Cold Start Problem in Recommendation System: A Solution Model Based on Clustering and Association Rule Techniques

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Cold Start Problem in Recommendation System: A Solution Model Based on Clustering and Association Rule Techniques

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***Abstract*- Generally cold start problem refers to the new user who are coming in big data as well it also related to new items which are included in any data set. Problem arises when companies or policy makers don't have the information about new user/item in recommendation of products. Recommendation system shows the user who is interested in particular product implementing contents based, collaborative based or hybrid approaches. Meanwhile recommender system faces the cold start issue which means the recommendation system is not recognizing the new product or new user. In another words the system doesn't have information about preferences in order to make recommendation. To overcome the cold start problem, in this paper we are suggesting a solution by combining clustering techniques and association rule. The study is based on extracts of different approached studies. This paper also lets you understand the proposed models to overcome the problem of cold start.**

Keywords- Cold-start, Prediction, Machine Learning, Deep Learning, Clustering, Association, Hybrid Filtering.

I. INTRODUCTION

Online store and selling of products is the trend in the market which is not only providing a range of products and choice to the customers but also connecting them with a range of products. The customer is a major important part of this chain. Companies are offering plans and schemes to attract customers. The product must be presented online to the customer who is interacting in the online network through websites, blogs, social media and apps. Recommendation systems are a catalytic approach to providing matchless products so that customers can take into account a wide range of choices, thus the ultimate goal is to add the maximum number of customers to the system. Other benefits may be retention of customer, personalization, keeping customer information, and cross-selling. There are three type of the recommendation systems are being used i.e. (i). Content based [5] (ii). Collaborative Filtering and (iii). Hybrid approaches [7]. Collaborative filtering [6] is the most commonly used approach as compared to other content based or hybrid recommendation, the reason is being that the system recommends new/other similar items by analyzing same user. Whilst the content base collaborative system is providing the information of items [3] which are being purchased with similar content by other users. Hybrid type is the mix of both approached content and collaborative recommendations [1].

The cold-start problem is a major issue in the recommendation system. Cold-start refers to a new user with a low number of ratings or a very small user profile. In the case of new items, the item has little or no rating that is not visible to customers. The researchers suggested several methods and techniques to solve the problem of cold-start. In this paper we are presenting a most important method based on the association rule and clustering techniques. In this research, we propose a method to alleviate the cold start problem and enhance the prediction quality of the item-based collaborative filtering by adding the contents of items.

II. RELATED WORK

Many recommender systems started off as rather basic query-based information retrieval systems, sometimes known as content-based recommender systems since they suggest websites with content that matches user requests [19]. Later, recommender systems used the collaborative filtering method [20], [21]. To manually locate persons who have similar views, it makes use of free explicit like-or-dislike annotations. The first to automate prediction was created by GroupLens, afterward Ringo had worked to comprehend it [22], [23]. Qing Li and Byeong Man Kim show how clustering approaches may be used to tackle the cold start problem in the item-based collaborative filtering framework [2]. Gavin Shaw, Yue Xu, and Shlomo Geva's work illustrates how to expand a user profile from a dataset using association rules [17]. According to the survey conducted by G. Tuzhilin and Adomavicius, the collaborative filtering technique, content-based and hybrid strategies, as well as the issues associated with recommender systems, are all thoroughly stated [5]. Popescul and Schein, on the other hand, suggested a distinct hybrid form of recommendation system to recommend presently not recommended items [6]. Rour, Shdbolt, Alani and Middleton describes the connection between ontologies and recommender systems and how to take use of this synergy to address the cold start problem [7]. Using taxonomy based background information, Ziegler, G. Schmidt and C.N. Lausen offer a technique for computing customized suggestions in a given field [8]. Cross-Level Association Rules are used in Chan, Chung, and Leung's hybrid recommendation algorithm to incorporate domain-specific content information into collaborative filters [9]. Yue Xu, N. Taouil, Geve, Gavnin Shaw and Pasquier offers a strategy for removing hierarchically redundant approximation basis rules from multileveled datasets by using hierarchy of dataset or using taxonomy without losing information for implementation [10], [11], [12], [13]. Riedl, Konstan and Schafer provided a framework for online dealing with the cold start problem, as well as an overview of recommenders and the e-commerce sites that use them [27]. In order to recommend the courses to students in online learning, Lobo and Sunita offered several permutations of algorithms [14]. In the work done by Xinyue Liub and Hui Lia clustering and association criteria were used to enhance recommendation for digital libraries [15]. Konstan, Riedl, Loren G and Herlocker, describe the important choices in assessing the collaborative filtering recommender system [16]. The important developments in the field of information retrieval are briefly summarized, written by Amit Singhal [17]. Badrul M. Sarwar present the fundamental ideas of collaborative filtering, as well as its drawbacks and a clustering-based approach for huge datasets [18]

Collaborative recommender systems gather product ratings from many users and present recommendations to a specific user based on those ratings. Collaborative filtering techniques have advanced quickly, not just in the research world but also in the business world. For instance, the Jeter system promotes jokes [24], the Flycasting system recommender system providing online radio [25], and the GAB system suggests web pages based on bookmarked pages [26]. Many businesses now use or provide recommender system solutions, including Amazon.com, CDNow.com, and Levis.com [27].

Despite being a successful system in research as well as practice, the collaborative filtering is unable to recommend new items to users who have no previous interactions with the system, and it completely rejects any information that can be gleaned from the contents of items, such as cast lists, movie genres, and synopses of movies, among other information. Additionally, the quality of recommendations is solely determined by user ratings rather than information content. So one another recommendation system have been developed that is suitable to use both customer's preferences as well as contents.

Proposed approaches to hybrid system, which combines content-based and collaborative filters together, can be categorized into two groups:

a. Linear combination
b. Sequential combination

a. **Linear combination**: One group is the linear combination of results of collaborative and content-based filtering as Figure 1 shows, and each creates a recommendation list without combining them to make a combined prediction. It calculates the weighted average by combining both two predictions. The weight of collaborative component is increased while number of users accessing an item increases. However it is too hard to say clearly that how weight is being calculated of all components in collaborative and content based system accordingly [28], [4].

b. **Sequential combination:** The second category consists of the successive use of collaborative filtering and content-based filtering. As shown in figure 2, in this method, persons that have similar interests are first identified using a content-based filtering algorithm. Additionally, a collaborative algorithm is used to forecast how the user would categorize domain-specific content obtained on the web and to suggest similar Web links to other users with related interests [29], [30].
Scalable Pearson correlation technique based on web page category is used to determine people' common interests. Instead than relying on user reviews, the Fab system creates user profiles using content-based methods. Prediction accuracy is therefore entirely dependent on content-based methodologies; incomplete profiles lead to incomplete correlations with other users, which leads to incomplete predictions.
The linear combination model only makes recommendations based on two separate recommender systems: a collaborative recommender system and a content-based recommender system. The sequential combination model disregards the critical information from user ratings while taking into account the beneficial information from user profiles.

III. RECOMMENDER MODELS TO SOLVE THE COLD-START PROBLEM

Researchers are continually adding to their work to suggest the best way to solve the recommender system's cold-start problem. As a result developing different models/methods using high level algorithms. Our proposed model comprises a simple method which is a hybrid method which contains the Collaborative method based on items. In this research paper this method is abbreviated as HMCC (Hybrid Method of Content-based Clustering).
The HMCC may combine the item information and user ratings to determine the item-item similarity in contrast to the sequential combination model, which ignores the helpful rating data from users and bases predictions entirely on the content information.
The HMCC technique is described in depth in the next section, and our experimental work is covered in section 4.

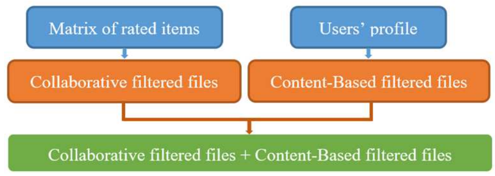

Figure 1: A linear combination of collaborative filtered files and content based filtered files.

1. Association rule and clustering techniques:

Figure 2: A sequential combination of content based filtered files and collaborative filtered files.

1.1. We are combining two techniques, *Association Rule* and *Clustering*. On the part of Association, the matching patterns and combinations that represents or matching a possible antecedent. If matching rule found in association rule with matching antecedent, add them to the profile. Weight assigning is important for each new topic.

$$Weight_{tx}=((\sum_{i=1}^{|A|} Weight_{ti})/|A|)*R_{conf} \quad (1)$$

$$NormalisedWeight_{tx}=((Weight_{tx})/(\sum^{n} Weight_{ti}))*Limit \quad (2)$$

$|A|$ = Number of topics of rule R in the antecedent.

In the second part of *Clustering Technique*, grouped items applying clustering algorithm and opted result in fuzzy set using group-rating matrix creation. In the part of fuzzy set theory, affiliated objects and clusters using K-means algorithm [1].

$$Pro(j,k)=1-(CS(j,k)/MaxCS(i,k)) \quad (3)$$

$Pro(j,k)$ = possibility of object j which is belonging to k cluster.
$CS(j,k)$ = customer similarity between object j and cluster k.
$MaxCS(I,k)$ = maximum counter similarity between an object and cluster k.
Consequently similarity opted from item rating matrix by using Pearson correlation.

1.2. Clustering approach for hybrid recommendation system:

This wonderful model is addressing cold-start problem by using through the clustering techniques in the item-based collaborative filtering framework. The approached used in this model is based on: 1). Grouping items by applying clustering algorithm and creating a group-rating matrix which is represented by fuzzy set. 2). Calculating the

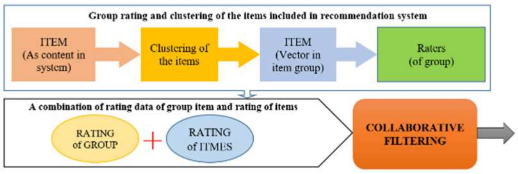

Figure 3: Approach to clustering in the suggested model

similarities between group-rating matrix and item-rating matrix. 3). At last making a prediction for an item by weighted average of deviation from the mean of neighbor.

1.3. Group rating: computing different groups of similar objects using k-means and fuzzy logic to calculate similarity in a content-based associative approach. Membership between cluster and object, and the cluster's mean value calculated as:

$$GCF_{fuz} = \sum_{i=0}^{c}\left(\sum_{j=1}^{n}\left(Pro_{i,j}^{b} \times Dis_{i,j}\right)\right) \quad (4)$$

$$Mean_j = \frac{\sum_{j=1}^{n}(Pro_{i,j})^{b} x_j}{\sum_{j=1}^{n} Pro_{i,j}^{b}} \quad (5)$$

$$Pro_{i,j} = \frac{\left(\frac{1}{Dis_{i,j}}\right)^{\frac{2}{b-1}}}{\sum_{r=1}^{c}\left(\frac{1}{Dis_{i,j}}\right)^{\frac{2}{b-1}}} \quad (6)$$

GCF_{fuz} = fuzzy global function, c = means the cluster number, b = free parameter has been chosen to adjust the blending of different clusters, *Disoi,j* = Euclidean distance between the mean value of cluster i and object *j*, X*j* = vector of object *j*, P*roi,j* = mean the membership between the cluster *i* and the object *j*.

1.4. Similarity: in the similarity section, using the found new rating matrix the item-based collaborative algorithm is calculated to find the similarities on basis of *Pearson correlation-based similarity* and *adjusted cosine similarity*.

Similarity which is based on correlation (Pearson)

$$Sim(k,l) = \frac{\sum_{u=1}^{m}(R_{u,k}-\overline{R}_k)(R_{u,l}-\overline{R}_l)}{\sqrt{\sum_{u=1}^{m}(R_{u,k}-\overline{R}_k)}^{2}\sqrt{\sum_{u=1}^{m}(R_{u,l}-\overline{R}_l)}^{2}} \quad (7)$$

Sim(k,l) = means the similarity between the item *k* and *l*.
m = total number of users who rated *k* and *l*.
Rk, *Rl* = average rating of the item *k* and *l*.
Ru,l , *Ru,l* = rating of user u on the item *k* and *l*.

Similarity which is based on cosine (Adjusted)

$$Sim(k,l) = \frac{\sum_{u=1}^{m}(R_{u,k}-\overline{R}_u)(R_{u,l}-\overline{R}_u)}{\sqrt{\sum_{u=1}^{m}(R_{u,k}-\overline{R}_u)}^{2}\sqrt{\sum_{u=1}^{m}(R_{u,l}-\overline{R}_u)}^{2}} \quad (8)$$

Sim(k,l) = means the similarity between the item *k* and *l*.
m = total number of users who rated *k* and *l*.
Rk, *Rl* = average rating of the item *k* and *l*.
Ru,k , *Ru,l* = rating of user *u* on the item *k* and *l*.

Using the *Linear combination of similarity* as follows:

$$sim(k,l)=sim(k,l)item\times(1-c)+sim(k,l)group\times c \quad (9)$$

1.5. Algorithm used for this research:

TABLE 1: applying K-means algorithm in clustering

Step 1	Input k clusters and the attributes of items;
Step 2	Pick k objects at random to serve as the first cluster centers;
Step 3	According to the mean value of the items in the cluster, reassignment of every item to the group of cluster to which it is most comparable;
Step 4	Calculate each cluster's item's mean value to update the cluster means;
Step 5	Repeat step 3 and step 4 until minor change;
Step 6	Calculate the probability between each cluster center and the objects;
Step 7	**Output**: A fuzzy set is used to describe the set of k clusters that minimizes the squared error criteria and the probability that each item belongs in each cluster center;
	End

TABLE 2: applying Fuzzy K-means algorithm in clustering

Step 1	Input k clusters and the attributes of items;
Step 2	Set both the parameters and the membership between in objects and the clusters to zero;
Step 3	Calculate each cluster's mean value again;
Step 4	Compute each object's membership again;
Step 5	Repeat steps 3 and 4 until the global cost function changes just little;
Step 6	Returning of the membership;
	End

1.6. Collaborative prediction

$$P_{u,k} = \overline{R}_k + \frac{\sum_{i=1}^{n}(R_{u,i}-\overline{R}_i)\times sim(k,i)}{\sum_{i=1}^{n}|sim(k,l)|} \quad (10)$$

Pu,k = prediction for user *u* of item *k*, *n* = total neighbor of *k* item, *Ru,i* = the user rating on the item *i*, *Rk* = average rating on item *k*, sim(*k, i*) means the similarity between item *k* and its' neighbor *i*; *Ri* means the average ratings on the item *i*
In this section an attempt has been made to develop the correct prediction so that the associated cold item can be observed. Prediction is being calculated by weighted average deviation. We are using top N

rule to search the similar user based on nearest N neighbor [2].

2. Addressing the cold-start problem:

The major advantage of this prediction model is that it predicts for the item which has been added newly. As shown in the equation, while user rating is zero, so it is hard to apply the equation for new item. Now we will use another method. Let's understand the following equation:

$$P_{u,k} = \frac{\sum_{i=1}^{n} R_{u,i} \times sim(k,i)}{\sum_{i=1}^{n} |sim(k,l)|} \quad (11)$$

We are using neatest neighbor in spite of R*k*.
Pu,k = prediction for user u for the item *k*.
Ru,i = user rating for item *k*.
n = neighbors of item *k*.
sim(k,i) = similarity of neighbor *i* with its item *k*.

3. Dataset used in experimental part:

TABLE 3. ITEM RATING BY USERS

Movie	User ID-1	User ID-2	User ID-3
Toy Story (1995)	4	3	0
Jumanji (199)	4	4	3
Grumpier Old Men (199)	3	5	0
Waiting to Exhale (1995)	5	2	0
First Knight (1995)			

TABLE 4. GROUP RATING IN CLUSTERS

Movie	Cluster-1	Cluster-2
Toy Story (1995)	94%	0.12%
Jumanji (199)	95%	0.03%
Grumpier Old Men (199)	1.1%	95%
Waiting to Exhale (1995)	97%	1.2%
First Knight (1995)	0.11%	94%

TABLE 5. RESULT AFTER PREDICTION

Movie	User ID-1	User ID-2	User ID-3
Toy Story (1995)	4	3	0
Jumanji (199)	4	4	3
Grumpier Old Men (199)	3	5	0
Waiting to Exhale (1995)	5	2	0
First Knight (1995)	0.5	2.5	2.5

- The dataset for such experiments was taken from MovieLens having the data 1048576 rating records in which 27278 thousand movies were rated by 7120 users.
- In this approach, three users i.e. User-1, User-2, and User-3 are selected for experimental part (Table-3).
- Five movies were selected (as item) on the basis of their genres, star casts, director and release year.
- The study focuses on the some movies released in 1995. Out of them four movies very popular or semi-popular whether the last movie i.e. First Knight having very low rating i.e. 0.1 to zero.
- Rating are scored in 1~5 integer value where 1 is very bad, 2 is bad, 3 is normal, 4 is good and 5 is very good rating.
- After applying the cluster rule, the cluster 1has the result as:
  - Cluster-1: Toy Story (94%), Jamanji (95%), Grumpier Old (1.1%), Waiting to Exhale (97%), and First Night (0~0.5).
  - In the parentheses, the numbers showing the predictions of corresponding cluster.
  - Table-4 shows matrix of group rating which was generated by group rating engine.

4. Experimental evaluation: dataset and evaluation metrics, behavior of method.

$$sim(G,S)items = \frac{(4-3)X(4-2.5)+(2-3)X(4-2.5)}{\sqrt{(4-3)^2+(2-3)^2}\sqrt{(4-2.5)^2+(2.5-2)^2}} \quad (10)$$

$$sim(G,S)group = \frac{(0.98-0.59)X(1-0.59)+(0.013-0.39)X(0.002-0.39)}{\sqrt{(4-3)^2+(2-3)^2}\sqrt{(4-2.5)^2+(2.5-2)^2}} \quad (11)$$

$$sim(G,S) = \times(1-0.4) + 0.9999 \times 0.4 = 0.9999 \quad (12)$$

The cold-start items without rating were examined after different conditions of the experiments and shown successfully in the prediction model. The dataset from Movielens was tested.
As a part of testing and evaluation, our recommendation system narrows down the cold-start problem as well as providing accuracy using Mean Absolute Error (MAE) by comparing the numerical score as opposed actual rating provided user in given dataset.

5. Behavioral analysis of testing of the method:

- Adjusted K-Mean is lighter than the fuzzy K-Mean. So in out testing the adjusted K-Mean is used due to reduce the complexity of algorithm. Figure 4 shows the clustering and relation between of K-Mean and fuzzy K-Mean

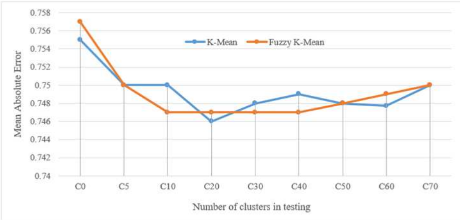

Figure 5: Clustering process

- Coefficient combination is similar to item based clustering hybrid method which is more impactful to group the user profiles, so HMUC (Hybrid Method of User-Based Clustering) is used in our model. As figure 5 shows. To obtain the best combination coefficient c in Equation 9, we run a series of experiments in which we change the combination coefficient from the range of 0 to 1 with an incessant step of 0.1. Figure 6 illustrates that when the coefficient reaches 0.4, the recommendation performance is ideal.

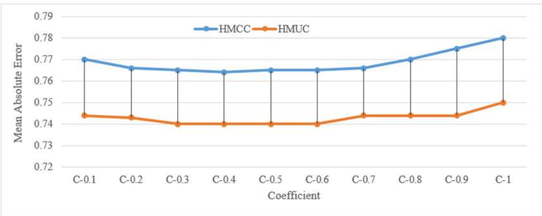

Figure 6: Coefficient measurement according to the Mean Absolute Error

- As figure 7 shows, neighborhood size is affecting the quality of the suggestive prediction through the HMUC.

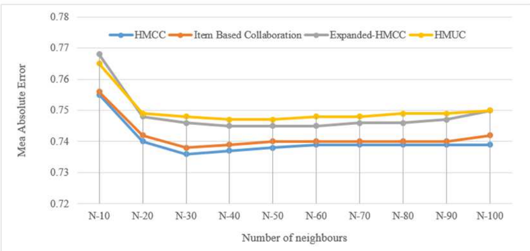

Figure 7: Comparison of the calculated neighbors

- At last we calculated the cold start problem is resolving and cold user/item is ready to show in our predictions. As figure 8 shows:
In our approach, we used two methods. First we calculated the weight of item and further more average of rating was also calculated. On the basis of new item we calculated Mean Absolute Error (MAE) which is performing well to predict the new item.
Thus the association rule and clustering rule are combined and making a new hybrid recommendation system which is abbreviated HMCC (Hybrid Method of Content-based Clustering) in this research.

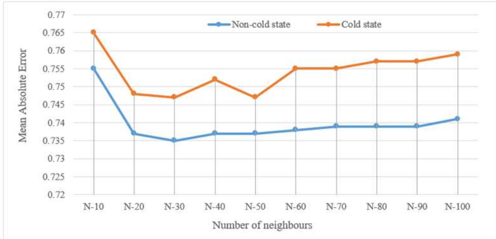

Figure 8: After applying the method showing the cold start v/s non cold start states

IV. THE JUSTIFICATION OF THIS APPROACH

A simple procedure is used for this approach which provides a good predictive outcome which is the application of clustering algorithm for the groups of items. It is presenting the clustering result using fuzzy set as well as making a group rating matrix by using group rating engine.
Additionally, our system is calculating the similarities in user ratings based on the Pearson correlation algorithm as well as it is also calculating the similarities in the clustering which is based on the adjusted-cosine algorithm.
At last the prediction of the item is calculated by taking a weighted average of the neighboring mean (See Table-3).
As shown in Table-1, the item *First Knight(1995)* is in the cold-start position which have the rating > 0.1 or no rating. We applied group-rating-matrix which is showing a strong filtering based on content. Calculating the similarities also makes it stronger prediction system.

V. DISCUSSION

Previously, researchers offered a variety of content-based techniques to addressing the cold start problem, but all were entirely dependent on user requests and preferences. Researchers proposed a collaborative filtering-based framework, which was later expanded to incorporate a hybrid method incorporating different ontologies and taxonomies. In this research, we are using a unique hybrid method that combines content-based and collaborative filtering by categorizing in a linear and sequential manner. It was additionally strengthened using the fuzzy set, group rating matrix, Pearson correlation approach, and modified cosine algorithm. Because of the weight average of adjacent means and the group rating matrix, it is a more truthful and effective recommendation system than previous ones. Furthermore, researchers may refine the N-Neighbor clustering approaches by combining them with other methods and algorithms to get the Top N-Recommendation for lower profile users and lower rated items.

VI. FUTURE PROSPECTS

On the basis of the above study a simple architecture can be designed based on the association rule and clustering technique through which lower profile of new user can be associated with association rule to enrich the user profile as well as low rating item can be accessed by clustering technique. The architecture may comprise sequential manner clustering technique. The system can generate the Top-N recommendation through association rule and clustering techniques. K-mean neighbor and logistic regression applying algorithm can be used applying on real dataset. Python, Hadoop or Matlab (or other tool) is sufficient for testing part. For the aim of e-commerce recommendation, other datasets may also be used.

VII. CONCLUSION

In this paper we proposed a combination of clustering techniques with the association rule for recommendation system to solve the cold-start problem. Applying approach is based on a simple method comprises linear regression, fuzzy logic and N-Neighbor Clustering techniques. Our model can be applies on any rich dataset. The model will produced the perfect result to show the lower profile user as well lower rating profile on the basis of Top N Recommendation.

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