Deep Learning Based Recommender System

Reema Alabduljabbar
Computer science
King Saud University
437202646@ksu.edu.sa

Rahaf Alturbaq
Computer science
King Saud University
437201944@ksu.edu.sa

Abrar Alsharidi
Computer science
King Saud University
437200508@ksu.edu.sa

Najat Alrajhi
Computer science
King Saud University
437925369@ksu.edu.sa

Abstract—

With the growing volume of online information, recommender systems have been an effective strategy to overcome information overload. In recent years, deep learning has garnered considerable interest in many research fields such as computer vision and natural language processing, owing not only to stellar performance but also to the attractive property of learning feature representations from scratch. The field of deep learning in recommender system is flourishing. This paper aims to provide a comprehensive review of recent research efforts on deep learning-based recommender systems Finally, We used Google Scholar and Saudi digital library as the main search engines.

Keywords : Deep Learning , Recommender System.

1. Introduction—

The proliferation of information available on the web overwhelms online users, especially when searching for a product or item. Recommender Systems (RSs) are useful software tools and techniques providing suggestions for items to be of use to a user [1]. They are used to predict the best items or products to the users according to their past behavior and possibly using other kinds of data [2]. During the last few decades, with the rise of Youtube, Amazon, Netflix and many other such web services, recommender systems have taken more and more place in our lives. From e-commerce to online advertisement , RSs are today unavoidable in our daily online journeys. All in all, these systems have been playing a vital and indispensable role in various information access systems to boost business and facilitate the decision-making process. In a very general way, recommender systems are algorithms aimed at suggesting relevant items to users (items being movies to watch, text to read, products to buy or anything else depending on industries) generated based on user preferences, item features, user/item past interactions, and some other additional information such as temporal (e.g., sequence-aware recommender) and spatial (e.g., POI) data. Recommendation models are mainly categorized into collaborative filtering, content-based recommender systems, and hybrid recommender systems based on the types of input data[7,18].

Deep learning has been changing recommendation architecture dramatically and bringing more opportunities to improve the performance (e.g., Recall, Precision, etc.) of recommender systems.[7]

Deep Learning provides a new toolkit for recommender systems practitioners to extract features and to model user generated data and item data that has the potential to provide large improvements in the quality of the recommendations provided to users. Part of the power of deep learning techniques in recommender systems stems from the fact that deep learning methods allow for much better feature extraction from item characteristics such as image, video and audio compared to traditional techniques[3].

2. Background—

Before we dive into the details of this section, we start with an introduction to the basic terminology and concepts regarding recommender systems and deep learning techniques with branches of each sections.

2.1 Recommender systems estimate users' preference on items and proactively recommend items that users might like. Recommendation models are usually classified into three categories: collaborative filtering, content-based, and hybrid. Collaborative filtering makes recommendations by learning from user/item historical interactions, either through explicit (e.g., user's previous ratings) or implicit feedback (e.g., browsing history), Content-based recommendation is based primarily on comparisons across items' and users' auxiliary information. A diverse range of auxiliary information such as texts, images, and videos can be taken into account. Hybrid models are recommender systems that integrate two or more types of recommendation strategies [7].

2.1.1 <u>CONTENT-BASED</u> : The system learns to recommend items that are similar to the ones that the user liked in the past. The similarity of items is calculated based on the features associated with the compared items. For example, if a user has positively rated a movie that belongs to the comedy genre, then the system can learn to recommend other movies from this genre.[19].

2.1.2 <u>COLLABORATIVE FILTERING</u> (CF) : The simplest and original implementation of this approach [93] recommends to the active user the items that other users with similar tastes liked in the past. The similarity in taste of two users is calculated based on the similarity in the rating history of the users. This is the reason why [94] refers to collaborative filtering as "people-to-people correlation."

Collaborative filtering is considered to be the most popular and widely implemented technique in RS.[19]

2.1.3 HYBIRD : models are recommender systems that integrate two or more types of recommendation strategies. A hybrid system combining techniques above tries to use the advantages of one of them to fix the disadvantages of other one. For instance, CF methods suffer from new-item problems, i.e., they cannot recommend items that have no ratings. This does not limit content-based approaches since the prediction for new items is based on their description (features) that are typically easily available. Given two (or more) basic RSs techniques, several ways have been proposed for combining them to create a new hybrid system.[19]

2.2 Deep learning Deep learning stems from the study of artificial neural networks [8]. The concept of deep learning was proposed by Hinton et al. [9] in 2006. He proposed an unsupervised greedy layer-by-layer training algorithm based on deep belief network (DBN), which brought hope to solve the optimization problem related to deep structure. Then he proposed the deep structure of multi-layer auto encoder. In addition, the convolutional neural network proposed by Lacuna et al. [10]. It is the first true multi-layer structure learning algorithm, which uses spatial relative relations to reduce the number of parameters to improve training performance. Deep learning combines low level features to form more abstract high-level representation attribute categories or features to discover distributed feature representations of data. Deep learning is a new field in machine learning research. It mimics the mechanism of the human brain to interpret data such as images, sounds and texts. Like the machine learning method, the deep learning method also divided into supervised learning and unsupervised learning. In this section, we describe commonly used deep learning models. First, we introduce the auto encoder (AE). Then, we present the details of restricted Boltzmann machine (RBM). Next, we present recurrent neural network (RNN) and convolutional neural network (CNN).

2.2.1 AUTOENCODER (AE) : is an unsupervised model attempting to reconstruct its input data in the output layer. In general, the bottleneck layer (the middle-most layer) is used as a salient feature representation of the input data. Autoencoder can be seen as a variant of the traditional multi-layer perceptron, first proposed by Rumelhart et al. [11] Autoencoder reconstructs the input data to learn the latent feature of the data through coding and decoding process. The structure is shown in figure 1.

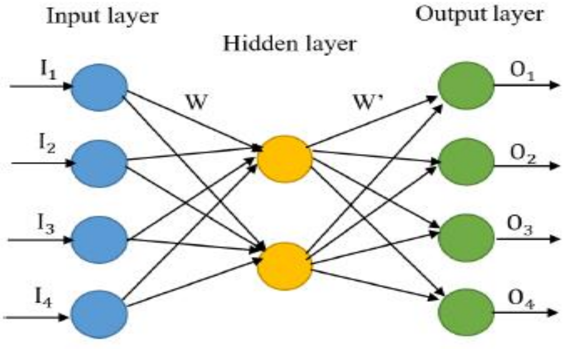


FIGURE 1. **Autoencoder.**

2.2.2 RESTRICTED BOLTZMANN MACHINE (RBM) : is an extension of Boltzmann machine. Restricted Boltzmann Machine (RBM) is a two-layer neural network consisting of a visible layer and a hidden layer. It is one of the earliest artificial neural networks capable of solving complex learning problems by learning the inherent intrinsic expression of data. The learning efficiency is greatly improved because the connection between the same layers is removed. Restricted here means that there are no interlayer communications in visible layer or hidden layer. It can be easily stacked to a deep net. The structure of restricted Boltzmann machine is shown in figure 2.

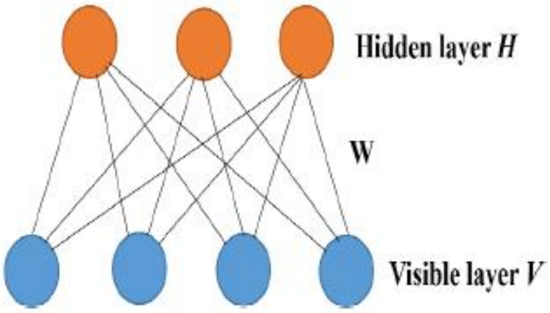


FIGURE 2. Restricted Boltzmann machine.

2.2.3 RECURRENT NEURAL NETWORK (RNN) : Recurrent Neural Network (RNN) is suitable for modeling sequential data. Unlike feed forward neural network, there are loops and memories in RNN to remember former computations. RNNs have been widely used in machine translation [15]. An ordinary full-connected network or a convolutional neural network is a structure which from the input layer to the hidden layer to the output layer, the layers are fully connected between layers, and the nodes are disconnected in each layer. This structure of neural network is often incompetent to model the sequential data. In a fully connected DNN and CNN network, the signals of each layer can only propagate to the next layer, and the processing of the samples is independent at each time. When the RNN accepts a new input, it combines the implied state vector with the new input to produce an output that depends on the entire sequence. RNNs are called recurrent because they perform the same task for every element of a sequence, with the output being depended on the previous computations. The structure of this type shown in figure 3.

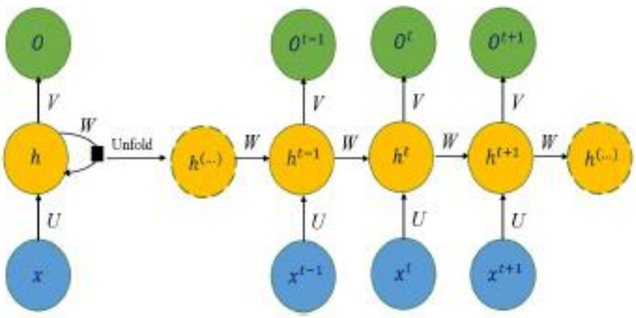
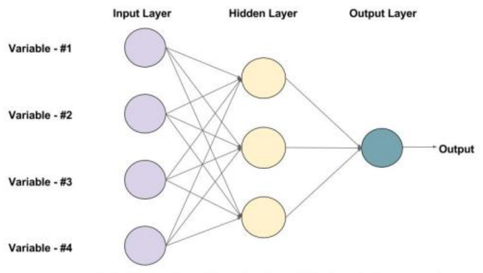


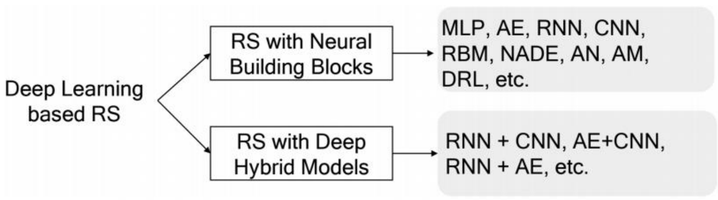
FIGURE 3. A recurrent neural network and the unfolding in time of the computation involved in its forward computation.

2.2.4 CONVOLUTIONAL NEURAL NETWORK (CNN) is a special kind of feed forward neural net-work with convolution layers and pooling operations. It can capture the global and local features and significantly enhances efficiency and accuracy. It performs well in processing data with grid-like topology. See the below figure.



An example of a Feed-forward Neural Network with one hidden layer (with 3 neurons)

2.3 Categories of Deep Learning Based Recommendation Models To provide a bird-eye's view of this field, we classify the existing models based on the types of employed deep learning techniques. We further divide deep learning-based recommendation models into the following two categories. Down figure summarizes the classification scheme [7].



- Recommendation with Neural Building Blocks. In this category, models are divided into eight sub-categories in conformity with the aforementioned eight deep learning models: MLP-,AE-, CNN-, RNN-, RBM-, NADE-, AM-, AN-, and DRL-based recommender systems. The deep learning technique in use determines the applicability of the recommendation model.For instance, MLP can easily model the nonlinear interactions between users and items ; CNNs are capable of extracting local and global representations from heterogeneous data sources such as textual and visual information; RNNs enable the recommender systems tomodel the temporal dynamics and sequential evolution of content information.

- Recommendation with Deep Hybrid Models. Some deep learning-based recommendation models utilize more than one deep learning technique. The flexibility of deep neural net-works makes it possible to combine several neural building blocks to complement one an-other and form a more powerful hybrid model. There are many possible combinations ofthese deep learning techniques, but not all have been exploited. Note that this differs fromthe hybrid deep networks in Deng et al.[31], which refer to the deep architectures that make use of both generative and discriminative components.[7]

2.3.1 DEEP LEARNING IN CONTENT-BASED RECOMMENDER SYSTEMS

Content-based recommender system is mainly based on items' and users' auxiliary information. A various range of auxiliary information such as texts, images and videos can be taken into account. Deep learning in content-based recommender systems are mainly used to effectively capture the non-linear and non-trivial user-item relationships and enable the codification of more complex abstractions as data representations in the higher layers. Furthermore, it catches the intricate relationships within the data itself, from abundant accessible data sources such as contextual, textual and visual information. The architecture of deep learning based recommender system shown in figure 6.

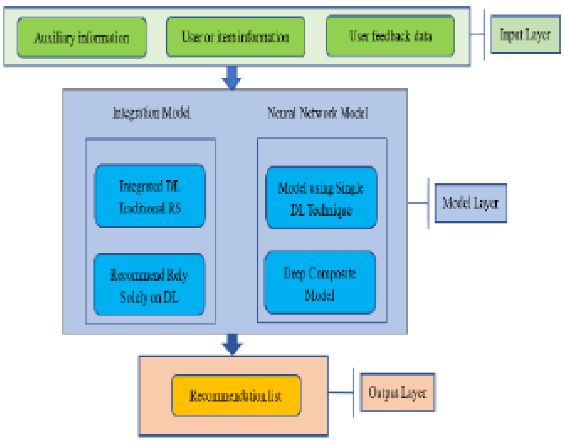


FIGURE 6. The architecture of deep learning-based recommender systems.

2 3.2 DEEP LEARNING IN COLLABORATIVE FILTERING RECOMMENDER SYSTEMS

Collaborative filtering (CF) is a widely used approach in recommender systems to solve many real-world problems. Traditional CF-based methods employ the user-item matrix which encodes the individual preferences of users for items for learning to make recommendation. In real applications, the rating matrix is usually very sparse, causing CF-based methods to degrade significantly in recommendation performance. Some improved CF methods utilize the increasing amount of side information to address the data sparsity problem as well as the cold start problem. However, the learned latent factors may not be effective due to the sparse nature of the user-item matrix and the side information. Some researchers utilize advances of learning effective representations in deep learning, propose deep learning-based collaborative filtering methods, which is a kind of model based collaborative filtering recommendation methods.

2.3.2.1 RESTRICTED BOLTZMANN MACHINE-BASED COLLABORATIVE FILTERING METHOD

visible layer and a hidden layer. It is one of the earliest artificial neural networks capable of solving complex learning problems by learning the inherent intrinsic expression of data. The learning efficiency is greatly improved because the connection between the same layers is removed. Mnih *et al.* The structure of this model shown in figure 8.

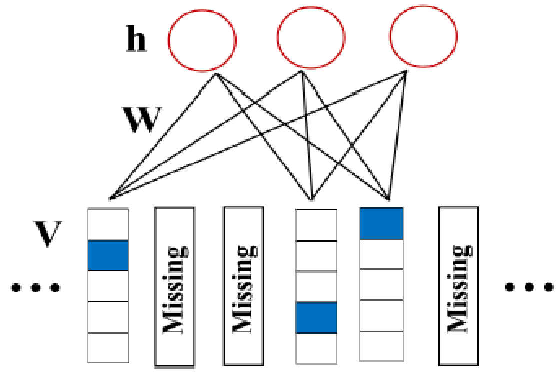


FIGURE 8. **RBM-based collaborative filtering model.**

2.3.2.2 RECURRENT NEURAL NETWORK-BASED COLLABORATIVE FILTERING METHOD

Recurrent neural network (RNN) is suitable for modeling sequential data. Unlike feedforward neural network, there are loops and memories in RNN to remember former computations. Variants such as Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) network are often deployed in practice to overcome the vanishing gradient problem. The basic idea of RNN-based collaborative filtering is to use RNN to model the effect of user historical sequence behavior on the user current behavior figure 9 is a basic RNN-based collaborative filtering method framework.

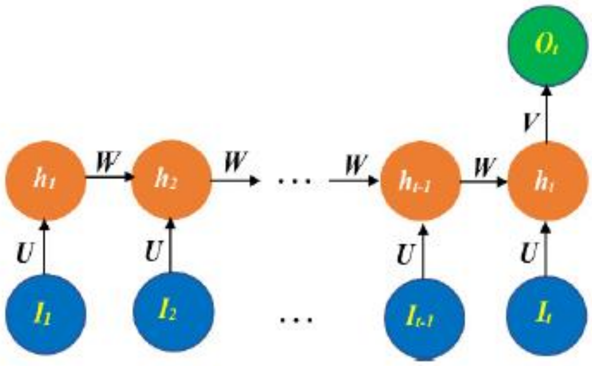


FIGURE 9. RNN-based collaborative filtering model.

2.3.3 DEEP LEARNING-BASED HYBRID RECOMMENDER SYSTEMS

Traditional CF-based methods employ the user-item matrix which encodes the individual preferences of users for items for learning to make recommendation. In real applications, the rating matrix is usually very sparse, causing CF-based methods to degrade significantly in recommendation performance. In this case, some improved CF methods utilize the increasing amount of side information to address the data sparsity problem as well as the cold start problem. The structure of this model shown in figure 10.

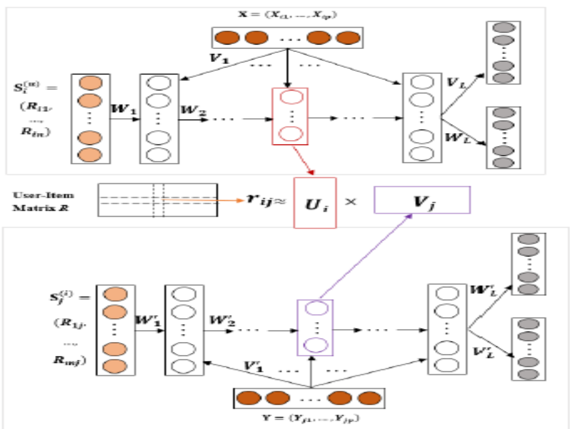


FIGURE 10. The architecture of stacked denoising autoencoder -based hybrid recommendation method.

2.3.4 COMBINATION OF DEEP LEARNING AND SOCIAL NETWORK-BASED RECOMMENDER SYSTEMS

Traditional recommender systems always ignore social relationships among users. But in our real life, when we are asking our friends for recommendations of nice digital cameras
or touching movies, we are actually requesting verbal social recommendations. Social recommendation is a daily occurrence, and we always turn to our friends for

recommendations [16]. Hence, in order to improve recommender systems and to provide more personalized recommendation results, we need to incorporate social network information among users. There are various types of social relationships among users in social networks, and users will interact with each other through social relationships.

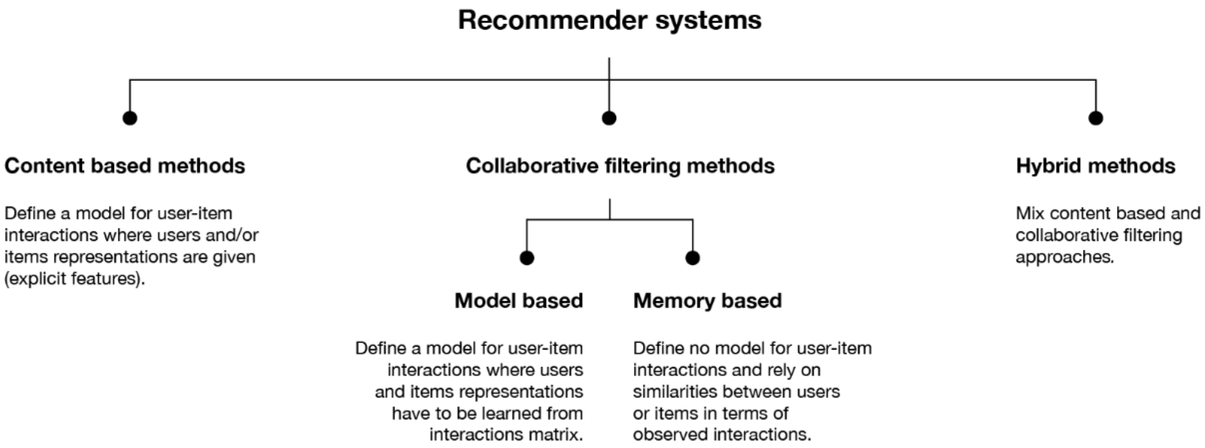
3. Related-Works–

Plenty of research has been done in the field of deep learning-based recommendation. However some works have explored recommender applications built on deep learning techniques, few have sought to provide an in-depth summary of current efforts or detail the open problems present in the area. This section seeks to provide such a comprehensive summary of current research on deep learning-based recommender systems, to identify open problems currently limiting real-world implementations.

[7] This paper aims to provide a comprehensive review of recent research efforts on deep learning-based recommender systems. In this paper they explained deep learning techniques which is MLP,AE, CNN, RNN RBM … etc with their structures. In addition to answering a "why deep neural network for recommendation?" question. Which can be summarized in several points, 1- Nonlinear Transformation 2- Representation Learnin 3- Sequence Modeling 4- Flexibility. Categories of deep neural network-based recommendation models into two categories first one Recommendation with Neural Building Blocks which contain 8 subcategories. The deep learning technique in use determines the applicability of the recommendation model, the second is recommendation with Deep Hybrid Models. Some deep learning-based recommendation models utilize more than one deep learning technique. They wrote about it in details in the end they dis-cussed the advantages/disadvantages of using deep learning techniques for recommendation tasks.

[18] In this article, they go through different paradigms of recommender systems. For each of them, they presented how they work, describe their theoretical basis and discuss their strengths and weaknesses. Also they wrote about the evaluation of a recommender system which divide into two sets evaluation based on well defined metrics and evaluation mainly based on human judgment and satisfaction estimation, they found it's difficult to evaluate: if some classical metrics such that MSE, accuracy, recall or precision can be used, one should keep in mind that some desired properties such as diversity (serendipity) and explain ability can’t be assessed this way ; real conditions evaluation (like A/B testing or sample testing) is finally the only real way to evaluate a new recommender system but requires a certain confidence in the model.

below figure is schema brief of types of RS.



4. Discussion—

The proposed system overcomes the weaknesses of content and CF approaches, by consolidating one through the other. The authors conducted many experiments, which simulate new-item situations in which the system worked great and outperformed baseline methods especially in extreme cold-items with no ratings [1].

Deep learning-based recommendation methods can effectively use multi-source heterogeneous data to alleviate the data sparsity and cold start problems. In the past three years, the research on deep learning-based recommender systems has attracted more and more attention from the academia and industry [15]. This section discusses the possible research direction of deep learning-based recommender system.
The result of the model training is to get the weights between the neurons of deep neural network. It is difficult to give a reasonable explanation directly to the recommendation results[17]

5. Conclusion—

The dramatic increase in the amount of data being produced by electronic and automated devices necessitates the need for intelligent techniques and applications that can properly and intelligently store, process, access and analyze information for maximum benefits to users. Deep learning-based recommender systems(DLRS) are of such leading solutions to these challenges, which are appropriate tools to quickly aid the process of information seeking.

Deep learning-based recommender systems can learn the latent representations of users and items from massive data, and then construct a recommendation model, finally generate an effective recommendation list for the user. The main tasks of the deep learning-based recommender systems are how to organize the massive multi-source heterogeneous data, build more suitable user models according to user preferences requirements, and improve the performance and user satisfaction. Compared with traditional recommender systems, deep learning-based recommender systems can use deep learning technique to automatically learn the latent features of user and item by integrating various types of multi-source heterogeneous data, model the sequence patterns of user behavior, more effectively reflect the user's different preferences and improve the accuracy of recommendation. It is hoped that this review will assist novice and new researchers to understand the development of DLRS. Moreover, expert researchers can use this review as a benchmark to develop DLRS and as a reference to the limitations of DLRS.

6. References—

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