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Recommendation system based on deep learning methods: a systematic review and new directions

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Abstract

These days, many recommender systems (RS) are utilized for solving information overload problem in areas such as e-commerce, entertainment, and social media. Although classical methods of RS have achieved remarkable successes in providing item recommendations, they still suffer from many issues such as cold start and data sparsity. With the recent achievements of deep learning in various applications such as Natural Language Processing (NLP) and image processing, more efforts have been made by the researchers to exploit deep learning methods for improving the performance of RS. However, despite the several research works on deep learning based RS, very few secondary studies were conducted in the field. Therefore, this study aims to provide a systematic literature review (SLR) of deep learning based RSs that can guide researchers and practitioners to better understand the new trends and challenges in the field. This paper is the first SLR specifically on the deep learning based RS to summarize and analyze the existing studies based on the best quality research publications. The paper particularly adopts an SLR approach based on the standard guidelines of the SLR designed by Kitchemen-ham which uses selection method and provides detail analysis of the research publications. Several publications were gathered and after inclusion/exclusion criteria and the quality assessment, the selected papers were finally used for the review. The results of the review indicated that autoencoder (AE) models are the most widely exploited deep learning architectures for RS followed by the Convolutional Neural Networks (CNNs) and the Recurrent Neural Networks (RNNs) models. Also, the results showed that Movie Lenses is the most popularly used datasets for the deep learning-based RS evaluation followed by the Amazon review datasets. Based on the results, the movie and e-commerce have been indicated as the most common domains for RS and that precision and Root Mean Squared Error are the most commonly used metrics for evaluating the performance of the deep leaning based RSs.

Keywords Recommender system · Collaborative filtering · Deep learning · Systematic literature review · Survey

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1 Introduction

Recommender systems (RS) is a tool that assists users by presenting services or products that are most likely of their interest (Khanian and Mohd 2016). Nowadays, the roles of RS in both academia and industries cannot be overemphasized. Many companies use RS in their sales promotion using various platforms. For example, the majority of the watched movies on YouTube and other online video databases come from the RS (Covington et al. 2016a).

With the recent achievements of deep learning in various applications such as Natural Languages Processing (NLP) (Poria et al. 2016), machine translation (Costa-jussà et al. 2017) and image processing (Goceri and Goceri 2017), deep learning models have been exploited for RSs thereby bringing more capabilities by addressing various challenges of the traditional RS models (Kunaver and Požrl 2017). Leveraging deep learning techniques for RS has become more popular due to a number of remarkable successes recorded in providing high-quality recommendations (Yao et al. 2017). Compared to the traditional recommendation architectures (Lu et al. 2015), deep learning based RS models provides a better representation learning of the user/item interactions (Zheng et al. 2017). Thus, developing a personalized deep learning-based RSs became a promising trend.

In recent times, different companies have exploited deep learning methods for further improving the diversity and performance of their RSs (Cheng et al. 2016; Okura et al. 2017). For example, Cheng et al. (2016) introduced a wide and deep architecture for google play recommendation. Covington et al. (2016b) proposed a deep learning-based method for the movie recommendation. Okura et al. (2017) used an RNN for news recommendation. All these approaches have shown remarkable successes and proved better performances over the classical RS methods.

With the many achievements of the deep learning-based RSs, the number of research works in the field has become exponentially increased. This leads to organizing various academic workshops and conferences by different related bodies so as to further provide an in-depth research awareness of the field in the research community. Hence the need for a comprehensive review and summarization of the successive research works to better understand the underlying opportunities and challenges of these techniques for helping the researchers in both the academia and industries. In other words, despite the several research works proposed to investigate deep learning based RSs, very few secondary studies were formally published to review existing works and analyze the open research issues on the field (Batmaz et al. 2018; Betru et al. 2017; Yao et al. 2017; Zhang et al. 2018).

Although the above studies have great influence and provide insights on the state of the art methods of deep learning based RS to some extent, no one among these existing secondary studies have particularly applied standard SLR approach which has been shown as the best method of presenting unbiased reviews (Kitchenham 2007; Kitchenham et al. 2009). Therefore, this paper presents an SLR method to better review, summarize and examine the trends of the published articles as a synthesis of best quality publications on the deep learning-based RS thereby providing insight and future direction for the researchers and practitioners in the field. Our SLR was conducted based on the guidelines described in Kitchenham (2007), Kitchenham et al. 2009). SLR has been shown as the best method of providing unbiased review of the state-of-the-art studies which use a systematic selection strategy of the published articles involving exclusion and inclusion criteria. SLR is an approach for evidence-based software engineering that aggregates evidence for providing the best insights for researchers and practitioners (Kitchenham et al. 2009). The main contributions of this SLR can be highlighted in the following:

- We present an SLR of the existing deep learning-based RS models. This will serve as guidance for the researchers and practitioners in the field to better understand the emerging trends and identify techniques for tackling unresolved issues.
- We also present detail descriptions of the open issues and challenges at stake and identify future roadmap in the area of deep learning-based RS.
- We provide quantitative analysis on the state-of-the-art deep learning-based RS which include the application domains, datasets and different metrics used for evaluating the performance of the deep learning-based RS approaches.

The rest of the paper is arranged as follows: Sect. 2 presents the related studies on the deep learning-based RS surveys. Section 3 presents the background of the study which covers overviews of the traditional RS and deep learning architectures. Section 4 describes the methodology used in the SLR. Section 5 reports the results of the SLR, Sects. 6 and 7 presents the limitations and conclusion of the paper respectively.

2 Related studies

In the past few years, different studies were conducted to review and survey the classical RS. One of the early significant works includes the work of Su and Khoshgoftaar (2009) who introduced a review on the collaborative filtering (CF) methods for RS. The authors analyze various recommendation approaches and made a comparison of the approaches in terms of their advantages and limitations. Many other secondary studies on the classical RS were also presented. For example, Burke (2002) introduced a qualitative survey of the hybrid RS. The author discussed the advantages and disadvantages of various recommendation methods and presented a taxonomy to classify different combination approaches for hybrid RS. A method in Véras et al. (2015) have been introduced to present a systematic review for classifying RSs in the television domain. The authors conducted an analysis of the different development and research perspective including algorithms, approaches, output devices, recommended items, and user profile.

Dehghani et al. (2015) introduced an SLR to survey the scholar context-aware RS. The authors identified the methods based on the contextual information used for developing various recommendation frameworks in digital libraries. The review was carried out based on the Kitchenham systematic review guidelines and comprised publications from 2001 to 2013. Alencar and Cowan (2018), used an SLR method to analyze the utilization of machine learning methods and their application domain for RS. The authors presented different alternative evaluation measures and identify new research directions for RS utilizing machine learning methods. Alejandra et al. (2018) employed an SLR approach to review the existing methods on the CF method that utilizes social network data for addressing cold start problem. The review was conducted based on the published papers between 2011 and 2017. Damaged et al. (2017) introduced a review based on the SLR to survey cross domain RSs by identifying the most popularly used building block definitions for Cross-domain RS and classifying current research in the scope of the identified definitions. Khanian and Mohd (2016) presented an SLR to review the state of the art methods of the CF models with the goal of understanding the trends of the recommendation system based on the implicit feedbacks by analyzing the published papers.

With the remarkable success of deep learning techniques in handling complex problems such as decision making (Betru et al. 2017) and visual understanding (Guo et al. 2016), deep learning methods have been exploited in building RS thereby providing a more improved recommendation with high accuracy. Despite the fact that several research works have been conducted on the deep learning based RS, very few secondary studies were formally published (Batmaz et al. 2018; Betru et al. 2017; Yao et al. 2017; Zhang et al. 2018) in the field. For example, Betru et al. (2017) presented a review of the state-of-the-art approaches on deep learning based RSs. However, this review typically focused on only three models of deep learning architectures. Therefore it is not comprehensive enough in the scope. Liu et al. (2017a, b) introduced a review and classification method of deep learning based RS. This study was particularly conducted based on only 13 publications as such the study is limited and cannot provide deep insight into the emerging approaches.

Recently Zhang et al. (2018) presented a review on the deep learning based RS models. The studies analyzed and classified over 100 publications. Despite the great influence of these studies in the research field, yet these studies are limited in that they particularly focused on the structural classification of the state-of-the approaches and ignore diving into the implementation details when examing the publication in the field. To further explore the state-of-art deep learning based RS methods, another recent survey was conducted by Batmaz et al. (2018) which presents a comprehensive review to identify challenges and remedies on the deep learning based RS. The authors review various challenges of the state-of-the-art approaches with the solutions to each of the challenges. Although, these studies comprehensively reviewed quite a number of the-state-of-art related publications, however, no one among all the existing secondary studies has yet adopted a standard SLR approach to systematically provide a methodology and search criteria for validating their research. Hence, in this paper, we have adopted the SLR method for our review based on the structured method with search strategy and selection criteria, following the guidelines used in Khanian and Mohd (2016), Kitchenham (2007), Kitchenham et al. (2009) for standard SLR.

3 Theoretical background

For a better understanding of the concepts, in this section, we present the theoretical background of the deep learning-based RS. This includes brief overviews of the traditional RS and the deep learning architectures used for RS.

3.1 Traditional recommender system

RSs are generally regarded as the software techniques that provide suggestions for items that are most likely of user's preference (Lu et al. 2015). The suggestions include various decision-making processes in real-world applications such as entertainment (Lee et al. 2018), e-commerce and social networks (Li et al. 2016). RSs have also been regarded as information filtering systems which attempt to solve the problem of information overload using information filtering techniques based on the user's relationship to the item (Wang et al. 2012). Depending on the information they used and the type of recommendation they provide, various approaches have been used to classify the RS techniques. The most commonly used classification (Adomavicius and Tuzhilin 2005a, b; Lu et al. 2015) includes collaborative filtering (CF), content-based (CB) and hybrid recommender technique.

3.1.1 Collaborative filtering methods

CF methods have been shown as the most widely used methods for RS (Wang et al. 2014). They generally rely on the previous user-item interaction to predict the user's preferences on items. Thus, they use collaborative powers of the ratings provided by several related users to make a recommendation. In practice, CF techniques generate recommendation by leveraging the relationship of either inter-user or inter-item (Yang et al. 2014). Some techniques use both types of relationships (Beel et al. 2016). Moreover, some techniques utilize optimization methods to creates a training model in a similar way classifiers used to create training models from the marked data. Basically, there are two types of the CF approaches, namely, the memory-based approach (Sharma et al. 2017) and model-based approach (Zheng et al. 2017b).

Pros and Cons of CF techniques CF methods are the most commonly used techniques for RS compared to the CB methods. One of the benefits of the CF models over CB approaches is the ability to work in a domain where the content associated items are insufficiently available and in a situation where contents are difficult to process such as opinions (Isinkaye et al. 2015). Another advantage of the collaborative technique is its ability to provide serendipitous recommendations.

Despite numerous advantages of the CF filtering methods over the CB methods, they have some potential drawbacks which are stated in the following.

Cold-start problem, which generally occurs when there is no adequate information about an item or a user in order to make relevant predictions (Kunaver and Požrl 2017). This typically reduces the performance of the RS. In practice, the profile of the new user or new item will be empty since there is no rating with the system, as a result, his preference can't be recognized by the system.

Data sparsity is a problem generally affects CF methods which occur as a result of insufficient information in the system (Kotkov et al. 2016). This is when the total number of the items rated by the user in the database is relatively few. This generally results in a sparse user-item matrix (Kunaver and Požrl 2017). It also leads to the inability to locate successful neighbors and eventually poor recommendation process.

Scalability is another issue associated with RS (Kotkov et al. 2016). Generally, as the volume of dataset increased, it will be difficult for the recommender technique that is initially designed to deal with the only limited volume of a dataset. Thus, it is very important to use recommendation techniques capable of scaling up in a successful manner as the volume of dataset increases in a database.

3.1.2 Content-based methods

CB filtering techniques basically rely on user/item descriptions for providing item recommendation (Wang and Wang 2014). For generating the related user/item data, information retrieval or web search mining is generally used (Ebesu and Fang 2017b). CB technique generally filters items according to the similarity of the contents the user is interested in Lu et al. (2015). Latent semantic indexing and vector space model are two commonly used methods to present these terms as a vector in a multidimensional space (Krishnamurthy et al. 2016). Different learning techniques such as a neural network (Deng 2014b), SVM and Bayesian classifiers (Kim et al. 2016) are generally used to learn a user profile.

Cons and pros of CB filtering CB filtering methods can be applied to address many of the drawbacks experienced in CF methods. Some of the advantages of the CB techniques over the CF method are given in the following.

User independence In the CB technique, ratings provided by the active user are usually exploited solely to build his own profile. As opposed to the CF approach which depends on the neighborhood ratings.

Transparency This is clear description of how the explicitly listing content features provide recommendation processes. Those features are yardsticks to measure in deciding the reliability of recommendation. Converse to the collaborative systems which are the black-boxes since the only description for an item recommendation is that unknown users with common tastes liked that item;

New item Unlike CF, CB methods are powerful in providing a recommendation for the items not previously rated by any user. As a consequence, CB filtering methods do not have a *first-rater* problem. This problem is usually suffered by the CF methods.

However, CB recommendation techniques also suffer from the many problems which are stated in the following.

CB filtering approaches usually provide obvious recommendations since they make use of content description (Lu et al. 2015). For instance, if users have never used items with particular keywords, there is no chance for that item to recommend. This is because the designed method is always unique to the user at hand. Thus the community experience from like users is not utilized. This tends to decrease the diversity of the items to be recommended which is not ideal.

Another major challenge of the CB techniques is that they are not good for the new user's recommendation, even though they are good for the recommendation of newly available items (Adomavicius and Tuzhilin 2005a, b). This follows due to the fact, that rating history is required to be in training the model for the target user (Lu et al. 2015). Hence, it is generally important, for a robust prediction to have an adequate rating for the target user. Thus, CB filtering approaches have many trade-offs from CF methods.

3.1.3 Hybrid recommendation approach

Hybrid RS approaches exploit the combination of two or more RS approaches (e.g. CF and CB) for generating an enhanced recommendation (Kunaver and Požrl 2017). The basic idea behind the hybrid recommendation techniques is that integrating different RS methods will improve and provide more enhanced recommendation than applying a single technique. Combining different techniques can suppress the drawbacks of an individual technique. Different methods can be used to achieve hybridization of RS (Adomavicius and Tuzhilin 2005a, b). This includes feature combination, feature augmentation (Aslanian et al. 2016), cascading and switching method (Paradarami et al. 2017).

3.2 Overviews of deep learning architecture

Deep learning concept was originally coined from the field of artificial neural network, hence, some times referred to as "new-generation neural networks" (Deng 2014a). Deep learning is regarded as a class of machine learning technique, that is used for representation learning (Liu et al. 2017b) by exploiting many layers of information-processing stages in hierarchical architectures. With the emergence of the deep neural network, there has been a remarkable achievement in many application fields such as computer visions (Sainath et al. 2013), NLP (Poria et al. 2016), image processing (Goceri and Goceri 2017) and RSs (Batmaz et al. 2018; Yao and Sun 2017). Researchers have been working tirelessly in a pursuit to exploit deep neural network to a wider range of applications. Depending on how the architectures are applied, generally deep learning architectures can be broadly categorized into three major classes, namely, generative, discriminative and hybrid deep architectures (Deng et al. 2014). However in all these deep learning methods a batch size should be choosen carefully for optimum parformance (Goceri and Gooya 2018) Fig. 1 and Table 1 shows the classification and comparison of the deep learning architectures respectively.

3.2.1 Generative deep architectures

These classes of architectures attempt to characterize the high order correlation properties of the visible data for pattern synthesis (Deng 2014a). Generative deep architectures are essentially applied for unsupervised learning methods (Schmidhuber 2015). The idea here is that specific supervisory information such as target class labels are not usually used during the learning process. Most of the deep network in this class typically uses the network to generate samples and are thus generative models. Typical examples of such models include Autoencoders (AEs), Restricted-Boltzmann-Machines (RBMs), Deep Believe Networks (DBNs), Deep-Boltzmann-Machines (DBMs) and the recently introduced Generative Advaserial Network (GAN).

Deep autoencoders Deep AE is specifically used for the unsupervised learning process (Deng 2014a). It is typically trained in copying its inputs to its outputs (Suzuki and Ozaki 2017). An AE is thus, a feedforward network, which tends to learn a distributed representation of data (Schmidhuber 2015). It is specifically used for learning dimensionality reduction of the set (Nweke et al. 2018). An AE essentially posses one hidden layer between the input and output layer with the more compact representation of hidden layers than input and output layers (Wu et al. 2016b). In the AE model, input and output layers typically have an exact same setting. This essentially allows an AE to be trained with the exact data

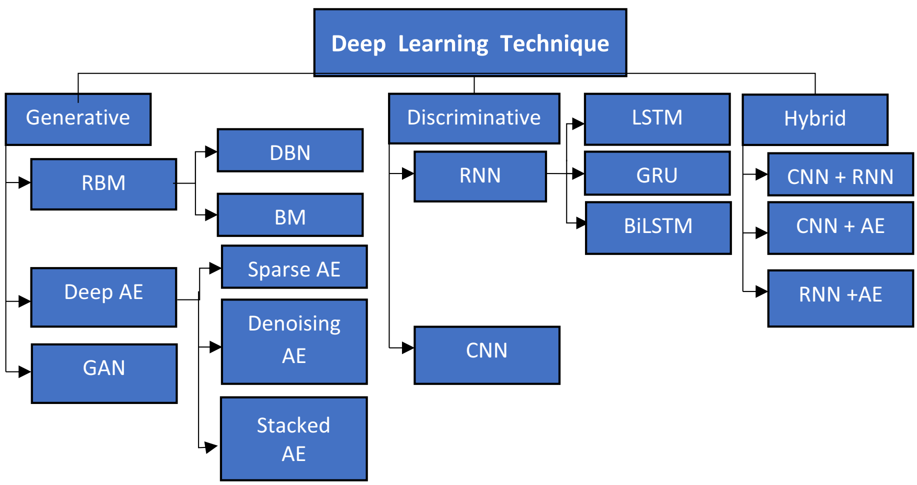


Fig. 1 Classification of deep learning architecture

Table 1 Comparisons of different deep learning mlodels

	Learning scenario	Description	Strength	Weakness	Main applications in RS
Deep AE	Unsupervised	A neural network trained to reconstruct their inputs under some constraints	It is capable of learning more complex feature representation via an unsupervised learning scheme	Less scalability to high dimensional data Rely on numerical optimization and high parameter tuning	Learning lower dimensional feature representations from text review
DBM	Unsupervised	Deep neural network with an undirected connection at every layer	Provides more robust feature extraction via unsupervised training	High computational time due to the large parameter tuning	Ensemble models
DBN	Unsupervised	Consists of a directed connection at the lower layer and undirected connection at two topmost layer	Powerful for extraction of hidden and useful features from audio data	Difficult to train due to the extenstive parameter initialization process	Audio and video based recommendation
RBM	Unsupervised	Bipartite, undirected graph comprising of the visible and hidden layer	Suitable for low-rank representation learning	Not tractable as such the *contrastive divergence* can be used to learn the parameters	Group-based recommendation
GAN	Unsupervised/ Supervised	Deep neural network consisting descriminator and generator	Suitable for unified supervised and unsupervised learning	Unstable learning process Difficulty in convergence	Descriminative and generative information retrieval
CNN	Supervised	Interconnected architecture inspired by biological visual cortex	Powerful for feature extraction with contextual information	Require high parameterization tuning	Feature representation learning from multiple sources: Audio, text, image, video, etc
MLP	Supervised	Modelling data with simple correlation	Nonlinear transformation	High complexity and slow convergence	Feature representation learning from audio, video and textual contents

that has fed into the input layer. The training process is quite similar to that of the traditional neural network with backpropagation (Guo et al. 2016). It only differs in the error computed by comparing the output to the data itself. Recently, different variants of the AE such as sparsed-autoencoder (Strub et al. 2016a, b), denoising-autoencoder (Li et al. 2015) and stacked-autoencoder (Suzuki and Ozaki 2017) have been introduced to provide robust feature representation for various applications.

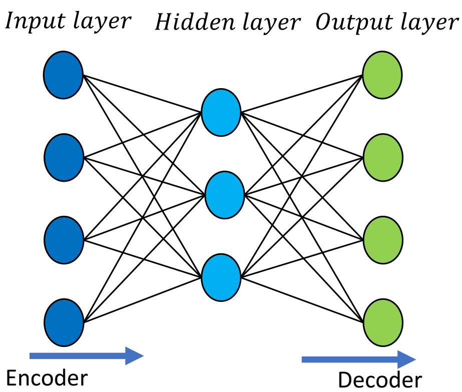
AE algorithm is very powerful in dealing with noisy data to learn the complex and hierarchical structure from the input data (Wei et al. 2017). Generally, the AE model can be utilized for building RS by filling the blanks of the interaction matrix directly in the construction layer or by learning lower dimensional features at the outer layer. However, the major issue of deep AE model is that they are not capable of searching for an optimal solution (Nweke et al. 2018). In addition, the training process of the AE model involves high computation time because of the high parameter tuning (Deng 2014a). Figure 2 illustrates the simple structure of the AE model.

Sparsed-autoencoder was basically developed for sparse feature representation from inputs-data by forcefully taking the sparsity term-model-loss function close to zero (Liu et al. 2017b). This model is typically applied in tasks where the analysis of highs complex-data such as videos and images is required. Essentially, using sparsed-autoencoder models ensure robust feature representation and learning applications. Therefore, sparse-autoencoder techniques are very effective for low dimensional feature extraction from input data using supervised-learning method (Strub et al. 2016b).

Denoising-autoencoder model generally uses a corrupted version of data to stochastically learns feature-representations using partial destruction of the raw input data (Nweke et al. 2018). Like other unsupervised deep-learning-methods, denoising AE is trained using layers initialization in which each layer is used to generate input data of the next layer presentation (Prieto et al. 2016). This allows the efficient capturing of the observed statistical-dependencies about inputs of data distribution. Furthermore, denoising-AE can be stacked to reduce the processing errors and was recently used for building complex tasks such as RS (Suzuki and Ozaki 2017).

Deep Boltzmann machines DBM is another typical example of deep unsupervised models that are generative in nature (Deng et al. 2014; Nweke et al. 2018). DBM consists of many layers of hidden-variables with nos direct connections-between then variables of the same-layers (Ng et al. 2015). DBM is a special variant of BM (Boltzmann-Machine). It is a network symmetrically-connected based on the stochastics mechanism. Generally,

Fig. 2 Autor Encoder



Boltzmann Machines are very slow to train and also very complex to study, although their learning algorithm seems to be simple (Pacheco et al. 2018). DBM has the advantage of learning complex internal representations which are very important in solving object and speech recognition problems (Deng et al. 2014). When the number of DBM hidden layers is reduced to one, this will result in the RBM (Restricted Boltzmann Machine) model. Figure 3b shows an illustration of simple DBM model.

Restricted Boltzmann machine RBM is an undirected generative-models that serve as a building block in greedy-layer by layers features modeling (Pacheco et al. 2018). It is typically composed of two different layers of visible and hidden layers consisting of input variables and hidden variables respectively (Liu et al. 2017b). Therefore, weights-connecting the neurons between visible-units and hidden units are conditionally independents without visible–visible connections. As shown in Fig. 3a, the neurons are restricted to form a bipartite graph. There is a full connection between the visible units and the hidden ones, while no link exists between units from the same layer. The models are trained with contrastive-divergences (CD) (Fischer and Igel 2014; Nweke et al. 2018) to provide unbiased-estimates of maximum likelihoods learning. RBM models are robust for automatically processing unsupervised information into feature vector leveraging unlabelled data by using layer-wise training. Nevertheless, RBM model experience major shortcomings which include high parameterization that makes it computationally expensive to train (Pacheco et al. 2018). On the other hand, one of the good qualities of RBM is that it helps in learning many hidden layers using the feature activations as the training data for the next layer (Hassan 2017). This leads to the emergence of deep belief network (DBN).

Deep belief network Traditional neural networks tend to have problems of optimization (Pacheco et al. 2018) which consequently leads to the poor performance of the network. In addition, they often do not utilize what is plenty. To address these issues, DBN networks were introduced (Schmidhuber 2015). DBN uses a deep architecture that cannot learn a representation of features from labeled and unlabeled data (Luo et al. 2018). DBN typically integrates both supervised and unsupervised learning steps to build a more robust and efficient model optimization (Pacheco et al. 2018). The unsupervised step can be used in learning the distribution of data without a prior knowledge, while the supervised step can

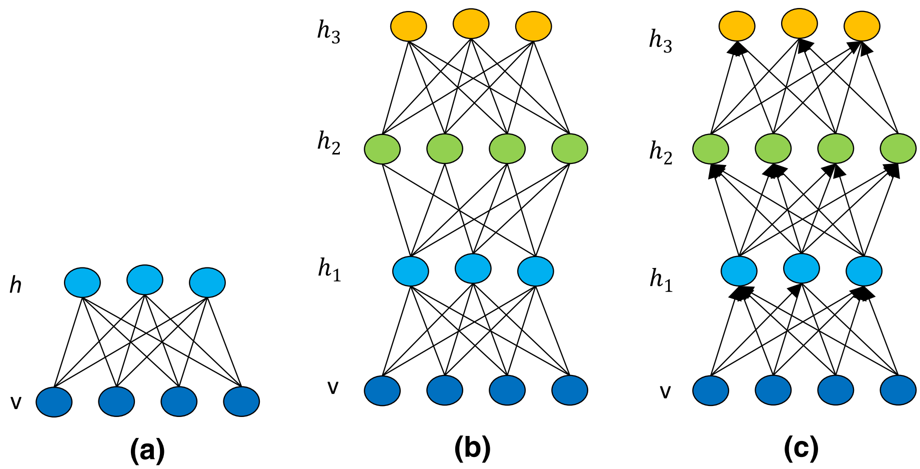


Fig. 3 **a–c** illustrate the RBM, DBM and DBN respectively

be used to execute a local search to get an optimized result (Deng 2014b). The DBN structure is shown in Fig. 3c.

Generative Adversarial Network GAN is a recently introduced deep learning method initially presented in Goodfellow et al. (2014). GAN provides an alternative method for the maximum likelihood of the estimation technique. It uses both unsupervised and supervised learning method where two neural networks interact in a zero-sum game. It specifically attempts to train a generative model which seek to estimate the target data distribution from the training data. It also uses the discriminative model that approximates the probability that a sample data comes from real training data rather than the output (Wang et al. 2017a). The training procedure of the GAN is highly sensitive to the learning rate and other parameters including the model structure. To attain effective convergence, numerous Ad hoc tricks are often required for improving the fidelity of the data generated. Figure 4 shows an illustration of the GAN structure.

To alleviate the difficulty and achieve better convergence in the training process, several extension of the GAN methods were introduced. This includes Loss Sensitive Generative Adversarial Network (LSGAN) and Wasserstein Generative Adversarial Network (WGAN) (Bentur et al. 2006). However, researches on the GAN remains shallow. Recently, some studies indicated that GAN can be utilized for supervised learning. Utilizing the unsupervised learning capability of GAN is promising in terms of the information retrieval and recommender system (Wang et al. 2018).

3.2.2 Discriminative architectures

This class of deep architectures is specifically used for providing a discriminative function for pattern classification (Wang and Raj 2015). They usually attempt to characterize the posterior distributions of classes conditioned on the visible data (Deng et al. 2014). Discriminative deep architectures are specifically applied for supervised deep learning (Nweke et al. 2018). Popular examples of such architectures include RNN, CNN, and MLP.

Convolutional-Neural-Network The CNN is a subtype of discriminative deep architecture which uses perceptrons in dealing with high dimensional data (Liu et al. 2017b).The idea of CNN was initially inspired by the visual cortex organization in animals (Lecun

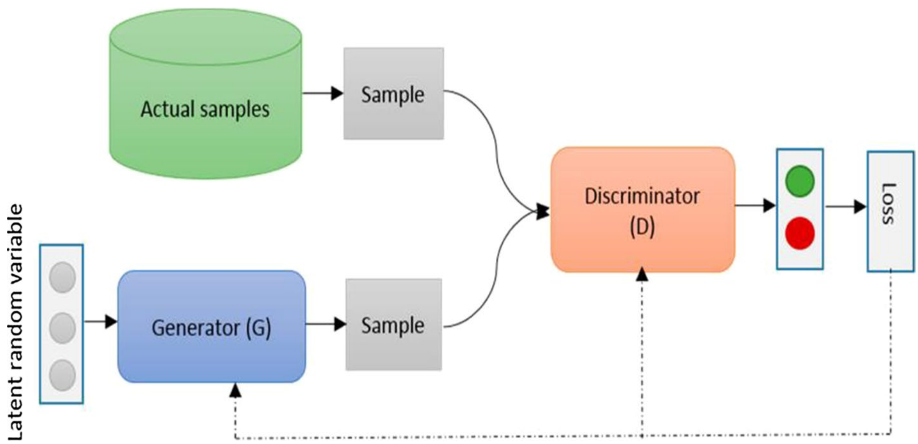


Fig. 4 An overview of the GAN model

et al. 2015). In CNN, each module comprises of a pooling and convolutional layer which are usually stacked up with one on top of another to form a deep architecture (Guo et al. 2016; Nweke et al. 2018). The convolutional layer often shares multiple weights, while the pooling layer sub-samples the output of the convolutional layer (Liu et al. 2017b). The pooling layers together with the shared weight in the convolutional layer provide the CNNs with-some invariance properties such as translation-invariances (Guo et al. 2016). Different pooling operations such as max polling, stochastic poolings, and average poolings have been applied for CNN models implementation in various applications including NLP (Kim 2014) and RSs (Zheng et al. 2017b). Figure 5 illustrates the general overview of the CNN architecture.

CNN models are very efficient in learning deep features from user textual review for modeling user and item latent factors (Zheng et al. 2017b). The key advantages of CNN model are the ability to use pooling operation for reducing training data dimensions and making it transitional invariant to changes and distortion. CNN models have been used for feature extraction to better model user and item representation for RS (Catherine and Cohen 2017; Kim et al. 2016, 2017). CNN model has been also shown very effective in image processing. As such many approaches have exploited the model to utilize image descriptions for building RSs.

Despite many success of the CNN model, however, it has one major drawback in that it requires a large number of hyperparameter tuning in achieving optimal features (Deng et al. 2014). In addition, it is challenging in supporting effective complex activity details (Nweke et al. 2018).

Recurrent Neural Network RNN is specifically used to model sequential data by simply incorporating temporal layers to capture sequential information (Liu et al. 2017b). As such, it generally becomes a suitable way to deal with the temporal dynamics of user behaviors as well as the sequential data. Unlike feedforward networks, RNN has memories and loops for remembering former processings (Nweke et al. 2018). RNN typically uses hidden units of the recurrent cell to learn complex changes. The hidden units can change according to information in the network to reflects the current status of the network. RNNs use the next hidden-states activation of the previously hidden state to process the current hidden-state.

However RNN modelss suffer from the exploding or vanishing gradient which makes it difficult to train (Prieto et al. 2016). This limits its performance in modelling long time activity and temporal dependency. Variations of RNN such as GRU (Gated Recurrent Unit) (Bansal et al. 2016) network and LSTM (Long Short Term Memory) (Zhou et al. 2018) are often used to address the issue of the vanishing gradient. They typically integrate different memories and gates to capture sequential activities. Recently, variants of the LSTM such as BiLSM (Yoon and Kim 2017) have been introduced to provide better performances.

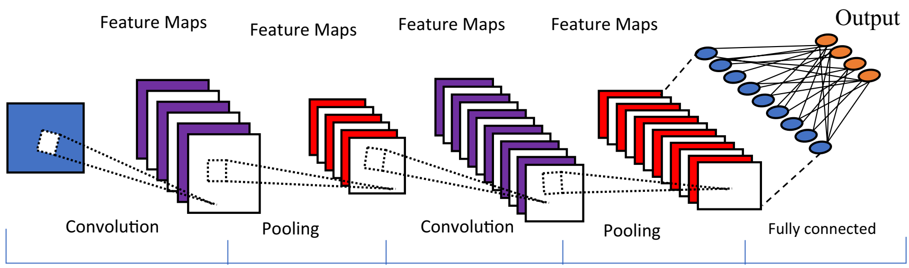


Fig. 5 The structure of the CNN architecture

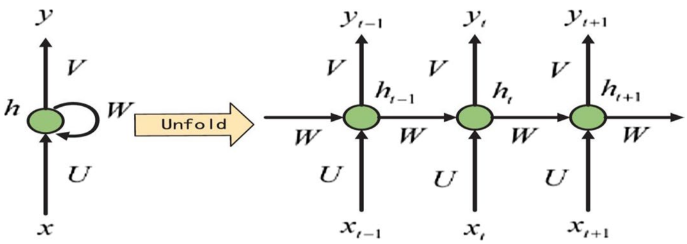


Fig. 6 A simple RNN structure

Fig. 7 A structural representation of the MLP model with two hidden layers

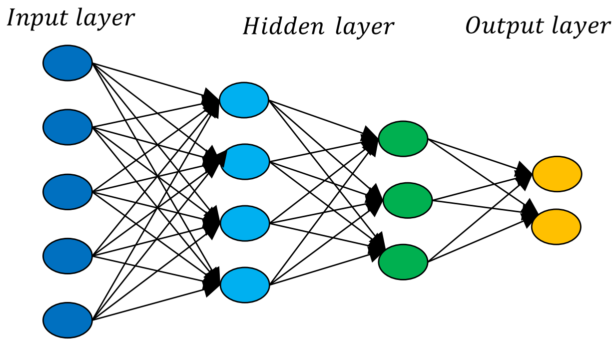


Figure 6 illustrates a typical structure of the RNN model. However, one major drawback of the RNN models especially LSTM is the high computation time due to the high number of parameter tuning. Different strategies such as high throughput parameter update method can be used to tackle the computation time (Nweke et al. 2018).

Multilayer Perceptron MLP is a feed-forward neural network model that has one or more layer and nonlinear activations. MLP is regarded as the simplest deep learning architecture (Deng et al. 2014). It is made up of at least one hidden layer which is interconnected in a feed-forward direction. It is basically the building blocks of the majority of the deep learning architectures. MLP can be used to transform the linear method of the RS into the nonlinear models for neural performance. As such they have been used in many applications including the RS approaches (Cheng et al. 2016; Guo et al. 2017; Lian and Chen 2018). A typical structure of the MLP model is show in Fig. 7.

4 SLR methodology

This section presents the methodology used in our SLR which is mainly based on the guidelines used in Kitchenham (2007) and Kitchenham et al. (2009). It consists of well-defined steps to analyze and evaluate the research papers in order to identify gaps in the existing research as well as to review their contributions to the RQs for drawing a conclusion. The SLR process basically comprises three steps: review planning, conducting the review and documenting of the review. Figure 8 shows the different components of each phase and outlines the outcomes of each phase. Each phase is described in the following subsection.

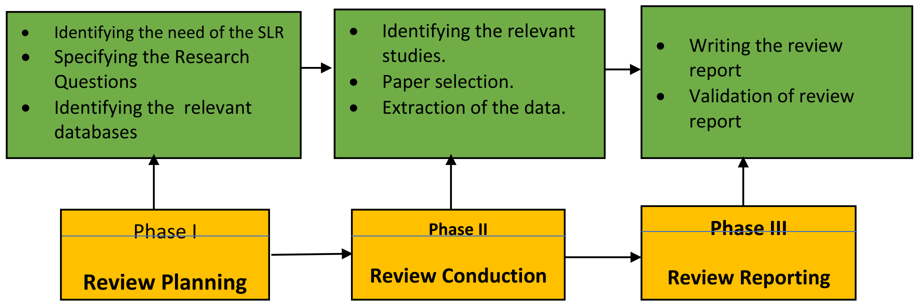


Fig. 8 Phases of the systematic literature review method

4.1 Review planning

The Review planning phase particularly involves preparation of the research work which includes identifying the need for the review, specifying the research questions and identifying the relevant online bibliographic databases.

4.1.1 Identifying the need for the review

As noted earlier, with the increasing number of the primary studies on deep learning-based RS, very few secondary studies were conducted in the field and that all of the existing studies were simply based on the classical survey and review of the state-of-the studies. Hence the need for conducting the SLR which has been indicated as the most suitable for presenting comprehensive and unbiased review of published studies. Our SLR is introduced with the aim of addressing the following research questions (RQs):

- *RQ1* What are the deep learning methods exploited for building the RS?
- *RQ2* What are the metrics used for evaluating the performance of deep learning-based RS?
- *RQ3* What are the application domains and the datasets used for evaluating deep learning-based RS?
- *RQ4* What are the open issues and the future research directions for the deep learning-based RS?

4.1.2 Identification of the bibliographic database

To gather the relevant publications for this review, an automatic search was conducted on the major digital libraries which include ACM (Association of computing machine) digital library, IEEE explores, ScienceDirect, Springer, and Web of Science. Other similar sources were not considered as they mainly index data from the primary sources. These libraries were chosen because of their popularity and being the rich source of research articles related to our RQs. As the first deep learning based RS is believed to have been introduced in 2007 (Salakhutdinov et al. 2007a), therefore 2007 was chosen to be the starting point of this review. This study covers related papers published from 2007 until 2018.

Search process The search strings were carefully designed considering the specified RQs. In this way, different search strings with different combinations of terms were applied while searching the relevant articles. The following keywords and synonyms for the research were used: *Recommendersystem*, *RecommendationSystem*, *CollaborativeFiltering*, *Deeplearning*, *NeuralNetwork*. After identifying the keywords and synonyms, the search strings will be applied to the above online digital libraries.

4.2 Conducting the review

The second stage of the SLR involves the selection of the primary studies by applying query strings for executing searches based on the identified inclusion/exclusion criteria in Table 2. The selected primary studies are validated through the quality assessment criteria and the data information is then extracted from each of the selected studies.

4.2.1 Paper selection

After identifying the relevant bibliographic databases and specifying the search strings, we applied the specified search strings in the search engines of the selected online databases and finally discovered 1480 publications as illustrated in Fig. 9. The databases return a different number of publications because of the different strategies they used in their search engines.

To select the most relevant studies for our focus research, we first remove the unrelated studies by examining the titles and reviewing the abstracts. If the abstract did not provide the necessary information, we proceed to the conclusion part. As a result, we obtained 275 papers. We then filtered the remaining articles by applying the inclusion/exclusion criteria, and we retained a list of 105 papers. The entire steps are summarized and illustrated in Fig. 9.

4.2.2 Quality assessment

To validate the accepted publication in term of quality, we apply standard quality checklist questions designed in Kitchenham (2007) as given in Table 3. To this end, following (Genc-nayebi and Abran 2017), we selected the studies that provide a 'yes' answer to at least seven questions. The quality assessment will be considered concurrently with the data

Table 2 Inclusion/exclusion criteria

Inclusion strategy	Exclusion strategy
Peer-reviewed and published studies that are written in the English language only	Duplicate reports of the same studies are excluded
Studies that are directly related to the deep learning-based RSs	Books, thesis, notes, tutorial and studies that are not related to the RQs are excluded in the review
Publication from conference and journal only	Papers that do not sufficiently describe an experiment study are excluded in this review
Papers published from 2007 to 2018 only	The publications that cannot be accessed by the authors are not included in this review

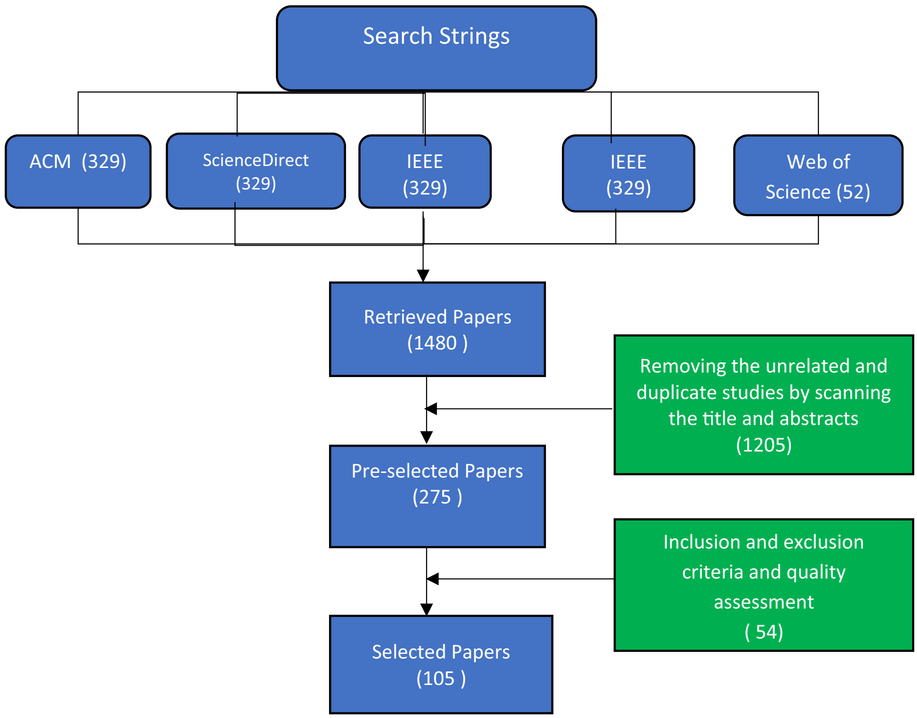


Fig. 9 The paper selection process

Table 3 Quality Checklist (Kitchenham 2007)

No.	Quality question
1	Are the aims of the research stated clearly?
2	Is reporting coherent and clear?
3	Has the context of diversity been explored?
4	Is there any link between data, interpretation, and conclusion?
5	Are the findings of the study credible?
6	If credible, are they important?
7	Could the study be replicated?
8	Is the research process adequately documented?
9	Are the data collection method clearly described?
10	Is the reporting clear and coherent

extraction to ensure the findings contribute significantly to the review (Kitchenham et al. 2009).

5 Results

This section presents the results of the SLR in order to respond to the specified RQs described in Sect. 3. The section is further divided into five subsections: The first subsection presents the search results analyzing the selected studies. The second subsection reports the various deep learning techniques used for RS. The third subsection identifies different datasets and the domains that deep learning based RS are applied. The fourth subsection reports different evaluation metrics used for measuring the accuracy of the deep learning-based RS and finally, the fifth subsection identifies the open issues and future directions for the deep learning-based RS.

5.1 Selected studies

This subsection presents the distribution of the selected publications considered in this study. Following the selection criteria described in Sect. 3 and after the quality assessment protocol, we finally selected 99 studies to be used for further processing. This particularly covers the journals and conference proceedings published from 2007 to 2018. The distribution of the studies and the year of publication are illustrated in Fig. 10.

It can be observed form the Fig. 10 that since the earliest remarkable study on deep learning base RS was introduced, there has been an increasing growth of the number of studies that used deep learning for RS. It can also be observed that most of the deep learning-based RS we identified were published in the last 6 years.

5.2 Deep learning methods for RS

This section addresses the RQ1 which aims to identify the deep learning-based RS studies included in this research. Table 4 presents the distribution of the deep learning methods for RS we identified from the selected studies considered for this SLR. We also

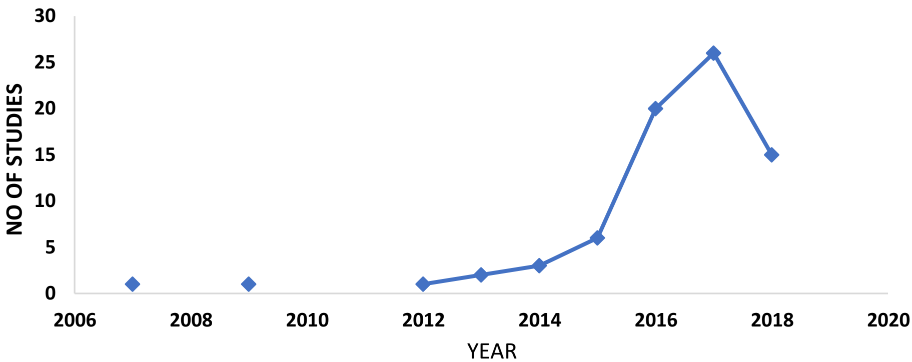


Fig. 10 Distribution of the selected studies and the years

Table 4 Distribution of the deep learning-based RS

Model	Description	Advantages	No of studies	References
CNN	Uses convolution and pooling operations for feature extraction	Allows feature extraction with contextual information	13	Tang and Wang (2018), Kim et al. (2016, 2017), Seo et al. (2017), Zheng et al. (2017b), Wang et al. (2017b), He and McAuley (2015), He (2016), Yu et al. (2018), Zheng et al. (2017a), Tuan (2017), Hu et al. (2018) and Tuan (2017)
RNN	consists of loops and memories for remembering previous computations. Different versions of RNN include LSTM and GRU models	Capture temporal dependencies and sequential information of words	20	Christakopoulou et al. (2018), Tan et al. (2016), Wu et al. (2016a), Quadrana et al. (2017), Hidasi et al. (2016a), Smirnova (2017), Wu et al. (2017), Christakopoulou et al. (2018), Donkers et al. (2017), Dai et al. (2016), Lu et al. (2018), Jing and Smola (2017), Chen et al. (2018, Hidasi et al. (2016b), Bansal et al. (2016), Jannach and Ludewig (2017), Ludewig and Jannach (2018), Li et al. (2017), Smirnova (2017) and Soh et al. (2017)
MLP	A feedforward deep network that uses set of input to generate a set of output	Transforms the linear into the nonlinear models for neural performance	12	He et al. (2017) 73 Cheng et al. (2016), Guo et al. (2017), Lian and Chen (2018), Chen and He (2017), Alashkar et al. (2017), Covington et al. (2016a), He and Chua (2017), Song et al. (2018) and Tay et al. (2018a, b)
AE	The generative model that reconstructs its input data in the output layer	Suitable for feature dimensionality reduction and extraction of hierarchical features	16	Dong et al. (2017), Unger et al. (2016), Wei et al. (2016, 2017), Sedhain et al. (2015), Wu et al. (2016c), Bai et al. (2017), Wang et al. (2014), Strub et al. (2016, Jian et al. (2016), Li and She 2017), Zuo et al. (2016), Cao and Yang (2017), Jhamb and Ebesu (2018), Liang et al. (2018) and Loyola et al. (2017)

Table 4 (continued)

Model	Description	Advantages	No of studies	References
RBM	A Two-layer network with a visible and hidden layer which can easily be stacked to form a deep network	Allows cross-correlation feature extraction for innate feature representation	08	Salakhutdinov et al. (2007b, 2016), Georgiev (2013), Wang and Kawagoe (2017, 2018), Yedder et al. (2017), Du et al. (2017) and Liu et al. (2015)
GAN	Generative semi-supervised deep learning method	Allows both generative and discriminative information retrieval	04	Cai et al. (2017), Wang et al. (2017a), He et al. (2018) and Wang et al. (2018)
CNN and RNN	Integrate CNN and RNN models for better predictive performance	Capture both semantic and sequential information of words	04	Lee et al. (2016), Zhang et al. (2016), Ebesu and Fang (2017a) and Tran et al. (2018)
CNN and AE	Combines CNN and AE for better feature representation learning	Allow probabilistic treatment for improving the performance of the RSs	2	Zhang et al. (2016), Lin et al. (2015)
RNN and AE	Integrates RNN and AE to better model latent features for robust model performance	Jointly models user/item factors while extracting the implicit relationship between them	1	Wang et al. (2016a)
RNN and DBN	Combines DBN and RNN method for mining important comments	Highly effective for the cold start problem	1	Yuan et al. (2017)

present a brief explanation, the main advantages and the number of studies identified for each deep learning method in the table.

Autoencoder methods AEs are unsupervised dimensionality reduction models via nonlinear transformation (Liu et al. 2017b). Generally, AE model can be applied to build an RS either by learning a low dimensional representation of features or by directly providing the missing entries of rating matrix in the construction layer (Bokde et al. 2015). In this SLR we identified several studies that basically utilize AE models for RS. Table 4 shows different studies that used AE for RS considered for this review. One of the primitive approaches that used AE for RS was proposed by Sedhain et al. (2015). The study aims to generate a vector for the users by taking their partial vectors into a low dimensional vector. This approach was later extended by incorporating side information, item description and user profile to address the problem of cold start (Strub et al. 2016a; Wu et al. 2016b, c).

AE has been shown to be powerful in feature representation learning (Zuo et al. 2016). As such several authors have utilized the model to better learn the item and user representation for improving the performance of the RS. Bai et al. (Wang et al. 2015), Jian et al. (2016) and Cao and Yan (2017) exploit stacked denoising AE (SDAE) to better learn feature representation for RS. For example, (Wang et al. 2015) develop a hierarchical Bayesian method which utilized SDAE and probabilistic matrix factorization for improving the performance of rating prediction. The authors first presented a Bayesian setting of a deep learning method and finally developed a collaborative deep learning approach by tightly integrating deep representation learning and CF method for the content information and rating matrix respectively. The model typically allows two-way interaction between the two. A similar method was introduced in Li and She (2017) to better learn probabilistic latent variables for content information and easily incorporate side information from multimedia source for RS. Li et (2015) designed a general deep learning method called deep CF which combines matrix factorization and deep representation learning by modeling the mappings between the latent factors used in CF and latent layers in deep models. The authors presented a natural instantiation of the proposed model by using the probabilistic matrix factorization. Loyola et al. (2017), Liang et al. (2018) and Zhuang et al. (2017) used AE to simultaneously learn the user/item latent factors and minimize the derivation of training data using the learned factor.

Deep belief network methods DBN is a multilayer structure that utilizes a stack RBMs for extracting deep feature representation of data (Hongliang and Xiaona 2015). DBN can be used for dimensionality reduction and high-level feature extraction from sparse data for solving cold start problem (Hu et al. 2014). As such many studies in the literature exploit the DBN for RS. For example, Wang and Wang (2014) use the DBN model to extract hidden useful features from the audio content for hybrid RS. The author first designed a content-based method for simultaneously extracting features from audio contents and personalized recommendation. To integrate CF and audio content information, the authors used automatically learned audio features. For the content based method, the model particularly utilizes probabilistic graphical approach and the DBN model designed by the deep learning community (Deng et al. 2014). DBN model has been exploited for a video RS by integrating the DBN with CF algorithm to alleviate the cold start problem (Hongliang and Xiaona 2015). The DBN method is specifically exploited to simply figure out the user profile and additionally find the neighborhood relationship. User-Based CF is utilized to compute the missing data and generate the recommended items. The parameters of the model are typically determined by training data sets. Oh et al. (2014) utilized the DBN model for analyzing user preferences for news recommendation. The model characterizes the user preferences by extracting the interest keywords from the different news documents interacted by that user in the past.

Restricted-Boltzmann-machine methods RBMs is a two-layer neural-networks consisting of hidden and visible layers which can easily be stacked to a deep network and specifically used to extract higher-level features from the raw input data (Liu et al. 2017b; Salakhutdinov et al. 2007b). Similar to other deep learning models, RBM can also be exploited for improving the RS. For example, Salakhutdinov et al. (2016) proposed RBM-CF (Restricted Boltzmann Machine CF) where the rating scores are typically represented using a one-hot-vector. The author used a two-layer undirected graphical architecture to model tabular data. The authors showed that efficient learning can be performed by following an approximation to a different objective function. Georgiev et al. (2013) proposed a combined user-based and item-based RBM-CFs in a unified framework. The model was based on the RBM architecture and an extension of the previous RBM based methods. The authors additionally used real values in the visible layer as opposed to multi nominal variables, thus exploit the natural order of the user/item ratings. They then finally explored the potential of integrating the data provided by the RBM-based method and the original data in a bootstrapping fashion. Wang and Kawagoe (2018) exploited RBM model for web page-based RS where users can be provided with the most interesting items predicted by the system based on the user/item past interaction. Wang and Kawagoe (2017) implemented an Ukiyo-e RS using RBM model. The authors particularly use the model for recommending Ukiyo-e prints to Ukiyo-e novices. Yedder et al. (2017) employed RBM to propose the neighborhood conditional RBM based on the similarity scores for CF recommendation system. Du et al. (2017) and Liu et al. (2015) utilized RBM method based on the multi-layer network architecture for better feature extraction to address cold start problem. The authors developed a model called Item Category aware Conditional Restricted Boltzmann Machine Frame model (IC-CRBMF) by integrating item category information as the conditional layer for optimizing the model parameters and improving the accuracy of the recommendation performance. The model typically comprises two different components based on the difference in the visible layer's presentation: IC-CRBMF item based and IC-CRBMF user based. IC-CRBMF item-based component uses item's rating vectors and the conditional layer is the item category. Unlike the IC-CRBMF user based which is just the given item's genre feature vector. As such the major distinction between the two components is the conditional layer and about genre feature vector while their modeling method is same and interrelated.

Generative adversarial neural network With the introduction of the GAN model (Goodfellow et al. 2014), many studies have proposed to exploit the model for developing and improving recommendation systems. Cai et al. (2017) exploited GAN to introduce a deep network model that combines vertex content and network structure into a unified architecture for personalized citation RS. It represents different types of vertices in the heterogeneous network in a continuous vector space. The distributed representation obtained in turn for calculating similarity scores. The model consists of two main components: content2vec which aims to learn an effective feature representation for preserving both the network structure and vertex content information, and generative adversarial bibliographic for preserving the network structure information. (Wang et al. 2017a) exploit GAN to propose a model for information retrieval task named IRGAN (Information Retrieval GAN). The author showed the capability of the model in three different information retrieval tasks, which include, question answering, web search, and recommendation. The model aimed to combine both generative and discriminative process into a unified method thereby making them play a minimax game similar to the discriminator and generator in GAN.

The discriminative retrieval attempts to differentiate relevant documents and non-relevant documents while the generative aspect tries to approximate true relevant distribution. He et al. (2018) introduced an adversarial personalized ranking method which uses adversarial training for improving the Bayesian personalized ranking. The model is capable of playing a minimax game between the original BPR loss and the adversary which add permutation for maximizing the BPF function. Wang et al. (2018) exploited GAN to propose a model which generate negative samples for the memory network-based streaming recommender. The authors demonstrated that the model performance can be improved by the GAN based sampler.

Convolutional neural network methods CNN model is a feed-forward network which uses convolutions and other additional layers such as pooling and softMax layer for feature extraction (Liu et al. 2017b). Following its successful applications in areas such as NLP (Li et al. 2016) and image classification (Chen et al. 2015), several methods have been introduced to exploit CNN model for RS. Most of the CNN based RS approaches particularly use CNN model for feature extraction (Seo et al. 2017a; Zheng et al. 2017b; Kim et al. 2016, 2017). For example (Zheng et al. 2017b) used two parallel CNN architectures for better modeling the user and item latent features from the user textual content. This approach addresses the cold start problem and improves the model interpretability by utilizing semantic information of word from the user text review. The model particularly uses the word embedding method for mapping the textual content into a lower dimensional semantic space as well as keeping the word contextual information. The extracted features are then convolved by the convolutional layer with different kernels and then passed to polling layer and fully connected layer consecutively. The output of the two parallel networks is then finally concatenated and used as input for the prediction layer where the factorization machine is used to estimate the user ratings on items. (Seo et al. 2017a) exploited CNN model to propose an interpretable network model which uses dual local and global attention for better accuracy of the personalized recommendation. The local attention helps the CNN to the better model user/item features. The global attention enables the model to better learn the semantic information of words from the user textual contents. Thus, the combination of the local and global attention typically allows the model to better learn interpretable item/user representation. Kim et al. (2016) developed a convolutional matrix factorization model by integrating the CNN model and matrix factorization to address the issue of the data sparsity for improving the performance of RS. The model is like the CDL model which uses the AE model for a recommendation. However, unlike the CDL model which specifically utilizes auto encoder for learning the item representation, the ConvMF uses CNN model for the feature representation learning. The major advantage of the MF over the CDL model is that the CNN model can capture contextual information using word embeddings and convolutional filters. This method was later extended by allowing the CNN model to better learn the document context of the item and users for better predictive performance (Kim et al. 2017).

Some studies identified in the review exploited CNN models for image extraction to improve the performance of RS. For example, Wang et al. (2017b) used CNN model to extract image features to build a visual content enhanced Point of Interest (VPOI) RS. The recommendation framework is designed based on the probabilistic matrix factorization by utilizing the interactions between visual content and latent location as well as the visual content and latent user factor. McAuley (He and McAuley 2015) introduced a visual-Bayesian-personalized ranking (VBPR)s model by incorporating visual features learned using CNN into MF. This model was later extended in He (2016) with exploring user's awareness and the visual-features that user considers when choosing an item. Yu et al. (2018) exploit CNN model for learning image features using coupled MF and tensor factorization for clothing recommendation. A similar method was proposed in Tang and Wang (2018) to embed sequential patterns using convolutional filters for image recommendation. Lee et al. (2018a) used CNN model to extract audio and musical features for improving the performance of RS. Zheng et al. (2017a) used a memory based CNN model to model the user's interest for the dynamic recommendation. Hu et al. (2018) designed a three-way neural interaction model using CNN model by incorporating meta-path-based context. Tuan (2017) introduced a CNN based model using character level encoding for session-based RS. The model combines session clicks and content information such as item category for improving the accuracy of the recommendation system. It exploited the 3-dimensional CNN technique with character level encoding of the input data. While the CNN model helps in capturing the spatiotemporal patterns, the character level network enables the model to learn various data type based on their raw textual information thereby simplifying the feature engineering effort.

Multilayer perceptron method MLP is another version of the feed-forward neural network which is regarded as the simplest deep learning architecture (Deng et al. 2014). MLP can be used to transform the linear method of the RS into the nonlinear models for neural performance. As such they have been used in many existing RS approaches. As shown in Table 4, several studies have been identified in this review to exploit MLP for RS. One of the primitive MLP approaches to exploit MLP for RS was proposed in He et al. (2017). The model uses a dual network for modeling the item and user information with regard to their relationship. The authors showed that MF can be given as instantiation of NCF and used a multi-layer perceptron to improve the NFC modeling with a high level of non-linearities. To allow the full neural combination with CF, the author's utilized multilayer perceptron for modeling user and item latent features. Where the input of one layer is generated from the output of the subsequent layer. The bottom input layer comprises of the user and item feature vectors which can be customized to support a wide range of modeling user and item such as context-based or context-aware. As the model is purely based on the collaborative settings, the author's utilized user and item identity as the input features, forming a binarized sparse vector with one hot encoding. This has been shown to effectively alleviate the problem of the cold start by exploiting content features to represent user/items. This method was later extended by Lian et al. (2017), and Wang et al. (2017) to the cross-domain recommendation.

In order to model the high order feature interactions, some studies integrated the MLP model and Factorization machine (MF) (Cheng et al. 2016; Guo et al. 2017; Lian and Chen 2018). The factorization machine particularly used inner products operation to captures the pairwise-operation between the features. (Chen and He 2017) introduced an attentive CF model using an attention mechanism integrated into the latent factor framework. The attention method is made up of an MLP which consists of component level and item-level neural attentions. Alashkar et al. (2017) used two identical MLPs model for makeup recommendation. The main rationale behind the model is to label expert rules. Covington et al. (2016a) exploit a multilayer perceptron (MLP) for a recommendation in YouTube based on the candidate ranking and candidate generation. He and Chua (2017, Song et al. (2018) integrated MLP with Factorization Machine to better model feature interaction and non-linearity of neural network RS. Tay et al. (2018a) introduced a latent relational model that uses MLP to model user/item interaction based on the latent relation vectors. Tay et al. (2018b) exploited MLP for multi-pointers learnings schemes that learn to combine multiple-views of user-item interaction. The model is a multi-hierarchical in nature. The pointer setting of the model extracts the named reviews for direct review to review matching for learning of the item/user representations.

Recurrent neural network methods RNN is basically designed for sequential data processing (Liu et al. 2017b). Thus, they become an ideal choice for dealing with sequential user behavior and temporal dynamic of user/item interaction (Christakopoulou et al. 2018). In this research, we identified many studies that basically use the RNN model for RS. Most of the RNN based RS method particularly exploit the RNN model for a session-based recommendation (Tan et al. 2016; Wu et al. 2016b; Quadrana et al. 2017; Hidasi et al. 2016a). For example, Tan et al. (2016) exploit RNN architecture for improving session based recommendation by examining and adapting different techniques. These techniques include data augmentation using sequence preprocessing and embedding dropout for enhancing training and reducing overfitting issue. Others include model pretraining and distillation to learn from small datasets. (Wu et al. 2016b) developed a deep RNN model for improving recommendation in e-commerce system via tracking how users browse the website using multiple layers. Each layer of the network determines how the websites are accessed and in what manner. The authors further integrate the RNN with feedforward network which represents the user/item relationship for improving the prediction performance. Quadrana et al. (2017) introduced a deep learning based RS based on the RNN model for the session-aware recommendation. The model specifically uses hierarchical RNN where the hidden state of a lower -level RNN at end of one user session is passed as an input to higher level RNN for prediction of the next session of the user. Hidasi et al. (2016a) proposed deep recurrent algorithm for a feature-rich session-based recommendation. The model uses the RNN architecture specifically for extracting high-quality features from visual information and modeling the sessions. The parallel RNN model comprises multiple RNN units, one for each representation of the item. The hidden states of the RNN are merged to generate the scores for all items. In this model, individual user sessions can be seen as a sequence of clicks. Unlike session-based RS where user-identifiers are not used, in this review, we also identified several studies that use RNN model with known user identifications (Christakopoulou et al. 2018; Wu et al. 2017; Donkers et al. 2017) for RS.

Some studies use RNNs model for feature representation learning to build RS. For example, Dai et al. (2016), Lu et al. (2018) introduced a coevolutionary latent model for capturing the coevolution of the user/item latent features for improving the performance of RS. Jing and Smo (2017) used LSTM models for multitasking learning to simultaneously predict the returning times of user and recommend-items. The model uses tools from survival analysis for return time prediction for future activity analysis. Chen et al. (2018) introduced a model using LSTM called Behavior-Intensive Neural Network (BINN) to better learn the discriminative behavior and item embedding for the sequential recommendation by combining user past preferences and current consumption motivation. In particular, the model consists of two main parts, namely, neural item embedding and discriminative behavior learning. To obtain a unified item representation, an item embedding method based on user interaction is designed. With the item embedding and the interactive behaviors, the model enables better learning of the historical preferences and present motivations of the target users. A similar method was proposed in Suglia et al. (2017) by exploiting the RNN model for top-N item recommendation. In particular, the authors used LSTM networks for jointly learning item and user representations for better item recommendation. Hidasi et al. (2016b), Bansal et al. (2016), Jannach and Ludewig (2017) and Ludewig and Jannach (2018) exploited RNN architecture to better extract features for the user's immediate next actions recommendation. Wu et al. (2016) introduced an RNN based method for predicting the probability that the user will access an item based on the time-heterogeneous feedback recommendation. The system uses different kinds of feedback signals and the associated timestamps deciding which items the user may be interested in and generate a recommendation. In this model, different feedbacks are represented by vectors making it able to treat diverse feedback in a balanced manner. A similar method was proposed in Soh et al. (2017) to exploit RNN model for the sequential recommendation. Li et al. (2017a) introduced a deep learning based method called Neural Rating Regression with Abstractive Tips (NRT). The model specifically utilizes a GRU model and is capable of rating prediction and generating abstractive tips with linguistic quality. The GRU architecture helps the model to better capture contextual information for translating user/item latent factors into a concise sentence. All the latent features and the neural parameters for the user/items are learned via multitasking learning method in an end to end training pattern.

Hybrid deep-learning-methods To further improves the performances of the RSs, several approaches have been proposed to use deep hybrid methods by combining different deep learning techniques. In this study, we identified many papers that use deep hybrid method for RS as shown in Table 4. For example, Zhang et al. (2016a) and Lin et al. (2015) integrated AE with CNN to extract visual and textual contents using the word embedding approach for better representation learning to improve the predictive performance of RS. Lee et al. (2016) combined CNN and RNN for quote RS. The model uses CNN model to learn semantics from tweets information and map them to a vector representation and LSTM to determine the target quotes for a given dialogue. Zhang et al. (2016b) proposed a deep hybrid model For hashtag recommendation based on a tweet with corresponding images. Ebesu and Fang et al. (2017a) integrated CNN and RNN models in an encoder framework to better capture the long dependencies of textual contents for citation recommendation. Tran et al. (2018) integrated CNN and RNN to address the sparsity problem using regularized matrix factorization., Wang et al. (2016a) utilized a combination of Denoising AE and RNN model for RS. The authors used the robust recurrent network to design a hierarchical Bayesian recommendation model named collaborative recurrent autoencoder (CRAE). Yuan et al. (2017) proposed a parallel deep neural network (DNNs) for users and items modeling by integrating the DBN and RNN to mine the valuable comments for building RS. Rating prediction is achieved using a shared layer. The authors showed that the model outperforms the traditional method in terms of rating prediction.

5.3 Evaluation metrics

Quality and high performance are the ultimate goals of any RS. To evaluate the performance of the RS, a different set of metrics have been introduced and used in different approaches. In this section, we present the various metrics used for evaluation of the deep learning based RS identified in this review. Table 5 shows the distribution of the reviewed studies w.r.t the prediction metrics.

Rating prediction metrics The main idea of the rating prediction metrics is to measure the extent at which the RS can predict the rating of users towards items (Carrera and La 2012). On the other hand, using rating predictive metrics, one can make a comparison between different algorithms to assess the one with fewer errors. These evaluation measures determine the correctness of the recommendation in terms of their error. The three metrics we discovered in the reviewed studies include MSE (Mean Squared Error), RMSE (Root Mean Squared Error), and MAE (Mean Absolute Error). These metrics compute the difference between the predicted and real ratings. So, lower values of the metrics indicate a higher accuracy.

Table 5 Distribution of the evaluation metrics

Category	Metrics	No. of studies	Studies
Classification	Precision	18	Cao and Yang (2017), Wu et al. (2016) Wu et al. (2016c, d, Zuo et al. (2016), Deng et al. (2017), Quadrana et al. (2017), Hu et al. (2018), Jhamb and Ebesu (2018), Wu et al. (2017), Lee et al. (2016), Tang and Wang (2018), Niu et al. (2018), Wang et al. (2017b), Yu et al. (2018), Jing and Smola (2017), Shen et al. (2016) and Zhang et al. (2016a)
	Recall	31	(Cao and Yang 2017), Bai et al. (2017), Bansal et al. (2016), Hidasi et al. (2016b), Wu et al. (2016a, c), Zuo et al. (2016), Deng et al. (2017), Ebesu and Fang (2017a), Quadrana et al. (2017), Hidasi et al. (2016b), Hu et al. (2018), Jhamb and Ebesu (2018), Wu et al. (2017), Tang and Wang (2018), Zheng et al. (2017a), Tuan (2017), Chen et al. (2018), Liang et al. (2018), Loyola et al. (2017), Niu et al. (2018), Smirnova (2017), Tan et al. (2016), Wang et al. (2017b), Yu et al. (2018), Hidasi et al. (2016b), Smirnova (2017), Donkers et al. (2017), Jing and Smola (2017), Wang et al. (2015) and Zhang et al. s(2016a)
	F1 score	03	Wu et al. (2016), Deng et al. (2017) and Suglia et al. (2017)
	AUC	06	Guo et al. (2017), Jia et al. (2015, 2016), Lian and Chen (2018), He (2016) and Hu et al. (2014)
Rating prediction	MSE	07	Li and She (2017), Liu et al. (2015), Seo et al. (2017), Tay et al. (2018b), Zheng et al. (2017b), Lu et al. (2018), Shen et al. (2016) and Hongliang and Xiaona (2015)
	RMSE	20	Zhuang et al. (2017), Deng et al. (2017), He and Chua (2017), Kim et al. (2016, 2017), Li et al. (2015), (2017a), Li and She (2017), Liu et al. (2015), Jian et al. (2016), Sedhain et al. (2015), Suzuki and Ozaki (2017), Dong et al. (2017), Unger et al. (2016), Wei et al. (2016, 2017), Strub et al. (2016), Hongliang and Xiaona (2015), Wang and Wang (2014) and Yuan et al. (2017)
	MAE	04	Cao and Yang (2017), Zhuang et al. (2017), Georgiev (2013) and (Li et al. 2017a)

Table 5 (continued)

Category	Metrics	No. of studies	Studies
Ranking	NDGC	09	Ebesu and Fang (2017a), He et al. (2017), Hu et al. (2018) Jhamb and Ebesu (2018), Lee et al. (2016, 2018b), Liang et al. (2018), Song et al. (2018) and Tay et al. (2018a)
	MRR	15	Hidasi et al. (2016b), Jannach and Ludewig (2017), Ebesu and Fang (2017a), Quadrana et al. (2017), Hidasi et al. (2016b), Wu et al. (2017), Lee et al. (2016), Tuan (2017), Chen et al. (2018), Loyola et al. (2017), Ludewig and Jannach (2018), Tan et al. (2016) Hidasi et al. (2016b), Donkers et al. 2017) and Jing and Smola (2017)
	HR	08	Jannach and Ludewig (2017), He et al. (2017), Jhamb and Ebesu (2018), Lee et al. (2016), Ludewig and Jannach (2018), Song et al. (2018), Tay et al. (2018a) and Unger et al. (2016)
	MAP	10	Covington et al. (2016b), Wu et al. (2016a), b, Ebesu and Fang (2017a), Jhamb and Ebesu (2018), Jia et al. (2016), Lee et al. (2018b), Tang and Wang (2018), Christakopoulou et al. (2018), Hu et al. (2014) and Zhang et al. (2016a)
Others		10	Salakhutdinov et al. (2007b), Soh et al. (2017), He and McAuley (2015), Tan et al. (2016), Lian et al. (2017), Covington et al. (2016b), Strub et al. (2016b), Oh et al. (2014), Wang et al. (2016b) and Guo et al. (2017)

Classification accuracy metrics Another category of the metric used to measure the accuracy of the RS is the classification metrics which simply assess the extent at which the RS correctly classify items based on the user's interest. In these metrics, the magnitude of the defect of the users rating prediction is usually neglected. The commonly used evaluation metrics in this scenario include recall, precision, F1 score and AUC (Area under the curve). Recall simply depict the proportion of the user preferred items that are obtainable. The precision simply describes the user's favorite items. F-Measure is a conciliation between the recall and precision. AUC simply measures the variations between the true positive/negative rate.

Ranking metrics Another type of accuracy metric is the ranking metric which measures the performance of RS in providing a recommendation of an ordered list of items to users in the case where the order of the items on the list is significant. The following are the ranking metrics for the deep learning-based RS evaluation included in the reviewed articles: Normalized-discounted-cumulative gains (NDCG)s which considers that highly relevant-items give more satisfaction than poorly ranked ones. Hit ratio (HR) which measures whether a user's target choice appears in the top-K recommendation list. Mean Reciprocals Ranks (MRR) which evaluate the ranking position of user's target choice in the recommendation list and Mean average precision (MAP)s which considers the precisions of the first K-recommended ranked items.

5.4 Datasets and domain

Table 6 presents the 16 datasets and the domains that we discovered in the included studies. For each dataset, we indicate the domain and the studies that applied it. The identified studies applied at least one dataset. In some cases, a study applies more than one dataset. Many of the data sets are rarely used. As such we put them under the others category.

It can be observed from Table 6 that the Movie Lens dataset appeared to be the most popularly used datasets based on the selected papers while the Last FM and Amazon have been identified as the second and third most popularly used datasets respectively. In addition, it can be seen from the table that many different publicly accessible datasets were applied for the deep learning-based RS evaluation. In conclusion, over 15 datasets were used in the selected papers whereas most of the researchers focused on popular datasets only.

5.5 Open issues and future research direction

This section addresses the RQ4 which aims to identify the open issues based on the state-of-the-art approaches and the future research direction of the deep learning-based RS. The section is categorized into two subsections: open issues and future research direction.

5.5.1 Open issues

State of the art approaches of deep learning architectures appeared to be substantial in providing a solid platform for improving RS. As the number of deep learning research paradigm is continuously trending toward RS. There is a tendency of architectural adjustment from the traditional RS to deep learning-based recommender techniques. In the following, we identify some emerging research trends which we believe are critical to the existing state of the field.

Table 6 Distribution of the dataset and the application domains

Datasets	Domain	No of studies	Studies
Movie lense	Movie	24	Wu et al. (2016), Zhuang et al. (2017), Wu et al. (2016b, c), Georgiev (2013), He et al. (2017), He and Chua (2017), Hu et al. (2018), Jhamb and Ebesu (2018), Kim et al. (2016), Kim et al. (2017), Lee et al. (2018), Tang and Wang (2018) Li et al. (2015), Li and She (2017), Liang et al. (2018), Liu et al. (2015), Sedhain et al. (2015), Song et al. (2018), Suglia et al. (2017), Tay et al. (2018a), Donkers et al. (2017), Dong et al. (2017), Strub et al. (2016) and Zhang et al. (2016a)
Last FM	Movie	08	Wu et al. (2016), Zuo et al. (2016), Hu et al. (2018), Donkers et al. (2017), Wu et al. (2017), Li and She (2017), Tay et al. (2018a) and Jing and Smola (2017)
Netflix	Movie	06	Cao and Yang (2017), Wu et al. (2016) Liang et al. (2018), Wei et al. (2016) Wang et al. (2015) and Hongliang and Xiaona (2015)
Movie	Movie	03	Hu et al. (2018), Jian et al. (2016) and Wei et al. (2017)
Delicious	Restaurant	02	Zuo et al. (2016), Li and She (2017)
Yelp	E-commerce	07	Dai et al. (2016), Wu et al. (2016), Li et al. (2017), Seo et al. (2017), Tay et al. (2018b), Lu et al. (2018) and Yuan et al. (2017)
Amazon	E-commerce	08	Kim et al. (2017), Zheng, et al. (2017), Tuan (2017), Li et al. (2017), S. Seo et al. (2017), Tay et al. (2018b), Yu et al. (2018) and Lu et al. (2018)
Video	Video	04	Covington et al. (2016b), Quadrana et al. (2017), Hidasi et al. (2016b) and Christakopoulou et al. (2018)
Douban		03	Zhuang et al. (2017), Suglia et al. (2017) and Strub et al. (2016)
twitter		01	Lee et al. (2016)
Epinion		01	Deng et al. (2017)
Flixter		01	Deng et al. (2017)
TMall		03	Jannach and Ludewig (2017), Jannach and Ludewig (2017) and Tang and Wang (2018)
Flickr		01	Niu et al. (2018)
IMDB	Movie	02	Tay et al. (2018a), Yuan et al. (2017)

Table 6 (continued)

Datasets	Domain	No of studies	Studies
Others		32	Bai et al. (2017), Bansal et al. (2016), Hidasi et al. (2016b), Ebesu and Fang (2017a), Guo et al. (2017), Jia et al. (2016), Salakhutdinov et al. (2007b), Jia et al. (2015), Chen et al. (2018), Loyola et al. (2017), Ludewig and Jannach 2018), Smirnova (2017), Soh et al. (2017), Suzuki and Ozaki (2017), Tan et al. (2016), Wang et al. (2017), He and McAuley (2015), He (2016), Tan et al. (2016), Hidasi et al. (2016b), Song et al. (2018), [58 Lian et al. (2017), Covington et al. (2016b) (Strub et al. 2016b), Unger et al. (2016), Shen et al. (2016), Hu et al. (2014), Wang and Wang (2014), Oh et al. (2014), Lin et al. (2015) and Wang et al. (2016b)

Cross Domain Recommendation In practice, single domain RS exclusively deals with a particular domain while overlooks the user's interest in the areas, which also exacerbate cold start and sparsity challenges (Seo et al. 2017). Solutions to such a problem can be provided by cross-domain recommendation which typically exploits the knowledge learned from the domains and generates the target recommendation. Transfer learning (Osia et al. 2017) which uses knowledge derived from one domain to assist in improving learning tasks in the domain is a typical example of the most popularly investigated topics in the cross-domain recommendation. The capability of deep learning in learning high-level abstraction makes it efficient to be used in transfer learning. Many various states of the art approaches (Elkahky et al. 2015; Ebesu and Fang 2017a; Rawat and Kankanhalli 2016; Wang et al. 2017c) prove the effectiveness of deep learning in tackling the generalization across various domains and providing better recommendation performance on cross-domain systems. Although very few works (Elkahky et al. 2015; Ebesu and Fang 2017a; Rawat and Kankanhalli 2016; Wang et al. 2017c) were conducted, however due to its promising potentials, more studies worth to be explored.

Multi-Task Learning Various works were carried out to investigate the efficacy of multi-tasking on RS (Elkahky et al. 2015; Wu et al. 2018) based on the deep learning methods which proved better performance compared to the single task learning. One of the advantages of utilizing multi-task learning in a deep neural network includes its ability to reduce the data sparsity problem through implicit data augmentation (Li et al. 2017). It is also important to point out that traditional recommender system can utilize multi-task (Ebadi and Krzyzak 2016) and be integrated into a tighter fashion using deep learning. Another advantage is that learning many tasks at a time can tackle overfitting by simplifying the shared hidden representation. These show the promising potentials of the deep learning methods for the multitasking RS.

Neural Attention Neural attention or attention mechanism is a technique that enables a neural network to focus on a subset of features by selecting a specific input (Tay et al. 2018b). It is a mechanism that can be intuitively applied to many deep learning architectures such as CNN and RNN. The main purpose of the attention technique is to provide a solution by allowing the network to better memorize inputs (Chen et al. 2017). For example, attention techniques when applied to CNN model help the model to capture the most informative input elements (Seo et al. 2017a). Attention-based RNN model enables the model to process noisy inputs. It also helps the LSTM to memorize input elements when dealing with the long-range dependencies (Lu et al. 2018) and could be leveraged in an RS to select the most representative elements and filter out the uninformative elements while providing better interpretability. This further motivates the usage of deep learning for RS. Thus, designating a better attentional model to the level of providing explain ability for RS is a promising direction to explore.

5.5.2 Future research direction

This subsection presents the potential future research opportunities to the deep learning RS identified in the reviewed studies. From each study, we identified and analyzed the challenges that authors sated as worthy of future work to explore. The future research direction of the deep learning-based RS we identified in the reviewed studies can be arranged into three categories: Incorporating more information, deeper architecture and optimization.

Incorporating more information Researchers have discovered that using additional side information of the user and item improves the performance of many RS models. As such many authors intend to incorporate more information as for a future direction to improve the performance of the RS model. These include user profiles information (Soh et al. 2017), social connections (Bai et al. 2017; Wu et al. 2016; Dai et al. 2016; Yu et al. 2018) and additional session based information (Jannach and Ludewig 2017; Wu et al. 2017; Liang et al. 2018; Deng et al. 2017). Others include external information by introducing additional regularization (Zhuang et al. 2017; Liang et al. 2018; Suglia et al. 2017), user behavior (Chen et al. 2018), contextual information (Smirnova 2017) and auxiliary information (He et al. 2017) such as knowledge base and temporal signals.

Deeper architecture Existing deep learning-based RS models basically depend on the neural architecture for the model performance. As such Many researchers are seeking to apply more deep architectures to user's data to explore additional multitask learning. For example, Bansal et al. (2016), Soh et al. (2017) and Strub et al. (2016), explore to apply deeper architectures by adding more layers as their future direction. Jhamb and Ebesu (2018), Kim et al. (2016) and Lee et al. (2018b) intended to use more attention network (Quadrana et al. 2017) as their future research. Another way to extend many deep learning-based models is to stack additional hidden layer. Therefore as the future research direction, some authors intend to stack additional hidden layers on top of the independent item- based and user-based feature detectors (Georgiev 2013). Other authors explore some strategies such as introducing pooling layers (Guo et al. 2017; Lian and Chen 2018) to strengthen the ability to learn the most useful higher order interaction.

Optimization As a future direction, Many authors intend to use distributed optimization algorithms to further reduce the computational costs of their method algorithms (Li et al. 2015). Some authors have found that more optimization can be achieved by exploring more system configurations and parameters setting (Jian et al. 2016), the sequence to sequence learning (Donkers et al. 2017; Smirnova 2017) and expansion of the datasets (Zuo et al. 2016).

6 Limitations

This study has been conducted as an SLR to review and analyze the primary studies on deep learning-based RS. Different factors may influence the validity of the study. In this section, we identify some limitations of the study which are highlighted as follows:

- One major limitation of this SLR is in the data extraction method. Although the data gathered is relatively sufficient, however, it was based on the perspective of the specified research questions. Hence there is every possibility that the readers can discover some attributes that were not covered in this review and can contribute significantly for better research trends.
- Although five bibliographic databases (as described in Sect. 3) were considered for retrieving the relevant studies, however, they are not exhaustive and as such, they may limit the validity of the study.

7 Conclusion

In this paper, we presented an SLR to summarize and analyze the state-of-the-art approaches on the deep learning-based RS, strictly based on the publications conducted from 2007 to 2018. The study was conducted with the goal of providing and helping the researchers and practitioners in the relevant fields to acquire an in-depth understanding of the deep learning-based RS. The study was based on the five major bibliographic databases which include IEEE explore, Science direct, ACM digital library, Springer and Web of Science databases. The main results of the study discovered various deep learning methods used for recommender systems, different datasets, and metrics popularly used for evaluating the performance of the deep learning-based RS. The paper also identified the most common domains that are used for the deep learning-based RS, the future research directions as well as the open issues for the deep learning-based RS. In this study, we identified many future research directions for the deep learning-based RS. These include incorporating more additional side information, developing a deeper architecture to improve the performance of the RS. These were directly derived as suggested by the authors in the included papers for the future study. Using more datasets was another possible work direction identified in the related studies.

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