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New Objective Functions for Social Collaborative Filtering

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ANU Link Recommender (LinkR) 

- Recommends 3 daily links on Facebook

 's App View

Non-friend Recommendation (only link context)

Rating + Optional Link Feedback

Friend Recommendation (friend message + link context)

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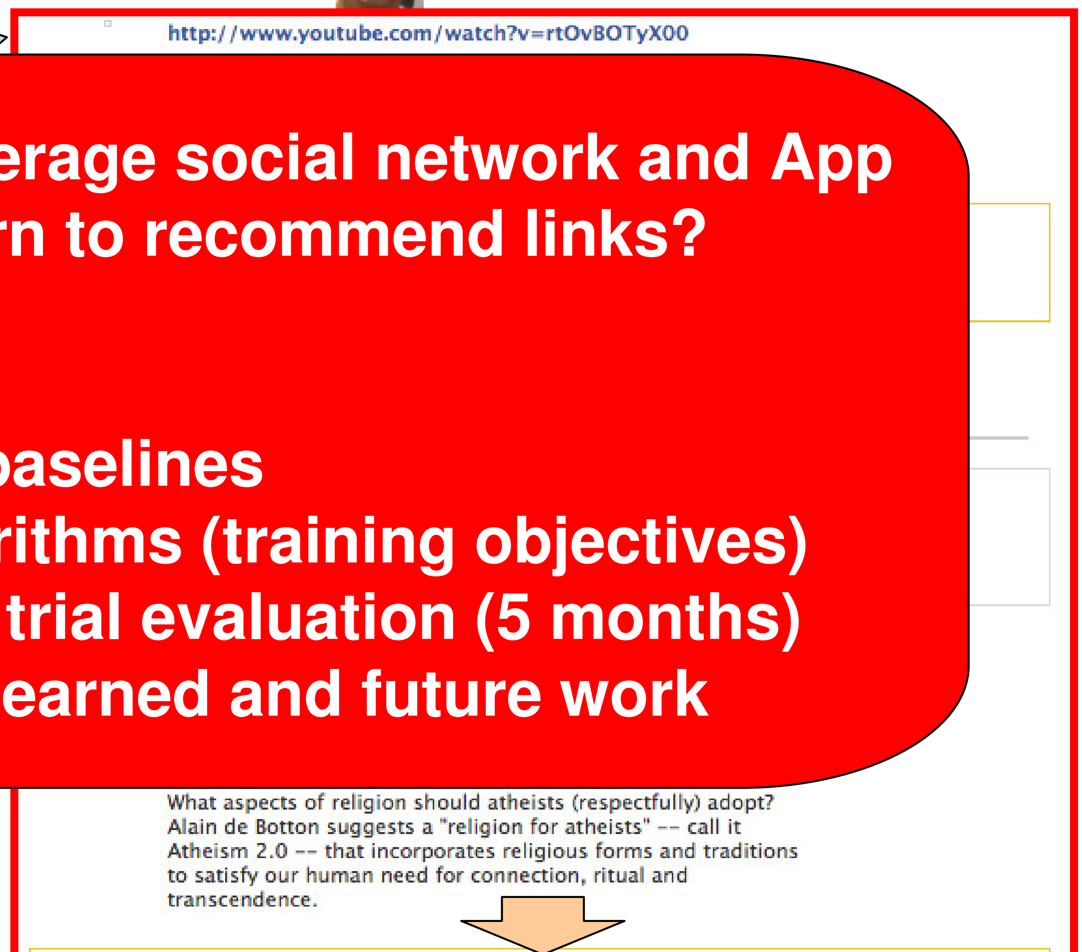
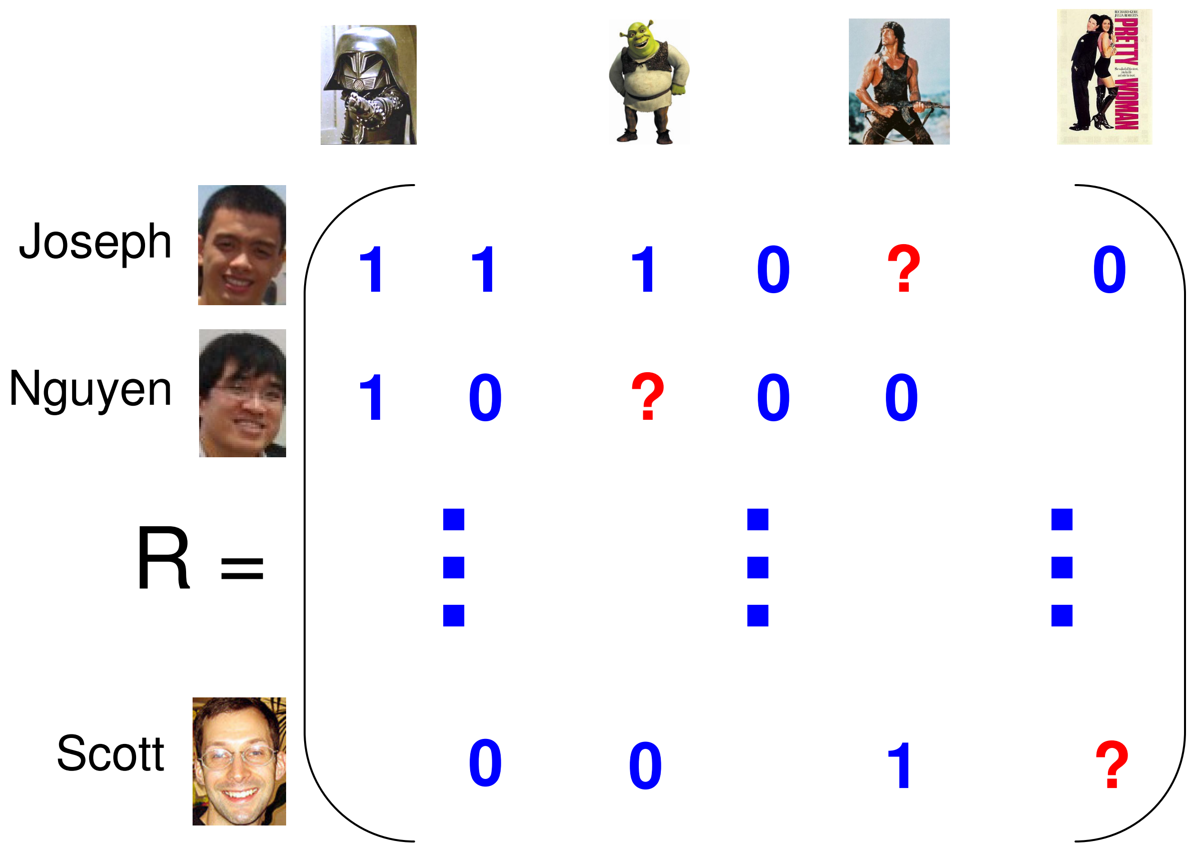


How to leverage social network and App data to learn to recommend links?

This talk:
- **Existing baselines**
- **New algorithms (training objectives)**
- **Live user trial evaluation (5 months)**
- **Lessons learned and future work**

Recommendation

- Predict missing from observed ratings?



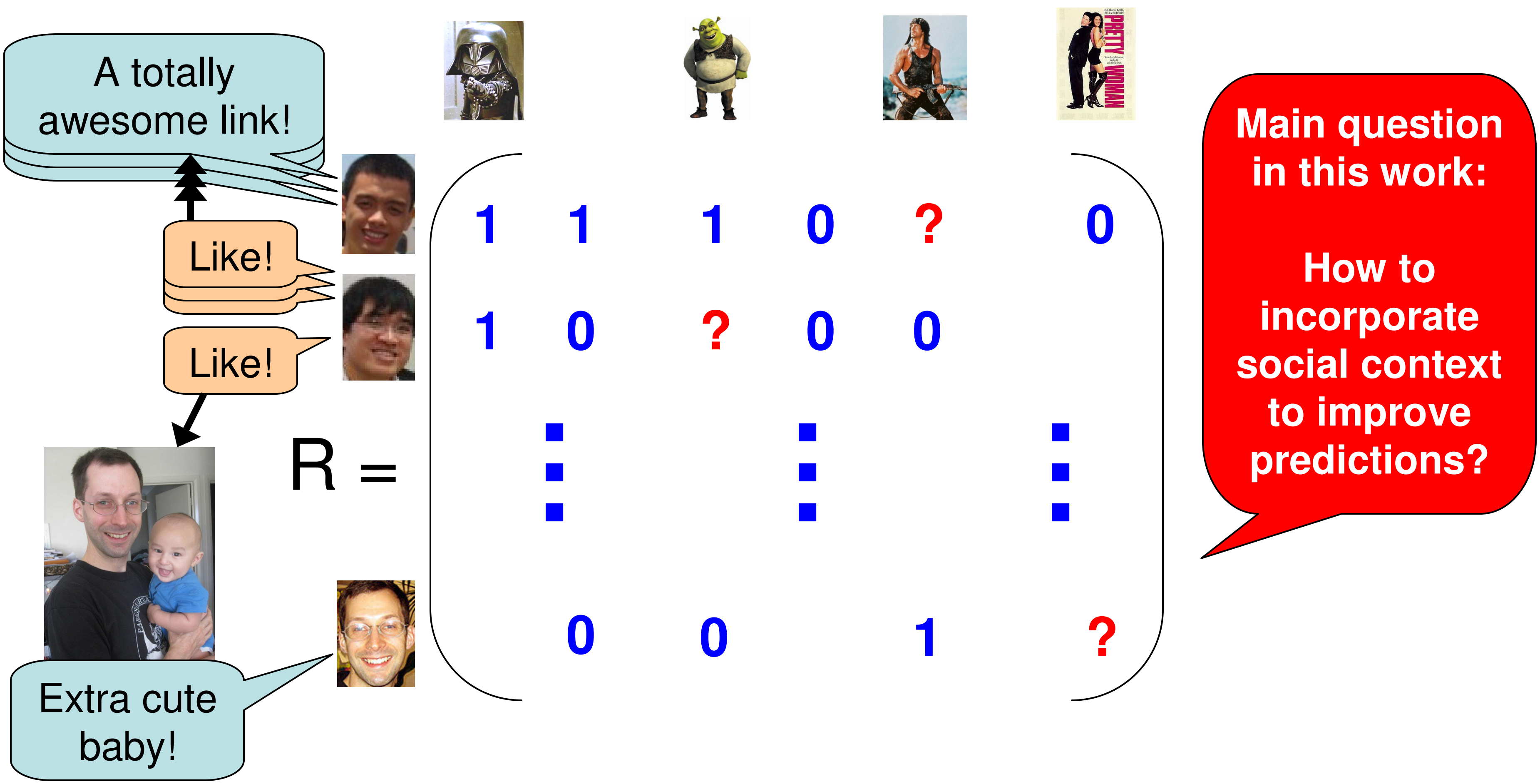
Canonical Example:

Netflix Competition

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

Social Recommendation

- Adds indirect social context to users

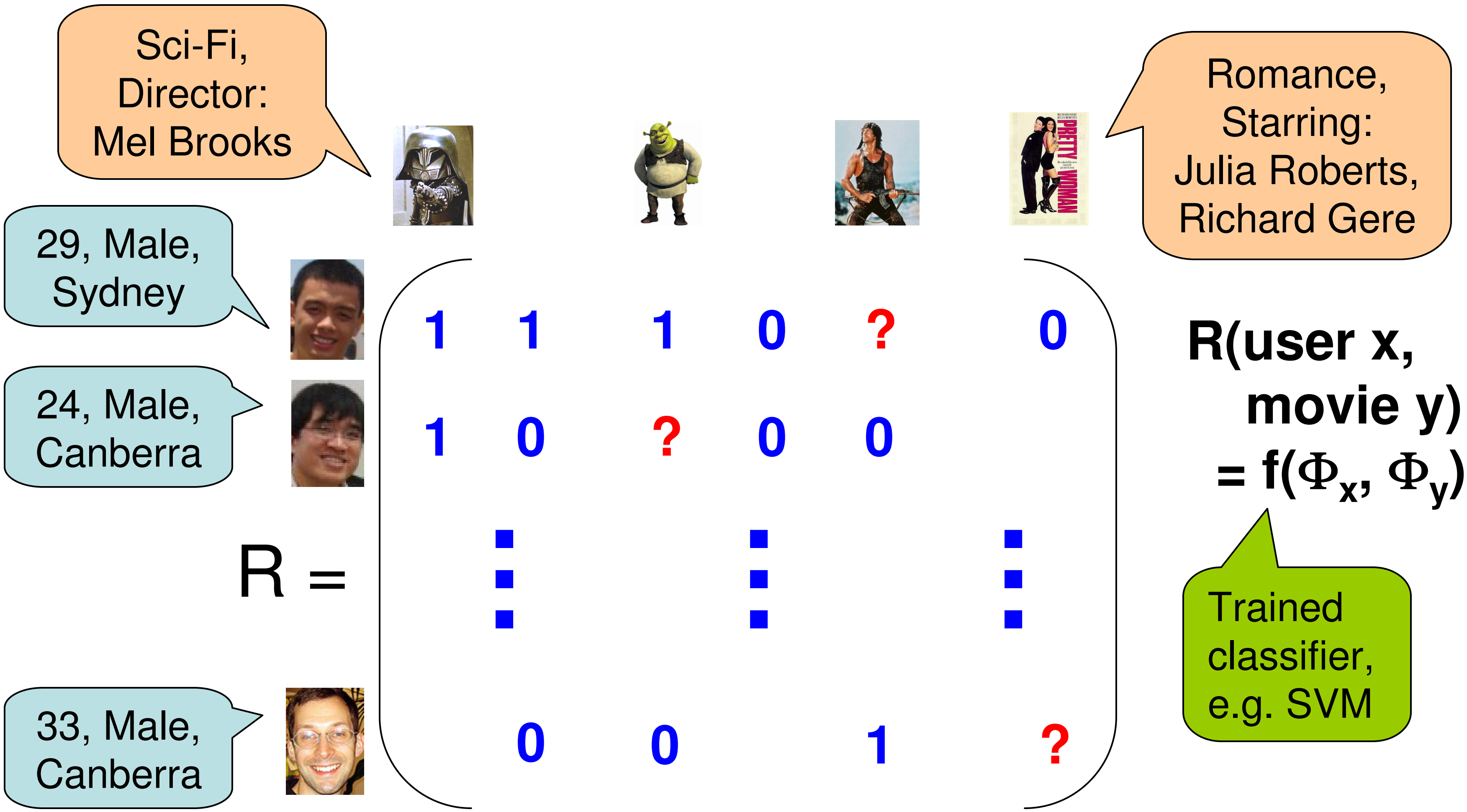


Question 1:

What existing (social) collaborative filtering techniques make good Facebook link recommenders?

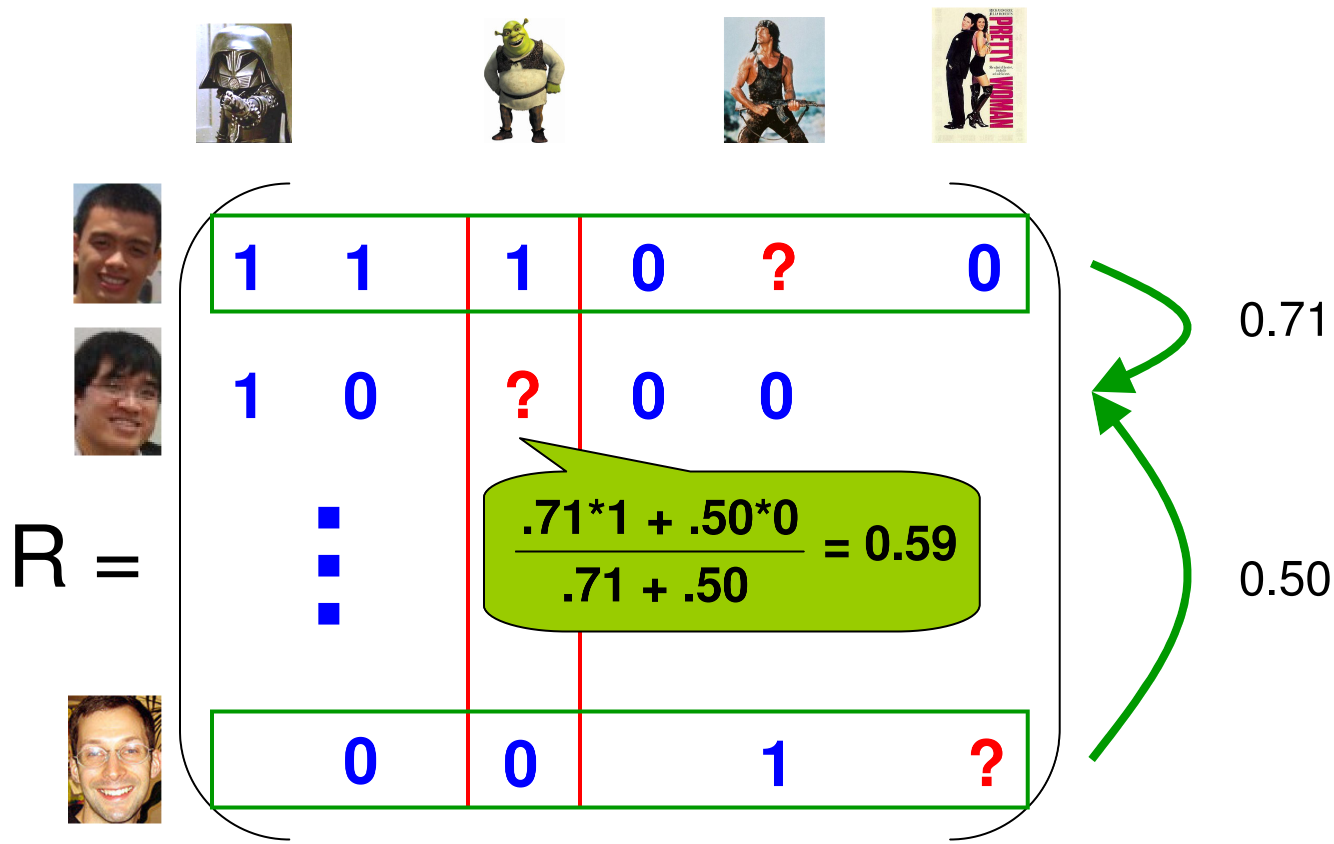
Content-based Filtering (CBF)

- Predict like / dislike directly from features



Collaborative Filtering (CF): KNN

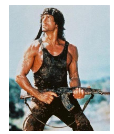
- No features? k-nearest neighbor, e.g., k=2



Collaborative Filtering: PMF

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








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

Latent Item Features

Latent User Features

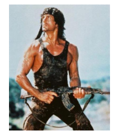
Standard PMF CF Objective (reg. not shown), novel objectives build on this.

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

Stern, Herbrich, Graepel, WWW-09

Features in CF: Matchbox







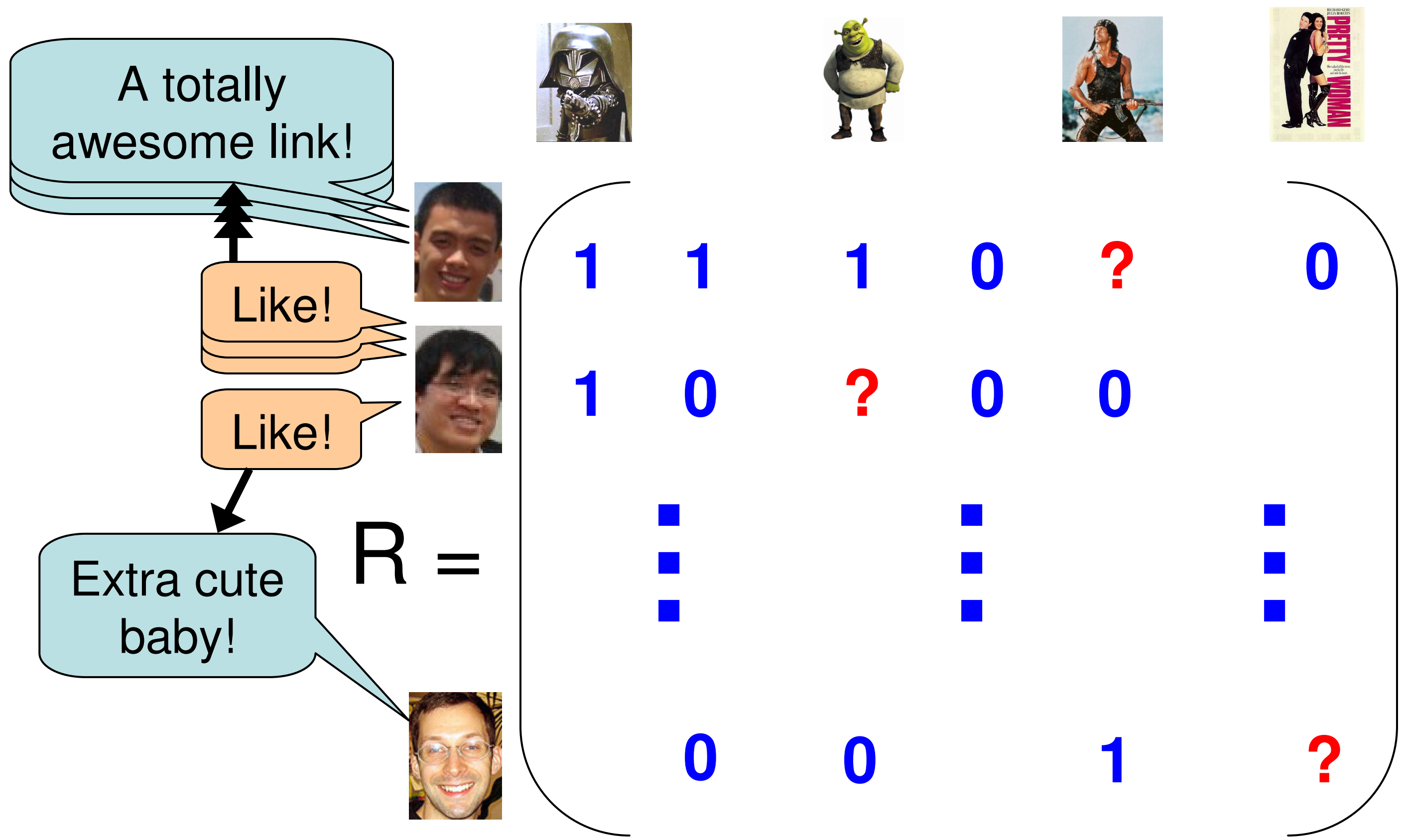

$$R = \begin{pmatrix} 1 & 1 & 1 & 0 & ? & 0 \\ 1 & 0 & ? & 0 & 0 & \\ & \vdots & & \vdots & & \vdots \\ & 0 & 0 & & 1 & ? \end{pmatrix} = \overbrace{\begin{pmatrix} \boxed{.7 \quad .3} \\ .5 \quad -.2 \\ \vdots \\ -.1 \quad .9 \end{pmatrix}}^{\boxed{(U\mathbf{x})^T}} \overbrace{\begin{pmatrix} \boxed{\begin{matrix}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

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

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

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

Social Collaborative Filtering



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

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

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.

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

We find that social CF based on matrix factorization works best.

Question 2:

Can we extend objectives to make it work better?

Yes, we introduce **new objective functions** for social collaborative filtering.

Objective Framework

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

Prediction objectives and regularizers to constrain learning.

Standard 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

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

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

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

Other social regularizers?

Social Regularizers

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

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

Social Recommendation Evaluation via User Trials

Link Recommendation on Facebook

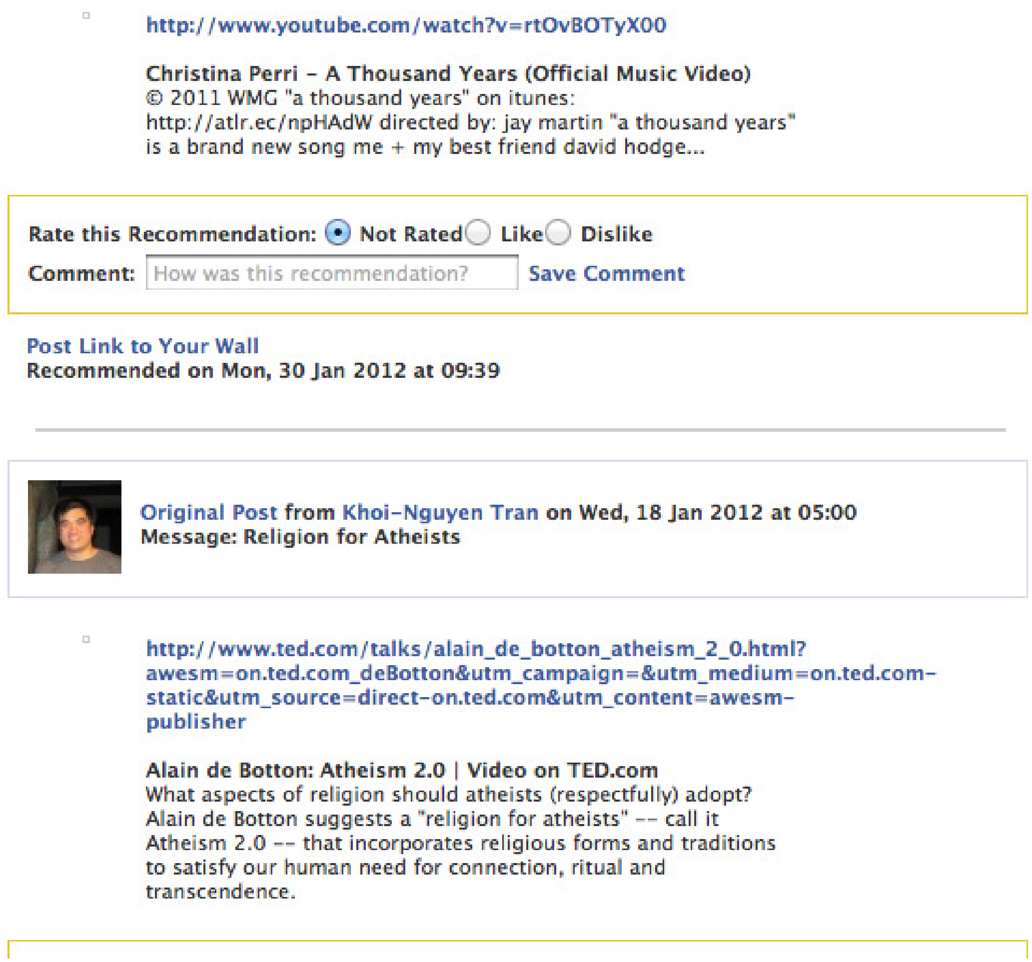
ANU Link Recommender (LinkR)

- Recap: 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	#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 $\geq$ 10	13	9	13	5	40
Users $\geq$ 30	9	3	11	3	26
Ratings All	819	526	901	242	2508
Ratings $\geq$ 10	811	505	896	228	2440
Ratings $\geq$ 30	737	389	851	182	2159
Clicks All	383	245	413	218	1259

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

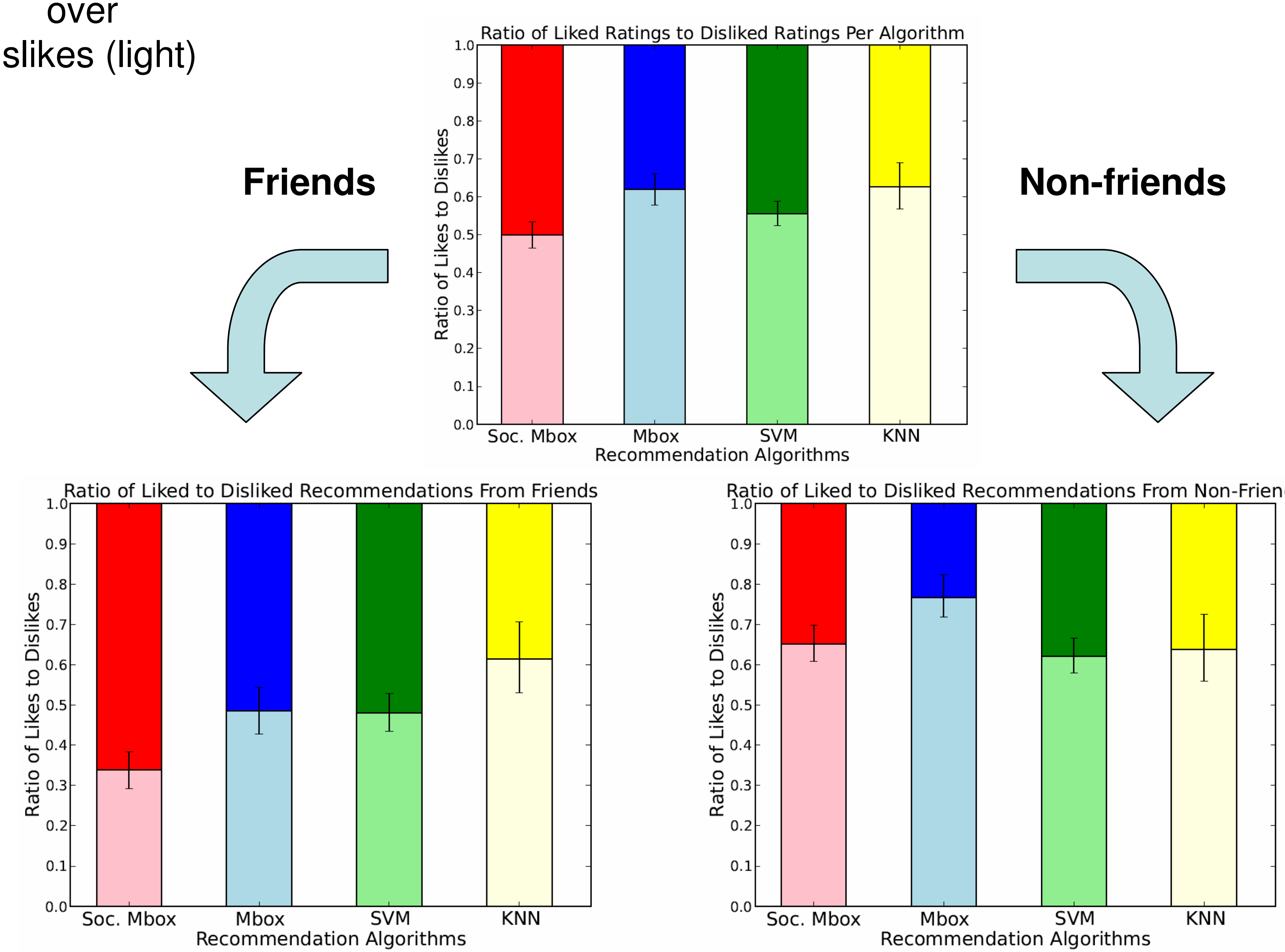
	SMB	Sp.MB	Sp.CP	SHyb.	Total
Users All	27	27	29	28	111
Users $\geq$ 10	15	11	8	12	46
Users $\geq$ 30	12	9	5	10	36
Ratings All	1434	882	879	614	3809
Ratings $\geq$ 10	1411	878	863	602	3754
Ratings $\geq$ 30	1348	850	802	570	3570
Clicks All	553	320	278	199	1350

Trial 1: Baselines

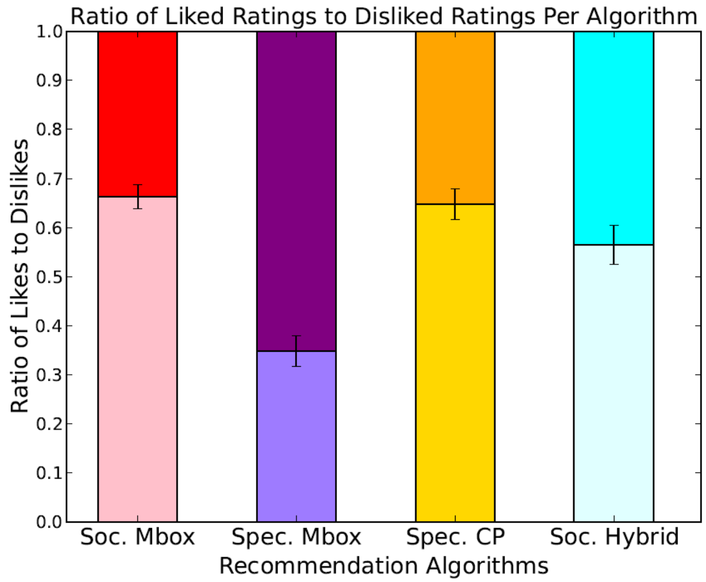
Likes (dark)
over
Dislikes (light)

Friends

Non-friends

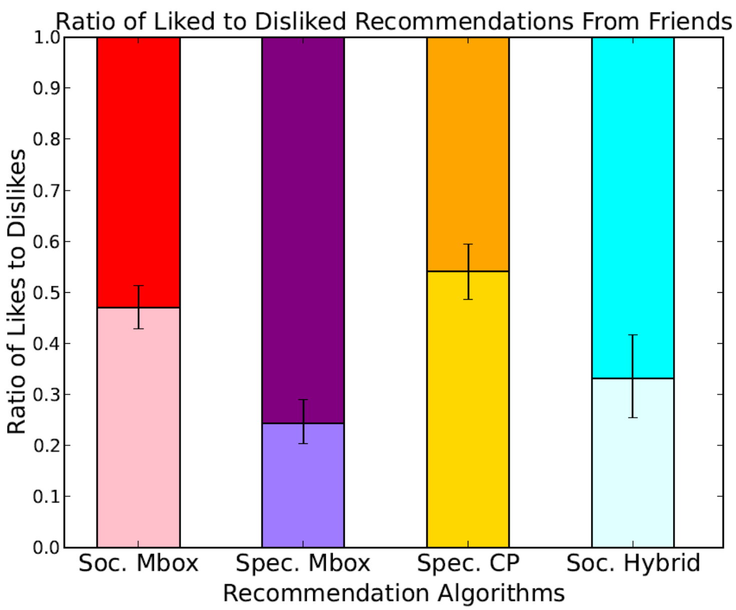


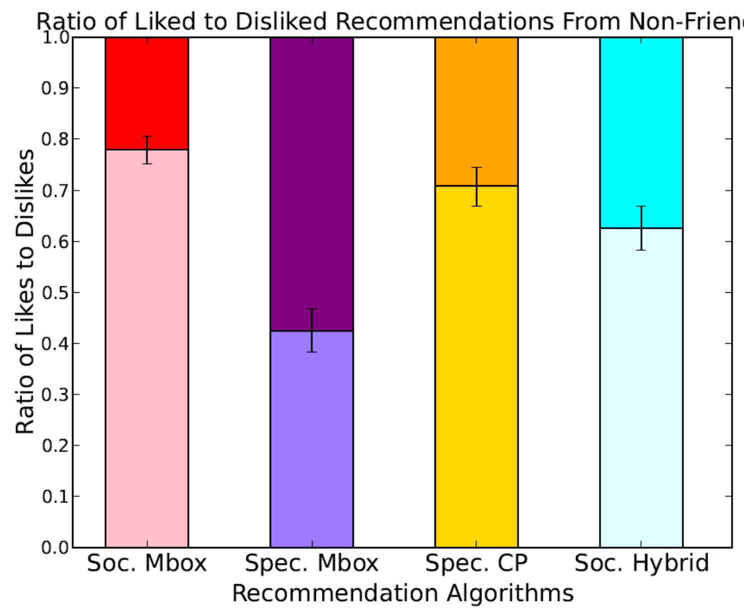
Trial 2: New Objectives



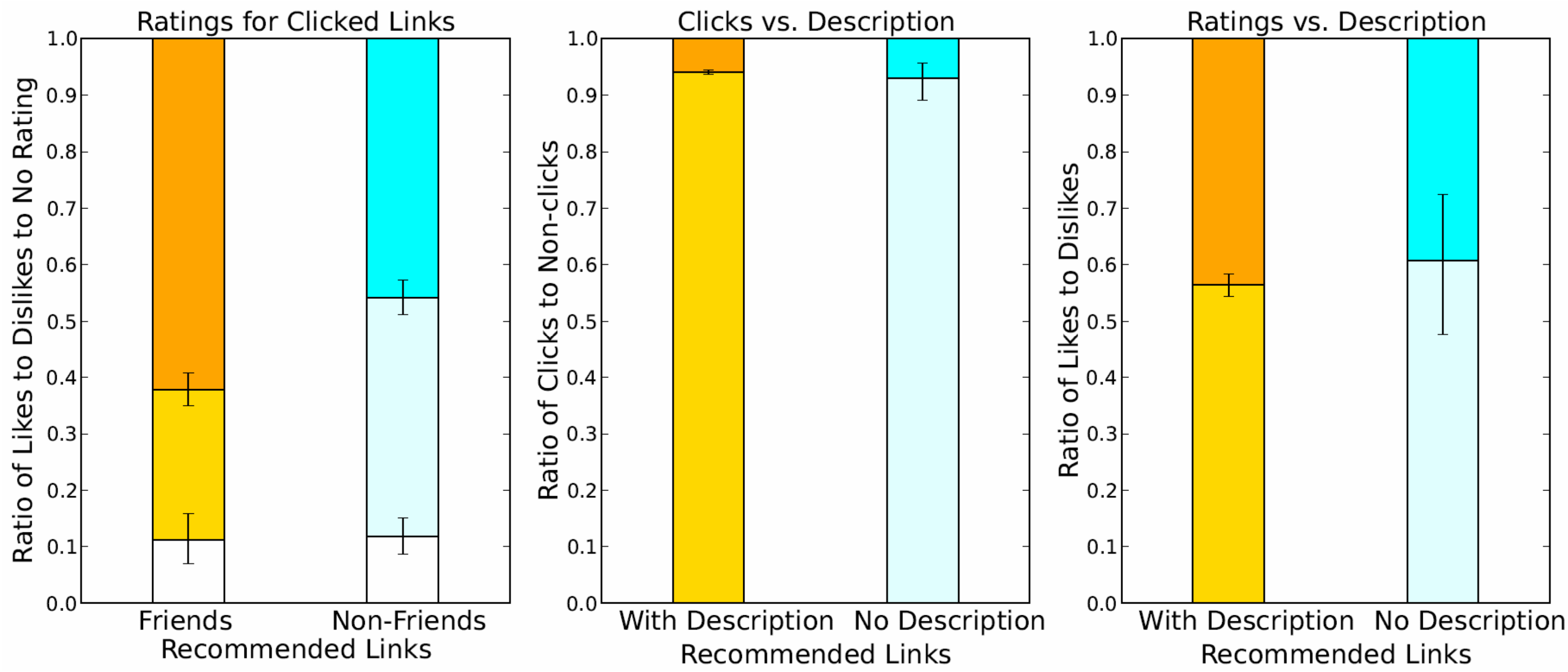
Friends

Non-friends

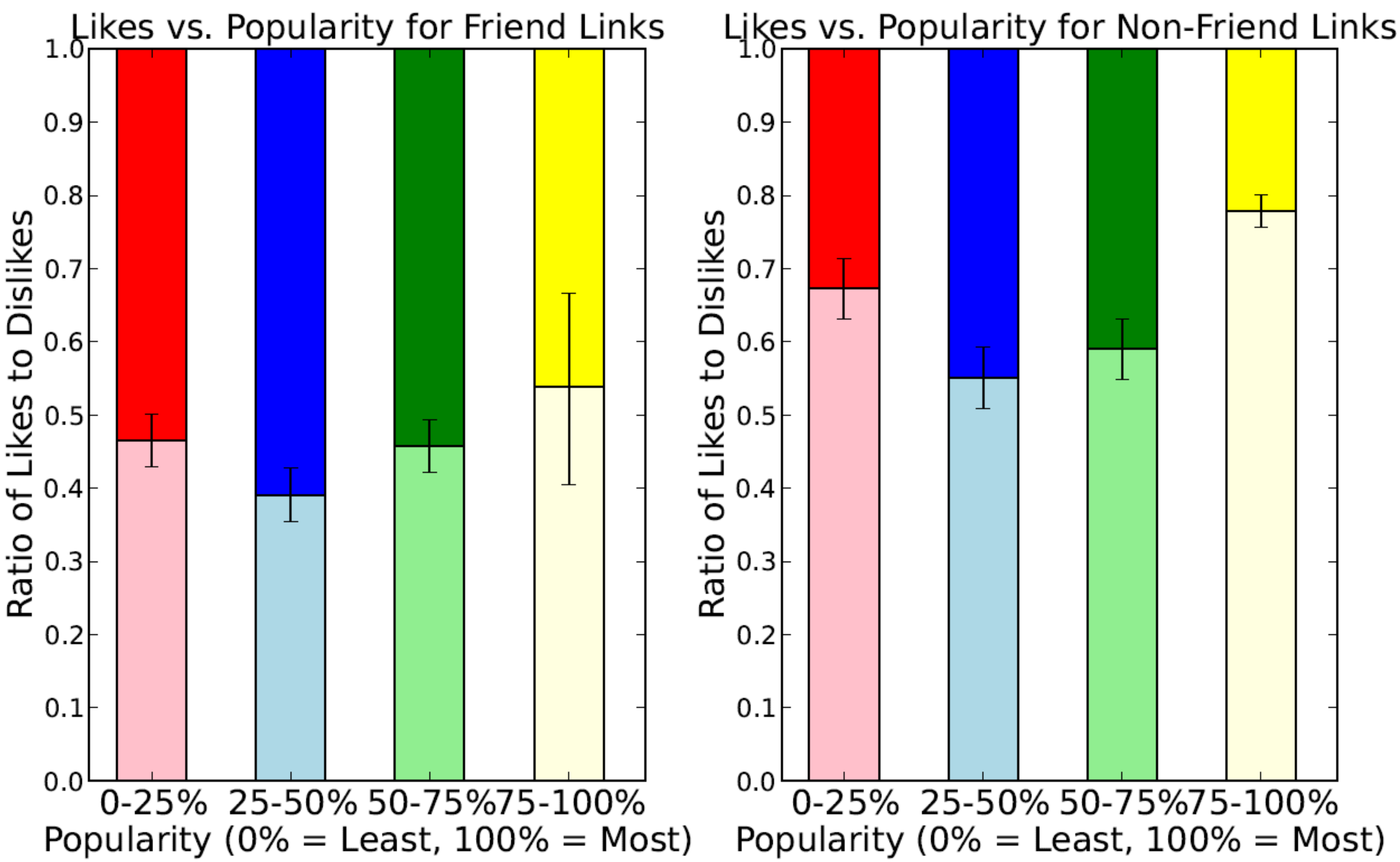




Click Behavior



Impact of Popularity



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

Experimental Design in Retrospect

- 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)

- But we were stuck with the original experimental design after the first trial
    - Hard to statistically compare small user groups
    - If do again, would instead interleave interactions (each recommendation comes from a randomly selected algorithm – so *all* users see *all* algorithms)
    - But main results of Spec. MB significant nonetheless

Conclusions

- 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?

- Overall
  - Machine learning works!
    - Better than more ad-hoc methods like KNN
    - Power of latent factorization methods
  - User 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…

Thank you!

Especially to Doug Aberdeen (Google Zurich) for supporting our Google Grant

And to Sally-Ann Williams for 100+ pairs of Google flip-flops, which have helped us attract users for our live trials!

Extra Slides

Aside: Matrix Definitions

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

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

Proposal I

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

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

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