Joint Triplet Loss Learning for Next New POI Recommendation

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ABSTRACT

Sparsity of the User-POI matrix is a well established problem for next POI recommendation, which hinders effective learning of user preferences. Focusing on a more granular extension of the problem, we propose a Joint Triplet Loss Learning (JTLL) module for the Next New (N²) POI recommendation task, which is more challenging. Our JTLL module first computes additional training samples from the users’ historical POI visit sequence, then, a designed triplet loss function is proposed to decrease and increase distances of POI and user embeddings based on their respective relations. Next, the JTLL module is jointly trained with recent approaches to additionally learn unvisited relations for the recommendation task. Experiments conducted on two known real-world LBSN datasets show that our joint training module was able to improve the performances of recent existing works.

CCS CONCEPTS
• Information systems → Recommender systems.

KEYWORDS
Recommender System; Triplet Loss; Joint Learning

1 INTRODUCTION

High sparsity of the User-POI matrix (i.e. percentage of zeroes in the matrix) is a long-standing problem that hinders effective learning of real-world predictive tasks, such as the Next New (N²) POI recommendation task, a task designed to predict and recommend a set of POIs for users to visit next, where they have never visited these POIs before [15]. While there are numerous existing works that seek to learn and alleviate sparsity of the User-POI matrix, these works include the additional incorporation of POI categories [1, 5, 10, 14, 17, 28–32, 34], the modeling of spatio-temporal relations [12], the learning of several User-Region matrices of different levels of granularity to better learn the sparse User-POI relationships [15], and others, proving to be effective methods for the recommendation task. However, an often overlooked relation that can also help to alleviate sparsity between users and POIs, are the POIs which the users has never visited before, or the unvisited relation. For example, given the search space of POIs in a region \( \{l_1, l_2, l_3, l_4, l_5, l_6\} \) to determine the next POI, where a user \( u_m \) has visited \( l_1 \) and \( l_2 \) before in her historical records, most existing works had focused on the learning of the visited relation (i.e. \( u_m \) visited \( \{l_1, l_2\} \)) for the personalized recommendation task, however, the unvisited POIs (i.e. \( \{l_3, l_4, l_5, l_6\} \)) are often not directly used to better learn the User-POI relations for this task. For instance, the dissimilarity between \( u_m \) and \( \{l_3, l_4, l_5, l_6\} \) can also be used to enrich the learning of user and POI representations, while learning the similarity between \( u_m \) and \( \{l_1, l_2\} \). Further, the additional learning of this unvisited relation can help to alleviate sparsity, given the severe sparsity problem of the User-POI matrix, for example, there now exist a dissimilarity relation between user \( u_m \) and \( \{l_3, l_4, l_5, l_6\} \) that can be learned, but was not possible with only using the visited relation by most existing works. Although most existing works have learned POI-POI relations between visited POIs by the user (e.g. \( \{l_1, l_2\} \)) for user \( u_m \) and the unvisited POIs (e.g. \( \{l_3, l_4, l_5, l_6\} \)), such as via spatial-temporal-preference factors [16], the unvisited relation, however, which is between the user \( u_m \) herself, and her own unvisited POIs \( \{l_3, l_4, l_5, l_6\} \), has not been learned. Motivated by this, in this paper, we propose a novel Joint Triplet Loss Learning (JTLL) module to learn both visited and unvisited relations for the \( N^2 \) POI recommendation task to further support sparsity alleviation. Specifically, we first design a triplet loss based loss function to reduce the distance of user and POI embeddings (user visited POI before), and increase the distance of user and POI embeddings (user never visited POI before). Then, we incorporate our JTLL module into existing works to better learn the User-POI matrix with a joint training framework.

To summarize, the following are the contributions of this paper:

- We propose a novel JTLL module to further alleviate the data sparsity problem by learning both visited and unvisited relations...
for the \( N^2 \) POI recommendation task. To the best of our knowledge, this is the first work which proposes a triplet loss based loss function, that uses User-POI visited and unvisited relations for this recommendation task.

- Our JTLL module includes a designed triplet loss function to learn both visited and unvisited relations directly. Further, we use a joint training framework with existing recommendation models to better learn User-POI relations.
- Experiments conducted on two standard real-world LBSN datasets show that our joint training module was able to improve the performances of recent existing works.

2 RELATED WORK

Extending from the next POI recommendation problem, a more challenging problem of Next New (\( N^2 \)) POI recommendation have received recent research interest. As this \( N^2 \) POI recommendation task focuses on only recommending unvisited or new POIs where the user has never visited before, approaches proposed cannot merely rely on users’ historical check-in sequence to perform well for this task. Early works explored conventional collaborative filtering and sequential approaches such as Matrix Factorisation (MF) and Markov Chains (MC) respectively. For example, [2] extended the Factorizing Personalized Markov Chain (FPMC) approach [22] that integrates both MF and MC, to include localised region constraints and recommend nearby POIs for the \( N^2 \) POI recommendation task. PRME-G [7], a metric embedding method, models both POIs and users in a sequential transition space and a user preference space respectively. As their method is not based on FPMC, it avoids the drawback of the independence assumption of FPMC to model the transitions [7]. Also a metric embedding approach, [8] jointly learns the different relationships of POI sequential transitions (POI-POI), user preferences (POI-User), regional (POI-Region) and categorical (POI-Category) information in a unified way, by projecting them on a shared low-dimensional hyperbolic space. The learned hyperbolic embeddings are used with the Einstein mid-point aggregation [9, 25] to integrate the effect of user preferences and sequential transitions for prediction. In [18], they proposed GLR_GT_LSTM, that uses an LSTM to model users’ transition behaviours with latent vectors of POIs and regions, based on temporal user preference and temporal successive transition influence, as well as the spatial influence of POIs for the \( N^2 \) POI recommendation task. While these existing works [2, 7, 8, 18] have demonstrated effectiveness for the \( N^2 \) POI recommendation task, they have a limitation of only considering POI samples visited within the next 6 hour threshold of the preceding POI check-in, learning and evaluating only short term preferences of the proposed methods. Following [15], in this work, we overcome this limitation by removing the threshold, to evaluate our proposed approaches for both short and long term preferences.

The closest related work to our JTLL module is the Personalized Ranking Metric Embedding (PRME) [7] approach, where it jointly learns POI embeddings in the sequential transition latent space, and both User and POI embeddings in the user preference latent space. For the learning of POI embeddings, the approach uses both observed POI (i.e. visited relation), and unobserved POI (i.e. unvisited relation) to optimize the learning of POI embeddings, where the euclidean distance between the previous and next visited POI should be small, and the distance between the previous and unvisited POI should be large. Although both PRME and our JTLL approach uses both visited and unvisited relations of user visits to learn our embeddings, there are several key differences. First, our proposed loss function is triplet loss based, classically involving the three roles of an anchor, a positive, and a negative. In PRME, for both POI and user representation learning, it is instead achieved with a standard pairwise metric embedding approach (i.e. only pairs of latent vectors are used at each time for the respective latent space). Second, the visited and unvisited relations of user visits is used in their sequential transition latent space to only learn POI embeddings, whereas our loss function in Eq. (1) uses the visited and unvisited relations to learn both user and POI embeddings, focusing more on the user representation learning. Third, our JTLL module is designed to overcome the limitation of existing works to additionally learn unvisited relations in a joint training framework and support sparsity alleviation, with evaluation results surpassing the state-of-the-art methods. PRME is a standalone approach that has been shown by various works [12, 33] to perform significantly poorer than a classical LSTM model for all metrics and all datasets, whereas our best performing JTLL variant, surpassed the same LSTM baseline significantly, as shown in Table. 2.

3 PRELIMINARIES

Problem Formulation. Let \( U = \{u_1, u_2, ..., u_M\} \) be a set of \( M \) users and \( L = \{l_1, l_2, ..., l_Q\} \) be a set of \( Q \) POIs. \( S \) is the set of visit sequences for all users where \( S = \{s_{u_1}, s_{u_2}, ..., s_{u_M}\} \). Each user's sequence \( s_{um} \) consist of sequential POI visits \( s_{um} = \{(l_{t_{1}}, loc_{t_{1}}, time_{t_{1}}), (l_{t_{2}}, loc_{t_{2}}, time_{t_{2}}), ..., (l_{t_{m}}, loc_{t_{m}}, time_{t_{m}})\} \), where \( l_{t_i} \) is the POI visited on time step \( t_i \), with its corresponding location coordinates \( loc_{t_i} \), and \( time_{t_i} \) as the timestamp of the visit made. As each user’s sequence \( s_{um} \) is partitioned into training and testing to predict future \( N^2 \) POIs, we denote the superscript \( train \) and \( test \) respectively (e.g. \( s_{train}^{2} \)).

Problem 1 (Next New (\( N^2 \)) POI Recommendation). Given user \( u_m \), from the sequential time steps of \( t_1 \) to \( t_{l-1} \) as her historical POI visit sequence \( s_{um}^{train} = \{(l_{t_{1}}, loc_{t_{1}}, time_{t_{1}}), (l_{t_{2}}, loc_{t_{2}}, time_{t_{2}}), ..., (l_{t_{l-1}}, loc_{t_{l-1}}, time_{t_{l-1}})\} \), the \( N^2 \) POI recommendation task is to consider a search space of POIs from \( L \setminus s_{um}^{train} \), where the historically visited POIs by the respective users are removed, to compute a \( N^2 \) POI ranked set \( y_{t_i} \) for the time step \( t_i \). Accordingly, the \( N^2 \) POI visited \( l_{t_i} \) should be highly ranked within \( y_{t_i} \).

4 APPROACH

4.1 Joint Triplet Loss Learning (JTLL)

Loss Function. Here, we propose the designed triplet loss function, based on the visited and unvisited relations of users for the recommendation task. First, we compute an additional set of training data, based on users who visit a given POI. Formally, given the available users’ historically visited POIs \( s_{um}^{train} \), we compute the training data \( t_{train} \), which is a set of tuples \((u_k, l_p) \in t_{train}\), and each tuple \((u_k, l_p) \) denotes the check-in event relation of user \( u_k \) having visited POI \( l_p \) in \( s_{um}^{train} \). Next, given each training tuple \((u_k, l_p) \in t_{train} \), and its embeddings of \( u_k \), \( l_p \) (in boldface letters)
from the weight matrices of user $\mathbf{W}^{User}$ and POI $\mathbf{W}^{POI}$ respectively, we design the following loss function, with inspirations from the triplet loss [23] and the negative sampling loss [21]:

$$J_{loss} = -\log(\sigma(\mathbf{u}_b^T \mathbf{h}_b^T)) - \sum_{\mathbf{u}_n \in \mathbf{i}_b^{Neg}} \log(\sigma(-\mathbf{u}_n^T \mathbf{h}_b^T)) \quad (1)$$

where $\sigma$ is the sigmoid activation function, POI $i_b$ serves as an anchor, $\mathbf{u}_b$ as a positive user who has visited POI $i_b$ before, $\mathbf{u}_n \in \mathbf{i}_b^{Neg}$ as a negative user from the set of users $\mathbf{i}_b^{Neg}$, who have never visited POI $i_b$ before, and can be computed from $s^{train}_{um}$. Intuitively, optimizing the loss function reduces the distance of positive users and the anchor POI (user visited POI before), and increases the distance of negative users and the anchor POI (user never visited POI before).

**Joint Training.** Our motivation of the JTLL module is to overcome the limitation of existing $N^2$ POI recommendation models to additionally learn unvisited relations. Therefore, we propose to use a joint training framework with parameter sharing, shown to be effective in other problems [20], to easily incorporate our JTLL module and a designated existing $N^2$ POI recommendation model, where the parameters $\{\mathbf{W}^{User}, \mathbf{W}^{POI}\}$ are shared among the two models for their own updates. Specifically, for each epoch, our JTLL module first optimizes Eq. (1) with the training data $s^{train}$, with gradient steps to the user $\mathbf{W}^{User}$ and POI $\mathbf{W}^{POI}$ weight matrices. Then, the designated $N^2$ POI recommendation model will perform its own optimization and updates to these shared parameters, as well as other parameters unique to the model, concluding the end of a single epoch. We illustrate the proposed joint training framework in Figure 1, based on our JTLL module.

### 5 EXPERIMENTS

#### 5.1 Datasets

We evaluate our JTLL module on two known LBSN datasets of Gowalla [3] and Foursquare [27]. For preprocessing, we perform the same preprocessing as [15], reproducing the same statistics in Table 1, where we include users with visits counts between 20 and 50 in the datasets, then removing POIs visited by less than 10 users. Accordingly, we use the first 80% visits and the last 20% visits of each user’s sequence for training and testing respectively, based on chronological order.

#### 5.2 Baseline Methods and Evaluation Metrics

- **TOP.** POIs are ranked using their global frequencies in $s^{train}$ to determine popular POIs. U-TOP ranks POIs based on each user’s historical sequence $s^{train}_{um}$, via their POI visiting frequencies.

| Dataset      | Country | User | POI | Visits |
|--------------|---------|------|-----|--------|
| Gowalla$^1$  | 41      | 11,864 | 3,359 | 86,670 |
| Foursquare$^2$ | 63     | 16,636 | 4,455 | 170,573 |

- **MF** [13]: A known collaborative filtering method for recommendation problems by factorizing the User-POI matrix.
- **RNN** [6]: A classical recurrent model that learns sequential dependencies of POI visit sequences, but suffers from vanishing gradient. The variants of LSTM [11] and GRU [4] includes different multiplicative gates to control information flow.
- **HST-LSTM** [12]: A LSTM-based model that incorporates spatio-temporal intervals between successive POIs into the existing gates of LSTM. Following [16, 33], we use their ST-LSTM variant here as the data does not include session information. STGCN [33] models short term preferences with a new cell state, as well as modeling the intervals with new distance and time gates.
- **LSTPM** [24]: A LSTM-based model that learns short term user preferences with a geo-dilated network, and long term user preferences via a nonlocal network.
- **STAN** [19]: A bi-attention model that incorporates spatio-temporal correlations of non-contiguous visits and non-adjacent POIs.
- **STP-UDGAT** [16]: A GAT-based method that models spatio-temporal-preference factors via different POI-POI graphs in an explore-exploit architecture.
- **Flashback** [26]: A RNN architecture that uses spatio-temporal intervals to compute an aggregated hidden state from past hidden states for prediction. Their best performing RNN variant is used here for evaluation.
- **HMT-RN** [15]: A multi-task model that learns User-POI and several User-Region matrices of different levels of granularity to alleviate sparsity. HMT-GRN is their best performing variant, after replacing the LSTM layer with their Graph Recurrent Network (GRN) layer.

For the recent baselines of STP-UDGAT and HMT-GRN, we use them each as the designated $N^2$ POI recommendation model in our joint learning framework (Figure 1), with our JTLL module, and denoting the extended variants as STP-UDGAT-JTLL and HMT-GRN-JTLL accordingly. Note that for both existing works of STP-UDGAT and state-of-the-art HMT-GRN, they do not learn the unvisited relations between users and POIs in their works, therefore, following our motivation, we extend these recent works with our JTLL module to additionally learn the unvisited relations, and further alleviating sparsity.

**Metrics.** Following [15] for the $N^2$ POI recommendation task, we use the standard metric of Acc@$K$ and Mean Reciprocal Rank (MRR), denoting them as $N^2$-Acc@$K$ for $K \in \{1, 5, 10, 20\}$ and $N^2$-MRR respectively. Note that all test ground truth POI samples are preprocessed to include only new or unvisited POI $i_b \notin s^{train}_{um}$ to correctly evaluate for this recommendation task.

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$^1$https://snap.stanford.edu/data/loc-gowalla.html

$^2$https://sites.google.com/site/yanglingqi/home
5.3 Experimental Settings
For our JTLL module, we use the Adam optimizer with a learning rate of 0.001, with a batch size of 64 tuples from the training data \( l^{\text{train}} \). Further, we apply a dropout of 0.8 to the user and POI embeddings from the weight matrices \( W^{\text{User}} \) and \( W^{\text{POI}} \) before optimizing the loss function in Eq. (1). For all other hyperparameters (e.g., number of epochs and embedding dimension size), we set it to be the same as the designated existing \( N^2 \) POI recommendation model for simplicity and ease of implementation. For the baseline methods, for MF, RNN, GRU, and LSTM, we use the same settings where applicable. For the other recent works of HST-LSTM, STGCN, LSTPM, STP-UDGAT, and HMT-GRN, we follow their recommended settings as described. For Flashback and STAN, we apply grid search and use the best performing models for evaluation, as their recommended hyperparameters do not work as well in our experiments.

5.4 Results
We report the evaluation results of our proposed JTLL module and the baselines in Table 2. For all baselines and models, except TOP and U-TOP which are deterministic, we show the averaged results before optimizing the loss function in Eq. (1). For all other hyperparameters (e.g., number of epochs and embedding dimension size), we set it to be the same as the designated existing \( N^2 \) POI recommendation model for simplicity and ease of implementation. For the baseline methods, for MF, RNN, GRU, and LSTM, we use the same settings where applicable. For the other recent works of HST-LSTM, STGCN, LSTPM, STP-UDGAT, and HMT-GRN, we follow their recommended settings as described. For Flashback and STAN, we apply grid search and use the best performing models for evaluation, as their recommended hyperparameters do not work as well in our experiments.
of 5 runs on different random seeds, as well as their respective standard deviations:

- We see that the variant of HMT-GRN-JTLL has the best performance in both Gowalla and Foursquare datasets, where existing state-of-the-art HMT-GRN is the designated N^2 POI recommendation model, with our JTLL module. More importantly, we can observe an unanimous increase of performance when comparing HMT-GRN-JTLL and HMT-GRN across both datasets and all metrics, demonstrating the effectiveness of our JTLL module, as well as the necessary learning of unvisited relations for this recommendation task.

- Comparing STP-UDGAT-JTLL with STP-UDGAT, we similarly see a significant increase of performance for STP-UDGAT-JTLL in the Gowalla dataset for all metrics. For the Foursquare dataset, however, we see that STP-UDGAT-JTLL only have the best result for N^2-Acc@1, and not the rest of the metrics. We believe that this is due to the use of the high 0.8 dropout in our experimental setting for regularization, which indeed allowed STP-UDGAT-JTLL to perform the best for N^2-Acc@1 (i.e. correctly predicting the next new POI itself), but hindered the general learning capability of the model. However, we see that the high dropout rate did not adversely affect the learning ability of the model for the Gowalla dataset, as STP-UDGAT-JTLL always have better performances than STP-UDGAT.

- Simpler baselines such as TOP and MF do not perform well for this task as they do not learn sequential dependencies of check-in event transitions. For U-TOP, as it ranks POIs based on historically visited POIs of the respective user, it is unable to rank new or unvisited POIs, and therefore, the scores of zeroes for all the metrics.

- For all other baselines, same as [15], we believe that they do not perform as well due to the sparsity problem. As HMT-GRN is designed to alleviate sparsity, it was thus able to achieve state-of-the-art results, however, with the inclusion of our JTLL module to additionally learn unvisited relations in a novel way, it is now able to perform better.

6 CONCLUSION

This work proposed a novel JTLL module to alleviate the data sparsity problem by learning both visited and unvisited relations from users. Our JTLL module first computes the additional training data of 5 runs on different random seeds, as well as their respective standard deviations:

- We see that the variant of HMT-GRN-JTLL has the best performance in both Gowalla and Foursquare datasets, where existing state-of-the-art HMT-GRN is the designated N^2 POI recommendation model, with our JTLL module. More importantly, we can observe an unanimous increase of performance when comparing HMT-GRN-JTLL and HMT-GRN across both datasets and all metrics, demonstrating the effectiveness of our JTLL module, as well as the necessary learning of unvisited relations for this recommendation task.

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