NEW RECOMMENDATION SYSTEM TECHNIQUE USED TO SOLVE SPARSITY, ACCURACY AND NOVELTY CHALLENGES

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Abstract - The recommender systems are the most significant research zone today because of the rapid development of data on the web. Recommender systems help users to settle on a choice about which item they have to buy, which movies they want to watch and which music they want to listen to on the web this likewise part of the E-commerce business. The most suitable and effective strategy of recommender systems is collaborative filtering techniques that it suggests things based on similarly invested users past rating and viewing lists. Collaborative filtering suffers from little rating on items from users this cause sparsity problem, and it's a challenge led to poor accuracy to recommender list to users. In this research, we need to solve the sparsity problem and increase the accuracy of recommendation by applying our experimental on users' implicit interaction records on items and explicit rating records on items. We use association rule to count play songs per transaction and compute similarities by cosine vector similarity to make a recommendation. Our experimental results applied on million song datasets- Last.fm datasets implicit and explicit data. Also, show that the new proposed algorithm has the best performance and more accuracy compared to basic collaborative filtering techniques when data are spare using precision, recall, and F-metrics evaluationsand recommend novel items to users.

Keywords - Recommender Systems, Collaborative Filtering, and Content-Based Filtering, Association Rule Mining.

I. INTRODUCTION

Currently, as a brand new technic of publicity and advertisements, we tend to use sets of data like movies, music and different kind of techniques to convince customers. Technology is developing thus quick and dissemination of information has exaggerated, as well as the needs of consumers that are more complex [1]. Manufacturers and suppliers had an issue in providing services that meet users' desires for the convenience of shopping for the service to a business that makes the competition has a lot of activity. During this era of competition, complicated information causes overload issues that successively are time intense [2]. As overwhelming info explosion renders looking out, extraction, analysis, and process hideous and formidably long time operations, recommender systems became a good call tool or assistant to dump such undesirable tasks. Worse yet, activities involving humans are inevitably subject to human errors, which will cause poor or wrong choices [1]. Recommendation systems are data filtering system that aids users in predicting rating or preference of associate degree item below users' thought. The systems supply users alternate picks while not having to figure out all the main points by themselves [3]. Recommender Systems (RS) will be a specific case of personalized information Retrieval during which there's no explicit query, however simply implicit info regarding the user's interests. The purpose of this prediction is to help users decide whether they want to buy, read, or view this item [2]. All recommender systems (RS) need a model of the users' interests to operate. We do this using explicitly or implicitly data, without ambiguity categorical their interests in things. On the opposite hand, implicit, feedback is generated by the RS itself, through inferences, it makes concerning the user's behavior. What constitutes implicit feedback depends on the application domain: generally, it'll be one or multiple evident and measurable parameters that arise out of the user's interactions with the RS [4]. In this research, we merge and use these two data implicit and explicit data from a million song data set (Last. Fm). A recommender system [5] has different filtering techniques:

a) Collaborative filtering is divided into item-based and model-based it finds the similarities between users' preferences.
b) Content based filtering find the similarities between items.
c) Demographic filtering recommends items to users based on demographic information similarities like age, gender, living area, education, etc.
d) Hybrid filtering it's a combination of collaborative filtering, content-based filtering, and hybrid filtering.

Figure 1 shows the difference between user-based filtering (collaborative filtering) and item-based (content-based filtering)

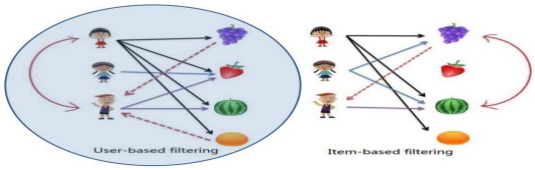


Fig 1.Difference between user-based filtering and item-based filtering.

In this paper, we focus on discuss recommender system steps to build a model and talk about recommender system challenges. We list some of the recommender system public datasets like million song datasets. We explain collaborative filtering techniques and types and how to compute the similarity measures. We demonstrate our new proposed algorithm that's used to solve sparsity, accuracy, and recommend to users novel items or songs while using precision, recall, and F measure metric.

The rest of this paper is organized as follows: a recommender system foundation in section II. Collaborative filtering discussed in section III. New proposed techniques described in detail in Section IV. Experimental evaluation in section V. Finally, a conclusion is given in Section IV.

II. RECOMMENDER SYSTEM FOUNDATIONS

In this section we will talk about recommendation system design guidelines and challenges facea recommender system. In this research, we will focus on sparsity, novelty, and accuracy to be solved in our new proposed algorithm and recommend novel items to users.

2.1 Design tips for Recommendation System

There are several works within the literature buildaccessible several guiding principles of the many aspects of constructing a recommender system. However, they deliver general principles that ought to guide the creating of a recommender once the initial technical selections are created [6]. During this section we will list several questions:

- a way to build a smart choose once begin with coming up with the system?
- Procedures: that recommendation procedure to apply?
- Design: a way to deploy a system, whether or not distributed or centralized?
- User summary: The information concerning users?
- Users: Active users and their objectives?
- Records: a style of a dataset and its features?
- Use: wherever will we have a tendency tend to apply the recommender?
- Why develop: The motives towards creating a recommender?
- Categories: the kind of suggestions provided by recommender?
- Metrics: Performance measures and metrics?
- Item ratings: the kind of ratings given by users?

An organized execution for the construct of advice system will finish in Java.

2.2 Recommendation system challenges [5]:

- Cold start problem: it's happens when we have a new product and new user to the system.
- Novelty and diversity: we have in the system new products to which user we will recommend this item and make our recommendation has more diversity to the user rather than which products he had seen on the system.
- Scalability: the ability to the system to work when the number of users and products on the system increased.
- Accuracy: we need to compute the accuracy of our prediction compared to the training data in the system.
- Sparsity: many users on the system buy a product and didn't rate the items they watch or purchase.

2.3 Recommendation system public datasets:

Researchers in the recommendation system need public data sets[8] to apply their experiments and algorithms to find the pros and cons of every algorithm, there are many public datasets has an implicit feedback and social information's and explicit data like million song data sets (Last.fm, LabROSA,TheEchoNest,MusicBrainz,Infochimps,7digital,musicXmatch,SecondHandSongs) every one of these datasets has different in size number of tracks and music tags, etc. Also, there are an public explicit datasets have a user's rating to items like (Netflix, Movie lines, Each Movie) [2] as seen in table 1 we list some of the current public data sets used today in recommender system techniques and size of data, number of users rating on items, number of users, number of items, rating styles and degree on data.

	Without social information						With social information (hosted by the GroupLens)		
	MovieLens 1M	MovieLens 10M	Netflix	Jester	EachMovie	Book-crossing	ML	Last.Fm	Delicious
Ratings	1 million	10 million	100 million	4.1 million	2.8 million	1.1 million	855,598	92,834	104,833
Users	6040	71,567	480,189	73,421	72,916	278,858	2113	1892	1867
Items	3592	10,681	17,770	100	1628	271,379	10,153	17,632	69,226
Range	{1,...,5}	{1,...,5}	{1,...,5}	−10, 10	[0,1]	{1,...,10}	{1,...,5}	Implicit	Implicit
Tags	N/A	N/A	N/A	N/A	N/A	N/A	13222	11946	53388
Tags assignment	N/A	N/A	N/A	N/A	N/A	N/A	47957	186479	437593
Friends relations	N/A	N/A	N/A	N/A	N/A	N/A	N/A	25434	15328
Items	Movies	Movies	Movies	Jokes	Movies	Books	Movies	Music	URL's

Table 1: public datasets of recommendation systems

III. COLLABORATIVE FILTERING

Collaborative filtering algorithm is a type of recommendation system widely used and successfully algorithms it's building a model using user rating to gain more novelty and diversity between recommended items to the user. However, collaborative filtering faces challenges of sparsity and recommendation accuracy [9].

3.1 Collaborative filtering algorithms guidelines :

There are general main steps to build an algorithm:

1. Every rated item by active users is retrieved.
2. We compute the similarity by a set of retrieved items to find the targeted users. We will find the k nearest neighbors of target items with similarities.
3. Target item prediction computed by sum weighted for active users rate on the k nearest similar items.

Collaborative filtering [10] divided into two categories:

1) Memory-based (Also, named as user based): this algorithm takes into concern the previous user-item rating to make the next prediction for this user. It has two main sections to compute the similarity: A user- item filtering fined the similarity between users rating items. In contrast, item–item filtering its compute similarity between users like this item and other items similar to this item's specification rated by other users in the system.
2) Model-based: this algorithm it's used to predict rating to items we will recommend to the user using machine learning this algorithm shown in figure 2 and broken into three subtypes.

3.2 Collaborative filtering Techniques used to solve sparsity:

In this section, we are going to talk about different collaborative filtering techniques wont to solve the sparsity problems and list some advantages and disadvantages for collaborative filtering recommendation. Data mining like (dimensionality reduction, association rule mining, web mining) used to solve sparsity by taking into a priority to search out find hidden patterns and relationships between items and users toanalyze users shopping behavior. Data mining techniques [11] have no sparsity problems and sensitive to the modifications of user preferences and it's sensible with hybrid recommendation techniques. However, its main disadvantage is that the issue of a way to understand the techniques and the way we can match inputs on datasets.

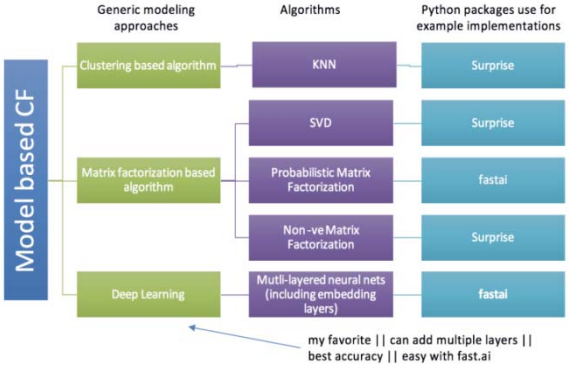


Fig 2. Model-based algorithm types of collaborative filtering approach.

Dimensionality reduction disadvantage [12]:

- Whereas reducing the dimensionality may result in lost useful information.
- Clustering based mostly used historical rating data to create clusters, but it ignores other data resources like social connections of users and also the correlations between items.
- It doesn't affect the modification in user preferences.

Association rule mining [12]:

- It doesn't take into concern the number of times the user used this item or purchase it per transaction.
- Ability to process with the massive number of items and users while applying association rule mining.
- Take into account only for correlations between items no user's profile data.

Implicit Feedback [12]:

- Recommendation process based on tracking users preferences behaviors like viewing list, liked items, preferred items in profile. It's good with hybrid techniques also; it needs to analyze user behaviors [13].
- Whereas finding similarity between users and items some, information lost while converting implicit data between purchased this item or not.

3.3 Collaborative filtering Similarity measures:

Collaborative filtering [12] calculates the similarity between two users or two items by matching the correlated items rated by both users. The most famous similarity measures are the Pearson correlation coefficient, cosine similarity.

Cosine Vector Similarity [14] (CVS) equation 1

$$W_{Xy} = \frac{x \cdot y}{|x| \times |y|} = \frac{\sum_{i=1}^{n} (r_{Xi})(r_{yi})}{\sqrt{\sum_{i=1}^{n} (r_{Xi})^2} \sqrt{\sum_{i=1}^{n} (r_{yi})^2}} \quad (1)$$

Pearson's Correlation Coefficient [15] (PCC) equation 2

$$w_{Xy} = \frac{\sum_{i=1}^{n} (r_{Xi} - \overline{r_x})(r_{yi} - \overline{r_y})}{\sqrt{\sum_{i=1}^{n} (r_{Xi} - \overline{r_x})^2 \sum_{i=1}^{n} (r_{yi} - \overline{r_y})^2}} \quad (2)$$

Where x and y are users rated a number of items n. The average rating of item x is rx and an average rating of item y are ry. The weight measures between the preferences /interests of users are WXy □ [-1, 1].also rxi and ryi are the ratings of the users x and y on item i. the similarity between active users are measured by any of these two equations. We can use eq (3) to predict the weighted average of rating on items like j by the formula predXj by using all neighbors of active users. The set of neighbors is represented by K..

$$pred_{Xj=}\overline{r_x} + \frac{\sum_{y=1}^{k} (r_{yj} - \overline{r_y}) \times w_{xy}}{\sum_{y=1}^{k} |W_{Xy}|} \quad (3)$$

Although, these equations used to compute the similarity[12] are successful in finding the nearest neighbor users but have some difficulty to find this when data are spare because many users don't like to rate viewed or purchased items and a large number of items on the system.

IV. NEW PROPOSED TECHNIQUE

In this section, we will discuss our new proposed technique used to increase the accuracy of predicted items will be recommended to users also solve the sparsity problem by using the merging between implicit and explicit data. Our data sets are part of million song data sets is last.FM datasets [16] used from the research paper [17].

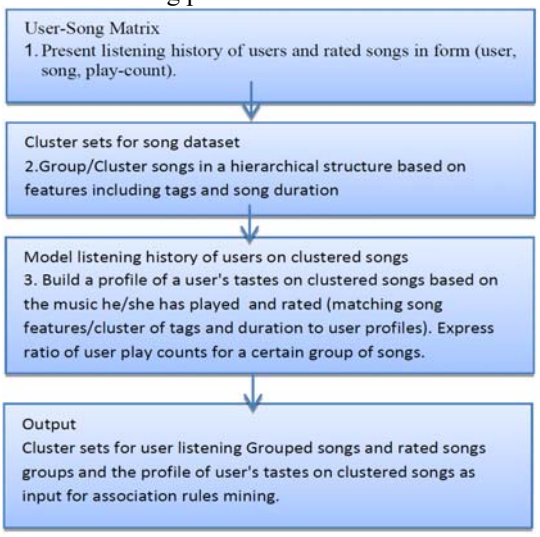
Our new techniques are best compared to the basic collaborative filtering techniques. The main advantage of our proposed algorithm is how to find the correlation between items in a spare data this be solved by using implicit data(Songs played, number of play counts to a specific song, play ratio for certain category of songs and tagging information.). Also, a similar behavior pattern can compute easily with our new algorithms this lead to a good recommendation.

The main idea we solve in this technique where data are spare in this case users don't have any co-played music, and we need to find similar preferences on a pop music as an example.

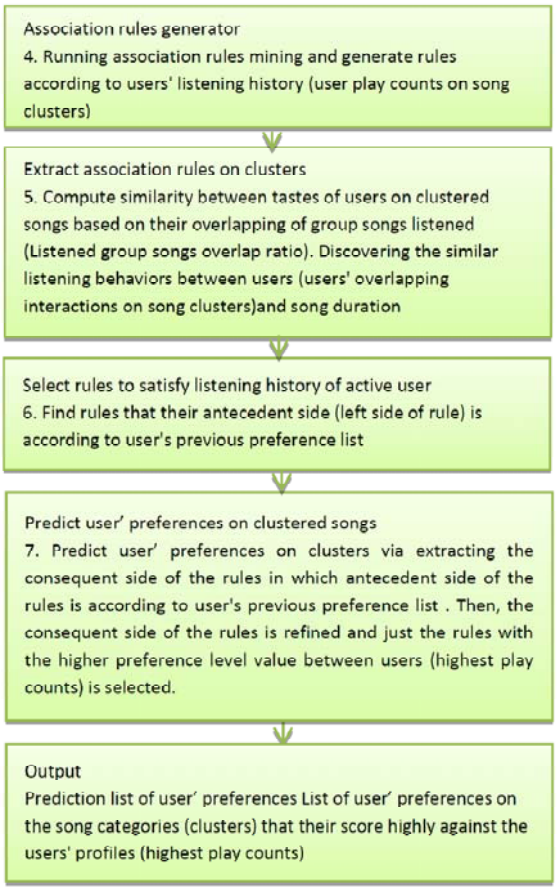
However, such a result is not right in more sparse rating data in basic collaborative filtering techniques. Even though both users do not have any co-played music, both of them are fans of pop music. Thus, we should consider them to be similar in case that they are sharing a very similar preference for pop music. We will compute the similarity between users on played songs groups by applying the clustering techniques and association rules to find hidden items between active users or users interested in items available on the system.

We will discuss the proposed algorithms phases:

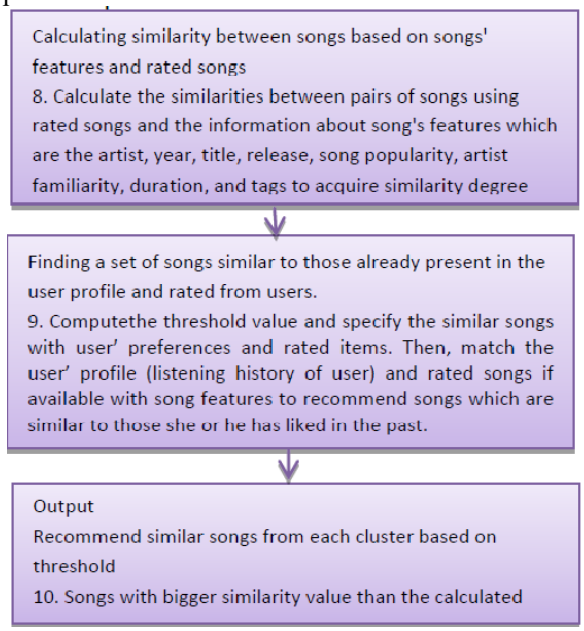
Phase I: Pre-processing Reducing data dimensionality for the rule mining part



Phase 2: Prediction process on users' unknown preferences based on association rules mining



Phase III: Recommendation Recommend a list of songs available in each cluster that match the user' preferences.



V. EXPERIMENTAL EVALUATIONS

This section will show the results of our experiments on last.fm million song data sets with merge between

implicit and explicit data to improve the accuracy of recommendation systems [16, 17]. We will compare our algorithm with traditional collaborative filtering techniques while a change in the data sparsity level.
This paper will focus in the music recommendation only so that we use million song datasets [6] because it's largest and free datasets in music domain. It is constructed from about one million songs and users, in which each user plays a small set of songs. These datasets have implicitdata for users' preferences and has item matrix spare and Last.fm dataset for tagging activity on songs.

5.1 Experimental methodology and evaluation metrics

We use precision and recall equation to measure the accuracy and evaluate these data sets between our new algorithm, and basic collaborative filtering [18].
The precision measure [18] the ability of the system to return relevant items among a set of irrelevant and relevant items and it's calculated by the equation (4) and description for accuracy metric seen in table 2.

Precision=TP/(TP+FP) (4)

The Recall measure [18] the ability of the system to return the relevant items only and it's calculated by the equation (5).

Recall=TP/(TP+FN) (5)

Predicted items/actual	Relevant	Irrelevant
Recommended	True Positive (TP)	False Positive (FP)
Not recommended	False Negative (FN)	True Negative (TN)

Table 2: RECOMMENDATION ACCURACY METRIC

Another evaluation metric is F measure [18] used to find the difference between precision and recall function and to an equal weight of each of them. The metric equation is (equation 5). It's higher result mean higher accuracy of recommendation.

F-measure = (2*Precision*Recall) / (Precision + Recall) (5).
We focus on number rated songs(this an explicit data) on user profile from 5-1 this will indicate the users which rate 5 to a song he is very likely it and rate from 2-1 he dislike this song. Also, we focus on user profile preferences implicit data we divide data into categories from 5-1 depending on the high number of playing or listing songs in such way the song In range 80-100% this like the rating 5, and songs from 1-20 % this like rating 1. Then we build a user-item rating matrix we will compare with basic collaborative filtering. That's the firstly preprocessing step. In order to find similarities and train models based on user profile preferences like (user-song-play count) 80% as a training dataset and 20 % as a test datasets. These steps applied to last.FM million song datasets.
We cluster data sets into three clusters determine the songs level like (level 0 – all songs), (level 1- songs tags (pop, rock, jazz, etc.)) and (level 3 – song duration (very short- one minute or less, short – from 1 minute to 3, medium form 3 minute to 5 , long- from 5 minute to 8, very long- more than 8 minute)).this used to help association rule mining by defining optimal numbers of clusters and used the songs durations to build it . Also, we need to reduce the size data send to the association rule to get the best performance extraction of an association rule.
After this firstly preprocessing step, we construct datasets with a sparsity level according to play count for songs. We classify data into ten groups sparsity levels from listing records, and it's level between (0.2 to 0.4), (0.4 -0.6),(0.6-0.8)and (0.8-1.0) the last one has the highest sparsity. Equation 6 calculates the sparsity level [13].
Sparsity measure = 1- (nR/ nUsers _ nItems) (6)
The symbol nR total number of play counts and nUsers number of users and nItems are a number of items or songs on the user-item matrix.

5.2 Experimental environment

We run our experiments on a framework machine 16 GB of RAM and Intel Core I7 CPU and windows 7. We used IntelliJIDEA software to write java programming code to run our recommender systems. Also, we used the WEKA environment to apply association rule and clustering-based techniques in our new algorithm.

5.3 Experimental results

In this section, we run our four experimental according to the sparsity level we mentioned in the previous section, and we show the difference accuracy result from our new proposed algorithm against basic collaborative filtering techniques. Table 3 shows the result of accuracy from precision, recall, and F-measure metric. Also, we need to mention that we used the merge datasets between implicit and explicit last.Fm data sets [13] to find high accuracy level about recommended items or songs to users.

Techniques	Sparsity from (0.2-0.4)		
	Precision	Recall	F-measure
Basic CF	0.54	0.71	0.61
New proposed techniques	0.96	0.64	0.76
Techniques	Sparsity from (0.4-0.6)		

	Precision	Recall	F-measure
Basic CF	0. 63	0.7	0.66
New proposed techniques	0.93	0.64	0.75
Techniques	Sparsity from (0.6-0.8)		
	Precision	Recall	F-measure
Basic CF	0.57	0.6	0.58
New proposed techniques	0.95	0.62	0.75
Techniques	Sparsity from (0.8-1.0)		
	Precision	Recall	F-measure
Basic CF	0.52	0.53	0.52
New proposed techniques	0.89	0.6	0.71

TABLE 3: Experimental results

According to the values in table 5, and the results are shown in figure 3 and figure 4 through the sparsity level, the accuracy with basic CF its decrease while the sparsity increased. But, our new algorithm controls the accuracy through the sparsity level against basic CF and improved by 22 % this because of the ability to find neighbors and association rule to recommend items to users and merging the implicit and explicit data (rating values to songs).

The value for precision in our proposed algorithm is good because we recommend less number of not matching songs to the user. We have a higher precision value it's improved by 37% .the recall based on songs not recommended to users, and it's improved in our algorithm by 10%.the F measure it's improved by 17% so that our proposed algorithm is the best in recommended songs to users.

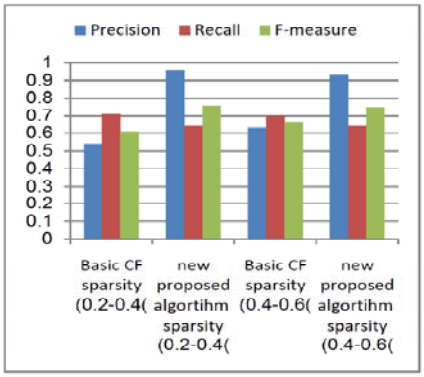


Fig. 3 experimental result while sparsity level from 0.2-0.6.

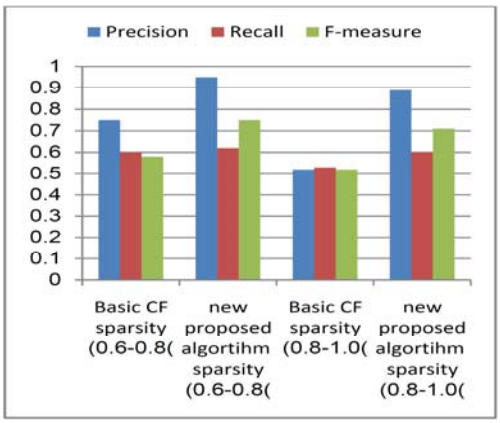


Fig. 4 experimental result while sparsity level from 0.6-1.0.

Our proposed algorithm advantages:

1. The ability to recommend items using user preferences not only rated items using users' item tags and a number of play count for songs.
2. We are merging between explicit data and implicit data to improve accuracy.
3. The ability to control accuracy while sparsity increased.
4. We use a number of playing count with association rule to find hidden relationships between users.
5. We can recommend to users songs similar to his preferences and ability to recommend novelty and diversity songs which, is one of a recommended items challenges.

VI. CONCLUSIONS AND FUTURE WORK

Recommendation systems are the most research area today. Due to the rapidly increasing in data size and social media information about users will help us to recommend items to users more accurate and the importance of big data [19]. In this research paper, we used the million song datasets (last.fm) it's a type of implicit data merged with explicit data users rated songs to improve the accuracy of prediction. we apply our experiments on a different level of sparsity, and our new algorithm improves in accuracy through F measure by 15% it's relevant to best accuracy result against basic collaborative filtering techniques which suffer from finding neighbors where data are spare and our algorithm also solve the novelty and diversity challenge to recommend songs to users.

In the future, what about applying this algorithm with big data sizes [20, 21] and using spark to improve recommendation systems [22]. Also, change the type of data like movies and apply our new algorithm then compare this algorithm with other recommendation systems techniques like k-means, hybrid representations, probabilistic learning.

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