

# Inferring Geographic Coincidence in Ephemeral Social Networks

Honglei Zhuang<sup>1</sup>, Alvin Chin<sup>2</sup>, Sen Wu<sup>1</sup>,  
Wei Wang<sup>2</sup>, Xia Wang<sup>2</sup>, Jie Tang<sup>1</sup>

<sup>1</sup>Tsinghua University

<sup>2</sup>Nokia Research Center Beijing

2012/9/26

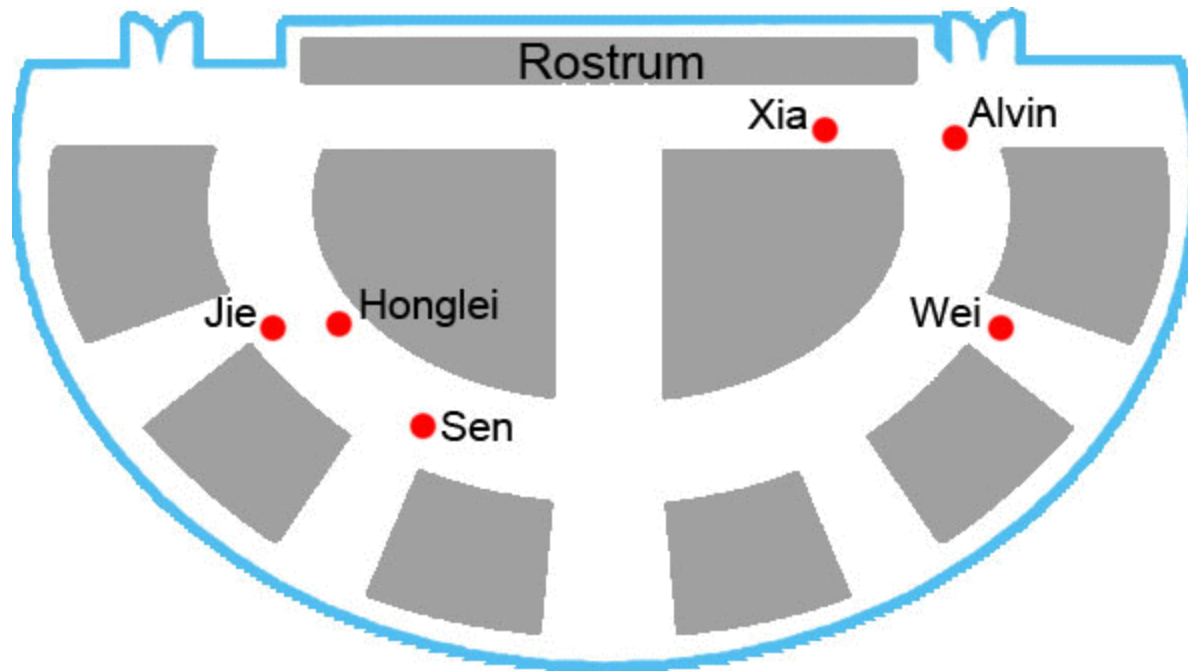


清華大學  
Tsinghua University

**NOKIA**

# What is an Ephemeral Social Network?

- A social network temporarily created during an event such as a conference, game or banquet.



# Questions: W<sup>3</sup>

- *Who do you want to meet at a conference?*
- *Who did you finally chat with?*
- *What made a conversation last up to 2 hours?*

# Research Problem

- An interesting and basic question to explore in an ephemeral social network is, can we **recommend and predict** whom a user will meet in the future?



# Nokia Find & Connect System

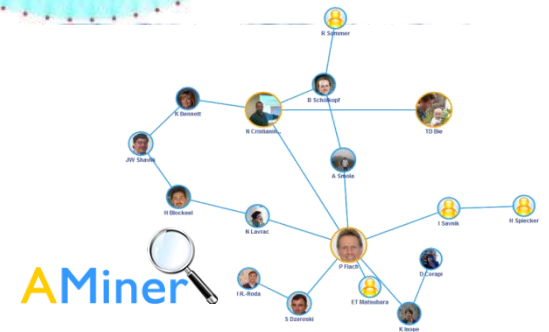
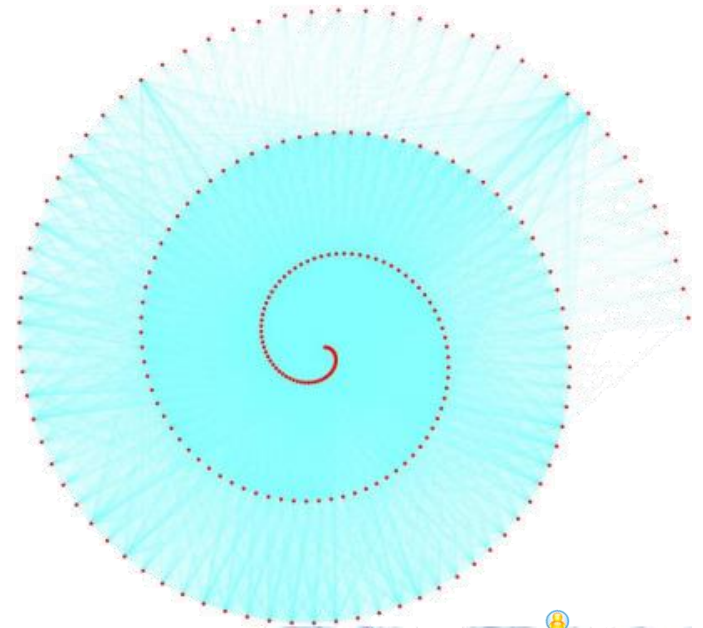


- Designed for events including UbiComp 2011.
- Allows users to locate friends, check users nearby, and share personal information.

# Data Sets

- **UbiComp**

- Location logs are collected by Find & Connect system during *UbiComp*.
- Author information, including publication list, coauthor relationship are provided by *ArnetMiner*.

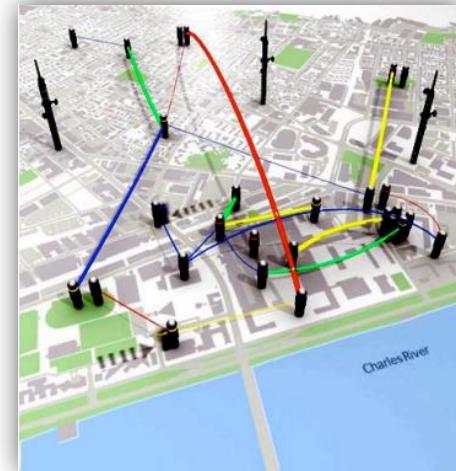


UbiComp2012: <http://www.ubicomp.org/ubicomp2011/>

ArnetMiner: <http://aminer.org> Nokia Internal Use Only

# Data sets (cont')

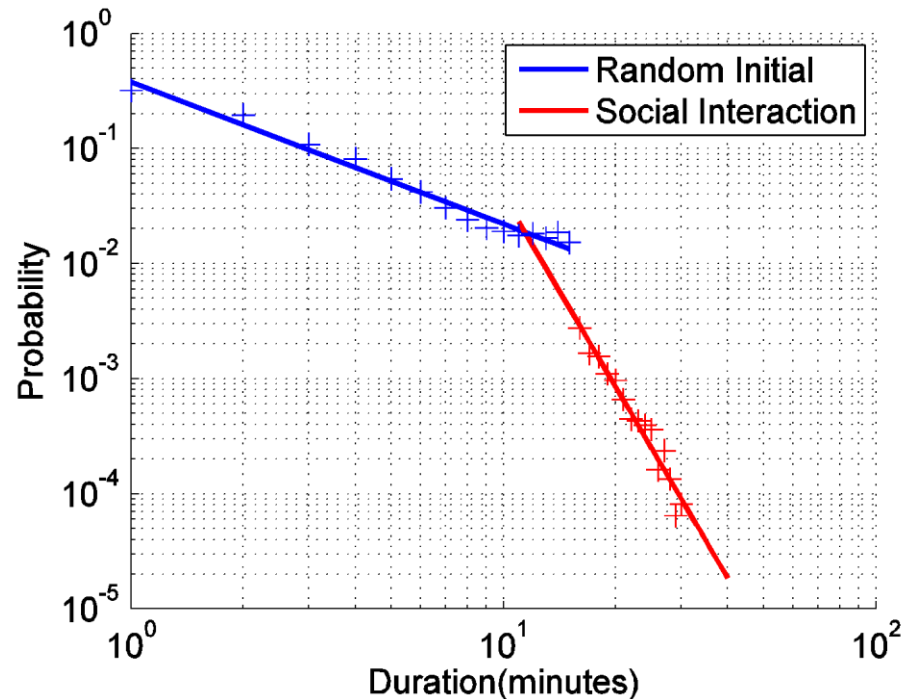
- **Reality** [Eagle et al. 2009]
  - Collected by MIT Media Lab from 2004-2005.
  - Physical proximity logs are recognized by Bluetooth device on mobile phones of 106 users.
  - A survey for all subjects provides the friendship network.



Data sets	UbiComp	Reality
User number	234	106
Duration	3 days	10 months
Logs number	69,844	~ 4,000,000
Normal network	Coauthor	Friendship

# Observation 1: 10-minute Phenomenon

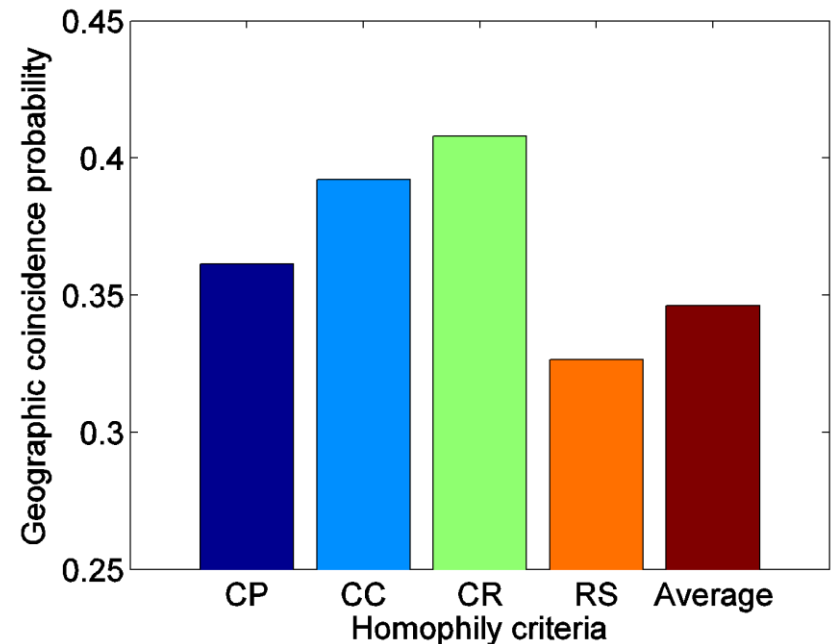
- Probability of a geographic coincidence vs. its duration.
- A two-stage power-law distribution where 10-minute is the inflexion point.
- Implication: geographic coincidences with real social interaction behind would usually last for longer than 10 minutes.





# Observation 2: Old Folks or New Ideas?

- Does homophily play an important role in geographic coincidences between people?
- Probability of geographic coincidences for user pairs with the most common paper, common conference, and common research interests.
- Users with high research similarity are less likely to encounter.
- Users with high common papers/conference/coauthors are still more likely to encounter.

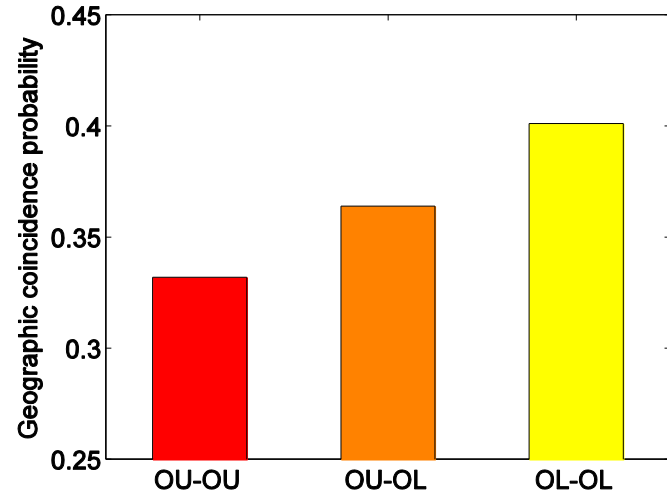


\*CP for coauthored papers, CC for common coauthors, CR for common conference, RS for similarity of research interests.

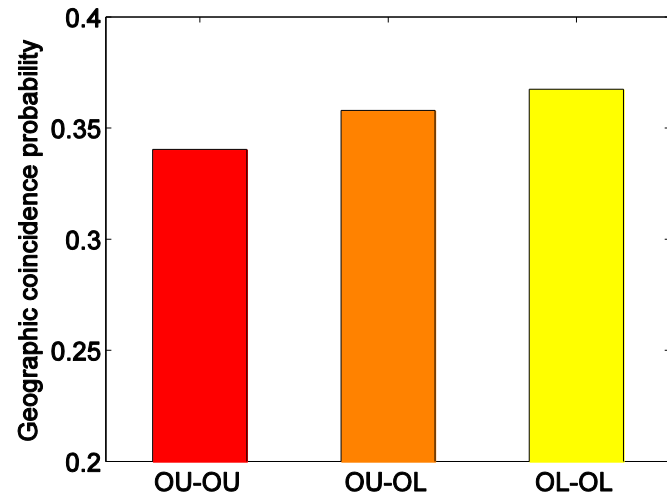
# Observation 3: Opinion Leaders

- Opinion leaders are more likely to have geographic coincidences with other people.
- A somewhat surprising observation is, two opinion leaders are even more likely to have geographic coincidences than the pair of an opinion leader and another ordinary user.

\*OU for ordinary users, OL for opinion leaders

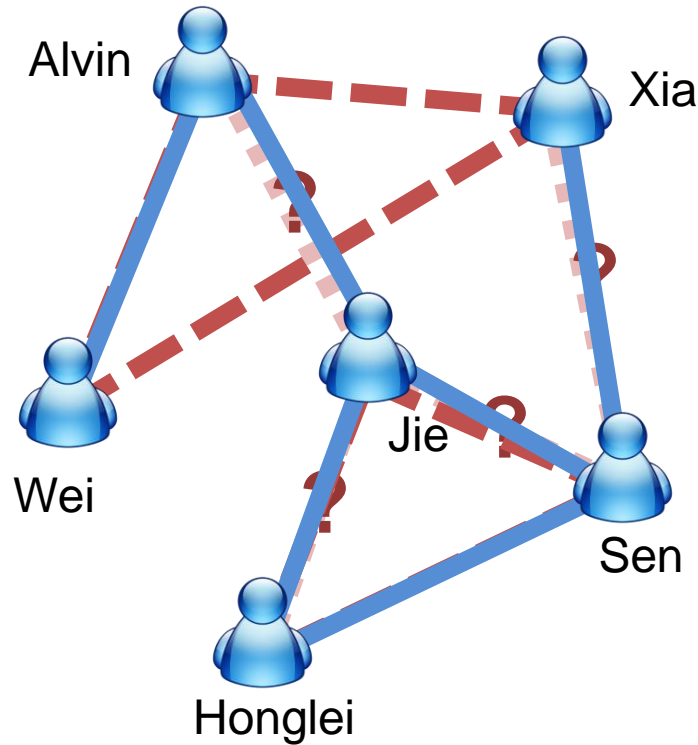


(a) Publication count



(b) H-index

# Problem Formulation

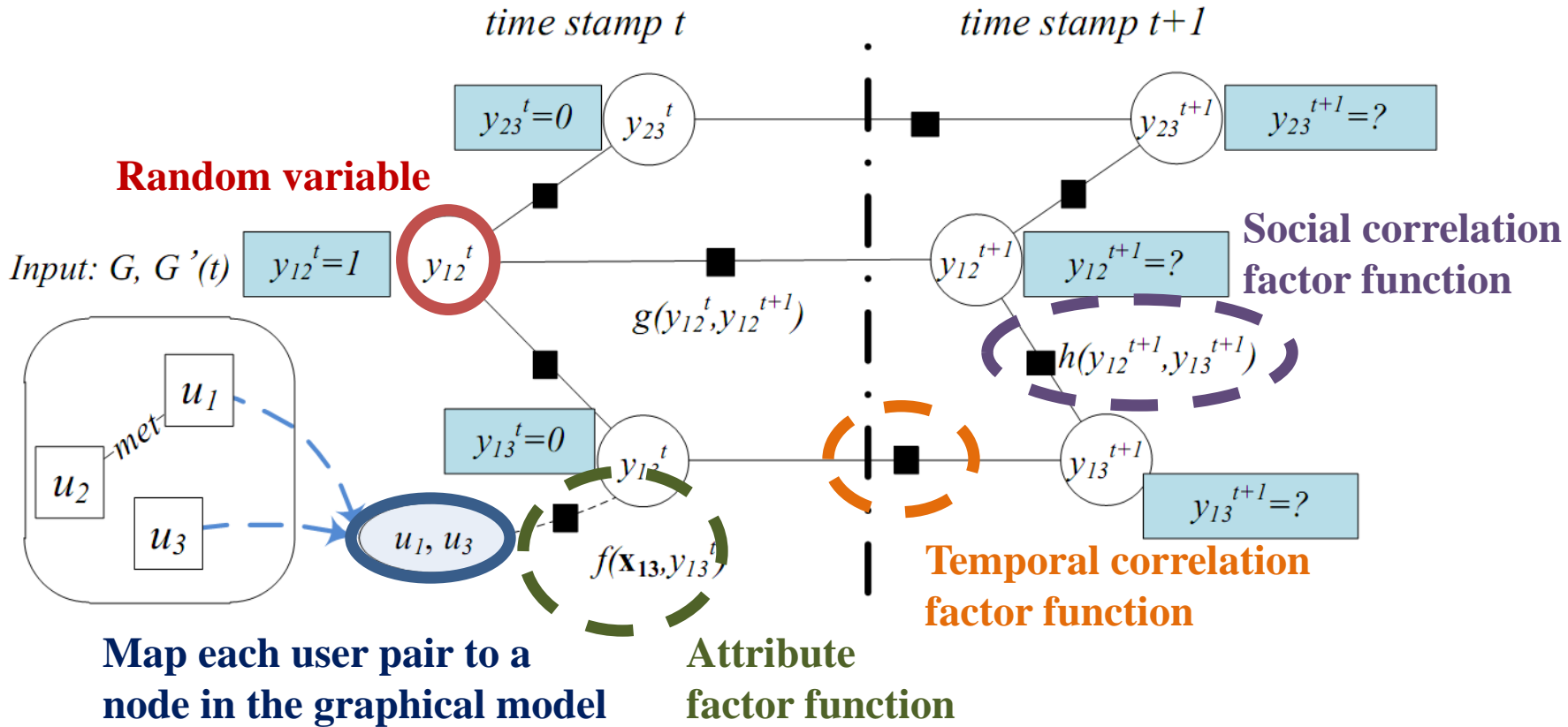


Input

Output

Problem formulation on network  $(G, E, W)(U^t, X^t, Y^t)$

# Factor Graph Model



# Factor Graph Model (cont')

- The objective function can be written as

$$\mathcal{O}(\theta) = \log \sum_{Y|Y_L} \exp \theta^T \mathbf{S} - \log \sum_Y \exp \theta^T \mathbf{S}$$

where

$$\theta = [\alpha^T, \beta^T, \lambda^T]^T$$

$$\mathbf{S} = [\sum_t \sum_{y_{ij}^t} \Phi(\mathbf{x}_{ij}, y_{ij}^t), \sum_{i,j} \sum_t \mathbf{g}(y_{ij}^t, y_{ij}^{t+1}), \sum_t \sum_{Y_c^t} \mathbf{h}(Y_c^t)]^T$$

- **Model Learning**

- To find a parameter configuration s.t.

$$\theta^* = \operatorname{argmax}_{\theta} P(Y_L | G, G')$$

- **Predicting geographic coincidences**

- Find a  $Y_U$  to optimize the objective function

$$Y_U^* = \operatorname{argmax}_{Y_U} P(Y | G, G')$$

# Experimental Results

- **Performance comparison**

**Table 2.** Prediction performance comparison(%)

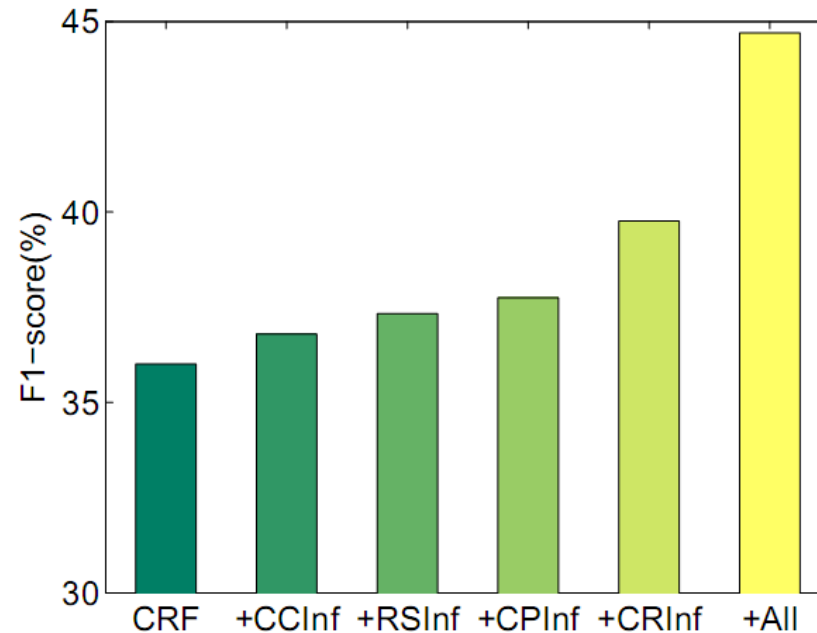
Date set	Method	Precision	Recall	F1-score
UbiComp	SVM	<b>34.5</b>	20.4	25.6
	CRF	33.2	39.4	36.0
	FGM	34.0	<b>65.4</b>	<b>44.7</b>
Reality	SVM	84.1	64.4	72.9
	CRF	73.6	<b>85.8</b>	79.2
	FGM	<b>85.1</b>	81.0	<b>83.0</b>

- **Baselines**
  - SVM – only uses attributes of users.
  - CRF – further consider the time correlation.

# Experimental Results (cont')

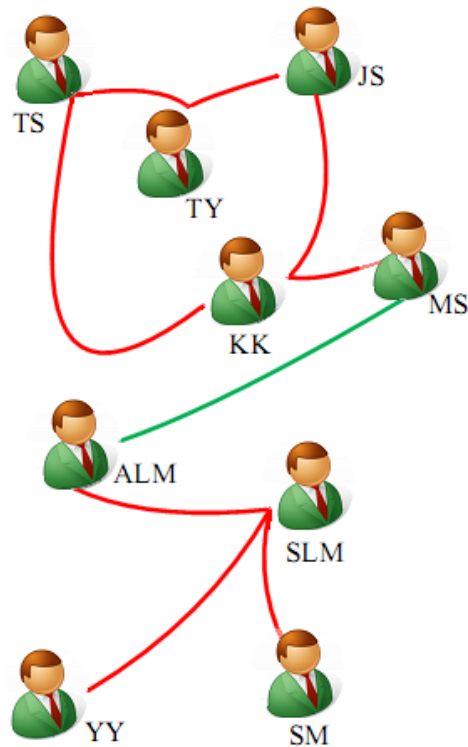
- **Social Correlation Factors Analysis**

- Performance achieved by only considering one particular social correlation.

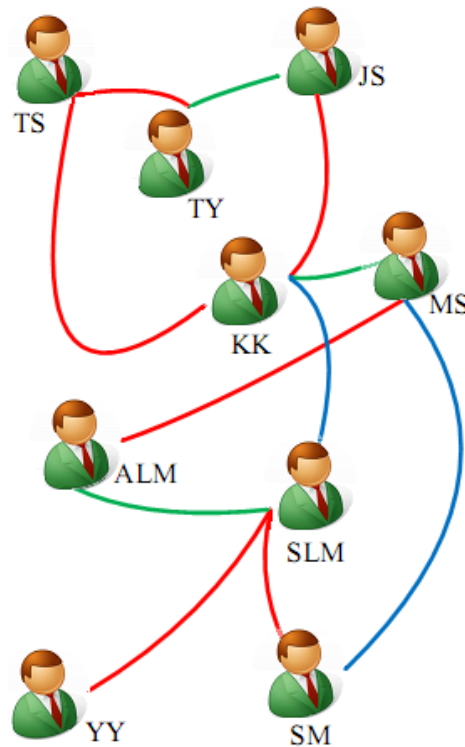


\*Figure for UbiComp data set. CPIInf for correlation factor defined by coauthor paper count, CCInf for common coauthor count, CRIInf for common conference ratio, RSInf for research similarity.

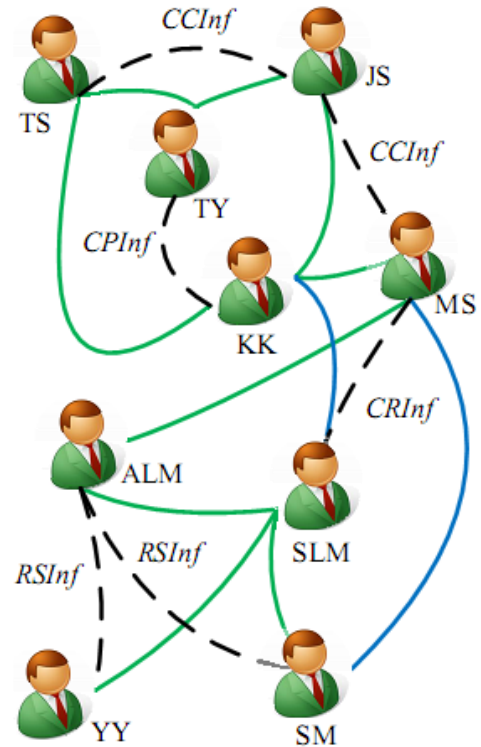
# Case Study



(a) SVM



(b) CRF



(c) FGM

\*Green for true positive, red for false negative, blue for false positive.

\*\*Dash lines for social correlation.



# Summary

- A formal definition of inferring geographic coincidences on ephemeral social networks.
- A series of observations has been conducted on the UbiComp data set.
  - Two-stage power-law distribution for duration where 10-minute becomes the watershed of random encounters and planned talks.
  - Both similar research experiences and different research interests motivate people to meet others.
- A Factor Graph Model has been proposed and tested on two data sets.
  - 3.8~8.7% improvement of F1-score over baselines.
  - Common conference correlation factors can improve the performance the most (~3%)

# Future Work

- Studies on ephemeral social network will create a new research direction. It is expected to provide insight on the evolution and formation of traditional social networks.
- By combining information from large-scale online social network (e.g. Facebook), can we further predict when and where a geographic coincidence will occur?
- By employing information from ephemeral social networks, can we predict a new link in online social network?

THANK YOU

2012/9/26