Personalized Location Recommendation on Location-Based Social Networks

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http://www.public.asu.edu/~hgao16/recsys2014.html
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Outline

- Introduction
- LBSN Data Properties and Mobile Patterns
- Location Recommendation on LBSNs
- Summary
Introduction

What is Location Recommendation?

Personalized Location Recommendation on Location-Based Social Networks

Why Personalized?

Why on LBSNs?
What is Location Recommendation?

- If this is the first time visiting **Foster City**, where should I go?

- Among hundreds of thousands of restaurants in **San Francisco Bay Area**, which one should I go for dinner?
Choice Paralysis

- More choices than ever before – it could cause more problems

- Choice Paralysis

  Recommendation is helpful
  - Help users filter uninteresting items
  - Reduce time in decision making
  - Defensive decision making
Location Recommendation

- A location (or Point of Interest) is a geographical point with specific functions (e.g., hotel, restaurant, museum, store) that a user may find useful or interesting.

- Location Recommendation (POI Recommendation)
  Recommend Locations (Point of Interests) to a user to fulfill his requirements and satisfy his interests
Introduction

Personalized Location Recommendation on Location-Based Social Networks

What is Location Recommendation?

Why Personalized?

Why on LBSNs?
Why Personalized?

- Examples of Location Recommender Systems

Among hundreds of thousands of restaurants in San Francisco Bay Area, which one I should go for dinner?

Yelp

Yelp can suggest some restaurants based on their ratings and your current locations automatically

- Based on Location Popularity
- Ignore Personal Interests
Why Personalized?

- Examples of Location Recommender Systems

If this is the first time visiting **Foster City**, where should I go?

**Foursquare**

Foursquare can suggest some places to visit and as some useful tips base on your locations

- Recently released the App with personalization (in Aug 2014*)

*http://searchengineland.com/new-foursquare-app-tips-tastes-deliver-big-personalization-199279
Introduction

Personalized Location Recommendation on Location-Based Social Networks

What is Location Recommendation?

Why Personalized?

Why on LBSNs?
What are Location-Based Social Networks?

Location-based social networks are social networks in which GPS features of mobile devices are used to locate people (and you) and that let you broadcast your location and other content from your mobile device.

Why on Location-Based Social Networks?

➢ Bridging the Gap between Real World and Online Social Networks
How Popular are Location-Based Social Networks?

- 26% of Americans access social networks on mobile devices
- 18% of smartphone owners use location-based social services
- Location-based marketing is anticipated to be a $1.8 billion business worldwide by 2015.

P. Finocchiaro. Mobile advertisers forecast to spend $1.8 billion on location-based campaigns in 2015. 2010.
Facebook Case

68% of Facebook's Users Are Mobile
Facebook's monthly active users, by type of access

http://www.hashmeta.com/blog/15-jaw-dropping-social-media-marketing-statistics-every-marketer-should-know/
Foursquare Case

By May 2014

- Over 50 million people worldwide
- Over 6 billion Check-ins

https://foursquare.com/about
http://mashable.com/2012/12/18/apple-foursquare-maps/
Problem Statement

Given a user $u$, a set of locations he has checked-in, recommend him some locations for his future visits based on the LBSN context related to him.
W⁴: Information Layout on LBSNs

**What**
User-Generated Content (e.g., Tweets)

**Who**
Friendships

**Where**
Check-in POIs

**When**
Time Stamps
Outline

- Introduction
- LBSN Data Properties and Mobile Patterns
- Location Recommendation on LBSNs
- Summary
A Check-in Example on LBSNs

**Who**
Felix
With: Jiliang

**Where**
Shanghai Flavor Shop
Sunnyvale, CA
August 1, 2013 via foursquare for iPhone

**When**
1 day ago

**What**
Best pan-fried pork bun and Shanghai wonton on the west coast!!
An Example of GPS Data

<table>
<thead>
<tr>
<th>GPS info</th>
<th>value</th>
</tr>
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<tbody>
<tr>
<td>Date &amp; Time</td>
<td>6/15/11 1:42:22 PM</td>
</tr>
<tr>
<td>Latitude</td>
<td>47.0826433333333</td>
</tr>
<tr>
<td>Lat. (DMS)</td>
<td>47° 4' 57.5159999999875&quot;</td>
</tr>
<tr>
<td>Longitude</td>
<td>-70.8890116666667</td>
</tr>
<tr>
<td>Long. (DMS)</td>
<td>-70° 53' 20.4419999999811&quot;</td>
</tr>
<tr>
<td>Sea level (m)</td>
<td>28.1</td>
</tr>
<tr>
<td>Fix Quality</td>
<td>GPS_FIX_QUALITY_DGPS</td>
</tr>
<tr>
<td>Fix Type</td>
<td>GPS_FIX_2D</td>
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<tr>
<td>Satellite count</td>
<td>3</td>
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<tr>
<td>Satellite in view</td>
<td>11</td>
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</table>
LBSN Data vs. GPS Data

- Socio-Spatial Properties
  - Explicit Social Friendships vs. Inferred Connections

- Sparse Data in Large Scale
  - Large Sparse Data vs. Small Dense Data

- Semantic Indications
  - Points of Interest vs. Longitude/Latitude Points
Socio-Spatial Properties [Scellato et al., 2011]

- Geographical Distance and Social Connections

![Graph showing the relationship between geographical distance and social connections](image)

- Socio-Spatial Properties
  - Geographical Distance
  - Social Connections

[Graphs illustrating the distribution of friends and users at different distances]
Socio-Spatial Properties [Cho et al., 2011]

- Trajectory Similarity and Social Connections

The graph shows the relationship between Trajectory Similarity and the probability of Friendship, indicating a positive correlation.
Sparse Data in Large Scale [Gao and Liu, 2014]

- User Driven Check-in Property on LBSNs
- Passively Recording in GPS data
- Privacy Concerns
Semantic Indications [Cheng et al., 2011] [Ye et al., 2011]

- Map GPS positions to Points of Interest (locations)
  - Whether a GPS point corresponds to a restaurant or just a point on highway
  - Distinguish two adjacent POIs on the same street or in the same building

- Associate Points of Interest with Users
  - User-Driven Check-in Actions
Human Mobility Patterns on LBSNs

- Inverse Distance Rule on Friendships
- Social Correlations in Geographical Trajectory
- Levy Flight of Check-ins
- Power-Law Distribution
- Short-Term Effects
- Temporal Periodic Patterns
- Multi-Center Check-in Distribution
- Sentiment and Topical Indications
## Overview of Mobility Patterns

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Inverse Distance Rule [Backstrom et al., 2010] [Ye et al., 2010]

- Death of Distance in Web 2.0?
  - Users who live close have higher probability to create friendship links

- Only One Thirds of Friendships are Independent of Geography
Social Correlations in Geographical Trajectory [Cho et al., 2011]

- Trajectory Similarity and Social Connections

![Graph showing social correlations in geographical trajectory similarity](image-url)
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Lévy Flight of Check-ins [Cho et al., 2011] [Cheng et al., 2012]

- **Lévy Flight**
  - People tend to move to nearby places and occasionally to distant places
  - 20% of consecutive check-ins happened within 1 km, 60% between 1 and 10 km, and 20% over 10 km
Power-Law Distribution [Gao et al., 2012a]

- A few places have many check-ins while most of places have few check-ins

- A user goes to a few places many times, and to many places a few times
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Short-Term Effect [Gao et al., 2012a]

- The effect of previously check-ins has different strength to the latest check-in

- The effect decreases as the time goes by
Common Properties of Text Data and LBSN Data

- Power-Law Distribution and Short-Term Effect
- Language Modeling vs. LBSN Mining

<table>
<thead>
<tr>
<th>Language Modeling</th>
<th>LBSN Modeling</th>
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<tbody>
<tr>
<td>Corpus</td>
<td>Check-in collection</td>
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<tr>
<td>Document</td>
<td>Individual check-ins</td>
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<tr>
<td>Document Structure</td>
<td>Check-in Structure</td>
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<tr>
<td>Paragraph</td>
<td>Monthly check-in sequence</td>
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<tr>
<td>Sentence</td>
<td>Weekly check-in sequence</td>
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<tr>
<td>Phrase</td>
<td>Daily check-in sequence</td>
</tr>
<tr>
<td>Word</td>
<td>Check-in location</td>
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Temporal Periodic Patterns [Cheng et al., 2011]

- Hour of the Day, Day of the Week, Weekday/Weekend
  - Go to a restaurant for lunch at 12:00 pm
  - Watch movies at Friday night
  - Shopping at mall during weekend
Multi-Center Check-in Distribution [Gao et al., 2013]

- **Temporal Perspective**
  - Probability of visiting a location (regular location) centers on certain time period(s) and decreases during other time period(s).
  - Biased probability decreasing speed around a center.
  - Various Peaks at multiple centers.

![Graph showing check-in frequency over time]

![Graph showing visit frequency over time]
Multi-Center Check-in Distribution [Cho et al., 2011]

- Geographical Perspective
  - Centers on certain location areas
  - Rarely checks-in at locations far away from the center

![Map and scatter plot showing multi-center check-in distribution.](image)
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Content in LBSNs is pervasively available
- Tags, tips or comments

Content contains semantic words that reflect a user’s interested topics and the location property
- “Spicy” and “Tofu”
- “What” does the user visit this location for?

Content can reflect users’ preferences
- “all great”
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Outline

Introduction

LBSN Data Properties and Mobile Patterns

Location Recommendation on LBSNs

Summary
W⁴: Information Layout on LBSNs

- **Content Indications**
- **Social Correlations**
- **Geographical Influences**
- **Temporal Dynamics**

**Content Layer**
- Audios
- Videos
- Photos
- Tips

**Social Layer**

**Geographical Layer**

**Timeline**

**LBSN**
Location Recommendation with LBSNs

Temporal Dynamics

Temporal

Geo

Social

Social Correlations

Content

Content Indications

Geographical Influence
“Existing Location” vs. “New Location”

- Human Repetitive Behavior
  - Movie Recommendation
    - watch the same movie for more than two times?
  - Item Recommendation
    - purchase the same camera once and once again?
  - Location Recommendation
    - check-in at the favorite restaurant for several times

- Repetitive Check-in Behavior (Existing Location) and
  Cold-Start Check-in Behavior (New Location)

Power-Law Distribution on Check-in Frequency
Location Recommendation in Social Media

Location Recommendation on LBSNs

- Geographical Influence
- Social Correlations
- Temporal Dynamics
- Content Indications
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Geographical Influence

- Modeling Check-in Distribution over Geographical Distance
- How check-in probability is influenced by Geo Distance

- Universal Distribution
  - Lévy Flight (Power-Law Distribution of Geographical Distance)
  - Multi-Center Gaussian Distribution

- Personalized Distribution
  - Kernel Density Estimation
Geographical Influence [Ye et al., 2011]

- Modeling Distribution of Geographical Distance
  - Power-Law Distribution of Geographical Distance (Lévy Flight)

\[ \hat{P}(d) \sim \alpha \ast d^\beta \]

- \( \hat{P}(d) \): probability of the two locations visited by the same user
- \( d \): Distance between two locations
- \( \alpha, \beta \): parameters of power-law distribution
Geographical Influence [Ye et al., 2011]

- Modeling Distribution of Geographical Distance
  - Power-Law Distribution of Check-in Distance (Lévy Flight)

\[ \hat{P}(d) \sim \alpha \times d^\beta \]

\( \alpha, \beta \): parameters of power-law distribution

To Recommend Locations:

\[ P(l_j | L_i) = \prod_{l_x \in L_i} \hat{P}(d_{l_j, l_x}) \]

- Select \( l_j \) which has the highest probability

Select the location with the highest probability to be co-visited with locations from the user’s check-in history
Geographical Influence [Ye et al., 2011]

Modeling Distribution of Geographical Distance

- Power-Law Distribution of Check-in Distance (Lévy Flight)

\[ \hat{p}(d) \sim \alpha \ast d^\beta \]

\[ p(d) = \frac{|\{(l_i, l_j)| D(l_i, l_j) = d, I(l_i, l_j) = 1\}|}{|\{(l_i, l_j)| D(l_i, l_j) = d\}|} \]

Minimize:

\[ \min_{\alpha, \beta} \sum_{(l_i, l_j) \in M} (\log P(d_{i,j}) - \log \hat{P}(d_{i,j}))^2 \]

= \sum_{(l_i, l_j) \in M} (\log P(d_{i,j}) - (\log \alpha + \beta \log d_{i,j}))^2

Ground Truth Observations
Geographical Influence [Cho et al., 2011]

- Modeling Distribution of Geographical Distance
  - Multi-Center Gaussian Distribution

\[
P \left[ x_u(t) = x_i | c_u(t) \right] = \begin{cases} 
\sim \mathcal{N} (\mu_H, \Sigma_H) & \text{if } c_u(t) = H \\
\sim \mathcal{N} (\mu_W, \Sigma_W) & \text{if } c_u(t) = W 
\end{cases}
\]
Geographical Influence [Zhang et al., 2013]

- Modeling Distribution of Geographical Distance
  - Kernel Density Estimation

- Setp 1: Distance Sample Collection
  Compute distance between every pair of locations that have been checked-in by the user, denoted as D
Geographical Influence [Zhang et al., 2013]

- Modeling Distribution of Geographical Distance
  - Kernel Density Estimation
  - Step 2: Define Distance Distribution

\[
\hat{f}(d) = \frac{1}{|D|h} \sum_{d' \in D} K \left( \frac{d - d'}{h} \right)
\]

D: Distance Sample Collection \hspace{1cm} K(\cdot): Kernel Function
h: Smoothing Parameter

- Step 3: Recommend a Location \(l_j\)

\[
\hat{f}(d_{ij}) = \frac{1}{|D|h} \sum_{d' \in D} K \left( \frac{d_{ij} - d'}{h} \right)
\]

\[
p(l_j | L_i) = \frac{1}{n} \sum_{i=1}^{n} \hat{f}(d_{ij})
\]

\(d_{ij} = \text{distance}(l_i, l_j), \forall l_i \in L_i\)
Summary of Geographical Influence

How check-in probability is influenced by Geo Distance

- **Universal Distribution**
  - Lévy Flight (Power-Law Distribution of Geographical Distance)
  - Multi-Center Gaussian Distribution

- **Personalized Distribution**
  - Kernel Density Estimation
Location Recommendation on LBSNs

- Geographical Influence
- Social Correlations
- Temporal Dynamics
- Content Indications
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<tr>
<td>Sentiment and Topical Indications</td>
<td></td>
<td></td>
<td></td>
<td>✔️</td>
</tr>
</tbody>
</table>
Social Correlations [Ye et al., 2010]

Friend-Based Collaborative Filtering

\[
\hat{r}_{i,j} = \frac{\sum_{u_k \in U_i} r_{k,j} w_{i,k}}{\sum_{u_k \in U_i} w_{i,k}}
\]

Inverse Distance Rule

- Assuming a power-law relation between trajectory similarity $y$ and geographical distance $x$
  
  \[
y = \alpha x^\beta
\]

- Similarity is computed as

\[
\omega_{i,k} = \frac{y(x = d(u_i, u_k), \alpha, \beta)}{\sum_{u_k \in U_i} y(x = d(u_i, u_k), \alpha, \beta)}
\]
Social Correlations [Cheng et al., 2012]

Matrix Factorization

\[ \min_{U,L} \sum_{(i,j) \in \Omega} (C_{i,j} - U_i L_j^T)^2 + \alpha \|U\|_F^2 + \beta \|L\|_F^2 \]

\[ \begin{array}{ccc}
  l_1 & l_2 & l_3 \\
  U_1 & x & x \\
  U_2 & x & x \\
  \vdots & \vdots & \vdots \\
  U_m & x & x \\
\end{array} \quad \begin{array}{ccc}
  f_1 & f_2 & f_3 \\
  U_1 & x & x \\
  U_2 & x & x \\
  \vdots & \vdots & \vdots \\
  U_m & x & x \\
\end{array} \quad \begin{array}{ccc}
  l_1 & l_2 & l_3 \\
  f_1 & x & x \\
  f_2 & x & x \\
  \vdots & \vdots & \vdots \\
  f_3 & x & x \\
\end{array} \quad \begin{array}{ccc}
  l_1 & l_2 & l_3 \\
  u_1 & x & x \\
  u_2 & x & x \\
  \vdots & \vdots & \vdots \\
  u_m & x & x \\
\end{array} \]
Social Correlations [Ma et al., 2011] [Cheng et al., 2012]

Matrix Factorization with Social Regularization

Social Correlations in Geographical Trajectory

Strong social friendship strength corresponds to high trajectory similarity

$$\min_{U} \frac{1}{2} \sum_{i} \sum_{j \in F_i} \text{sim}(u_i, u_j) \left\| U_i - U_j \right\|_F^2$$

Basic Matrix Factorization Model
Social Correlations [Ma et al., 2011] [Yang et al., 2013]

Matrix Factorization with Social Regularization

\[
\min_{U,L} \frac{1}{2} \sum_{(i,j) \in \Omega} (C_{i,j} - U_i L_j^T)^2 + \frac{1}{2} \alpha \|U\|_F^2 + \frac{1}{2} \beta \|L\|_F^2 + \frac{1}{2} \lambda \sum_i \left\|U_i - \sum_{j \in F_i} \text{sim}(u_i, u_j)U_j \right\|_F^2
\]

Basic Matrix Factorization Model

Social Correlations in Geographical Trajectory

- Matrix Factorization with Social Regularization

- \( U_{f_1} \)
- \( U_{f_2} \)
- \( U_{f_n} \)
- \( U_i \)
- \( L_j \)
- \( C_{i,j} \)
- \( \text{sim}(u_i, u_{f_1}) \)
- \( \text{sim}(u_i, u_{f_2}) \)
- \( \text{sim}(u_i, u_{f_n}) \)
Some Observations for Geo-social Location Recommendation

- Social information can consistently improve the recommendation performance, however, the improvement is very limited.


[Graph 2] Prediction accuracy vs. fraction of training set: MFC, MFT, Order-1, Order-2, HM, SHM

[Ye et al., 2011]

[Gao et al., 2012a]
Summary of Social Correlations

- **Friend-Based Collaborative Filtering**
  - Memory-Based

- **Matrix Factorization with Social Regularization**
  - Model-Based
Location Recommendation in Social Media

Location Recommendation on LBSNs

- Geographical Influence
- Social Correlations
- Temporal Dynamics
- Content Indications
### Overview of Mobility Patterns

<table>
<thead>
<tr>
<th>Mobility Patterns</th>
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<th>Content</th>
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<td></td>
<td></td>
<td>✔️</td>
</tr>
</tbody>
</table>
Temporal Dynamics [Gao et al., 2012a]

- Temporal Chronological (Sequential Patterns)
  - Shopping in the mall after dinner at a restaurant
  - Visiting a bar after work

- Temporal Cyclic (Periodic Patterns)
  - Going to a restaurant around 11:30 am
  - Watching a movie at a theater on Friday night
  - Shopping during weekends
Temporal Dynamics [Cheng et al., 2013]

- Temporal Chronological (Sequential Patterns)
  - Short-Term Effect (Order-K Markov Chain)

\[ p(l \in L_u^t | L_u^{t-1}) = \frac{1}{|L_u^{t-1}|} \sum_{i \in L_u^{t-1}} p(l \in L_u^t | i \in L_u^{t-1}) \]
Temporal Dynamics [Gao et al., 2012a]

- **Temporal Chronological (Sequential Patterns)**
  - Consider the combination of various order-k Markov patterns
  - Power-Law Property and Short-Term Effect
Temporal Dynamics [Gao et al., 2012a]

- Temporal Chronological (Sequential Patterns)
  - Consider the combination of various order-k Markov patterns
  - Power-Law Property and Short-Term Effect

Modeling Power-Law Distribution

Pitman-Yor Process

\[ G_0 \sim PY(d_0, \gamma_0, G_0) \]

Modeling Short-Term Effect

Hierarchical Pitman-Yor Process

\[ G_u \sim PY(d_{|u|}, \gamma_{|u|}, G_{\pi(u)}) \]
Temporal Dynamics [Gao et al., 2013b]

- Temporal Chronological (Sequential Patterns)
  - Shopping in the mall after dinner at a restaurant
  - Visit a bar after work

- Temporal Cyclic (Periodic Patterns)
  - Go to a restaurant around 11:30 am
  - Watch a movie at a theater on Friday night
  - Shopping during weekends
Temporal Dynamics [Gao et al., 2013b]

- Temporal Cyclic (Periodic Patterns)

\[
P(r(t)|c_u = l, H_{u,t}) \sim \sum_{i=1}^{k} A_i \mathcal{N}(r(t)|\mu_{u,l}^i, \sigma_{u,l}^i)
\]
Temporal Dynamics [Gao et al., 2013a]

- Temporal Cyclic (Periodic Patterns)
  - One user’s daily check-in activity w.r.t. his top 5 frequently visited locations

- Temporal Non-uniformness
  - A user presents different check-in preferences at different hours of the day

- Temporal Consecutiveness
  - A user presents similar check-in preferences at nearby hours of the day
Modeling Temporal Non-uniformness [Gao et al., 2013a]

- A user presents different check-in preferences at different hours of a day

\[
\min_{U_i \geq 0, L_j \geq 0} \sum_{(i, j) \in \Omega} \left( C_{i, j} - U_i L_j^T \right)^2
\]

\[
\min_{U_i \geq 0, L_j \geq 0} \sum_{t=1}^{24} \sum_{(i, j) \in \Omega} Y_{i, j}^t \left( C_{i, j}^t - U_i^t L_j^T \right)^2
\]
Modeling Temporal Consecutiveness [Gao et al., 2013a]

- A user presents similar check-in preferences at nearby hour of the day

\[
\min_{U \geq 0} \sum_{t=1}^{T} \sum_{i=1}^{m} \psi_i(t, t-1) \| U_t(i,:) - U_{t-1}(i,:) \|_F^2
\]

\[
\psi_i(t, t-1) = \frac{C_t(i,:) \cdot C_{t-1}(i,:)}{\sqrt{\sum_j C_t^2(i,:) \sqrt{\sum_j C_{t-1}^2(i,:)}}}
\]
Framework of Location Recommendation with Temporal Effects

[Gao et al., 2013a]
Location Recommendation with Time Preference: UT
[Yuan et al., 2013]

- Splitting data into 24 slots based on hours
  - Nov. 6 2012, 10:30 → 10
- Introducing time dimension into user-location matrix c
  - $c_{u,l} \rightarrow c_{u,t,l}$
- Leveraging time factor when
  - Computing the similarities between users over time

\[
W_{u,v} = \frac{\sum_l c_{u,l}c_{v,l}}{\sqrt{\sum_l c_{u,l}^2} \sqrt{\sum_l c_{v,l}^2}} \rightarrow W^{(t)}_{u,v} = \frac{\sum_{t=1}^{T} \sum_{l=1}^{L} c_{u,t,l}c_{v,t,l}}{\sqrt{\sum_{t=1}^{T} \sum_{l=1}^{L} c_{u,t,l}^2} \sqrt{\sum_{t=1}^{T} \sum_{l=1}^{L} c_{v,t,l}^2}}
\]

- Making predictions

\[
\hat{c}_{u,t,l} = \frac{\sum_{v} W_{u,v}^{(t)} c_{v,t,l}}{\sum_{v} W_{u,v}^{(t)}}
\]
Enhancing UT by Smoothing [Yuan et al., 2013]

- Data in each slot becomes even sparser after splitting
- Check-in behaviors of users at different time are correlated
- Smoothing $c_{u,t,l}$ based on the similarity between different time slots

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

\[
\tilde{w}_{u,v}^{(t)} = \frac{\sum_{t=1}^{T} \sum_{l=1}^{L} \tilde{c}_{u,t,l} \tilde{c}_{v,t,l}}{\sqrt{\sum_{t=1}^{T} \sum_{l=1}^{L} \tilde{c}_{u,t,l}^2} \sqrt{\sum_{t=1}^{T} \sum_{l=1}^{L} \tilde{c}_{v,t,l}^2}}
\]
Summary of Temporal Dynamics

- **Temporal Chronological (Sequential Patterns)**
  - Short-Term Effect
  - Power-law Distribution

- **Temporal Cyclic (Periodic Patterns)**
  - Multi-Center Gaussian Distribution
  - Temporal Non-uniformness and Temporal Consecutiveness
Location Recommendation in Social Media

Location Recommendation on LBSNs

Geographical Influence

Social Correlations

Temporal Dynamics

Content Indications
### Overview of Mobility Patterns

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<td></td>
<td></td>
<td>✔</td>
<td>✔</td>
</tr>
</tbody>
</table>
Why Sentiment in Content is Important?

- Check-in behavior represents users’ habitual behavior and may not be sufficient to reflect users’ preferences
  - High check-in frequencies may represent positive opinions
  - Fewer checked locations are not necessarily less favored

- Sentiment extracted from content contains more precise information about a user’s preference on a location
  - In addition to positive feedback, there could also be negative feedback from content
Sentiment-enhanced Location Recommendation [Yang et al., 2013]

- Step 1: Extracting check-in preferences from check-in data e.g., check-in frequency $C_{i,j}$

$$\min_{U,L} \sum_{(i,j) \in \Omega} (C_{i,j} - U_i L_j^T)^2 + \alpha \|U\|_F^2 + \beta \|L\|_F^2$$

- Step 2: Extracting sentiment preferences from content
  - Sentiment scores are highly centralized around 0
  - A slight bias towards positive sentiment

<table>
<thead>
<tr>
<th>Sentiment Scores</th>
<th>Preference Scores</th>
</tr>
</thead>
<tbody>
<tr>
<td>[-1, -0.05]</td>
<td>1</td>
</tr>
<tr>
<td>(0.05, -0.01]</td>
<td>2</td>
</tr>
<tr>
<td>(-0.01, 0.01]</td>
<td>3</td>
</tr>
<tr>
<td>[0.01, 0.05]</td>
<td>4</td>
</tr>
<tr>
<td>[0.01, 1]</td>
<td>5</td>
</tr>
</tbody>
</table>
Sentiment-enhanced Location Recommendation [Yang et al., 2013]

- Step 3: Constructing a sentiment preference matrix $S$

- Step 4: Combining check-in preferences and sentiment preferences

$$\hat{C}_{i,j} = f(C_{i,j}, S_{i,j})$$

- Step 5: Performing traditional CF based on the combined preferences

$$\min_{U,L} \sum_{(i,j) \in \Omega} (\hat{C}_{i,j} - U_i L_j^T)^2 + \alpha \|U\|_F^2 + \beta \|L\|_F^2$$
Geographical Topics from Content in LBSNs

- Geographical topics are discovered from LBSNs [Yin et al., 2011]
  - Assigning semantic topics to locations
  - Reflecting users’ interests
  - Connecting users and locations in the semantic level
Building an aggregated LDA model to discover geographical topics

- User interest topic distribution $\theta_i$
- Location topic distribution $\pi_j$

Defining topic and location influence index

$$TL_{ij} = (1 - D_{JS}(\theta_i, \pi_j))$$

Jensen-Shannon Divergence
Summary of Content Indications

- **Sentiment Indication**
  - Sentiment-enhanced Check-in Preference

- **Topical Indication**
  - Connecting users and locations in the semantic level
Modeling Multiple Information on LBSNs

- Geo-Temporal
- Geo-Social
- Temporal-Content
- Social-Temporal
- Social
- Content
- Social-Content
- Geo-Content
Modeling Multiple Information on LBSNs

- **Joint Model**
  - Consider multiple information as a component
  - Study different aspects of the component

- **Fused Model**
  - Model each information individually
  - Combine the models together
Joint Model (Feature-Based) [Noulas et al., 2012]

- Features-based

\[(\text{user } i, \text{ location } j) \rightarrow \text{Label} \]

Features

1. i visited j
2. 0, otherwise

<table>
<thead>
<tr>
<th>Feature</th>
<th>APR</th>
<th>ACC@10</th>
<th>ACC@50</th>
</tr>
</thead>
<tbody>
<tr>
<td>Random Baseline</td>
<td>0.5</td>
<td>0.0001</td>
<td>0.0005</td>
</tr>
<tr>
<td><strong>User Mobility</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Historical Visits</td>
<td>0.68</td>
<td>0.30</td>
<td>0.36</td>
</tr>
<tr>
<td>Categorical Preference</td>
<td>0.84</td>
<td>0.006</td>
<td>0.05</td>
</tr>
<tr>
<td>Social Filtering</td>
<td>0.61</td>
<td>0.17</td>
<td>0.24</td>
</tr>
<tr>
<td><strong>Global Mobility</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Place Popularity</td>
<td>0.86</td>
<td>0.07</td>
<td>0.16</td>
</tr>
<tr>
<td>Geographic Distance</td>
<td>0.78</td>
<td>0.08</td>
<td>0.19</td>
</tr>
<tr>
<td>Rank Distance</td>
<td>0.78</td>
<td>0.08</td>
<td>0.19</td>
</tr>
<tr>
<td>Activity Transition</td>
<td>0.60</td>
<td>0.03</td>
<td>0.06</td>
</tr>
<tr>
<td>Place Transition</td>
<td>0.60</td>
<td>0.17</td>
<td>0.20</td>
</tr>
<tr>
<td><strong>Temporal</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Category Hour</td>
<td>0.56</td>
<td>0.01</td>
<td>0.02</td>
</tr>
<tr>
<td>Category Day</td>
<td>0.57</td>
<td>0.01</td>
<td>0.03</td>
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<tr>
<td>Place Day</td>
<td>0.76</td>
<td>0.07</td>
<td>0.16</td>
</tr>
<tr>
<td>Place Hour</td>
<td>0.79</td>
<td>0.09</td>
<td>0.20</td>
</tr>
</tbody>
</table>

Predictor:
- M5 Tree
- Linear Ridge Regression
Joint Model (Geo-Social Correlations)

- gSCorr [Gao et al., 2012b]
  - Friends with long distance share a small number of commonly visited locations
  - Non-friends with short distance share a large number of commonly visited locations
  - Users are segmented into four geo-social circles

<table>
<thead>
<tr>
<th>F</th>
<th>$S_{FD}$: Local Friends</th>
<th>$S_{F\bar{D}}$: Local Non-friends</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\bar{D}$</td>
<td>$S_{F\bar{D}}$: Local Non-friends</td>
<td>$S_{\bar{F}D}$: Distant Non-friends</td>
</tr>
<tr>
<td>D</td>
<td>$S_{FD}$: Distant Friends</td>
<td></td>
</tr>
</tbody>
</table>
A framework is proposed for location recommendation based on geo-social circles.

\[ P_u^t(l) = \Phi_1 P_u^t(l|S_{FD}) + \Phi_2 P_u^t(l|S_{F\bar{D}}) + \Phi_3 P_u^t(l|S_{FD}) + \Phi_4 P_u^t(l|S_{\bar{F}D}). \]
Observations about Geo-social Circles

- Local friends are more important than distant friends
- Distance friends contain more additional information than local friends when combining with local non-friends
- These four geo-social circles contain complementary information although their contributions differ

<table>
<thead>
<tr>
<th>Methods</th>
<th>Top-1</th>
<th>Top-2</th>
<th>Top-3</th>
</tr>
</thead>
<tbody>
<tr>
<td>$S_{FD}$</td>
<td>6.51%</td>
<td>8.31%</td>
<td>9.32%</td>
</tr>
<tr>
<td>$S_{FD}$</td>
<td>3.65%</td>
<td>4.75%</td>
<td>5.34%</td>
</tr>
<tr>
<td>$S_{FD}$</td>
<td>18.37%</td>
<td>24.10%</td>
<td>27.34%</td>
</tr>
<tr>
<td>$S_{FD} \cup S_{FD}$</td>
<td>18.62%</td>
<td>24.44%</td>
<td>27.79%</td>
</tr>
<tr>
<td>$S_{FD} \cup S_{FD}$</td>
<td>19.01%</td>
<td>24.95%</td>
<td>28.35%</td>
</tr>
<tr>
<td>$S_{FD} \cup S_{FD}$</td>
<td>8.33%</td>
<td>10.79%</td>
<td>12.23%</td>
</tr>
<tr>
<td>$S_{FD} \cup S_{FD} \cup S_{FD}$</td>
<td>19.21%</td>
<td>25.19%</td>
<td>28.69%</td>
</tr>
</tbody>
</table>
Fused Model

- **Sum Rule**

\[
P = \sum_{i=1}^{n} \alpha_i P_i \quad \Rightarrow \quad P = \alpha P_1 + (1 - \alpha)P_2
\]

- **Product Rule**

\[
P = \prod_{i=1}^{n} P_i \quad \Rightarrow \quad P = P_1 \cdot P_2
\]

Conditional Probability & Prior Probability
Fused Model (Geo-Social)

- A fusion model (Sum Rule): USG [Ye et al., 2011]
  - The probability score of i-th user at j-th location is
    \[
    S_{i,j} = (1 - \alpha - \beta)S_{i,j}^{nu} + \alpha S_{i,j}^{s} + \beta S_{i,j}^{g}
    \]

- A fusion model (Product Rule): iGSLR [Zhang et al., 2013]
  - Geographical influence is modeled by kernel density estimation
  - Social Correlations is modeled by Friend-based CF
    \[
    S_{i,j} = P_{i,j}P(l_j \mid L_i)
    \]
Fused Model (Geo-Temporal)

- A fusion model (Sum Rule): UTE+SE [Yuan et al., 2013]
  - The probability score of user u at location l at time t is
    \[ c_{u,t,l} = \alpha \times \bar{c}_{u,t,l}^{(t)} + (1 - \alpha) \times \bar{c}_{u,t,l}^{(s)} \]

- A fusion model (Product Rule): PMM [Cho et al., 2011]
  \[
P [x(t) = x] = P [x_u(t) = x | c_u(t) = H] \cdot P [c_u(t) = H] + P [x_u(t) = x | c_u(t) = W] \cdot P [c_u(t) = W]
  \]
Fused Model (Temporal-Social)

- A Social-Historical Model: SHM [Gao et al., 2012a]
  - Users’ historical information is modeled by Hierarchical PitmanYor process

\[
P_{i,j}^{SH} = \alpha P_{i,j} + (1 - \alpha) \sum_{u_k \in N_i} w_{i,k} P_{k,j}
\]
Fused Model (Social-Content)

- A Sentiment-Enhanced Model: LBSMF [Yang et al., 2013]
  - Sentiment information is combined with check-in preference
  - Social information is incorporated with matrix factorization

\[
\min_{U,L} \frac{1}{2} \left\| C - UL^T \right\|_F^2 + \frac{1}{2} \alpha \left\| U \right\|_F^2 + \frac{1}{2} \beta \left\| L \right\|_F^2 + \frac{1}{2} \lambda \sum_i \left\| U_i - \sum_{j \in F_i} \text{sim}(u_i, u_j)U_j \right\|_F^2
\]

- Sentiment-Enhanced Check-in Matrix
- Social Influence
Evaluation Metrics

- **Precision & Recall**
  - Precision@N: How many locations that recommended to the user have been visited by the user
  - Recall@N: How many location visited by the user have been recommended to the user

\[
\text{precision@N} = \frac{\sum_{u_i \in U} |\text{TopN}(u_i) \cap L(u_i)|}{\sum_{u_i \in U} |\text{TopN}(u_i)|}
\]

\[
\text{recall@N} = \frac{\sum_{u_i \in U} |\text{TopN}(u_i) \cap L(u_i)|}{\sum_{u_i \in U} |L(u_i)|}
\]

- **RMSE**

\[
\text{RMSE} = \sqrt{\frac{1}{2} \sum_{i,j} (\hat{r}_{i,j} - r_{i,j})^2}
\]

- **NDCG** (Normalized Discounted Cumulative Gain)
Recommendation Effectiveness [Ye et al., 2011] [Gao et al., 2013a]

- Recommendation effectiveness w.r.t. to the data sparseness
  - The effectiveness of recommender systems with sparse dataset (i.e., low-density user-item matrix) is usually not high.
  - The reported P@5 is 5% over a data with $8.02 \times 10^{-3}$ density, and 3.5% over a data with $4.24 \times 10^{-5}$ density.
Recommendation Effectiveness [Yin et al., 2013]

- **Location-Aware**
  - Perform recommendation based on the user’s current location
  - Nearby locations have higher probability to be recommended than distant locations

![Graph showing Recall@k vs Rank for different methods including LA-LDA, LCA-LDA, CA-LDA, LDA, CKNN, IKNN, and USG.](image)
## Overview of Mobility Patterns

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References


References


References


References


Future Work

- Temporal-based Content Analysis
- Tensor-Based Methods
- Relationships Among Multiple Information
- Location-Based Mobile Applications
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