The Evolution of Social Strategies across the Lifespan

Yuxiao Dong, Nitesh V. Chawla, Jie Tang, Yang Yang, Yang Yang

@NetMob’15
As of 2014, there were 7.3 billion mobile subscriptions, larger than the global population\textsuperscript{[1]}. Users average 22 calls, 23 messages, and 110 status checks per day.

Younger have 2x more social friends and 4x more opposite-gender circles than older.

1. International Telecommunications Union (ITU) at the 2013 Mobile World Congress.
2. Photo credit goes to Breaking Bad.
Large-scale mobile data
- An anonymous country and no communication content.
- > 7 million mobile users.
  - Gender: Male (55%) / Female (45%)
  - Age: Young (18-24) / Young-Adult (25-34) / Middle-Age (35-49) / Senior (>49)
- > 1 billion communication records (calls and messages).

Two networks:

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<th>#nodes</th>
<th>#edges</th>
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<td>32,445,941</td>
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<tr>
<td>SMS</td>
<td>4,505,958</td>
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Big Mobile Data

Europe and Mobile (CALL) population pyramids.
Opportunity

What are the social strategies that people use to interact with others across the lifespan?
> Human needs are defined according to the existential categories of
  - being, having, doing, and *interacting*[^1].

> Two basic social needs are to[^2]
  - Meet new people
  - Strengthen existing relationships

> Social strategies are used by people to meet social needs.
  - Human needs are constant across historical time periods.
  - *The strategies by which these needs are satisfied change over time[^1,3].*

Social Strategy

- EGO network
- Social TIE
- Social TRIAD

Female
Male
Social Strategy: Ego

Correlations between user demographics and network properties (CALL).

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?
Social Strategy: Ego

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

**CALL**
X-axis: age of central user.
Y-axis: age of friends.
Positive Y: female friends;
Negative Y: male friends;
Spectrum: distribution

Female friends’ age

Male friends’ age

Female friends’ age

Male friends’ age
How frequently do you call your mother vs. your significant other?
Social Strategy: Tie

CALL

X-axis: age of one user.
Y-axis: age of the other user.
Spectrum: #calls per month.

(a), (b), (c) are symmetric.
CALL
X-axis: age of one user.
Y-axis: age of the other user.
Spectrum: #calls per month.

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

“Brother” phenomenon

Social Strategies
Young male maintain more frequent and broader social connections than young female.
Social Strategy: Tie

CALL
X-axis: age of one user.
Y-axis: age of the other user.
Spectrum: #calls per month.

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

E, F vs. G:

G: M-F:
>30 calls per month
E/F: M-M or F - F:
10~15 calls per month

Social Strategies
Interactions between two young opposite-gender people are much more frequent than those between young same-gender people.
Social Strategy: Tie

CALL

X-axis: age of one user.
Y-axis: age of the other user.
Spectrum: #calls per month.

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

H, I vs. J:

H, I: M-M or F-F:
Frequent same-age interactions

J: M-F:

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

How do people maintain social triadic relationships across their lifetime?
Social Strategy: Triad

CALL

X-axis: minimum age of 3 users.
Y-axis: maximum age of 3 users.

Spectrum: distribution

(a) Triad FFF demog. dist.
(b) Triad FFM demog. dist.
(c) Triad FMM demog. dist.
(d) Triad MMM demog. dist.
Social Strategy: Triad

CALL
X-axis: minimum age of 3 users.
Y-axis: maximum age of 3 users.

Spectrum: distribution

M,N,P,Q:
Intense red areas

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

CALL
X-axis: minimum age of 3 users.
Y-axis: maximum age of 3 users.
Spectrum: distribution

E,H vs. F,G:
#same-gender triads are \(~6\) times more than #opposite-gender triads.

Social Strategies
People’s attention to opposite-gender groups quickly disappears, and the insistence on same-gender social groups lasts for a lifetime.
To what extent can user demographics be inferred from communications?
Demographic Prediction

**Input:**
\[ G = (V, E, Y^L, Z^L), X \]

**Output:**
\[ f(G, X) \rightarrow (Y^U, Z^U) \]

- **V:** node set
- **E:** edge set
- **\( Y^L \):** nodes with labeled gender
- **\( Z^L \):** nodes with labeled age
- **\( Y^U \):** nodes with unlabeled gender
- **\( Z^U \):** nodes with unlabeled age
### Demographic Prediction

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Data: active users (#contacts >= 5 in two months)

1.09 million users in CALL
304 thousand users in SMS

50% as training data
50% as test data
### Demographic Prediction

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### Machine Learning Models:

- Logistic Regression
- Support Vector Machine
- Naïve Bayes
- Random Forest
- Bagging
- Factor Graph Model

**WhoAmI—our model**
# Demographic Prediction

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**Evaluation Metrics:**
- Weighted Precision
- Weighted Recall
- Weighted F1
## Demographic Prediction

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**Predictability of Demographics**

We can infer **80%** of the users’ **GENDER** in the CALL network correctly. We can infer **73%** of the users’ **AGE** in the SMS network correctly.

The CALL behavior reveals more users’ **GENDER** information than SMS. The SMS behavior reveals more users’ **AGE** information than CALL.
Conclusion

- Unveil the demographic-based social strategies across the lifespan.
- Propose *WhoAmI* to demonstrate the predictability of demographics.

Younger

- Male have 2x more social friends
- Female have 4x more opposite-gender circles

Older

- More stable

1. Photo credit goes to Breaking Bad.
Acknowledgements

Army Research Laboratory (ARL)
U.S. Air Force Office of Scientific Research (AFOSR)
Defense Advanced Research Projects Agency (DARPA)

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National Basic Research Program of China (973)
National High-Tech R&D Program

Reid A. Johnson @ University of Notre Dame
Thanks

Q & A

Yuxiao Dong, Yang Yang, Jie Tang, Yang Yang, Nitesh V. Chawla.
Inferring User Demographics and Social Strategies in Mobile Social Networks.
Proceeding of the 20th ACM SIGKDD Conference on Knowledge Discovery and Data Mining (KDD’ 14), ACM, 2014.
Appendix

1. Statistical Test
2. Social Strategies in CALL (part 2)
3. Social Strategies in SMS
4. WhoAmI---Factor Graph
Appendix

Statistical Test
Null Model

- Users’ gender and age are randomly shuffled.
- 10,000 times.
- Empirical data $x$
- Null model $\tilde{x}$

$$z(x) = \frac{x - \mu(\tilde{x})}{\sigma(\tilde{x})}$$
Social Strategy: Triad

CALL

X-axis: minimum age of 3 users.
Y-axis: maximum age of 3 users.

Spectrum: dist.-observed
Social Strategy: Triad

CALL
X-axis: minimum age of 3 users.
Y-axis: maximum age of 3 users.
Spectrum: dist.---Null Model

Shuffled distribution of demographic triads
Social Strategy: Triad

CALL

\textbf{X-axis:} minimum age of 3 users.

\textbf{Y-axis:} maximum age of 3 users.

\textbf{Spectrum:} dist.--- Z-score

\[ |Z\text{-score}| > 3.3 \quad (p < 0.001) \] is considered to be extremely statistically significant.
Appendix

Social Strategies in CALL (part 2)
Social Strategy: Ego

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

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

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

CALL

X-axis: age of one user.
Y-axis: 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 different generations.

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

Social Strategies in SMS
Social Strategy: Ego

Female friends’ age

Male friends’ age

SMS
X-axis: age of central user.
Y-axis: age of friends.
Positive Y: female friends;
Negative Y: male friends;
Spectrum: distribution
Social Strategy: Triad

SMS
X-axis: minimum age of 3 users.
Y-axis: maximum age of 3 users.

Spectrum: distribution
Appendix

WhoAmI

--- A Double Dependent-Variable Factor Graph Model

Code is available at: http://arnetminer.org/demographic
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 $X$;

Input:

\[ G = (V^L, V^U, E, Y^L), X \]

Output:

\[ f(G, X) \rightarrow (Y^U) \]

\[ G = (V^L, V^U, E, Z^L), X \]

Output:

\[ f(G, X) \rightarrow (Z^U) \]

Miss the interrelation between $Y$ and $Z$!
**Demographic Prediction**

**Input:**

\[ G = (V, E, Y^L, Z^L), X \]

**Output:**

\[ f(G, X) \rightarrow (Y^U, Z^U) \]

- **V**: node set
- **E**: edge set
- **Y^L**: nodes with labeled gender
- **Z^L**: nodes with labeled age
- **Y^U**: nodes with unlabeled gender
- **Z^U**: nodes with unlabeled age
Modeling social strategies on social triad

Triadic factor $h()$  
Dyadic factor $g()$

Random variable $Y$: Gender  
Random variable $Z$: Age

Joint Distribution:  
\[ P(Y, Z|G, X) = \prod_{v_i \in V} f(y_i, z_i, x_i) \times \prod_{e_{ij} \in E} [g(y_e, z_e)] \times \prod_{e_{ijk} \in G} [h(y_e, z_e)] \]

Modeling social strategies on social tie

Modeling interrelations between gender and age

Attribute factor $f()$

Modeling social strategies on social ego

Code is available at: http://arnetminer.org/demographic
Joint Distribution:

\[ P(Y, Z|G, X) = \prod_{v_i \in V} f(y_i, z_i, x_i) \times \prod_{e_{ij} \in E} g(y_e, z_e) \times \prod_{e_{ijk} \in C} h(y_c, z_c) \]

Attribute factor:

\[ f(y_i, z_i, x_i) = \frac{1}{W_v} \exp\{a_{y_i, z_i} \cdot x_i\} \]

Dyadic factor:

\[ g(y_e, z_e) = \begin{cases} 
\frac{1}{W_{e1}} \exp\{\beta_1 \cdot g_1(y_i, y_j)\} \\
\frac{1}{W_{e2}} \exp\{\beta_2 \cdot g_3(y_i, z_i)\} \\
\cdots \\
\frac{1}{W_{e6}} \exp\{\beta_6 \cdot g_6(z_i, z_j)\} 
\end{cases} \]

Interrelations between gender Y & age Z

Triadic factor:

\[ h(y_c, z_c) = \begin{cases} 
\frac{1}{W_{c1}} \exp\{\gamma_1 \cdot h_1(y_i, y_j, y_k)\} \\
\frac{1}{W_{c2}} \exp\{\gamma_2 \cdot h_2(y_i, y_j, z_i)\} \\
\cdots \\
\frac{1}{W_{c20}} \exp\{\gamma_{20} \cdot h_{20}(z_i, z_j, z_k)\} 
\end{cases} \]
Objective function:

\[
\mathcal{O}(\alpha, \beta, \gamma) = \sum_{v_i \in V} \alpha y_i z_i x_i + \sum_{e_{ij} \in E} \sum_{p=1}^{6} \beta_p g'_p(\cdot) + \sum_{c_{ijk} \in G} \sum_{q=1}^{20} \gamma_q h'_q(\cdot) - \log W
\]

Model learning: gradient descent

\[
\frac{\partial \mathcal{O}(\theta)}{\partial \alpha} = E[\sum_{v_i \in V} x_i] - E_{P_\alpha(Y,Z|X)}[\sum_{v_i \in V} x_i]
\]

\[
\frac{\partial \mathcal{O}(\theta)}{\partial \beta} = E[\sum_{e_{ij} \in E} g'(\cdot)] - E_{P_\beta(Y,Z|X,G)}[\sum_{e_{ij} \in E} g'(\cdot)]
\]

\[
\frac{\partial \mathcal{O}(\theta)}{\partial \gamma} = E[\sum_{c_{ijk} \in G} h'(\cdot)] - E_{P_\gamma(Y,Z|X,G)}[\sum_{c_{ijk} \in G} h'(\cdot)]
\]

   Code is available at: http://arnetminer.org/demographic
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 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