A Review on Product Recommendation Engine Using K Means Clustering & Collaborative Filtering

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Abstract- *In this paper, age of information load, it becomes a herculean task for user to get the relevant things from vast number of information. This huge number of data demand specially designed Recommender system that can plays an important role in suggesting relevant information preferred by the users. From this point, this paper presents a modest approach to enhance prediction in Movie Lens dataset with high scalability by applying user-based collaborative filtering methods on clustered data. The proposal consists of three consequence phases: preprocessing phase, similarity phase, prediction phase. The experimental results obtained by conducting K-means clustering and correlation coefficient similarity measures against Movie Lens datasets lead to an increase in the scalability of recommender system.*

Keywords: *K-means, Product recommendation, clustering, Collaborative filtering.*

I. INTRODUCTION

Internet has turn out to be an important part of social life, there is an exponential growth in the amount of electronic information and on-line facilities available, this has led to the problem of overloading extensive information - where required information are difficult to be retrieved by people from the huge set of choices. Today the problem is how to choose the right item out of huge amount of information and not about how to acquire accurate facts to make a decision. Many applications have been revealed and recommender system is one of them to fulfil the demand of intelligent data analysis .This paper is concentrated on clustering user-based collaborative filtering against MovieLens user-movie rating dataset. The paper is prepared as follows: the related works are presented in section 2, on section 3 a passing background in recommendation process and memory-based collaborative filtering algorithm and its prediction approach is described, in section 4 clustering concepts are presented, the proposed model is presented in section 5, the experimental results in section 6 and to end with the conclusion.

Recommender systems have become quite common and are used in various fields .With the development of Internet technologies, the flow of data from all areas leads to the problem of information overload. To solve this problem, many major websites and e-commerce sites use various convenient and effective recommendation systems to improve their quality of service and to attract and retain loyal users. For example, Amazon book recommendations, marketplace apps, YouTube videos, and Internet search results.

Recommender Systems With the increase in the use of e-commerce sites, it has become very easy for the users to find the items of their interest without wasting a lot of time. Websites like Amazon and Ebay examples for Recommender systems which provide recommendations to the users based on their search history and purchase history. Recommender systems provide recommendations of almost all the items ranging from books to movies to music. FaceBook and Twitter are also recommender sites which provide recommendations for friends. NetFlix.com is very famous as a movie recommender website. Yahoo News and Google news are very famous for news. When a user tries to find an item using search engines, for example, Google Search engine and Yahoo Search engine, the user needs to type the exact name of the item. The data in the internet is huge which makes it very difficult for the user to find the items of his interest. Hence, there is a need for a system which learns the likes and dislikes of the user and generates recommendations based on his interest. Many algorithms need to be used while designing a recommender system. Recommender systems employ Information Filtering technique that focuses on providing the recommendations of the items to the users that are likely to be of the users interest. A recommender system is defined as: if U is the set of users and I is the set of all possible items that can be recommended, then there exists a function from U*I to R where R is a totally ordered set of nonnegative integers or real numbers within a certain range.

Recommender System

Recommender system is an Information Retrieval application that assists customers discovering interested items from a vast collection of things.it recommends everything from movies, news, books, songs and Web sites to more complicated suggestions for electronic gadgets, matrimonial matches, and financial services. Recommendation algorithms generally categorize into :

1. Collaborative filtering.
2. Content-based filtering.
3. Demographics-based filtering.
4. Hybrid approaches.

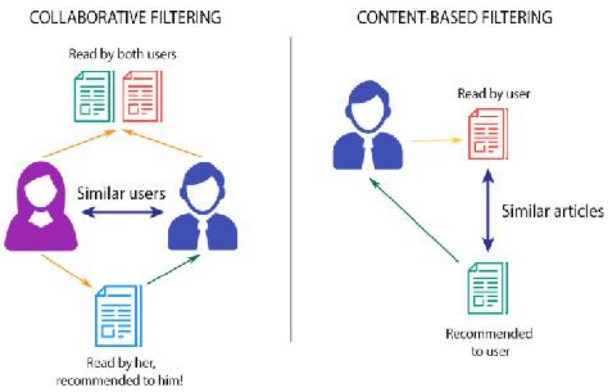

Fig.1.1 Recommendation techniques

Collaborative Filtering

Collaborative filtering is the most widely used approach in terms of recommendations for providing services to users. The essence of this approach is to improve the ability of active users to find accurate and reliable neighbors. However, the collected data are extremely sparse in the custom item ranking matrix, and many of the existing similarity measurement methods used in collaborative filtering are not very efficient, which results in poor performance. Collaborative filtering is a successful techniques in recommender systems, which recommends items to a user by analyzing the user's data; these data can be obtained by tracking browsing history, purchase records, rating records, etc. Collaborative filtering (CF) does not use the content properties of items and can only search for similar users based on how users rated items. In a typical CF system, a user-item matrix is created in which a user's preference for an item is represented as a rating. CF estimates the similarity between a target user and other users, finds a neighborhood by selecting similar users, and then predicts the rating of each unrated item for the target user using the neighborhood ratings. CF has the advantage that recommendations can only be made using ratings. This feature, however, also has some disadvantages: items that no one has rated cannot be recommended, and accurate recommendation results are difficult to obtain for users who have rated only a few items. In addition, a profile injection attack against CF is another issue related to this feature. Attacking users or competing companies can insert fake user profiles into the user element matrix to influence predicted ratings, increasing the likelihood that their elements will be recommended or decreasing the likelihood that opponents' elements will be recommended. CF algorithms are generally divided into memory-based and model-based collaborative filtering algorithms. In memory-based CFRSs, a custom member scoring matrix is built to generate appropriate recommendations, and the algorithm can also be further broken down into collaborative filtering based on users and members. The user-based CF algorithm computes the similarity between a target user and a neighboring user, and then the recommender system generates recommendations based on the interests of a highly-rated similar user. In CF, user-based recommendations are generated based on the assumption that a user with similar qualities to the target user in the present may have similar desires in the future. Likewise, the item-based collaborative filtering algorithm computes a similarity score between different items and provides recommendations to an active user. To make recommendations with CF based on items, item similarity is calculated with the assumption that items that are similar to previously consumed items may be purchased in the future. Model-based CF approaches are widely used to address data reduction and scalability issues through the use of a custom member rating database. The user-based collaborative filtering (CF) algorithm is divided into three stages: creating a user model, finding the closest set of neighbors, and making recommendations.

The computational similarity method, which allows inferring the similarity between an active user and available users, plays an important role in the process of predicting the rating of a recommender system.

When ratings are explicitly presented, similarity can be easily determined using the Pearson's correlation coefficient (PCC) or Pearson's similarity metric (PSim), given that similar users tend to rate an item with similar rating points. Empirical analysis of different similarity measures relative to the CF recommender system shows that PSim performs better than other existing similarity measures when calculating relationships between users.

K-Means Clustering

K means algorithm is an iterative algorithm that tries to partition the dataset into Kpre-defined distinct nonoverlapping subgroups (clusters) where each data point belongs to only one group. It tries to make the intra-cluster data points as similar as possible while also keeping the clusters as different (far) as possible. It assigns data points to a cluster such that the sum of the squared distance between the data points and the cluster's centroid (arithmetic mean of all the data points that belong to that cluster) is at the minimum. The less variation we have within clusters, the more homogeneous (similar) the data points are within the same cluster.

The way k means algorithm works is as follows:

1. Specify the number of clusters K.
2. Initialize centroids by first shuffling the dataset and then randomly selecting K data points for the centroids without replacement.
3. Keep iterating until there is no change to the centroids. i.e assignment of data points to clusters isn't changing.
   - Compute the sum of the squared distance between data points and all centroids.
   - Assign each data point to the closest cluster (centroid).
   - Compute the centroids for the clusters by taking the average of the all data points that belong to each cluster.

The approach k means follows to solve the problem is called Expectation-Maximization. The E-step is assigning the data points to the closest cluster. The M-step is computing the centroid of each cluster. Below is a break down of how we can solve it mathematically (feel free to skip it).

Clustering Algorithms

CF is a system that predicts what items should be recommended to target users based on ratings made by users who are similar to those target users. Therefore, we can expect an increase in forecasting accuracy due to the early grouping of similar users into the same cluster. If attacking user profiles are grouped into one cluster, predictions for other trusted users can be made without being affected by the attacks. On the other hand, if the profiles of the attacking users are similar to those of many trusted users, grouping users can increase the impact of the attacks. The main purpose of the clustering algorithm is to group similar users into one cluster. In clustering-based approaches, neighboring users from a cluster are selected for target users they approach.

Clustering is the task of grouping a set of objects so that objects in one cluster are more similar to each other than they are to those in other clusters. Clustering is often used as an unsupervised machine-learning tool to find a hidden structure in large datasets. It is based on grouping items in a dataset into several groups, or clusters, such as items in the same group being, on average, more similar than they are to items in different groups. In clustering algorithms, each item in the whole dataset is considered as a point in n-dimensional space, where n is the number of features of the item.

In recommendation systems, similarity-based measures have traditionally been used to determine neighboring users for a target user. In real-time recommender systems, not all users can rate, are in interested in, or can familiarize themselves with all available items. When there is a relationship or interaction between a user and an item, the user–item rating matrix will be sparse. This critical issue affects the accuracy of rating predictions by the recommendation engine and is known as the sparsity problem. With the increasing need to solve the sparsity problem, but inability to do so, similarity-based models are inadequate for defining an effective list of similar users. In parallel, similarity measures are computationally complex, and using them as the data scale increases will lead to an exponential increase in complexity. To solve problems, such as similaritybased measures when selecting neighboring users, clustering techniques can be used to separate users into different clusters. Typically, clustering can be defined as the process of grouping or organizing users in a database into a cluster while maintaining a higher degree of similarity between them in that cluster. Hence, when a target user is found to be similar to a cluster of users, the user is then added to that cluster, and items of interest to the users of that particular cluster are recommended to the target user. Using clustering techniques in recommendation systems helps to identify groups of users with similar tastes, and this approach greatly improves performance by being immune to sparsity issues. Commonly used clustering techniques include fuzzy, selforganizing maps (SOM), and k-means clustering. The combination of different clustering algorithms, or the same clustering algorithm with different settings, is known as a cluster ensemble (CE). Clustering ensembles can overcome the instability issues of autonomous clustering models.

Clustering Techniques Clustering is an unsupervised classification technique in pattern recognition and data mining. Large number of applications uses it. In clustering, an unlabeled objects is defined as vectors in a multidimensional space, are gathered into groups in such a way that objects within one cluster are similar according to some conditions and dissimilar in different clusters. In clustering, the input space is partitioned into K areas depending on some similarity/dissimilarity metric, where K may or may not be given a priori. A similarity measure has to be defined based on which cluster assignments can be done Different type of clustering is used for recommender system like K-means, fuzzy C-mean, chameleon and hierarchical.

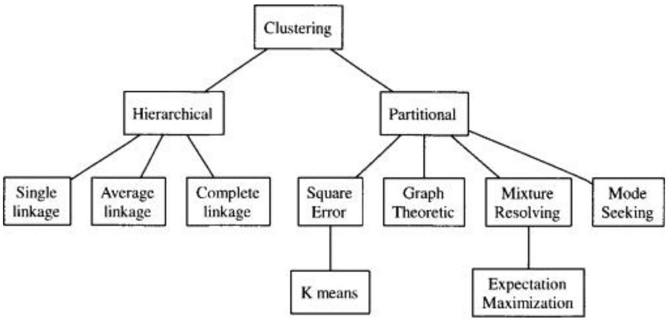

Fig.1.2 Clustering Algorithm

CF with Clustering User Preferences

The authors of proposed a powerful new collaborative filtering algorithm based on clustering user preferences to reduce the impact of data sparsity. User groups were first introduced to differentiate between users with different preferences. Then, given the preferences of an active user, a set of nearest neighbors from the corresponding user group (or groups) was achieved. Additionally, a new similarity measurement method was proposed to calculate the similarity between users. Finally, experimental results on two sets of test data showed that the proposed algorithm was effective at improving the performance of recommender systems. Developing recommendation technology can mainly be divided into two categories: a model-based approach and a memory-based approach . The model-driven approach first builds a prediction model based on a custom member rating matrix and then predicts scores of the target members. Unlike the model-based approach, the memory-based approach first calculates the similarity between users/items, selects the top k similar users/items as active neighbors, and then generates predicted results. A memory-based approach can be divided into a user-based or element-based approach. The authors focused on improving the performance of custom recommender systems to reduce the impact of data sparsity. Modifications and improvements to collaborative filtering are mainly found as two aspects: modification of the similarity measure and the choice of a user's neighbor when predicting a rating. Pearson's correlation coefficient and cosine are often used as measures of similarity in recommender systems., which emphasizes the importance of common ranking elements. Intuitively, if users have more general rating elements, then they are more similar. According to the method of the cosine measure of similarity, the rating scale is not taken into account, and to solve the problem of shortage, an adjusted method of measuring cosine similarity was proposed . In addition to the methods for measuring similarity suggested above, researchers also proposed many modified approaches for the selection of neighbors. For example, Kaleli proposed an entropy-based optimization to generate a more qualified set of neighbors. It assigned a degree of uncertainty for each user and required neighbors with minimum differences in DU value and a maximum similarity value with the active user. Boumaza and Brun introduced the concept of global neighbors, which are the neighbors of all active users. Kim and Yang presented a threshold-based neighbor selection approach; in this approach, neighbors were determined in a certain range of choices based on the similarity of preferences. Anand and Bharadwaj presented a recommendation framework combining both local and global similarities to address the problem of data sparsity, which allows to vary the importance given to global user similarity relative to local user similarity. The authors of presented an efficient collaborative filtering algorithm based on clustering user preferences that differ from those above. On the one hand, user groups are introduced to select more accurate and reliable neighbors for an active user.

Users with different preferences have different rating habits. Thus, users can be combined into different user groups.

1) An optimistic user group in which users prefer to rate high;
2) A pessimistic group of users, in which users prefer to give low ratings;
3) A neutral user group in which users tend to give reasonable ratings for products. On the other hand, the authors noted that most of the previous similarity measurement methods were not suitable to account for user preference factors, and they proposed a new similarity measurement method for calculating the similarity between users in the clustering process. Moreover, extensive experiments showed that the algorithm proposed in can significantly improve performance on sparse-rating data

II. LITERATURE REVIEW

2.1 Kyoung-jaeKim (2008)

In this paper, The Internet is emerging as a new marketing channel, so understanding the characteristics of online customers' needs and expectations is considered a prerequisite for activating the consumer-oriented electronic commerce market. In this study, we propose a novel clustering algorithm based on genetic algorithms (GAs) to effectively segment the online shopping market. In general, GAs are believed to be effective on NP-complete global optimization problems, and they can provide good near-optimal solutions in reasonable time. Thus, we believe that a clustering technique with GA can provide a way of finding the relevant clusters more effectively. The research in this paper applied K-means clustering whose initial seeds are optimized by GA, which is called GA K-means, to a real-world online shopping market segmentation case.

Paritosh Nagarnaik (2015)

In this paper In recent years recommendation systems have changed the way of communication between both websites and users. Recommendation system sorts through massive amounts of data to identify interest of users and makes the information search easier. For that purpose many methods have been used. Collaborative Filtering (CF) is a method of making automatic predictions about the interests of customers by collecting information from number of other customers, for that purpose many collaborative base algorithms are used. CHARM algorithm is one of the frequent patterns finding algorithm which is capable to handle huge dataset, unlike all previous association mining algorithms which do not support huge dataset.

Ya-YuehShih (2008)

In this paper, Recommender systems are techniques that allow companies to develop one-to-one marketing strategies and provide support in connecting with customers for e-commerce. There exist various recommendation techniques, including collaborative filtering (CF), content-based filtering, WRFM-based method, and hybrid methods. The CF method generally utilizes past purchasing preferences to determine recommendations to a target customer based on the opinions of other similar customers. The WRFM-based method makes recommendations based on weighted customer lifetime value – Recency, Frequency and Monetary. This work proposes to use customer demands derived from frequently purchased products in each industry as valuable information for making recommendations. Different from conventional CF techniques, this work uses extended preferences derived by combining customer demands and past purchasing preferences to identify similar customers.

Xiaoyuan Su (2009)

To study, Collaborative filtering (CF) is one of the most successful recommender techniques. Broadly, there are memory-based CF techniques such as the neighborhood-based CF algorithm; model-based CF techniques such as Bayesian belief nets CF algorithms, clustering CF algorithms, and MDP-based CF algorithms; and hybrid CF techniques such as the content boosted CF algorithm and Personality diagnosis. As a representative memory-based CF technique, neighborhood-based CF computes similarity between users or items, and then use the weighted sum of ratings or simple weighted average to make predictions based on the similarity values. Pearson correlation and vector cosine similarity are commonly used similarity calculations, which are usually conducted between co-rated items by a certain user or both users that have co-rated a certain item.

Badrul Sarwar (2001) In this paper we analyze different item-based recommendation generation algorithms. We look into different techniques for computing item-item similarities (e.g., item-item correlation vs. cosine similarities between item vectors) and different techniques for obtaining recommendations from them (e.g., weighted sum vs. regression model). Finally, we ex- perimentally evaluate our results and compare them to the basic k-nearest neighbor approach. Our experiments suggest that item-based algorithms provide dramatically better performance than user-based algorithms, while at the same time providing better quality than the best available userbased algorithms.

Rakesh K. Lenka (2018) The present scenario there is a serious need of scalability for efficient analytics of big data. In order to achieve this, technology like MapReduce, Pig and HIVE came into action but when the question comes to scalability; Apache Spark maintains a great position far ahead. In this research paper, it has designed and developed an improved hybrid distributed collaborative model for filtering recommender engine. Execution time, scalability and robustness of the engine are the three evaluation parameters; has been considered for this present study. The present work keeps an eye on recommender system built with help of Apache Spark. Apart from this, it has been proposed and implemented the bisecting KMeans clustering algorithms. It has discussed about the comparative analysis between KMeans and Bisecting KMeans clustering algorithms on Apache Spark environment.

Nikita Mariam Santhosh (2021) Recommendation systems (RS) have become a hot topic in the study, intending to assist consumers in finding goods online by offering choices that closely match their interests. Recommending a product to customers exclusively based on a quantitative review may result in the recommendation of a product that is irrelevant. Various recommendation algorithms are used by online e-commerce companies like Amazon and Flipkart to offer different choices to different customers. Amazon now uses item-to-item collaborative filtering, which expands to enormous data sets and produces high-quality real-time suggestions. This type of filtering compares the users purchased and rated items to similar things, the results are then compiled into a user-friendly list of recommendations. The goal of this research is to create a product suggestion system for an e-commerce platform that is tailored to the preferences of customers. Collaborative Filtering is one of the methods for generating suggestions. Recommend products to consumers based on their previous purchases and the ratings left by other customers who purchased comparable things. This paper discusses a model-based collaborative filtering approach, which assists in the development of predictive items for a specific user by recognizing patterns based on preferences gleaned from various user data.

SongJie Gong (2010) in this paper Personalized recommendation systems can help people to find interesting things and they are widely used with the development of electronic commerce. Many recommendation systems employ the collaborative filtering technology, which has been proved to be one of the most successful techniques in recommender systems in recent years. With the gradual increase of customers and products in electronic commerce systems, the time consuming nearest neighbor collaborative filtering search of the target customer in the total customer space resulted in the failure of ensuring the real time requirement of recommender system. At the same time, it suffers from its poor quality when the number of the records in the user database increases. Sparsity of source data set is the major reason causing the poor quality. To solve the problems of scalability and sparsity in the collaborative filtering, this paper proposed a personalized recommendation approach joins the user clustering technology and item clustering technology. Users are clustered based on users' ratings on items, and each users cluster has a cluster center. Based on the similarity between target user and cluster centers, the nearest neighbors of target user can be found and smooth the prediction where necessary. Then, the proposed approach utilizes the item clustering collaborative filtering to produce the recommendations. The recommendation joining user clustering and item clustering collaborative filtering is more scalable and more accurate than the traditional one.

Chih-LunLiao (2016) in this paper In collaborative filtering recommender systems, products are regarded as features and users are requested to provide ratings to the products they have purchased. By learning from the ratings, such a recommender system can recommend interesting products to users. However, there are usually quite a lot of products involved in E-commerce and it would be very inefficient if every product needs to be considered before making recommendations. We propose a novel approach which applies a self-constructing clustering algorithm to reduce the dimensionality related to the number of products. Similar products are grouped in the same cluster and dissimilar products are dispatched in different clusters. Recommendation work is then done with the resulting clusters. Finally, re-transformation is performed and a ranked list of recommended products is offered to each user. With the proposed approach, the processing time for making recommendations is much reduced. Experimental results show that the efficiency of the recommender system can be greatly improved without compromising the recommendation quality.

Gilda Moradi Dakhel (2011) in this paperthe Collaborative Filtering is the most successful algorithm in the recommender systems' field. A recommender system is an intelligent system that can help users to come across interesting items. It uses data mining and information filtering techniques. The collaborative filtering creates suggestions for users based on their neighbors' preferences. But it suffers from its poor accuracy and scalability. This paper considers the users are m (m is the number of users) points in n dimensional space (n is the number of items) and represents an approach based on user clustering to produce a recommendation for active user by a new method. It uses k-means clustering algorithm to categorize users based on their interests. Then it uses a new method called voting algorithm to develop a recommendation. We evaluate the traditional collaborative filtering and the new one to compare them. Our results show the proposed algorithm is more accurate than the traditional one, besides it is less time consuming than it.

Conclusion:

In this paper, K-means clustering method is explored to address the scalability issue which is a fundamental challenge in recommender systems. Applying K-means clustering offline on user-movie rating matrix reduced the sparseness and reduced the scalability problem of the model since the computation of finding similar users to the target user is only calculated for users within same cluster, thus reducing the target user's neighbor number. If a movie is selected by these users, it will be suitable to the target user. According to the prediction results, Pearson correlation coefficient similarity measure achieved relatively good results to find the closest neighbors to the target user. Recommender systems can help people to find interesting things and they are widely used in our life with the development of electronic commerce. Many recommendation systems employ the collaborative filtering technology, which has been proved to be one of the most successful techniques in recommender systems in recent years. With the gradual increase of customers and products in electronic commerce systems, the time consuming nearest neighbor collaborative filtering search of the target customer in the total customer space resulted in the failure of ensuring the real time requirement of recommender system

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