Splitting-merging Clustering Algorithm for Collaborative Filtering Recommendation System

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Abstract: Collaborative filtering (CF) is a well-known and successful filtering technique that has its own limits, especially in dealing with highly sparse and large-scale data. To address this scalability issue, some researchers propose to use clustering methods like K-means that has the shortcomings of having its performances highly dependent on the manual definition of its number of clusters and on the selection of the initial centroids, which leads in case of ill-defined values to inaccurate recommendations and an increase in computation time. In this paper, we will show how the Merging and Splitting clustering algorithm can improve the performances of recommendation with reasonable computation time by comparing it with K-means based approach. Our experiment results demonstrate that the performances of our system are independent on the initial partition by considering the statistical nature of data. More specially, results in this paper provide significant evidences that the proposed splitting-merging clustering based CF is more scalable than the well-known K-means clustering based CF.

1 INTRODUCTION

In general, recommendation systems use mainly three types of filtering techniques: content based filtering (CBF), collaborative filtering (CF) and hybrid filtering (the combination of content based filtering and collaborative filtering)(Burke, 2002). The CBF recommendation technique recommends specific items that are similar to those that have been already positively rated in the past by the active user. CBF uses only the content of the items in order to make a recommendation (Pazzani and Billsus, 2007). The CF recommendation technique recommends items that were preferred in the past by similar users to the active user. CF techniques make the assumption that the active user will be interested in items appreciated by similar users. Finally, the hybrid based filtering techniques recommend items by combining CF and content-based filtering (Burke, 2002). CF is widely used in the fields of e-commerce (Linden et al., 2003), e-learning (Bobadilla et al., 2009), e-government (Shambour and Lu, 2011), TV programs (Zhang et al., 2013), music (Cohen and Fan, 2000) and books (Benkoussas et al., 2014). Methods in CF can be either memory-based or model-based. Memory-based algorithms operate on the whole user-item rating matrix and make recommendations by identifying the neighborhood of the target user to whom the recommendations will be made based on his preferences (Herlocker et al., 1999). The memory based filtering algorithms are easy to implement and they perform very well in many real world applications (Lu et al., 2015). However, they face important problems limiting their applications with sparse and/or large data. Data sparsity is common when users rate only a small number of items creating a very sparse user-item matrix (Su and Khoshgoftaar, 2009). On the scalability side, the memory based filtering algorithms do not scale satisfactory when the users and items in ratings database increase (Lu et al., 2015). To solve this last scalability issue, model-based techniques were proposed. Model based techniques use machine learning algorithms on users-rating training data to learn a model and to make predictions on the users-rating test data or on real data. Several algorithms have been used for model based CF. Among the machine leaning algorithms used, let's list Bayesian networks (Su and Khoshgoftaar, 2006), matrix factorization (Bokde et al., 2015), probabilistic latent space models (Hofmann and Puzicha, 1999), neural networks(Feng and Huiyou, 2006) and clustering methods(Salah et al., 2016). Clustering methods using K-means algorithm

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have been widely used in model based CF because of K-means simplicity and low complexity. However, the usability of K-means is limited by the fact that the clustering results are heavily dependent on the user defined variants, i.e., the selection of the initial centroids and the number of clusters. In practice, K-means algorithm configuration difficulties can easily lead to inaccurate recommendation and dramatic computation time increases. To avoid the shortcomings of the K-means algorithm and at the same time to solve scalability but also sparsity in CF, we propose to use an automatic clustering approach. The proposed clustering method can automatically determine a pseudo-optimal number of clusters according to the statistical nature of data so that the initial centroids seeds are not critical to the clustering (Guan et al., 2003b); (Guan et al., 2003a). This paper proposes a recommendation method that alleviates the scalability difficulty of CF and improves the K-means CF-based recommendation approaches proposed in literature by performing extensive experiments using three different data sets classified as small, medium and large from MovieLens(Harper and Konstan, 2015). To the best of our knowledge, this is the first time that large data with 10 millions entries were used in clustering based CF. The rest of the article is organized as follows: Section 2 presents related works on traditional CF as well as different algorithms including the clustering methods used. Section 3 describes the proposed approach to automatic clustering for CF. Section 4 provides experimental results and Section 5 outlines conclusions and future work.

2 RELATED WORK

CF relies on past users items ratings. It predicts user preferences on items that have not been seen yet based on the historical preference judgments (rating values) from a community of users. The preference judgments are usually structured as a user-item rating matrix. Note that user rating can be either implicit or explicit (Jawaheer et al., 2010). CF approach uses only the past users' behaviors and does not require any user profile. It has the advantage of not requiring any external data such as demographic information hence reducing the time consumed by the recommendation process ((Su and Khoshgoftaar, 2009)). Techniques used in CF can be either memory based or model based (Su and Khoshgoftaar, 2009).

2.1 Memory based Filtering

Memory based filtering uses the entire user-item data to generate a prediction. Based on some similarities, the algorithms find a set of users with similar tastes or preferences, called neighbors, to target user. These neighbors have a history of agreeing with the target user.They rate different items similarly. Once neighbors of users are found, the algorithms predict the preferences on new items for the target user. These algorithms are known as nearest-neighbor CF.

General Approach of k-nn based CF

The most prevalent algorithms used in collaborative filtering are k nearest neighbor CF. It was the first automated CF system introduced by GroupLens(Resnick et al., 1994). The k nearest neighbor for collaborative filtering follows three phases to generate a recommendation:

2.1.1 Phase 1: Similarity Weighting

The first step in k-nn based CF is to weight all users with respect to similarity. The similarity reflects the correlation, distance or weight among users. Various approaches have been proposed to compute the similarity $sim(a,v)$ between users a and v based on ratings of items that both users have rated. Different similarity measures have been proposed and evaluated in the literature. Among these measures we can list: Cosine vector, Pearson correlation, Spearman rank correlation, mean squared difference and these are few similarity measures used in CF among others (Al-Shamri, 2014), (Liu et al., 2014). Popular approach for similarity weighting in CF is Pearson correlation. As a result, we used Pearson correlation in the proposed modeled based filtering algorithm. In many research works the Pearson correlation tends to lead to better results (Ekstrand et al., 2011). The Pearson correlation between the active user a and v is given as follows:

$$sim(a,v) = \frac{\sum_{i \in I}(r_{a,i} - \bar{r_a})(r_{v,i} - \bar{r_v})}{\sqrt{\sum_{i \in I}(r_{a,i} - \bar{r_a})^2 \sum_{i \in I}(r_{v,i} - \bar{r_v})^2}} \quad (1)$$

where I is the set of co-rated items by the two users a and v. $r_{a,i}$ and $r_{v,i}$ refer to the rating of the target item i by the user a and v respectively. $\bar{r_a}$ and $\bar{r_v}$ are the average rating of the co-rated items of the users a and v respectively. Pearson correlation can be a problem when it computes similarities between users who have rated only few items. To alleviate this difficulty some researchers propose an improved Pearson correlation by adding a significance weighting factor that would devalue similarity weights based on a small number of co-rated items (Herlocker et al., 2002). Some experiments have shown a threshold value of 50 to be useful in improving prediction accuracy. The threshold can

be applied by multiplying the similarity function by $\min\{|I_a \bigcap I_v|/50, 1\}$, where $|I_a \bigcap I_v|$ is the number of co-rated item by the users a and v (Ekstrand et al., 2011).

2.1.2 Phase 2: Neighborhoods Selection

As shown in different analysis (Herlocker et al., 1999), a number of k neighbors between 20 and 50 is usually a reasonable starting point in CF. In our experiments we used the best k selected technique. We tried different number of neighborhood on training set to find the best one.

2.1.3 Phase 3: Prediction

After that the similarities between the active user with other users are computed and that k neighbors are selected, the CF system combines the items rating from those k users to predict the user's preferences for an item. The formula used to generate prediction is the weighted average of deviation from the neighbor's mean, using the similarity calculated in Eq. (1):

$$p_{a,i} = \bar{r_a} + \frac{\sum_{v=1}^{k}(r_{v,i} - \bar{r_a}) * sim(a,v)}{\sum_{v=1}^{k}|sim(a,v)|} \qquad (2)$$

where $p_{a,i}$ represents the prediction for the active user a on the target item i. k is the selected number of neighbors and $sim(a,v)$ is the weighted similarity calculated by Eq. (1). Herlocker et al. (Herlocker et al., 1999) found that the weighted average deviation of neighbor's rating from that neighbor's mean rating performs significantly better than the non-normalized ratings approach. In our experiment we chose to use eq. (2).

2.1.4 Challenges of Memory based Collaborative Filtering

Memory based CF have been very successful due to their simplicity and their good performances. However, and as previously mentioned, they suffer from limitations such as scalability and data sparsity. In practice recommender systems are used for large numbers of user-items data. Hence, memory based CF has difficulty scaling for systems such as amazon.com or e-bay e-commerce. These systems contain millions of users and items. In this paper we propose an approach that can deal with this scalability issue, and we test it on millions of users and items. In addition, most recommender systems dealing with millions of items have active users rating only a small number of them (sparsity) resulting in a poor recommendation accuracy. Another illustration of the sparsity case is when a new user or item occurs, making difficult to find similar neighbors as there is no information available on them. More details on memory based collaborative filtering challenges can be found in ((Adomavicius and Tuzhilin, 2005);(Su and Khoshgoftaar, 2009); (Lu et al., 2015). To overcome these difficulties researchers have proposed model based filtering approaches.

2.2 Model based Filtering

Model based filtering first builds a model on the training set (offline data set) to predict the items for the active users on the test set (online). Since the model is built offline, the system uses less memory and the prediction time decreases ((Darvishi-Mirshekarlou et al., 2013), (Gong et al., 2009)). The model based CF provides more accurate predictions for sparse data and addresses scalability problems as shown in (Huang and Yin, 2010), (Birtolo et al., 2011) and (Birtolo and Ronca, 2013). Several popular model based filtering approaches are based on probabilistic latent semantic CF and clustering techniques (Su and Khoshgoftaar, 2009). The goal of the latent semantic analysis is to discover latent features that explain observed ratings (Koren, 2010). Techniques of latent semantic analysis count probabilistic latent space models (Hofmann and Puzicha, 1999), neural network (Salakhutdinov et al., 2007) and latent Dirichlet allocation or based on topic modeling (Wilson et al., 2014). The clustering CF techniques are extensively used to address the scalability and sparsity problems. Researchers including (Huang and Yin, 2010), (Birtolo et al., 2011), (Roh et al., 2003) and (Birtolo and Ronca, 2013) show in their experiments that clustering CF provide more accurate predictions for sparse data than memory based filtering while addressing the scalability issue as well as the items cold start problems. In the next sub section, we give an overview on clustering methods for CF.

2.2.1 Clustering based CF

In CF, the clustering techniques can be used to group either the items into clusters that have same users' preferences or users into clusters with similar items ratings. In users' CF, users who have same items' preferences are grouped in restricted clusters. Therefore, when a new user is identified as similar to a user cluster, items liked by that user group are recommended to the new user ((Tsai and Hung, 2012), (Sarwar et al., 2002)). In their clustering methods, Ungar and Foster ((Ungar and Foster, 1998)) clustered users and rated items separately using variations of K-means with Expectation Maximization (EM) and Gibbs sampling

(Geman and Geman, 1984). Their experiments showed that the results of EM clustering based CF on real data were not very promising but when they used the repeated K-means with Gibbs sampling their results got better. Moreover, their model could be easily extended to much complex models and it may handle clustering with multiple attributes. However, Gibbs sampling is computationally expensive ((Ungar and Foster, 1998)). Kohrs *et al.* (Kohrs and Merialdo, 1999) applied hierarchy clustering using the top down approach for CF with sparse rating matrix. Their approach was more efficient than other traditional CF when applied to few users and provided high prediction values even for users who rated only a limited number of items. Hierarchical clustering is particularly efficient in providing recommendations for new users who rated only few items. Xue et al. (Xue et al., 2005) applied the K-means algorithm to cluster users before analyzing the clusters obtained and choosing an adequate cluster for the active user. They applied the smoothing strategies to the unseen items using the same idea used in natural language processing (Brown et al., 1992) where the cluster is used as topic in order to alleviate the sparsity difficulty. They showed that their approach outperformed other CF approaches on small data sets. Sarwar et al.(Sarwar et al., 2002) addressed the scalability issues by users clustering and used the user cluster as the neighborhood. (Ma et al., 2016) showed the efficiency of their newly proposed clustering based CF in rating predictions with addressing the data sparsity and cold start problems. Rong et al. (Hu et al., 2013) proposed a clustering method for CF. Their approach was divided into two phases: clustering and CF. The clustering method was based on K-means used as pre-processing for CF. By using clustering techniques, the data size was reduced so that the online computation time of CF algorithm decreased significantly. One could argue that the results of their approach depends strongly on the number of clusters. Unfortunately this number of clusters is initially unknown. These recent studies point out that a clustering algorithm computing automatically the cluster numbers could further improve the performance of the recommendation. This motivated us to develop the CF approach presented in the next section.

3 GENERAL APPROACH OF CLUSTERING BASED CF

The main contribution of this paper is to propose a recommendation method that alleviates the scalability and sparsity difficulties of CF by introducing the splitting and merging clustering based on K-means+ algorithm and by performing extensive experiments using three different data sets classified as small, medium and large from MovieLens data sets (Harper and Konstan, 2015). Generally, CF using clustering algorithm is based on the following steps:

- step 1: Cluster users $u \in U$ in K clusters using any clustering algorithm
- step 2: Evaluate the distance between active user and centroids
- step 3: Choose the closest cluster for the active user
- step 4: Select the n nearest neighbor from the chosen active user's cluster
- Step 5: Predict items' active user preferences.

In this paper the clustering methods used in step 1 for CF are K-means and splitting merging K-means+ clustering algorithm as detailed in the two following sub-sections.

3.1 K-means Clustering Algorithm for CF

K-means clustering is the most well-known and commonly used partitional clustering method. It is very simple, fast and straightforward. Many researchers show that K-means is very efficient for model based CF ((Dakhel and Mahdavi, 2011), (Xue et al., 2005)). Algorithm 1 presents the different steps of K-means clustering method.

Algorithm 1: K-Means algorithm.

Input:U: training users; K: the number of clusters
Output: K centroids, $\{C_1, C_2, ..., C_K\}$
Step 1: **Initialization**: Randomly select K users uniformly at random from U, as initial starting points. Calculate centroids as the means value of the users for each cluster.
Alternate steps
repeat
Step 2: assign each user to the cluster with nearest centroid;
Step 3: update the centroid clusters, i.e., calculate the mean value of the users for each cluster
until (no user changes its cluster membership or any other stopping condition is satisfied)

K-means is relatively scalable when processing large data sets as its complexity is $O(|U| \times K \times t)$, where t is the number of iterations, $|U|$ is the total number of users and K is the number of clusters. It can also converge to local optimum in a relatively small number of iterations. However, the usability of

K-means is limited since clustering results are heavily dependent on the user defined variants, i.e., the selection of the initial centroids seeds and the number of clusters. Consequently, these shortcomings lead to inaccurate recommendation and increase the computation time of collaborative filtering. To overcome the K-means algorithm issue and in the same time to solve both problems scalability and sparsity in CF, we applied K-means+ ((Guan et al., 2003a),(Guan et al., 2003b)). K-means+ can automatically determine a pseudo optimal number of clusters according to the statistical nature of the data. The initial centroid seeds are not critical to the K-means+ clustering ((Guan et al., 2003b), (Guan et al., 2003a), (Huang et al., 2005)). K-means is sensitive to outliers and noise in data since a small number of such data can substantially influence the mean value. The resulting cluster centroids may not be excellent representatives of their cluster. However, K-means+ can handle noise and outliers in the data. The clusters with outliers in K-means+ can be split depending on the data distribution of the cluster. In a sparse matrix as in the case of CF, data contains outliers that are not appropriate for clustering algorithms like K-means. In such situation, K-means can end up with several empty clusters to which no data points are allocated during the assignment step. Two approaches are proposed to handle empty clusters: (1) deleting the empty clusters or (2) replacing the empty cluster with newly created non-empty clusters. The second approach chooses the point that is farthest away from its current centroid, replaces it as the centroid of the empty cluster, and then perform the re-clustering. This strategy as proposed by (Hansen and Mladenovic, 2001) eliminates the farthest point that contributes most to the total sum of squared errors. In our experiments, in case of empty clusters situation, K-means+ follows the first approach by removing the empty clusters using a splitting and merging strategy. The second approach was deemed too complicated and computationally expensive.

3.2 Proposed Splitting Merging Clustering Approach for CF

Our proposed collaborative filtering model is based on K-means+ and is characterized by exploiting the statistical nature of the data to adjust autonomously the number of clusters K. K-means+ partitions the data into an appropriate number of clusters without requiring an adhoc fixed number of clusters like K-means. K-means+ considers the statistical nature of data distribution. By splitting and merging clusters, it self-adjusts the number of clusters K. If the initial value of K is too small, the splitting strategy is used to increase the number of clusters; likewise the merging strategy reduces the number of clusters in case it is too large. Algorithm 2 presents the general steps of the clustering method k-means+ ((Guan et al., 2003a), (Guan et al., 2003b)).

Algorithm 2: Splitting and merging clustering algorithm.

Input:U: training users; K: the initial number of clusters
Output: $K\prime$ clusters of users; $K\prime$ centroids, $C_1, C_2, ..., C_{K\prime}$; $K\prime$ is the adjusted number of clusters;
Step 1: **Initialization**: arbitrarily choose K users uniformly at random from U, as initial starting points. Calculate centroids as the means value of the users for each cluster.
Apply K-means;
Search for an empty Cluster
if (there are empty clusters) **then**
  delete the empty clusters
end if
$hasOutlier \leftarrow true$
/*Splitting Steps*/
while ($hasOutlier$) **do**
  search all the clusters
  if (there is an outlier) **then**
    $hasOutlier \leftarrow true$
    remove the first found outlier
    Create a new cluster with this deleted outlier
    Apply K-means with centroids of new clusters as initial solution
    Search for an empty Cluster
    if (there are empty clusters) **then**
      delete the empty clusters
    end if
  else
    $hasOutlier \leftarrow false$
  end if
end while
/*merging steps*/
for $i = 1$ *to* $K\prime - 1$ **do**
  for $j = i + 1$ *to* $K\prime$ **do**
    if ($cluster_i$ *and* $cluster_j$ *can be merged*) **then**
      group $cluster_i$ *and* $cluster_j$ (Reassign users in cluster i and users in cluster j to the same cluster)
    end if
  end for
end for

The algorithm 2 first performs k-means on a random number between 2 and n. The outliers are detected and removed by a confident area $d1$ with radius of five standard deviation σ of each cluster. Indeed, the data points that are far beyond the threshold $d1 = 5\sigma$ are considered as outliers and they are removed from each cluster. Then the removed data are assigned as centroids of a new clusters. Once this splitting phase is done the adjacent clusters whose overlap is over the threshold $d2 = 1.414(\sigma_1 + \sigma_2)$ are merged. The threshold $d2$ represents the correlation coefficient

between two different clusters. Hence the clustering results are not sensitive to the initial partitions and to the number of clusters. Consequently, the effect of outliers in *K*-means+ is well handled. More details on the significance of the two thresholds $d1$ and $d2$ can be found in (Guan et al., 2003a) and (Guan et al., 2003b). Our proposed clustering based CF method proceeds into two phases. The first phase (offline phase) is done on the training set or on the historical users-items ratings data. In this phase users are clustered in different groups such that users with similar preferences are grouped in the same cluster. In the second phase (online phase on testing set), the nearest neighbor based CF is applied on the active user into two steps. The first step aims at choosing the closest cluster for the active user by calculating the distance between the active user and the centroid of the classes. Therefore, the cluster of the active user is determined by the closest distance between the active user and the centroid of the corresponding cluster. The second step of this phase applies the *k*-nearest neighbor based CF filtering as presented in section 2.1 on active user's cluster only (do not include all users data) as in the classical CF technique. Consequently, the online execution time (or the testing time) of collaborative filtering is reduced as well as the resulting sparsity difficulty.

4 EXPERIMENT

4.1 Datasets

In the experimentation we considered three data sets from the movie rating application MovieLens. More details on the different MovieLens data sets can be found in (Harper and Konstan, 2015). The first data set used is MovieLens 100,000 ratings, we called it **SML**. It contains $100,000$ ratings provided by 943 users for 1682 movies. Movies are rated on an integer scale going from 1 (bad) to 5 (excellent) with 0 for not rated movies. The second data set called **MML** in the paper is a medium size MovieLens data set. MML contains slightly more than 1 million ratings and 209 ratings rated by 6040 users on 3900 movies using the same integer scale as SML. The third data set called **LML** is a large MovieLens data set. LML contains 10 millions and 5 ratings applied to 10681 movies by 71567 users of the online movie recommender service MovieLens http://files.grouplens.org/datasets/movielens/ml-10m-README.html. The ratings of LML data set is different from SML and MML. Rates in LML are made on a 5-stars scale and with half-star increments. As a result there is 10 rates possibilities ranged from 0.5 to 5 with 0 standing as a not rated item.

4.2 Metrics

To evaluate the quality of our CF algorithm, we used the *Mean Absolute Error* (*MAE*) because of its versatility in CF literature ((Breese et al., 1998), (Herlocker et al., 2004), (Zahra et al., 2015)). The MAE calculates the average absolute deviation between predicted rating provided by CF algorithm and true rating assigned by user in the testing data test. It is defined as:

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|p_i - r_i| \quad (3)$$

where n is the total of ratings provided by the test set, p_i is the predicted rating provided by the CF algorithm and r_i is the actual rating assigned by user to item i. The lower the MAE, the more accurately the recommendation engine predicts user ratings.

4.3 Evaluation Methodology

In this study, we used 5 fold cross validation technique to evaluate the developed algorithms for collaborative filtering on SML and MML data set; 20% of the users were randomly selected to be test set and the 80% remaining were used for training. From each user in the test set, ratings for 20% of items were withheld, and rating predictions were computed for those withheld items. Finally, the average results on the five folds including the *MAE* cluster numbers and the execution time were reported. For LML data set we have divided the data set into two folds. One fold with 80% of users was used for training and the 20% remaining were used for testing.

5 RESULTS AND DISCUSSION

To compare the performance of the different algorithms in terms of scalability, we calculated the predictive accuracy using, as previously mentioned the MAE but also the execution time to get a prediction on the test data set. We tested this way the three algorithms: the nearest neighbor based CF, the *k*-means ($k \geqslant 3$) clustering based CF and *K*-means+ clustering based CF. In this comparative study, different numbers of clusters ranging from 3 to 150 have been used as initial condition for clustering methods. The classical collaborative filtering is designated in the graph as *k*-nn CF with a number of clusters equal to one.

The results over SML dataset in figure 1 show that the CF based on splitting and merging clearly outperforms the CF based *K*-means algorithm when the number of clusters is greater than 20 and it is slightly better with a smaller number of clusters. As shown in figure 1, the performances obtained by the classical CF is slightly better than our proposed clustering based CF and much better than k-means based CF specifically when the number of clusters is greater than 20. The results over MML dataset in figure 2 show that K-means+ outperforms *K*-means while slightly not being as good as classical CF. However, it is two times faster than the classical collaborative filtering when the initial number of clusters is 150 as presented in figure 3. The results over LML data set in table 1 show that *K*-means+ and *K*-means based CF have the same performances as the traditional CF based *k*-nn while being faster. As shown in table 1, the online prediction by *K*-means based CF is two times faster than traditional CF and the online prediction by *K*-means+ is three times faster than traditional CF and it is almost two times faster than *K*-means based CF. As we mentioned in related work, the CF algorithms suffer from the scalability problem. However, *K*-means+ based CF is less time consuming than traditional CF method. As seen in figure 3 and table 1, our proposed *K*-means+ based CF algorithm outperforms *K*-means based CF and has almost the same prediction time on MML data sets. It is also faster than both classical CF and *K*-means based CF methods. Our proposed method with *K*-means+ takes about one fifth of the traditional CF average prediction running time. As shown in figure 4, on average, the final number of clusters obtained by K-means+ is decreased. For example, considering the initial number of cluster *K*=150, on average the final number of clusters is about *K*=7. This could explain why the performances of CF based *K*-means+ is better than CF based on *K*-means. However, the CPU time for online prediction will increase a little bit because the closest cluster to the target user will have more users than it would with *K*-means. For very large data set (LML), the proposed *K*-means+ based CF has less online computational time on testing data with a comparable prediction accuracy as shown in table 1.

Figure 5 summarizes our results using different initial centroids approaches. In this experiment we have tested two approaches, the first one selects *K* users from training set uniformly and randomly and the second one, splits the users in *K* subsets and then calculates centroids as the means value of the users for each subset. As shown in figure 5, the proposed CF based *K*-means+ algorithm provides almost same predictions with different initial centroid seeds

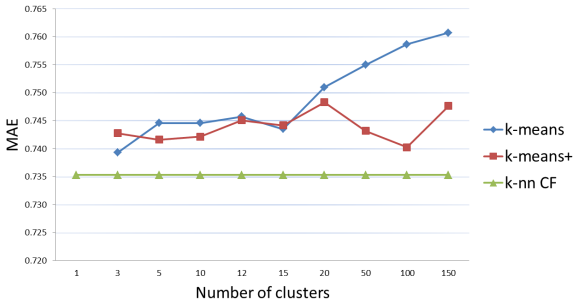


Figure 1: MAE for varying number of clusters on SML data.

Figure 2: MAE for varying number of clusters on MML data.

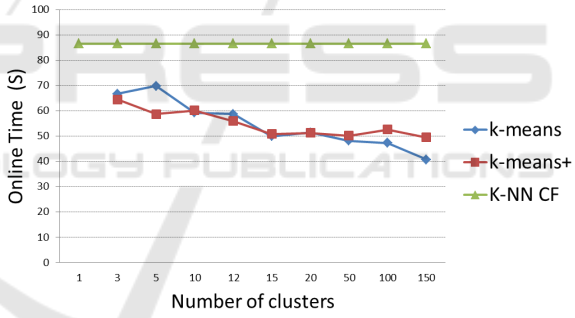
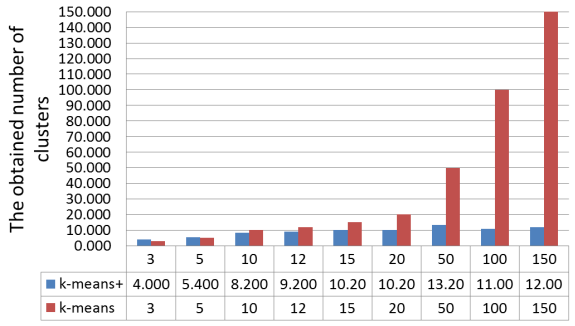


Figure 3: Online time in seconds for varying number of clusters on MML data set.



	3	5	10	12	15	20	50	100	150
k-means+	4.000	5.400	8.200	9.200	10.20	10.20	13.20	11.00	12.00
k-means	3	5	10	12	15	20	50	100	150

Figure 4: The average number of clusters obtained by *K*-means+ on training set (MML data).

approaches. As a result, CF based *K*-means+ approach seems more robust and stable to the initial centroid seeds than *K*-means.

Table 1: Comparative results on LML data set with initial number of clusters K = 100.

	K-means	K-means+	k-NN CF
Average MAE	0.656199389	0.656794361	0.654921579
Average online time on testing data in seconds	2.211	1.542	7.020
Online prediction time per item in seconds	0.00568455	0.00396411	0.018059

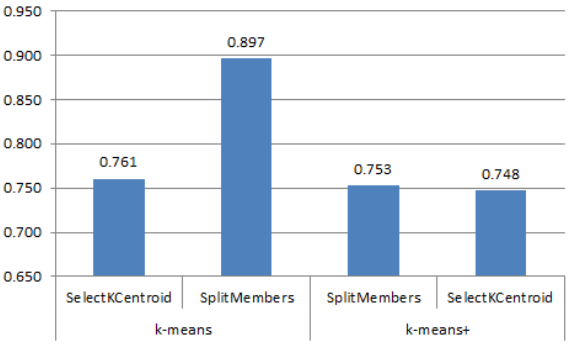


Figure 5: The average MAE of different initial centroids selection approaches on K-means and K-means+ over the SML test sets with K=150.

6 CONCLUSION AND FUTURE WORK

Recommender systems have become an essential functionality for many E-commerce Web applications. Many systems use k nearest neighbor based CF algorithms that are very efficient in filtering interesting items to users. However, k nearest neighbor based CF algorithms have difficulties to scale. To address this scalability issue, we investigated the application of a clustering method based on a splitting and merging heuristic for model based collaborative filtering. We considered an aspect that is usually ignored in CF, the statistical nature of the data. The experimental results obtained show that the recommendation method based on splitting and merging heuristic is a viable approach for scalable collaborative filtering. The comparative results have shown that splitting-merging clustering algorithm has a lower prediction error compared to K-means clustering method especially for large amount of data with high dimensional space. Moreover, the experimental results we obtained on Movielens data illustrate the robustness of the K-means+ clustering algorithm and the fact that initial centroid seeds are not critical to the clustering results as they are for K-means. In our study we considered only user collaborative filtering but it would be interesting to investigate the application of our proposed clustering method to item based collaborative filtering and to compare the results with user based collaborative filtering. More precisely, we will, in future works, apply our proposed clustering method to the item based filtering method. Once the items are clustered and the closest cluster to the new item is determined, the item based CF will be applied to produce the recommendation to the target user. Besides, we will investigate the application of other type of Splitting and merging algorithms for CF. Among the algorithms we would like to test are (Laplante et al., 2015) and (Wang and Belacel, 2008).

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