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OPTIMIZED DEEP COLLABORATIVE FILTERING FOR MOVIE RECOMMENDER SYSTEMS

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ABSTRACT: Entertainment industry has continuously taken an immense interest in ensuring a personalized experience for each of its viewers in this internet era. Recommender systems are a subclass of systems for filtering information and suggest item especially in streaming services. For finding users with similar products, streaming services such as product recommender systems are important. This paper presents a deep learning approach based on collaborative filtering by incorporating stochastic gradient optimization technique, in order to provide more reliable predictions that can handle cold start and overfitting problems. In user and item based collaborative filtering multiple items are associated for highly identifiable items. Such items are used to train the model of deep learning to predict user ratings on new products and to give final recommendations. The experimental result of the proposed model has been compared with that of the state of art models in terms of Mean Absolute Error and Root Mean Square Error.

KEYWORDS: Recommendation System, Deep Learning, Collaborative Filtering, Multilayer Perceptron, Neural network

I. INTRODUCTION

Now a days, item determination has been made progressively complex because of enormous number of choice accessible on the web. At that time people may be confused about whether the product is good or bad based on comments. Recommender framework gives customized proposals to the users. Recommender information can be collected either explicit through reviews or implicit through monitoring the user behaviors on the application.

There are different sifting approaches of Recommender frameworks like Collaborative Filtering, Content-based Filtering, and Hybrid Filtering. Content-based[1] Filtering utilizes the previous preferences of users to recommend items or services. In Collaborative Filtering(CF)[2],items are recommended to the user based on ratings. It can be divided into two categories User-based Collaborative Filtering and Item-based collaborative filtering. In user-based CF, recommendations are based on similar users. In item-based CF, in this busy world, not all users would take their time to rate an item, moreover users taste and profile do change frequently than ever.In user based CF, suggestions depend on comparable users. Using item based CF, the likeness of the motion pictures can compute better in situations where recommendations should be made without contrasting comparative user profiles. This is helpful for new item which is yet to be evaluated could likewise be recommended to the user for survey.

Nour Nassar et.al , proposed method consist of two phases. First phase is prediction of criterial rating second phase overall rating prediction. First phase comprised of three steps criteria rating is achieved with the combined strategy of deep neural network and matrix factorization. In the first hidden layer matrix factorization method element wise product is calculated using the user ID and Item ID. Due to that loss function is minimized. By embedding the User Id and Item ID concatenation operation done on the deep neural network then RELU activation function is applied to make weighting strategy. After that ML and DNN are concatenated to get the criteria rating. The computed criteria rating are normalized and given as input to the overall ratings DNN. Next phase concentrates overall rating prediction which is identified with the help of deep neural network. The proposed method experimented using Movie lens dataset with the evaluation metrics of MAE, F-Measure, and Fraction of Concordant pair. [3]

Deep Learning (DL): DL is a subclass of AI. It learns deep learning (ie) different degrees of taking in portrayal from information. The different methods of Deep Learning are as per the following,

Multilayer Perceptron (MLP): MLP[4] is a feed-forward neural system with many concealed layers between the info layer and yield layer. This procedure has a bigger number of concealed layers and better demonstrating power. The learning pace of this model is a neighborhood ideal, which requires all the more preparing information and increasingly computational force.

Autoencoder: It is a type of unaided realizing, which needs an unlabeled information; it recovers input information as opposed to enter yield sets. The capacity of an encoder to make a concealed layer which comprises of neurons, to portray the info [5]. There is a decoder which regenerates the input from the hidden layer vector is smaller than the input layer; which would be useful for compressed representation of data and reducing dimensional.

Convolutional Neural Network (CNN): It comprises of a convolution layer and pooling tasks. This model upgrades productivity and precision dependent on neighborhood and worldwide highlights [6].
Repetitive Neural Network (RNN): This model is appropriate for consecutive procedure. It very well may be characterized into LSTM (Long Short Term Memory) and GRU (Gated Recurrent Unit)[7]. Limited Boltzman Machine (RBM): It is a two-layer organize, which comprises of obvious and concealed layer. In Confined methods there is no intra-layer among covered up and noticeable units.
In this paper presents a model is proposed to enhance scalability, improve the prediction accuracy and to uncover the hidden structure behind the data. Figure1 shows the concepts of deep learning with Recommender System.

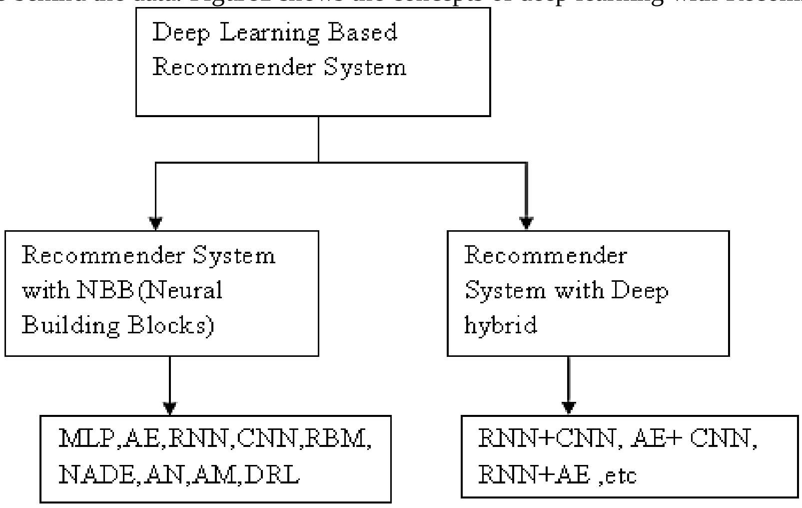

Figure 1. Deep Learning with Recommender System

The rest of the paper is organized as follows. Section 2 provides the related works, section 3 presents proposed work, section 4 presents the results and discussion and section 5 concludes the work.

II. RELATED WORKS

This section deals with recent and most prominent contribution in this domain.
In deep neural network the author proposed a novel collaborative filtering based algorithm. In conventional algorithms continuous increase of the number of the epochs creates over fitting problem. The proposed algorithm overcomes the over fitting problem for the continuous increase of number of epochs by applying the batch normalization technique on each layer of the neural network. The neural network layer receives the input as normalized user-rating vector and normalized item-rating vector. The model is trained using back propagation with a stochastic gradient descent method. Soft max function is incorporated to identify the conditional probability of each ratings. Based on the conditional probability the prediction was made. The algorithm was experimented using movie lens 100k and 1M dataset[8].
A data clustering based recommendation system model was proposed by Katarya et al. [9]. A cuckoo search based K-Means clustering model has been proposed process. This is a collaborative filtering based model. A data-sparsity handling technique for the recommendation was proposed by Li et al. [10]. This model is based on handling two major issues in the recommendation system; handling data sparsity and identifying and handling concept drift.
Representation learning via Dual-Autoencoder for recommendation is a learning framework introduced by fuzhen et.al. The author claimed that Matrix factorization method does not provide sufficient learning information from ratings or check-in matrices. So, the author proved that, deep learning to learn good representation than the matrix factorization method. In this framework hidden representation of users and items are learnt using auto encoder then the model solution is derived using gradient descent method. Through the auto encoder simultaneously user and item based latent representations are formulated. Then it is mapped with the encoding and decoding process. Afterwards training data deviations are minimized by the learnt representation. Trade off variables is regularized. To derive the local optima solution for all the variables gradient descent approach is applied with partial derivation to obtain better RMSE and MAE values. Four data sets are experimented and the return result achieves better RMSE and MAE values based on the auto encoding and gradient descent methods [11].
A multiview deep learning model shows how to make features based user and items to a latent factor space where the similarity between user and item themselves[12].The author's proposed model overcome the difficulties of collaborative filtering such as data sparsity, cold-start and scalability problem using deep learning. Matrix factorization method collects the inert interest of the user and analyze the contextual review. Main objective of

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the study is to recommend products/ services based on the inert interest of the user. Both rating information and side information are considered for the contextual reviews. Generalized matrix factorization are constructed using the rating information which was received from the feed back information. The user and items always forms the non linearity. The results are combined with in the collaborative learning process to get low-rank matrix[13].Isam et.al[14] ,developed new framework for deep learning based context aware recommender systems. The model has been complicated and make it susceptible to overfitting problems.

Collaborative Filtering Bayesian Poisson Factorization model was proposed by Zhang et al.[15].This method to address cold start problem. It refers to a scenario where it is not possible to provide reliable recommendations due to lack of ratings or user profile information. Though the new user problem is heavily discussed, the new community and new item problems are also found to be equally important, when it comes to the creation of a successful recommender system. New user problem represents the scenario in which the user would not have provided enough ratings to get personalized recommendations. New users often tend to feel that they are being ignored and may even leave the service.

III. PROPOSED MODEL

Deep learning which is a branch of artificial neural network aims in finding mathematical manipulation for non-linear regression. Deep Neural Network (DNN) is stacking large numbers of hidden layers, which are learning complex functions. In movie recommender system, latent models approach is used in collaborative filtering that can handle sparsity, cold start and overfitting problem. Our approach is the extensions of traditional recommender systems where most of the conventional recommender system model are appropriate for linear transformations. In existing, recommender system can be used to add non-linear transformation and interpret into deep neural extensions.

Input shape parameters are passed to the first layer. Next 3D temporal embedding layers support input length and input dimensional. Input dimensional, takes input as n vectors, where n is the user and item features. This is the shape of each row entries, when the batch dimension not included. The user and item embedding's are learned in a maximum distance between user and minimum their performed items. Each item can be represented as a vector S_i and the user can be represented as a S_u vector.It is a powerful technique for mapping both user- and item profiles to joint latent factor space of dimensionality.

The outcome of user and item embedding's are changed into a deep sparse model. It contains n number of sparse similar user-item features. These sparse features are densely connected to the neural network. Dense embedding's create many hidden layers which of neurons, to describe the input. This layer should normalize the user and item embedding's by adjusting and scaling the activation using Rectified linear unit. The activation was performed through an activation layer and activation argument based on threshold frequency. To improve the speeds of neural learning rate ,features are normalized. It reduces the amount by what the hidden unit values are shifted around. Each hidden unit adds some noise and the architecture are trained to reconstruct the error free noise model using less dropout ratio which is incorporated in dropout layer.By subtracting the batch mean and dividing by the batch standard deviation using batch normalization, the output of a previous activation layer can be normalized. This process increases the stability of neurons, to overcome the overfitting and improve generalization error.

The proposed design is adaptable and uses Relu activation function for better predictions. Neural networks that use the role of rectifier for the hidden layers are called rectified networks. The rectified function is linear for half the input domain and non linear for the other half. The rectified function is referred to as a linear function or character function. This is also easy to calculate the derivate of the rectified linear function. Remember that the activation function derivate is needed when updating a node's weights as part of the error backpropagation process.

Deep learning neural networks are trained using the stochastic gradient descent optimization algorithm.SGD class provided by keras that implements the stochastic gradient descent optimizer with a learning rate and momentum. It is an optimization based model ,which operates based on the incremental learning principle. The model begins with a minimal constraints based solution and builds incrementally over the already built in solution to obtain the complete rule set. The learning rate is a hyper parameter tuning, which controls how to change the model each time and the model weights are modified in response to the estimated error. If the learning rate is too large the model to converge quickly is passed to suboptimal solution whereas if its too small the process get stuck.

It is extremely straight and efficient for feature representation and also to solve the regression problem. Before creating a training repository, we need to compile the learning process, through compile method. To train the proposed model with 50 epochs, with each epoch using 10 batches with size 64. For improving stateful recurrent network batch size arguments are passed to the hidden layer along with the testing data. The communication among user and item is characterized by the scoring function.

After training and testing , the error is printed out by epoch size-wise. Once the compilation process is over, next to explore the entire network can be trained with prediction function for enhancing user profile, item features and can alleviate the effort in feature engineering. Recommender system using deep learning model to produces increasingly general and abstract representation; which improves precision and diversity of recommendation.

IV. RESULTS AND DISCUSSIONS

The proposed model has implemented using keras and sklearn packages. This model uses Movielens dataset [16] for measuring the prediction performance. This dataset contains 1 million reviews and is a standard benchmark data used in Recommendation System. It contains details about movies, users, genres and ratings. This dataset is divided into training and testing data in 70:30 ratios respectively.

Performance of the proposed models are measured using MAE(Mean Absolute Error) is given by,

$$MAE = \frac{1}{N}\sum_{i=1}^{n} |y_i - y'_i| \qquad (1)$$

RMSE (Root Mean Square Error) is given by,

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{n}\left(y_i - y'_i\right)^2} \qquad (2)$$

Where y_i and y_i' are the actual and the predicted ratings for the N test reviews.

A comparison of MAE values obtained is shown in figure2. The low values of MAE and RMSE indicates the high power of the predictive models. Our model exhibits the best MAE values compared with the other models[16][17].

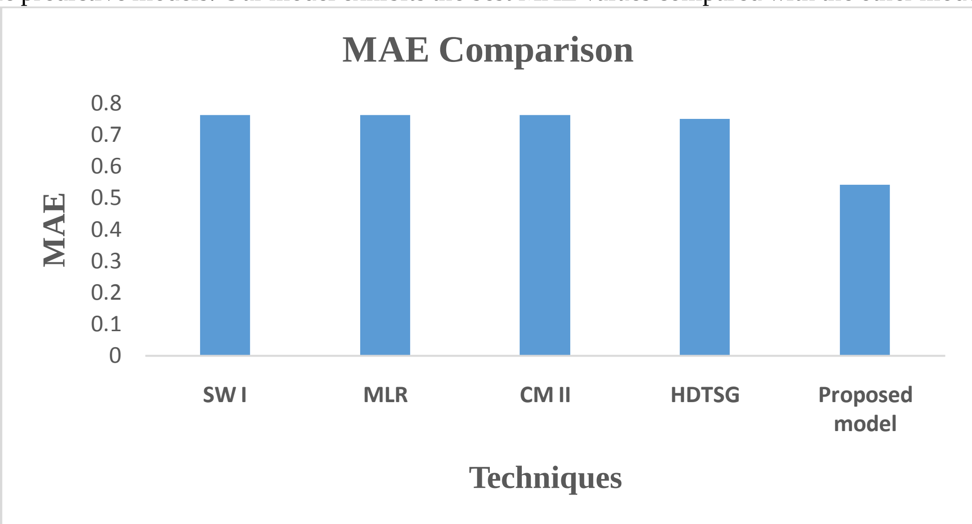

Figure 2. MAE Comparison

A comparison of the RMSE values obtained in figure 3. Our model exhibits the lowest RMSE values compared to all other methods. Table1 shows performance analysis of proposed method in terms of MAE and RMSE.

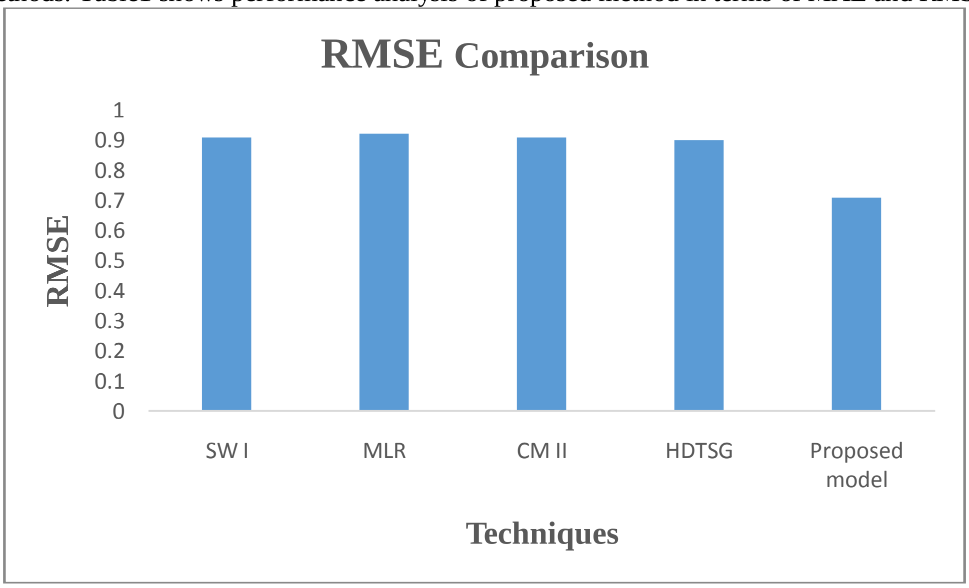

Figure 3: RMSE Comparison

TABLE 1: PERFORMANCE COMPARISON

MODEL	MAE	RMSE
SW I	0.7616	0.9096
MLR	0.7611	0.9212
CM II	0.7615	0.9086
HDTSG	0.75	0.9
Proposed model	0.54	0.71

V. CONCLUSION

Recommendation system helps us out of the information overload that is bestowed upon us by the information era. In this paper, we have proposed a deep collaborative filtering model for movie recommender systems to provide better predictions. Experiments indicate that the proposed model shows better outcomes regarding MAE and RMSE. The major advantage of this model is that it handles cold start issues. Further, future enhancements directed towards reducing MAE values.

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