Fine-Grained User Location Prediction using Meta-Path Context with Attention Mechanism

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Abstract

The prevalence of Location-Based Social Networks (LBSNs) significantly improves the location-aware capability of services by providing Geo-tagged information. Relied on a great number of user check-in data in the location-based social networks, their essential mobility modes are able to be comprehensively studied, which is basic for forecasting the next venue where a specific user is going to visit considering his relevant historical check-in data. Since there exist different kinds of nodes and interactions between nodes, these information could be look upon as a network that is made up of heterogeneous information. In this network a few of different semantic meta paths could be obtained. Enlightened from the competitive advantage of embedding method relied upon meta-path contexts in the heterogeneous information network, we study a joint deep learning scheme exploring different meta-path context information to forecast fine-grained location. In order to capture different semantics in a user-location interaction, we adopt a

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simple but high-efficient attention method to learn the meta-path importance or weights. In the terms of model optimization, considering we have only positive sample data and there exists intrinsically latent feedback in check-in information, herein a pairwise learning method is utilized for maximizing the margin between visited and invisible venues. Experiment in different datasets validate the competitive performance of the suggested approach under different assessment criterion.

Keywords: Geo-social network (GSN), attention mechanism, meta-path contexts learning, location-based social networks (LBSNs), pairwise learning, user location prediction.

1 Introduction

The fast improvement of mobile communication techniques and intelligent mobility end-devices has witnessed the growing success of social networks, especially Geo-Social Networks (GSNs) or LBSNs which are combined social networks with location information. Herein, the representative platforms of location-based social networks, such as Foursquare,[1] Dianping, Instagram, Douban, Gowalla, Flickr, and Yelp,[2] are great absorbing tens of thousands of consumers registering in each day and using the location-aware services for improving their daily life. Via utilizing these location-aware services offered by the fore-said sites, a vast number of user check-in data (for example, negative, positive or neutral comments on specific clubs and generated check-in data in a few of certain venues.) can be generated, which contains Geo-tagged identifier information or data. Those information or data are content-rich in the facets of relevant temporal-spatial contexts and semantic contexts, which could be further utilized to mine or probe into user mobility modes and thus forecasting where the specific consumer is planning to go in terms of himself next visit. The great number of applications for user location prediction or location-aware services has fully demonstrated important advantage in the intelligent recommendations, such as travelling venue and path recommendations [1, 20], advertising product recommendation [18, 32], etc.

Currently, though forecasting the next venue or location where users plan to visit has become one of hot-spot topics and the large number of embedding

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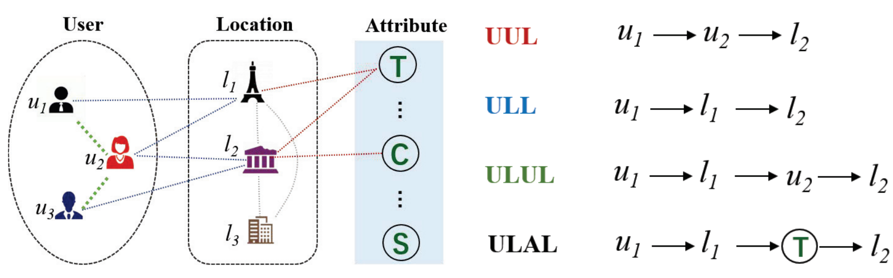
[1] https://foursquare.com/
[2] https://www.yelp.com/

platforms [14, 16, 24, 25] have been suggested to obtained the distribution representation and location of users in potential space, those work basically regard the location-based social network as one kind of homogeneous network, which ignores the potential semantics in interactions among a variety of nodes. Indeed, as noted in [3, 4, 26, 28], the location-based social networks is a kind of heterogeneous network where various kinds of nodes and relationships can be obtained or learned. Thus, for heterogeneous information network the embedding methods are novel rising learning frameworks with elasticity in characterizing different heterogeneous information [21], which can be naturally applied to model interactions between user node, location node, and attribute node.

In particular, a typical sequential relation in HIN, which is referred to as meta-path context and widely used to extract semantic interactions connecting diverse kinds of nodes [7], could be exploited to capture the hidden semantics information in the user and location pair, that is to say, the preference of one user to the certain location. Once we can quantify the user preference for each candidate location, we can finally predict his/her next visit location. It is worth noting that we aim to predict the fine-grained location (i.e. POI-level venue) in this paper, which differs from a lot of previous researches that only take a coarse-grained area [10] or a venue category [29] as the prediction result.

To demonstrate the motivation, Figure 1 shows a graphical case. As we have seen, especially, Figure 1(a) exist three kinds of heterogeneous nodes, namely user, location and attribute. In the same time, it has four kinds of relations, which includes UU relation, UL relation, LL relation, and LA relation. For Figure 1 (b), four kinds of meta paths in terms of $< u_i, l_j >$ pair



(a) The schematic illustration in location-based social network.

(b) A simple case of meta-path contexts in terms of $<u_1, l_2>$

Figure 1 The hierarchical architecture in location-based social networks and the cases of meta-path contexts of a specific mode in heterogeneous information network.

can be obtained, and an example for $< u_1, l_2 >$ pair is given. Particularly, the venue classification which is correlated with one certain venue is employed as one of the corresponding properties. Actually, all Point-of-Interests (abbr. POI) in location based social networks liking Foursquare are divided into ten kinds of types,[3] that is to say, 'Arts & Entertainment', 'College & University', 'Event', 'Food', 'Nightlife Spot', 'Outdoors & Recreation', 'Professional & Other Places', 'Residence', 'Shop & Service' and 'Travel & Transport'. According to the above convention, every one category is specified and abbreviated by a capital letter, i.e. the first letter of its category, in which 'Arts & Entertainment' is labeled 'A', 'College & University' is labeled 'C', 'Food' is labeled 'F', and so forth. Furthermore, here exist four kinds of relations. In other words, User-User relation (UU-relation) that stands for the corresponding social friendships, Location-Location relation (LL-relation) that stands for the successive transition state or the corresponding Geo-influence, User-Location relation (UL-relation) that stands for the relevant check-in behavior of user, and Location-Attribute relation (LA-relation) that stands for which decided category the venue or location belongs in. As far as the meta-path contexts concern, while being concentrated upon these issues of location/venue prediction, here-into, the related researchers just probe into their interactions between users and their check-in venues, namely, meta paths of the corresponding $< u_i, l_j >$ pairs. In view of that long meta-paths may generate different noise [9], just only short meta-paths are used for our proposal, in which the corresponding sequence length is not more than four. In the same time, for the certain UL-relation pair $< u_i, l_j >$, there exist four kinds of meta-paths which can be abstracted from corresponding relations, namely, 'ULL', 'UUL', 'ULUL', and 'ULAL'. For $< u_1, l_2 >$ pair, the specific case of meta-path contexts can be found in Figure 1(b). Four meta-paths contexts are conflated within their interaction between one specific user and his check-in venue, that is to say, the specific triple-tuple $< u_i, meta\text{-}paths, l_j >$ is leveraged to characterize corresponding contexts for-why user u_i visits this location l_j. Take 'ULL' and 'ULAL' as two examples. The former indicates that user u_i visits venue l_j because l_j is geographically near to another location where u_i has visited before, while the latter indicates that u_i visits venue l_j because l_j has the same attribute to another location he/she has visited.

In order to overcome this issue about user location prediction, a joint deep neutral network scheme is suggested, which integrates meta-path contexts with the attention mechanism [2]. Firstly, based on the predefined sampling

[3] http://api.foursquare.com/v1/categories

rules, a simple random walk way is employed to extract the meta-path cases from every $< u_i, l_j >$ pair under each meta-path context. Secondly, CNN (convolutional neural network) [12] is utilized and embed into the meta-path contexts. Thirdly, the attention mechanism is leveraged to adaptively learn the matching weight of every meta path context. In the same time, the multi-layer perceptron (MLP) is implemented to convert the vector representation into a real value. Finally, a pairwise learning method is adopted to optimize these parameters. For model evaluation, two LBSN data-sets are used and these experiment results demonstrate the effectiveness of the proposed approach based on two evaluation metrics.

The rest is arranged as follows. In Section 2, related research is reviewed. In Section 3 our proposed joint scheme is proposed, which integrates meta-path contexts and attention mechanism. In Section 4, the effectiveness of location prediction model is evaluated. Finally, the conclusion and direct of effort are presented in Section 5.

2 Related Works

Recently, user location prediction in location-based social networks or Geo-social networks has been becoming an exciting and severe issue. A great number of previous research handles them depended upon collaborative filtering (CF) methods including matrix factorization [13, 17, 28, 31]. The essential goal of matrix factorization strategies is to decompose the matrix of UL interaction into two lower dimensional matrices, in which each matrix separately represents one potential representation of users and locations. And then the scalar product of two vectors is utilized to match the visit possibility of the user in the candidate venue. Nevertheless, most of strategies relied on collaborative filtering generally confront with cold-start challenge while fresh users or locations appear in training data-sets, which would ultimately make their ineffectiveness.

In last few years, embedding technologies, particularly HIN based embedding techniques [7, 9, 21] have been paid growing much attention. Because semantic relations can be described clearly between various types of nodes utilizing meta-paths [5], these HIN embedding technologies are getting more and more attractive and competitive in recommendation especially user location recommendation. Therefore, they can be minimally adjusted or revised and obtain high effectiveness in this field.

In [21], the general HIN embedding scheme to mine potential structure features of users and items is suggested by Shi et al., while Fu et al. [7]

introduce a novel and scalable framework called *metapath2vec* for meta-path context learning.

A novel scheme is suggested by Hu et al. [9] for the sake of characterizing a triple-way interaction $< u_i, meta\text{-}path, l_j >$ in semantic content recommendation. Especially, the co-attention mechanism is used to characterize the weight information in every meta path context. Enlightened from this research [9], a joint deep learning scheme in user location prediction is conceived and proposed, which integrates meta-path contexts with attention mechanism by us. Different from another scheme [9], in our scheme the various random walk way is employed to extract meta-path cases relied upon predetermined regulations. In the same time, attention mechanism in meta-path contexts learning is simplified. Furthermore, considering we have only positive sample data because the latent feedback exists in check-in records, in this paper a pairwise learning method is utilized for maximizing the margin between visited and unseen venues, and then obtaining the optimization of relevant arguments.

3 Preliminaries and the Proposed Model

3.1 Preliminaries

Herein, the next venue of user depended upon the previous check-in data that is generated will be predicted. As for one given data set, we presume there exist M users and N locations, separately $\mathfrak{U} = \{u_1, u_2, \ldots, u_i, \ldots u_M\}$, and $\mathfrak{L} = \{l_1, l_2, \ldots, l_i, \ldots l_N\}$. As far as this data set is concerned, potentially, the certain social relations are contained between different users. A location is predefined as a venue or place that is uniquely identified liking a super market, and is associated with Geo-coordinate information and type implying which kind of location that should be labeled or marked. Relied upon the relevant records, one sign-in or check-in matrix $X \in \mathbb{R}^{M \times N}$ of the user-location can be built, in which each entry $x_{u,i} \in \{0, 1\}$ stands for whether or not user u visited venue location i.

In view of these elemental theories, the user location prediction in location-based social networks can be formulated and handled utilizing these preliminaries.

Definition 1. ***User Next-Location Prediction.*** *Set a latent-feedback matrix* $X \in \mathbb{R}^{M \times N}$ *contains check-in data for every user* u *existing* $C_u = \{< u, l_1, t_1 >, < u, l_2, t_2 >, < u, l_3, t_3 >, \ldots < u, l_n, t_n >\}$*, where each* $< u, l_i, t_i >$ *indicates user* u *check-in data at one specific venue or location* l_i

and one specific time t_i. The next location can be predicted in which u plans to visit after t_n. For implementing this target, all N feasible locations should be firstly sorted, and thus the specific location is ranked at the supreme in this list, where user u would visit next with higher probability.

Definition 2. ***Meta-Path [22].*** *A meta-path ρ is a sequence path with this form $A_1 \xrightarrow{R_1} A_2 \xrightarrow{R_2} \cdots \xrightarrow{R_l} A_{l+1}$ in networked graph $G = (A, R)$, which indicates a composition relationship $R = R_1 \circ R_2 \circ \cdots \circ R_{l+1}$ between the categories A_1 and A_{l+1}, in which A stands for the aggregate set of categories, R stands for the composition relation, $\circ$ stands for the operator on the corresponding relations, l is the subscript. The networked graph in heterogeneous information network stands for the meta-structure of this corresponding graph, which describes category information and interaction relationships.*

Definition 3. ***Meta-Path based Context (abbr. Meta-path Context) [22].*** *Given a specific user u and the item l (e.g. location or venue), the meta-path context can be defined as a finite set that contains different path cases according to the corresponding meta paths which link two nodes within the heterogeneous information network.*

3.2 Overview of the Proposed Scheme

Motivated from the mainly theory of [9], in this paper the meta-path context is employed to build semantics model of location predication within $< u_i, l_j >$. Definitely, four meta-paths are extracted from Figure 1(b), and meta-path context that integrates user-location embedding is merged via attention mechanism. Because of the combination of these semantic information, the proposed scheme can provide more interpretability than the formerly research. As Figure 2 is shown, a novel joint deep learning structure is suggested, which integrates the meta-path contexts with attention mechanism.

3.3 Detailed Description of the Proposed Scheme

Firstly, a lookup layer is deployed in order to convert the one-hot encoding for representation of the users and locations into low-dimension vectors, which is a common practice in deep neural networks [8]. After this step, for each input $< u_i, l_j >$, we can use the embedding of user u_i as x_i, and the embedding of position l_j as y_j. We assume that their sizes are all d. We implemented

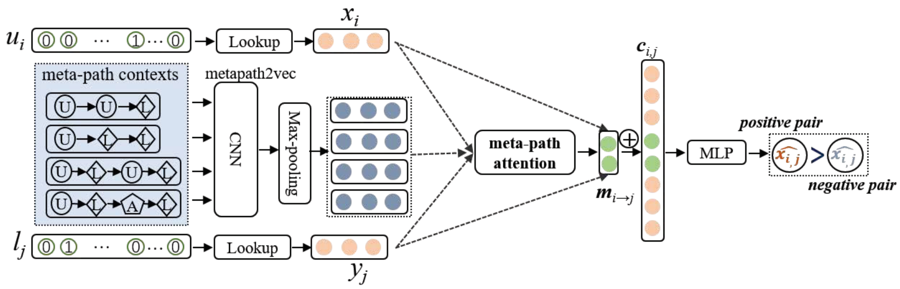


Figure 2 The proposed deep learning structure for user location prediction in LBSNs.

the open source it metapath2vec project[4] to initialize the embedding of user nodes, location nodes, and attribute nodes.

Secondly, aiming at each meta-path context which has been extracted above, we have to sample the corresponding meta-path instance from the given LBSN. Unlike [9] and [5], we have predefined five sample rules for each possible relationship between any possible pairs (i.e., the transition probability from the current node to the next node), namely 'U $\to$ U', 'U $\to$ L', 'L $\to$ L', 'L $\to$ U' and 'A $\to$ L'. Please note that we ignore the relationship 'L $\to$ A', because we can directly get the corresponding type (attribute) of a given place. Table 1 shows the rules for each relationship. In fact, for each input $< u_i, l_j >$, we start a random walk from the node u_i according to each meta-path, and end sampling at the node l_j. Given a meta-path, we keep sampling until we collect 10 different sequences.

Thirdly, for the sampled node sequences, we still use convolutional neural network (CNN) to embed them into low-dimensional vectors, which is similar to [11]. Besides, as we obtain 10 instances, for each meta-path, they may deliver different results even using the same CNN filter. For each path instance p, we use CNN to embed p into a vector h_p. Then, we utilize the max-pooling operation to take the maximum value of each dimension in every meta-path context. Consequently, we get the embedding c_p for each meta-path p, i.e. $c_p = max - pooling(\{h_p\}_{p=1}^{10})$. Next, we introduce a simple attention strategy for learning weight of every meta path context. In the same time, following [9], the double-layer architecture is formed and the activation function to be $ReLu$ function is preset. In the end, we can determine the aggregate meta path context of the embedding input $< u_i, l_j >$ pair: $m_{i\to j} = \sum_{p \in MP_{u_i \to l_j}} (\lambda_{u_i, l_j, p} \cdot c_p)$, where $MP_{u_i \to l_j}$ represents the predefined

[4]https://ericdongyx.github.io/metapath2vec/m2v.html

Table 1 The sampling rules for each relationship existing in the four meta paths, namely 'UUL', 'ULL', 'ULUL', and 'ULAL'

Relation	Rule	Description
U → U	$p_{u_i \to u_j} = \frac{\lvert R_{u_i} \cap R_{u_j} \rvert}{\lvert R_{u_i} \cup R_{u_j} \rvert}$	In fact, the Jaccard coefficient can measure the similarity between users. R_{u_i} represents the set of locations that the user u_i has visited. When sampling the next user node, the normalized similarity is used to ensure which the total of friendly similarity for every user is 1.
U → L	$p_{u_i \to l_j} = \frac{\lvert C_{u_i \to l_j} \rvert}{\lvert C_{u_i} \rvert}$	Indeed, this is the historical frequency of user u_i visiting location l_j, where $\lvert C_{u_i} \rvert$ is the total check-in number of user u_i, and $\lvert C_{u_i \to l_j} \rvert$ is the number of visits of user u_i to location l_j. Likewise, use the normalized frequency.
L → L	$p_{l_i \to l_j} = exp(-\alpha \lvert\lvert o_i - o_j \rvert\rvert^2)$	We use Gaussian radial basis function kernels (such as RBF kernels) to assign greater weights to places near geographic locations. o_i and o_j are the geographic coordinates of the location l_i and l_j, respectively. α is a hyperparameter, which is set to 60 according to [15]. Use normalized values.
L → U	$p_{l_i \to u_j} = \frac{\lvert C_{u_i \to l_j} \rvert}{\sum\limits_{q \in 1,2,\ldots M} \lvert C_{u_q \to l_j} \rvert}$	Similar to 'U → L', we use the opposite meaning, which considers the ratio of user u_i's number of visits to location l_j among all users.
A → L	$p_{A_i \to l_j} = \frac{\lvert R_{l_j} \rvert}{\sum\limits_{l_q \in A_i} \lvert R_{l_q} \rvert}$	Similar to 'L → U', we use the proportion of the popularity of location l_j in the corresponding category A_i as the transition probability from attribute node to location node, where R_{l_j} is the total number of check-ins performed by all users at location l_j.

meta-path sets, and $\lambda_{u_i,l_j,p}$ is the corresponding weight for each meta-path context.

Fourthly, after obtaining the embedding of the meta path context $< u_i, l_j >$, we combine it with the previous user embedding x_i and the location embedding y_j, so we get: $c_{i,j} = x_i \oplus m_{i \to j} \oplus y_j$. Then following the idea in [8], we feed $c_{i,j}$ into the Multilayer Perceptron (MLP) module to model the overall interaction in a non-linear way. Therefore, we finally get a true value, which is similar to the preference of user u_i at the location l_j: $\hat{x}_{i,j} = MLP(c_{i,j})$. We also implemented a tower structure for the MLP module, in which the dimension of the latter layer is half the dimension of previous one.

Finally, we introduce how to optimize the model regarding the involved parameters. As we only have positive samples because user check-in data generated in LBSNs are indeed a kind of implicit feedback, to get the negative samples, we adopt a popular negative sampling method in [4], through which we can retrieve several negative samples for each positive sample $< u_i, l_j >$. In detail, due to the severe imbalance between positive and negative samples, we arbitrarily pick two negative samples for each given positive sample $< u_i, l_j >$ to avoid the model parameters being extremely sensitive to minority samples. Toward the objective function in our framework, suppose all the related parameters denoted by $\mathbf{\Theta}$, and the all the positive samples together with negative samples denoted by $\Re$, our objective is to ensure that for each positive sample s_i^p and negative sample s_i^n, the approximated value of s_i^p is larger than that of s_i^n. Therefore, we can formulate the objective function following Bayesian personalized ranking (BPR) [19] from implicit feedback:

$$p(\Re|\mathbf{\Theta}) = \prod_{u \in \mathfrak{U}} p(\Re_u|\mathbf{\Theta}) = \sum_{u \in \mathfrak{U}} \sum_{< s_i^p, s_i^n > \in \Re_u} p(\varsigma(s_i^p) > \varsigma(s_i^n)|\mathbf{\Theta}) \tag{1}$$

where $\varsigma(.)$ function obtains the final approximate value of a given sample, that is, the $\hat{x}_{i,j}$ of the sample $< u_i, l_j >$. Maximum likelihood estimation (MLE) is utilized in order to infer parameters. The final optimization goal $\mathfrak{J}$ is obtained as follows:

$$\mathfrak{J} = \sum_{u \in \mathfrak{U}} \sum_{< s_i^p, s_i^n > \in \Re_u} \ln \sigma(\varsigma(s_i^p) - \varsigma(s_i^n)) - \epsilon ||\mathbf{\Theta}||_2{}^2 \tag{2}$$

where $\sigma(.)$ is a sigmoid function, ϵ is a hyperparameter of regularization, which is set to 0.1, and $||.||_2$ represents the Frobenius norm. We use stochastic gradient descent algorithm [4] to derive the updating rules for related parameters.

4 Experiments

4.1 Datasets and Evaluation Metrics

In order to evaluate the performance of the proposed scheme, in this paper two data sets from Foursquare are used. One data set is offered by Xu et al. [27], which contains over 764,328 check-in records of 10,901 users. Another one that includes the check-in records of 4,163 users is from Yin et al. [30].

Among these two data sets, specific relations with undirected friendship are included. In order to mitigate the effect of the noise, the data is used, which contains users of no less than 10 check-in records and no less than 10-visitor locations. The corresponding statistics results are given in [23]. Moreover, the first 80% data for each user is divide to training stage, the second 10% data is divided to validation stage, and the rest 10% data is divided to testing stage. In the mean time, the proposed scheme is performed via Keras with TensorFlow, in which super-arguments are preset in terms of [9].

Two general metrics are used to evaluate the proposed scheme for user location prediction. One is $Acc@N$, another is APR. Their detail can be seen in references [4, 26, 28].

4.2 Comparison Methods

In order to comparison, three models are adopted. They are **PRME**[5] [6], **GE**[6] [25], and **MCRec**[7] [9], which leverages meta-path contexts for item recommendation. One of the most significant difference of this model compared to ours is that **MCRec** adopts the mutual enhancement mechanism. We directly use it to computes the approximated value of users' preference for a venue, then we can rank all candidate locations based on these values.

4.3 Experiment Analysis

In the first place, in order to differentiate these schemes, the proposed model is briefly denoted as **MP_Loc_Pre**. In Table 2, the numerical results are summarized with reference to $Acc@10$, $Acc@50$ and APR. On the one hand, user location prediction schemes in LBSNs integrating meta-path context fulfilled higher prediction accuracy, while homogeneous information based models obtain lower prediction performance. This fact indicates that incorporating meta-path based contexts in such tasks can effectively improve location prediction accuracy. For another thing, although the best numerical results on several metrics are achieved by **MCRec** model, our method can still obtain comparable and even better results on other metrics. Considering that we do not leverage the alternative enhancement mechanism which may improve the representation of users, locations as well as meta-path contexts, it is still a satisfactory result since we use less auxiliary information.

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[5]Code provided at: https://github.com/flaviovdf/prme

[6]Code provided at: https://www.dropbox.com/s/6hwdtovq25ml4fk/code_c ikm2016.zip.

[7]Code provided at: https://github.com/librahu/MCRec

Table 2 Effectiveness comparison of user location prediction

	NY			CA		
	Acc@10	Acc@50	APR	Acc@10	Acc@50	APR
MP_Loc_Pre	**0.283**	0.411	0.773	**0.248**	0.347	0.830
PRME	0.226	0.336	0.762	0.174	0.242	0.755
GE	0.257	0.373	0.768	0.220	0.305	0.824
MCRec	0.280	**0.414**	**0.776**	0.244	**0.354**	**0.833**

Table 3 Individual effect (Acc@10 metric) of each meta-path context for location prediction task, where the first column on the right of the datasets represents the performance of the baseline method

	MPL	UUL	ULL	ULUL	ULAL
NY	0.226	0.258	0.237	0.244	0.248
CA	0.195	0.217	0.204	0.208	0.211

Second, we want to verify the impact of different meta-path contexts. We select the Most Popular Location (MPL) as the baseline algorithm and gradually incorporate one of the four proposed meta-paths into the framework. Through this way, we can analyze the individual effect of each meta-path context. The final results are displayed in Table 3. To make it brief, we only take the results on Acc@10 metric as an example. As can be seen, meta-path ‘UUL’ delivers the best performance improvement compared with other meta-paths, which reveals the significant role of ‘word-of-mouth’ effect in user check-in behavior. As a contrast, meta-path ‘ULL’ has the weakest impact for performance upgrade, which is consistent to the finding in [4] that geographical influence is indeed a coarser measure than temporal-spatial factors.

To sum up, the proposed deep learning scheme merging meta path context can effectively forecast next-visit venue when known historical data. Although its prediction performance is not as high as some state-of-the-art approach, it can achieve satisfactory results considering less information in the LBSNs.

5 Conclusion

In LBSNs, this issue of user venue or location prediction relied upon his historical check-in records are paid growing attention. Herein, enlightened by the competitive advantage from embedding technologies for heterogeneous information network, we proposed a joint deep neural network scheme, which merges meta-path contexts with attention mechanism. To capture different semantics in a user-location interaction, we adopt a simple but high-efficient attention method to learn the meta-path importance or weights. In the terms of model optimization, considering we have only positive sample data and there exists intrinsically latent feedback in check-in information, herein a pairwise learning method is utilized for maximizing the margin between visited and invisible venues. Experiment in different data-sets validate the competitive capability of the suggested approach with references to different assessment criterion.

In the paper, The proposed user location prediction approach for LBSNs is time independent, in next work, we hope to incorporate the temporal factor into the model, propose a time-aware location prediction method, and extend the application scenario.

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