Time-aware Point-of-interest Recommendation

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Introduction
As of January 2013, Foursquare had over 3 billion check-ins made by 30 million users.

Figure 1: An example of check-in
A point of interest (POI) is a specific point location that someone may find interesting and be willing to check in.

Objective of POI recommendation: discover new places
How to recommend a point-of-interest?
User-based collaborative filtering method performs well [Ye et al., 2011b]

Problem of existing methods:
No existing work has considered the time factor for POI recommendations in LBSNs.

Proposal:
Explore users’ temporal behavior and define a new time-aware POI recommendation problem;
Further, study users’ spacial behavior and employ a unified POI recommendation framework.
Introduction

Contributions

- Define a new time-aware POI recommendation problem
- Fuse the spacial and temporal influences with a framework to make the time-aware POI recommendation
- Conduct experiments on real-world LBSN datasets and demonstrate that time has significant influence and the proposed models perform better
Related Work

Collaborative Filtering
[Koren et al., 2009], [Ding and Li, 2005], [Su and Khoshgoftaar, 2009]

POI Recommendation & POI Prediction
[Ye et al., 2011b], [Ye et al., 2010], [Cheng et al., 2012], [Cho et al., 2011], [Clements et al., 2010]

Location Identification and Recommendation
[Zheng et al., 2009], [Leung et al., 2011], [Cao et al., 2010]

Recommendation with Temporal Information
[Ye et al., 2011a], [Ding and Li, 2005], [Xiang et al., 2010]

Contextual-aware Recommendation
[Adomavicius et al., 2005]
Models

- Utilizing Temporal Influence
- Utilizing Spacial Influence
- Unified Framework
User-based Collaborative Filtering

UCF in formula:

\[ \hat{c}_{u,l} = \frac{\sum_v w_{u,v} c_{v,l}}{\sum_v w_{u,v}} \]

where \( \hat{c}_{u,l} \) denotes the score that \( u \) will check-in a POI \( l \), \( w_{u,v} \) is the similarity between user \( u \) and user \( v \).

Notes

Let \( c_{v,l} = 1 \) if \( v \) has checked in \( l \); and \( c_{v,l} = 0 \) otherwise.
Incorporating Temporal Influence

Check-in Representation

user-POI matrix $\rightarrow$ user-time-POI cube (UTP)

Recommendation Formula

$$\hat{C}_{u,l} = \frac{\sum_v w_{u,v} c_{v,l}}{\sum_v w_{u,v}} \rightarrow \hat{C}_{u,t,l} = \frac{\sum_v w_{u,v}^{(t)} c_{v,t,l}}{\sum_v w_{u,v}^{(t)}}$$

Similarity Estimation

$$w_{u,v} = \frac{\sum_l c_{u,l} c_{v,l}}{\sqrt{\sum_l c_{u,l}^2} \sqrt{\sum_l c_{v,l}^2}} \rightarrow w_{u,v}^{(t)} = \frac{\sum_{t=1}^T \sum_{l=1}^L c_{u,t,l} c_{v,t,l}}{\sqrt{\sum_{t=1}^T \sum_{l=1}^L c_{u,t,l}^2} \sqrt{\sum_{t=1}^T \sum_{l=1}^L c_{v,t,l}^2}}$$
Enhancement by Smoothing

**Drawback** of aforementioned method: Sparsity

**Example**

User $u$ checks in $l_1$ and $l_2$ at $t_1$ and $t_2$; while user $v$ checks in $l_1$ and $l_2$ at $t_2$ and $t_1$.

- Similarity between $u$ and $v$ with temporal influence: 0
- Similarity between $u$ and $v$ without temporal influence: 1

**Proposal:** Smoothing by time slot similarity

**Formulation**

$$\tilde{c}_{u,t,l} = \sum_{t' = 1}^{T} \frac{\rho_{t,t'} \sum_{t'' = 1}^{T} \rho_{t,t''}}{\rho_{t,t'}} c_{u,t',l}$$

$$\tilde{w}_{u,v}(t) = \frac{\sum_{t=1}^{T} \sum_{l=1}^{L} \tilde{c}_{u,t,l} \tilde{c}_{v,t,l}}{\sqrt{\sum_{t=1}^{T} \sum_{l=1}^{L} \tilde{c}_{u,t,l}^2} \sqrt{\sum_{t=1}^{T} \sum_{l=1}^{L} \tilde{c}_{v,t,l}^2}}$$
Incorporating Spacial Influence

Observation

Power law distribution: \( wi(dis) = a \ast dis^k \)

Conditional probability

\[
p(l_j | l_i) = \frac{wi(dis(l_i,l_j))}{\sum_{l_k \in L, l_k \neq l_i} wi(dis(l_i,l_k))}
\]

Recommend by spacial influence

\[
\hat{c}^{(s)}_{u,l} = P(l | L_u) \propto P(l)P(L_u | l) = P(l) \prod_{l' \in L_u} P(l' | l)
\]
Enhancement by Temporal Popularity

Temporal Popularity

The probability of checking in a POI should reflect both its popularity at the specific time and the distance to the user’s current location.

\[
P_t(l) = \beta \frac{|Cl_{l,t}|}{\sum_{l' \in L} |Cl'_{l',t}|} + (1 - \beta) \frac{|Cl_l|}{\sum_{l' \in L} |Cl'_{l'}|},
\]

where \( Cl_l \) is the number of check-ins at \( l \), \( |Cl_{l,t}| \) is the number of check-ins at \( l \) at time \( t \), and \( beta \) is the weighting parameter.

Enhanced by temporal popularity

\[
\hat{c}^{(se)}_{u,t,l} = P_t(l) \prod_{l' \in L_u} P(l'|l)
\]
Unified Framework

Linear combination:

\[ c_{u,t,l} = \alpha \times \overline{c}^{(t)}_{u,t,l} + (1 - \alpha) \times \overline{c}^{(s)}_{u,t,l} \]

where \( c_{u,t,l} \) denotes the score that user \( u \) will check in POI \( l \) at time \( t \), \( \overline{c}^{(t)}_{u,t,l} \) and \( \overline{c}^{(s)}_{u,t,l} \) denote the score from temporal influence and spacial influence respectively.

Notes

\( \overline{c}^{(t)}_{u,t,l} \) and \( \overline{c}^{(s)}_{u,t,l} \) are normalized by min-max method.
Experimental Setup

- Metrics: Accuracy of POI recommendation (precision & recall)
- Data: Two datasets from Foursquare and Gowalla

<table>
<thead>
<tr>
<th>Dataset</th>
<th>No. of Check-ins</th>
<th>No. of Users</th>
<th>No. of POIs</th>
</tr>
</thead>
<tbody>
<tr>
<td>Foursquare</td>
<td>194,108</td>
<td>2,321</td>
<td>5,596</td>
</tr>
<tr>
<td>Gowalla</td>
<td>456,988</td>
<td>10,162</td>
<td>24,250</td>
</tr>
</tbody>
</table>
Methods for Comparison

- **U**: User-based CF [Ye et al., 2011b]
- **UTF**: U with Time Function [Ding and Li, 2005]
- **UT**: U with Temporal preference
- **UTE**: UT with smoothing Enhancement
- **SB**: Spacial influence based Baseline [Ye et al., 2011b]
- **S**: Spacial influence based recommendation
- **SE**: S with popularity Enhancement
- **U+SB**: Combination of U and SB [Ye et al., 2011b]
- **UTE+SE**: Combination of UTE and SE
Results

Figure 2: Performance of Methods Utilizing Temporal Influence

(a) Pre@$N$ - Foursquare

(b) Rec@$N$ - Foursquare

(c) Pre@$N$ - Gowalla

(d) Rec@$N$ - Gowalla
Results

Figure 3: Performance of Methods Utilizing Spacial Influence

(a) Pre@$N$ - Foursquare
(b) Rec@$N$ - Foursquare
(c) Pre@$N$ - Gowalla
(d) Rec@$N$ - Gowalla
Results

Figure 4: Performance of Unified Methods

- (a) Pre@N - Foursquare
- (b) Rec@N - Foursquare
- (c) Pre@N - Gowalla
- (d) Rec@N - Gowalla
Discussion—Effect of the Length of Time Slot

Figure 5: Performance of varying length of time slot

(a) Pre@5 - Foursquare
(b) Rec@5 - Foursquare
Figure 6: Performance of different time of a day
Conclusion & Further Work

Conclusion

- First work on time-aware POI recommendations.
- Propose a new approach exploring the spacial influence.
- Experimental results show that the proposed methods beat all baselines, and improve the accuracy of POI recommendations by more than 37% over the state-of-the-art method.

Further work

- Exploit other time dimensions in POI recommendations, e.g., the day of a week.
- Exploit category information in POI recommendations.
Some insights from me

1. Good writing
2. Clarity
3. Details