A hybrid recommender system using Multi Layer Perceptron Neural Network

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Abstract*—Recommender systems try to personalized preferences, obviously this predicting based on previous users taste. Many RS suffer from Cold-start problem, it pertains to the issue which the system cannot invoke any reasoning for users whom they have not yet accumulated proper information. In this paper, we will propose a hybrid recommender system based on collaborative filtering (CF) techniques and content-based filtering (CBF) which combined by artificial neural network (ANN) to be an appropriate model for both cold-start and ordinary users. In our proposed method, Mutual Information techniques help us to select the best property to make our model. The comparison is performed on MovieLens and Netflix datasets. Our results show that our prediction results are more accurate than other methods with the same dataset.

***Keywords*— Recommender system; semantic filtering; Content-Based Filtering; collaborative filtering; accuracy**

I. Introduction

Widespread using the Internet is the basis of quick development of e-business. Methods of exchanging are a controversial issue among organizations and customers, due to the rapid spread of the internet in various aspects of our life. Plenty of research has been carried out to support and provide online shopping. This process leads to saving time during shopping against traditional methods. Indeed the e-business environment provides this facility to customers [1].

The online shopping environment provides information evaluation, commodities comparison and making recommendation among related items to customers for making a better decision in less time and also saving money to obtain practical information of purchase.

Websites in the field of e-business provide personal and customized services which are the most popular as well as the most practical services to make a relationship with customers and also apply business and merchandise classification [2].

Attractive design and providing practicable services lead to improving the relationship with customers and competition capability. It is a powerful incentive to find a solution for solving this issue which is titled data overflow.

Now there are two different solutions are introduced by researchers. Utilizing information recovery and information filtering concepts for the first solution which the lack of recognition inferior items is the majority limitation of these concepts about providing a recommendation. This disadvantage leads to providing another solution with the title of recommendation systems. These systems have solved the problem of the prime solution [2]. The recommendation systems play a key role to provide offers according to customers' requirement among a huge number of items in the virtual environment. Therefore, plenty of research has been carried out on this issue [3, 4].

Recommender systems generate personal recommendation by analyzing customer behavior because of their smart features [5]. They have widespread applied in various practical applications, for instance: recommend movies[6-9], music[10], books[11], tourism[12], hotels[13], restaurant[14], TV programs[15], electronic payment[16], documentaries[17] and news channels[18]. Lack of progress in the process of selection is a common problem for users because they will be encountered to the huge amount of information, therefore they would be suffered to find their favorite item. To solve this problem, designing practical algorithm have been paid attention. These algorithms can be divided into two categories: 1) Content-based recommender algorithm [19], it predicts based on similarity of content with former items which have been ranked by them [20]. 2) Collaborative filtering [21], which they will apply recommendations based on users' settings [22].

Selecting appropriate feature in both categories is a prime method of pre-processing of data which it implies to learn machines and recognize models. The technique utilizes frequently in the probability theory and theory. It contents various information such as classification and regression. One of the accepted methods for measuring tendency in the filtering methods which utilized by researchers is Mutual Information (MI) [23].mutual information is a criterion to demonstrate linear and non-linear tendency measure between

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two random variables. The mutual information theory has been used to choose practical feature in this research.
The collaborative filtering approach is suffered from the cold-start problem. The cold-start problem can divide into two categories: 1) items cold-start2) Users cold-start.
For instance : the second category will explain the new user who has been logged in recently and there is no background of its behavior in the system. In this situation, the recommender system cannot offer appropriate item. This inefficiency leads to working system improperly. The different approaches have been provided by the researcher to offer an appropriate recommendation to users who have been registered recently. Some research focused on users who there are less recorded favorites items and score in the system. On the other hand, some research result is about cold-start problems. These method work based on demographic information [24], other users' comments [25, 26] are social tags [27, 28]. This article utilized demographic information for preventing the cold-start problem.
This paper is in 6 separate phase: Phase 2 is a summary of related works. The proposed technique is said in phase 3. Section 4 is allocated to the test and results. In the end, Section 5 gives the consequence and proposed subsequent works.

II. Related Work

Recommendation strategies have some of the feasible classifications. Of hobby on this dialogue isn't always the form of jointing or the houses of the user's interplay with the recommender, but instead the resources of information on Which recommendations are fully utilized and those records are placed?. specifically, recommender structures have (i) history data, the facts that the system has the advice method starts off evolved, (ii) input records, the records that consumer ought to speak to the machine a good way to generate a recommendation, and (iii) a set of rules that combines historical past and input facts to reach at its recommendations. Assume that I is the set of gadgets over which pointers are probably made , U is the set of customers whose alternatives are mentioned, U is the consumer for whom guidelines want to be generated, and that I is a few objects for which we would love to anticipate U's preferences [29, 30, and 54].
The recommender device approach is to collect the earlier ratings specific by way of customers after that are expecting the new rating of unknown items after which endorse the best rating items to users. Numerous techniques had been created to discover right answers, commonly admitted that the collaborative filtering strategies are more awesome and useful than content material-based totally methods. There are corporations of recommendation techniques for collaborative filtering:
• model-based totally strategies expect that there are essential hidden features to define how a person rates an object. If you could find these then the techniques can expect a score.
• memory-based also known as community or ok nearest associates methods are heuristics that expect score based totally on the score that customers granted to all preceding objects.
Pearson Correlation Coefficient measure is the most common similarity formula for collaborative filtering approach [31, 32, and 33]. Numerous Statistical Coefficients might utilize as comparability measures for Collaborative Filtering recommender machine. The very last aim in Collaborative Filtering is get fixed of buddies which can be closed as viable as given energetic consumer by means of using similarity measure that more advantageous the accuracy[29]. Traditionally, the gathering of statistical metrics was utilized in Collaborative Filtering in conjunction with the cosine, Euclidean, Pearson Correlation Coefficient, constraint Correlation, and mean-squared variations and; the relatedness concept became introduced to provide the significa nce of the relationship among customers and objects [55-58]. Table I indicates a class of the content-based CF similarity degree.PIP known as exploratory similarity scale that better than traditional actuarial similarity measure such as Pearson Correlation, cosine, etc. [59]. UERROR known as forestall first real ratings and subsequently recognize divination errors for each user, and NCS is a metric based on neural science (model-based collaborative filtering) and suited for cold-start users [60].

TABLE I. EXAMINED COLLABORATIVE FILTERING SIMILARITY SCALES

Description	**Methods**		
	Not based on models Not trust extraction	***Trust Extraction***	***Model-Based***
conventional Not (it is not appropriate to cold start users)	JMSD,CORR,CCOR R,COS,ACOS,MSD, EUC		GEN
opportune to cold-start users	PIP	UERROR	NCS
General ratings	SING	TRUST	

Equation (1), offers the PCC components for computing correlation among customers x and y.

$$pcc_{x,y} = \frac{\sum_{i\in I}(r_{x,i}-\bar{r}_x)(r_{y,i}-\bar{r}_y)}{\sqrt{\sum_{i\in I}(r_{x,i}-\bar{r}_x)^2}\sum_{i\in I}(r_{y,i}-\bar{r}_y)^2} \quad (1)$$

Content-based recommendation systems examine object description to pick out objects that are of unique interest to the customer. Due to the fact the information of recommendation, systems vary based at the representation of items. The immoderate degree structure of a content-based advice technique is executed in 3 steps, every of that is dealt with by way of a separate element:

A. CONTENT ANALYZER

At the same time as information's has no structure (e.g. textual content), a few kind of pre-processing step is needed to extract structured relevant facts. The principle responsibility of the main responsibility of the element is to symbolize the content of items (e.g. documents, internet pages, information, product descriptions and so forth.) coming from information resources in a shape appropriate for the following processing steps. Data items are analyzed via characteristic extraction techniques to be able to shift item representation from the unique information area to the goal one (e.g. web pages represented as keyword vectors). This illustration is the doorway to the profile learner and filtering element; on this section, we use the mutual information; Mutual information is one of many quantities that measure how a great deal one random variable can tell us approximately another objects. It is far as a dimensionless quantity with (commonly) module of bits and can be perception of as the reduction in doubt about one random variable is givens expertise of every other. Excessive mutual statistics represents a large decrease in uncertainty; low mutual information illustrates a light discount, and zero mutual data suggests the impartial between variables.

B. PROFILE LEARNER

This unit gathers record adviser of the user preferences and attempts to generalize the information that lets you to gather the users' profile. Typically, the generalization method realized via machine learning strategies [34], which may be in a position to infer a version of individual hobbies beginning from items favored or disliked within the past. For example, the profile learner of an internet page recommender can accomplish a connection feedback method [35]which the getting to recognize technique combines vectors of useful and penurious examples into a prototype vector representing the consumer preferences. Study examples are internet pages on which a amazing or poor feedback has been supplied by using the user; in this phase, we use items and customers demographic information; Demographics are characteristics of a populace. Traits inclusive of race, ethnicity, gender, age, education, profession, occupation, income level, and marital repute.

C. FILTERING PART

This unit extracts the users profile to define related items by conform the profile delegation to that item to be recommended. The end consequence is a duplex or non-stop relation decision (computed using some similarity metrics [36]), the latter case resulting in a classified object of possibly thrilling items. Inside the above-cited instance, the matching found out by way of calculation the cosine similarity between the archetype resultant and the object resultants. in this section to analyzing data and recommend item we used regression tree; Decision tree learning uses a selection method to perception related to items to inferences about the object's goal value (displayed in the leaves). It's one of the prediction modeling method applied in information, machine learning and census mining. Tree methods, which the aim changeable can take a divided set of values that mentioned to cluster; in the ones tree constructions, leaves form of clusters and the branches illustrate connection of capabilities. Decision trees that contain consecutive values named regression trees.

III. RESEARCH METHODOLOGY

The framework of the proposed system is given in Fig. 1.As shown in Fig. 1, the framework is combination of two recommender's systems well-known algorithms contains Collaborative Filtering (CF) and Content Base Filtering (CBF).

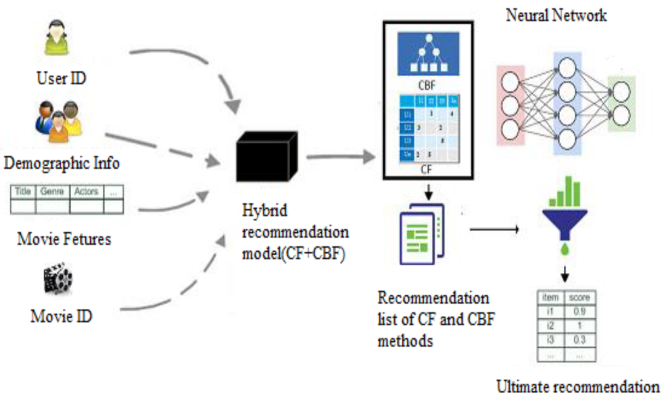

Fig. 1. Research methodology

We can make clear our strategies little by little until we get the result:

1- So as to analyze the proposed gadget, experiments have done the use of the Movielens dataset; the GroupLens research venture on the University of Minnesota accrued the dataset (www.grouplens.org/.../datasets/). This data set includes 1,000,000 scores (inside the variety 1–five) from 6040 customers on 39000 films; and Netflix dataset, This database carries training facts within the shape of approximately 100 million ratings from approxim ately 480,000 users on 17,770 films. Every rating in this database is an integer between one and five. A probe set is provided which can be used to test algorithms. Furthermore, Netflix posted a qualifying set which consists of person-item pairs however no rankings (the gadgets correspond to movies on this database). The ranking of a submitted answer is based totally on this facts set.

2- One of these matrices includes the User_Id_Number in rows, Item_Id_Number in columns and their scores in variety 1 to 5 within the right cell that we know as User_Item_matrix as display in Table II. Generating user/item matrix based on score matrix.

TABLE II. USER_ITEM_MATRIX

	User IDs				
Movie IDs		1	2	3	4
	1	5	3	?	2
	2	3	5	?	1
	3	?	?	1	5
	4	4	2	?	?

3. Calculation of similarity by Pearson Correlation Coefficient (PCC) based on users as shown in Table III,

TABLE III. USER_USER_MATRIX

	User IDs				
User IDs		1	2	3	4
	1	1	0.5	0	0.8
	2	0.5	1	0.1	1
	3	0	0.1	1	0
	4	0.8	1	0	1

4. Prediction the score of items which have not got score yet in the similarity matrix by Pearson Correlation Coefication as shown in Table IV.

TABLE IV. USER_ITEM_SCORE-MATRIX

	User IDs				
Movie IDs		1	2	3	4
	1	5	3	1	2
	2	3	5	2	1
	3	1	3	1	5
	4	4	2	1	1

5. Specifying appropriate feature by mutual information
6. Creating regression tree based on users demographic information and movie ontology information
7. Prediction the rate of items in the regression tree which have not got score yet.
8. Compute RMSE, MAE for our data.
9. Combination the predicted score and the ultimate prediction array by perceptron neural network.
10. Compute RMSE, MAE for last recommendation list.

IV. EXPERIMENTAL RESULT

A. Datasets:

Right here we are going to measure our model via quantitative measures. MovieLens 1M and NetFlix databases have used to calculate our technique in other to they appointed reference in the research letter.

B. Assessment metrics:

Comparing recommender systems are viable in exclusive ways.

$$RMSE = \frac{\sum_{i=1}^{N} |p_i - q_i|^2}{N} \tag{2}$$

$$MAE = \frac{\sum_{i=1}^{N} |p_i - q_i|}{N} \tag{3}$$

RMSE (Root mean squared error) and MAE (mean Absolute error) are statistical metrics that computes variations between the anticipated ratings and the real one. the first metric that we used to assessment our studies method is RMSE, squares the variations among the real and expected scores over all items, and then averages and roots the summation .RMSE can be defined as (2), [37].The MAE (mean Absolute blunders) measures is the other one metric that we observe .it computes the common distance among real object rankings and new rankings that expected for object. The end result of the MAE is better whilst it suggests lower fee [38]. Equation (3) represent MAE formula .wherein in closing both equation pi is the predicted rating for item i , ri stands for the real rating for object i , N denotes the total variety that evaluate score.

C. Effects and evaluation

On this section, we will examine our proposed system as a model aimed at registered users. We have been contrasted our proposed method with special strategies designed for registered users. So, The following details are available: 1) Some of the registered users is separated in two: The training set: 80% of users in dataset is selected randomly; The Test set: 20% of users is selected randomly. 2) We consider the users from test set don't have any rating in training set. 3) We try to predict rate that user Ui give an item by our proposed hybrid method. The forecast results compared with the actual rating .By MAE and RMSE measures, Experiments compared in the similar database situations.

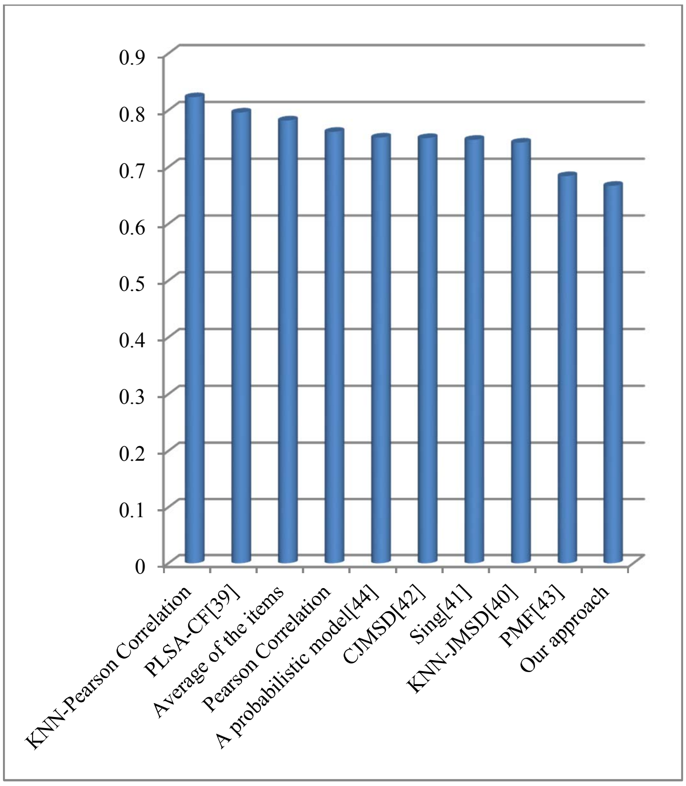

Fig. 2. MAE of different techniques for MovieLens

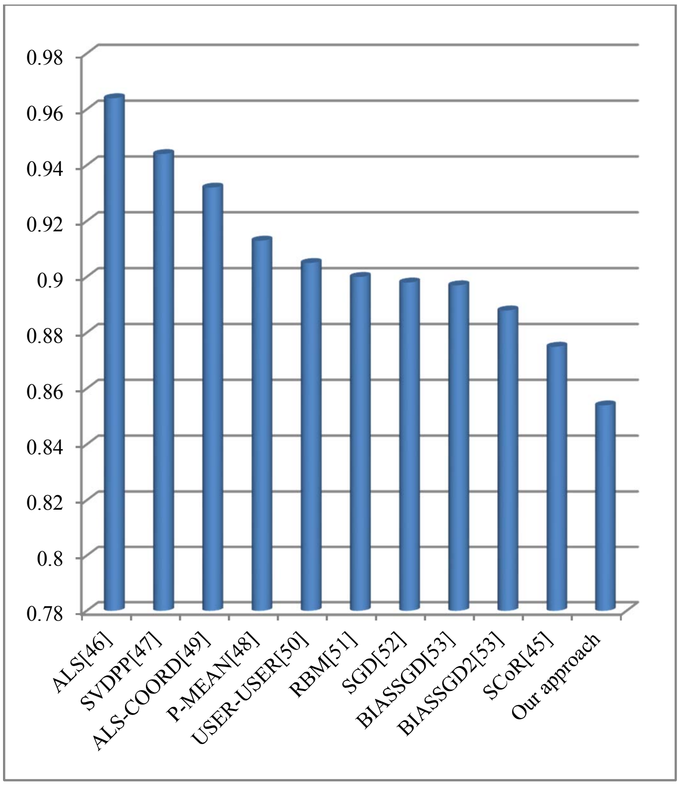

Fig. 4. RMSE of different techniques for MovieLens

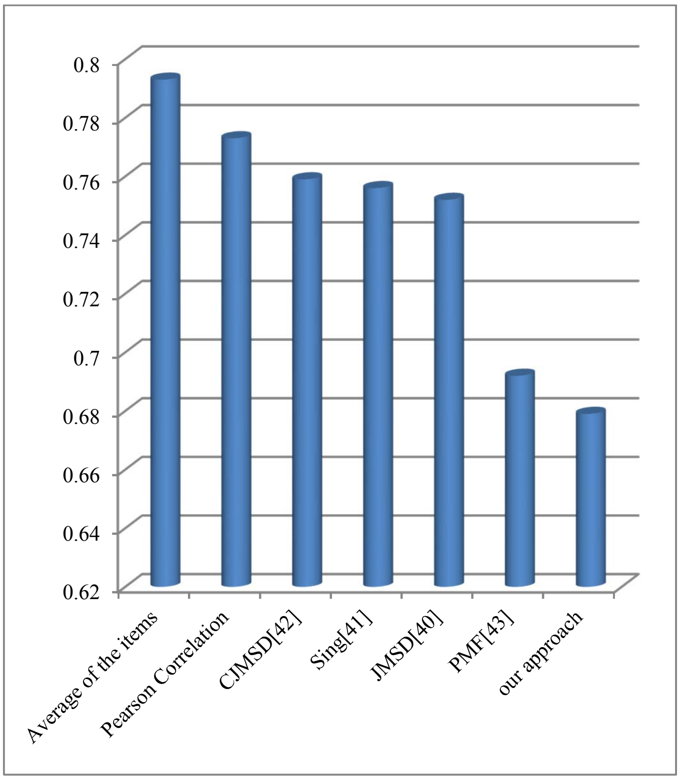

Fig. 3. MAE of different techniques for Netflix

IV. CONCLUSION AND FUTURE WORK

We proposed a hybrid recommender systems based on collaborative-filtering and content-based filtering which contains property of information such as: demographic information of users and item semantic informati on, similarly to the essential statistics of ranking given by manner of customers to objects. We executed the object-based definitely ontological semantic filtering to rent the underlying semantic relationships amongst items, person-based definitely demographic information to discover users gr eater exactly, and using MI to select the relevant feature for create an appropriate regression tree. RMSE and MAE are used to calculate forecast accuracy our method in real time by Movielens and Netflix datasets. Experimental effects show that the aggregate of CBF and CF methods resulted in the development of recommender systems forecast accuracy contrasted to the opposite associated methods. Conjunction of mutual information has ended in addition development of the forecast accuracy of the recommendation systems. This work can be improved.

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