Colorful Social Networks: inferring social ties in large networks

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New Born Baby
Real social networks are complex...

- Nobody exists merely in one social network.
  - Public network vs. private network
  - Business network vs. family network

- However, existing networks (e.g., Facebook and Twitter) are trying to lump everyone into one big network.
  - FB/QQ tries to solve this problem via lists/groups
  - however...

- Google circles
Even complex than we imaged!

- Only 16% of mobile phone users in Europe have created custom contact groups
  - users do not take the time to create it
  - users do not know how to circle their friends

- The Problem is that online social network are black white...
Example 1. From BW to Color (KDD’10)
Example 2. From BW to Color
(PKDD’11, Best Paper Runnerup)

Enterprise email network

How to infer

CEO
Manager
Employee

User interactions may form *implicit groups*
What is behind?

Publication network

Mobile communication network

Twitter’s following network
What is behind?

Questions:
- What are the **fundamental forces** behind?
- A **generalized framework** for inferring social ties?
- How to **connect** the different networks?
Learning Framework for Inferring Social Ties

KDD 2010, CIKM 2011,
PKDD 2011 (Best Paper Runnerup)
Output: potential types of relationships and their probabilities:
(type, prob, [s_time, e_time])
The problem is cast as, for each node, identifying which neighbor has the highest probability to be his/her advisor, i.e., $P(y_i=j | x_i, x_{-i}, y)$, where $x_j$ and $x_i$ are neighbors.
Overall Framework

- $a_i$: author $i$
- $p_j$: paper $j$
- $py$: paper year
- $pn$: paper#
- $st_{i,y_i}$: starting time
- $ed_{i,y_i}$: ending time
- $r_{i,y_i}$: probability
**Time-constrained Probabilistic Factor Graph (TPFG)**

- Hidden variable $y_x$: $a_x$'s advisor
- $st_{x,y_x}$: starting time
- $ed_{x,y_x}$: ending time
- $g(y_x, st_x, ed_x)$ is pairwise local feature
- $f_x(y_x, Z_x) = \max g(y_x, st_x, ed_x)$ under time constraint
- $Y_x$: set of potential advisors of $a_x$
Maximum likelihood estimation

- A general likelihood objective func can be defined as

\[ P(y_1, \ldots, y_N) = \frac{1}{Z} \prod_{i=1}^{N} f_i(y_i \mid \{y_x \mid x \in Y_i^{-1}\}) \]

with

\[ f_i(y_i \mid \{y_x \mid x \in Y_i^{-1}\}) = g(y_i, st_{ij}, ed_{ij}) \prod_{x \in Y_i^{-1}} \phi(y_x, ed_{ij}, st_{xi}) \]

where \( \Phi(.) \) can be instantiated in different ways, e.g.,

\[ \phi(y_x, ed_{ij}, st_{xi}) = \begin{cases} 1, & y_x \neq i \lor ed_{ij} < st_{xi} \\ 0, & y_x = i \land ed_{ij} \geq st_{xi} \end{cases} \]
Inference algorithm of TPFG

- \( r_{ij} = \max P(y_1, \ldots, y_{na} | y_i = j) = \exp (\text{sent}_{ij} + \text{recv}_{ij}) \)
Results of Model 1

- DBLP data: 654,628 authors, 1,076,946 publications, years provided.
- Ground truth: MathGenealogy Project; AI Genealogy Project; Faculty Homepage

<table>
<thead>
<tr>
<th>Datasets</th>
<th>RULE</th>
<th>SVM</th>
<th>IndMAX</th>
<th>Model 1</th>
</tr>
</thead>
<tbody>
<tr>
<td>TEST1</td>
<td>69.9%</td>
<td>73.4%</td>
<td>75.2%</td>
<td>80.2%</td>
</tr>
<tr>
<td>TEST2</td>
<td>69.8%</td>
<td>74.6%</td>
<td>74.6%</td>
<td>81.5%</td>
</tr>
<tr>
<td>TEST3</td>
<td>80.6%</td>
<td>86.7%</td>
<td>83.1%</td>
<td>88.8%</td>
</tr>
</tbody>
</table>

- heuristics
- Supervised learning
- Empirical parameter
- Optimized parameter

Supervised learning

Empirical parameter

Optimized parameter
The problem is cast as, for each relationship, identifying which type has the highest probability.
Modeling with exponential family

**Partially Labeled Model**

\[
P(y_i \mid Y_{-i}) \propto \exp \left\{ \sum_{c_i} \sum_k \mu_k h_k (Y_{c_i}) \right\}
\]

\[
P(x_i \mid y_i) \propto \exp \left\{ \sum_{j=1}^d \alpha_j g_j (x_{ij}, y_i) \right\}
\]

**Likelihood objective function**

\[
P(Y \mid X, G) = \frac{P(X, G \mid Y)P(Y)}{P(X, G)} \propto P(X \mid Y) \cdot P(Y \mid G) = P(Y \mid G) \prod_i P(x_i \mid y_i)
\]
Learning Algorithm

- Maximize the log-likelihood of labeled relationships

\[ O(\theta) = \sum_{i=1}^{(|E|)} \sum_{j=1}^{d} \alpha_j h_k(Y_{ci}) + \sum_{c} \sum_{k} \mu_k h_k(Y_c) - \log Z \]

```
Input: learning rate \( \eta \)
Output: learned parameters \( \theta \)
Initialize \( \theta \); 
repeat
    Calculate \( \mathbb{E}_{P_\theta(Y|Y^L,G)}S \) using LBP;
    Calculate \( \mathbb{E}_{P_\theta(Y|G)}S \) using LBP;
    Calculate the gradient of \( \theta \) according to Eq. 7:
    \[ \nabla_{\theta} = \mathbb{E}_{P_\theta(Y|Y^L,G)}S - \mathbb{E}_{P_\theta(Y|G)}S \]
    Update parameter \( \theta \) with the learning rate \( \eta \): 
    \[ \theta_{\text{new}} = \theta_{\text{old}} - \eta \cdot \nabla_{\theta} \]
until Convergence;
```

**Algorithm 1: Learning PLP-FGM.**

Variant gradient decent method
Results of Model 2

• **Email.** An email network comprised of 136,329 emails between 151 Enron employees.
  – To infer the manager-subordinate relationship

• **Mobile.** A communication network consisting of calling, bluetooth and location logs of 107 mobile users for 10 months
  – To infer friendships from the communication network

• **Twitter.** A following network including 112,044 Twitter users and about 500,000 following links among them for 2 months
  – To infer reciprocal relationships between users
## Results of Model 2

<table>
<thead>
<tr>
<th>Datasets</th>
<th>Method</th>
<th>Precision</th>
<th>Recall</th>
<th>F1-measure</th>
</tr>
</thead>
<tbody>
<tr>
<td>Email</td>
<td>SVM</td>
<td>79.1</td>
<td>88.6</td>
<td>83.6</td>
</tr>
<tr>
<td></td>
<td>Model 2</td>
<td>88.6</td>
<td>87.2</td>
<td>87.9</td>
</tr>
<tr>
<td>Mobile</td>
<td>SVM</td>
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<td>64.9</td>
<td>76.4</td>
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<tr>
<td></td>
<td>Model 2</td>
<td>89.4</td>
<td>75.2</td>
<td>81.6</td>
</tr>
<tr>
<td>Twitter</td>
<td>SVM</td>
<td>69.1</td>
<td>61.0</td>
<td>65.0</td>
</tr>
<tr>
<td></td>
<td>Model 2</td>
<td>97.0</td>
<td>55.0</td>
<td>70.0</td>
</tr>
</tbody>
</table>

• Comparison methods:
  – SVM: with the same local features
  – Model 2: the proposed model with all features
Questions?

• Machine learning vs. social theories

• How to generalize the model to other networks?
Generalized framework by connecting to social theories

WSDM 2012
Social Theories

- Social balance theory
- Two-step flow theory
- Social status theory
- Structural hole theory

(A) (B) (C) (D)
Social Theories—Two-step flow

- Social balance theory
- Two-step flow theory
- Social status theory
- Structural hole theory

Two-step information propagation
Social Theories—Social status

- Social balance theory
- Two-step flow theory
- Social status theory
- Structural hole theory
Social Theories—Structural hole

- Social balance theory
- Two-step flow theory
- Social status theory
- Structural hole theory

![Diagram of structural hole theory](image)
**Definition 1. Structural Hole.** Let $G = (V, E)$ denote a social network, where $V = \{v_1, v_2, \cdots, v_n\}$ is a set of $n$ users, and $E \subseteq V \times V$ is a set of undirected social relationships between users. Further assume that the vertices of the social network can be grouped into $l$ subsets $C = \{C_1, \cdots, C_l\}$ (called community). Then structural holes of the social network can be defined as a subset of $k$ vertices in the network, which can maximize a quality function:

$$\max_{V_{SH}} Q(V_{SH}, C), \text{ with } |V_{SH}| = k$$

(1)
Algorithm

\[ I(v, i) = \max_{(u, v) \in E, i \in S} \{ I(v, i), \alpha_i \cdot I(u, i) + \beta_S \cdot H(u, S) \} \]

\[ H(v, S) = \min_{i \in S} \{ I(v, i) \} \]

\textbf{Theorem 1.} Given \( \alpha_i \) and \( \beta_S \), the functions \( I(v, i) \) and \( H(v, S) \) exists for any graph \( G = (V, E) \), if and only if,

\[ \max_{i} \{ \alpha_i + \max_{i \in S} \{ \beta_S \} \} \leq 1 \]

\textbf{Proof.} On one hand, suppose there exists \( i \) and \( i \in S \) such that \( \alpha_i + \beta_S > 1 \). Let \( S = \{ i, p_1, \cdots, p_{|S|-1} \} \). Consider the following graph \( G = (V, E) \), there are two vertices \( v_1 \) and \( v_2 \) connected by one edge \( (v_1, v_2) \), and \( v_1 \) appears in communities \( C_i, C_{p_1}, \cdots C_{p_{|S|-1}} \), and \( v_2 \) appears in communities \( C_i \), and we have \( r(v_1) = r(v_2) = 1 \). Figure 2 shows the case for \( |S| = 2 \).

Thus, \( I(v_1, i) = I(v_1, p_1) = \cdots = I(v_1, p_{|S|-1}) = r(v_1) = 1 \). According to rule 3, we get \( H(v_1, S) = 1 \). According to rule 2, we have \( I(v_2, i) \geq \alpha_i \cdot I(v_1, i) + \beta_S \cdot H(v_1, S) = \alpha_i + \beta_S > 1 \), which is impossible.

On the other hand, if for each \( i \) and \( i \in S \), we have \( \alpha_i + \beta_S \leq 1 \). We use induction to prove that, after infinite number of iterations, it also satisfies that \( I(v, i) \leq 1 \).

In the first iteration, we have \( I^{(0)}(v, i) \leq r(v) \leq 1 \). Suppose after the \( k \)-th iteration, we have \( I^{(k)}(v, i) \leq r(v) \leq 1 \). Hence, in the \( (k + 1) \)-th iteration, for each \( i \in S \), we have \( I^{(k+1)}(v, i) \leq \alpha_i \cdot I^{(k)}(u, i) + \beta_S \cdot H^{(k)}(u, S) \leq (\alpha_i + \beta_S)I^{(k)}(u, i) \leq I^{(k)}(u, i) \leq 1 \). \( \square \)
Generalization—Redefining the problem across heterogeneous networks

Input: Heterogeneous Networks

Publication network

Adam

Bob

Chris

Danny

2005
Paper 1

2003
Paper 2

2008
Paper 3

2006
Paper 4

Output: Inferred social ties in different networks

Knowledge Transfer for Inferring Social Ties

Adam

Bob

Chris

Danny

Co-author

Advisor

Co-author

Advisor

Family

Colleague

Colleague

Colleague

Friend

Friend

Colleague
Transfer Factor Graph Model

Coauthor network

Input: social network

Bridge via social theories

mobile
Mathematical Formulation

Features defined in different networks

\[
O(\alpha, \beta, \mu) = O_S(\alpha, \mu) + O_T(\beta, \mu)
\]

\[
= \sum_{i=1}^{\left| V_S \right|} \sum_{j=1}^{d} \alpha_{ij} g_{ij}(x_{ij}^S, y_{i}^S) + \sum_{i=1}^{\left| V_T \right|} \sum_{j=1}^{d'} \beta_{ij} g'_{ij}(x_{ij}^T, y_{i}^T)
\]

\[
+ \sum_{k} \mu_k \left( \sum_{c \in G_S} h_k(Y_c^S) + \sum_{c \in G_T} h_k(Y_c^T) \right)
\]

\[
- \log Z
\]

Triad-based features shared across networks
New Results

- **Epinions**: a network of product reviewers: 131,828 nodes (users) and 841,372 edges
  - to infer the trust relationships between users
- **Slashdot**: 82,144 users and 59,202 edges
  - to infer “friend” relationships between users
- **Mobile**: 107 mobile users and 5,436 edges
  - to infer friendships between users
- **Coauthor**: 1,036,990 authors and 1,900,260 coauthorships
  - to infer advisor-advisee relationships
- **Enron**: 136,329 emails between 151 Enron employees
  - to infer manager-employee relationships
## New Results

<table>
<thead>
<tr>
<th>Datasets</th>
<th>Method</th>
<th>Precision</th>
<th>Recall</th>
<th>F1-measure</th>
</tr>
</thead>
<tbody>
<tr>
<td>Epinions + Slashdot</td>
<td>SVM</td>
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<td>99.65</td>
<td>87.94</td>
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<td>76.07</td>
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<td></td>
<td>Triad Factor Graph</td>
<td><strong>94.14</strong></td>
<td>94.46</td>
<td><strong>94.30</strong></td>
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<td>Epinions + Mobile</td>
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<tr>
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<td><strong>100.00</strong></td>
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<td>74.40</td>
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<td>78.26</td>
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<td>Triad Factor Graph</td>
<td>95.56</td>
<td>78.18</td>
<td><strong>86.00</strong></td>
</tr>
</tbody>
</table>
Two Concluding Remarks

• Connecting social theories to machine learning models can significantly improve the performance of inferring social ties

• Combining heterogeneous networks into one unified model can help social relationship analysis
ArnetMiner.org
- Academic research social network analysis and mining system

提供全面的研究者网络分析与挖掘功能

Papers published: ACM TKDD, MLJ, DKE, JIS; KDD’08-10, SDM’09, ICDM’07-10, CIKM’07-10

http://arnetminer.org/
Colorful Social Graph In ArnetMiner
Instant Social Graph Search
ArnetMiner Today

* Arnetminer data:
  > 1.5 M researcher profiles
  > 3M papers
  > 34M citation relationships
  > 8K conferences
  > 80M logs

* > 1,000,000 users from more than 200 countries
* Continuously 20+% increase of visits per month

* >300,000 page views per day
ArnetMiner Today

* Arnetminer data:
  > 1.5 M researcher profiles
  > 3M papers
  > 34M citation relationships
  > 8K conferences
  > 80M logs

Messages from Users

… I’ve happened to visit your Arnetminer, and shocked. It was really impressive, its usefulness and your works!!! … [from …@selab.snu.ac.kr]

...I would first of all congratulate you on the excellent work you have done in Arnetminer and I am much inspired… [from ...@nu.edu.pk]

Title: Semantic Technologies for Learning and Teaching in Web 2.0.
— Thanassis Tiropanis, Hugh Davis, Dave Millard, Mark Weal

…Exposing the expertise of the institution to the outside world in order to attract funding and students. ArnetMiner is the most representative example of such tools at the moment…

Contextualised queries and searches, searches across repositories potentially in different departments or institutions, and matching of people for collaborative activities. Best example of the surveyed technologies to this end is ArnetMiner.
Arnetminer’s User Distribution

Top 10 countries
1. USA
2. China
3. Germany
4. India
5. UK
6. Canada
7. Japan
8. Spain
9. France
10. Italy
Arnetminer is widely used

- The largest publisher: Elsevier
Related Publications

- Jie Tang, Tiancheng Lou, and Jon Kleinberg. Inferring Social Ties across Heterogeneous Networks. **WSDM’12**.
- Chi Wang, Jiawei Han, Yuntao Jia, Duo Zhang, Yintao Yu, Jie Tang, Jingyi Guo. Mining Advisor-Advisee Relationships from Research Publication Networks. **KDD’10**.
- Wenbin Tang, Honglei Zhuang, and Jie Tang. Learning to Infer Social Relationships in Large Networks. **PKDD’11.** (Best Student Paper Runner-up)
- Chenhao Tan, Lillian Lee, Jie Tang, Long Jiang, Ming Zhou, and Ping Li. User-level sentiment analysis incorporating social networks. **KDD’11**.
- Chenhao Tan, Jie Tang, Jimeng Sun, Quan Lin, and Fengjiao Wang. Social Action Tracking via Noise Tolerant Time-varying Factor Graphs. **KDD’10**.
- Jie Tang, Jimeng Sun, Chi Wang, and Zi Yang. Social Influence Analysis in Large-scale Networks. **KDD’09.** (Top 4 cited papers among KDD 2009's papers)
- Jie Tang, Jing Zhang, Limin Yao, Juanzi Li, Li Zhang, and Zhong Su. ArnetMiner: Extraction and Mining of Academic Social Networks. **KDD’08**.
- Jie Tang, Ho-fung Leung, Qiong Luo, Dewei Chen, and Jibin Gong. Towards Ontology Learning from Folksonomies. **IJCAI’09**.

Others: **SIGMOD’09, ACL’07, SIGIR’11, ICDM’07-11, CIKM’07-11, SDM’09, ISWC’(06,09), DKE, JIS**, etc.
Thanks!

Q&A

System: http://arnetminer.org
HP: http://keg.cs.tsinghua.edu.cn/jietang/
Basic Features/Constraints

• Features
  – First-paper-year-diff
  – Conference coverage
  – Coauthor ratio
  – Paper count

• Constraints
  – $a_y$ can only advise $a_x$ after he graduated
  – If $a_y$ advises $a_x$ since the year $st_x$, $a_y$ must have a longer history of publication than $a_x$ before $st_x$.

The model can incorporate other intuitions as factor functions.