Social Recommendation with Interpersonal Influence

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Outline

• What is a social recommendation
• Background
• Preliminary studies
• Our approach
• Empirical results
• Conclusions
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What is a social recommendation

• A person (sender) recommends a certain item to another one (receiver)
  – Daily life: a professor recommends a reference book to his student, or a girl recommends a clothing shop to her roommate
  – Online: sends a notification to recommend an item to online friend, e.g., douban.com, facebook.com, etc.
Traditional and social recommendation

Traditional recommendation: system-to-man
Traditional and social recommendation

Traditional recommendation: system-to-man

Social recommendation: man-to-man
Traditional and social recommendation (cont.)

• Man-to-man vs system-to-man: interpersonal influence
  – Social recommendations from friends are more reliable, accuracy and appropriate than the traditional recommendations [Sinha 2001]
If we can model social recommendations...

- Better understand social activities
- Investigate new applications
  - e.g. automatically recommend a product to a potential costumer by reminding him that a certain friend has already bought it.
To model social recommendations

- A social recommendation is a triple
  - (sender, receiver, item)
To model social recommendations (cont.)

• Conventional approaches capture partial aspects
  – Standard recommendation methods: focusing on (receiver, item)
    • content-based, collaborative filtering, matrix factorization, etc.
  – Trust-based recommendation methods: relying on manually assigned trust or correlation between (receiver, item) pairs
  – Innovation diffusion models: focusing on (sender, receiver)
    • Independent cascade, linear threshold
To model social recommendations (cont.)

• Our Approach
  – *Social utility* defined to measure the usefulness of a triple (sender, receiver, item) with three factors
    • Receiver interest
    • Item quality
    • Interpersonal influence
  – Acceptance tendency increases with social utility
    • A probabilistic model could be built to predict
A concept to clarify

• Is interpersonal influence something like user similarity?
  – User similarity: content-dependent, sociality-free
  – Interpersonal influence: content-free, sociality-dependent
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Traditional recommendation systems

• To predict how useful an item $a$ might be to a user $u$
  – Ways to extrapolate utility $f(u,a)$ based on a (small) known subspace of $UxA$
    • Content-based
    • Collaborative filtering
    • Matrix factorization
    • etc.
Collaborative filtering

• User-based: estimate utility with similar users
  – Users sharing similar transactions hold similar interests

• Item-based: estimate utility with similar items
  – Items sharing similar customers have similar qualities
  
  e.g. Amazon believes “customers who bought X-men also bought Star Trek”
Collaborative filtering (cont.)

• Trust-based: taking *user trust* into consideration
  – Manually assigned: scalability limited
  – Automatically mined:
    • Profile- and item-level trust [O’Donovan 05]: using global authority instead of interpersonal influence
    • User preference, general acceptance and social influence [He 09]: influence measured by behavior similarity
Innovation diffusion models

• Social network: a group of relationships and interactions within a set of individuals
• Innovation diffusion: individuals are likely to act like what friends do
  – Spread probability is determined by neighboring individuals
  – Typical application: viral marketing
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Data

• Data collected from douban.com
  – 35,211 users
  – 231,600 directed edges
  – 7,987 items (movies, books and music)
  – 1,174,627 social recommendations
    • 62,451 successful social recommendations
Factor Analysis

- Does interpersonal influence take effect in a social recommendation?
- Calculate two factors: receiver-item utility and sender-receiver influence

\[
Utility(v, a) = \frac{1}{|A(v)|} \sum_{a' \in A(v)} \frac{|C_a \cap C_{a'}|}{\sqrt{|C_a| \cdot |C_{a'}|}}
\]

\[
Influence(u, v) = \frac{|Acc(u, v)|}{|Rec(u, v)|}
\]
Conclusion: interpersonal influence does affect social recommendations
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A Simple Scenario

• Brown recommends *Twilight* to Ariel
  – Ariel: a big fan of drama and fantasy movies
  – *Twilight*: a drama and thriller movie named with a box office record
  – Brown: recommended several pretty cool drama and fantasy movies before
A Simple Scenario (cont.)

• What makes Ariel decide to watch the movie?

<table>
<thead>
<tr>
<th></th>
<th>drama</th>
<th>fantasy</th>
<th>thriller</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ariel is a fan of</td>
<td>√</td>
<td>√</td>
<td></td>
</tr>
<tr>
<td>Box office record in</td>
<td>√</td>
<td></td>
<td>√</td>
</tr>
<tr>
<td>Ariel believes Brown’s taste on</td>
<td>√</td>
<td>√</td>
<td></td>
</tr>
</tbody>
</table>
Social Utility

• Social utility: usefulness of the item, recommended by the human sender, to the receiver.
Social Utility (cont.)

• Divide tastes into D domains
  – categories, subjects, styles
• Hidden variables are D-dim vectors
  – $I_u$: interests of user $u$
  – $Q_a$: quality of item $a$
  – $T_{u,v}$: interpersonal influence of user $v$ on $u$

$$f(u, v, a) = ||I_v \ast T_{uv} \ast Q_a||$$
Acceptance Probability

• Tendency to accept a social recommendation increases with its social utility

• Linear assumption

\[ p(\text{acc}|u, v, a) \propto f(u, v, a) \]

... and with certain constraints

\[ p(\text{acc}|u, v, a) = f(u, v, a) = \|I_v \ast T_{uv} \ast Q_a\| = \sqrt{\sum_{d=1}^{D} (I_{v,d}T_{uv,d}Q_{a,d})^2} \]
Learning

- Maximize social utility of accepted social recommendations, and minimize refused ones
  \[ \{\hat{I}, \hat{Q}, \hat{T}\} = \arg \max_{\{I, Q, T\}} \prod_{(u,v,a)} f(u, v, a)^{\delta(u,v,a)}(1 - f(u, v, a))^{1-\delta(u,v,a)} \]

- Objective function
  \[ L = \sum_{(u,v,a)} (\delta(u, v, a) \ln f(u, v, a) + (1 - \delta(u, v, a)) \ln(1 - f(u, v, a))) \]

- Iteratively update all I, T and Q with gradient ascent until convergence
  \[ \frac{\partial}{\partial I_{v,d}} L = \sum_{(u,v,a)} \frac{\delta(u, v, a) I_{v,d} T_{uv,d}^2 Q_{a,d}^2}{f^2(u, v, a)} - \frac{(1 - \delta(u, v, a)) I_{v,d} T_{uv,d}^2 Q_{a,d}^2}{f(u, v, a)(1 - f(u, v, a))} \]
Prediction

• For an unknown recommendation triple \((u, v, a)\), the model predicts \(\delta(u, v, a)\) whether it will succeed by comparing its social utility \(f(u, v, a)\) with a certain threshold \(\mu_p\)

\[
\hat{\delta}(u, v, a) = \begin{cases} 
1, & f(u, v, a) \geq \mu_p, \\
0, & f(u, v, a) < \mu_p.
\end{cases}
\]

– \(\mu_p\) is selected to best distinguish accepted/refused ones
– \(\mu_p\) can vary to make predictions tighter or looser
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Experiments

• 90% recommendations to train and 10% to test
• Methods to compare
  – Our model (Influence-based)
  – User-based collaborative filtering (Resnick)
  – Trust-based collaborative filtering
  – Independent cascade
Learning process

- Objective function increases until convergence
Learning process (cont.)

\[ F1 = \frac{2 \times \text{precision} \times \text{recall}}{\text{precision} + \text{recall}} \]
Selecting D

- Model with multiple aspects outperforms one with single aspect
Prediction accuracy

- Our method achieves better accuracy: higher F1 measure and lower 0-1 loss

<table>
<thead>
<tr>
<th>Method</th>
<th>F1 measure</th>
<th>Average 0-1 loss</th>
</tr>
</thead>
<tbody>
<tr>
<td>Resnick</td>
<td>0.113</td>
<td>0.723</td>
</tr>
<tr>
<td>Trust-based</td>
<td>0.142</td>
<td>0.457</td>
</tr>
<tr>
<td>Independent Cascade</td>
<td>0.175</td>
<td>0.215</td>
</tr>
<tr>
<td>Influence-based</td>
<td><strong>0.221</strong></td>
<td><strong>0.125</strong></td>
</tr>
</tbody>
</table>
Prediction precision-recall curve

![Graph showing prediction precision-recall curves for different models: Influence-based, Independent Cascade, Trust-based, and Resnick.](image)
Significance Check

• Our method could best distinguish accepted and refused recommendations

<table>
<thead>
<tr>
<th>Method</th>
<th>Average and variance of predictions</th>
<th>T-test</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>accepted recommendations</td>
<td>refused recommendations</td>
</tr>
<tr>
<td>Resnick</td>
<td>0.177(0.061)</td>
<td>0.456(0.525)</td>
</tr>
<tr>
<td>Trust-based</td>
<td>-0.156(0.536)</td>
<td>-0.525(0.609)</td>
</tr>
<tr>
<td>Independent Cascade</td>
<td>0.159(0.080)</td>
<td>0.047(0.032)</td>
</tr>
<tr>
<td>Influence-based</td>
<td>0.157(0.073)</td>
<td>0.016(0.008)</td>
</tr>
</tbody>
</table>
## Case study: Adam’s behavior

<table>
<thead>
<tr>
<th>Item recommended</th>
<th>Slumdog Millionaire</th>
<th>Slumdog Millionaire</th>
<th>Mad Detective</th>
</tr>
</thead>
<tbody>
<tr>
<td>Recommended by</td>
<td>Bob</td>
<td>Carol</td>
<td>Carol</td>
</tr>
<tr>
<td>Adam’s reaction</td>
<td>ignore</td>
<td>accept</td>
<td>ignore</td>
</tr>
<tr>
<td>Resnick utility</td>
<td>0.83</td>
<td>0.83</td>
<td>-0.27</td>
</tr>
<tr>
<td>Trust-based utility</td>
<td>-0.52</td>
<td>-0.52</td>
<td>-0.49</td>
</tr>
<tr>
<td>Independent Cascade probability</td>
<td>0.22</td>
<td>0.66</td>
<td>0.66</td>
</tr>
<tr>
<td>Influence-based social utility</td>
<td>0.65</td>
<td>0.82</td>
<td>0.77</td>
</tr>
</tbody>
</table>
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Conclusion

• Social recommendation: a new and better way than standard recommender systems
• Modeling with receiver interests, item quality, interpersonal influence
• Prediction error down by 26%, compared with conventional methods
Thanks

• Comments are welcome.

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