Learning Interaction Models of Structured Neighborhood on Heterogeneous Information Network

JIARUI JIN, KOUNIANHUA DU, and WEINAN ZHANG, Shanghai Jiao Tong University, China
JIARUI QIN, YUCHEN FANG, and YONG YU, Shanghai Jiao Tong University, China
ZHENG ZHANG and ALEXANDER J. SMOLA, Amazon Web Services, United States

Heterogeneous information network (HIN) has been widely used to characterize entities of various types and their complex relations. Recent attempts either rely on explicit path reachability to leverage path-based semantic relatedness or graph neighborhood to learn heterogeneous network representations before predictions. These weakly coupled manners overlook the rich interactions among neighbor nodes, which introduces an early summarization issue. In this paper, we propose GraphHINGE (Heterogeneous INteract and aggregate), which captures and aggregates the interactive patterns between each pair of nodes through their structured neighborhoods. Specifically, we first introduce Neighborhood-based Interaction (NI) module to model the interactive patterns under the same metapaths, and then extend it to Cross Neighborhood-based Interaction (CNI) module to deal with different metapaths. Next, in order to address the complexity issue on large-scale networks, we formulate the interaction modules via a convolutional framework and learn the parameters efficiently with fast Fourier transform. Furthermore, we design a novel neighborhood-based selection (NS) mechanism, a sampling strategy, to filter high-order neighborhood information based on their low-order performance. The extensive experiments on six different types of heterogeneous graphs demonstrate the performance gains by comparing with state-of-the-arts in both click-through rate prediction and top-N recommendation tasks.

CCS Concepts: • Information systems → Data mining; • Computer systems organization → Heterogeneous (hybrid) systems.

Additional Key Words and Phrases: Recommender System; Neighborhood-based Interaction; Heterogeneous Information Network

ACM Reference Format:
Jiarui Jin, Kounianhua Du, Weinan Zhang, Jiarui Qin, Yuchen Fang, Yong Yu, Zheng Zhang, and Alexander J. Smola. 2020. Learning Interaction Models of Structured Neighborhood on Heterogeneous Information Network. ACM Transactions on Information Systems 1, 1, Article 1 (January 2020), 33 pages. https://doi.org/10.1145/0000XXX.0000XXX

1 INTRODUCTION
Recommender systems have been playing an increasingly important role in various online services for helping users find items of interest. However, the existing methods are challenged by problems of data sparsity and cold start, i.e., most items receive only a few feedbacks (e.g., ratings and clicks) or no feedback at all (e.g., for new items). Previous approaches usually leverage side information to

Permission to make digital or hard copies of all or part of this work for personal or classroom use is granted without fee provided that copies are not made or distributed for profit or commercial advantage and that copies bear this notice and the full citation on the first page. Copyrights for components of this work owned by others than ACM must be honored. Abstracting with credit is permitted. To copy otherwise, or republish, to post on servers or to redistribute to lists, requires prior specific permission and/or a fee. Request permissions from permissions@acm.org.

© 2020 Association for Computing Machinery.
1046-8188/2020/1-ART1 $15.00
https://doi.org/10.1145/0000XXX.0000XXX

ACM Transactions on Information Systems, Vol. 1, No. 1, Article 1. Publication date: January 2020.
obtain better user/item representations to tackle these issues [20, 34, 51], which facilitate the learning of user preference and finally promote the recommendation quality. Although this auxiliary data is likely to contain useful information [18, 23, 42], it is difficult to model and use the heterogeneous and complex information in recommender systems.

Recently, the heterogeneous information network (HIN)*, consisting of multiple types of nodes and/or links, has been used as a powerful modeling method to fuse complex information and successfully applied to many recommender system tasks, which are called HIN-based recommendation methods [42, 44]. In Fig. 1, we present an instance of movie data characterized by an HIN. HIN is built from historical feedback and side information. The nodes can be users, movies, or entities of side information (e.g., directors, movie genres), and two nodes are linked together based on relevance or co-occurrence. We can easily see that the HIN contains multiple types of entities connected by different types of relations. Hence, HIN is able to integrate various recommendation tasks, e.g., user-user relations for content-based recommendations and user-movie-user relations (i.e., users who have viewed the same movie may also share the same preference) for collaborative recommendation [45]. A variety of graph mining methods have been proposed on HINs to capture the rich semantic information, which roughly fall into the following two categories. One school is graph-based methodologies, which promotes expressive ability by taking the local structures into consideration. For example, graph convolution networks [25, 63] can integrate high-order neighborhood information in an end-to-end way, and graph attention networks [49, 56] can capture key information to simulate user preferences. However, these technologies usually compress the information of a node and its neighborhood into a single embedding vector before making the prediction [11, 42]. In such a case, only two nodes and one edge are activated, yet other nodes and their connections are mixed and relayed, which introduces an early summarization issue [34]. As an example illustrated in Fig. 1, a system is recommending a movie to user 𝑢_B based on an instance of HIN where we can model user 𝑢_A and define its metapath-guided neighborhoods (e.g, \( \mathcal{N}_{UUMD}(u_A) = \{(u_A, m_A, d_A), (u_A, m_A, d_C), (u_A, m_B, d_B)\} \)). (b) three types of nodes (user, movie, director) and four types of relations (user-user, user-movie, user-director, movie-director) in solid lines. (c) metapaths involved (e.g., User-User (UU), User-Movie (UM), User-User-Movie (UUM), User-Movie-Director (UMD) and User-Director-Movie (UDM)). (d) metagraphs involved which can be presented by combination of metapaths (e.g., User-Director-Movie (UDM), User-User-Movie (UUM)). We will further illustrate the difference among several definitions in Fig. 2.

\[ \text{Fig. 1. The network schema and meta relations of Heterogeneous Information Network (HIN).} \]

\*The terms ‘heterogeneous information network’ and ‘heterogeneous graph’ are used interchangeably in the related literature [42, 56]. In this paper, we mainly use ‘heterogeneous information network’ (HIN).
HIN, where $u_B$ has shown her preference for $m_B$ and $m_C$. We know that $m_B$ is directed by $d_B$, and $m_C$ is directed by $d_C$. Hence, the connections between $m_B$ and $d_B$, $m_C$ and $d_C$, could be helpful for recommendation, meanwhile, the connections between $m_B$ and $d_C$, $m_C$ and $d_B$, are nonsense and not expected. We argue that these meticulous local structures are valuable, and a good recommender system should be able to capture these valuable patterns and filter out other noise.

The other school is metapath-based approaches. A metapath means composite relation connecting two objects at the network schema level. It has been adopted to capture semantic information \[28, 56\]. Taking the movie data in Fig. 1 as an example, the relations between user and item can be revealed by the metapath User-User-Movie (UUM) for the co-user relation and User-Director-Movie (UDM) for the co-director relation. However, as stated in \[42\], metapath-based methods, heavily relying on explicit path reachability, may obtain bad performance when path connections are sparse or noisy. Also, rich structured information of nodes outside metapaths (e.g., their neighborhoods) is omitted in these approaches.

Based on the above analysis, when designing HIN-based recommendation, state-of-the-art methods have not well solved, even may not be aware of, the following challenges, which we address in this paper:

- **(C1)** How to tackle the early summarization issue? Due to the complex structures and large scales of the graphs, it is hard to make predictions directly. Hence, we consider the interactive\(^\dagger\) local structures are valuable and helpful. For example, a system is recommending a movie to user $u_B$ based on an HIN as Fig. 1 shows. When we consider a candidate movie such as $m_C$, it is natural to consider their co-users and co-directors; namely there may exist a relationship between $u_B$ and $m_C$ since they share the same neighbor user $u_C$. Actually, this is an example of ‘AND’ operation between users’ neighborhoods. This interactive structured information characterized by ‘AND’ can be categorized as the similarity between the same type of nodes (e.g., user and user) and the co-rating between different types of nodes (e.g., user and movie). We argue that these local structures are hidden and not fully utilized in previous methods.

- **(C2)** How to mine cross semantic information? The intuitive motivation behind cross semantic mining is natural. As aforementioned, an HIN shown in Fig. 1 can integrate various kinds of recommendations according to semantic relations such as user-movie-user relation for collaborative recommendation and user-user relation for content-based recommendation \[45\]. Similar to hybrid recommendation \[62\], we aim to build combinations of various semantics and interactions between them. In HIN, considering that each kind of metapath represents a specific type of semantic information, we aim to mine interactive patterns between different metapaths to form cross semantic features. A recent attempt \[28\] focused on measuring the semantic proximity by interactive-paths connecting source and target nodes. However, it suffered from high computations and overlooked rich information hidden in these node neighborhoods.

- **(C3)** How to design an end-to-end framework to capture and aggregate the interactive patterns between neighborhoods? Recent works \[34, 36\] investigated the methods of mining interactive patterns through inner product and aggregate with deep neural network (DNN). However, HIN contains diverse semantic information reflected by metapaths \[47\]. Also, there are usually various nodes in different types involved in one path. Different paths/nodes may contribute differently to the final performance. Hence, besides a powerful interaction module, a well-designed aggregation module to distinguish the subtle difference of these paths/nodes and select the informative ones is required.

\(^\dagger\)In this paper, we specifically use ‘interactive’ patterns or ‘interactions’ to denote the interactive patterns or interactions between features, nodes, paths, and neighborhoods of nodes, as illustrated in Fig. 4.
• (C4) How to learn the whole system efficiently? Learning interactive information on HINs is always time-consuming, especially when faced with paths in different types and lengths for metapath-based approaches [28] and large-scale high-order information for graph-based approaches [34]. A methodology to efficiently and effectively learn the rich interactive information on HINs is always expected.

• (C5) How to integrate high-order neighborhood information? Introducing high-order neighborhood information has shown to be effective but time-consuming and intractable for complex operations on large graphs [14, 34, 60]. One solution to facilitate high computation is to design a sampling strategy such as neighbor sampling [14], walk-based sampling [60], and importance sampling [4]. Hence, when modeling high-order neighborhood information, it is a severe challenge to design a mechanism to select useful information while filtering out the noise.

To tackle these challenges, we propose GraphHINGE (Heterogeneous INteract and aggregatE) to capture and aggregate the interactive patterns between each pair of nodes through their structured neighborhoods. First, we extend the definition of the neighborhood in homogeneous graphs to the metapath-guided neighborhood in heterogeneous graphs. Next, we design a heterogeneous graph neural network architecture with two modules to capture and aggregate key information of sampled neighborhoods in the previous step. The first module, namely the interaction module, constructs an interactive neighborhood and captures latent information with ‘AND’ operation. Specifically, we introduce the Neighborhood-based Interaction (NI) module to model interactive patterns of source and target nodes' structured neighborhoods guided by the same metapaths (i.e., the same semantics). We also extend to the Cross Neighborhood-based Interaction (CNI) module to deal with different metapaths. The second module is the aggregation module, which mainly consists of two components: (i) an element-level attention mechanism to measure the impacts of different interaction elements inside each path and (ii) a path-level attention mechanism to aggregate the content embeddings of different paths. Furthermore, we formulate the interaction operation via a convolutional framework and learn efficiently with fast Fourier transform (FFT). In order to efficiently integrate high-order neighborhood information, we propose to utilize the performances of low-order neighborhoods to guide the selection of their high-order neighborhoods.

To summarize, the main contributions of our work are:

• We analyze an important, but seldom exploited, early summarization issue on HINs. We structure the node neighborhoods with metapaths, and propose an end-to-end framework named GraphHINGE to capture and aggregate the interactive patterns on HINs.

• We develop the neighborhood-based interaction (NI) module to model interactive patterns in neighborhoods guided by the same metapaths and extend to the cross neighborhood-based interaction (CNI) module for different metapaths.

• We formulate the interaction module via a convolutional framework and propose an efficient end-to-end learning algorithm incorporated with FFT.

• We design a novel neighborhood-based selection (NS) mechanism to efficiently select and integrate useful high-order neighborhood information.

We conduct extensive experiments on six benchmark datasets of different graph types, including two with large-scale graphs. Our results demonstrate the superior performance of GraphHINGE compared with state-of-the-art methods in both click-through rate prediction and top-N recommendation tasks.
2 RELATED WORK

2.1 Heterogeneous Information Network based Recommendation

As an emerging direction, HIN [43] can naturally characterize complex objects and rich relations in recommender systems. There is a surge of works on learning representation in heterogeneous networks, e.g., metapath2vec [9], HetGNN [63], HIN2vec [11], eoe [59]; and their applications, e.g., relation inference [46], classification [64], clustering [37], author identification [5], user profiling [6]. Among them, HIN-based recommendation has been increasingly attracting researchers’ attention, which roughly falls into two folds. One direction is to leverage structured information of HIN to enhance the representation of user and item in recommendation [10, 18]. For instance, Feng and Wang [10] incorporated social network, tag semantics and item profiles to alleviate the cold start issue with the heterogeneous information network contained in the social tagged system. Hu et al. [18] proposed to integrate both local and global information from HIN to enhance the recommendation performance. Wang et al. [54] (KGAT) modeled the high-order connectivities in collaborative knowledge graphs in an end-to-end manner to enhance the recommendation. The other direction is to define specific metapaths in HIN to capture the corresponding semantic information [19, 61]. For example, Yu et al. [62] introduced metapath-based methods to represent the connectivity between users and items along different paths into a hybrid recommender system. Yu et al. [61] leveraged personalized recommendation framework via taking advantage of different types of entity relationships in HIN. Luo et al. [29] proposed a collaborative filtering based social recommendation to effectively utilize multiple types of relations. Shi et al. [45] proposed to integrate heterogeneous information and obtain prioritized and personalized weights representing user preferences on paths by a weighted heterogeneous information network. Shi et al. [44] introduced a matrix factorization based dual regularization framework to flexibly integrate different types of information through adopting the similarity of users and items as regularization on latent factors of users and items. Recently, Hu et al. [19] proposed a novel deep neural network with the co-attention mechanism for leveraging rich meta-path based context for top-N recommendation. As stated in [42], most existing HIN-based recommendation methods rely on the path-based similarity, which may not fully mine latent features of users and items. Instead, we provide the generic definition of metapath-guided neighborhood, and propose a novel framework to capture rich structured interactive patterns hidden in the neighborhoods from both user and item sides.

2.2 Graph Representation

Graph representation learning is mainly leveraged to learn latent, low dimensional representations of graph vertices, while preserving graph structure, e.g., topology structure and node content. In general, graph representation algorithms can be categorized in two types. One school is unsupervised graph representation algorithm, which aims at preserving graph structure for learning node representations [12, 32, 40, 48, 50]. For instance, Perozzi et al. [32] (DeepWalk) utilized random walks to generate node sequences and learn node representations with methods borrowed from word2vec learning. Grover and Leskovec [12] (Node2vec) further exploited a biased random walk strategy to capture more flexible contextual structures. Ribeiro et al. [40] (Struc2vec) constructed a multilayer graph to encode structured similarities and generate a structured context for nodes. Tang et al. [48] (LINE) proposed an edge-sampling algorithm to improve both the effectiveness and efficiency of the inference. Wang et al. [50] (SDNE) built multiple layers of non-linear functions to capture highly non-linear network structures. Another school is semi-supervised model [21, 25, 49], where there exist some labeled vertices for representation learning. For example, Bruna et al. [3] first designed the graph convolution operation in Fourier domain by the graph Laplacian. Then, Defferrard et al. [8] further employed the Chebyshev expansion of the graph Laplacian to
Fig. 2. An illustrated example for several definitions in this paper. We use structured neighborhood to denote the original neighborhood in an HIN. We show the generic definition of metapath-guided neighborhood in Definition 2, which includes several paths (e.g., $(u_A, m_B, d_B)$) guided by the metapath (e.g., UMD). For convenience, we use ‘neighborhood’ to denote the metapath-guided neighborhood, unless otherwise stated.

improve the efficiency. Huang et al. [21] (LANE) incorporated label information into the attributed network embedding while preserving their correlations. Kipf and Welling [25] (GCN) proposed a localized graph convolutions to improve the performance in a classification task. Veličković et al. [49] (GAT) used self-attention network for information propagation, which leverages a multi-head attention mechanism. Hamilton et al. [14] (GraphSAGE) proposed to sample and aggregate features from local neighborhoods of nodes with mean/max/LSTM pooling. Wu et al. [57] (DEMO-Net) designed a degree-aware feature aggregation process to explicitly express in graph convolution for distinguishing structure-aware node neighborhoods. Abu-El-Haija et al. [1] (MixHop) proposed to aggregate feature information from both first-order and higher-order neighbors in each layer of network, simultaneously. Most of the current graph neural networks (GNNs) essentially focus on fusing network topology and node features to learn node embedding, which can be regarded as plug-in graph representation modules in heterogeneous graph, such as HetGNN [63], HAN [56] and HERec [42]. Recently, He et al. [16] (LightGCN) largely simplified the design of GCN to make it more concise and effective for graph-based recommendation. Zhu et al. [66] (BGCN) inspired by He and Chua [15] proposed a bilinear aggregator to express the local nodes interactions and enhance representations. In this paper, our purpose is not only to deliver graph representation learning techniques on HIN, but also provides a novel efficient structured neighborhood-based interaction module to capture interactive information on HIN, which to our knowledge should be the first work in the literature.

2.3 Cross Feature Modeling

Cross feature modeling aims to mine interactive information among features, especially for multi-field categorical data, to address the data sparsity and improve the performance. For example, Rendle [38] (FM) projected each feature into a low-dimensional vector and modeled feature interactions by inner product. Juan et al. [24] (FFM) further enabled each feature to have multiple vector representations to interact with features from other fields. An efficient algorithm for training arbitrary-order higher-order FM (HOFM) was proposed in [2] by introducing the ANOVA kernel. Recent attempts, such as Attention FM [58] and Neural FM [17], investigated to improve FM by incorporating a multi-layer perceptron (MLP). Moreover, Cheng et al. [7] (Wide & Deep) jointly trained a wide model for artificial features and a deep model for raw features. Guo et al. [13] (DeepFM) incorporated an FM layer to replace the wide component in Wide & Deep to explicitly model the pairwise feature interactions. Qu et al. [35] (PNN) proposed to leverage MLP to model the interaction of a product layer and feature embedding while Qu et al. [36] (PIN) generalized such product operators in PNN and DeepFM to a network-in-network architecture to model pairwise
Table 1. A summary of main notations in this paper.

| Notation | Explanation |
|----------|-------------|
| $s; t; o$ | Source (node); target (node); object (node) |
| $I; E$ | Metapath length; dimension of embedding |
| $L; P; K$ | Number of paths; number of metapaths; number of metapath combinations |
| $\rho_p; \rho_p^l; (\rho_s, \rho_t)_k$ | $l$-th path guided by metapath $\rho_p$ for source $s$, $\rho_t$ for target $t$ |
| $N_{\rho_o}^i(o)$ | $i$-th step metapath $\rho_o$ guided neighborhood of object $n_o$ according to Definition 2 |
| $H[N_{\rho_o}^i(o)]_l$ | Embedding matrix of $l$-th path neighborhood of $n_o$ according to Eq. (3) |
| $H[N_{\rho_s}(s), N_{\rho_t}(t)]_l$ | Interaction matrix of $l$-th path of neighborhoods of $s$, $t$ according to Eq. (9) |
| $\cdot; \circ; \oplus$ | Product; convolution; concatenation/stack operation |

feature interactions with sub-networks. DeepFM and PIN cannot explicitly model higher-order feature interactions, which could further improve model performance. Wang et al. [53] (CrossNet) introduces a cross operation to learn explicit feature interactions. Lian et al. [26] (xDeepFM) used a Compressed Interaction Network (CIN) to enumerate and compress all feature interactions, for modeling an explicit order of interactions. Liu et al. [27] (FGCNN) combined a convolutional neural network (CNN) and MLP to generate new features for feature augmentation. Instead of operating on tabular data, in this paper, we investigate to incorporate with structured information and enhance the representation with graph neural network to model the cross features in an HIN, which should be the first time to our knowledge.

3 PRELIMINARIES

In this section, we introduce the concept of the content-associated heterogeneous information network that will be used in the paper.

**Definition 1. Neighborhood-based Interaction-enhanced Recommendation.** The HIN-based recommendation task can be represented as a tuple $\langle U, I, A, R \rangle$, where $U = \{u_1, \ldots, u_p\}$ denotes the set of $p$ users; $I = \{i_1, \ldots, i_q\}$ means the set of $q$ items; $a \in A$ denotes the attributes associated with objects, and $r \in R$ represents the relations (e.g., ratings and/or clicks) between different types of objects. The purpose of recommendation is to predict the relation/connection $r(u_s, i_t)$ (e.g., click-through rate and link) between two objects, namely source user $u_s$ and target item $i_t$. In our setting, interactions between source and target neighborhoods are leveraged to enhance the performance.

To clarify the definition of the term ‘neighborhood’, we model our recommendation task in the setting of **Heterogeneous Information Network** (HIN). An HIN is defined as a graph $G = (V, E)$, which consists of more than one node type or link type. In HINs, **network schema** is proposed to present the meta structure of a network, including the object types and their relations.

Fig. 1(a) shows a toy example of HINs and the corresponding network schema is presented in Fig. 1(b). We can see that the HIN consists of multiple types of objects and rich relations. The set of objects (e.g., $U$ (user), $I$ (movie), $A$ (director)) and relations (e.g., $R$ (relation)) constitute $V$ and $E$ in the HIN. The relations here can also be explained as preferences between different types of nodes (e.g., $r(u_A, d_C)$) and similarities between the same type of nodes (e.g., $r(u_A, u_C)$). Hence, one example of **Definition 1** is that when predicting relation $r(u_A, m_C)$ between source user $u_A$ and

---

\[\text{Different from previous works [16, 55] built on user-item bipartite graph, HINs here not only include historical data between users and items, but also contain heterogeneous attributes related to users and/or items.}\]
target movie $m_C$, we consider existing relations between their neighborhoods, namely $r(m_A, d_C)$, $r(m_B, u_C)$, to help the final prediction.

In order to capture the structured and semantic relation, the metapath [47] is proposed as a relation sequence connecting two objects. As illustrated in Fig. 1(c), the User-Movie-Director (UMD) metapath indicates that users favor movies and that these movies are guided by some directors [28, 56]. Besides the metapath, there are some other structures such as metagraph [22, 65] (as illustrated in Fig. 1(d)) on HINs to capture complicated semantics, which can be presented by a set of metapaths. In order to build a unified structure to model these semantics, we introduce the definition of metapath-guided neighborhood as follows.

**Definition 2. Metapath-guided Neighborhood.** Given an object $o$ and a metapath $\rho$ (start from $o$) in an HIN, the metapath-guided neighborhood is defined as the set of all visited objects when the object $o$ walks along the given metapath $\rho$. In addition, we denote the neighborhoods of object $o$ after $i$-th steps sampling as $N^i_\rho(o)$. Specifically, $N^0_\rho(o)$ is $o$ itself. For convenience, let $N^l_\rho(o)$ denote $N^{l-1}_\rho(o)$, where $l$ means the length of metapath. Note that different from the similar concept proposed in [56], which is used to derive homogeneous neighbors on heterogeneous graphs, the metapath-guided neighborhood in this paper can preserve semantic contents since it consists of heterogeneous information.

Taking Fig. 1 as an instance, given the metapath ‘User-Movie-Director (UMD)’ and a user $u_A$, we can get the corresponding metapath-guided neighborhoods as $N^1_\rho(u_A) = \{(u_A, m_A), (u_A, m_B)\}$, $N^2_\rho(u_A) = N^2_\rho(u_A) = \{(u_A, m_A, d_A), (u_A, m_A, d_C), (u_A, m_B, d_B)\}$.

**Remark.** Note that different from the metapath proposed in previous works [28, 56], where a path follows the specific schema connects the source and target nodes; the metapath adopted here is to guide the neighborhood sampling. Hence, there only exists a requirement about where a path starts and no requirement about where a path ends.

Many efforts have been made for HIN-based recommendations. However, most of these works focus on leveraging graph neural networks to aggregate structured message but overlook the effect of early summarization and rich interactive information. Given the above preliminaries, we are ready to introduce our GraphHINGE model as a solution.

4 METHODOLOGY

4.1 Overview

The basic idea of our methodology is to design an end-to-end GraphHINGE framework that involves an interaction module to capture the rich interactive patterns hidden in HINs and an aggregation module to integrate the information for the final prediction. Fig. 3 illustrates an example. Assume that user Sheldon Cooper favors action movies (i.e., $I_{\text{Action Movie}}$) and fiction movies (i.e., $I_{\text{Fiction Movie}}$),
our task is to predict his preference on movie $m_{\text{Tenet}}$ directed by director $d_{\text{Christopher Nolan}}$. This task can be formulated via link prediction between $u_{\text{Sheldon Cooper}}$ and $m_{\text{Tenet}}$ nodes based on the HIN shown in Fig. 3(a). In this HIN, movie types $t_{\text{Action Movie}}$ and $t_{\text{Fiction Movie}}$ are neighbors of user $u_{\text{Sheldon Cooper}}$, and director $d_{\text{Christopher Nolan}}$ is a neighbor of $m_{\text{Tenet}}$. In this paper, we propose to find the co-relations between neighbors to help with the final prediction. As Fig. 3(b) illustrates, director $d_{\text{Christopher Nolan}}$ is good at action movies (i.e., $t_{\text{Action Movie}}$) and fiction movies (i.e., $t_{\text{Fiction Movie}}$). Therefore, we can infer that there is a link between user $u_{\text{Sheldon Cooper}}$ and movie $m_{\text{Tenet}}$ (i.e., $u_{\text{Sheldon Cooper}}$ favors $m_{\text{Tenet}}$) in Fig. 3(c). As stated in [36, 39], these interactive patterns cannot simply be captured by neural networks and require explicitly modelling ‘AND’ operations in interaction modules.

As illustrated in Fig. 4(a), a naive solution is to extend previous feature-based interaction modules into the HIN case. As Fig. 4(b) shows, feature-based interaction modules such as FM [38] are designed to capture interactive patterns from data in the multi-field categorical form. If we directly extend these interaction modules into the HIN case by treating nodes as features and types as fields as illustrated in Fig. 4(c), nodes will be regarded equally and interact with each other freely. However, one should be noted that nodes located at different topological positions would contribute differently to the final prediction. For instance, nodes close to the source/target node can be more informative than those far away from source/target node when predicting whether there is a link between the source and target nodes.

Therefore, as Fig. 4(d) shows, instead of nodes, we define interaction as an operation between paths guided by the metapaths. According to Fig. 2, different from traditional paths connecting source and target nodes, paths here represent neighborhoods. Thus this interaction module is called the neighborhood-based interaction (NI) module. Note that the metapaths on HINs always show the semantics. In the NI module, we generate the interactive patterns with neighborhoods of users and items guided by the same metapaths (i.e., the same semantics). For instance, Fig. 4(d) illustrates the interactive patterns between user $u_B$ and movie $m_C$ guided by UMD, which denotes that user...
To generate meaningful node sequences, the key technique is to design an effective random walk strategy that is able to capture the complex semantics reflected in HINs. Hence, we propose to use the metapath-guided random walk method with restart. Given an HIN $\mathcal{G} = \langle \mathcal{V}, \mathcal{E} \rangle$ and a metapath $\rho : A_0, \ldots, A_i, \ldots, A_{l-1}$, where $A_i \in \mathcal{A}_i$ denotes the $i$-th node guided by metapath $\rho$ (note that we $u_B$ likes movie $m_C$ directed by director $d_C$. Following the semantics, NI investigates whether there exists common/similar neighbor nodes (e.g., director $d_C$, movie $m_A$) of user $u_B$ and movie $m_C$. It is natural to consider extracting rich structured information of user $u_B$ and movie $m_C$ under different semantics even with different lengths. As illustrated in Fig. 4(e), we further extend NI to CNI module, where we operate to seek for correlations between two neighborhoods guided by different semantics (e.g., source $s = u_B$ and target $t = m_C$’s neighbor $u_B$).

With the help of interaction modules, our approach is able to leverage metapaths to guide the selection of different-step and -type neighbors, capture and aggregate the abundant interactive patterns. Moreover, we represent different types of metapaths with a unified learning procedure and design an efficient learning algorithm with fast Fourier transform (FFT). We provide the overall framework of our model in Fig. 5. First, we use the multiple-object HIN containing $\langle \text{user}, \text{item}, \text{attribute}, \text{relation} \rangle$ as the input. Second, we select metapath-guided neighborhoods for source and target nodes via neighbor samplings (Fig. 5(a)). Third, we introduce the interaction module and formulate it via a convolutional framework to generate interaction information among their neighborhoods (Fig. 5(b)). Specially, the NI module is designed to model the interactive patterns between source and target nodes under the same semantics, which is illustrated in solid lines, while the CNI module can implement interactions under different semantics and provide additional cross semantic information besides interaction information generated by the NI module, which is shown in dotted and solid lines. After that, we capture the key interactions and aggregate information through attention mechanisms in both node and path levels (Fig. 5(c)). Finally, our model provides the final prediction. We illustrate the architecture in detail in the following subsections.

### 4.2 Neighborhood Sampling

To generate meaningful node sequences, the key technique is to design an effective random walk strategy that is able to capture the complex semantics reflected in HINs. Hence, we propose to use the metapath-guided random walk method with restart. Given an HIN $\mathcal{G} = \langle \mathcal{V}, \mathcal{E} \rangle$ and a metapath $\rho : A_0, \ldots, A_i, \ldots, A_{l-1}$, where $A_i \in \mathcal{A}_i$ denotes the $i$-th node guided by metapath $\rho$ (note that we
include user set $\mathcal{U}$ and item set $\mathcal{I}$ in attribute set $\mathcal{A}$ for convenience), the walk path is generated according to the following distribution:

$$P(n_{k+1} = x | n_k = v) = \begin{cases} \frac{1}{|N^1_\rho(v)|} & (v, x) \in \mathcal{E} \text{ and } v \in \mathcal{A}_k, \mathcal{A}_{k+1} \\ 0, & \text{otherwise} \end{cases}$$

(1)

where $n_k$ is the $k$-th node in the walk, $N^1_\rho(v)$ means the first-order neighborhood of node $v$ guided by metapath $\rho$. A walk will follow the pattern of the metapath repetitively until it reaches the predefined length and always start from the source/target node. It is worth noting that, according to Definition 2, there is no need to sample a complete path from source to target nodes.

### 4.3 Neighborhood-based Interaction Module

In previous HIN-based recommendations, most approaches leverage graph representation techniques to find key nodes or metapaths [56] and capture the complex structure [63]. To further mine interaction information and deal with the early summarization issue, we propose an interaction module based on metapath-guided neighborhoods.

Due to the heterogeneity of nodes, different types of nodes have different feature spaces. Hence, for each type of nodes (e.g., node with type $\phi_i$), we design a type-specific transformation matrix $M_{\phi_i}$ to project the features of different types of nodes into a unified feature space. The projection process can be shown as follows:

$$e_i = M_{\phi_i} \cdot e'_i,$$

(2)

where $e'_i$ and $e_i$ are the original and projected features of node $i$, respectively. By the type-specific projection operation, our model is able to handle arbitrary types of nodes.

Considering that neighbors in different distances to the source/target node usually contribute differently to the final prediction, we divide the sampled metapath-guided neighborhood into several inner-distance and outer-distance neighborhood groups. As illustrated in Fig. 6, when we set distance as 1, we can get inner-distance Group 1 and outer-distance Group 5. In a similar way, we can obtain $2I - 1$ groups, where $I$ denotes the metapath length. We argue that interactions should only be employed in corresponding groups. In order to perform interaction in each neighborhood group, we need to face two situations. If there is only one node in Group, we adopt an element-wise product (i.e., ‘AND’) operation to measure their similarity or co-ratings (e.g., $r(u_A, m_B)$ in Group 0 case). When there are more than one nodes, we first do interaction by production and then aggregate by summarization, (e.g., $r(u_A, d_C) + r(m_B, m_B)$ in Group 1 case).

Inspired by work in signal processing field [31], this neighborhood division and interaction can be formulated as a unified operation named convolution. Roughly speaking, the convolution mainly contains three kinds of operations on paths, namely shift, product, and sum, which are employed repeatedly until they meet the end of the path. Take Fig. 7(a) for example. Our task is to calculate the interaction between source user neighborhood path ($u_A, m_B, d_B, m_D$) and target movie neighborhood path ($m_B, d_C, m_C, u_C$). First, we inverse the order of target movie path and obtain ($u_C, m_C, d_C, m_B$). We shift it from left to right and product the overlapping nodes during the shift. As shown in Fig. 7(a), the first overlapping happens between source and target nodes, namely the 0-hop neighborhood. We conduct the product operation and obtain the co-ratings between different types of nodes $r(u_A, m_B)$ (as Fig. 7(b) shows). Then, we repeatedly shift, product, and sum, and then reach the situation where all nodes are overlapped. The result in this situation is the similarity between the same type of nodes $r(u_A, u_C) + r(m_B, m_C) + r(d_B, d_C) + r(m_D, m_B)$ (as shown in Fig. 7(c)). In a similar way, the last interaction happens between different types of nodes $r(m_D, u_C)$ (as shown in Fig. 7(d)).
Let $H[N_\rho(o)]$ denote the embedding matrix of metapath $\rho$ guided neighborhood of object $o$. $H[N_\rho(o)]_l$ represents the embedding matrix of the $l$-th path, which can be formulated as

$$H[N_\rho(o)]_l = [e'_0 \oplus e'_1 \oplus \cdots \oplus e'_{L-1}],$$

where $l = 0, 1, \ldots, L - 1$, $e'_l$ means the embedding of the node in the $i$-th step of the $l$-th path guided by metapath $\rho$, $\oplus$ denotes the stack operation. Hence, as illustrated in Fig. 8(a), $H[N_\rho(o)]$ is a $\mathbb{R}^{L \times N \times E}$ matrix, where $L$ is the number of paths guided by the metapath, $I$ is the length of the metapath, $E$ is the dimension of the node embedding. Based on convolutional operations, we further define the interaction between neighborhoods of source and target objects as

$$H[N_\rho(s), N_\rho(t)]_l = H[N_\rho(s)]_l \odot H[N_\rho(t)]_l,$$

where $\odot$ denotes the convolutional operation. According to the definition of convolution, one can write the formulation as

$$H[N_\rho(s), N_\rho(t)]_{l,n} = \sum_{a+b \mod N=n} H[N_\rho(s)]_{l,a} \cdot H[N_\rho(t)]_{l,b}.$$  

One can find that $H[N_\rho(s), N_\rho(t)] \in \mathbb{R}^{L \times N \times E}$ (as shown in Fig. 8(c)), where $N$ is the length of convolution outputs and it equals $2I - 1$ where $I$ denotes the metapath length.

The well-known convolution theorem states that circular convolutions in the spatial domain are equivalent to pointwise products in the Fourier domain. Let $\mathcal{F}$ denote the fast Fourier transform (FFT) and $\mathcal{F}^{-1}$ its inverse, and we can compute convolution as

$$H[N_\rho(s), N_\rho(t)] = \mathcal{F}^{-1}(\mathcal{F}(H[N_\rho(s)]) \cdot \mathcal{F}(H[N_\rho(t)])).$$

Fig. 6. An illustrated example of the motivation in the interaction module design. Neighborhoods are grouped according to the distance to the source/target node. Interaction is only employed between corresponding neighborhoods in each group.
Let $H[N_\rho]$ denote $H[N_\rho(s), N_\rho(t)]$ in the following sections for convenience. As stated in [30], the time complexity of plain convolution is $O(I^2)$, and it is reduced to $O(I \log(I))$ when using FFT. According to the analysis above, we can conclude that not only can this structure capture both nodes similarities and co-ratings in grouped neighborhoods, but also it can be implemented with high efficiency.

### 4.4 Cross Neighborhood-based Interaction Module

In the previous section, we introduce the neighborhood-based interaction module built on HIN with the user’s and item’s neighborhoods guided by the same metapaths. In HINs, each metapath represents one corresponding semantic information [28, 56]. For instance, as illustrated in Fig. 1(c), UM metapath shows that user $u_h$ likes movie $m_C$, while UU shows that users $u_h$ and $u_c$ are friends. It’s natural to consider the hidden relation between user $u_c$ and movie $m_C$ under the combination of these two different semantics. To this end, a well-designed interaction module should also take the interactions between different metapaths into consideration. As shown in Fig. 5(b), the interaction operations in the NI module are illustrated in solid lines. These interactions implemented between neighborhoods of user $u_A$ and movie $m_B$ guided by the same metapaths are designed to capture the interactive information under the specific semantics. In order to enhance the interaction module with interactive patterns between different semantics, we further propose to model the interaction operations with different metapaths even in different lengths, as illustrated with the dotted lines in Fig. 5(b). We call it the Cross Neighborhood-based Interaction (CNI) module. Note that the NI module is actually a special case of the CNI module, where the interaction operation is limited between neighborhoods guided by the same metapaths. The solid and dotted lines in Fig. 5(b) together represent the interaction operations in our CNI module.

Let $H[N_{\rho_s}(s)]$ and $H[N_{\rho_t}(t)]$ denote the embedding matrices of neighborhood guided by metapath $\rho_s$ of source node $s$ and neighborhood guided by $\rho_t$ of target node $t$, respectively. $H[N_{\rho_s}(a)]_I$ represents the embedding matrix of the $I$-th path, which can be formulated as

$$H[N_{\rho_s}(s)]_I = \left[ e_0^{\rho_s} \oplus e_1^{\rho_s} \oplus \cdots \oplus e_{I-1}^{\rho_s} \right], \quad H[N_{\rho_t}(t)]_I = \left[ e_0^{\rho_t} \oplus e_1^{\rho_t} \oplus \cdots \oplus e_{I-1}^{\rho_t} \right];$$  \hspace{1cm} (7)
where $l = 0, 1, 2, \ldots, L - 1$, $\rho_i^l$ means the embedding of the node in the $i$-th step of the $l$-th path guided by metapath $\rho_o$. $\oplus$ denotes the stack operation, $I_o$ is the path length. Here, $o$ can denote both $s$ for source node and $t$ for target node.

As illustrated in Fig. 8(e) and (f), $H[N_{\rho_o}(o)] \in \mathbb{R}^{L \times I_o \times E}$, where $L$ is the number of paths sampled by each metapath, $E$ means the dimension of the node embedding. Based on convolutional operations, we further define the interaction between neighborhoods of source and target objects as

$$H[N_{\rho_s}(s), N_{\rho_t}(t)]_l = H[N_{\rho_s}(s)]_l \odot H[N_{\rho_t}(t)]_l,$$

where $\odot$ denotes the convolutional operation. Here, we define the convolution as the sum of the product operations, which can be formulated as

$$H[N_{\rho_s}(s), N_{\rho_t}(t)]_{l,m} = \sum_{a+b \mod M = m} H[N_{\rho_s}(s)]_{l,a} \cdot H[N_{\rho_t}(t)]_{l,b},$$

where $H[N_{\rho_s}(s), N_{\rho_t}(t)] \in \mathbb{R}^{L \times M \times E}$ (as shown in Fig. 8(h)), $M$ is the length of convolution outputs and it is equal to $I_s + I_t - 1$ where $I_s, I_t$ denote the metapath length of source and that of target node, respectively. Note that when $l = I_s = I_t$, CNI and NI modules share the same formulation. In fact, the NI module is a special case of the CNI module when the lengths of metapaths of the source and target are the same. We propose to replace the convolutional operation with the fast Fourier transform (FFT) using the discrete analogue of the convolution theorem as

$$H[N_{\rho_s}(s), N_{\rho_t}(t)] = \mathcal{F}^{-1}(\mathcal{F}(H[N_{\rho_s}(s)]) \cdot \mathcal{F}(H[N_{\rho_t}(t)])).$$

We use $H[\langle \rho_s, \rho_t \rangle]$ to denote $H[N_{\rho_s}(s), N_{\rho_t}(t)]$ for convenience. As stated in [33], the time complexity of plain convolution is $O(I^2)$, and it is reduced to $O(I \log(I))$ when using FFT, where $I = \max\{I_s, I_t\}$. According to the analysis above, we can see that not only can this structure mine the interactions between different metapaths, but also it can be regarded as the extension of NI and accelerated with FFT.

In the CNI module, let $\langle \rho_s, \rho_t \rangle$ denote the combinations of metapaths $\rho_s$ and $\rho_t$ for convenience, where $\rho_s$ guides the neighborhood $N_{\rho_s}(s)$ on source node $s$ side and $\rho_t$ guides the neighborhood...
\(N_{p_i}(t)\) on target node \(t\) side. We further use \(\langle \rho_s, \rho_t \rangle_k\) to denote the \(k\)-th metapath combination, where \(k = 0, 1, 2, \ldots, K - 1\).

### 4.5 Aggregation Module

Considering that the NI module in Section 4.3 is a special case of the CNI module in Section 4.4, without loss of generality, we introduce an aggregation module based on the interaction result of the CNI module in this section. Specifically, we consider the aggregation module in two sides. On the first side, from Fig. 8, we can see that elements in the interaction matrix \(H[N(\rho_s, \rho_t)]\) contain interactions between various types of nodes. Hence, it is natural to capture the key interaction at the element-level during the aggregation procedure. For instance, the interaction between \(u_A\) and \(m_B\) is important when predicting the relation between \(u_A\) and \(m_B\) in Fig. 1. On the second side, for each type of metapath \(\rho\) (or metapath combination \(\langle \rho_s, \rho_t \rangle\)), we sample \(L\) paths according to Eq. (1). Therefore, a good aggregation module is required to distinguish useful paths and filter out the noise at the path-level. For example, following the UMD schema, we sample \(L\) paths to predict the relation between \(u_A\) and \(m_B\), among which path \((u_A, m_A, d_c)\) may be more helpful than path \((u_A, m_A, d_A)\) in Fig. 1. On the third side, for every source-target pair \((s, t)\), HIN contains multiple types of (cross) semantic information represented with different metapaths \(\rho_0, \rho_1, \ldots, \rho_{p-1}\) where \(P\) is the number of metapaths (or metapath combinations \(\langle \rho_s, \rho_t \rangle_0, \langle \rho_s, \rho_t \rangle_1, \ldots, \langle \rho_s, \rho_t \rangle_{K-1}\) where \(K\) is the number of metapath combinations). This further causes various interaction matrices \(H[N(\rho_0)], H[N(\rho_1)], \ldots, H[N(\rho_{p-1})] (or H[N(\rho_s, \rho_t)_0], H[N(\rho_s, \rho_t)_1], \ldots, H[N(\rho_s, \rho_t)_{K-1}])\). To capture the key message in a complex graph, we need to fuse multiple semantics revealed by different metapaths. Take Fig. 1 as an example, UM should be paid more attention than UMD.

From the statements above, one can see that metapath \(\rho_p\) and metapath combination \(\langle \rho_s, \rho_t \rangle_k\) are used interchangeably in NI and CNI modules. For convenience, we mainly use metapath \(\rho_p\) in the following sections and one can easily extend it to the metapath combination \(\langle \rho_s, \rho_t \rangle_k\) case. In light of the analysis above, we adopt an attention mechanism at two levels, i.e., element- and path-level. As illustrated in Fig. 9, at element-level, we seek to capture the key elements of each path of the interaction matrix (i.e., \(H[N(\rho_p)]\), as shown in (a)) and aggregate interactive information of each path into an embedding vector (as shown in (b)). We then design a path-level attention mechanism to further aggregate the information from different paths including all paths guided by the involved metapaths. Following element- and path-level attention mechanisms, we are able to get the final prediction (as shown in (c)). The detailed descriptions are listed as follows:

**Element-level Attention.** Let \(\rho_p^l\) denote the \(l\)-th path guided by metapath \(\rho_p\), then \(H[N(\rho_p^l)]\) is the same. Similar to [56], we leverage an attention mechanism to learn the weights among various kinds of interaction elements in path \(\rho_p^l\)\(^*\) as

\[
h_{0j} = (h_0W_T)^T \cdot (h_jW_S),
\]

where \(W_T, W_S\) are trainable weights and \(h_j\) is an element of interaction matrix \(H[N(\rho_p^l)]\) (i.e., \(H[N(\rho_p)]\)), where \(j = 0, 1, \ldots, M - 1\) and \(l = 0, 1, \ldots, L - 1\). \(h_{0j}\) can show how important interaction element \(h_i\) will be for interaction element \(h_0\). \(h_0\) is the first element of \(H[N(\rho_p)]\), which denotes the interaction result of source node \(s\) and target node \(t\). To retrieve a general attention value in path \(\rho_p^l\), we further

\(^*\)In this section, we omit the superscript \(\rho_p^l\) for simplification; e.g., we use \(h_{0j}, h_0, h_j, \alpha_j\), and \(z\) to denote \(h_{0j}^\rho, h_0^\rho, h_j^\rho, \alpha_j^\rho\), and \(z^\rho\), respectively.

ACM Transactions on Information Systems, Vol. 1, No. 1, Article 1. Publication date: January 2020.
Fig. 9. An illustrated example of the aggregation module to aggregate the interaction matrix $H[N(p_s), N(p_t)]$ (a) (i.e., $H[N(p_{s,p})] \in \mathbb{R}^{L \times M \times E}$) according to Eq. (9). We first adopt element-level attention mechanism to obtain $Z[N(p_s), N(p_t)]$ (b) (i.e., $Z[N(p_{s,p})] \in \mathbb{R}^{L \times E}$) according to Eq. (13), and then employ path-level attention mechanism to obtain $Z \in \mathbb{R}^{E}$ (c) according to Eq. (16).

normalize this value in path scope as

$$
\alpha_j = \text{softmax}(h_{0j}/i) = \frac{\exp(h_{0j}/i)}{\sum_{i=0}^{M-1} \exp(h_{0i}/i)},
$$

where $i$ denotes the temperature factor. To jointly attend to the paths from different representation subspaces and learn stably, we leverage the multi-head attention as in previous works [56] to extend the observation as

$$
z = \sigma(W_q \cdot \frac{1}{H} \sum_{n=1}^{H} \sum_{j=0}^{M-1} \alpha_{jn}(h_j)W_{Ch} + b_q),
$$

where $H$ is the number of attention heads and $W_C, W_q, b_q$ are trainable parameters. Hence, the metapath-based embedding $z$ is aggregated based on the metapath-guided neighborhood with single path (i.e., $H[N(p)]$). In other words, for each path $p^p$, we have a specific embedding vector $z^p$ (i.e., $z$ in Eq. (13)). Note that in our setting, there are $P$ metapaths in an HIN and $L$ paths guided by each metapath. So, the embedding obtained from element-level attention is $Z[N] \in \mathbb{R}^{(L \times P) \times E}$, which is the concatenation of the set of $\{Z[N_{p0}], Z[N_{p1}], \ldots, Z[N_{p_{P-1}}]\}$:

$$
Z[N] = [Z[N_{p0}] \oplus Z[N_{p1}] \oplus \cdots \oplus Z[N_{p_{P-1}}]],
$$

where $Z[N_{pp}] \in \mathbb{R}^{L \times E}$ and $p = 0, 1, 2, \ldots, P - 1$.

**Path-level Attention.** Similarly, we adopt a self-attention mechanism to learn the attention vector among various path embeddings in $Z[N]$. For each path $z_i \in Z[N]$, after an MLP, it is fed to a softmax layer:

$$
\beta_i = \text{softmax}(z_i/u) = \frac{\exp(z_i/u)}{\sum_{j=0}^{L \times P - 1} \exp(z_j/u)},
$$

where $u$ denotes the temperature factor. With the learned weights as coefficients, we can fuse these semantics-specific embeddings to obtain the final embedding $Z$ via

$$
Z = \sum_{j=0}^{L \times P - 1} \beta_j \cdot z_j.
$$

ACM Transactions on Information Systems, Vol. 1, No. 1, Article 1. Publication date: January 2020.
Fig. 10. An illustrated example of the combination of neighborhood-based selection (NS) and interaction (NI) modules. We first sample and store metapath-guided neighborhoods of source and target nodes ($u_A$ and $m_B$ in this case) in the buffer. Due to the large amount of high-order metapath-guided neighborhoods, we first use low-order neighborhoods to generate sample rates according to Eq. (15) for selection. We next sample high-order neighborhoods according to the sample rates and generate the final prediction of link rate according to Eq. (16). Both NS and NI modules are under supervision according to Eq. (17). Hence, we have obtained the final aggregation result, which involves interaction information at both element- and path-level.

### 4.6 Optimization Objective

The final prediction result $\hat{Y}$ can be derived from final embedding $Z$ via a nonlinear projection (e.g., MLP). The loss function of our model is a log loss:

$$
\mathcal{L}(Y, \hat{Y}) = \sum_{i, j \in Y^+ \cup Y^-} (y_{ij} \log \hat{y}_{ij} + (1 - y_{ij}) \log(1 - \hat{y}_{ij}))
$$

where $y_{ij}$ is the label of the instance (i.e. source node $i$ and target node $j$), and $Y^+$, $Y^-$ denote the positive instances set and the negative instances set, respectively.

### 4.7 Combination of Neighborhood-based Selection & Interaction

Previous approaches [28, 34] often suffer from high computations, especially when working on interactions of high-order neighborhoods and metapaths of different lengths. These high-order neighborhoods or cross semantic interactions could result in (i) size explosion of metapath-guided neighborhoods; (ii) noise in interaction results. Equipped with Definition 2, we consider to filter the sampled neighborhood guided by complex metapaths through the results of those guided by simple metapaths. The key motivation behind this is that if low-order neighborhoods are useful in the current task, it is likely that high-order neighborhoods extended from these neighborhoods are useful. Take Fig. 1 as an example, User-Movie-User-Movie (UMUM) can be extended from User-Movie (UM). Hence, we can first investigate the impact of each UM neighborhood and filter UMUM neighborhoods based on the results of UM neighborhoods.

As illustrated in Fig. 10, when we study whether there exists a link between user $u_A$ and movie $m_B$ based on the given HIN, if we select UM and UMUM as the metapaths, we can sample metapath-guided neighborhoods for $u_A$ and $m_B$, and store them in the buffer. We then can examine the effect of each UM path and generate sample rates to capture the key paths and filter the noisy paths, which can be formulated as

$$
\mathbb{H}[\mathcal{N}_{\rho_\circ}^1(s), \mathcal{N}_{\rho_\circ}^1(t)]_{l,m} = \sum_{a+b \mod M=m} \mathbb{H}[\mathcal{N}_{\rho_\circ}^1(s)]_{l,a} \cdot \mathbb{H}[\mathcal{N}_{\rho_\circ}^1(t)]_{l,b},
$$

where $\mathcal{N}_{\rho_\circ}^1(o)$ denotes the 1-th neighborhood of $o$ guided by metapath $\rho_\circ$ (e.g., UM in the above case). It is straightforward to extend Eq. (18) to use lower or higher-order neighborhoods as the
After the filter operation, we can next aggregate the information and obtain the attention vector (e.g., $\mathbf{v}$). The key difference between the training procedures of NI and CNI modules is to train a well-performed model for the prediction. Hence, $H$ is equivalent to $\mathbf{v}$.

\[
\mathbf{v} = \mathbf{F}(H[N_{\rho_s}(s), N_{\rho_t}(t)]) = \mathbf{F}(H[N_{\rho_s}(s)]) \cdot \mathbf{F}(H[N_{\rho_t}(t)]).
\]  

(19)

After the filter operation, we can next aggregate the information and obtain the attention vector for each path following Eqs. (11), (12), (13), (15), (16). We treat the attention vector generated by Eq. (15) over the sampled paths as the sample rate on both low- and high-order neighborhoods (see Fig. 10).

Note that this neighborhood-based selection procedure can closely incorporate with the neighborhood-based interaction module. For instance, as shown in Fig. 10, we evaluate the effects of two UM paths (e.g., $(u_A, m_A)$ and $(u_A, m_B)$) through the neighborhood-based selection (NS) module, and then the generated sample rate may push us to focus more on $(u_A, m_B)$ and its related paths. Hence, we update the inputs of the neighborhood-based interaction (NI) module as $(u_A, m_B)$ and $(u_A, m_B, u_B, m_C)$. In order to update the NS module, we follow the learning procedure of GraphHINGE, where we supervise the whole model according to Eq. (17). The key difference between the training procedures of NI and NS modules is that input of NI module is the whole data, including both low- and high-order neighborhoods, while the input of NS module only contains low-order neighborhoods.

The overall procedure of the neighborhood-based selection (NS) module is given in Algorithm 1. Given an HIN $G$, the task of NS module is to generate useful metapath-guided neighborhoods of source $s$ and target $t$. As Algorithm 1 shows, we first divide sampled paths into $G$ groups (as illustrated in Fig. 11). Let $\rho^{i-j}$ denote the $j$-th path of the $i$-th group in line 4. Especially, we use $\rho^{g-0}$ to denote the low-order path in the $g$-th group. Then we push low-order paths into the neighborhood-based selection module and obtain sample rates to sample all paths over the group in line 9. Note that the goal of the NS module is to select appropriate high-order neighborhoods according to the performance of their corresponding low-order neighborhoods, while the goal of NI and CNI modules is to train a well-performed model for the prediction.

\[\text{Algorithm 1: Neighborhood-Based Selection (NS) Module}\]

\[
\begin{align*}
&1: & \text{Given an HIN } G, & \text{ the task of NS module is to generate useful metapath-guided neighborhoods of } s & \text{ and target } t. \\
&2: & \text{We first divide sampled paths into } G & \text{ groups (as illustrated in Fig. 11). Let } \rho^{i-j} & \text{ denote the } j \text{-th path of the } i \text{-th group in line 4. Especially, we use } \\
&3: & \rho^{g-0} & \text{ to denote the low-order path in the } g \text{-th group. Then we push low-order paths into the } \\
&4: & \text{neighborhood-based selection module and obtain sample rates to sample all paths over the group in line 9. Note that the goal of the NS module is to select appropriate high-order neighborhoods according to the performance of their corresponding low-order neighborhoods, while the goal of NI and CNI modules is to train a well-performed model for the prediction.}\n\end{align*}
\]

In this section, we store the low-order paths (e.g., UM and MU paths) on the top of each group, as illustrated in Fig. 11. Hence, $H[N_{\rho^{g-0}}(s), N_{\rho^{g-0}}(t)]$ is equivalent to $H[N_{\rho_{s}}(s), N_{\rho_{t}}(t)]$ in the Fig. 11 case.
Algorithm 1 Neighborhood-based Selection (NS) Module

Input: HIN $G = (V, E)$; node feature $\{e_i, i \in V\}$; metapath (combination) set $\{\rho_0, \rho_1, \cdots, \rho_{p-1}\}$; source node $s$ and target node $t$

Output: filtered buffer $B$ containing metapath-guided neighborhoods of $s$ and $t$

1: Initialize all parameters and buffer $B = \emptyset$.
2: Sample metapath-guided neighborhoods according to Eq. (1).
3: Store neighborhoods in $B$.
4: Divide paths into $G$ groups $\{\rho_0^{0-0}, \rho_1^{0-1}, \cdots, \rho_0^{0-(L_0-1)}, \cdots, \rho^{(G-1)-0}, \rho^{(G-1)-1}, \cdots, \rho^{(G-1)-(L_G-1)}\}$ according to their inclusion relations.
5: repeat
6: for each low-order path in groups $\rho_0^{0-0}, \cdots, \rho^g-0, \cdots, \rho^{(G-1)-0}$ do
7: Obtain interaction result $H[N_{\rho^g-0}(s), N_{\rho^0-0}(t)]$ according to Eq. (19).
8: Calculate element-level embedding $z$ according to Eq. (13).
9: Calculate path-level attention vector $\beta$ (i.e., sample rate) according to Eq. (15).
10: Obtain final prediction $Z$ according to Eq. (16).
11: Calculate loss $L(Y, \hat{Y})$ according to Eq. (17), and Back propagation.
12: end for
13: until convergence
14: Select paths within each group according to their generated sample rates.

4.8 Overall Algorithm

The learning algorithm of GraphHINGE is given in Algorithm 2. In the HIN-based recommendation scenario, each source node $s$ corresponds to a user $u_s$, and each target node $t$ corresponds to an item $i_t$. The task in this work can be either stated as link predictions on HINs or click-through predictions on HIN-based recommendations. Also, one can easily extend the task into top-N recommendations.

As Algorithm 2 shows, we first obtain filtered buffer $B$ in line 2. We then sample neighborhoods $N_{\rho_0}(s), N_{\rho_1}(t)$ of $s$, $t$ from $B$ in line 5. One should be noted that $\langle \rho_s, \rho_t \rangle$ in line 4 means metapath combinations in the CNI module where the metapaths of source and target nodes are set with $\rho_s$ and $\rho_t$, respectively. Next, we calculate interactive information $H[N_{\rho_s}(s), N_{\rho_t}(t)]$ through the cross interaction module described in Section 4.4 in line 6. To fuse the interaction results, we leverage the element-level attention mechanism to obtain representation $Z[N_{\rho_p}]$ in line 8. We repeat the above procedure for different paths and obtain various embeddings $Z[N_{\rho_0}], Z[N_{\rho_1}], \cdots, Z[N_{\rho_{p-1}}]$. To capture the key path in the current task, we employ the path-level attention mechanism to get embedding $Z$ in line 10. Finally, we obtain the final prediction $\hat{Y}$ via MLP layers in line 11 and update parameters through back propagation in line 12.

4.9 Model Analysis

According to Algorithm 2, we here give the analysis of the proposed GraphHINGE model as follows:

Complexity. The proposed CNI module is highly efficient and can be easily parallelized. We provide the model efficiency analysis for both the interaction module and the aggregation module. As stated in [30], in the interaction module, the complexity of the FFT-based method is $O(L_p I_p \log(I_p))$ where $L_p$ and $I_p$ denote the number of paths guided by $\rho$ and metapath length respectively. As for the aggregation module, given a metapath $\rho$, the time complexity of the attention mechanism is $O(V_p K + E_p K)$, where $V_p$ is the number of nodes, $E_p$ is the number of metapath-based node pairs, $K$ is the number of attention heads. The attention can be computed individually across all nodes and metapaths. The overall complexity is linear to the number of nodes and metapath-based node
Algorithm 2 GraphHINGE

Input: HIN $G = (V, E)$; node feature $\{e_i, i \in V\}$; metapath (combination) set $\{\rho_0, \rho_1, \cdots, \rho_{P-1}\}$; source node $s$ and target node $t$

Output: final link prediction $\hat{Y}$ between $s$ and $t$

1: Initialize all parameters.
2: # (Obtain filtered buffer $B$ according to Algorithm 1). $\triangleright$ for GraphHINGE$^+$SELECT
3: repeat
4: for each metapath (combination) $\rho_p ((\rho_s, \rho_t))$ in $B$ do
5: Find metapath-guided neighborhoods of $s,t$: $N_{\rho_s}(s), N_{\rho_t}(t)$ from $B$.
6: Obtain interaction result $H[N_{\rho_s}(s), N_{\rho_t}(t)]$ according to Eq. (6).
7: # (Obtain $H[N_{\rho_s}(s), N_{\rho_t}(t)]$ according to Eq. (10)). $\triangleright$ for GraphHINGE$^+$CROSS
8: Calculate element-level embedding $Z[N_{\rho_p}]$ according to Eq. (13).
9: end for
10: Fuse path-level embedding $Z$ according to Eq. (16).
11: Obtain final predication $\hat{Y}$ via MLP.
12: Calculate loss $\mathcal{L}(Y, \hat{Y})$ according to Eq. (17), and Back propagation.
13: until convergence pairs. The proposed model can be easily parallelized, because the computation of the element- and path-level attentions can be parallelized across node pairs and metapaths, respectively.

Interpretability. The proposed model has potentially good interpretability for the learned interaction embedding through similarities and co-ratings among neighbor nodes. Also, with the learned importance in node- and path-level, the proposed model can pay more attention to some meaningful interactions or metapaths for the specific task and give a more comprehensive description of a heterogeneous graph. Based on the attention values, we can check which interactions or metapaths make the higher (or lower) contributions to our task, which is beneficial to analyze and explain our results.

5 EXPERIMENT

In this section, we present the details of the experiment setups and the corresponding results. To illustrate the effectiveness of our proposed model, we compare it with some strong baselines on recommendation tasks, including click-through rate (CTR) predictions and top-N recommendations. We start with six research questions (RQ) to lead the experiments and the following discussions.

- (RQ1) How does GraphHINGE compare to the existing state-of-the-art and other baselines in click-through rate prediction and top-N recommendation tasks?
- (RQ2) What is the influence of different components in GraphHINGE? Are the proposed interaction and aggregation modules necessary for improving performance?
- (RQ3) What are the effects of the cross interaction module, neighborhood-based selection module, and other variants of GraphHINGE?
- (RQ4) How do various hyper-parameters, including the length and type of metapath-guided neighborhoods, the amount of training data, and the number of paths in each metapath-guided neighborhood, impact the model performance?
- (RQ5) What patterns does the proposed model capture for the final recommendation decision?
- (RQ6) What is the influence of the FFT technique? Does FFT accelerate the training procedure and gain high performance with low time cost?
Table 2. Statistics of the six datasets. The last column reports the metapaths in each dataset.

| Datasets       | Relations (A-B) | A      | B      | A-B    | Metapath | Sparsity |
|----------------|-----------------|--------|--------|--------|----------|----------|
| Amazon         | User-Item       | 6,170  | 2,753  | 195,791| UIUI     | 98.85%   |
|                | Item-View       | 2,733  | 3,857  | 5,694  | UIVI     | 99.95%   |
|                | Item-Brand      | 2,733  | 334    | 2,754  | UBI      | 99.70%   |
|                | Item-Category   | 2,733  | 22     | 5,654  | UICI     | 90.91%   |
| Movielens      | User-Movie      | 1,682  | 1,682  | 82,798 | UMUM     | 97.87%   |
|                | Movie-Movie     | 1,682  | 1,682  | 82,798 | UMUM     | 97.87%   |
|                | User-Occupation | 943    | 21     | 943    | UDOM     | 91.24%   |
|                | Movie-Genre     | 1,682  | 18     | 2,664  | USDM     | 90.35%   |
| Amazon Book    | User-Book       | 115,521| 348,613| 645,803| UBUB     | 99.99%   |
|                | Movie-20M       | 71,315 | 123,527| 4,552,019| UMUM | 99.95%   |
|                | Book-Attribute  | 348,613| 348,611| 1,547,854| UBA     | 99.99%   |
| Aminer         | Paper-Author    | 127,623| 101    | 127,632| PAPA     | 99.99%   |
|                | Paper-Conference| 127,623| 101    | 127,632| PCPA     | 99.99%   |
|                | Paper-Reference | 127,623| 147,251| 392,119| PPRA     | 99.99%   |
|                | Paper-Label     | 127,623| 10     | 127,623| PLPA     | 90.00%   |
| Douban Book    | User-Book       | 13,024 | 22,347 | 792,062| UBUB     | 99.73%   |
|                | Book-Year       | 22,347 | 64     | 21,192 | UBBR     | 98.32%   |
|                | Book-Publisher  | 22,347 | 1,815  | 21,773 | UBFP     | 99.95%   |
|                | Book-Year       | 22,347 | 64     | 21,192 | UBBR     | 98.32%   |
|                | Book-Publisher  | 22,347 | 1,815  | 21,773 | UBFP     | 99.95%   |
|                | Book-Year       | 22,347 | 64     | 21,192 | UBBR     | 98.32%   |
|                | Book-Publisher  | 22,347 | 1,815  | 21,773 | UBFP     | 99.95%   |
|                | Book-Year       | 22,347 | 64     | 21,192 | UBBR     | 98.32%   |
|                | Book-Publisher  | 22,347 | 1,815  | 21,773 | UBFP     | 99.95%   |

5.1 Dataset Description

We adopt six widely used datasets from different domains, namely Amazon e-commerce dataset*, Aminer academic dataset†, Movielens movie dataset‡, and Douban Book dataset§. In order to evaluate whether GraphHINGE can scale to large scale datasets, we also compare our model with the baselines on Amazon Book dataset (which combines Amazon Book* and Freebase, and Amazon Book contains over 22.5 million ratings collected from 8 million users and 2.3 million items), and Movie-20M dataset (which combines Movielens-20M‡ and Freebase, and Movielens-20M contains ratings collected from the Movielens website). We treat a rating as a relation record, indicating whether a user has rated an item. Also, we provide the main statistics of the six datasets, which are summarized in Table 2. The first row of each dataset corresponds to the numbers of users, items, and interactions, while the other rows correspond to the statistics of other relations. We also report the selected metapaths for each dataset in the second last column of the table.

5.2 Compared Methods

We use eight baseline methods, which mainly can be concluded into three folds. We list the brief descriptions of these strong baselines as follows:

The first class is heterogeneous and attributed graph embedding models containing HAN, HetGNN, and IPE.

- **HAN**: Wang et al. [56] introduced a hierarchical attention mechanism to capture node-level and semantics-level information.
- **HetGNN**: Zhang et al. [63] introduced a unified framework to jointly consider heterogeneous structured information as well as heterogeneous contents information, adaptive to various HIN tasks.
- **IPE**: Liu et al. [28] proposed the interactive paths embedding to capture rich interaction information among metapaths.

The second class is HIN-based recommendation models including NeuMF, LGRec, and MCRec.

- **NeuMF**: He et al. [17] introduced a generalized model consisting of a matrix factorization (MF) component and an MLP component.
- **LGRec**: Hu et al. [18] proposed a unified model to explore and fuse local and global information for recommendation.
- **MCRec**: Hu et al. [19] leveraged rich metapath-based context to enhance the recommendation performance on HINs.

The final class is non-neural-network-based models, which include ItemKNN and UserKNN.

---

*http://jmcauley.ucsd.edu/data/amazon/
†https://www.aminer.org/data
‡https://grouplens.org/datasets/movielens/
§https://book.douban.com/
Table 3. The results of CTR prediction in terms of ACC, F1, LogLoss. Note: ‘*’ indicates the statistically significant improvements over the best baseline, with p-value smaller than $10^{-5}$ in two-sided t-test. The best results for each metric are bold and the second best ones are underlined.

| Model          | Movielens ACC | Movielens F1 | Movielens LogLoss | Amazon ACC | Amazon F1 | Amazon LogLoss | Aminer ACC | Aminer F1 | Aminer LogLoss | DoubanBook ACC | DoubanBook F1 | DoubanBook LogLoss |
|----------------|---------------|--------------|-------------------|-----------|-----------|----------------|-----------|-----------|----------------|----------------|-------------|------------------|
| HAN [56]       | 0.8616        | 0.8634       | 0.3270            | 0.7688    | 0.7789    | 0.4917         | 0.8959    | 0.8824    | 0.5256         | 0.8110         | 0.8111     | 0.4048          |
| HetGNN [63]    | 0.8510        | 0.8567       | 0.3528            | 0.7493    | 0.7410    | 0.5082         | 0.8019    | 0.7943    | 0.3817         | 0.8012         | 0.8014     | 0.4125          |
| IPE [28]       | 0.8645        | 0.8693       | 0.3223            | 0.7850    | 0.7511    | 0.4866         | 0.9209    | 0.8976    | 0.2944         | 0.8270         | 0.8189     | 0.3999          |
| NeuMF [17]     | 0.8512        | 0.8556       | 0.3523            | 0.7130    | 0.7008    | 0.5598         | 0.6983    | 0.6454    | 0.4932         | 0.8180         | 0.8142     | 0.4043          |
| LGRec [18]     | 0.8544        | 0.8581       | 0.3490            | 0.7127    | 0.7100    | 0.5589         | 0.8308    | 0.8130    | 0.3642         | 0.8158         | 0.8172     | 0.3988          |
| MRec [19]      | 0.8612        | 0.8645       | 0.3280            | 0.7394    | 0.7374    | 0.5101         | 0.9113    | 0.9116    | 0.2302         | 0.8203         | 0.8215     | 0.3937          |
| ItemKNN [41]   | 0.8066        | 0.8062       | 0.3890            | 0.6274    | 0.6355    | 0.6781         | 0.5512    | 0.5339    | 0.5914         | 0.7274         | 0.6940     | 0.5008          |
| UserKNN [52]   | 0.8061        | 0.8045       | 0.3920            | 0.6574    | 0.6471    | 0.6688         | 0.5974    | 0.5877    | 0.5577         | 0.7321         | 0.7319     | 0.4967          |
| GraphHINGE  
GraphHINGE$_{CROSS}$ | 0.8823 | 0.8828 | 0.2959 | 0.8659 | 0.8905 | 0.2867 | 0.9535 | 0.9564 | 0.1218 | 0.8320 | 0.8308 | 0.3891 |
| GraphHINGE  
GraphHINGE$_{SELECT}$ | 0.8865 | 0.8840 | 0.2878 | 0.8650 | 0.8915 | 0.2533 | 0.9617 | 0.9710 | 0.1146 | 0.8326 | 0.8314 | 0.3809 |
| GraphHINGE  
GraphHINGE$_{ALL}$ | 0.8864 | 0.8862 | 0.2804 | 0.8945 | 0.8949 | 0.2594 | 0.9541 | 0.9509 | 0.1216 | 0.8321 | 0.8323 | 0.3808 |

- **ItemKNN**: A traditional collaborative filtering approach based on $k$-nearest-neighborhood (KNN) and item-item similarities [41].
- **UserKNN**: A neighborhood-based method using collaborative user-user similarities on $k$-nearest-neighborhood (KNN) [52].

Notice that we do not compare GraphHINGE with several state-of-the-art methods on homogeneous graphs, since these approaches often perform poorly when extending to heterogeneous graphs setting. It is worth noting that HAN, HetGNN, IPE, and MRec are recently proposed, state-of-the-art models.

![Fig. 12. An illustrated example of GraphHINGE and its variants, namely GraphHINGE$_{ALL}$, GraphHINGE$_{CROSS}$ and GraphHINGE$_{SELECT}$. Note that GraphHINGE, which includes the neighborhood-based interaction module and the aggregation module, only conducts interaction operations between aligned paths guided by the same metapaths (e.g., $(u_A, m_A) \circ (m_B, u_B)$, $(u_A, m_B) \circ (m_B, u_C)$, $(u_A, m_B, d_B, m_B) \circ (u_B, d_B, m_B, u_A)$). Compared with GraphHINGE, GraphHINGE$_{ALL}$ operates interaction between all the paths, involving more interactive information (e.g., $(u_A, m_A) \circ (m_B, u_C)$, $(u_A, m_B) \circ (m_B, u_B)$); GraphHINGE$_{CROSS}$ allows interaction operations between paths guided by different metapaths (e.g., $(u_A, m_B, d_B, m_B) \circ (m_B, u_B)$, $(u_A, m_A) \circ (m_B, d_B, m_B, u_A)$). GraphHINGE$_{SELECT}$ develops the neighborhood-based selection module to select appropriate high-order neighborhoods for GraphHINGE. Note that compared with GraphHINGE, GraphHINGE$_{ALL}$ and GraphHINGE$_{CROSS}$ involve additional information and GraphHINGE$_{SELECT}$ does not.](image-url)
Table 4. The results of top-N recommendation in terms of MAP, NDCG@3, NDCG@5. Note: ‘*’ indicates the statistically significant improvements over the best baseline, with p-value smaller than $10^{-6}$ in two-sided t-test. The best results for each metric are bold and the second best ones are underlined.

| Model       | MovieLens | Amazon | Animator | Dounot Book |
|-------------|-----------|--------|----------|-------------|
|             | MAP   | NDCG@3 | NDCG@5  | MAP   | NDCG@3 | NDCG@5  | MAP   | NDCG@3 | NDCG@5  |
| HAN [56]    | 0.5810 | 0.8350 | 0.8275  | 0.5793 | 0.7989 | 0.8012  | 0.7439 | 0.8846 | 0.9490  |
| HetGNN [63] | 0.5730 | 0.8511 | 0.8623  | 0.5011 | 0.6289 | 0.6370  | 0.5203 | 0.8500 | 0.9206  |
| IPE [28]    | 0.5969 | 0.8693 | 0.8799  | 0.5945 | 0.8340 | 0.8410  | 0.7780 | 0.9560 | 0.9687  |
| NeumIF [17] | 0.8166 | 0.8515 | 0.8675  | 0.4939 | 0.7206 | 0.7356  | 0.5101 | 0.8414 | 0.9203  |
| LGRec [18]  | 0.8277 | 0.8504 | 0.8734  | 0.5127 | 0.7311 | 0.7435  | 0.6308 | 0.8530 | 0.9304  |
| MCRec [19]  | 0.5923 | 0.8735 | 0.8862  | 0.5442 | 0.7618 | 0.7756  | 0.7463 | 0.8917 | 0.9462  |
| ItemKNN [41] | 0.5116 | 0.8008 | 0.8015  | 0.5074 | 0.6576 | 0.6671  | 0.4409 | 0.7339 | 0.8845  |
| UserKNN [52] | 0.5153 | 0.8022 | 0.8037  | 0.5043 | 0.6471 | 0.6492  | 0.4506 | 0.7339 | 0.8903  |

Table 5. The results of CTR prediction in terms of ACC, F1, LogLoss, and top-N recommendation in terms of MAP, NDCG@3, NDCG@5. Note: ‘*’ indicates the statistically significant improvements over the best baseline, with p-value smaller than $10^{-6}$ in two-sided t-test. The best results for each metric are bold and the second best ones are underlined.

| Model                  | Amazon Book | Movie-20M | Amazon Book | Movie-20M |
|------------------------|-------------|-----------|-------------|-----------|
|                        | ACC    | F1      | LogLoss    | ACC    | F1      | LogLoss    |
| HAN [56]               | 0.7510 | 0.7330 | 0.4533  | 0.8666 | 0.8667 | 0.3144  |
| HetGNN [63]            | 0.7430 | 0.7412 | 0.4877  | 0.8451 | 0.8457 | 0.3442  |
| IPE [28]               | 0.7692 | 0.7686 | 0.4504  | 0.8512 | 0.8510 | 0.3537  |
| NeumIF [17]            | 0.7377 | 0.7295 | 0.5490  | 0.8642 | 0.8645 | 0.3255  |
| LGRec [18]             | 0.7590 | 0.7598 | 0.5420  | 0.8650 | 0.8645 | 0.3233  |
| MCRec [19]             | 0.7539 | 0.7541 | 0.4532  | 0.8669 | 0.8677 | 0.3155  |
| ItemKNN [41]           | 0.6181 | 0.6222 | 0.6990  | 0.7249 | 0.7301 | 0.5120  |
| UserKNN [52]           | 0.6234 | 0.6277 | 0.6680  | 0.7214 | 0.7209 | 0.5176  |
| GraphHINGE CNN         | 0.7833 | 0.7918 | 0.4493  | 0.8689 | 0.8711 | 0.5108  |
| GraphHINGE CNN Select  | 0.8290 | 0.8376 | 0.5550  | 0.8680 | 0.8704 | 0.5267  |
| GraphHINGE CNN All     | 0.9616 | 0.9611 | 0.1173  | 0.8702 | 0.8699 | 0.1080  |

5.3 Evaluation Metric

In this paper, we evaluate the models in two tasks: click-through rate prediction and top-N recommendation. In click-through rate prediction task, we evaluate a model according to the performance on each data point, where we adopt ACC, LogLoss, and F1 score. In top-N recommendation task, we take the position into consideration, where we adopt ACC, LogLoss, and F1 score. In this context embedding method is quite similar to the path instance.
embedding technique in [19]. The aggregation module is the same as GraphHINGE. This variant is designed to show the performance gain by our interaction module.

- **GraphHINGEGCN**: This variant replaces the attention mechanism of GraphHINGE with a standard Graph Convolutional Network (GCN). That is, the element-level features are fed to GCN layers to get content embedding without fully considering different types of nodes and metapaths on HINs. The interaction module is the same as GraphHINGE. Hence, this variant is designed to show the performance gain by our aggregation module.

- **GraphHINGE_{FFT}**: This variant replaces FFT technique as introduced in Eq. (6) with the combination of product and sum operations as introduced in Eq. (5). Therefore, this variant is proposed to show the efficiency of FFT technique.

In order to investigate the impact of different settings, cross neighborhood-based interaction (CNI) module, and neighborhood-based selection (NS) module, we set following variants of GraphHINGE model here.

- **GraphHINGE^{+}_ALL**: This variant conducts interaction between all paths in source and target neighborhoods, while GraphHINGE only operates between aligned paths. Note that this setting improves performance but suffers from high time complexity (i.e., $O(L_p^2I_p \log(I_p))$). Therefore, this variant can be regarded as a higher performance and complexity version of GraphHINGE.

- **GraphHINGE^{+}_CROSS**: This variant replaces the neighborhood-based interaction (NI) module with the cross neighborhood-based interaction (CNI) module. Hence, it allows the interaction operations between neighborhoods guided by different metapaths even in different lengths. This variant is designed to show the performance of the CNI module.

- **GraphHINGE^{+}_SELECT**: This variant is the combination of GraphHINGE and neighborhood-based selection (NS) module, as introduced in Section 4.7. Therefore, this variant is proposed to illustrate the performance of our NS module.

We further illustrate the difference between GraphHINGE and its variants in Fig. 12.

### 5.5 Overall Performance (RQ1)

The comparison results of our proposed model and baselines on the six datasets are reported in Tables 3, 4, 5. The major findings from experimental results are summarized as follows:

- Our model GraphHINGE is consistently better than all baselines on the six datasets. The results indicate the significance of capturing interactive information and the effectiveness of GraphHINGE on both CTR prediction and top-N recommendation, since GraphHINGE adopts a principled way to leverage interactive information to enhance the model performance on prediction tasks.

- Among the three kinds of baselines, the best of metapath-based methods (MCRec, IPE) outperform graph-based or feature-based neural network methods (HetGNN, NeuMF) and non-neural network methods (ItemKNN, UserKNN) in most cases. An intuitive explanation is that those metapath-based methods can better capture the rich high-order structured information on HINs. It should be noted that our model GraphHINGE based on metapath-guided neighborhood is able to jointly consider low- and high-order neighborhood information and capture interactive patterns.

- Among HIN-based baselines, the recently proposed methods MCRec and IPE gain better performance than the others. It is easy to notice that both of them try to capture context information or interactive patterns among paths. GraphHINGE outperforms those approaches. A possible reason is that simple aggregation of semantic messages on paths may lose some key information. It should be noted that GraphHINGE not only captures interaction information but also focus on key paths through the attention mechanism.
Among all the methods, non-neural network approaches (ItemKNN, UserKNN) do not work well. One possible reason is that neural networks have good representation ability, which can largely improve the performances.

Among all the datasets, GraphHINGE outperforms state-of-the-art baseline models by a wide margin on those datasets (e.g., Amazon, Aminer, and Amazon Book) with high data sparsity. A possible explanation is that GraphHINGE leverages the interaction module to capture interactive information, which can mine more useful hidden relations than traditional methods.

5.6 Ablation Study (RQ2)
In order to investigate the contribution of each component to the final recommendation performance, we design two variants of GraphHINGE, namely GraphHINGE\textsubscript{CNN} and GraphHINGE\textsubscript{GCN} to study the neighborhood-based interaction (NI) and the aggregation modules, respectively. The comparison results of our model and these variants on six datasets are shown in Tables 3, 4, 5. The major findings from experimental results are summarized as follows:

- Result (GraphHINGE > GraphHINGE\textsubscript{CNN}) indicates that our convolutional interaction strategy can better capture interaction information (i.e., similarities between the same type of nodes and ratings between different types of nodes) than simply employing CNN layers.
- Result (GraphHINGE > GraphHINGE\textsubscript{GCN}) shows that the attention mechanism can better utilize the metapath-based interactive information, since the element- and path-level interactions may contribute differently to the final performance. Ignoring such influence may not be able to achieve optimal performance.

5.7 Impacts of CNI & NS Module (RQ3)
In order to investigate the performances of the cross neighborhood-based interaction (CNI) and the selection (NS) modules, we develop two more variants of GraphHINGE, namely GraphHINGE\textsubscript{CROSS} for CNI module and GraphHINGE\textsubscript{SELECT} for NS module. Also, we design GraphHINGE\textsubscript{ALL} to investigate the potential of the interaction module. The comparison results of our model and these variants on the six datasets are shown in Tables 3, 4 and 5. The major findings from experimental results are summarized as follows:

- Result (GraphHINGE\textsubscript{CROSS} > GraphHINGE) illustrates that in most cases, patterns in cross interaction information can help the model obtain more accurate predictions. Also, one can find that in some datasets (e.g., Douban Book), GraphHINGE outperforms GraphHINGE\textsubscript{CROSS}. One possible reason is that these cross interactive patterns obtained from different metapaths may include noise in some cases, which can impair the performance.
- Result (GraphHINGE\textsubscript{SELECT} > GraphHINGE) shows that the NS module can find valuable high-order neighborhoods to enhance the performance of GraphHINGE. The reason behind this is that almost in most HINs, high-order neighborhoods often are large-scale and full of noisy information. NS module is one of the solutions to find the key information and filter out the noise.
- Result (GraphHINGE\textsubscript{ALL} > GraphHINGE) illustrates that if we do not consider the time complexity, GraphHINGE can improve performance by involving more interaction information. We later show the comparison of time complexity in Section 5.13.

5.8 Impact of Metapath (RQ4)
In this section, we investigate the impact of different metapaths on the prediction performance. To do this, we first include low-order metapaths (e.g., UI, UB, and UM) and then gradually incorporate metapaths into the proposed model. For ease of analysis, we include the NeuMF as the reference...
baseline. In Fig. 13, we can observe that the performance of GraphHINGE overall improves with the incorporation of more metapaths. Meanwhile, metapaths seem to have different effects on the prediction performance. Particularly, we can find that, when adding UMGM, GraphHINGE has a significant performance boost in the Movielens dataset. A similar situation happens when adding UIVI in the Amazon dataset. These findings indicate that different metapaths contribute differently to the final result, consistent with previous observations in Section 5.6.

5.9 Impact of N-Hop Neighborhood (RQ4)
In this section, we investigate the impact of different lengths of neighborhoods (i.e., n-hop neighborhood). When changing the length of the neighborhood, we make other factors (e.g., metapath type) fixed. For example, when the metapath is UMUM, we study UM for length 2, UMUM for length 4, and UMUMUM for length 6. We conduct similar procedures for the other metapaths and obtain the results in Fig. 14. We can observe that the performance of GraphHINGE first increases, next reaches the best performance and then decreases as the length of metapath increases. The possible reason may be that as the length of the neighborhood increases, the metapath-guided neighborhood can contain more information. When the length of the neighborhood is not very large, the information is mainly useful for the final performance. However, when the length exceeds a certain value, the information includes noisy messages which harm the recommendation performance. These findings indicate that different lengths of metapaths contribute differently to the final performance. Also, it should be noted that our model is able to interact and aggregate neighbors in different lengths, as introduced in Section 4.4 and 4.5.
5.10 Impact of Amount of Data (RQ4)

In this section, we further evaluate the robustness of GraphHINGE with different amounts of training data. We first randomly select a subset of training data (i.e., 25% ~ 100%) to generate the new training data, and then use these data to train our methods. For a fair comparison, we use the same data for evaluation across all experiments. As Fig. 15 shows, when the amount of training data increases, the performance of GraphHINGE raises, especially during the period of the amount of training data expanding from 25% to 50%.

Fig. 15. Performance change of GraphHINGE with different amount of training data in terms of ACC and LogLoss.

5.11 Impact of Number of Paths (RQ4)

In this section, we investigate the performance change with different number of paths for each metapath. As illustrated in Fig 16, as the number of paths increases, the performance of GraphHINGE becomes better. It is easy to understand since a larger number of paths always means more data for training. There is a drop in the Douban Book dataset when the number of paths increases from 64 to 128. A possible reason is that the data might involve some noise. However, one should note that a larger number of paths also means higher time complexity.

Fig. 16. Performance change of GraphHINGE with different number of paths for each metapath in terms of ACC and LogLoss.

5.12 Case Study (RQ5)

A major contribution of GraphHINGE is the incorporation of the element- and path-level attention mechanism, which takes the interaction relation into consideration in learning effective representations for recommendation. Besides the performance effectiveness, another benefit of the attention mechanism is that it makes the recommendation result highly interpretable. To see this, we select...
the user u692 in Movielens dataset as an illustrative example. Two interaction records of this user have been used here, namely m805 and m920. In Fig. 17, we can see that each user-movie pair corresponds to a unique attention distribution, summarizing the contributions of the metapaths. The relation between u692-m805 pair mainly relies on the metapaths UMUM and UMMM, while u692-m920 pair mainly relies on metapath UMG (denoted by 1 in Fig. 17). By inspecting into the dataset, it is found that at least five first-order neighbors of u692 have watched m805, which explains why user-oriented metapaths UMUM plays the key role in the first pair. As for the second pair, we find that the genre of m805 is g3, which is the favorite movie genre of u692. This explains why genre-oriented metapath UMG plays the key role in the second interaction. Our path-level attention is able to produce path-specific attention distributions.

Fig. 17. An illustrated example of the interpretability of interaction-specific attention distribution for GraphHINGE. The number denotes the logic flow of interpretation.

If we wonder more specific reasons, we can have a look at the element-level attention. Here, we plot the interactive attention values in Fig. 17. We can observe that the attention value of the similarity for the same type elements is very high (denoted by 1 in Fig. 17). By inspecting into the dataset, we can find that there are metapaths connected between u692 and m920. In other words, some parts of the metapath-guided neighborhood of u692 and m920 overlap, which causes high similarity. Also, the co-ratings between two neighborhoods play another key role (denoted by 2 in Fig. 17). It is natural, since in these neighborhoods, many users are fans of g3, and movies are in the type of g3, which causes the co-ratings among them to become really high. According to the analysis above, we can see that the distributions of attention weights are indeed very skew, indicating some interactions and metapaths are more important than the others.

5.13 Complexity Study (RQ6)

In this section, we investigate whether the FFT technique can truly accelerate the convolution operation through comparisons between GraphHINGE and GraphHINGE_{FFT}. For ease of analysis, we include all the baseline models. We evaluate the inference time of one batch data on three different datasets. The detailed experiment settings can be found in Section 5.14. As shown in Fig. 18, results demonstrate the performance gain of the FFT technique. We further study the time complexity of GraphHINGE_{ALL}. One can easily see that the result is consistent with the previous analysis in Section 5.4. Notice that the convolution operation in GraphHINGE also can be implemented directly with Application Programming Interface (API) in Pytorch. Hence, we also include this implementation (denoted as GraphHINGE_{Conv.}) in the experiment. In Fig. 18, one can see that this implementation is better than ours. But one should note that this implementation has involved several system optimization techniques that may also include FFT.

5.14 Implementation Details

Data Processing. Each dataset is processed as follows. Since the relations between users and items are originally in rating format, we convert ratings to binary feedbacks: ratings with 4-5
stars are converted to positive feedbacks (denoted as ‘1’), and other ratings are converted to negative feedbacks (denoted as ‘0’). After the datasets are processed, we split each dataset into training/validation/test sets at a ratio of 6:2:2.

**Hyper-parameter Setting.** The embedding dimension of GraphHINGE is 128. As stated in Section 4.2, we perform the metapath-guided random walk method with restart. The number of attention heads is 3. The temperatures are set to 0.2. GraphHINGE samples 16 paths for each metapath in metapath-guided neighborhood while GraphHINGE<sub>^+</sub> first samples 128 paths and then adopt neighborhood-based selection (NS) module to learn to select 16 paths from sampled 128 candidate paths for each metapath in metapath-guided neighborhoods. The length of the metapath-guided neighborhoods<sup>º</sup> equals to the length of the metapath. We investigate the impacts of different lengths of neighborhoods in Section 5.9.

**Model Configuration.** For fair comparisons, we implement the proposed method and baselines as following: (i) In the data processing procedure, we sample and store paths guided by metapaths in a unified framework. For instance, when sampling data from Movielens following UMUM metapath, we can obtain 16 paths connecting \( u_0 \) and \( m_0 \) (denoted as \( \rho(u_0 \rightarrow m_0) \)), as well as 16 paths in metapath-guided neighborhoods of \( u_0 \) (denoted as \( N(u_0) \)) and 16 paths in metapath-guided neighborhoods of \( m_0 \) (denoted as \( N(m_0) \)). That is, the first node of both path \( \rho(u_0 \rightarrow m_0) \) and metapath-guided neighborhood \( N(u_0) \) is sampled from the same source node \( u_0 \). The difference is that the path \( \rho(u_0 \rightarrow m_0) \) must end with target node \( m_0 \) while the neighborhood \( N(u_0) \) can end with any node in the type of movie. (ii) For metapath-based baselines such as MCRec and IPE, we feed models with the same paths. For graph-based baselines, such as HAN [56] and HetGNN [63], we generate n-hop neighbor nodes from sampled paths. (iii) The embedding dimensions of all baselines are set to 128 (same as GraphHINGE).

**Hardware Setting.** The models are trained under the same hardware settings with an Amazon EC2 p3.8×large instance<sup>1</sup>, where the GPU processor is NVIDIA Tesla V100 processor and the CPU processor is Intel Xeon E5-2686 v4 (Broadwell) processor.

### 5.15 Deployment Feasibility Analysis

In this section, we mainly discuss the feasibility of the industrial deployment of GraphHINGE framework. First, it is not difficult to switch the current model pipeline to GraphHINGE, because

---

<sup>º</sup>For simplification, we use ‘length of (the metapath-guided) neighborhoods’ to denote ‘length of paths in the metapath-guided neighborhoods’.

<sup>1</sup>Detailed setting of AWS E2 instance can be found at https://aws.amazon.com/ec2/instance-types/?nc1=h_ls.
the main change brought from GraphHINGE is how to utilize graph structure. Previous methods such as GraphSAGE [14] developed sample and aggregation frameworks, where neighbors are first sampled and then aggregated to obtain the final prediction. Interactive patterns need to be built to update the model pipeline to GraphHINGE, while the whole HIN-based recommendation remains almost the same but adding an additional interaction module between sampling and aggregation modules. As Fig. 5 shows, the sampling and aggregation modules have no substantial difference from that of traditional solutions.

Efficiency is another essential concern in industrial applications. We analyze the time complexity of GraphHINGE that contains interaction and aggregation modules. As stated in Section 5.13, the time complexity of the interaction model is $O(L_\rho I_\rho \log(I_\rho))$ and that of the aggregation model is $O(V_\rho K + E_\rho K)$. Note that the overall complexity is linear to the number of nodes and metapath-based node pairs. From the perspective of metapath-guided neighborhood construction, we propose a novel neighborhood-based selection module to update the buffer (as illustrated in Fig. 10), where we first adopt a neighborhood sampling strategy to obtain the raw neighborhood paths, and then use the performance of low-order neighborhood to distinguish useful high-order neighborhood and filter out the noise.

6 CONCLUSION AND FUTURE WORK

In this paper, we introduce the problem of ‘early summarization’ and propose a novel framework named GraphHINGE to address this issue. We first introduce the definition of metapath-guided neighborhoods to preserve the heterogeneity of HINs. Then, we elaborately design an interaction module to capture the similarity of each source and target node pair through their neighborhoods, where we propose the neighborhood-based interaction (NI) module for neighborhoods guided by the same metapaths and the cross neighborhood-based interaction (CNI) module for neighborhoods guided by different metapaths. To fuse the rich semantic information, we propose the element- and path-level attention mechanism to capture the key interactions from element and path levels respectively. Extensive experimental results have demonstrated the superiority of our model in effectiveness, interpretability, and efficiency.

Currently, our approach is able to capture interactive information only in the structured (graph) side effectively. However, there is rich semantic information on both the structured (graph) side and the non-structured (node) side. In the future, a promising direction is extending the neighborhood-based interaction and aggregation modules to capture key messages from both sides and adapt to more general scenarios.

ACKNOWLEDGMENTS

The corresponding author Weinan Zhang thanks the support of National Natural Science Foundation of China (Grant No. 61702327, 61772333, 61632017). We would also like to thank Wu Wen Jun Honorary Doctoral Scholarship from AI Institute, Shanghai Jiao Tong University.
REFERENCES

[1] Sami Abu-El-Haija, Bryan Perozzi, Amol Kapoor, Nazanin Alipourfard, Kristina Lerman, Hraky Harutyunyan, Greg Ver Steeg, and Aram Galstyan. 2019. Mixhop: Higher-order graph convolutional architectures via sparsified neighborhood mixing. In ICML.

[2] Mathieu Blondel, Akinori Fujino, Naonori Ueda, and Masakazu Ishihata. 2016. Higher-order factorization machines. In NeurIPS.

[3] Joan Bruna, Wojciech Zaremba, Arthur Szlam, and Yann LeCun. 2013. Spectral networks and locally connected networks on graphs. In ICLR.

[4] Jie Chen, Tengfei Ma, and Cao Xiao. 2018. Fastgcn: fast learning with graph convolutional networks via importance sampling. ICLR (2018).

[5] Ting Chen and Yizhou Sun. 2017. Task-guided and path-augmented heterogeneous network embedding for author identification. In WSDM.

[6] Weijian Chen, Yulong Gu, Zhaochun Ren, Xiangnan He, Hongtao Xie, Tong Guo, Dawei Yin, and Yongdong Zhang. 2019. Semi-supervised User Profiling with Heterogeneous Graph Attention Networks. In IJCAI.

[7] Heng-Tze Cheng, Levent Koc, Jeremiah Harmsen, Tal Shaked, Tushar Chandra, Hrishi Aradhye, Glen Anderson, Greg Corrado, Wei Chai, Mustafa Ispir, et al. 2016. Wide & deep learning for recommender systems. In Dlrs@RecSys.

[8] Michaël Defferrard, Xavier Bresson, and Pierre Vandergheynst. 2016. Convolutional neural networks on graphs with fast localized spectral filtering. In NeurIPS.

[9] Yuxiao Dong, Nitesh V Chawla, and Ananthram Swami. 2017. metapath2vec: Scalable representation learning for heterogeneous networks. In KDD.

[10] Wei Feng and Jianyong Wang. 2012. Incorporating heterogeneous information for personalized tag recommendation in social tagging systems. In KDD.

[11] Tao-yang Fu, Wang-Chien Lee, and Zhen Lei. 2017. Hin2vec: Explore meta-paths in heterogeneous information networks for representation learning. In CIKM.

[12] Aditya Grover and Jure Leskovec. 2016. node2vec: Scalable feature learning for networks. In KDD.

[13] HuiFeng Guo, Ruiming Tang, Yunnin Ye, Zhenguo Li, and Xiuqiang He. 2017. DeepFM: a factorization-machine based neural network for CTR prediction. IJCAI (2017).

[14] Will Hamilton, Zhitao Ying, and Jure Leskovec. 2017. Inductive representation learning on large graphs. In NeurIPS.

[15] Xiangnan He and Tat-Seng Chua. 2017. Neural Factorization Machines for Sparse Predictive Analytics. In SIGIR.

[16] Xiangnan He, Kuan Deng, Xiang Wang, Yan Li, Yongdong Zhang, and Meng Wang. 2020. LightGCN: Simplifying and Powering Graph Convolution Network for Recommendation. In SIGIR.

[17] Xiangnan He, Lizi Liao, Hanwang Zhang, Liqiang Nie, Xia Hu, and Tat-Seng Chua. 2017. Neural collaborative filtering. In WWW.

[18] Binbin Hu, Chuan Shi, Wayne Xin Zhao, and Tianchi Yang. 2018. Local and global information fusion for top-n recommendation in heterogeneous information network. In CIKM.

[19] Binbin Hu, Chuan Shi, Wayne Xin Zhao, and Philip S Yu. 2018. Leveraging meta-path based context for top-n recommendation with a neural co-attention model. In KDD.

[20] Jin Huang, Wayne Xin Zhao, Hongjian Dou, Ji-Rong Wen, and Edward Y Chang. 2018. Improving sequential recommendation with a neural co-attention model. In KDD.

[21] Xiao Huang, Jundong Li, and Xia Hu. 2017. Label informed attributed network embedding. In WSDM.

[22] Zhipeng Huang, Yudian Zheng, Reynold Cheng, Yizhou Sun, Nikos Mamoulis, and Xiang Li. 2016. Meta structure: Computing relevance in large heterogeneous information networks. In KDD.

[23] Jiaru Ji, Jiari Qin, Yuchen Fang, Kounianhua Du, Weina Zhang, Yong Yu, Zheng Zhang, and Alexander J Smola. 2020. An Efficient Neighborhood-based Interaction Model for Recommendation on Heterogeneous Graph. In KDD.

[24] Yuchin Juan, Yong Zhuang, Wei-Sheng Chin, and Chih-Jen Lin. 2016. Field-aware factorization machines for CTR prediction. In RecSys.

[25] Thomas N Kipf and Max Welling. 2016. Semi-supervised classification with graph convolutional networks. ICLR (2016).

[26] Jianxun Lian, Xiaohuan Zhou, Fu Zheng Zhang, Zhongxia Chen, Xing Xie, and Guangzhong Sun. 2018. xdeepfm: Combining explicit and implicit feature interactions for recommender systems. In KDD.

[27] Bin Liu, Ruiming Tang, Yingzhi Chen, Jinkai Yu, HuiFeng Guo, and YuZhou Zhang. 2019. Feature generation by convolutional neural network for click-through rate prediction. In WWW.

[28] Zemin Liu, Vincent W Zheng, Zhou Zhao, Zhao Li, Hongxia Yang, Minghui Wu, and Jing Ying. 2018. Interactive paths embedding for semantic proximity search on heterogeneous graphs. In KDD.

[29] Chen Luo, Wei Pang, Zhe Wang, and Chenghua Lin. 2014. Hete-cf: Social-based collaborative filtering recommendation using heterogeneous relations. In ICDM.
[30] Michael Mathieu, Mikael Henaff, and Yann LeCun. 2013. Fast training of convolutional networks through ffts. *ICLR* (2013).

[31] Alan V Oppenheim. 1999. *Discrete-time signal processing*. Pearson Education India.

[32] Bryan Perozzi, Rami Al-Rfou, and Steven Skiena. 2014. Deepwalk: Online learning of social representations. In *KDD*.

[33] Harry Pratt, Bryan Williams, Frans Coenen, and Yalin Zheng. 2017. Fcnn: Fourier convolutional neural networks. In *ECML*.

[34] Yanru Qu, Ting Bai, Weinan Zhang, Jianyun Nie, and Jian Tang. 2019. An End-to-End Neighborhood-based Interaction Model for Knowledge-enhanced Recommendation. *KDD Workshop*.

[35] Yanru Qu, Han Cai, Kan Ren, Weinan Zhang, Yong Yu, Ying Wen, and Jun Wang. 2016. Product-based neural networks for user response prediction. In *ICDM*.

[36] Yanru Qu, Bohui Fang, Weinan Zhang, Ruiming Tang, Minzhe Niu, Hui Feng Guo, Yong Yu, and Xiuxiang He. 2018. Product-based neural networks for user response prediction over multi-field categorical data. *TOIS* (2018).

[37] Xiang Ren, Jialu Liu, Xiao Yu, Urvasi Khandelwal, Quanquan Gu, Lidan Wang, and Jiawei Han. 2014. Cluscite: Effective citation recommendation by information network-based clustering. In *KDD*.

[38] Steffen Rendle. 2010. Factorization machines. In *ICDM*.

[39] Steffen Rendle, Walid Krichene, Li Zhang, and John Anderson. 2020. Neural Collaborative Filtering vs. Matrix Factorization Revisited. *arXiv* (2020).

[40] Leonardo FR Ribeiro, Pedro HP Saverese, and Daniel R Figueiredo. 2017. struc2vec: Learning node representations from structural identity. In *KDD*.

[41] Badrul Sarwar, George Karypis, Joseph Konstan, and John Riedl. 2001. Item-based collaborative filtering recommendation algorithms. In *WWW*.

[42] Chuan Shi, Binbin Hu, Wayne Xin Zhao, and S Yu Philip. 2018. Heterogeneous information network embedding for recommendation. *TKDE* (2018).

[43] Chuan Shi, Yitong Li, Jiawei Zhang, Yizhou Sun, and S Yu Philip. 2016. A survey of heterogeneous information network analysis. *TKDE* (2016).

[44] Chuan Shi, Jian Liu, Fuzhen Zhuang, S Yu Philip, and Bin Wu. 2016. Integrating heterogeneous information via flexible regularization framework for recommendation. *KAIS* (2016).

[45] Chuan Shi, Zhiqiang Zhang, Ping Luo, Philip S Yu, Yadong Yue, and Bin Wu. 2015. Semantic path based personalized recommendation on weighted heterogeneous information networks. In *CIKM*.

[46] Yizhou Sun, Jiawei Han, Charu C Aggarwal, and Nitesh V Chawla. 2012. When will it happen?: relationship prediction in heterogeneous information networks. In *WSDM*.

[47] Yizhou Sun, Jiawei Han, Xifeng Yan, Philip S Yu, and Tianyi Wu. 2011. Pathsim: Meta path-based top-k similarity search in heterogeneous information networks. *VLDB* (2011).

[48] Jian Tang, Meng Qu, Mingzhe Wang, Ming Zhang, Jun Yan, and Qiaozhu Mei. 2015. Line: Large-scale information network embedding. In *WWW*.

[49] Petar Veličković, Guillem Cucurull, Arantxa Casanova, Adriana Romero, Pietro Lio, and Yoshua Bengio. 2017. Graph attention networks. *ICLR* (2017).

[50] Daixin Wang, Peng Cui, and Wenwu Zhu. 2016. Structural deep network embedding. In *KDD*.

[51] Hongwei Wang, Fuzheng Zhang, Jialin Wang, Miao Zhao, Wenjie Li, Xing Xie, and Minyi Guo. 2018. Ripplenet: Propagating user preferences on the knowledge graph for recommender systems. In *CIKM*.

[52] Jun Wang, Arjen P De Vries, and Marcel JT Reinders. 2006. Unifying user-based and item-based collaborative filtering approaches by similarity fusion. In *SIGIR*.

[53] Ruoxi Wang, Bin Fu, Gang Fu, and Mingliang Wang. 2017. Deep & cross network for ad click predictions. In *ADKDD*.

[54] Xiang Wang, Xiangnan He, Yixin Cao, Meng Liu, and Tat-Seng Chua. 2019. Kgat: Knowledge graph attention network for recommendation. In *KDD*.

[55] Xiang Wang, Xiangnan He, Meng Wang, Fuli Feng, and Tat-Seng Chua. 2019. Neural graph collaborative filtering. In *Proceedings of the 42nd international ACM SIGIR conference on Research and development in Information Retrieval*. 165–174.

[56] Xiao Wang, Houye Ji, Chuan Shi, Bai Wang, Yanfang Ye, Peng Cui, and Philip S Yu. 2019. Heterogeneous Graph Attention Network. In *WWW*.

[57] Jun Wu, Jingrui He, and Jiejun Xu. 2019. Net: Degree-specific graph neural networks for node and graph classification. In *KDD*.

[58] Jun Xiao, Hao Ye, Xiangnan He, Hanwang Zhang, Fei Wu, and Tat-Seng Chua. 2017. Attentional factorization machines: Learning the weight of feature interactions via attention networks. In *IJCAI*.

[59] Linchuan Xu, Xiaokai Wei, Jiannong Cao, and Philip S Yu. 2017. Embedding of embedding (oe): Joint embedding for coupled heterogeneous networks. In *WSDM*.
[60] Rex Ying, Ruining He, Kaifeng Chen, Pong Eksombatchai, William L. Hamilton, and Jure Leskovec. 2018. Graph convolutional neural networks for web-scale recommender systems. In KDD.

[61] Xiao Yu, Xiang Ren, Yizhou Sun, Quanquan Gu, Bradley Sturt, Urvashi Khandelwal, Brandon Norick, and Jiawei Han. 2014. Personalized entity recommendation: A heterogeneous information network approach. In WSDM.

[62] Xiao Yu, Xiang Ren, Yizhou Sun, Bradley Sturt, Urvashi Khandelwal, Quanquan Gu, Brandon Norick, and Jiawei Han. 2013. Recommendation in heterogeneous information networks with implicit user feedback. In RecSys.

[63] Chuxu Zhang, Dongjin Song, Chao Huang, Ananthram Swami, and Nitesh V Chawla. 2019. Heterogeneous graph neural network. In KDD.

[64] Yizhou Zhang, Yun Xiong, Xiangnan Kong, Shanshan Li, Jinhong Mi, and Yangyong Zhu. 2018. Deep collective classification in heterogeneous information networks. In WWW.

[65] Huan Zhao, Quanming Yao, Jianda Li, Yangqiu Song, and Dik Lun Lee. 2017. Meta-graph based recommendation fusion over heterogeneous information networks. In KDD.

[66] Hongmin Zhu, Fuli Feng, Xiangnan He, Xiang Wang, Yan Li, Kai Zheng, and Yongdong Zhang. 2020. Bilinear Graph Neural Network with Neighbor Interactions. In IJCAI.