Recommender Systems

Class	Data Mining
Program	Master in Computer Engineering
University	Sapienza University of Rome
Semester	Fall 2017
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Sources:

- Ricci, Rokach and Shapira: Introduction to Recommender Systems Handbook [link]
- Bobadilla et al. Survey 2013 [link]
- Xavier Amatriain 2014 tutorial on rec systems [link]
- Ido Guy 2011 tutorial on social rec systems [link]
- Alex Smola's tutorial on recommender systems [link]

Why recommender systems?

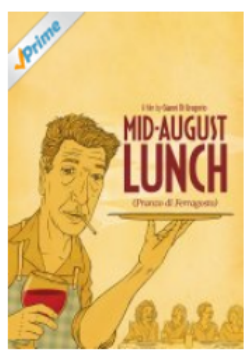
Definition

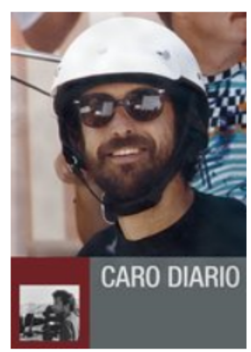
Recommender systems are software tools and techniques providing suggestions for items to be of use to a user.

User-based recommendations


'THE GODFATHER' MEETS 'NIXON'
IL DIVO
THE SPECTACULAR LIFE OF GIULIO ANDREOTTI


ITALY
LOVE IT OR LEAVE IT
A DOCU-TRIP BY GUSTAV HOFER & LUCA RAGAZZI


Prime
MID-AUGUST
LUNCH
(Pranzo di Ferragosto)


CARO DIARIO


L'ECLISSE


To Rome With Love


ACADEMY AWARD NOMINEE · BEST FOREIGN LANGUAGE FILM
AFTER THE WEDDING

Assumptions

- Users rely on recommendations
- Users lack sufficient personal expertise
- Number of items is very large
  - e.g. around 10^{10} books in Amazon
- Recommendations need to be personalized

Amazon as of December 2015

Paperback (30,020,393)
Hardcover (11,107,514)
Kindle Edition (2,861,600)
Audible Audio Edition (87,578)
Printed Access Code (30,338)
Digital Access Code (4)
Loose Leaf (94,891)
Audio CD (433,467)
Board Book (168,736)

Who uses recommender systems?

- Retailers and e-commerce in general
  - Amazon, Netflix, etc.
- Service sites, e.g. travel sites
- Media organizations
- Dating apps
- ...

Why?

- Increase number of items sold
  - 2/3 of Netflix watched are recommendations
  - 1/3 of Amazon sales are from recommendations
  - ...

Why? (cont.)

- Sell more diverse items
- Increase user satisfaction
  - Users enjoy the recommendations
- Increase user fidelity
  - Users feel recognized (but not creeped out)
- Understand users (see next slides)

By-products

- Recommendations generate by-products
- Recommending requires understanding users and items, which is valuable by itself
- Some recommender systems are very good at this (e.g. factorization methods)
- Automatically identify marketing profiles
- Describe users to better understand them

The recommender system problem

Estimate the **utility** for **a user** of **an item** for which the user has **not expressed** utility

What information can be used?

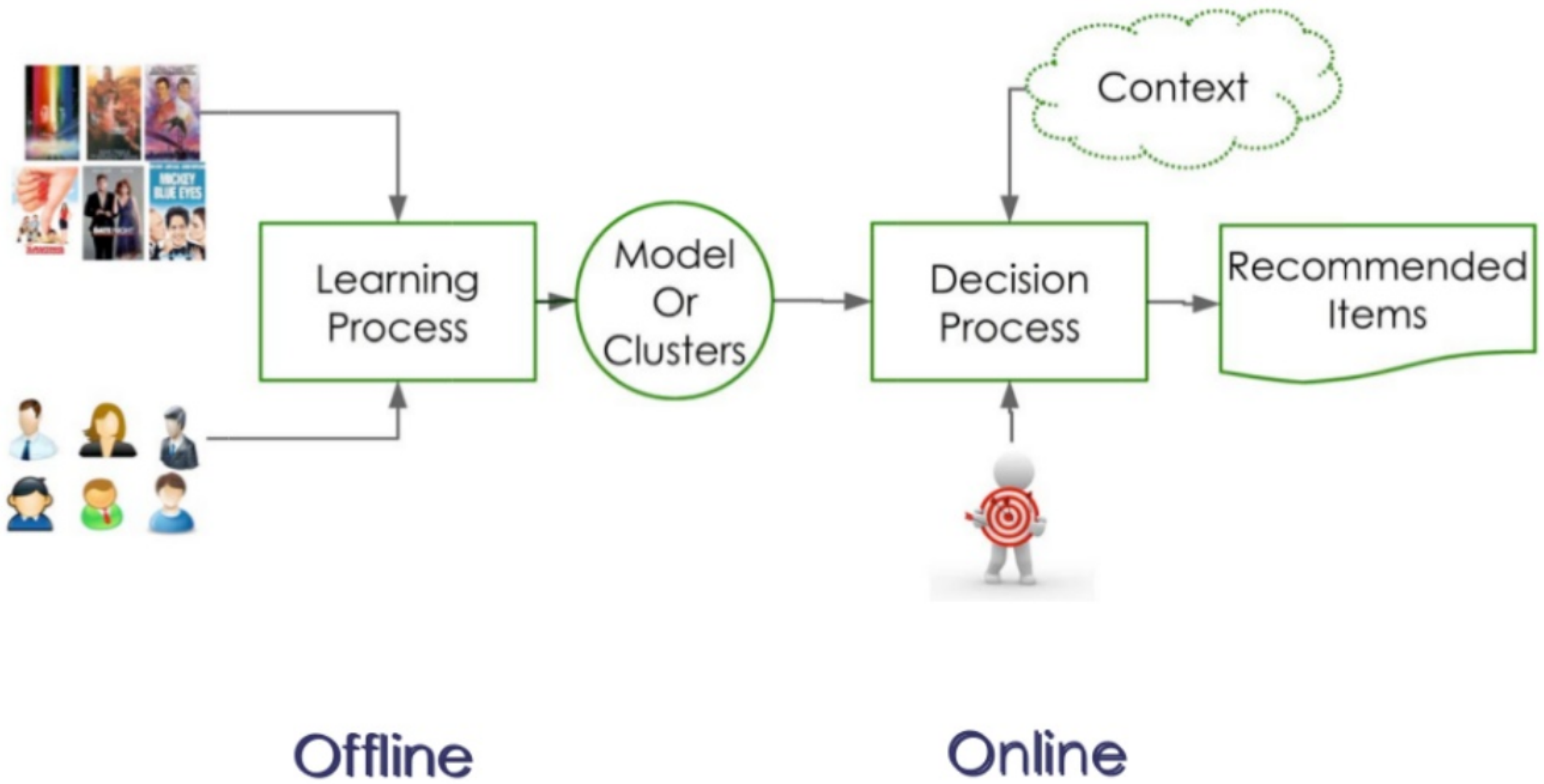
Types of problem

- Find some good items (most common)
- Find all good items
- Annotate in context (why I would like this)
- Recommend a sequence (e.g. tour of a city)
- Recommend a bundle (camera+lens+bag)
- Support browsing (seek longer session)
- ...

Data sources

- Items, Users
  - Structured attributes, semi-structured or unstructured descriptions
- Transactions
  - Appraisals
    - Numerical ratings (e.g. 1-5) 
    - Binary ratings (like/dislike)
    - Unary ratings (like/don't know)
  - Sales
  - Tags/descriptions/reviews

Recommender system process



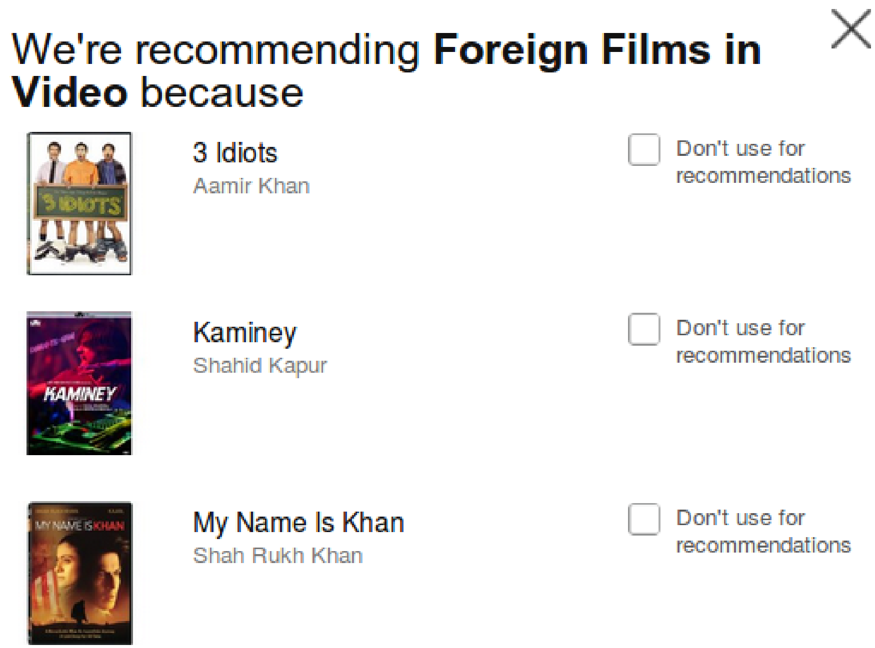
Why is part of the processing done offline?

Aspects of this process

- Data preparation
  - Normalization, removal of outliers, feature selection, dimensionality reduction, ...
- Data mining
  - Clustering, classification, rule generation, ...
- Post-processing
  - Visualization, interpretation, meta-mining, ...

Desiderata for recommender system

- Must inspire trust
- Must convince users to try the items
- Must offer a good combination of novelty, coverage, and precision
- Must have a somewhat transparent logic
- Must be user-tunable



Human factors

- Advanced systems are **conversational**
- Transparency and scrutability
  - Explain users how the system works
  - Allow users to tell the system it is wrong
- Help users make a good decision
- Convince users in a persuasive manner
- Increase enjoyment to users
- Provide serendipity

Serendipity

- “An aptitude for making desirable discoveries by accident”
- Don't recommend items the user already knows
- Delight users by expanding their taste
  - But still recommend them something somewhat familiar
- It can be controlled by specific parameters

Peregrinaggio di tre giovani figliuoli del re di Serendippo; Michele Tramezzino, Venice, 1557. Tramezzino claimed to have heard the story from one Christophero Armeno who had translated the Persian fairy tale into Italian adapting Book One of Amir Khusrau's Hasht-Bihisht of 1302 [link]

High-level approaches

- Memory-based
  - Use data from the past in a somewhat “raw” form
- Model-based
  - Use models built from data from the past

Approaches

- Collaborative filtering
- Content-based (item features)
- Knowledge-based (expert system)
- Personalized learning to rank
  - Estimate ranking function
- Demographic
- Social/community based
  - Based on connections
- Hybrid (combination of some of the above)

Collaborative filtering

Collaborative Filtering approach

- User has seen/liked certain items
- Community has seen/liked certain items
- Recommend to users items similar to the ones they have seen/liked
  - Based on finding similar users
  - Based on finding similar items

Algorithmic elements

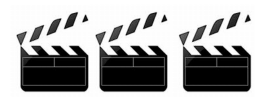
- M users and N items
- Transaction matrix $R_{M \times N}$
- Active user
- Method to compute similarity of users
- Method to sample high-similarity users
- Method to aggregate their ratings on an item

k nearest users algorithm

- Compute common elements with other users
- Compute distance between rating vectors
- Pick top 3 most similar users
- For every unrated item
  - Average rating of 3 most similar users
- Recommend highest score unrated items

Ratings data

ITEMS



USERS

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

Try it! Generate recommendations

ITEMS

USERS

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

$$\mathrm{dist}(i,j) = \frac{\sum_{\alpha \in U_i \cap U_j} |r_i(\alpha) - r_j(\alpha)|}{|U_i \cap U_j|}$$

Given the red user
Determine 3 nearest users
Average their ratings on unrated items
Pick top 3 unrated elements

Compute user intersection size

ITEMS

USERS

	1	2	3	4	5	6	7	8	9	10	11	12	$\lvert U_i \cap U_j \rvert$	$\mathrm{sim}(i,j)$
1	1			5					2		3		0	
2	5		1		5		4			5	3	2	3	
3		5	5			1		3			2	4	3	
4		3			5	4				5		1		
5				2	5	4			4	5			3	
6	4		3			1			4		2		1	
7		4	1		4		5				4	1	3	

Compute user similarity

ITEMS

USERS

	1	2	3	4	5	6	7	8	9	10	11	12	$\lvert U_i \cap U_j \rvert$	$\mathrm{sim}(i,j)$
1	1			5					2		3		0	
2	5		1		5		4			5	3	2	3	0.33
3		5	5			1		3			2	4	3	2.67
4		3			5	4				5		1		
5				2	5	4			4	5			3	0.00
6	4		3			1			4		2		1	3.00
7		4	1		4		5				4	1	3	0.67

Pick top-3 most similar

ITEMS

USERS

	1	2	3	4	5	6	7	8	9	10	11	12	$\lvert U_i \cap U_j \rvert$	$\mathrm{sim}(i,j)$
2	5		1		5		4			5	3	2	3	0.33
4		3			5	4				5		1		
5				2	5	4			4	5			3	0.00
7		4	1		4		5				4	1	3	0.67

Estimate unrated items

ITEMS

USERS

	1	2	3	4	5	6	7	8	9	10	11	12	$\lvert U_i \cap U_j \rvert$	$\mathrm{sim}(i,j)$
2	5		1		5		4			5	3	2	3	0.33
4	5.0	3	1.0	2.0	5	4	4.5	-	4.0	5	3.5	1		
5				2	5	4			4	5			3	0.00
7		4	1		4		5				4	1	3	0.67

Recommend top-3 estimated

ITEMS

USERS

	1	2	3	4	5	6	7	8	9	10	11	12	$\lvert U_i \cap U_j \rvert$	$\mathrm{sim}(i,j)$
2	5		1		5		4			5	3	2	3	0.33
4	5.0	3	1.0	2.0	5	4	4.5	-	4.0	5	3.5	1		
5				2	5	4			4	5			3	0.00
7		4	1		4		5				4	1	3	0.67

Improvements?

- *How would you improve the algorithm?*
- *How would you provide explanations?*

Item-based collaborative filtering

ITEMS

USERS

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

- Would user 4 like item 11?

Item-based collaborative filtering

ITEMS

USERS

	1	2	3	4	5	6	7	8	9	10	11	12
1	1			5					2		3	
2	5		1		5		4			5	3	2
3		5	5			1		3			2	4
4		3			5	4				5		1
5				2	5	4			4	5		
6	4		3			1			4		2	
7		4	1		4		5				4	1
	2.0	1.5	2.3	2.0	1.0	1.0	1.0	1.0	1.5	2.0	-	2.0

- Compute pair-wise similarities to target item

Item-based collaborative filtering

ITEMS

USERS

	1	2	3	4	5	6	7	8	9	10	11	12
1	1			5					2		3	
2	5		1		5		4			5	3	2
3		5	5			1		3			2	4
4		3			5	4				5		1
5				2	5	4			4	5		
6	4		3			1			4		2	
7		4	1		4		5				4	1
					1.0	1.0	1.0	1.0			-	

- Pick k most similar items

Item-based collaborative filtering

ITEMS

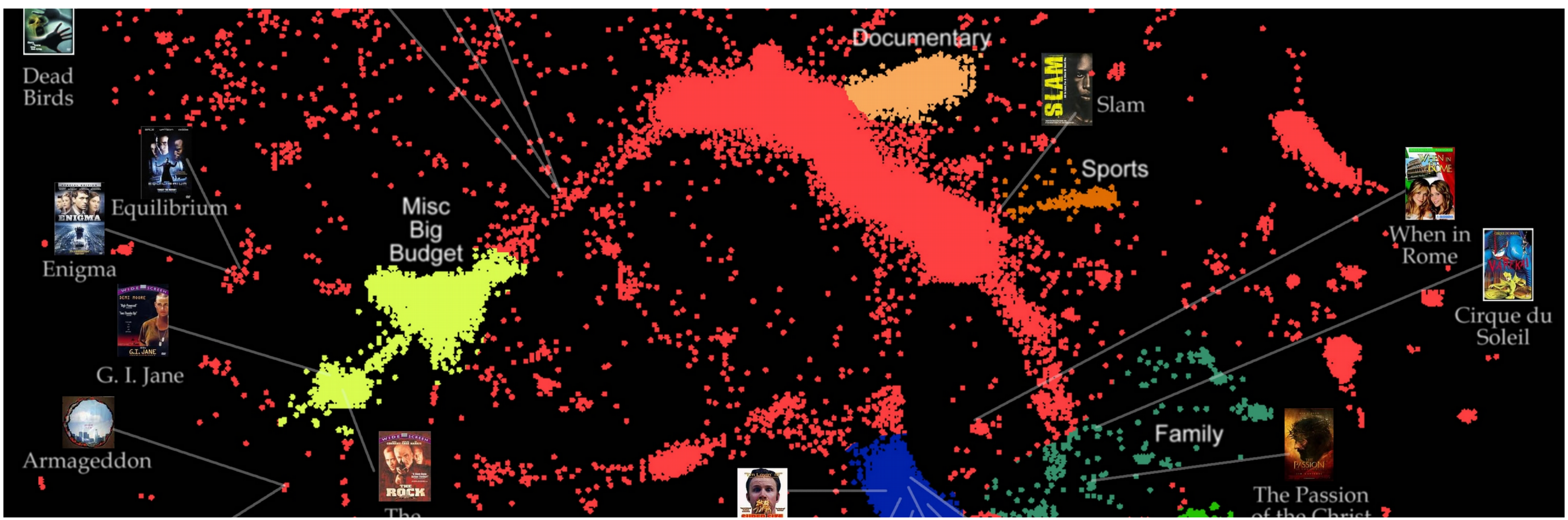
USERS

	1	2	3	4	5	6	7	8	9	10	11	12
1	1			5					2		3	
2	5		1		5		4			5	3	2
3		5	5			1		3			2	4
4		3			5	4				5	4.5	1
5				2	5	4			4	5		
6	4		3			1			4		2	
7		4	1		4		5				4	1
					1.0	1.0	1.0	1.0			-	

- Average ratings of target user on item

Performance implications

- Similarity between users is uncovered slowly
- Similarity between items is supposedly static
  - Can be precomputed!
- Item-based clusters can also be precomputed



[source]

Weaknesses

- Assumes standardized products
  - E.g. a touristic destination at any time of the year and under any circumstance is the same item
- Does not take into account context
- Requires a relatively large number of transactions to yield reasonable results

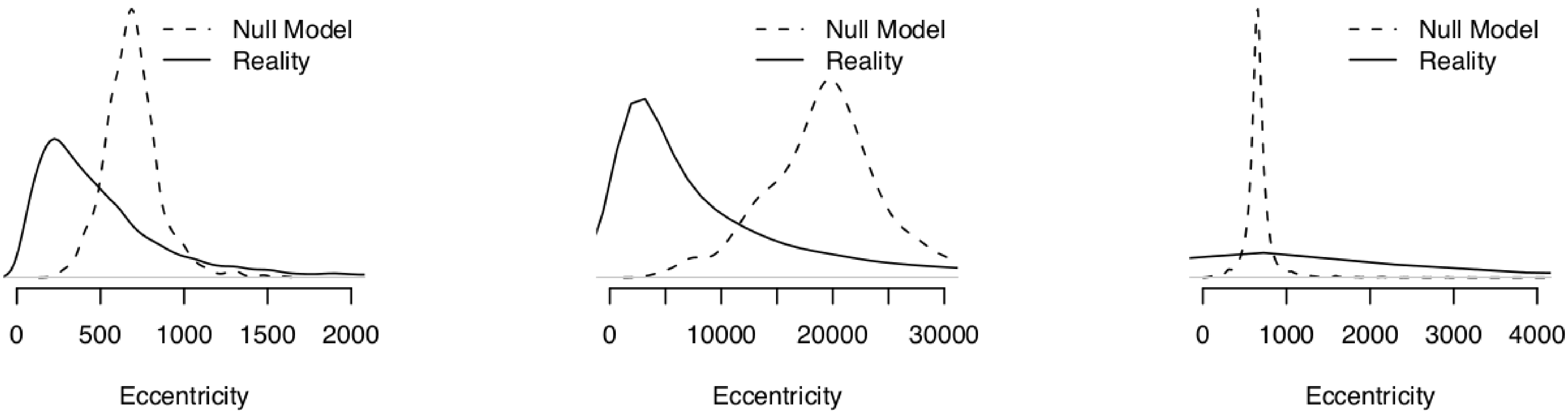
Cold-start problem

- What to do with a new item?
- What to do with a new user?

Assumptions

- Collaborative filtering assumes the following:
  - We take recommendations from friends
  - Friends have similar tastes
  - A person who have similar tastes to you, could be your friend
  - Discover people with similar tastes, use them as friends
- BUT, people's tastes are complex!

Ordinary people and extraordinary tastes



(a) Netflix (b) Yahoo! Music (c) Web Browsing (Nielsen)

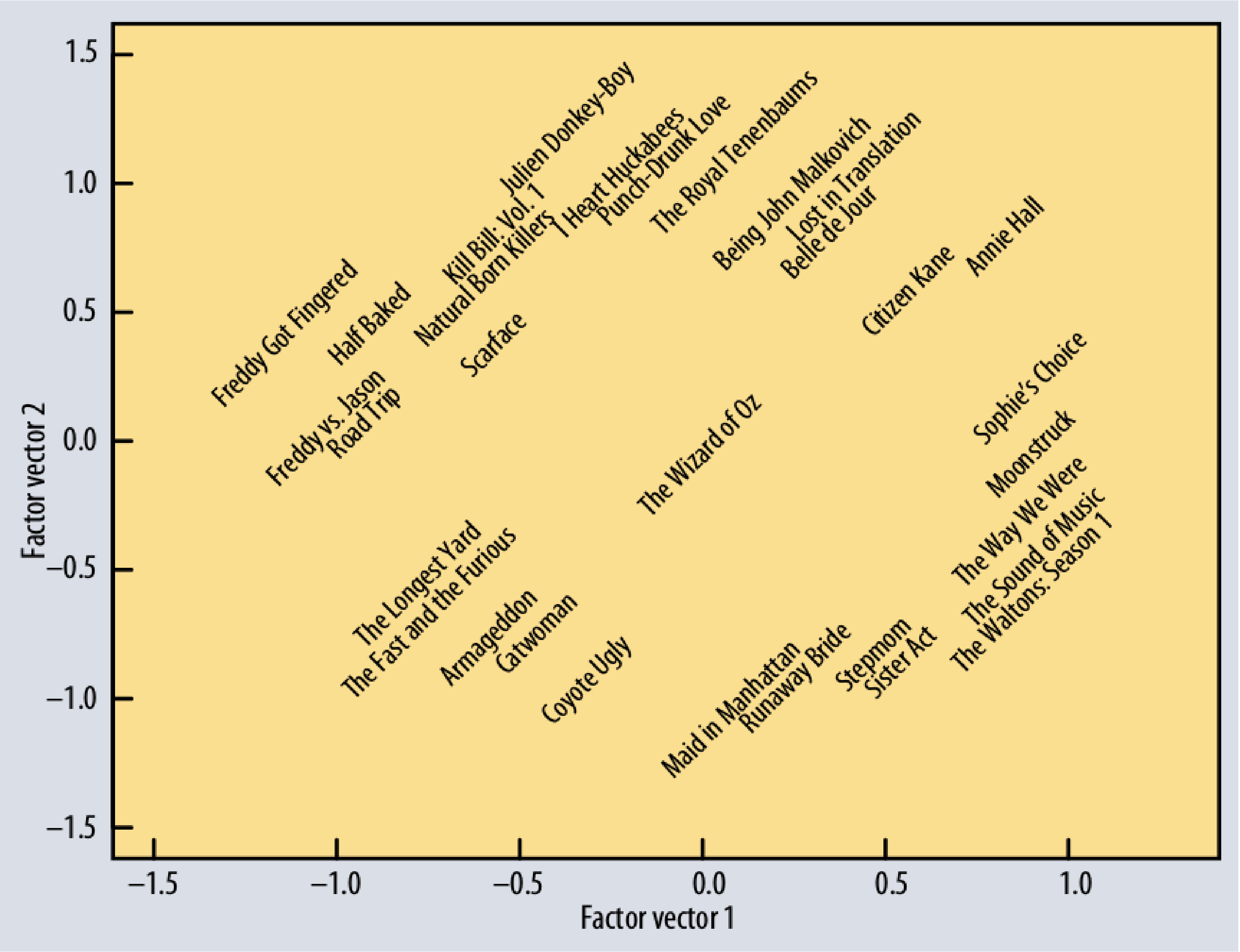
Distribution of user eccentricity: the median rank of consumed items.

In the null model, users select items proportional to item popularity

[Goel et al. 2010]

Matrix factorization approaches

2D projection of interests



[Koren et al. 2009]

SVD approach

$$R_{n \times m} = U_{n \times f} S_{f \times f} V_{f \times m}$$

- R is the matrix of ratings
  - n users, m items
- U is a user-factor matrix
- S is a diagonal matrix, strength of each factor
- V is a factor-item matrix
- Matrices USV can be computed used an approximate SVD method

General factorization approach

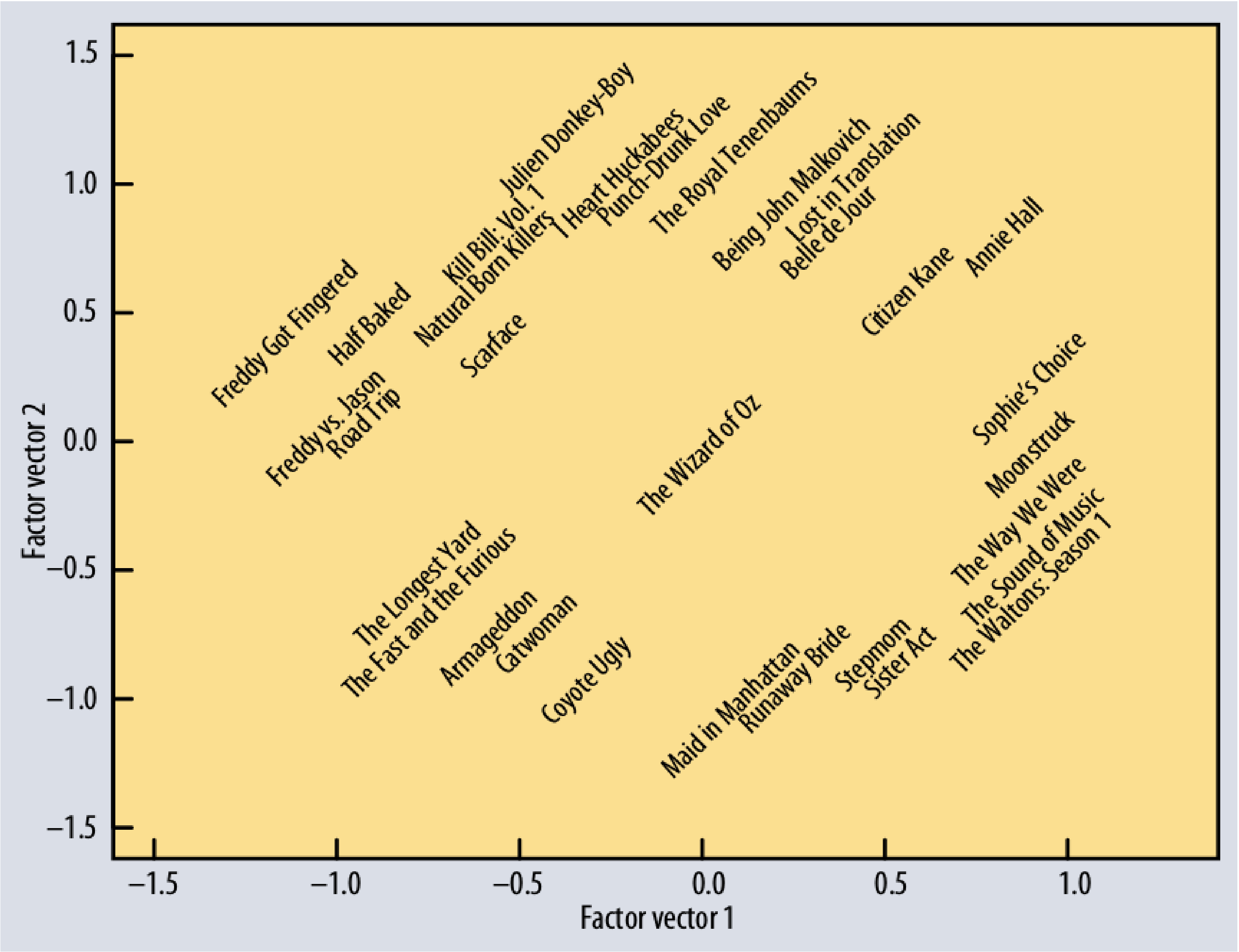
$$R_{n \times m} = P_{n \times f} Q_{f \times m}$$

- R is the matrix of ratings
  - n users, m items
- P is a user-factor matrix
- Q is a factor-item matrix

(Sometimes we force P, Q to be non-negative: factors are easier to interpret!)

$$R_{n\times m} = P_{n\times f} Q_{f\times m}$$

What is this plot?



[Koren et al. 2009]

Computing expected ratings

- Given:
  - user vector $p_u \in \mathbb{R}^f$
  - item vector $q_i \in \mathbb{R}^f$
- Expected rating is $\hat{r}_{ui} = \langle p_u, q_i \rangle$

Model directly observed ratings

$$\min_{q\cdot,p\cdot} \sum_{(u,i)\in R_o} \underbrace{(r_{ui} - \langle p_u, q_i \rangle)^2} + \lambda(||q_i||^2 + ||p_u||^2)$$

- R_o are the observed ratings
- We want to minimize a reconstruction error
- Second term avoids over-fitting
  - Parameter λ found by cross-validation
- Two basic optimization methods

1. Stochastic gradient descend

$$\min_{q\cdot,p\cdot} \sum_{(u,i)\in R_o} (r_{ui} - \langle p_u, q_i \rangle)^2 + \lambda(||q_i||^2 + ||p_u||^2)$$

- Compute reconstruction error

$$e_{ui} = r_{ui} - \langle p_u, q_i \rangle$$

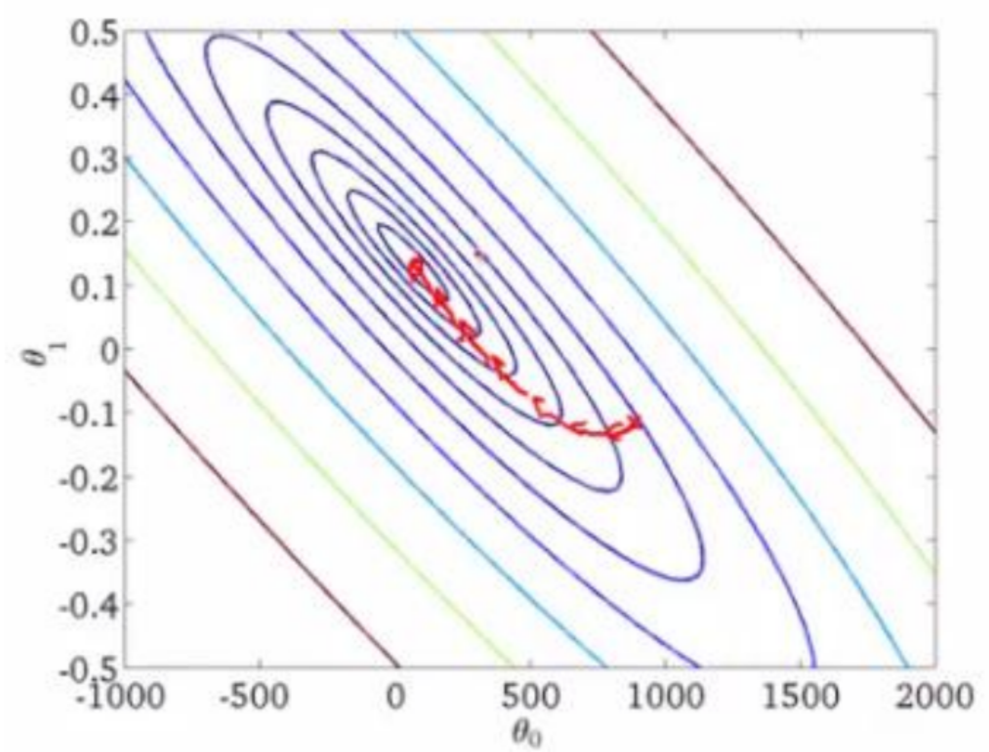
- Update in opposite direction to gradient

$$\begin{aligned} p_u &\leftarrow p_u - \eta_t q_i e_{ui} - \eta_t \lambda p_u \\ q_i &\leftarrow q_i - \eta_t p_u e_{ui} - \eta_t \lambda q_i \end{aligned}$$

learning speed

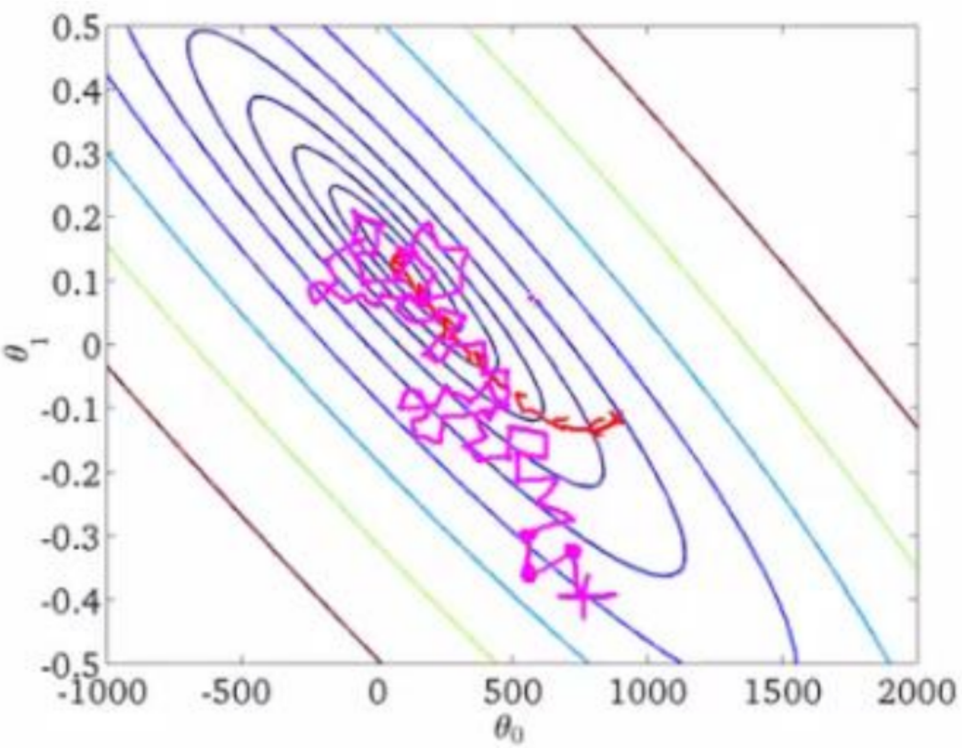
http://sifter.org/~simon/journal/20061211.html

Illustration: batch gradient descent vs stochastic gradient descent



Batch: gradient

$$x \leftarrow x - \eta \nabla F(x)$$



Stochastic: single-example gradient

$$x \leftarrow x - \eta \nabla F_i(x)$$

[source]

A simpler example of gradient descent

Fit a set of n two-dimensional data points (x_i, y_i) with a line $L(x)=w_1+w_2x$, means minimizing:

$$F(w) = \sum_{i=1}^{n} (L(x_i) - y_i)^2 = \sum_{i=1}^{n} (w_1 + w_2 x_i - y_i)^2$$

The update rule is to take a random point and do:

$$\begin{bmatrix} w_1 \\ w_2 \end{bmatrix} \leftarrow \begin{bmatrix} w_1 \\ w_2 \end{bmatrix} - \eta \begin{bmatrix} 2(w_1 + w_2 x_i - y_i) \\ 2x_i(w_1 + w_2 x_i - y_i) \end{bmatrix}$$

https://en.wikipedia.org/wiki/Stochastic_gradient_descent

2. Alternating least squares

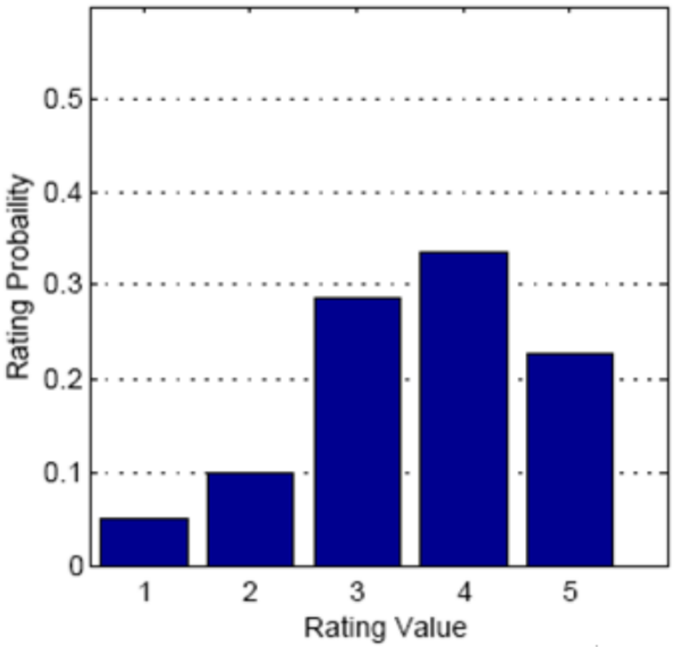
$$\min_{q\cdot,p\cdot} \sum_{(u,i)\in R_o} (r_{ui} - \langle p_u, q_i \rangle)^2 + \lambda(||q_i||^2 + ||p_u||^2)$$

- With vectors p fixed:
  - Find vectors q that minimize above function
- With vectors q fixed
  - Find vectors p that minimize above function
- Iterate until convergence
- Slower in general, but parallelizes better

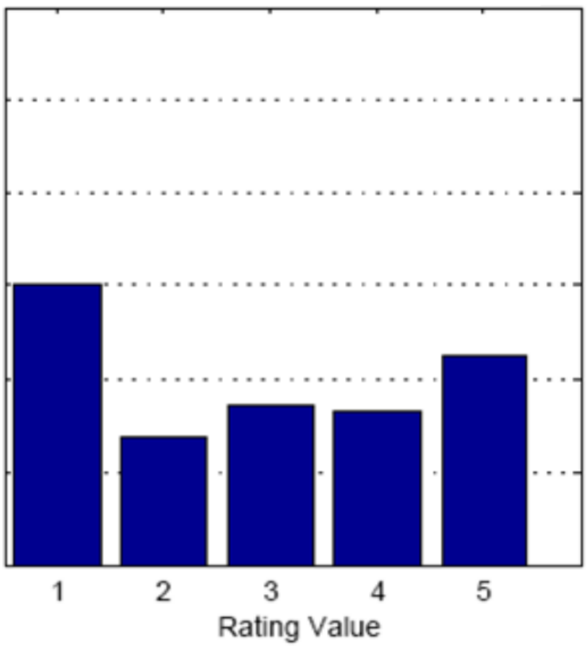
https://xkcd.com/1098/

Ratings are not normally-distributed

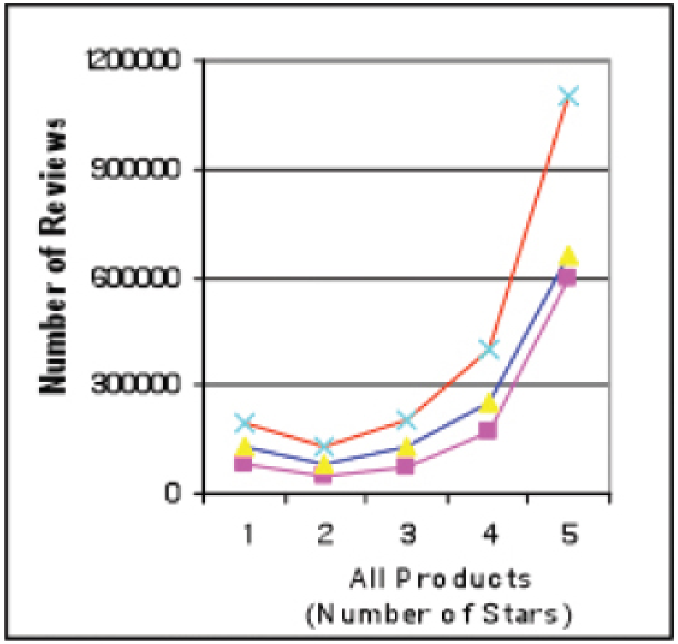
Netflix ratings



Yahoo! music ratings



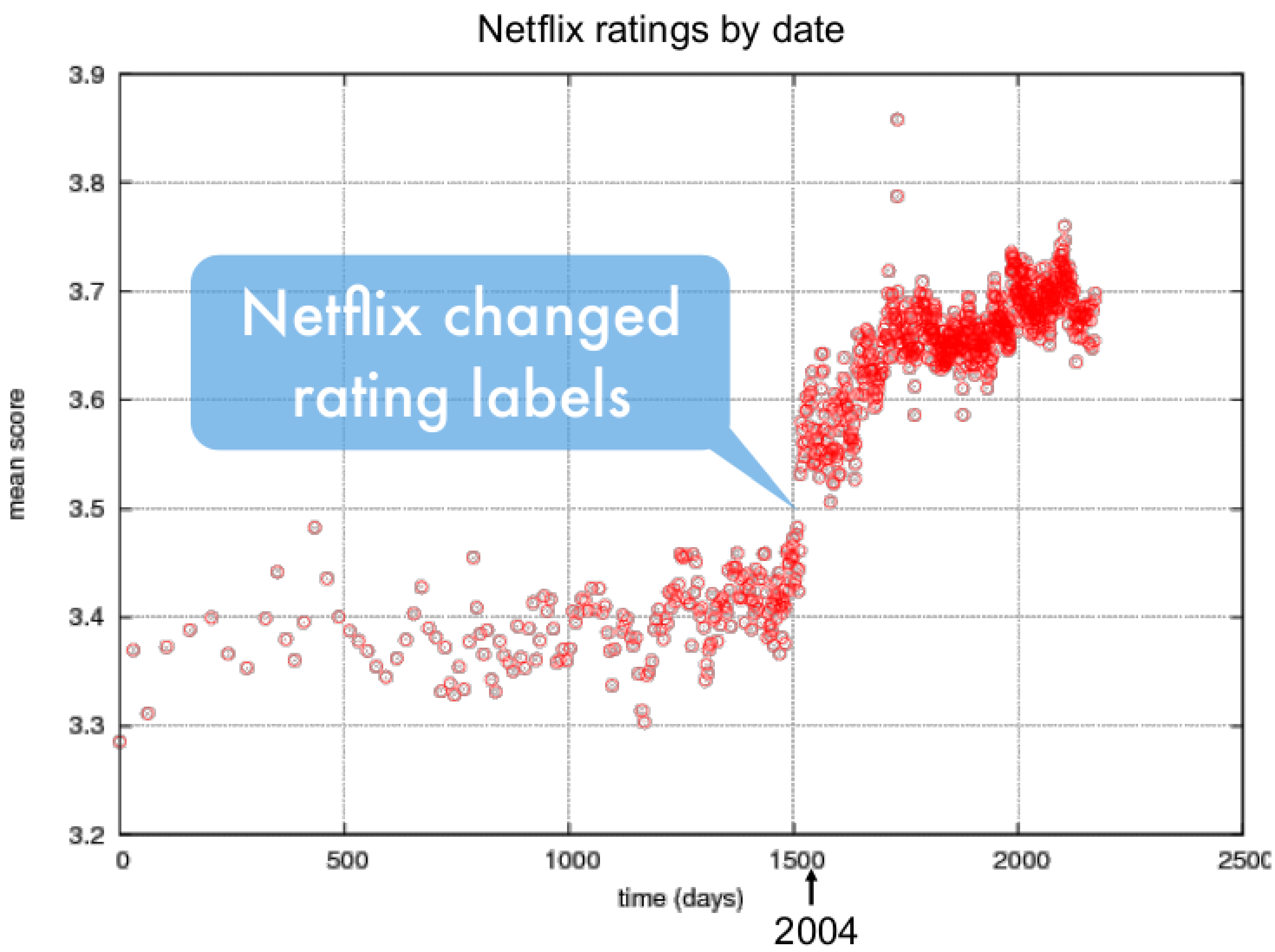
Amazon
(DVDs, Videos, Books)



Sometimes referred to as the “J” distribution of ratings

[Marlin et al. 2007, Hu et al. 2009]

How you label ratings matters



In general, there are many biases

- Some movies always get better (or worse) ratings than others
- Some people always give better (or worse) ratings than others
- Some systems make people give better (or worse) ratings than others, e.g. labels

$$\hat{r}_{ui} = \mu + b_u + b_i + \langle p_u, q_i \rangle$$

- Time-sensitive user preferences

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

Other approaches

Other approaches

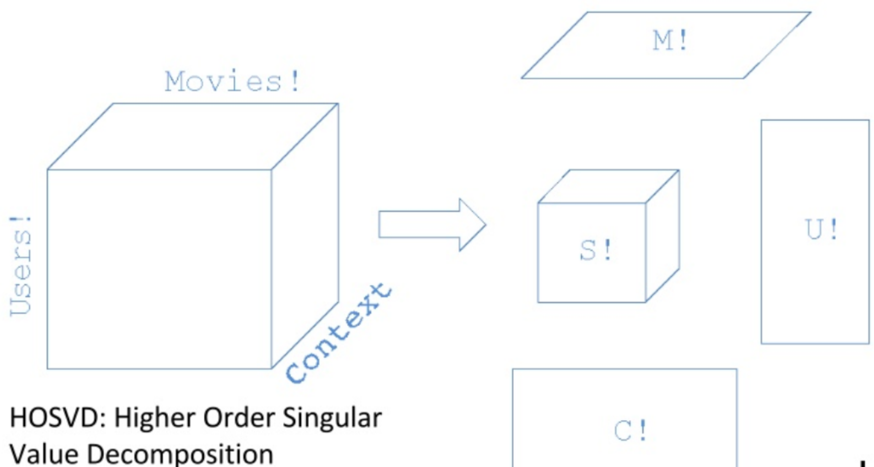
- Association rules (sequence-mining based)
- Regression (e.g. using a neural network)
  - e.g. based on user characteristics, number of ratings in different tags/categories
- Clustering
- Learning-to-rank

Hybrid methods (some types)

- Weighted
  - E.g. average recommended scores of two methods
- Switching
  - E.g. use one method when little info is available, a different method when more info is available
- Cascade
  - E.g. use a clustering-based approach, then refine using a collaborative filtering approach

Context-sensitive methods

- Context: where, when, how, ...
- Pre-filter
- Post-filter
- Context-aware methods
  - E.g. tensor factorization



HOSVD: Higher Order Singular Value Decomposition

HOSVD Model

Evaluation

Evaluation methodologies

- User experiments
- Precision @ Cut-off
- Ranking-based metrics
  - E.g. Kendall's Tau
- Score-based metrics
  - E.g. RMSE

http://www-users.cs.umn.edu/~cosley/research/gl/evaluating-herlocker-tois2004.pdf

Example user testing

- [Liu et al. IUI 2010] News recommender

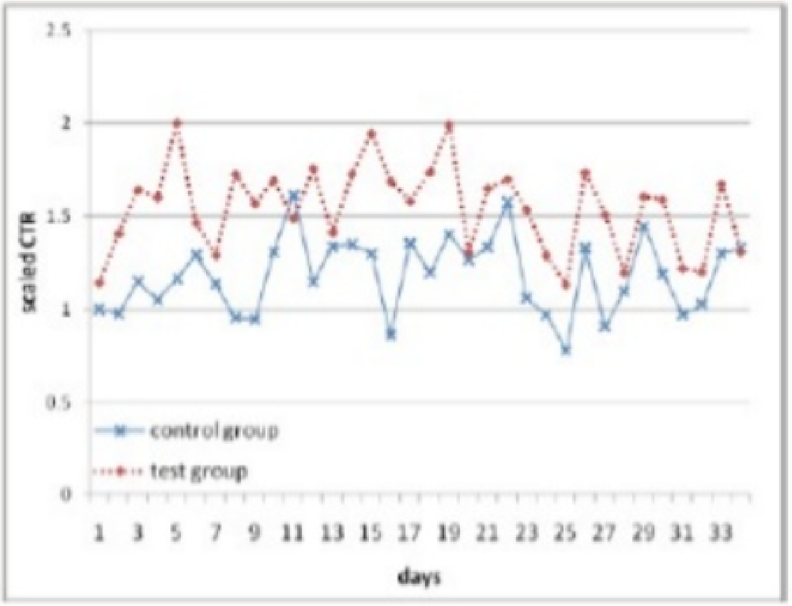


Figure 4. CTR of the recommended news section

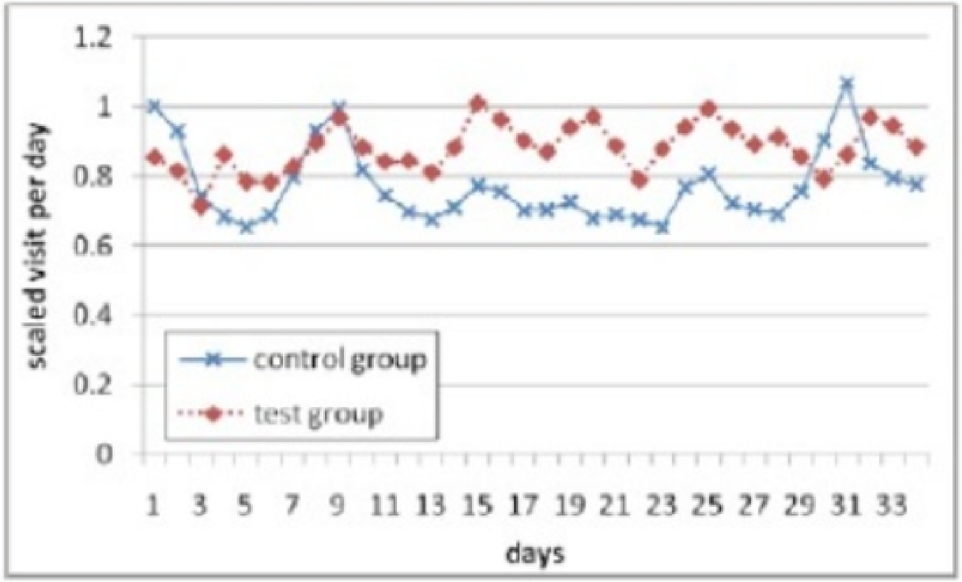


Figure 6. Frequency of website visit per day

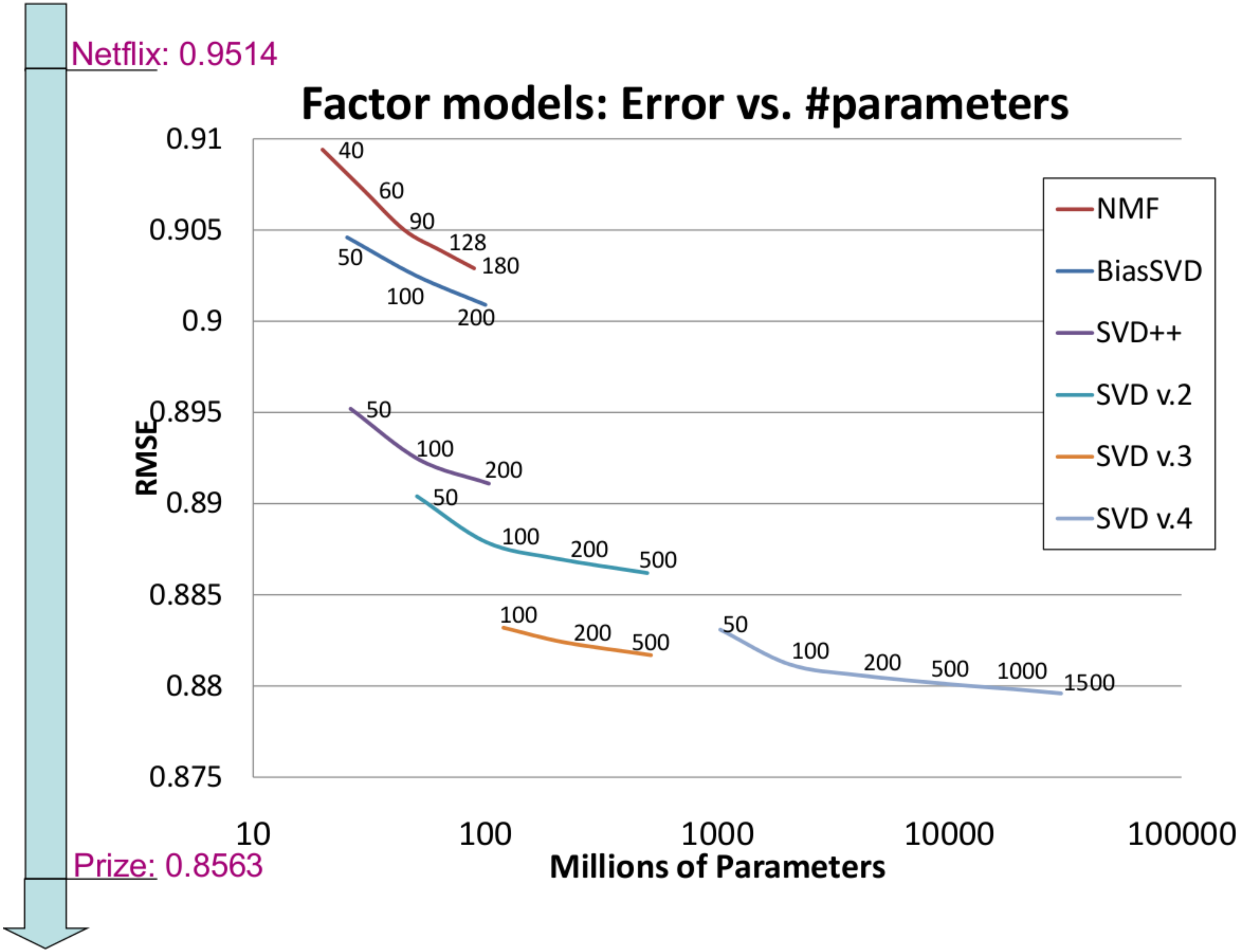
Score-based metric: RMSE

- "Root of mean square error"

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

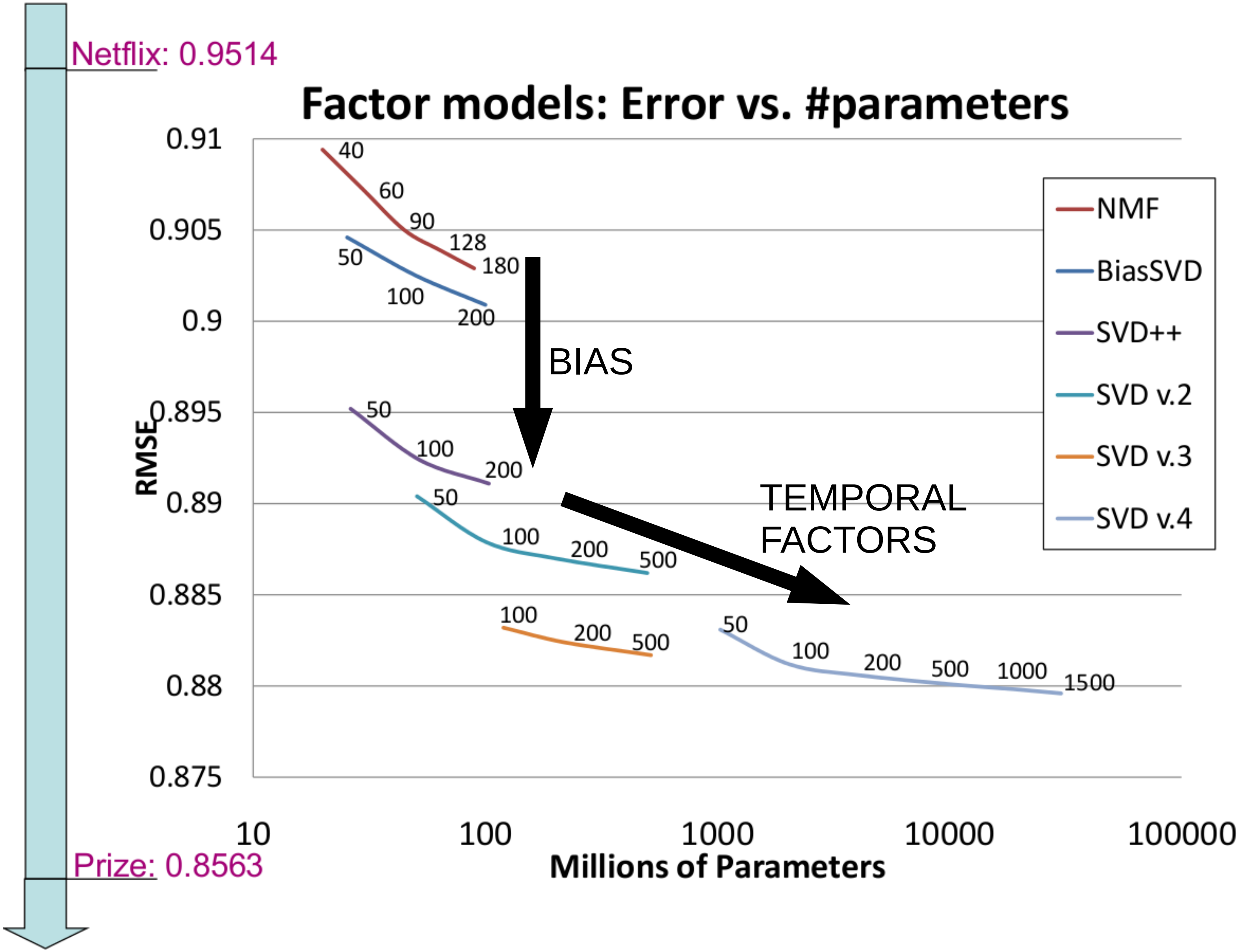
- Problem with all score-based metrics: niche items with good ratings (by those who consumed them)

Evaluation by RMSE



[Slide from Smola 2012]

Evaluation by RMSE



[Slide from Smola 2012]

Netflix challenge results

- It is easy to provide reasonable results
- It is hard to improve them