Learning Graph-based POI Embedding for Location-based Recommendation

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Outline

1. Location-based Recommendation
2. Graph-based Embedding Model
3. Experiments
4. Conclusions
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Social Networks (SNs)

2004 - 2010
Location-based Social Networks (LBSNs)

Mobile communication + Positioning technologies

2010 - …
Location-based Recommendation

- To recommend points-of-interest (POIs) that a user is interested in but has not visited
  - To users: discovering new places, knowing their cities better
  - To merchants: launch mobile advertisements to targeted users.

- Given a user $u$ with his/her current location $l$ and time $\tau$, recommend top-$k$ POIs that $u$ would be interested in.

![Diagram of user preferences and location](image)
Challenges

- **Data Sparsity**
  - Physically visit a POI is more expensive than rating a movie online.
  - Privacy or safety concerns.

- **Context Awareness**
  - Not only considering personal preferences, but also the spatiotemporal context.
  - User tends to have different choices and needs at different times and places.

- **Cold Start**
  - New POIs (e.g., business) are emerging every day.

- **Dynamic of Personal Preferences**
  - Users’ preferences are changing with the time going on.
How to overcome?

Exploit and integrate multi factors in a unified way.
Transition probabilities from one checked-in POI to other POIs is a non-uniform distribution.
People tend to visit nearby POIs or explore POIs near the ones that they have visited before.
Users’ mobility behaviors exhibit strong temporal cyclic patterns, and the daily pattern (hours of the day).
Contents of POIs checked-in by the same user tend to semantically similar.
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Graph-based Embedding Model

We introduce four kinds of graphs to model Sequential Effect, geographical influence, temporal cyclic effect and semantic effect, respectively.

- **POI-POI Graph** captures the sequential patterns of check-in POIs. If $v_i$ and $v_j$ are often checked in sequentially, their correlation will be larger.

- **POI-Region Graph** captures the geographical influence. If POI $v_i$ is located in region $r_j$, there will be an edge $e_{ij}$ between them.

- **POI-Time Graph** captures the temporal cyclic effect. The weight $w_{ij}$ of the edge between POI $v_i$ and time slot $t_j$ is defined as the frequency of POI $v_i$ checked in at time slot $t_j$.

- **POI-Word Graph** captures the semantic effect. If word $w_i$ can describe POI $v_j$, there will be an edge $e_{ij}$ between them.

**Goal**: to embed the above four graphs into a shared low dimensional space $\mathbb{R}^d$, and get the vector representations of POIs, regions, time slots and words, i.e., $\vec{v}$, $\vec{r}$, $\vec{t}$ and $\vec{w}$.
Get the vector representations of POIs, regions, time slots and words, i.e., \( \vec{v}, \vec{r}, \vec{t} \) and \( \vec{w} \).

Dynamic User Preference Modeling:

\[
\vec{u}_\tau = \sum_{(u,v_i,\tau_i) \in D_u \cap (\tau_i < \tau)} \exp^{-(\tau-\tau_i)} \cdot \vec{v}_i
\]  

(1)

Recommendation Using GE

\[
S(q, v) = \vec{u}_\tau^T \cdot \vec{v} + \vec{r}^T \cdot \vec{v} + \vec{t}^T \cdot \vec{v}
\]  

(2)
Optimization

- All the graphs share the vector representations of POIs.
- Optimizing four graphs in turn, and update vector representations.

**Bipartite Graph Embedding**

\[ O = -\sum_{e_{ij} \in \varepsilon} w_{ij} \log p(v_j | v_i) \]  \hspace{1cm} (3)

**Joint Embedding Learning**

\[ O = O_{vv} + O_{vr} + O_{vt} + O_{vw} \]  \hspace{1cm} (4)

\[ O_{vv} = -\sum_{e_{ij} \in \varepsilon_{vv}} w_{ij} \log p(v_i | v_j) \]

\[ O_{vr} = -\sum_{e_{ij} \in \varepsilon_{vr}} w_{ij} \log p(v_i | r_j) \]

\[ O_{vt} = -\sum_{e_{ij} \in \varepsilon_{vt}} w_{ij} \log p(v_i | t_j) \]

\[ O_{vw} = -\sum_{e_{ij} \in \varepsilon_{vw}} w_{ij} \log p(v_i | w_j) \]
Experiments

- **Datasets**

  - On two real large-scale LBSNs datasets: Foursquare and Gowalla.

<table>
<thead>
<tr>
<th></th>
<th>Foursquare</th>
<th>Gowalla</th>
</tr>
</thead>
<tbody>
<tr>
<td># of users</td>
<td>114,508</td>
<td>107,092</td>
</tr>
<tr>
<td># of POIs</td>
<td>62,462</td>
<td>1,280,969</td>
</tr>
<tr>
<td># of check-ins</td>
<td>1,434,668</td>
<td>6,442,892</td>
</tr>
<tr>
<td>time span</td>
<td>Sep 2010-Jan 2011</td>
<td>Feb 2009-Oct 2010</td>
</tr>
</tbody>
</table>

- **Comparison Approaches**

  - **SVDFeature.** Beyond user-POI matrix, implement it by incorporating POI content, POI geographical location and check-in time.

  - **JIM.** It strategically integrates semantic effect, temporal effect, geographical influence and word-of-mouth effect.

  - **PRME-G.** Based on embedding techniques, but utilized two latent spaces: sequential transition space and user preferences space.

  - **Geo-SAGE.** Exploits POI content information and the crowd’s preference at a region.
Evaluation

- Split the dataset into the training set $D_{\text{train}}$ and test set $D_{\text{test}}$ according to their check-in timestamps.

- **Accuracy@k** evaluation

\[
\text{Accuracy@k} = \frac{\#hit@k}{|D_{\text{test}}|}
\]

- **hit@k** for a single test case as either the value 1, if the ground truth POI $v$ appears in the top-k results, or the value 0.

- $k = \{1, 5, 10, 15, 20\}$
Recommendation Effectiveness

- GE model outperforms other competitor models significantly.
- GE and PRME-G achieves much higher recommendation accuracy than other comparison methods in top-1 recommendation.
### Variants of GE

#### Impact of Different Factors

- **GE-S1** Without sequential effect
- **GE-S2** No POI-Region graph
- **GE-S3** No POI-Time graph
- **GE-S4** No POI-Word graph

Sequential Effect > Temporal Effect > Content Effect > Geographical Influence.
Variants of GE

- **Exploring Various Temporal Patterns**
  - GE Daily pattern (24 hours of a day)
  - GE-S5 Weekly pattern (day of the week)
  - GE-S6 Weekday/weekend pattern
  - GE-S3 No POI-Time graph

Exploiting daily pattern, weekly pattern or weekday/weekend pattern can largely improve performance.

Improvement brought by exploiting **daily pattern** is the most significant.
Test for Cold Start Problem

- **Cold start POIs**: no check-in information, that is no user has checked in there.

- **PRME-G model** does not work in the cold-start scenario.

- **GE model** still performs best.
- **Accuracy of GE model** deteriorate slightly.

![Figure 4: Recommendation for Cold-start POIs](image)
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Conclusions

- We are the first to investigate the joint effect of sequential effect, geographical influence, temporal cyclic effect and semantic effect.

- We develop a graph-based embedding model to learn the representations of POIs, time slots, geographical regions and content words in a shared low-dimension space.

- We propose a novel method for dynamic user preferences modeling based on the learnt embedding of POIs, to support real-time recommendation.

- We conduct extensive experiments to evaluate the performance of our recommender method on two real large-scale datasets, and verified its effectiveness.

- Moreover, we found that both sequential effect and temporal cyclic effect play a dominant role in location-based recommendation and the daily pattern is the most significant temporal cyclic pattern in users’ daily behaviors.
Thank you

Q&A: If you have any questions please contact the authors.

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