Personalized Location Recommendation on Location-Based Social Networks

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

Oct 06, 2014

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 I should 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

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Why on LBSNs?

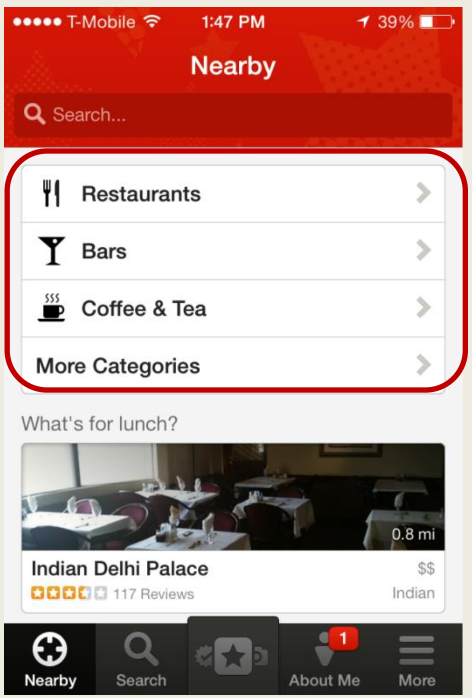
Why Personalized?

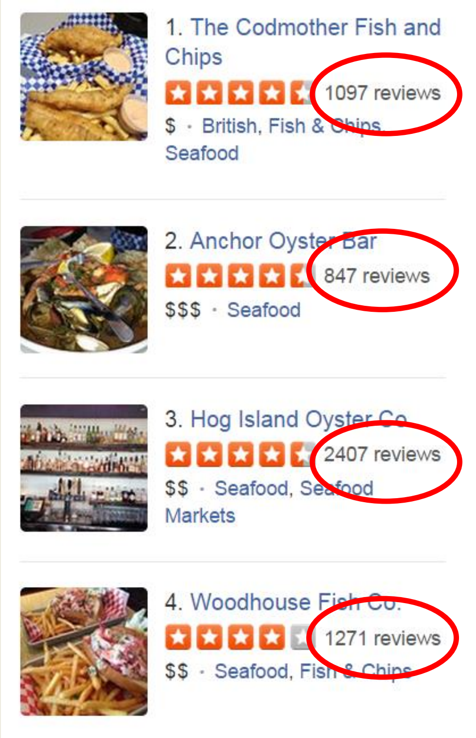
- **Examples of Location Recommender Systems**

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**

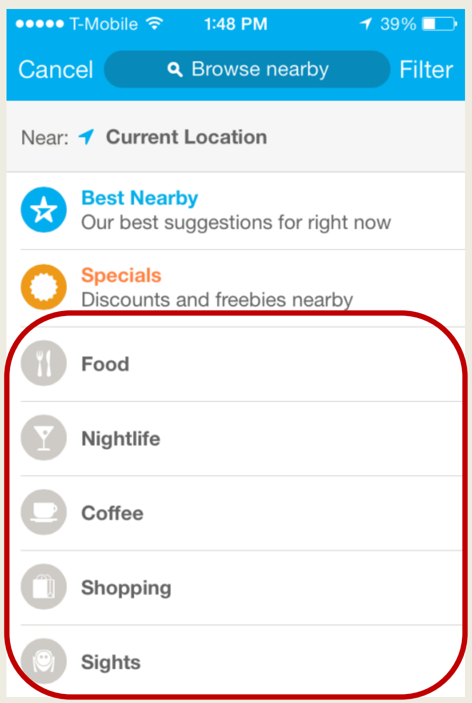
Why Personalized?

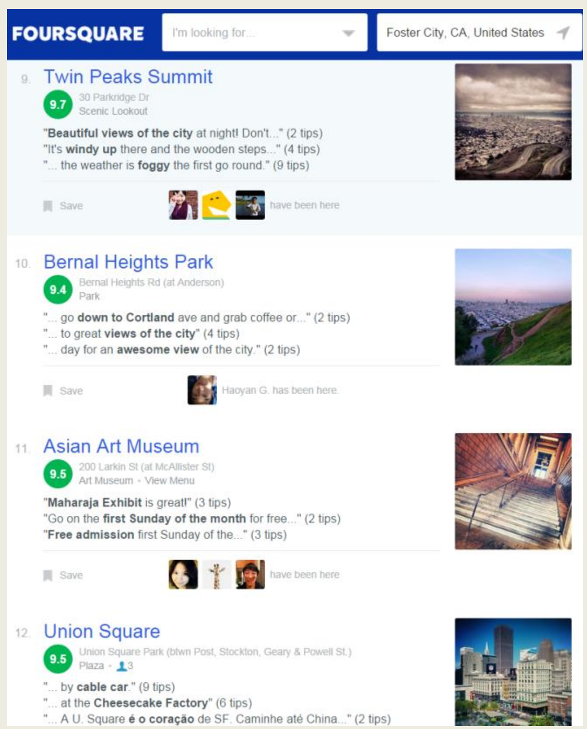
- **Examples of Location Recommender Systems**

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

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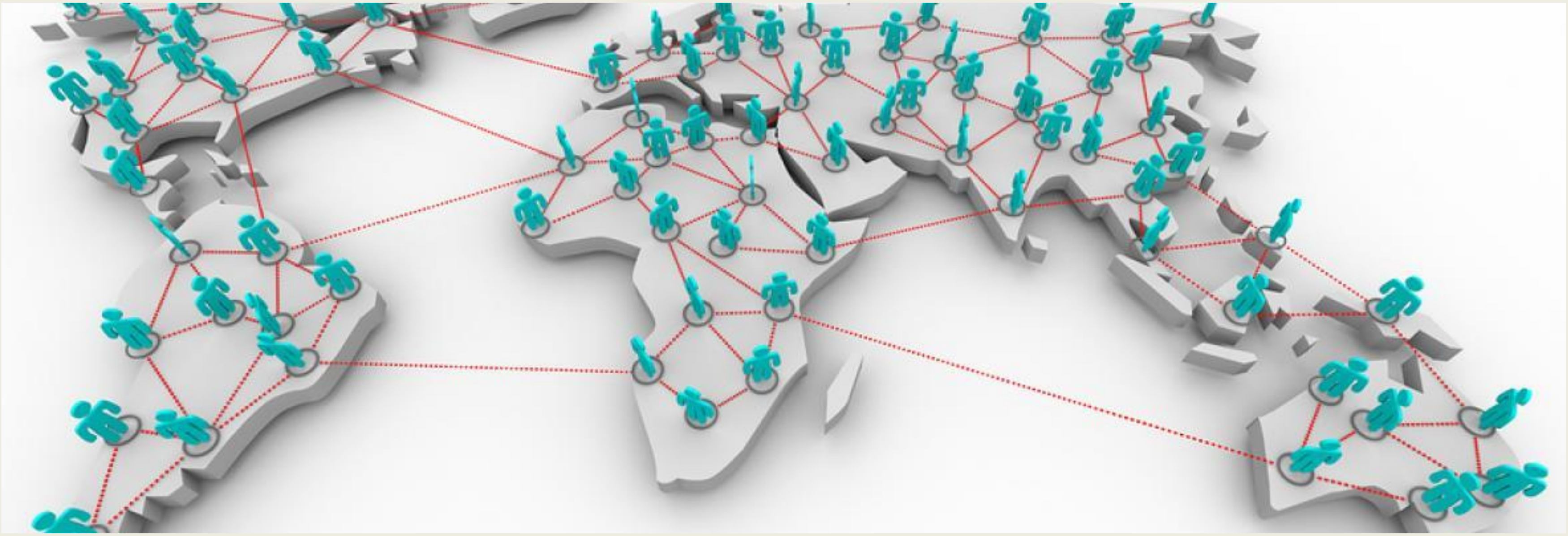
Why on LBSNs?

What are Location-Based Social Networks?

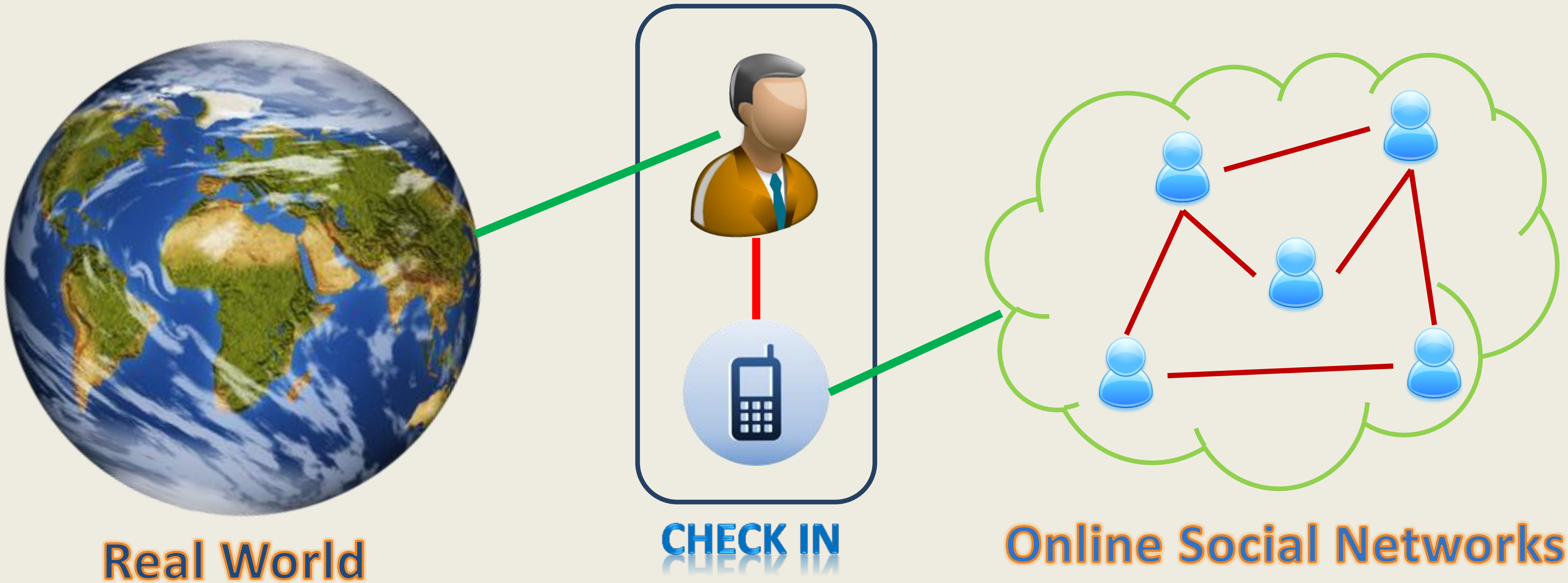
Location-based social networks are social networks in which GPS features of mobile devices are used to locate people (and you) and that let you broadcast your location and other content from your mobile device.



http://www.quickanddirtytips.com/business-career/communication/what-are-location-based-social-networks

Why on Location-Based Social Networks?

- Bridging the Gap between Real World and Online Social Networks



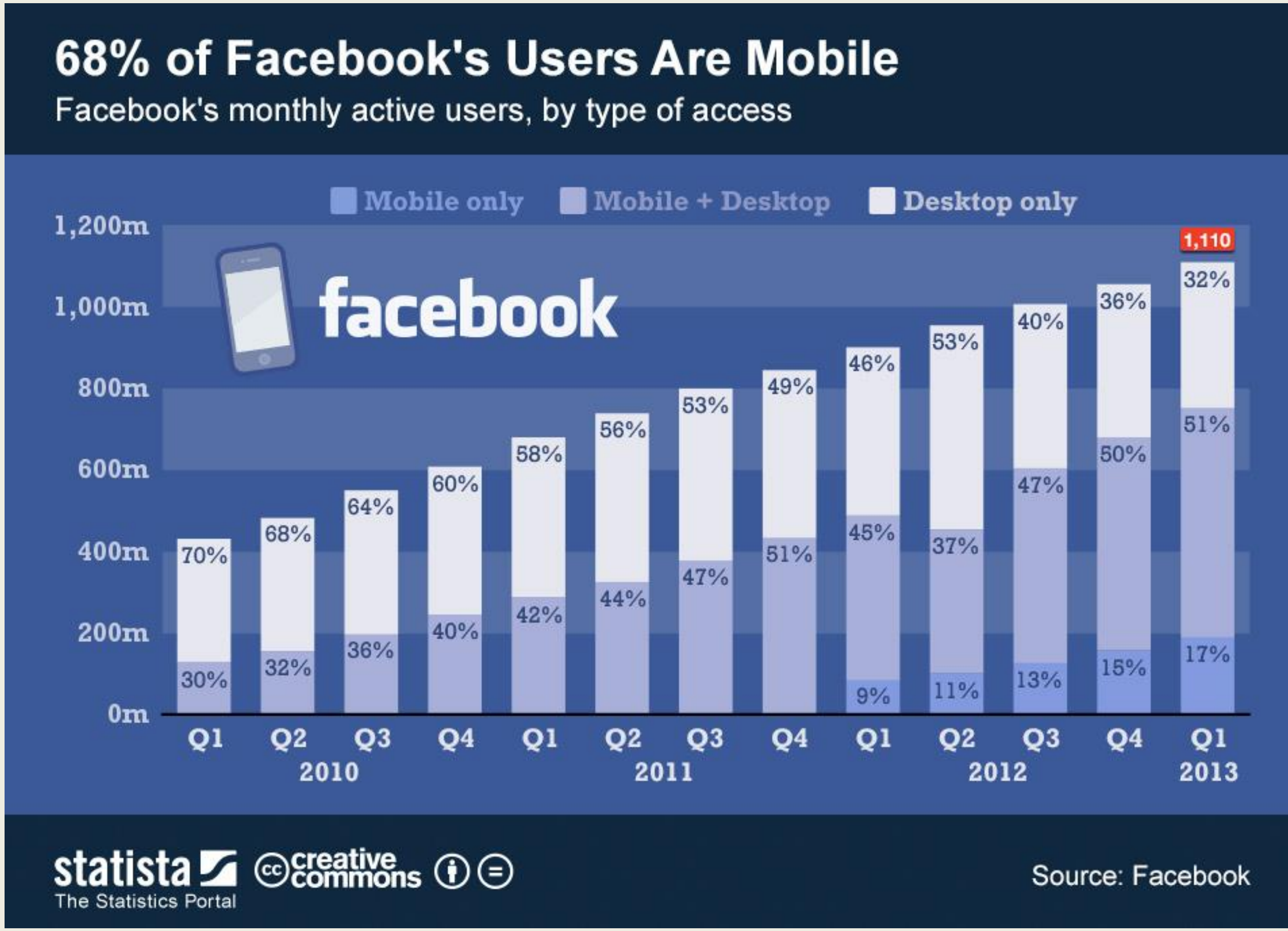
How Popular are Location-Based Social Networks?

- 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.

Typical Location-based Social Networking Services

K. Zickuhr. Three-quarters of smartphone owners use location-based services. *Pew Internet & American Life Project*, 2012.
P. Finocchiaro. Mobile advertisers forecast to spend $1.8 billion on location-based campaigns in 2015. 2010.

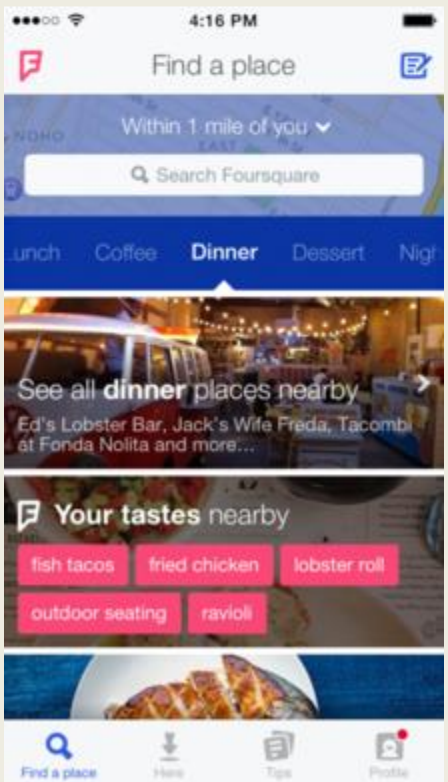
Facebook Case



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

Foursquare Case

FOURSQUARE



By May 2014

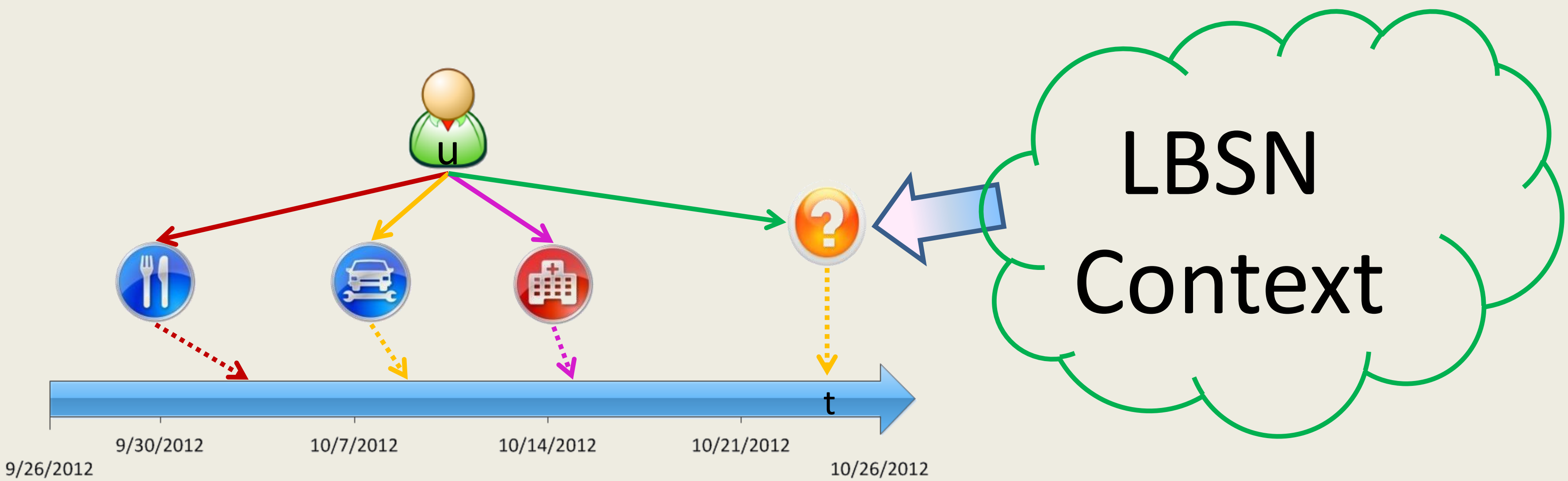
- ❖Over 50 million people worldwide
- ❖Over 6 billion Check-ins

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

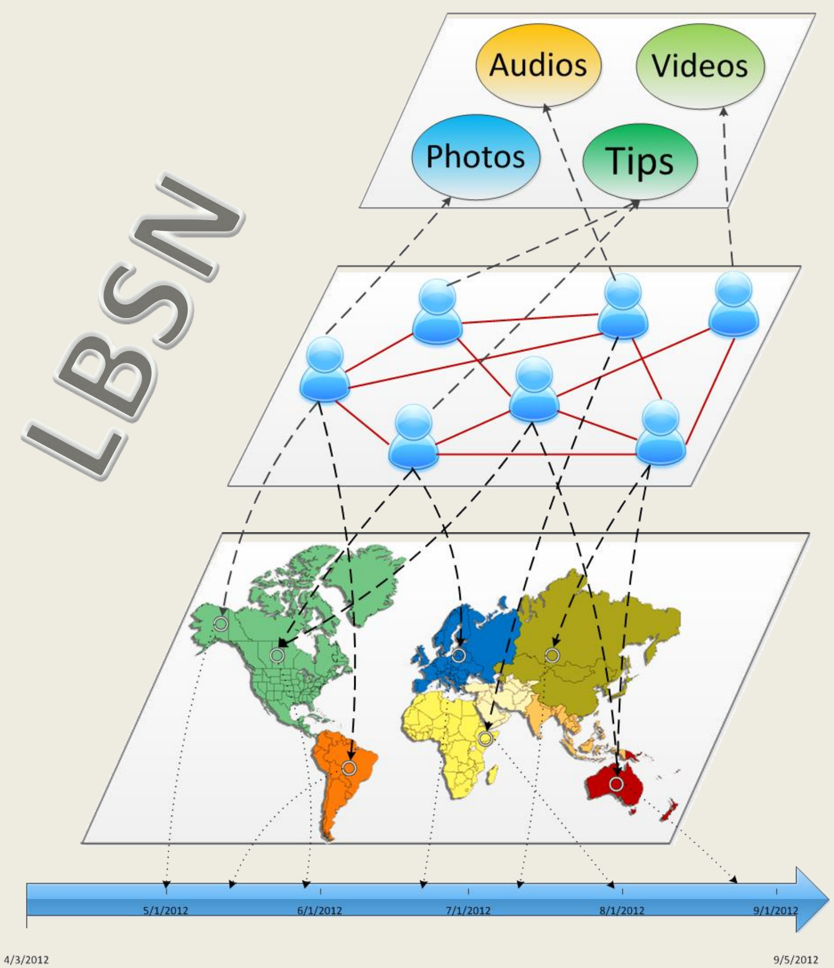
Personalized Location Recommendation on LBSNs

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



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

Social Layer → **Who**
Friendships

Geographical Layer → **Where**
Check-in POIs

Timeline → **When**
Time Stamps

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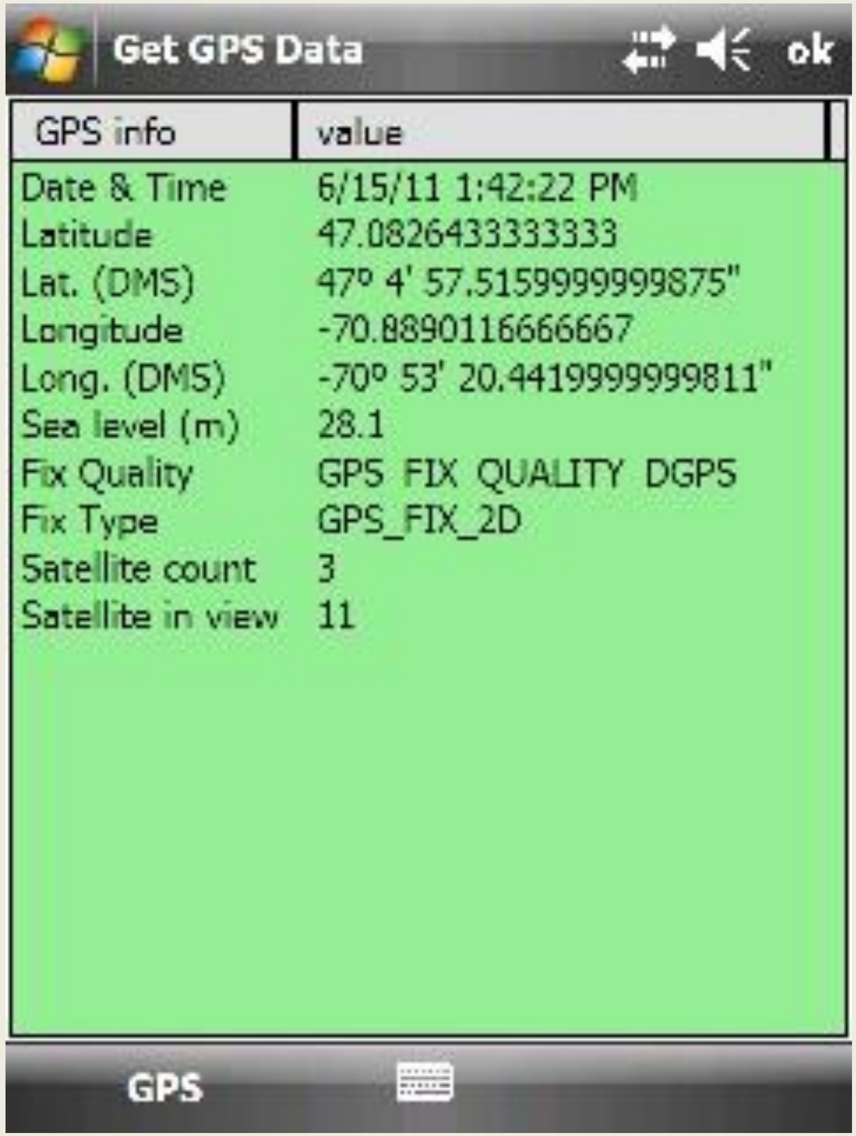
A Check-in Example on LBSNs

An Example of GPS Data



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**

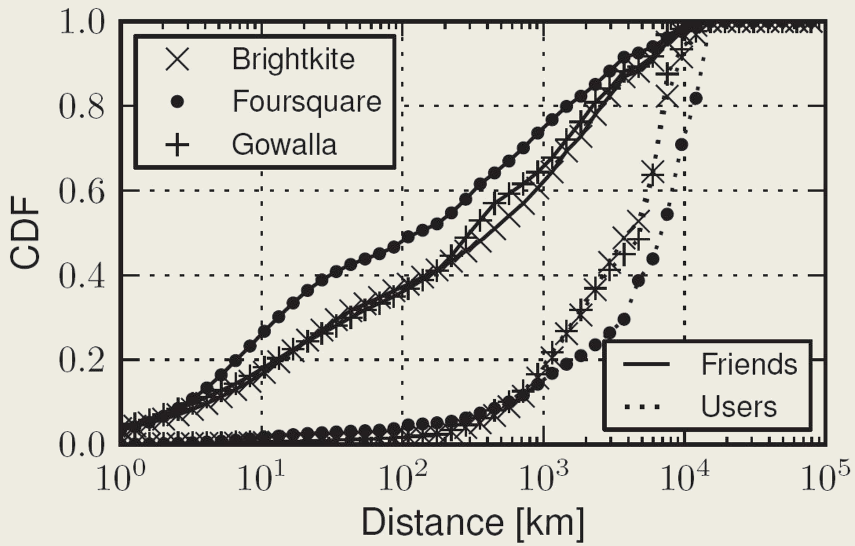
  Points of Interest vs. Longitude/Latitude Points

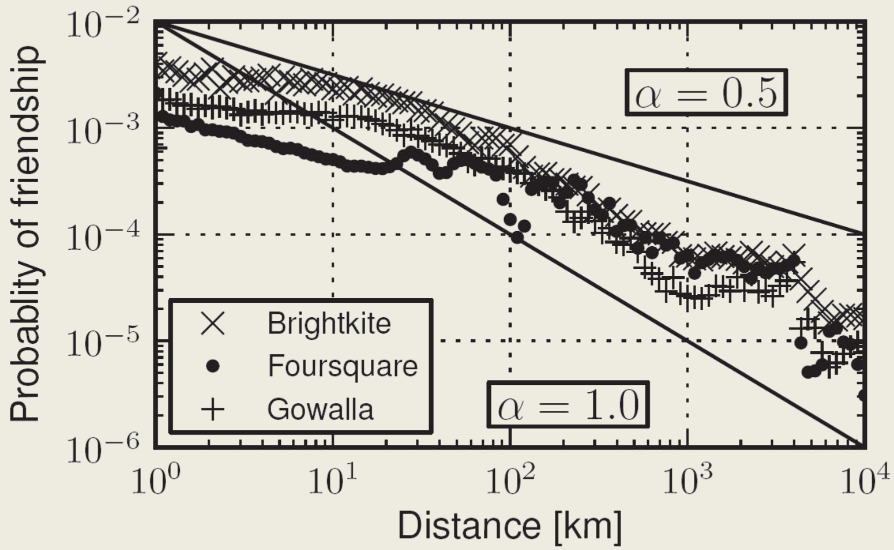
Socio-Spatial Properties [Scellato et al., 2011]

- **Geographical Distance and Social Connections**

Geographical Distance → Social Connections

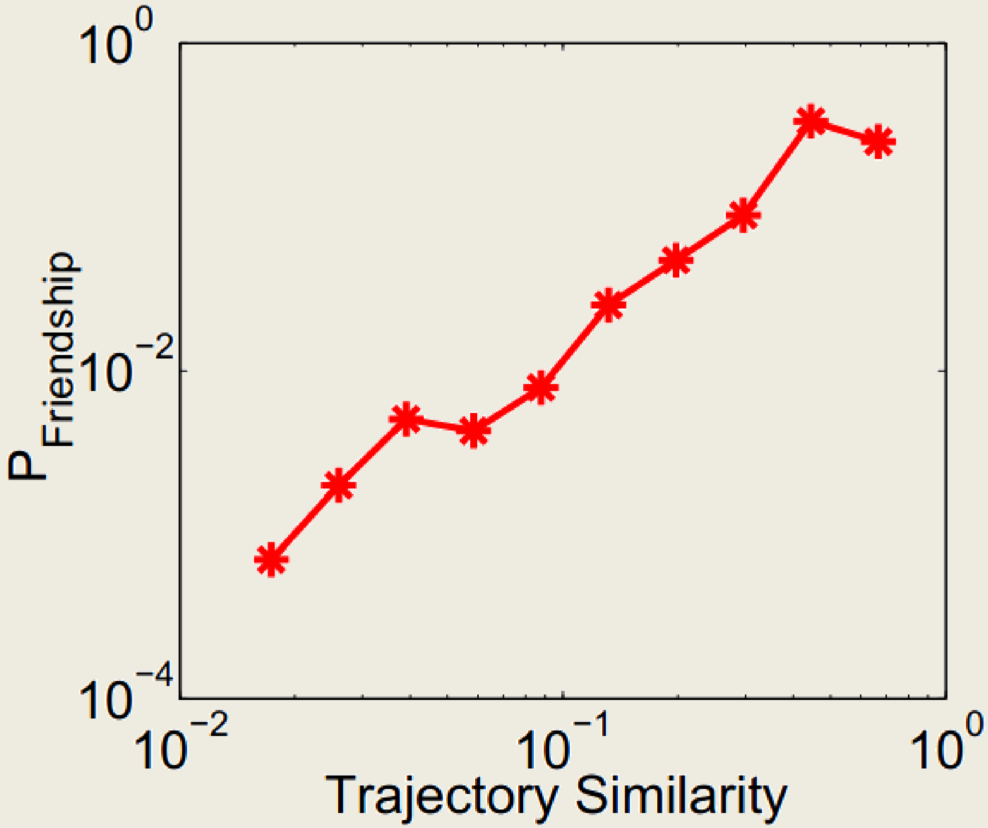
Geographical Distance ← Social Connections





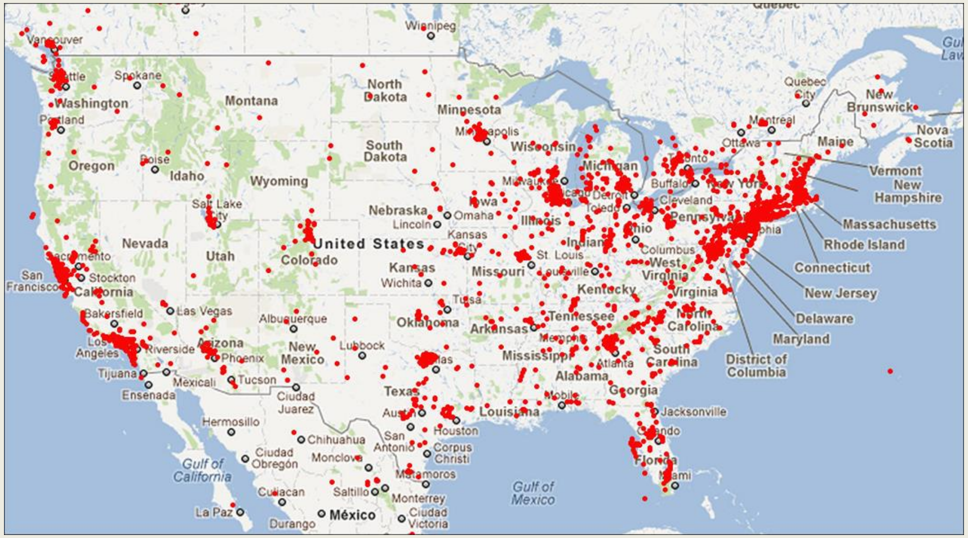
Socio-Spatial Properties [Cho et al., 2011]

➢ **Trajectory Similarity and Social Connections**



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

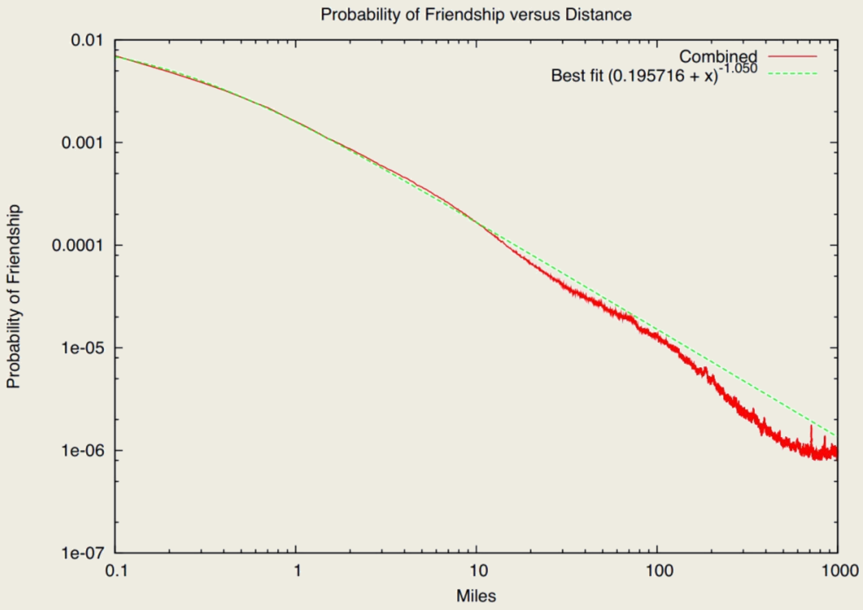
Mobility Patterns	Geo	Social	Temporal	Content
Inverse Distance Rule		✓		
Social Correlations in Geographical Trajectory		✓		
Levy Flight of Check-ins				
Power-Law Distribution				
Short-Term Effects				
Temporal Periodic Patterns				
Multi-Center Check-in Distribution				
Sentiment and Topical Indications				

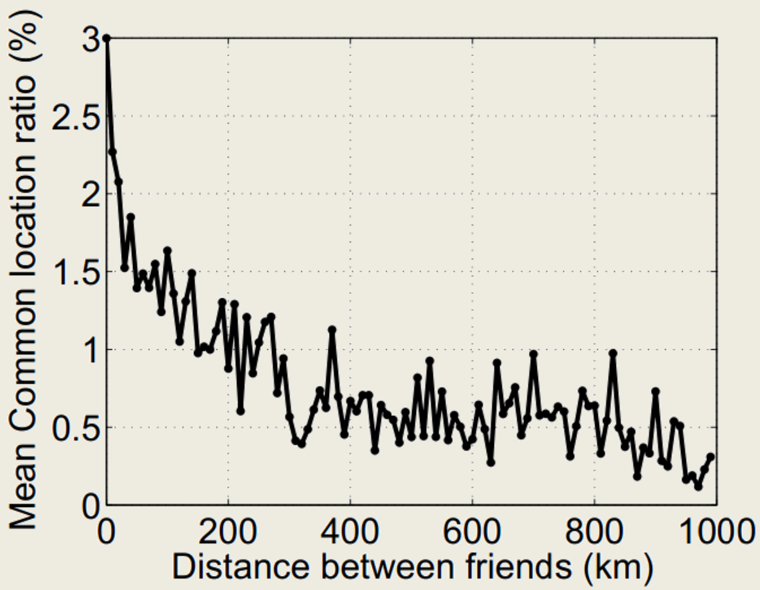
Inverse Distance Rule [Backstrom et al., 2010] [Ye et al., 2010]

➢ **Death of Distance in Web 2.0?**

❖ Users who live close have higher probability to create friendship links

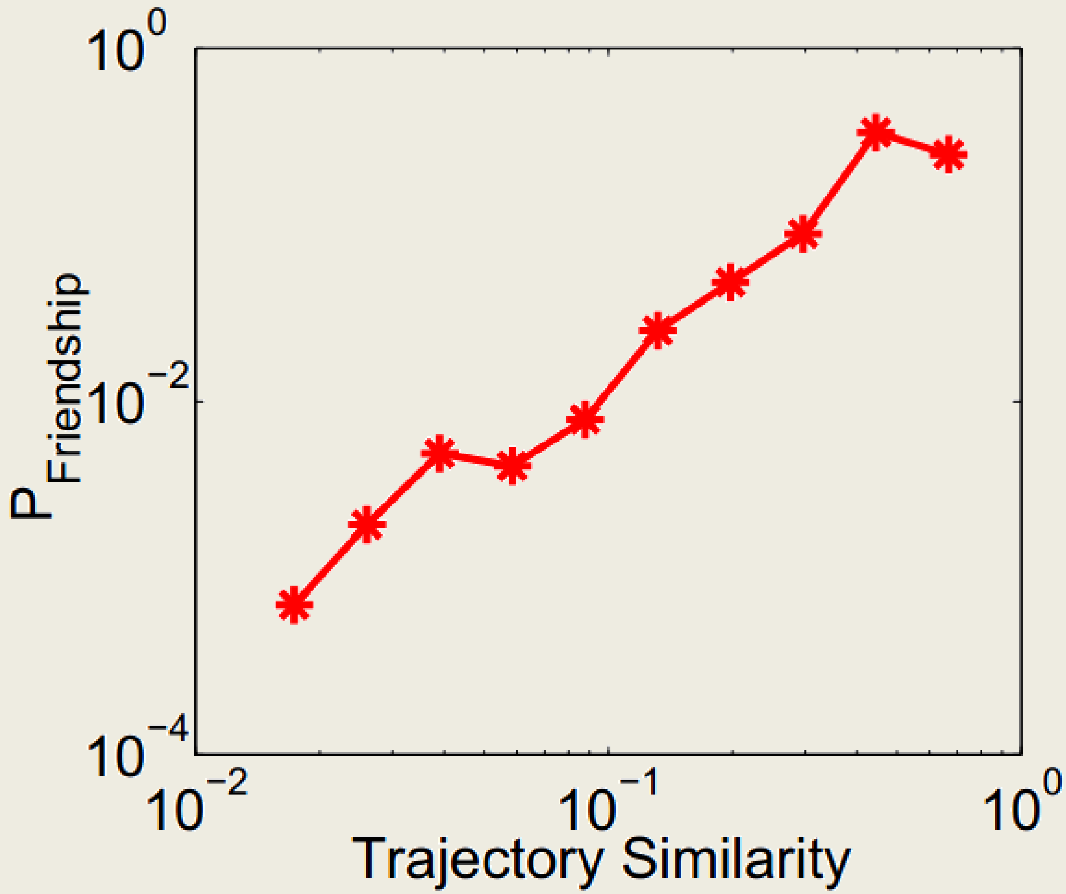
➢ **Only One Thirds of Friendships are Independent of Geography**





Social Correlations in Geographical Trajectory [Cho et al., 2011]

➢ **Trajectory Similarity and Social Connections**



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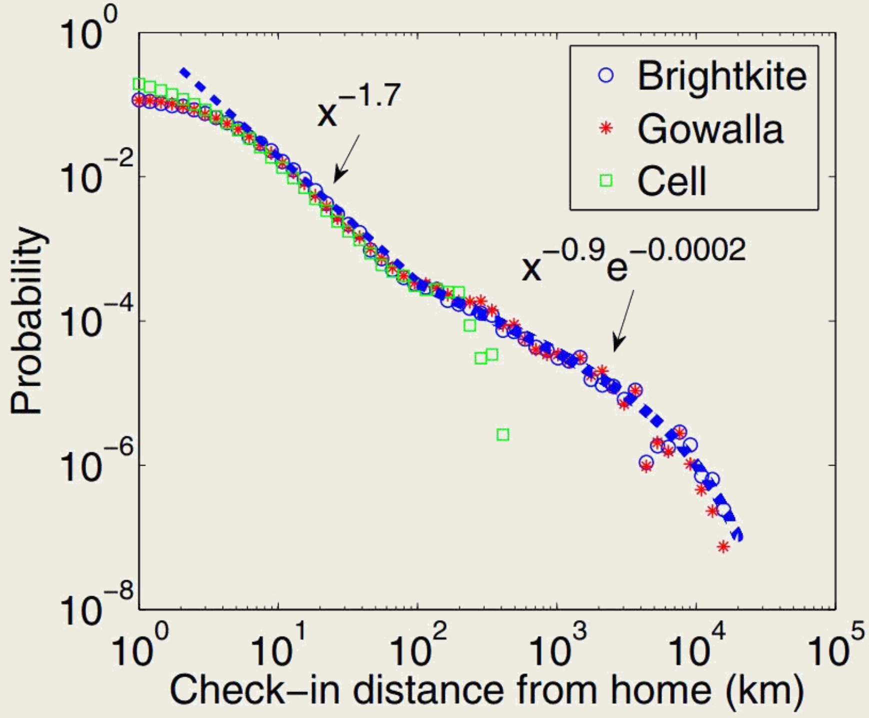
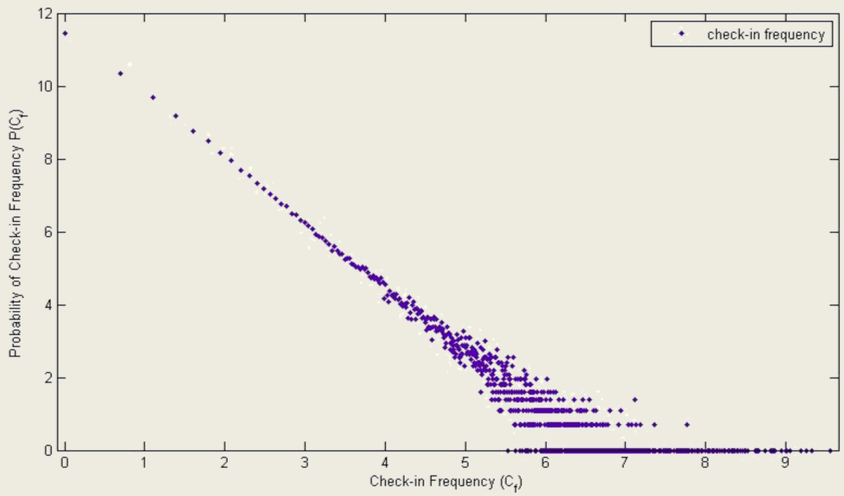
Multi-Center Check-in Distribution				
Sentiment and Topical Indications				

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**

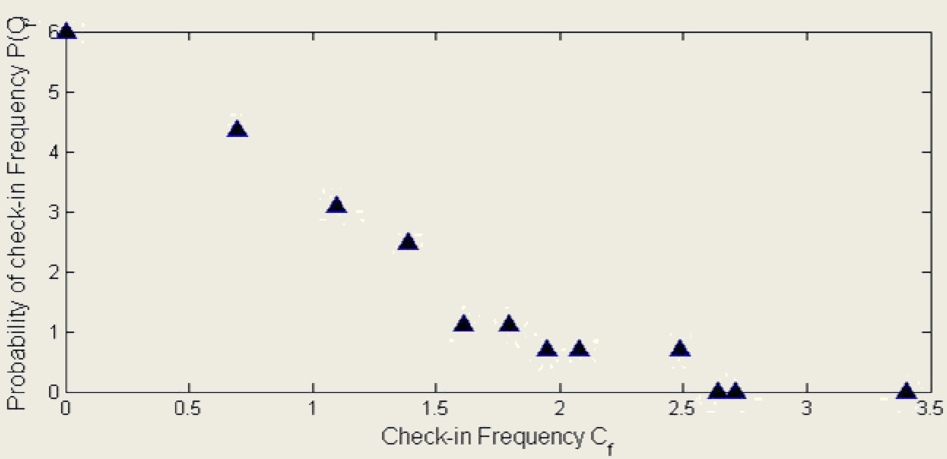


Power-Law Distribution [Gao et al., 2012a]



- 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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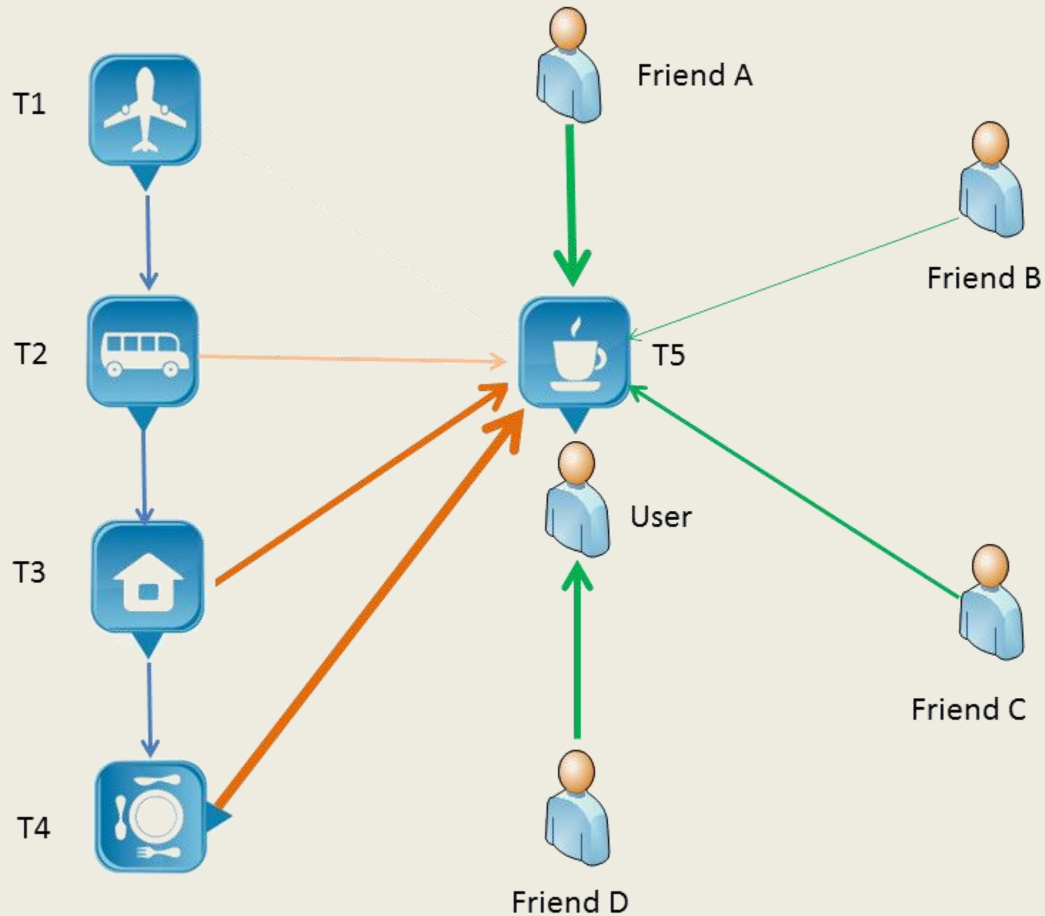
Sentiment and Topical Indications				

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

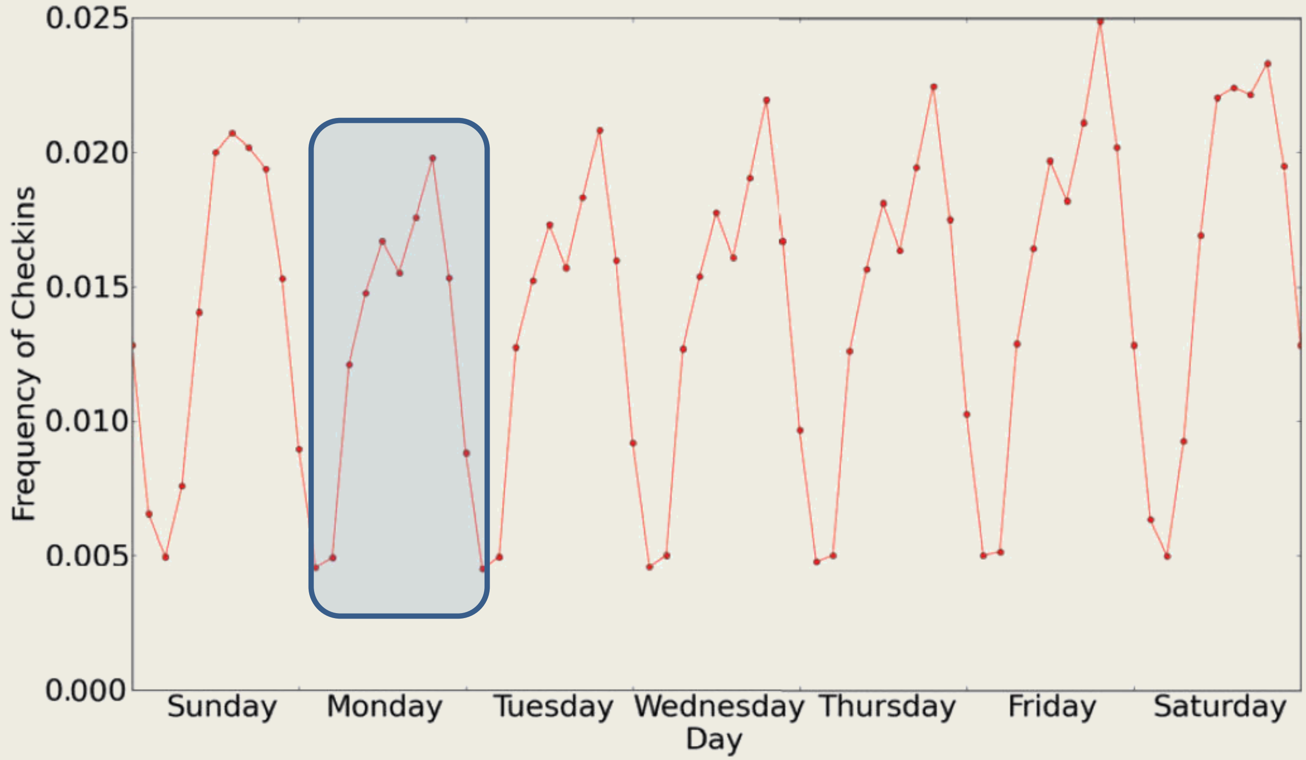
- **Power-Law Distribution and Short-Term Effect**

- **Language Modeling vs. LBSN Mining**

<table>
<tr><th colspan="2">Language Modeling</th><th colspan="2">LBSN Modeling</th></tr>
<tr><td colspan="2">Corpus</td><td colspan="2">Check-in collection</td></tr>
<tr><td colspan="2">Document</td><td colspan="2">Individual check-ins</td></tr>
<tr><td rowspan="4">Document Structure</td><td>Paragraph</td><td rowspan="4">Check-in Structure</td><td>Monthly check-in sequence</td></tr>
<tr><td>Sentence</td><td>Weekly check-in sequence</td></tr>
<tr><td>Phrase</td><td>Daily check-in sequence</td></tr>
<tr><td>Word</td><td>Check-in location</td></tr>
</table>

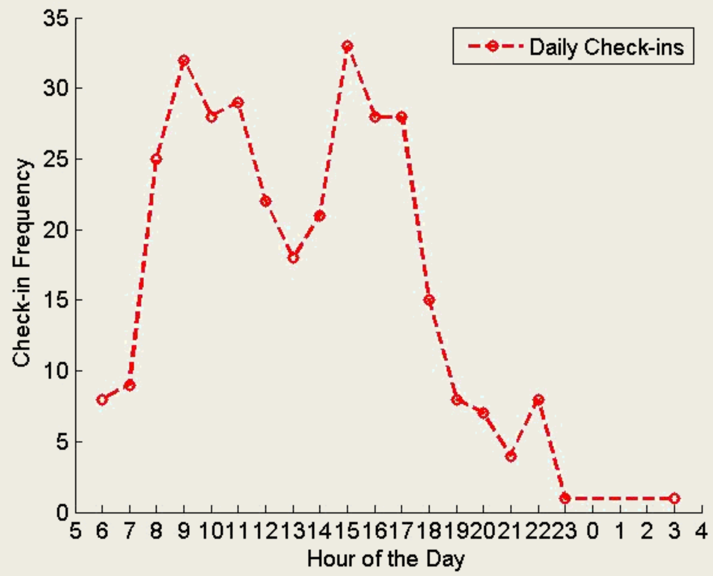
Temporal Periodic Patterns [Cheng et al., 2011]

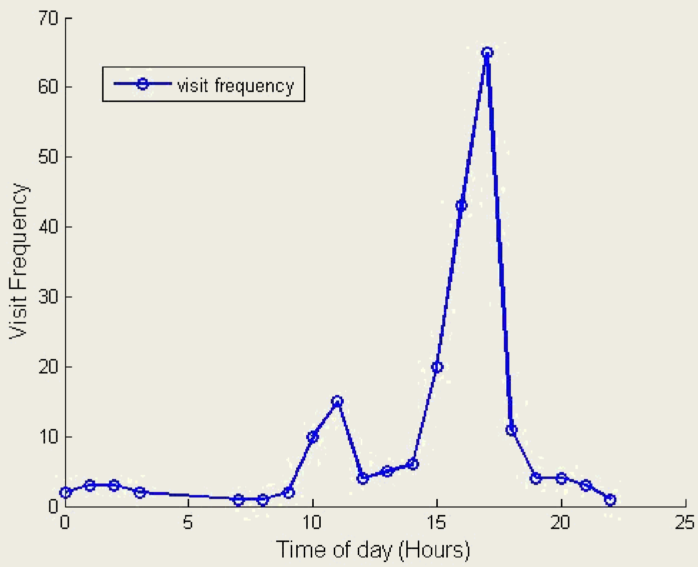
- **Hour of the Day, Day of the Week, Weekday/Weekend**
- Go to a restaurant for lunch at 12:00 pm
- Watch movies at Friday night
- Shopping at mall during weekend



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 Peeks at multiple centers



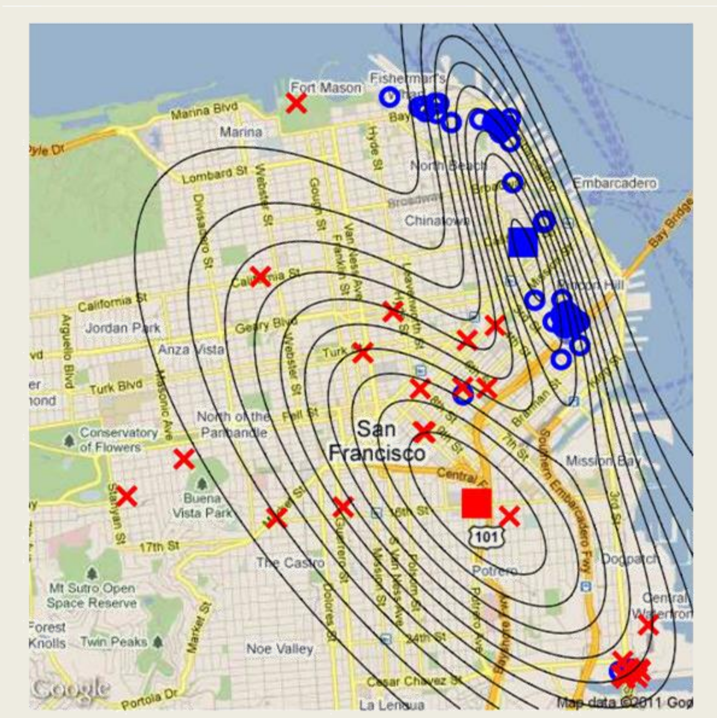


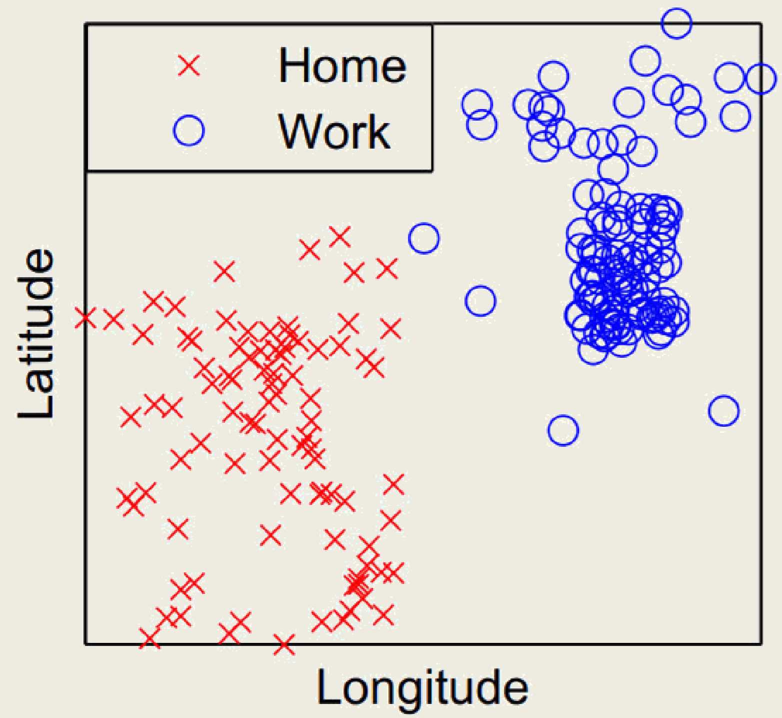
Multi-Center Check-in Distribution [Cho et al., 2011]

➢ **Geographical Perspective**

❖ Centers on certain location areas

❖ Rarely checks-in at locations far away from the center





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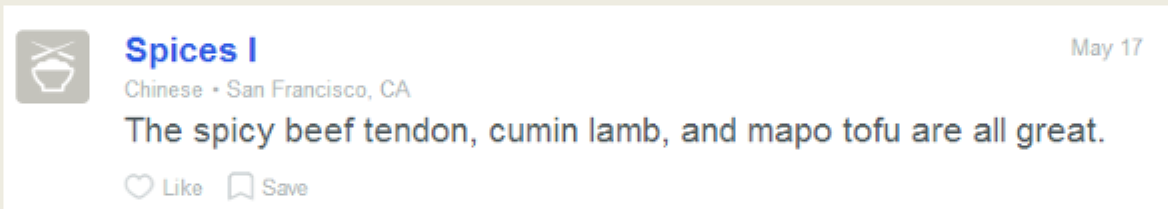
Sentiment and Topical Indications				✓

Sentiment and Topical Indications

- 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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References

[**Scellato et al., 2011**]S. Scellato, A. Noulas, R. Lambiotte, C. Mascolo. Socio-Spatial Properties of Online Location-Based Social Networks. In ICWSM, pp, 329—336, 2011.

[**Gao and Liu, 2014**] H. Gao, and H. Liu. Data Analysis on Location-Based Social Networks. Mobile Social Networking, pp, 165—194, 2014.

[**Ye et al., 2011**] M. Ye, K. Janowicz, C. Mülligann, W. Lee. What you are is when you are: the temporal dimension of feature types in location-based social networks. In ACM GIS, pp, 102—111, 2011.

[**Backstrom et al., 2010**] L. Backstrom, E. Sun, C. Marlow. Find me if you can: improving geographical prediction with social and spatial proximity. In WWW, pp, 61—70, 2010.

[**Cho et al., 2011**] E. Cho, S. Myers, and J. Leskovec. Friendship and mobility: user movement in location-based social networks. In Proceedings of the 17th ACM SIGKDD international conference on Knowledge discovery and data mining, pp, 1082—1090, 2011.

[**Gao et al., 2012a**] H. Gao, J. Tang, and H. Liu. Exploring social-historical ties on location-based social networks. In ICWSM, 2012.

[**Cheng et al., 2011**] Z. Cheng, J. Caverlee, K. Lee, D. Sui. Exploring Millions of Footprints in Location Sharing Services. In ICWSM, pp, 82—88, 2011 .

[**Gao et al., 2013**] H. Gao, J. Tang, X. Hu, H. Liu. Modeling temporal effects of human mobile behavior on location-based social networks. In CIKM, pp, 1673—1678, 2013 .

[**Cheng et al., 2012**] C. Cheng, H. Yang, I. King, M. Lyu. Fused Matrix Factorization with Geographical and Social Influence in Location-Based Social Networks. In AAAI, pp, 1-8, 2012.

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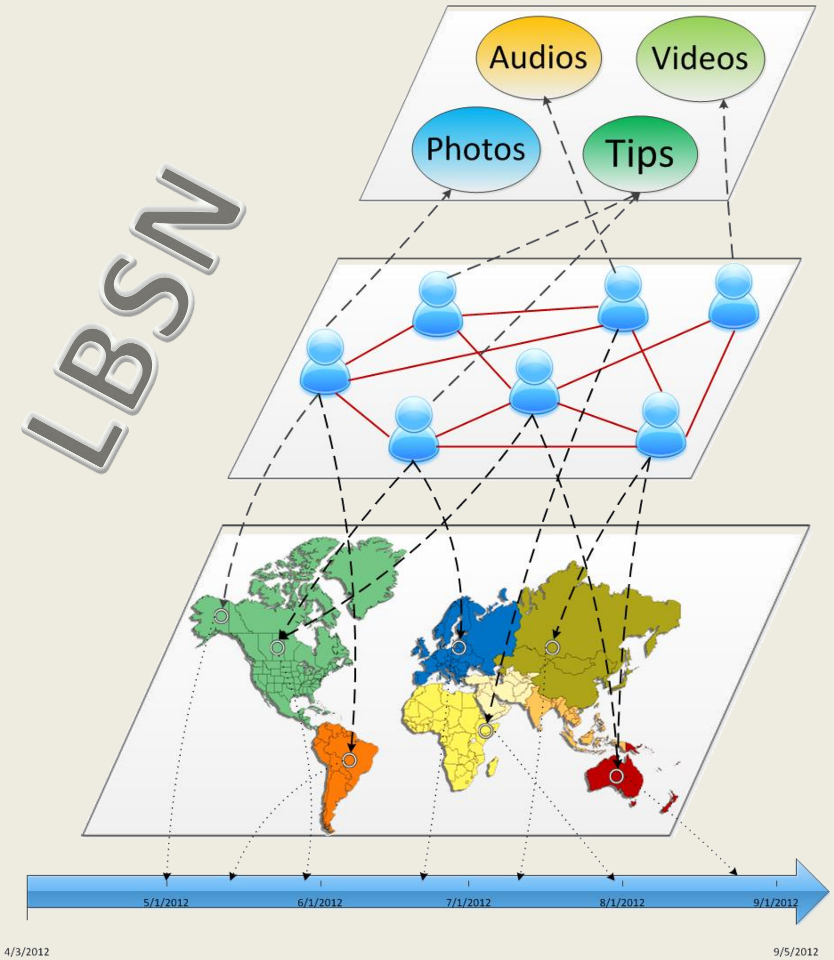
W⁴: Information Layout on LBSNs



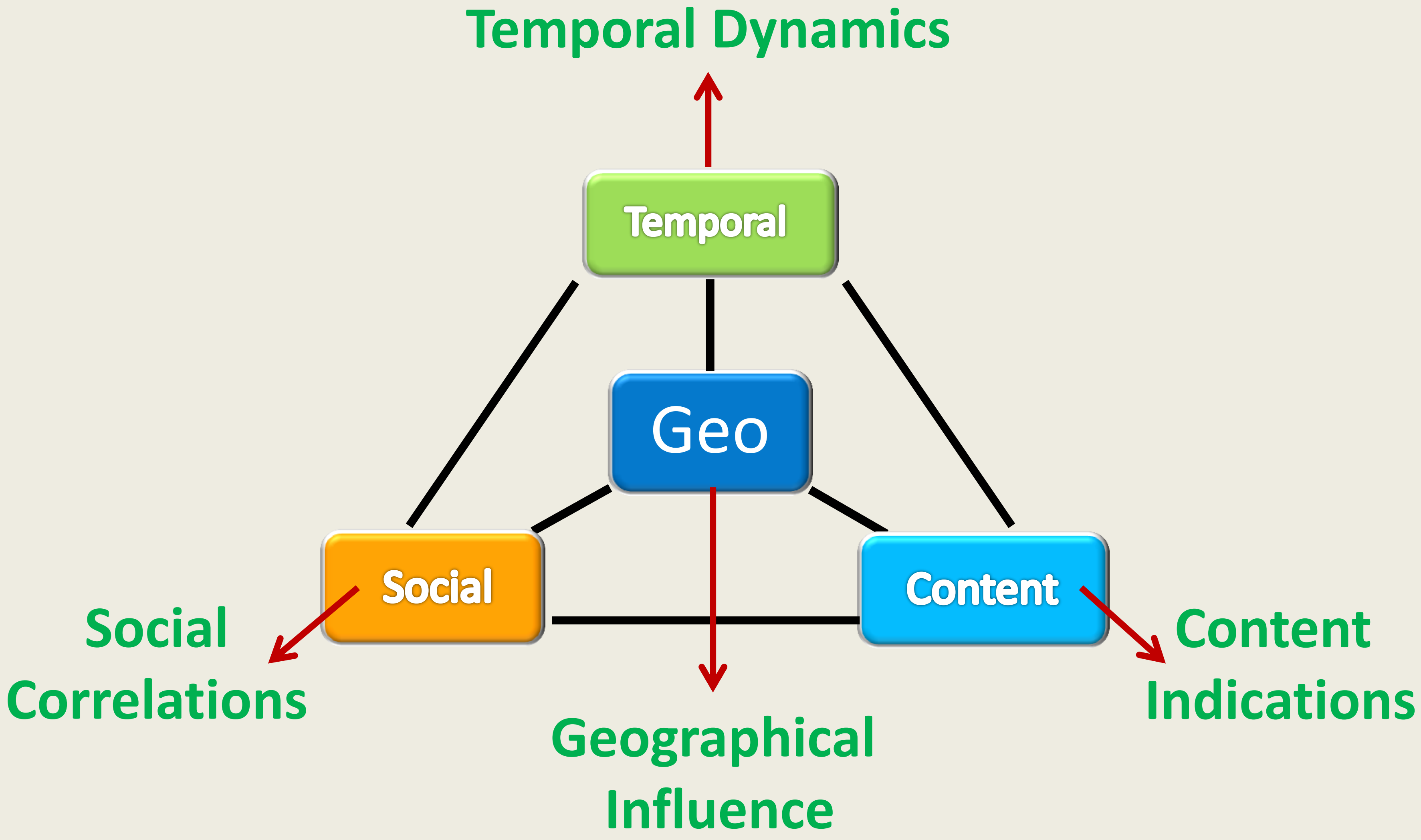
Content Layer → **Content Indications**

Social Layer → **Social Correlations**

Geographical Layer → **Geographical Influences**

Timeline → **Temporal Dynamics**

Location Recommendation with LBSNs



"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

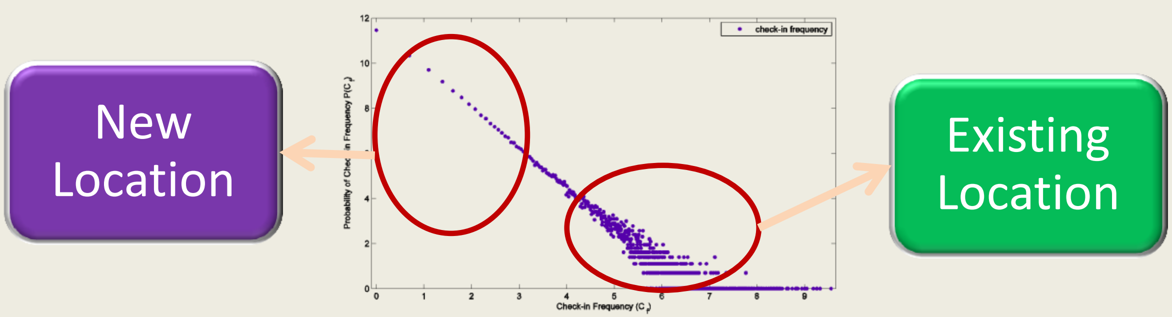
    check-in at the favorite restaurant for several times

- 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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Multi-Center Check-in Distribution	✓		✓	
Sentiment and Topical Indications				✓

Geographical Influence

➢ **Modeling Check-in Distribution over Geographical Distance**

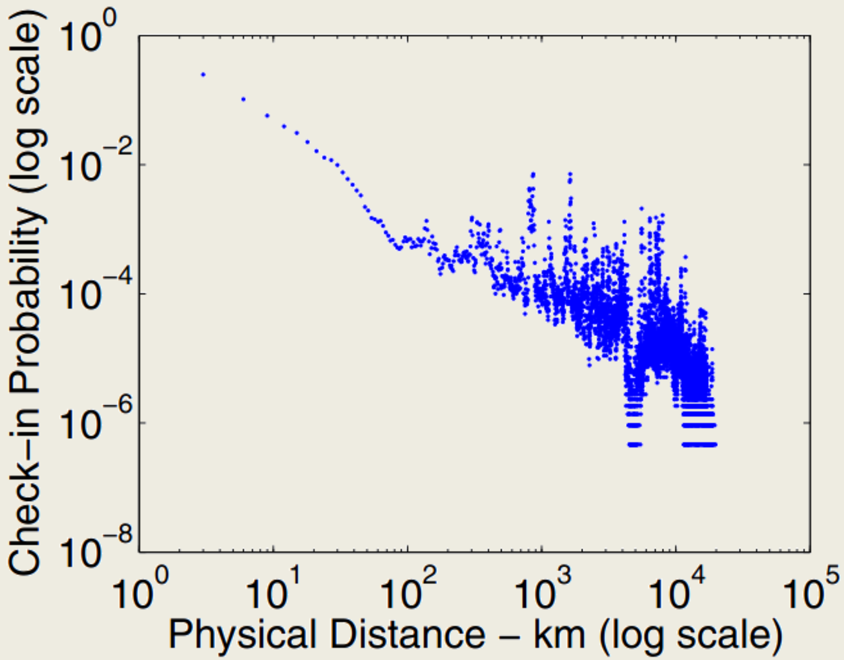
➢ **How check-in probability is influenced by Geo Distance**

- **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**)



$$\hat{P}(d) \sim \alpha * d^{\beta}$$

d: Distance between two locations

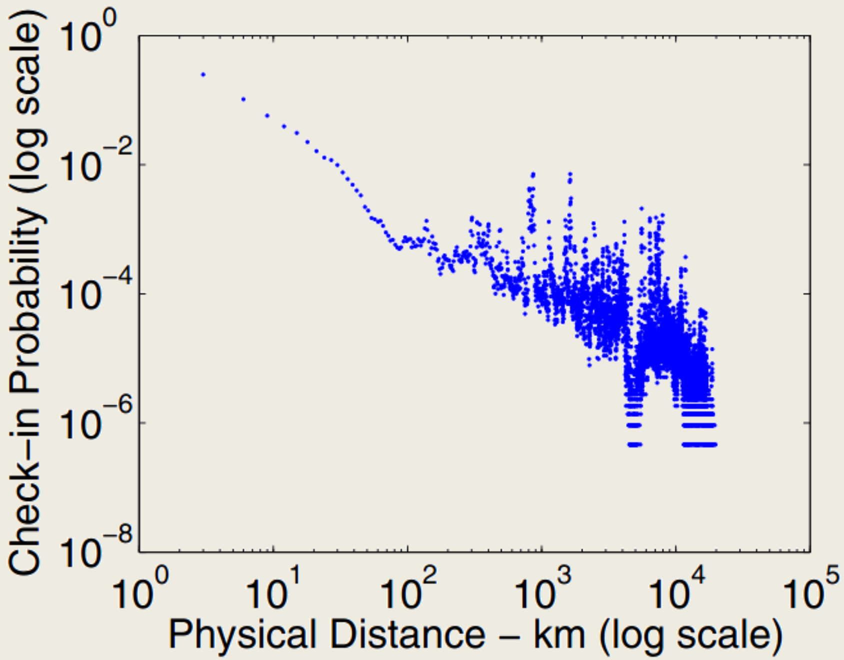
$\hat{P}(d)$: probability of the two locations visited by the same user

α,β: 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**)



$$\hat{P}(d) \sim \alpha * d^{\beta}$$

α,β: parameters of power-law distribution

To Recommend Locations:

$$\mathrm{P}(l_j | L_i) = \prod_{l_x \in L_i} \hat{P}\left(d_{l_j, l_x}\right)$$

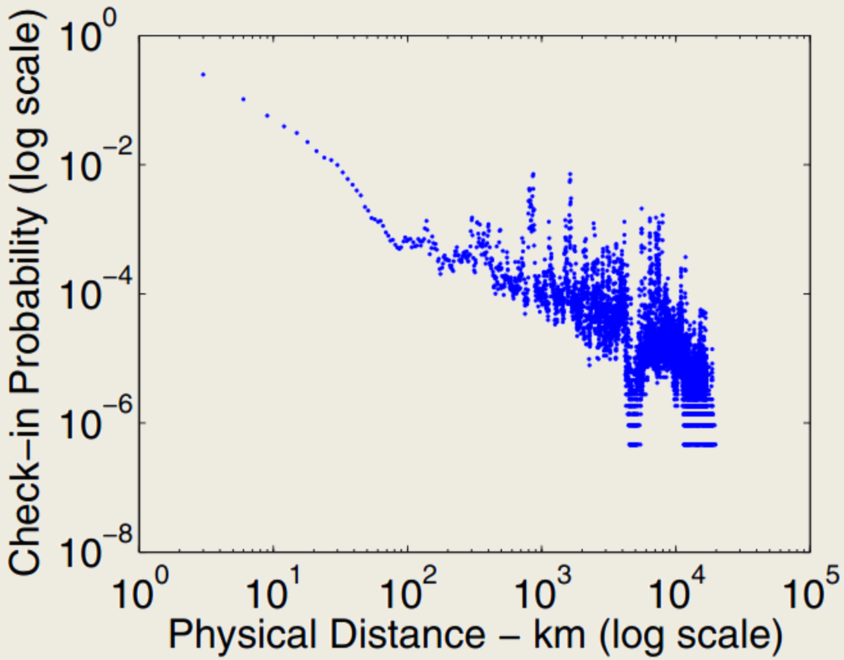
❖ Select l_j which has the highest probability

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**)



$$\hat{p}(d) \sim \alpha * d^{\beta}$$

$$\min_{\alpha,\beta} \sum_{(l_i,l_j)\epsilon M} (\log P(d_{i.j}) - \log \hat{P}(d_{i,j}))^2$$

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

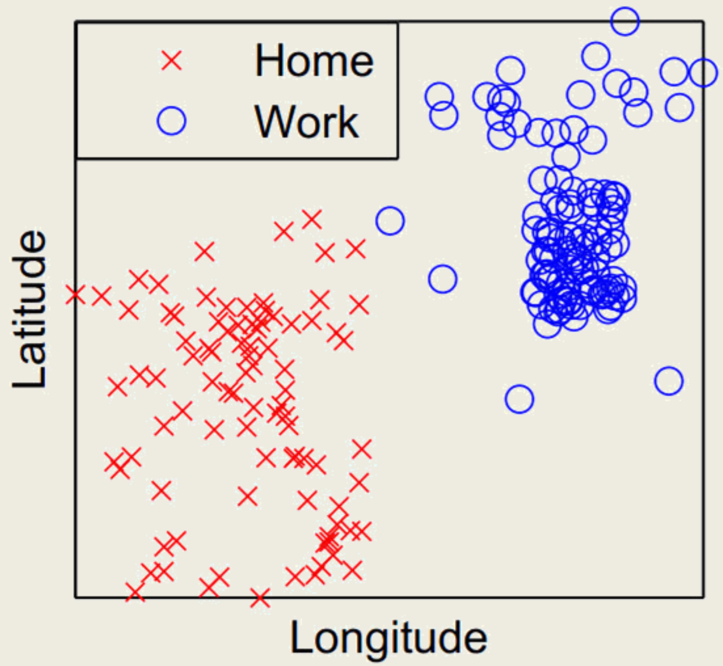
Ground Truth Observations

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

Geographical Influence [Cho et al., 2011]

➢Modeling Distribution of Geographical Distance

◆ Multi-Center Gaussian Distribution

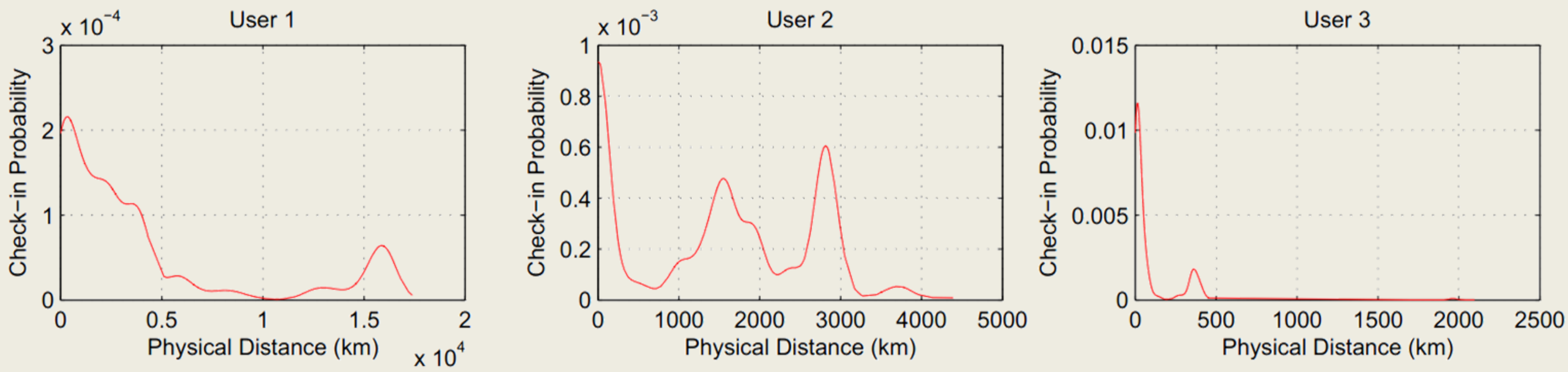


$$P\left[x_u(t) = x_i | c_u(t)\right] = \begin{cases} \sim \mathcal{N}(\mu_H, \Sigma_H) & \text{if} \quad c_u(t) = H \\ \sim \mathcal{N}(\mu_W, \Sigma_W) & \text{if} \quad c_u(t) = W \end{cases}$$

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 **K(·): Kernel Function**

h: Smoothing Parameter

☐ Setp 3: **Recommend a Location** l_j

$$\left.\begin{aligned} \hat{f}(d_{ij}) &= \frac{1}{|D|h} \sum_{d' \in D} K\left(\frac{d_{ij}-d'}{h}\right) \\ d_{ij} &= distance(l_i, l_j), \forall l_i \in L_i \end{aligned}\right\} \quad p(l_j|L_i) = \frac{1}{n}\sum_{i=1}^{n} \hat{f}(d_{ij})$$

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 in Social Media

Location Recommendation on LBSNs

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

Overview of Mobility Patterns

Mobility Patterns	Geo	Social	Temporal	Content
Inverse Distance Rule	✓	✓		
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				✓

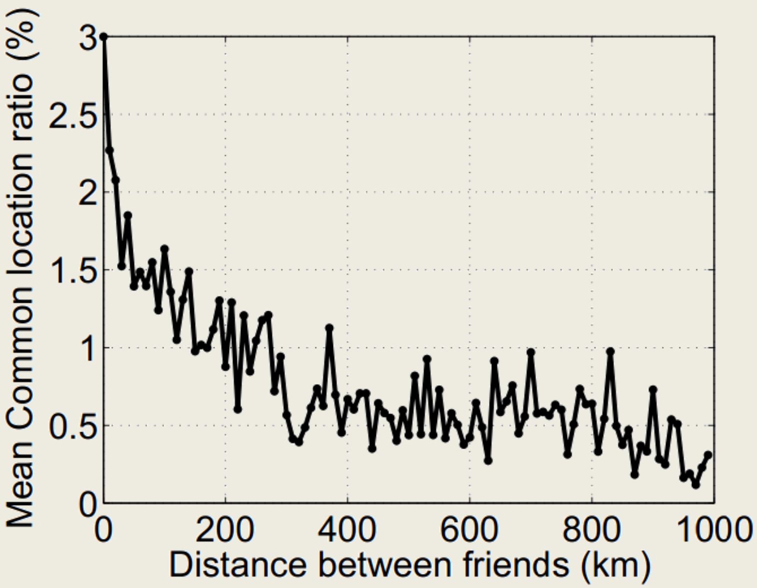
Social Correlations [Ye et al., 2010]

➢ **Friend-Based Collaborative Filtering**

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

Trajectory Similarity

Inverse Distance Rule



– Assuming a power-law relation between trajectory similarity y and geographical distance x

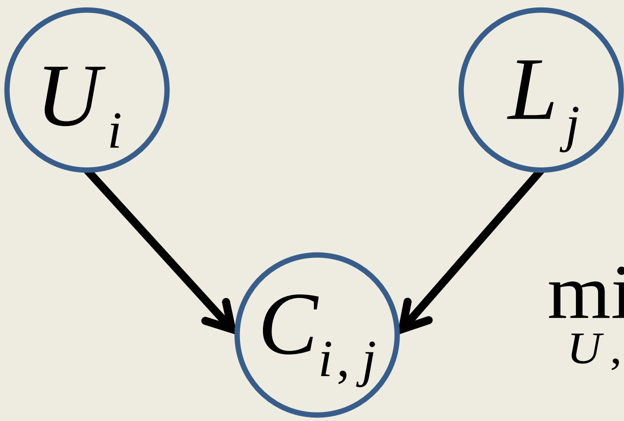
$$y = \alpha x^{\beta}$$

– Similarity is computed as

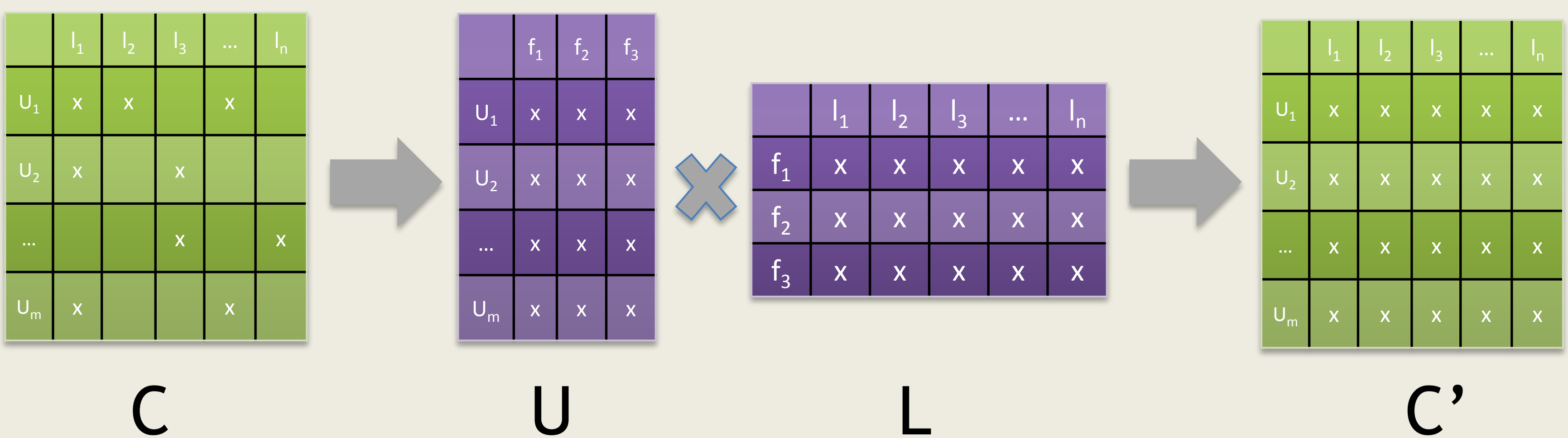
$$w_{i,k} = \frac{y(x = d(u_i, u_k), \alpha, \beta)}{\sum_{u_k \in U_i} y(x = d(u_i, u_k), \alpha, \beta)}$$

Social Correlations [Cheng et al., 2012]

- Matrix Factorization

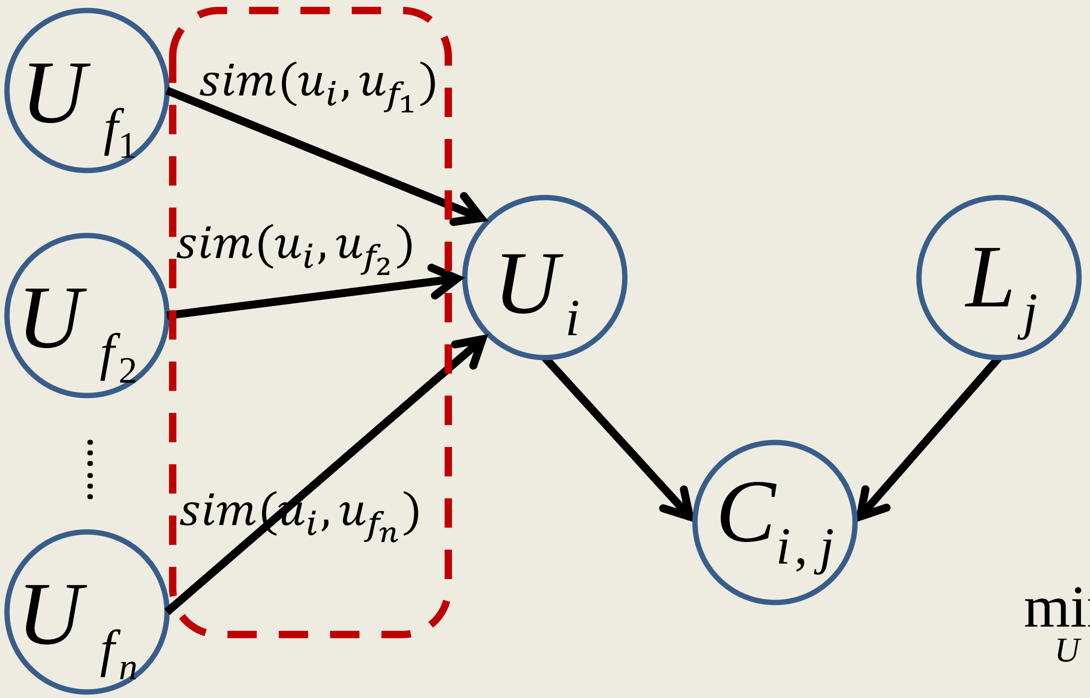


$$\min_{U,L} \sum_{(i,j)\in\Omega} (C_{i,j} - U_i L_j^T)^2 + \alpha \|U\|_F^2 + \beta \|L\|_F^2$$

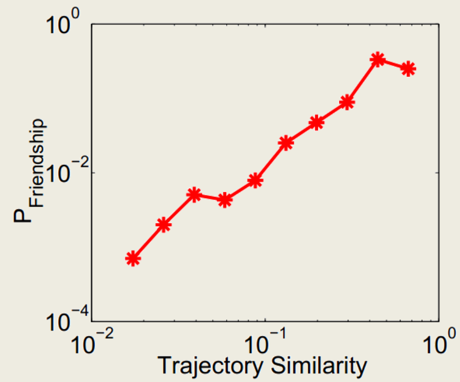


Social Correlations [Cheng et al., 2012]

- Matrix Factorization with Social Regularization



Social Correlations in Geographical Trajectory



Strong social friendship strength corresponds to high trajectory similarity

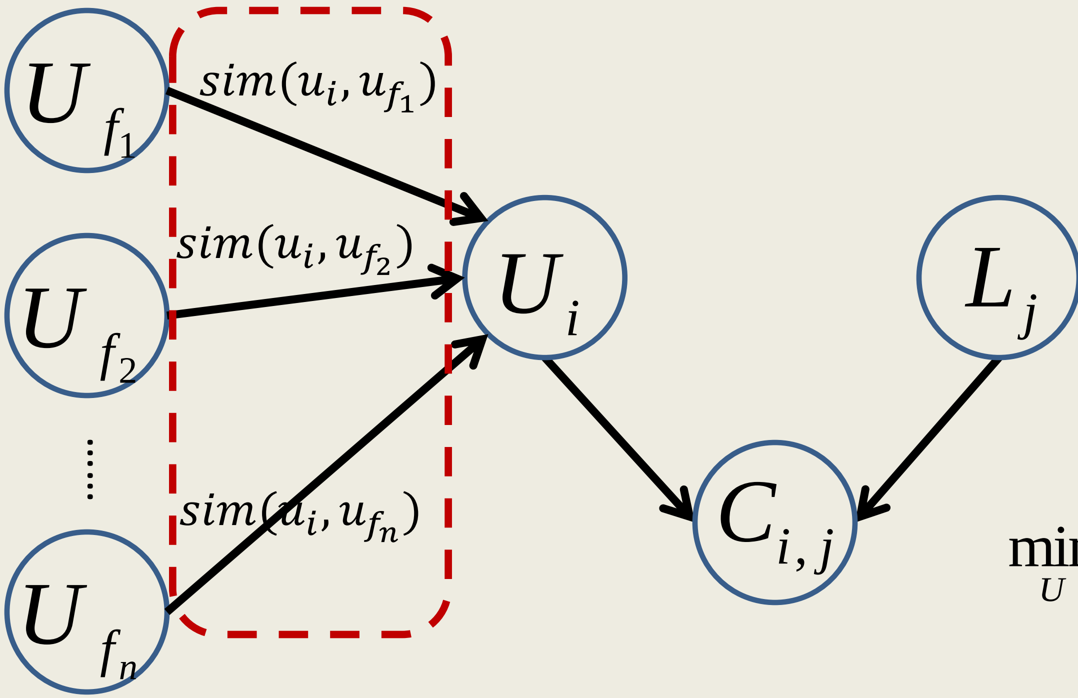
$$\min_{U} \frac{1}{2} \sum_{i} \sum_{j \in F_i} sim(u_i, u_j) \left\| U_i - U_j \right\|_F^2$$

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

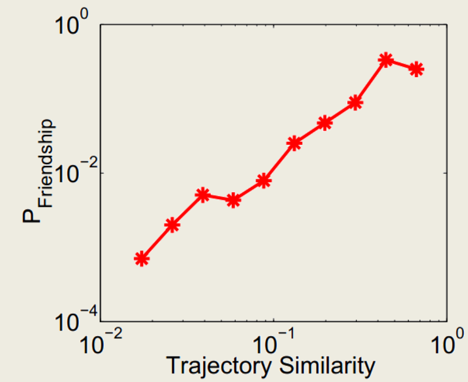
Basic Matrix Factorization Model

Social Correlations [Yang et al., 2013]

- Matrix Factorization with Social Regularization



Social Correlations in Geographical Trajectory



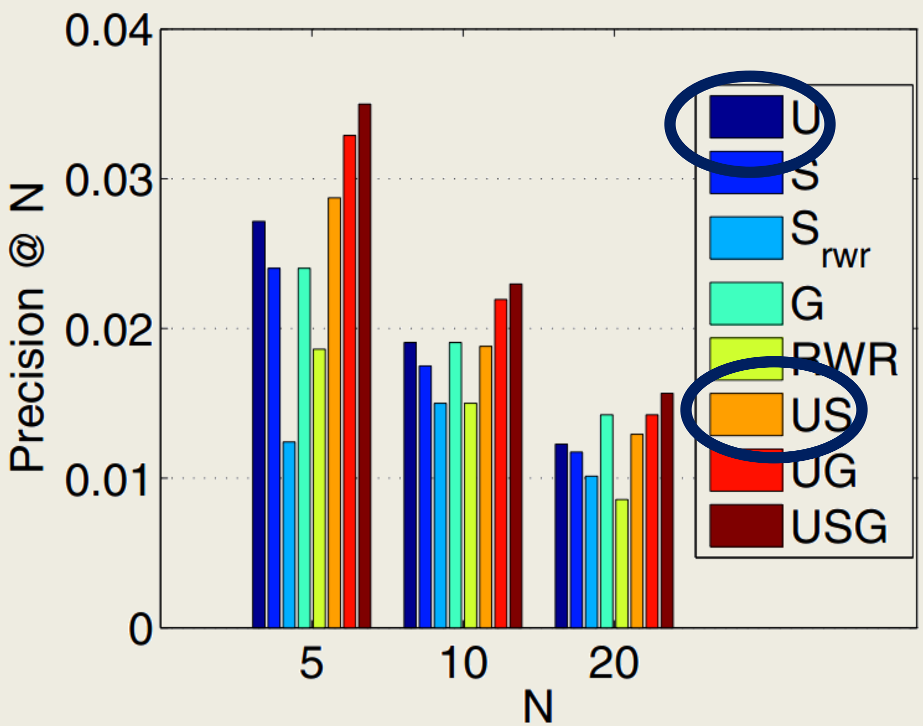
$$\min_{U} \frac{1}{2} \sum_i \left\| U_i - \sum_{j \in F_i} sim(u_i, u_j) U_j \right\|_F^2$$

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

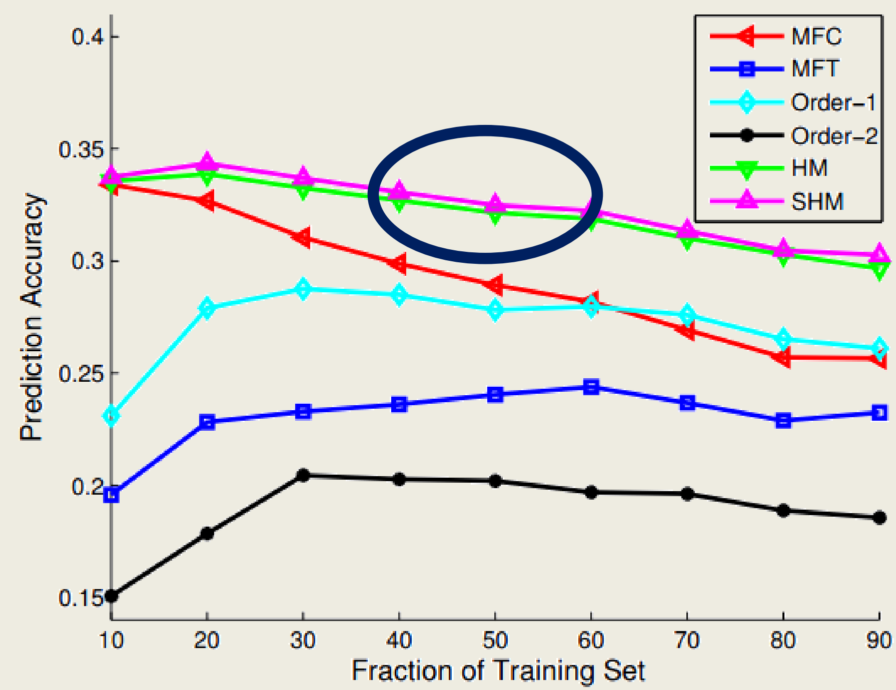
Basic Matrix Factorization Model

Some Observations for Geo-social Location Recommendation

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



[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

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Temporal Periodic Patterns			✓	
Multi-Center Check-in Distribution	✓		✓	
Sentiment and Topical Indications				✓

Temporal Dynamics [Gao et al., 2012a]

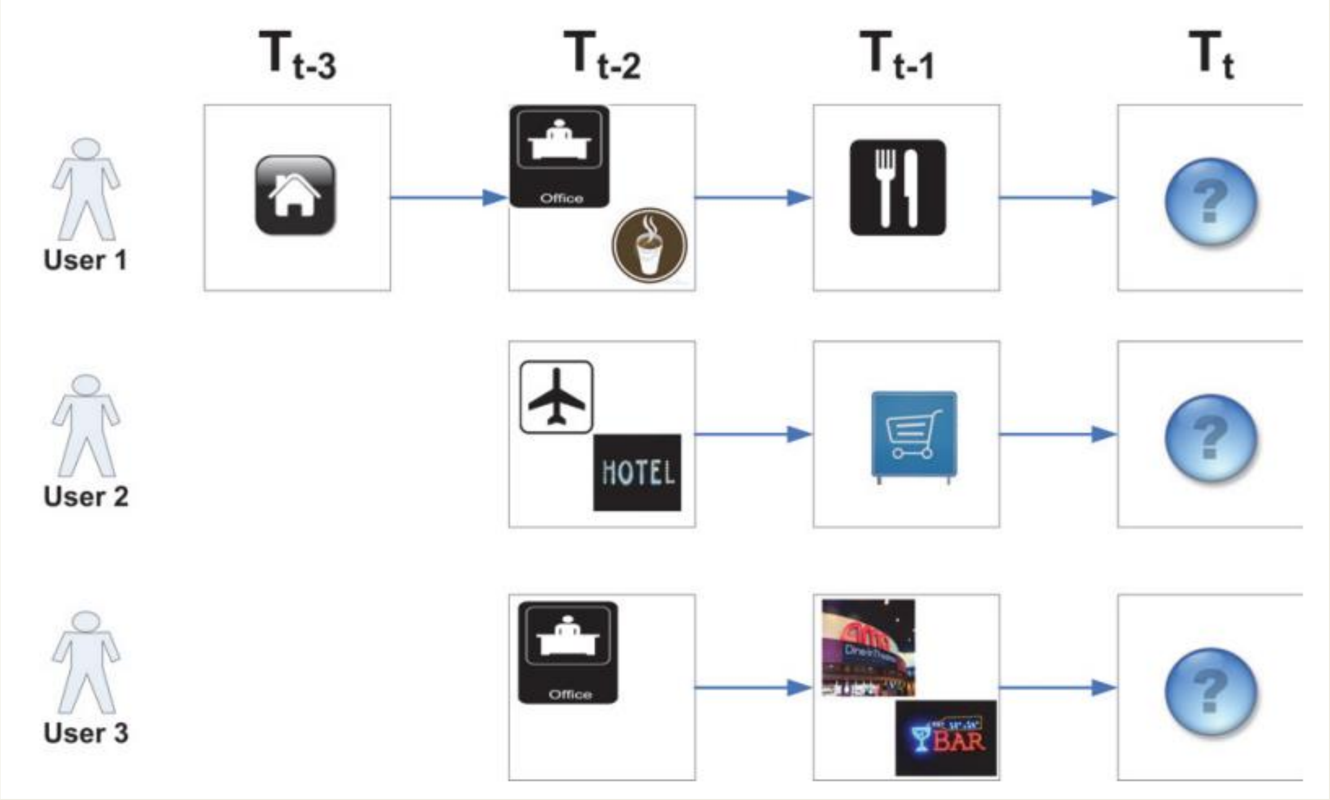
- **Temporal Chronological (Sequential Patterns)**
  - Shopping in the mall after dinner at a restaurant
  - Visiting a bar after work

- **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)

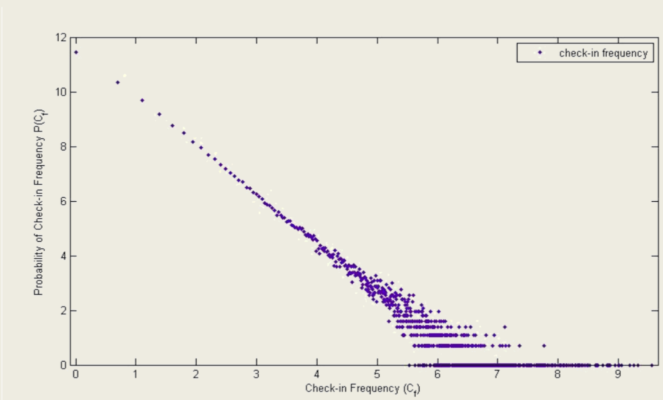


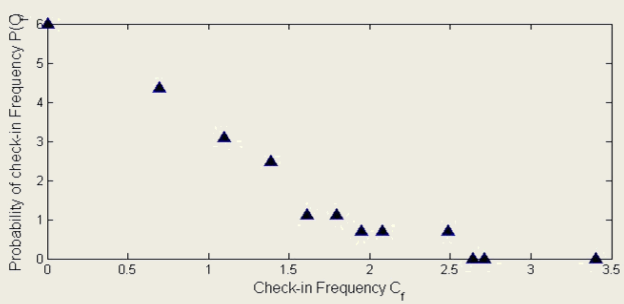
$$p(l \in \mathcal{L}_u^t | \mathcal{L}_u^{t-1}) = \frac{1}{|\mathcal{L}_u^{t-1}|} \sum_{i \in \mathcal{L}_u^{t-1}} p(l \in \mathcal{L}_u^t | i \in \mathcal{L}_u^{t-1})$$

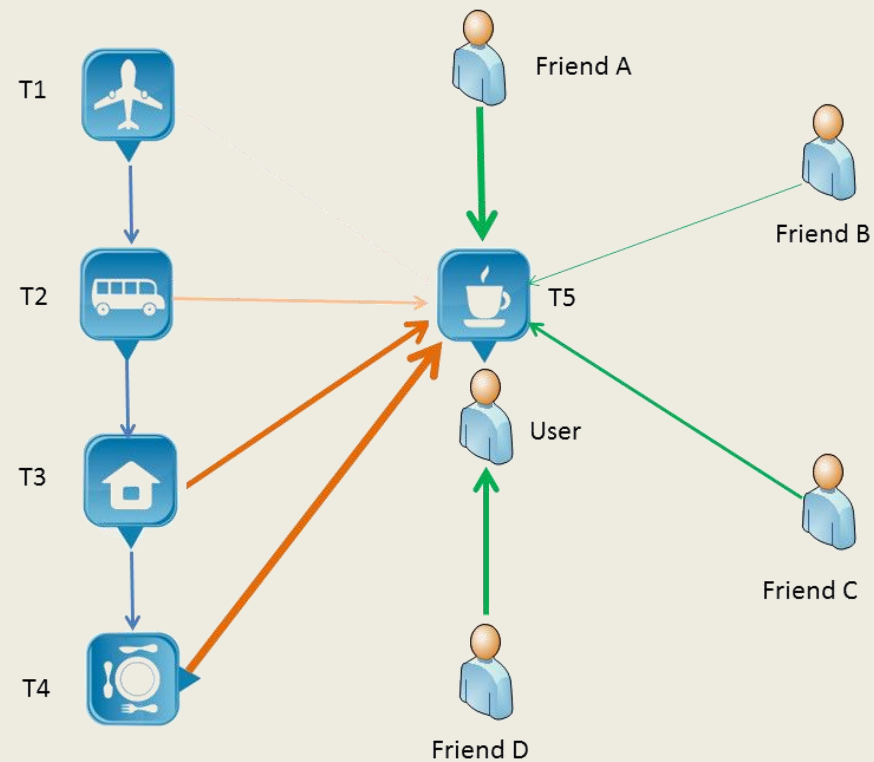
Temporal Dynamics [Gao et al., 2012a]

➢Temporal Chronological (Sequential Patterns)

- Consider the combination of various order-k Markov patterns
- Power-Law Property and Short-Term Effect







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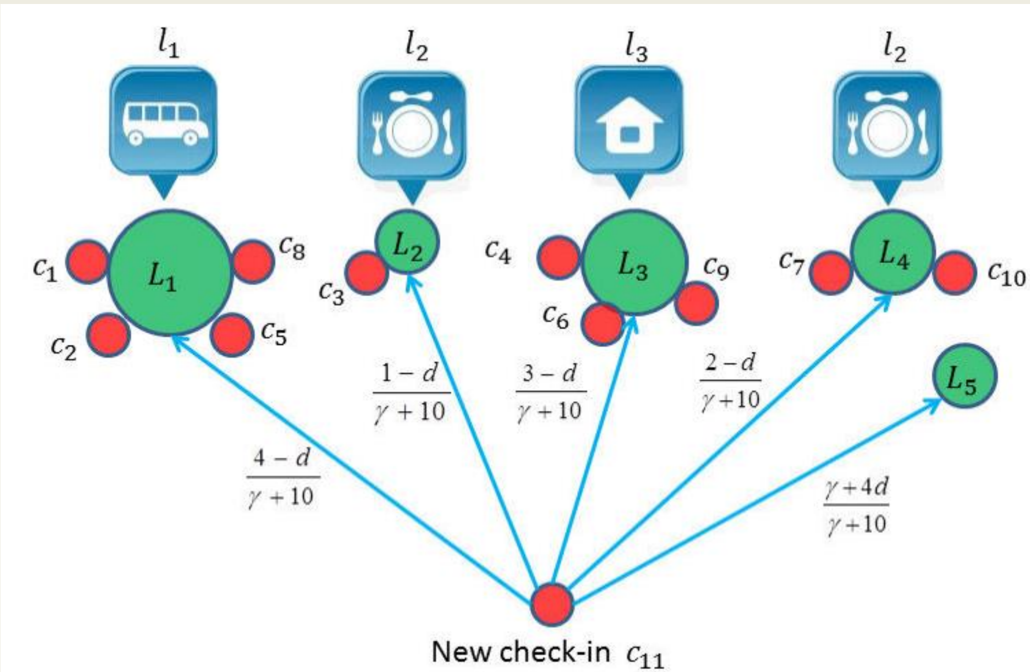

$$P(c_{11} = l_2 | c_1, \ldots, c_{10}) = \frac{3-2d}{\gamma+10} + \frac{\gamma+4d}{\gamma+10} G_0(l_2)$$

Modeling Power-Law Distribution

Pitman-Yor Process

$$G_\emptyset \sim PY(d_0, \gamma_0, G_0)$$

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]

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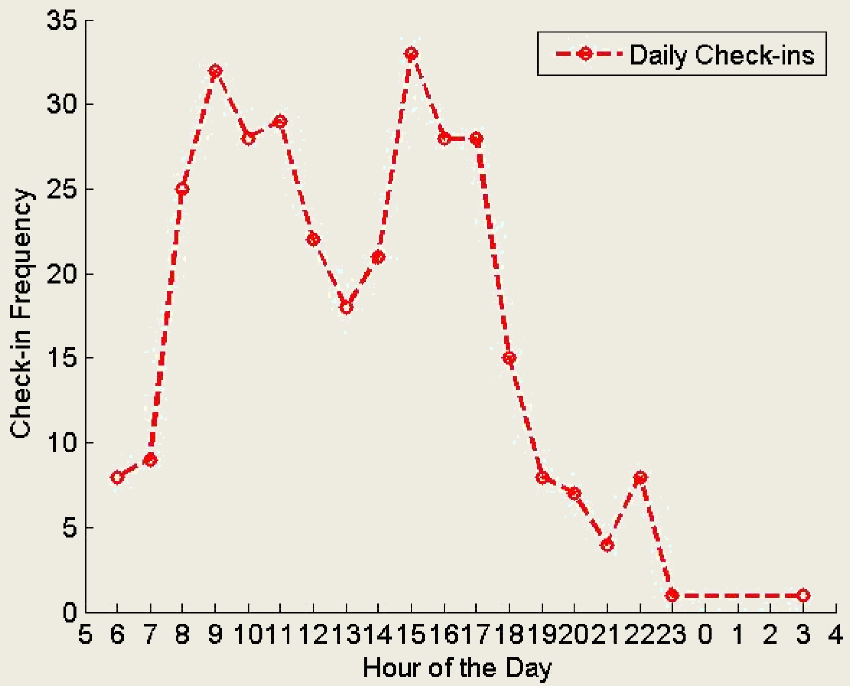
Temporal Dynamics [Gao et al., 2013b]

➢Temporal Cyclic (Periodic Patterns)

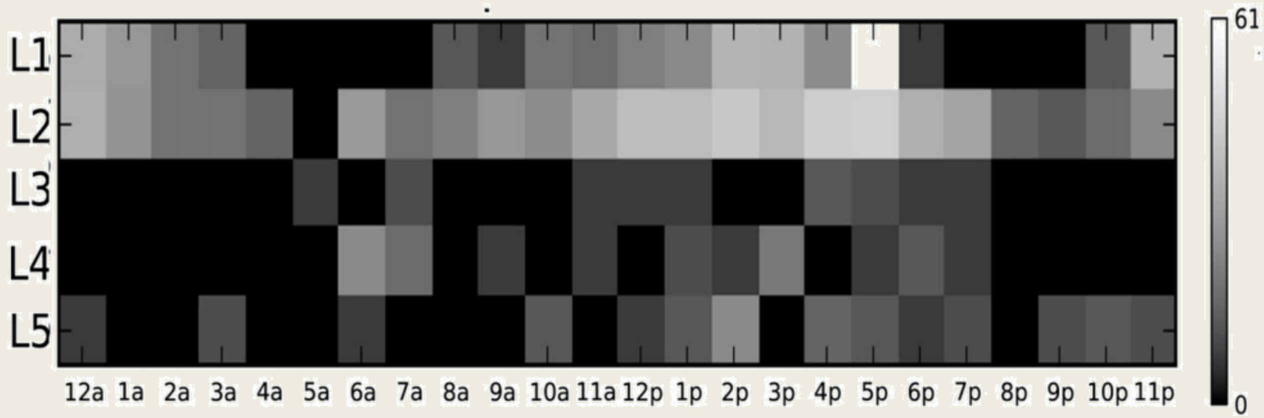


$$P(r(t)|c_u = l, H_{u,t}) \sim \sum_{i=1}^{k} A_i \mathcal{N}(r(t)|\mu^i_{u,l}, \sigma^i_{u,l})$$

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

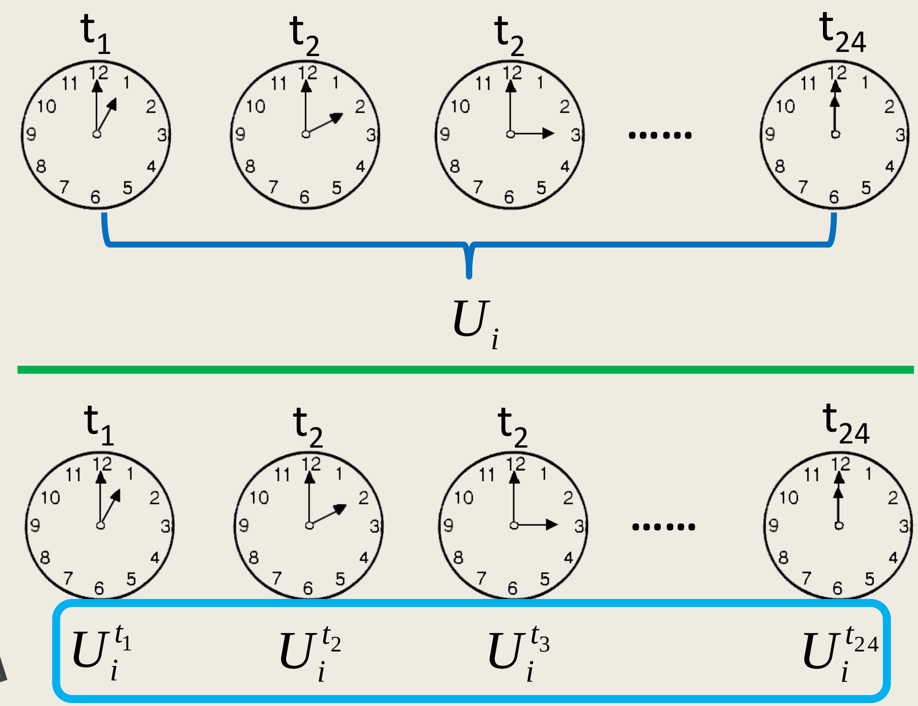
A user presents similar check-in preferences at nearby hours of the day

Modeling Temporal Non-uniformness [Gao et al., 2013a]

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

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

$$\min_{U_i \geq 0, L_j \geq 0} \boxed{\sum_{t=1}^{24}} \sum_{(i,j)\in\Omega} Y_{i,j}^t (C_{i,j}^t - \boxed{U_i^t} L_j^T)^2$$



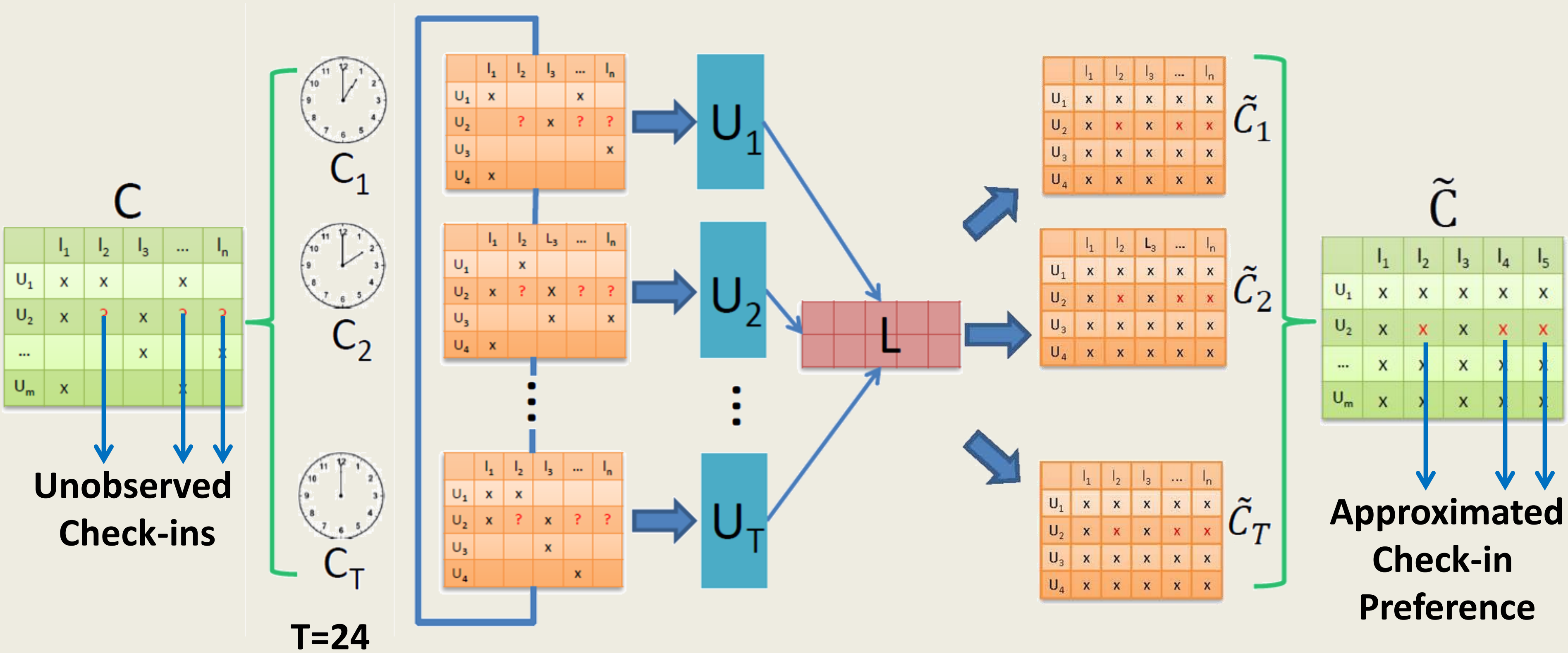
Modeling Temporal Consecutiveness [Gao et al., 2013a]

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

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

$$\psi_i(t, t-1) = \frac{C_t(i,:) \cdot C_{t-1}(i,:)}{\sqrt{\sum_j C_t^2(i,:)} \sqrt{\sum_j C_{t-1}^2(i,:)}}$$

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

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

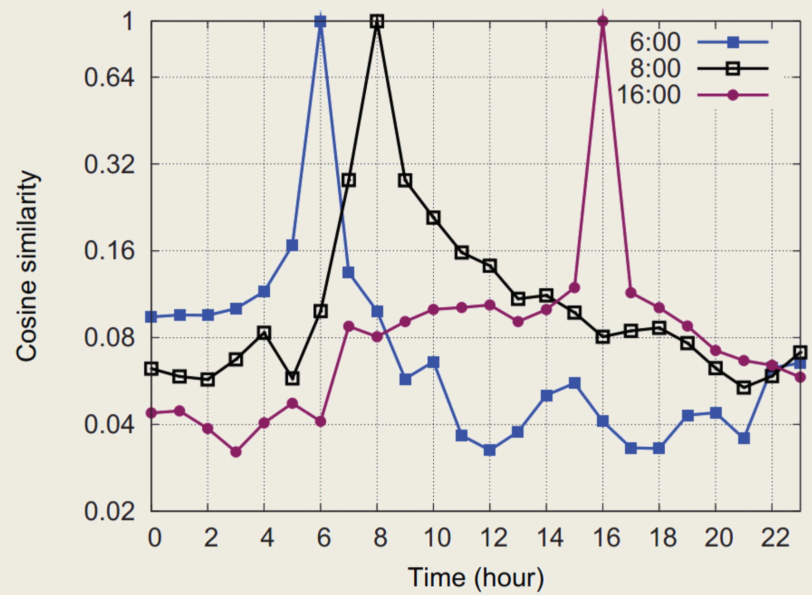
Sparse

  - 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

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Power-Law Distribution	✓		✓	
Short-Term Effects			✓	
Temporal Periodic Patterns			✓	
Multi-Center Check-in Distribution	✓		✓	
Sentiment and Topical Indications				✓

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

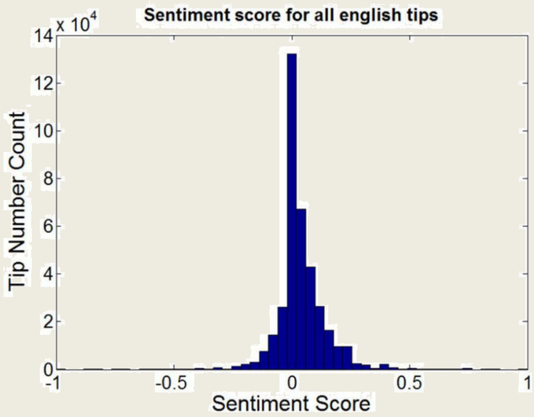
- Sentiment extracted from content contains more precise information about a user's preference on a location
  - In addition to positive feedback, there could also be negative feedback from content

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



Sentiment Scores	Preference Scores
[-1,-0.05]	1
(0.05,-0.01]	2
(-0.01,0.01)	3
[0.01,0.05)	4
[0.01,1]	5

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

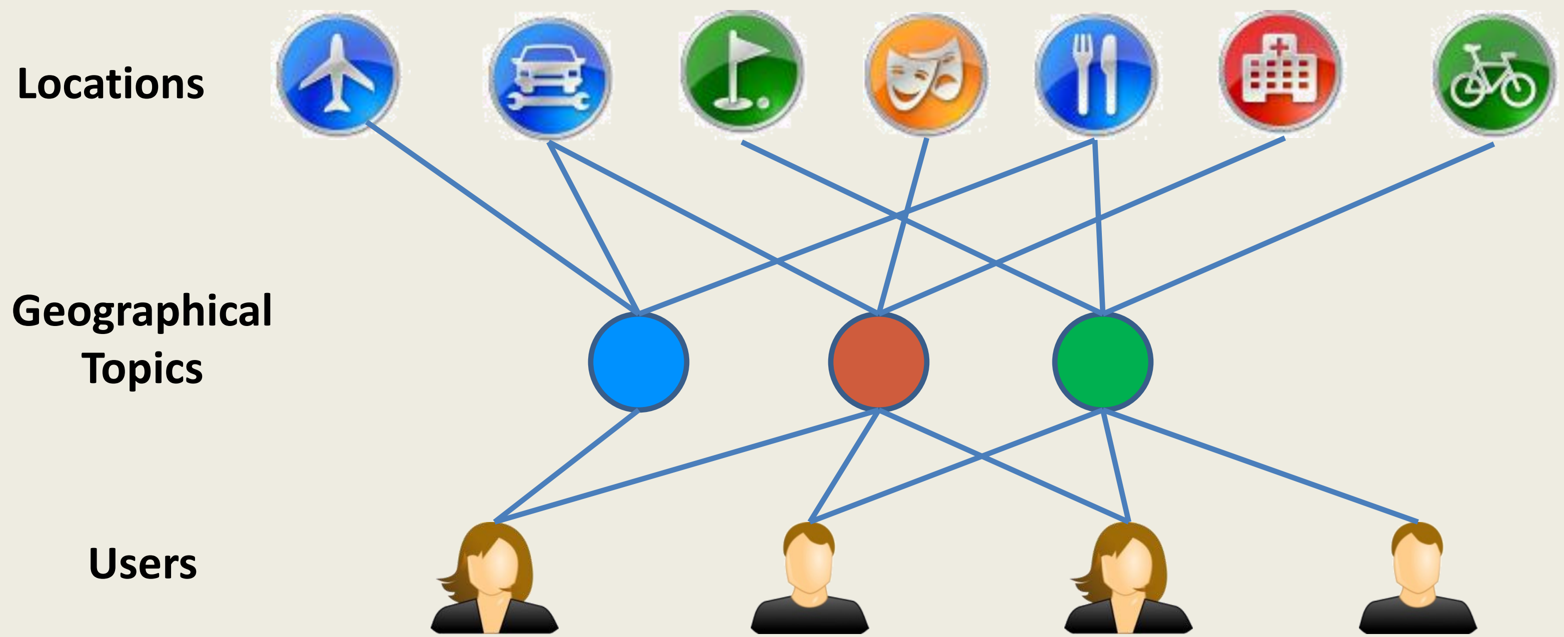
$$\widehat{C}_{i,j} = f(C_{i,j}, S_{i,j})$$

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

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

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



Topic-aware Location Recommendation [Liu and Xiong, 2013]

- Building an aggregated LDA model to discover geographical topics
  - User interest topic distribution θ_i
  - Location topic distribution π_j
- Defining topic and location influence index

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

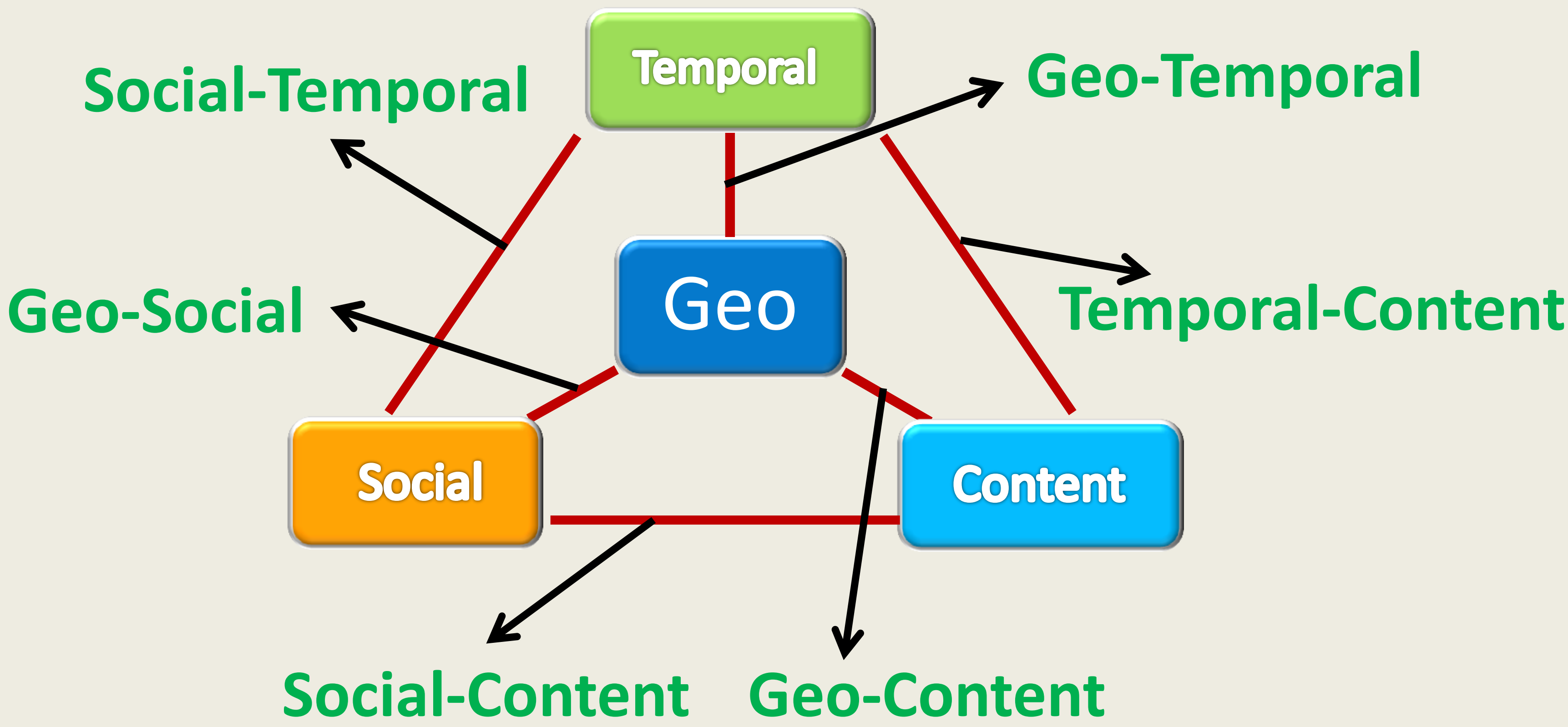
Jensen-Shannon Divergence

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



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

(user i, location j) → Label: 1, i visited j; 0, otherwise

(user i, location j) → Features

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

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

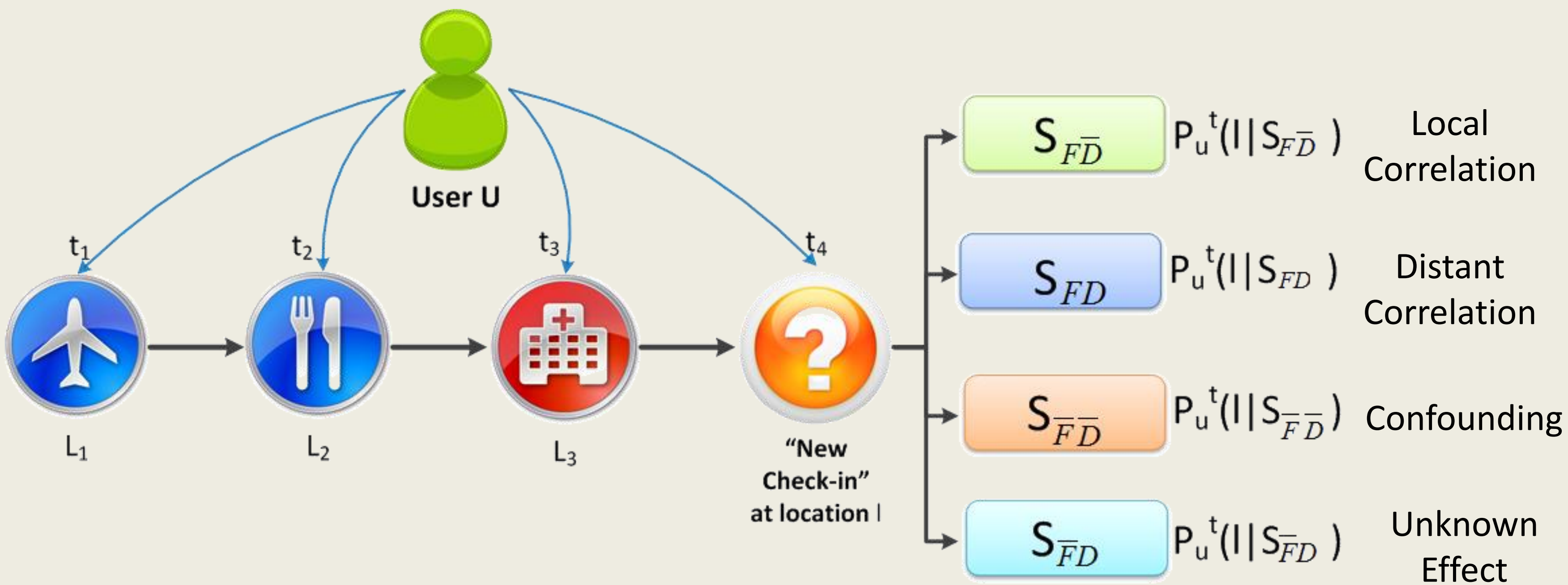
Geo-Social Circles

	F	$\bar{F}$
$\bar{D}$	$S_{F\bar{D}}$: Local Friends	$S_{\bar{F}\bar{D}}$: Local Non-friends
D	S_{FD}: Distant Friends	$S_{\bar{F}D}$: Distant Non-friends

A Geo-Social Location Recommendation Framework

- A framework is proposed for location recommendation based on geo-social circles

$$P_u^t(l) = \Phi_1 P_u^t(l|S_{\bar{F}\bar{D}}) + \Phi_2 P_u^t(l|S_{F\bar{D}})$$
$$+ \Phi_3 P_u^t(l|S_{FD}) + \Phi_4 P_u^t(l|S_{\bar{F}D}).$$



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

Methods	Top-1	Top-2	Top-3
$S_{F\bar{D}}$	6.51%	8.31%	9.32%
S_{FD}	3.65%	4.75%	5.34%
$S_{\bar{F}\bar{D}}$	18.37%	24.10%	27.34%
$S_{\bar{F}\bar{D}} \cup S_{F\bar{D}}$	18.62%	24.44%	27.79%
$S_{\bar{F}\bar{D}} \cup S_{FD}$	19.01%	24.95%	28.35%
$S_{F\bar{D}} \cup S_{FD}$	8.33%	10.79%	12.23%
$S_{\bar{F}\bar{D}} \cup S_{F\bar{D}} \cup S_{FD}$	**19.21%**	**25.19%**	**28.69%**

Fused Model

- Sum Rule

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

- Product Rule

$$P = \prod_{i=1}^{n} P_i \Rightarrow P = P_1 \cdot P_2$$

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

$$S_{i,j} = (1 - \alpha - \beta) S^{u}_{i,j} + \alpha S^{s}_{i,j} + \beta S^{g}_{i,j}$$

User preference: User-oriented CF | **Social Correlations: FCF** | **Geographical Influence**

- 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

$$S_{i,j} = P_{i,j} P(l_j \mid L_i)$$

Social Correlations | **Geographical Influence**

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

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

Temporal Influence — **Geographical Influence**

- A fusion model (Product Rule): PMM **[Cho et al., 2011]**

$$\begin{aligned} P\left[x(t)=x\right] = & \boxed{P\left[x_u(t)=x \mid c_u(t)=H\right]} \cdot \boxed{P\left[c_u(t)=H\right]} \\ & + P\left[x_u(t)=x \mid c_u(t)=W\right] \cdot P\left[c_u(t)=W\right] \end{aligned}$$

Geographical Influence — **Temporal Influence**

Fused Model (Temporal-Social)

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

$$P_{i,j}^{SH} = \alpha P_{i,j} + (1-\alpha)\sum_{u_k \in N_i} w_{i,k} P_{k,j}$$

Temporal Influence (term $\alpha P_{i,j}$)

Social Influence (term $\sum_{u_k \in N_i} w_{i,k} P_{k,j}$)

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

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

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

$$precision@N = \frac{\sum_{u_i \in U} |TopN(u_i) \bigcap L(u_i)|}{\sum_{u_i \in U} |TopN(u_i)|}$$

$$recall@N = \frac{\sum_{u_i \in U} |TopN(u_i) \bigcap L(u_i)|}{\sum_{u_i \in U} |L(u_i)|},$$

- **RMSE**

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

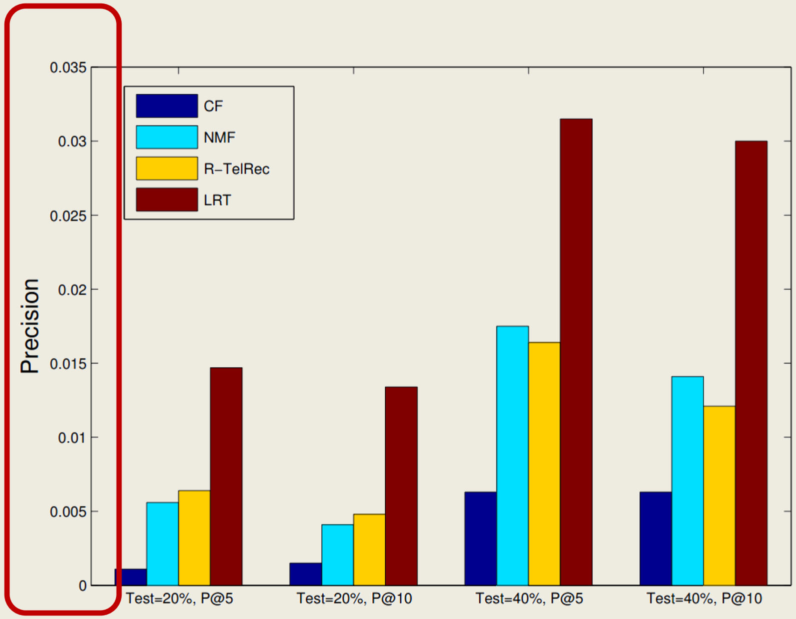
- **NDCG** (Normalized Discounted Cumulative Gain)

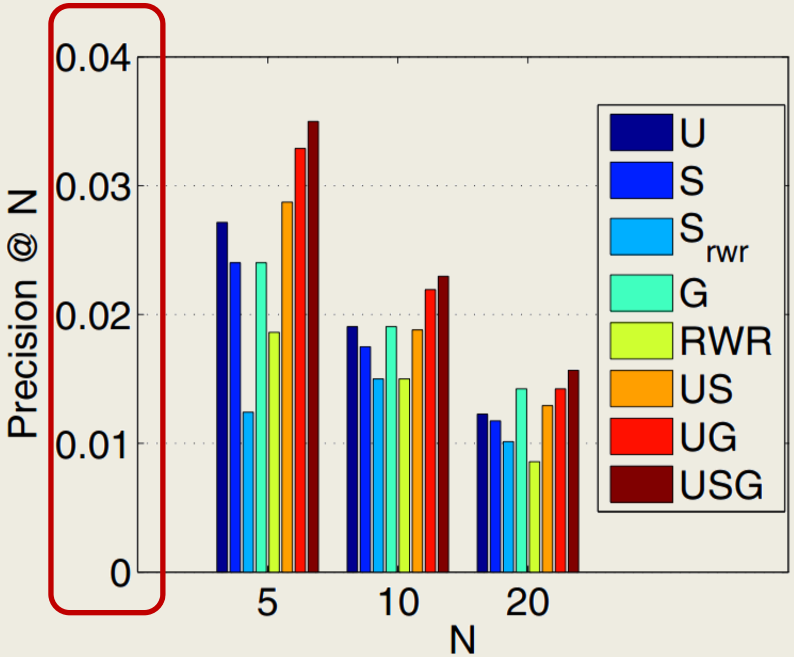
Recommendation Effectiveness [Ye et al., 2011] [Gao et al., 2013a]

➢ 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.

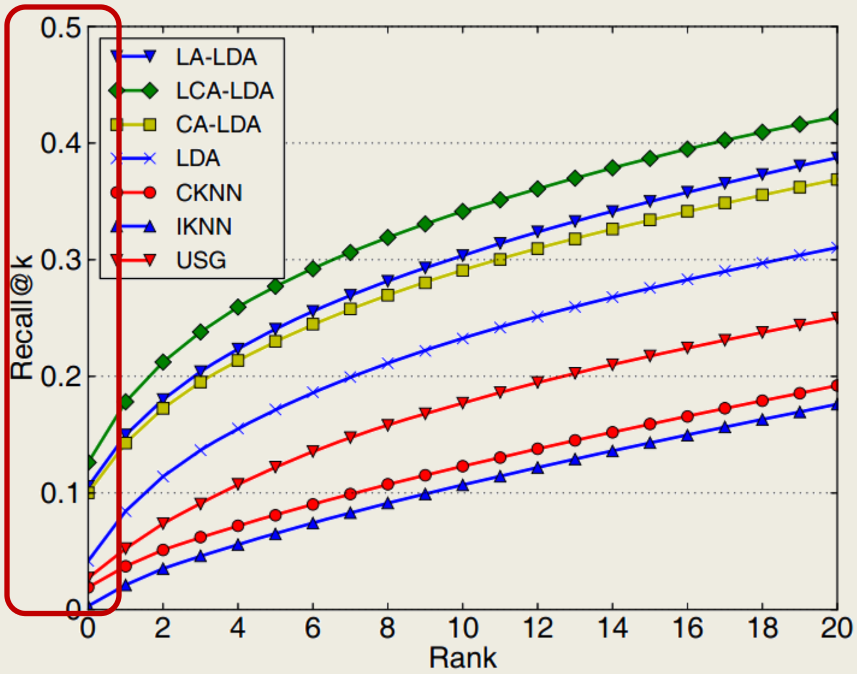
- The reported P@5 is 5% over a data with 8.02 x 10^{-3} density, and 3.5% over a data with 4.24 x 10^{-5} density.





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



Outline

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

Overview of Mobility Patterns

Existing Work	Geographical Influence	Social Correlations	Temporal Dynamics	Content Indications
[Ye et al., 2011], [Zhang et al., 2013] [Ye et al., 2010] , [Ye et al., 2011] [Gao et al., 2012b] , [Cheng et al., 2012]	+	+		
[Cheng et al., 2013], [Gao et al., 2013a] , [Ye et al., 2013]			+	
[Zhou et al., 2012] , [Long and James, 2013], [Ye et al., 2012]		+		
[Yang et al., 2013] , [Hu and Ester, 2014] [Ying et al., 2012], [Bao et al., 2012]		+		+
[Yuan et al., 2013]	+		+	
[Cho et al., 2011]	+	+	+	
[Gao et al., 2012a] , [Gao et al., 2013b]		+	+	
[Liu and Xiong, 2013] [Yin et al., 2013]	+			+
[Hu and Ester, 2013], [Liu et al., 2013]				+
[Noulas et al., 2012]	+	+	+	+

References

[**Ye et al., 2011**]M. Ye, P. Yin, W. Lee, and D. Lee. Exploiting geographical influence for collaborative point-of-interest recommendation. In Proceedings of the 34th international ACM SIGIR conference on Research and development in Information Retrieval, pp, 325—334, 2011.

[**Cho et al., 2011**] E. Cho, S. Myers, and J. Leskovec. Friendship and mobility: user movement in location-based social networks. In Proceedings of the 17th ACM SIGKDD international conference on Knowledge discovery and data mining, pp, 1082—1090, 2011.

[**Cheng et al., 2012**] C. Cheng, H. Yang, I. King, and M. Lyu. Fused Matrix Factorization with Geographical and Social Influence in Location-Based Social Networks. In AAAI, pp, 1-8, 2012.

[**Gao et al., 2012a**] H. Gao, J. Tang, and H. Liu. Exploring social-historical ties on location-based social networks. In ICWSM, 2012.

[**Cheng et al., 2013**] C. Cheng, H. Yang, M. Lyu, and I. King. Where you like to go next: Successive point-of-interest recommendation. In IJCAI, pp, 2605-2611, 2013.

[**Gao et al., 2013a**] H. Gao, J. Tang, H. Xia, and H. Liu. Exploring temporal effects for location recommendation on location-based social networks. In Proceedings of the 7th ACM conference on Recommender systems, pp, 93—100, 2013.

[**Yang et al., 2013**] D. Yang, D. Zhang, Z. Yu, and Z. Wang. sentiment-enhanced personalized location recommendation system. In Proceedings of the 24th ACM Conference on Hypertext and Social Media, pp, 119—128, 2013.

References

[**Gao and Liu, 2014**] H. Gao, and H. Liu. Data Analysis on Location-Based Social Networks. Mobile Social Networking, pp, 165—194, 2014.

[**Yuan et al., 2013**] Q. Yuan, G. Cong, Z. Ma, A. Sun, and N. Thalmann. Time-aware Point-of-interest Recommendation. In Proceedings of the 36th international ACM SIGIR conference on Research and development in information retrieval, pp, 363—372, 2013.

[**Gao et al., 2012b**] H. Gao, J. Tang, and H. Liu. gSCorr: modeling geo-social correlations for new check-ins on location-based social networks. In Proceedings of the 21st ACM international conference on Information and knowledge management, pp, 1582—1586, 2012.

[**Zhou et al., 2012**] D. Zhou, B. Wang, S. Rahimi, and X. Wang. A study of recommending locations on location-based social network by collaborative filtering. Advances in Artificial Intelligence, pp, 255—266, 2012.

[**Zhang et al., 2013**] J. Zhang, and C. Chow. iGSLR: personalized geo-social location recommendation: a kernel density estimation approach. ACM SIGSPATIAL, pp, 324—333, 2013.

[**Yin et al., 2011**] Z. Yin, L. Cao, J. Han, C. Zhai, and T. Huang. Geographical topic discovery and comparison. Proceedings of the 20th international conference on World wide web, pp, 247—256, 2011.

[**Liu and Xiong, 2013**] B. Liu, and H. Xiong. Point-of-Interest Recommendation in Location Based Social Networks with Topic and Location Awareness. SIAM Conference on Data Mining, pp, 396—404, 2013.

References

[**Ye et al., 2010**] M. Ye, P. Yin, and W. Lee. Location recommendation for location-based social networks. In Proceedings of the 18th SIGSPATIAL International Conference on Advances in Geographic Information Systems, pp, 458—461, 2010.

[**Bao et al., 2012**]J. Bao, Y. Zheng, and M. Mokbel. Location-based and preference-aware recommendation using sparse geo-social networking data. In ACM SIGSPATIAL, 2012.

[**Scellato et al., 2011**]S. Scellato, A. Noulas, R. Lambiotte, and C. Mascolo. Socio-Spatial Properties of Online Location-Based Social Networks. In ICWSM, pp, 329—336, 2011.

[**Ying et al., 2012**]J. Ying, E. Lu, W. Kuo, and V. Tseng. Urban point-of-interest recommendation by mining user check-in behaviors. In UrbComp, pp, 63—70, 2012.

[**Noulas et al., 2012**]A. Noulas, S. Scellato, N. Lathia, and C. Mascolo. Mining User Mobility Features for Next Place Prediction in Location-Based Services. In ICDM, pp, 1038—1043, 2012.

[**Yin et al., 2013**]H. Yin, Y. Sun, B. Cui, Z. Hu, and L. Chen. Lcars: A location-content-aware recommender system. In ACM SIGKDD, pp, 221—229, 2013.

[**Hu and Ester, 2013**]B. Hu, and M. Ester. Spatial topic modeling in online social media for location recommendation. In ACM RecSys, pp, 25—32, 2013.

[**Liu et al., 2013**]B. Liu, Y. Fu, Z. Yao, and H. Xiong. Learning geographical preferences for point-of-interest recommendation. In ACM SIGKDD, pp, 1043—1051, 2013.

References

[**Gao et al., 2013b**]H. Gao, J. Tang, X. Hu, and H. Liu. Modeling temporal effects of human mobile behavior on location-based social networks. In ACM CIKM, pp, 1673—1678, 2013.

[**Long and James, 2013**]X. Long , and J. James. A hits-based poi recommendation algorithm for location-based social networks. In ASONAM, pp, 642—647, 2013.

[**Ye et al., 2013**]J. Ye , Z. Zhu, and H. Cheng. What's Your Next Move: User Activity Prediction in Location-based Social Networks. In SDM, 2013.

[**Ye et al., 2012**]M. Ye , X. Liu, and W. Lee. Exploring social influence for recommendation: a generative model approach. In SIGIR, pp, 671—680, 2012.

[**Hu and Ester, 2014**]B. Hu, and M. Ester. Social Topic Modeling for Point-of-Interest Recommendation in Location-based Social Networks. In ICDM, 2014.

Future Work

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

Acknowledgements

- Projects are partially supported by **National Science Foundation, Army Research Office** and **The Office of Naval Research**

Revolutionary Research . . . Relevant Results

- Members of Data Mining and Machine Learning Lab at ASU provided valuable feedback and suggestions