Hybrid model for movie recommendation system using content K-nearest neighbors and restricted Boltzmann machine

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Article Info

ABSTRACT

One of the most commonly used techniques in the recommendation framework is collaborative filtering (CF). It performs better with sufficient records of user rating but is not good in sparse data. Content-based filtering works well in the sparse dataset as it finds the similarity between movies by using attributes of the movies. RBM is an energy-based model serving as a backbone of deep learning and performs well in rating prediction. However, the rating prediction is not preferable by a single model. The hybrid model achieves better results by integrating the results of more than one model. This paper analyses the weighted hybrid CF system by integrating content K-nearest neighbors (KNN) with restricted Boltzmann machine (RBM). Movies are recommended to the active user in the proposed system by integrating the effects of both content-based and collaborative filtering. Model efficacy was tested with MovieLens benchmark datasets.

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1. INTRODUCTION

Recommender system [1] is preferable in the era of information overload to help users discover interesting things from an extensive collection of data. Collaborative filtering (CF) [2], [3] algorithms are commonly used to create recommender systems because they efficiently use the users' rating information. An item rating matrix can be used to explore other invisible or unfound items for similar users. Hybrid RS combines CF recommendation and content-based RS. The CF-based recommendation is applicable in many application domains [4], [5]. Model-based Collaborative filtering approach uses many machine learning [6] based models such as Random forest [7], support vector machine (SVM) [8], and matrix factorization [9] for predicting the users' likeness. It is estimated that many streaming services companies create a lot of revenue by applying movie recommendation techniques. Various models have been proposed to improve the productivity of the movie recommendation [10] framework.

CF methods are broadly divided into two categories: memory-based and model-based. In a sparse data set, the memory-based model does not perform well, unlike the model-based CF. K-nearest neighbors [11]-[13] based model is successfully applied in many classification models. RBM [14] has attained much attention in recent CF literature, as it has a compatible graphical structure with SVD and PMF. Salakhutdinov *et al.* [15] demonstrated the use of RBM in CF and scored 6 percent higher than the standard baseline predictor system of Netflix. It also serves as building blocks for DBN architecture [16] and many other deep learning [17]-[19] models.

Chunchun Li and Jun Li [20] have used dual cRBM to address dual user and item patterns. In their model rating matrix reflects a latent matrix of features. They used separate RBM for each user, proposing a restricted RBM (cRBM) recommendation for Netflix movies.

The Content-based recommendation focuses primarily on movie description or details, while CF focuses on user ratings for the movie. If rating information is considered, it is possible to collect extremely sparse data as few consumers choose to give the rating of the product after purchase. RBM, along with Content KNN, is used to address this issue. Fischer and Igel [21] discussed different RBM learning algorithms such as CD and parallel tempering. The modified CD algorithm called 'Lean Contrastive Divergence' was proposed by Ning *et al.* [22] to increase the speed of the learning and prediction process. Pujahari *et al.* [23] proposed a CF model by taking the preference relationship as an input to RBM and by combining the side information of the movies, trying to generate the ranking of the items. Kilani *et al.* suggested a hybrid RS [24] based genetic algorithm using MF and KNN that uses both latent factor and neighborhood data to recommend items to an active user. In literature it is shown that ensemble models [25], [26] works better in text-based analytics [27]-[29], intrusion detection[30] and in classification of sounds signals [31].

The content-based KNN works well by finding similarities between movies based on the movie's descriptions and other attributes. It does not depend on the users' rating. In comparison to the CF model [32], RBM performs well in large databases. Contributions of this work are stated as below:
- Studying the impact of various similarity measures in user-based and item-based collaborative filtering.
- Designing a recommender system to deal with the sparse dataset by using the movies' profile such as year of release, genre, and description features.
- Designing a model-based recommender system using Restricted Boltzmann Machine.
- Proposing a weighted hybrid model based on content KNN and RBM for capturing both content-based filtering and higher-order model-based collaborative filtering.

2.   RESEARCH METHOD

Consider U as the consumer vector; and M as the movie vector where p, q is the user and movie numbers, respectively. R is the matrix with the form p x q. r_{um}, $\hat{r}_{um}$ denotes the real rating of the consumer 'u' for the movie 'm' and the expected ratings. The similarity between user 'u' and user 'v' can be calculated using (1) [33]. $\bar{r}_u$ and $\bar{r}_v$ represents the average rating of user 'u' and user 'v', respectively. Rating of user 'u' for movie 'm' can be calculated using (5).

$$sim_{u,v} = \frac{\sum_{m \in M_{uv}}(r_{um}-\bar{r}_u)(r_{vm}-\bar{r}_v)}{\sqrt{\sum_{m \in M_{uv}}(r_{um}-\bar{r}_u)^2}\sqrt{\sum_{m \in M_{uv}}(r_{vm}-\bar{r}_v)^2}} \tag{1}$$

$$M_{uv} = M_u \cap M_v \tag{2}$$

$$\bar{r}_u = \frac{\sum_{m \in M_{uv}} r_{um}}{|M_{uv}|} \tag{3}$$

$$\bar{r}_v = \frac{\sum_{m \in M_{uv}} r_{vm}}{|M_{uv}|} \tag{4}$$

$$\hat{r}_{um} = b_{um} + \frac{\sum_{v \in N_m^k(u)} sim_{u,v} \cdot (r_{vm}-b_{vm})}{\sum_{v \in N_m^k(u)} sim_{u,v}} \tag{5}$$

$b_{um} = \mu + b_u + b_m$ is u's baseline estimate [34] for movie m.

The parameters b_u and b_m indicate user 'u' and movie 'm' rating deviations. Generally, stochastic gradient descent (SGD) or alternating least squares (ALS) algorithm solves these parameters. To find similarities between movies 'x' and 'y', modified cosine-similarity measure in (6) is used.

$$sim_{p,q} = \frac{\sum_{u \in U_{xy}}(r_{ux}-\bar{r}_u)(r_{uy}-\bar{r}_u)}{\sqrt{\sum_{u \in U_{xy}}(r_{ux}-\bar{r}_u)^2}\sqrt{\sum_{u \in U_{xy}}(r_{uy}-\bar{r}_u)^2}} \tag{6}$$

The problem with this baseline is that to find similarity between user 'u' and 'v', the ratings provided by user's 'u' and 'v' are taken into account. It does not fit well in sparse data.

2.1. RBM

RBM is an energy-based, probabilistic model with only two layers of the neural network structure: a hidden layer and a visible layer. This two-layer network has the restriction that there is no connection between two nodes in the same layer. It is commonly used in collaborative filtering to learn the distribution of probability over a ranking matrix. This network is trained through gradient descent and backward propagation, where each iteration is having a forward pass and backward pass (reconstruction). Information exchange between neurons in the same layer is limited in RBM. There is a relation between two separate layers of neurons. RBM is trained in forward and backward passes, and the inputs are rebuilt in the backward pass. This is achieved over several epochs before it converges on a set of weights and distortions that minimizes the reconstruction error.

It describes a distribution over V with a layer of binary secret unit 'h'. The input layer V is a matrix of k × m dimension and $V_p^k = 1$, if user rating for the movie 'm' is 'k'. The likelihood of each visible/input binary matrix V column is modeled with the distribution "Softmax." Hidden user functions 'h' is likely to be modeled with sigmoid function. The energy of the state (V, h) is given in (7) [21].

$$E(V, h) = -a^T V - b^T h W - h^T W V \qquad (7)$$

In the learning process, the training vector V's log-likelihood to weight can be determined using (8).

$$\frac{\partial loglog\ prob(V)}{\partial W_{pq}} = \langle \vartheta_p h_q \rangle_{data} - \langle \vartheta_p, h_q \rangle_{model} \qquad (8)$$

Where, $\langle \vartheta_p, h_q \rangle_{model}$ is the expectation of the distribution whose complexity is very high. In [6], CD (Contrastive Divergence) is used to estimate expectation. The weight can be modified using stochastic ascent given in (9).

$$\Delta w_{pq} = \alpha \big(\langle \vartheta_p h_q \rangle_{data} - \langle \vartheta_p, h_q \rangle_{model} \big) \qquad (9)$$

Where, α is the learning rate. To overcome the complexity, we have used 1-step CD and the values are updated using (10).

$$\Delta w_{pq} = \alpha \big(\langle \vartheta_p h_q \rangle_{data} - \langle \vartheta_p, h_q \rangle_{reconstruction} \big) \qquad (10)$$

In the proposed model, a hybrid model is considered with equal weightage for both RBM and content KNN model. Figure 1 depicts the training of the hybrid model.
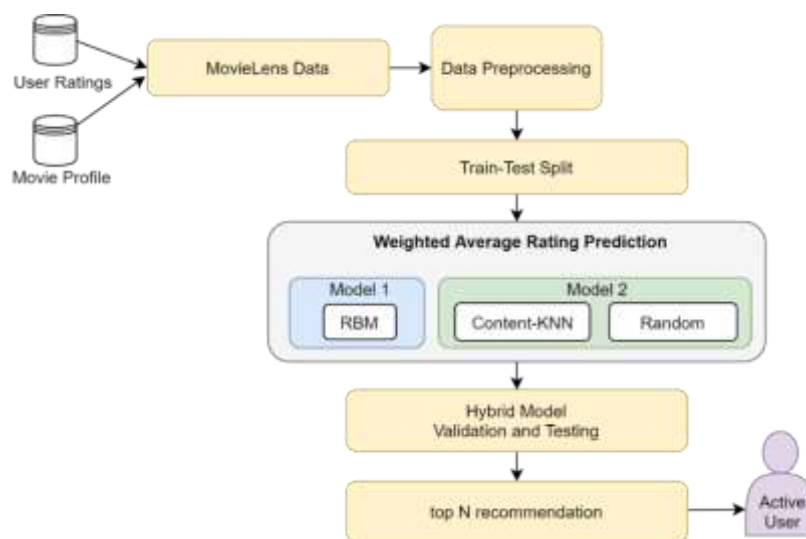

Figure 1. The proposed hybrid model

On the MovieLens dataset, our proposed model is implemented. This dataset contains user interests and movie profiles. This data collection is then subjected to preprocessing of data, in which some samples of data are obtained. The 70-30 test division is imposed on the preprocessed data. In this step of estimation, the RBM is used, and the RBM is combined with the content KNN. Content KNN finds the similarity between different movies based on attributes of movies such as year of release, genre, box office hit rate, and descriptions of the movie. The weighted average is obtained from the above model, and the validated model is used to produce a top N recommendation for the active user.

3.   RESULTS AND DISCUSSION

In python 3.8, the above designed algorithms have been implemented, and NumPy, pandas, surprise are the main libraries used for implementation. RBM network is trained in the forward pass by feeding training information on the visible layer and training weights and biases between them during the backward pass. To generate the output of any hidden neuron, an activation function rectified linear units (ReLU) [35] has been used. ReLU is preferred here as it does not activate all the neurons at the same time.

For the model training, each user's rating from the training set is passed as a batch into the RBM. The nodes in the visible layer reflect the user's ratings on each movie. Interconnection weights are learned to reconstruct the ratings for user-movie pairs that are missing. Here, each individual rating is treated as five visible nodes, one for each possible rating value. Rating in the RBM of five movies having ratings 5, NA, 3, NA and 2, respectively, is shown in Figure 2. Rating of first movie is 5, hence 5th column is set to 1. Similarly, column 2 of movie 5 is set to 1.
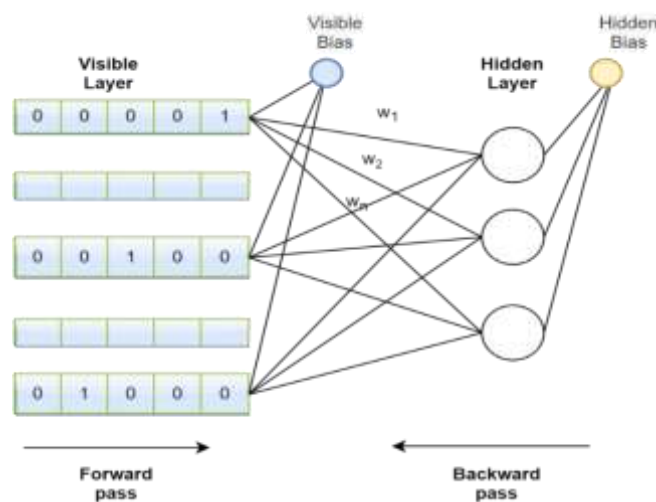

Figure 2. Representation of rating information in RBM

There is a need to estimate missing ratings for movies 2 and 4. The mutual weight and bias can be used to predict the missing score once the model is trained. Many scores are missing in the real dataset. Instead of training on any possible mix of users and movies, the model is trained on the available data by removing the missing scores. In general, using contrastive divergence and Gibb's sampling, the model samples the probability distribution. The resulting weights and biases are reused for other users after the model has been trained for one user.

The number of visible nodes is calculated as the product of number of movies and rating values given by the user. In the dataset ML100K, the number of movies is 8211, and number of users in the train set is 671. So, the maximum number of ratings possible for the user is 8211*5=41055 and the training rating matrix dimension is 671×41055. The hidden node represents the latent variable. The numbers of hidden node are taken 50 for the experiment. Epochs represent the number of iterations to take for the forward and backward pass. In each epoch, to minimize the error between actual and reconstructed rating value, the model will be trained across all the users in the train set. The number of epochs is set to 5 to 30 with an increment of 5. The impact of the epochs in the performance metrics is shown in Figure 3. The learning rate controls how quickly the error converges and it is set to 0.001. Batch size controls the number of users to be processed at a time, and it is set to 100. Once the model is trained, the updated weight and biases are used to get the

recommendation for the active user. The softmax activation function is used in the visible layer to get the probability score that indicated the likeness of the user for a product.

RBM is combined with Content KNN to consider the advantages of both content-based filtering and model-based collaborative filtering model. Content KNN works well even for new users and RBM works well for large user ratings. The performance of various ensemble models has been evaluated on MovieLens1M and 100K datasets downloaded from the grouplens.org site. 70% data is used for training the model and 30% data is used to test the model.

Figure 4 depicts the results of User-based and Item-based CF under various similarity measures such as cosine, pearson, and mean squared difference (MSD). Item-based CF performs better under MSD similarity. In Content KNN, by finding the similarity based on year of release and genre, RMSE scores in ML100K dataset are 1.0624 and 1.0548, respectively. It indicates that genre plays a major role in recommending the movies. Accuracy measure is not considered here, as the model is not a classification model.

Results of combining RBM with Content KNN are shown in Table 1. w1 and w2 represent weight assigned to RBM and content KNN, respectively. A series of experiments are performed to see the impact of w1 and w2. To generate the rating prediction of the target user-movie pair, a weighted average is computed by considering w1 and w2 weights of the models. Root mean square error (RMSE), mean absolute error (MAE) [36] scores of the hybrid algorithms are shown in Table 1. A lower value indicates better results. ML1M, ML100K represents MovieLens one million and 100K ratings, respectively. For content KNN, the K value is set to 40. Figure 3 and Table 2 illustrate the RMSE score of various algorithms in different epochs of training RBM. The average value of RMSE is calculated in the Random model for different epochs.

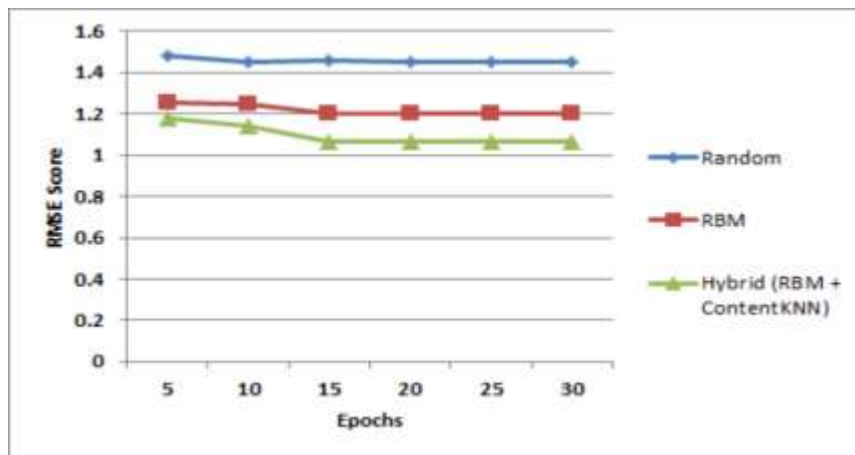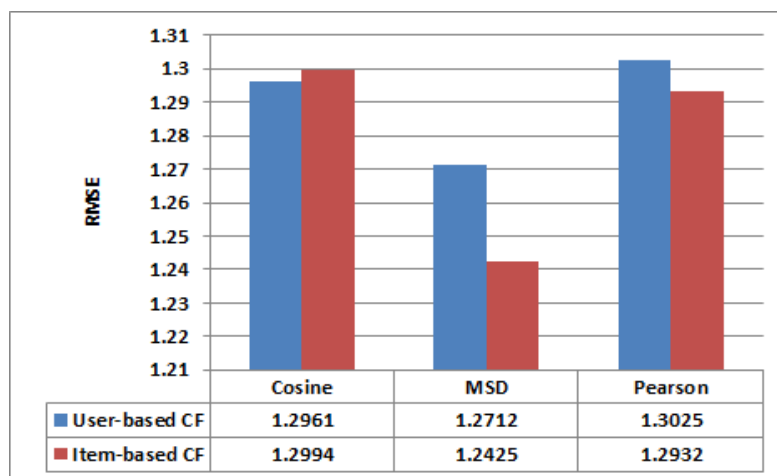

Figure 3. RMSE score of various models on ML1M data

	Cosine	MSD	Pearson
User-based CF	1.2961	1.2712	1.3025
Item-based CF	1.2994	1.2425	1.2932

Figure 4. RMSE score of User-based and Item-based CF

Table 1. Performance metrics of RBM and Hybrid models on MovieLens data

Dataset	RMSE		MAE	
	ML100K	ML1M	ML100K	ML1M
Random	1.5067	1.4615	1.20	1.16
RBM	1.2126	1.1985	0.96	0.86
ContentKNN	1.0548	1.0322	0.74	0.72
RBM+ContentKNN	1.1155	1.0652	0.93	0.76
RBM + Random	1.3254	1.2578	1.05	0.98

Table 2. RMSE score of various models on ML1M data

Epochs	5	10	15	20	25	30
Random	1.4821	1.4547	1.4615	1.4505	1.4505	1.4505
RBM	1.2513	1.2466	1.1985	1.1985	1.1985	1.1985
Hybrid (RBM + ContentKNN)	1.1812	1.1406	1.0652	1.0652	1.0652	1.0652

4. CONCLUSION

Collaborative filtering and content-based recommendation are the popular techniques in filtering movies from a large collection. In CF, the mean square difference performs better as compared to cosine and Pearson similarity measures. In content KNN, genre-based calculation highly impacts the recommendation. RBM fits well in model-based collaborative filtering and content KNN in very sparse dataset. The goal of this paper is to use a weighted hybrid model to see both RBM and content KNN's combined impact on the movie recommendation. Both the models are assigned with equal weightage. The effect of the hybrid model on rating data from MovieLens 100 K and 1 M is thoroughly investigated. Table 1 displays the RMSE and MAE score of different models. RBM with content KNN is shown to have better efficiency. Random movie recommendation is the worst performer. In the future, RBM and content KNN can be extended to the fields of teaching, music, news, and other recommendations.

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