World Wide Web Conference 2012

New Objective Functions for Social Collaborative Filtering

Joseph Noel, Scott Sanner, Khoi-Nguyen Tran,
Peter Christen, Lexing Xie, Edwin Bonilla,
Ehsan Abbasnejad, Nicolas Della Penna

The Australian National University (ANU)
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?



$$
\begin{array}{l}
\text{Joseph} \\
\text{Nguyen} \\
\\
\text{Scott}
\end{array}
\quad
R = \begin{pmatrix}
1 & 1 & 1 & 0 & ? & 0 \\
1 & 0 & ? & 0 & 0 & \\
 & \vdots & & \vdots & & \vdots \\
 & 0 & 0 & & 1 & ?
\end{pmatrix}
$$

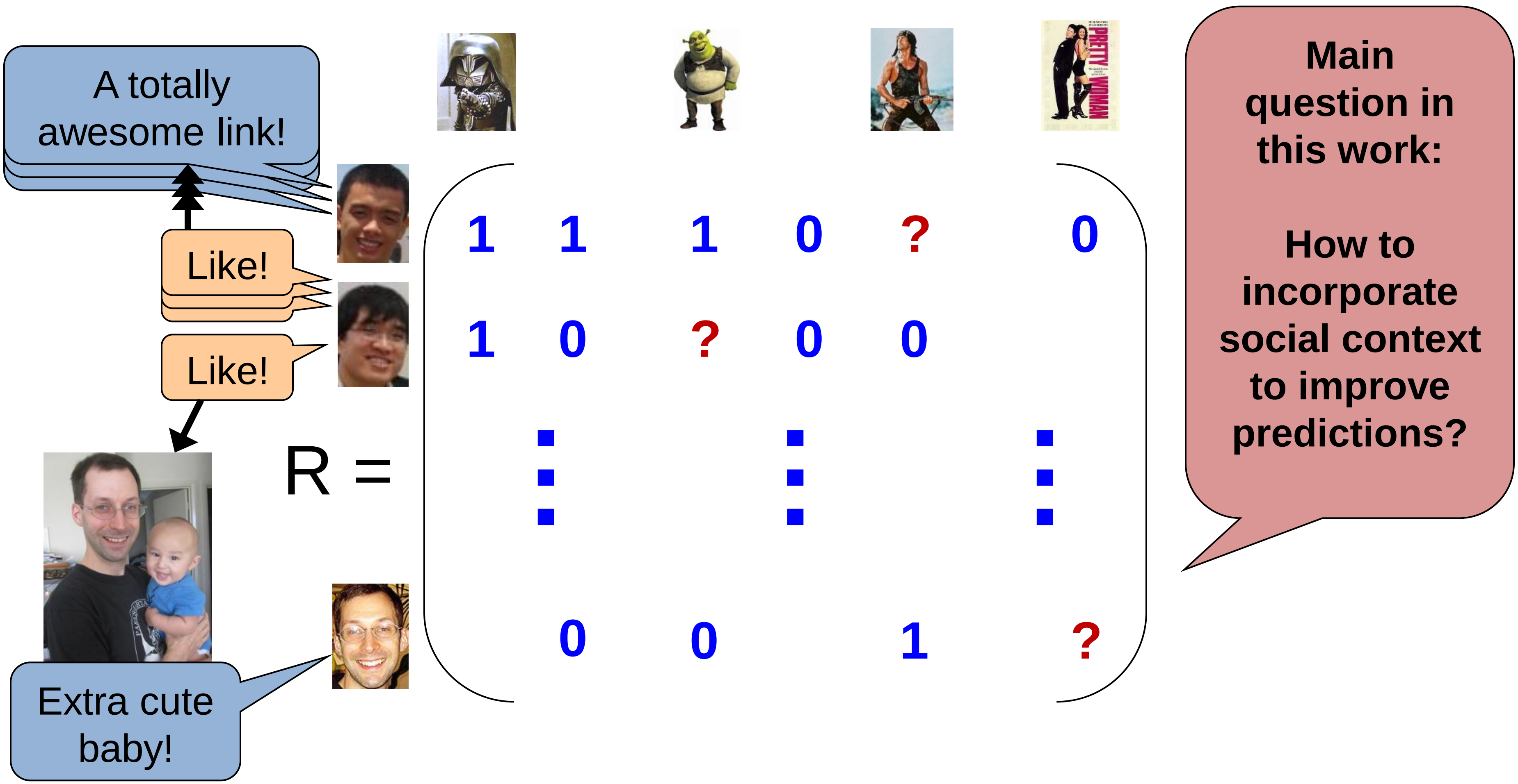
Canonical Example:

Netflix Competition

…1-5 ratings, here: like (1), dislike (0)

Social Recommendation

- Adds indirect social context to users



CURRENT SOLUTIONS

Content-based Filtering (CBF)

- Predict like / dislike directly from features

Sci-Fi, Director: Mel Brooks

Romance, Starring: Julia Roberts, Richard Gere

29, Male, Sydney

24, Male, Canberra

33, Male, Canberra

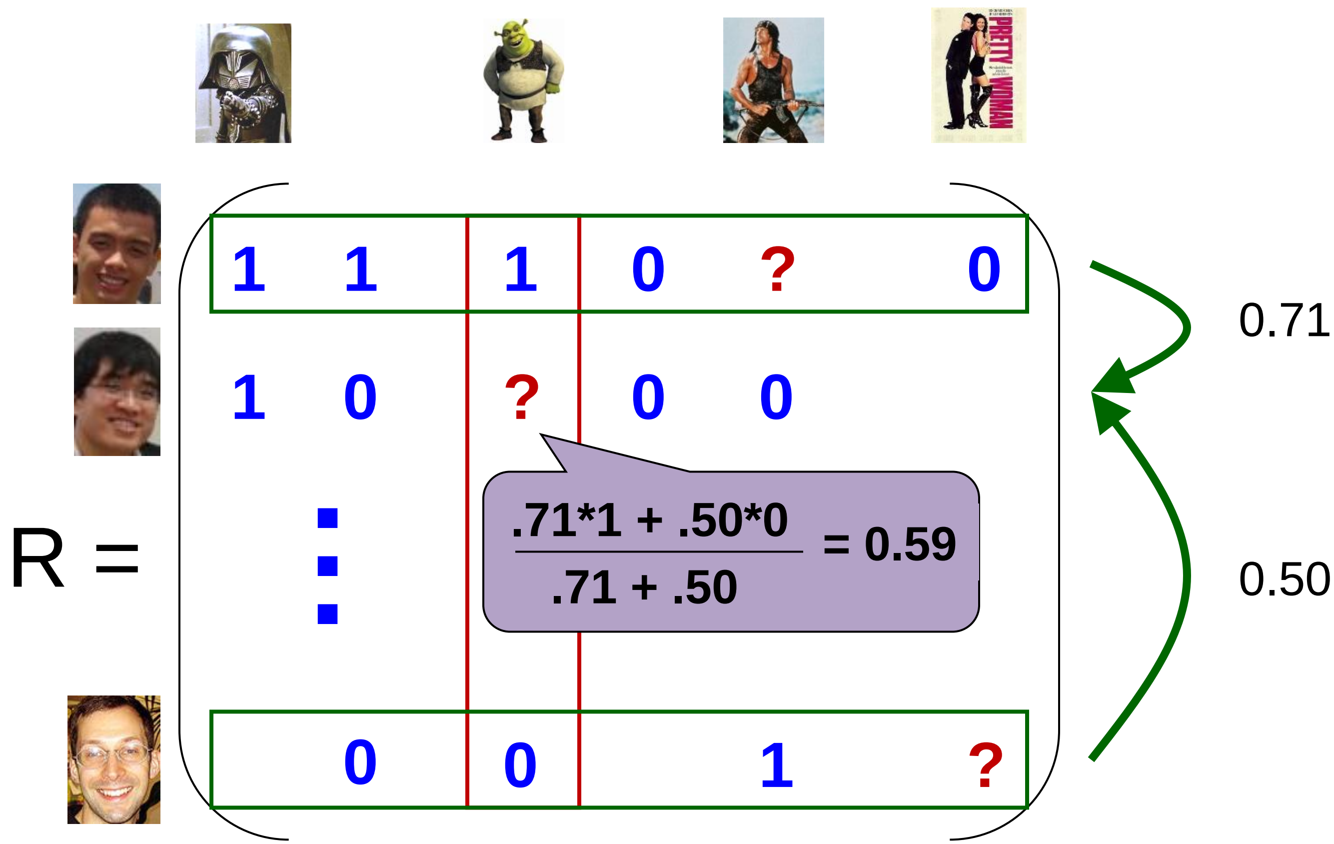
$$R = \begin{pmatrix} 1 & 1 & 1 & 0 & ? & 0 \\ 1 & 0 & ? & 0 & 0 & \\ & \vdots & & \vdots & & \vdots \\ & 0 & 0 & & 1 & ? \end{pmatrix}$$

R(user x, movie y) = f(Φ_x, Φ_y)

Trained classifier, e.g. SVM

Collaborative Filtering (CF): KNN

- No features? k-nearest neighbor, e.g., k=2



Collaborative Filtering: PMF

- Or low k-rank matrix factorization, e.g. k=2






$$R = \begin{pmatrix} 1 & 1 & 1 & 0 & ? & & 0 \\ 1 & 0 & ? & 0 & 0 & & \\ & \vdots & & \vdots & & & \vdots \\ & 0 & 0 & & 1 & & ? \end{pmatrix} = \overset{U^T}{\begin{pmatrix} .7 & .3 \\ .5 & -.2 \\ \vdots & \\ \boxed{-.1 \quad .9} & \end{pmatrix}} \overset{V}{\begin{pmatrix} \boxed{\begin{matrix} .9 \\ .3 \end{matrix}} & \cdots & \begin{matrix} .1 \\ -.7 \end{matrix} \end{pmatrix}}$$

Latent Item Features

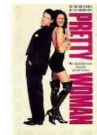
Latent User Features

Standard PMF CF Objective (reg. not shown), novel objectives build on this.

$$\min_{U,V} \sum_{(\mathbf{x},\mathbf{y}) \in D} \frac{1}{2} (R_{\mathbf{x},\mathbf{y}} - U_{\mathbf{x}}^T V_{\mathbf{y}})^2$$

Features in CF: Matchbox



$\boxed{(Ux)^T}$ $\boxed{Vy}$



$$R = \begin{pmatrix} 1 & 1 & 1 & 0 & ? & 0 \\ 1 & 0 & ? & 0 & 0 & \\ \vdots & & \vdots & & & \vdots \\ & 0 & 0 & & 1 & ? \end{pmatrix} = \begin{pmatrix} \boxed{.7 \quad .3} \\ .5 \quad -.2 \\ \vdots \\ -.1 \quad .9 \end{pmatrix} \begin{pmatrix} .9 & \cdots & .1 \\ .3 & & -.7 \end{pmatrix}$$

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

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

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

Social Collaborative Filtering

A totally awesome link!

Like!

Like!

Extra cute baby!

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

$$Int_{\mathbf{x},\mathbf{z}} = \frac{\#\ \text{interactions b}}{\frac{1}{N(N-1)} \sum_{\mathbf{x}',\mathbf{z}' \neq \mathbf{x}'} \#\ \text{interac}}$$

$$S_{\mathbf{x},\mathbf{z}} = \ln\left(Int_{\mathbf{x},\mathbf{z}}\right)$$

PMF + Social Regularization

$$\min_{U} \sum_{\mathbf{x}} \sum_{\mathbf{z} \in friends_{\mathbf{x}}} \frac{1}{2}\left(S_{\mathbf{x},\mathbf{z}} - \langle U_{\mathbf{x}}, U_{\mathbf{z}} \rangle\right)^2$$

PMF + Social Spectral Reg.

$$\min_{U} \sum_{\mathbf{x}} \sum_{\mathbf{z} \in friends_{\mathbf{x}}} \frac{1}{2} S^{+}_{\mathbf{x},\mathbf{z}} \|U_{\mathbf{x}} - U_{\mathbf{z}}\|_2^2$$

NEW SOLUTIONS

Objective Framework

$$\min_{\mathbf{w},\, U,\, V} Obj = \sum_i \lambda_i\, Obj_i$$

Prediction objectives and regularizers to constrain learning.

Standard Error Objective

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

Other predictors aside from MF?

Standard Regularizers

$$Obj_{ru} = \frac{1}{2}\|U\|^2_{\mathrm{Fro}} = \frac{1}{2}\,\mathrm{tr}(U^T U) \qquad Obj_{rv} = \frac{1}{2}\,\mathrm{tr}(V^T V)$$

$$Obj_{rw} = \frac{1}{2}\|\mathbf{w}\|^2_2 = \frac{1}{2}\mathbf{w}^T\mathbf{w}$$

Social Regularizers

$$Obj_{rs} = \sum_{\mathbf{x}} \sum_{\mathbf{z} \in friends(\mathbf{x})} \frac{1}{2} (S_{\mathbf{x},\mathbf{z}} - \langle U\mathbf{x}, U\mathbf{z}\rangle)^2$$

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**

Don't predict $S_{x,z}$, use it to vary regularization strength!

$$Obj_{rss} = \sum_{\mathbf{x}} \sum_{\mathbf{z} \in friends(\mathbf{x})} \frac{1}{2} S^{+}_{\mathbf{x},\mathbf{z}} \| U\mathbf{x} - U\mathbf{z} \|_2^2$$

$$= \sum_{\mathbf{x}} \sum_{\mathbf{z} \in friends(\mathbf{x})} \frac{1}{2} S^{+}_{\mathbf{x},\mathbf{z}} (\mathbf{x} - \mathbf{z})^T U^T U (\mathbf{x} - \mathbf{z})$$

Proposal II

– Directly **model information diffusion**

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

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?

Reweight user regularization according to latent dimensions for co-preferred item.

$$Obj_{cp} = \sum_{(\mathbf{x},\mathbf{z},\mathbf{y}) \in C} \frac{1}{2}\left(P_{\mathbf{x},\mathbf{z},\mathbf{y}} - \langle U\mathbf{x}, U\mathbf{z} \rangle_{V\mathbf{y}}\right)^2$$

$$= \sum_{(\mathbf{x},\mathbf{z},\mathbf{y}) \in C} \frac{1}{2}\left(P_{\mathbf{x},\mathbf{z},\mathbf{y}} - \mathbf{x}^T U^T \operatorname{diag}(V\mathbf{y}) U\mathbf{z}\right)^2$$

  - And also spectral variant

USER TRIALS

ANU Link Recommender (LinkR)

- Recommend 3 daily links on Facebook

 's App View

Non-friend Recommendation (only link context)

Rating + Optional Link Feedback

Friend Recommendation (friend message + link context)

http://www.youtube.com/watch?v=rtOvBOTyX00

Christina Perri - A Thousand Years (Official Music Video)
© 2011 WMG "a thousand years" on itunes:
http://atlr.ec/npHAdW directed by: jay martin "a thousand years" is a brand new song me + my best friend david hodge...

Rate this Recommendation: Not Rated Like Dislike
Comment: How was this recommendation? Save Comment

Post Link to Your Wall
Recommended on Mon, 30 Jan 2012 at 09:39

Original Post from Khoi-Nguyen Tran on Wed, 18 Jan 2012 at 05:00
Message: Religion for Atheists

http://www.ted.com/talks/alain_de_botton_atheism_2_0.html?awesm=on.ted.com_deBotton&utm_campaign=&utm_medium=on.ted.com-static&utm_source=direct-on.ted.com&utm_content=awesm-publisher

Alain de Botton: Atheism 2.0 | Video on TED.com
What aspects of religion should atheists (respectfully) adopt? Alain de Botton suggests a "religion for atheists" -- call it Atheism 2.0 -- that incorporates religious forms and traditions to satisfy our human need for connection, ritual and transcendence.

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	#Records (App Users)	#Records (App User and Friends)
Users	103	39,850
Column	**#Non-empty (App Users)**	**#Non-empty (App User and Friends)**
Gender	102	36,401
Birthday	103	27,624

Breakdown	Count (App Users)	Count (App User and Friends)
Male	73	19,742
Female	29	16,659
High School	104	29,503
College	115	29,223
Graduate School	56	7733

App Users	Posts	Tags	Comments	Likes
Wall	27,955	5,256	15,121	11,033
Link	3,974	—	5,757	4,279
Photo	4,147	22,633	8,677	5,938
Video	211	2,105	1,687	710
App Users and Friends	**Posts**	**Tags**	**Comments**	**Likes**
Wall	3,384,740	912,687	2,152,321	1,555,225
Link	514,475	—	693,930	666,631
Photo	1,098,679	8,407,822	2,978,635	1,960,138
Video	56,241	858,054	463,401	308,763

LinkR Usage Statistics

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

	SMB	MB	SVM	KNN	Total
Users All	26	26	28	28	108
Users ≥ 10	13	9	13	5	40
Users ≥ 30	9	3	11	3	26
Ratings All	819	526	901	242	2508
Ratings ≥ 10	811	505	896	228	2440
Ratings ≥ 30	737	389	851	182	2159
Clicks All	383	245	413	218	1259

Trial 2 – Oct. 14, 2011 to Feb. 10, 2012

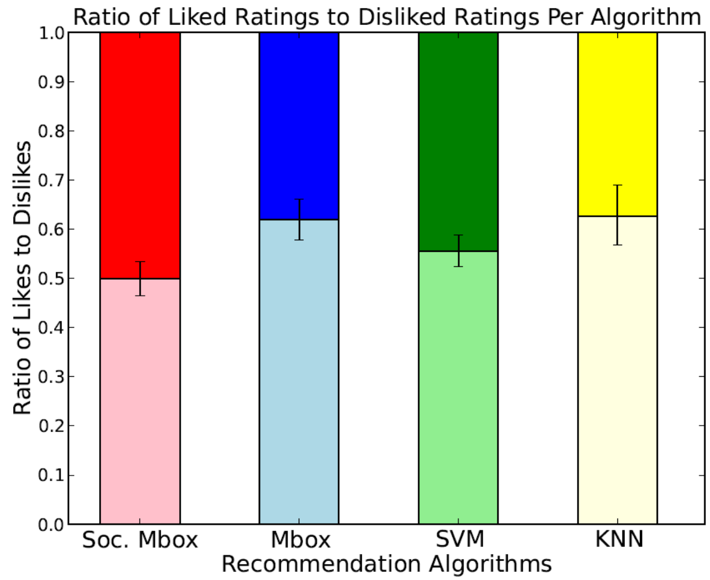
	SMB	Sp.MB	Sp.CP	SHyb.	Total
Users All	27	27	29	28	111
Users ≥ 10	15	11	8	12	46
Users ≥ 30	12	9	5	10	36
Ratings All	1434	882	879	614	3809
Ratings ≥ 10	1411	878	863	602	3754
Ratings ≥ 30	1348	850	802	570	3570
Clicks All	553	320	278	199	1350

RESULTS

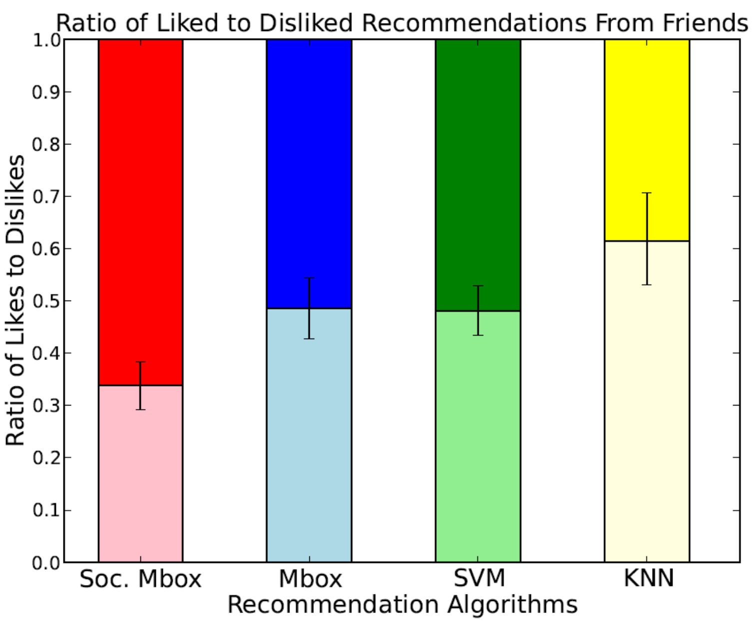
Trial 1: Baselines

Likes (dark)
over
Dislikes (light)

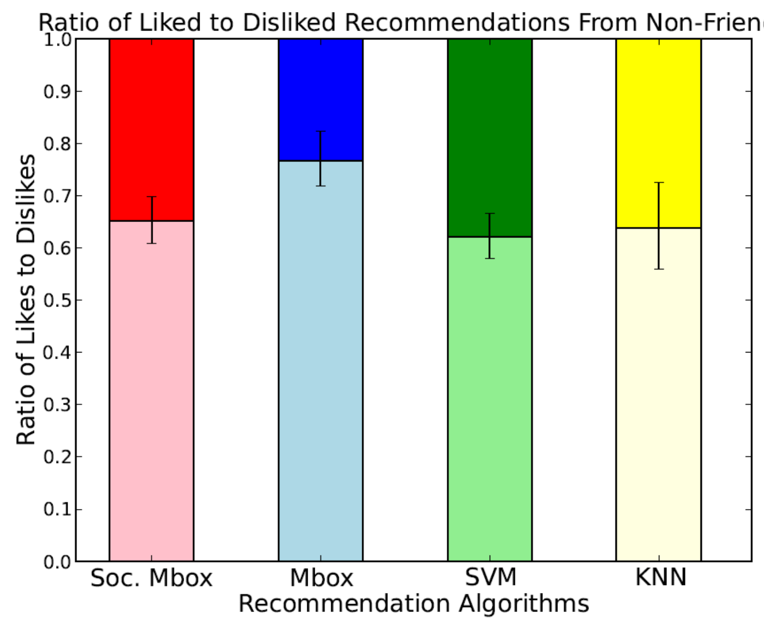
Lower is better



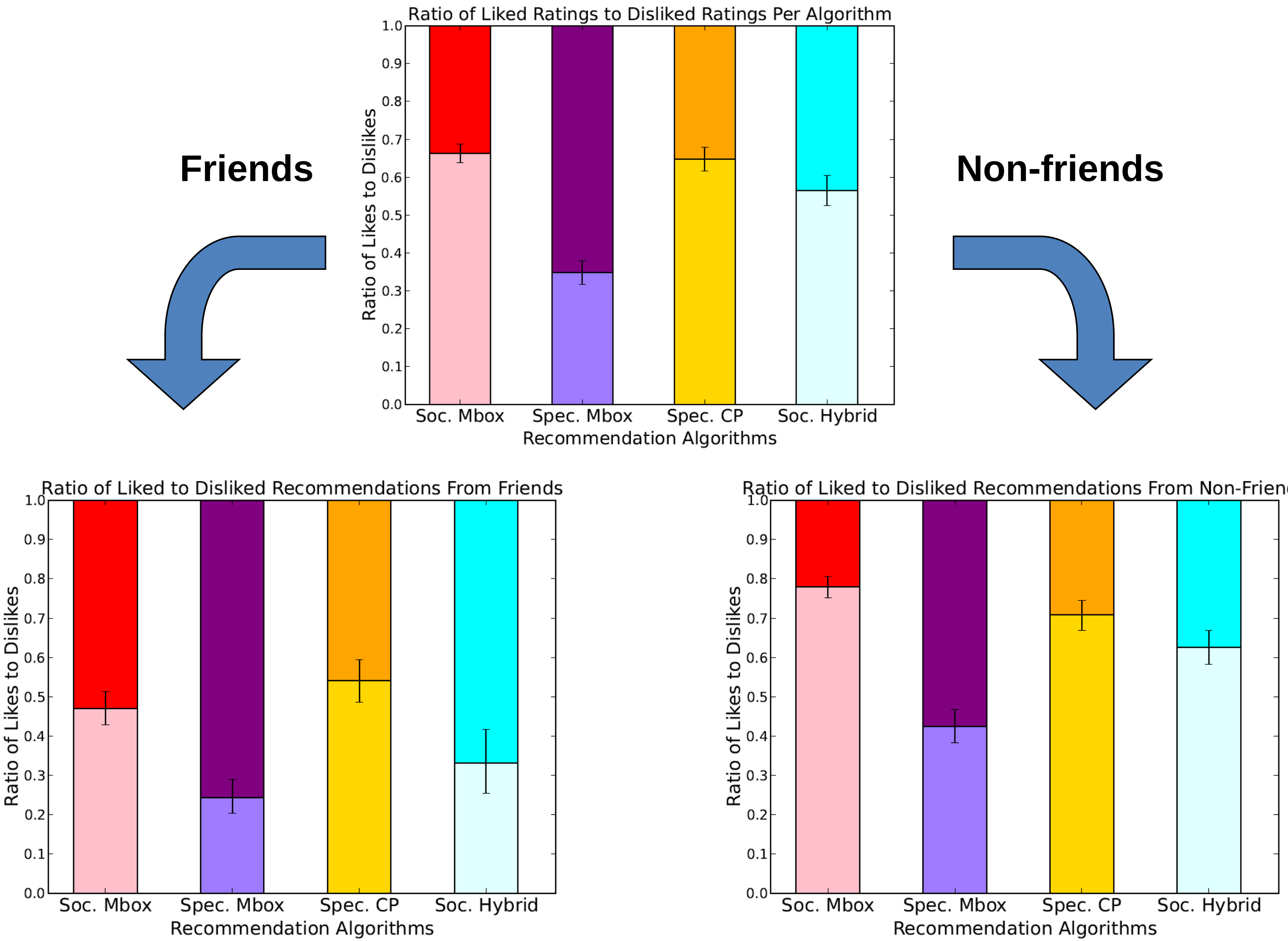
Recommendations from Friends



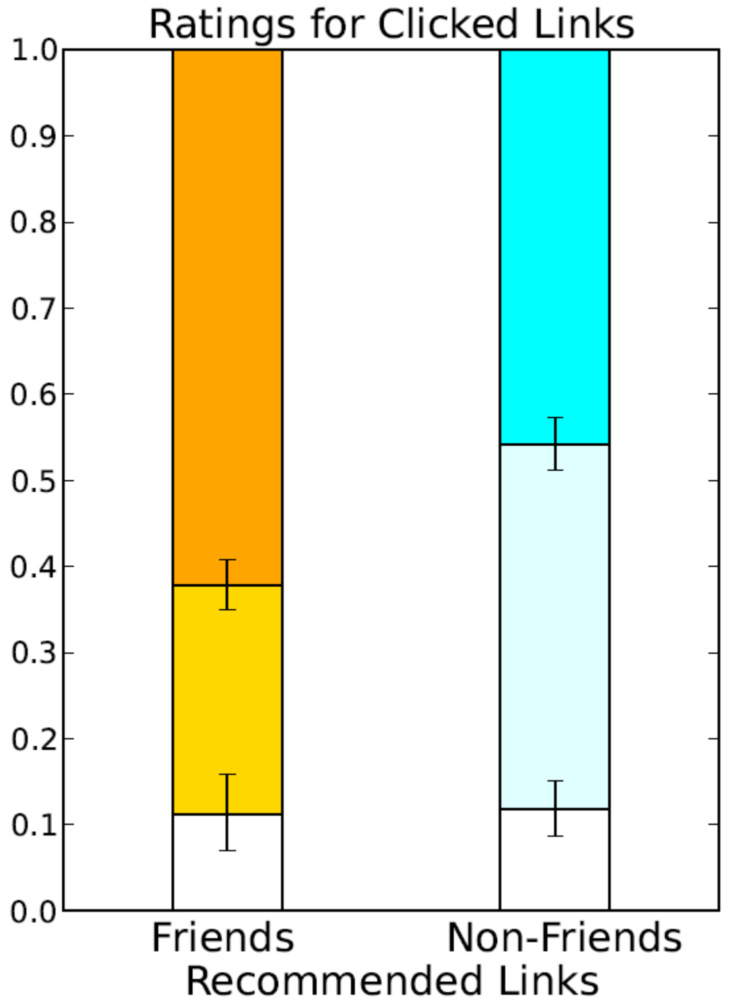
Recommendations from non-Friends



Trial 2: New Objectives



Click Behavior

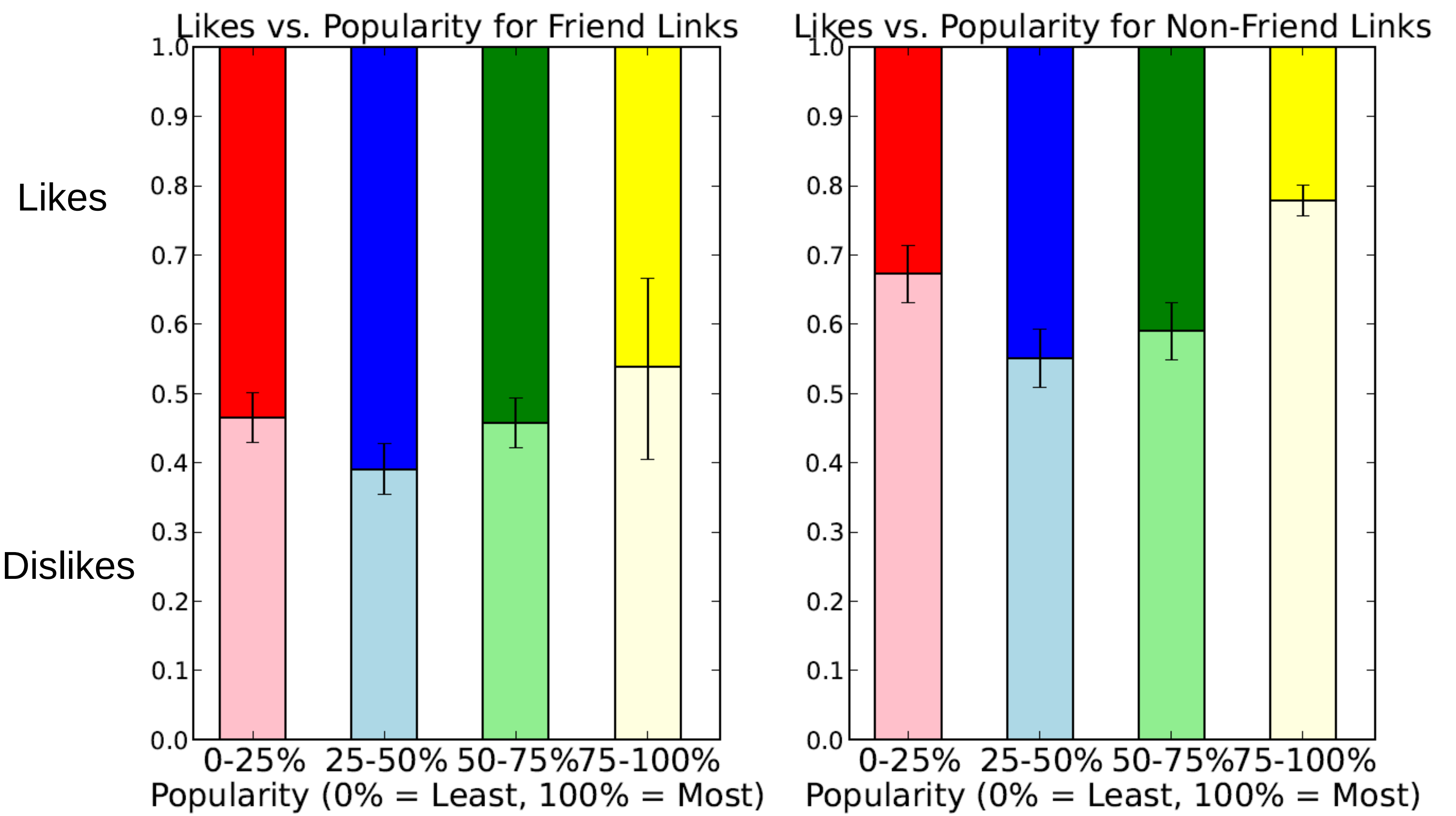


Likes

Dislikes

No Rating

Impact of Popularity



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 !

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- 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

$$U = \begin{bmatrix} U_{1,1} & \cdots & U_{1,I} \\ \vdots & U_{k,i} & \vdots \\ U_{K,1} & \cdots & U_{K,I} \end{bmatrix}$$

$$V = \begin{bmatrix} V_{1,1} & \cdots & V_{1,J} \\ \vdots & V_{k,j} & \vdots \\ V_{K,1} & \cdots & V_{K,J} \end{bmatrix}$$

Proposal I

- Use interactions to learn latent projection of user **and features**

$$
\begin{aligned}
Obj_{rs} &= \sum_{\mathbf{x}} \sum_{\mathbf{z} \in friends(\mathbf{x})} \frac{1}{2}\left(S_{\mathbf{x},\mathbf{z}} - \langle U\mathbf{x}, U\mathbf{z}\rangle\right)^2 \\
&= \sum_{\mathbf{x}} \sum_{\mathbf{z} \in friends(\mathbf{x})} \frac{1}{2}\left(S_{\mathbf{x},\mathbf{z}} - \mathbf{x}^T U^T U\mathbf{z}\right)^2
\end{aligned}
$$

Individual Link Comments

Individual Link Comments

Comment Type	#	%
not interested	88	36.5%
wrong language	37	15.4%
really liked it!	35	14.5%
bad YouTube	25	10.4%
seen it already	25	10.4%
problem / dead	20	8.3%
outdated	7	2.9%
miscellaneous	4	1.7%

Survey

User Survey Comments
want more control over recommendations made (music, blogs, news)
want option to see > 3 recommendations
links need description / context or explanation of recommendation
more variety, diversity