A SURVEY OF DEEP LEARNING BASED RECOMMENDER SYSTEM

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ABSTRACT

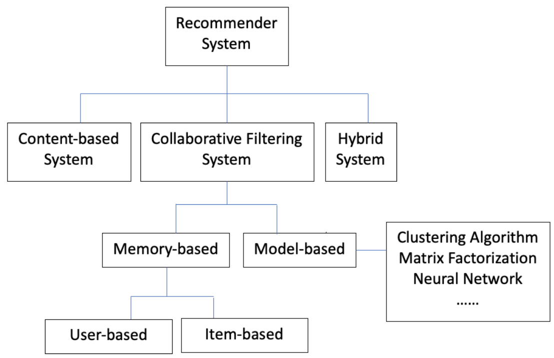
Recommender systems are used in various areas like content consumption and product recommendation. In recent years, deep learning has gained significant success in natural language processing and computational vision and has been applied in the field of recommender systems. In this survey, we give a review of the recent development of deep learning based recommender systems. We introduce the development of deep learning based recommender systems and describe the typical deep learning methods widely used in recommender systems. Some architecture of different models is present and compared.

Keywords Recommender System · Neural Network · Collaborative Filtering · Embedding · Knowledge Graph

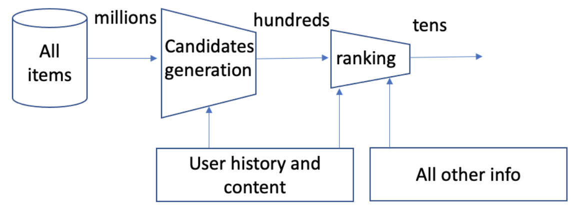
1 Introduction

Given the exploding growth of information on the Internet and access to overwhelming choices, recommender systems have been indispensable tools to retrieve and rank items for different users. Recommender systems have been widely used in content consumption (movie, music, news, ...) and E-commerce. It usually utilizes user-item interaction and side information about items or users to capture users' short- and/or long-term interest and then make predictions or recommendations. With the recent development of machine learning, especially deep learning, a significant amount of progress has been made to improve the quality of recommender systems, facing challenges such as accuracy, sparsity, cold-start, scalability, etc. And many advanced recommendation algorithms have been developed and deployed by platforms such as Youtube [1], Netflix [2], eBay [3], TikTok [4] etc.
However, there was a lack of extensive review on deep learning based recommender systems until S. Zhang et al. [5], and Z. Batmaz et al. [6] published their comprehensive, in-depth reviews. Short surveys are good for beginners in the field compared with comprehensive reviews. Several short surveys [7, 8] have been formally published. However, they failed to cover specific topics like knowledge graphs, sequence embedding, and attention-based models. Thus, this survey will focus on important progress and recent developments, especially the knowledge graph. Hopefully, this survey can provide some information and insight about recommender systems. This survey is organized as follows: Section 1 is a brief introduction to the recommender system from a high-level perspective. Section 2 briefly describes the recent development of the recommender system. Section 3 introduces the basic concepts and terminologies of deep learning techniques used in recommender systems. Section 4 discusses the usage of knowledge graphs in recommender systems. Section 5 puts together the architecture of different recommender system models and makes a comparison. Finally, Section 6 gives a conclusion and expectation of future work.

As shown in Figure 1(a), recommender systems can be classified into three categories [9]: collaborative filtering (CF) systems, content-based systems, and hybrid systems. The collaborative filtering systems utilize the interaction of users and items to find related or similar users and items. They can be further classified into memory-based and model-based methods. The memory-based method is to identify similar users (user-based) or items (item-based) based on the user-item matrix, which usually suffers from sparse data issues. The model-based method applies machine learning models like matrix factorization or neural networks to predict the rating of a new item. Content-based systems exploit side information like text, visual (picture), and audio descriptions of items. Hybrid systems are a combination of the above and utilize multiple approaches.
Figure 1(b) shows a general structure of a recommender system. We divide the recommender system into retrieval and ranking stages due to the vast number of items.



(a) Classification of recommender systems



(b) Structure of a recommender system

Figure 1: Summary of recommender systems

2 Development of Recommender System

Content-based filtering uses item features to recommend other similar items based on the user's previous actions, explicit or implicit. Collaborative filtering uses similarities between users and items simultaneously. For instance, to predict the ratings of certain items for one user, we look for users who have similar tastes and use the ratings from these users to predict.
Netflix Prize competitions [2], began on Oct, 2006, sparked interest in matrix factorization (MF) [10], due to its superior performance compared with classic nearest-neighbor techniques. MF can be considered as a simple embedding model. Figure 2 gives an example for MF, where the $m \times n$ user-item matrix decomposes into $m \times d$ user embedding matrix and $n \times d$ item embedding matrix ($d = 2$ in this example). Factorization machine (FM) [11] is a generalization of the linear regression and matrix factorization models. FM captures the linear and pairwise interactions between features where the interaction is the dot-product of features. Moreover, the so-called neural collaborative filtering extends the model capacity by learning the highly non-linear interaction with the neural network.

Figure 2: An example of MF. Image taken from [12]

Compared with traditional matrix factorization, which decomposes the user-item matrix to obtain user and item latent vectors, neural collaborative filtering models utilize the neural networks to construct the user and item latent vector. The commonly used networks are multiple layer perception (MLP), convolutional neural network (CNN), recurrent neural network (RNN), long-short-term-memory (LSTM), gated recurrent unit (GRU), etc. As illustrated in Figure 3, many models have been proposed, including Deep Crossing [13], Factorisation-machine supported Neural Networks (FNN) [14], Product-based Neural Network (PNN) [15], Wide & Deep Model [16], DeepFM [17], Deep & Cross Network (DCN) [18], Attentional Factorization Machines (AFM) [19], Deep Interest Network (DIN) [20], and Deep Interest Evolution Network (DIEN) [21]. Further discussion can be found in Section 5.

deep neural networks for youtube recommendations [1] is a classic paper showing how the neural network is used in video retrieval and ranking in the real world. In this paper, video retrieval is considered an extreme multiclass classification problem. As shown in Figure 4, embedded video watches and search tokens are averaged and concatenated

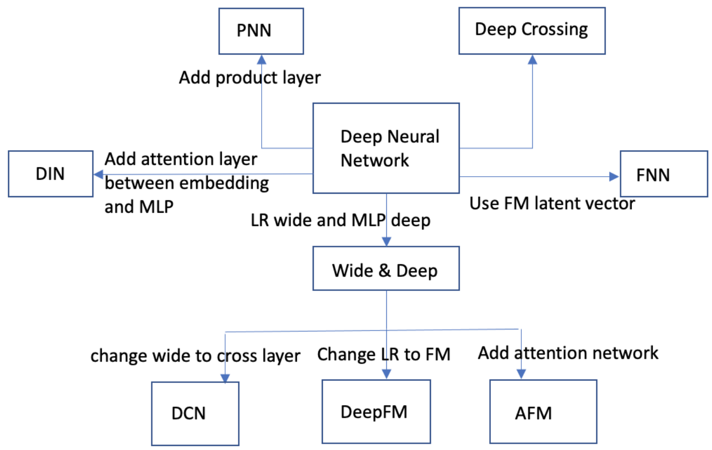


Figure 3: An overview of deep learning models.

with other demographic embeddings and fed into a fully connected neural network. A similar neural network is used for ranking. The main difference is the number of input features, much more features are used for ranking, such as *time since last watch*, *number of previous impressions*.

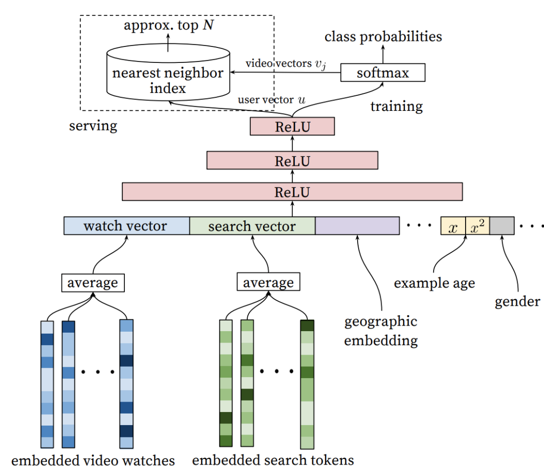


Figure 4: An overview of DNN for youtube. Image taken from [1]

The transformer has been the start-of-art feature extractor since it was proposed in the field of natural language processing (NLP). It has achieved start-of-art performance in various tasks, and it is natural to use attention networks in recommender systems. Many recommender system models with attention mechanism have been proposed, including DeepCoNN [22], TransNet [23], D-ATT [24]. A detailed discussion is out of the scope of this survey.

Recently, much effort has been made to integrate knowledge graphs into recommender systems because knowledge graphs can enhance recommendation by providing side information. Embedding-based and path-based methods are developed to take advantage of knowledge graphs in recommendation tasks. A detailed discussion can be found in Section 4.

3 Techniques of Deep Learning

This section describes the basic concepts of some deep learning technologies and their application in recommender systems.

3.1 Autoencoder

An autoencoder is a type of neural network attempting to reconstruct its input data in the output layer. For recommendation, autoencoders are mainly used in learning low-dimensional representation (embedding) of features at the hidden layer or predicting the missing value at the reconstruction layers for purposes of recommendations. AutoRec [25], CDAE [26] are examples of recommender system using autoencoders.

3.2 Convolutional Neural Network

Convolutional neural networks (CNN)[27, 28] is a class of neural networks widely used in the field of computer vision (CV). As shown in Figure 5, a typical CNN is usually composed of convolutional layers, pooling (subsampling) layers, and fully connected layers. A CNN can capture global and local information and is powerful in extracting features, making it attractive in dealing with the image or textual data.

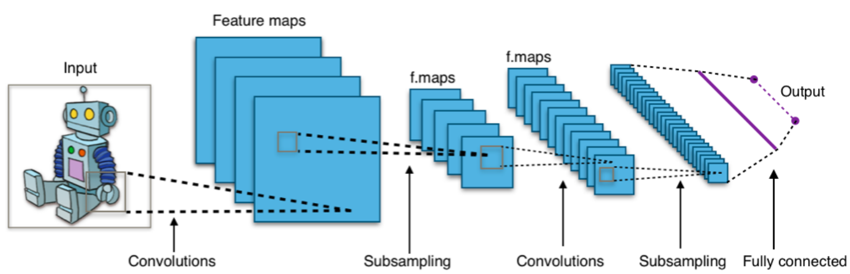


Figure 5: A typical CNN architecture. Image taken from [29]

CNN has been used in fashion-trend [30, 31], and style preference [32] where visual appearance is considered for the personal ranking. CNN is also used for point-of-interest (POI) recommendation by exploiting images [33], and document encoding for news recommendation [34]. ConvMF [35] is proposed to integrate CNN into probabilistic matrix factorization (PMF), where the CNN generates latent vectors for documents. J. McAuley et al. [36] applied CNN to uncover relationships between the appearances of pairs of objects. There are hybrid models such as attention-based CNNs [37] proposed for review rating prediction.

3.3 Recurrent Neural Network

A recurrent neural network (RNN) [38] is a type of neural network where connections between nodes form a directed or undirected graph along a temporal sequence. Previous values of the hidden units are saved and passed into the hidden units along with input values. As shown in Figure 6, the hidden layer h_t at time t depends not only input vector x_t, but also hidden layer h_{t-1} at time $t-1$

$$h_t = \sigma_h(W_h x_t + U_h h_{t-1} + b_h) \tag{1}$$

Equation 1 shows how the hidden value is calculated, where σ_h is the activation fuction,W,U and b are parameter matrices and vector.

Variants such as long short-term memory (LSTM) [40], gated recurrent unit (GRU) [41] are also proposed to overcome the gradient vanishing issue.
RNN, LSTM, and GRU are suitable for time-aware or time-dependent recommender systems. In recommender systems, the recommendation may depend on the time, and the user and item features may influence each other, and both evolve. H. Dai et al. [42] proposed a novel deep coevolutionary network model (DeepCoevolve), which uses RNN to learn user and item features based on time-dependent user-item interaction graph. T. Bansal et al.[43] proposed architecture with bi-directional RNN and GRU for text item recommendations. T. Donkers et al. [44] proposed a user-based GRU for a sequential recommendation. B. Hidasi et al. [45] report the use of RNN in a session-based recommendation.

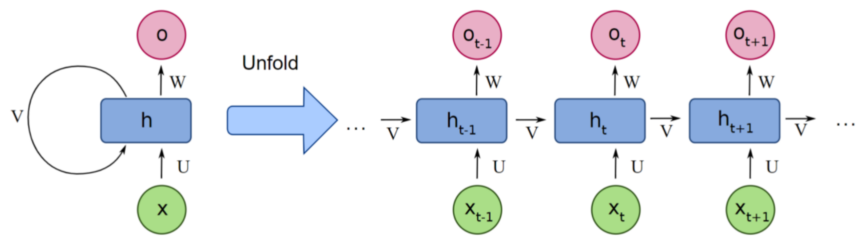


Figure 6: A RNN structure unfold by time. Image taken from [39]

3.4 Sequence Embedding

Sequence Embedding is not an architecture but an approach to get embedding for entities, becoming popular after word2vec [46]. word2vec is a technique for natural language processing (NLP). It uses a neural network to learn word association and has been a powerful tool since published in 2013. A detailed explanation of word2vec can be found in [47]. It uses continuous bag-of-word (CBOW) or continuous skip-gram for model training. In principle, any meaningful sequence can utilize a similar approach to generate embedding vectors for items. Users' history of behaviors (view/click/book/purchase) is a perfect example of coherent sequences and thus can be used for generating item embedding. item2vec [48] is a extension of word2vec. It ignores the spatial information and treats each pair of items in the same set as a positive example, and the objective function is as follow:

$$\frac{1}{K}\sum_{i=1}^{K}\sum_{j\neq i}^{K}\log p(w_j|w_i) \tag{2}$$

Airbnb has used a skip-gram model to learn the listing embeddings for the task of listing recommendations/ranking in search at Airbnb [49]. Click sessions were obtained from users, where each session is an uninterrupted sequence of listing ids were clicked by the user, and the skip-gram model is used to learn listing representations.

3.5 Attention-based methods

Transformer [50] has been a powerful feature extractor used in NLP models such as Bert [51], GPT-3 [52]. The key idea is the attention function. An attention function maps a query and a set of key-value pairs to an output, and the output is the weighted sum of values.

$$Attention(Q;K;V) = softmax(\frac{QK^T}{\sqrt{d_k}})V \tag{3}$$

In equation 3, Q represent queries, K the keys and V the values. Self-attention based sequential model (SASRec) [53] is an example showing how an attention mechanism is used for sequential recommendation problems. As shown in Figure 7, at each time step, the input is the previous items, and the output is the next item.

Q. Zhang et al. [54] used attention mechanism in hashtag recommendation for multimodal microblog. Y. Tay et al. [55] proposed a Multi-Pointer Co-Attention Networks and claimed it outperformed DeepCoNN [22], TransNet [23], and D-ATT [24].

4 Knowledge Graph

A knowledge graph sometimes is referred to as a knowledge base. A knowledge graph is a graph-structured representation of knowledge, a collection of interlinked entities, i.e., event, concept, or product. Knowledge graph embedding methods have been developed with the help of sequence embedding. Both DeepWalk [56] and node2vec [57] use random walks to get sequences from the knowledge graph and then use the sequence embedding method to get entity embedding.
Another approach represents relationships between entities as translations in the embedding space. Relationship between entities is usually written as a triplet (h, r, t), where h is the head entity, t is the tail entity and r is the relationship. Models using this approach such as TransE [58], TransH [59], TransR [60], TransD [61] have been

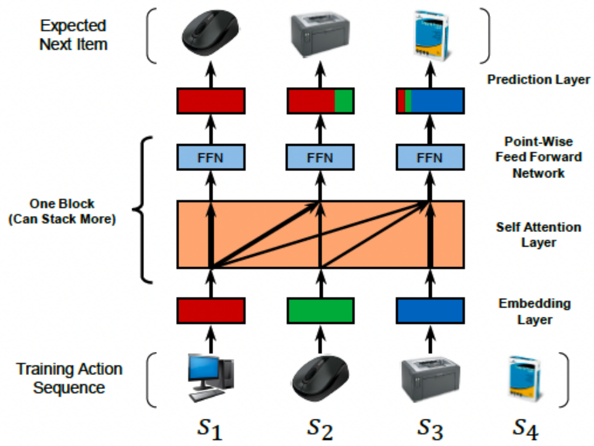


Figure 7: SASRec. Image taken from [53]

proposed to embed knowledge graphs. As illustrated in Figure 8, TransR mapps entity embeddings from entity space to relation space, and the difference between h_r and t_r is the relationship r.

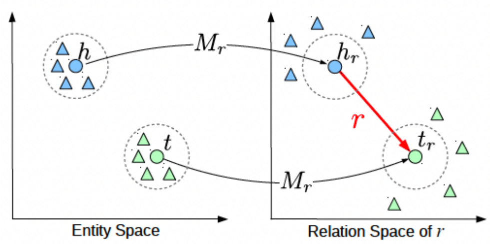


Figure 8: Simple illustration of TransR. Image taken from [60]

Knowledge graphs can enhance the recommender system in three ways: (1) Knowledge graphs introduce semantic relatedness among items; (2) Knowledge graphs contain different types of relationships, which may extend users' interests and increase the diversity of recommended items; (3) Knowledge graphs connect users' historical records and the recommended ones, improving explainability. Various models have been proposed to integrate knowledge graphs into the recommender system. They can be classified into three categories [62]: 1. Embedding-based methods 2. Path-based methods 3. Unified methods.

4.1 Embedding-based methods

The embedding-based methods use the embeddings learned from the knowledge graph directly to enrich the representation of users or items. For instance, Collaborative Knowledge Based (CKE) model [63] uses Bayesian transR, Bayesian stacked denoising auto-encoders (SDAE), and Bayesian stacked convolutional auto-encoders (SCAE) to obtain structural embedding, textual embedding and visual embedding, and add up these embedding with the latent item offset vector.
Deep Knowledge-Aware Network (DKN) [34] was proposed in news recommendation, where news title embeddings are learned with Kim CNN [64]. Words from news titles are concatenated with corresponding entities learned by TransD and then fed into the CNN. The attention mechanism is also used in the model.
Other works include entity2rec [65], SHINE [66], RCF [67], etc.
The works above directly used the raw latent vectors learned from knowledge graph embedding. Some work has been proposed to improve the recommendation performance by refining the entity embeddings.

4.2 Path-based methods

The knowledge graph is often named heterogeneous information networks (HIN) in path-based models. Path-based methods use the connectivity patterns of entities. Connectivity similarity is learned and used to enhance recommendation. PathSim [68] is commonly used to measure the similarity. For example, Personalized Entity Recommendation (PER) [69] model defines meta-path $\mathcal{P}$ and evaluate the score between user i and item j along path $\mathcal{P}$ with PathSim.
PER model needs to pre-define meta path $\mathcal{P}$. Models without pre-defined meta-paths have been proposed. One example is Knowledge-aware Path Recurrent Network (KPRN) [70]: *KPRN takes a set of paths of each user-item pair as input, and outputs a score indicating how possible the user will interact the target item.* This can be seen in Figure 9. The input embedding layers contain three layers: entity, entity type, and relation type. After fed into the LSTM layers, it's expected to predict the interaction between the start entity (Alice, e_1) and the end entity (I see Fire, e_5).

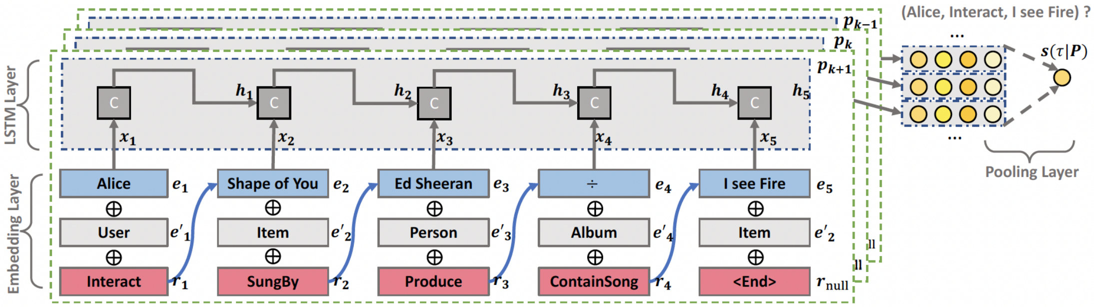


Figure 9: Schematic overview of KPRN. Image taken from [70]

Besides KPRN, there are other models proposed, such as Recurrent Knowledge Graph Embedding (RKGE) [71], Meta-Graph based recommendation fusion over HIN [72], Meta-path based Recommendation with A Neural Co-Attention Model [73].
Path-based methods generally extract meta-path or automatically learn the path pattern to help enhance recommendations.

4.3 Unified methods

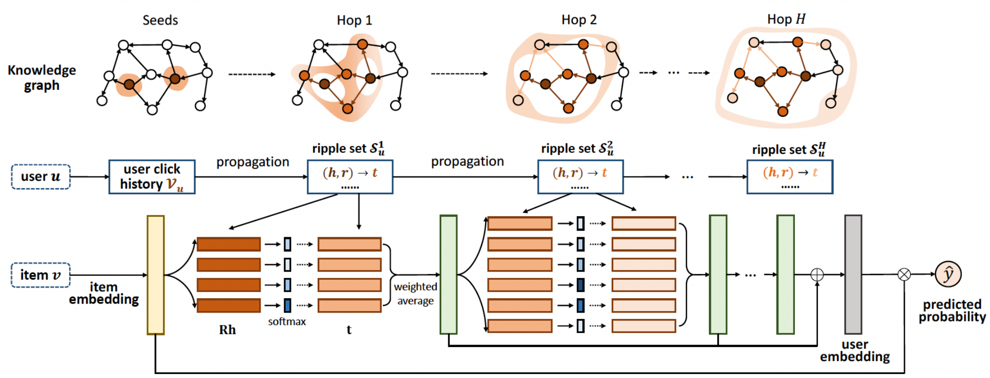
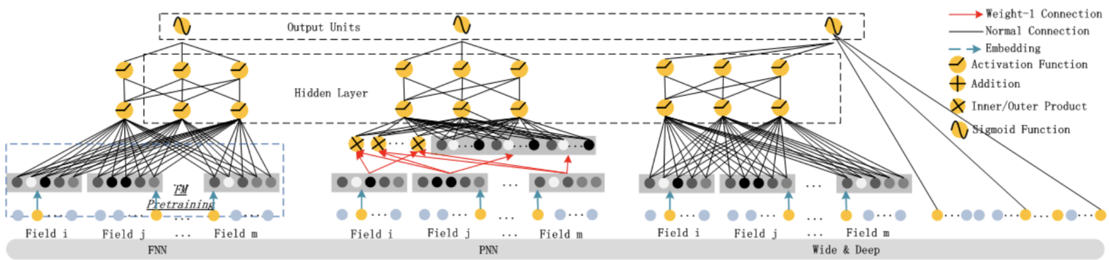
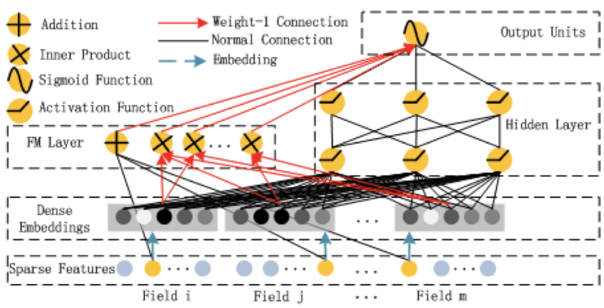


Figure 10: The overall framework of the RippleNet. Image taken from [74]

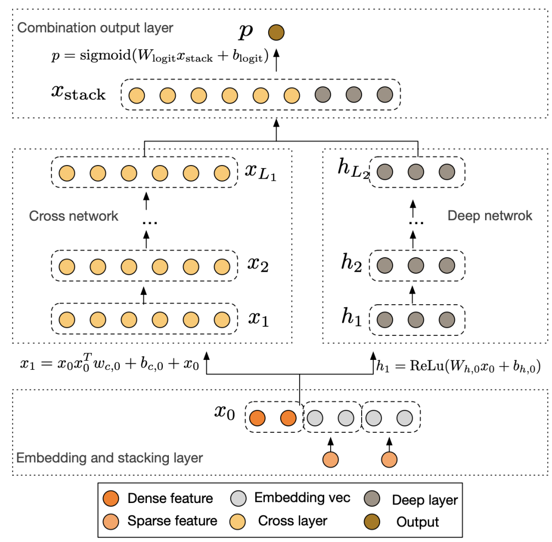
Unified methods benefit from both embedding-based and path-based methods.
RippleNet [74] is the first work to combine embedding-based and path-based methods in knowledge graph aware recommendation. In RippleNet, the user embedding is obtained by a user's history. The key idea behind RippleNet is *preference propagation*. As illustrated in Figure 10, in short, the user's clicked items are seed entities, and (h, r, t) is the corresponding $1 - hop$ ripple set, where h is in the seed entities, and t is in the $1 - hop$ entities, which is the h of $2 - hop$ ripple set. The $k - hop$ ripple set is obtained from $(k-1) - hop$ ripple set. Relevance probability P_i is calculated between item v and the head h_i of the $k - hop$ ripple set. Vector o^k is weighted sum of tail t_i, where the



(a) FNN, PNN, Deep & Wide, Image taken from [17]



(b) DeepFM. Image taken from [17]



(c) DCN, Image taken from [18]

Figure 11: Different Architectures

weight is P_i. The user embedding is the sum of all order vectors o^k.

Y. Cao et al. [75] proposed a model unifying knowledge graph learning and recommendation.

5 Architectures of Deep Learning based Recommender Systems

In this section, we directly compare some typical architectures.
The deep crossing model proposed by Microsoft in 2016 is the classic and base model of deep learning recommendation. It converts features into dense embeddings, concatenates them into a stacking layer, and feeds them into multiple residual units. Compared with Deep Crossing, FNN uses the latent vector learned from FM as the initial embeddings instead of random initialization. PNN adds a product layer between the embeddings and the hidden layers, where the product layer can be an inner product or an outer product. The Wide & Deep model connects a wide part (memorization) and a deep part (generalization) and feeds into the final sigmoid function. Figure 11(a) shows the difference between FNN, PNN, and Wide & Deep. As illustrated in Figure 11(b), the DeepFM replaces the wide part of the Wide % Deep model with an FM component, capturing order-2 features interaction more efficiently because it has inner product unites. Figure 11(c) shows that DCN is similar to DeepFM, and it replaces the wide part with a cross network to increase the feature interactions. The definition and calculation of cross layer can be in [18]. AFM [19] is nothing but FM with attention mechanism, DIN [20] applies attention mechanism in the neural network, and DIEN [21] learns the evolution of interest.

6 Conclusion and future work

S. Zhang et al. [5] have pointed out some future research directions and open issues, such as *Explainable Recommendation with Deep Learning*, *Cross Domain Recommendation with Deep Neural Networks*, *Deep Multi-Task Learning for Recommendation*, and *a suite of standardized evaluation datasets*. We encourage readers to explore this review to figure out more open issues.
The astronomical amount of data generated on the Internet poses enormous challenges for information seeking. Deep learning-based recommender systems (DLRS) are leading solutions to these challenges. Although far from comprehensive, we hope readers can get a general understanding of the recent progress in the recommender system from this survey.

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