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Travel Route Recommendation by Considering User Transition Patterns

Travel route recommendation services that recommend a sequence of points-of-interest (POIs) for tourists are very useful in location-based social networks (LBSNs). Currently, most of the work that addresses this task are focusing on personalization and POI features, which estimate user-location relations while rarely considering transitions, i.e., the relationships between locations. To this end, we propose a latent factorization model that learns transition patterns with enhanced spatial-temporal features between locations. Furthermore, we recommend travel routes by combining knowledge on locations and transitions. Experimental results with public datasets reveal that our approaches improve upon the performance of conventional methods.

Key words: travel route recommendation, LBSN, sightseeing, matrix factorization

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Introduction

The development of LBSN services has increased the number of user-location interaction behaviours via various devices. It is an important task to help tourists planning their travel routes in an unfamiliar city. Travel route recommendation, which is addressed in this paper, aims to recommend a sequence of POIs and to satisfy tourists' trip constraints.

Recent studies formulate travel route recommendation problems based on the orienteering problem model (Tsiligirides, 1984) in which tourists earn a reward when they visit one POI. The travel path with the maximum reward score under several trip constraints will be recommended (Friggstad et al., 2018; Lim et al., 2015; Vansteenwegen et al., 2011). The user-location relations (i.e., matching users and locations) are studied, and reward scores are assigned to POIs which can be regarded as tourist preferences on POIs.

Generally, a travel route consists of nodes (i.e., locations) and edges (i.e., the transition between locations). Transition patterns can be regarded as location-location relations. The higher the weight on the transition, the tighter the connection between two locations. Transition patterns may also imply some valuable sightseeing routes (paths), since some POIs are in a sequential structure or a large area, and walking through these paths is also a part of the trip (e.g., a park or a street along the way to the next POI).

However, related work rarely considers the edges (i.e., transition knowledge) of the specific target travel city. Most of them model edges as constraints: In general orienteering-problem based approaches (Vansteenwegen et al., 2011; Kurata et al., 2011), the travel time cost on transitions is considered; traffic conditions are considered in (Chen et al., 2015), which uses traffic-aware edge constraints; uncertain travel time between POIs is considered in (Zhang et al., 2016). In (Zhuang et al., 2017), POIs are recommended by using enriched location-location features. In (Liu et al., 2016), the users' next visited location is predicted, while a deep learning approach with tong short-term memory (LSTM) that integrates next-location prediction into travel route planning is proposed in (Xu et al., 2017), which can be regarded as leveraging transition patterns. In (Chen et al., 2016), transition reward is included into the travel route recommendation objective function, and travel routes based on both POIs and transition probability are recommended. Their transition probability is factorized from explicit feature-pairs such as the POI popularity and category (i.e., shopping-park or popular-unpopular pairs).

Therefore, the dependency between locations caused by spatial-temporal factors has not been considered so far in previous works that combine both points and transitions to recommend travel route. In this paper, we propose a spatial-temporal enhanced latent factorization model to study the connections between locations, and the experimental results reveal the efficiency of spatial-temporal influences between locations.

Travel Route Recommendation

1. Objective function: Given a user query (p_s, p_e, L) in which p_s and p_e represent the origin and destination points, respectively. L represents the travel length budget, i.e., how many POIs one wants to visit. A common travel route recommendation problem definition and objective function are given in (Lim et al., 2015; Chen et al., 2016). Basically, there are N POIs; and let $P = \{p_1, p_2, \dots, p_N\}$ in the target travel city. A travel route is recommended according to the user query by solving the following objective function:

$$\max \sum_{i=1}^{N-1} \sum_{j=2}^{N} x_{ij} R(p_j | p_i) \tag{1}$$

R is the reward function; N is the available number of POIs in the city; x_{ij} is a binary indicator that equals 1 when users travel from p_i to p_j, and equals 0 otherwise. It is subject to several constraints such as the requirement that a travel route must start from p_s and end at p_e and the travel budget. In this paper, we consider the travel length budget. Due to the space limitation, please refer to related work for the details of that constraints.

Similar to (Chen et al., 2016), we model transition rewards into the reward function in Eq. 1 as below:

$$R(p_j|p_i) = \alpha R_P(p_j) + (1-\alpha)R_T(p_j|p_i), \quad (2)$$

where R_P and R_T represent point reward and transition reward, which are defined in the following sections; and $\alpha \in (0,1)$ is a trade-off parameter that indicates the importance of the point and transition rewards.

2. POI reward: We assign rewards to POIs by considering user-location relations. Since it is a well-studied area, we directly leverage the proposed method in (Chen et al., 2016) to assign rewards to POIs. It is called PoiRank, which uses Rank Support Vector Machine (RankSVM) (Ching-Pei, 2014) with features such as category, popularity, and average visit duration to rank all POIs. Finally, a softmax function is used to transfer rank scores to POI rewards. They are represented as $R_P(p_j)$.

3. Transition reward: To improve the recommended travel route quality, which makes the route planning order aware, we regard transition patterns as rewards on transitions. Since transitions that we can observe are incomplete and the new POI has no transitions, we need to infer transition rewards from observed data. Unlike explicitly factorize feature pairs in (Chen et al., 2016), we use a latent matrix factorization method with enhanced spatial-temporal features to infer the transition patterns. Transition rewards are represented as:

$$R_T(p_j|p_i) = \hat{T}_{i,j}, \quad (3)$$

where $\hat{T}_{i,j}$ is the inferred transition reward matrix as defined below.

1) Weighted transition matrix: There are users' transitions between locations, i.e., moving from POI p_i to p_j according to travel routes data. In this manner, we capture a weighted transition matrix represented by $T' \in \mathbb{R}^{|V|\times|V|}$, where each entry $T'_{i,j}$ denotes the observed transition frequency between POIs p_i and p_j, and $|V|$ is the number of POIs in a particular city. Then T is equal to T' normalized by the maximum entry; T is regarded as the

relative transition weights between locations; similar to the idea of collaborative filtering, in which POIs may have common connections to other POIs owing to common features that match very well. One reasonable solution is to factorize the observed weighted transition matrix T as below:

$$T \approx V_s M V_t^{\,T}, \tag{4}$$

where $V_s \in \mathbb{R}^{|V| \times k}$ and $V_t \in \mathbb{R}^{|V| \times k}$ represent latent features of a source and a destination point, respectively. M is the interaction matrix that represents the relationship between locations, and k specifies the number of latent features.

2) Spatial-temporal influences: Spatial and temporal influences are very important in location recommendation tasks. Inspired by (Lian et al., 2014), we can explicitly embed spatial-temporal influences to improve our weighted transition matrix factorization model.

For spatial influence, we consider the simple assumption that the closer POIs are the more likely they are visited. We calculate the distances between POIs using the Haversine formula (Sinnott 1984), then take the reciprocal and normalize each entry by the maximum value in the matrix to construct the POI spatial influence matrix $G \in \mathbb{R}^{|V| \times |V|}$. The spatial influence matrix can be regarded as additional global knowledge that each entry represents the confidence of location-location spatial influence, where the distance is smaller when the influence is larger. The spatial influence matrix can be written as $G \approx V_g V_g^{\,T}$, where V_g represents the spatial feature between POIs and it can get be obtained by factorizing G through standard non-negative matrix factorization (NMF) (Lee et al., 1999).

For temporal influence, we consider the relationship between the check-in time of each POI and the user transition time interval. Each POI has an available open time window and visits vary over 24 hours (e.g., Figure 1). We assume that the visit time of a location over a day follows a mixed Gaussian distribution and has visit peaks. Also, we observe that users' transitions between locations in different cities are almost all less than 2 hours (e.g., Figure 2), and we use a Poisson distribution to fit it. For example, two locations' spatial influences are higher due to a smaller distance (i.e., a transition from one to the other is more likely), while their visit peaks have a big gap (e.g., one has a peak in the morning and the other in the night) that indicates that the transition possibility would not be very high. Therefore, if two locations' visit peaks better match the users' transition interval, the temporal influence is higher.

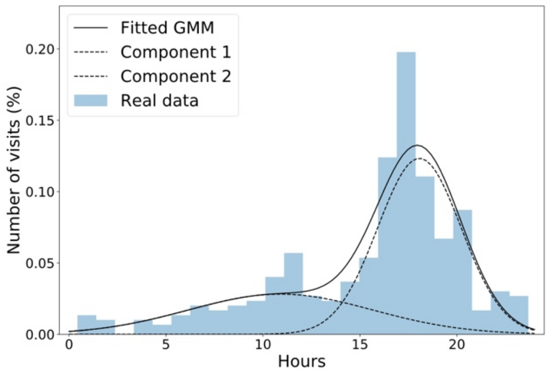

Figure 1: Visit time distributions; examples of two POIs over 24 hours

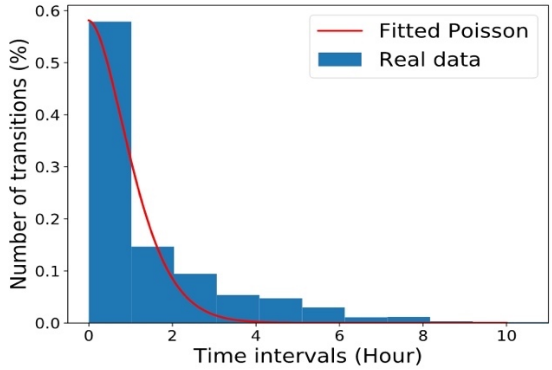

Figure 2: Visit time interval distributions in the Toronto dataset

A gaussian mixture model (GMM) is applied to fit the check-in data. It automatically fits the data and the GMM component ranges from 1 to 3, which corresponds to morning, afternoon, and night. Then the temporal influence matrix $C' \in \mathbb{R}^{|V|\times|V|}$ is constructed by matching the mean differences between locations with the fitted transition time interval distribution. C is equal to the normalized C' that represents the temporal influence between POIs. We represent our constructed temporal influence matrix C as $C \approx V_c V_c^T$, where V_c represents the latent temporal features between POIs and it can be obtained through standard NMF.

We explicitly combine the spatial and temporal influences linearly to enrich Eq. 4 as:

$$T \approx V_s M V_t^T + V_g M V_g^T + V_c M V_c^T \tag{5}$$

The latent factors V_s, V_t and M can be computed by solving the following function:

$$\min_{V_s, V_t, M} \left\| I \odot (T - V_s M V_t^T - V_g M V_g^T - V_c M V_c^T) \right\|^2 + \lambda[\ \|V_s\|^2 + \|M\|^2 + \|V_t\|^2\ ], \tag{6}$$

where $\|\cdot\|^2$ denotes the Frobenius norm; I is a binary weighted matrix with entries $I_{s,t}$ indicating whether transitions have been observed; and λ is the regularization parameter.

Finally, we can infer the transition matrix using Eq. 5 and normalize it by the maximum entry to obtain the transition reward matrix $\hat{T}$. We use the Theano framework (https://github.com/Theano/Theano) to learn latent variables and solve the objective function in Eq. 1 with the Gurobi optimization package (http://www.gurobi.com).

Experiment

To evaluate our proposed approaches, we apply our methods to public location-based social network datasets provided by (Chen et al., 2016; Lim et al., 2015). These datasets capture user travel routes extracted from Flickr photos; the statistics are listed in Table 1.

In our experimental settings, we randomly split each city dataset into five. We use five-fold cross-validation to evaluate different approaches, which means that when testing on a part of the dataset, we use the other data to train different models. Specifically, we consider users' real-life travel routes with more than 3 check-ins and test the following methods on each city dataset:

PoiPop: Recommends a travel route only based on the ordered POI popularity.

PoiRank, Markov, Rank+Markov: Proposed in (Chen et al., 2016), these methods recommend routes based on i) the ranking of POI scores, ii) transition probabilities through explicit feature pairs, and iii) their combination.

Table 1: Statistics of Travel Route Datasets

Dataset	#Photos	#Check-ins	#Travel routes	#Users
Edinburgh	82,060	33,944	5,028	1,454
Glasgow	29,019	11,434	2,227	601
Osaka	392,420	7,747	1,115	450
Toronto	157,505	39,419	6,057	1,395

Tmf, GTmf, TGTmf: Our proposed methods that recommend routes based on i) weighted transition matrix factorization, ii) spatial influence, and iii) spatial-temporal influence.

Rank + Tmf, Rank + GTmf, Rank + TGTmf: Our proposed methods that combine location and transition rewards.

To compare all the mentioned approaches, we evaluate the performance of each method based on users' real-life travel routes using the following metrics:

F_1 score: The F_1 score is a common metric for evaluating POI and travel route recommendations. It evaluates the recommended results with the user's real travel route using the harmonic mean of recall and precision of recommended locations.

Pairs-F_1 score: Proposed in (Chen et al., 2016), the Pairs-F1 score is used to evaluate both POI identity and visiting simultaneously. Pairs-F_1 computes the F_1 score of a pair of points and has a value between 0 and 1. It will achieve a score of 1 if and only if the POIs and the visiting order are exactly the same as the user's real travel route.

Results

The performance of the different approaches for each of the city datasets is summarized in Table 2 and Table 3, in terms of F_1 score and Pairs-F_1 score, respectively. The best method for each dataset is shown in bold and the second best in italic.

PoiRank improves upon the performance of PoiPop, which is only based on POI popularity, by leveraging more features. Among all the transition-based approaches, directly factorizing the weighted transition matrix had no effect that compares to the explicit factorization method Markov, which indicates that the latent factor model includes those features. Subsequently, the performance improved drastically when additional spatial and temporal influences were considered. Generally, we found that the combination method with a trade-off parameter α of around 0.7 achieves the best performance, which indicates that point rewards are relatively more important. Furthermore, the methods Rank+GTmf and Rank+TGTmf that we proposed outperformed baseline methods on different datasets, which indicates that spatial and temporal information is efficient in the transition patterns inference.

Table 2: Performance in Terms of F_1 Score

	Edinburgh	Glasgow	Osaka	Toronto
PoiPop	0.660 ± 0.158	0.690 ± 0.164	0.640 ± 0.130	0.664 ± 0.120
PoiRank	0.679 ± 0.145	0.708 ± 0.148	0.724 ± 0.160	0.749 ± 0.164
Markov	0.667 ± 0.152	0.741 ± 0.165	0.688 ± 0.152	0.711 ± 0.151
Tmf	0.661 ± 0.157	0.660 ± 0.157	0.660 ± 0.136	0.691 ± 0.157
GTmf	0.658 ± 0.170	0.769 ± 0.190	0.671 ± 0.172	0.691 ± 0.157
TGTmf	0.682 ± 0.172	*0.777 ± 0.184*	0.729 ± 0.186	0.722 ± 0.175
Rank + Markov	0.705 ± 0.162	0.756 ± 0.165	0.720 ± 0.166	0.743 ± 0.165
Rank + Tmf	0.689 ± 0.161	0.733 ± 0.172	0.738 ± 0.174	0.745 ± 0.160
Rank + GTmf	*0.709 ± 0.163*	0.772 ± 0.189	*0.741 ± 0.169*	*0.764 ± 0.172*
Rank + TGTmf	**0.717 ± 0.163**	**0.786 ± 0.178**	**0.753 ± 0.187**	**0.767 ± 0.170**

Table 3: Performance in Terms of Pairs-F_1 Score

	Edinburgh	Glasgow	Osaka	Toronto
PoiPop	0.399 ± 0.253	0.407 ± 0.296	0.324 ± 0.193	0.364 ± 0.201
PoiRank	0.399 ± 0.226	0.437 ± 0.252	0.468 ± 0.281	0.512 ± 0.293
Markov	0.385 ± 0.233	0.503 ± 0.298	0.416 ± 0.261	0.442 ± 0.256
Tmf	0.380 ± 0.236	0.375 ± 0.246	0.360 ± 0.200	0.420 ± 0.261
GTmf	0.412 ± 0.277	0.558 ± 0.332	0.398 ± 0.273	0.476 ± 0.296
TGTmf	0.403 ± 0.279	*0.576 ± 0.328*	0.496 ± 0.319	0.540 ± 0.308
Rank + Markov	0.446 ± 0.265	0.526 ± 0.299	0.470 ± 0.292	0.502 ± 0.292
Rank + Tmf	0.419 ± 0.252	0.492 ± 0.298	0.501 ± 0.308	0.505 ± 0.288
Rank + GTmf	*0.461 ± 0.277*	0.563 ± 0.330	*0.509 ± 0.304*	*0.539 ± 0.303*
Rank + TGTmf	**0.471 ± 0.276**	**0.588 ± 0.325**	**0.537 ± 0.326**	**0.547 ± 0.306**

Conclusion

This paper describes a technique that uses locations and transitions extracted from travel route data to recommend travel routes according to user queries. Experiment results demonstrate that our approaches outperform conventional methods on different datasets by using spatial-temporal enhanced transition patterns inference. In our future work, we would like to apply the method proposed in this paper to Kyoto city and evaluate it with real tourists.

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