ARTICLE

APPLICABILITY OF DEEP LEARNING TECHNIQUES IN RECOMMENDER SYSTEMS

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ABSTRACT

Recommender Systems (RecSys) have been used in various areas since the dawn of the Internet. State-of-the-art RecSys approaches rely on Machine Learning (ML) and Deep Learning (DL) in order to create more accurate and personalized recommendations for users. These DL techniques have been gaining the momentum due to its performance in high quality recommendations. Here we are reviewing DL based RecSys models. The focus is on the DL techniques such as Multilayer Perceptron, Auto encoder, Convolutional Neural Network, and Recurrent Neural Network and their effectiveness in the area of Recommender Systems. The selected 21 papers are categorized according to the DL techniques applied and extracted the details of recommender System type, applications domain, Data Set etc. This review helps the developers and researchers to get a comprehensive idea of the currently used DL techniques for various RecSys models, which will help them for finding most accurate DL technique for their RecSys and dataset.

KEY WORDS
Deep Learning, Recommender System Models, Collaborative Filtering, Content Based Filtering

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INTRODUCTION

The explosive growth of information and their frequency is overwhelming in this information processing era. Information in the form of computer interpretable data is parsed and processed from one end point to another across a wide range of platforms and devices around the world. With the availability of huge amounts of data and content accessible to users, the exploration of the data becomes difficult due the number of choices at hand, which creates a problem for all parties involved. The content creators have a hard time to get their work to relevant users, the users have a hard time finding this content and the company providing the service where the content resides on are faced with the problem of providing the right content for the right users, and in many times, are forced to prioritize the most popular content for all users.

RecSys concern themselves act as the foundations of these challenges. In order to provide accurate recommendations for a given individual, the process at hand must be analyzed for personalized recommendations to prevail over blind recommendation that do not take any features regarding the user into account. Providing personalized and recommendations are a challenging task that many entities deal with and prioritize today. Companies want to better their services by providing personalized recommendations to their users for a multitude of reasons, such as the exploration of their data, prioritization or awareness. Classical approaches such as Collaborative Filtering (CF) and Matrix Factorization (MF) have previously prevailed in this area of interest and some systems depend on Ensemble Methods (EM) to create more accurate and personalized recommendations for their users [1, 2, 3, 4, 5].

Nowadays DL has become a popular approach in a wide range of areas such as image recognition, natural language processing, automatic speech recognition and biomedical informatics and seems to prevail in classification tasks. Therefore, it is of interest to see if different type of network architectures can be applied to the problem of recommendation in order to create personalized recommendations by using DL. It is of interest to see investigate if it is possible to represent the problem of recommendation as a multiclass classification problem, in order to analyze what kind of DL networks are applicable for creating multi-feature personalized recommendations. Some promising research area is emerging which gives motivation to use DL as a tool for creating recommendations. With this paper we aim to explore this new promising area of research by exploring the chances of DL in RecSys.

Rest of the paper is organized as follows, Section II contains brief introduction of the various Recommender Systems exists in the literature, Section III contain the description of related survey works in the field of deep learning based recommender systems, Section IV contain the description of selected 21 deep learning based RecSys models, classified in terms of the different DL techniques used, Section V tabulated the extracted data from the selected papers. Section VI concludes review work with future directions and Section VII mention the acknowledgement statement.

RECOMMENDER SYSTEMS

Recommender Systems are everywhere and we use them every day, directly or indirectly, in our digital interactions: when we buy that book that Amazon recommends us based on our previous history, when we listen to that playlists tailored to our taste in Spotify, or when we watch with the family that that movie recommended in Netflix, and discover new friend connections in Face book, or read that news articles we care about that Twitter offers, or when we apply to that ideal job hinted by LinkedIn. RecSys help us finding that valuable item among an ocean of choices. It helps us to deal with choice overload; it assists people for

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facing the difficulties of decision making with a choice among many options by a cognitive process. RecSys is an active and fast growing field of research.

MATERIALS AND METHODS

RecSys collect and exploit numerous sorts of info concerning users, products, and interactions between users and products to come up with a customized list of things that matches user's current wants. Sohail et al [6] categorized 8 types of recommender systems (RS) as shown in [Table 1]. These categories broadly cover the techniques which have been used by the masses or the current generation researchers are frequently applying it.

Table 1: Recommenders system categories and techniques

Types of RecSys	Subcategory	Techniques
Collaborative Filtering (CF) based RS	Item based	Association rule mining between preferences of neighbor of users, Rating, Choice of individuals for varied items, Similarity in the preferences of different users for common items, Tagging
	User based	
	Model based	Bayesian networks, clustering, Machine learning, Graph modeling
Reclusive Methods (RM) based RS	Heuristic method	Rule induction, nearest neighborhood, Rocchio's algorithm, tagging, rating, etc.
	Model based techniques	Bayesian networks, clustering, Machine learning, Graph modeling
	Web mining	Opinion mining, web usage mining, etc
Hybrid recommender systems	CF dominated RM	Techniques of CF, RM applied with each other in different combinations
	RM dominated CF	
	CF and RM coalesced into one	
	Subsequent Integration of separately applied CF and RM	
	Integration of CF and RM with (KBS)	Techniques of CF and RM are applied with KBS, and other fuzzy, social network, etc
	Integration of CF with other than RM	
	Integration of RM with other than CF	
Demographic filtering based RS		Correlation, similarity measures, etc
Knowledge based Recommender System (KBS)	Constraint based	Machine learning, Bayesian network, AI, etc.
	Case based	
Context Aware Recommender System	Location aware, Temporal, Trust aware	User feedback, AI techniques, machine learning, etc.
Social network based RS	Foafing, trade relationship, etc.	Similarities measures, user profiling, etc.
Soft Computing techniques based RS	Fuzzy genetics, fuzzy linguistics,	OWA, ORWA, fuzzy model, etc.

RELATED REVIEWS

DL based RecSys is become widely popular from 2016. Now it becomes a promising research area. Many recent short reviews are available in the literature that deals with the state of the art deep RecSys. The number of publications is increasing day by day in the area of DL based RecSys. The leading international conference RecSys by ACM begins to conduct regular workshops and conferences from the year 2016.

There is a plenty of literature reviews exists in the area of traditional RecSys. Even though there is a huge scope for systematic literature reviews on Deep RecSys, it is not that much explored. The prominent and most systematic review on DL based RecSys is by Shuai Zhang et al [7]. This survey lays a foundation in this area that can highly dependable for the researchers who wish to enter into this area. They are proving a classification scheme of current works in a well defined manner, state of the art research area and discussing challenges and open issues deeply.

Another recent survey, by Ayush Singhal et al. [8], contains the summary of DL based collaborative systems and application domains. The other paper gives the narrow narration about the deep RecSys. In [9], Rim Fakhfakh et al. give major emphasis on the Challenges and issues in DL based RecSys The all existing reviews are not systematic they just tries to summarize the works in this area of research.

Mu et al [10] carried out a detailed survey recently on the various techniques and gives more research direction in the area. With this paper, we aim to help the researchers, students, and practitioners working in the field of RecSys by exploring the scope of DL Techniques in their field. Our aim is to help them by the following contributions.

- A brief overview of state of the art DL approaches used along with RecSys.
- An overview of various RecSys models along with applied DL techniques and datasets, from the literature.

Our aim is to provide a comprehensive review of recent researches happened in the field of DL based RecSys for making an improvement in classic RecSys.

DL BASED RECSYS MODELS

DL is a field of Machine Learning that allows computational models that are composed of multiple processing layers of representation and abstraction that help to make sense of data such as text, image, sound and video. DL technique is a hot and emerging area in both data mining and machine learning communities. These models can be trained by either supervised or unsupervised approaches. DL models are initially applied to the field of Language Processing, Computer Vision and Audio, and Speech. It outperformed many state-of-the-art models. Later deep models have shown their effectiveness for various NLP tasks. These tasks include semantic parsing, machine translation, sentence modeling and a variety of traditional NLP tasks. DL has recently been proposed for building RecSys for both collaborative and content based approaches. DL becomes a powerful tool to tackle RecSys tasks such as music, news, fashion articles, and mobile apps recommendation. This paper takes a glimpse of current research in this field, which aims to identify new opportunities for research and industrial applications, to enhance the recommender experience.

Multilayer Perceptron based RecSys model

MultiLayer Perceptron [MLP] is a feed forward neural network. Between input and output layer multiple hidden layers. It is an efficient gradient descent based nonlinear function approximators for error minimization in the approximation of a function. This tries to define a mapping from y=f(x;θ) and learns the value of the parameters θ that results in the best function approximation. There are mainly 4 recommendation models that utilize multilayer perceptrons [11-15]. The pictorial representations of these models have shown in [Fig. 1].

He et al. [11] developed a general framework using MLP to model the user-item interaction matrix by capturing the non linear relationship. NCF technique replaces the matrix factorization(MF) and utilized Negative sampling for data size reduction, which improves the learning efficiency. The proposed CF model is compared with existing MF approaches on Pinterest and MovieLens datasets and showed statistically significant improvements on both datasets. Neural Collaborative filtering model is depicted in [Fig. 1(a)].

CCCFNet[12] is an extension of NCF for cross domain applications. CCCFNet consists of two neural networks one for users and other for items. In this model user items interactions are represented as a dot product in the last layer. It is a multi-view cross domain recommendations that makes use of two components for embedding content information. One is collaborative filtering factor used for representing user and item latent factors. Other one is content information component that matches user's preferences on item features and item features. The architecture model is at [Fig. 1(b)].

Cheng et al.[13] proposed another model for both regression and classification problems. Here it is used in Google play for app recommendations. The model has two components: wide and deep. Wide component is a simple linear model such as single layer perceptrons where as deep component is a multilayer perceptron. Memorization and generalization is made possible by using those components. In this memorization is achieved by wide component and generalization is achieved by the deep component. Compared to NCF both accuracy and diversity is improving in this model. For optimization stochastic back propagation is utilized. According to the predicted score recommendation list is generating. [4] Extends wide and deep model by incorporating a locally connected network by replacing the DL component, which helps to decrease the running time. Wide & DL Model architecture is depicted in [Fig. 1(c)]. [14] introduces DeepFM model as shown in [Fig. 1(d)], for alleviating the feature engineering problems such as solving which feature is selected for memorizing and which feature is for memorizing in wide and DL models. That is depends only on DL and factorization machines. Here higher order feature interactions are implementing via DL (MLP) and low order interactions through factorization machine. The prediction score is calculated by

$$\hat{r}_{u,i} = \sigma\left(y_{FM}(x) + Y_{MLP}(x)\right)$$

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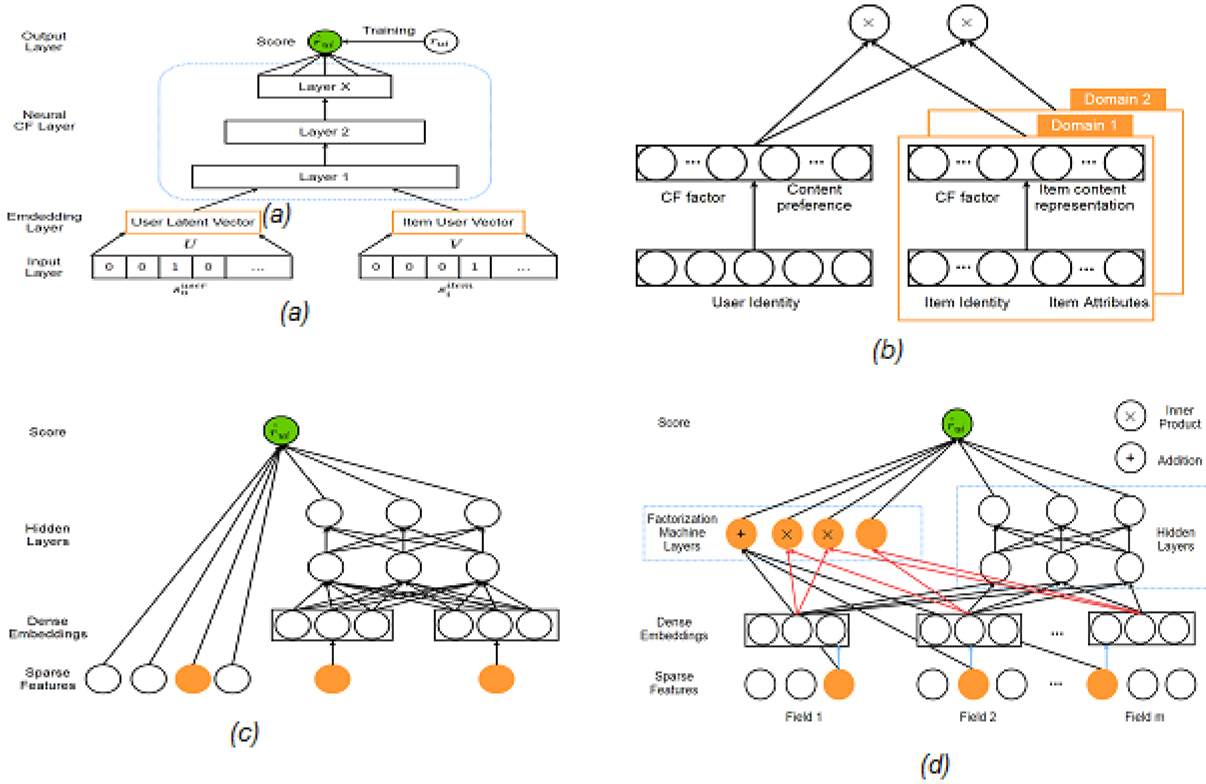

Fig. 1: MultiLayer Perceptron based RecSys Models (a. Neural Collaborative Filtering[11], b. CCCFNet[12], c. Wide & DL Model[13] d. DeepFM Model[14])

Zhang et al.[15] propose a hashing based DL framework called Discrete DL (DDL). It maps users and items to Hamming space. From that hamming space a user's preference for a particular item can be calculated efficiently by using hamming distance. Online recommendation efficiency is improved significantly by this computation scheme. Cold start problem and data scarcity problems are also alleviated by using discrete DL model by unifying item content information and user-item interaction. The extraction of effective item representation from the item content information is done by applying Deep Belief Network (DBN). DDL provides a good trade-off between recommendation efficiency and accuracy.

Auto Encoder based RecSys model

An auto encoder is a trained neural network that attempt to copy its input to its output. For describing the representation code of the input, it has a hidden layer h. The network consists of two parts: an encoder function h =f(x) and a decoder function r = g (h) that produces a reconstruction. Four auto encoder based RecSys are extracted from the literature [16-22] are shown in [Fig. 2.]

Sedhain et al. [16] proposed AutoRec, an auto encoder based RecSys. The aim of AutoRec is the reconstruction of inputs such as user partial vectors r^u or item partial vectors r^i in the output. Corresponding to both inputs two variations are there U-AutoRec (User based) and I-AutoRec (Item based). The reconstruction function for the input r^i in I-AutoRec is

$$h(r^i;\theta) = f(W.g(V.r^i + \mu) + b)$$

Where $f(.)$ and $g(.)$ are the activation functions, W,V,μ,b are parameters. While considering the performance I-AutoRec is better than u-AtoRec. Here activation function combinations, moderate increase in hidden unit size, adding more layers will increase the capacity and performance of AutoRec. I-AutoRec model is shown in the [Fig. 2(a)]. Strub et al. [17] extends the AutoRec to make it more robust by employing the de-noising techniques and including user side information such as item description and user profiles for mitigating the cold start problem. This model is known as Collaborative Filtering Neural Network [CFN], which also have two variants I-CFN and U-CFN taking r^i and u^i as input respectively. In this correption approaches such as salt and pepper noise, Gaussian noise and masking are utilized to deal with missing elements. In CFN Side information is integrated with every layer that will help to improve accuracy, training process speed and make the model to be more robust.

Auto encoder based collaborative filtering [ACF] proposed by Ouyang et al [18] is the first one in this type of RecSys. It deal with integer ratings (1-5), it divides the rating into five partial vectors. ACM predicts rating by summarizing each entry of the five vectors, and then scaled by the maximum rating 5. RBM is used t pre-train the parameters as well as to avoid local optimum. Short comings of this model are it can only deal with integer ratings and while decompose the rating vector that increase the sparse problem in input data and leads to inaccurate prediction. AutoRec, CFN and ACF are used for rating prediction whereas CDAE (Collaborative DE noising Auto-Encoder) proposed by Wo et al.[19] is used for ranking prediction.

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User's feedback is the input to CDAE. The entry value is 1 whether the user likes the movie otherwise it is 0. Gaussian distribution is used for solving Gaussian noise problem. The reconstruction is defined as

$$h(\tilde{r}^{u}_{pref}) = f(W_2 . g(W1 . \tilde{r}^{u}_{pref} + V_u + b_1) + b_2)$$

Where $V_u \in R^K$ denotes the weight matrix for user node. For each user this weight matrix is unique and it improves the performance too.

Wang et al [20, 21] proposes two Auto-Encoder integrated RecSys models: CDL (Collaborative DL) and CDR (Collaborative Deep Ranking) CDL for rating prediction where as CDR is for top n recommendations in a pair wise frame work. CDL uses Stacked De-noising Auto-Encoder [SDAE]. CDR outperforms CDL in their experiments. They are similar in structure and different in some iteration. Both make use of two tightly coupled components, one is a deep neural network used as a perception component and the other is a task specific component. A frame work is proposed by Li et al. [22] for unifying DL approaches with collaborative filtering model. It is called Deep Collaborative Filtering Framework. It is an easy and well defined frame work for incorporating DL techniques in collaborative filtering. The framework is formulated as follows

$$\arg\min_{U,V} l(R, U, V) + \beta(||U||_F^2 + ||V||_F^2) + \gamma L(X, U) + \delta L(Y, V)$$

Where β, γ, δ are trade off parameter, X, Y are side information l(.) is the lost and $\gamma L(X, U) + \delta L(Y, V)$ is the hinges for connecting deep and collaborative models.

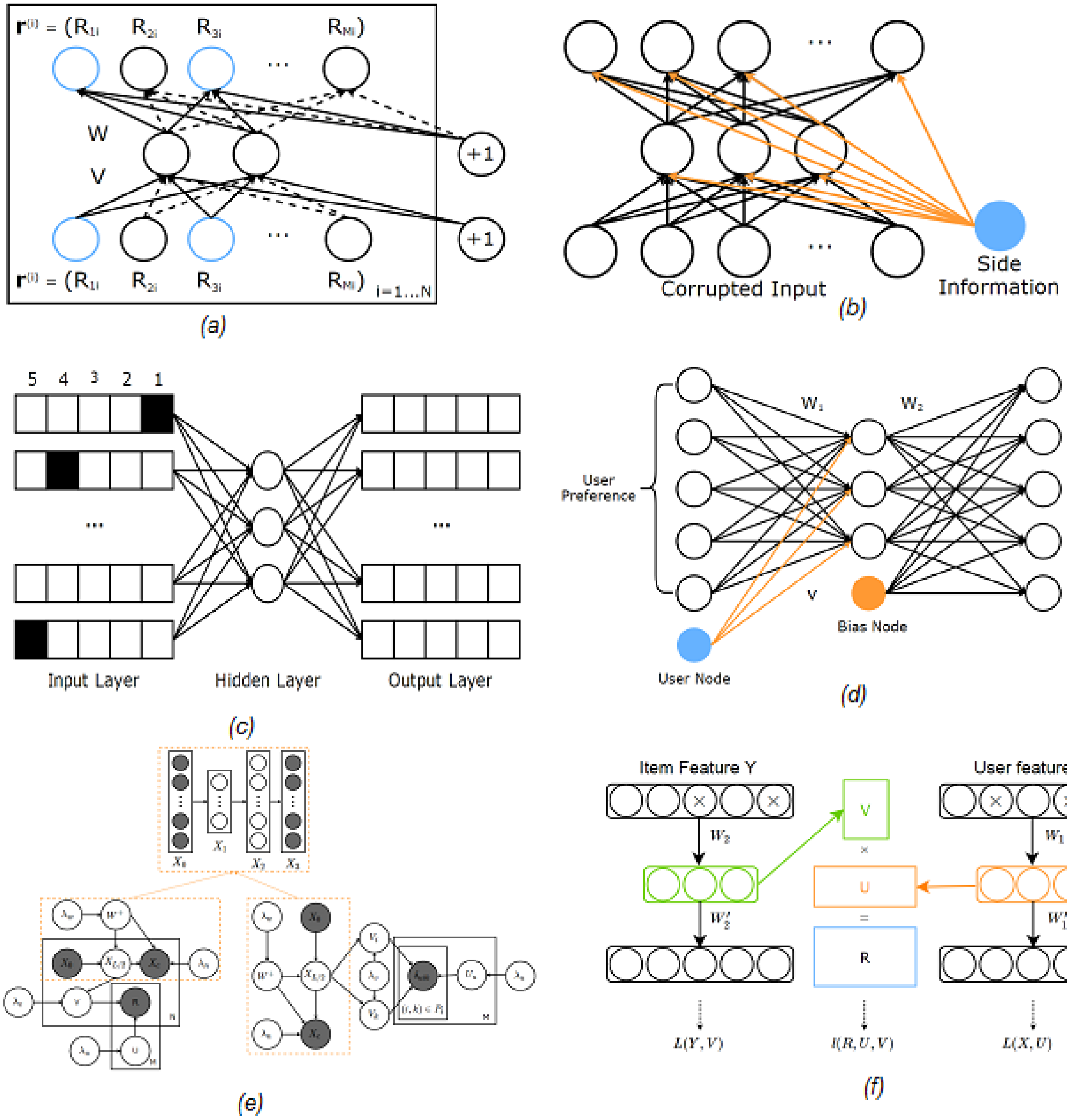

Fig.2: AutoEncoder based RecSys Models. (a). AutoRec Model[16], (b). CFN Model[17], (c). ACF Model[18], (d). CDAE Model[19], (e). Graphical Model of CDL(left) and CDR (Right)[20,21], (f). Deep Collaborative filtering Framework [22]

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Convolutional Neural Network based RecSys model

Convolutional Neural Networks[CNN] are a specialized kind of neural network for processing data that has a known grid-like topology such as time-series data [1-D grid], and image[2-D grid] of pixels. In CNN convolution is used in place of matrix multiplication in at least one of their layers otherwise it is a simple neural network [23-27]. The models are depicted in [Fig.3].

Gong et al. [23] solves hash tag RecSys as a multiclass classification problem. It is an attention based model. The part of the proposed model are global channel, which is made up of max pooling layers and convolutional filters, and local channel which is the attention layer for selecting trigger words for tagging. All words are imputed to the global channel where as local channel is used for selecting the trigger words. Nguyen et al. [24] proposed a personalized tag RecSys .in this paper they are extracting visual features from the images by using max pooling layer of CNN. For differentiating relevant and irrelevant tag according to a particular person , a Bayesian personalized Ranking algorithm is utilized. DeepCoNN(Deep Cooperative Neural Network) proposed by Zheing et al[25] incorporated two CNNs: one for user behaviors and another for item reviews. Factorization machines are used to find the interaction between two CNNs in the last layers for rating predictions. It combines the benefits of both CNN and Matrix factorization for solving scarcity problem by different layers as shown in the [Fig.3(c)].

ConvMF [26] is another model which utilizes probability matrix factorization along with CNN. Item representations are learned by using CNN and task specific recommendation are performed using PMF. The structure is similar to the CDL whereas instead of Auto-Encoder here CNN is used. Wen et al.[27] propose a dance background recommendation system that utilize CNN for image extraction. It focuses on dancers digital footprints images that they have browsed, liked, or used previously. To support the recommendation system, this work also proposes a Deep MF model based on PMF that effectively combines a content-based method and the conventional rating-based method. The content-based method uses the image's visual content to do the recommendation, and the visual content of a dance image is represented by both an object feature and a style feature. The detailed architecture is shown in Fig. 3(e)].

Recurrent Neural Network based RecSys model

Recurrent neural networks are a family of neural networks for processing sequential data x1, x2,...., xn. When feed forward neural networks are extended to include feedback connections, they are called recurrent neural networks. LSTM and GRU are two different variations of RNN. RNN viewed the user interest as a sequence prediction technique. Similar sequence are identified and recommended. The concepts used in RNN for RecSys is extracted [28-32] and depicted in [Fig. 4].

Hidasi et al. [28] proposed a RecSys model for session based recommendation based on Recurrent Neural Networks (RNN). Session based RecSys considers users current login interests only for recommendations. It may lead to scarcity of training data. Here the proposed model efficiently implemented session based RecSys by using GRU. If there is N number of items the state of the item is represented as 1-N encodings. And tries to assign the session value for each item as 1 if it is active in that session otherwise it is 0. Likelihood and session based parallel mini batches algorithm is used for further processing of the output. Tan et al. [29] modified the model [28] by changing the input from 1-N encodings to click sequences and they add necessary preprocessing and dropout procedures for handling those inputs. They train the model first by complete input and then tune it with most recent inputs. For decreasing the number of parameters they use item embedding techniques, this leads to faster computation. Recurrent Recommender Network (RRN) [30] is a non parametric model for recommendation built on Recurrent Neural Networks. Here two LSTMs are used for modeling seasonal evolution of items and user preferences over time. One LSTM is for user state $u_{u,t}$ and the other for item state$v_{i,t}$. This model considered user stable long term interests as well as dynamic short term interests also. The predicted rating of j given by user i at time t is represented as

$$\hat{r}_{ui|t} = f(u_{ut}, v_{it}, u_u, v_i)$$

Where u_u, v_i are learned from matrix factorization and the others are from LSTM.
Like attention based MLP and CNN, attention mechanism can also incorporated with RNN [31]. It helps to learn the sequential property and for recognizing informative words from micro blogs for hash tag recommendation. Here LSTM is utilized for learning hidden states and also attention based is based on LDA distribution after the nonlinear transformation and softmax normalization. Cross entropy minimization is used for training this model. Beutel et al. [32] created a deep context aware RecSys using Latent Cross to include contextual features more expressively. Latent cross is utilized to get the element wise product of the neural network hidden states and the context embedding. It uses different contexts along with ratings for video recommendation based on Recurrent Neural Network. The deep RNN architecture is shown in the [Fig. 4(e)].

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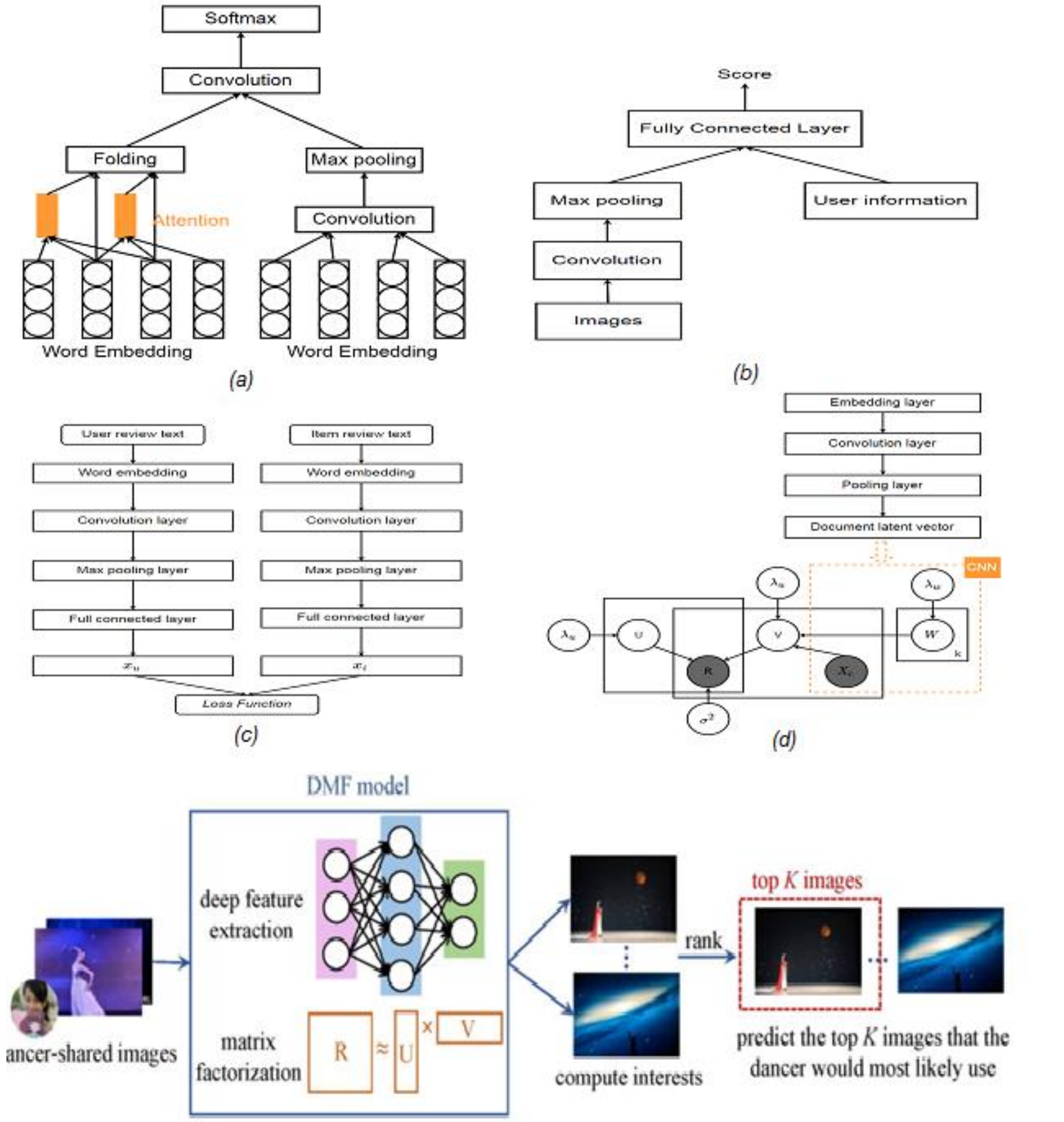

Fig. 3: CNN based RecSys Models. (a). Attention Based CNN model[23], (b). Personalised CNN Tag Recommendation Model[24], (c). DeepCoNN Model[25] (d). ConvMF Model[26], (e). Dance background image recommendation system.[27]

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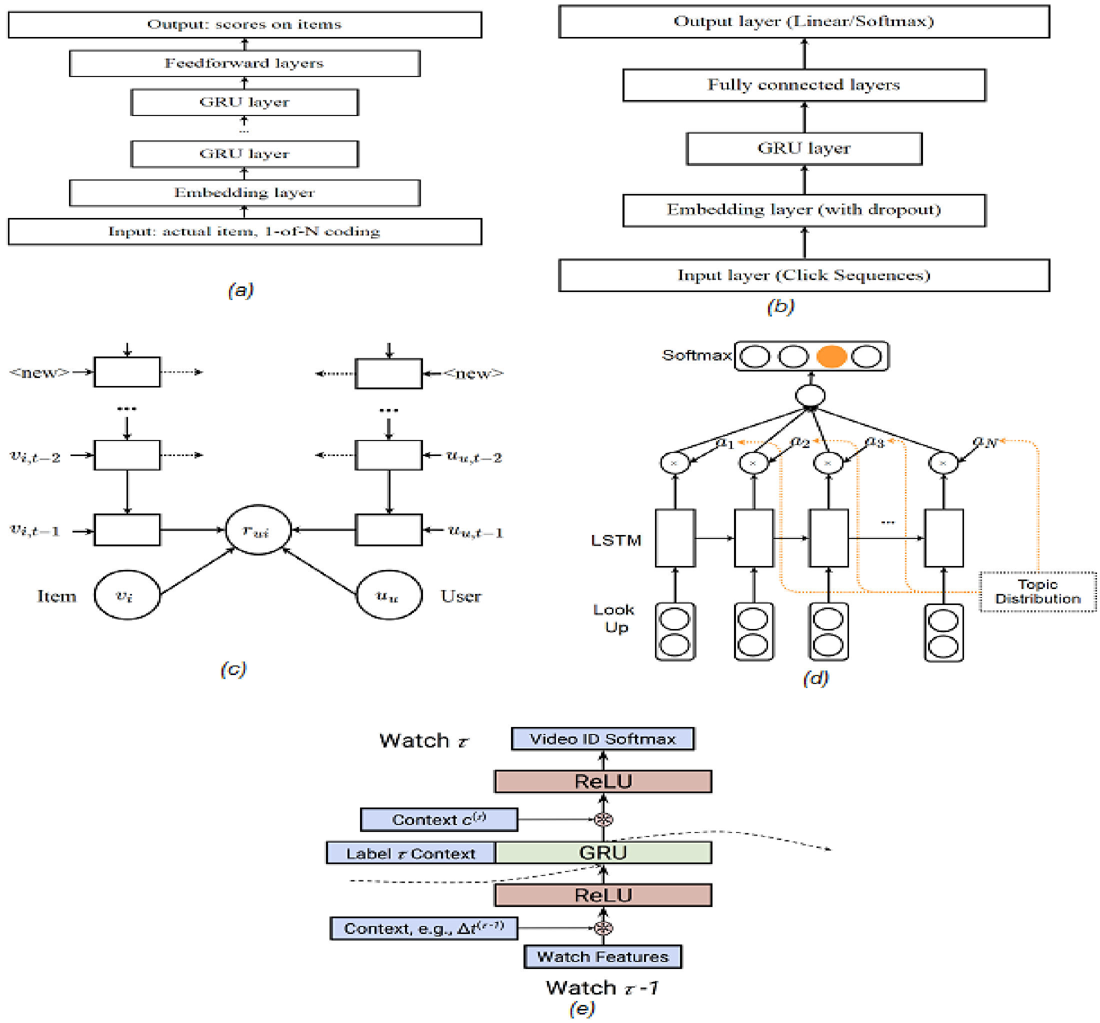

Fig. 4: RNN Based RecSys Models. (a). Session-based recommendation With RNN[28], (b). Improved Session-based recommendation With RNN[29], (c). Recurrent Recommender Network (RRN) Model [30], (d). Attention based RNN Model for Tag Recommendation.[31], (e). Latent cross based RecSys architecture.[32]

DATA EXTRACTION

The data extracted from the selected papers which utilized the concept of DL for RecSys Models are tabulated as in [Table 3]. This review is focused on the 4 DL techniques such as Multilayer perceptrons, Autoencoder, Convolutional Neural Networks and Recurrent Neural Networks.

Table 2: Deep learning techniques, corresponding RecSys Models and used application domains

DL Techniques	RecSys Model	RecSys Type	Concepts used	Application Domain
Multilayer Perceptions	Neural Collaborative Filtering[11] Model	Collaborative Filtering	MLP is used for user-item interactions and nonlinearities. Negative Sampling	Movie Recommendation
	CCCFNet[12]	Content and Collaborative Filtering	Cross Domain Recommendation Multi- view modeling	Movie and Music cross domain
	Wide and Deep Learning Model[13]	Collaborative Filtering	Single layer Perceptron Multi-layer Perceptron	Google App domain
	DeepFM Model[14]	Collaborative Filtering	Factorization Machine Multilayer perceptron	CTR Prediction
	Discrete DL[15]	Content based RecSys	Hashing Deep belief network	E-Commerce
Auto Encoder	AutoRec[16]	Collaborative Filtering	User based representation Item based representation	Movie Recommentation
	CFN[17]	Collaborative Filtering	Denoising	Movie Recommendation Jock Recommendation
	ACF[18]	Collaborative Filtering	Integer rating RBM	Movie Recommendation

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	CDAE[19]	Collaborative Filtering	Ranking prediction Gaussian distribution	Movie Recommendation
	CDL[20]	Collaborative Filtering	Rating prediction SDAE	Article Recommendation
	CDR[21]	Collaborative Filtering	Ranking prediction Implicit feedback	Article recommendation
	DCIF[22]	Collaborative Filtering	Stacked DE noising	Article Recommendation Movie Recommendation
Convolutional Neural Network	Attention based CNN Model[23]	Collaborative filtering	Multi class classification Attention learning	Hash tag Recommendation
	Personalised CNN Model[24]	Collaborative filtering	Image feature extraction	Hash tag Recommendation
	DeepCoNN[25]	Content based filtering	Combines CNN and MF	Product Recommendation
	ConMF Model[26]	Context aware Recommendation	Probability Matrix Factorization	Document recommendation
	Dance background image recommendation model[27]	Content based Recommendation	Probability Matrix Factorization Deep feature extraction	Image recommendation
Recurrent Neural Network	Session based recommendation based on RNN[28]	Content based filtering	GRU Parallel mini batch algorithm	You tube video recommendation
	Improved Session based recommendation with RNN[29]	Content based filtering	Embedding techniques	You tube video recommendation
	RRN[30]	Collaborative filtering	Non parametric model	Video Recommendation
	Attention based RNN Model[31]	Collaborative filtering	Attention mechanism Non linear transformation	Hash tag recommendation
	Latent cross based context aware recommendation Model[32]	Context Aware Recommendation	Latent cross technique	Youtube video recommendation

CONCLUSION AND FUTURE WORK

This paper describes the literature review of the various DL techniques used in the field of RecSys. The major emphasis is on the DL architectures and their working on each paper on study. Compared to Data Mining techniques, DL techniques are more effective for RecSys because nowadays RecSys are dealing with big data, especially the volume of dataset is huge. Even though there are large opportunities for DL based RecSys, they are not explored yet. This paper can be a base for the researchers to start their research in this filed.

The conventional readily available datasets are only used for experimentation in the RecSys. Recommendation systems are still based on the conventional applications such as ecommerce site, movie, music, etc., with the help of DL, the scope of RecSys can spread to the new, complicated and unexplored fields by utilizing the real time datasets. The current research literature has focused on the collaborative and content based RecSys. In future deep RecSys have great opportunities in research , they include: for the better understanding of the users and items, for multitask learning, multi view RecSys for improving scalability, for session based RecSys, cross domain recommendations, context aware recommendations, etc.. The DL seems to be a powerful solution to overcome the limitations in this field and enhance the recommendation systems experience.

CONFLICT OF INTEREST

None

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FINANCIAL DISCLOSURE

None

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