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A Research on Collaborative Filtering Based Movie Recommendations: From Neighborhood to Deep Learning Based System

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***Abstract**:Recommender System or Recommendation Engine gaining popularity as it can tackle information overload problem. Initially it was considered as a domain of Information Retrieval system and was limited to few applications. With the advancement of different state-of-the-art modeling approaches recommender system can be applicable to many application domains. Movie Recommender System (MRS) is widely explored domain and used by many streaming service providers like Netflix, Amazon Prime, YouTube and many more. This system makes use of users' data to explore and recommends personally as per their taste. In this paper a detailed study on recently published article related to movie recommendation is carried out. Popular techniques for MRS are commonlycategorized into collaborative filtering, content-based and hybridmethod. Neighborhood-based, latent factor based, neural network based and deep learning based techniques have been continuously evolved with application to MRS. Recently proposed models have been reviewed and it is found that hybrid method performs better as compared to individual model.*

***Keywords:**Movie Recommender System, Latent Factor Model, Deep Learning Model, Collaborative filtering.*

I. INTRODUCTION

Since the past few years, largeamount and variety of data are gathered from various sourceslike sensor data, machine data, transaction data, social media data and many more. ThisInformation Overloadproblem[1]creates lots ofchallengeswhile filtering data to make appropriate decisions. In order to solve the problems or issues of "InformationOverload" recommendation system (RS) plays a vital role. The main idea of RS is to analyze thepast user behavior and preferences, prepare a model, put the analytics so that, not only it willrecommend items according to the user's choice but also can recommend the things/products which are unknown to the user, but similar to the taste of user.

Broadly the RS is having 3 forms. Content-based Filtering: recommends items/products based on a description of the items/products in accordance with users' profile. Collaborative Filtering: It takes users preference and behavior information for recommendation.The hybrid recommendation system[2][3] is a combination ofCollaborative Filtering recommendation and Content Based recommendation system.

Recommender system has been applied to many application areas like Music[4], Friend [5], Trip [6], Movie [7][8][9], News[10], Social-Media recommendation [11], and many more. Recommending similar movies to the active user as per the likeness is called Movie Recommender System (MRS). It helps the viewer to overcome information overload problem and filtering the relevant movies very quickly. XiaomeiBai*et al.* reviewed algorithms and methods in paper recommendation domain [12]. Joan Borràs*et al.* surveyed tourism recommender system [13] and Ruihui Mudiscussed about deep learning based [14] recommender system. Mahdi Jalili*et al.* reviewedevaluation [15] of collaborative filtering based algorithms. However in view of exploring current state-of-the-art solution in MRS there is a need of review on approaches to MRS.

This paper's main goal is to provide a detailed review on different methods and modelsapplied on movie recommendation which will help others to get the knowledge of how movie recommender system works and the current advancement of techniques for design and development of MRS. Continuous improvement in the modeling of MRS creates win-win situation for both the streaming service provider and the customer.In section II fundamentals of movie recommender system has been discussed and in section III widely acceptedmodels for collaborative filtering has been discussed. Section IV includes conclusion.

II. MOVIE RECOMMENDER SYSTEM FUNDAMENTALS

A. Problem Overview

Movie Recommendation System (MRS) has three major components user profile, movie features and recommendation algorithm/model.

Definition 1: Formally MRS can be defined as predicting the preference score of user u_i on movie m_j for a given profile p_u of user u_i by using recommendation model and then recommending the top movies to the active user.

Definition 2: if the recommended movies vary from user to user as per their taste then it is known as personalized MRS.

Active user is the end user that is currently using the system. Profile p_u includes behavior, implicit and explicit ratinginfo of the user u.

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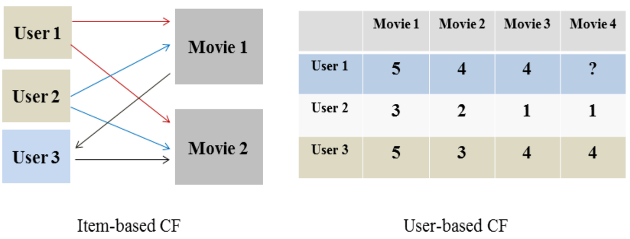
Performance of the recommendation algorithm influences the overall quality of the MRS.Hence research on MRS mainly focuses on design and implementation of recommendation model and validated through proper metrics.Classifications of MRS approaches are depicted in Fig. 3.

B. Content-based Filtering (CBF)

This model is based on an hypothesis that users taste is similar for similar kind of content[16] and two movies are considered to be similar if their content attributes are similar. Content attribute may include actors, genre, release date, director, studio, story, one sentence description, scenes, soundtrack and many more. Movies that are similar in accordance tothe choice of the active user can be recommended. Nevertheless these models also exploit features of user profile like age, gender, nationality, demographic information and many more to increase the quality of recommendation.

C. Collaborative Filtering (CF) Model

In this model similarity between movies are calculated based on a collaborative behavior[17]. CF based model [15] can be categorized into memory-based and model-based model. Neighborhood based model is generally treated as memory based model. There are broadly two techniques widely used in memory-based model: User-based&Item-based. In user-based filtering similarity between users are calculated using the rating matrix and in item-based filtering similarity between movies are intended for modeling.



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

Fig. 1.Example of collaborative filtering

In the Fig. 1 of User-based CF, User1's preferences are most likely same as the User 3's preferences. As User 3 has liked movie 4, User1 may also like Movie 4. In Fig 1 of Item- based CF, two movies movie 1 & 2 are similar by considering the rating behavior of the first two users 1 & 2. User 3 has watched movie 2, hence movie 1 may be recommended to the user 3.Different approaches for model-based models are latent factor based, neural network based and deep learning based model.

D. Hybrid Model

In order to take the advantages of both CF and CBF approach many hybrid models have been proposed in the literature. As discussed in [16], there are seven different ways to prepare hybrid model. These techniques are weighted-hybrid, switching-hybrid, mixed-hybrid,Cascade hybrid, Feature-combining hybrid, Feature-augmentation hybrid, and Meta level hybrid.

Another approach of combining contentand collaborative filtering is depicted in Fig. 2 (taken from [18]). It has been claimed that hybrid model outperforms individual CBF and CF. Fig 2(a) represents combining results of different model whereas Fig 2(c) shows design of a single model based on both CBF and CF. Fig 2(b) and (d) shows one model can be a part of other model.

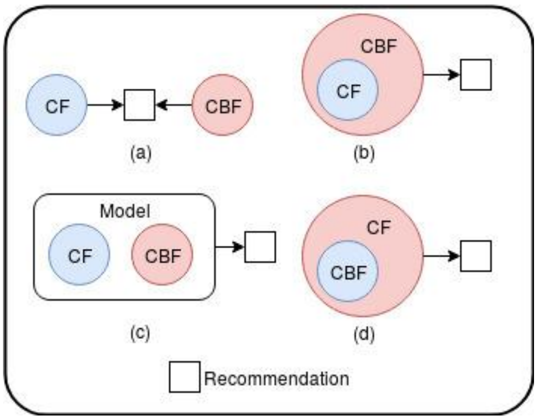


Fig. 2. Different ways to combine CBF and CF

III. APPROACHES TO MOVIE RECOMMENDATION

There are many ways to design movie recommendation. But by looking into trends in recent publications, models considered for review is depicted in Fig. 3.

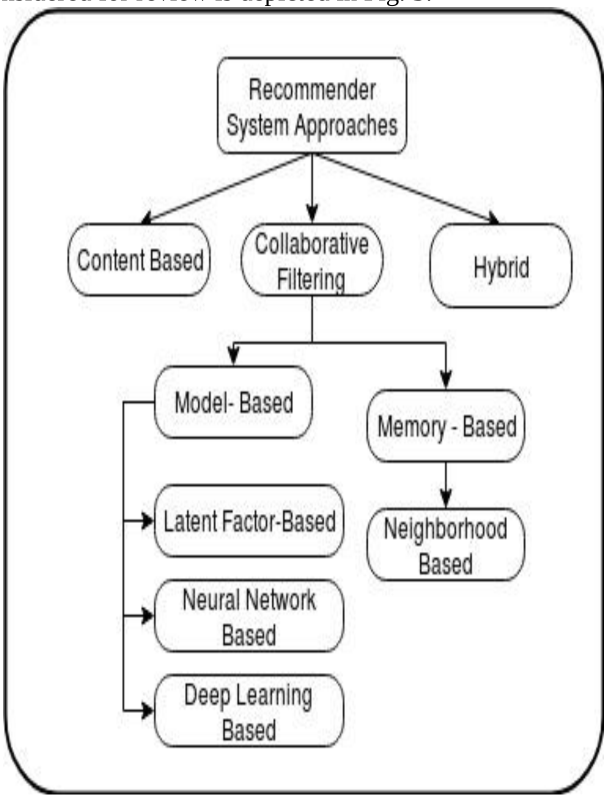


Fig. 3. CF based models for movie recommendations

A. Neighborhood-Based Model

This heuristic-based model comes under memory-based approach of CF as the user-movie ratings are stored in memory. These models are generally used to predict the unknown ratings either in user-based or item-based model. KNN inspired neighborhood based model generally consists of following steps[19]:

1. Choose a similarity measure
2. Choose a K value and calculate the K nearest neighbours
3. Predict the ratings
4. Recommend top ranking items

To calculate similarity mostly used measures are cosine similarity, adjusted cosine similarity and Pearson correlation similarity.

Consider U $[u_1, u_2, u_3 \ldots\ldots, u_P]$ is a vector that represents users and M $[m_1, m_2, m_3 \ldots\ldots, m_q]$ is a vector that represent movies where p, q are the number of users and movies respectively. $R$is the rating matrix having dimension $p\ x\ q$. Letr_{um} denotes rating of user u for movie m. Calculation of r_{um} in user-based model is depicted in (1) where μ is the mean rating of each user.

$$\hat{r}_{um} = b_{um} + \frac{\sum_{v \in N_m^k(u)} sim_{u,v} \cdot (r_{vm} - b_{vm})}{\sum_{v \in N_m^k(u)} sim_{u,v}} \qquad (1)$$

$b_{um} = \mu + b_u + b_m$ is the baseline estimate[20] of user u for movie m. The parameters $b_u$and b_m indicate the rating deviations of user u and movie m. These parameters are generally solved by SGD[21] or ALS[22] algorithm.$sim_{u,v}$represents similarity between u and v as per the chosen measure.

Daniel Valcarce et al.presented a memory based model prefs2vec[23] that represent user and item in a better way to get the user-item preferences like rating. This technique outperforms in view of ranking, accuracy, diversity, and novelty metrics.

To deal with the sparseness of data in the dataset,Mlungisi Duma et al. [24]proposed a model called NNAISGAwith the use of Artificial Immune System (AIS)and Genetic Algorithm (GA). The accuracy is represented in table I.

Table- I: Summary of neighborhood-based model

Paper/Year	Proposed Model	Dataset Used	Quality Measures/Value
[23],2019	Prefs2vec	MovieLens 20M	0.4504(prefs2vec -UB) 0.0666(prefs2vec -IB)
[24],2019	NNAISGA	MovieLens	1.4596 ± 0.3922 RMSE

B. Latent Factor Model

This mathematical model is comes under memory-based approach of CF as it requires learning phase to find optimal parameters. After learning phase the model can be used for recommendation. It represents R as a dot product of two matrices X and Y where X is the user feature matrix and Y is the item feature matrix. It decreases the memory requirement by using dimensionality reduction techniques. Based on latent factor widely adopted models are SVD (singular value decomposition)[25], SVD++[26], MF (Matrix Factorization), PMF (Probabilistic MF)[27] and NMF (Non-negative MF).

Latent factor model generally consists of following steps[19]:

1. Derive the latent features X and Y such that $R \approx XY^T$
2. Find an objective function
3. Update the values in feature matrix X and Y
4. Predict the unknown rating using updated X and Y latent feature matrices
5. Recommend top ranking items

In SVD[26]as popularized during the Netflix Prize the prediction r_{um} can be calculated as

$$\hat{r}_{um} = b_{um} + {y_m}^T x_u \qquad (2)$$

In (2) x_u and y_m denotes latent feature vector of user u and movie m respectively.

Michail Vlachos *et al.*[28] addressed the problem of generating interpretability and cold start in MRS by using generative model. Considering both positive and implicit feedback overlapping co-cluster of users and movies is found. By using a cluster of 16 Graphical Processing Unit (GPU) they got 270 times more speed than baseline.

A deformable convolutional network matrix factorization (DCNMF) model is suggested by Honglong Chen et.al[29] that combines the concept of Deformable convolutional network (DCN) and probabilistic matrix factorization (PMF) for rating prediction that shows better improvement in two popular public dataset ML-1m and ML-10m.RMSE is used here for performance calculation.

Table- II: Summary of latent factor based model

Paper/ Year	Proposed Model	Techniques	Dataset Used	Quality Measures/Value
[28], 2019	"OCuLaR" (Overlapping co-CLuster Recommendation algorithm)	Generative Model, MF	Movie Lens, Netflix	0.1809 (recall@50) 0.4021 (MAP@50)
[29], 2019	Deformable convolutional network matrix factorization (DCNMF)	DCN[a], PMF	ML-1m and 10m	0.63801 RMSE ML-1m 0.57364 RMSE ML-10m
[30], 2016	compact latent factor model	SGD, Sampling technique	ML-1m	AUC[b] 0.7778 ± 0.0060
[31], 2017	ESVD(enhanced SVD), Multi- Layer ESVD	RSVD	Netflix, ML-100K	0.9570 (RMSE-ML) 0.9319 (RMSE-Netflix)
[32], 2018	Field-Aware-Matrix Factorization	FFM[c], MF	ML1M	0.0096 Hit Ratio 0.7039 MRR[d]
[33], 2017	Bayesian non-negative matrix factorization (BNMF)	KMeans, KMeans+, MF	Movie Lens, Netflix	0.68 (MAE-ML) for K=20
[34], 2017	2-probabilities focused method	Dempster–Shafer theory	ML-100K, Flixster	MAE 1.53921
[35], 2017	probabilistic model	Pearson correlation	ML1M, Netflix	RMSE 0.867-ML-1M 0.867- ML-1M

[a] DCN: Deformable convolutional network
[b] AUC: Area under the ROC curve
[c] FFM: Field-aware factorization machine
[d] MRR: Mean Reciprocal Rank

A latent factor model is proposed by C. Liu and X. Wu to deal with context-aware recommendation and cold-start problem [30] . SGD with sampling technique is applied to for ranking loss optimization. They have conducted the experiments on four different dataset including MovieLens 1M Data Set.

Xin Guan*et al.*proposed a matrix factorization model called as ESVD[31] which is an enhanced form of support vector machine (SVM) model that best deals with the missing values. Further it is extended to multi-layer ESVD that train the model iteratively for better accuracy. The RMSEcalculated on Netflix and Movielens dataset gives better performance.

Another matrix factorization(MF) model named as Field-Aware Matrix Factorization is suggested by Zhiyuan Zhang*et al.*[32]that emphasizes on mining the suitable side information to improve the accuracy of prediction. For validation HR and MRR metricshave been used on MovieLens1M dataset.

Jesús Bobadilla *et el.*[33]recommended a Bayesian NMF (BNMF) method for the improvement in the current clustering output in collaborative based recommendation. The execution time of this proposed BNMF algorithm is better as compared to other classical Matrix Factorization models.

A 2-probabilities focused method is developed by Van-Doan Nguyen and Van-NamHuynh[34] for combining users preference information on products or services in MRS based on Dempster–Shafer theory. The proposed model performance is compared with the 2-points focused combination model using ML 100K and Flixster datasets.

Inorder to deal with cold start problem associated with mainly non-registered users, Antonio Hernando *et al.*[35]proposed a mathematicalprobabilistic model using inference rules with uncertainty.Model is applied on MovieLens 1M and Netflix dataset where performance is evaluated using Mean absolute error(MAE). Recent works on latent factor based models and their performance is represented in table II.

C. NNBased Model

DidarDivaniSanandaj[36]and Sasan H. Alizadeh proposed a hybrid recommendation model by combining with Artificial Neural network(ANN) to deal with the cold-start problem. They have applied their model on Movielens and Netflix dataset where they got less RMSE score as compared to other models.

According to MojtabaSadeghianand Mohammad Khansari[37] one of the major drawback of recommender system is lacking of understanding similarity between users' choice and items. To overcome this issue, a Hybrid model is applied on MovieLens dataset by combining Network Science technology and Machine learning approaches.Table-III represents performance of neural net based model.

Table- III: Summary of neural network based model

Paper/ Year	Proposed Model	Techniques	Dataset Used	Quality Measures
[36], 2018	Hybrid model	ANN, CF, CBF	MovieLens, Netflix	0.85(ML-RMSE) 0.66(ML-MAE) 0.675 (Netflix-MAE)
[37], 2019	Hybrid model	network models and clustering methods	MovieLens	0.89542132 - MSE

D. Deep Learning (DL) Based Model

DL is an emerging field of Artificial Intelligence (AI).When multiple hidden layers are used in multilayer perceptron, that becomes a Deep Learning structure. This approach is first introduced by Hinton *et al.* in the year 2006[38]. Basically there are five Deep Learning techniques likeAutoencoder (AE) [39], Restricted Boltzmann Machine(RBM)[40][41], RNN[42], CNN[43][44], and Deep belief network(DBN)[45] popular for MRS.Recent works related to these deep learning techniques are discussed below.

Table- IV: Summary of deep learning based model

Paper /Year	Proposed Model	Techniques	Dataset Used	Evaluation Metrics/Quality Measure
[46], 2018	Soft-ATT Corr-ATT	AE, NeuCF, DMF, DeepFM	ML-100K ML-1m	NDCG HR 0.402(soft) 0.410(corr) 0.686(soft) 0.688(corr)
[47], 2017	Dual-Autoencoder (ReDa).	AE, Gradient Descent	ML-100K ML-1M	0.9231 (70%-RMSE) 0.7248 (70%-MAE)
[48], 2017	AE-based matrix completion (AEMC). DL-based matrix completion (DLMC)	AE, Deep network	ML-100K ML-1M	18.39(NMAE -0.3 missing rate)(ML-100K) 18.03(NMAE -0.3 missing rate)(ML-1M)
[47], 2017	IRCD-CCS IRCD-ICS	DL neural network.	Netflix	RMSE 1 .082 (IRCD-CCS) 1.048 (IRCD-ICS)
[48], 2017	AE-COFILS	SVD, SL, SDA	ML 100k ML 1M MovieTweetings 10k	RMSE 0.838- ML 1M 0.885-100k 1.747-10k

FuzhenZhuang*et al.* presented a Deep learning model knows as ReDa[49]using dual autoencoders. A gradient descent model has been developed to learn the hidden factors. This model also uses the Autoencoder technique in order to minimize the training error by applying the latent factor generated from the previous model.

Another approach named as DLMC is a matrix completion model using DL discussed by Jicong Fan *et al.*[50]. The proposed model is based on AEMC which is used to generate anAutoencoder to represent nonlinear latent factors. The primary aim of this model is to deal with the missing data in the matrix in order to get the complete matrix for further processing.This model provides comparatively higher accuracies as compared to other baselines.

Han Xiao *et al.*[46]proposed a neural network model by collecting users' rating from different standpoint. The user and items are coded properly through a sequence of stages. Finally the rating matrix is constructed by taking the output from the final stage. Authors have tested it on MovieLens 100K (Movie), MovieLens 1M (Movie-1M) Dataset.

Inorder to deal with the issues of complete and incomplete cold start problem [47], Jian Wei *etal.*proposed two models IRCD-CCS and IRCD-ICS. The concept of this newly proposed two approaches are based on the hybrid framework of CF and DL neural network.

Julio Barbieri*et al.*[48] proposed a technique named Autoencoder COFILS to minimize the data sparsity and to test varieties of supervised learning(SL).

Stacked DenoisingAutoencoder (SDA) with switching SVD is used to extract the nonlinear features from data.This model is investigated on ML100k, 1M datasets where the accuracy is better as compared to other model-based CF techniques. Recent works on DL based MRS and their performance is shown in Table-IV.

IV. CONCLUSION

Movie Recommender system (MRS) is the widely explored domain of RS.In this paper an overview of different approaches to movie recommendation system is carried out. We categorized the recent publication into four groups according to their proposed approaches: Neighborhood, Latent factor, neural network and Deep learning based methods. All these modeling techniques have pros and cons. After a detailed survey we found that latent factor based and DL based techniques are mostly used for movie recommendations. Popular dataset used in MRS are MovieLens and Netfilx data. Accuracy of different approaches with dataset used has been listed in table I – IV. It has been found that hybrid model outperforms all other techniques. In future, more research on hybrid and ensemble model is required to achieve better performance.

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