New Objective Functions for Social Collaborative Filtering

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National ICT Australia Ltd (NICTA) and ANU

linkr.anu.edu.au
Overview

• Problem: Social Recommendation
• Current Solutions
• New Solutions
• Live Facebook User Trials and Results

• Conclusions and Future Work
THE PROBLEM
The Problem

• Internet: vast amount of content
  – 800+ million Facebook users
  – Average 300 friends on Facebook

• How to find personal interests?
  – What do you like?

• (Social) Recommendation
  – What would you like?
  – How to exploit social networks?
Recommendation

- Predict **missing** from **observed** ratings?

**Canonical Example:**

Netflix Competition

...1-5 ratings, here: like (1), dislike (0)
Social Recommendation

- Adds indirect social context to users

\[ R = \begin{pmatrix}
1 & 1 & 1 & 0 & ? & 0 \\
1 & 0 & ? & 0 & 0 \\
\vdots & \vdots & \vdots & \vdots & \vdots \\
0 & 0 & 0 & 1 & ? \\
\end{pmatrix} \]

Main question in this work:

How to incorporate social context to improve predictions?
CURRENT SOLUTIONS
Content-based Filtering (CBF)

- Predict like / dislike directly from features

\[ R = \begin{pmatrix}
1 & 1 & 1 & 0 & ? & 0 \\
1 & 0 & ? & 0 & 0 & 0 \\
0 & 0 & 1 & ? & \end{pmatrix} \]

- Sci-Fi, Director: Mel Brooks
- Romance, Starring: Julia Roberts, Richard Gere

\[ R(\text{user } x, \text{ movie } y) = f(\Phi_x, \Phi_y) \]

Trained classifier, e.g. SVM
Collaborative Filtering (CF): KNN

• No features? k-nearest neighbor, e.g., \( k=2 \)

\[
\begin{pmatrix}
1 & 1 & 1 & 0 & ? & 0 \\
1 & 0 & ? & 0 & 0 & 0 \\
\vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\
0 & 0 & 1 & ? & \end{pmatrix}
\]

\[
\text{R} = \frac{0.71 \times 1 + 0.50 \times 0}{0.71 + 0.50} = 0.59
\]
Collaborative Filtering: PMF

• Or low \( k \)-rank matrix factorization, e.g. \( k=2 \)

\[
R = \begin{pmatrix}
1 & 1 & 1 & 0 & ? & 0 \\
1 & 0 & ? & 0 & 0 & 0 \\
0 & 0 & 1 & ? & 0 & 0
\end{pmatrix}
\]

\[
\begin{align*}
U^T & = \begin{pmatrix}
.7 & .3 \\
.5 & -.2 \\
.3 & -.7
\end{pmatrix} \\
V & = \begin{pmatrix}
.9 \\
.9 \\
.1
\end{pmatrix}
\end{align*}
\]

Standard PMF CF Objective (reg. not shown), novel objectives build on this.
Features in CF: **Matchbox**

\[
R = \begin{pmatrix}
1 & 1 & 1 & 0 & ? & 0 \\
1 & 0 & ? & 0 & 0 & 0 \\
0 & 0 & 1 & ? & & \\
\end{pmatrix}
\]

\[
(Ux)^T = \begin{pmatrix}
.7 & .3 \\
.5 & -.2 \\
.9 & .3 \\
\end{pmatrix}
\]

\[
Vy = \begin{pmatrix}
.9 & .1 \\
.3 & -.7 \\
\end{pmatrix}
\]

Project features into latent space – helps cold-start problem.

Reduces to previous PMF CF if \( x, y \) are indicators.

\[
\min_{U, V} \sum_{(x, y) \in D} \frac{1}{2} (R_{x,y} - [\sigma]x^T U^T V y)^2
\]
Social Collaborative Filtering

\[ R = \begin{bmatrix}
1 & 1 & 1 & 0 & ? & 0 \\
1 & 0 & ? & 0 & 0 \\
0 & 0 & 1 & ? \\
\end{bmatrix} \]

- **PMF + Social Regularization**
  \[
  \min_U \sum_x \sum_{z \in \text{friends}_x} \frac{1}{2} (S_{x,z} - \langle U_x, U_z \rangle)^2
  \]

- **PMF + Social Spectral Reg.**
  \[
  \min_U \sum_x \sum_{z \in \text{friends}_x} \frac{1}{2} S_{x,z}^+ \| U_x - U_z \|_2^2
  \]

\[ Int_{x,z} = \frac{1}{N(N-1)} \sum_{x',z' \neq x'} \# \text{ interactions by } x \]

\[ S_{x,z} = \ln (Int_{x,z}) \]

Check out this awesome link!

Like!

Extra cute baby!

Like!
NEW SOLUTIONS
Objective Framework

\[
\min_{w, U, V} \text{Obj} = \sum_{i} \lambda_i \text{Obj}_i
\]

**Standard Error Objective**

\[
\text{Obj}_{pmcf} = \sum_{(x,y) \in D} \frac{1}{2} (R_{x,y} - [\sigma] x^T U^T V y)^2
\]

**Standard Regularizers**

\[
\text{Obj}_{ru} = \frac{1}{2} \|U\|_F^2 = \frac{1}{2} \text{tr}(U^T U) \quad \text{Obj}_{rv} = \frac{1}{2} \text{tr}(V^T V)
\]

\[
\text{Obj}_{rw} = \frac{1}{2} \|w\|_2^2 = \frac{1}{2} w^T w
\]

**Social Regularizers**

\[
\text{Obj}_{rs} = \sum_x \sum_{z \in \text{friends}(x)} \frac{1}{2} (S_{x,z} - \langle Ux, Uz \rangle)^2
\]

Prediction objectives and regularizers to constrain learning.

Other predictors aside from MF?

This is first proposal... feature-based S.R.

Other social regularizers?
Proposal 1 ½

• Use interactions to learn latent **spectral** projection of **user and features**

\[
\text{Obj}_{rss} = \sum_{x} \sum_{z \in \text{friends}(x)} \frac{1}{2} S_{x,z}^+ \left\| Ux - Uz \right\|_2^2
\]

\[
= \sum_{x} \sum_{z \in \text{friends}(x)} \frac{1}{2} S_{x,z}^+ (x - z)^T U^T U (x - z)
\]

Don’t predict \( S_{x,z} \); use it to vary regularization strength!
Proposal II

– Directly model information diffusion

\[ Obj_{phy} = \sum_{(x,y) \in D} \frac{1}{2} (R_{x,y} - [\sigma] w^T f_{x,y} - [\sigma] x^T U^T V y)^2 \]

Features such as:
Did user z (a friend of x), also like y?
Proposal III

• Exploit the fact that users have common interests in restricted areas
  – Use co-preferences $P_{x,z,y}$
    • Did users $x$ and $z$ (dis)like item $y$?

$$Obj_{cp} = \sum_{(x,z,y) \in C} \frac{1}{2} (P_{x,z,y} - \langle U_x, U_z \rangle V_y)^2$$

$$= \sum_{(x,z,y) \in C} \frac{1}{2} (P_{x,z,y} - x^T U^T \text{diag}(V_y) U z)^2$$

– And also spectral variant

Reweight user regularization according to latent dimensions for co-preferred item.
USER TRIALS
ANU Link Recommender (LinkR)

- Recommend 3 daily links on Facebook

  - **Non-friend Recommendation** (only link context)
  - **Rating + Optional Link Feedback**
  - **Friend Recommendation** (friend message + link context)
Trials and Algorithms

• **Trial 1: Baselines**
  
  – **SVM** (Content-based filtering – CBF)
  
  – **KNN** (Collaborative filtering – CF)
  
  – Matchbox – **MB** (CF + CBF)
  
  – Social Matchbox – **SMB** (CBF + CF + Soc. Reg)

• **Trial 2: New Objectives**
  
  – **SMB**
  
  – Spectral Reg. variant of SMB – **Sp. MB**
  
  – SMB + Information Diffusion – **S. Hybrid**
  
  – MB + Spectral Copreference Reg. – **S. CP**
## LinkR Statistics

<table>
<thead>
<tr>
<th>Table</th>
<th>#Records (App Users)</th>
<th>#Records (App User and Friends)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Users</td>
<td>103</td>
<td>39,850</td>
</tr>
<tr>
<td>Gender</td>
<td>102</td>
<td>36,401</td>
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<tr>
<td>Birthday</td>
<td>103</td>
<td>27,624</td>
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<table>
<thead>
<tr>
<th>Column</th>
<th>#Non-empty (App Users)</th>
<th>#Non-empty (App User and Friends)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Breakdown</th>
<th>Count (App Users)</th>
<th>Count (App User and Friends)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Male</td>
<td>73</td>
<td>19,742</td>
</tr>
<tr>
<td>Female</td>
<td>29</td>
<td>16,659</td>
</tr>
<tr>
<td>High School</td>
<td>104</td>
<td>29,503</td>
</tr>
<tr>
<td>College</td>
<td>115</td>
<td>29,223</td>
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<tr>
<td>Graduate School</td>
<td>56</td>
<td>7733</td>
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</table>

<table>
<thead>
<tr>
<th>App Users</th>
<th>Posts</th>
<th>Tags</th>
<th>Comments</th>
<th>Likes</th>
</tr>
</thead>
<tbody>
<tr>
<td>Wall</td>
<td>27,955</td>
<td>5,256</td>
<td>15,121</td>
<td>11,033</td>
</tr>
<tr>
<td>Link</td>
<td>3,974</td>
<td>—</td>
<td>5,757</td>
<td>4,279</td>
</tr>
<tr>
<td>Photo</td>
<td>4,147</td>
<td>22,633</td>
<td>8,677</td>
<td>5,938</td>
</tr>
<tr>
<td>Video</td>
<td>211</td>
<td>2,105</td>
<td>1,687</td>
<td>710</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>App Users and Friends</th>
<th>Posts</th>
<th>Tags</th>
<th>Comments</th>
<th>Likes</th>
</tr>
</thead>
<tbody>
<tr>
<td>Wall</td>
<td>3,384,740</td>
<td>912,687</td>
<td>2,152,321</td>
<td>1,555,225</td>
</tr>
<tr>
<td>Link</td>
<td>514,475</td>
<td>—</td>
<td>693,930</td>
<td>666,631</td>
</tr>
<tr>
<td>Photo</td>
<td>1,098,679</td>
<td>8,407,822</td>
<td>2,978,635</td>
<td>1,960,138</td>
</tr>
<tr>
<td>Video</td>
<td>56,241</td>
<td>858,054</td>
<td>463,401</td>
<td>308,763</td>
</tr>
</tbody>
</table>
# LinkR Usage Statistics

## Trial 1 – Aug. 25, 2011 to Oct. 13, 2011

<table>
<thead>
<tr>
<th></th>
<th>SMB</th>
<th>MB</th>
<th>SVM</th>
<th>KNN</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Users All</td>
<td>26</td>
<td>26</td>
<td>28</td>
<td>28</td>
<td>108</td>
</tr>
<tr>
<td>Users ≥ 10</td>
<td>13</td>
<td>9</td>
<td>13</td>
<td>3</td>
<td>40</td>
</tr>
<tr>
<td>Users ≥ 30</td>
<td>9</td>
<td>3</td>
<td>11</td>
<td>3</td>
<td>26</td>
</tr>
<tr>
<td>Ratings All</td>
<td>819</td>
<td>526</td>
<td>901</td>
<td>242</td>
<td>2508</td>
</tr>
<tr>
<td>Ratings ≥ 10</td>
<td>811</td>
<td>505</td>
<td>896</td>
<td>228</td>
<td>2440</td>
</tr>
<tr>
<td>Ratings ≥ 30</td>
<td>737</td>
<td>389</td>
<td>851</td>
<td>182</td>
<td>2159</td>
</tr>
<tr>
<td>Clicks All</td>
<td>383</td>
<td>245</td>
<td>413</td>
<td>218</td>
<td>1259</td>
</tr>
</tbody>
</table>


<table>
<thead>
<tr>
<th></th>
<th>SMB</th>
<th>Sp.MB</th>
<th>Sp.CP</th>
<th>SHyb.</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Users All</td>
<td>27</td>
<td>27</td>
<td>29</td>
<td>28</td>
<td>111</td>
</tr>
<tr>
<td>Users ≥ 10</td>
<td>15</td>
<td>11</td>
<td>8</td>
<td>12</td>
<td>46</td>
</tr>
<tr>
<td>Users ≥ 30</td>
<td>12</td>
<td>9</td>
<td>5</td>
<td>10</td>
<td>36</td>
</tr>
<tr>
<td>Ratings All</td>
<td>1434</td>
<td>882</td>
<td>879</td>
<td>614</td>
<td>3809</td>
</tr>
<tr>
<td>Ratings ≥ 10</td>
<td>1411</td>
<td>878</td>
<td>863</td>
<td>602</td>
<td>3754</td>
</tr>
<tr>
<td>Ratings ≥ 30</td>
<td>1348</td>
<td>850</td>
<td>802</td>
<td>570</td>
<td>3570</td>
</tr>
<tr>
<td>Clicks All</td>
<td>553</td>
<td>320</td>
<td>278</td>
<td>199</td>
<td>1350</td>
</tr>
</tbody>
</table>
RESULTS
Likes (dark) over Dislikes (light)

Lower is better

Recommendations from Friends

Recommendations from non-Friends
Trial 2: New Objectives

Friends

Non-friends
Impact of Popularity

Likes vs. Popularity for Friend Links

Likes vs. Popularity for Non-Friend Links

Popularity (0% = Least, 100% = Most)
CONCLUSIONS AND FUTURE WORK
Conclusions

• Feature-based social spectral regularization
  – Undeniably the top-performer
  – As good as direct information diffusion features
  – Interactions stronger than co-preferences
    • Or co-preferences harder to optimize?
Conclusions

• Overall
  – Machine learning works!
    • Better than more ad-hoc methods like KNN
    • Power of latent factorization methods
  – Use socially informed regularizers!
    • In general, users who interact a lot have similar preferences!
Future Work

• Are all interactions equal?

• No!
  – Learning predictiveness of fine-grained interactions can do as well as MF, but with simple classifiers!
  – Work in progress...
Special Thanks to

- **Doug Aberdeen** (Google Zurich) for supporting our Google Grant
- **Sally-Ann Williams** (Google Sydney) for 100+ pairs of Google flip-flops, which helped attract many users to our study!

**THANK YOU!**

[linkr.anu.edu.au](https://linkr.anu.edu.au)

- More information
- Link to Facebook app
- Contact Us!
Additional Slides
Experimental Design in Retrospect

- Experimental design
  - Originally wanted to do active learning
    - In our Google Grant proposal
    - But with user uptake, difficult to evaluate this
      - Need very active users (only 25% were active)
  - Algorithms trialed can be evaluated for varied usage
    - All data counts, good!
    - But stuck to original experimental design for consistency
      - Hard to statistically compare small user groups
      - If do again, would interleave interactions
  - But main results of Spec. MB fairly sound
Aside: Matrix Definitions

\[
U = \begin{bmatrix}
U_{1,1} & \cdots & U_{1,I} \\
\vdots & \ddots & \vdots \\
U_{K,1} & \cdots & U_{K,I}
\end{bmatrix}
\]

\[
V = \begin{bmatrix}
V_{1,1} & \cdots & V_{1,J} \\
\vdots & \ddots & \vdots \\
V_{K,1} & \cdots & V_{K,J}
\end{bmatrix}
\]
Proposal I

• Use interactions to learn latent projection of user and features

\[
Obj_{rs} = \sum_{x} \sum_{z \in friends(x)} \frac{1}{2} (S_{x,z} - \langle Ux, Uz \rangle)^2
\]

\[
= \sum_{x} \sum_{z \in friends(x)} \frac{1}{2} (S_{x,z} - x^T U^T U z)^2
\]
## Individual Link Comments

<table>
<thead>
<tr>
<th>Comment Type</th>
<th>#</th>
<th>%</th>
</tr>
</thead>
<tbody>
<tr>
<td>not interested</td>
<td>88</td>
<td>36.5%</td>
</tr>
<tr>
<td>wrong language</td>
<td>37</td>
<td>15.4%</td>
</tr>
<tr>
<td>really liked it!</td>
<td>35</td>
<td>14.5%</td>
</tr>
<tr>
<td>bad YouTube</td>
<td>25</td>
<td>10.4%</td>
</tr>
<tr>
<td>seen it already</td>
<td>25</td>
<td>10.4%</td>
</tr>
<tr>
<td>problem / dead</td>
<td>20</td>
<td>8.3%</td>
</tr>
<tr>
<td>outdated</td>
<td>7</td>
<td>2.9%</td>
</tr>
<tr>
<td>miscellaneous</td>
<td>4</td>
<td>1.7%</td>
</tr>
</tbody>
</table>
## Survey

User Survey Comments

<table>
<thead>
<tr>
<th>Comment</th>
</tr>
</thead>
<tbody>
<tr>
<td>want more control over recommendations made (music, blogs, news)</td>
</tr>
<tr>
<td>want option to see &gt; 3 recommendations</td>
</tr>
<tr>
<td>links need description / context or explanation of recommendation</td>
</tr>
<tr>
<td>more variety, diversity</td>
</tr>
</tbody>
</table>