MACHINE LEARNING
DEPARTMENT

8.1 Neighbors

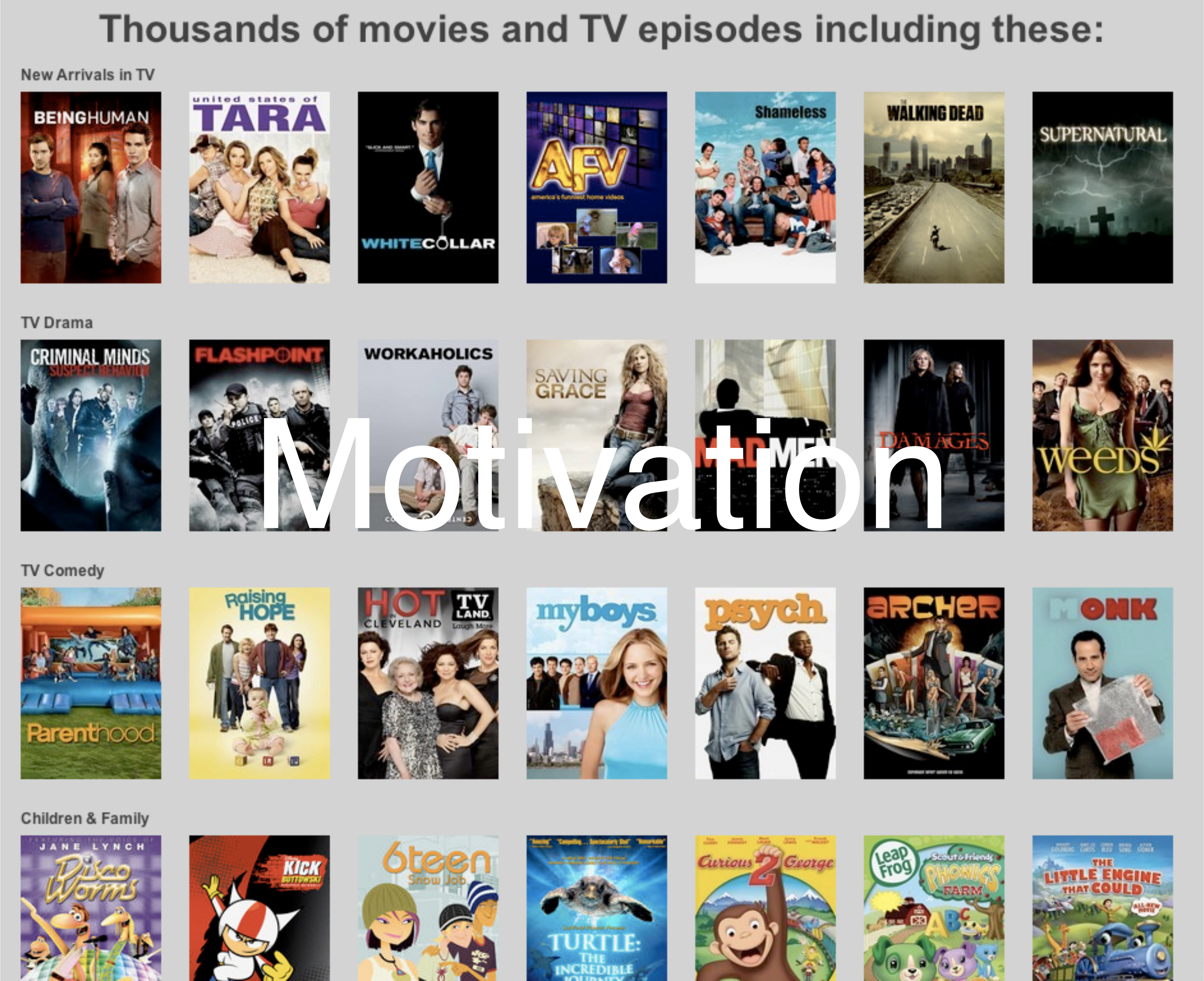
8 Recommender Systems

Alexander Smola
Introduction to Machine Learning 10-701
http://alex.smola.org/teaching/10-701-15

Significant content courtesy of Yehuda Koren

Carnegie Mellon University

Motivation



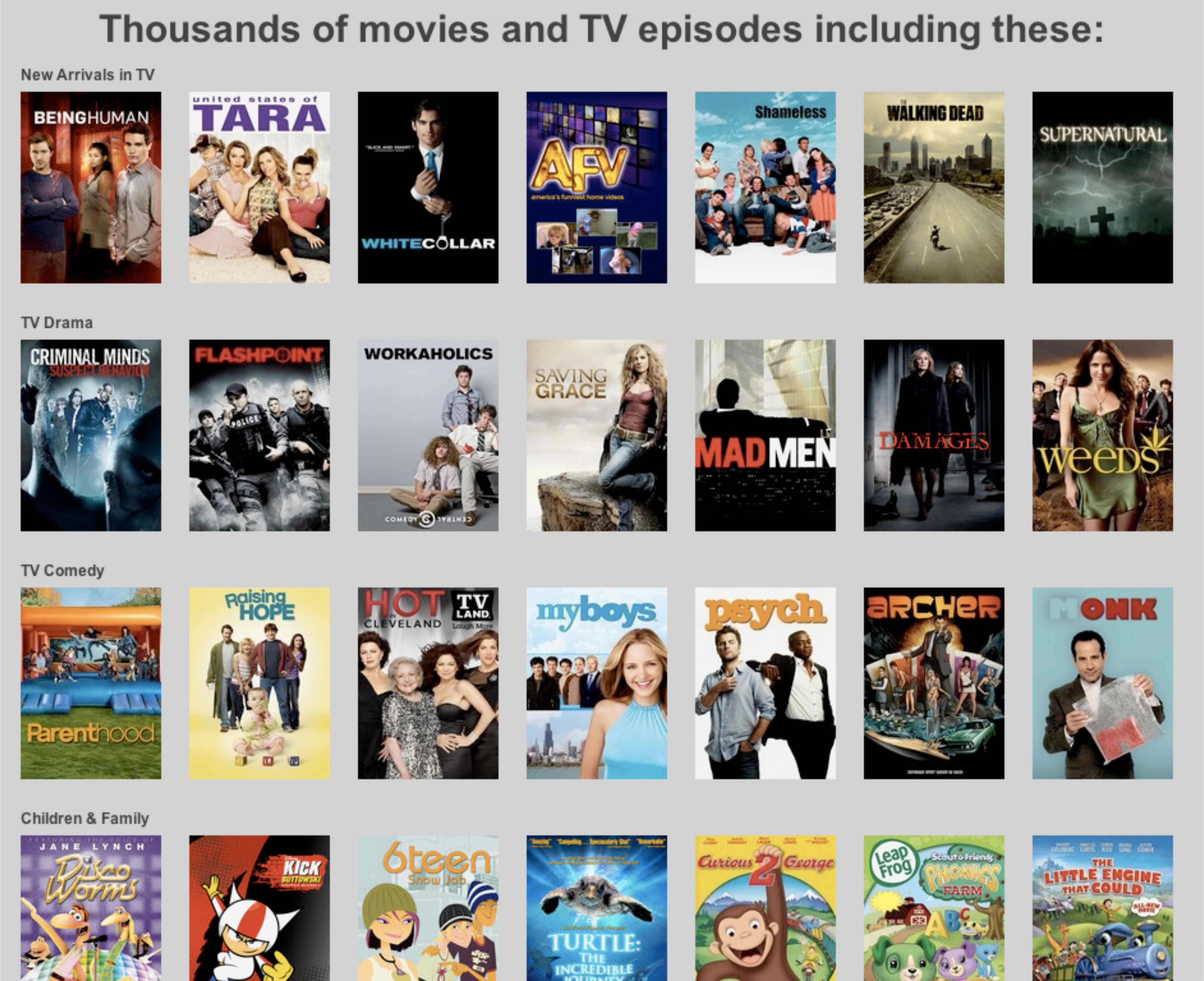
Thousands of movies and TV episodes including these:

New Arrivals in TV

TV Drama

TV Comedy

Children & Family



Thousands of movies and TV episodes including these:

New Arrivals in TV

TV Drama

TV Comedy

Children & Family

Thousands of movies and TV episodes including these:

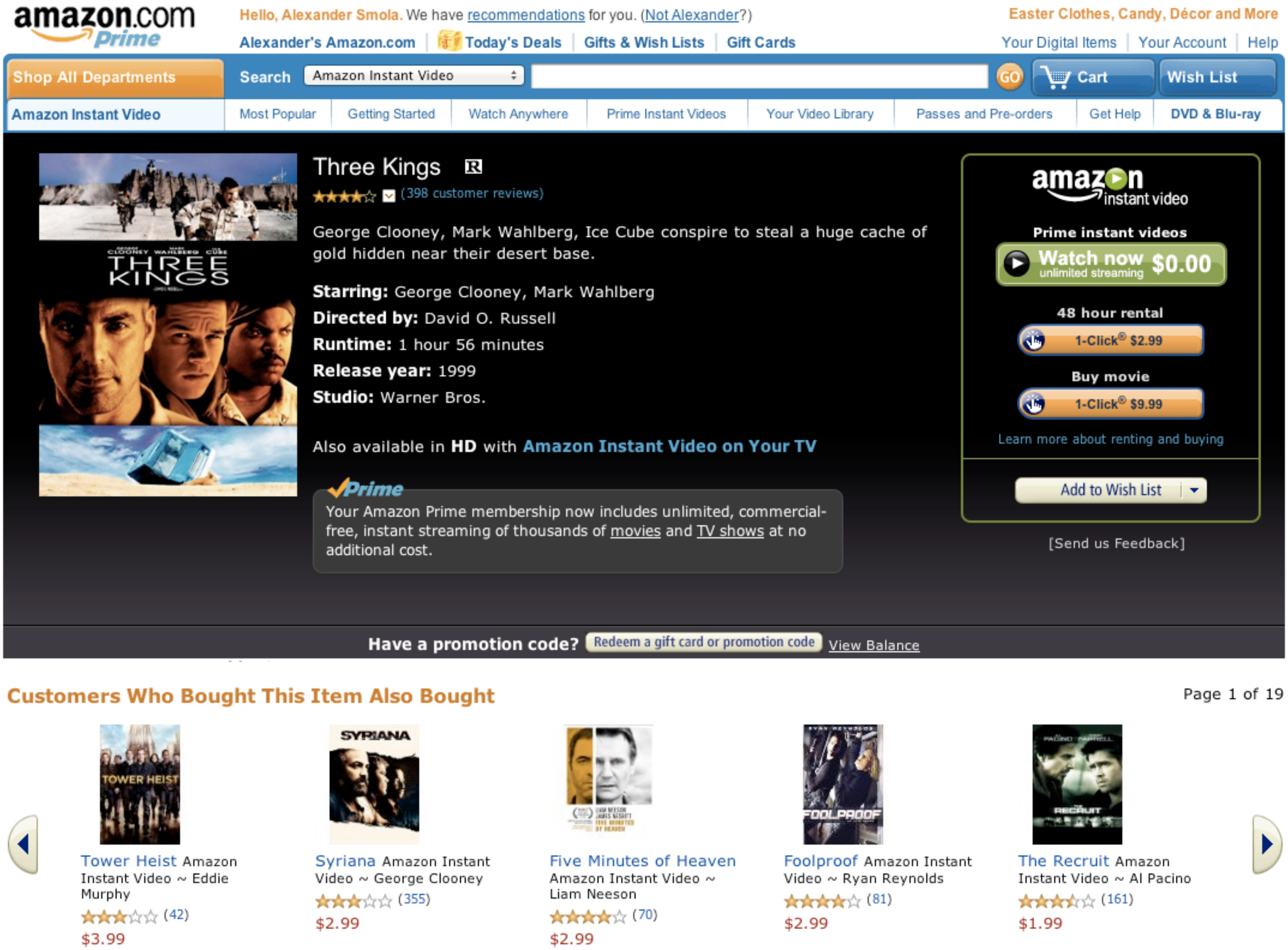
New Arrivals in TV

TV Drama

TV Comedy

Children & Family

Netflix



amazon.com Prime

Hello, Alexander Smola. We have recommendations for you. (Not Alexander?)

Easter Clothes, Candy, Décor and More

Alexander's Amazon.com | Today's Deals | Gifts & Wish Lists | Gift Cards

Your Digital Items | Your Account | Help

Shop All Departments | Search: Amazon Instant Video | GO | Cart | Wish List

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Three Kings R

★★★★☆ (398 customer reviews)

George Clooney, Mark Wahlberg, Ice Cube conspire to steal a huge cache of gold hidden near their desert base.

Starring: George Clooney, Mark Wahlberg

Directed by: David O. Russell

Runtime: 1 hour 56 minutes

Release year: 1999

Studio: Warner Bros.

Also available in **HD** with **Amazon Instant Video on Your TV**

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Five Minutes of Heaven Amazon Instant Video ~ Liam Neeson ★★★★☆ (70) $2.99

Foolproof Amazon Instant Video ~ Ryan Reynolds ★★★★☆ (81) $2.99

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Just For Today

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view: **All** | New Releases | Coming Soon

More results

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by Stephen Boyd (March 8, 2004)
Average Customer Review: (13)
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List Price: ~~$84.00~~
Price: $68.13
44 used & new from $61.32
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3. **Doing Bayesian Data Analysis: A Tutorial with R and BUGS**
by John K. Kruschke (November 10, 2010)
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Price: $77.98
44 used & new from $68.40
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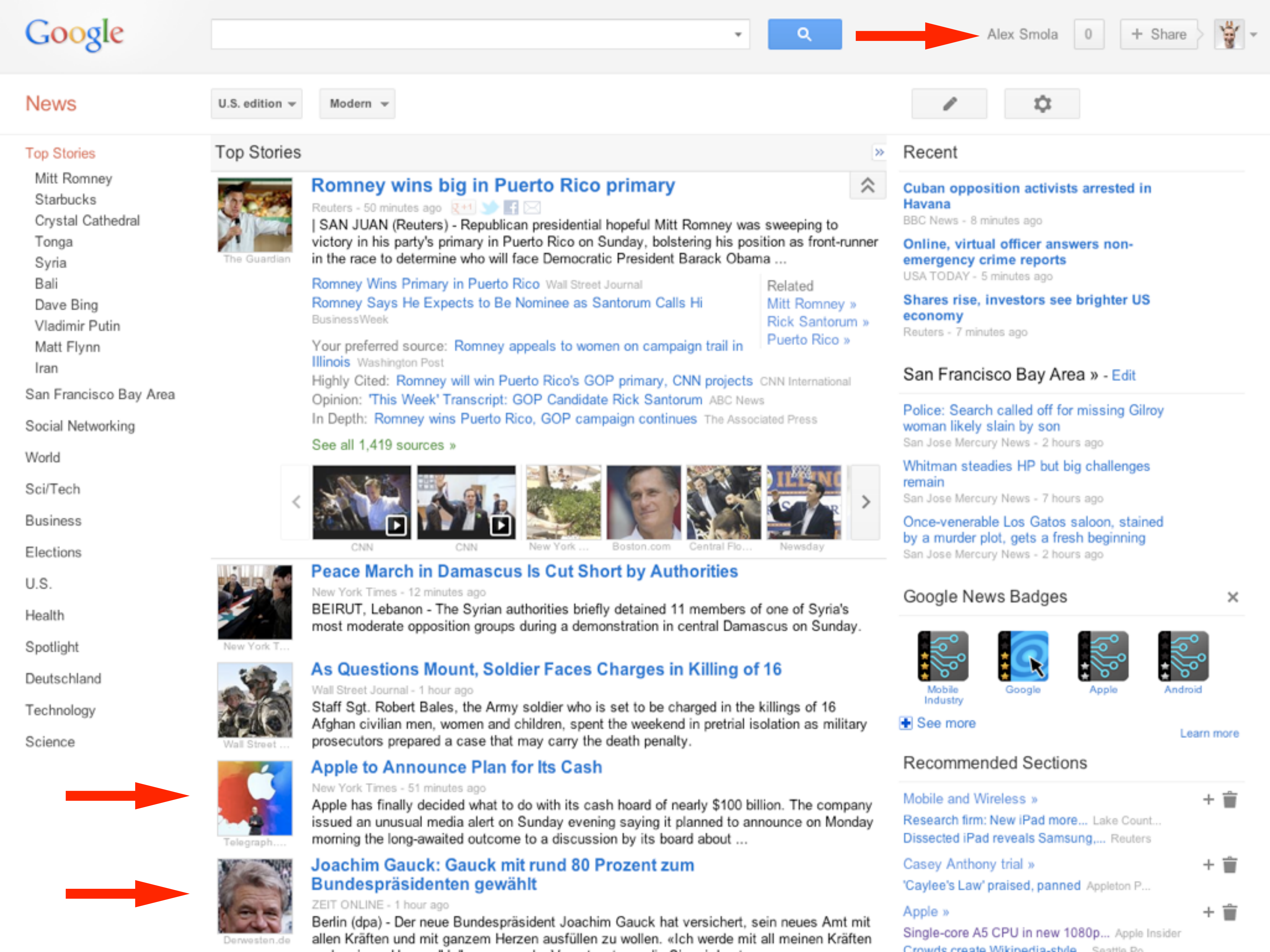

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Wall Street ...
Wall Street Journal - 1 hour ago
Staff Sgt. Robert Bales, the Army soldier who is set to be charged in the killings of 16 Afghan civilian men, women and children, spent the weekend in pretrial isolation as military prosecutors prepared a case that may carry the death penalty.

Apple to Announce Plan for Its Cash
Telegraph....
New York Times - 51 minutes ago
Apple has finally decided what to do with its cash hoard of nearly $100 billion. The company issued an unusual media alert on Sunday evening saying it planned to announce on Monday morning the long-awaited outcome to a discussion by its board about ...

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Derwesten.de
ZEIT ONLINE - 1 hour ago
Berlin (dpa) - Der neue Bundespräsident Joachim Gauck hat versichert, sein neues Amt mit allen Kräften und mit ganzem Herzen ausfüllen zu wollen. «Ich werde mit all meinen Kräften

Recent

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BBC News - 8 minutes ago

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USA TODAY - 5 minutes ago

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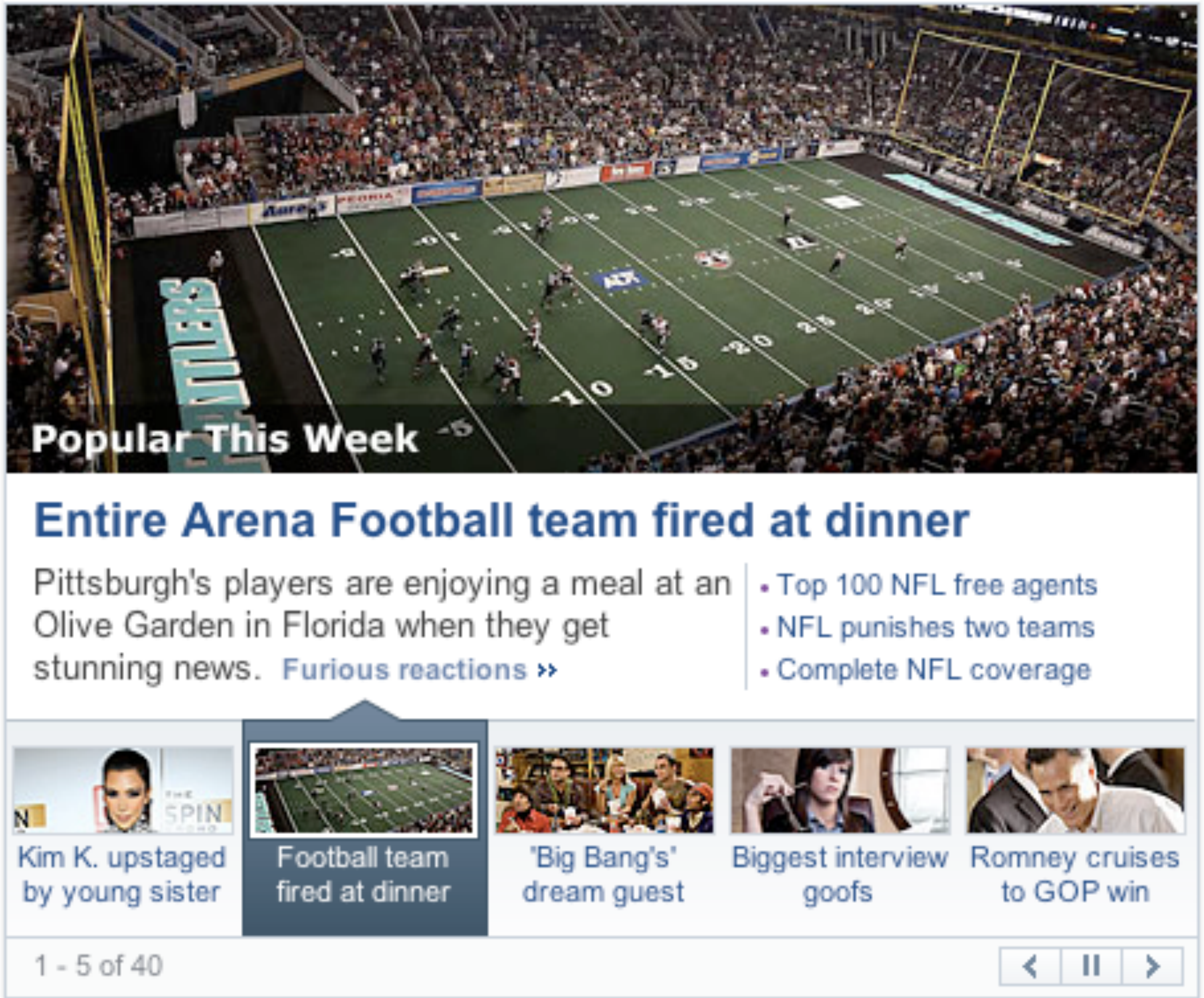
Personalized Content



Popular This Week

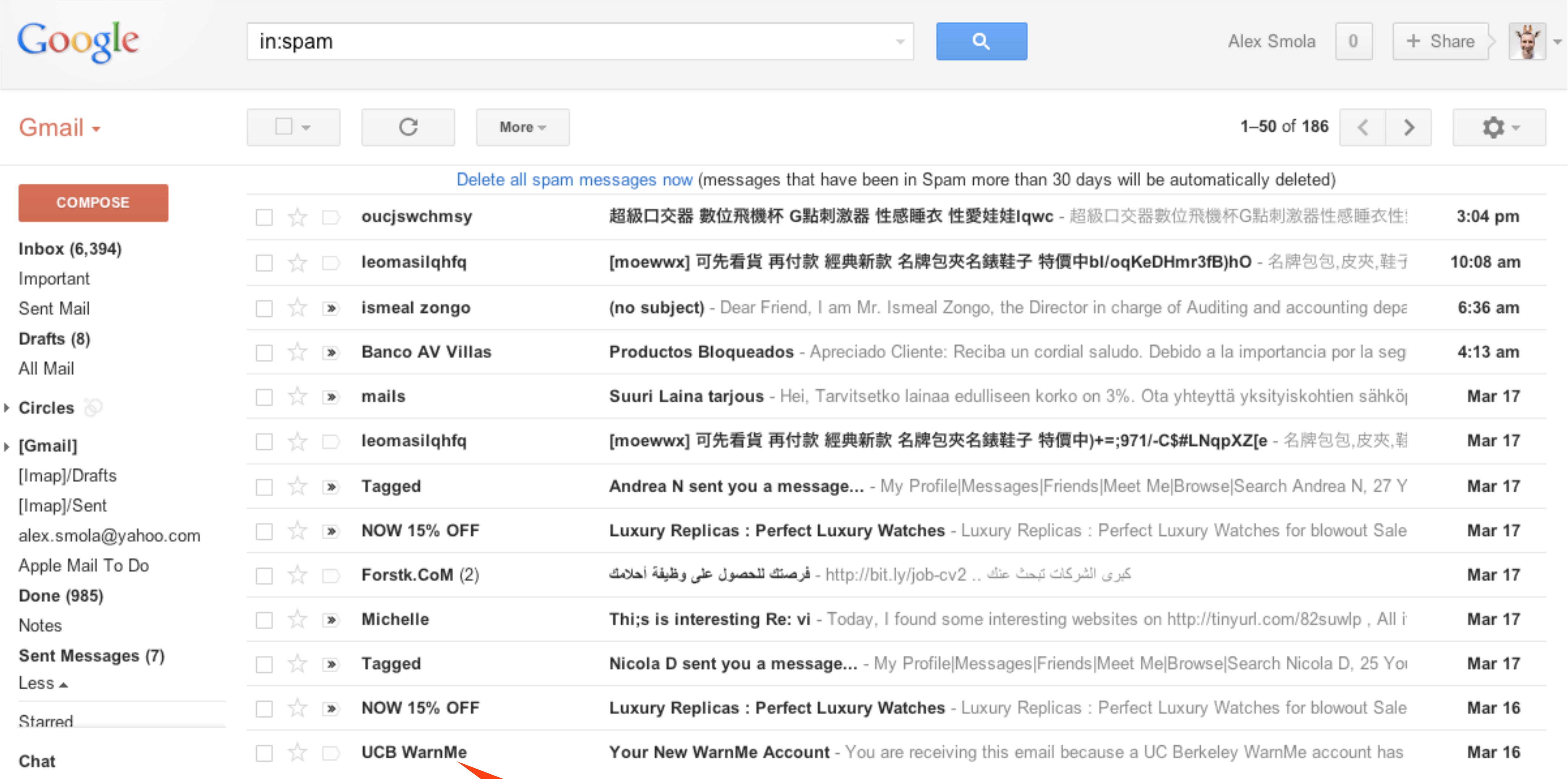
Entire Arena Football team fired at dinner

Pittsburgh's players are enjoying a meal at an Olive Garden in Florida when they get stunning news. Furious reactions »

- Top 100 NFL free agents
- NFL punishes two teams
- Complete NFL coverage

adapt to general popularity
pick based on user preferences

Spam Filtering



in:spam

Alex Smola 0 + Share

Gmail

More

1–50 of 186

COMPOSE

- **Inbox (6,394)**
- Important
- Sent Mail
- **Drafts (8)**
- All Mail
- **Circles**
- **[Gmail]**
- [Imap]/Drafts
- [Imap]/Sent
- alex.smola@yahoo.com
- Apple Mail To Do
- **Done (985)**
- Notes
- **Sent Messages (7)**
- Less
- Starred
- **Chat**

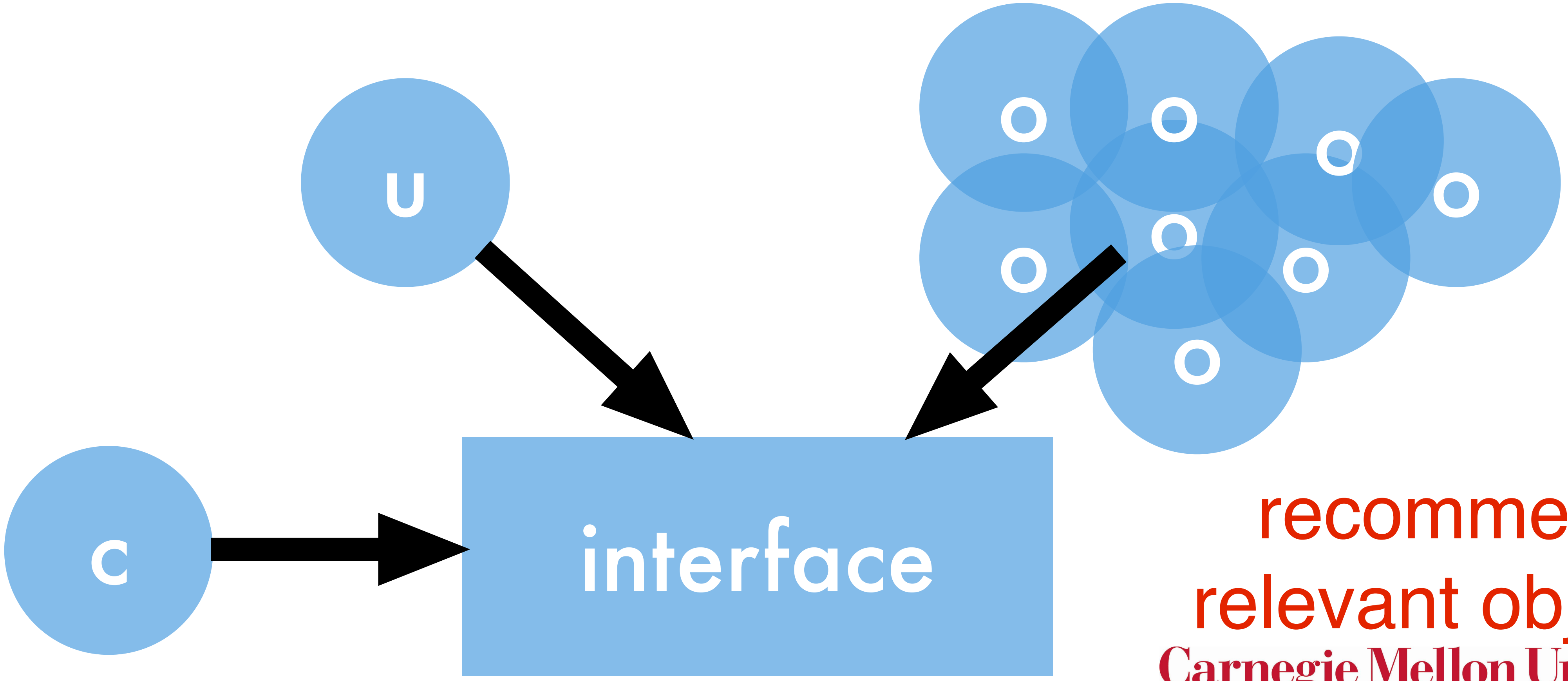
Delete all spam messages now (messages that have been in Spam more than 30 days will be automatically deleted)

oucjswchmsy	**超級口交器 數位飛機杯 G點刺激器 性感睡衣 性愛娃娃lqwc** - 超級口交器數位飛機杯G點刺激器性感睡衣性	**3:04 pm**
leomasilqhfq	**[moewwx] 可先看貨 再付款 經典新款 名牌包夾名錶鞋子 特價中bl/oqKeDHmr3fB)hO** - 名牌包包,皮夾,鞋	**10:08 am**
ismeal zongo	**(no subject)** - Dear Friend, I am Mr. Ismeal Zongo, the Director in charge of Auditing and accounting depa	**6:36 am**
Banco AV Villas	**Productos Bloqueados** - Apreciado Cliente: Reciba un cordial saludo. Debido a la importancia por la seg	**4:13 am**
mails	**Suuri Laina tarjous** - Hei, Tarvitsetko lainaa edulliseen korko on 3%. Ota yhteyttä yksityiskohtien sähkö	**Mar 17**
leomasilqhfq	**[moewwx] 可先看貨 再付款 經典新款 名牌包夾名錶鞋子 特價中)+=;971/-C$#LNqpXZ[e** - 名牌包包,皮夾,	**Mar 17**
Tagged	**Andrea N sent you a message...** - My Profile|Messages|Friends|Meet Me|Browse|Search Andrea N, 27 Y	**Mar 17**
NOW 15% OFF	**Luxury Replicas : Perfect Luxury Watches** - Luxury Replicas : Perfect Luxury Watches for blowout Sale	**Mar 17**
Forstk.CoM (2)	**فرصتك للحصول على وظيفة أحلامك** - http://bit.ly/job-cv2 .. كبرى الشركات تبحث عنك	**Mar 17**
Michelle	**Thi;s is interesting Re: vi** - Today, I found some interesting websites on http://tinyurl.com/82suwlp , All i	**Mar 17**
Tagged	**Nicola D sent you a message...** - My Profile|Messages|Friends|Meet Me|Browse|Search Nicola D, 25 Yo	**Mar 17**
NOW 15% OFF	**Luxury Replicas : Perfect Luxury Watches** - Luxury Replicas : Perfect Luxury Watches for blowout Sale	**Mar 16**
UCB WarnMe	**Your New WarnMe Account** - You are receiving this email because a UC Berkeley WarnMe account has	**Mar 16**

Something went wrong!

A more formal view

- User (requests content)
- Objects (that can be displayed)
- Context (device, location, time)
- Interface (mobile browser, tablet, viewport)



recommend
relevant objects

Examples

- Movie recommendation (Netflix)
- Related product recommendation (Amazon)
- Web page ranking (Google)
- Social recommendation (Facebook)
- News content recommendation (Yahoo)
- Priority inbox & spam filtering (Google)
- Online dating (OK Cupid)
- Computational Advertising (Yahoo)

Running Example

Training data

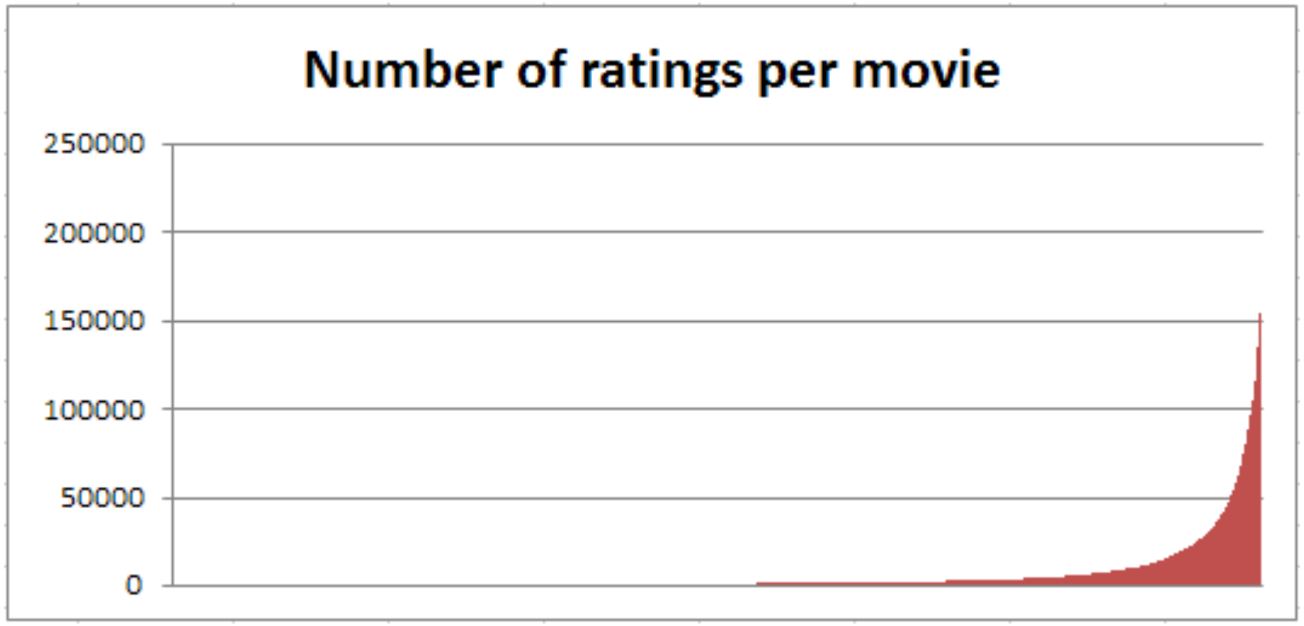
user	movie	date	score
1	21	5/7/02	1
1	213	8/2/04	5
2	345	3/6/01	4
2	123	5/1/05	4
2	768	7/15/02	3
3	76	1/22/01	5
4	45	8/3/00	4
5	568	9/10/05	1
5	342	3/5/03	2
5	234	12/28/00	2
6	76	8/11/02	5
6	56	6/15/03	4

Test data

user	movie	date	score
1	62	1/6/05	?
1	96	9/13/04	?
2	7	8/18/05	?
2	3	11/22/05	?
3	47	6/13/02	?
3	15	8/12/01	?
4	41	9/1/00	?
4	28	8/27/05	?
5	93	4/4/05	?
5	74	7/16/03	?
6	69	2/14/04	?
6	83	10/3/03	?

Challenges

- Scalability
  - Millions of objects
  - 100s of millions of users
- Cold start
  - Changing user base
  - Changing inventory (movies, stories, goods)
  - Attributes
- Imbalanced dataset
  User activity / item reviews
  are power law distributed



http://www.igvita.com/2006/10/29/dissecting-the-netflix-dataset/

Netflix competition yardstick

- Least mean squares prediction error
  - Easy to define

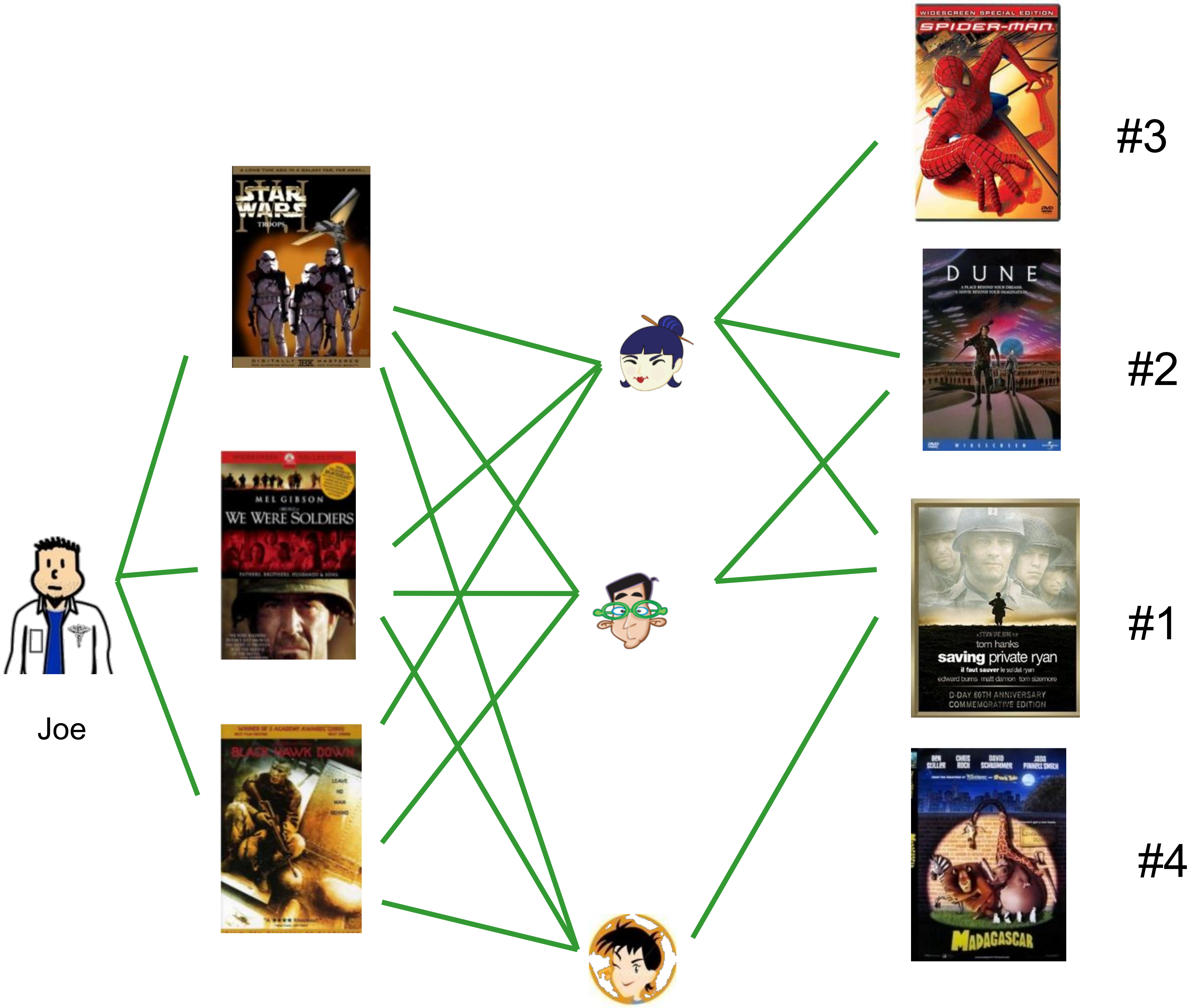
$$\mathrm{rmse}(S) = \sqrt{|S|^{-1} \sum_{(i,u) \in S} (\hat{r}_{ui} - r_{ui})^2}$$

  - Wrong measure for composing sessions!

  - Consistent (in large sample size limit this will converge to minimizer)

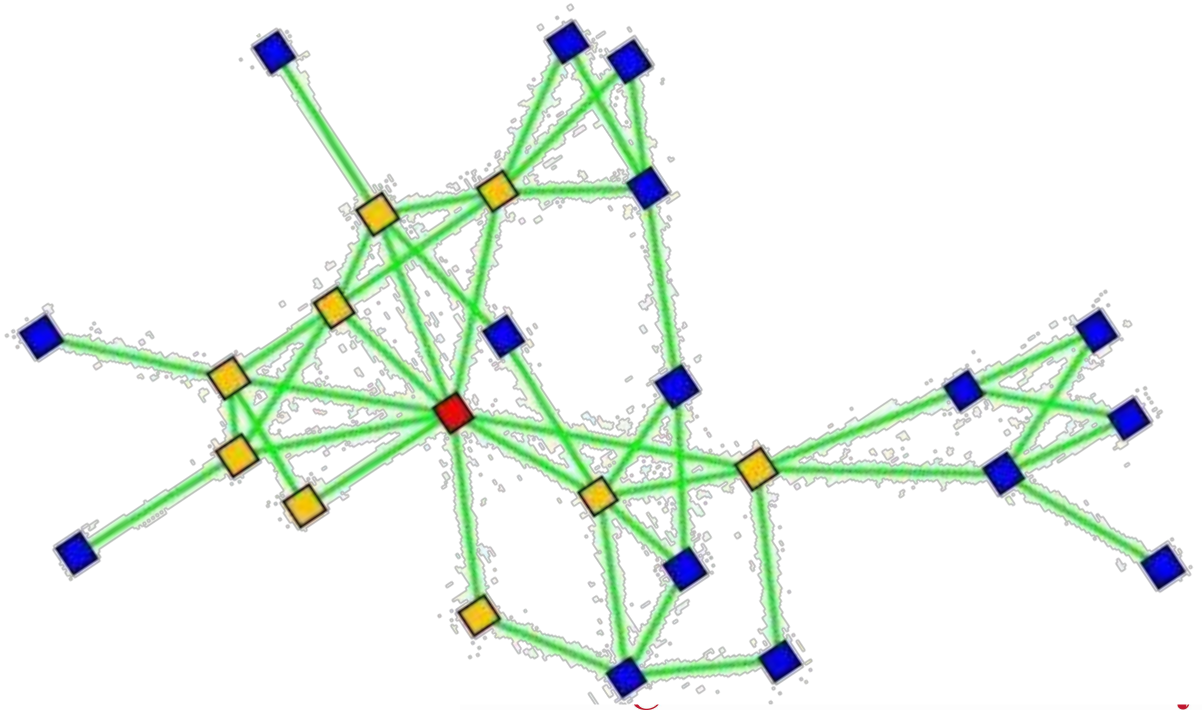

FAMILY VS. FRAT
NEAREST
NEIGHBORS
RECOMMENDER
#NEIGHBORSMOV
MAY 9
FROM THE GUYS WHO BROUGHT YOU THIS IS THE END

Basic Idea

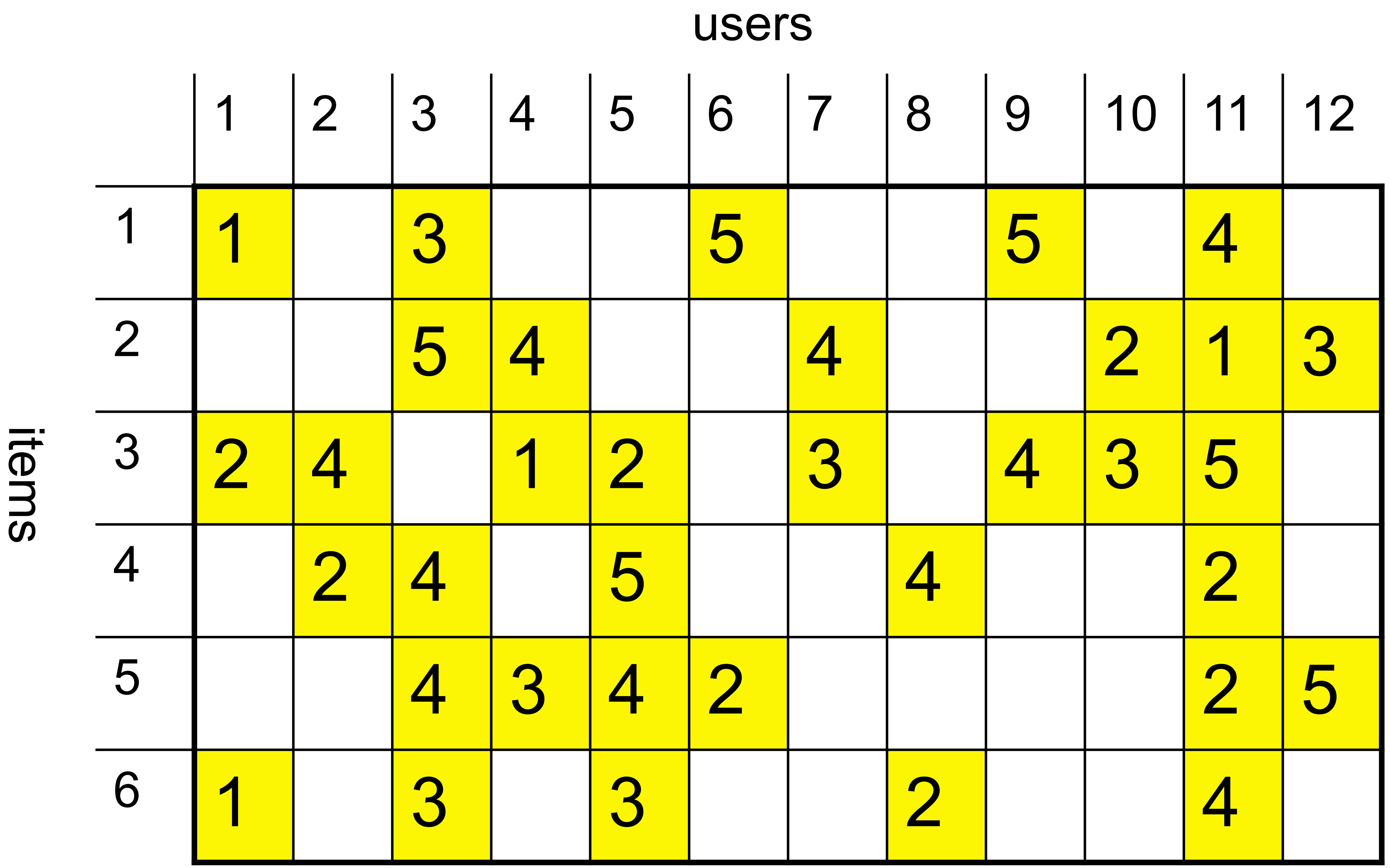


Basic Idea

- (user,user) similarity to recommend items
    - good if item base is smaller than user base
    - good if item base changes rapidly
    - traverse bipartite similarity graph
- (item,item) similarity to recommend new items that were also liked by the same users
    - good if the user base is small is small
- Oldest known CF method



Neighborhood based CF



users

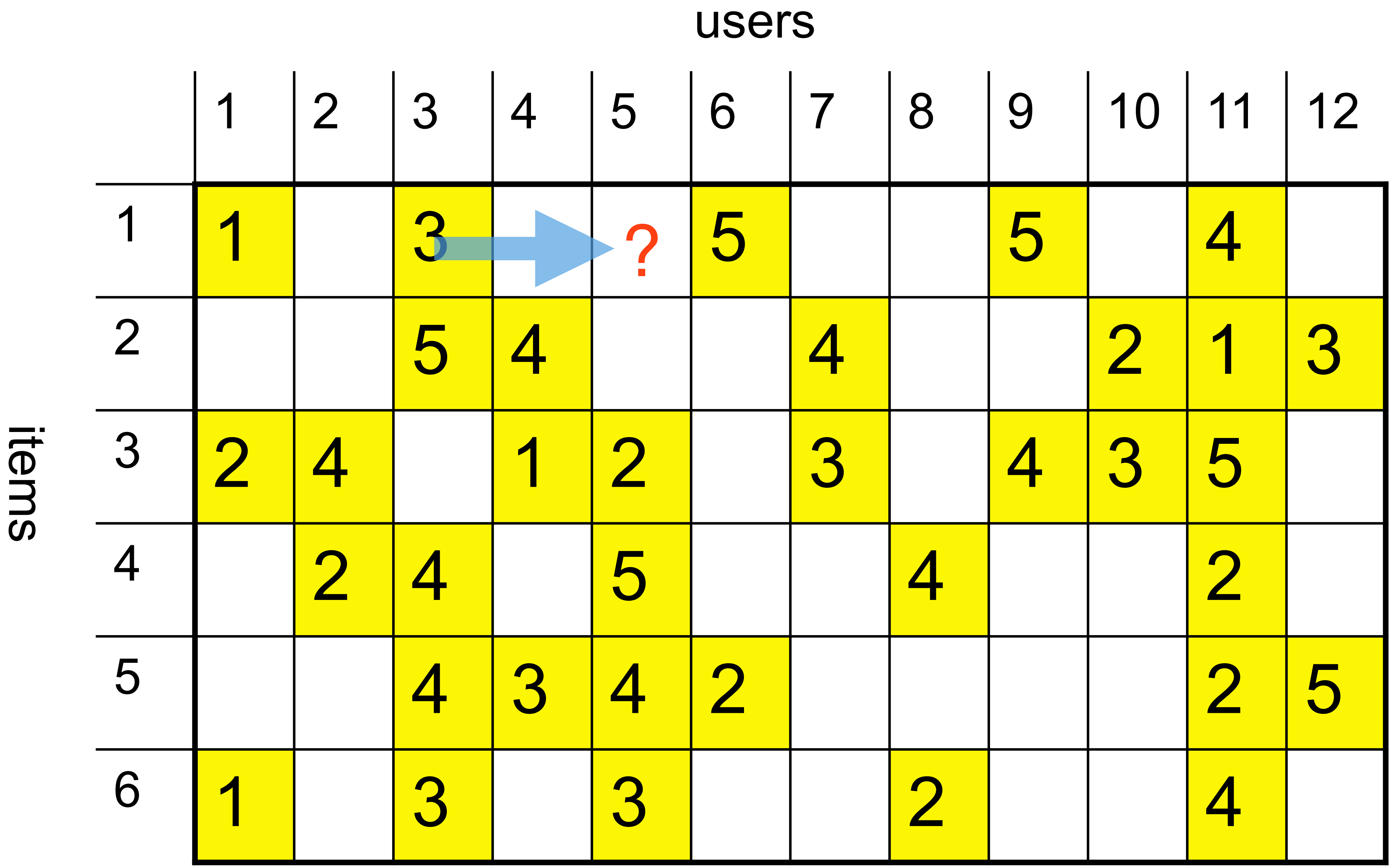
items

	1	2	3	4	5	6	7	8	9	10	11	12
1	1		3			5			5		4	
2			5	4			4			2	1	3
3	2	4		1	2		3		4	3	5	
4		2	4		5			4			2	
5			4	3	4	2					2	5
6	1		3		3			2			4	

☐ - unknown rating

🟨 - rating between 1 to 5

Neighborhood based CF



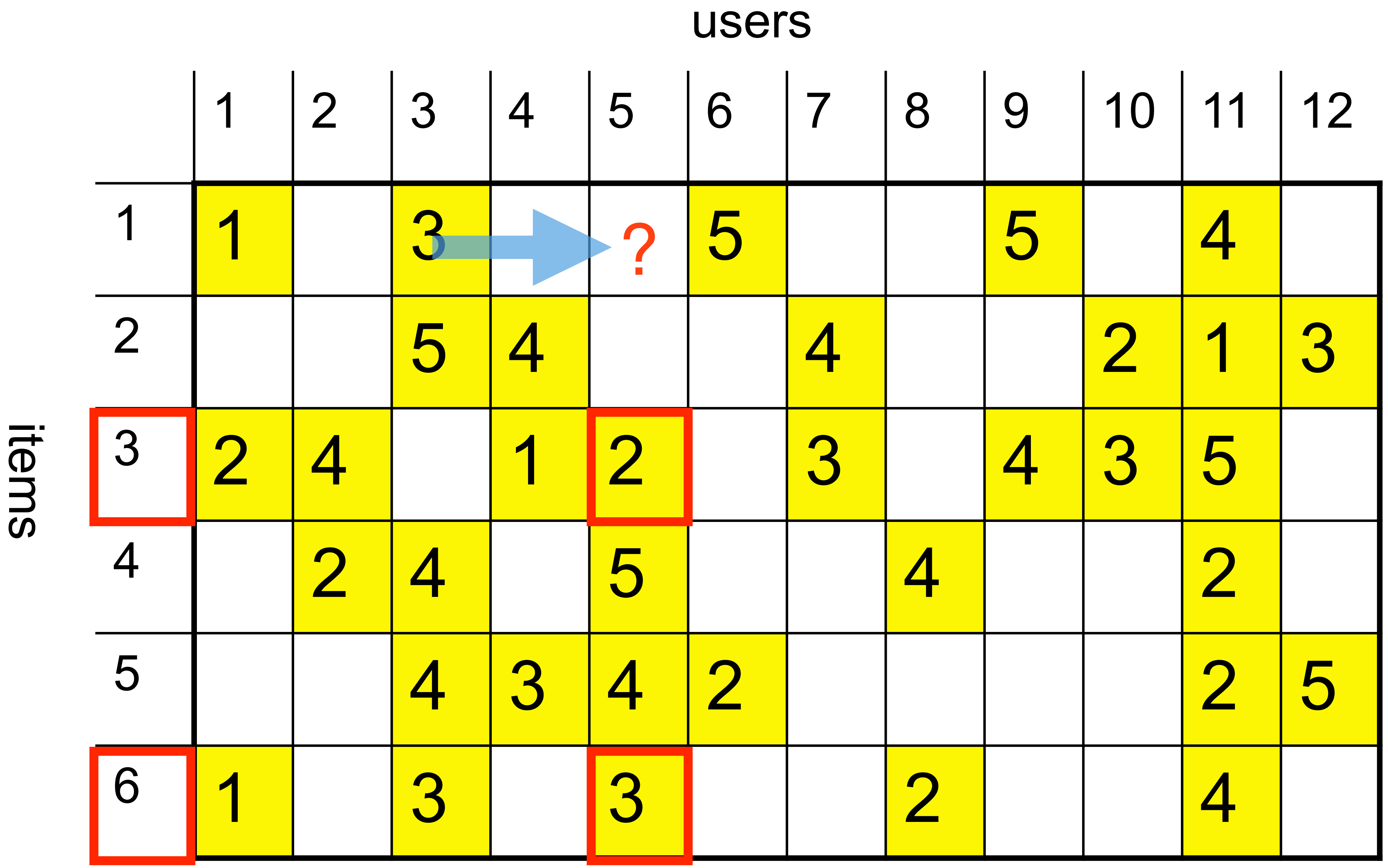
users

items

	1	2	3	4	5	6	7	8	9	10	11	12
1	1		3		?	5			5		4	
2			5	4			4			2	1	3
3	2	4		1	2		3		4	3	5	
4		2	4		5			4			2	
5			4	3	4	2					2	5
6	1		3		3			2			4	

☐ - unknown rating 🟨 - rating between 1 to 5

Neighborhood based CF



users

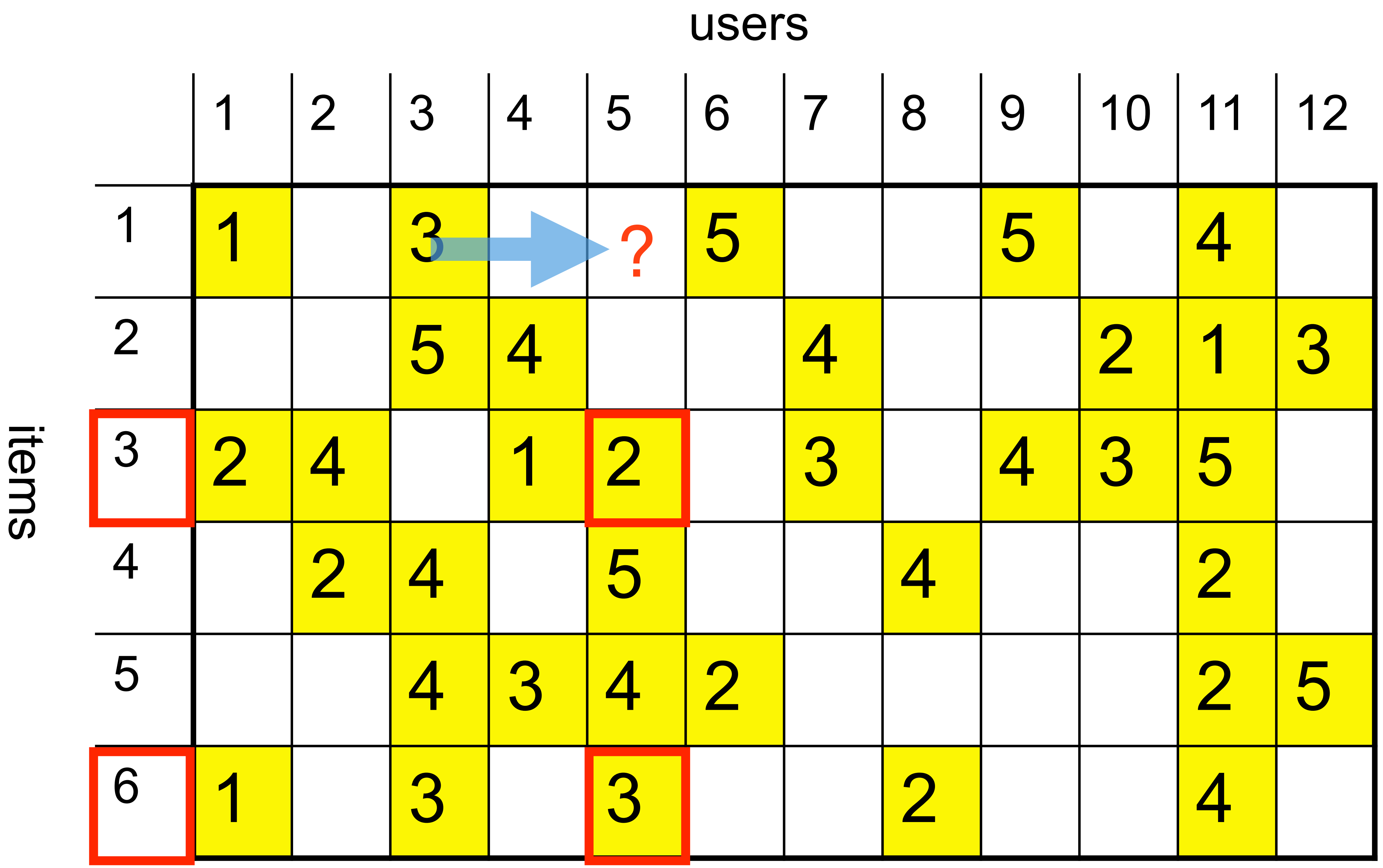
items

	1	2	3	4	5	6	7	8	9	10	11	12
1	1		3		?	5			5		4	
2			5	4			4			2	1	3
3	2	4		1	2		3		4	3	5	
4		2	4		5			4			2	
5			4	3	4	2					2	5
6	1		3		3			2			4	

☐ - unknown rating

🟨 - rating between 1 to 5

Neighborhood based CF



users

items	1	2	3	4	5	6	7	8	9	10	11	12
1	1		3		?	5			5		4	
2			5	4			4			2	1	3
3	2	4		1	2		3		4	3	5	
4		2	4		5			4			2	
5			4	3	4	2					2	5
6	1		3		3			2			4	

similarity

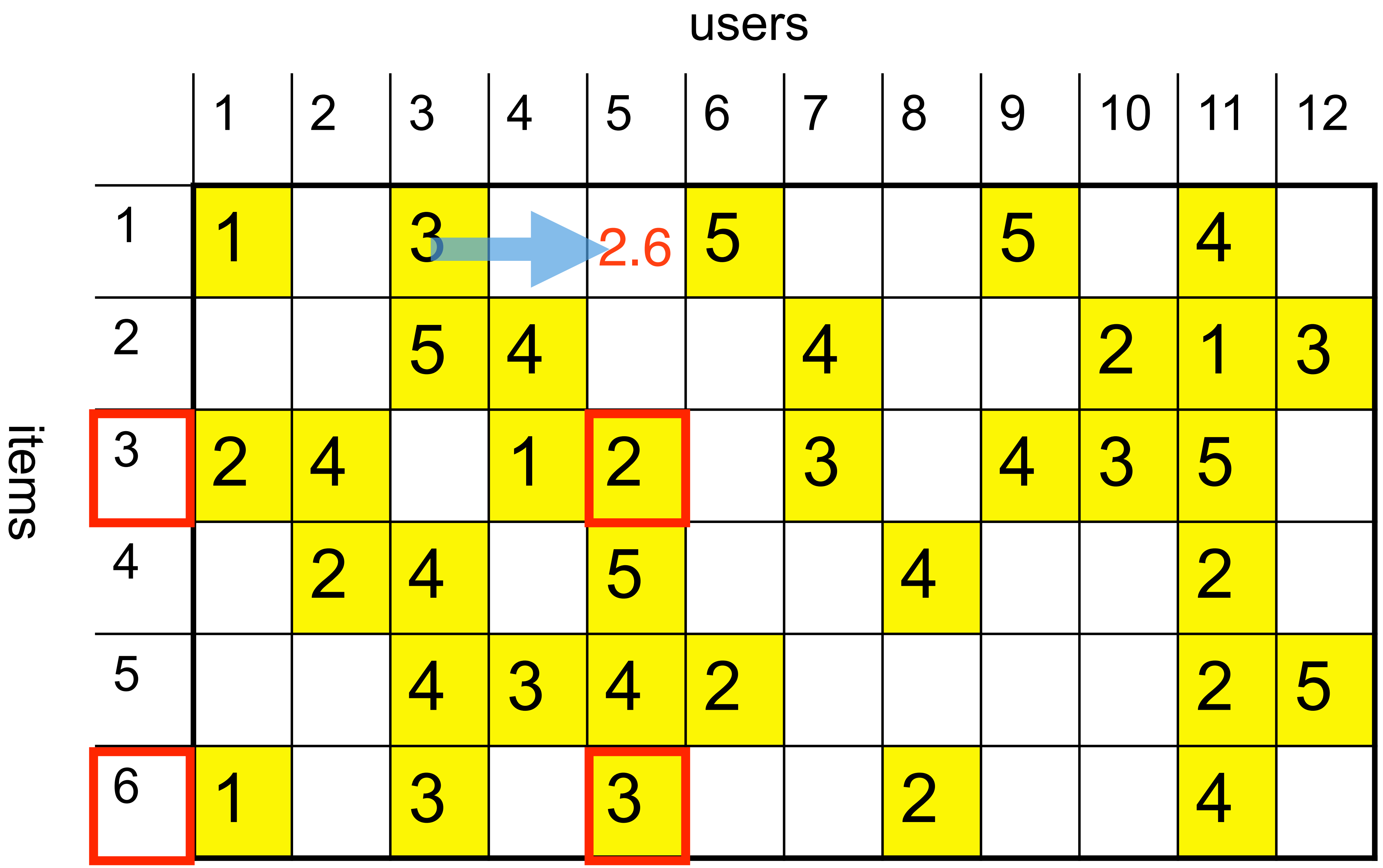
s13 = 0.2

s16 = 0.3

☐ - unknown rating

🟨 - rating between 1 to 5

Neighborhood based CF



users

items

	1	2	3	4	5	6	7	8	9	10	11	12
1	1		3		2.6	5			5		4	
2			5	4			4			2	1	3
3	2	4		1	2		3		4	3	5	
4		2	4		5			4			2	
5			4	3	4	2					2	5
6	1		3		3			2			4	

similarity

s13 = 0.2

s16 = 0.3

weighted average

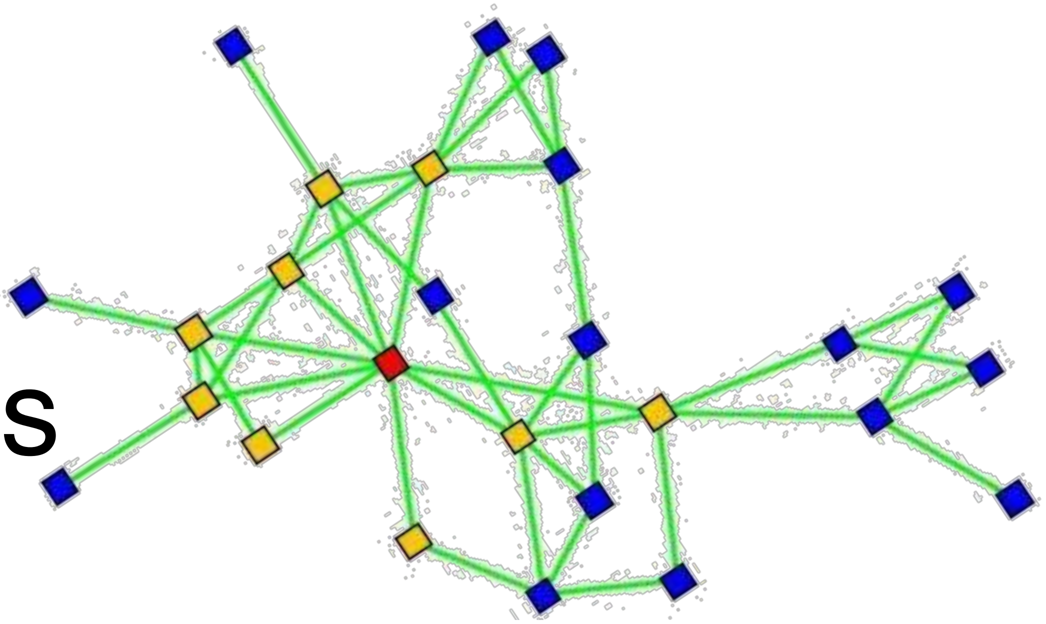
$$\frac{0.2 \cdot 2 + 0.3 \cdot 3}{0.2 + 0.3} = 2.6$$

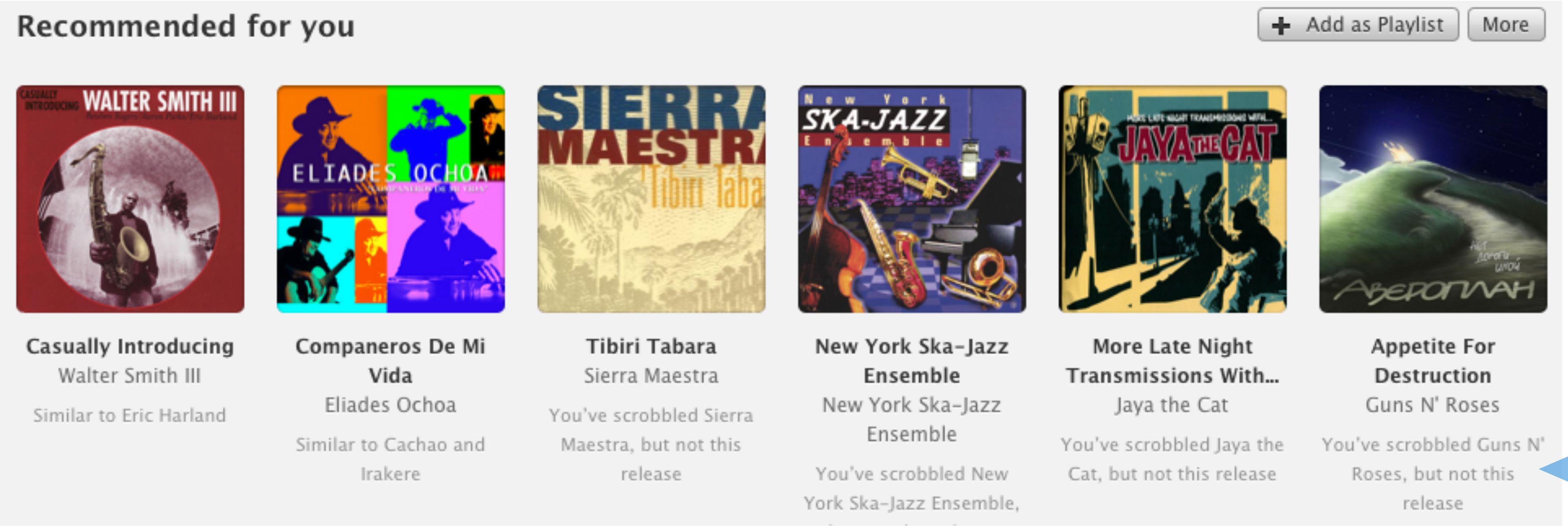
☐ - unknown rating

🟨 - rating between 1 to 5

Properties

- Intuitive
- No (substantial) training
- Handles new users / items
- Easy to explain to user





Recommended for you

Casually Introducing
Walter Smith III
Similar to Eric Harland

Companeros De Mi Vida
Eliades Ochoa
Similar to Cachao and Irakere

Tibiri Tabara
Sierra Maestra
You've scrobbled Sierra Maestra, but not this release

New York Ska-Jazz Ensemble
New York Ska-Jazz Ensemble
You've scrobbled New York Ska-Jazz Ensemble,

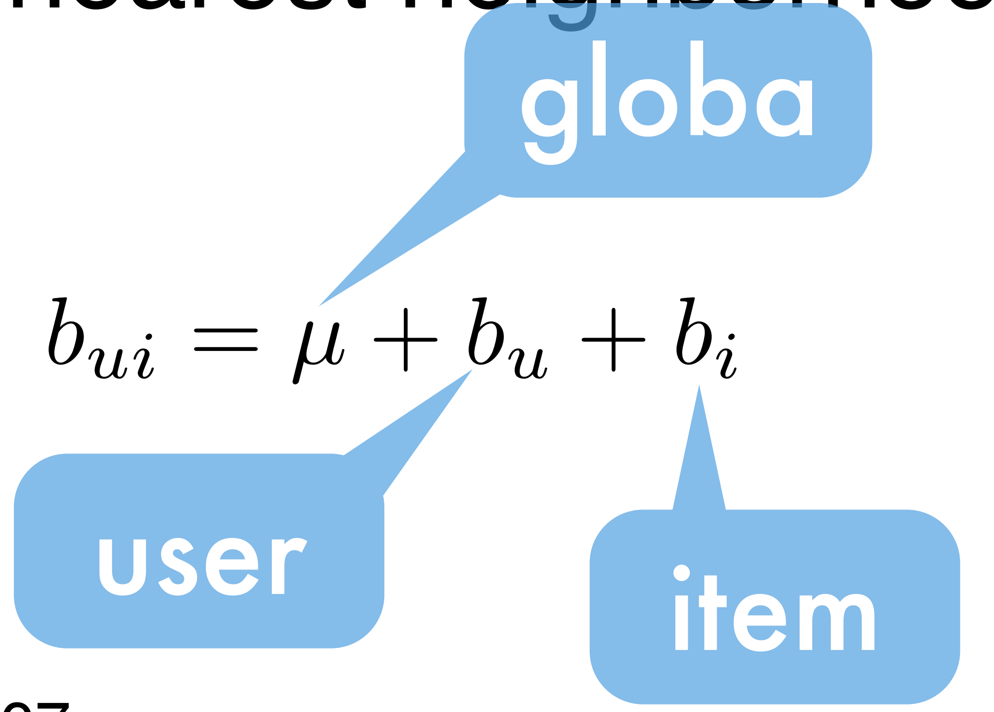
More Late Night Transmissions With...
Jaya the Cat
You've scrobbled Jaya the Cat, but not this release

Appetite For Destruction
Guns N' Roses
You've scrobbled Guns N' Roses, but not this release

- Accuracy & scalability questionable

Normalization / Bias

- Problem
  - Some items are significantly higher rated
  - Some users rate substantially lower
  - Ratings change over time
- Bias correction is crucial for nearest neighborhood recommender algorithm
  - Offset per user
  - Offset per movie
  - Time effects
  - Global bias



$$b_{ui} = \mu + b_u + b_i$$

Bell & Koren ICDM 2007

http://public.research.att.com/~volinsky/netflix/BellKorICDM07.pdf

Baseline estimation

- Mean rating is 3.7
- Troll Hunter is 0.7 above mean
- User rates 0.2 below mean
- Baseline is 4.2 stars
- Least mean squares problem

$$\underset{b}{\text{minimize}} \sum_{(u,i)} (r_{ui} - \mu - b_u - b_i)^2 + \lambda \left[\sum_u b_u^2 + \sum_i b_i^2 \right]$$

- Jointly convex. Alternatively remove mean & iterate

$$b_i = \frac{\sum_{u \in R(i)} (r_{ui} - \mu - b_u)}{\lambda + |R(i)|} \text{ and } b_u = \frac{\sum_{i \in R(u)} (r_{ui} - \mu - b_i)}{\lambda + |R(u)|}$$

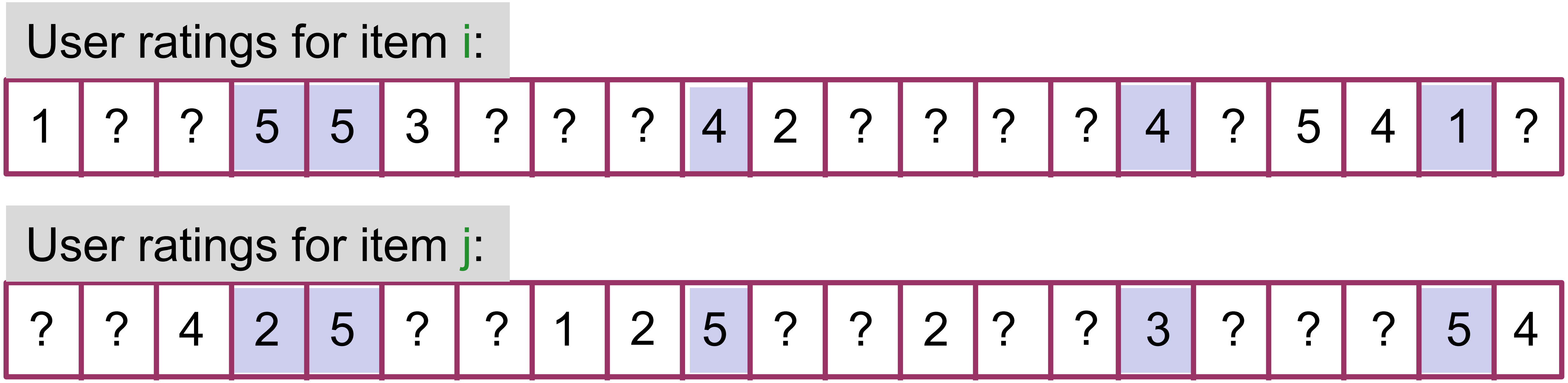
Parzen Windows style CF

- Similarity measure s_{ij} between items
- Find set $s_k(i,u)$ of k-nearest neighbors to movie i that were rated by user u
- Weighted average over the set

$$\hat{r}_{ui} = b_{ui} + \frac{\sum_{j \in s_k(i,u)} s_{ij}(r_{uj} - b_{uj})}{\sum_{j \in s_k(i,u)} s_{ij}} \text{ where } b_{ui} = \mu + b_u + b_i$$

- How to compute s_{ij}?

(item,item) similarity measures



User ratings for item i:

1	?	?	5	5	3	?	?	?	4	2	?	?	?	?	4	?	5	4	1	?

User ratings for item j:

?	?	4	2	5	?	?	1	2	5	?	?	2	?	?	3	?	?	?	5	4

- Pearson correlation coefficient
  - nonuniform support
  - compute only over shared support
  - shrinkage towards 0 to address problem of small support (typically few items in common)

$$s_{ij} = \frac{\mathrm{Cov}[r_{ui}, r_{uj}]}{\mathrm{Std}[r_{ui}]\mathrm{Std}[r_{uj}]}$$

(item,item) similarity measures

- Empirical Pearson correlation coefficient

$$\hat{\rho}_{ij} = \frac{\sum_{u \in U(i,j)} (r_{ui} - b_{ui})(r_{uj} - b_{uj})}{\sqrt{\sum_{u \in U(i,j)} (r_{ui} - b_{ui})^2 \sum_{u \in U(i,j)} (r_{uj} - b_{uj})^2}}$$

- Smoothing towards 0 for small support

$$s_{ij} = \frac{|U(i,j)| - 1}{|U(i,j)| - 1 + \lambda} \hat{\rho}_{ij}$$

- Make neighborhood more peaked $s_{ij} \to s_{ij}^2$
- Shrink towards baseline for small neighborhood

$$\hat{r}_{ui} = b_{ui} + \frac{\sum_{j \in s_k(i,u)} s_{ij} (r_{uj} - b_{uj})}{\lambda + \sum_{j \in s_k(i,u)} s_{ij}}$$

Similarity for binary data

- Pearson correlation meaningless
  - Views
  - Purchase behavior
  - Clicks
- Jaccard similarity (intersection vs. joint)
- Observed/expected ratio
Improve by counting per user (many users better than heavy users)

m_i users acting on i

m_{ij} users acting on both i and j

m total number of users

$$s_{ij} = \frac{m_{ij}}{\alpha + m_i + m_j - m_{ij}}$$

$$s_{ij} = \frac{\text{observed}}{\text{expected}} \approx \frac{m_{ij}}{\alpha + m_i m_j / m}$$

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MACHINE LEARNING
DEPARTMENT

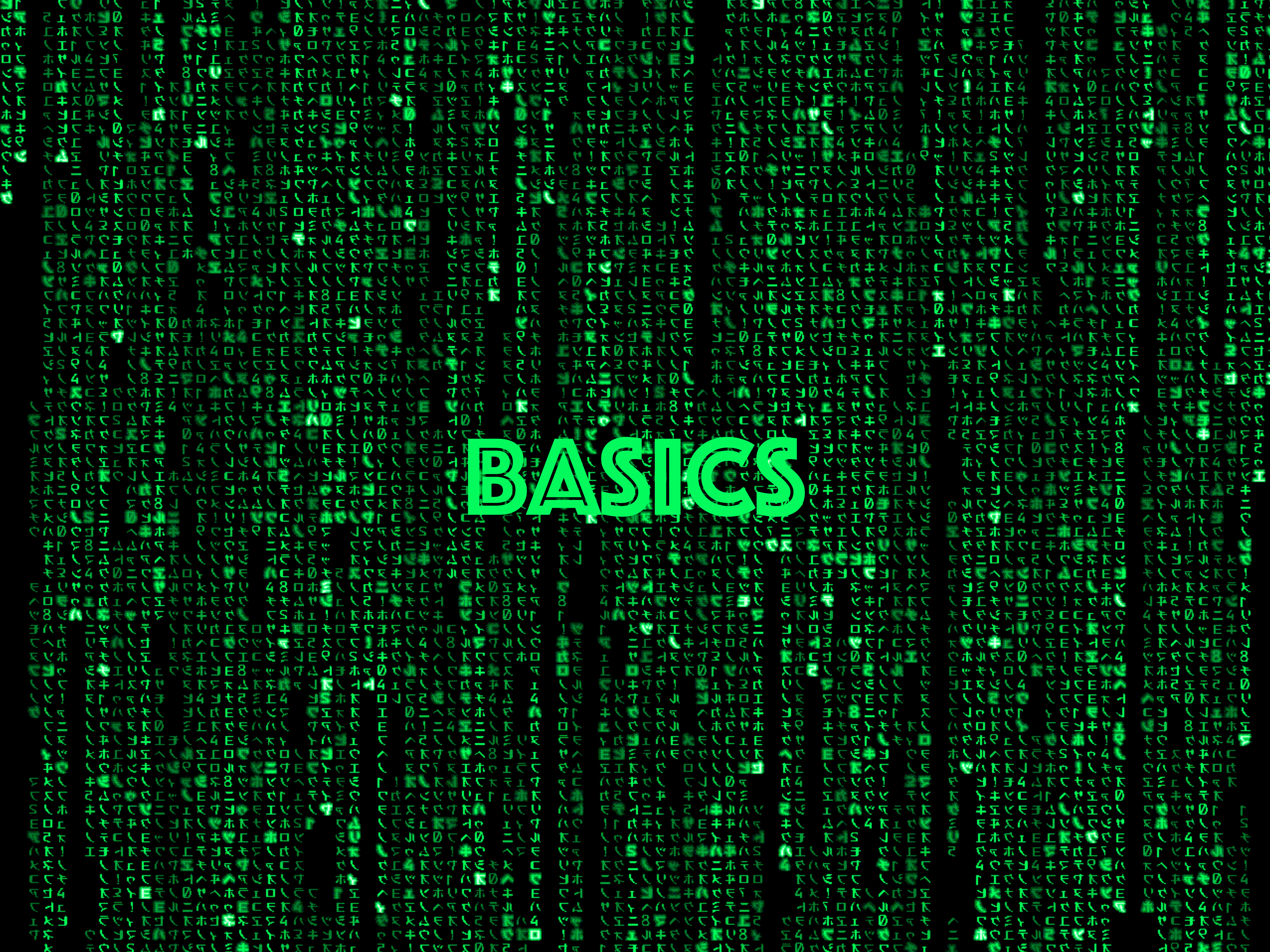
8.2 Matrix Factorization

8 Recommender Systems

Alexander Smola
Introduction to Machine Learning 10-701
http://alex.smola.org/teaching/10-701-15

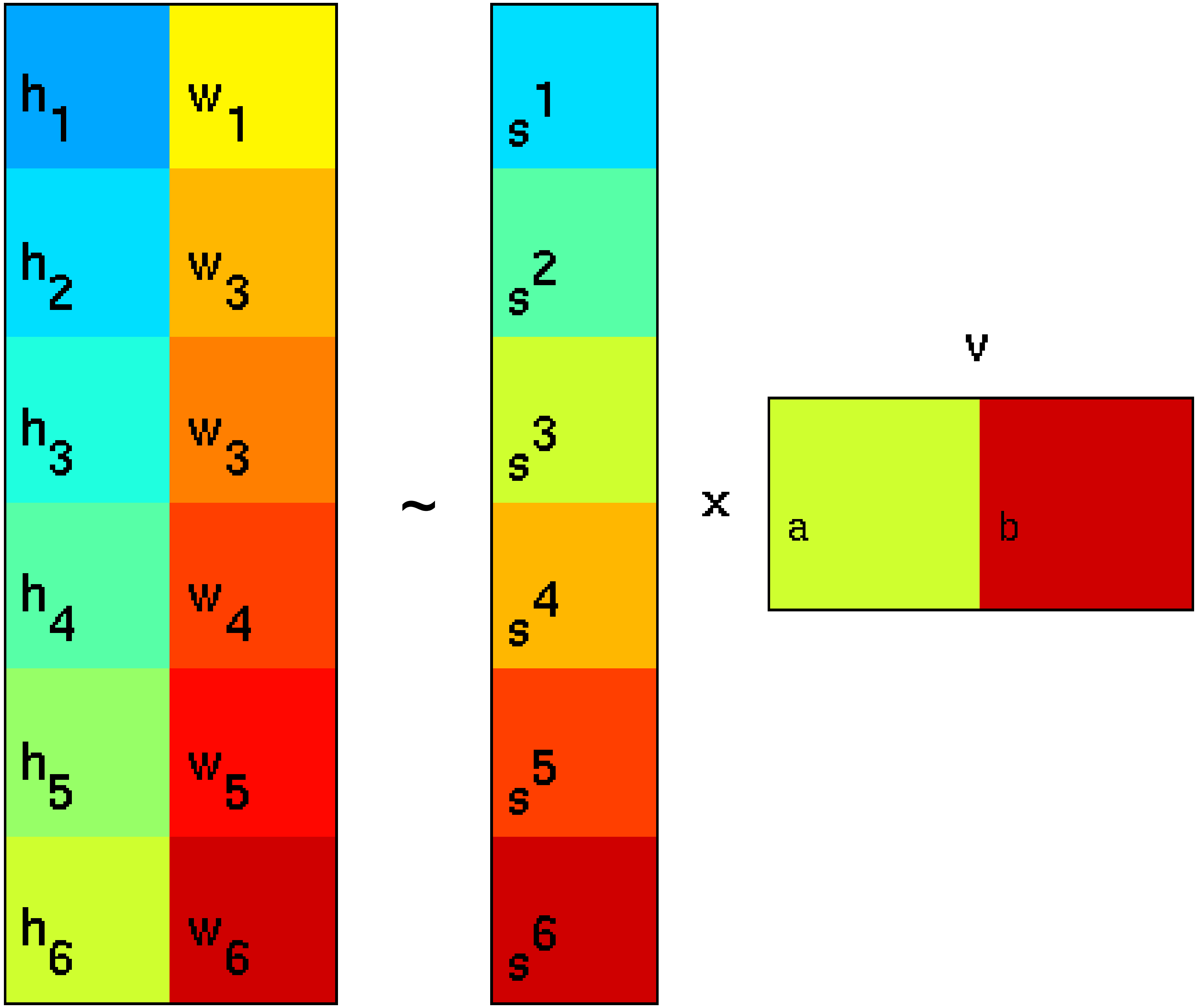
Significant content courtesy of Yehuda Koren

Carnegie Mellon University



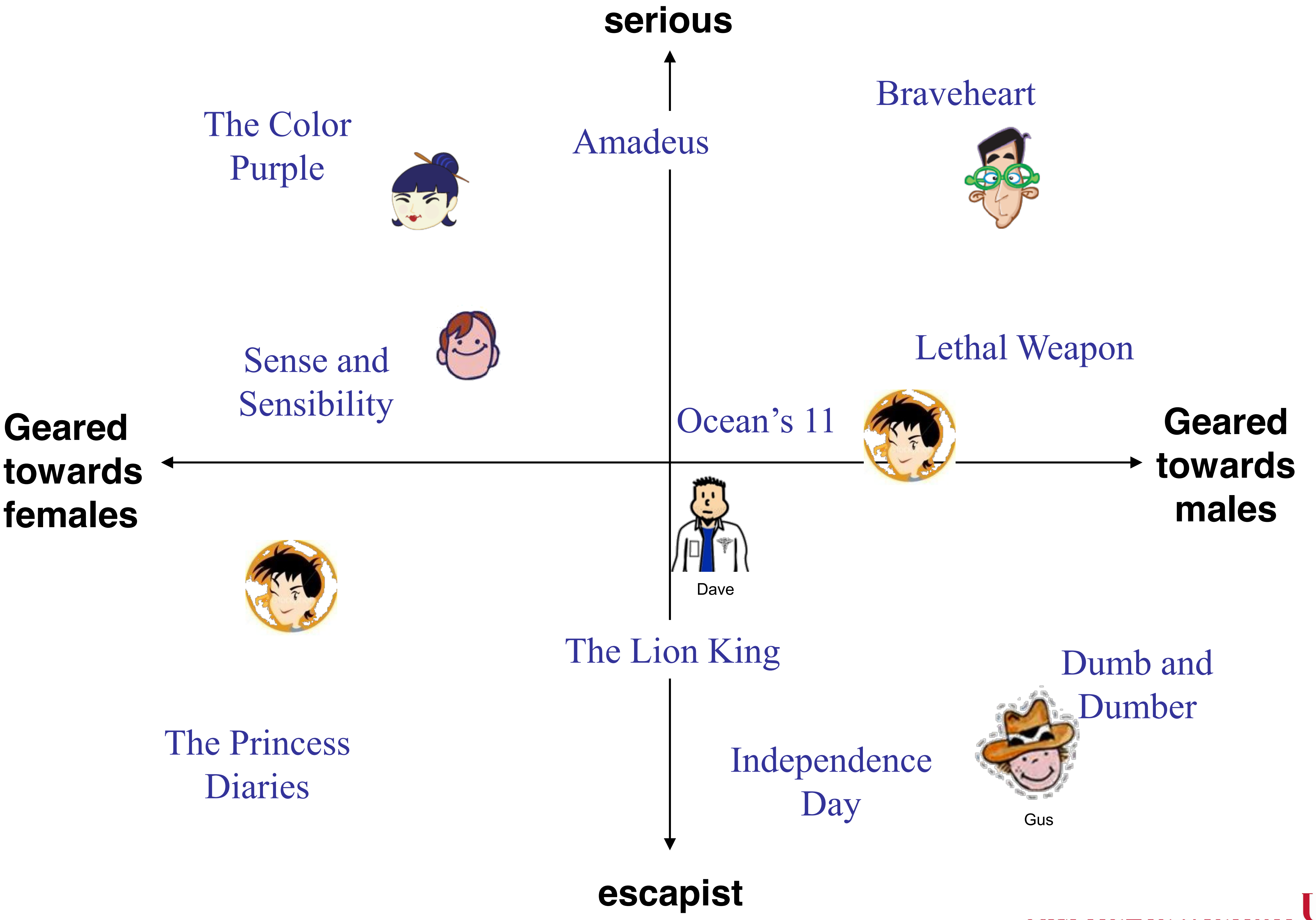
BASICS

Basic Idea



$$M \approx U \cdot V$$

Latent variable view



serious

The Color Purple

Amadeus

Braveheart

Sense and Sensibility

Lethal Weapon

Geared towards females

Ocean's 11

Geared towards males

The Lion King

Dumb and Dumber

The Princess Diaries

Independence Day

escapist

Basic matrix factorization

users

items

1		3			5			5		4	
		5	4			4			2	1	3
2	4		1	2		3		4	3	5	
	2	4		5			4			2	
		4	3	4	2					2	5
1		3		3			2			4	

~

~

items

.1	-.4	.2
-.5	.6	.5
-.2	.3	.5
1.1	2.1	.3
-.7	2.1	-2
-1	.7	.3

●

users

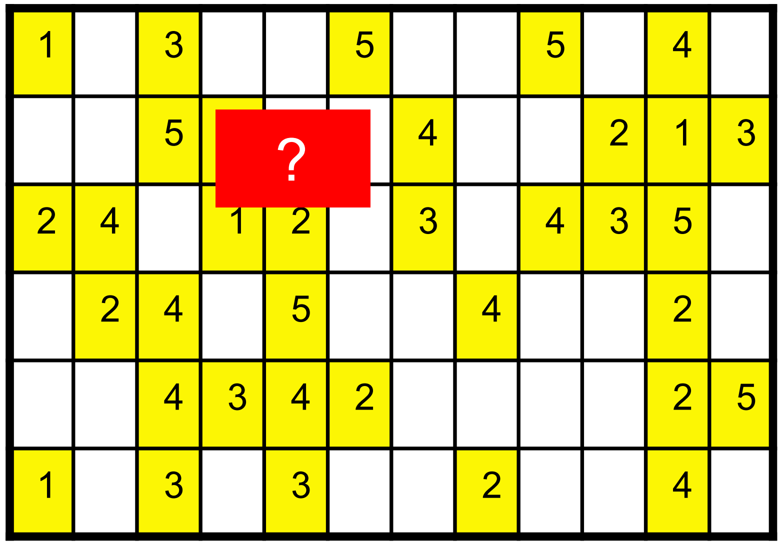
1.1	-.2	.3	.5	-2	-.5	.8	-.4	.3	1.4	2.4	-.9
-.8	.7	.5	1.4	.3	-1	1.4	2.9	-.7	1.2	-.1	1.3
2.1	-.4	.6	1.7	2.4	.9	-.3	.4	.8	.7	-.6	.1

A rank-3 SVD approximation

Estimate unknown ratings

users

items



1		3			5			5		4	
		5		?		4			2	1	3
2	4		1	2		3		4	3	5	
	2	4		5			4			2	
		4	3	4	2					2	5
1		3		3			2			4	

~

~ items

.1	-.4	.2
-.5	.6	.5
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-1	.7	.3

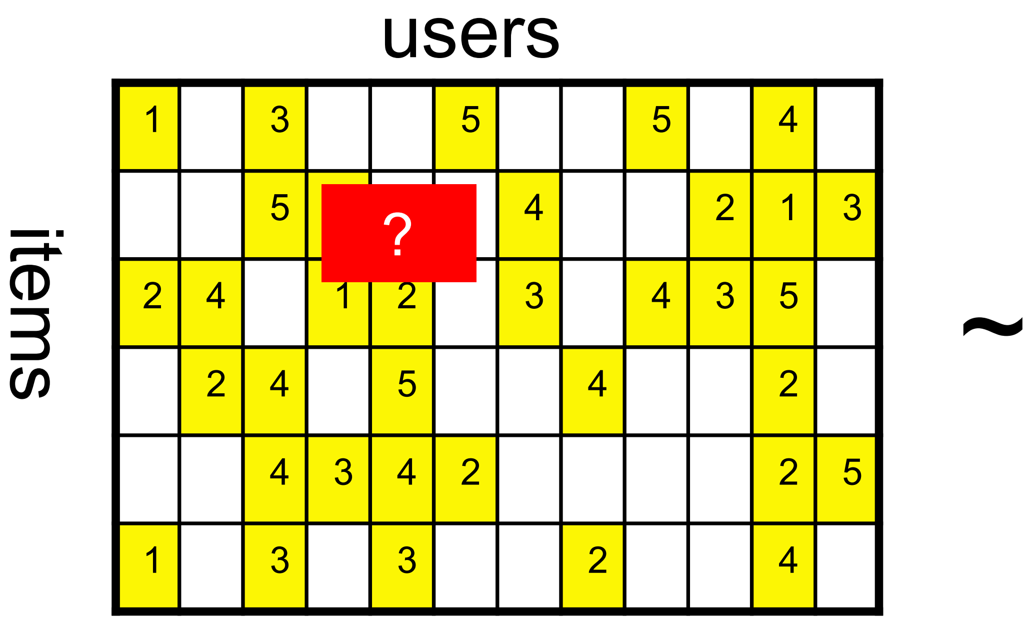
●

users

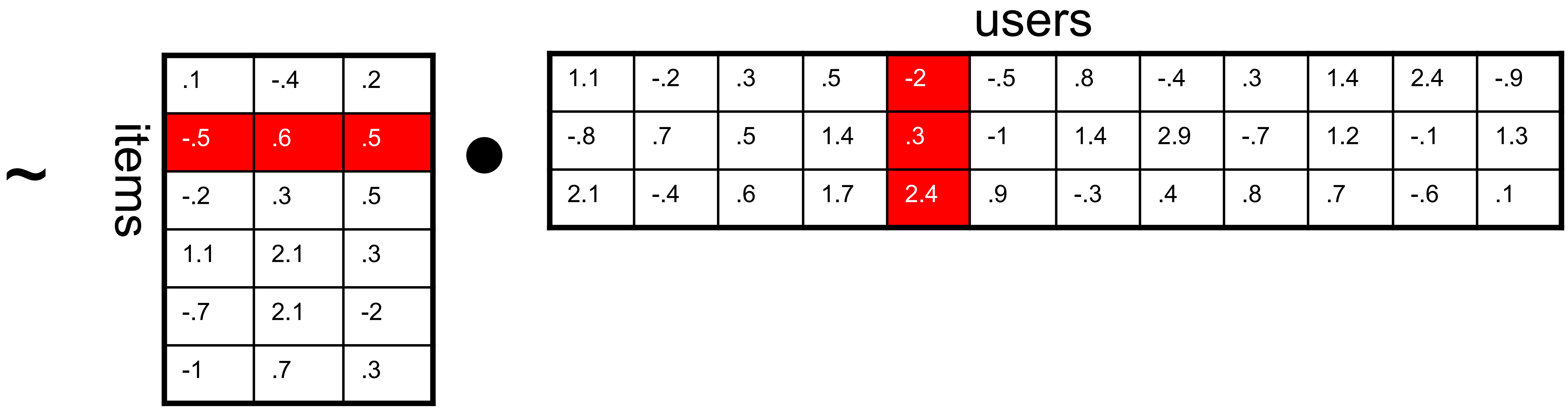
1.1	-.2	.3	.5	-2	-.5	.8	-.4	.3	1.4	2.4	-.9
-.8	.7	.5	1.4	.3	-1	1.4	2.9	-.7	1.2	-.1	1.3
2.1	-.4	.6	1.7	2.4	.9	-.3	.4	.8	.7	-.6	.1

A rank-3 SVD approximation

Estimate unknown ratings



1		3			5			5		4	
		5		?		4			2	1	3
2	4		1	2		3		4	3	5	
	2	4		5			4			2	
		4	3	4	2					2	5
1		3		3			2			4	

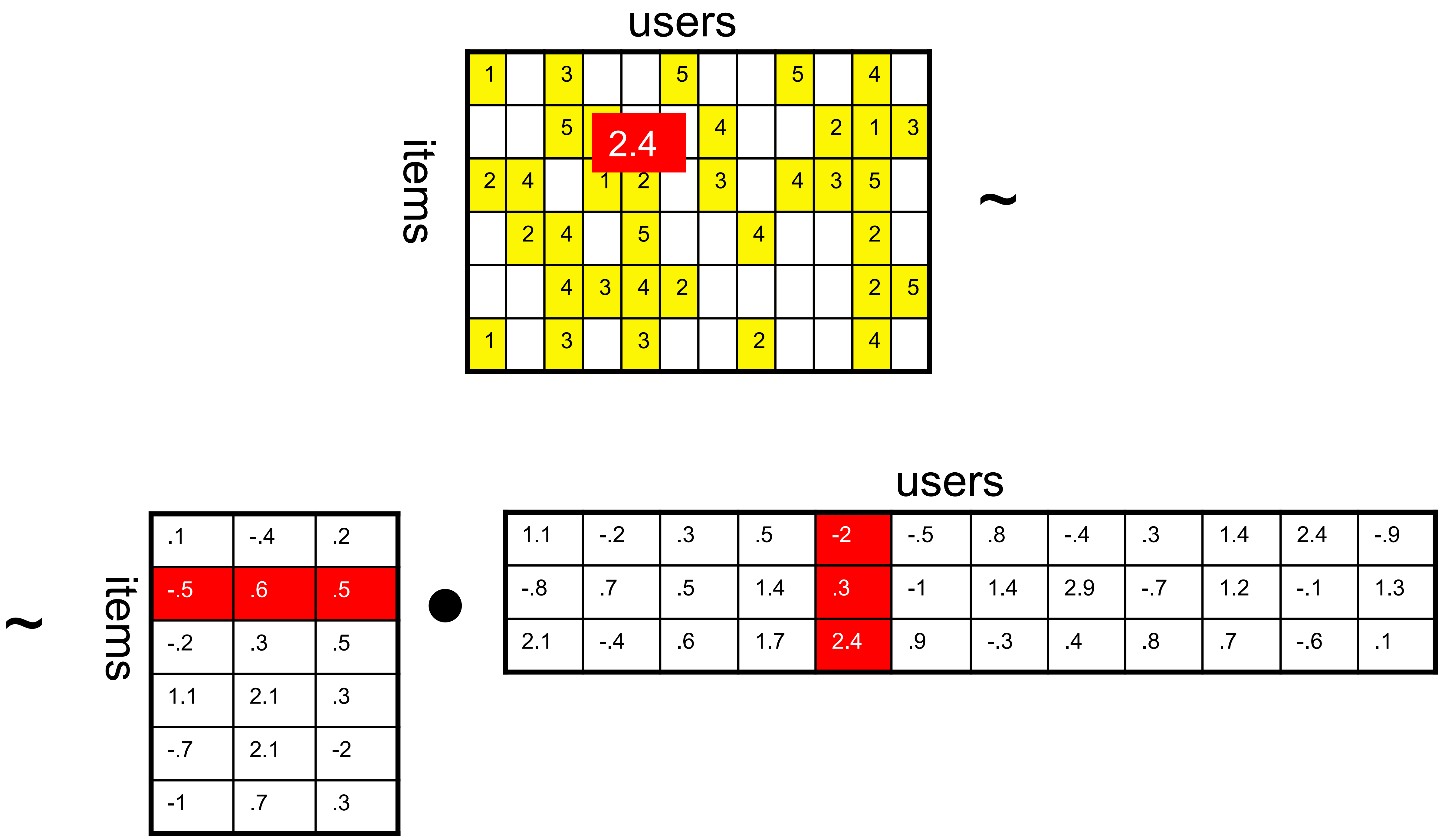


.1	-.4	.2
-.5	.6	.5
-.2	.3	.5
1.1	2.1	.3
-.7	2.1	-2
-1	.7	.3

1.1	-.2	.3	.5	-2	-.5	.8	-.4	.3	1.4	2.4	-.9
-.8	.7	.5	1.4	.3	-1	1.4	2.9	-.7	1.2	-.1	1.3
2.1	-.4	.6	1.7	2.4	.9	-.3	.4	.8	.7	-.6	.1

A rank-3 SVD approximation

Estimate unknown ratings



users

items

1		3			5			5		4	
		5		2.4		4			2	1	3
2	4		1	2		3		4	3	5	
	2	4		5			4			2	
		4	3	4	2					2	5
1		3		3			2			4	

~

~

items

.1	-.4	.2
-.5	.6	.5
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1.1	2.1	.3
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-1	.7	.3

●

users

1.1	-.2	.3	.5	-2	-.5	.8	-.4	.3	1.4	2.4	-.9
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A rank-3 SVD approximation

Properties

1		3			5			5		4	
		5	4			4			2	1	3
2	4		1	2		3		4	3	5	
	2	4		5			4			2	
		4	3	4	2					2	5
1		3		3			2			4	

~

.1	-.4	.2
-.5	.6	.5
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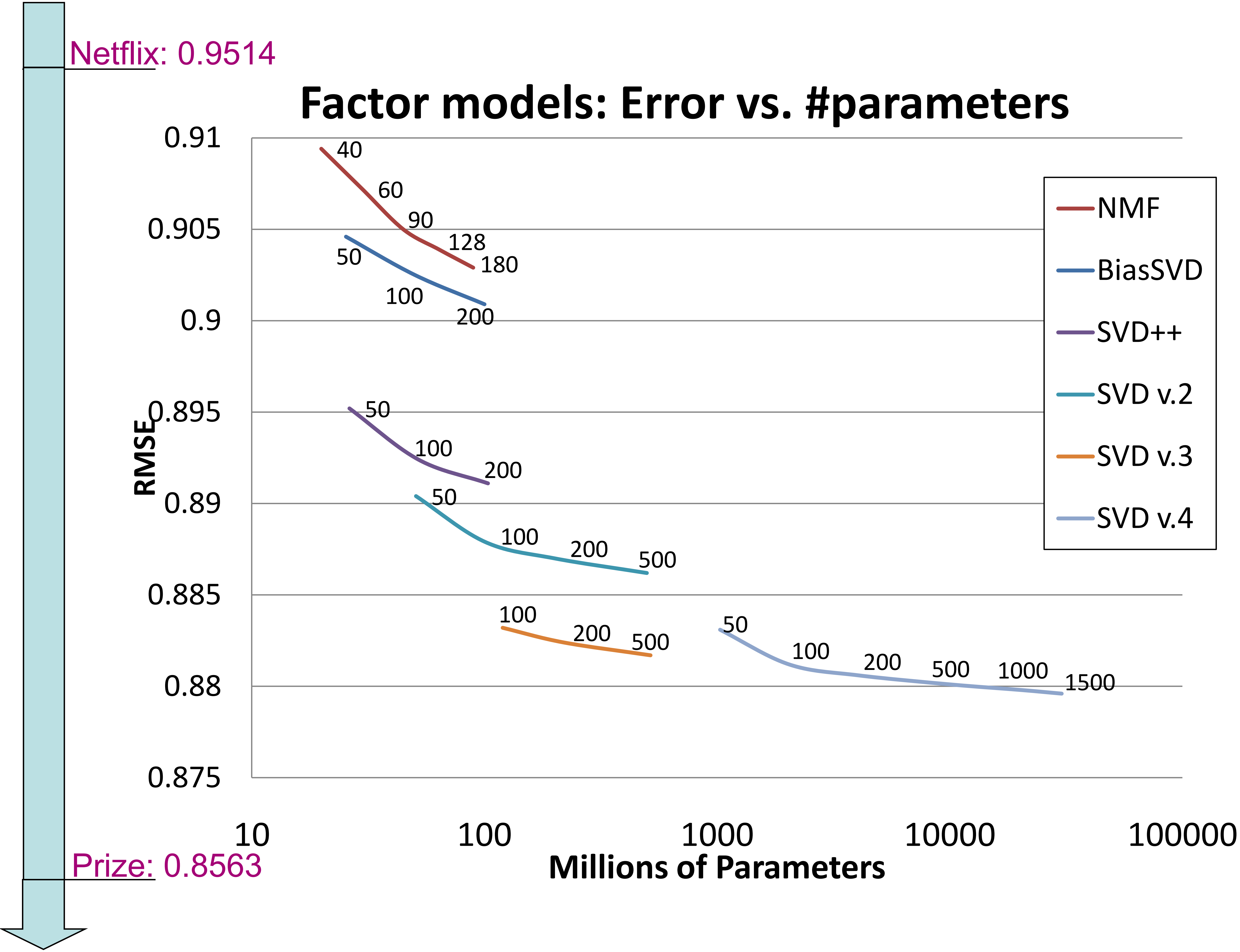
1.1	2.1	.3
-.7	2.1	-2
-1	.7	.3

1.1	-.2	.3	.5	-2	-.5	.8	-.4	.3	1.4	2.4	-.9
-.8	.7	.5	1.4	.3	-1	1.4	2.9	-.7	1.2	-.1	1.3
2.1	-.4	.6	1.7	2.4	.9	-.3	.4	.8	.7	-.6	.1

- SVD is undefined for missing entries
    - stochastic gradient descent (faster)
    - alternating optimization
- Overfitting without regularization
  particularly if fewer reviews than dimensions
- Very popular on Netflix

Factor models: Error vs. #parameters



Risk Minimization View

- Objective Function

$$\underset{p,q}{\text{minimize}} \sum_{(u,i)\in S} (r_{ui} - \langle p_u, q_i \rangle)^2 + \lambda \left[\|p\|^2_{\text{Frob}} + \|q\|^2_{\text{Frob}} \right]$$

- Alternating least squares

$$p_u \leftarrow \left[\lambda \mathbf{1} + \sum_{i|(u,i)\in S} q_i q_i^\top \right]^{-1} \sum_i q_i r_{ui}$$

$$q_i \leftarrow \left[\lambda \mathbf{1} + \sum_{u|(u,i)\in S} p_u p_u^\top \right]^{-1} \sum_i p_u r_{ui}$$

good for MapReduce

Risk Minimization View

- Objective Function

$$\underset{p,q}{\text{minimize}} \sum_{(u,i)\in S} (r_{ui} - \langle p_u, q_i \rangle)^2 + \lambda \left[\|p\|^2_{\text{Frob}} + \|q\|^2_{\text{Frob}} \right]$$

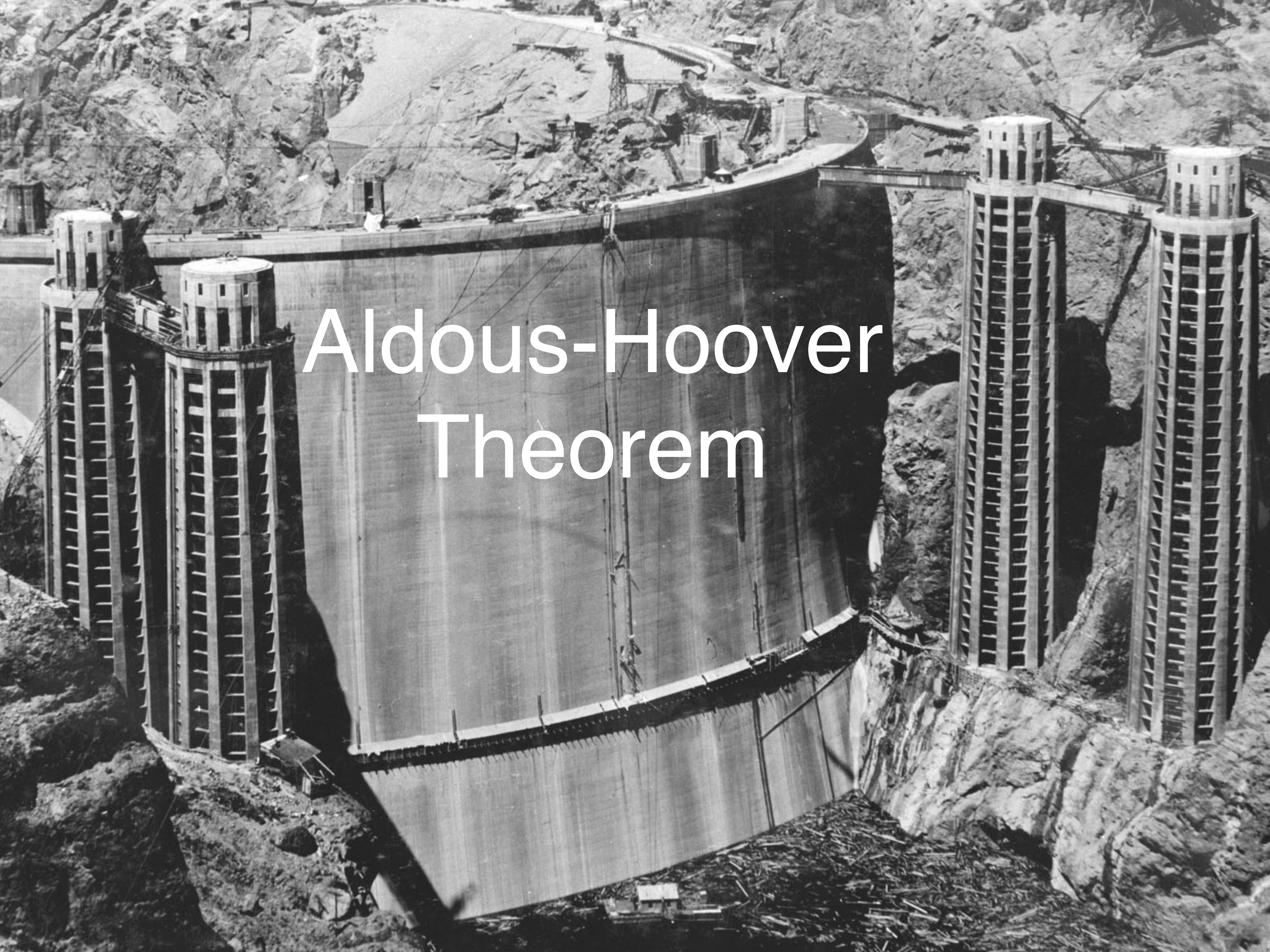
- Stochastic gradient descent

$$p_u \leftarrow (1 - \lambda\eta_t)p_u - \eta_t q_i (r_{ui} - \langle p_u, q_i \rangle)$$

$$q_i \leftarrow (1 - \lambda\eta_t)q_i - \eta_t p_u (r_{ui} - \langle p_u, q_i \rangle)$$

much faster

  - No need for locking
  - Multicore updates asynchronously (Recht, Re, Wright, 2012 - Hogwild)
  - 20 minutes on a laptop for 1000+ dimensions



Aldous-Hoover Theorem

deFinetti Theorem

- Independent random variables

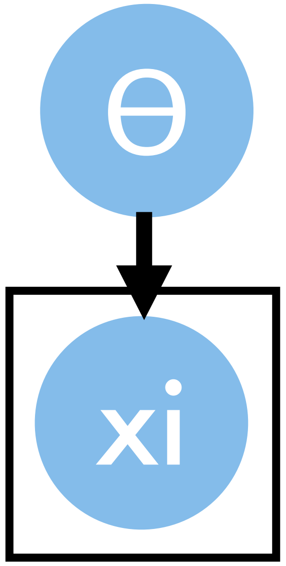
$$p(X) = \prod_{i=1}^{m} p(x_i)$$

- Exchangeable random variables

$$p(X) = p(x_1, \ldots, x_m) = p(x_{\pi(1)}, \ldots, x_{\pi(m)})$$

- There exists a conditionally independent representation of exchangeable r.v.

$$p(X) = \int dp(\theta) \prod_{i=1}^{m} p(x_i|\theta)$$



This motivates latent variable models

Aldous Hoover Factorization

- Matrix-valued set of random variable
  Example - Erdos Renyi graph model

$$p(E) = \prod_{i,j} p(V_{ij})$$

- Independently exchangeable on matrix

$$p(E) = p(E_{11}, E_{12}, \ldots, E_{mn}) = p(E_{\pi(1)\rho(1)}, E_{\pi(1)\rho(2)}, \ldots, E_{\pi(m)\rho(n)})$$

- Aldous Hoover Theorem

$$p(E) = \int dp(\theta) \int \prod_{i=1}^{m} dp(u_i) \prod_{j=1}^{n} dp(v_j) \prod_{i,j} p(E_{ij}|u_i, v_j, \theta)$$

Aldous Hoover Factorization

	u1	u2	u3	u4	u5	u6
v1	e11	e12			e15	e16
v2				e24		
v3		e32				
v4			e43			e46
v5					e55	

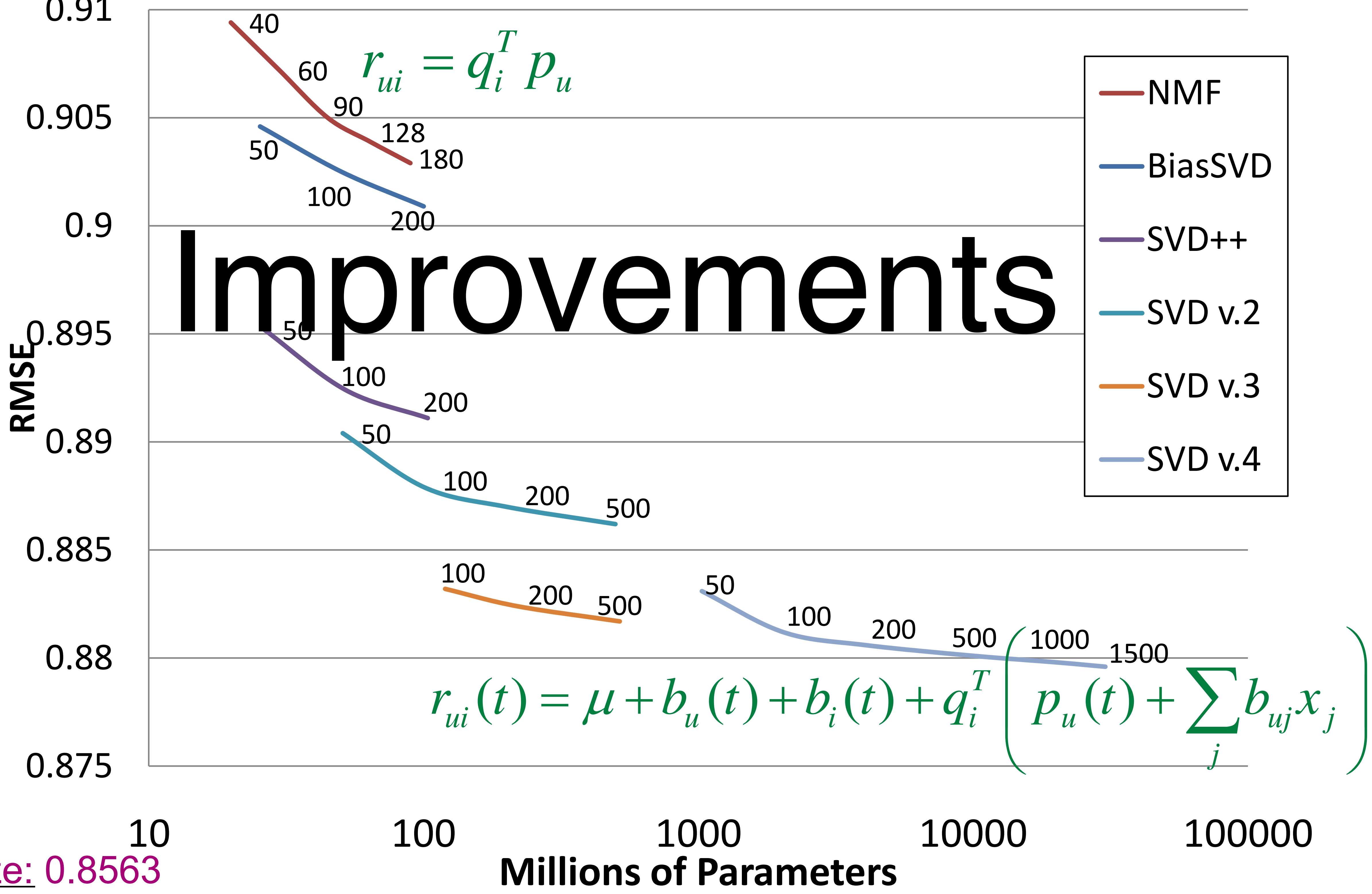
- Rating matrix is (row, column) exchangeable
- Draw latent variables per row and column
- Draw matrix entries independently given pairs
- Absence / presence of rating is a signal
- Can be extended to graphs with vertex attributes

Aldous Hoover variants

- Jointly exchangeable matrix
  - Social network graphs
  - Draw vertex attributes first, then edges
- Cold start problem
  - New user appears
  - Attributes (age, location, browser)
  - Can estimate latent variables from that
- User and item factors in matrix factorization problem can be viewed as AH-factors

Netflix: 0.9514

Factor models: Error vs. #parameters



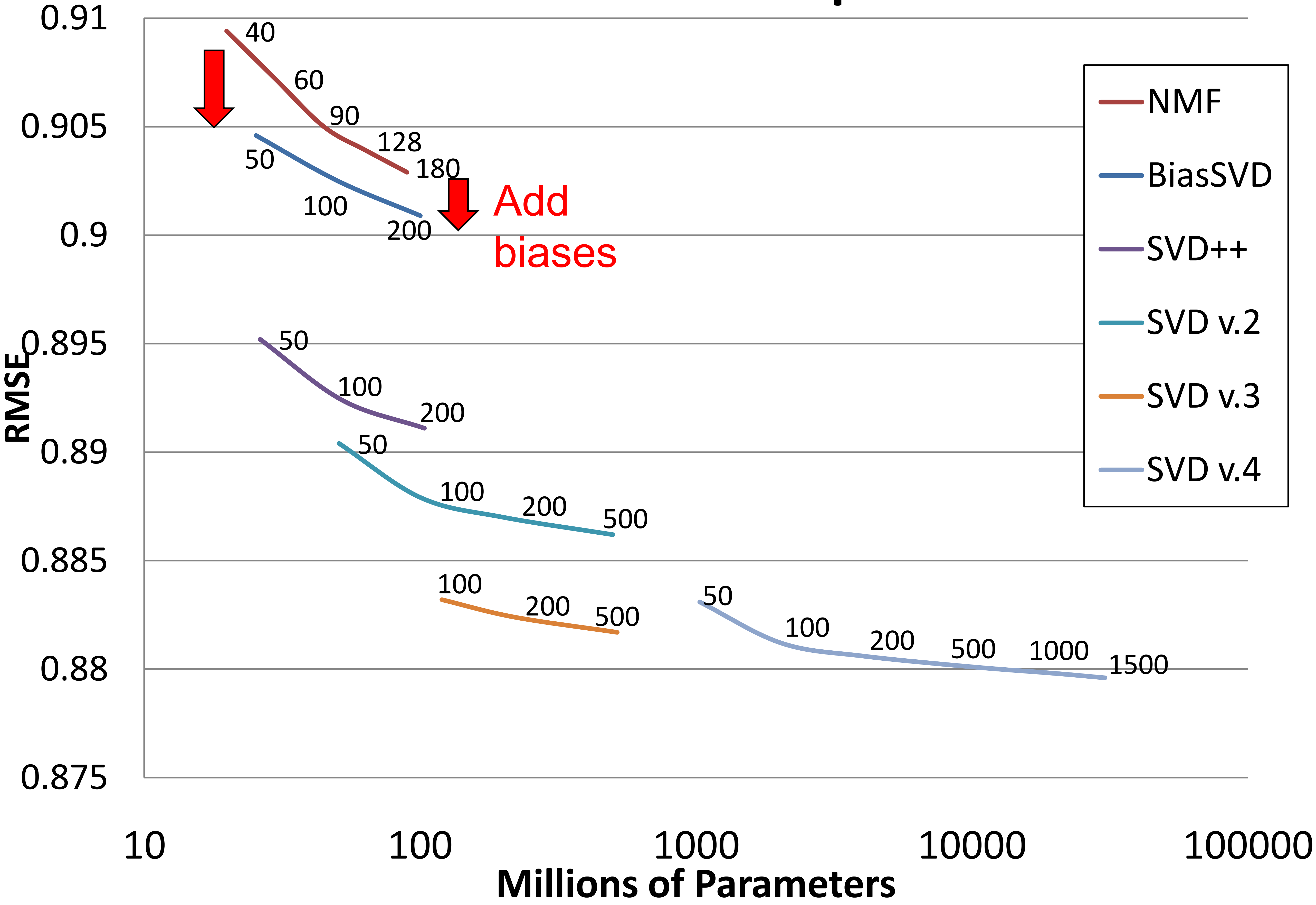
$$r_{ui} = q_i^T p_u$$

Improvements

$$r_{ui}(t) = \mu + b_u(t) + b_i(t) + q_i^T \left(p_u(t) + \sum_j b_{uj} x_j \right)$$

Prize: 0.8563

Factor models: Error vs. #parameters



Add biases

Bias

- Objective Function

$$\underset{p,q}{\text{minimize}} \sum_{(u,i)\in S} (r_{ui} - (\mu + b_u + b_i + \langle p_u, q_i \rangle))^2 +$$

$$\lambda \left[\|p\|^2_{\text{Frob}} + \|q\|^2_{\text{Frob}} + \left\|b_{\text{users}}\right\|^2 + \left\|b_{\text{items}}\right\|^2 \right]$$

- Stochastic gradient descent

$$p_u \leftarrow (1 - \lambda\eta_t)p_u - \eta_t q_i \rho_{ui}$$

$$q_i \leftarrow (1 - \lambda\eta_t)q_i - \eta_t p_u \rho_{ui}$$

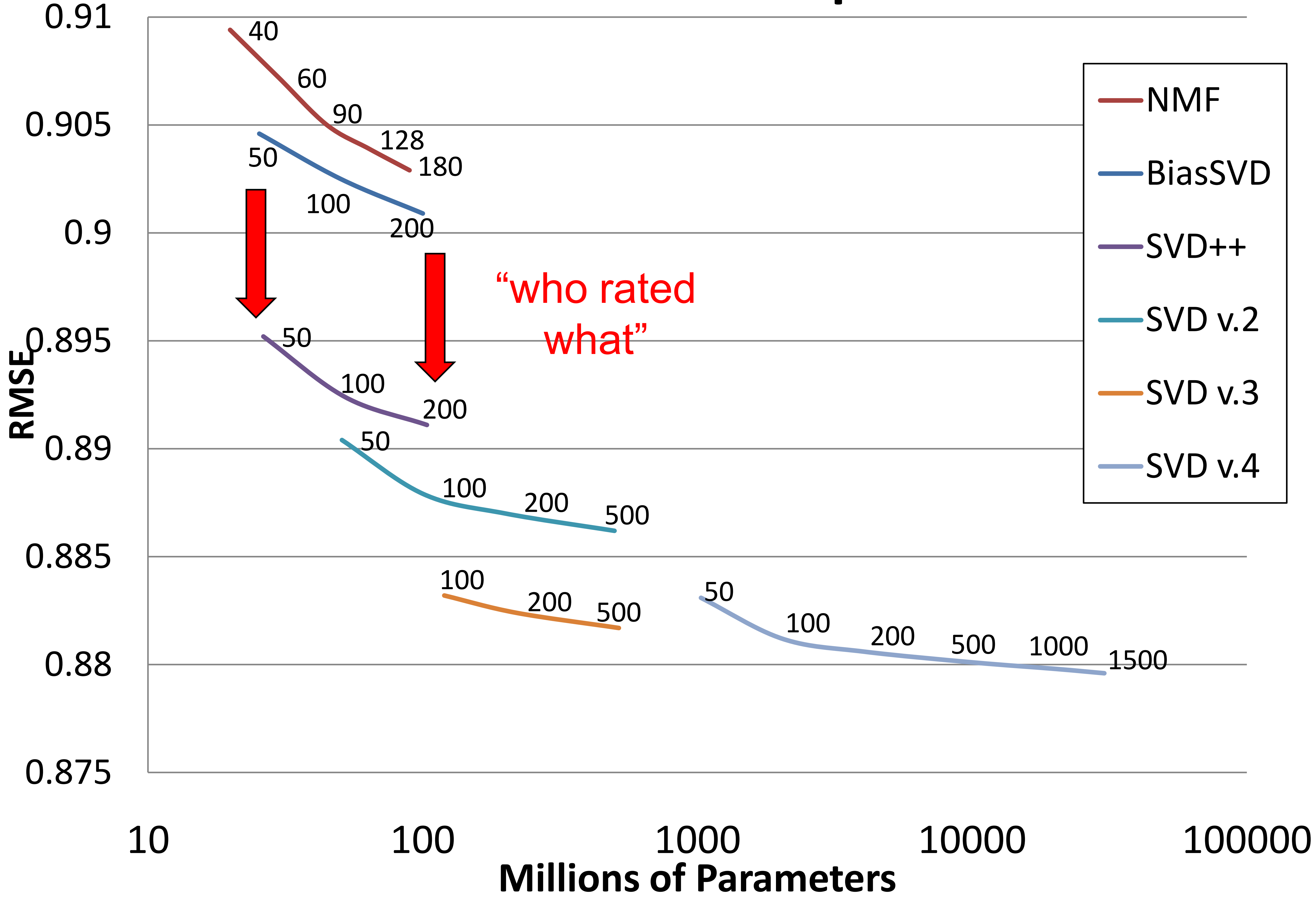
$$b_u \leftarrow (1 - \lambda\eta_t)b_u - \eta_t \rho_{ui}$$

$$b_i \leftarrow (1 - \lambda\eta_t)b_i - \eta_t \rho_{ui}$$

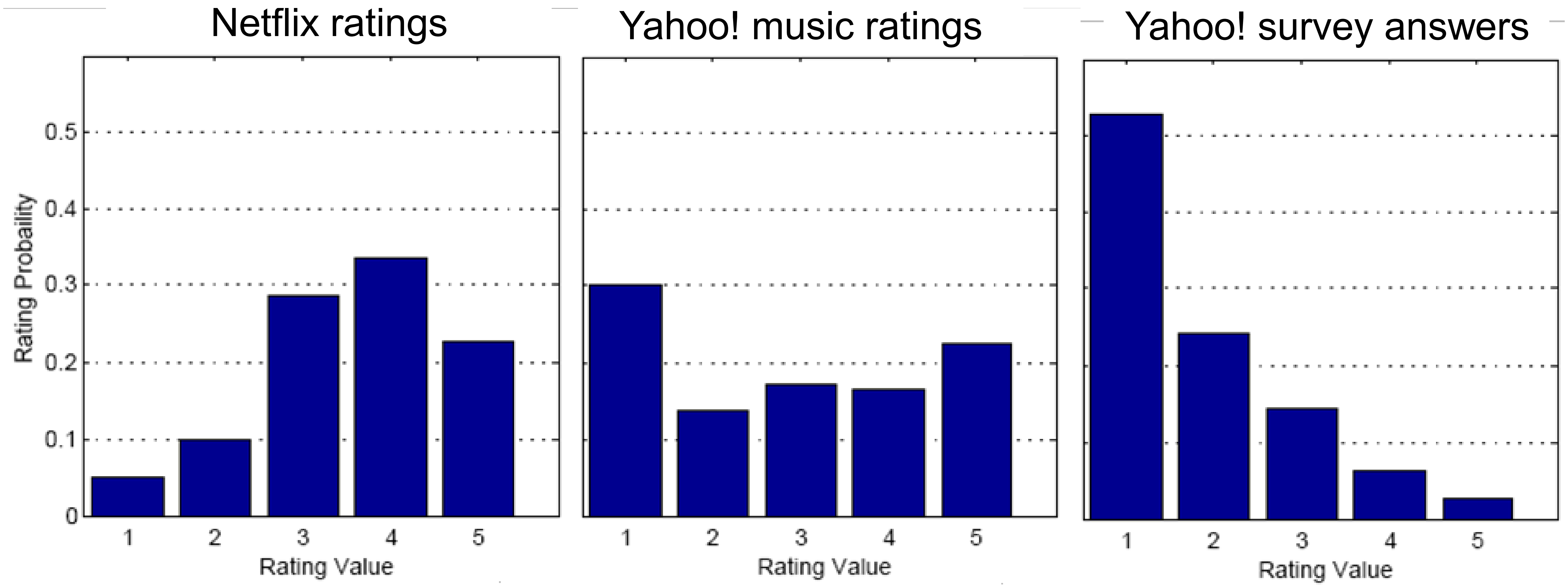
$$\mu \leftarrow (1 - \lambda\eta_t)\mu - \eta_t \rho_{ui}$$

$$\text{where } \rho_{ui} = (r_{ui} - (\mu + b_i + b_u + \langle p_u, q_i \rangle))$$

Factor models: Error vs. #parameters

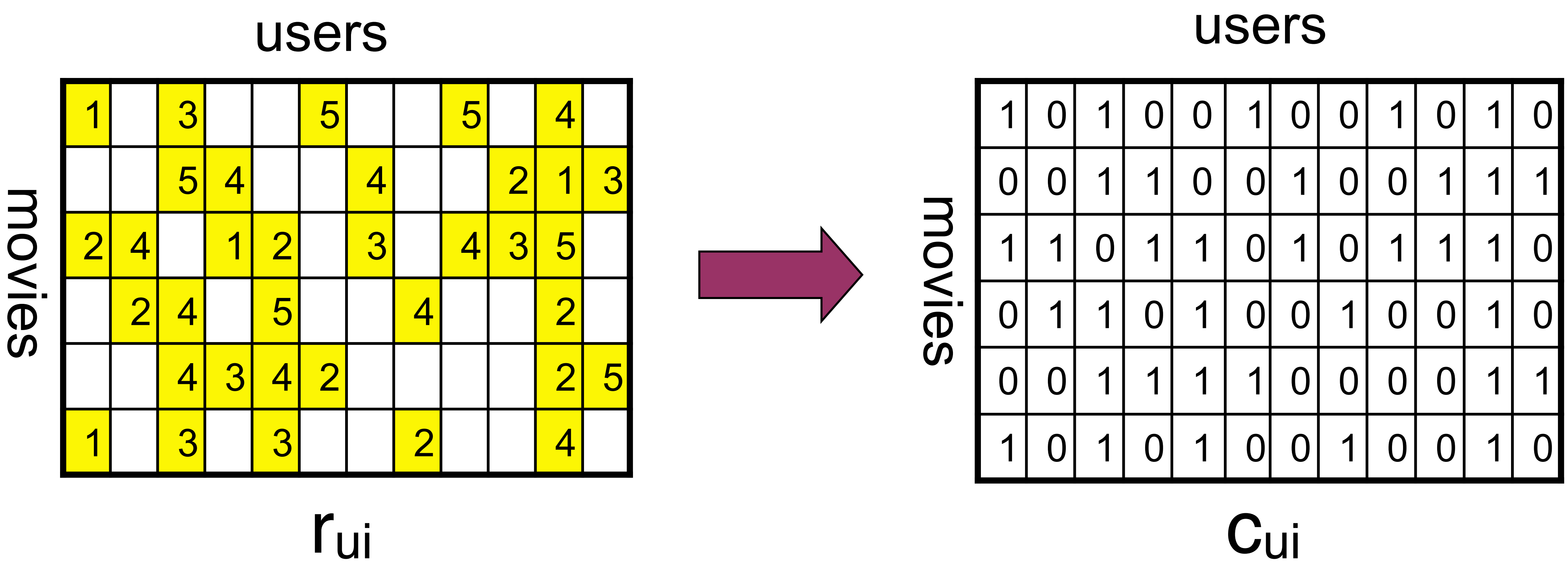


Ratings are not given at random



- Marlin et al. “Collaborative Filtering and the Missing at Random Assumption” UAI 2007

Movie rating matrix



1		3			5			5		4	
		5	4			4			2	1	3
2	4		1	2		3		4	3	5	
	2	4		5			4			2	
		4	3	4	2					2	5
1		3		3			2			4	

1	0	1	0	0	1	0	0	1	0	1	0
0	0	1	1	0	0	1	0	0	1	1	1
1	1	0	1	1	0	1	0	1	1	1	0
0	1	1	0	1	0	0	1	0	0	1	0
0	0	1	1	1	1	0	0	0	0	1	1
1	0	1	0	1	0	0	1	0	0	1	0

- Characterize users by which movies they rated
  Edge attributes (observed, rating)
- Adding features to recommender system

$$r_{ui} = \mu + b_u + b_i + \langle p_u, q_i \rangle + \langle c_u, x_i \rangle$$

regression

Alternative integration

- Key idea - use related ratings to average
- Salakhudtinov & Mnih, 2007

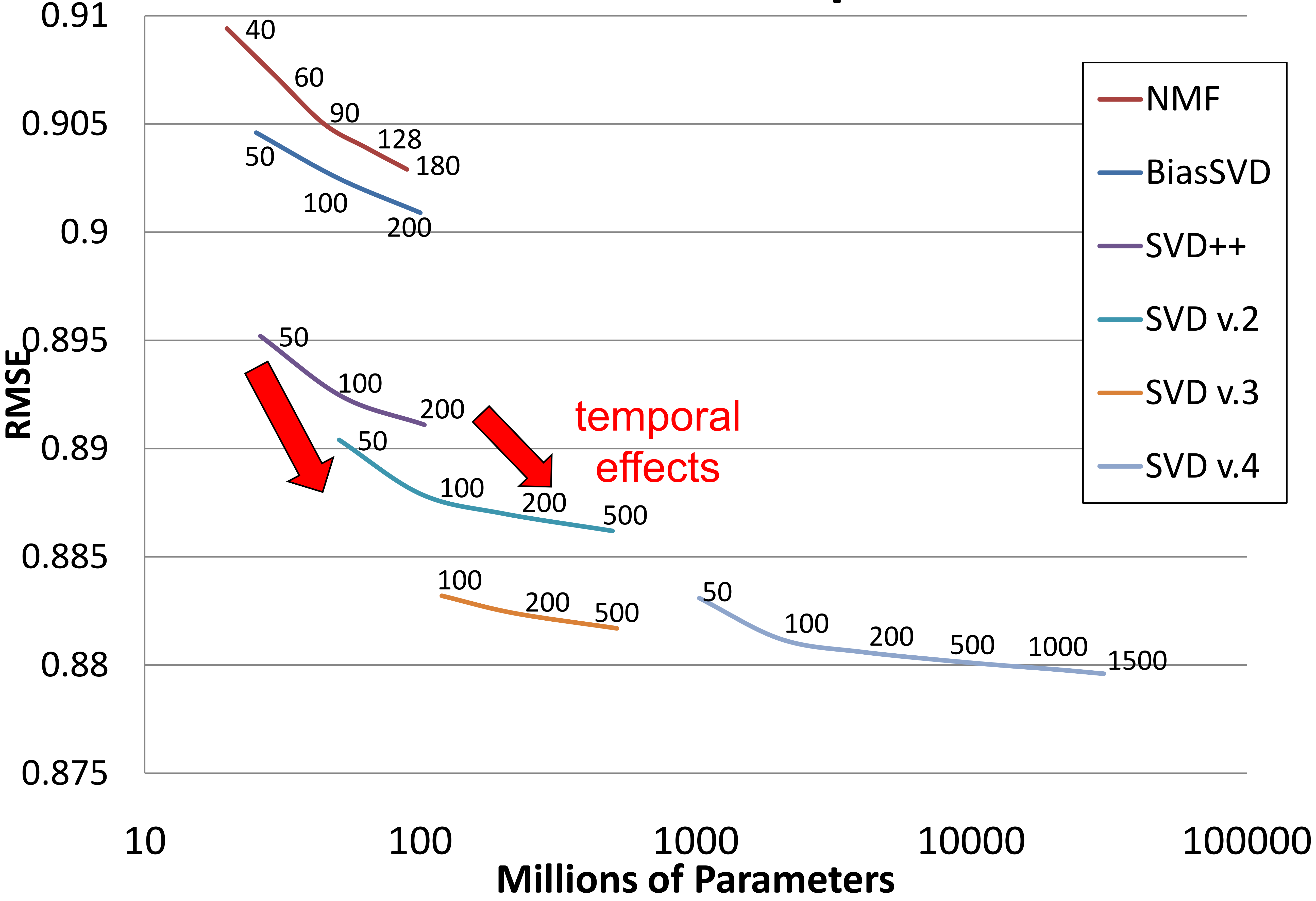
$$q_i \leftarrow q_i + \sum_u c_{ui} p_u$$

- Koren et al., 2008

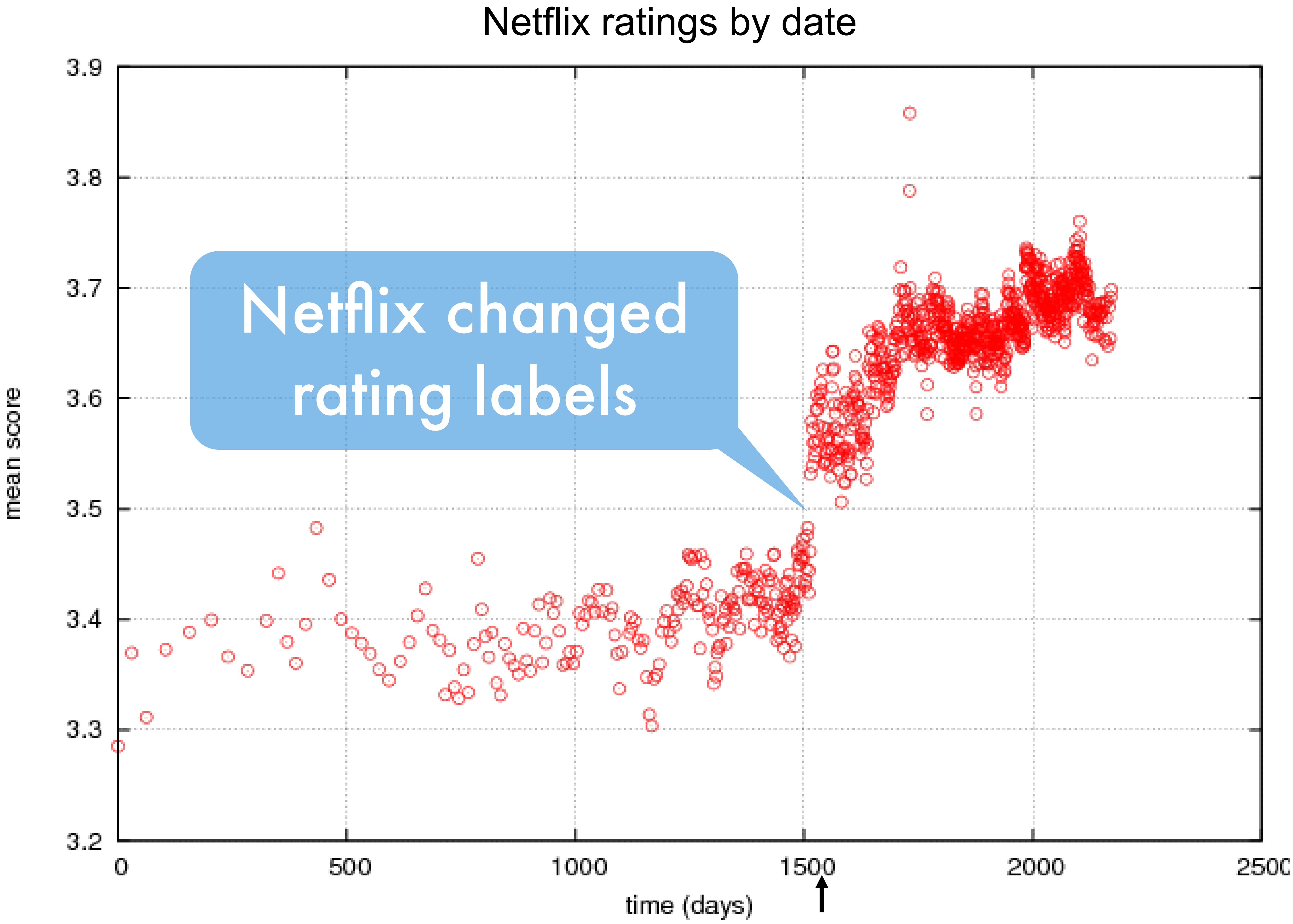
$$q_i \leftarrow q_i + \sum_u c_{ui} x_j$$

Overparametrize items by q and x

Factor models: Error vs. #parameters



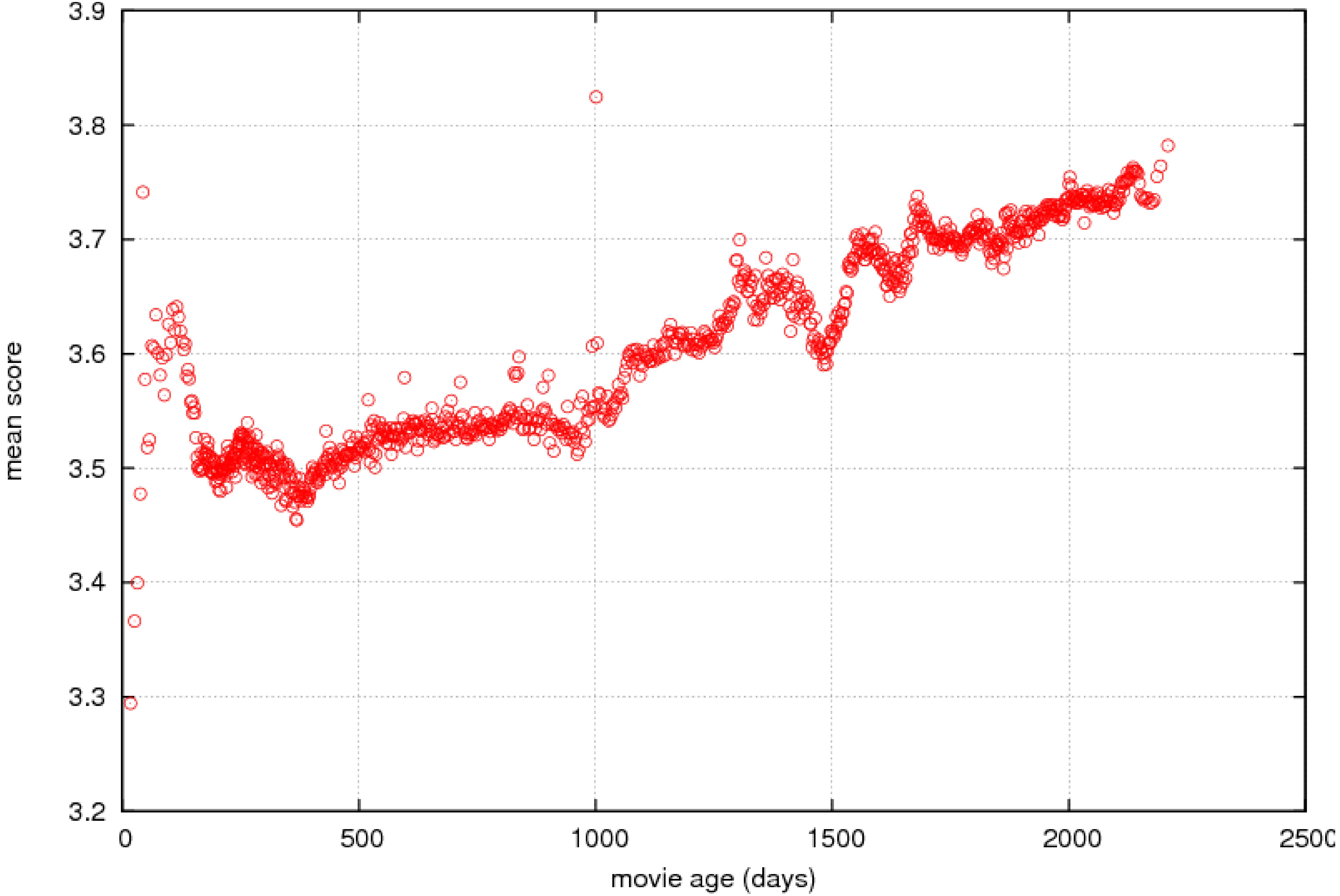
Something Happened in Early 2004…



Netflix changed rating labels

2004

Are movies getting better with time?



Carnegie Mellon University

Sources of temporal change

- Items
  - Seasonal effects
(Christmas, Valentine’s day, Holiday movies)
  - Public perception of movies (Oscar etc.)
- Users
  - Changed labeling of reviews
  - Anchoring (relative to previous movie)
  - Change of rater in household
  - Selection bias for time of viewing

Modeling temporal change

- Time-dependent bias
- Time-dependent user preferences

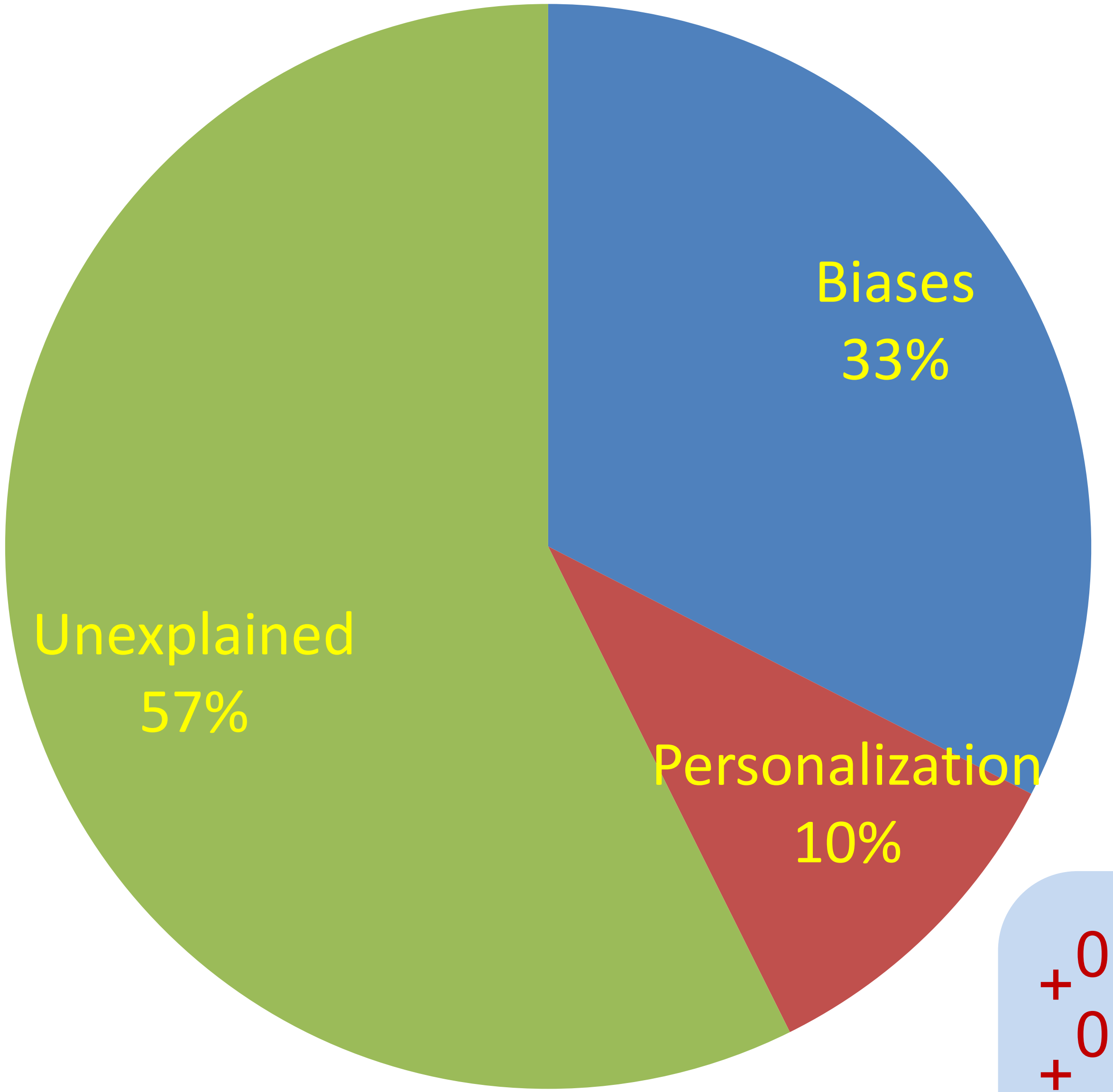
$$r_{ui}(t) = \mu + b_u(t) + b_i(t) + \langle q_i, p_u(t) \rangle$$

- Parameterize functions b and p
  - Slow changes for items
  - Fast sudden changes for users
  - Good parametrization is key

Koren et al., KDD 2009 (CF with temporal dynamics)

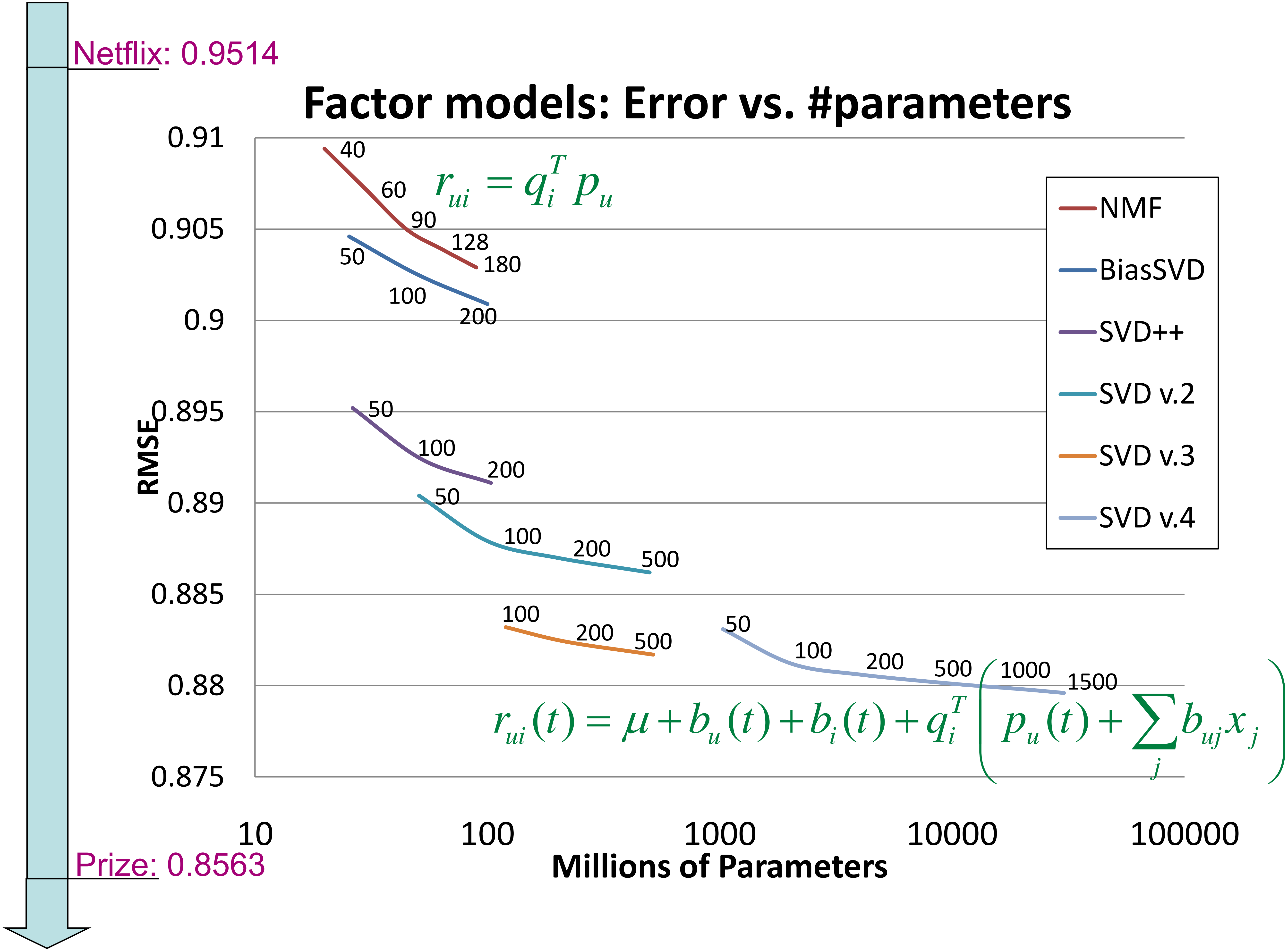
Bias matters

Sources of Variance in Netflix data



$$
\begin{array}{l}
0.732 \text{ (unexplained)} \\
+\,0.415 \text{ (biases)} \\
+\,0.129 \text{ (personalization)} \\
\hline
1.276 \text{ (total variance)}
\end{array}
$$

Factor models: Error vs. #parameters



$$r_{ui} = q_i^T p_u$$

$$r_{ui}(t) = \mu + b_u(t) + b_i(t) + q_i^T \left(p_u(t) + \sum_j b_{uj} x_j \right)$$

More ideas

- Explain factorizations
- Cold start (new users)
- Different regularization for different parameter groups / different users
- Sharing of statistical strength between users
- Hierarchical matrix co-clustering / factorization

MACHINE LEARNING
DEPARTMENT

8.3 Session Modeling

8 Recommender Systems

Alexander Smola
Introduction to Machine Learning 10-701
http://alex.smola.org/teaching/10-701-15

Significant content courtesy of Yehuda Koren

Session Modeling

"You Can Look at Models, Or You Can Be One", with this Fun Kids Modeling Program For Boys and Girls Ages 3-5

Summer Session

Fashion Photography

Good Grooming

Fashion Shows

Manners

T.V. Commercials

Bring out your child's personality-

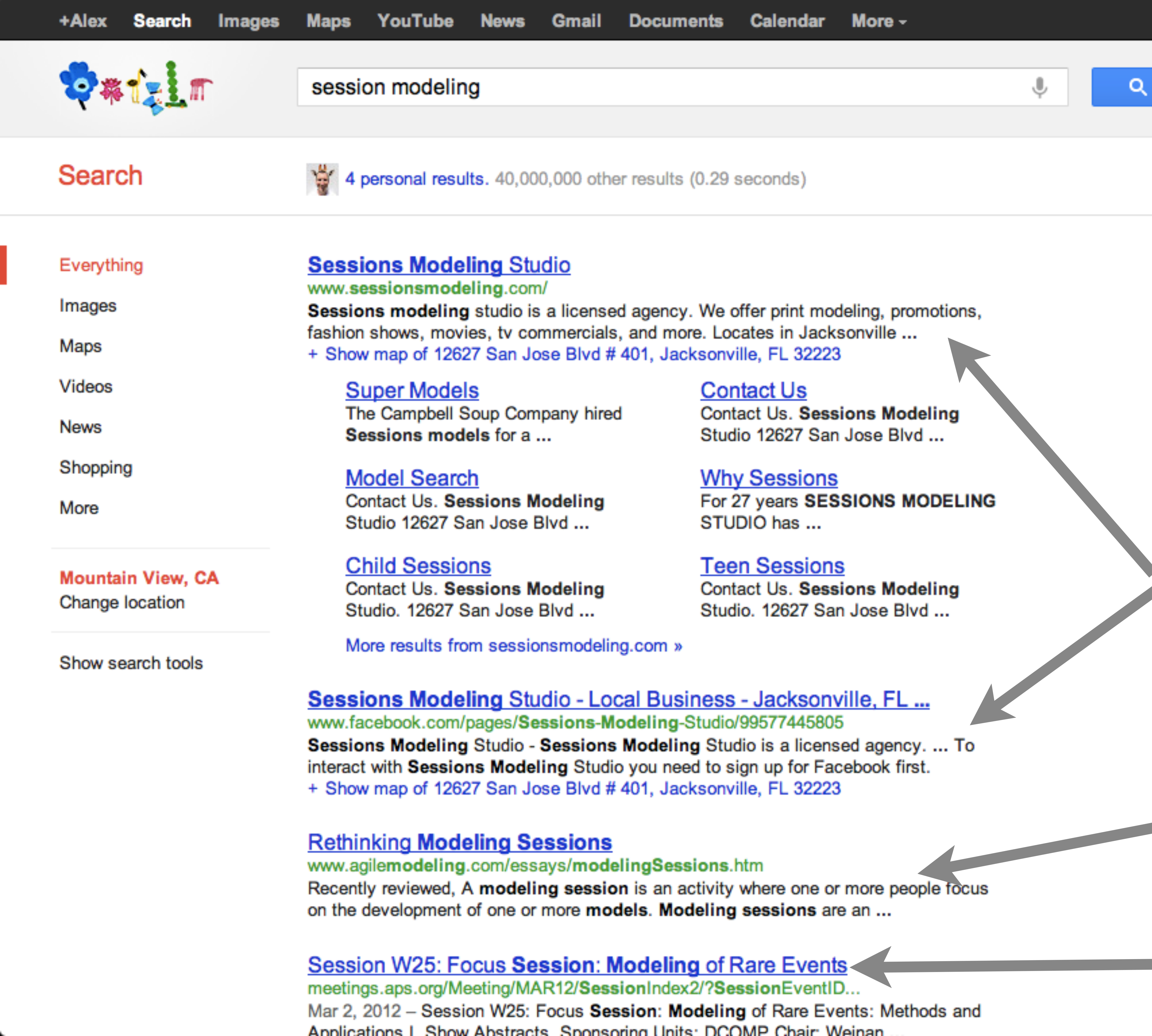
(6) day modeling program covers it all!

CAMP	DAYS	FASHION SHOW *
1	6/25-6/28	6/29
2	7/08-7/12	7/13
3	7/22-7/26	7/27
4	8/05-8/09	8/10

User interaction

- Explicit search query
  - Search engine
  - Genre selection on movie site
- Implicit search query
  - News site
  - Priority inbox
  - Comments on article
  - Viewing specific movie (see also ...)
  - Sponsored search (advertising)

Space, users’ time and attention are limited.



session modeling

Search

4 personal results. 40,000,000 other results (0.29 seconds)

Sessions Modeling Studio
www.**sessionsmodeling**.com/
Sessions modeling studio is a licensed agency. We offer print modeling, promotions, fashion shows, movies, tv commercials, and more. Locates in Jacksonville ...
+ Show map of 12627 San Jose Blvd # 401, Jacksonville, FL 32223

Super Models
The Campbell Soup Company hired **Sessions models** for a ...

Contact Us
Contact Us. **Sessions Modeling** Studio 12627 San Jose Blvd ...

Model Search
Contact Us. **Sessions Modeling** Studio 12627 San Jose Blvd ...

Why Sessions
For 27 years **SESSIONS MODELING** STUDIO has ...

Child Sessions
Contact Us. **Sessions Modeling** Studio. 12627 San Jose Blvd ...

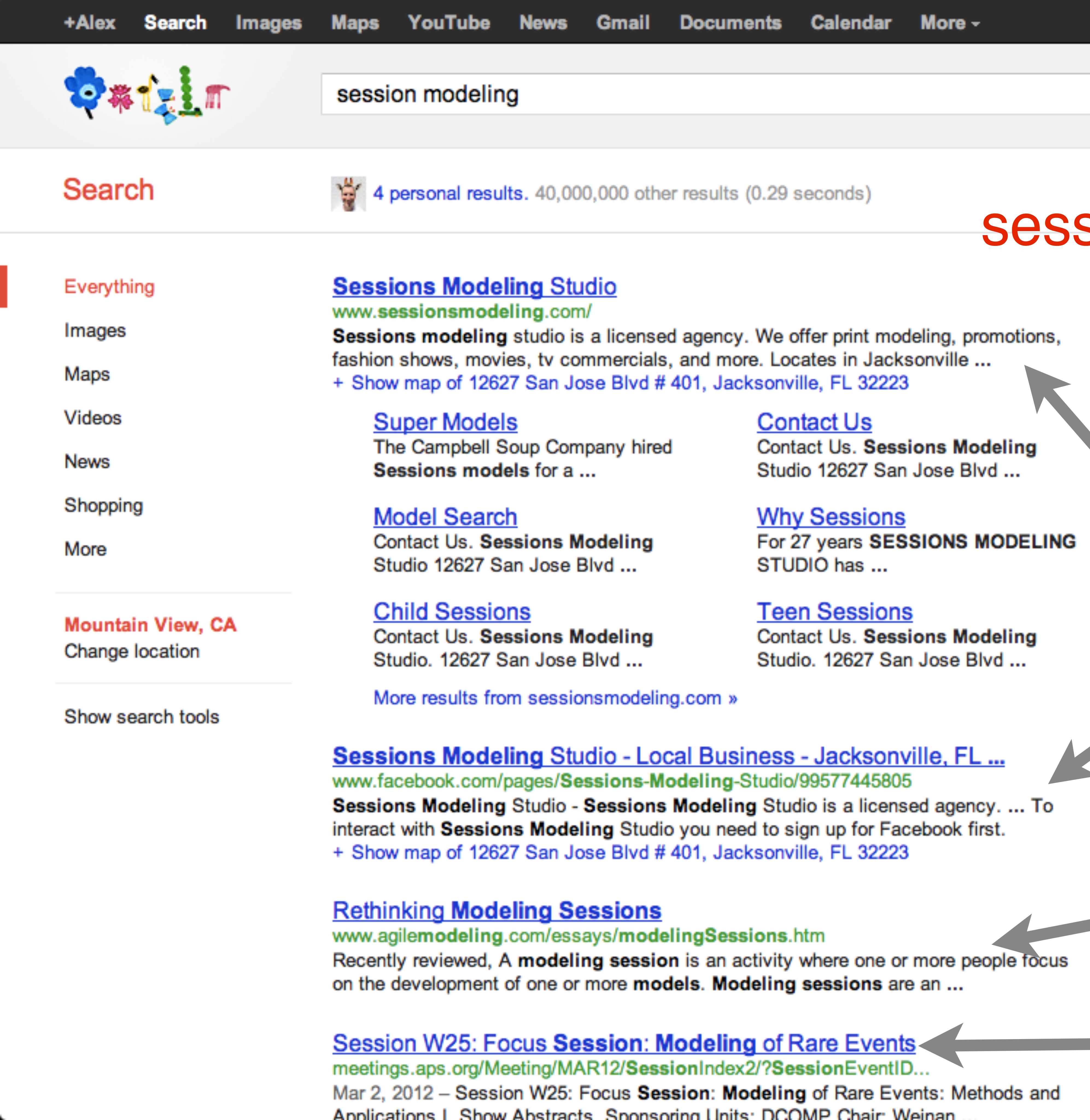
Teen Sessions
Contact Us. **Sessions Modeling** Studio. 12627 San Jose Blvd ...

More results from sessionsmodeling.com »

Sessions Modeling Studio - Local Business - Jacksonville, FL ...
www.facebook.com/pages/**Sessions-Modeling**-Studio/99577445805
Sessions Modeling Studio - **Sessions Modeling** Studio is a licensed agency. ... To interact with **Sessions Modeling** Studio you need to sign up for Facebook first.
+ Show map of 12627 San Jose Blvd # 401, Jacksonville, FL 32223

Rethinking **Modeling Sessions**
www.agile**modeling**.com/essays/**modelingSessions**.htm
Recently reviewed, A **modeling session** is an activity where one or more people focus on the development of one or more **models**. **Modeling sessions** are an ...

Session W25: Focus **Session**: **Modeling** of Rare Events
meetings.aps.org/Meeting/MAR12/**Session**Index2/?**Session**EventID...
Mar 2, 2012 – Session W25: Focus **Session**: **Modeling** of Rare Events: Methods and Applications I. Show Abstracts. Sponsoring Units: DCOMP Chair: Weinan ...



+Alex Search Images Maps YouTube News Gmail Documents Calendar More

session modeling

Search

4 personal results. 40,000,000 other results (0.29 seconds)

Everything
Images
Maps
Videos
News
Shopping
More

Mountain View, CA
Change location

Show search tools

Sessions Modeling Studio
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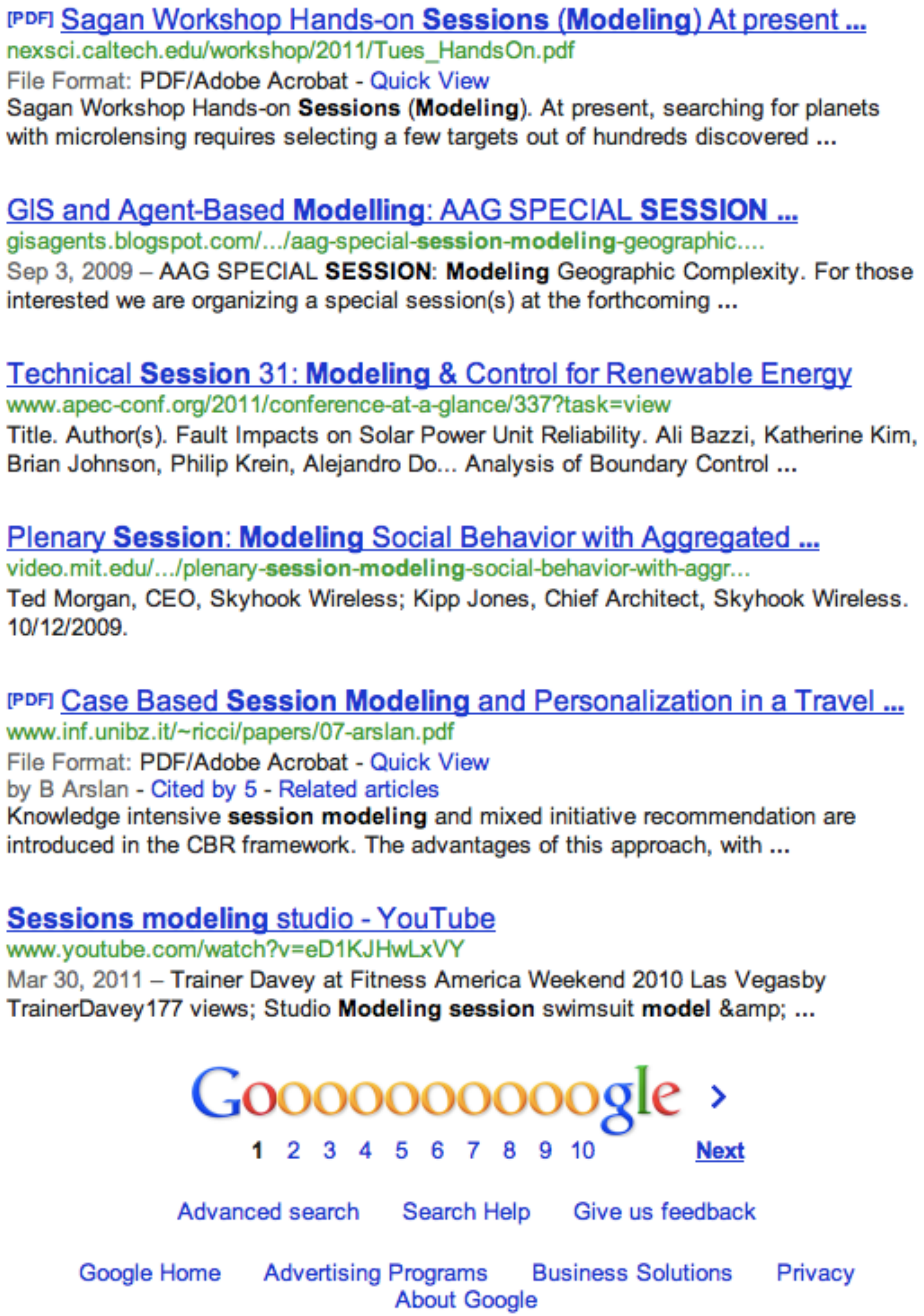
+ Show map of 12627 San Jose Blvd # 401, Jacksonville, FL 32223

Rethinking **Modeling Sessions**
www.agile**modeling**.com/essays/**modelingSessions**.htm
Recently reviewed, A **modeling session** is an activity where one or more people focus on the development of one or more **models**. **Modeling sessions** are an ...

Session W25: Focus **Session**: **Modeling** of Rare Events
meetings.aps.org/Meeting/MAR12/**Session**Index2/?**Session**EventID...
Mar 2, 2012 – Session W25: Focus **Session**: **Modeling** of Rare Events: Methods and Applications I. Show Abstracts. Sponsoring Units: DCOMP Chair: Weinan ...

session? models?



[PDF] Sagan Workshop Hands-on **Sessions (Modeling)** At present ...
nexsci.caltech.edu/workshop/2011/Tues_HandsOn.pdf
File Format: PDF/Adobe Acrobat - Quick View
Sagan Workshop Hands-on **Sessions** (**Modeling**). At present, searching for planets with microlensing requires selecting a few targets out of hundreds discovered ...

GIS and Agent-Based **Modelling**: AAG SPECIAL **SESSION** ...
gisagents.blogspot.com/.../aag-special-**session-modeling**-geographic....
Sep 3, 2009 – AAG SPECIAL **SESSION**: **Modeling** Geographic Complexity. For those interested we are organizing a special session(s) at the forthcoming ...

Technical **Session** 31: **Modeling** & Control for Renewable Energy
www.apec-conf.org/2011/conference-at-a-glance/337?task=view
Title. Author(s). Fault Impacts on Solar Power Unit Reliability. Ali Bazzi, Katherine Kim, Brian Johnson, Philip Krein, Alejandro Do... Analysis of Boundary Control ...

Plenary **Session**: **Modeling** Social Behavior with Aggregated ...
video.mit.edu/.../plenary-**session-modeling**-social-behavior-with-aggr...
Ted Morgan, CEO, Skyhook Wireless; Kipp Jones, Chief Architect, Skyhook Wireless. 10/12/2009.

[PDF] Case Based **Session Modeling** and Personalization in a Travel ...
www.inf.unibz.it/~ricci/papers/07-arslan.pdf
File Format: PDF/Adobe Acrobat - Quick View
by B Arslan - Cited by 5 - Related articles
Knowledge intensive **session modeling** and mixed initiative recommendation are introduced in the CBR framework. The advantages of this approach, with ...

Sessions modeling studio - YouTube
www.youtube.com/watch?v=eD1KJHwLxVY
Mar 30, 2011 – Trainer Davey at Fitness America Weekend 2010 Las Vegasby TrainerDavey177 views; Studio **Modeling session** swimsuit **model** & ...

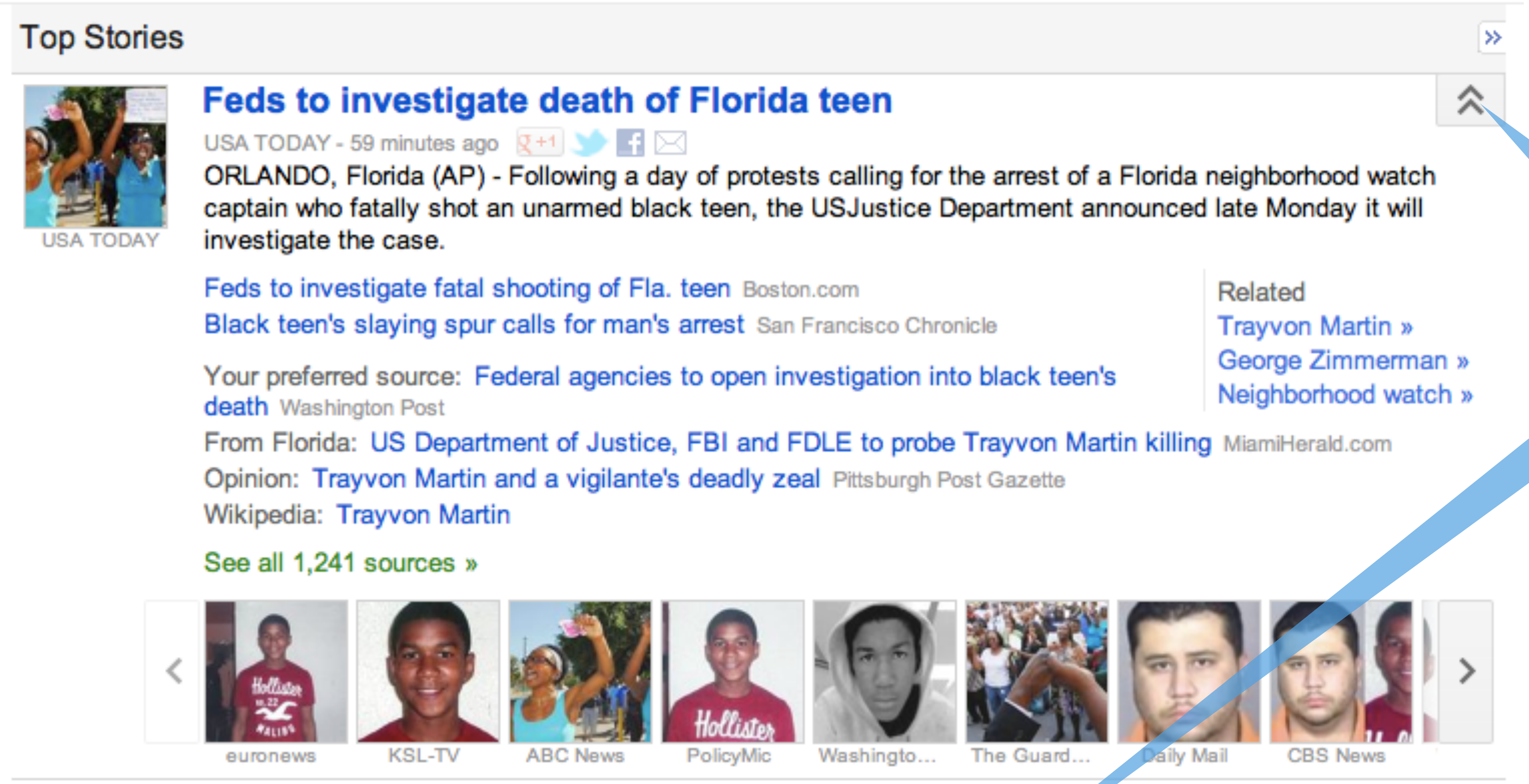
Did the user
SCROLL DOWN?

Bad ideas ...

- Show items based on relevance

  - Yes, this user likes Die Hard.
  - But he likes other movies, too
- Show items only for majority of users
  ‘apple’ vs. ‘Apple’

User response



Feds to investigate death of Florida teen

USA TODAY - 59 minutes ago

ORLANDO, Florida (AP) - Following a day of protests calling for the arrest of a Florida neighborhood watch captain who fatally shot an unarmed black teen, the USJustice Department announced late Monday it will investigate the case.

Feds to investigate fatal shooting of Fla. teen Boston.com
Black teen's slaying spur calls for man's arrest San Francisco Chronicle

Your preferred source: Federal agencies to open investigation into black teen's death Washington Post
From Florida: US Department of Justice, FBI and FDLE to probe Trayvon Martin killing MiamiHerald.com
Opinion: Trayvon Martin and a vigilante's deadly zeal Pittsburgh Post Gazette
Wikipedia: Trayvon Martin

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Feds to investigate death of Florida teen

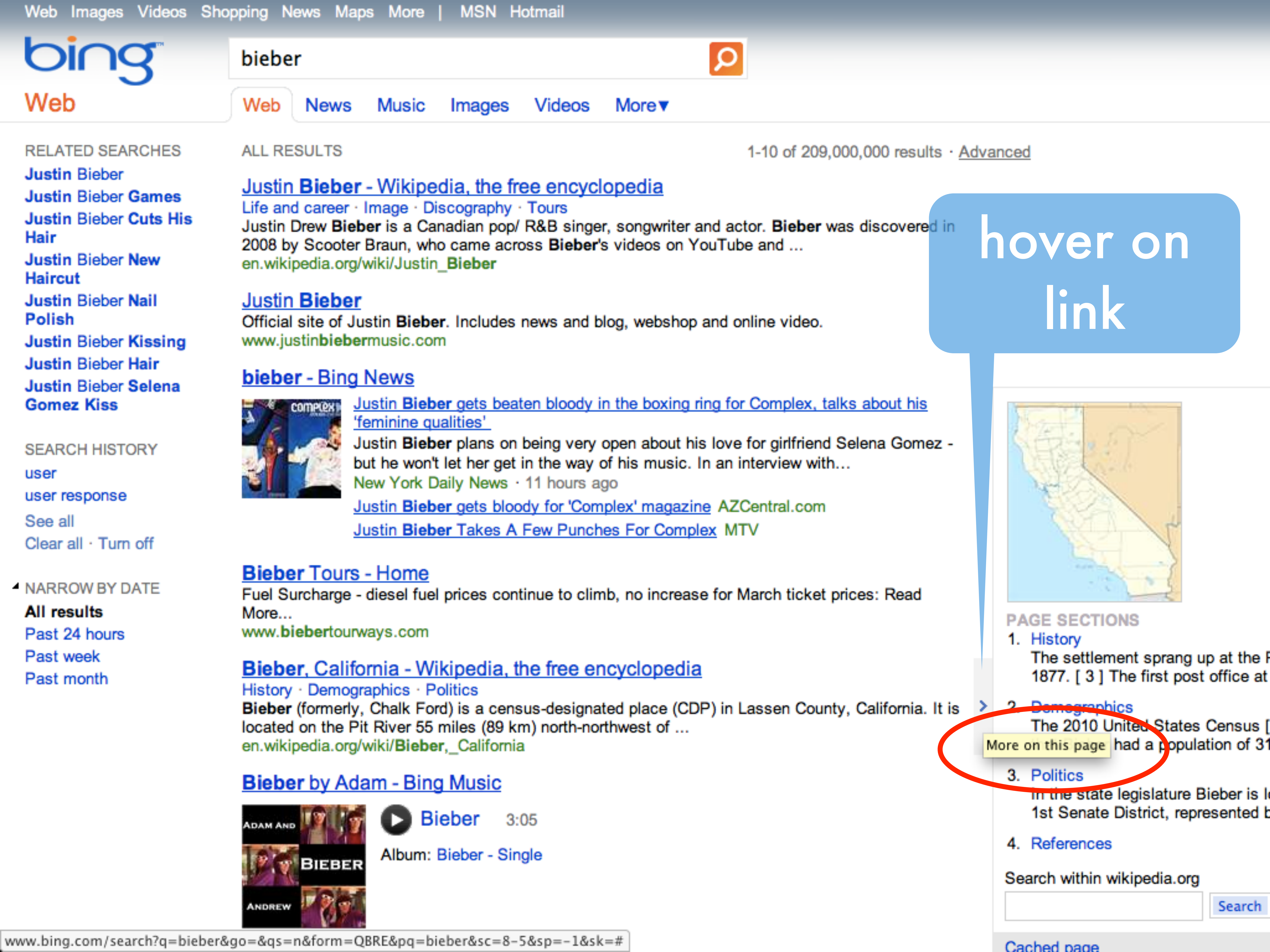
USA TODAY - 59 minutes ago

ORLANDO, Florida (AP) - Following a day of protests calling for the arrest of a Florida neighborhood watch captain who fatally shot an unarmed black teen, the USJustice Department announced late Monday it will investigate the case.

collaps

implicit
user interest

log it!



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user response

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Justin Bieber - Wikipedia, the free encyclopedia

Life and career · Image · Discography · Tours

Justin Drew **Bieber** is a Canadian pop/ R&B singer, songwriter and actor. **Bieber** was discovered in 2008 by Scooter Braun, who came across **Bieber**'s videos on YouTube and ...

en.wikipedia.org/wiki/Justin_**Bieber**

Justin Bieber

Official site of Justin **Bieber**. Includes news and blog, webshop and online video.

www.justin**bieber**music.com

bieber - Bing News

Justin **Bieber** gets beaten bloody in the boxing ring for Complex, talks about his 'feminine qualities'

Justin **Bieber** plans on being very open about his love for girlfriend Selena Gomez - but he won't let her get in the way of his music. In an interview with...

New York Daily News · 11 hours ago

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Justin **Bieber** Takes A Few Punches For Complex MTV

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Fuel Surcharge - diesel fuel prices continue to climb, no increase for March ticket prices: Read More...

www.**bieber**tourways.com

Bieber, California - Wikipedia, the free encyclopedia

History · Demographics · Politics

Bieber (formerly, Chalk Ford) is a census-designated place (CDP) in Lassen County, California. It is located on the Pit River 55 miles (89 km) north-northwest of ...

en.wikipedia.org/wiki/**Bieber**,_California

Bieber by Adam - Bing Music

Bieber 3:05

Album: Bieber - Single

PAGE SECTIONS

1. History

The settlement sprang up at the F

1877. [3] The first post office at

2. Demographics

The 2010 United States Census [

had a population of 31

3. Politics

In the state legislature Bieber is l

1st Senate District, represented b

4. References

More on this page

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Search

Cached page

www.bing.com/search?q=bieber&go=&qs=n&form=QBRE&pq=bieber&sc=8-5&sp=-1&sk=#

Response is conditioned on available options

- User search for ‘chocolate’

user picks this

- What the user really would have wanted
  - User can only pick from available items
  - Preferences are often relative

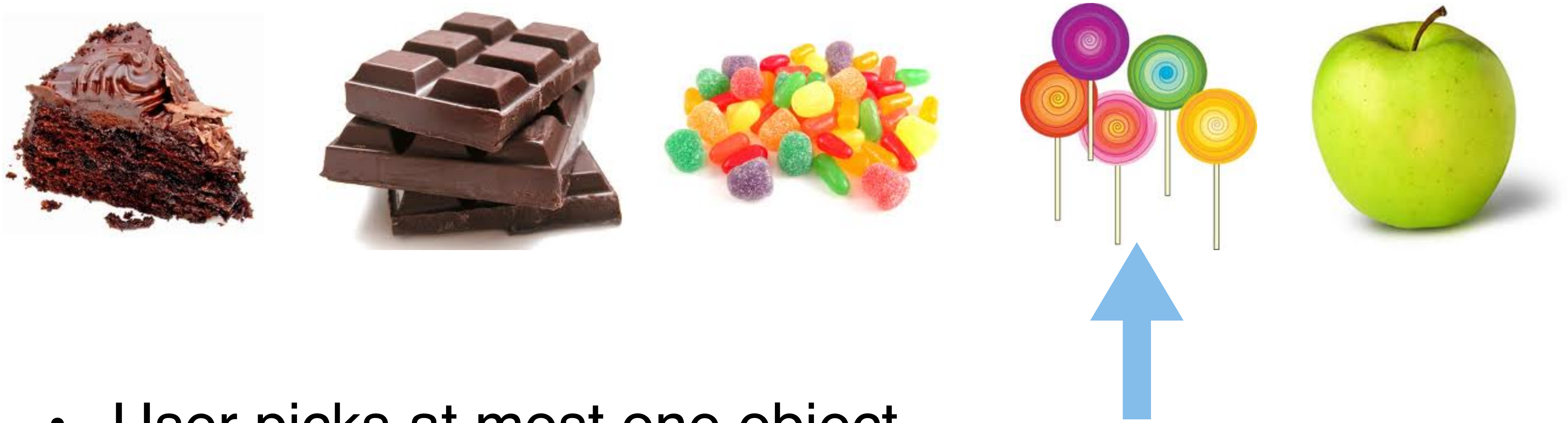
Models

Independent click model

- Each object has click probability
- Object is viewed independently
    - Used in computational advertising (with some position correction)
    - Horribly wrong assumption
    - OK if probability is very small (OK in ads)

$$p(x|s) = \prod_{i=1}^{n} \frac{1}{1 + e^{-x_i s_i}}$$

Logistic click model



no click

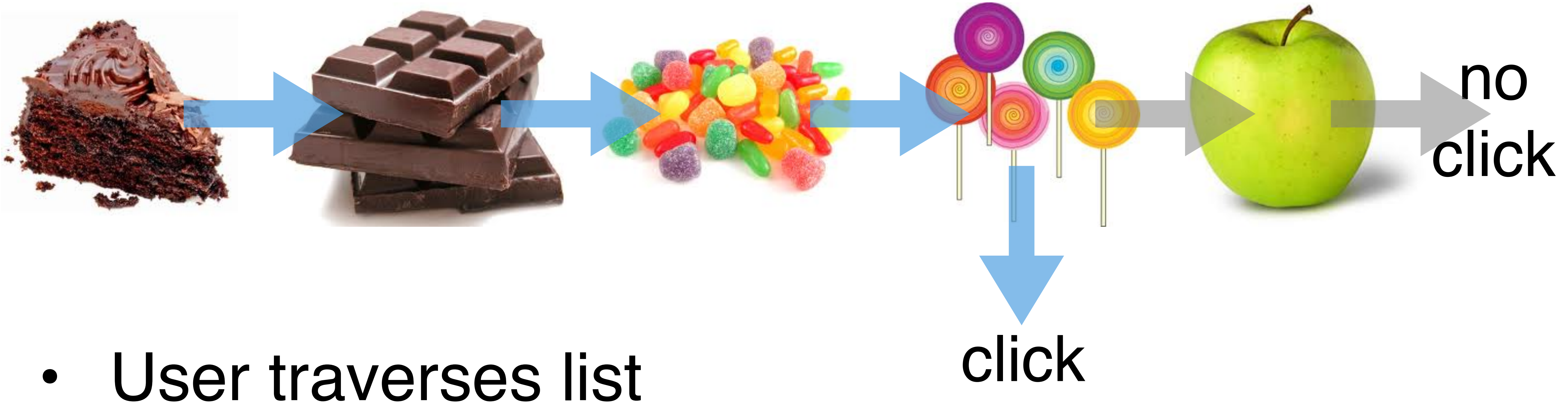
- User picks at most one object
- Exponential family model for click

$$p(x|s) = \frac{e^{s_x}}{e^{s_0} + \sum_{x'} e^{s_{x'}}} = \exp\left(s_x - g(s)\right)$$

no click

- Ignores order of objects
- Assumes that the user looks at all before taking action

Sequential click model

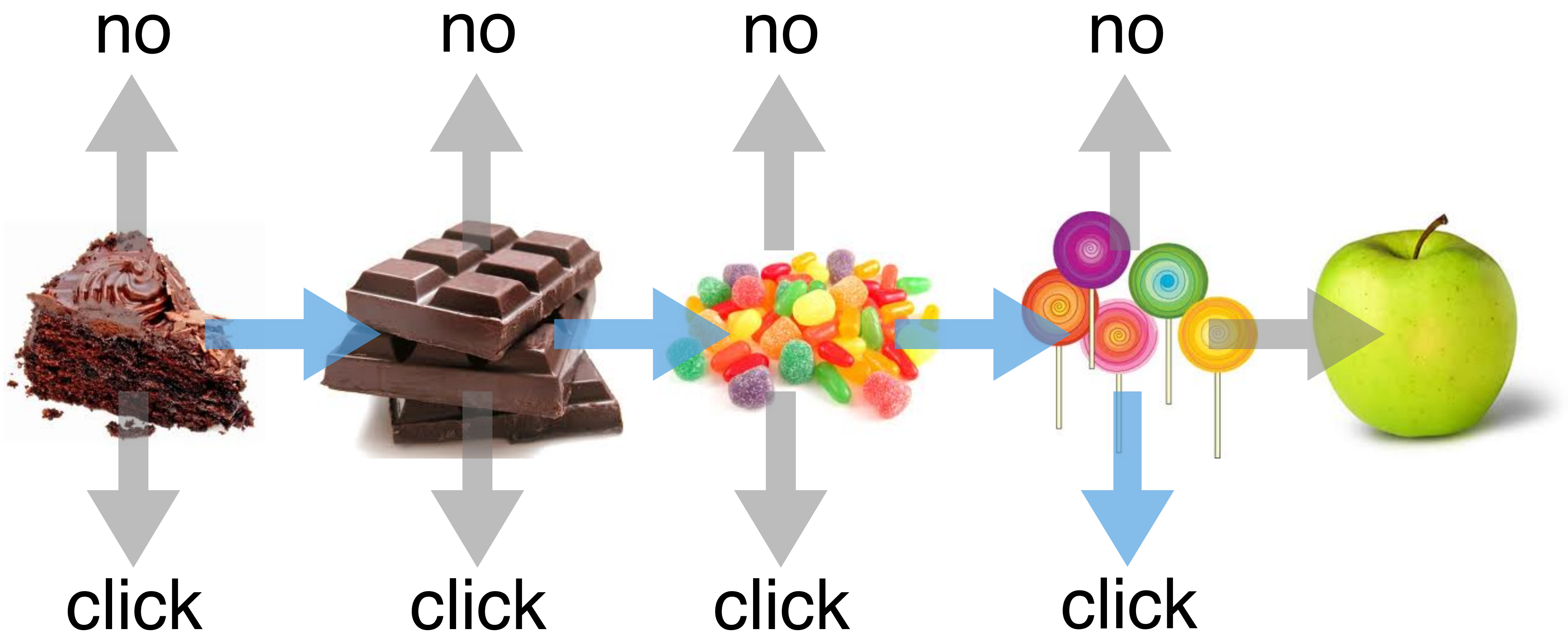


- User traverses list
- At each position some probability of clicking
- When user reaches end of the list he aborts

$$p(x=j|s) = \left[\prod_{i=1}^{j-1} \frac{1}{1+e^{s_i}}\right] \frac{1}{1+e^{-s_j}}$$

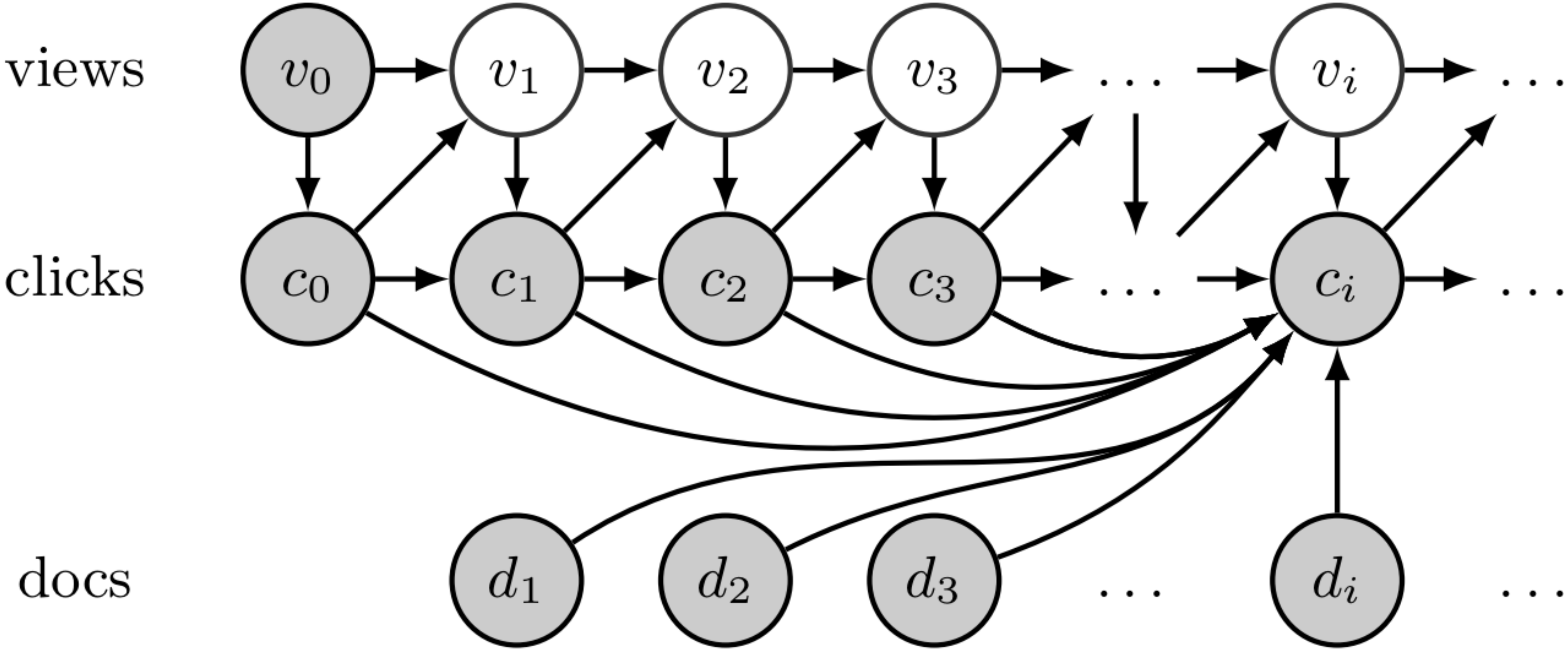
- This assumes that a patient user viewed all items

Skip click model



- User traverses list
- At each position some probability of clicking
- At each position the user may abandon the process
- This assumes that user traverses list sequentially

Context skip click model



- User traverses list
- At each position some probability of clicking which depends on previous content
- At each position the user may abandon the process
- User may click more than once

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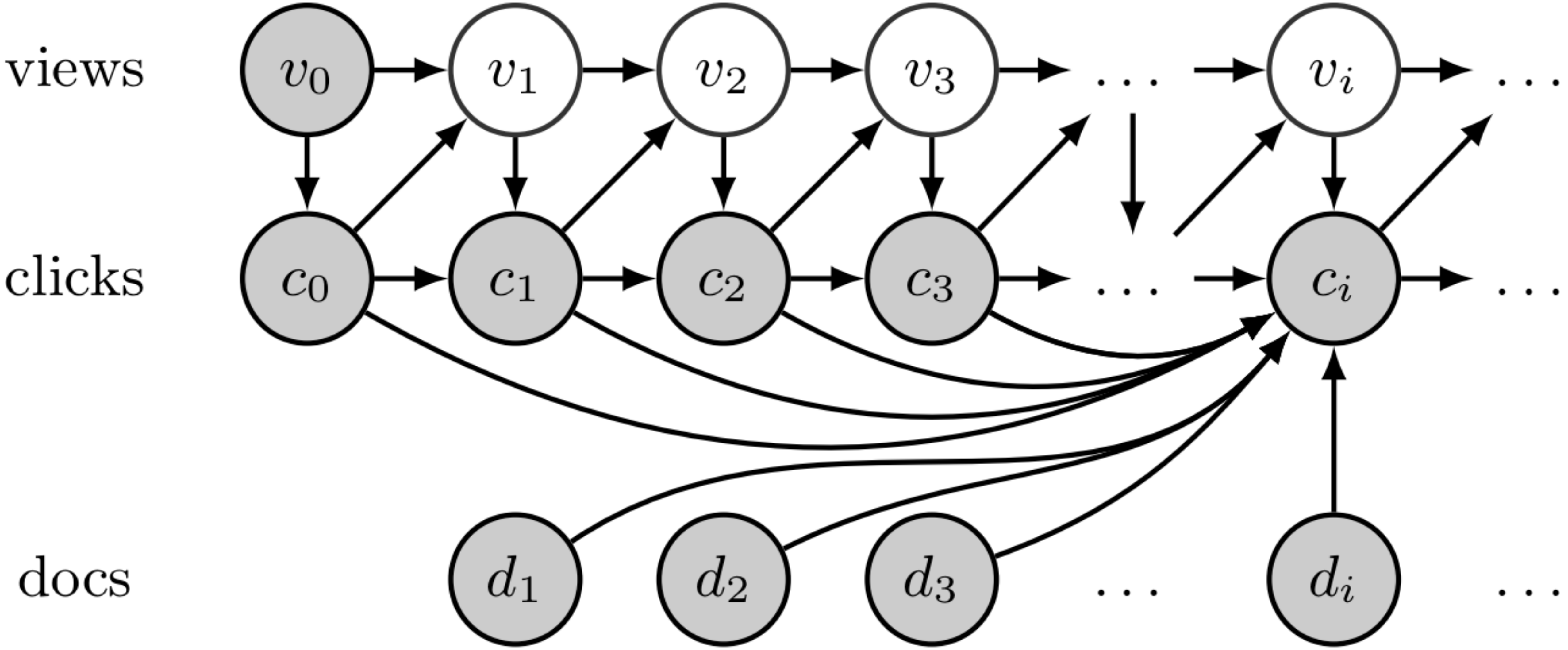
Context skip click model



$$p(v, c|d) = \prod_{i=1}^{n} \left[p(v_i|v_{i-1}, c_{i-1}) p(c_i|v_i, c^{i-1}, d^i) \right]$$

Context skip click model

- Viewing probability

$$p(v_i = 1 | v_{i-1} = 0) = 0$$

user is gone

$$p(v_i = 1 | v_{i-1} = 1, c_{i-1} = 0) = \frac{1}{1 + e^{-\alpha_i}}$$

$$p(v_i = 1 | v_{i-1} = 1, c_{i-1} = 1) = \frac{1}{1 + e^{-\beta_i}}$$

user returns

- Click probability (only if viewed)

prior context

$$p(c_i = 1 | v_i = 1, c^{i-1}, d^i) = \frac{1}{1 + e^{-f(|c^{i-1}|, d_i, d^{i-1})}}$$

$$p(v, c | d) = \prod_{i=1}^{n} \left[p(v_i | v_{i-1}, c_{i-1}) p(c_i | v_i, c^{i-1}, d^i) \right]$$

Incremental gains score

$$
\begin{aligned}
& f(|c^{i-1}|, d_i, d^{i-1}) \\
:=& \rho(S, d^i|a,b) - \rho(S, d^{i-1}|a,b) + \gamma_{|c^{i-1}|} + \delta_i \\
:=& \sum_{s \in S} \sum_j [s]_j \left(a_j \sum_{d \in d^i} [d]_j + b_j \left(\rho_j(d^i) - \rho_j(d^{i-1}) \right) \right) \\
& + \gamma_{|c^{i-1}|} + \delta_i
\end{aligned}
$$

- Submodular gain per additional document
- Relevance score per document
- Coverage over different aspects
- Position dependent score
- Score dependent on number of previous clicks

Optimization

- Latent variables

$$p(v, c|d) = \prod_{i=1}^{n} \left[p(v_i|v_{i-1}, c_{i-1}) p(c_i|v_i, c^{i-1}, d^i) \right]$$

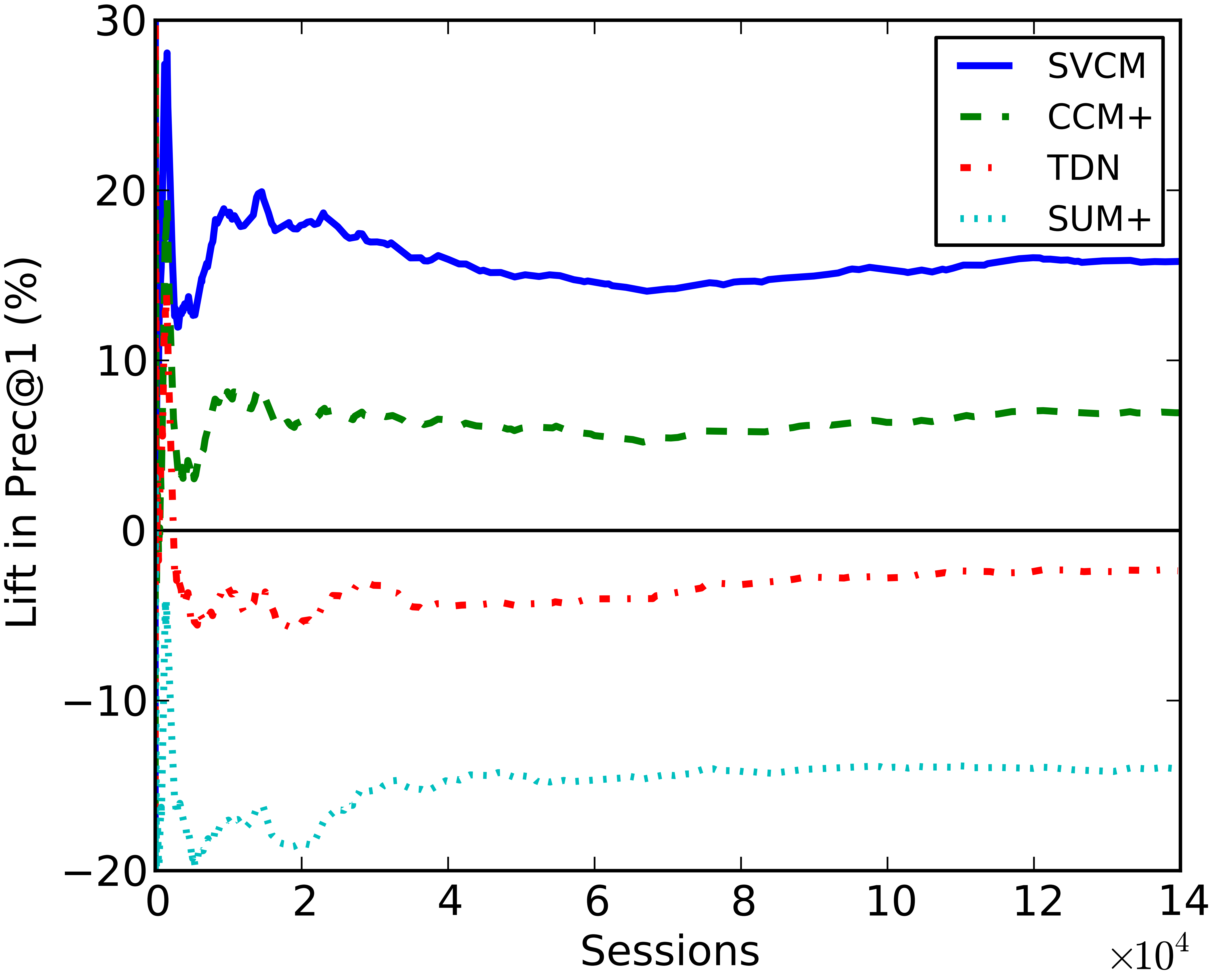
We don't know v whether user viewed result

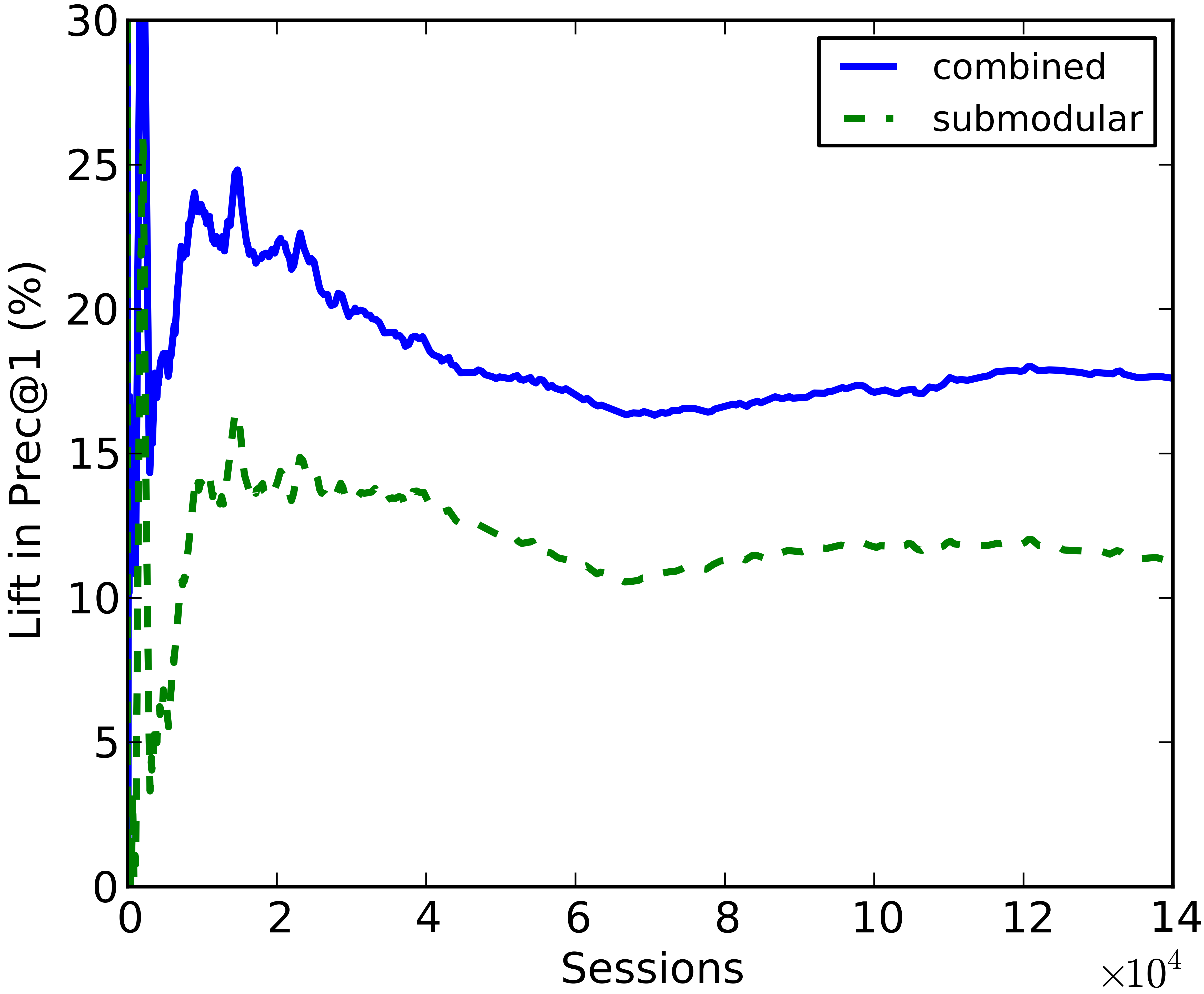
- Use variational inference to integrate out v (more next week in graphical models)

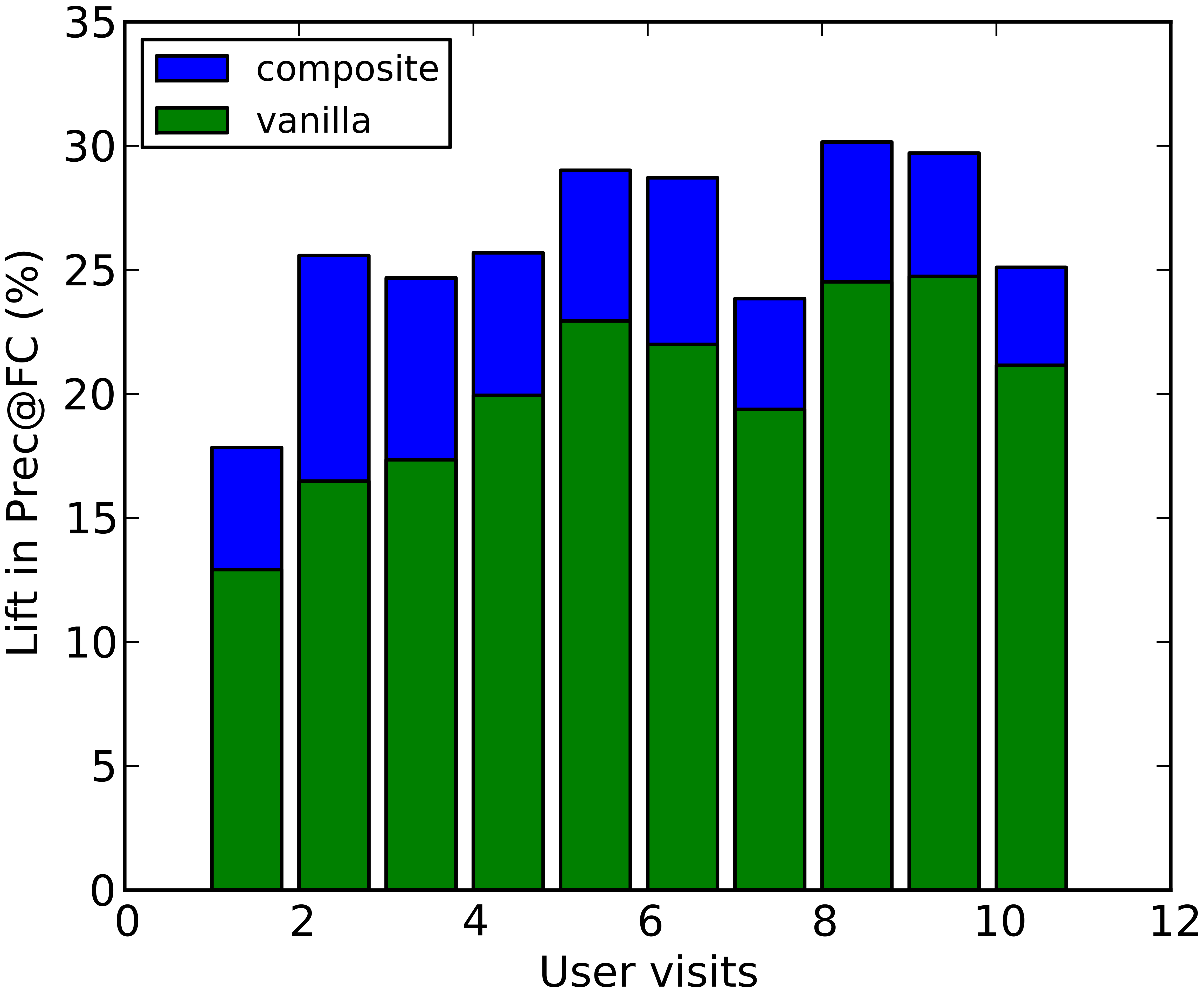
$$\begin{aligned} -\log p(c) &\leq -\log p(c) + D(q(v)\|p(v|c)) \\ &= \mathbf{E}_{v \sim q(v)} \left[-\log p(c) + \log q(v) - \log p(v|c) \right] \\ &= \mathbf{E}_{v \sim q(v)} \left[-\log p(c, v) \right] - H(q(v)). \end{aligned}$$

Optimization

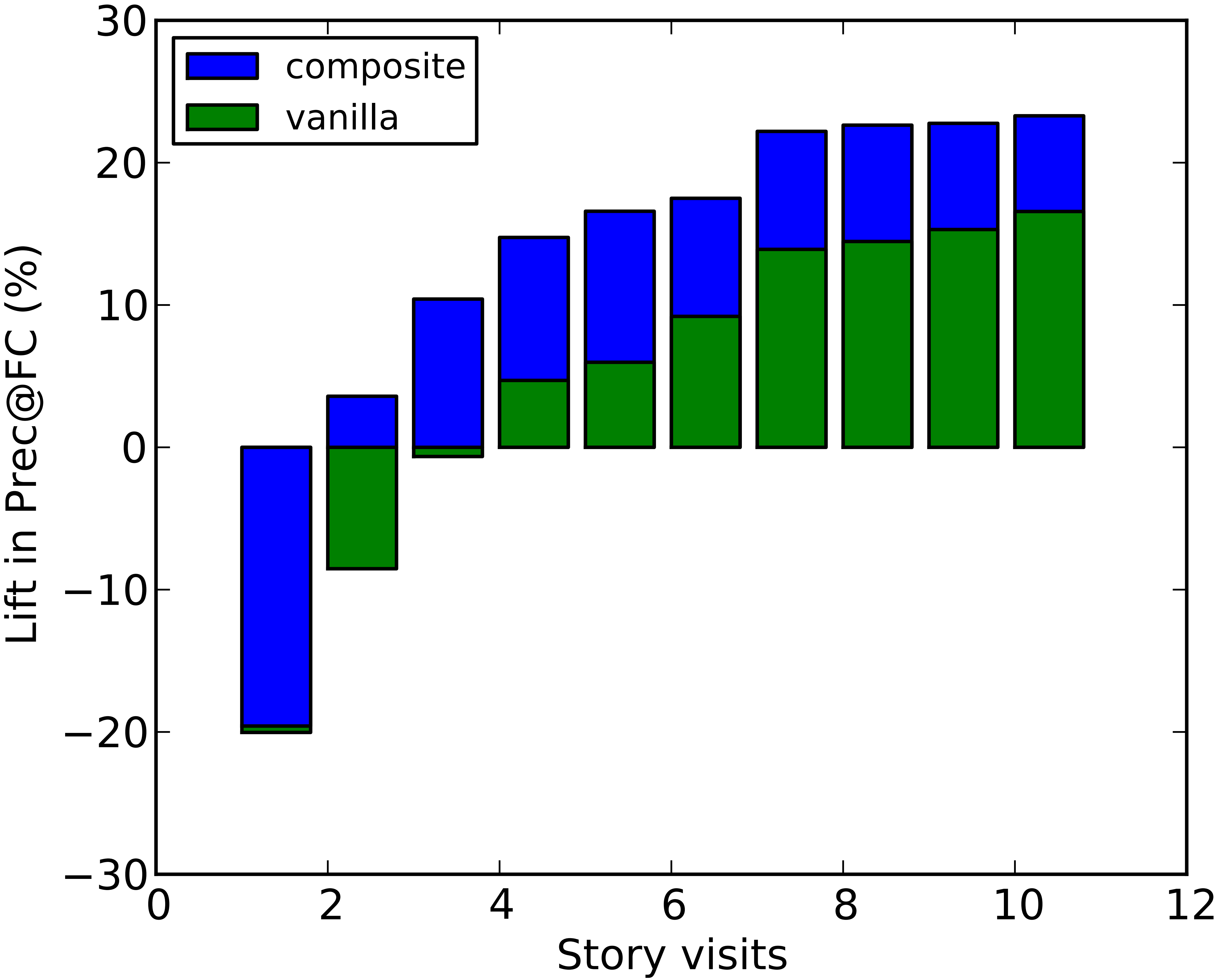
- Compute latent viewing probability given clicks
  - Easy since we only have one transition from views to no views (no DP needed)
  - Expected log-likelihood under viewing model
  - Convex expected log-likelihood
- Stochastic gradient descent
- Parametrization uses personalization, too (user, position, viewport, browser)


SVCM
CCM+
TDN
SUM+
Lift in Prec@1 (%)
30
20
10
0
−10
−20
0
2
4
6
8
10
12
14
Sessions
$\times10^4$


30
25
20
15
10
5
0
Lift in Prec@1 (%)
0
2
4
6
8
10
12
14
Sessions
$\times 10^4$
combined
submodular



composite
vanilla
Lift in Prec@FC (%)
0
5
10
15
20
25
30
35
User visits
0
2
4
6
8
10
12


composite
vanilla
Lift in Prec@FC (%)
30
20
10
0
−10
−20
−30
0
2
4
6
8
10
12
Story visits

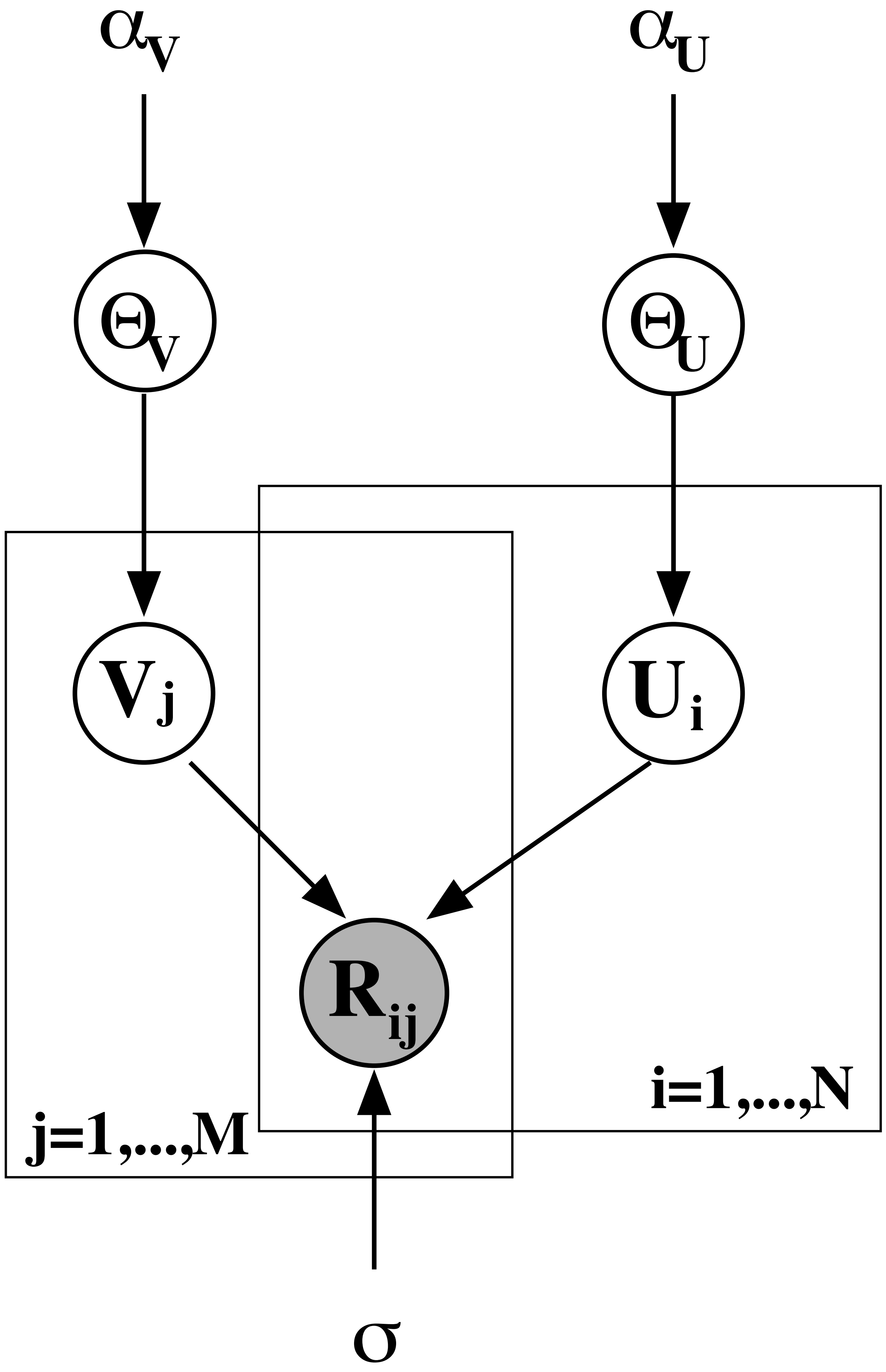
8.4 Feature Representation

8 Recommender Systems

Alexander Smola
Introduction to Machine Learning 10-701
http://alex.smola.org/teaching/10-701-15

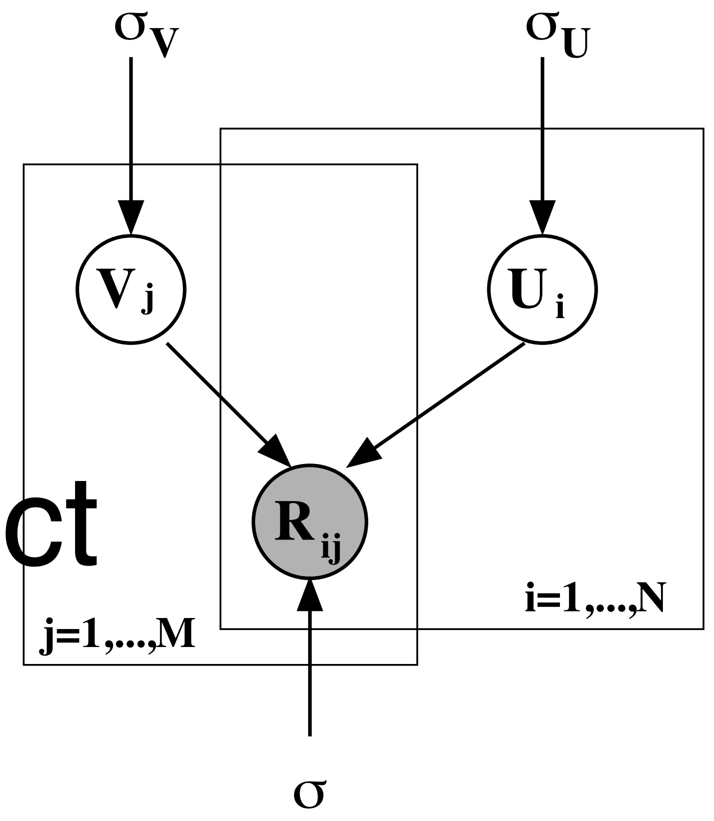
Significant content courtesy of Yehuda Koren

Bayesian Probabilistic Matrix Factorization



Statistical Model

- Aldous-Hoover factorization
  - normal distribution for user and item attributes
  - rating given by inner product
- Ratings



$$p(R_{ij}|U_i, V_j, \sigma^2) = \mathcal{N}(R_{ij}|U_i^T V_j, \sigma^2)$$

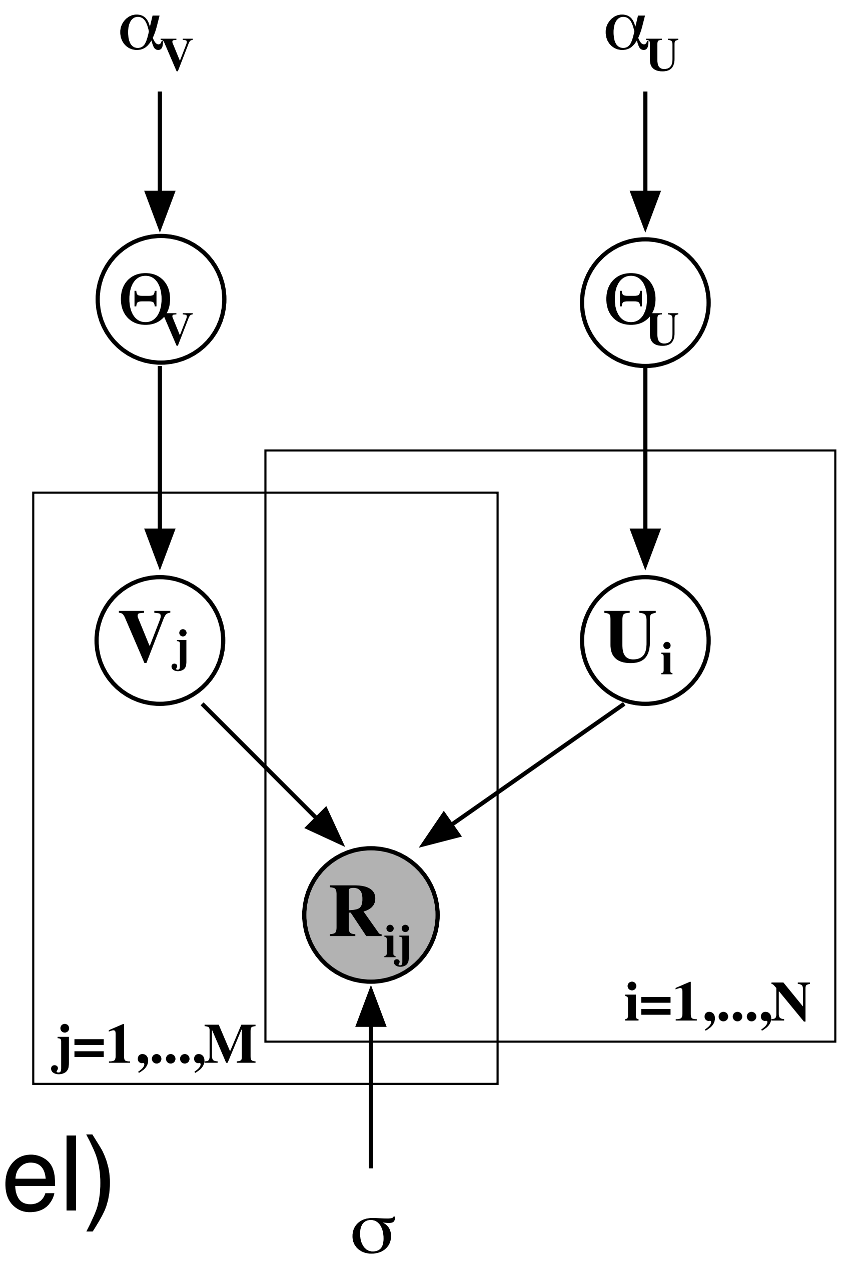
- Latent factors

$$p(U|\sigma_U^2) = \prod_{i=1}^{N} \mathcal{N}(U_i|0, \sigma_U^2 \mathrm{I}), \quad p(V|\sigma_V^2) = \prod_{j=1}^{M} \mathcal{N}(V_j|0, \sigma_V^2 \mathrm{I})$$

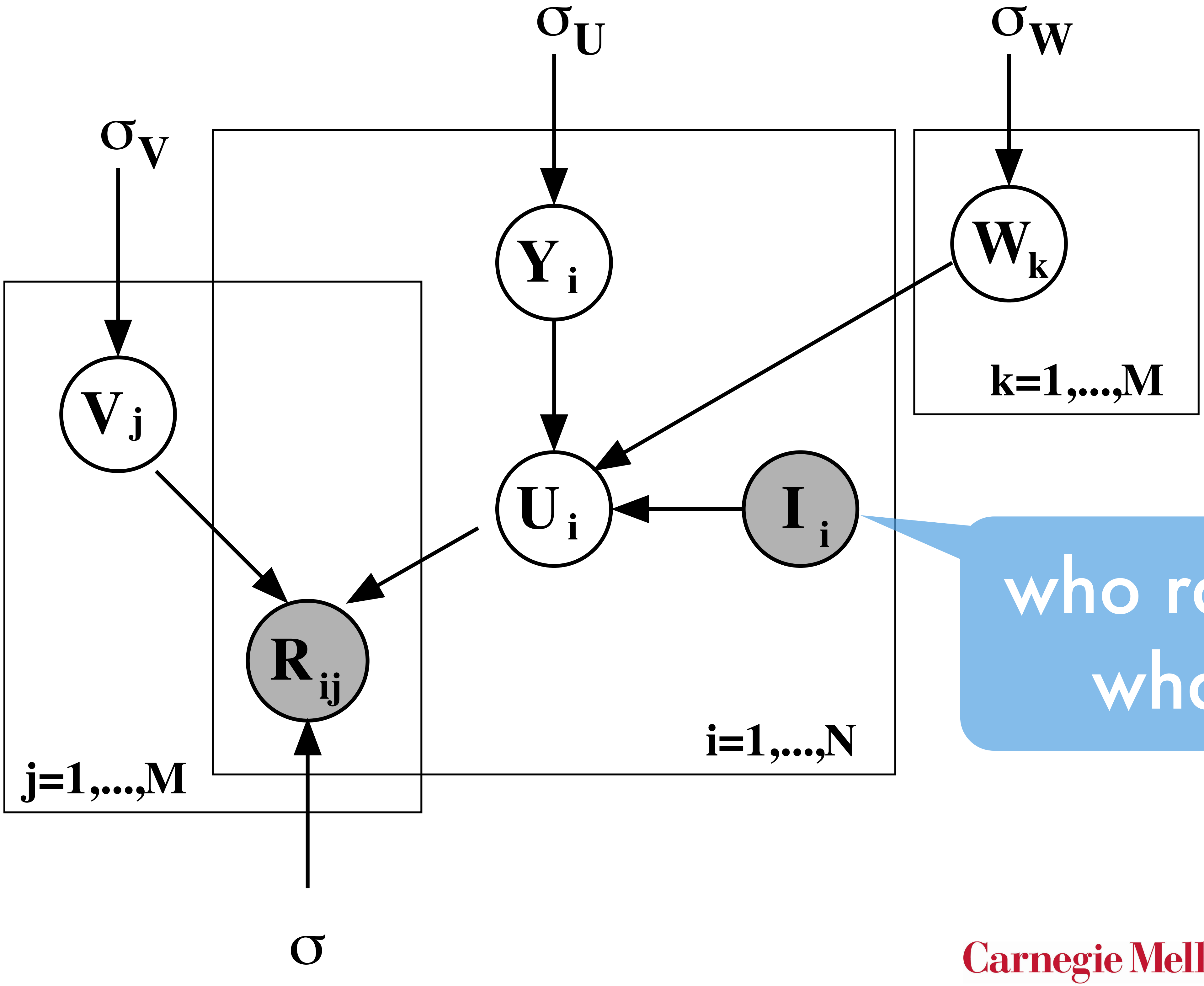
Salakhudtinov & Mnih, ICML 2008 BPMF

Details

- Priors on all factors
- Wishart prior is conjugate to Gaussian, hence use it
- Allows us to adapt the variance automatically
- Inference (Gibbs sampler)
  - Sample user factors (parallel)
  - Sample movie factors (parallel)
  - Sample hyperparameters (parallel)

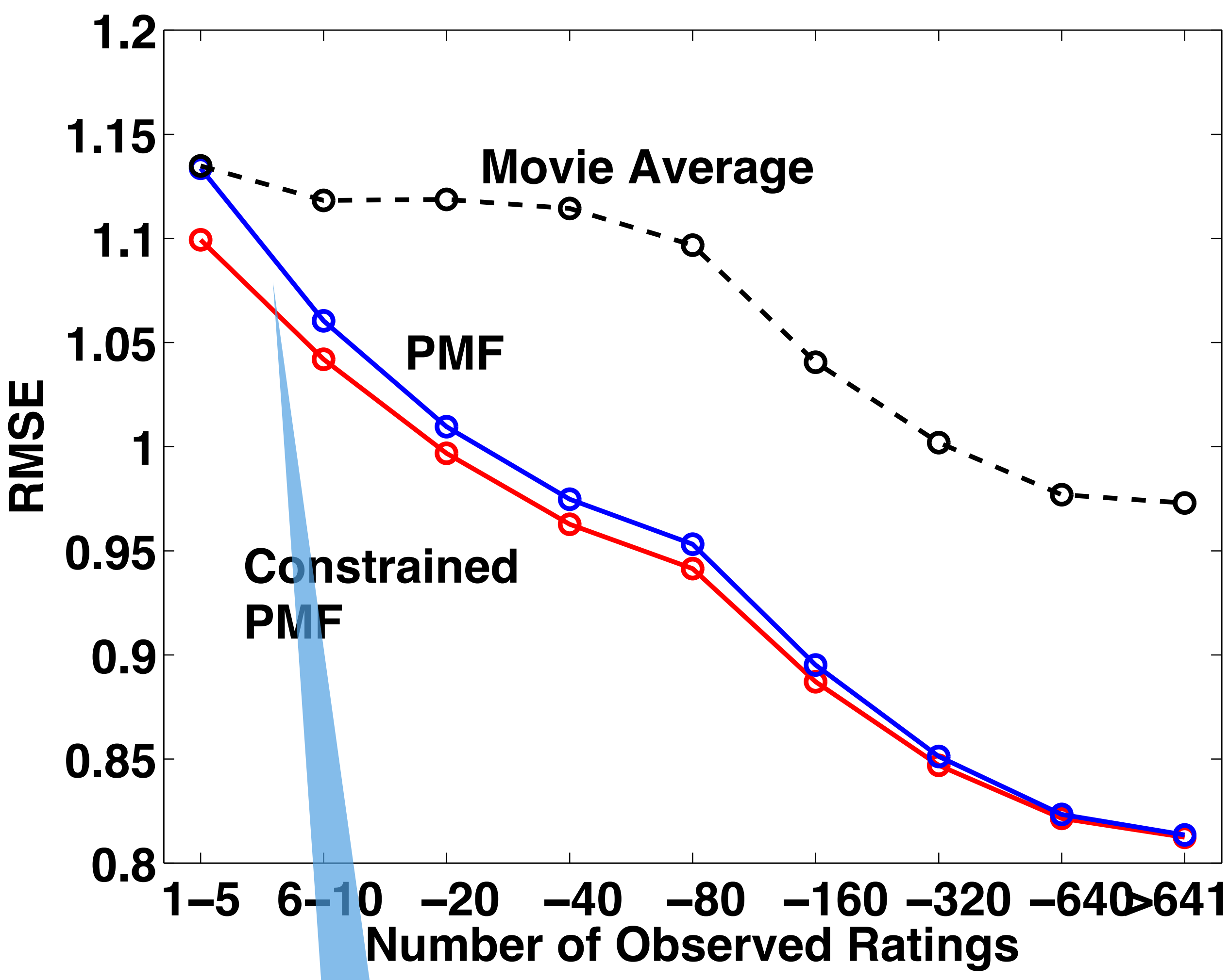


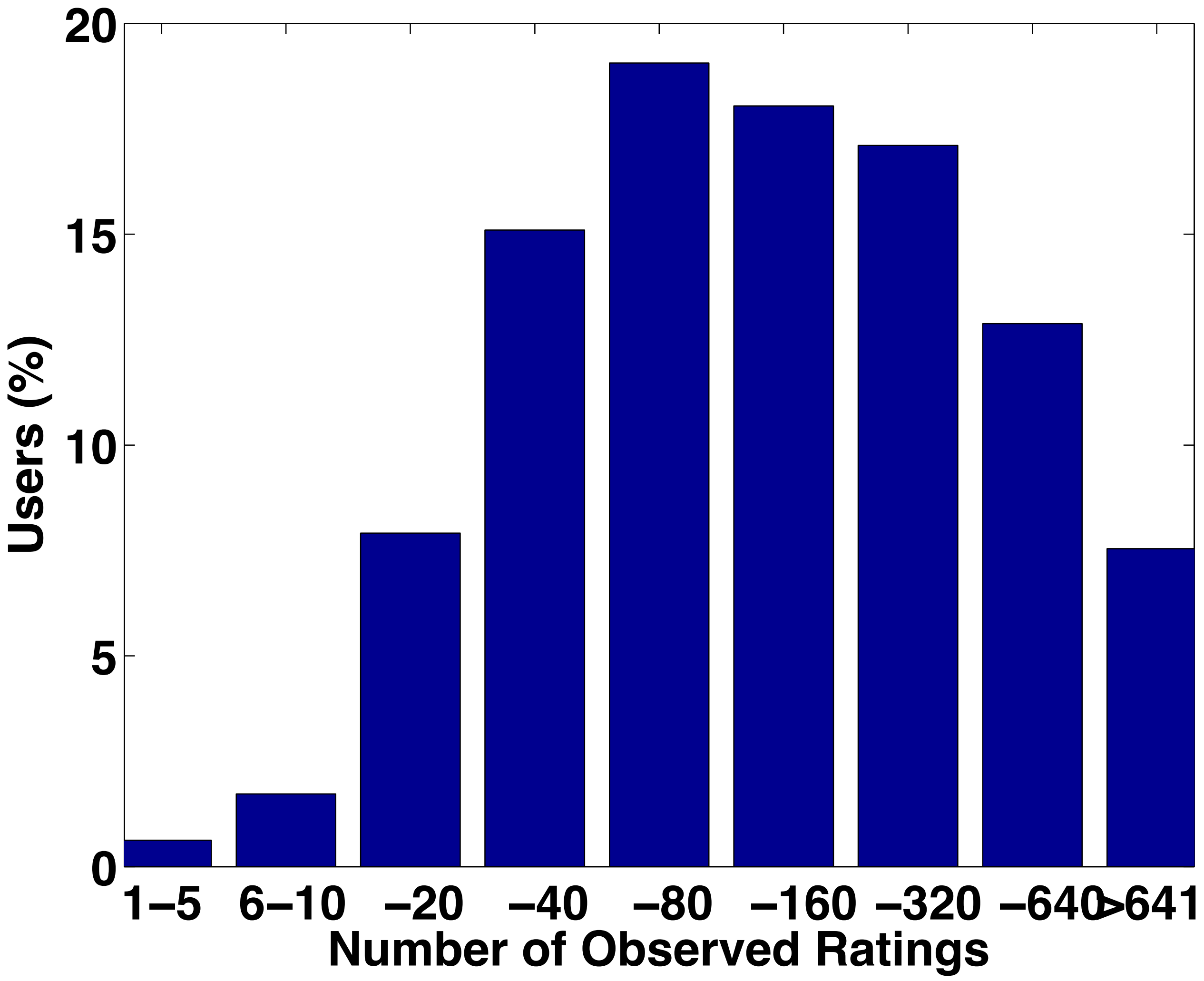
Making it fancier



who rated what

Results (Mnih & Salakthudtinov)





helps for infrequent users

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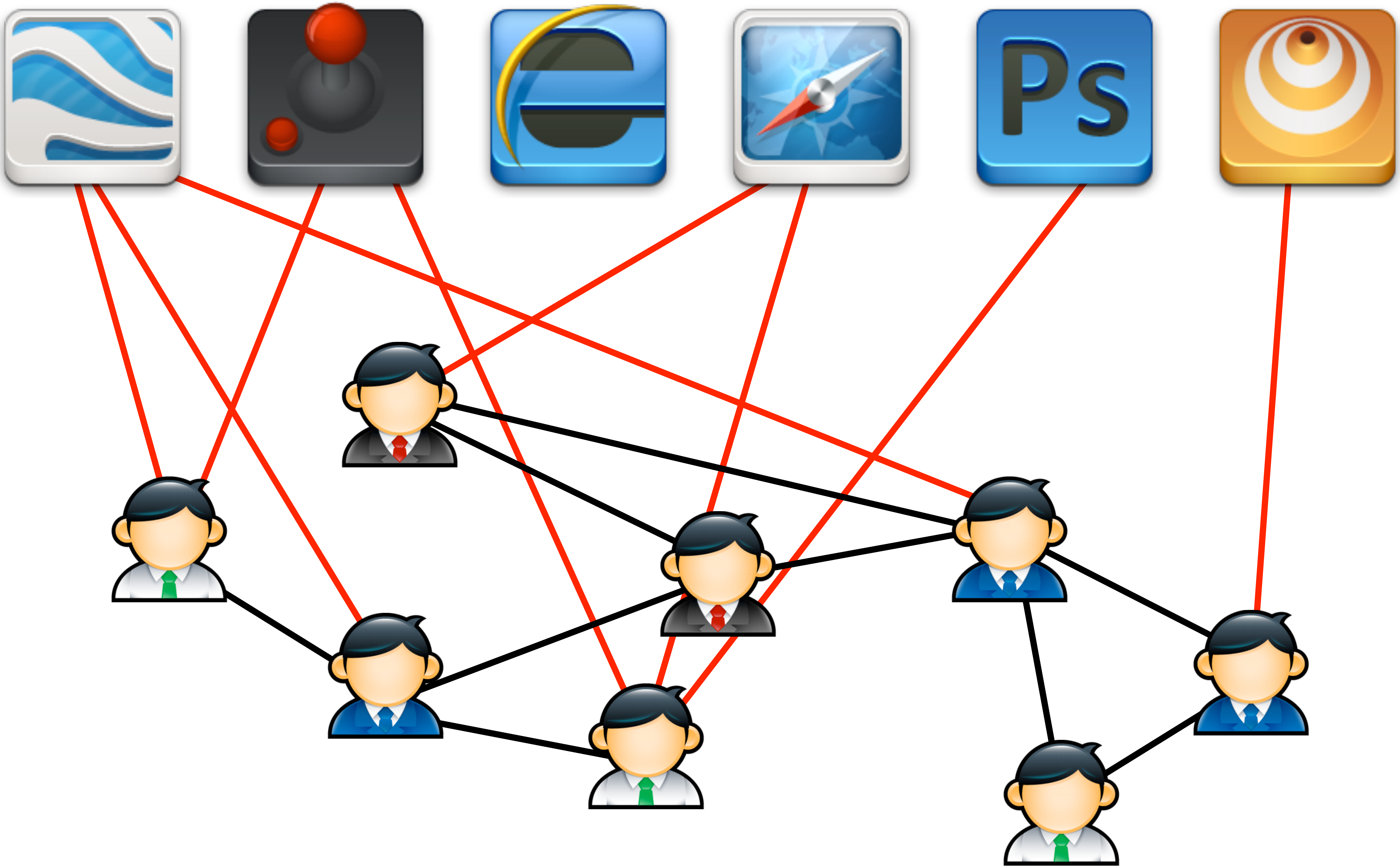
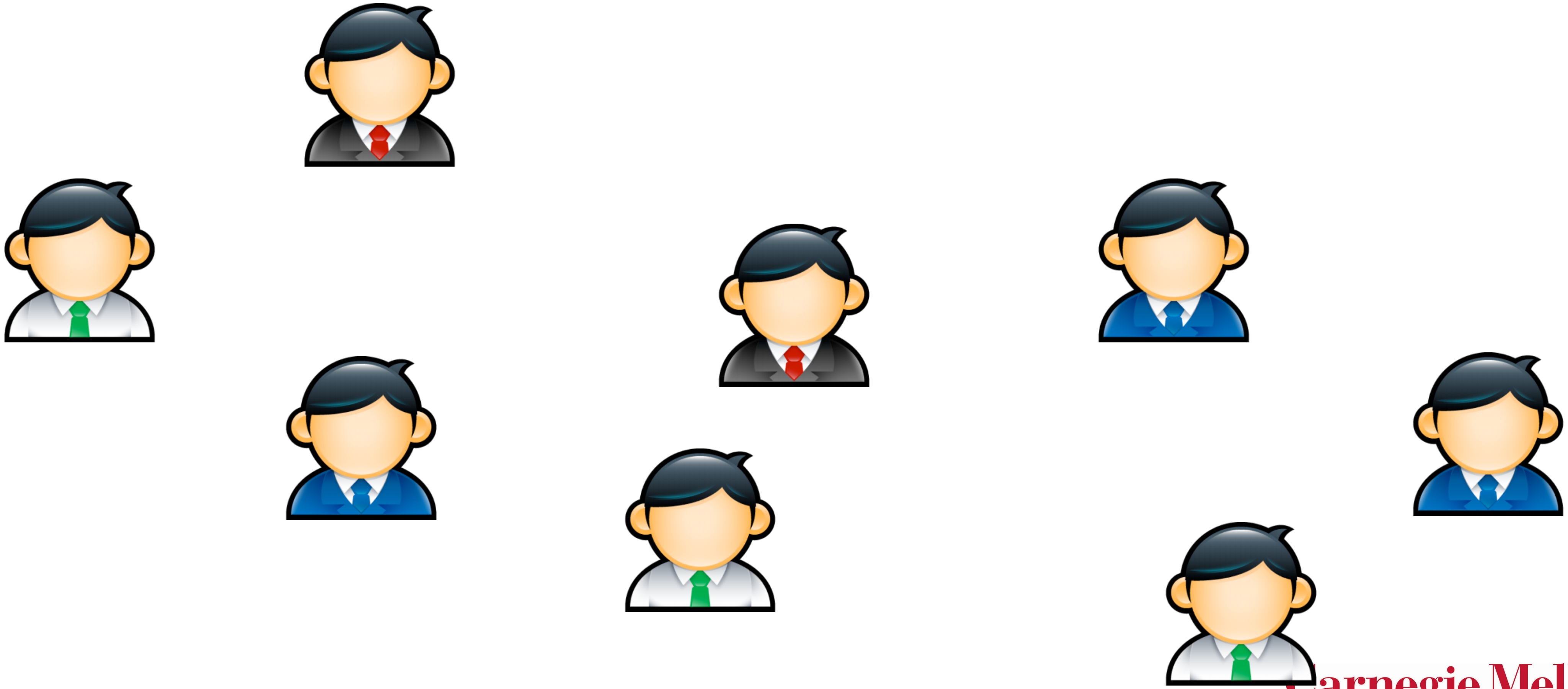
Multiple Sources



Social Network Data

Data: users, connections, features

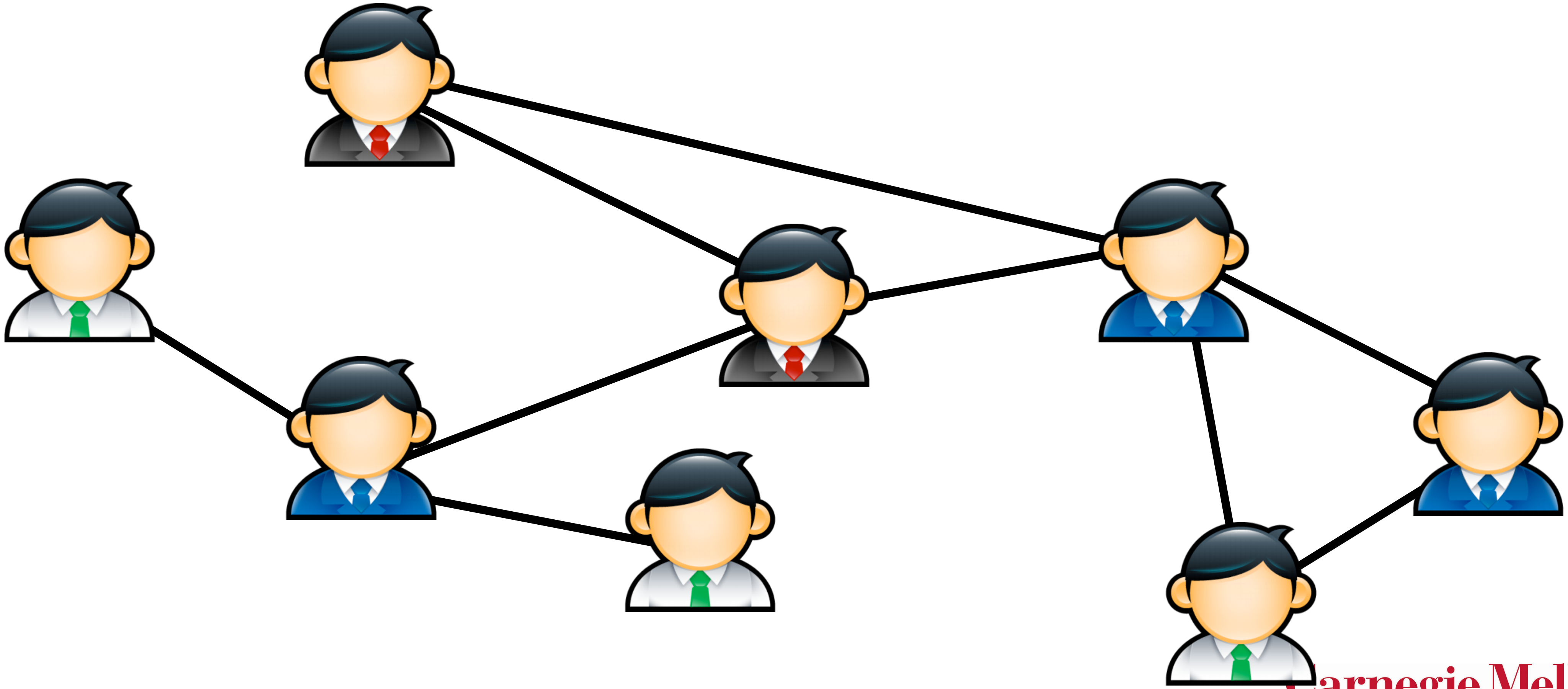
Goal: suggest connections



Social Network Data

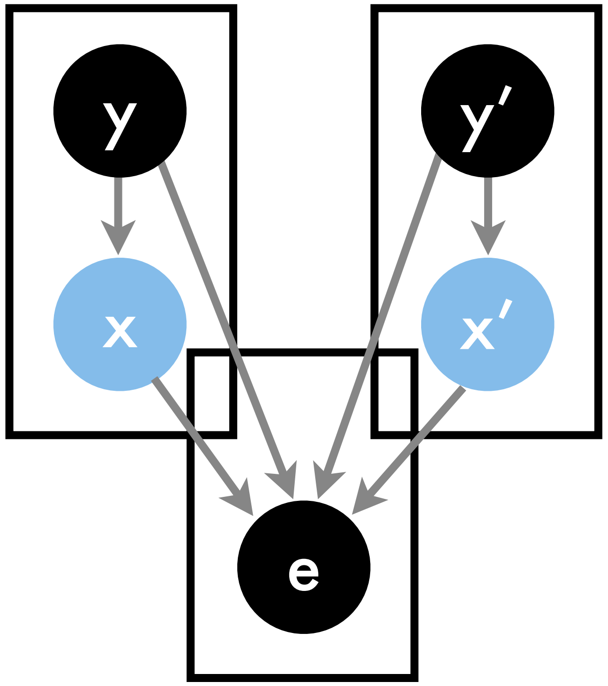
Data: users, connections, features

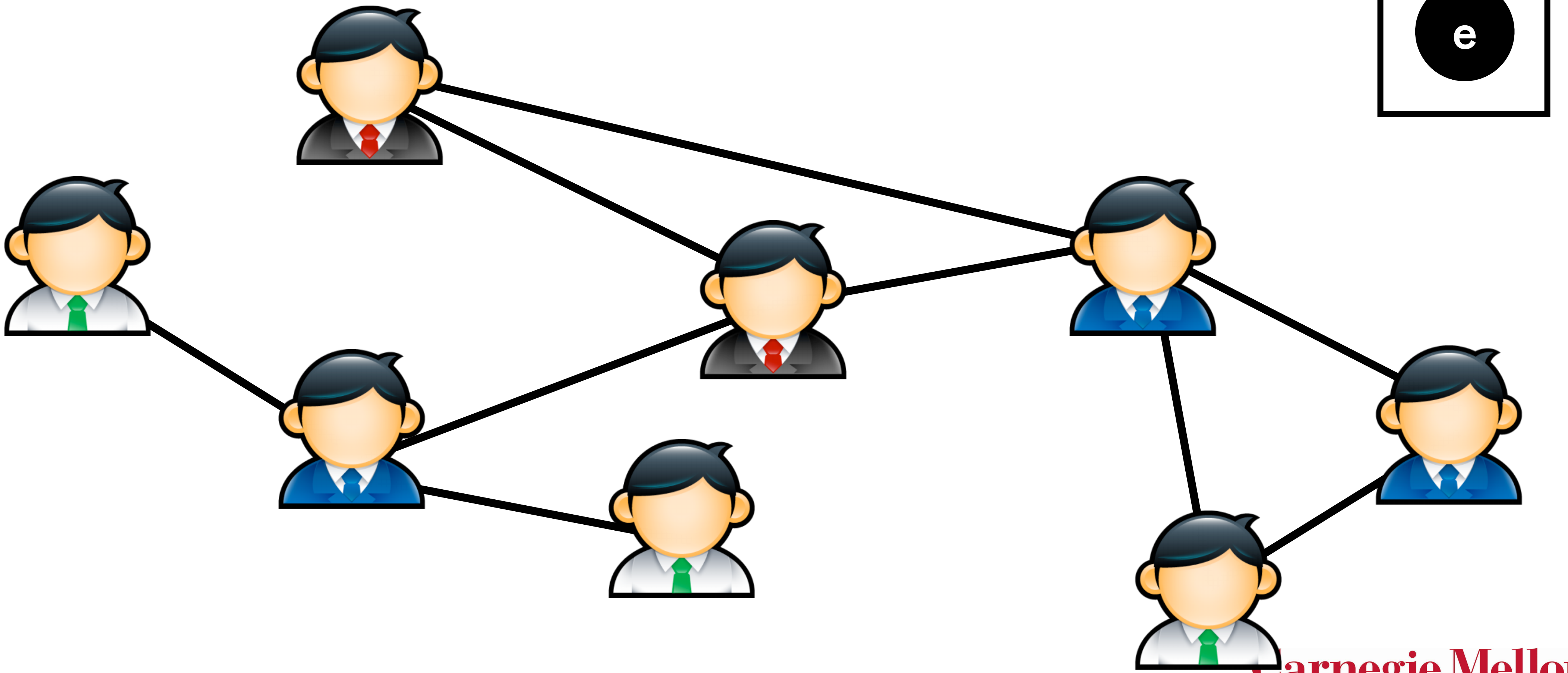
Goal: suggest connections



Social Network Data

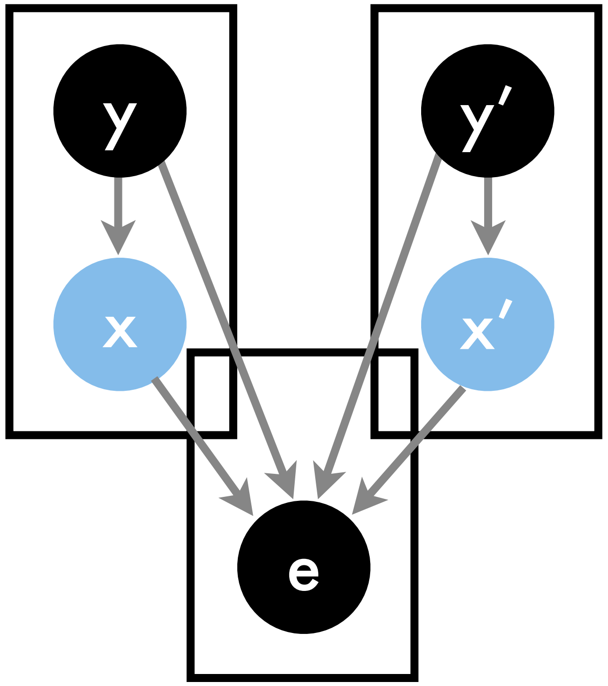
Data: users, connections, features
Goal: suggest connections





Social Network Data

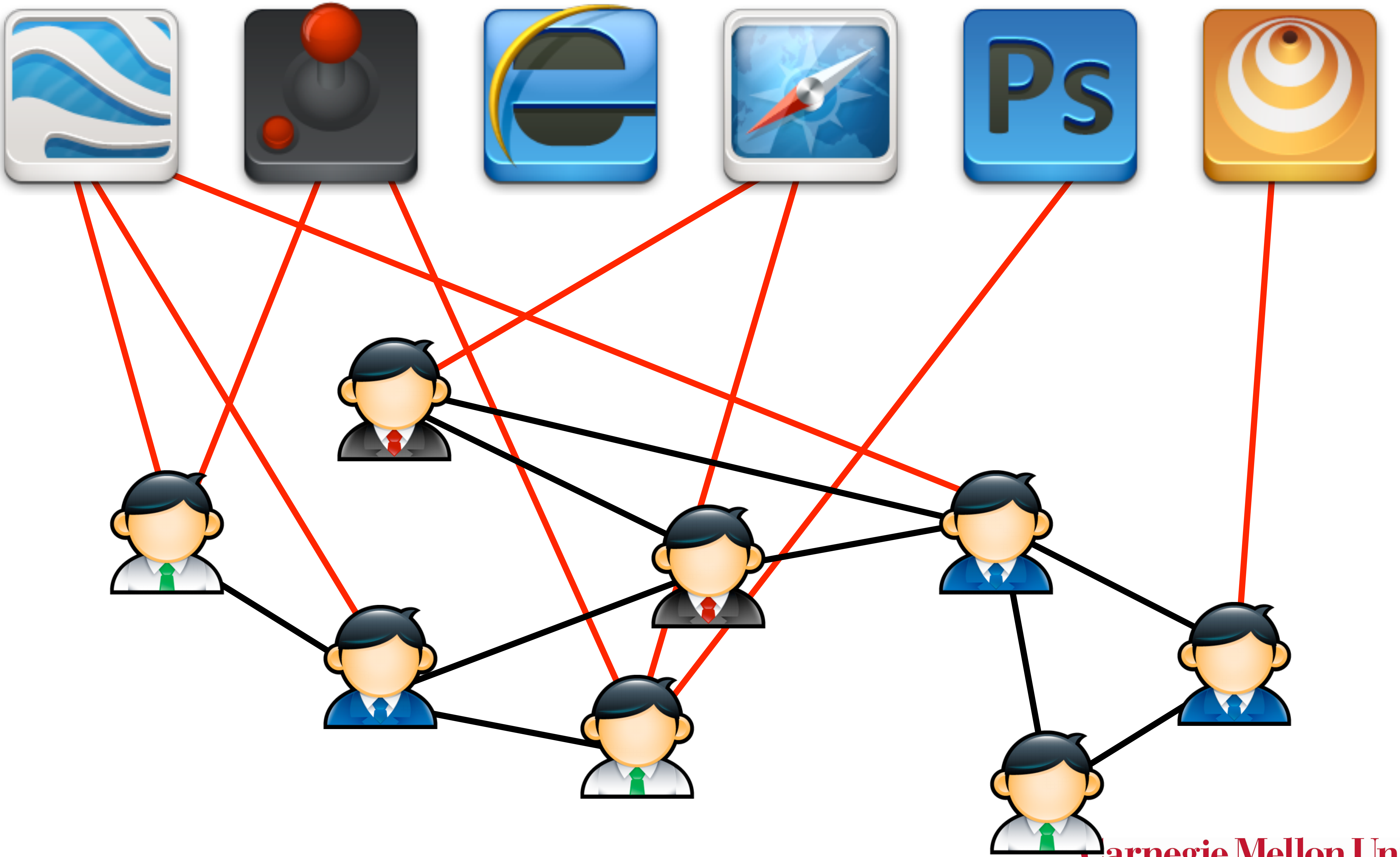
Data: users, connections, features
Goal: model/suggest connections



$$p(x, y, e) = \prod_{i \in \text{Users}} p(y_i) p(x_i | y_i) \prod_{i,j \in \text{Users}} p(e_{ij} | x_i, y_i, x_j, y_j)$$

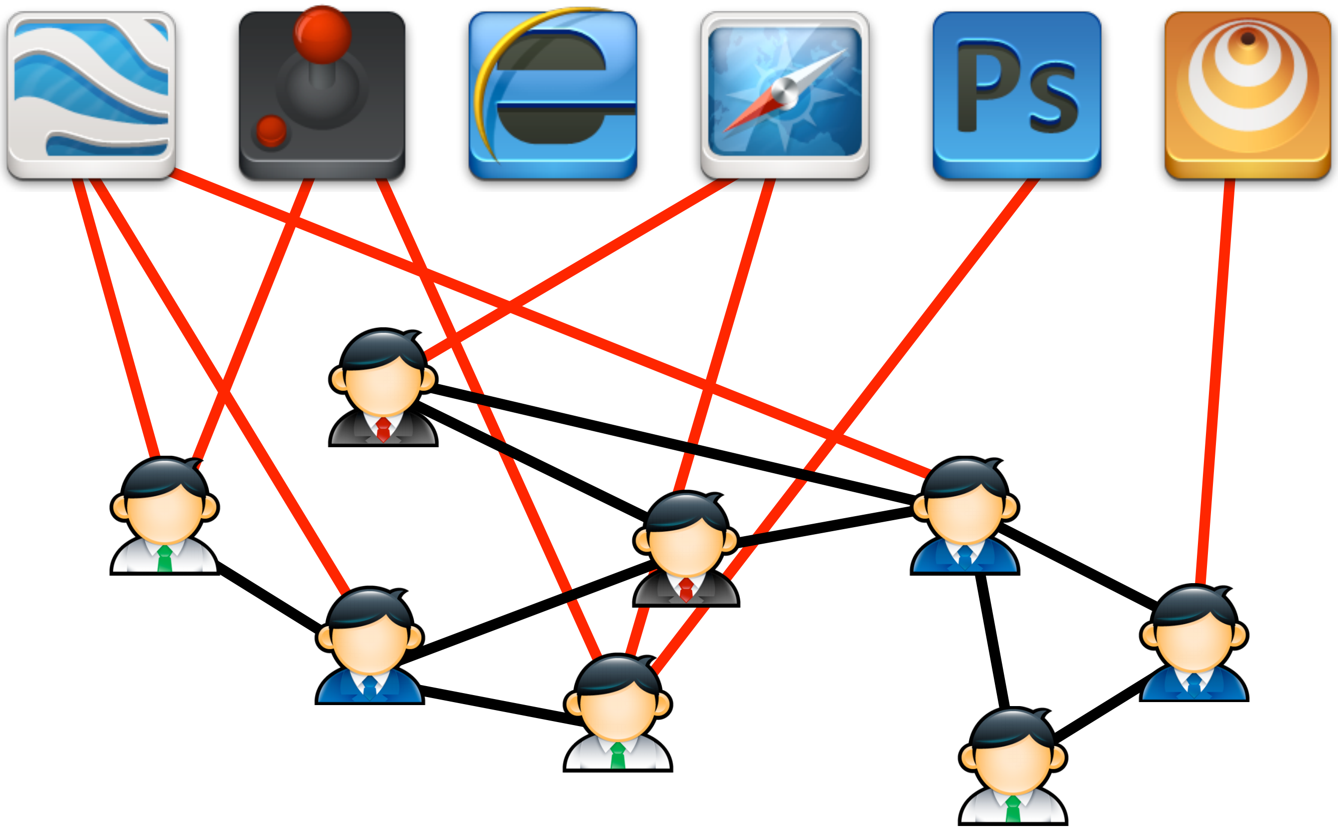
Direct application of the Aldous-Hoover theorem.
Edges are conditionally independent.

Applications



Applications

social network = friendship + interests



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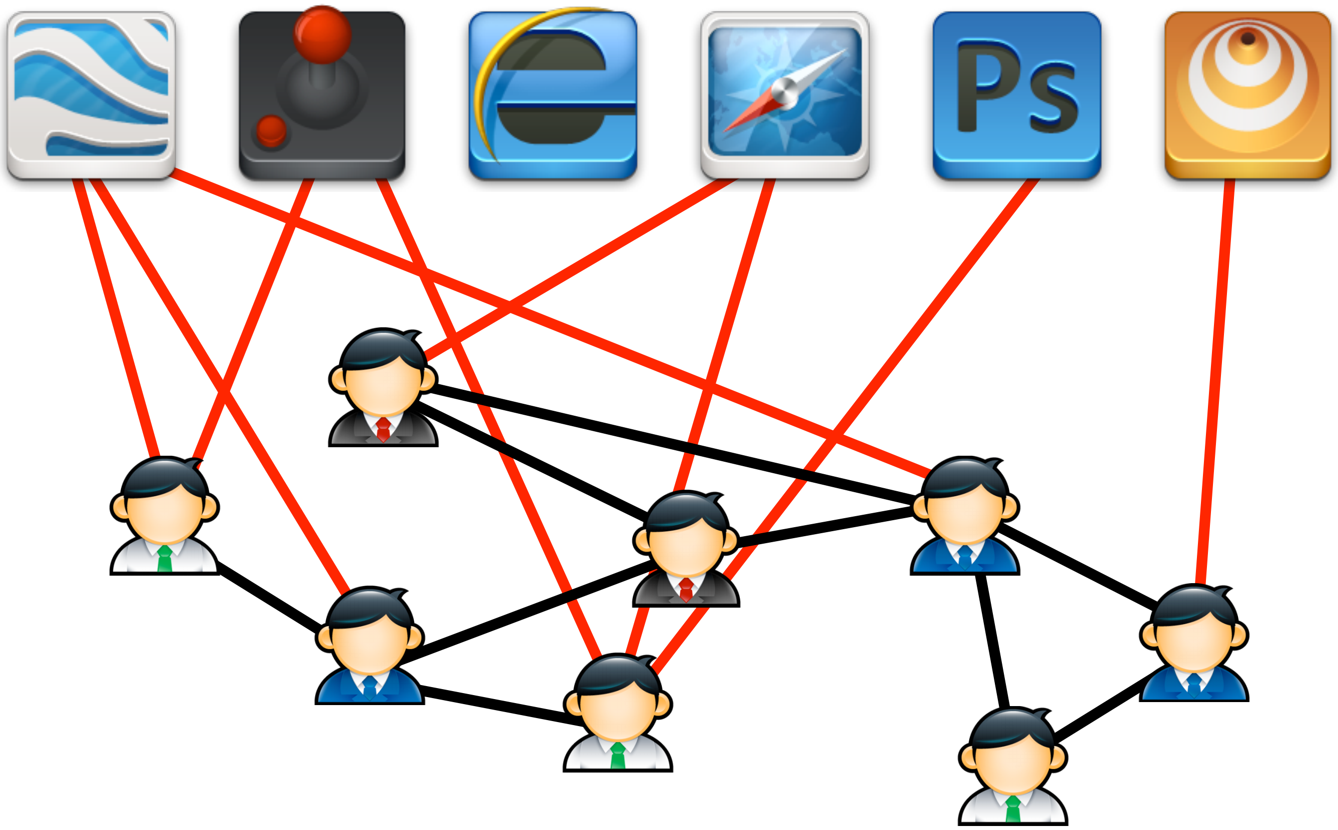
Applications

social network = friendship + interests

recommend users based on friendship & interests

recommend apps based on friendship & interests



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Social Recommendation

recommend users based on friendship & interests

- boost traffic
- make the user graph more dense
- increase user population
- stickiness

recommend apps based on friendship & interests

- boost traffic
- increased revenue
- increased user participation
- make app graph more dense

... usually addressed by separate tools ...

Homophily

recommend users based on friendship & interests

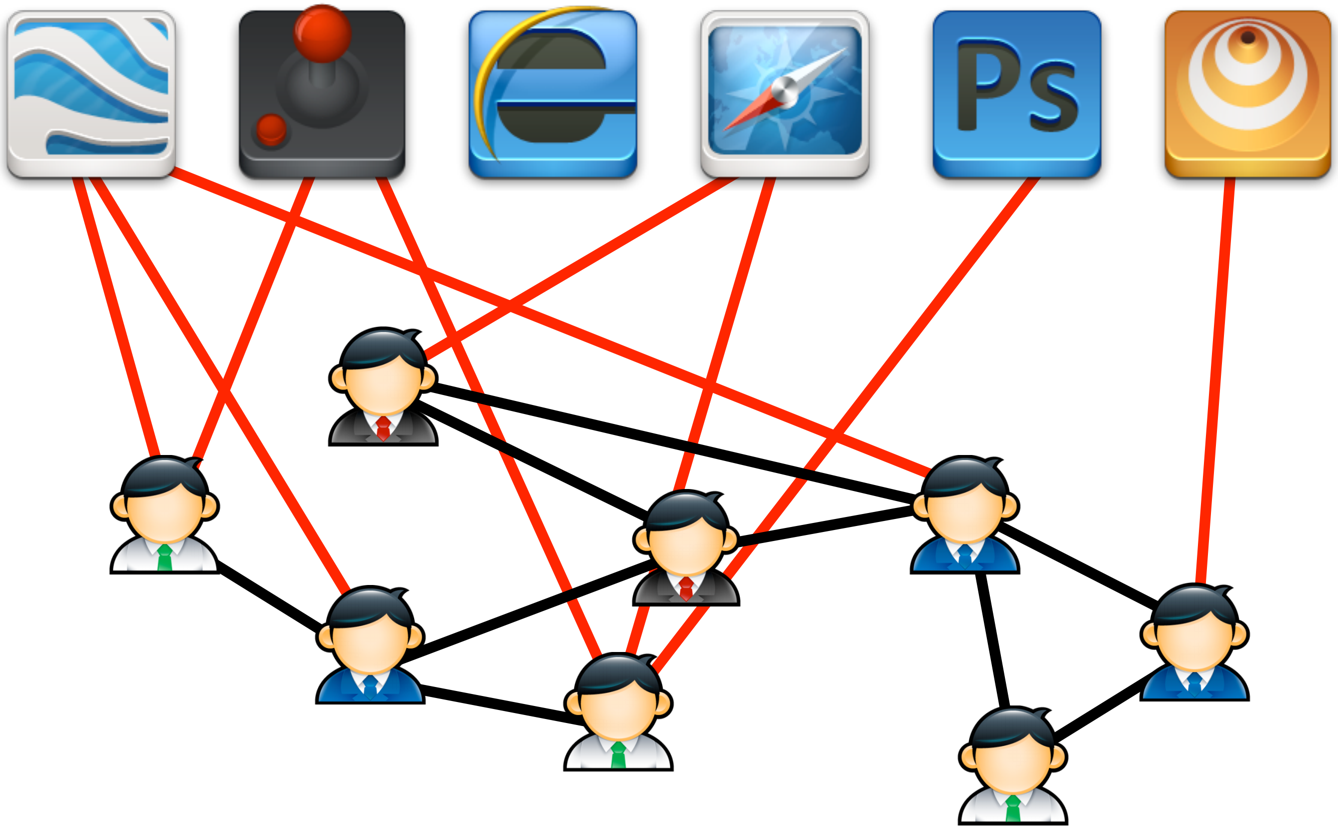
- users with similar interests are more likely to connect

recommend apps based on friendship & interests

- friends install similar applications

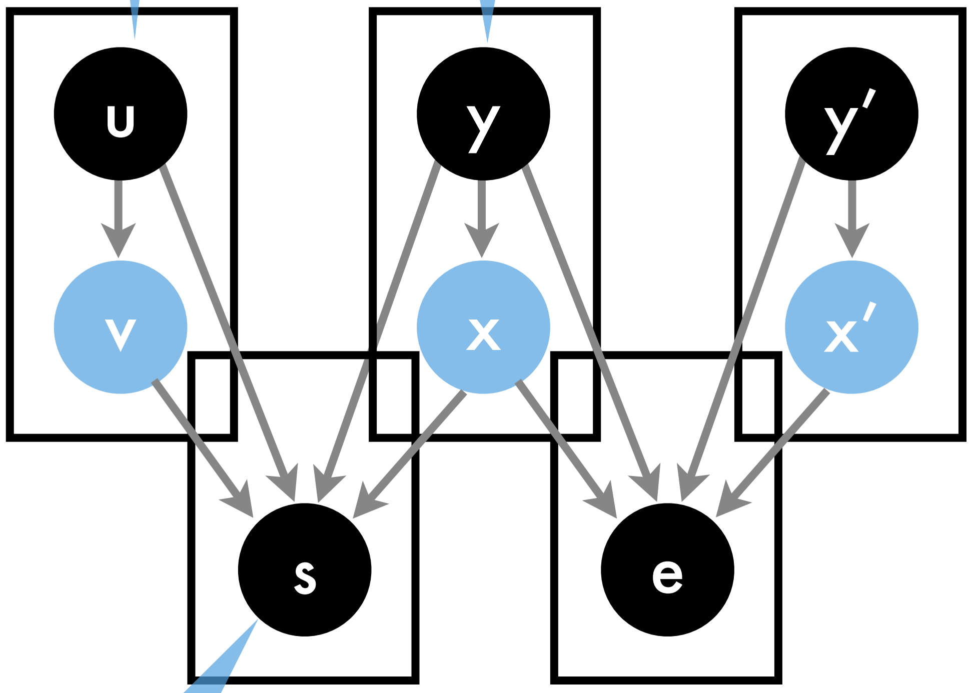
Highly correlated. Estimate both jointly

Model



(latent) app features

(latent) user features



app install

Model

- Social interaction

$$x_i \sim p(x|y_i)$$

$$x_j \sim p(x|y_j)$$

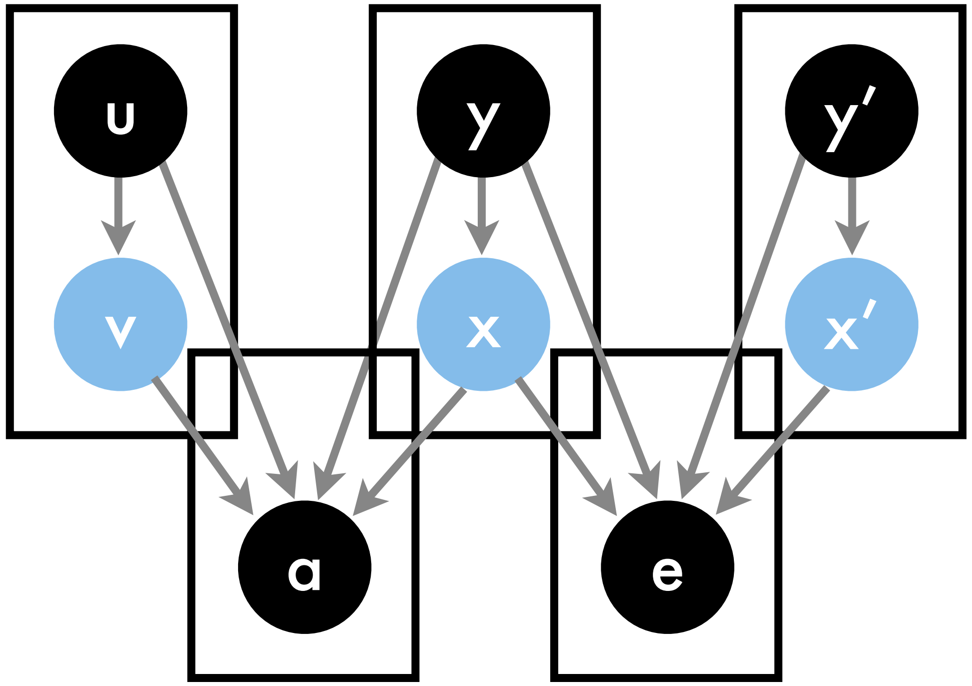
$$e_{ij} \sim p(e|x_i, y_i, x_j, y_j, \Phi)$$

- App install

$$x_i \sim p(x|y_i)$$

$$v_j \sim p(v|u_j)$$

$$a_{ij} \sim p(a|x_i, y_i, u_j, v_j, \Phi)$$



Model

- Social interaction

$$x_i \sim p(x|y_i)$$

$$x_j \sim p(x|y_j)$$

$$e_{ij} \sim p(e|x_i, y_i, x_j, y_j, \Phi)$$

cold start

latent features

$$x_i = Ay_i + \epsilon_i$$

$$v_j = Bu_j + \tilde{\epsilon}_j$$

- App install

$$x_i \sim p(x|y_i)$$

$$v_j \sim p(v|u_j)$$

$$a_{ij} \sim p(a|x_i, y_i, u_j, v_j, \Phi)$$

$$e_{ij} \sim p(e|x_i^\top x_j + y_i^\top W y_j)$$

$$a_{ij} \sim p(a|x_i^\top v_j + y_i^\top M u_j)$$

bilinear features

Optimization Problem

minimize $\lambda_e \sum_{(i,j)} l(e_{ij}, x_i^\top x_j + y_i^\top W y_j) +$

Optimization Problem

minimize $\lambda_e \sum_{(i,j)} l(e_{ij}, x_i^\top x_j + y_i^\top W y_j) +$

social

Optimization Problem

minimize $$\lambda_e \sum_{(i,j)} l(e_{ij}, x_i^\top x_j + y_i^\top W y_j) +$$

social

$$\lambda_a \sum_{(i,j)} l(a_{ij}, x_i^\top v_j + y_i^\top M u_j) +$$

app

Optimization Problem

minimize

$$\lambda_e \sum_{(i,j)} l(e_{ij}, x_i^\top x_j + y_i^\top W y_j) +$$

social

$$\lambda_a \sum_{(i,j)} l(a_{ij}, x_i^\top v_j + y_i^\top M u_j) +$$

app

reconstruction

$$\lambda_x \sum \gamma(x_i | y_i) + \lambda_v \sum \gamma(v_i | u_i) +$$

Optimization Problem

minimize

$$\lambda_e \sum_{(i,j)} l(e_{ij}, x_i^\top x_j + y_i^\top W y_j) +$$

social

$$\lambda_a \sum_{(i,j)} l(a_{ij}, x_i^\top v_j + y_i^\top M u_j) +$$

app

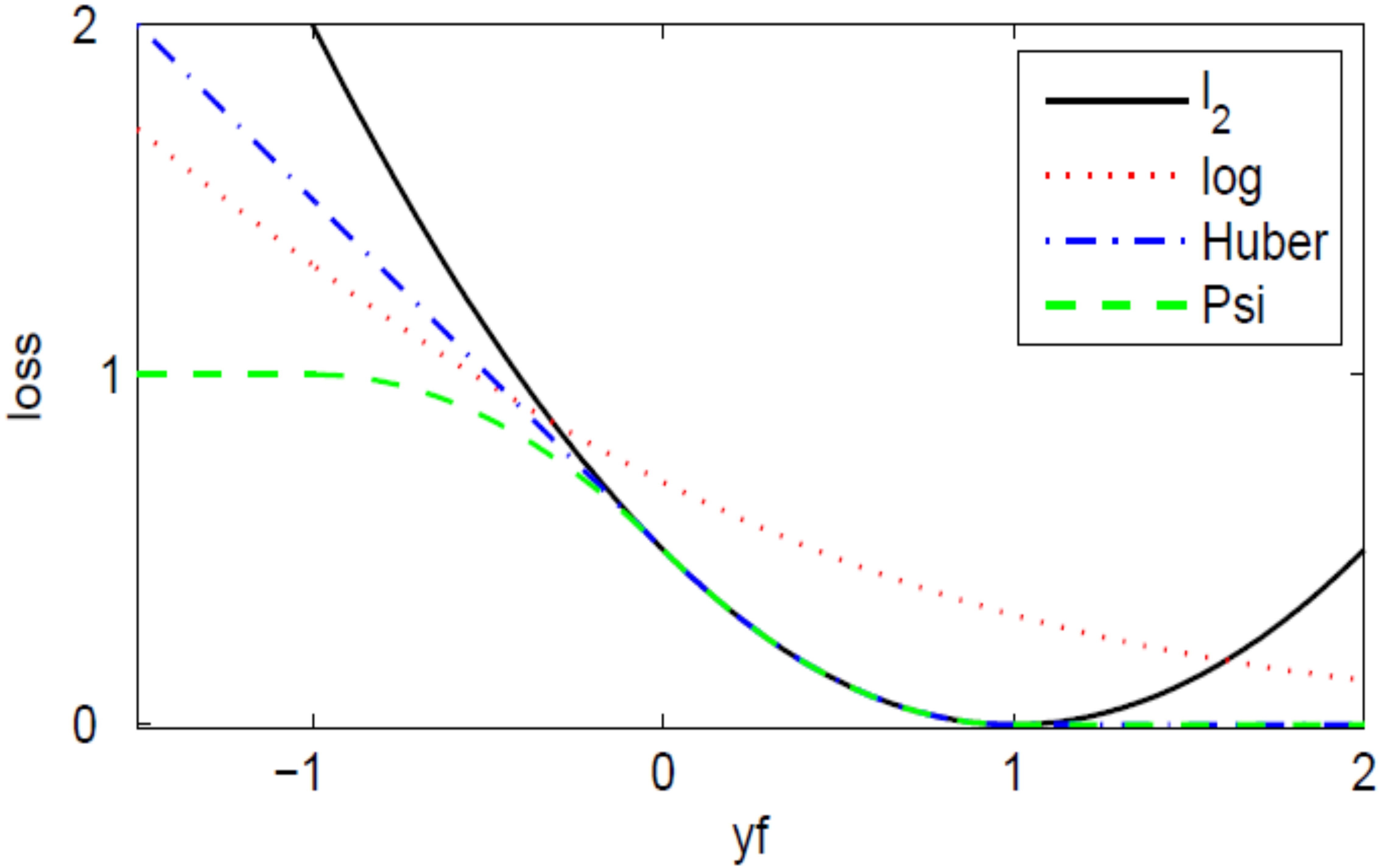
reconstruction

$$\lambda_x \sum_{i} \gamma(x_i|y_i) + \lambda_v \sum_{i} \gamma(v_i|u_i) +$$

$$\lambda_W \left\|W\right\|^2 + \lambda_M \left\|M\right\|^2 + \lambda_A \left\|A\right\|^2 + \lambda_B \left\|B\right\|^2$$

regularizer

Loss Function



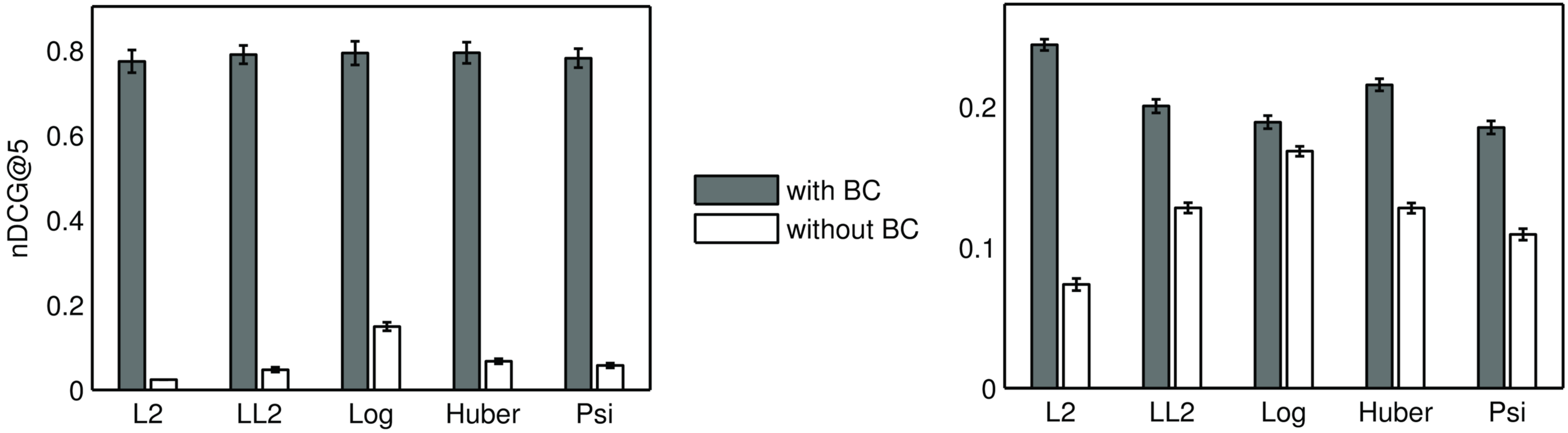
Loss

- Much more evidence of application non-install (i.e. many more negative examples)
- Few links between vertices in friendship network (even within short graph distance)

- Generate ranking problems (link, non-link) with non-links drawn from background set

Loss

- Much more evidence of application non-install



non-links drawn from background set

application recommendation

social recommendation

Optimization

- Nonconvex optimization problem
- Large set of variables

$$x_i = Ay_i + \epsilon_i$$
$$v_j = Bu_j + \tilde{\epsilon}_j$$

- Stochastic gradient descent on x, v, ε for speed
- Use hashing to reduce memory load, i.e.

$$e_{ij} \sim p(e|x_i^\top x_j + y_i^\top W y_j)$$
$$a_{ij} \sim p(a|x_i^\top v_j + y_i^\top M u_j)$$

$$x_{ij} = \sigma(i,j) X[h(i,j)]$$

binary hash

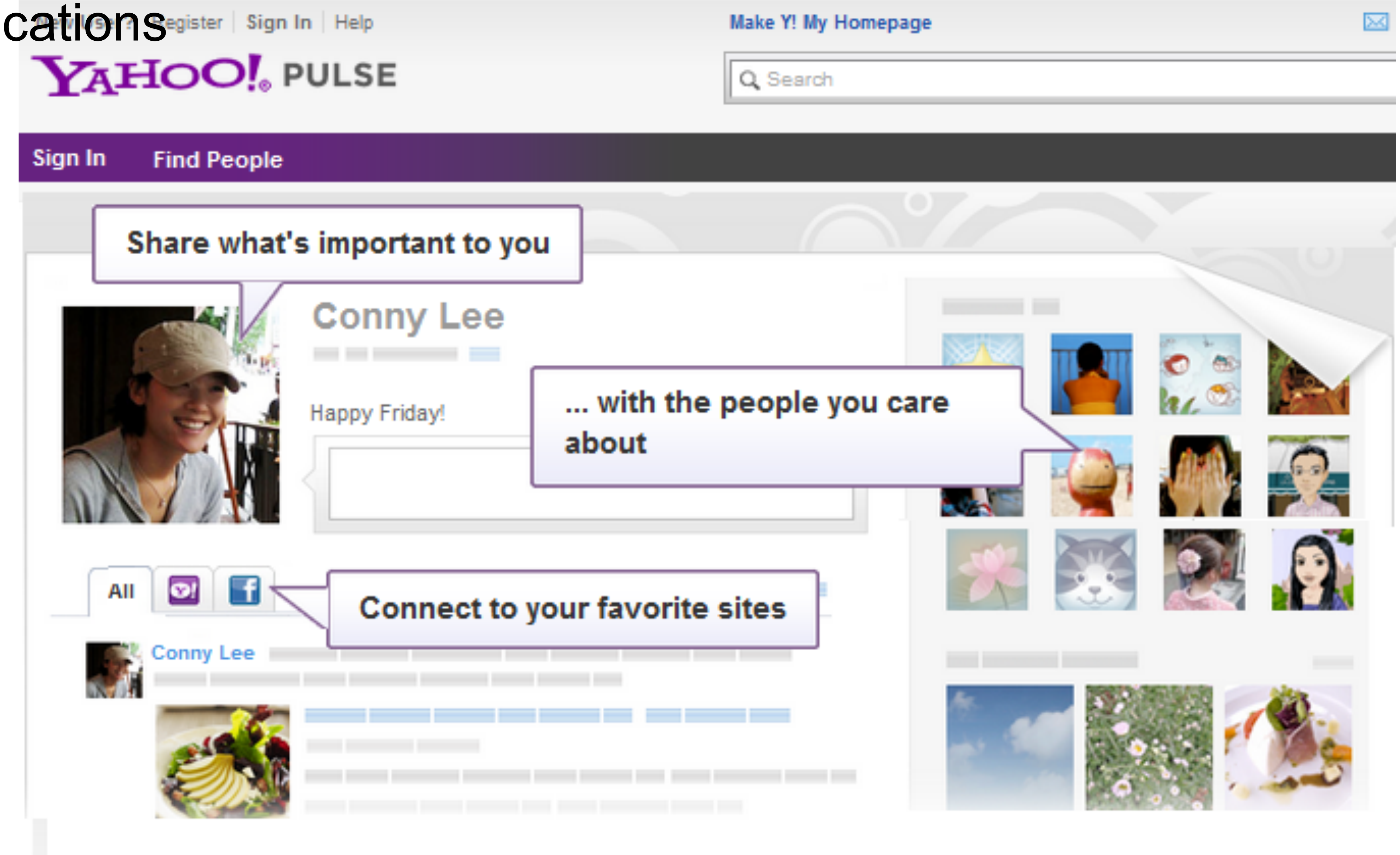
hash

Y! Pulse

1.2M users, 386 items

6.1M friend connections

29M interest indications



Sign In | Help

Make Y! My Homepage

YAHOO! PULSE

Search

Sign In

Find People

Share what's important to you

Conny Lee

Happy Friday!

... with the people you care about

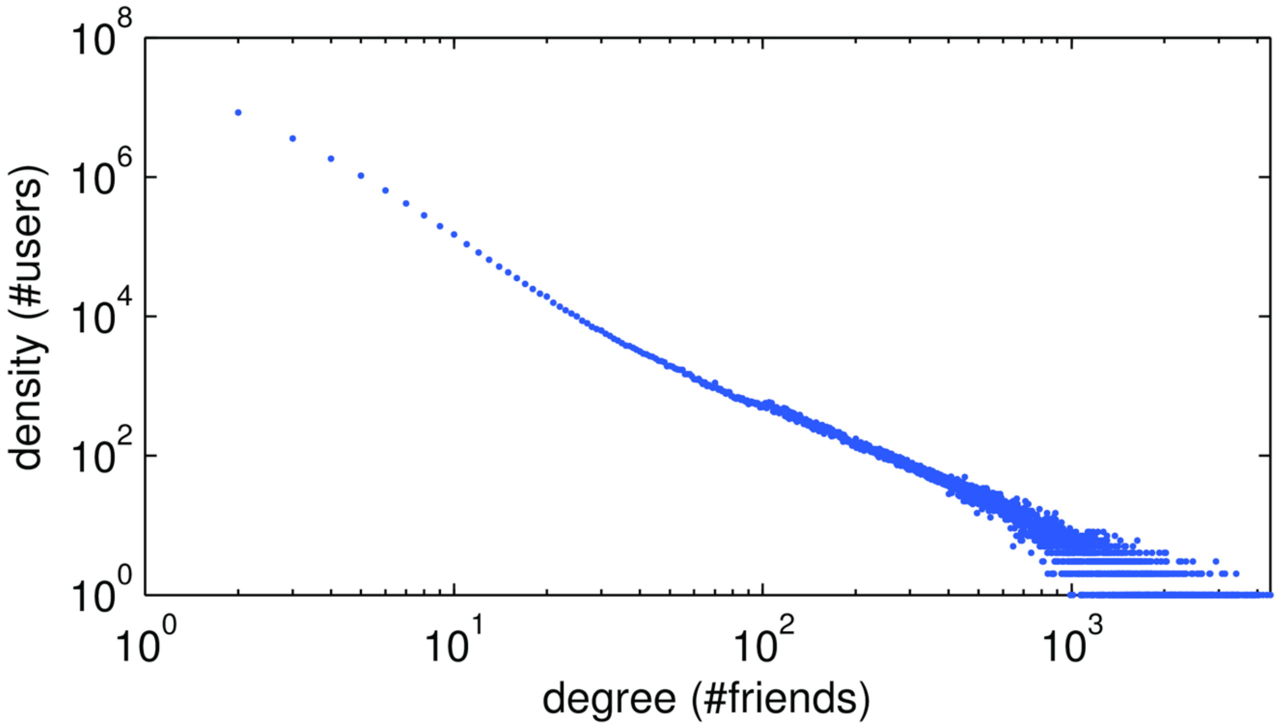
All

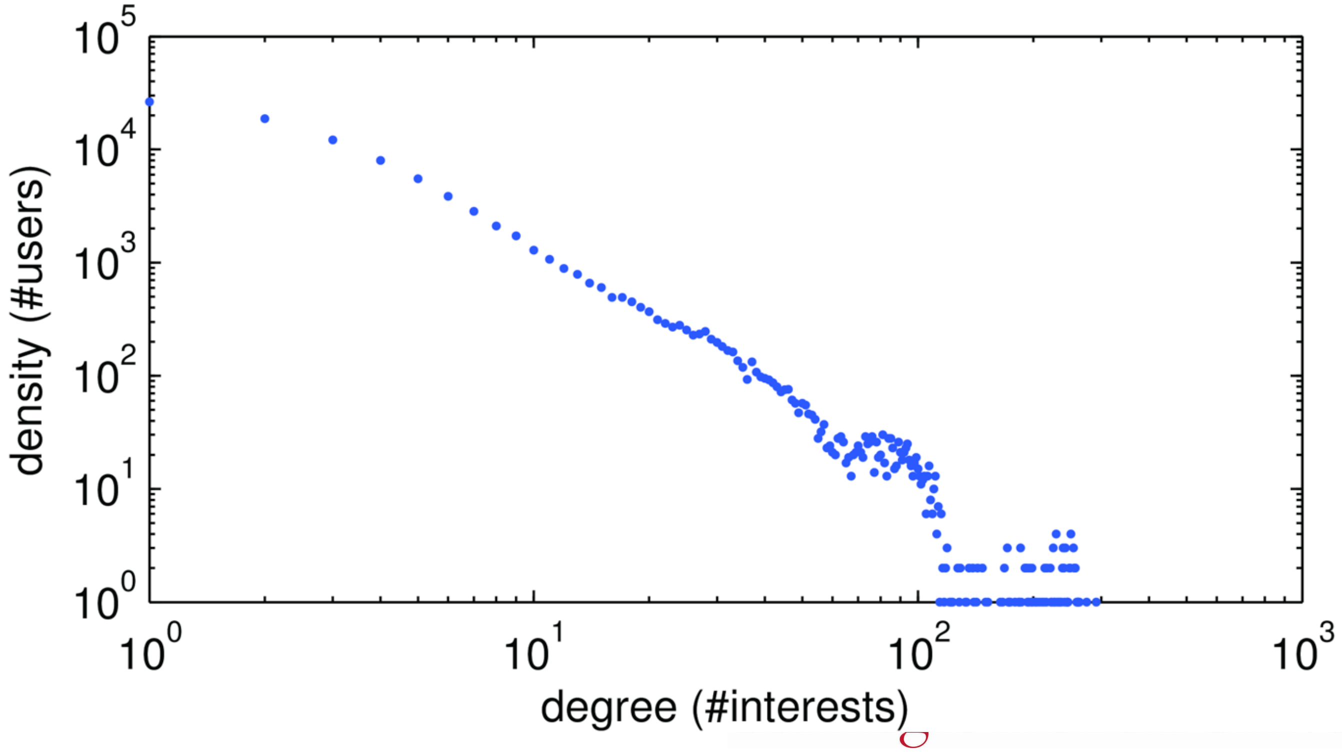
Connect to your favorite sites

Conny Lee

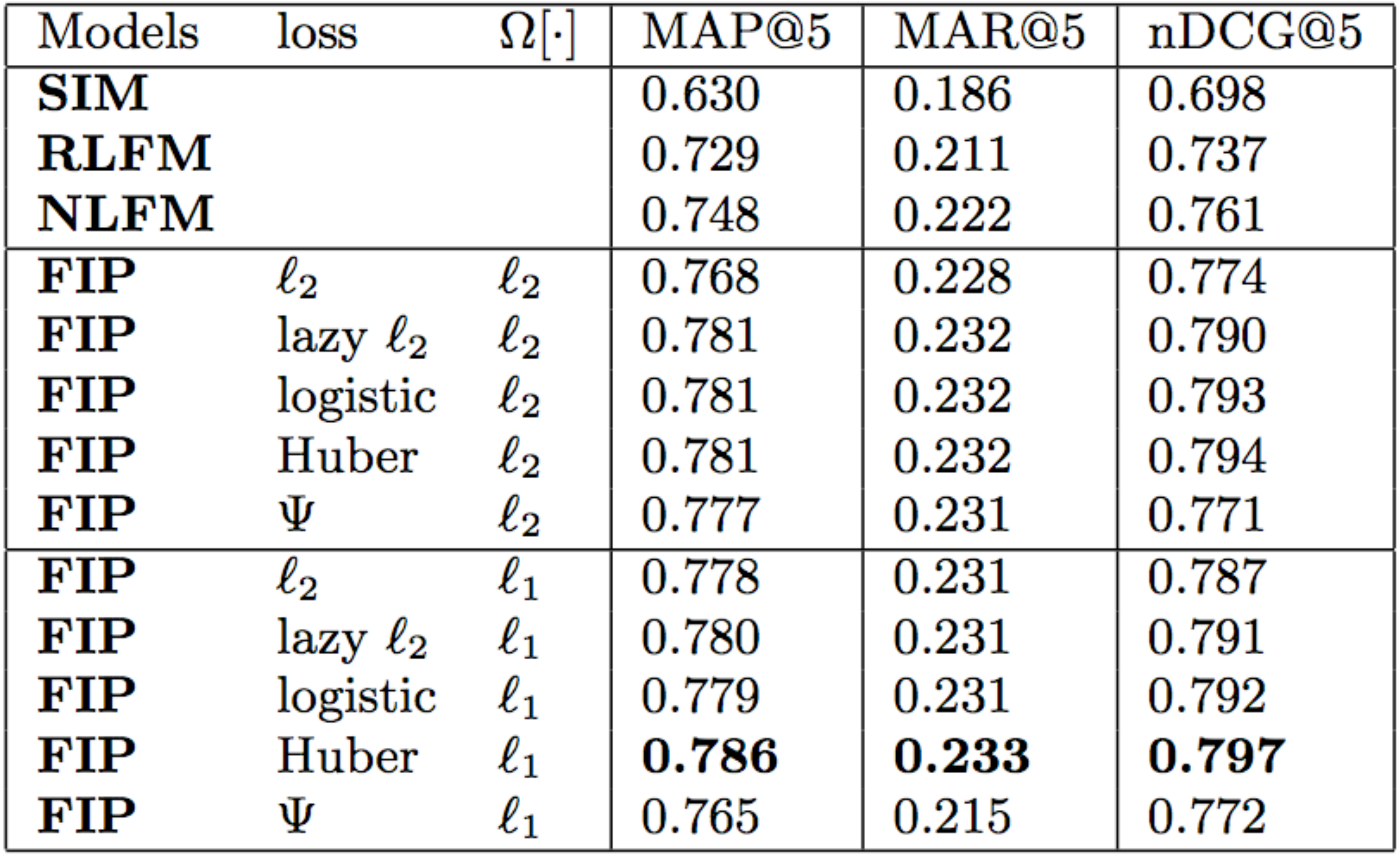
Y! Pulse Data

1.2M users, 386 items
6.1M friend connections
29M interest indications





App Recommendation

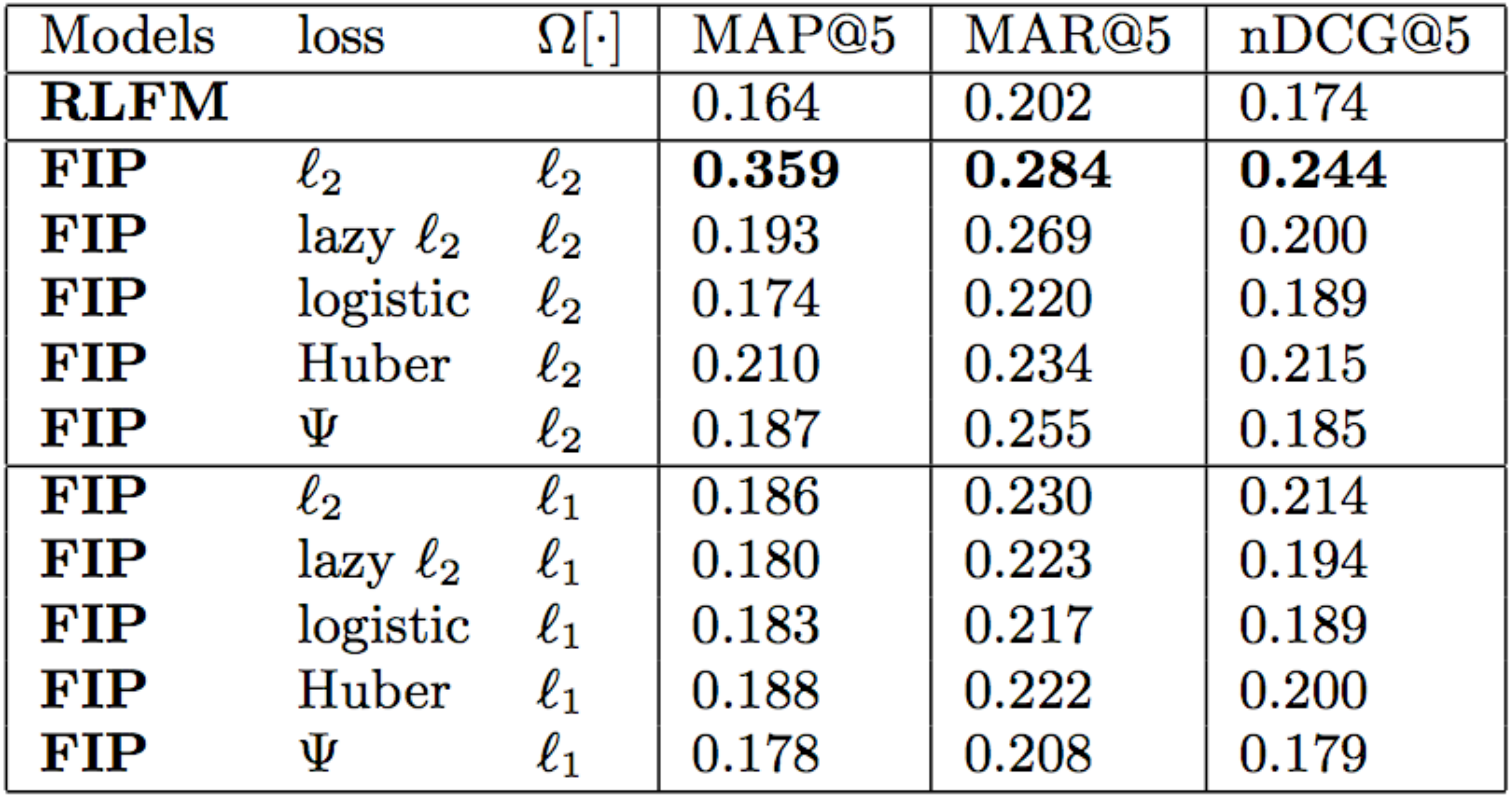


Models	loss	$\Omega[\cdot]$	MAP@5	MAR@5	nDCG@5
SIM			0.630	0.186	0.698
RLFM			0.729	0.211	0.737
NLFM			0.748	0.222	0.761
FIP	ℓ_2	ℓ_2	0.768	0.228	0.774
FIP	lazy ℓ_2	ℓ_2	0.781	0.232	0.790
FIP	logistic	ℓ_2	0.781	0.232	0.793
FIP	Huber	ℓ_2	0.781	0.232	0.794
FIP	Ψ	ℓ_2	0.777	0.231	0.771
FIP	ℓ_2	ℓ_1	0.778	0.231	0.787
FIP	lazy ℓ_2	ℓ_1	0.780	0.231	0.791
FIP	logistic	ℓ_1	0.779	0.231	0.792
FIP	Huber	ℓ_1	**0.786**	**0.233**	**0.797**
FIP	Ψ	ℓ_1	0.765	0.215	0.772

SIM: similarity based model;

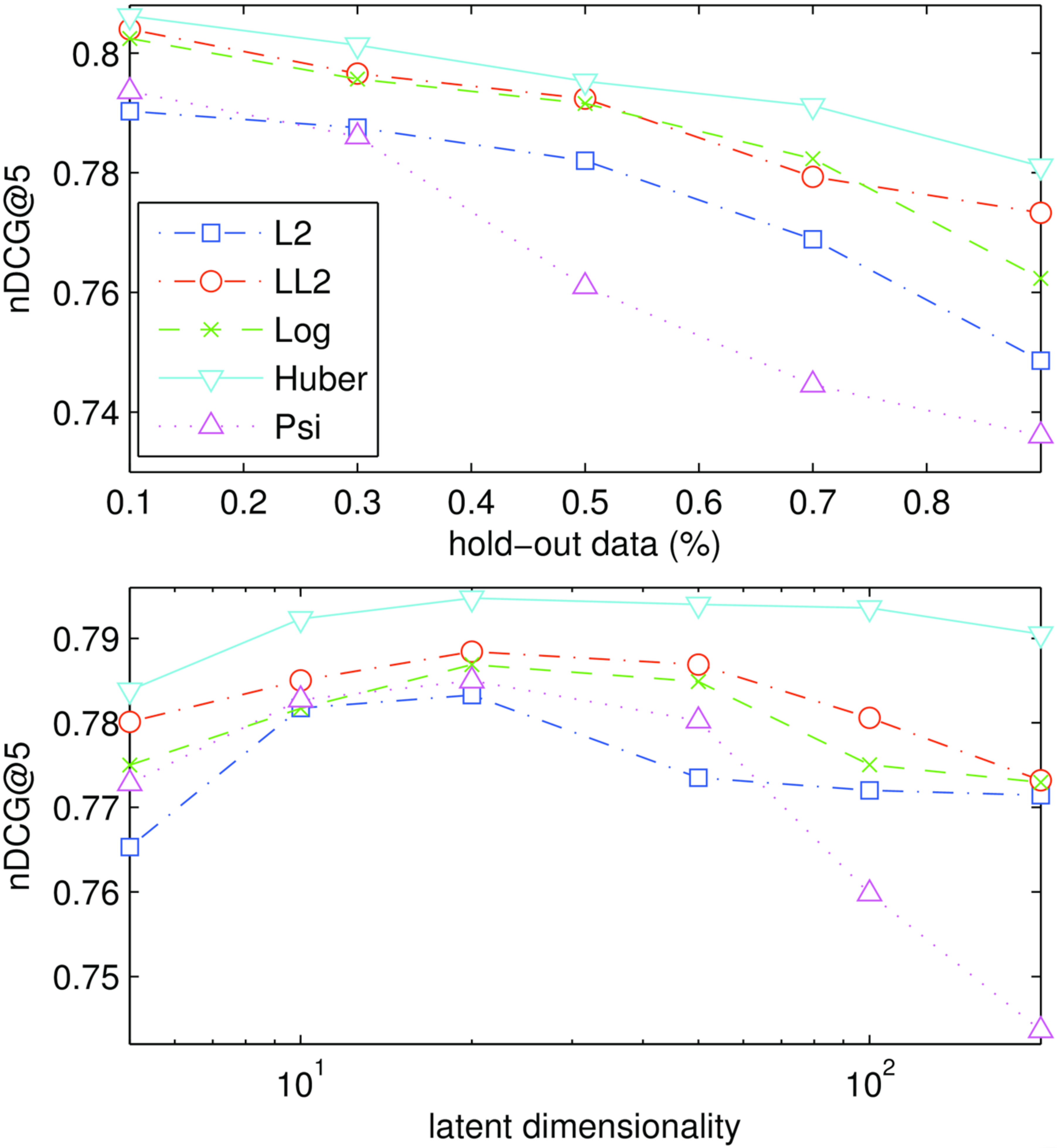
RLFM: regression based latent factor model (Chen&Agarwal); NLFM: SIM&RLFM

Social recommendation



Models	loss	$\Omega[\cdot]$	MAP@5	MAR@5	nDCG@5
RLFM			0.164	0.202	0.174
FIP	ℓ_2	ℓ_2	**0.359**	**0.284**	**0.244**
FIP	lazy ℓ_2	ℓ_2	0.193	0.269	0.200
FIP	logistic	ℓ_2	0.174	0.220	0.189
FIP	Huber	ℓ_2	0.210	0.234	0.215
FIP	Ψ	ℓ_2	0.187	0.255	0.185
FIP	ℓ_2	ℓ_1	0.186	0.230	0.214
FIP	lazy ℓ_2	ℓ_1	0.180	0.223	0.194
FIP	logistic	ℓ_1	0.183	0.217	0.189
FIP	Huber	ℓ_1	0.188	0.222	0.200
FIP	Ψ	ℓ_1	0.178	0.208	0.179

app recommendation
L2 penalty



8.5 Hashing

8 Recommender Systems

Alexander Smola
Introduction to Machine Learning 10-701
http://alex.smola.org/teaching/10-701-15

Significant content courtesy of Yehuda Koren

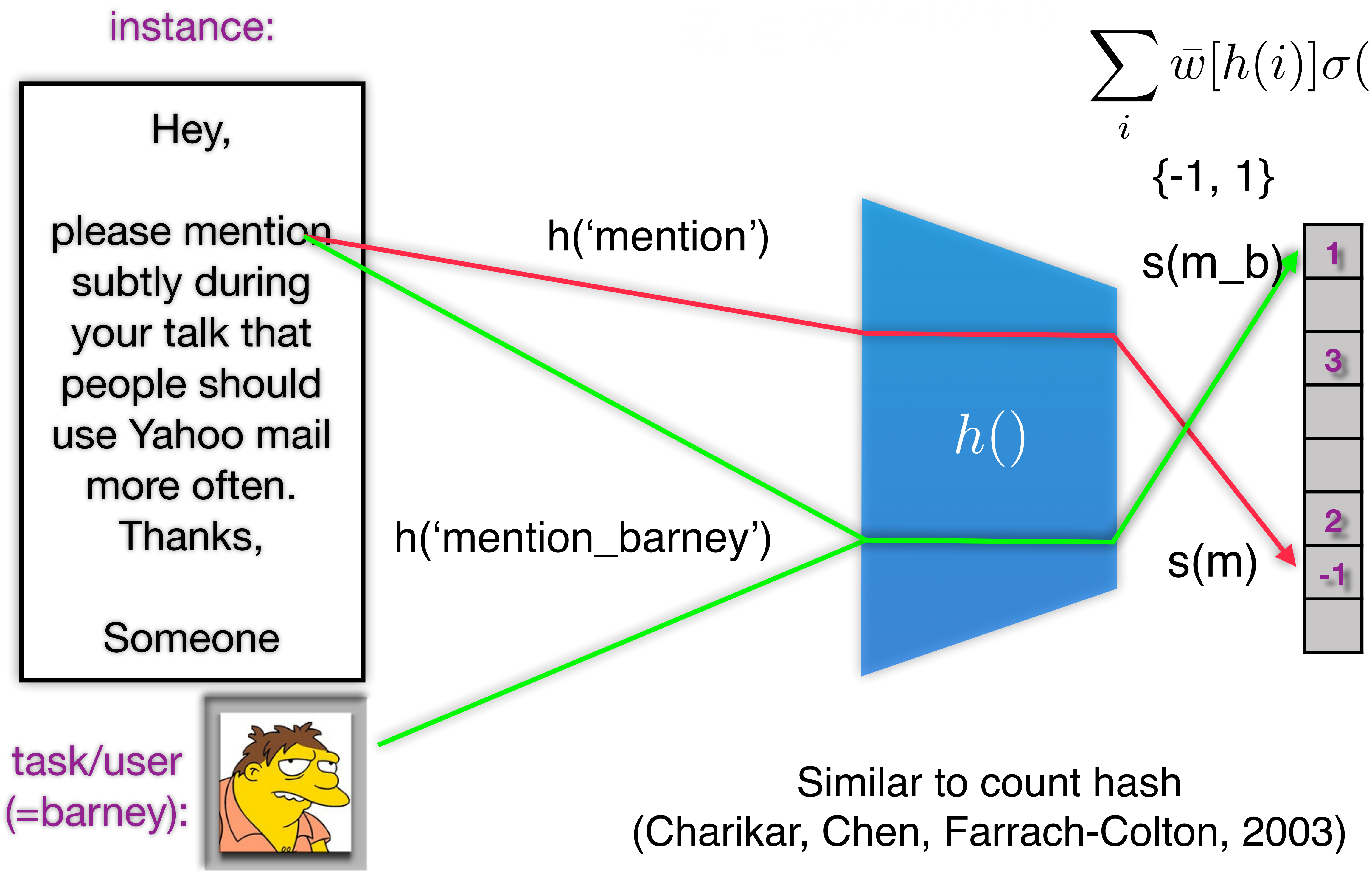
Parameter Storage

- We have millions of users
- We have millions of products
- Storage - for 100 factors this requires
  106 x 106 x 8 = 8TB
- We want a model that can be kept in RAM (<16GB)
  - Instant response for each user
  - Disks have 20 IOP/s at best (SSDs much better)
- Privacy (what if parameter vector leaks)

Recall - Hash Kernels

$$\sum_i \bar{w}[h(i)]\sigma(i)x_i$$

{-1, 1}



instance:

Hey,

please mention subtly during your talk that people should use Yahoo mail more often.

Thanks,

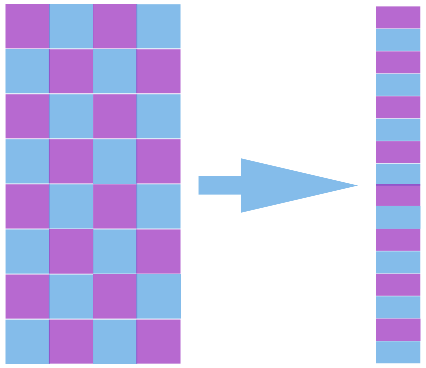
Someone

task/user (=barney):

Similar to count hash
(Charikar, Chen, Farrach-Colton, 2003)

Collaborative Filtering

- **Hashing compression**



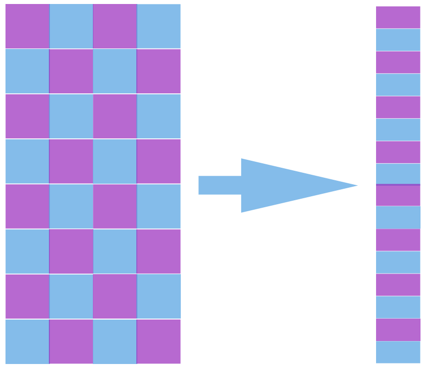
$$u_i = \sum_{j,k:h(j,k)=i} \xi(j,k)U_{jk} \text{ and } v_i = \sum_{j,k:h'(j,k)=i} \xi'(j,k)V_{jk}.$$

$$X_{ij} := \sum_k \xi(k,i)\xi'(k,j)u_{h(k,i)}v_{h'(k,j)}.$$

- **Approximation is O(1/n)**
  - To show that estimate is unbiased take expectation over Rademacher hash.

Collaborative Filtering

- **Hashing compression**



$$u_i = \sum_{j,k:h(k,j)=i} \xi(k,j)U_{kj} \text{ and } v_i = \sum_{j,k:h'(k,j)=i} \xi'(k,j)V_{kj}.$$

$$X_{ij} := \sum_k \xi(k,i)\xi'(k,j)u_{h(k,i)}v_{h'(k,j)}.$$

- **Expectation**

expectation vanishes

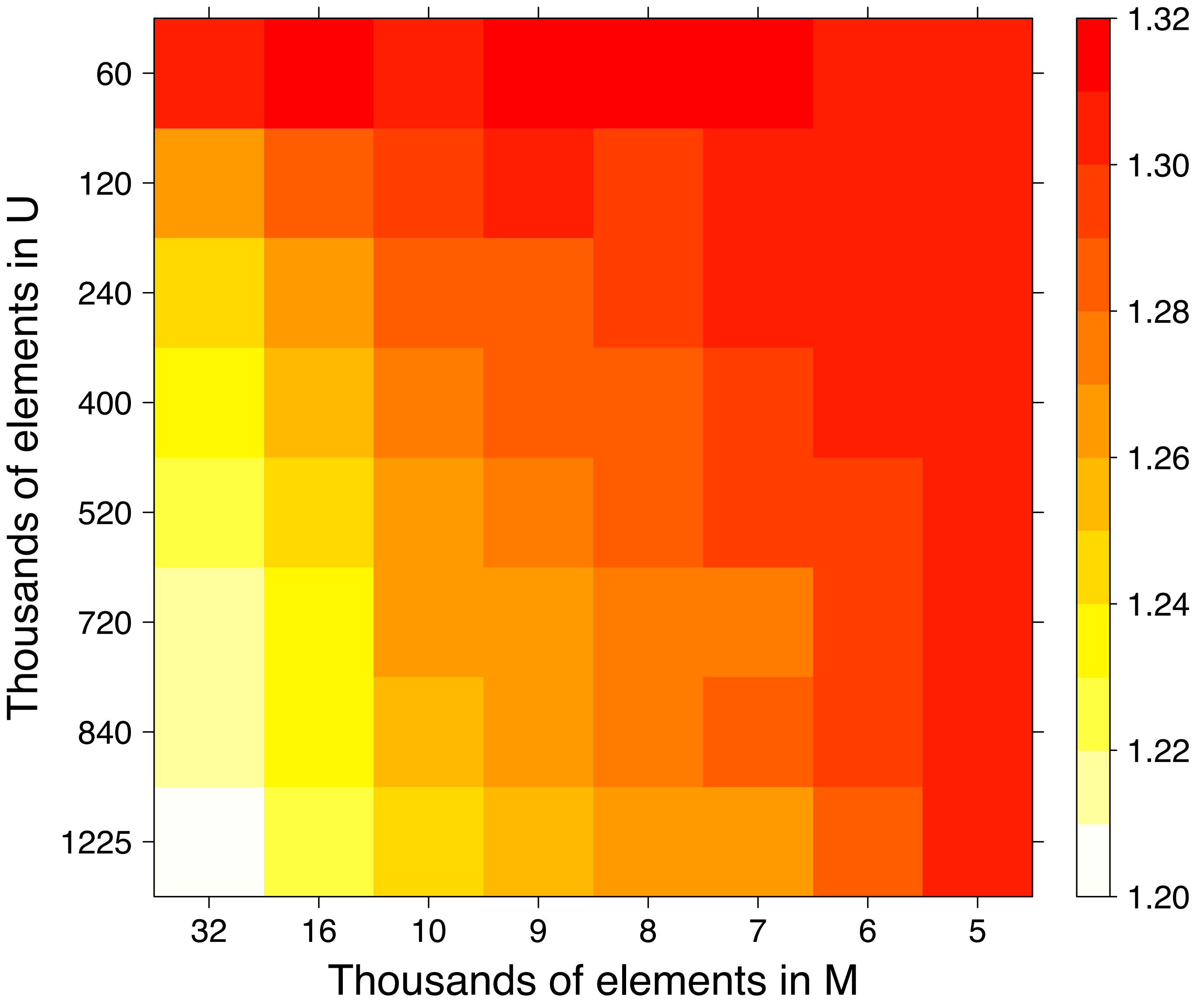
$$X_{ij} := \sum_k \xi(k,i)\xi'(k,j) \sum_{l,k:h(k,l)=h(k,i)} \sum_{o,k:h'(k,o)=h'(k,j)} \xi(k,l)\xi'(k,o)U_{kl}V_{ko}$$

Collaborative Hashing

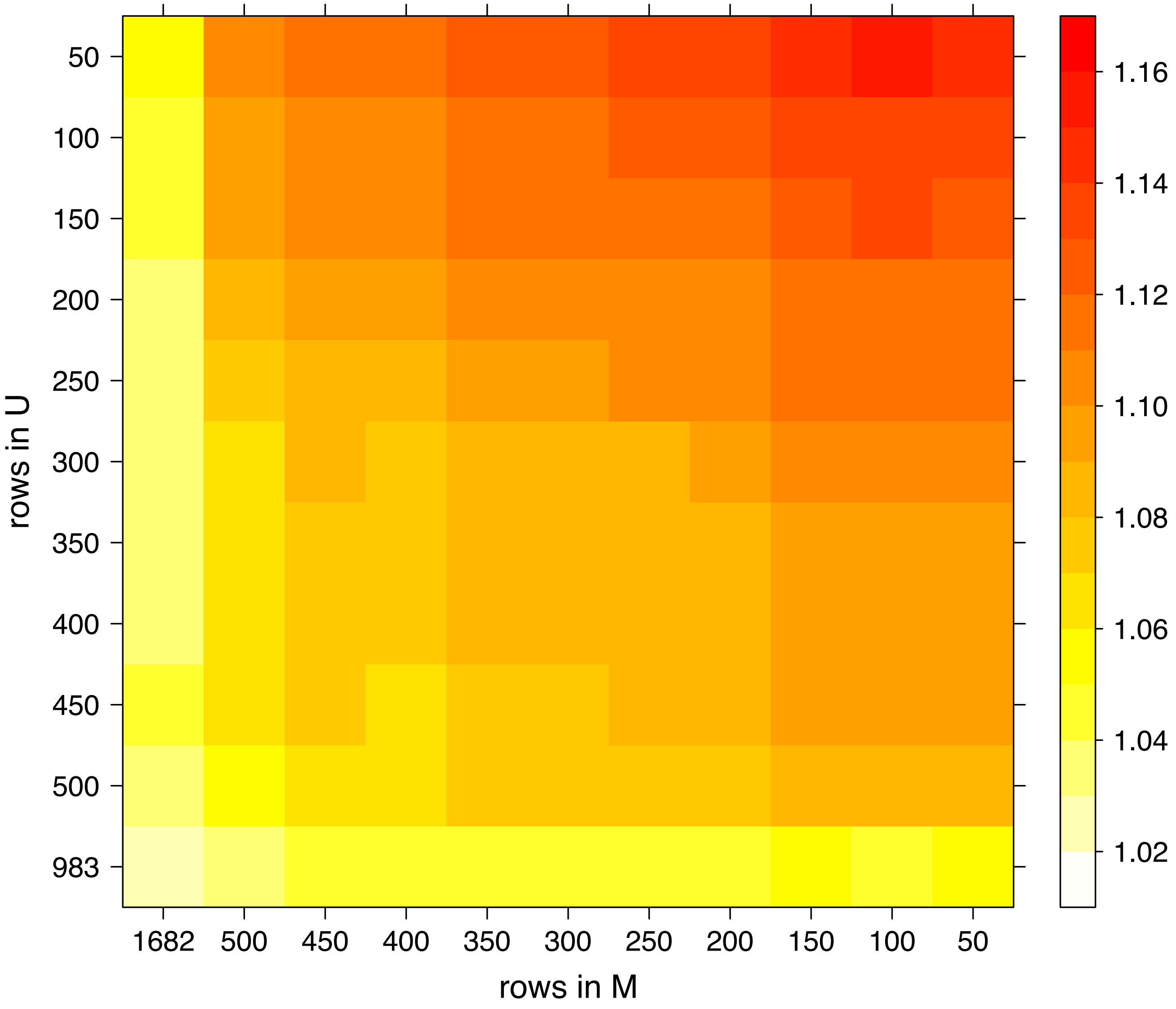
- Combine with stochastic gradient descent
- Random access in memory is expensive (we now have to do k lookups per pair)
- Feistel networks can accelerate this

- Distributed optimization without locking

Examples



Eachmovie



MovieLens

Summary

- Neighborhood methods
  - User / movie similarity
  - Iteration on graph
- Matrix Factorization
  - Singular value decomposition
  - Convex reformulation
- Ranking and Session Modeling
  - Ordinal regression
  - Session models
- Features
  - Latent dense (Bayesian Probabilistic Matrix Factorization)
  - Latent sparse (Dirichlet process factorization)
  - Coldstart problem (inferring features)
- Hashing

Further reading

- Collaborative Filtering with temporal dynamics http://research.yahoo.com/files/kdd-fp074-koren.pdf
- Neighborhood factorization http://research.yahoo.com/files/paper.pdf
- Matrix Factorization for recommender systems http://research.yahoo.com/files/ieeecomputer.pdf
- CoFi Rank (collaborative filtering & ranking) http://www.cofirank.org/
- Yehuda Koren’s papers http://research.yahoo.com/Yehuda_Koren