

# Inferring User Demographics and Social Strategies in Mobile Social Networks

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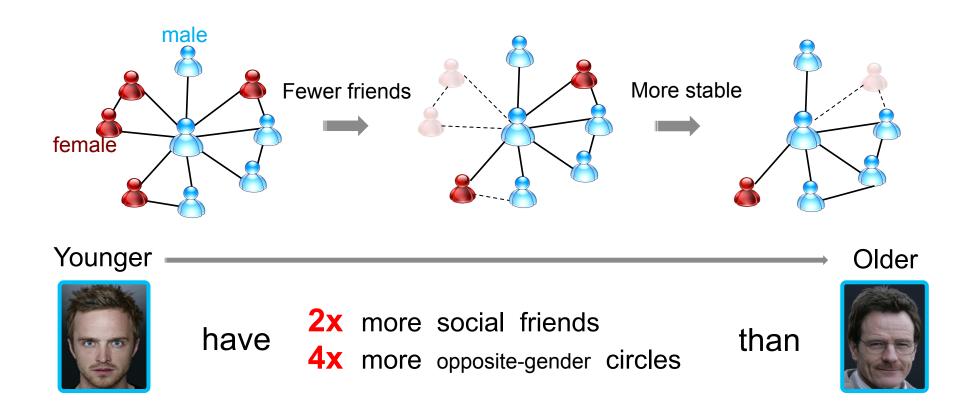
\*Tsinghua University





#### Did you know:

As of 2014, there are **7.3** billion mobile phones, larger than the global population. Users average **22** calls, **23** messages, and **110** status checks **per day**.



Yuxiao Dong, Yang Yang, Jie Tang, Yang Yang, Nitesh V. Chawla. Inferring User Demographics and Social Strategies in Mobile Social Networks. KDD 2014.

# Big Mobile Data

- Real-world large-scale mobile data
  - An anonymous country.
  - No communication content.
  - Aug. 2008 Sep. 2008.
  - > 7 million mobile users + demographic information.
    - Gender: Male (55%) / Female (45%)
    - Age: Young (18-24) / Young-Adult (25-34) / Middle-Age (35-49) / Senior (>49)
  - > 1 billion communication records (call and message).

#### Two networks:

Network	#nodes	#edges
CALL	7,440,123	32,445,941
SMS	4,505,958	10,913,601

### What We Do

- How do people communicate / interact with each other with mobile phones?
  - Infer human social strategies on demographics.
- To what extent can user demographic profiles be inferred from their mobile communication interactions?
  - Infer user demographics based on social strategies.
- Applications:
  - Viral marketing
  - Personalized services
  - User modeling
  - Customer churn warning

**–** ...

# Infer human social strategies on demographics

user demographics + mobile social network

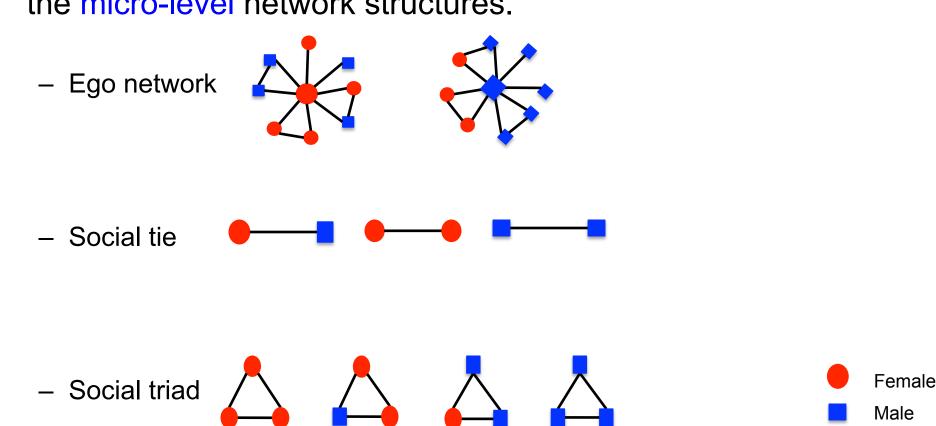
→ social strategies

# Social Strategy

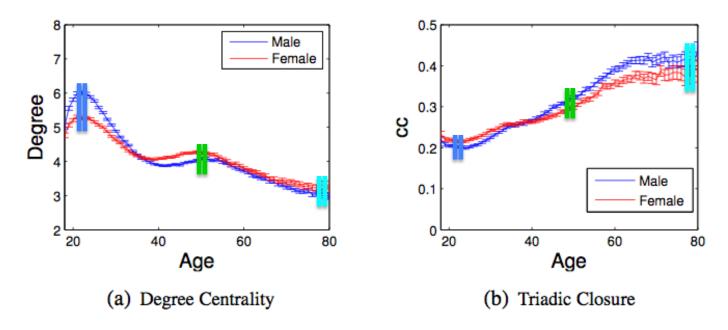
- Human needs are defined according to the existential categories of being, having, doing, and interacting<sup>[1]</sup>. Two basic human needs<sup>[2]</sup> are to
  - Meet new people → Social needs.
  - Strengthen existing relationships → Social needs.
- Social strategies are used by people to meet social needs.
  - Human needs are constant across historical time periods.
  - However, the strategies by which these needs are satisfied change over time<sup>[1,3]</sup>.
- Barabasi and Dunbar<sup>[3]</sup>:
  - "Women are more focused on opposite-sex relationships than men during the reproductively active period of their lives." ... "As women age, their attention ships from their spouse to younger females---their daughters."
  - "Human social strategies have more complex dynamics than previously assumed."
- 1. http://en.wikipedia.org/wiki/Fundamental human needs
- 2. M.J. Piskorski. Social strategies that work. Harvard Business Review. Nov. 2011.
- 3. V. Palchykov, K. Kaski, J. Kertesz, A.-L. Barabasi, R. I. M. Dunbar. Sex differences in intimate relationships. Scientific Reports 2012.

# Social Strategy

 We study demographic-based social strategy with respect to the micro-level network structures.

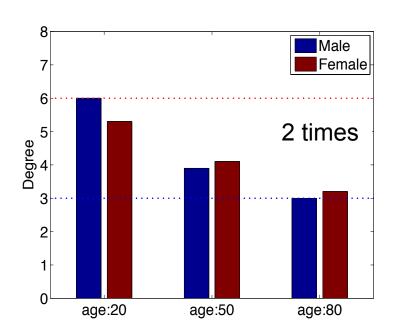


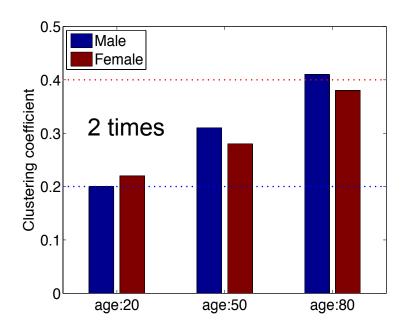




Correlations between user demographics and network properties.







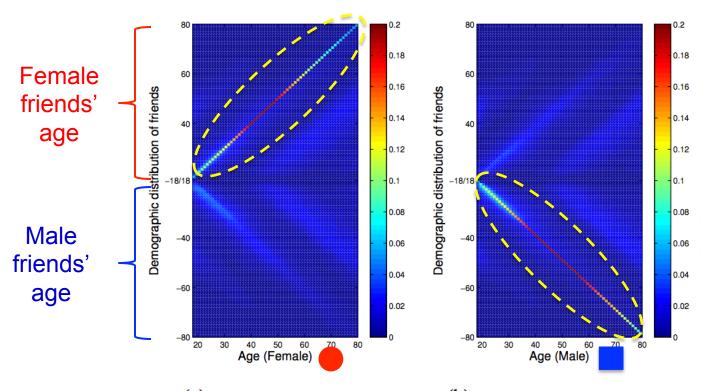
Correlations between user demographics and network properties.

Social Strategies: Young people are active in broadening their social circles, while seniors have the tendency to maintain small but close connections.



In your mobile phone contact list, do you have more **female** or **male** friends?





X: age of central user.

Y: age of friends.

Positive Y: female friends;

**Negative Y:** male friends;

**Spectrum:** distribution

(a) Demog. dist. of Female's friends

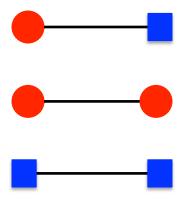
(b) Demog. dist. of Male's friends



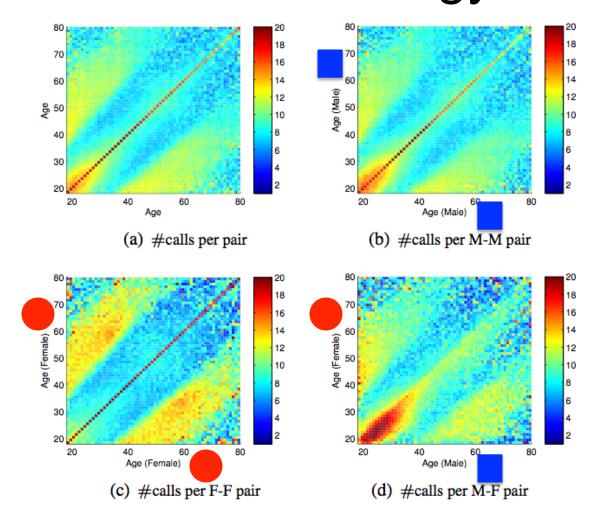


Social Strategies: People tend to communicate with others of both similar gender and age, i.e., demographic homophily.

How frequently do you call your mother vs. your significant other?







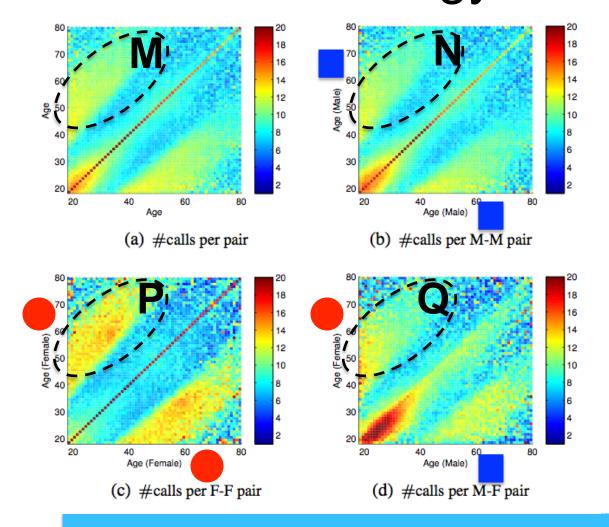
**X:** age of one user.

**Y:** age of the other user.

Spectrum: #calls per month

(a), (b), (c) are symmetric.





X: age of one user.

**Y:** age of the other user.

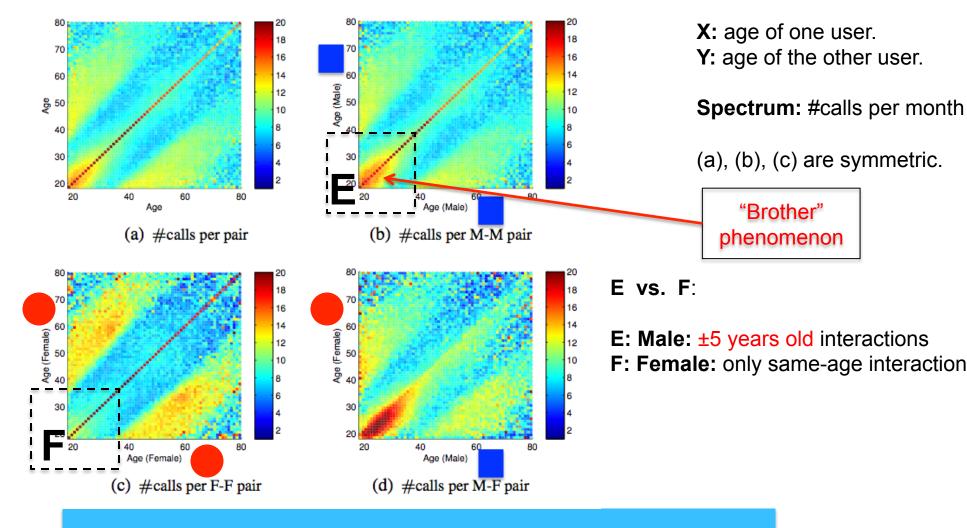
Spectrum: #calls per month

(a), (b), (c) are symmetric.

**M**,**N**,**P**,**Q**:

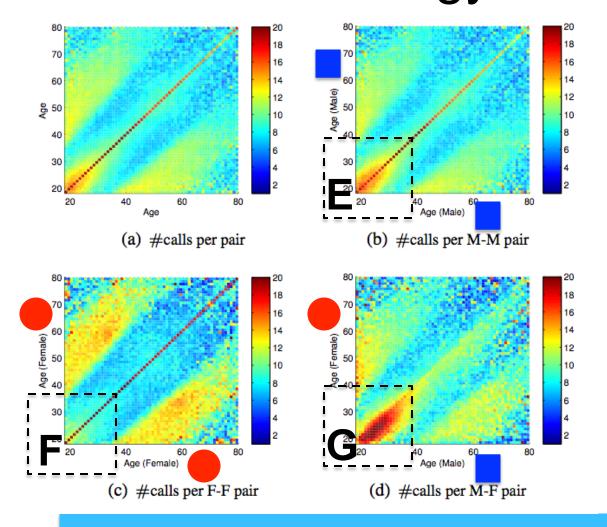
**10~15** calls per month are made between parents and children.

Social Strategies: Frequent cross-generation interactions are maintained to bridge age gaps.



Social Strategies: Young male maintain more frequent and broader social connections than young females.





X: age of one user.

**Y:** age of the other user.

Spectrum: #calls per month

(a), (b), (c) are symmetric.

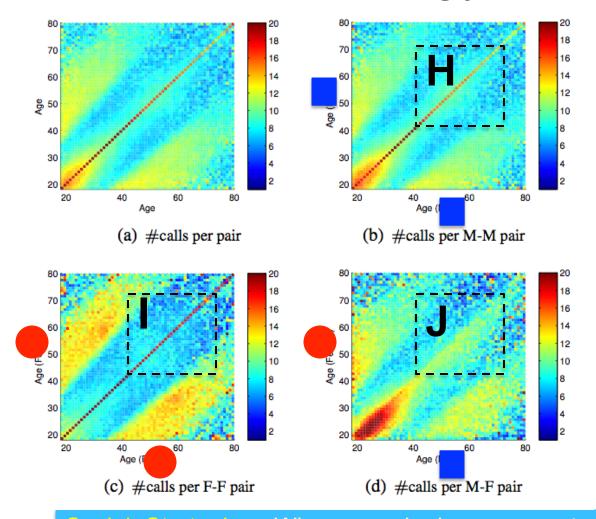
E,F vs. G:

**G:** f-m: >30 calls per months

**E/F:** m-m or f-f: 10~15 calls

Social Strategies: Opposite-gender interactions are much more frequent than those between young same-gender users.





X: age of one user.

**Y:** age of the other user.

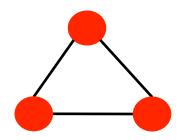
Spectrum: #calls per month

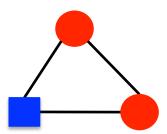
(a), (b), (c) are symmetric.

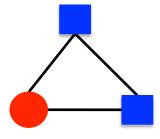
H,I vs. J:

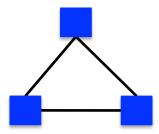
Social Strategies: When people become mature, reversely, same-gender interactions are more frequent than those between opposite-gender users.

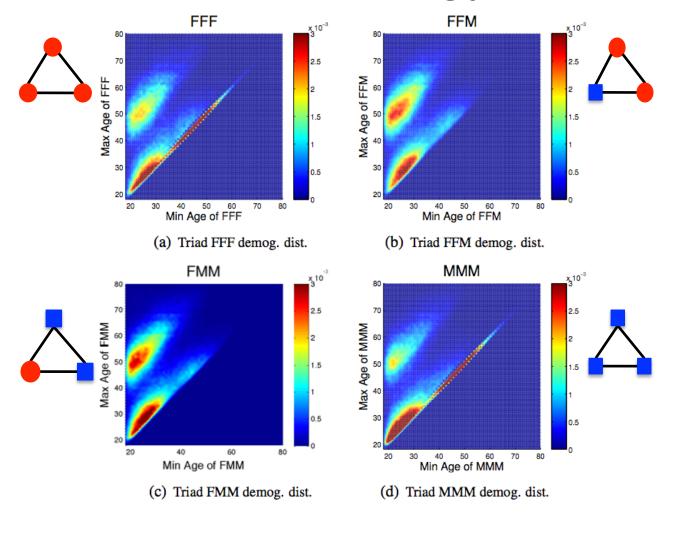
How do people maintain their social triadic relationships across their lifetime?







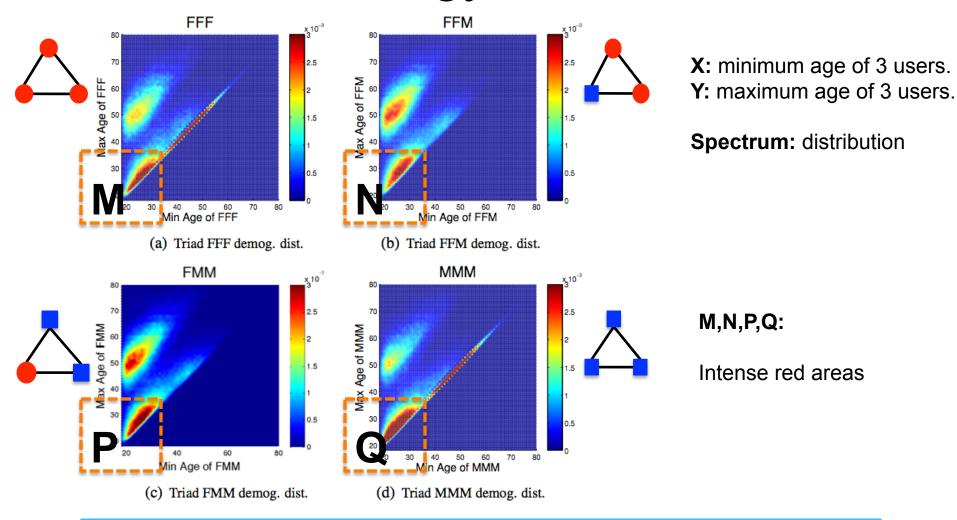




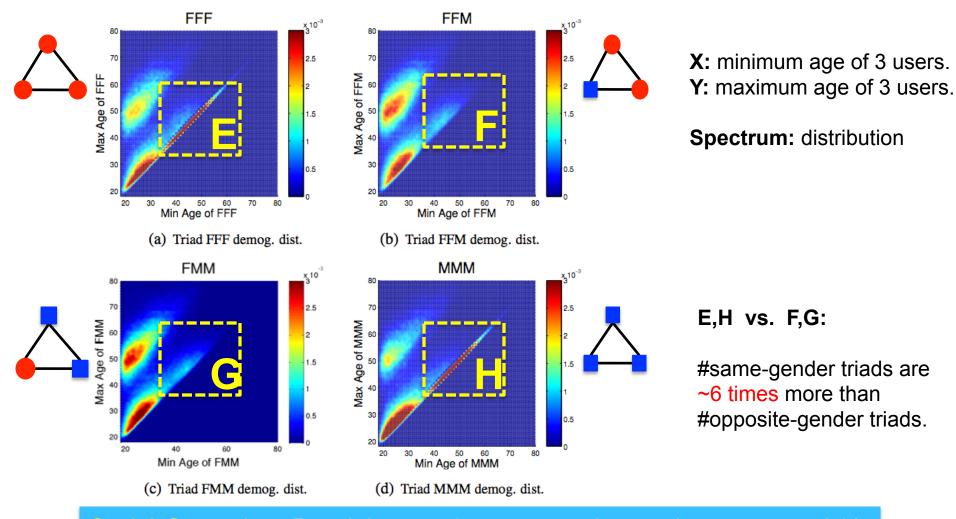
**X:** minimum age of 3 users.

Y: maximum age of 3 users.

**Spectrum:** distribution



Social Strategies: People expand both same-gender and oppositegender social groups during the dating and reproductively active period.



Social Strategies: People's attention to opposite-gender groups quickly disappears, and the insistence and social investment on same-gender social groups lasts for a lifetime.

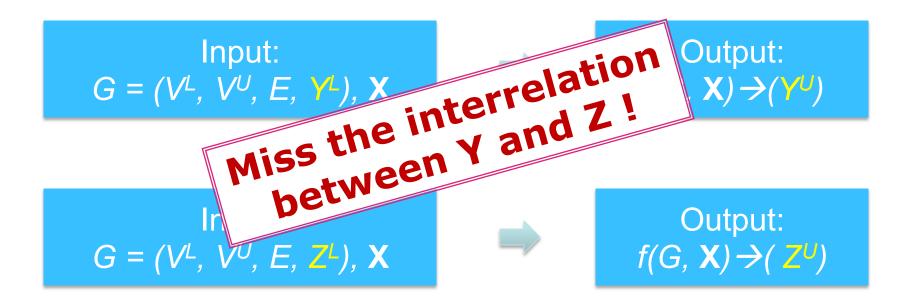
# Infer user demographics based on social strategies

social strategies + mobile social network

→ user demographics

# Problem: Demographic Prediction

- Gender or Age Classification
  - Infer users' gender Y and age Z separately.
  - Model correlations between gender Y and attributes X;
  - Model correlations between age Z and attributes X;



# Problem: Demographic Prediction

- Double Dependent-Variable Classification
  - Infer users' gender Y and age Z simultaneously.
  - Model correlations between gender Y and attributes X;
  - Model correlations between age Z and attributes X;
  - Model interrelations between Y and Z;

Input: 
$$G = (V^L, V^U, E, Y^L, Z^L), X$$

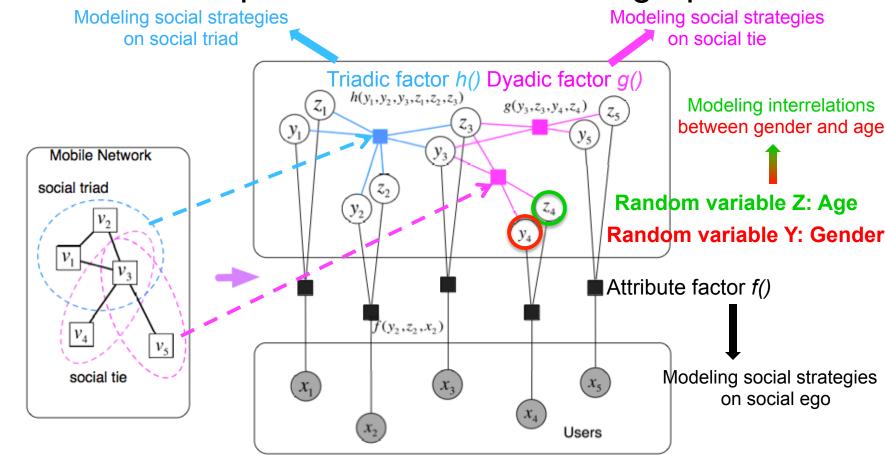


Output:  $f(G, \mathbf{X}) \rightarrow (\mathbf{Y}^{U}, \mathbf{Z}^{U})$ 

- Gender:
  - Male (55%) / Female (45%)
- Age:
  - Young (18-24) / Young-Adult (25-34) / Middle-Age (35-49) / Senior (>49)

### WhoAmI Method

### --- A double dependent-variable factor graph



$$\text{Joint Distribution: } P(Y,Z|G,\mathbf{X}) = \prod_{v_i \in V} f(y_i,z_i,\mathbf{x}_i) \times \prod_{e_{ij} \in E} [g(\mathbf{y}_e,\mathbf{z}_e)] \prod_{e_{ijk} \in G} [h(\mathbf{y}_c,\mathbf{z}_c)]$$



### WhoAml: Model Initialization

$$\text{Joint Distribution:} \quad P(Y,Z|G,\mathbf{X}) = \prod_{v_i \in V} f(y_i,z_i,\mathbf{x}_i) \times \prod_{e_{ij} \in E} [g(\mathbf{y}_e,\mathbf{z}_e)] \prod_{e_{ijk} \in G} [h(\mathbf{y}_c,\mathbf{z}_c)]$$

Attribute factor:

$$f(y_i, z_i, \mathbf{x}_i) = \frac{1}{W_v} \exp\{\alpha_{y_i z_i} \cdot \mathbf{x}_i\}$$

Dyadic factor:

$$g(\mathbf{y}_e, \mathbf{z}_e) = \begin{cases} \frac{1}{W_{e_1}} \exp\{\beta_1 \cdot g_1'(y_i, y_j)\} \\ \frac{1}{W_{e_2}} \exp\{\beta_2 \cdot g_3'(y_i, z_i)\} \\ \dots \\ \frac{1}{W_{e_6}} \exp\{\beta_6 \cdot g_6'(z_i, z_j)\} \end{cases}$$

Interrelations between gender Y & age Z

Triadic factor:

$$h(\mathbf{y}_{c}, \mathbf{z}_{c}) = \begin{cases} \frac{1}{W_{c_{1}}} \exp\{\gamma_{1} \cdot h'_{1}(y_{i}, y_{j}, y_{k})\} \\ \frac{1}{W_{c_{2}}} \exp\{\gamma_{2} \cdot h'_{2}(y_{i}, y_{j}, z_{i})\} \\ \dots \\ \frac{1}{W_{c_{20}}} \exp\{\gamma_{20} \cdot h'_{20}(z_{i}, z_{j}, z_{k})\} \end{cases}$$



# WhoAml: Objective Function

Objective function: 
$$\mathcal{O}(\alpha,\beta,\gamma) = \sum_{v_i \in V} \alpha_{y_i z_i} \mathbf{x}_i + \sum_{e_{ij} \in E} \sum_{p=1}^6 \beta_p g_p'(\cdot)$$
$$+ \sum_{c_{ijk} \in G} \sum_{q=1}^{20} \gamma_q h_q'(\cdot) - \log W$$

Model learning: gradient descent

$$\frac{\partial \mathcal{O}(\theta)}{\partial \alpha} = \mathbf{E}[\sum_{v_i \in V} f(y_i, z_i, \mathbf{x}_i)] + \mathbf{E}_{P_{\alpha}(Y, Z|X)}[\sum_{v_i \in V} f(y_i, z_i, \mathbf{x}_i)]$$

$$\frac{\partial \mathcal{O}(\theta)}{\partial \beta} = \mathbf{E}[\sum_{e_{ij} \in E} g(\mathbf{y}_e, \mathbf{z}_e)] - \mathbf{E}_{P_{\beta}(Y, Z|X, G)}[\sum_{e_{ij} \in E} g(\mathbf{y}_e, \mathbf{z}_e)] \longrightarrow \text{Circles?} \rightarrow \text{LBP}^{[1]}$$

$$\frac{\partial \mathcal{O}(\theta)}{\partial \gamma} = \mathbf{E}[\sum_{c_{ijk} \in G} h(\mathbf{y}_c, \mathbf{z}_c)] - \mathbf{E}_{P_{\gamma}(Y, Z|X, G)}[\sum_{c_{ijk} \in G} h(\mathbf{y}_c, \mathbf{z}_c)]$$

K. P. Murphy, Y. Weiss, M. I. Jordan. Loopy Belief Propagation for Approximate Inference: An Empirical Study. UAI'99.



		Gender			Λορ						
Network	Method	D			Age						
		wPrecision	wRecall/Accu	wF1-Measure	wPrecision	wRecall/Accu	wF1-Measure				
	LRC										
	SVM										
	NB	Data: active users (#contacts >=5 in two months)									
CALL	RF										
CALL	Bag										
	RBF										
	FGM	>1.09 million users in CALL >304 thousand users in SMS									
	DFG										
	LRC	2001 thousand doors in one									
	SVM										
	NB										
SMS	RF	50% as training data									
SIVIS	Bag	50% as t									
	RBF	30 /0 as t	<del>est uata</del>								
	FGM										
	DFG										

Network	Method	Gender			Age						
		wPrecision	wRecall/Accu	wF1-Measure	wPrecision	wRecall/Accu	wF1-Measure				
	LRC	Barrier .									
	SVM	Baselines									
	NB										
CALL	RF										
CALL	Bag	LRC: Lo	LRC: Logistic Regression								
	RBF	SVM: Support Vector Machine NB: Naïve Bayes									
	FGM										
	DFG										
	LRC	RF: Ra	indom Forest								
	SVM	BAG: Bagged Decision Tree									
	NB	RBF: Gaussian Radial Basis Function Neural Network									
SMS	RF				on resultative						
5W5	Bag	FGIVI. Fa	FGM: Factor Graph Model  DFG: WhoAml: Double Dependent-Variable Factor Graph								
	RBF	DEO 111									
	FGM	DFG: W	noami: Doubl	e pependent-	variable Facto	or Graph					
	DFG										

Network	Method	Gender			Age		
		wPrecision	wRecall/Accu	wF1-Measure	wPrecision	wRecall/Accu	wF1-Measure
	LRC						
	SVM	Evaluation	Metrics:				
	NB	_ vendento	· moureor				
CALL	RF						
CALL	Bag	Weighted	d Precision				
	RBF						
	FGM	Weighted					
	DFG	Weighted	d F1 Measure				
	LRC	Accuracy	/				
	SVM	·					
	NB						
SMS	RF						
SMS	Bag						
	RBF						
	FGM						
	DFG						

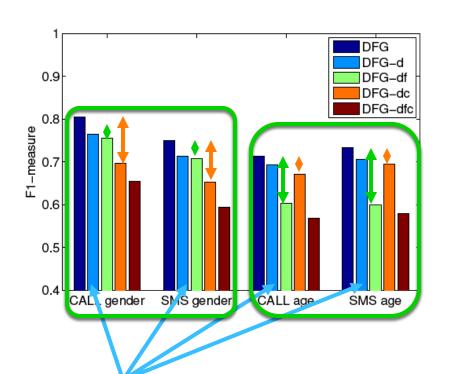
Network	Method	Gender			Age		
		wPrecision	wRecall/Accu	wF1-Measure	wPrecision	wRecall/Accu	wF1-Measure
	LRC	0.7327 (0.0003)	0.7289 (0.0003)	0.7245 (0.0005)	0.6350 (0.0005)	0.6466 (0.0003)	0.6337 (0.0005)
	SVM	0.7327 (0.0004)	0.7287 (0.0003)	0.7242 (0.0003)	0.6369 (0.0004)	0.6463 (0.0005)	0.6273 (0.0005)
	NB	0.7222 (0.0004)	0.7227 (0.0003)	0.7222 (0.0004)	0.6246 (0.0011)	0.6224 (0.0002)	0.6223 (0.0002)
CALL	RF	0.7437 (0.0003)	0.7310 (0.0002)	0.7415 (0.0003)	0.6382 (0.0010)	0.6482 (0.0008)	0.6388 (0.0009)
CALL	Bag	0.7644 (0.0005)	0.7648 (0.0004)	0.7643 (0.0005)	0.6607 (0.0010)	0.6688 (0.0004)	0.6592 (0.0005)
	RBF	0.7283 (0.0015)	0.7275 (0.0005)	0.7252 (0.0017)	0.6194 (0.0062)	0.6272 (0.0068)	0.6218 (0.0068)
	FGM	0.7658 (0.0096)	0.7662 (0.0115)	0.7659 (0.0113)	0.6998 (0.0094)	0.6989 (0.0087)	0.6935 (0.0089)
	DFG	0.8088 (0.0139)	0.8076 (0.0148)	0.8063 (0.0131)	0.7266 (0.0097)	0.7140 (0.0094)	0.7132 (0.0091)
	LRC	0.6766 (0.0013)	0.6758 (0.0006)	0.6689 (0.0014)	0.6702 (0.0011)	0.6890 (0.0008)	0.6630 (0.0008)
	SVM	0.6749 (0.0006)	0.6750 (0.0005)	0.6690 (0.0007)	0.6654 (0.0163)	0.6884 (0.0006)	0.6607 (0.0006)
SMS	NB	0.6231 (0.0003)	0.6655 (0.0011)	0.6603 (0.0021)	0.6563 (0.0014)	0.6588 (0.0015)	0.6570 (0.0012)
	RF	0.6399 (0.0009)	0.6749 (0.0009)	0.6757 (0.0009)	0.6623 (0.0013)	0.6775 (0.0008)	0.6598 (0.0011)
	Bag	0.6905 (0.0005)	0.6918 (0.0009)	0.6901 (0.0009)	0.6907 (0.0008)	0.6987 (0.0009)	0.6791 (0.0009)
	RBF	0.6712 (0.0006)	0.6592 (0.0131)	0.6468 (0.0139)	0.6295 (0.0062)	0.6640 (0.0051)	0.6356 (0.0042)
	FGM	0.7132 (0.0040)	0.7138 (0.0050)	0.7133 (0.0057)	0.7154 (0.0046)	0.7154 (0.0046)	0.7059 (0.0058)
	DFG	0.7589 (0.0187)	0.7549 (0.0159)	0.7507 (0.0178)	0.7409 (0.0199)	0.7303 (0.0208)	0.7337 (0.0198)

The proposed *WhoAmI* (DFG) outperforms baselines by up to 10% in terms of F1.

We can infer 80% of the users' GENDER in the CALL network correctly. The CALL behaviors reveal more users' GENDER information than SMS.

We can infer 73% of the users' AGE in the SMS network correctly. The SMS behaviors reveal more users' AGE information than CALL.

# Experiment: Results



DFG-d: stands for ignoring the interrelations between gender and age.

DFG-df: stands for further ignoring **tie** features.

DFG-dc: stands for further ignoring **triad** features.

**DFG-dcf**: stands for further ignoring **tie** and **triad** features.

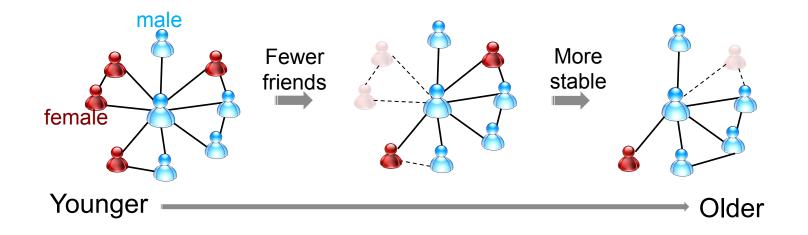
The positive effects of interrelations between gender and age.

Social Triad features are more powerful for inferring users' gender.

Social Tie features are more powerful for inferring users' age.

### Conclusion

 Unveil the demographic-based social strategies used by people to meet their social needs:



- Propose WhoAml, a Double Dependent-Variable Factor Graph, for inferring users' genders and ages simultaneously.
- Demonstrate the proposed WhoAml method in a large-scale mobile social network.

# Acknowledgements

- Army Research Laboratory
- U.S. Air Force Office of Scientific Research (AFOSR) and the Defense Advanced Research Projects Agency (DARPA)
- National High-Tech R&D Program
- Natural Science Foundation of China
- National Basic Research Program of China



# Thank You!

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**#University of Notre Dame** 



\*Tsinghua University





# Big Network Data

facebook.

- 1.26 billion users
- 700 billion minutes/month



- 280 million users
- 80% of users are 80-90's



- 555 million users
- •.5 billion tweets/day





- 560 million users
- influencing our daily life



- 79 million users per month
- 9.65 billion items/year

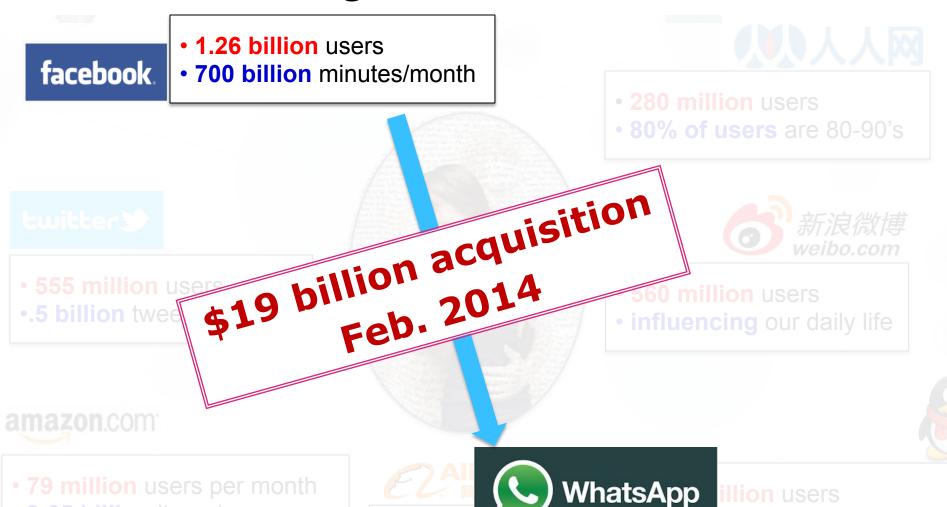


- 500 million users
- 35 billion on 11/11



- 800 million users
- ~50% revenue from network life

# Big Network Data



• 35 billion on 11/11

• 9.65 billion items/year

# Big Mobile Network Data

700



• 7.3 billion mobile devices in 2014<sup>[1]</sup>

• >100% of global population

79 million users per

9.65 billion items/year

• 35 billion on 11/11

• ~50% revenue from network life

1. http://www.itu.int/ International Telecommunications Union (ITU) at 2013 Mobile World Congress.

# Big Mobile Network Data

- In 2013, 97% of adults have a mobile phone in the US<sup>[1]</sup>
  - made 3 billion phone calls per day
  - sent 6 billion text messages per day
- This talk (15 mins):
  - 21 million calls & 42 million messages
- On average, in one day each mobile user in the US<sup>[2]</sup>
  - makes, receives or avoids 22 phone calls
  - sends or receives text messages 23 times
  - checks her/his phone 110 times.

<sup>1. &</sup>lt;a href="http://www.accuconference.com/blog/Cell-Phone-Statistics.aspx">http://www.accuconference.com/blog/Cell-Phone-Statistics.aspx</a>

<sup>2.</sup> http://www.dailymail.co.uk/news/article-2276752/Mobile-users-leave-phone-minutes-check-150-times-day.html

### Related work

- Previous work on mobile social networks mainly focuses on macro-level models<sup>[1,2]</sup>.
  - No Demographics.
- Reality Mining<sup>[3]</sup>
  - The friendship network of 100 specific users (student of faculty in MIT).
  - Demographics + Human interactions.
- The 2012 Nokia Mobile Data Challenge<sup>[4]</sup>
  - Infer user demographics by using communication records of 200 users.

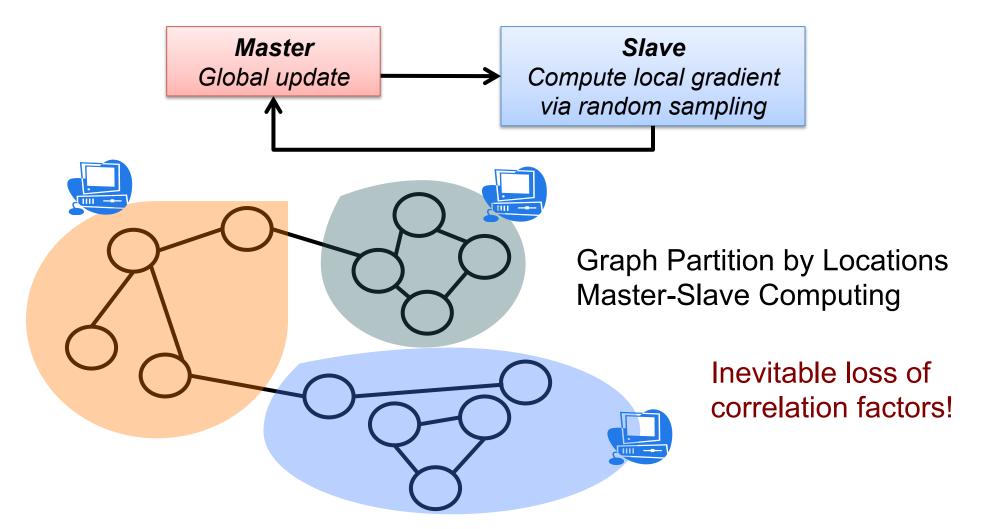
<sup>1.</sup> J.P. Onnela, J. Saramaki, J. Hyvonen, G. Szabo, D. Lazer, K. Kaski, J. Kertesz, A.-L. Barabasi. Structure and tie strengths in mobile communication networks. PNAS 2007.

<sup>2.</sup> M. Seshadri, S. Machiraju, A. Sridharan, J. Bolot, C. Faloutsos, J. Leskovec. Mobile call graphs: Beyond power-law and lognormal distributions. KDD'08.

<sup>3. &</sup>lt;a href="http://realitycommons.media.mit.edu/">http://realitycommons.media.mit.edu/</a>

<sup>4. &</sup>lt;a href="https://research.nokia.com/page/12000">https://research.nokia.com/page/12000</a>

# WhoAml: Distributed Learning



<sup>1.</sup> Jie Tang, Sen Wu, Jimeng Sun. Confluence: Conformity influence in large social networks. KDD'13.

# **Experiment: Features**

### Given one node v and its ego network:

#### – Individual feature:

 Individual attribute: degree, neighbor connectivity, clustering coefficient, embeddedness and weighted degree.

#### – Friend feature:

- Friend attribute: # of connections to female/male, young/young-adult/middle-age/senior friends (from labeled friends).
- Dyadic factor: both labeled and unlabeled friends for social tie structures in v's ego network.

#### – Circle feature:

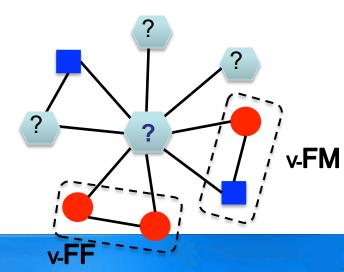
- Circle attribute: # of demographic triads, i.e., v-FF, v-FM, v-MM; v-AA, v-AB, v-AC, v-AD, v-BB, v-BC, v-BD, v-CC, v-CD, v-DD. (A/B/C/C denote the young/young-adult/middle-age/senior)
- Triadic factor: both labeled and unlabeled friends for social triad structures in v's ego network.

### LCR/SVM/NB/RF/Bag/RBF:

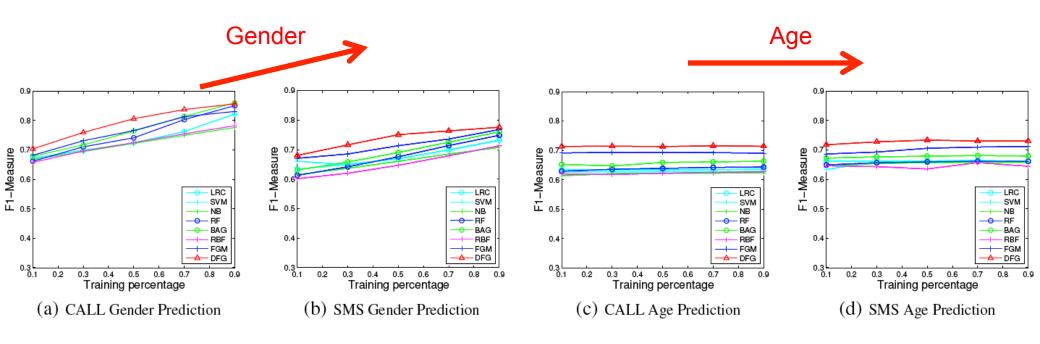
Individual/Friend/Circle Attributes

#### FGM/DFG

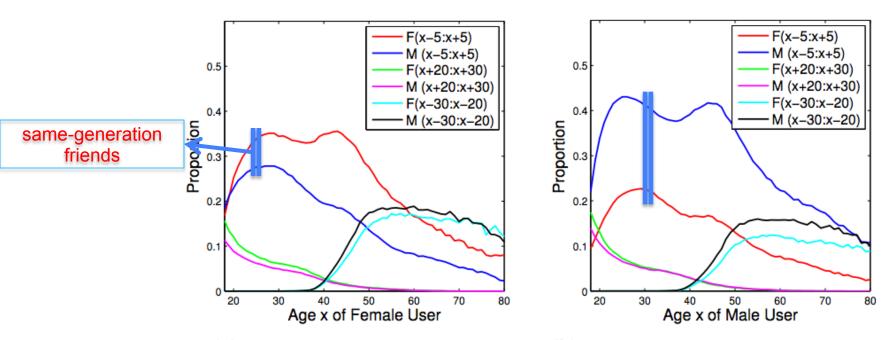
- Individual/Friend/Circle Attributes
- Structure feature: Dyadic factors
- Structure feature: Triadic factors



# **Experiment: Results**



Performance of demographic prediction with different percentage of labeled data

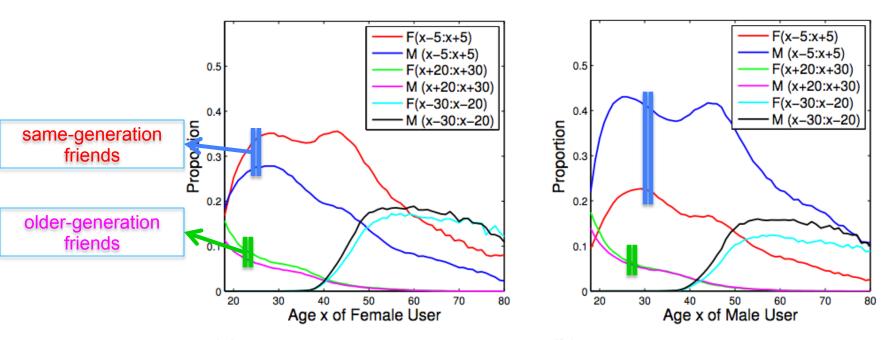


(a) Proportion of Female's friends' age (b) Proportion of Male's friends' age





Social Strategies: The young put increasing focus on the same generation, but decrease it after entering middle-age.

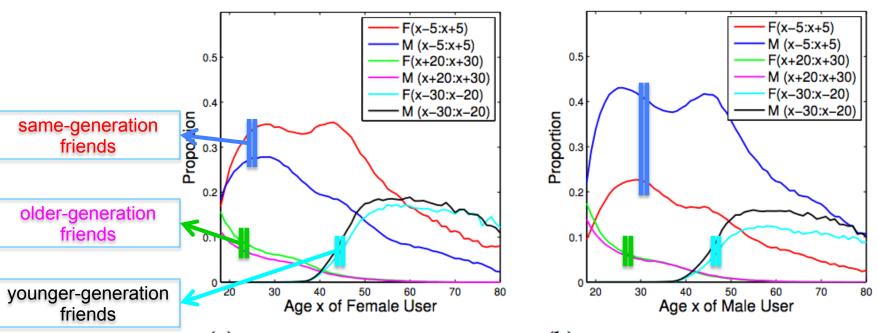


(a) Proportion of Female's friends' age (b) Proportion of Male's friends' age





Social Strategies: The young put decreasing focus on the older generation across their lifespans.



(a) Proportion of Female's friends' age (b) Proportion of Male's friends' age





Social Strategies: The middle-age people devote more attention on the younger generation even along with the sacrifice of homophily.