

An Application-oriented Review of Deep Learning in Recommender Systems

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Abstract—The development in technology has gifted huge set of alternatives. In the modern era, it is difficult to select relevant items and information from the large amount of available data. Recommender systems have been proved helpful in choosing relevant items. Several algorithms for recommender systems have been proposed in previous years. But recommender systems implementing these algorithms suffer from various challenges. Deep learning is proved successful in speech recognition, image processing and object detection. In recent years, deep learning has been also proved effective in handling information overload and recommending items. This paper gives a brief overview of various deep learning techniques and their implementation in recommender systems for various applications. The increasing research in recommender systems using deep learning proves the success of deep learning techniques over traditional methods of recommender systems.

Index Terms—Recommender system, Deep learning, Collaborative filtering, Deep neural network, Social recommender system.

I. INTRODUCTION

In the modern age where vast amount of data is generated every second, it becomes difficult to select relevant items from the overwhelming set of choices. Many of the times it is difficult to reach a decision without having prior knowledge about the items. The result is that people rely on the advices or recommendations of their friends or some expert. Recommender systems (RSs) have been proved helpful in handling information overload [1]. RSs are important information filtering tools in recommending relevant, interested and striking items to users. Typically, a RS compares the user profile with profile of similar users or it use the past history or behavior of users to recommend items [2]. The rating matrix is used to determine the preferences of user for an item. A number of techniques have been proposed for RSs but deep learning is a new research area in recommendation. In previous years, deep

learning methods have been extensively used in various applications like object detection [3], playing games [4], automatic text generation for images [5], image processing [6], inclusion of sound in silent movies [7], music recommendation [8,9], etc. An increasing use of deep learning techniques in generating meaningful recommendations can be seen in recent years. A workshop on "Deep Learning for Recommender Systems" in conjunction with an international conference "RecSys" from year 2016 reveals the significance and proliferation of deep learning in RS. We can realize its significance by the huge number of publications in this area. The main motivation behind this research is to reveal the advancement in the field of RS. We present an outline of the state-of-the art research in this area.

The rest of this paper is structured in the following style. Section II gives the overview of RS and the traditional technique for RSs. Section III discusses the concept of deep learning and its techniques. Section IV surveys the related work of deep learning in RSs in different domains. Section V gives a few works done in social recommender system employing deep learning. Lastly, Section VI concludes the paper.

II. RECOMMENDER SYSTEMS

Recommender systems are the information retrieval systems which recommend only selective items from the enormous collection of items. Thus, RSs are essential in reducing the problem of information overload. RSs are vital tools in promoting sales in e-commerce websites [10]. They aim to recommend items such as movies, music, books, events, products, etc. According to a survey report, about 60% of videos are watched using the recommendations by YouTube and 80% of movies watched is recommended by Netflix. Reference [2] presents the evolution of RS into three generations, namely web 1.0, web 2.0 and web 3.0. Traditional algorithms for designing RSs are mainly of three types: collaborative filtering, content-based filtering and hybrid algorithms. In collaborative filtering based algorithms [11], the systems find the similar users and use their

tastes and preferences to recommend items to the customers. Collaborative filtering based algorithms have been extensively used in traditional RSs. Collaborative filtering approaches can be further of two types: user-based and item-based approaches [12]. In user-based collaborative filtering approach, the users with same preferences are grouped and recommendation to any item is given by evaluating the preferences of that group. On the other hand, item-based approach assumes that the preference of people remain stable or drift very slightly. In content-based filtering algorithms, the system searches for the similar type of contents or items by using the past behavior of user and then recommend the similar contents to the user. However, the hybrid algorithms combine the features of collaborative filtering and content-based algorithms to give recommendations to the user. The hybrid techniques may use some features of collaborative filtering approach into content-based filtering approach or it may use the features of content-based filtering approach into collaborative filtering approach. But these approaches face various issues such as cold-start, data sparsity, privacy [13], scalability and trust [14].

A good RS takes into account the changing system's contents and the dynamic users' preferences. Rana and Jain [76] explore various parameters which are important for the dynamism in RS. These parameters are: serendipity, novelty, temporal characteristic, context, dynamic environment and diversity. On the other hand, Shokeen and Rana [77, 79] explore the dynamics involved for the success of RSs that are based on social networking data. Such RSs are termed as social recommender systems. They also give a review on different aspects of these systems. These aspects are: tagging, communities, trusted relations, communities and cross-domain knowledge.

III. DEEP LEARNING

Deep learning is a subfield of machine learning. It is a technique that learns features directly from data. The computation models in deep learning consist of several processing layers to learn data representation [15]. The deep learning models learn high level features from low-level features where data can take any form from text to audio and images. Unlike other neural network methods, deep learning networks consist of two or more than two layers in which features from previous layers are aggregated to build more complex features in the next layers. The deep learning based methods can be trained using either supervised or unsupervised learning approaches. The main motivation behind the proliferation of deep learning models is their accuracy, easy adaption to new problems, enormous amount of available data and less time to train GPUs.

Fig. 1 demonstrates deep neural network consisting of an input layer, hidden layers and an output layer. As the number of layers increase in these networks, the data representation becomes more complex.

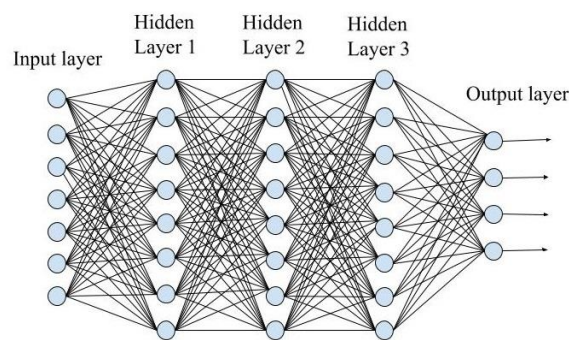


Fig.1. Deep Neural Network

When large amount of data is available for training, deep learning models give best results as compared to non-deep learning methods. Fig. 2 shows a diagram of any active node to be used in hidden layers and output layer of deep learning models. In this figure, the set of inputs to a neuron or node j is denoted by $\{x_1, x_2, x_3, \dots, x_n\}$ and weights of the inputs for neuron j is represented by $\{w_{1j}, w_{2j}, \dots, w_{nj}\}$. Σ denotes the transfer function that multiplies each input with its weight and then sums it. We denote this sum by net_j for the neuron j . The activation function $f(S)$ performs computation of net_j and if the value is greater than threshold θ , it gives output o_j for neuron j .

In literature, a diverse number of deep learning techniques have been used for recommendation. These techniques include convolutional neural networks [8] [16], deep neural networks [17,18], deep belief networks, deep autoencoders [19-21], multiperceptron layer [22], restricted boltzmann machine [23,24] and recurrent neural networks [25,26]. Some of the authors have used a single deep learning technique to build the recommendation model while others have integrated two or more than two techniques for generating recommendations. Also, some RSs are based on the hybrid models which are based on the integration of deep learning methods with traditional methods of RSs [22] [27-29]. An advantage of using multiple deep learning methods for model construction is that one technique can counteract the effects of other technique. This hybridization can generate an efficient model.

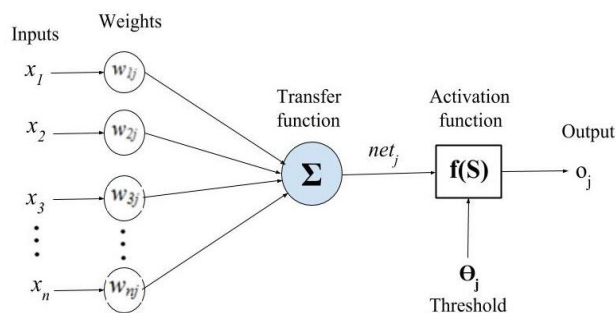


Fig.2. Architecture of an Active Node

A. Deep Learning Techniques

In this subsection, we also give a brief explanation of some of the deep learning techniques. These techniques are as follows:

Convolutional neural network:

A network with convolutional layers and pooling operations is termed as convolutional neural network. This technique increases the efficiency of network by capturing both local and global features. This network performs better in grid-like networks.

Deep neural network:

A deep neural network is similar to an artificial neural network in terms of structure but differs in terms of layers. Deep neural networks encompass multiple hidden layers that can model complex relationships. A deep neural network is multi-layer perceptron that uses back-propagation to learn the network. Stacked denoising autoencoders is one of the approaches used in building deep neural networks [30]. Wang et al. [19] proposed relational stacked deep autoencoder (RSDAE), which is a probabilistic model, to integrate deep representation learning and relational learning. It has been shown through real-world datasets that RSDAE model outperforms the state-of-the-art.

Deep belief network:

Deep belief networks (DBN) are generative models consisting of complex layers of latent and stochastic variables. The latent variables are generally termed as feature detectors. There are symmetric and undirected connections between the upper two layers whereas directed connections exist at the lower layers [31]. The learning in deep belief nets occur layer-by-layer where the data values from one layer are used to train the next layer and so on.

Restricted Boltzmann machine:

A restricted Boltzmann machine (RBM) is an artificial neural network that learns the probability distribution through inputs. On the basis of the nature of task, they can be supervised or unsupervised. RBMs are the modified form of Boltzmann machine, with the constraint that there exists bipartite graph between neurons. RBMs plays an important role in dimensionality reduction [32], collaborative filtering [23] and classification [33]. On stacking RBMs, deep belief networks are formed. Recently, authors in [75] have attempted to minimize the long training time of deep neural networks by modifying RBM.

Deep Autoencoders:

Deep autoencoders is a special variety of deep neural networks and follows unsupervised learning approach. A deep autoencoder comprises two consistent DBN containing usually five layers. The first half refers to the encoding part of DBN and the second half is the decoding DBN. Deep autoencoders are non-linear autoencoders as

the layers in deep autoencoders are restricted Boltzmann machines [34]. In initialization stage, the data is processed through multiple layers of restricted Boltzmann machines. The processing allows deep auto encoders to abstract high-dimensional data from latent features [35]. An extended form of stacked autoencoders is stacked denoising autoencoders.

Recurrent neural networks:

Recurrent neural networks are dynamical, feedbackward systems that consist of memory to retain previous computations. These networks are useful in modeling sequential data.

IV. DEEP LEARNING IN RECOMMENDER SYSTEMS

In literature, a number of algorithms and techniques have been proposed to build RSs. It is interesting to note that collaborative filtering is the widely used technique in RSs. But most of these algorithms face data sparsity and cold-start problem issues. Recently, deep learning based techniques implementation RSs have proved helpful in alleviating these issues. It becomes easy to predict null rating values with deep learning [36]. Some deep learning-based RSs have also incorporated information from social networks to improve the recommendations. With time, some methods have been modified and revised. A comprehensive survey of RSs using deep learning has been made by many researchers. It is essential to say that collaborative filtering is the winning approach employed by many RSs. But in real-world datasets, the sparsity in data leads to decreasing the performance of the collaborative filtering approach. Many researchers have combined collaborative filtering approach with deep learning methods to resolve the issues related to data sparseness and cold-start problem [9, 19, 27, 28]. Collaborative deep learning has given more successful results when compared to traditional collaborative filtering techniques [37, 38]. With deep learning, it is easy to predict the null rating values [36]. Deep collaborative filtering has also been tested for movie recommendation [37]. [29] have proposed a collaborative deep learning model that uses deep learning to retrieve the textual information and collaborative filtering to obtain the feedback from the ratings matrix. [27, 39] employ deep neural networks to explore item content characteristics and then apply these characteristics into the timeSVD++ collaborative filtering model. Cheng et al. [40] have proposed a wide and deep learning framework to integrate the features of deep neural networks and linear models. In this framework, wide linear models are used to learn sparse features connections whereas deep neural networks are used to generalize earlier hidden features. The framework successfully utilizes the capabilities of both models to train the network.

Many attempts have been made for introducing tags related information to RS to enhance the performance of conventional RS. But user-defined tags undergo various challenges such as ambiguity, redundancy and sparsity.

To deal with these challenges, deep neural networks extract the information from tags and process the information through multiple layers to retrieve more advanced and abstract data [41]. Authors in [42] have provided a very short survey of deep learning methods used in RSs. Zhang et al. [43] present a comprehensive review of deep learning techniques based RSs. A few recent works in this area which have been included in this section have not been covered in the past survey.

A. Entertainment

For entertainment, researchers have deployed deep learning techniques for music recommendation. Wang and Wang [9] have worked in this area and proposed a content based recommendation model that combines deep belief network and probabilistic graph models. The model is used in training network to learn features. This model works better than the traditional hybrid models. Oord et al. [8] have used deep convolutional neural networks to predict the hidden features in musical audio when they cannot be obtained directly from usage data. Liang et al. [44] proposed a recommendation system based on a content model and a collaborative model. The system pre-trains a multi-layer neural network on semantic tagging data and treats it to extract the content features. The high-level representation generated by the last hidden layer of network is used as a prior in the collaborative model for the latent representation of songs. Recently, researchers use heterogeneous information to improve the quality of RSs. Zhang et al. [45] have investigated in this direction and proposed a collaborative knowledge base embedding framework to learn hidden and semantic representation simultaneously. They have used denoising auto-encoders and convolutional auto-encoders to mine semantic data from multiple forms of data. They have designed components to mine semantic data from multiple forms of data. Denoising auto-encoders extract textual data representations and then convolutional auto-encoders are used to mine visual representations. Recently, deep neural architecture is employed by Oramas et al. [18] to propose a multimodal approach for song recommendation. The approach combines audio and text information with user feedback information using deep neural networks.

B. Cross-domain

Nowadays, users have multiple accounts on social networks. The data from multiple sites assist RS in reducing the cold-start problem [46–51]. Authors in [46] have worked in this direction to integrate cross-domain data. They have used multi-view deep neural networks to integrate the data from multiple social media sites to enhance the quality of RS. They have also suggested various dimensionality reduction methods to scale their framework to large datasets. The dimensionality reduction methods are: top features, k-means, local sensitive hashing and reduction in number of training examples. Huang et al. [52] focus on retrieving images by extracting the clothing attributes from cross-domains. They propose a Dual Attribute-aware Ranking Network (DARN) to learn the retrieved features. With DARN, it is

easy to integrate semantic attributes with visual similarity attributes into the feature learning phase. The system retrieves the clothing images similar to the given offline clothing images. In another work, [22] use multi-view neural networks and propose a cross-domain RS to overcome the data sparsity problem. Recently, Khan et al. [51] give a broad survey of cross-domain RSs.

C. Medicine

Recently, researchers have also started applying deep learning in health care domain. The processing of medical data with deep learning methods is useful in boosting the prediction power of health care systems. The use of deep learning methods in clinical datasets can help in treatment recommendation, personalized prescription, disease risk prediction and clinical dataset analysis. [53] have presented a review of deep learning techniques in clinical imaging, genomics, electronic heart records and wearable device data. Manogaran et al. [54] propose a deep learning method using Adaptive Neuro-Fuzzy Inference System (ANFIS) and Multi Kernel Learning. They have used Multi Kernel Learning to segregate features of heart disease patients and healthy people. Their approach aims to solve unsupervised learning problems. They have incorporated ANFIS method that uses adaptive and non-adaptive nodes. Yuan et al. [55] give a deep learning-based socialized RS to recommends healthcare services to users based on the trust and distrust relationships with the target user. The system also considers the structure information and the node information of users in the network. The entire information is then fused into a deep learning-based model. This model is a multilayer perceptron and measures the trust strength by assessing the weights of features. The model gives the reliable healthcare recommendations even for the cold-start users. Katzman et al. [56] propose a deep neural network-based RS called *DeepSurv* for personalized treatment recommendation.

D. Industrial

With the excessive sparsity in features of real-world datasets, it is challenging to scale the features to meet the industrial requirements. One way to handle the problem of data sparsity in industry is to implement deep learning. Covington et al. [57] revealed the huge impact of deep learning on YouTube video recommendations. They propose a deep neural architecture based RS that divides the task of recommendation into two phases: candidate generation and ranking. The candidate generation model is used to select a subset of videos from the video corpus. Then, the ranking model uses the nearest neighbor score of the selected candidates to build a set of top-n videos. Chen et al. [58] have proposed a locally connected deep learning framework to deal with huge industrial datasets. Their framework condenses the model size by transforming sparse data into dense data. The reduction in model size ultimately produces effective results in less time.

E. Images

Deep learning is the widely used technique in image processing. Yang et al. [59] have used the deep learning approach for personalized image recommendations in which visual data and user's preferences over images are used to learn hybrid representation. This is achieved by designing a dual-net deep network where input images and user's preferences are first mapped into a same latent semantic space and then the decision is made by calculating the distance between images and users. They have also proposed a comparative deep learning (CDL) technique to train the deep network. CDL is based on the idea that the distance between a user and a positive image is less than the distance between the user and a negative image. The results demonstrate that this technique is better than other approaches in image recommendations. A more recent work shows that images related with an individual attempts to generate visual user interest profile which acts as a foundation for both recommendation and optimization. Zhou et al. [60] employ deep learning to extract semantic information from the visual content.

F. Miscellaneous

Various application areas are associated with textual recommendations such as scientific paper recommendations, blog posts and news articles which require text to be recommended to users. For this, Bansal et al. [61] propose a method leveraging deep neural networks to give vector demonstration for the textual content. Gradient descent is directly used to train the text-

to-vector mapping, thereby offering chance to execute multi-task learning. Authors in [62] have recently developed personalized scientific research paper RS using recurrent neural networks. This technique effectively searches hidden semantic features of research papers as compared to the conventional bag-of-word techniques. Recently, Xu et al. [63] address the uncontrolled vocabulary issue of social tags through deep neural network approach. In this approach, the tag-based user and item profiles are mapped to more abstract deep features. They propose a deep-semantic similarity-based personalized model that consists of many hidden layers due to which it becomes more time-consuming and expensive to train large online recommendation system. To alleviate this problem, they propose a hybrid deep learning model that integrates autoencoders with the above model. The model outperforms the existing techniques in personalized recommendations. Currently, deep learning is also being used in favorite restaurant prediction [64], online news RS [20], generation of user interest profile [60], session-based recommendation [26, 78]. Recurrent neural networks are recently used in session recommenders. Recurrent neural networks in [26] utilizes the past session data of users to improve the recommendations before the session starts. It shows promising results in dealing with the cold-start problem.

In this paper, we have taken a dataset of 45 papers specifically concerned with deep learning in RSs. Table 1 classifies these papers on the basis of different applications. We also list the type of deep learning method used in designing RS for these applications.

Table 1. Classification of papers on the basis of applications

Applications	References	Type of Model
Entertainment	Wang and Wang [9]	Deep belief network
	Van de Oord et al. [8]	Deep convolutional network
	Liang et al. [44]	Multilayer perceptron
	Zhang et al. [45]	Denosing autoencoder, Convolutional autoencoder
	Oramas et al. [18]	Deep neural network
Cross-domain	Elkahky et al. [46]	Deep neural network
	Huang et al. [52]	Deep convolutional network
	Lian et al. [22]	Multilayer perceptron
Medicine	Manogaran et al. [54]	Deep neural network
	Yuan et al. [55]	Multilayer perceptron
	Katzman et al. [56]	Deep neural network
Industrial	Covington et al. [57]	Deep neural network
	Chen et al. [58]	Multilayer perceptron
Images	Lei et al. [65]	Convolutional neural network and Multilayer perceptron
	Zhou et al. [60]	Convolutional neural network
Miscellaneous	Bansal et al. [61]	Deep neural network and Multilayer perceptron
	Hassan [62]	Recurrent neural network
	Zhenghua Xu [63]	Autoencoder
	Jia et al. [24]	Restricted Boltzmann Machine
	Chu and Tsai [64]	Convolutional neural network
	Cao et al. [20]	Autoencoder
	Ruocco et al. [26]	Recurrent neural network
	Quadrana et al. [78]	Recurrent neural network

V. DEEP LEARNING IN SOCIAL RECOMMENDER SYSTEMS

The combination of social networks with RS is termed as social recommender system [79]. Social recommender systems employ the data from social networking sites and thus improve the recommendations [80]. These recommendation systems are more capable than traditional RSs. The user trust information further helps in improving the recommendations. Jia et al. [24] combined knowledge from different social networks to ascertain the correlation between the online information and event participation. They propose a model called CLER (Collaborative Learning Approach for Event Recommendation) that considers both the similarity between events and users and the feature descriptions. Deng et al. [35] propose DLMF (Deep learning based matrix factorization) approach for social network trust based recommendations. They use deep encoders to train the initial values and hidden features of users and items.

Final latent features of items and users are learned by minimizing the objective function. Also, privacy is one of the issues in social recommender systems as these systems rely on user personal details. To address this problem, Dang et al. [66] propose a rating prediction approach called "dTrust" that exploits the topology of trust-user-item network. This approach uses deep feed-forward neural network to combine user relations and user-item ratings to predict ratings. To learn user features from large, sparse and diverse social networks, [67] propose DUIF (Deep User-Image Feature) as a deep learning framework to give useful recommendations. This framework employs user and images features to evaluate similarities between them.

More recently, Wang et al. [68] use deep neural networks to propose neural collaborative social ranking (NCSR) method to integrate user-item interactions from information domains and user relations from social domain for cross-domain social recommendation. They consider the users with multiple accounts on social networks as silk routes to recommend items from information domain to social users.

Table 2 shows the period wise statistics of these papers from year 2013 to 2017. It is clear from the table that deep learning is extensively used in recent years to enhance the performance of RSs. Moreover, deep learning has also opened the doors for improving the accuracy of social recommender systems.

Table 2. Period wise statistics of papers on deep learning based RS

Period	#Papers	#Paper References
2013	1	[8]
2014	2	[9], [29]
2015	5	[19], [37], [44], [46], [52]
2016	17	[16], [21], [24], [25], [28], [36], [40], [41], [45], [47], [57], [60], [61], [69], [70], [65], [71]
2017	20	[17], [18], [20], [22], [26], [27], [38], [42], [43], [51], [53], [62]–[64], [66], [68], [72]–[74], [78]

VI. CONCLUSION

A voluminous research has been done and is also proceeding in recommender systems using deep learning. It is an active research area where profound work is still required to advance the process of learning. We have used a dataset of 45 papers specifically concerned with deep learning in recommender systems that validates its exploration in recent years. Studies on dimensionality reduction could be a remarkable future work in enhancing the proficiency of RSs. This can be achieved by importing rich ideas from other spheres of machine learning. Also, the recent growth in social networks is beneficial in improving the capabilities of recommender systems. In the future work, we would like to compare the performance of some deep learning-based RSs with non-deep learning based RSs.

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