rmn

Where R_{ij} represents the score of item j rated by an active user i. If user i has not rated item j, then R_{ij} = 0. The symbol m represents the total number of users, and n represents the total number of items.

B. *AHC Clustering Approach*

Agglomerative hierarchical clustering is one type of hierarchical clustering which is represented as a bottom-up clustering method. It begins by allowing every object form its own cluster and iteratively groups cluster into larger clusters, till all the objects are in a one single cluster or otherwise assured termination condition is met. Then the single cluster is assumed as the hierarchies root to form further clusters. It determines the two clusters which are neighbouring to each other for the merging step and it combines the two to form one cluster. In this section, clustering based collaborative filtering approach utilizes the agglomerative hierarchical clustering algorithm for clustering process. Assume there are number of users and each user is initialized to be a cluster of its own. By the side of each reduction step, the two most similar clusters are merged until the maximum similarity happens. The AHC clustering algorithm is given in Table.2.

Table 2.Agglomerative Hierarchical Clustering Algorithm

Procedure call agg_hierarchical_clustering ()
Input: User-Item Rating Matrix
Output: User Clusters
begin
1. Consider each user vector $u_1, u_2, .. u_k$ where k is the number of distinct items rated by all users
2. Set threshold_cutoff value
3. Consider the first user and put in cluster1 C_1
4. Repeat the steps 4-8 ∀remaining users
5. Find the similarity of the $user_i$ with all the clusters formed
6. Put the $user_i$ in the cluster with more similarity
7. If the $user_i$ is not in the threshold value of any cluster
8. Create a new cluster
End

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C. *Tensor Factorization for CF*

In this section, the TF is proposed to refine the above AHC clustering results and produce the recommendations. The main objective is to combine an entity composed with multiple contexts. For Collaborative Filtering approaches, the standard matrix decomposition models are popular that can be generalized to higher-order relations in terms of tensor factorizations (TF) [26]. The TF approach generalizes well to an arbitrary amount of context variables during which adding relatively less computational overhead. Given the factors U, M, C, S which constitute the proposed model, there is a choice of ways to ensure that the model complexity does not grow without bound. An easy way is to enhance a regularization term based on the l_2 norm of these factors [27]. In the case of a matrix, this norm is also called as the Frobenius norm which is expressed in eq.(1)as follows.

$$\Omega[U,M,C] \coloneqq \frac{1}{2}[\lambda_U \|U\|^2_{Frob} + \lambda_M \|M\|^2_{Frob} + \lambda_C \|C\|^2_{Frob}] \qquad \text{eq. (1)}$$

Likewise, the complexity of the central tensor S can be reduced by imposing a l_2 norm penalty which is expressed in eq. (2) as follows:

$$\Omega[s] \coloneqq \frac{1}{2}[\lambda_S \|S\|^2_{Frob}] \qquad \text{eq. (2)}$$

Generally, this techniques is try to minimize a regularized risk functional by integrating $L(F,Y)$and $\Omega[U,M,C]$. Finally, the objective function for the minimization problem is expressed in eq. (3) as follows [28]:

$$R[U,M,C,S] \coloneqq L(F,Y) + \Omega[U,M,C] + \Omega[s] \qquad \text{eq. (3)}$$

There are various approaches can be utilized to minimize this objective function. The subspace descent is a recent approach in Matrix Factorization (MF) methods and could be utilized in the tensor setting. In subspace descent one optimizes repeatedly over individual components of the model whereas observance the remaining components are fixed, for example, optimize over the U matrix whereas keeping the remaining matrices and tensor fixed, then over M etc.

This method has an advantages of quick convergence, however, it requires the optimization procedure to be run in a batch setting. It becomes progressively infeasible to resolve factorization problems when the input dataset sizes increases through batch optimization. As an alternative, a simple online algorithm is performs based on Stochastic Gradient Descent (SGD) in the factors U_{i*}, M_{j*}, C_{k*} and S for a given rating Y_{ijk} concurrently. So as to calculate the updates for the SGD algorithm, there is a need to calculate the gradients of the loss function and eventually the objective function in regard to the individual components of the model and it is expressed in eq. (4) as follows:

$$\partial_{U_{i*}} L(F_{ijk}, Y_{ijk}) = \partial_{F_{ijk}} L(F_{ijk}, Y_{ijk}) S \times_M M_{j*} \times_C C_{k*}$$
$$\partial_{M_{j*}} L(F_{ijk}, Y_{ijk}) = \partial_{F_{ijk}} L(F_{ijk}, Y_{ijk}) S \times_U U_{i*} \times_C C_{k*} \qquad \text{eq. (4)}$$

$$\partial_{C_{k*}} L(F_{ijk}, Y_{ijk}) = \partial_{F_{ijk}} L(F_{ijk}, Y_{ijk}) S \times_U U_{i*} \times_M$$
$$\partial_S L(F_{ijk}, Y_{ijk}) = \partial_{F_{ijk}} L(F_{ijk}, Y_{ijk}) U_{i*} \otimes M_{j*} \otimes C_{k*}$$

The TF method is easy to execute ever since it utilizes only one row of U, M, and C at that time. Additionally, it is quite easy to parallelize by doing several updates individually delivered by the user that the (i,j,k) sets are all non-overlapping. In this know that the algorithm measures linearly to the number of ratings K and the dimensionality of the factors d_U , d_M, d_C . As a final point, it simply simplifies to the case of N context dimensions via accumulating one additional update per context variable in TF.

D. *Selecting Nearest Neighbors*

From the above section, the target item nearest clustering centers and tensor are selected and the similarity between the target item and items in the selected clustering centers has been calculated. In the next step, the Top K similar items are selected based on the cosine similarity measure which is calculated based on the angle between two vectors of

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ratings as the target item t and the remaining item r in the database. The cosine similarity formula is given in eq. (5) as follows:

$$sim_{Neighbor}(t,r) = \frac{\sum_{i=1}^{m} R_{u_it}R_{u_ir}}{\sqrt{\sum_{i=1}^{m} R_{u_it}^2 \times R_{u_it}^2}} \qquad \text{eq. (5)}$$

In this above equation, R_{u_it} is denoted as the rating of the target item t by user u_i, R_{u_ir} is described as the rating of the remaining item r by user u_i, and m is the number of all rating users to the item t and item$r$.

E. *Producing Recommendations*

From the membership of the item value, the weighted average of neighbour's ratings has been determined, where weight assigned by their similarity to the target item. Then the rating of the target user u to the target item t is given in eq. (6) as follows:

$$Recommendation_{u,t} = \frac{\sum_{i=1}^{c} R_{u_i} \times sim(t,i)}{\sum_{i=1}^{c} sim(t,i)} \qquad \text{eq. (6)}$$

In the above equation, R_{ui} is denoted as the rating of the target user u to the neighbour item,$sim(t,i)$ is defined as the similarity of the target item t and the neighbour it user i for all the co-rated items, and m is the number of all rating users to the item t and item$r$.

IV. Experimental Results And Discussion

In this section, to evaluate the proposed method three random subsamples of Netflix Prize dataset has been used. Specially, the first subsample was provided by selecting 100 users from the set of all Netflix users ranked from 2000 to 2100 with their individual rating. The second and third subsample of Netflix dataset were produced in same way, but the 100 users are selected from the group of users ranked from 10,000 to 30,000 with their individual rating. At last, every dataset was randomly divided into ten subsets for the 10-fold cross validation. Further, the existing cluster based CF, cluster based MF-CF and proposed cluster based TF-CF is compared with some metrics such as accuracy, MAE, Precision and computation time.

A. *Accuracy Comparison*

The Fig.2 shows the accuracy comparison result of existing cluster based CF, cluster based MF-CF and proposed cluster based TF-CF algorithm. From the Fig.5, it is obvious that the proposed system has high accuracy rate of 98.5% which is higher than the existing algorithms. The reason is that the proposed system has less execution time than the existing algorithms.

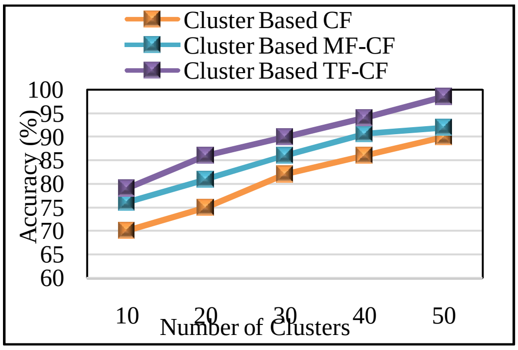

Fig.2.Accuarcy Comparison Result

B. *Mean Absolute Error Comparison*

To evaluate the accuracy of this algorithm, Mean Absolute

Error (MAE), which is a measure of the deviation of recommendations from their true user-specified ratings, is used in this work. MAE is computed in eq. (7) as follow:

$$MAE = \frac{1}{n}\sum_{u,i}\left|p_{u,i} - r_{u,i}\right| \qquad \text{eq. (7)}$$

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In this formula, n is the number of rating-prediction pairs, $r_{u,i}$is the rating that an active user u gives to a recovery service i,$p_{u,i}$ denotes the predicted rating of i for u.

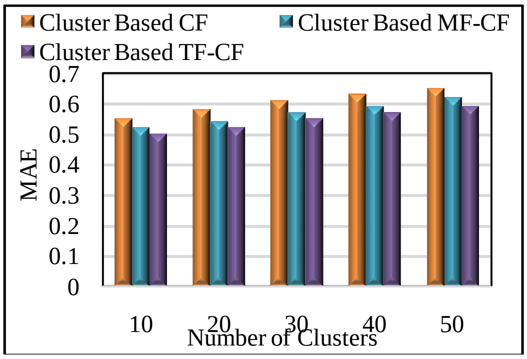

Fig.3. MAE Comparative Result

The Fig.3 shows the precision comparison result of existing cluster based CF, cluster based MF-CF and proposed cluster based TF-CF algorithm. From the Fig.3, it is well known that the proposed system works better than existing system with less MAE. The existing system has the MAE which is higher than the proposed algorithm. The reason is that the proposed system has high coverage rate than the existing algorithms.

C. *Precision Comparison*

The Fig.4 shows the precision comparison result of existingcluster based CF, cluster based MF-CF and proposed cluster based TF-CF algorithm. From the Fig.3, it is well known that the proposed system works better than existing system with the high precision result. The existing system has precision result which is less than the proposed algorithm. The reason is that the proposed system has less MAE than the existing algorithms.

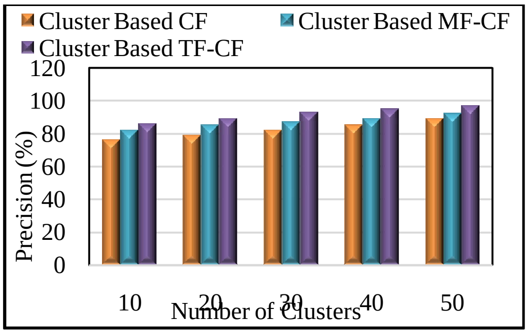

Fig.4. Precision Comparative Result

D. *Computation Time Comparison*

The Fig.5 shows the precision comparison result of existing cluster based CF, cluster based MF-CF and proposed cluster based TF-CF algorithm. From the Fig.3, it is well known that the proposed system works better than existing system with the less computation time. The existing system has effective computation time which is higher than the proposed algorithm. The reason is that the proposed system has high accuracy rate than the existing algorithm.

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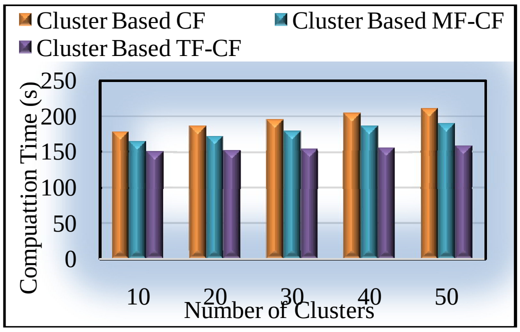

Fig.5. Computation Time Comparative Result

V. CONCLUSION

Finally, Hybrid Clustering based TF-CF is proposed in this work to produce recommendation to the user on Big Data. Initially, users are clustered into some clusters via an AHC algorithm which is done before applying CF technique. After that, the rating similarities between users and the rating of items within the same cluster are computed and finally the recommendation is provide by using the TF-CF technique. Since the number of users in a cluster is much less than that of in the whole system, the proposed TF-CF based Clustering costs less online computation time with high success rate. Like this, similar users can be clustered together using AHC that improves the coverage of recommendations. The experimental results show that the proposed Hybrid cluster-based TF-CF techniques has the ability of allowing CF-based algorithms to scale to Big data sets and at the same time yield high-quality recommendations with high accuracy rate.In future, the swarm based clustering method can be applied with bloom filter that will improve the accuracy of the recommendation result and also the relevance feedback based recommendation system can be developed to improve the quality of the recommendations.

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BIOGRAPHY

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