# An Efficient Recommender System using Collaborative Filtering Methods with K-separability Approach

1. Ms. Smita Krishna Patil, ME S.P.I.T., Mumbai, smitasukrut@gmail.com
2.Mrs. Yogita Deepak Mane, ME S.P.I.T., Mumbai, yogita.ydmane@gmail.com
3.Mrs. Kanchan Rufus Dabre, ME S.P.I.T., Mumbai, kanchandabre@gmail.com
4. Mr. Puneet Raman Dewan, BE A.C.E.,Mumbai, puneetd30@gmail.com
5.Dr. Dhananjay R. Kalbande, Asst.Professor S.P.I.T.,Mumbai, k_dhananjay@yahoo.com

***Abstract*—This paper propose an efficient recommender system using collaborative filtering mechanism with k-separability approach for web based marketing. We follows the collaborative recommender method in which a user rating is aggregation of various characters using matrix but dataset becomes very noisy and difficult to separate. So, the K-Separability approach extends linear separability of data clusters into k>2 segments on the discriminating hyperplane. It can be implemented by single layer or 2-layer perceptron. K-Separability is able to uncover complex statistical dependencies i.e. positive or negative. Finally, We don't need to filter the neighborhood of the target filter as other systems. All neighborhoods are considered and extremely useful in case of sparse dataset.**

***Index Terms*— Neural network, Data mining, Collaborative filtering, Recommender system, K-separability**

## I. INTRODUCTION

Now a days' every internet user is aware about the online shopping. Most people go for online shopping rather than window shopping. Habit of online shopping is increasing a day by day from youngsters to everyone due to its 24x7 availability. Online shopping is based on the recommender system. Recommender system is a platform that can be used to reduce the searching cost of consumers, increase the effectiveness of firm's promotion strategies and enhance consumer's loyalty.

This paper propose a web-based collaborative filtering mechanism for firm's product bundling strategy. There are 3 different types of recommender techniques[8]: Content-based recommenders, Collaborative recommender and Hybrid recommenders.

Content Based Recommender System recommend an item to a user based upon a description of the item and a profile of the user's interests[1]. This system include implementation strategies for representing items, creating a user profile that describes the types of items the user likes/dislikes, comparing the user profile to some reference characteristics with the aim to predict whether the user is interested in an unseen item. Collaborative filtering is the process of filtering for information or patterns using techniques involving collaboration among multiple agents, viewpoints, data sources, etc. Hybrid recommender systems combine two or more recommendation techniques to gain better performance with fewer of the drawbacks of any individual one. Most commonly, collaborative filtering is combined with some other technique in an attempt to avoid the ramp-up problem. Among these Collaborative filtering (CF) system is the most successful one, which employ statistical techniques to find a set of customers who have a history of agreeing with the target use.

Collaborative Filtering (CF) recommendation is a knowledge sharing technology for distribution opinions and facilitating contacts in network society between people with similar interests. The CF recommendation is the process of multiple users sharing information on the preferences and actions of an affinity group tracked by a system which, then, tries to make useful recommendations to individual users based on the patterns it predicts. CF recommendation also provides a complementary tool for information retrieval systems that facilitates users' navigation in a meaningful and personalized way.

## II. COLLABORATIVE FILTERING RECOMMENDATION ALGORITHM

### A. *Efficient Recommender System*

A recommender system used to predict a user behavior that a user will give in relation to an item. In this system such predictions are used to enable items to be recommended to user. Collaborative filtering recommendation algorithm searches a number of nearest neighbor of target users, then according to the score of items that these nearest neighbors proposes, to forecast the forecasting the score of items that target users might have proposed, to select a number of items that have the highest forecasting score as recommended results to feedback to target users[7]. It is the core of collaborative filtering recommendation algorithm that to form recommendation results through the score that these nearest neighbors propose to items. As the algorithm applied the most widely at present, compared with other methods, collaborative filtering algorithm has some advantages: it is easy to realization, and to form higher accuracy recommendation results, and to carry on cross-type recommendation, and good self-adapt ability and so on.

The disadvantages of collaborative filtering recommendation algorithm is also very obvious, which causes that these researchers make efforts to improve the algorithm or to combine with data mining technology in order to solve its those problems [7]. Collaborative filtering recommendation algorithm mainly has the following challenges:

• Sparsity problem: Due to the extreme sparsity of data, when forming the nearest neighbor sets of the target users, collaborative filtering recommendation algorithm often result in the loss of information, which cause to reduce the recommendation effect.

• Cold -star problem: When a new item firstly appears, because the new item has no assessment of the user, only collaborative filtering recommendation algorithm is unable to forecast the score so as to form the recommendation.

### *B. Data Mining And Clustering Technology*

Data mining is an uncommon process to extract the previously unknown and potentially useful information and knowledge from massive, incomplete, disturbed, fuzzy and random data [2,6,7]. This technology is widely used in classification, prediction and pattern recognition and so on. Neural network is one of the most important algorithms of data mining technology. Clustering technology classify a group of individuals into different category according with their similarity. Its purpose is to make it small distance as possible that the distance between individuals belonging to the same category and meanwhile make it large distance as possible that the distance between individuals belonging to the different category.

### *C. Neural Network*

Neural network refers to the information processing systems or computer software system that can simulate the structure and function of the biological brain[2]. It is nonlinear complex network system consisting of a large number of processing units that are similar to neurons. The structure of neural network is determined by the basic processing unit and their interconnection methods. The field of neural networks may be thought to be related to artificial intelligence, machine learning, parallel processing, statistics, and other fields.

## III. RELATED WORK

In this paper, we propose a recommendation system by applying Collaborative Filtering method[9]. First step, Clustering Using Adaptive Resonance Theory(ART) is used to generate different kinds of customer group based on user rating matrix and product bundling strategy, in which members have same attributes or habits. Second step, computation of singular value decomposition (SVD) of the co-raters matrix using k-separability approach. Third step is Data Mining Using association rule techniques is used to find the relations between item X and item Y in given support and confidence values. Fourth step is we need to train our system and last step the performance matrix is calculated to generate personal product bundling list and top-N recommendations.

### *A. Recommendation system based on collaborative filtering*

Recommendation system apply data analysis techniques to the problem of helping users find the items they would like to purchase at E-Commerce sites by producing a list of Top N recommended items for a given user. The framework for system is shown below:

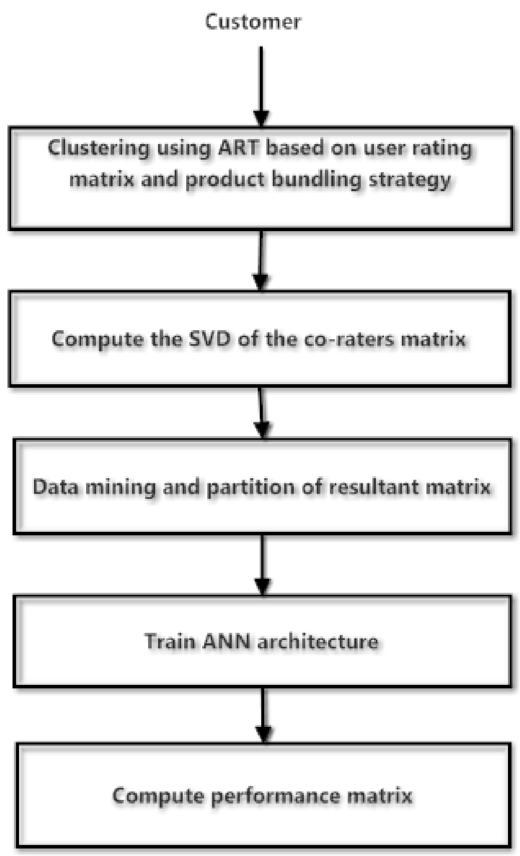


**Fig 1:** Flow of recommender system based on collaborative filtering with k-separability

*B. Adaptive Resonance Theory(ART)*

The Adaptive Resonance Theory (ART) network, is an unsupervised learning, based on competition, that finds categories autonomously and learns new categories if needed. This model is developed to solve the problem of instability occurring in feed forward system. It is one of the most popular competitive and fast neural network models, for clustering and solving in a number of real-world problems. Model include ART1, is designed for clustering binary vectors and ART2 is designed to accept continuous valued vectors. For each pattern presented to the network, an appropriate cluster unit is chosen and the weights of the cluster unit are adjusted to let the cluster unit learn the pattern.

In this step, ART model receives data input from customers' information database(CDB), calculates and clusters the binary vectors according to their attributes , and provides the output of clustering vectors. CDB has stored all the customers' information. CDB consists of basic attributes of customer such as city, age, gender, education etc. The detailed code scheme is shown in fig below:

| Attributes | City | Age | Gender | Education |
|---|---|---|---|---|
| Binary Code | B1-B4 | B5-B6 | B7~B8 | B9~B12 |

**Table1:** Binary Code scheme for customer's attributes

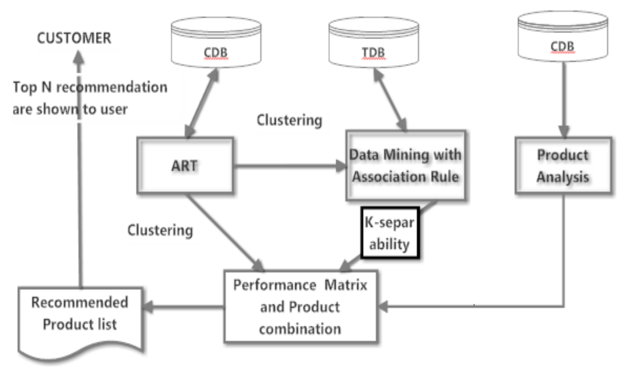


**Fig2**: Framework of recommendation system based on collaborative filtering

*C. Data Mining and Associative Rule*

Data mining, the extraction of hidden predictive information from large databases, is a powerful new technology with great potential to help companies focus on the most important information in their data warehouses. Data mining tools predict future trends and behaviors, allowing businesses to make proactive, knowledge-driven decisions. The automated, prospective analyses offered by data mining move beyond the analyses of past events provided by retrospective tools typical of decision support systems. Data mining tools can answer business questions that traditionally were too time consuming to resolve. They scour databases for hidden patterns, finding predictive information that experts may miss because it lies outside their expectations. Association rules is a way to find interesting associations among large sets of data items. Clustering algorithms are classified into Hierarchical clustering, Data partitioning and Data grouping. Here using association rule we can find the association between two products in the transaction database such that the presence of products in one set implies the presence of the products from the other set. Clustering is the division of data into groups of similar objects. Each group (a cluster) consist of objects that are similar between themselves and dissimilar to the objects of other groups. Once the clusters are created, predictions for an individual can be made by averaging the opinions of the other users in that cluster. Association rule is selected in this step to find associations between sets of data items in the whole transaction database (TDB)and in the given category of customer's TDB. Transaction Items are read and expressed as:

$$\text{Data\_Item}_x = \{k\}, S$$

And k denote product name or code and S is the bought item. When both the support value and confidence value are greater than the given threshold, a association rule between x and y is founded and represented as:

$$\text{Data\_Item}_x \longrightarrow \text{Data\_Item}_y$$

We have determined itemsets based on a predefined support. We have data items that often sold together eg. An insurance policy. We need to know what is the driver within a frequent itemset. What are the items that once bought can drive the customer to buy other items? Here customer who buys a Accidental Death Benefit, most of the time he will also buy a Dismemberment Benefit. But if there are some unknown facts that forces customer to buy items that apparently don't have any relationship? This is where association rule become useful.

*D. Recommendation and product bundling*

The main function of this step is to choose the appropriate product combination recommended to customer. We need to find all the situations where customers who bought a subset of frequent itemset. Most of the time customer also bought the remaining items in the same frequent itemset. We have to set a threshold, a percentage that will help us considering a rule useful. Let's say the threshold value is 80%. Given a frequent itemset say(S1,S2,S3), if a customer who buys a subset formed by S1 and S2, also buys S3 80% of the times, then it is worth to consider a rule. So, the favorite degree of items denoted by RS value, is a primary factor when decide which kind of products should be recommended but not others. This percentage is called the confidence of the rule and is defined as the ratio of the number of transactions that include all items in a particular frequent itemset to the number of transactions that include all items in the subset. After customer clustering and association rule mining, Product Bundling strategy is established and products are recommended. Consider an insurance example, customers with the items they bought.

| **Customer** | **Sale** | | | |
|---|---|---|---|---|
| C1 | S1 | | S3 | |
| C2 | | S2 | | |
| C3 | | | | S4 |
| C4 | | S2 | S3 | S4 |
| C5 | | S2 | S3 | |
| C6 | | S2 | S3 | |
| C7 | S1 | S2 | S3 | S4 |
| C8 | S1 | | S3 | |
| C9 | S1 | S2 | S3 | |
| C10 | S1 | S2 | S3 | |

**Table2**: Bundling strategy

We will consider (S1,S2,S3) frequent item set. It was brought by 3 customers out of 10, so it meets the support requirement, Some association rules that can be generated from this itemsets and calculate the confidence:

(S1,S3) -> (S2)

(S1,S3) was bought by 5 customers but only 3 of them also bought S2. Confidence is 60%.

(S2,S3) -> (S1)

(S2,S3) was bought by 3 customers but only 3 of them also bought S1. Confidence is 50%.

(S1,S2) -> (S3)

(S1,S2) was bought by 3 customers and all 3 of them bought S3 as well. Confidence is 100%. So this rule has a very strong confidence(above 90%) and has to be considered. So the calculation formula is:

Confidence((Sk,Sk+1)-(Sk+2)) =
[Support(Sk,Sk+1,Sk+2)/Support(Sk,Sk+1)]*100

## IV. PROPOSED WORK

*A. k-separability*

K-separability is Originally proposed by **W. Duch**, it is a Special case of the more general method of Projection Pursuit. It is an Application to Feed-Forward ANNs. It Extends linear separability of data clusters into k > 2 segments on the discriminating hyperplane.

Many popular classifiers, including MLPs, RBFs, SVMs, decision tress, nearest neighbor and other similarity based methods requires special approaches or cannot handle at all complex problems such as those exemplified by parity problems: given a training set of binary strings {b1,b2,b3,….} determine if the number of bits equal to 1 is odd or even. In principle universal approximators, such as neural networks are capable of handling such problems and there is a whole literature on architectures and neural activation functions that enable the solution of parity problem. However, solutions proposed so far are manually designed to solve this particular problem and thus will not work well for slightly different problems of similar kind.

Dealing with the difficult learning problems like parity off-the-shelf algorithms for more than 3-bit problems give result s at the baserate (50%) level. Knowing beforehand that the data represents parity problem allows for setting an appropriate MLP architecture to solve it, but for large n in real situation it will be very difficult to guess how to choose an appropriate model.

Looking at the image of the training data in the space defined by the activity of the hidden layer neurons one may notice that a perfect solution may be found in hidden space – all data falls into separate clusters – but the clusters are non separable, therefore the perceptron output layer is unable to provide useful result. Changing the goal of learning from linear separability to other forms of separability should make the learning process much easier. It would be very useful to break the notion of non-linearly separable problems into well defined classes of problems with increasing difficulty.

Adaptive system, such as feedforward neural networks, SVMs, similarity-based methods and other classifier, use composition of vector mappings

$$Y(S)=M^{(m)}(M^{(m-1)}\ldots(M^{(2)}(M^{(1)}(S))\ldots))$$

*B. Extending linear separability to 3-separability*

A highly non-separable dataset. It can be learned by a 2-layered perceptron, or by a single layer percpetron that implements k-separability. The activation function must partition the input space into distinct areas that is soft-windowed activation function.

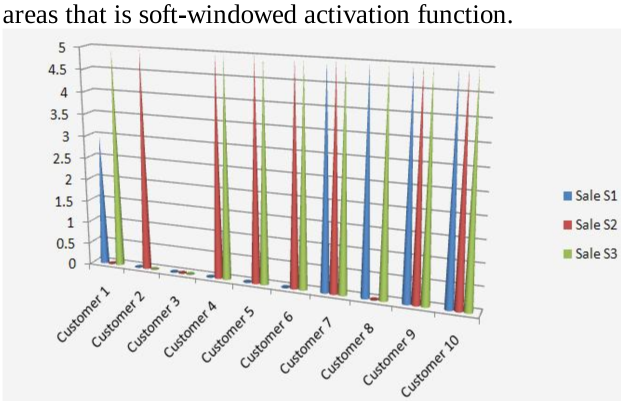


**Fig3**: Input Space Partitioning graph based on sale

*C. Generalizing to k-separability*

In this step we go for complex datasets, generalization by induction method and we also use a Recommendation Engine. Complex dataset which combines the output of two or more neuron, e.g. A 3-separable dataset can be learned by the combines output of 2 neurons. In generalization method, m-neuron output gives 2m+1 regions on the discriminating line and also gives k = 2m + 1-separable dataset.

After this step we will use recommendation Engine, which create a 2-layered perceptron. Consists of n-sized input vector, m-sized hidden layer, single output layer.

Overall, an $n \longrightarrow m \longrightarrow 1$ projection. It build a model (NN) for each user. It takes as Input, The ratings of the n "neighbors" of the target user on an item he hasn't evaluated and produce Output, a "score" for the unseen item.

## V. Collaborative Recommender System

In our algorithm **input will be** the user ratings' matrix and the target user and output will be a model (NN) for the target user.

**Algorithm:**

Step 1: Select from the user ratings' matrix all the co-raters of the target user based on product bundling strategy using ART.
Step 2: Calculate the Singular Value Decomposition matrix of the co-raters matrix, retaining only the non-zero Singular Values.
Step 3: Partition the resultant matrix in 3 different sets; the Training Set, the validation Set and the Test Set and apply data mining using association rule.
Step 4: Train a Constructive ANN Architecture.
Step 5: Calculate the Performance Metrics on the Test Set.

Our experiment contains the database result for an insurance policy survey. It contains the ratings of multiple users on different policies. It produces a sparse matrix that is .3% of nonzero elements. Each user has rated at least 2 policies 10 on average but discrete exponential distribution provides result that 60% of all users have rated 4 policies or less and 40% of all users have rated 1 policy. So we have followed a purely Collaborative Strategy, taking into account only the user ratings and not any other demographic information Two questions are arises, first is Many users rated only one policy. What will be the system performance in this case? Group A contains the few raters user that contains all users who have rated 8-9 policies. Second question is What will be the performance of system in average case? Group B contains the moderate raters user that contains all users who have rated 4-5 policies. This may be used in comparison to other implementations. We randomly picked 10 users from each group (50 users in total) so the results were averaged for each group. Three metrics obtained: Precision metrics, Recall metrics and F-measure metrics.

From observation we have concluded that our system achieves good results in both usergruops and out performs the other approaches. Recall is higher in the few raters group because they seem to rate only the policies they felt beneficial.

A. Performance Result

| Methodology | Precision | Recall | F-measure |
|---|---|---|---|
| Group A | 75.3% | 82.2% | 79.37% |
| Group B | 74.0% | 88.8% | 78.97% |
| Market Analysis | 74% | 73% | 74% |
| Insurance activity | 66% | 74% | 70% |
| Liabilities | 67.9% | 69.7% | 68.8% |
| Risk assessment | 61% | 75% | 67% |
| Investments | 73% | 56% | 63% |
| Derivatives | 64.4% | 46.8% | 54.2% |
| Capital adequacy | 62% | 54% | 59% |

**Table3**: Performanance Result

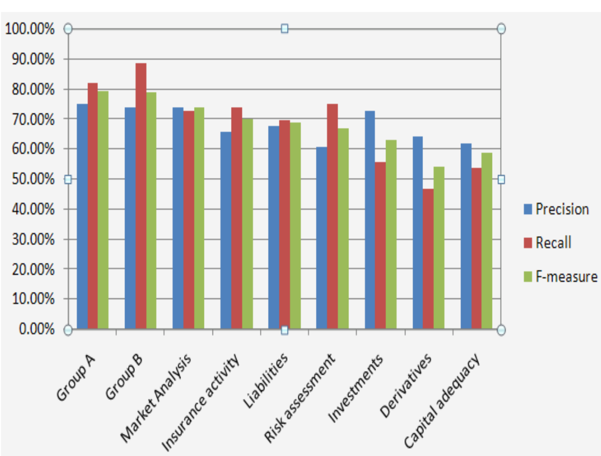


**Fig5:** Rated items per user

## VI. Conclusion

We have presented a complete Collaborative Recommender System that is specifically fit for those cases where information is limited**.** The recommendation system based on collaborative filtering with k-separability approach to create a product bundling strategy. Since the recommendation system applies Neural network for customer clustering and Data Mining to find association rules, it achieves a high hit probability between actual bundling manner and recommended strategy. Our system achieves a good trade-off between Precision and Recall, a basic requirement for Recommenders. This is due to the fact that k-separability is able to uncover complex statistical dependencies (positive and negative). We don't need to filter the neighborhood of the target user as other systems do (e.g. by using the Pearson Correlation Formula). In this system all "neighbors" are considered and it is extremely useful in cases of sparse datasets.

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