Learning Dynamic User Interest Sequence in Knowledge Graphs for Click-Through Rate Prediction

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Learning Dynamic User Interest Sequence in Knowledge Graphs for Click-Through Rate Prediction

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Abstract—Despite that path-based and embedding-based models with knowledge graphs (KGs) achieve better recommendation performance compared with other deep learning based methods, such improvement is limited due to a lack of modeling user's dynamic interest. To address this issue, we explore a principled model to provide semantic understanding of each item in user's historical interest sequence in KGs. Specifically, we propose a multi-granularity dynamic interest sequence learning method, which is based on knowledge-enhanced path mining and interest fluctuation signal discovery, to obtain semantic-enhanced paths. Furthermore, the paths are embedded by the SEP2Vec, and merged through the proposed entropy-aware pooling layer to obtain the user preference representation, which is then used to learn dynamic user interest sequence. Experimental results on two public datasets of movie and music recommendation, and two industrial datasets of personalized local service recommendation in Alipay App have illustrated that the proposed model can achieve significantly better prediction performance compared with other known baselines.

Index Terms—Knowledge graphs, Deep Learning, Recommendation systems.

1 Introduction

Click-through rate prediction in recommendation systems (RSs) has become a significant decision aid for online personalized recommendation in a variety of scenarios, including movie, music, and mini programs recommendation which is shown in Figure 1. Recent research shows that accurate recommendation results can not only shorten user's information acquisition time, but also enhance their willingness to purchase [1], [8], [9], [11], [33]. To model user preference from their massive behavioral data, many prior efforts have been devoted to traditional recommendation methods, especially deep learning based recommendation systems (DLRSs) such as libFM [14], PER [12], Wide&Deep [13] and xDeepFM [5]. Despite its effectiveness, DLRSs suffer from the inability of modeling user preference with side information, e.g., item attributes, attribute networks and so on [10]. Moreover, they consider the topological structures of KGs without modeling the semantics of entities and relations encoded in KGs, thus failing to fully exploit KGs for recommendation.

In the literature, some researchers have started to utilize KGs to characterize user preference in recommendation systems. They focus on combining KGs, an important source of information, to make better recommendation decisions. Thus, how to integrate side information from KGs into recommendation system to express high-level semantics becomes an important issue [30]. As one branch, path-based methods such as DKRL [19], [20], CKE [18], DKN [15] and RippleNet [16], use the side information in KGs by exploring the similarities between users and items with well-designed paths (usually named meta-path). Another line of research leverages the KG embedding techniques such as MKR [17], KTUP [11], RuleRec [24] and CFKG [25] to jointly conduct the two tasks of recommendation and KG completion with shared item embeddings. However, the fact is that the path-based methods usually rely on manually designed meta-

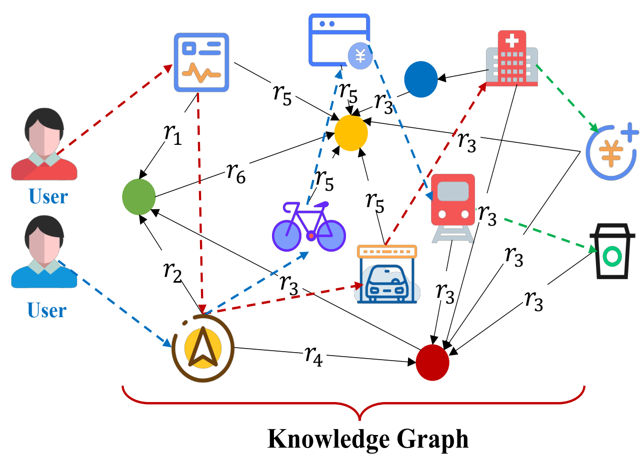

Fig. 1: A demonstration of KG-based local service recommendation.

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paths or its variants and fail to completely explore all the informative paths in KGs, thus limiting their capability to generate high-quality recommendations. As for the embedding based ones, although these methods can automatically explore the entities information and their relations, they lack a good use of KGs to understand the semantics of each item in user interest sequence. Thus, they fail to fully explore KGs for recommendation, especially when the KG embedding module is not directly adapted to the recommendation task.

Although studies aforementioned have been carried out in the general area of RS, there are still much more to be explored in the specific area of KG-based RS. Essentially, modeling user sequential preference for mining user dynamic interest with KGs is still less well-studied. For example, [21] improves the efficiency of preference representation by modeling user sequential interest pattern and short-term preferences. However, extending existing dynamic network embedding models [26], [27], [29] are not enough to fully capture complicated user preference over time in the semantic level due to the lack of attribute side information. On the contrast, the proposed method can model not only the semantics of entities over time, but their relations by encoding different granularity power of paths in characterizing user preferences, thus providing a unified approach to learn the representations of both entities and relations.

In general, the major difference between our work and the above models is that we provide a new perspective for RS with the help of learning dynamic user interest sequence from KGs. Considering the limitations of existing methods, it is of critical importance that our model can learn the semantics of user dynamic interest in an efficient, explicit, and end-to-end manner. Specifically, to model dynamic user interest, the proposed multi-granularity dynamic interest sequence learning method provides semantic understanding of each item in user historical interest sequence in KGs.

The main contributions in this paper are summarized as follows:

- To fully capture the complicated user preference over time in the semantic level, we propose a novel multi-granularity dynamic interest sequence learning method by mining knowledge-enhanced path and discovering interest fluctuation signal in KGs.
- An entropy-aware pooling method is proposed to merge the multi-granularity embedding of dynamic interest sequence in an adaptive way.
- We advance the learning on KGs for RS by testing two large-scale industrial datasets, and show the efficiency of the proposed method.

2 Related Work

In recent years, RS has been successfully applied in many fields, such as search engines [42], E-service website [40] and news platform [41]. Generally, traditional industrial-level RS mainly focuses on collaborative filtering based methods [43], [44] and deep learning based methods [10], [38], which may not be able to utilize side information [39] such as item attributes, user profiles and contexts. Additionally, they also perform poorly in situations where users and items have few interactions.

Some KG embedding based models have been widely applied to industrial-level recommendation tasks to enhance semantic interaction of user-item. For example, PER [14] treats the KG as a heterogeneous information network, and then constructs meta-path [45] to model the semantic interaction between user-item pairs. [18] has proposed a hybrid RS model named CKE, which can jointly learn the latent representations by collaborative filtering as well as learning semantic representations of items via KGs. [15] also proposed a KG embedding based method for news recommendation. However, these methods usually cannot learn entity embedding from KGs in an end-to-end fashion, which increases the complexity of model design. Moreover, the performance of this kind of meta-path based method heavily relies on the quality of manually designed meta-paths. And the fact is that it is not an adaptive approach, because it is hard to design a meta-path without sufficient experience in specific areas [16], [46].

Prior efforts usually leverage features obtained by KG embedding to learn the semantic representation of items in KGs. Several KG-based RS methods have been proposed to learn the structural information in KGs more directly. For example, as the representative of an outward propagation method, the RippleNet [16] can model the propagation of user preferences over entities by automatically and iteratively extending user's potential interests along paths in KGs, which is similar to ripple propagating on the water. It should be noticed that this kind of methods usually learn the representation for user behaviors through entity embedding in a KG indirectly, instead of using user and item features from KG embedding [47]. To further explore user preferences in KG, a multi-task feature learning approach for KG enhanced recommendation [17] which is named MKR is proposed to share the information between DLRS and the KG by an end-to-end multi-task learning framework. However, these methods ignore to mine the semantics of the relations between each neighbouring items in user's behaviors, thus failing to fully capture KG semantics for user preference exploration.

Furthermore, to fully exploit semantic relationships encoded in KGs for recommendation, it requires to capture not only the semantics of different paths but also their distinctive saliency in describing user preferences toward items [28]. To address this issue, RNN-based methods [22] are introduced into KG-based RS. KPRN [5] and RKGE [2] are proposed to construct user-item interactions via KGs which can improve the interpretability of RS. Moreover, an attention-enhanced knowledge-aware user preference model (AKUPM) [48] is proposed to model user's preference with their click history and to explore the relationships which are essentially determined by the interactions among entities in KGs. Although these methods can automatically learn the semantic representation and model the relationships between entities from user-item interactions in KGs, it is still limited due to a lack of fully exploration of user's dynamic interests via KGs.

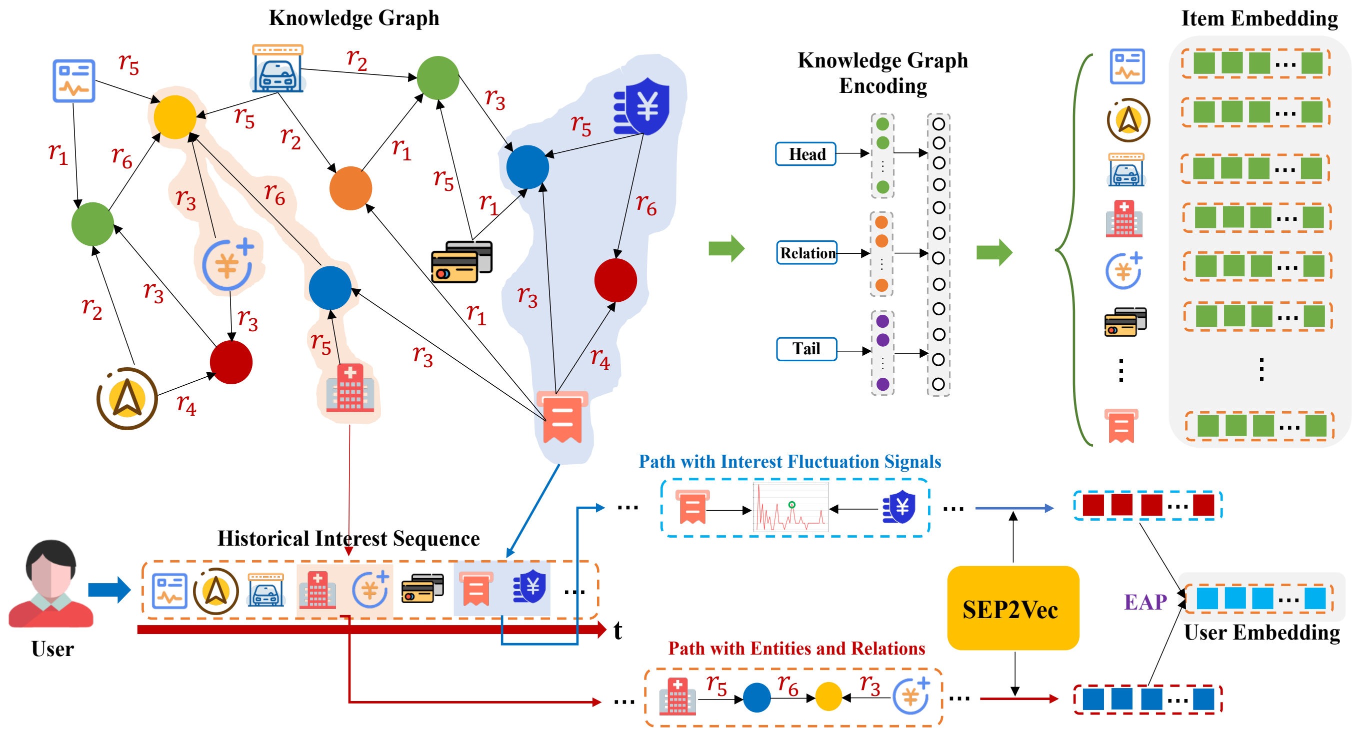

Fig. 2: Graphical illustration of learning dynamic user interest sequences in KGs for local service recommendation. This figure is composed of two parts. The bottom part shows the multi-granularity dynamic interest sequence learning based on KG path mining (red dotted frame) combined with interest fluctuation signal discovery (blue dotted frame) to obtain semantic-enhanced paths. Furthermore, the paths can be embedded by the SEP2Vec model, and be merged through the entropy-aware pooling (EAP) layer to obtain the user embeddings. The top part shows the learning process of item embedding based on KG encoding.

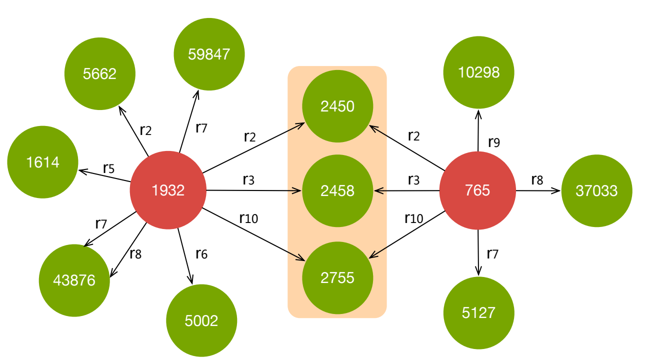

Fig. 3: A demonstration of bridge entities between entities in a KG. We can see that the two entities (in red color) have three bridge entities in the KG (in background color).

3 PRELIMINARIES

An RS with KGs can be formulated as follows. We start by introducing some notations (listed in Table 1). Given a user set $U = \{u_1, u_2, \dots, u_{|U|}\}$, an item set $V = \{v_1, v_2, \dots, v_{|V|}\}$, we can define the user-item implicit feedback matrix as $R = \{R_{uv} | u \in U, v \in V\} \in \mathbb{R}^{|U| \times |V|}$, where R_{uv} denotes historical user-item interactions, which is an indicator function of whether user u has an interaction with item v. The type of an interaction can be clicks, music/movie plays, payments and so on, depending on the application scenario and the business objective.

Furthermore, we define a KG as follows. Let $\mathcal{E} = \{e_1, e_2, ..., e_m\}$ and $\mathcal{R} = \{r_1, r_2, ..., r_n\}$ denote the sets of entities and relations, respectively. Then, a KG can be defined as a directed graph $G = (\mathcal{E}, \mathcal{L})$ with an entity type mapping function $\phi : \mathcal{E} \to \mathcal{A}$ and a link type mapping function $\psi : \mathcal{L} \to \mathcal{R}$, where $\mathcal{A}$ denotes the set of entity attributes. Each edge $l \in \mathcal{L}$ can be mapped to an entity relation $\psi(l) \in \mathcal{R}$.

In addition, there are two kinds of paths in the multi-granularity dynamic interest sequence learning. The first kind, namely path $\mathcal{P}_{e_i,e_j}$, is defined as the shortest one connecting entities e_i and e_j in the KG. Moreover, the number of shared entities, which is termed as bridge entities, that connect both two entities e_i and e_j is defined as n_{e_i,e_j}. To understand the bridge entities in KGs more clearly, one can refer to Figure 3. Then, we also define the historical interest sequence for user u as $S_u = \{s_1, s_2, ..., s_t, ...\}$, where s_t is an entity and t is the time index. User u moves to entity s_t from s_{t-1}. Next, the second kind, namely path $\mathcal{P}_{s_{t-1},s_t} = \{s_{t-1}, n_{s_{t-1},s_t}, s_t\}$, is defined as a sequence of s_t, s_{t-1} and n_{s_{t-1},s_t}. Furthermore, with the given user u, the corresponding historical interest sequence S_u, the KG G, and the user-item implicit feedback matrix R, we can define our task to predict whether user u has the potential interest in item v, which is not in his/her historical interest sequence. The task can be formulated as follows:

$$\widehat{y}_{uv} = \mathcal{F}_{\Theta}(u, v | R, S_u, G), \tag{1}$$

where $\mathcal{F}(\cdot)$ denotes the underlying model with parameters

TABLE 1: Notation and description

Notation	Description
U	The user set
V	The item set
R	The user-item implicit feedback matrix
$\mathcal{E}$	The sets of entities
$\mathcal{R}$	The sets of relations
$\mathcal{A}$	The set of entity attributes
ϕ	The entity type mapping function
ψ	The link type mapping function
G	The knowledge graph
$\mathcal{P}_{e_i,e_j}$	The shortest path connecting e_i and e_j in KG
n_{e_i,e_j}	The number of shared entities between e_i, e_j
S_u	The historical interest sequence for user u
$\mathcal{P}_{s_{t-1},s_t}$	A sequence of s_t, s_{t-1} and n_{s_{t-1},s_t}

Θ that we aim to learn, and $\widehat{y}_{uv}$ means the predicted probability of user-item interaction between user u and item v.

4 METHODOLOGY

Different from traditional DLRS methods, effective KG based approaches are expected to understand users from rich historical behaviors in the semantic level. Thus, learning users' dynamic interest sequences by mining side information from KGs are critical. In this section, we describe the framework for the proposed model which is also shown in Figure 2.

4.1 Dynamic Interest Sequence Learning

Facing with a large amount of user activity data, how to learn the semantics between items in historical interest sequences is a key problem. In this section, we exploit user sequential behaviors by dynamic interest sequence learning (DISL) with KGs (outlined in Algorithm 1).

4.1.1 Knowledge-enhanced Path Mining

A KG usually contains a lot of relations among entities, which provides rich semantic information. Traditional sequential recommendation methods usually model user long-term preference and build a static representation, and then predict click probability by merging the learned item representation. In our model, to fully utilize semantic information among entities and relations in KGs for exploiting user dynamic sequential behaviors, we mine paths from KGs to encode the user historical sequences into semantic-enhanced paths. Specifically, we construct the user historical interest sequence S_u from user-item implicit feedback matrix R according to the timestamps. Next, we extract path $\mathcal{P}_{e_i,e_j}$ for each neighboring entity pair $< e_i, e_j >$ in S_u from the KG, where e_i is s_{t-1} and e_j is s_t. Then, we connect these paths end to end, and the semantic-enhanced path based on the KG can be obtained as $P_p = \{\mathcal{P}_{e_1,e_2}, \mathcal{P}_{e_2,e_3}, ..., \mathcal{P}_{e_{t-1},e_t}, ...\}$. It should be noted that a KG can be complicated and may contain different entity types and relation types in different orders and with various lengths. In addition, considering that the increase in path length will cause more noise and more irrelevant semantic information, we randomly sample one of the shortest paths (maximum path length $K = 3$ for $\mathcal{P}_{e_i,e_j}$) between two entities in KGs as the semantic-enhanced path to improve the efficiency [2], [4], [5].

Algorithm 1 DISL (U, V, R, S, G, d)

Require:
U: User set, R: Rating matrix, S: User's historical sequences, G: KG, d: Embedding size
Ensure:
$E(u) \in \mathbb{R}^d$: User Embedding

```
while u ∈ U do
    for (s_{t-1}, s_t) ∈ S_u do
        P_{s_{t-1},s_t} ← MineKGPath(G, s_{t-1}, s_t)
        B_{s_{t-1},s_t} ← CalBridgeNum(G, s_{t-1}, s_t)
    end for
    P_p = {P_{s_1,s_2}, ..., P_{s_{t-1},s_t}, ...}
    P_s = {s_1, n_{e_1,e_2}, ..., s_{t-1}, n_{e_{t-1},e_t}, s_t, ...}
    E(u) ← EAP(SEP2Vec(P_p), SEP2Vec(P_s))
end while=0
```

Algorithm 2 SEP2Vec ($\mathcal{P}$, R, ω, d, τ)

Require:
$\mathcal{P}$: Path matrix, R: Rating matrix, ω: window size, d: embedding size, τ: number of training epochs
Ensure:
$\mathcal{P}_{emb} \in \mathbb{R}^d$: Embedding of semantic-enhanced path

```
while iter = 1 < τ do
    H ← GetUserId(R)
    Initialization: Sample Θ and Φ from P, H
    PV-DM(Θ, Φ, ω, d) [3]
end while=0
```

4.1.2 Interest Fluctuation Signal Discovery

Based on user historical behavior data, we can find that the similarity between neighboring items is changing along user's interest sequence. Specifically, user preferences appear to be fluctuating over a period of time. If we can timely capture this interest fluctuation of users, it will be easier to understand their click behaviors. As shown in Figure 3, two similar items usually have more shared entities in a KG, and the number of shared entities n_{e_i,e_j} between entities e_i and e_j can reflect the similarity between two items. For example, two similar films often have the same theme, even with the same actors and directors. The fluctuation of such similarity in neighboring items is termed as user interest fluctuation signal, and is characterized by n_{e_i,e_j}.

Furthermore, in order to exploit user interest fluctuation signals more effectively, we propose a fluctuation-signal-strength-based user historical sequence encoding method to obtain the semantic-enhanced paths in the second granularity. Specifically, given the historical interest sequence for user u as $S_u = \{s_1, s_2, ..., s_t, ...\}$, the number of bridge entities corresponding to each neighboring items in a KG can be calculated as $\{n_{s_1,s_2}, n_{s_2,s_3}, ..., n_{s_{t-1},s_t}, ...\}$, which is then aggregated

TABLE 2: The negative feedback records in selected user's future behavior (NSE is short for numbers of shared entities).

Last Click	Next Item	NSE	Rating
NO.132	NO.2040	2	0
NO.132	NO.402	1	0
NO.132	NO.523	0	0
NO.132	NO.915	1	0
NO.132	NO.1026	0	0
NO.132	NO.1317	2	0
NO.132	NO.1049	2	0
NO.132	NO.1132	2	0
NO.132	NO.66	3	0
NO.132	NO.822	2	0

TABLE 3: The positive feedback records in selected user's future behavior (NSE is short for numbers of shared entities).

Last Click	Next Item	NSE	Rating
NO.132	NO.2105	3	1
NO.132	NO.1735	2	1
NO.132	NO.2185	4	1
NO.132	NO.829	6	1
NO.132	NO.213	5	1
NO.132	NO.165	5	1
NO.132	NO.379	4	1
NO.132	NO.943	3	1
NO.132	NO.842	4	1
NO.132	NO.616	2	1

with S_u as $P_s = \{s_1, n_{s_1,s_2}, s_2, ..., s_{t-1}, n_{s_{t-1},s_t}, s_t, ...\} = \{\mathcal{P}_{s_1,s_2}, \mathcal{P}_{s_2,s_3}, ..., \mathcal{P}_{s_{t-1},s_t}, ...\}$.

4.1.3 An Example of the Interest Fluctuation Signal

To intuitively demonstrate how the interest fluctuation signal works in the proposed DISL model, we randomly sample a user and his historical behavior from MovieLens-1M dataset and give an example of the interest fluctuation signal in this section.

Generally, user's interest fluctuation signal is a typical time series signal extracted from KGs. For example, users may be interested in action movies over a period of time, and then show no interest for some other time. These can be expressed in the interest fluctuation signal which is very important for effectively modeling user preferences.

More specifically, we illustrate an example of historical interest sequence from MovieLens-1M as $1977 \xrightarrow{2} 748 \xrightarrow{9} 738 \xrightarrow{3} 1776 \xrightarrow{6} 1778 \xrightarrow{2} 765 \xrightarrow{5} 1554 \xrightarrow{3} 2087 \xrightarrow{4} 16 \xrightarrow{2} 309 \xrightarrow{2} 1806 \xrightarrow{4} 1459 \xrightarrow{6} 1211 \xrightarrow{3} 1417 \xrightarrow{3} 2314 \xrightarrow{3} 1629 \xrightarrow{2} 1461 \xrightarrow{3} 1584 \xrightarrow{4} 1042 \xrightarrow{3} 839 \xrightarrow{6} 840 \xrightarrow{5} 838 \xrightarrow{3} 1124 \xrightarrow{3} 1867 \xrightarrow{3} 1458 \xrightarrow{3} 841 \xrightarrow{4} 1457 \xrightarrow{3} 1206 \xrightarrow{3} 875 \xrightarrow{2} 299 \xrightarrow{3} 534 \xrightarrow{3} 1943 \xrightarrow{3} 1709 \xrightarrow{3} 1528 \xrightarrow{3} 353 \xrightarrow{3} 243 \xrightarrow{5} 938 \xrightarrow{3} 1464 \xrightarrow{3} 132$, where the value above the arrow between the two item ID denotes the numbers of shared entities. The corresponding interest fluctuation signal of this case is shown in Figure 4.

Moreover, we also provide the selected user's positive and negative feedback records in future behavior in Table 3 and Table 2 respectively. As we can see from Table 3 and Table 2, when user clicks a item (No.132), the recommended items in positive set (in Table 3) almost have more shared entities compared with the negative ones (in Table 2). In addition, we can also find that all the items from both positive and negative feedback sets have internal consistency in number of shared entities in KG. These intuitively show the influence of user's real-time preferences reflected in interest fluctuation signal on his next click behavior.

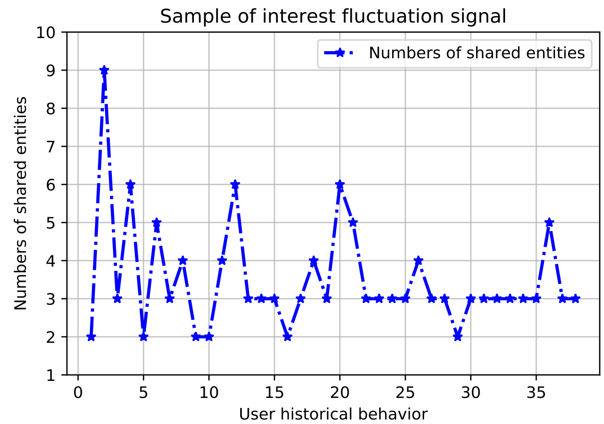

Fig. 4: Instance of interest fluctuation signal.

4.2 Semantic-enhanced Path Embedding

As is outlined in Algorithm 2, SEP2Vec is employed to obtain the embeddings of the paths P_p and P_s from multi-granularity dynamic interest sequences. The user ID in R is mapped to a unique vector as the index, which is represented by a column in matrix H and each set of semantic-enhanced paths from different granularity can be seen as a special word [31], which is also mapped to a unique vector, which is represented by the column in matrix $\mathcal{P}$. The indices and the contextual special words are concatenated to predict the next word in fixed-length surroundings sampled from a sliding window over semantic-enhanced paths. Specifically, given an semantic-enhanced path $\mathcal{P}_M$ $(M = p, s)$, the objective of SEP2Vec is to maximize the averaged log probability

$$\frac{1}{L}\sum_{t=\omega}^{L-\omega} \log p(\mathcal{P}_{M_{t-1,t}} | \mathcal{P}_{M_{t-1-\omega,t-\omega}}, ..., \mathcal{P}_{M_{t-1+\omega,t+\omega}}), \quad (2)$$

where L is the length of $\mathcal{P}_M$, ω is the size of the sliding window. The prediction task is typically done via a multiclass classifier based on softmax as

$$p(\mathcal{P}_{M_{t-1,t}} | \mathcal{P}_{M_{t-1-\omega,t-\omega}}, ..., \mathcal{P}_{M_{t-1+\omega,t+\omega}}) = \frac{e^{y_{\mathcal{P}_{M_{t-1,t}}}}}{\sum_j e^{y_j}}. \quad (3)$$

Each y_j is un-normalized log-probability for each output node $j \in (1, 2, ..., L)$ in the path set, computed as

$$y = b + Wh(\mathcal{P}_{M_{t-1-\omega,t-\omega}}, ..., \mathcal{P}_{M_{t-1+\omega,t+\omega}}; \mathcal{P}, H), \quad (4)$$

where W, b are the softmax parameters, h is constructed by a concatenation of node vectors extracted from $\mathcal{P}$ and the index vector extracted from H, which can be thought of as a special node vector [3]. In addition, we use stochastic gradient decent (SGD) to train the SEP2Vec and the gradient obtained by backpropagation can be used to update parameters of the model.

4.3 Model Optimization

4.3.1 Preference Characterization

As the two semantic-enhanced paths extracted by knowledge-enhanced path mining and interest fluctuation signal discovery, they may play different roles in modeling the semantics in user dynamic interest sequences. Specifically, one path depicts the user behavior process in an explicit manner, and the other depicts the user interest fluctuations in an implicit manner. We design an entropy-aware pooling (EAP) method to achieve information fusion between explicit semantics and implicit signals from the output of SEP2Vec model. Essentially, sample entropy can effectively describe the stability of time series signals and is not easily affected by the length of the signals [34]. Therefore, we implement the EAP by representing the stability of user interest fluctuation signal with sample entropy. Specifically, the sample entropy $SampEn(m, r, N)$ of the dynamic interest fluctuation signal $\{n_{s_1,s_2}, n_{s_2,s_3}, ..., n_{s_{t-1},s_t}, ...\}$ which contains N values is obtained according to the following process. Note that according to [35], we set $m = 1$ and r is 0.2 times of standard deviation. Firstly, the user interest fluctuation signal is divided into $(N - m + 1)$ subsegments as $X_m(1), ..., X_m(N - m + 1)$, where $X_m(i) = \{x(i), x(i+1), \ldots, x(i+m-1)\}$, $x(i) = n_{s_i,s_{i+1}}$ and $i = \{1, 2, \ldots, N - m + 1\}$. Next, the distance between $X_m(i)$ and $X_m(j)$ is defined as:

$$d[X_m(i), X_m(j)] = \max_{k=0,...,m-1}(|x(i+k) - x(j+k)|). \quad (5)$$

Then, the number of $d[X_m(i), X_m(j)] < i$ for each $\{i|1 \le i \le N - m + 1\}$ is counted, which is expressed by $N_m(i)$, and $C_i^m(r)$ is obtained by:

$$C_i^m(r) = N_m(i)/(N - m). \quad (6)$$

Subsequently, the probability that two sequences are similar for m points is:

$$\phi^m(r) = \frac{1}{N-m}\sum_{i=1}^{N-m} C_i^m(r). \quad (7)$$

Similarly, the probability that two sequences are similar for $m+1$ points is:

$$\phi^{m+1}(r) = \frac{1}{N-(m+1)}\sum_{i=1}^{N-(m+1)} C_i^{m+1}(r). \quad (8)$$

Furtehrmore, the sample entropy is defined as:

$$SampEn(m, r, N) = -\ln(\frac{\phi^{m+1}(r)}{\phi^m(r)}). \quad (9)$$

Finally, the EAP can choose different pooling modes [36] for each user according to the entropy value. As an experience-based trade-off strategy, if it is stable, i.e., the entropy value is less than 0.5, the avg-pooling will be selected, and otherwise, the max-pooling.

4.3.2 Click-Through Rate Prediction

As is shown in Figure 2, each item v is associated with an item embedding $E(v) \in \mathbb{R}^d$, where d is the dimension of the embedding. Item embedding can incorporate one-hot ID and other context information of the item, which depends on the specific application scenario. In this paper, we map the encoded one-hot ID information into item embedding [16] during the embedding-lookup process. Note that all the items V are included in the entity set $\mathcal{E}$. Finally, the user embedding and item embedding are combined to output the predicted click probability:

$$\widehat{y}_{uv} = \frac{1}{1+\exp(-E(u)^T E(v))}. \quad (10)$$

Furthermore, we define the click-through rate prediction task in RS as a binary classification problem, where an observed user-item interaction is assigned a target value 1, otherwise 0. Specifically, we use the cross entropy as the loss function,

$$L = -\left(\sum_{(u,v)\in R^+} \log \widehat{y}_{uv} + \sum_{(u,v)\in R^-} \log(1-\widehat{y}_{uv})\right), \quad (11)$$

where R^+ and R^- are the positive and negative rating records.

5 Experimental Results

In this section, we present our experimental results. We describe the data first, and then, the baselines for comparison, evaluation metric, and parameter settings. Furthermore, we show experimental results and provide the corresponding analysis.

5.1 Data Description and Experiment Settings

5.1.1 Public Dataset

We use the following open benchmark datasets **MovieLens-1M** and **Last.FM** in our experiments. The statistics of the two datasets are shown in Table 4. Since the rating record data of the MovieLens-1M dataset is explicit (it uses a 5-score scale which indicates how much the user likes the movie), we transform them into 0 if the rating score is less than 4, and otherwise, 1, which is a fairly widespread practice [16], [17]. In addition, to obtain the historical interest sequences for user u, the user behavior sequences are generated in the two datasets according to the timestamps in the rating records. It should be noted that the timestamps recorded in the Last.FM dataset is the time when the user interacts with a musician by any means, and this kind of user-item interaction may occur more than once. We complete the timestamp extraction by recording the time of the last interaction. Furthermore, in our experimenters, we use two corresponding accessible knowledge graphs [16], [17] for datasets MovieLens-1M and Last.FM.

- **MovieLens-1M**[1]**:** It is a widely used benchmark public dataset for movie recommendations [6], which contains 10,000,054 ratings and 95,580 tags applied

1. https://grouplens.org/datasets/movielens/1m/

TABLE 4: Detailed statistics of MovieLens-1M and Last.FM Datasets. (sparsity shows the sparsity of each dataset (i.e., #sparsity=1-#interactions / (#users $\times \#item$)).

Data Sources	MovieLens-1M	Last.FM
#users	6,036	1,872
#items	2,445	3,846
#interactions	753,772	42,364
#sparsity	0.9489	0.9941
#sequence length	46.755	7.62
#train samples	452,264	25,408
#valid samples	150,754	8,469
#test samples	150,754	8,469
#KG triples	20,782	15,518
#entities	182,011	9,366
#relations	12	60

TABLE 5: Detailed statistics of Alipay-A and Alipay-B Datasets.(i.e., #sparsity=1-#interactions / (#users$\times \#items$)).

Data Sources	Alipay-A	Alipay-B
#users	212,089	2,963,532
#items	311	25,386
#interactions	2,121,437	68,018,027
#sparsity	0.9678	0.9990
#sequence length	5.904	104.524
#train samples	2,094,360	67,233,659
#valid samples	27,077	784,368
#test samples	27,077	784,368
#KG triples	206,865	445,212
#entities	10,753	65,763
#relations	12	8

TABLE 6: Detailed hyperparameter settings for DISL.

Dataset	d	lr	bs
MovieLens-1M	128	0.002	1024
Last.FM	64	0.0002	512
Alipay-A	32	0.0001	1024
Alipay-B	16	0.001	1024

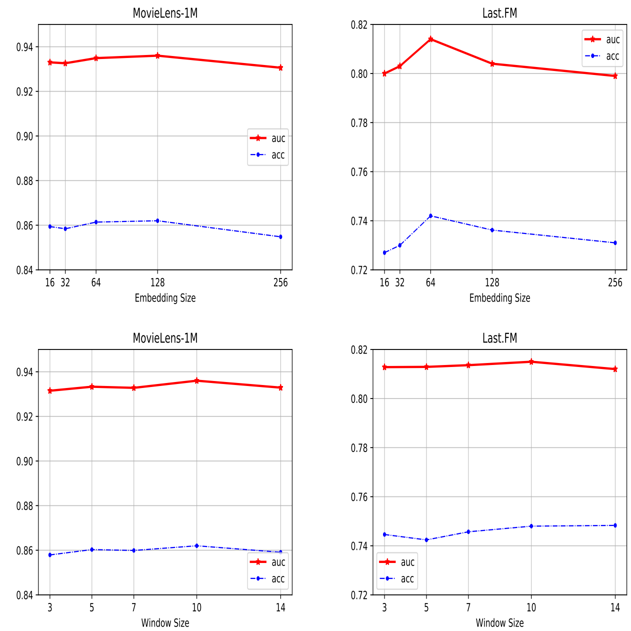

Fig. 5: Sensitivity of embedding size d and window size ω.

to 10,681 movies by 71,567 users of the online movie recommender service MovieLens system.

- **Last.FM[2]:** This dataset [7] is a widely used benchmark dataset for music recommendations, which contains social networking, tagging, and musician listening information from a set of 2,000 users in Last.FM online music system.

5.1.2 Industrial Datasets

The statistics of the two following industrial scenarios datasets is shown in Table 5. Volume of Alipay Dataset is much larger than both MovieLens and Last.FM, which brings more challenges.

- **Alipay Dataset-A (Alipay-A):** It includes rich article recommendations of services in the fields such as medical insurance, fitness and exercise, accidents, health and so on. The dataset is collected from server logs contains 2.1 million pieces of explicit feedbacks from 212,089 users.
- **Alipay Dataset-B (Alipay-B):** It contains 68 million interactions of over 2.9 million users on more than 25 thousand items. According to the user's location, hobby, and personality attributes, local services for daily life are recommended, such as "Go hiking together on weekends", "What to eat at noon" and so on.
- **Antfin Digital Local Service KG:** It is a large-scale KG used to accurately depict digital local services, covering more than 30 entity types and 70 relation types, with a total of 370 million entities and 29.4 billion relations.

We collect traffic logs from the two online local service recommendation scenarios in Alipay APP, which contain timestamp, user id, item id. We gather user feedback (1 for click and 0 for no click) data across one month (e.g., from June 7, 2019 to July 6, 2019) as the training set and that from the next day (e.g., July 7, 2019) as the test set. Furthermore, we select all the entities and corresponding relations involved in our two online local service recommendation scenarios from the Antfin Digital Local Service KG. Such entities types include category, region, crowd label, function word, keywords, service brand and so on. In addition, it also consists of many kinds of relations (more than 15) among the selected entities. The detailed statistics and distributions of the datasets and the extracted KGs are shown in Table 5.

2. https://grouplens.org/datasets/hetrec-2011/

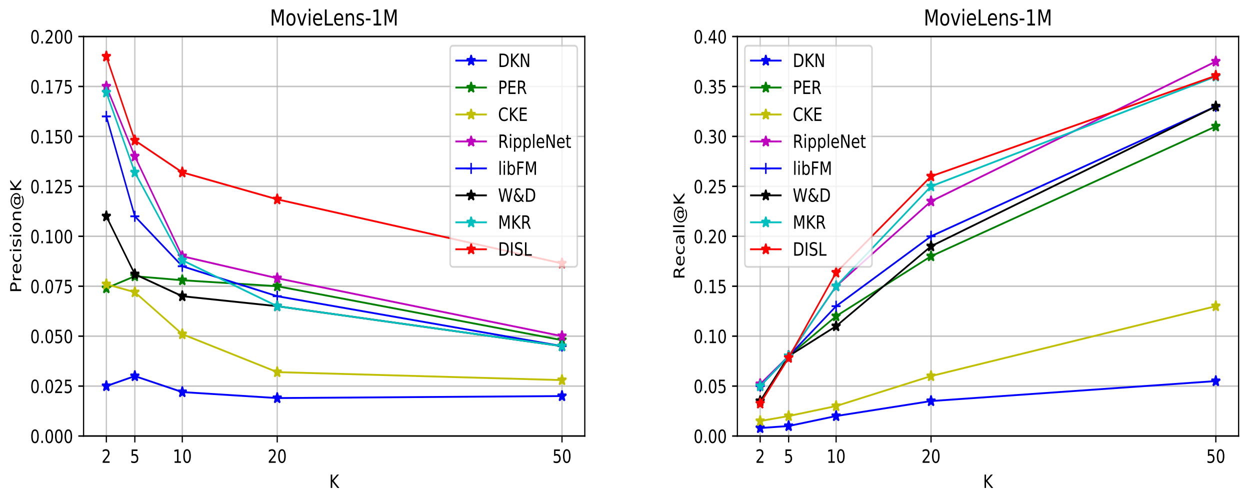

Fig. 6: The results of Precision@K and Recall@K in top-K recommendation on MovieLen-1M dataset.

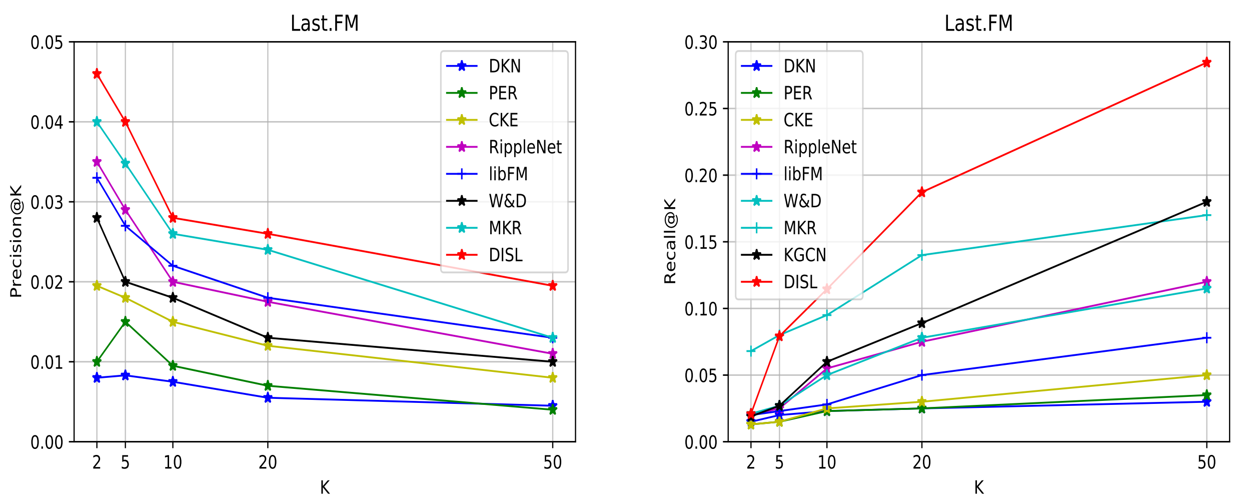

Fig. 7: The results of Precision@K and Recall@K in top-K recommendation on Last.FM dataset.

5.2 Experimental Settings

5.2.1 Evaluation Metrics

We use Area Under the Curve (AUC), Accuracy (ACC), precision@TopK and recall@TopK to evaluate the performance of the methods on public datasets, and use AUC for performance evaluation on industrial datasets.

5.2.2 Baselines

We compare our proposed DISL with both DLRS [12], [13], [14] and KGRS [15], [16], [17], [18], [32] baselines. Note that, in order to ensure the fairness of the comparison, we quote the results and follow all settings reported by each method in their original literature.

- **LibFM** [14]: It is a classic feature-based factorization model for CTR prediction. We concatenate user ID, item ID, and the corresponding averaged entity embeddings learned by TransR [23] as the input.
- **PER** [12]: It extracts meta-path based features to represent the interactions between users and items. In this paper, we use all this kind of features for PER, e.g., "movie-genre-movie".
- **Wide&Deep** [13]: It is a general DLRS combining a (wide) linear channel with a (deep) nonlinear channel. Similar to LibFM, we use the embeddings of users, items, and entities as the input.
- **CAFSE** [37]: It is a sequential RS method, which uses CNN and attention-based sequential feature extractor module to capture the possible features of user behaviors at different time intervals.
- **CKE** [18]: It is implemented as CF plus structural knowledge module in this paper.
- **DKN** [15]: It treats entity embedding and text embedding as multiple channels and combines them together in CNN. In this paper, we use movie names, music titles, insurance news titles and top life topics as the input for textual channels.
- **RippleNet** [16]: It models the propagation of user preferences over entities by automatically and iteratively extending user's potential interests along

TABLE 7: Performance comparison (best performance is in bold and increase rate compared to the best is in bracket).

Model	Overall Performance of CTR Prediction of Two Public Datasets			
	MovieLens-1M		Last.FM	
	AUC	ACC	AUC	ACC
LibFM [14]	0.892(-4.4%)	0.812(-5.0%)	0.777(-3.8%)	0.709(-4.3%)
PER [12]	0.71(-22.6%)	0.664(-19.8%)	0.633(-18.2%)	0.596(-15.6%)
Wide&Deep [13]	0.898(-3.8%)	0.82(-4.0%)	0.756(-5.9%)	0.688(-6.4%)
CAFSE [37]	0.811(-12.5%)	-	-	-
AKUPM [48]	0.918(-1.8%)	0.845(-1.7%)	-	-
CKE [18]	0.801(-13.5%)	0.742(-12.0%)	0.744(-7.1%)	0.673(-7.9%)
DKN [15]	0.655(-28.1%)	0.589(-27.3%)	0.602(-21.3%)	0.581(-17.1%)
RippleNet [16]	0.913(-2.3%)	0.835(-2.7%)	0.768(-4.7%)	0.691(-5.1%)
MKR [17]	0.917(-1.9%)	0.843(-1.9%)	0.797(-0.8%)	**0.752**
KGCN [32]	0.919(-1.7%)	0.845(-1.7%)	0.845(-1.7%)	0.721(-3.1%)
DISL (no interest fluctuation signal)	0.924(-1.2%)	0.849(-1.3%)	0.804(-1.1%)	0.736(-1.6%)
DISL (no entropy-aware pooling)	0.930(-0.6%)	0.856(-0.6%)	0.814(-0.1%)	0.742(-1.0%)
DISL (entropy-aware pooling)	**0.936**	**0.862**	**0.815**	0.748(-0.4%)

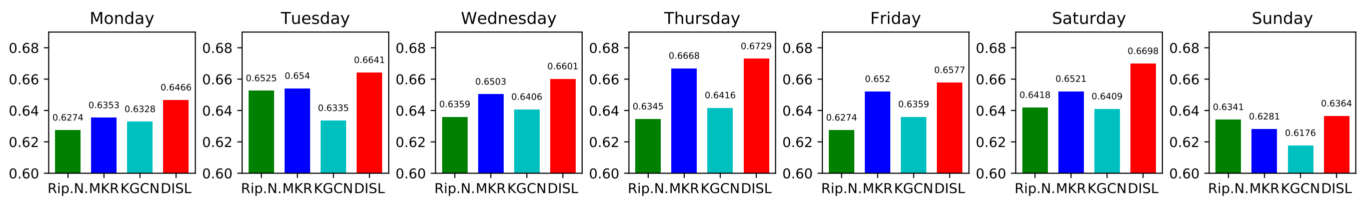

Fig. 8: Performance of RippleNet, MKR, KGCN and the proposed model on Alipay-A dataset for one week.

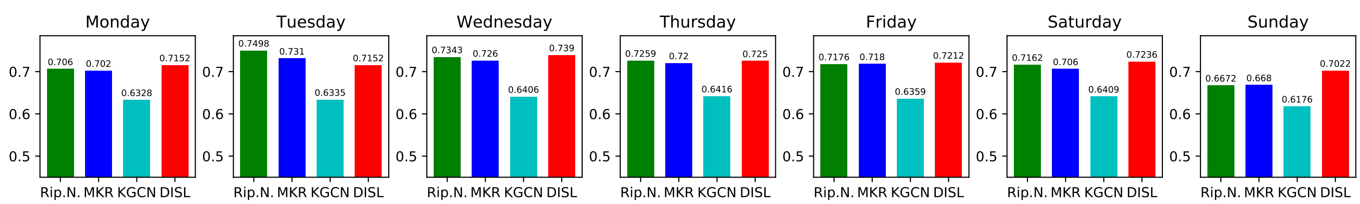

Fig. 9: Performance of RippleNet, MKR, KGCN and the proposed model on Alipay-B dataset for one week.

paths in KGs.

- **MKR** [17]: It is a multi-task feature learning approach for recommendation, which combines a KGE task to recommendation task.
- **KGCN** [32]: It is knowledge graph convolutional networks for RS, which uses the technique of graph convolutional networks (GCNs) to process KGs for the purpose of recommendation.
- **AKUPM** [48]: It is a KGRS model, which can model users with their click history and explore the relationships which are essentially determined by the interactions among entities in KGs.

5.2.3 Parameter Settings

There are some parameters in DISL, *i.e.*, embedding size d, learning rate lr and batch size bs. In addition, there are also parameters in SEP2Vec, *i.e.*, sampling window size ω and number of epochs τ. For efficiency and performance, it is set to $\omega = 10, \tau = 50$ and other parameters are set the same as the defaults in Gensim (3.4.0). Furthermore, in order to guarantee the optimal parameters in DISL, we conduct a grid search and show the optimal hyper-parameters in Table 6. In particular, we show the sensitivity of the embedding size and sampling window size ω in SEP2Vec for public datasets in Figure 5.

5.3 Experimental Results and Analysis

Table 7, Figure 6 and Figure 7 have shown the experimental results of the proposed DISL model compared with other baselines in both CTR prediction and Top-K tasks. As we can see, PER, DKN and CKE perform poorly because they only consider the topological structure of KGs without fully considering the semantics information of KGs. In contrast, instead of using KGs, some well-known DLRS baselines such as LibFM and Wide & Deep can achieve better performance by introducing user feature, item feature and other information.

In addition, as a sequential recommendation method, CAFSE can capture the possible characteristics of user behavior at different time intervals, but the improvement is not notable without the help of a KG. Moreover, although AKUPM can model user preference with their sequential click history and explore the relationships among the clicks via the KG, such improvement in MovieLen-1M dataset is also limited. Furthermore, we can also observe that some KG based methods, such as RippleNet, MKR and KGCN, can achieve competitive results. However, because these models do not fully mine the semantic information in the user's dynamic interest sequence, the improvement is limited compared with the proposed DISL.

Moreover, for further comparison on larger datasets, we also conduct experiments on the real industrial tasks. After analyzing the results on public datasets, we select three strongest KGRS models, namely RippleNet, MKR and KGCN, as the baselines. The experimental results in Figure 8-9 show the AUC on test dataset of one week in July, 2019 for Alipay-A and January, 2020 for Alipay-B. The proposed model, DISL, outperforms the baselines, and DISL has an average improvement of 2.1%,1.0%,1.4% on Alipay-A and 0.4%,1.0%,0.5% on Alipay-B, compared with Ripplenet, MKR, and KGCN respectively. Moreover, the performance of DISL also comes with a low variance (0.00014 on Alipay-A and 0.00011 on Alipay-B), which suggests that it is robust and stable. In addition, we can also find that performance is dependent on the length of user interest sequence. The experimental results indicate that the longer sequence yields better performance (longer average sequence and higher AUC in MovieLen-1M and Alipay-B).

6 Conclusion and Future Work

This paper proposes a novel multi-granularity dynamic user interest sequence learning method to understand the semantics of each item in historical interest sequence in KGs. Specifically, the representation for semantic-enhanced path by the knowledge-enhanced path mining and interest fluctuation signal discovery are learned by the proposed SEP2Vec model for user preference characterization. In addition, we explored the use of KG-based methodology in real industrial-level online recommendation tasks, opposing to small-scale benchmark datasets, and achieved significant benefits for online applications.

For future work, instead of a static KG, we will further explore the dynamic KGs and knowledge representation learning for a better semantic understanding of the each item in user's historical interest sequence.

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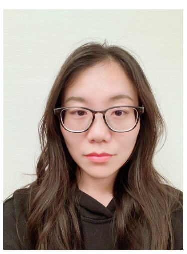

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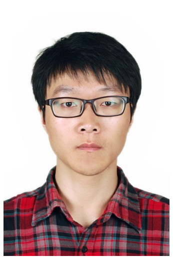

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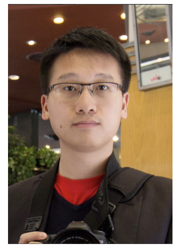

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