Time-aware Point-of-interest Recommendation

Quan Yuan, Gao Cong, Zongyang Ma,
Aixin Sun, and Nadia Magnenat-Thalmann

School of Computer Engineering
Nanyang Technological University

Outline

Introduction

Introduction

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

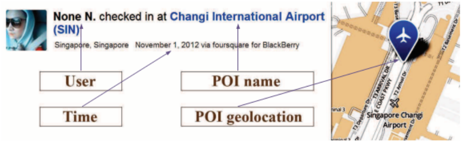
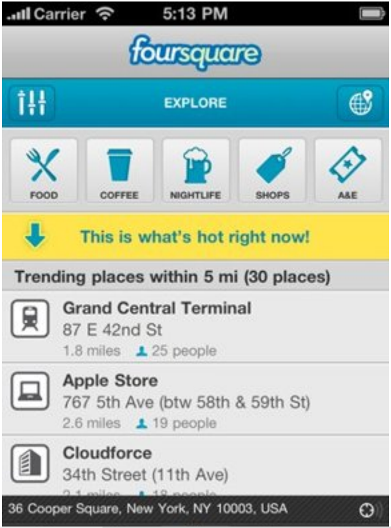


Figure 1 : An example of check-in

Introduction

- 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



Introduction

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

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

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

Incorporating Spacial Influence

Observation

Power law distribution: $wi(dis) = a * dis^k$

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

$$\hat{c}_{u,l}^{(s)} = P(l|L_u) \propto P(l)P(L_u|l) = P(l) \prod_{l' \in L_u} P(l'|l)$$

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.

$$P_t(l) = \beta \frac{|CI_{l,t}|}{\sum_{l' \in L} |CI_{l',t}|} + (1-\beta) \frac{|CI_l|}{\sum_{l' \in L} |CI_{l'}|},$$

where CI_l is the number of check-ins at l, $|CI_{l,t}|$ 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 1 : Data statistics (after pre-processing)

Dataset	**No. of Check-ins**	**No. of Users**	**No. of POIs**
Foursqaure	194,108	2,321	5,596
Gowalla	456,988	10,162	24,250

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

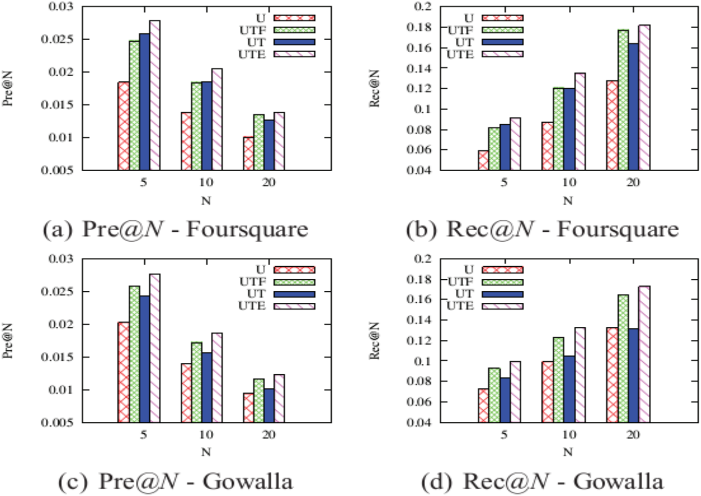
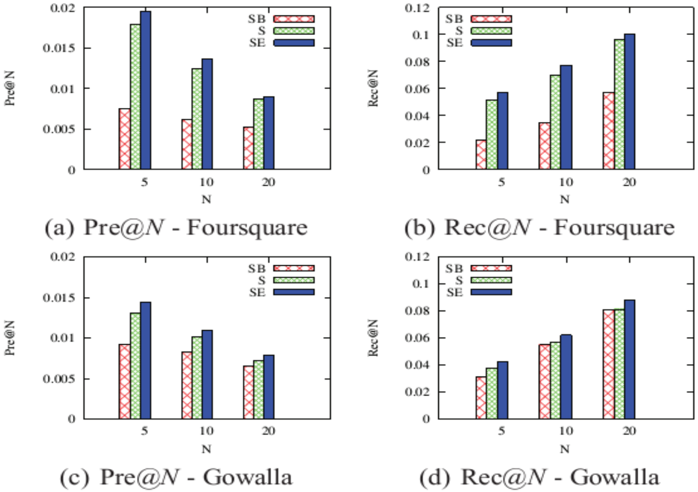


Figure 2 : Performance of Methods Utilizing Temporal Influence

Results



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

Figure 3 : Performance of Methods Utilizing Spacial Influence

Results

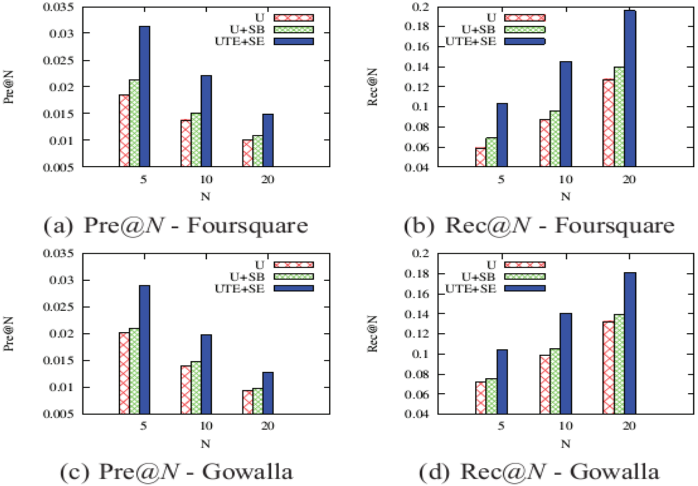


Figure 4 : Performance of Unified Methods

Discussion—Effect of the Length of Time Slot

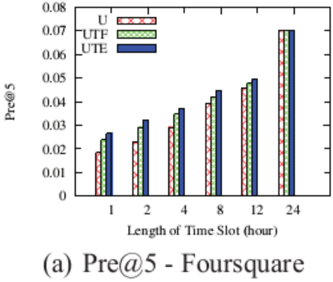
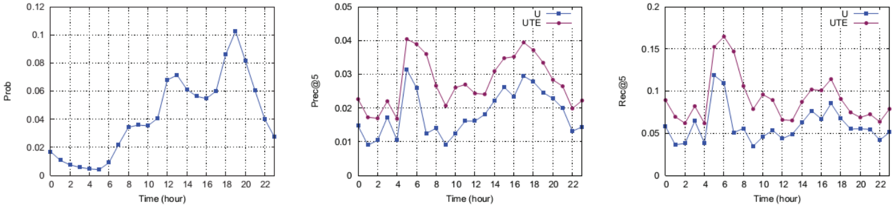


Figure 5 : Performance of varying length of time slot

Discussion—Case Study



(a) Distribution of check-in in a day (b) Pre@5 - Foursquare (c) 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