State-of-the-Art Review of Deep Learning Techniques in Recommendation System

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Abstract: On the basis of achievements of deep learning, its use in the field of recommendation system has gained a lot of attention. This paper provides a review on the various techniques of deep learning which are used in recommendation system. The ability of deep learning models to analyse the user-item relationship efficiently is the reason for using it instead of the traditional recommendation models. This paper consists of the introduction of basic terms and concepts in both recommendation system and deep learning. Then there is a description of the researches on deep neural network based recommendation system

1 INTRODUCTION

The advancement in the field of information technology in recent times has made the access of huge amount of data very easy. There are a vast variety of products and services whose description is easily available along with their comments and reviews. Due to this overload of information (Gantz et al., 2012), it becomes very difficult for the user to choose an appropriate product according to his requirements.

To deal with the above problems, recommendation systems are used. Recommendation Systems provide the users with personalized recommendations. There are many areas where recommendation system is being used, such as music, books, movies, shopping etc. Most of the online vendors have a recommendation engine already equipped. Recommendations are done on the basis of user's previous items choice or the items preferred by similar user or on the basis of the description of item. Here the item refers to the product or services which is to be recommended. Recommendation system is classified into three parts based on their approach: (Çano et al., n.d.) Content based, collaborative filtering and hybrid.

Recently, the use of artificial neural networks has become very popular in the problems which require complex computations and huge amount of input data. Deep learning is a part of ANN architectural models of deep neural network are efficiently built and trained. Deep neural networks have its applications in various fields such as speech recognition, image processing, object recognition, image processing, NLP tasks etc. Due to various advantages of deep learning, researchers have been encouraged to use its associated techniques in the field of recommendation system also.

Deep learning is being used successfully in recommendation system as well as many other fields in computer science and has shown significant improvements in the existing models. In 2007, a collaborative filtering method for movie recommendation system was given by (Salakhutdinov et al., 2007) which utilized the hierarchical model of deep learning.

In 2015, (Sedhain et al., 2015) with the use of auto encoders, predicted the values which were missing in the user-item matrix.

The sparsity issue in recommendation system in collaborative filtering was addressed by (H. Wang et al., 2015).

Various surveys have been done in the area of deep neural network based recommendation system. The state-of-the-art survey for deep recommendation system has been done by (September & 2016, 2016). In 2017, a comprehensive review on deep learning based recommendation system has been done by (Zhang et al., 2019). The paper proposed the classifications on the basis of their structure, that is neural network models and integration models.

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This paper is organized in various sections as follows. First, it consists of the introduction of recommendation and deep learning techniques. Section two consists of background and related terminologies. In Section three, there is a review of the various approaches of deep neural networks in the area of recommendation system and its classification. Section 5 includes the concluding part.

2 BACKGROUND AND TERMINOLOGIES

A recommendation system is used for information filtering and outputs a list of specific products in a personalized manner. For examining how the two fields that is recommendation system and deep learning are integrated together, one should know the basic of both these fields. This section of the paper includes a brief description about the fundamental classifications and challenges of both the fields. First, there is an introduction of types of recommendation system and then the details about deep learning methods.

2.1 Recommendation System

It is very important for a user to filter the huge amount of data available, to find a useful, tailored and relevant content. The recommendations that are predicted by the recommendation System helps the users in taking a decision.

In a traditional recommendation system, the recommendations can be made in two different manners, i.e., predicting a particular item or preparing a ranking list of items for a particular user (Park et al., n.d.). The recommendation system is divided into three broad categories: Content based (Park et al., n.d.), Collaborative filtering and hybrid recommendation system (Park et al., n.d.).

- Content based recommendation system: In content-based recommendation, the items which are similar in content is searched. The profile of user is established on the basis of items on which the user is interested in. According to the profile generated, the recommendation system searches the database for the appropriate items using the descriptive attributes of the item. If we use this recommendation system (Lops et al., 2011) for an item which is newly added, then content based recommendation system works very efficiently. The problem with new inserted item is that it may not have any rating, but still the algorithm works since it uses descriptive information for recommendations. The limitation of this method is that it cannot recommend diverse range of products since the algorithm does not take the information from similar users.
- Collaborative filtering recommendation systems: This recommendation system assumes that users' who have previously preferred same items, would have same choice in future also. In this system, the recommendations are done on the basis of similar users' pattern rather than descriptive features of items. A correlation among the users is determined, depending upon the choice of similar users, the items are recommended.
  There are two methods which the CF algorithm follows: memory based algorithm and model based algorithms.
  In memory based algorithm the complete user-item matrix is taken into consideration for identifying similarity. After finding out the nearest neighbour, on the basis of neighbours past rating, the recommendations are provided. In model based algorithms, an offline model is built with the use of machine learning algorithms and data mining methods. These models include clustering models, Decision models, Bayesian model and singular value decomposition model.
- Hybrid Recommendation System: Hybrid recommendation system is a combination of content based and collaborative filtering model, it incorporates the benefits of both the methods and tries to eliminate the limitations of the above models (Tran et al., 2000). There are many hybrid systems proposed, some of them are as following:
  Cascade: The output of one approach is later on used by other approach
  Switching: Recommendation output is given on the basis of current situation and either of the one approach is used.
  Weighted: the combination of the scores of various approaches is used for recommendation

2.2 Deep Learning

Deep learning is based on learning many layers of representations with the help of artificial neural networks, and is a part of machine learning. Deep learning has its applications in various fields such as Computer vision, recognition of speech, natural language processing etc. The important factors which increase the importance of deep neural network as the

state-of-the-art machine learning methods are as following:
Big data: As the amount of data increases, better representations are learnt by the deep learning model.
Computational power: The complex computations of the deep learning model is done using the GPU.
In this section, there is a description of various deep learning models which are used in recommendation systems.

2.2.1 Autoencoder

It is a type of a feed forward network in which some representations from the encoded input are found by the training, so that the input can be restored back from these representations. An autoencoder consists of three layers, which are the input layer, the hidden layer and the output layer. There are equivalent numbers of neurons in the input layer and the output layer. The representations are obtained from the hidden layer, and with the help of these representations, the input layer is reconstructed at the output layer (Deng et al., n.d.).

In the learning process, two mappings are used, with the help of encoder and decoder. Encoder is used for mapping the data form input to hidden layer while decoder is used to map the data from hidden to output layer (Strub et al., n.d.).

2.2.2 Recurrent Neural Network

The use of sequential information is done in RNN, which is a class of artificial neural network. In RNN, the sequence of values, i.e., $x^{(0)}$, $x^{(1)}$,..., $x^{(t)}$ is processed. On each element of the sequence, the same task is performed and the output is based on previous computations. RNN (Wu et al., n.d.) uses an internal memory to hold the values of previous computations, so that it may be used later. Some major problems that occur in RNN is exploding gradient or vanishing gradient. To remove this problem, Long short term memory (LSTM) and gated recurrent unit is used. It is used when the processing is to be done for predicting events which has comparatively longer interval and delays. LSTM has a processor to distinguish the useful information from the information which are not useful. This processor is known as cell. There are three gates in LSTM namely input gate, output gate and forget gate. The information that does not complies with the algorithm's certification, is forgotten with the help of forgot gate. RNN are useful while dealing with temporal dynamics of interactions and when the user's behavior has a certain sequence of pattern.

2.2.3 Convolution Neural Network

It is a neural network of fed forward type. In CNN (Wu et al., n.d.), the use of convolution operations is done rather than the usual matrix multiplication in one or more layers. There are many applications in which CNNs are applied such as object recognition, self-driving cars, audio processing etc. while transforming the input to output, the CNN uses three major components that are convolution layer, pooling layer and fully connected layers. These three are stacked together to form a CNN. The layers of CNN are used for the following operations.

Convolution: It is a core operation and is used for extracting the features from the input. It is done by applying convolution filters involving some mathematical operation.

Non linearity: An additional operation is used for introducing non linearity after every convolution operation and usually ReLU is used.

Pooling: This operation is done for reducing the dimensionality of the feature maps and decreases the processing time.

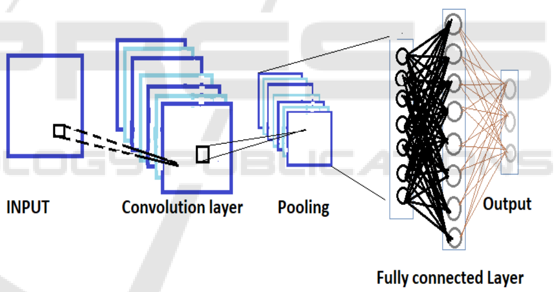

Figure 1: Convolutional Neural Network Model

2.2.4 Restricted Boltzmann Machine

It consists of two layers of neural network namely a visible and a hidden layer. The complex computations and learning in RBM (Wu et al., n.d.) is based on inherent intrinsic expression of data. The word "restricted' is used for intra-layer communication as it is not present in both hidden layer and visible layer. Due to this restriction, the learning efficiency increases. There is a full connection between the nodes of different layers which are stacked together and there is no connection between the nodes of same layer. Since RBM uses a simple forward encoding operation, so it is very fast when compared to other models such as autoencoder.

3 DEEP NEURAL NETWORK BASED RECOMMENDATION SYSTEM

DL techniques are widely used in various real world applications such as sentiment analysis, speech recognition image classification, text classification etc. Various researchers also include deep neural network based techniques in the field of recommendation system to improve its performance as compared to traditional recommendations systems. This section describes the various categories recommendation systems which are based on deep learning. The categorization is based on the types of recommendation systems used which is as follows:

- Collaborative filtering recommendation system based on deep neural network.
- Content-based recommendation system based on deep neural network.
- Hybrid recommendation system based on deep neural network.
- Social network-based recommendation system based on deep neural network.
- Context aware recommendation system based on deep neural network.

Integration model and neural network model are the two categories of deep neural network based recommendation system. Integration model is further divided into two categories on the basis of whether it combines any traditional recommendation system model with deep neural network technique or depends solely on deep learning method.

Neural network model is also divided into two categories on the basis of deep neural network based technique used: models which uses single deep neural network based technique and deep neural network based composite model. In deep neural network based composite model, different deep neural network techniques are used to build a hybrid system having more capability. The framework of recommendation system based on deep neural network is presented in Figure 2.

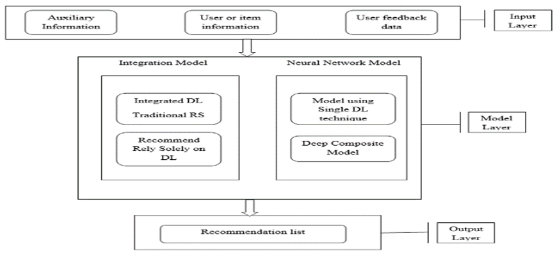

Figure 2. Deep neural network based Recommendation system

3.1 Collaborative Filtering Recommendation Systems based on Deep Neural Networks

Collaborative filtering (CF) is one of the commonly implemented techniques in recommendation systems in order to tackle various real-life issues. The state of the art CF-based methods uses the rating matrix for recommending the items. But this approach faces the problem of data sparseness and cold start problem. The sparsity of the user-item matrix, the learned features is not effective which reduces the performance of recommendation system. Various researchers propose deep neural network based collaborative filtering techniques to enhance its effectiveness in recommendation.

3.1.1 Collaborative Filtering Method based on Generative Adversarial Network

Generative Adversarial Network is a neural network which is generative and having discriminator and generator functions. These both functions are simultaneously trained in competition with one another in architecture of minimax game. The first model to implement GAN in the field of Information Retrieval is (IRGAN) (J. Wang et al., 2017) which stands for Information retrieval generative adversarial network. The state of the art GAN model has two modules a discriminator and a generator. The generative retrieval module predicts appropriate documents with given query, whereas discriminative retrieval module predicts relevancy given with a pair of query and document.

The IRGAN model combines above two Information Retrieval models in order to play a minimax game with them: the generative retrieval model produces (or selects) relevant documents that are relevant documents like ground truth, while the discriminating retrieval model separates the relevant documents from those generated by the generative retrieval model.

3.1.2 Recurrent Neural Network based Collaborative Filtering Method

In order to deal with the information in sequential form, recurrent neural network (RNN) proves to be a very effective network. Concepts of loops are used in place of feedforward network to remember sequences. Variants of RNN viz. Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) network are used to deal with the problems of long term dependencies and vanishing gradient problem.

In collaborative filtering method based on RNN, the impact of user historical sequence is modelled on the current behavior of user, recommendation is performed and user's behavior is predicted [19]. Figure 7 shows the framework of collaborative filtering method based on RNN (Wu et al., n.d.). Let the input set is $\{I_1, I_2 \ldots I_t\}$, and output is $O_t = \sigma(f(W \cdot h_{t-1} + V \cdot I_t) \cdot V)$, σ represents a softmax function, f represents the activation function, which specifies the selection probability of any item at time t. h_t represents the hidden state vector.

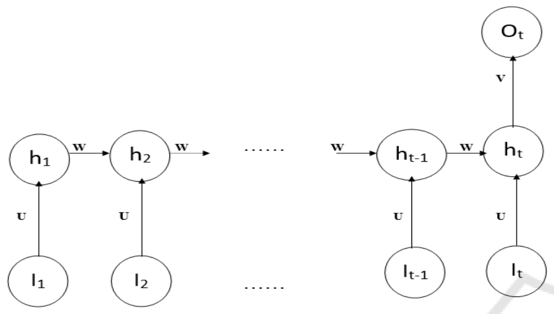

Figure 3. Collaborative filtering model based on RNN.

3.1.3 Collaborative Filtering Method based on Autoencoder

The first ever developed autoencoder-based collaborative recommendation model is Autoencoder based Collaborative filtering (Sedhain et al., 2015). It decomposes the vectors by integer ratings. The model proposed by (Sedhain et al., 2015) takes user or item based ratings as inputs in rating matrix R. The output is produced by the process of encoding and decoding by optimizing the parameters of model and reducing the reconstruction error. Consider an example, if the range of integers [1-5] represents the rating score, then each r_{ui} can be divided into five vectors.

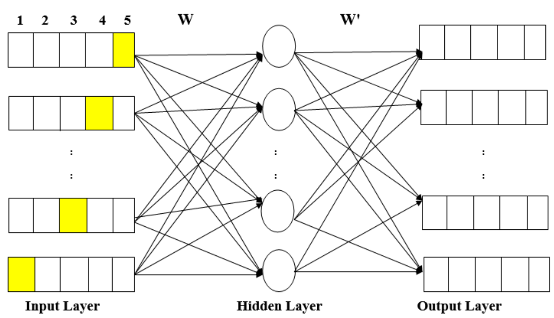

Figure 4. Collaborative filtering method based on Autoencoder

Above figure represents the 1 to 5 rating scale in which blue boxes represents the user rated item. The cost function which is to be reduced is taken as Mean Square Error. The rating prediction in this approach is found by making the summary of each of the five vectors, which are scaled by rating K. Pretraining of parameters and local optimum avoidance is performed by RBM. Stacking multiple autoencoder collectively shows the slight improvement in accuracy. This method based on autoencoder suffers from the problem of dealing with non-integer ratings and sparseness of input data due to decomposition of partial observed vectors.

Collaborative Denoising Auto-Encoder (Strub et al., n.d.) is primarily used for prediction rankings. User feedback is taken as input to the CDAE. If the user enjoys a movie, the input value is 1 otherwise it is 0. It shows the vector preference to display the user's interest in some item. Gaussian noise corrupts the CDAE input.

3.1.4 Collaborative Filtering Method based on Restricted Boltzmann Machine

Restricted Boltzmann Machine (RBM) is a two-layer neural network capable to deal with typical learning based problems. The efficiency of learning is improved by removing the connections between same layers. This recommendation method is proposed by (Salakhutdinov et al., 2007). Further a conditional RBM model is proposed to consider information in form of feedback. The visible layer of RBM can take only binary values so only one hot vector can be used to represent the rating score. The architecture of RBM based model is represented as shown in Figure 5.

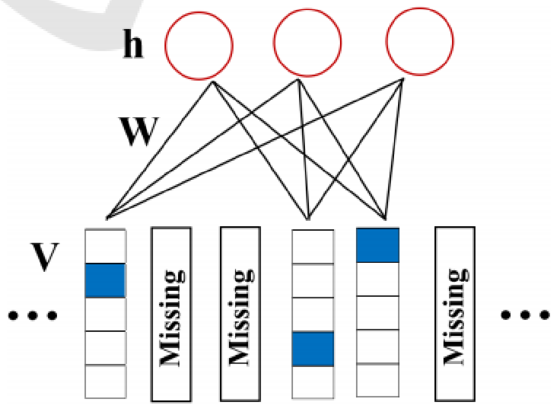

Figure 5. Collaborative filtering model based on RBM.

There are equal hidden layers in each RBM and have softmax units which are visible for movie ratings given by user. There is one training case in each RBM unit with combined weights and biases. Hidden units hold the binary states which are different for separate users. Let there are *N* movies rated by user and there are *n* visible units. Suppose *M* represents $X \times N$ size matrix where $r_{ui}^{x} = 1$ if movie *i* is rated as x by user *u,* otherwise $r_{ui}^{x} = 0$. So,

$$p(r_{ui}^{x} = 1|h) = \frac{\exp\,(rb_i^x + \sum_{j=1}^{T} h_j j w_{ij}^x}{\sum_{l=1}^{X} \exp\,(b_i^l + \sum_{j=1}^{T} h_j w_{ij}^l)} \tag{1}$$

$$p(h_j = 1|\mathrm{M}) = \sigma\,(\mathrm{b_j} + \sum_{i=1}^{N} \sum_{k=1}^{T} r_{ui}^{x}\, \mathrm{w_{ij}^x}) \tag{2}$$

where σ (x) represents a logistic function, r_{ui}^{x}: interaction, b_i^x :bias of rating *x* for movie *i* and b_j: hidden unit bias.

3.2 Content-based Recommendation Systems based on Deep Neural Networks

Content-based recommendation systems recommend on the basis of descriptive attributes of items and users' profiles such as texts, pictures and videos (Meteren et al., n.d.).

The use of deep neural network in content-based recommendation systems is to capture the non-linear relationships between user and item (Meteren et al., n.d.). It also captures the intra-relationship between data, from large available data sources.

3.3 Hybrid Recommendation System based on Deep Neural Networks

The state-of-the-art CF-based approach uses the ranking matrix to suggest products. But this method suffers from a data sparsity and a cold start crisis. Due to the scarce existence of the user-item matrix, the features learned are not accurate, which decreases the efficiency of the recommendation framework. Hybrid recommendation model based on deep neural networks incorporates a content-based recommendation model with collective recommendation-based filtering models, which combines the mechanism of feature learning and recommendation into a single model. (Meteren et al., n.d.) suggested a layered, self-encoder-based hybrid paradigm that learns the latent space factors of users and items and simultaneously performs mutual filtering from the ranking matrix.

An autoencoder is a variant of neural network, having encoder and decoder as two components. The encoder converts the input into its hidden representation, while the decoder converts the hidden representation back to the restored input form. The parameters corresponding to the autoencoder are trained to minimize the error due to the reconstruction, which is measured by the loss function. Denoising autoencoder (DAE) tries to reconstruct the input from a corrupted version for improved representation from the input. More variants of autoencoder have been developed for better outcomes. The hybrid recommendation model based on the stacked denoising autoencoder uses both the rating matrix and the side information and integrates both the SDAE (Meteren et al., n.d.) and the matrix factorisation. Matrix factorization is a widely used model with improved accuracy, and SDAE is a powerful model for extracting high-level features from inputs. The integration of the above two model will become a powerful model for more benefits.

3.4 Social Network-based Recommendation System using Deep Neural Networks

Conventional recommendation models never consider social connections among the users. But we always take verbal recommendations from our friends in reality. These verbal recommendations are termed as social recommendation which occurs daily (Meteren et al., n.d.). Hence, for improved recommendation systems and for more personalized recommendations, social network must be employed among users. Every user will interact with various types of social relationships.

The quality of recommendation system is very crucial task which can be achieved by implementing the effect of social relationship among the users. Items with location attributes and sequential pattern of user behaviour in spatial and temporal frame are used to form spatiotemporal pattern which is used to improve recommendation accuracy. Recently, a very few recommendation techniques have been proposed which is based on the users' trust relations improve conventional recommendation systems. These trust based recommendation models proves to be an effective move in the field of recommendation system models.

In current scenario an integration of deep learning and social network based recommendation system provides a platform for various research solutions. The limitations which are inherent to the social recommendation must be addressed in the future research.

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3.5 Context-aware Recommendation Systems based on Deep Neural Networks

A context-aware recommendation system, integrates context based information into a recommendation model. This integration is effectively performed by the deep learning techniques in different conditions of recommending item. Deep neural network based methods are used to extract the latent space presentation from the context based information. Deep learning-based model can be integrated into diverse data to reduce data sparsity problem. Sequential nature of data plays a significant part in implementing user behaviours. Recently, recurrent neural networks (RNNs) are commonly used in a variety of sequential simulation activities. However, for real-world implementations, these approaches have trouble modeling contextual knowledge, which has been shown to be very essential for behavioural modelling.

Currently this method based on deep neural networks focused towards situation information. A novel approach is proposed called context-aware recurrent neural networks. It uses two types of matrices: input and transition matrices. They both are specific to the context and adaptive in nature. Input matrices are used to extract various situations such as time, place, weather condition where actually the user behaves.

3.6 Comparisons

As deep learning plays a significant role in most of the fields as it has the capability of dealing with large and complex problems with improved results. Deep learning technology also contributes in the field of recommendation system for improved customer satisfaction. Deep learning technology overcomes the shortcomings of traditional models to get high quality recommendations (Liang et al., 2018).

All the above discussed methods of recommendation systems use deep neural networks and hence also achieve the quality in recommending items to the users (Liang et al., 2018). Different recommendation models use different deep learning methods to obtain improve results.

The summary of various deep neural network based recommendation systems are given below:

Table 1: Comparison

Application of Deep Learning in	Findings
Content-based recommendation systems	Extract non-linear user-item relationship and intricate relationship with data itself.
Collaborative filtering recommendation systems	Takes the user-item ranking matrix as input and uses a deep neural network based model to learn the latent space presentation that corresponds to users or objects. Use the loss function to construct a deep neural network-based model optimization function. On the basis of the latent space presentation, recommendations are made.
Hybrid recommendation systems	Integrate the individual or object learning process and the suggestion process into a single architecture.
Social network-based recommendation systems	Focuses on social relationship between users, and extracts the effect of location of user, movement patterns and other various factors.
Context-aware recommendation systems	Deep neural network based methods combines the context information into the recommendation model and obtain the latent space presentation of the context based information. Also reduce data sparsity in model.

4 CONCLUSIONS

The massive volume of data generates the necessity of applications and technology to efficiently process and information analysis for providing the maximum benefit to the target users. Recommendation system based on deep neural networks proves to be optimal solution for above mentioned challenges. Deep neural network based recommendation systems can easily learn the features of items along with users from large volume of information, to build a system for effective recommendation to users. This article compares the conventional recommendation models with the deep neural network based recommendation techniques which extracts the features of users along with items to increase the accuracy of recommending items to users. It also integrates data from multiple sources to extract the preferences of users.

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