Social Media Analytics: Part 2: Rich Interactions

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Social Media: Interactions

- In Social Media users **interact** with one another and the content they both create and consume.

- Traditional social network analysis only distinguishes between pairs of people that are **linked** vs. **not-linked**.

- But, user interactions in social media are **much richer**.
Part 2 of the Tutorial: Outline

- How to learn to recommend/predict links in social networks?
- User interactions in social media:
  - Strength: strong vs. weak ties
  - Friends vs. Foes
  - Trust vs. Distrust
- How people evaluate one another and the content that is being produced by others?
Part 1: Information flow in networks

Part 2: Rich interactions
- 2.1: Recommending links in networks
- 2.2: Predicting tie strength
- 2.3: Predicting friends vs. foes
- 2.4: How do people evaluate others?
Part 1: Information flow in networks

Part 2: Rich interactions

2.1: Recommending links in networks
2.2: Predicting tie strength
2.3: Predicting friends vs. foes
2.4: How do people evaluate others?
Link prediction task:
- Given $G[t_{0},t_{0}']$ a graph on edges up to time $t_{0}'$ output a ranked list $L$ of links (not in $G[t_{0},t_{0}']$) that are predicted to appear in $G[t_{1},t_{1}']$.

Evaluation:
- $n=|E_{\text{new}}|$: # new edges that appear during the test period $[t_{1},t_{1}']$
- Take top $n$ elements of $L$ and count correct edges.
**Link prediction via node distance**

- **Predict links evolving collaboration network**

<table>
<thead>
<tr>
<th></th>
<th>training period</th>
<th></th>
<th>Core</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>authors</td>
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<td>collaborations</td>
<td>authors</td>
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<td>5241</td>
<td>9498</td>
<td>15842</td>
<td>1438</td>
</tr>
</tbody>
</table>

- **Core**: Since network data is very sparse
  - Consider only nodes with in-degree and out-degree of at least 3
For every pair of nodes \((x,y)\) compute:

<table>
<thead>
<tr>
<th>Metric</th>
<th>Formula</th>
</tr>
</thead>
<tbody>
<tr>
<td>graph distance</td>
<td>((\negated)) length of shortest path between (x) and (y)</td>
</tr>
<tr>
<td>common neighbors</td>
<td>(</td>
</tr>
<tr>
<td>Jaccard’s coefficient</td>
<td>(</td>
</tr>
<tr>
<td>Adamic/Adar</td>
<td>(</td>
</tr>
<tr>
<td>preferential attachment</td>
<td>(</td>
</tr>
<tr>
<td>Katz_(\beta)</td>
<td>(\sum_{\ell=1}^{\infty} \beta^\ell \cdot</td>
</tr>
</tbody>
</table>

where \(\text{paths}_{x,y}^{(\ell)} := \{\text{paths of length exactly } \ell \text{ from } x \text{ to } y\}\)

- Sort the pairs by score and predict top \(n\) pairs as new links

\[
E_{new}^* := E_{new} \cap (\text{Core} \times \text{Core})
\]

\(\Gamma(x)\) ... degree of node \(x\)
Results: Improvement over random

\[
\sum_{z \in \Gamma(x) \cap \Gamma(y)} \frac{1}{\log |\Gamma(z)|}
\]
How to learn to predict new friends in networks?

- Facebook’s People You May Know
- Let’s look at the data:
  - 92% of new friendships on FB are friend-of-a-friend
  - More common friends helps
Supervised Link Prediction

- Recommend a list of possible friends
- Supervised machine learning setting:
  - Training example:
    - For every node $s$ have a list of nodes she will create links to $\{v_1, ..., v_k\}$
    - E.g., use FB network from May 2011 and $\{v_1, ..., v_k\}$ are the new friendships you created since then
  - Problem:
    - For a given node $s$ learn to rank nodes $\{v_1, ..., v_k\}$ higher than other nodes in the network
- Supervised Random Walks based on word by Agarwal & Chakrabarti
Supervised Link Prediction

- How to combine node/edge attributes and the network structure?
  - Learn a strength of each edge based on:
    - Profile of user $u$, profile of user $v$
    - Interaction history of $u$ and $v$
  - Do a PageRank-like random walk from $s$ to measure the “proximity” between $s$ and other nodes
  - Rank nodes by their “proximity” (i.e., visiting prob.)
Supervised Random Walks

- Let \( s \) be the center node
- Let \( f_w(u,v) \) be a function that assigns a strength to each edge:
  \[
a_{uv} = f_w(u,v) = \exp(-w^T\Psi_{uv})
  \]
  - \( \Psi_{uv} \) is a feature vector
    - Features of node \( u \)
    - Features of node \( v \)
    - Features of edge \( (u,v) \)
  - \( w \) is the parameter vector we want to learn
- Do Random Walk with Restarts from \( s \) where transitions are according to edge strengths
- How to learn \( f_w(u,v) \)?
Personalized PageRank

- Random walk transition matrix:

\[ Q'_{uv} = \begin{cases} \frac{a_{uv}}{\sum_w a_{uw}} & \text{if } (u, v) \in E, \\ 0 & \text{otherwise} \end{cases} \]

- PageRank transition matrix:

\[ Q_{ij} = (1 - \alpha)Q'_{ij} + \alpha 1(j = s) \]

  - with prob. \( \alpha \) jump back to \( s \)

- Compute PageRank vector: \( p = p^T Q \)

- Rank nodes by \( p_u \)
Each node $u$ has a score $p_u$

Destination nodes $D = \{v_1, \ldots, v_k\}$

No-link nodes $L = \{\text{the rest}\}$

What do we want?
Want to find $w$ such that $p_l < p_d$

$$\min_w F(w) = ||w||^2$$

such that

$\forall d \in D, l \in L : p_l < p_d$

Hard constraints, make them soft
Want to minimize:

\[
\min_w F(w) = ||w||^2 + \lambda \sum_{ld} h(p_l - p_d)
\]

- **Loss:** \(h(x) = 0\) if \(x < 0\), \(x^2\) else
How to minimize $F$?

\[
\min_w F(w) = \|w\|^2 + \lambda \sum_{ld} h(p_l - p_d)
\]

- $p_l$ and $p_d$ depend on $w$
  - Given $w$ assign edge weights $a_{uv} = f_w(u,v)$
  - Using transition matrix $Q = [a_{uv}]$
    compute PageRank scores $p_u$
  - Rank nodes by the PageRank score

- Want to find $w$ such that $p_l < p_d$
How to minimize $F$?

\[
\min_w F(w) = \|w\|^2 + \lambda \sum_{l,d} h(p_l - p_d)
\]

Take the derivative!

\[
\frac{\partial F}{\partial w} = 2w + \sum_{l,d} \frac{\partial h(p_l - p_d)}{\partial w}
\]

We know:

\[
p = p^T Q \quad \text{i.e.} \quad p_u = \sum_j p_j Q_{ju}
\]

So:

\[
\frac{\partial p_u}{\partial w} = \sum_j Q_{ju} \frac{\partial p_j}{\partial w} + p_j \frac{\partial Q_{ju}}{\partial w}
\]

Solve by power iteration!
To optimize $F$, use gradient based method:

- Pick a random starting point $w_0$
- Compute the personalized PageRank vector $p$
- Compute gradient with respect to weight vector $w$
- Update $w$
  - Optimize using quasi-Newton method
Data: Facebook

- Facebook Iceland network
  - 174,000 nodes (55% of population)
  - Avg. degree 168
  - Avg. person added 26 new friends/month
- For every node \( s \):
  - Positive examples:
    - \( D = \{ \text{new friendships of } s \text{ created in Nov '09} \} \)
  - Negative examples:
    - \( L = \{ \text{other nodes } s \text{ did not create new links to} \} \)
  - Limit to friends of friends
    - on avg. there are 20k FoFs (max 2M)!
Node and Edge features for learning:

- **Node:**
  - Age
  - Gender
  - Degree

- **Edge:**
  - Age of an edge
  - Communication
  - Profile visits
  - Co-tagged photos

**Baselines:**

- Decision trees and logistic regression:
  - Above features + 10 network features (PageRank, common friends)

**Evaluation:**

- AUC and precision at Top20
Facebook: predict future friends
- Adamic-Adar already works great
- Logistic regression also strong
- SRW gives slight improvement

<table>
<thead>
<tr>
<th>Learning Method</th>
<th>AUC</th>
<th>Prec@20</th>
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<tbody>
<tr>
<td>Random Walk with Restart</td>
<td>0.81725</td>
<td>6.80</td>
</tr>
<tr>
<td>Adamic-Adar</td>
<td>0.81586</td>
<td>7.35</td>
</tr>
<tr>
<td>Common Friends</td>
<td>0.80054</td>
<td>7.35</td>
</tr>
<tr>
<td>Degree</td>
<td>0.58535</td>
<td>3.25</td>
</tr>
<tr>
<td>DT: Node features</td>
<td>0.59248</td>
<td>2.38</td>
</tr>
<tr>
<td>DT: Network features</td>
<td>0.76979</td>
<td>5.38</td>
</tr>
<tr>
<td>DT: Node+Network</td>
<td>0.76217</td>
<td>5.86</td>
</tr>
<tr>
<td>DT: Path features</td>
<td>0.62836</td>
<td>2.46</td>
</tr>
<tr>
<td>DT: All features</td>
<td>0.72986</td>
<td>5.34</td>
</tr>
<tr>
<td>LR: Node features</td>
<td>0.54134</td>
<td>1.38</td>
</tr>
<tr>
<td>LR: Network features</td>
<td>0.80560</td>
<td>7.56</td>
</tr>
<tr>
<td>LR: Node+Network</td>
<td>0.80280</td>
<td>7.56</td>
</tr>
<tr>
<td>LR: Path features</td>
<td>0.51418</td>
<td>0.74</td>
</tr>
<tr>
<td>LR: All features</td>
<td>0.81681</td>
<td>7.52</td>
</tr>
<tr>
<td>SRW: one edge type</td>
<td>0.82502</td>
<td>6.87</td>
</tr>
<tr>
<td>SRW: multiple edge types</td>
<td>0.82799</td>
<td>7.57</td>
</tr>
</tbody>
</table>
Part 1: Information flow in networks

Part 2: Rich interactions
- 2.1: Recommending links in networks
- **2.2: Predicting tie strength**
- 2.3: Predicting friends vs. foes
- 2.4: How do people evaluate others?
Tie strength

“The strength of a tie is a combination of the amount of TIME, the emotional INTENSITY, the INTIMACY, and the reciprocal SERVICES which characterize the tie.”

[Grannovetter]

- Gilbert & Karahalios surveyed 35 Facebook users to label 2,184 friendships (links)

- Describe each link by 70+ features
- Train a regression model to predict tie strength
Five aspects of tie strength

- **How strong is your relationship with this person?**
  - barely know them
  - we are very close

- **How would you feel asking this friend to loan you $100 or more?**
  - would never ask
  - very comfortable

- **How helpful would this person be if you were looking for a job?**
  - no help at all
  - very helpful

- **How upset would you be if this person unfriended you?**
  - not upset at all
  - very upset

- **If you left Facebook for another social site, how important would it be to bring this friend along?**
  - would not matter
  - must bring them!
Attributes of the friendship (1)

- Features that are used for learning
  - Intensity
    - wall words exchanged
    - friend-initiated wall posts
    - part.-initiated wall posts
    - inbox messages together
    - inbox thread depth
    - part.’s status updates
    - friend’s status updates
  - Intimacy
    - participant’s friends
    - friend’s friends
    - days since last comm.
    - wall intimacy words
    - inbox intimacy words
    - together in photo
    - miles between hometowns
Attributes of the friendship (2)

- Features that are used for learning
  - Social Distance
    - age difference
    - # occupations difference
    - educational difference
    - political difference
  - Reciprocal services
    - Links exchanged by wall
    - Applications in common
  - Structural
    - mutual friends
    - groups in common
    - Cosine similarity of interests
  - Emotional support
    - Positive emotion words
    - Negative emotion words
Results: How strong is relationship

- Train a linear (regression) model

- Results for the “How strong is your relationship?”
## Results: Most predictive features

<table>
<thead>
<tr>
<th>Feature</th>
<th>Score</th>
</tr>
</thead>
<tbody>
<tr>
<td>Days since last communication</td>
<td>-0.762</td>
</tr>
<tr>
<td>Days since first communication</td>
<td>0.755</td>
</tr>
<tr>
<td>Intimacy × Structural</td>
<td>0.4</td>
</tr>
<tr>
<td>Wall words exchanged</td>
<td>0.299</td>
</tr>
<tr>
<td>Mean strength of mutual friends</td>
<td>0.257</td>
</tr>
<tr>
<td>Educational difference</td>
<td>-0.223</td>
</tr>
<tr>
<td>Structural × Structural</td>
<td>0.195</td>
</tr>
<tr>
<td>Reciprocal Serv. × Reciprocal Serv.</td>
<td>-0.19</td>
</tr>
<tr>
<td>Participant-initiated wall posts</td>
<td>0.146</td>
</tr>
<tr>
<td>Inbox thread depth</td>
<td>-0.137</td>
</tr>
<tr>
<td>Participant’s number of friends</td>
<td>-0.136</td>
</tr>
<tr>
<td>Inbox positive emotion words</td>
<td>0.135</td>
</tr>
<tr>
<td>Social Distance × Structural</td>
<td>0.13</td>
</tr>
<tr>
<td>Participant’s number of apps</td>
<td>-0.122</td>
</tr>
<tr>
<td>Wall intimacy words</td>
<td>0.111</td>
</tr>
</tbody>
</table>
Part 1: Information flow in networks

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So far we viewed links as positive but links can also be negative

**Question:**
- How do edge signs and network interact?
- How to model and predict edge signs?

**Applications:**
- Friend recommendation
  - Not just whether you know someone but what do you think of them
Each link $A \rightarrow B$ is explicitly tagged with a sign:

- **Epinions**: Trust/Distrust
  - Does A trust B’s product reviews? (only positive links are visible)

- **Wikipedia**: Support/Oppose
  - Does A support B to become Wikipedia administrator?

- **Slashdot**: Friend/Foe
  - Does A like B’s comments?

<table>
<thead>
<tr>
<th></th>
<th>Epinions</th>
<th>Slashdot</th>
<th>Wikipedia</th>
</tr>
</thead>
<tbody>
<tr>
<td>Nodes</td>
<td>119,217</td>
<td>82,144</td>
<td>7,118</td>
</tr>
<tr>
<td>Edges</td>
<td>841,200</td>
<td>549,202</td>
<td>103,747</td>
</tr>
<tr>
<td>+ edges</td>
<td>85.0%</td>
<td>77.4%</td>
<td>78.7%</td>
</tr>
<tr>
<td>- edges</td>
<td>15.0%</td>
<td>22.6%</td>
<td>21.2%</td>
</tr>
</tbody>
</table>
Consider edges as undirected

- Start with intuition [Heider ’46]:
  - Friend of my friend is my friend
  - Enemy of enemy is my friend
  - Enemy of friend is my enemy

- Look at connected triples of nodes:

```
[Unbalanced]
```

Consistent with “friend of a friend” or “enemy of the enemy” intuition

Inconsistent with the “friend of a friend” or “enemy of the enemy” intuition
Theory of Status

- **Status theory** [Davis-Leinhardt '68, Guha et al. '04, Leskovec et al. '10]
  - Link $A \rightarrow B$ means: $B$ has **higher** status than $A$
  - Link $A \rightarrow B$ means: $B$ has **lower** status than $A$
  - Based on signs/directions of links from/to node $X$ make a prediction
- Status and balance can make **different** predictions:
How do these two theories align with ways people create links:

- Not just “which is right” but how are aspects of each reflected in the data
- Provide insights into how these linking systems are being used

Outline:

- Study links as undirected: Balance theory
- Study links as directed and evolving: Status theory
- Predicting signs of edges
Our networks are really directed
- trust, opinion (, friendship)

How many $\triangle$ are now explained by balance?
- Half (8 out of 16)

Is there a better explanation?
- Yes. Theory of Status.
Alternate theory: Status

- Links are directed and created over time
- Status theory [Davis-Leinhardt ‘68, Guha et al. ’04, Leskovec et al. ‘10]
  - Link A → B means: B has higher status than A
  - Link A ← B means: B has lower status than A
- Status and balance can give different predictions:

![Diagram showing status and balance](image)
Evolving Directed Networks

- Links are directed
- Links are created over time
  - X has links to/from A and B
  - Now, A links to B
- To compare balance and status we need to formalize:
  - Links are embedded in triads – provides context for signs
  - Users are heterogeneous in their linking behavior
16 types of contextualized links

- **Link contexts:**
  - A **contextualized link** is a triple \((A,B;X)\) such that directed \(A-B\) link forms after there is a two-step semi-path \(A-X-B\).
  - \(A-X\) and \(B-X\) links can have either direction and either sign:
    - 16 possible types
Different users make signs differently:
- **Generative baseline** (frac. of + given by A)
- **Receptive baseline** (frac. of + received by B)

How do different link contexts cause users to deviate from baselines?

**Surprise**: How much behavior of A/B deviates from baseline when they are in context
Status: Two Examples

- Two basic examples:

  ![Diagram 1]
  More negative than gen. baseline of A
  More negative than rec. baseline of B

  ![Diagram 2]
  More negative than gen. baseline of A
  More negative than rec. baseline of B
Consistency with Status

- Determine node status:
  - Assign X status 0
  - Based on signs and directions of edges set status of A and B

- Surprise is **status**-consistent, if:
  - **Gen.** surprise is status-consistent if it has *same* sign as status of B
  - **Rec.** surprise is status-consistent if it has the *opposite* sign from the status of A

- Surprise is **balance**-consistent, if:
  - If it completes a balanced triad

Status-consistent if:
- Gen. surprise < 0
- Rec. surprise < 0
# Status vs. Balance (Epinions)

- **Results for Epinions: Trust vs. Distrust**

<table>
<thead>
<tr>
<th>$t_i$</th>
<th>count</th>
<th>$P(+)$</th>
<th>$s_{out}$</th>
<th>$s_{in}$</th>
<th>$B_{out}$</th>
<th>$B_{in}$</th>
<th>$S_{out}$</th>
<th>$S_{in}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$t_1$</td>
<td>178,051</td>
<td>0.97</td>
<td>95.9</td>
<td>197.8</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
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<tr>
<td>$t_2$</td>
<td>45,797</td>
<td>0.54</td>
<td>-151.3</td>
<td>-229.9</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>○</td>
</tr>
<tr>
<td>$t_3$</td>
<td>246,371</td>
<td>0.94</td>
<td>89.9</td>
<td>195.9</td>
<td>✓</td>
<td>✓</td>
<td>○</td>
<td>✓</td>
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<tr>
<td>$t_4$</td>
<td>25,384</td>
<td>0.89</td>
<td>1.8</td>
<td>44.9</td>
<td>○</td>
<td>○</td>
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<td>✓</td>
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<td>$t_5$</td>
<td>45,925</td>
<td>0.30</td>
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<td>✓</td>
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<td>✓</td>
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<td>11,215</td>
<td>0.23</td>
<td>-15.5</td>
<td>-193.6</td>
<td>○</td>
<td>○</td>
<td>✓</td>
<td>✓</td>
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<td>✓</td>
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<td>124.1</td>
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<td>○</td>
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<td>0.82</td>
<td>207.0</td>
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<td>○</td>
<td>✓</td>
<td>✓</td>
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<tr>
<td>$t_{10}$</td>
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<td>35,093</td>
<td>0.53</td>
<td>-7.4</td>
<td>-260.1</td>
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<td>20,933</td>
<td>0.71</td>
<td>17.2</td>
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<td>✓</td>
<td>✓</td>
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<td>0.79</td>
<td>23.5</td>
<td>24.0</td>
<td>○</td>
<td>○</td>
<td>✓</td>
<td>✓</td>
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<td>$t_{14}$</td>
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<td>0.69</td>
<td>-12.8</td>
<td>-53.6</td>
<td>○</td>
<td>○</td>
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<td>○</td>
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<td>0.76</td>
<td>6.4</td>
<td>24.0</td>
<td>○</td>
<td>○</td>
<td>○</td>
<td>✓</td>
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<tr>
<td>$t_{16}$</td>
<td>4,133</td>
<td>0.77</td>
<td>11.9</td>
<td>-2.6</td>
<td>✓</td>
<td>○</td>
<td>✓</td>
<td>○</td>
</tr>
</tbody>
</table>

Number of correct predictions: 8, 7, 14, 13
Global Structure of Signed Nets

- Intuitive picture of social network in terms of densely linked clusters
- How does structure interact with links?
- Embeddedness of link (A,B): number of hared neighbors
Global structure: Embeddedness

- Embeddedness of ties:
  - Embedded ties tend to be more positive

- A natural connection to closure based social capital [Coleman ‘88]

- Public display of signs (votes) in Wikipedia further strengthens this
Predicting edge signs

Edge sign prediction problem
- Given a network and signs on all but one edge, predict the missing sign

Machine Learning formulation:
- Predict sign of edge (u,v)
- Class label:
  - +1: positive edge
  - -1: negative edge
- Learning method:
  - Logistic regression

\[
P(+|x) = \frac{1}{1 + e^{-(b_0 + \sum_i^n b_i x_i)}}
\]

Dataset:
- Original: 80% +edges
- Balanced: 50% +edges

Evaluation:
- Accuracy and ROC curves

Features for learning:
- Next slide
For each edge (u,v) create features:

- **Triad counts (16):**
  - Counts of signed triads
  - edge $u \rightarrow v$ takes part in

- **Degree (7 features):**
  - Signed degree:
    - $d^+_\text{out}(u)$, $d^-\text{out}(u)$,
    - $d^+_\text{in}(v)$, $d^-\text{in}(v)$
  - Total degree:
    - $d_{\text{out}}(u)$, $d_{\text{in}}(v)$
  - Embeddedness
    - of edge (u,v)
Error rates:
- Epinions: 6.5%
- Slashdot: 6.6%
- Wikipedia: 19%

Signs can be modeled from local network structure alone
- Trust propagation model of [Guha et al. ‘04] has 14% error on Epinions

Triad features perform less well for less embedded edges

Wikipedia is harder to model:
- Votes are publicly visible
Do people use these very different linking systems by obeying the same principles?
  - How generalizable are the results across the datasets?
    - Train on row “dataset”, predict on “column”

<table>
<thead>
<tr>
<th></th>
<th>All23</th>
<th>Epinions</th>
<th>Slashdot</th>
<th>Wikipedia</th>
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<tbody>
<tr>
<td>Epinions</td>
<td>0.9342</td>
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<td>Slashdot</td>
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<td>0.9351</td>
<td></td>
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<tr>
<td>Wikipedia</td>
<td>0.9272</td>
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<td>0.8021</td>
</tr>
</tbody>
</table>

Almost perfect generalization of the models even though networks come from very different applications
### Balance and Status: Complete model

<table>
<thead>
<tr>
<th>Feature</th>
<th>Bal</th>
<th>Stat</th>
<th>Epin</th>
<th>Slashd</th>
<th>Wikip</th>
</tr>
</thead>
<tbody>
<tr>
<td>const</td>
<td>1</td>
<td>1</td>
<td>-0.2</td>
<td>0.02</td>
<td>-0.2</td>
</tr>
<tr>
<td>+→−→+−−</td>
<td>-1</td>
<td>0</td>
<td>-0.5</td>
<td>-0.9</td>
<td>-0.4</td>
</tr>
<tr>
<td>−→+→+−−</td>
<td>-1</td>
<td>0</td>
<td>-0.4</td>
<td>-1.1</td>
<td>-0.3</td>
</tr>
<tr>
<td>+−→→−−−</td>
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<td>-1</td>
<td>-0.7</td>
<td>-0.6</td>
<td>-0.8</td>
</tr>
<tr>
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<td>0</td>
<td>0.3</td>
<td>0.4</td>
<td>0.05</td>
</tr>
<tr>
<td>+−→→−−−</td>
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<td>1</td>
<td>-0.01</td>
<td>-0.1</td>
<td>-0.01</td>
</tr>
<tr>
<td>−−→→+→+</td>
<td>-1</td>
<td>-1</td>
<td>-0.9</td>
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<td>-0.2</td>
</tr>
<tr>
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<td>-0.03</td>
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<td>0.08</td>
<td>0.4</td>
<td>0.1</td>
</tr>
<tr>
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<td>-1</td>
<td>-1</td>
<td>-1.3</td>
<td>-1.1</td>
<td>-0.4</td>
</tr>
<tr>
<td>−→→→+−−</td>
<td>-1</td>
<td>1</td>
<td>-0.1</td>
<td>-0.2</td>
<td>0.05</td>
</tr>
<tr>
<td>−−→→+→+</td>
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<td>-0.1</td>
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<td>-0.09</td>
<td>-0.01</td>
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<tr>
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<td>0</td>
<td>-0.05</td>
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<tr>
<td>−−→→+→+</td>
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<td>0</td>
<td>-0.04</td>
<td>-0.3</td>
<td>0.05</td>
</tr>
<tr>
<td>←−→−−−−</td>
<td>1</td>
<td>1</td>
<td>-0.02</td>
<td>0.2</td>
<td>-0.2</td>
</tr>
</tbody>
</table>
Both theories agree well with learned models

Further observations:

- Backward-backward triads have smaller weights than forward and mixed direction triads
- Balance is in better agreement with Epinions and Slashdot while Status is with Wikipedia
- Balance consistently disagrees with “enemy of my enemy is my friend”
Part 1: Information flow in networks

Part 2: Rich interactions
- 2.1: Recommending links in networks
- 2.2: Predicting tie strength
- 2.3: Predicting friends vs. foes
- 2.4: How do people evaluate others?
People express positive and negative attitudes/opinions:

- **Through actions:**
  - Rating a product
  - Pressing “like” button

- **Through text:**
  Sentiment analysis
  [Pang-Lee ‘08]
  - Writing a comment, a review
People Express Opinions

- **About items:**
  - Movie and product reviews
    - [IMDb](http://www.imdb.com)
    - [Amazon](http://www.amazon.com)

- **About other users:**
  - Online communities
    - [Epinions.com](http://www.epinions.com)
    - [Wikipedia](http://www.wikipedia.com)

- **About items created by others:**
  - Q&A websites
    - [Stack Overflow](http://www.stackoverflow.com)
    - [Yahoo Answers](http://www.yahooanswers.com)
Any user A can evaluate any user B:

- Positive (+) vs. negative (−) evaluation

In what (online) settings does this process naturally occur at large scale?

- **Epinions**: Trust/Distrust (1M evals)
  - Does A trust B’s product reviews?

- **Wikipedia**: Support/Oppose (150k votes)
  - Does A support B to become Wiki admin?

- **Stackoverflow**: Up/down vote (6M votes)
  - Does A think B contributed a good answer?
How do properties of *evaluator A* and *target B* affect A’s vote?

Two natural (but competing) hypotheses:

1. Prob. that B receives a positive evaluation depends primarily on the characteristics of B
   - There is some objective criteria for a user to receive a positive evaluation
How do properties of evaluator A and target B affect A’s vote?

Two natural (but competing) hypotheses:

(2) Prob. that B receives a positive evaluation depends on relationship between characteristics of A and B

- **Similarity**: Prior interaction between A and B
- **Status**: A compares status of B to her own status
Ways to quantify status (seniority, merit) of a user:

- Total number of *edits* of a user:
  - The more edits the user made the higher status she has

- Total number of *answers* of a user:
  - The more answers given by the user the higher status she has
How does the prob. of A evaluating positively depend on the status of A and status of B?

- Model it as a function of status $S_A$ of A and $S_B$ of B separately?
- Model as the status difference $S_A - S_B$?
- Model as the status ratio $S_A / S_B$?
How does status of B affect A’s evaluation?

- Each curve is fixed status difference: $\Delta = S_A - S_B$

Observations:

- Flat curves: Prob. of positive evaluation doesn’t depend on B’s status
- Different levels: Different values of $\Delta$ result in different behavior

Status difference remains salient even as A and B acquire more status
How does status of B affect A’s evaluation?

- Each curve is fixed status difference: $\Delta = S_A - S_B$

Observations:

- Below some threshold targets are judged based on their absolute status
- And independently of evaluator’s status
How does prior interaction shape evaluations?

1. Evaluators are more supportive of targets in their area
2. More familiar evaluators know weaknesses and are more harsh

Observation:
Prior interaction/similarity increases prob. of a positive evaluation
Observation:
- Evaluation depends less on status when evaluator A is more informed.

Consequence:
- Evaluators use status as proxy for quality in the absence of direct knowledge of B.

Status is a proxy for quality when evaluator does not know the target.
Observation:
- Evaluators with higher status than the target are more similar to the target

Selection bias:
- High-status evaluators are more similar to the target

Elite evaluators vote on targets in their area of expertise
Evaluator A evaluates target B

Prob. of positive evaluation of A as a function of status difference: $\Delta = S_A - S_B$

- Hypothesis: Monotonically decreases
Puzzle: Status

- Prob. of positive evaluation of B as a function of status difference: $\Delta = S_A - S_B$

- Observations:
  - A is especially negative when status equals: $S_A = S_B$
  - “Mercy bounce” for $S_A > S_B$

How to explain the bounce?
Why most harsh at zero difference?

How to explain low aggregate evaluations given by users to others of same status?

- Not due to users being tough on each other
  - Similarity increases the positivity of evaluations

Possible (but wrong) explanation:

- Most targets have low status (small $\Delta > 0$)
- Low-status targets are judged on abs. status
  - The rebound persists even for high-status targets
Social media sites are governed by (often implicit) user evaluations.

Wikipedia voting process has an explicit, public and recorded process of evaluation.

Main characteristics:
- Importance of relative assessment: Status
- Importance of prior interaction: Similarity
- Diversity of individuals’ response functions

Application: Ballot-blind prediction
Ballot-blind prediction

- Predict Wikipedia elections without seeing the votes
  - Observe identities of the first $k(=5)$ people voting (but not how they voted)
  - Want to predict the election outcome (promotion/no promotion)

- Why is it hard?
  - Don’t see the votes (just voters)
  - Only see first 5 voters (10% of the election)
**Idea:** Split the status-similarity space \((s, \Delta)\) into 4 quadrants

**Model deviation in voter’s behavior when they evaluate a candidate from a particular quadrant:**

- \(d(s, \Delta)\) ... avg. deviation in fraction of positive votes
  - When voters evaluate a candidate \(C\) from a particular \((s, \Delta)\) quadrant, how does this change their behavior
Ballot-blind: the Model

- \(d(s, \Delta)\) ... signed deviation in the fraction of positive votes when \(E\) evaluates \(C\) of similarity \(s\) and status difference \(\Delta\)
  - \(P(E_i=1)\) ... prob. evaluator \(E\) votes + in election \(i\)
- The models:
  - Global \(M1:\) \[P(E_i = 1) = P_i + d(\Delta_i, s_i)\]
  - Personal \(M2:\)
    \[P(E_i = 1) = \alpha \cdot P_i(\Delta_i, s_i) + (1 - \alpha) \cdot d(\Delta_i, s_i)\]
    where \(P_i\) is empirical frac. of + votes of \(E\)
Results: Wikipedia

- Predictive accuracy of baselines:
  - Guessing: 52%
  - If we know votes: 85%
  - Bag-of-features $B_1$: 69%

- Model based on status and similarity:
  - Does not see votes
  - Sees only first 5 votes (10% of the lection)
  - Global model $M_1$: 76%
  - Personal model $M_2$: 75%

Audience composition predict audience’s reaction
Conclusion and reflections

- Online social systems are globally organized based on status
- Users use evaluations consistently regardless of a particular application
  - Near perfect generalization across datasets
- Audience composition helps predict audience’s reaction
- What kinds of opinions do people find helpful?
What do people find helpful?

What do people think about our recommendations and opinions?

Amazon.com for Dummies (Paperback)
by Nita Friedman (Author) "No one (except maybe Amazon.com founder Jeff Bezos) ever imagined that one day there would be a way that you could buy everything from books..." (more)
Key Phrases: secure server button, new page that appears, browse box, Amazon Payments, Associates Central, Society Stories (more...)

Available from these sellers.

4 of 14 people found the following review helpful:

problems with navigating amazon.com?, November 18, 2005
By Gary Kuhlman "speedk0re" (Irvine, CA USA) - See all my reviews

ok so i've never read this book, but if you need a book to navigate amazon.com, then you should just give me your money instead. i mean, i know it's hard to type a word and press enter, and then press buy; i think the real difficulty of amazon.com is how the author managed to write XXX pages about navigating amazon.com. having said that, it almost makes me want to buy this book, so i'm changing my 1 Star to 2.

Help other customers find the most helpful reviews
Was this review helpful to you? Yes No

4/13/2011

Jure Leskovec: How people evaluate one another?
People find conforming opinions more helpful
Review helpfulness: Deviation

- Positive reviews are more helpful

[Danescu et al., 2009]
Tutorial Outline

- Part 1: Information flow in networks
- Part 2: Rich interactions
- Conclusion and reflections
Part 1: Information flow

- Messages arriving through networks from real-time sources requires new ways of thinking about information dynamics and consumption

- “Tell me about X” vs. “Tell me what I need to know now”
Diffusion of Topics and Sentiment
- How news cascade through on-line networks
- Do we need new notions of rank/importance?

Incentives and Diffusion
- Using diffusion in the design of on-line systems
- Connections to game theory

When will one cascade overtake the other?
Part 1: Opportunities

- A number of novel opportunities:
  - Predictive modeling of the spread of new ideas and behaviors
  - Opportunity to design systems that make use of diffusion process

- Applications:
  - Search
  - Real-time search
  - Social search
Part 2: Rich Interactions

- Links are more than just links
  - Strengths
  - Sentiment
  - They reveal what we think of others

- Main characteristics:
  - Importance of relative assessment: Status
  - Importance of prior interaction: Similarity
Part 2: Connections

- Don’t predict just who we link to but also what we think of them
- Evaluations range from evaluating a person to the content they produced
- Different dimensions of the evaluation:
  - Is the content technically correct?
  - Do I agree/disagree with the answer?
Part 2: Opportunities

- Composition of an audience can tell us something about the audience’s reaction
  - Predict outcomes simply from the statuses and similarities of the users who show up to provide evaluations, without ever seeing the values of the evaluations themselves
  - Connections to collaborative filtering

- Design reputation systems that account for status and similarity and encourage interaction
<table>
<thead>
<tr>
<th>The Road Ahead</th>
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</thead>
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<table>
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<tr>
<th>Strengths</th>
<th>Weaknesses</th>
</tr>
</thead>
<tbody>
<tr>
<td>■ free form facilitates capturing the true voice of customer, wisdom of crowd</td>
<td>■ language analysis and mining are challenging</td>
</tr>
<tr>
<td>■ can be expressed through voice, text messaging on mobile phones, etc.</td>
<td>■ susceptible to spam, self-serving use by companies</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Threats</th>
<th>Opportunities</th>
</tr>
</thead>
<tbody>
<tr>
<td>■ privacy and security issues: possible to assimilate detailed knowledge about person’s activities, whereabouts</td>
<td>■ promise of collective problem solving: coordination, cooperation</td>
</tr>
<tr>
<td>■ can lead to anti-social behavior!</td>
<td>■ mobile use supports dealing with societal problems, disaster situations: social network is geospatial proximity</td>
</tr>
</tbody>
</table>