CS 277, Data Mining

Recommender Systems

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Thanks to Yehuda Koren and Jure Leskovec for contributing material for many of these slides.

Progress Reports

- First Progress Report due on Monday
- Hand in hardcopy in class, also upload electronic version to EEE directory
- Required:
  - 2 to 4 pages
  - Clear indication of work that was done *since* initial proposal
  - You can assume the reader (me) has read your proposal (so no need to repeat information)
  - Feel free to use figures/tables
  - Expect at a minimum that you have started to look at your data
  - For teams please report at the beginning “who did what”

Reading on Recommender Systems (on Web page)

- Good overviews
  - Recommender systems, Melville and Sindwhani, Encyclopaedia of Machine Learning, 2010 (a good starting point)
  - Chapter on recommendation algorithms from the online text Mining of Massive Data Sets, Rajaraman, Leskovec, and Ullman.
  - Amazon.com recommendations: item-to-item collaborative filtering, Linden, Smith, and York, 2003 (overview of the basic components of Amazon's recommender system)

- Matrix Factorization
  - Matrix factorization techniques for recommender systems, Koren, Bell, Volinsky, IEEE Computer, 2009
  - Advances in collaborative filtering, Koren and Bell, chapter from the Recommender Systems Handbook, 2011

- Other Aspects
  - Recommender systems: from algorithms to user experience, Konstain and Riedl, 2012 (emphasizes that the user experience is important, not just predictive accuracy)
  - Factorization machines with libFM, S. Rendle, 2012, with associated publicly-available software for libFM

"Ratings" Data

- Data with users u and items i
  - E.g., items are products purchases, movies viewed, songs listened to, etc

- Can represent as an N x M sparse matrix
  - N = number of users, M = number of items

- Entries r_{ui}

  Explicit Ratings: r_{ui} = user u's rating of item i (e.g. on a scale of 1 to 5)

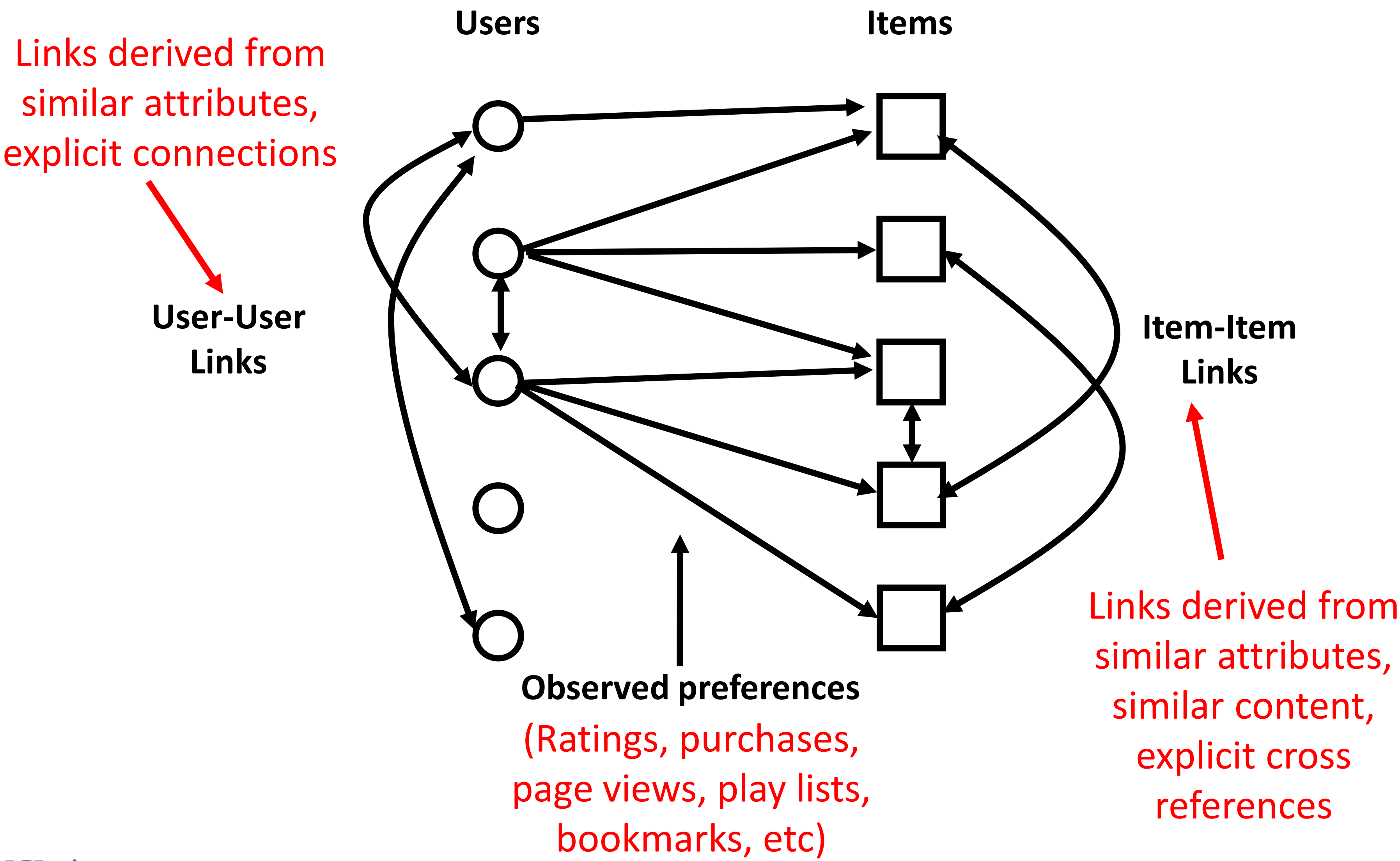
  Implicit Ratings: r_{ui} = 1 if user u purchased/read/listened to item i

  r_{ui} = 0 if no purchase or rating

  (note that 0 means a user's preference is unknown, not that they don't like the item)

- Automated recommender systems
  - Given a user and their ratings (if any) recommend to this user other items that the user may be interested in

The Recommender Space as a Bipartite Graph



General Approaches to Automated Recommender Systems

1. Content-based Recommendations
   - Use attributes/features of items to recommend similar items
   - Ignores ratings data

2. Collaborative filtering
   - Use ratings matrix to recommend items, ignores item and user content data
   - 2 broad types:
     (1) Nearest-neighbor methods
     (2) Matrix factorization methods

3. Hybrid methods
   - Combine both content and ratings data (often provides "state of the art" performance)

The $1 Million Question

Ratings Data

17,700 movies

480,000 users

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

Training Data

100 million ratings (matrix is 99% sparse)

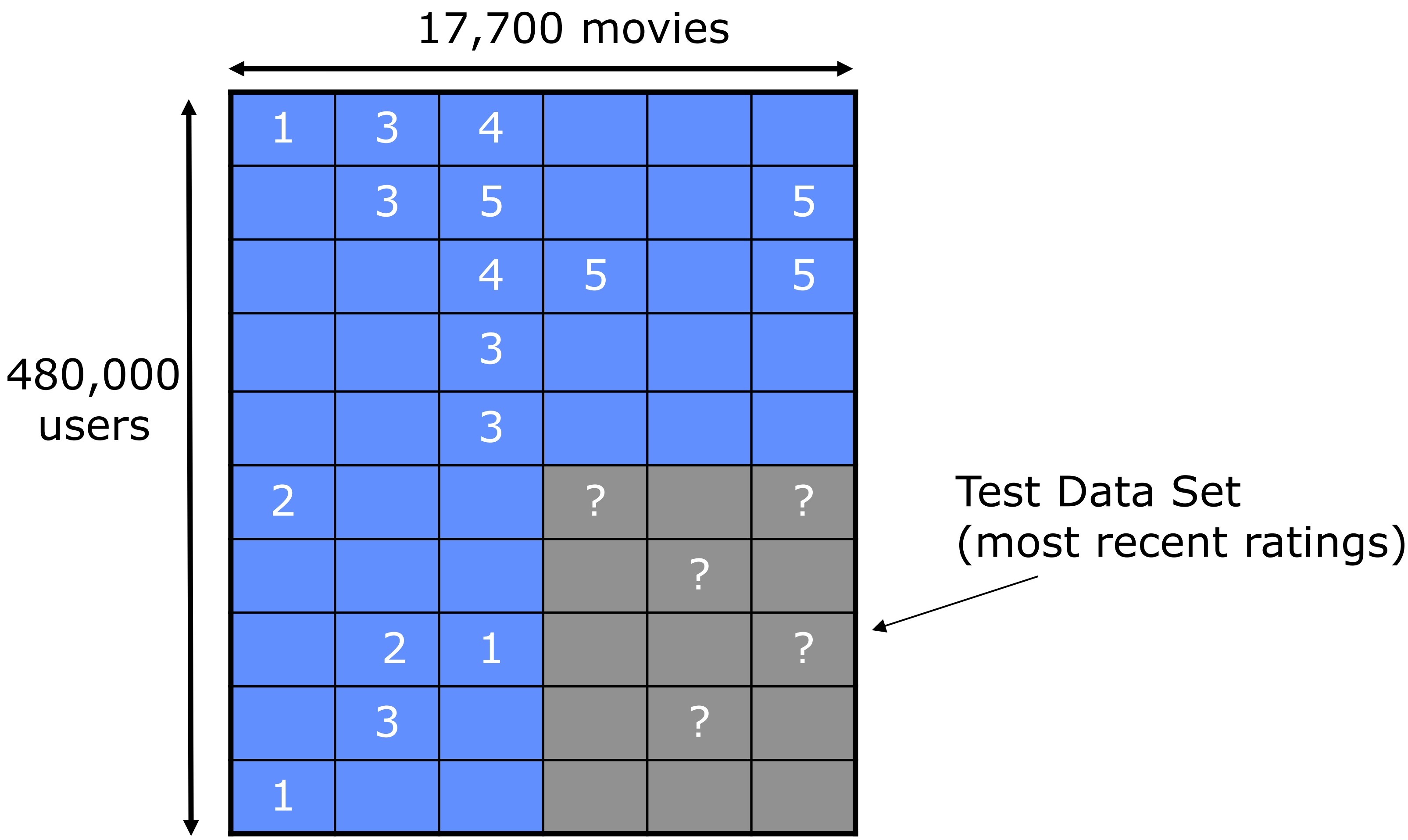
Rating = [user, movie-id, time-stamp, rating value]

Generated by users between Oct 1998 and Dec 2005

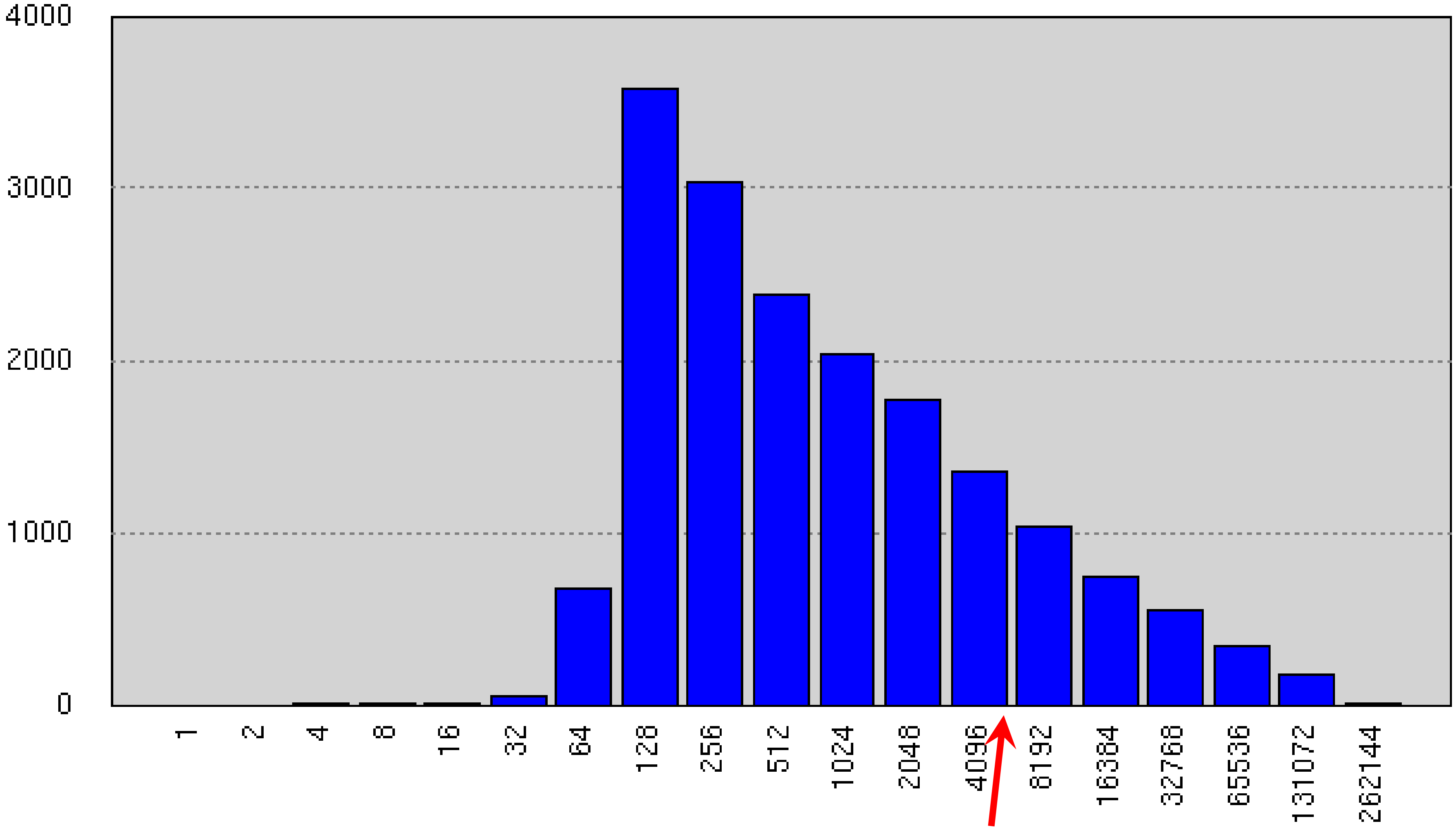
Users randomly chosen among set with at least 20 ratings

- Small perturbations to help with anonymity

Ratings Data

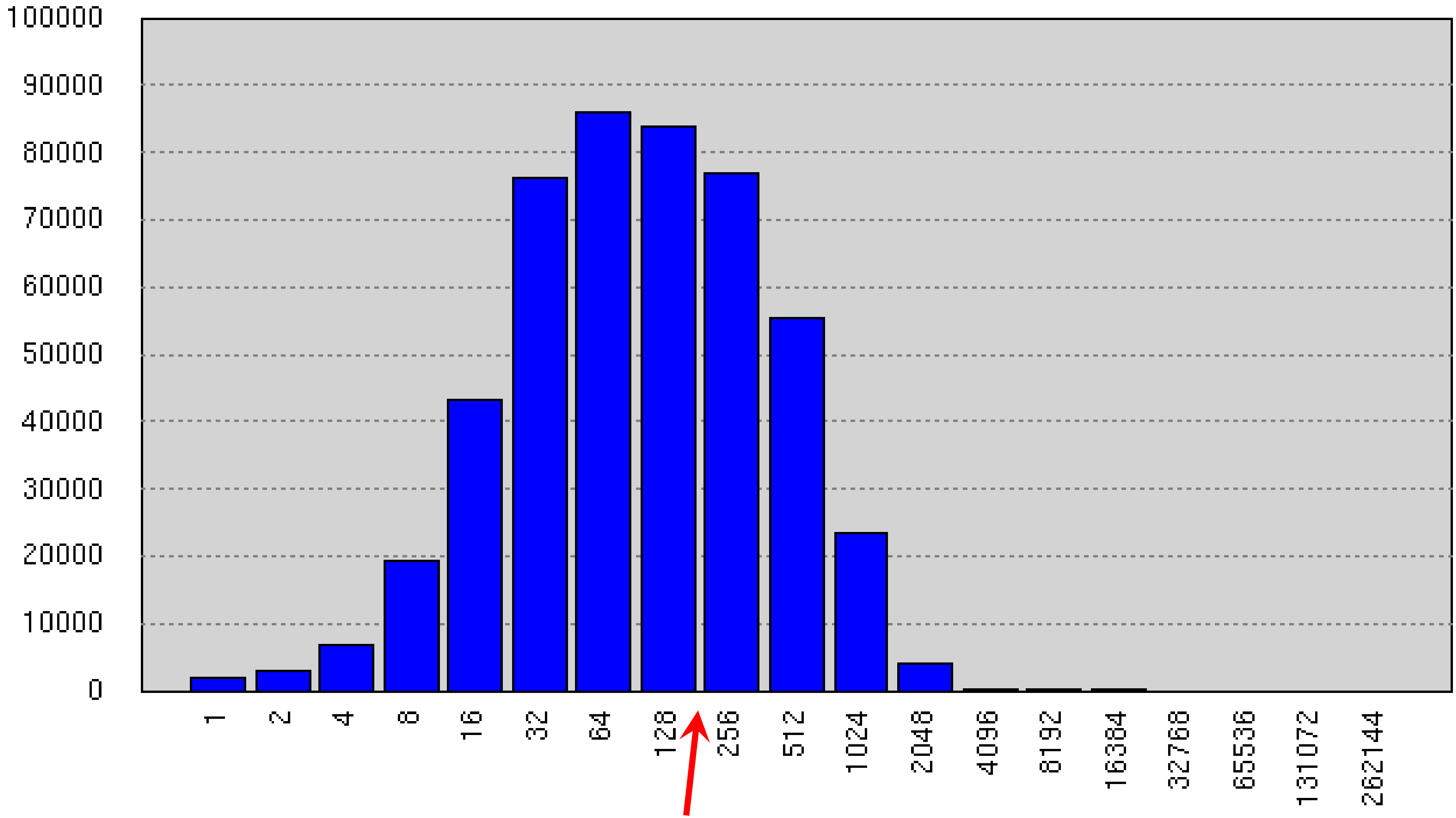


Ratings per Movie in the Training Data



Average number of ratings/movie: 5672

Ratings per User in the Training Data



Average number of ratings/user: 208

Most Loved Movies	Avg rating	Count
The Shawshank Redemption	4.593	137812
Lord of the Rings :The Return of the King	4.545	133597
The Green Mile	4.306	180883
Lord of the Rings :The Two Towers	4.460	150676
Finding Nemo	4.415	139050
Raiders of the Lost Ark	4.504	117456

Most Rated Movies
Miss Congeniality
Independence Day
The Patriot
The Day After Tomorrow
Pretty Woman
Pirates of the Caribbean

Highest Variance
The Royal Tenenbaums
Lost In Translation
Pearl Harbor
Miss Congeniality
Napolean Dynamite
Fahrenheit 9/11

Users with the Most Ratings

User ID	# Ratings	Mean Rating
305344	17,651	1.90
387418	17,432	1.81
2439493	16,560	1.22
1664010	15,811	4.26
2118461	14,829	4.08
1461435	9,820	1.37
1639792	9,764	1.33
1314869	9,739	2.95

Scoring

Minimize root mean square error

Mean square error = $1/|R| \sum_{(u,i) \varepsilon R} (r_{ui} - \hat{r}_{ui})^2$

Does not necessarily correlate well with user satisfaction

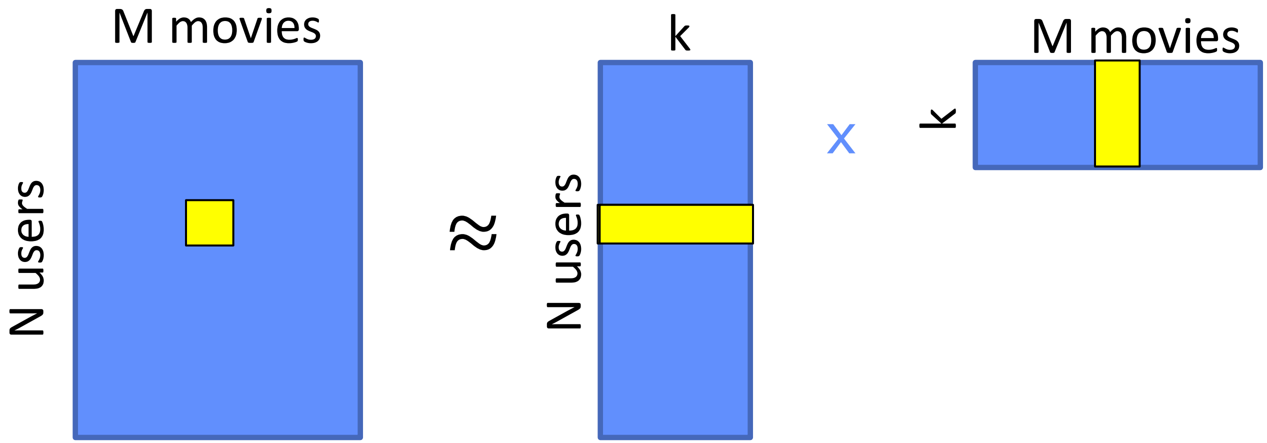
But is a widely-used well-understood quantitative measure

Key Technical Ideas

Key Technical Ideas

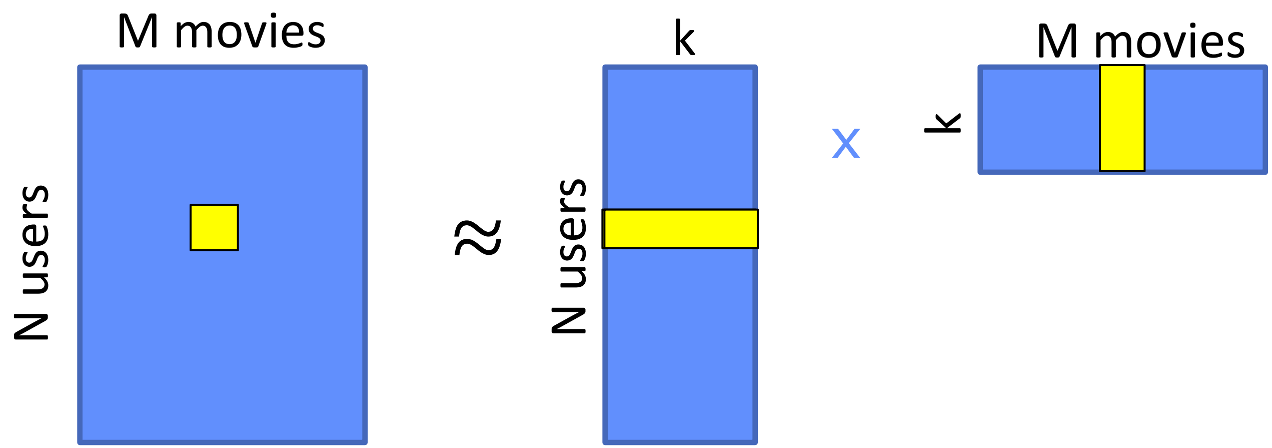
- Matrix factorization for recommender systems
- Learning the parameters of our model by gradient descent
- Making this learning very fast with stochastic gradient descent

Matrix Factorization of Ratings Data



Factorize the large N x M matrix into 2 “skinny” matrices,
k is much smaller than N or M, e.g., k = 100

Matrix Factorization of Ratings Data



$$r_{ui} \approx q^t_i \; p_u$$

k-dim factor vector
for movie i

k-dim factor vector
for user u

Idea: represent users and movies in a k-dimensional “latent factor” space,
to capture general properties of user and movie characteristics

Matrix Approximation with SVD

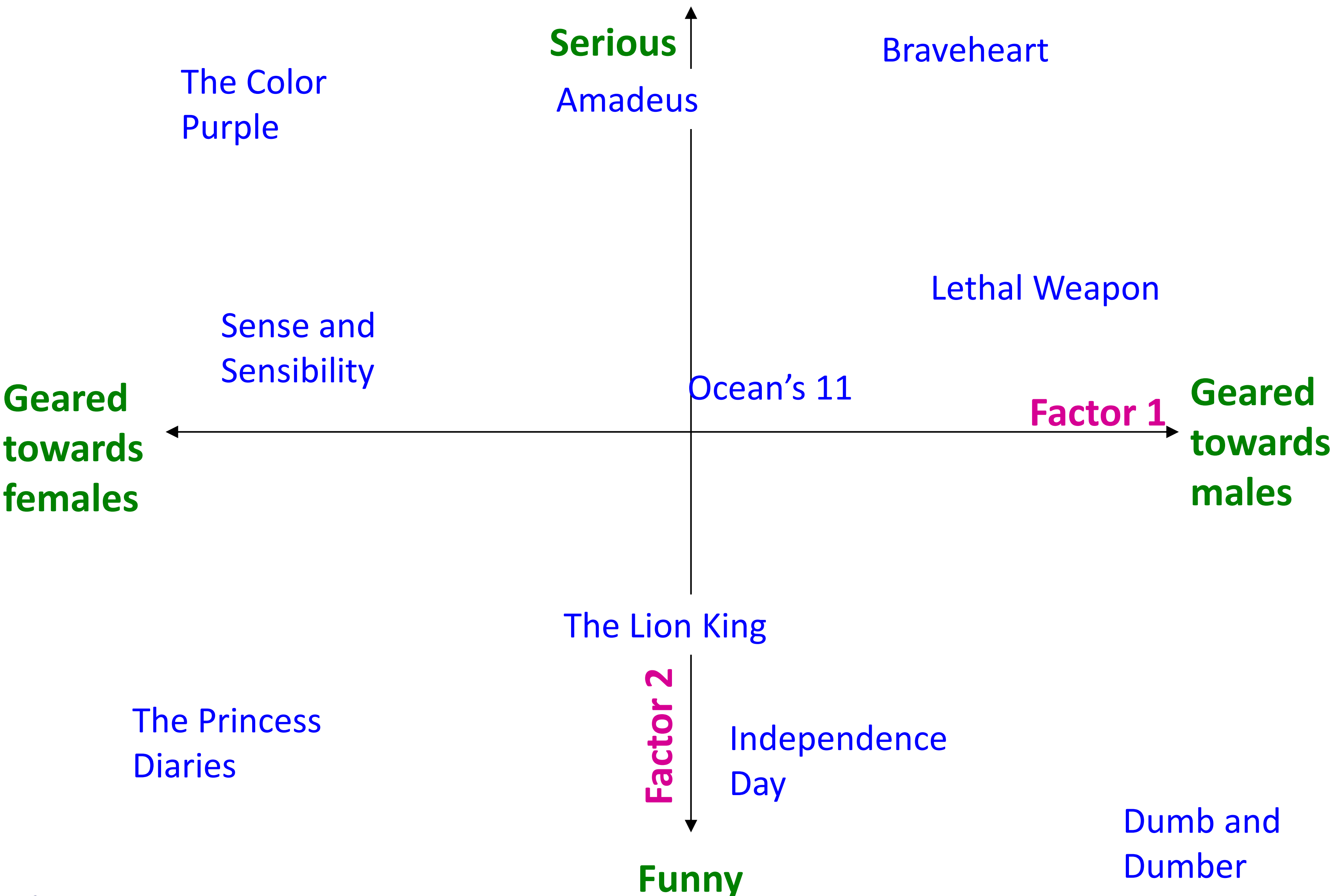
$$\underset{N \times M}{R} \approx \underset{N \times k}{U} \quad \underset{k \times k}{\Sigma} \quad \underset{k \times M}{V^t} = \underset{N \times k}{P} \quad \underset{k \times M}{Q^t}$$

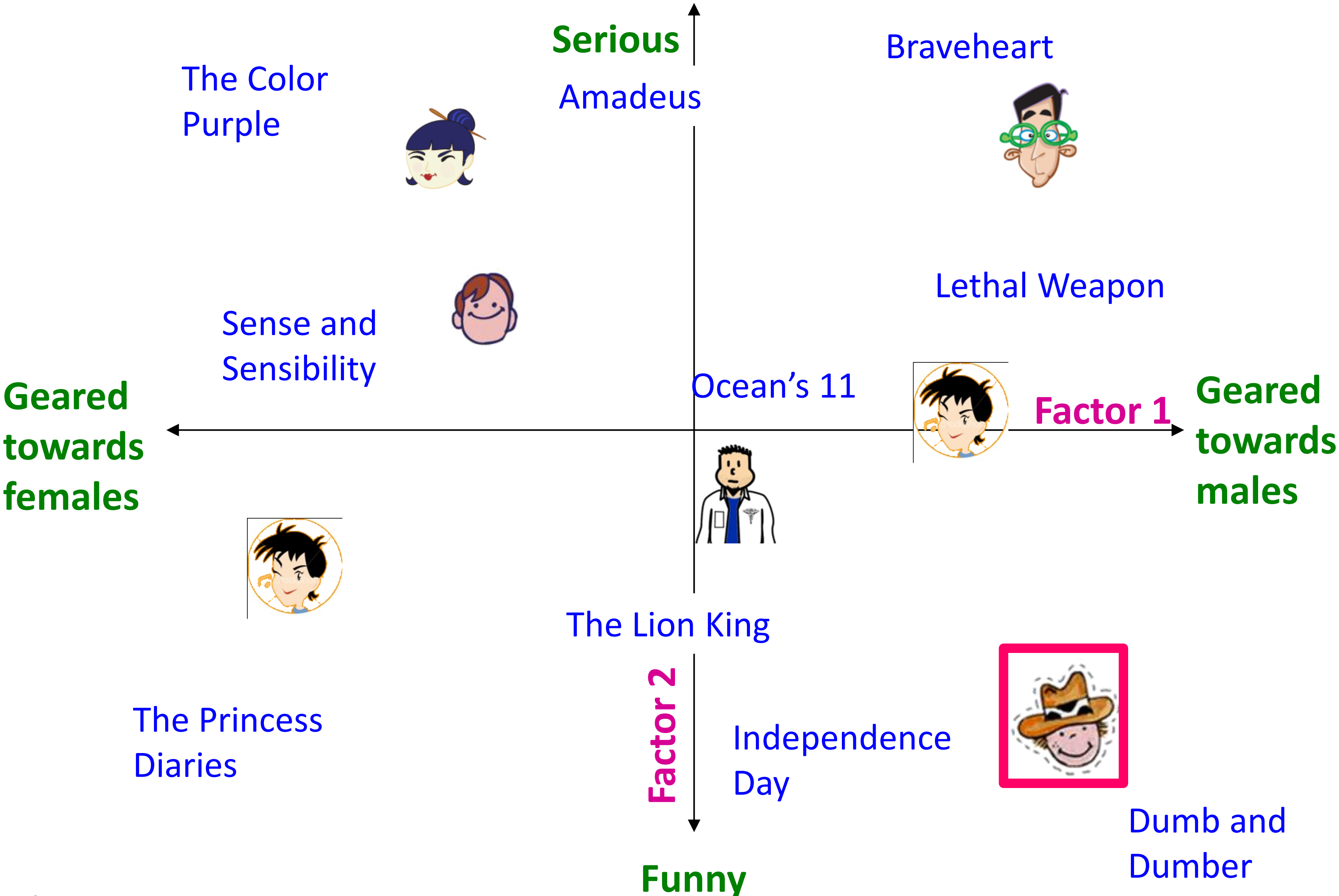
where: columns of V are first f eigenvectors of R^tR

Σ is diagonal with f largest eigenvalues

rows of U are coefficients in reduced dimension V-space

This approximation is the best rank-f approximation to matrix R
in a least squares sense (principal components analysis)


Serious
The Color Purple
Amadeus
Braveheart
Lethal Weapon
Sense and Sensibility
Ocean's 11
Geared towards females
Factor 1
Geared towards males
The Lion King
Factor 2
The Princess Diaries
Independence Day
Dumb and Dumber
Funny



Serious
Braveheart
The Color Purple
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Sense and Sensibility
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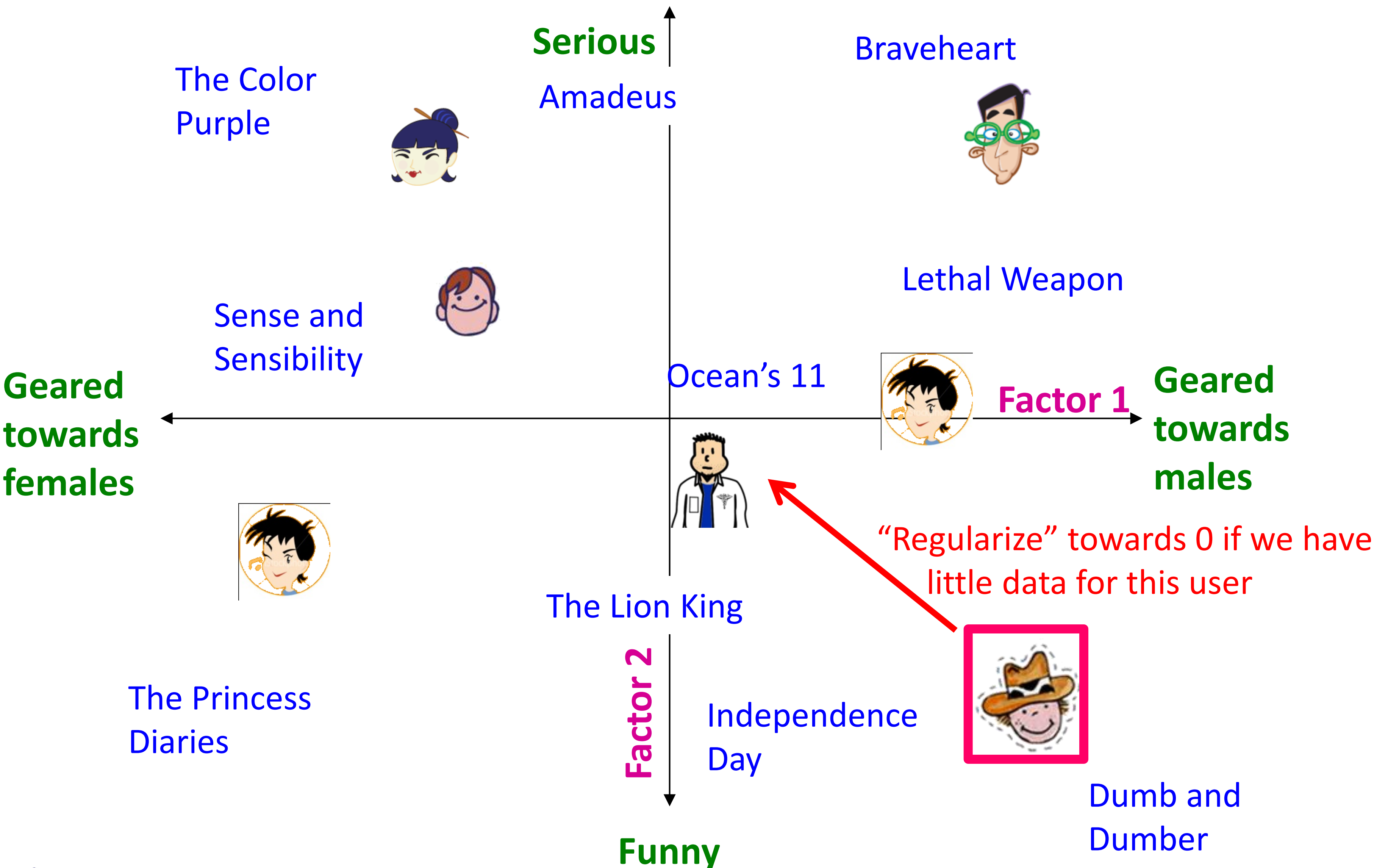
Serious
Braveheart
The Color Purple
Amadeus
Lethal Weapon
Sense and Sensibility
Ocean's 11
Geared towards females
Factor 1
Geared towards males
"Regularize" towards 0 if we have little data for this user
The Lion King
Factor 2
The Princess Diaries
Independence Day
Dumb and Dumber
Funny

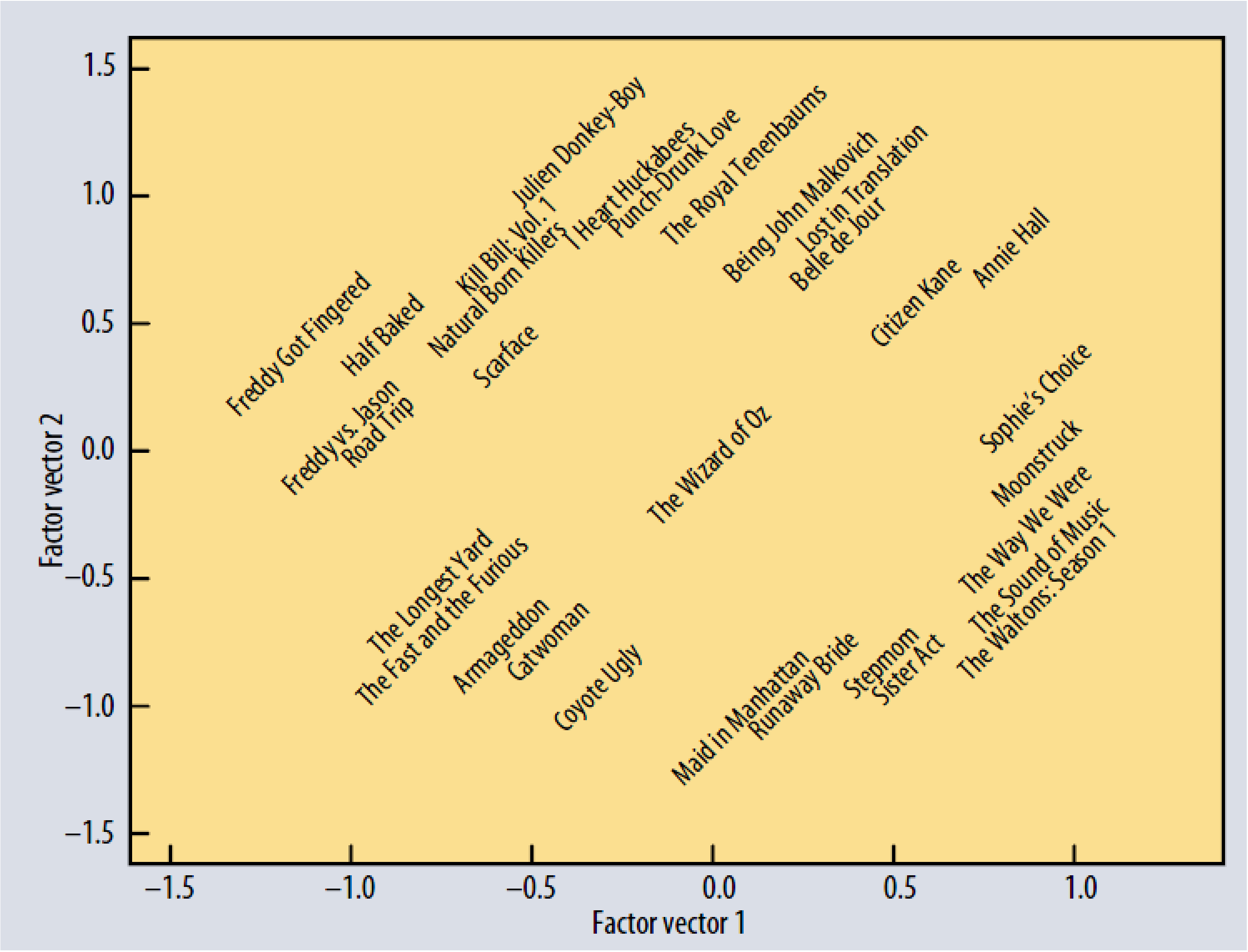

Figure from Koren, Bell, Volinksy, IEEE Computer, 2009

Computation of Matrix Factors

Problem 1:

Finding the k factors is equivalent to performing a singular value decomposition of a matrix, i.e.,

Let R be an $N \times M$ matrix

SVD computation has complexity $O(NM^2 + M^3)$

Computation of Matrix Factors

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Finding the k factors is equivalent to performing a singular value decomposition of a matrix, i.e.,

Let R be an *N x M* matrix

SVD computation has complexity $O(NM^2 + M^3)$

Problem 2:

Most of the entries in R are missing, i.e.,

only 100×10^6 / (480k x 17k) ~ 1% are present

Dealing with Missing Data

$$r_{ui} \approx q^t_i \; p_u$$

$$\min_{q,p} \sum_{(u,i)\, \varepsilon\, R} (r_{ui} - q^t_i \; p_u)^2$$

sum is only over known ratings

Dealing with Missing Data

$$r_{ui} \approx q^t_i \; p_u$$

$$\min_{q,p} \sum_{(u,i)\,\varepsilon\,R} (r_{ui} - q^t_i \; p_u)^2$$

Add regularization

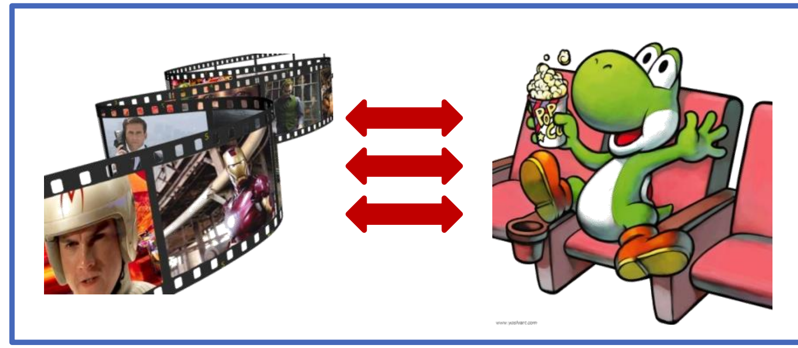
$$\min_{q,p} \sum_{(u,i)\,\varepsilon\,R} (r_{ui} - q^t_i \; p_u)^2 + \lambda \left(|q_i|^2 + |p_u|^2 \right)$$

Components of a rating predictor

user bias

movie bias

user-movie interaction



Baseline predictor

- Separates users and movies
- Often overlooked
- Benefits from insights into users' behavior
- Among the main practical contributions of the competition

User-movie interaction

- Characterizes the matching between users and movies
- Attracts most research in the field
- Benefits from algorithmic and mathematical innovations

(slide from Yehuda Koren)

A baseline predictor

- We have expectations on the rating by user u of movie i, even without estimating u's attitude towards movies like i

- Rating scale of user u
- Values of other ratings user gave recently (day-specific mood, anchoring, multi-user accounts)

- (Recent) popularity of movie i
- Selection bias; related to number of ratings user gave on the same day ("frequency")

(slide from Yehuda Koren)

Modeling Systematic Biases

$$r_{ui} \approx \mu + b_u + b_i + \text{user-movie interactions}$$

overall "intercept" (μ)

bias for user u (b_u)

bias for movie i (b_i)

$$q^t_i \; p_u$$

Example:

Intercept/mean μ = 3.7

You are a critical reviewer: your ratings are 1 lower than the mean -> b_u = -1

Star Wars gets a mean rating of 0.5 higher than average movie: b_i = + 0.5

Predicted rating for you on Star Wars = 3.7 - 1 + 0.5 = 3.2

Objective Function: Minimize as a Function of Parameters

goodness of fit

$$\min_{q,p} \left\{ \sum_{(u,i)\, \varepsilon\, R} (r_{ui} - (\mu + b_u + b_i + q^t_i\, p_u))^2 \right.$$

$$\left. + \lambda \left(|q_i|^2 + |p_u|^2 + |b_u|^2 + |b_i|^2 \right) \right\}$$

regularization

Typically selected via grid-search on a validation set

We will use stochastic gradient descent to find parameters

Note: biases $\boldsymbol{b_u}$, $\boldsymbol{b_i}$ as well as interactions $\boldsymbol{q_i}$, $\boldsymbol{p_u}$ are treated as parameters (we estimate them)

Principle of Gradient Descent

Let θ be our current parameter vector and $E(\theta)$ be our error function.

θ is a vector of parameters of dimension $p \times 1$.

The gradient of θ, $\nabla_\theta(E)$ is a p-dimensional gradient vector, where entry j is the partial derivative of E with respect to the jth component of the parameter vector θ.

To move downhill in θ space, we take a step in the opposite direction of the gradient, i.e.,

$$\theta^{\text{new}} = \theta^{\text{old}} - \gamma \nabla_\theta(E)$$

where γ is the step size.

For the jth component, we move/update the parameter θ_j as follows:

$$\theta_j^{\text{new}} = \theta_j^{\text{old}} - \gamma \frac{\partial E}{\partial \theta_j}$$

Gradient Descent Algorithm for Parameter Learning

1. Initialize all parameters to some initial values (e.g., randomly or heuristically)

2. Given the current parameter vector θ, compute the gradient $\nabla_\theta(E)$

3. Update each parameter j:

$$\theta_j^{\text{new}} = \theta_j^{\text{old}} - \gamma \frac{\partial E}{\partial \theta_j}$$

4. Check if the algorithm has converged, e.g., if $E(\theta^{\text{new}}) - E(\theta^{\text{old}}) < \epsilon$

5. If not converged, return to step 2

How to set the Learning Rate?

$$\theta_j^{\text{new}} = \theta_j^{\text{old}} - \gamma \frac{\partial E}{\partial \theta_j}$$

In practice we may also want to decrease the step-size at each iteration, e.g., replace γ by $\alpha\gamma$ at each iteration, where (e.g.,) $\alpha = 0.9$. Theoretically this is necessary to ensure convergence.

There is no general theory on how to select the step size α and the schedule for decreasing it over time.

Good settings will vary by problem and data set.

In practice finding good settings requires trial and error.

Learning a Recommender Model with Biases

Prediction model:

$$\hat{r}_{ui} = \mu + b_u + b_i$$

Error:

$$E = \sum_{u,i} \left(r_{u,i} - \hat{r}_{ui} \right)^2 = \sum_{u,i} e_{u,i}^2$$

where

$e_{u,i}$ = prediction error on rating $r_{u,i} \;=\; r_{u,i} - \hat{r}_{ui} \;=\; r_{u,i} - (\mu + b_u + b_i)$

Gradient Descent for One Parameter

Gradient descent to learn μ:

$$\frac{\partial E}{\partial \mu} = \frac{\partial}{\partial \mu} \sum_{u,i} e_{u,i}^2 \; = \; \sum_{u,i} \frac{\partial}{\partial \mu} e_{u,i}^2$$

Chain rule:

$$\frac{\partial e_{u,i}^2}{\partial \mu} = \frac{\partial e_{u,i}^2}{\partial e_{u,i}} \times \frac{\partial e_{u,i}}{\partial \mu}$$

where

$$\frac{\partial e_{u,i}^2}{\partial e_{u,i}} \times \frac{\partial e_{u,i}}{\partial \mu} = 2e_{u,i} \times \frac{\partial e_{u,i}}{\partial \mu} = 2e_{u,i} \times -1 \; = \; -2e_{u,i}$$

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The total gradient, summed across all rating pairs (u, i) is:

$$\frac{\partial E}{\partial \mu} = -\sum_{u,i} e_{u,i}$$

where the sum is over all R observed ratings.

To minimize a function we need to move in the opposite direction of the gradient, so the gradient direction we take for the μ component of the gradient is in the direction $\sum_{u,i} e_{u,i}$.

Gradient Descent for User and Item Bias Parameters

We can use a similar derivation to get the updates for b_u and b_i (these are vectors of parameters of size N and M respectively)

$$\frac{\partial E}{\partial b_u} = -\sum_{u,i} e_{u,i}$$

$$\frac{\partial E}{\partial b_i} = -\sum_{u,i} e_{u,i}$$

Recall that the general gradient update equation is as follows:

$$\theta_j^{\text{new}} \; = \; \theta_j^{\text{old}} - \gamma \frac{\partial E}{\partial \theta_j}$$

Gradient Updates for All Bias Parameters

This leads to gradient update equations for μ, b_u, b_i as follows:

$$
\begin{aligned}
\mu^{\text{new}} &= \mu^{\text{old}} + \gamma \sum_{u,i} e_{u,i} \\
b_u^{\text{new}} &= b_u^{\text{old}} + \gamma \sum_{u,i} e_{u,i}, \quad u = 1, \ldots, N \\
b_i^{\text{new}} &= b_i^{\text{old}} + \gamma \sum_{u,i} e_{u,i}, \quad i = 1, \ldots, M
\end{aligned}
$$

Gradient Updates for All Bias Parameters

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b_i^{\text{new}} &= b_i^{\text{old}} + \gamma \sum_{u,i} e_{u,i}, \quad i = 1, \ldots, M
\end{aligned}$$

The complexity of each update is $O(R + M + N)$ where:

- R is the number of ratings in the sum
- N and M are the number of users and items respectively

First-Order and Second-Order Methods

The algorithm on the previous slide is "first-order."

More sophisticated algorithms also use "second-order" information, with a $p \times p$ matrix of 2nd-order partial derivatives, where $p = M + N$ is the number of parameters.

This incurs a cost of $O(p^2)$ for updates versus $O(p)$ for gradient descent.

Even though the 2nd-order may take more accurate steps per iteration, overall convergence time may be slower, particularly for large p.

Impractical for large p, e.g., large N and/or M.

Stochastic Gradient Method

Idea: compute an estimate of the gradient on small parts of the data and then update parameters

For example, we can compute the gradient using just a single rating (u*,i*), and then update:

$$\begin{aligned} \mu^{\text{new}} &= \mu^{\text{old}} + \gamma e_{u*,i*} \\ b_{u*}^{\text{new}} &= b_{u*}^{\text{old}} + \gamma e_{u*,i*} \\ b_{i*}^{\text{new}} &= b_{i*}^{\text{old}} + \gamma e_{u*,i*} \end{aligned}$$

This is called the **stochastic gradient** method.

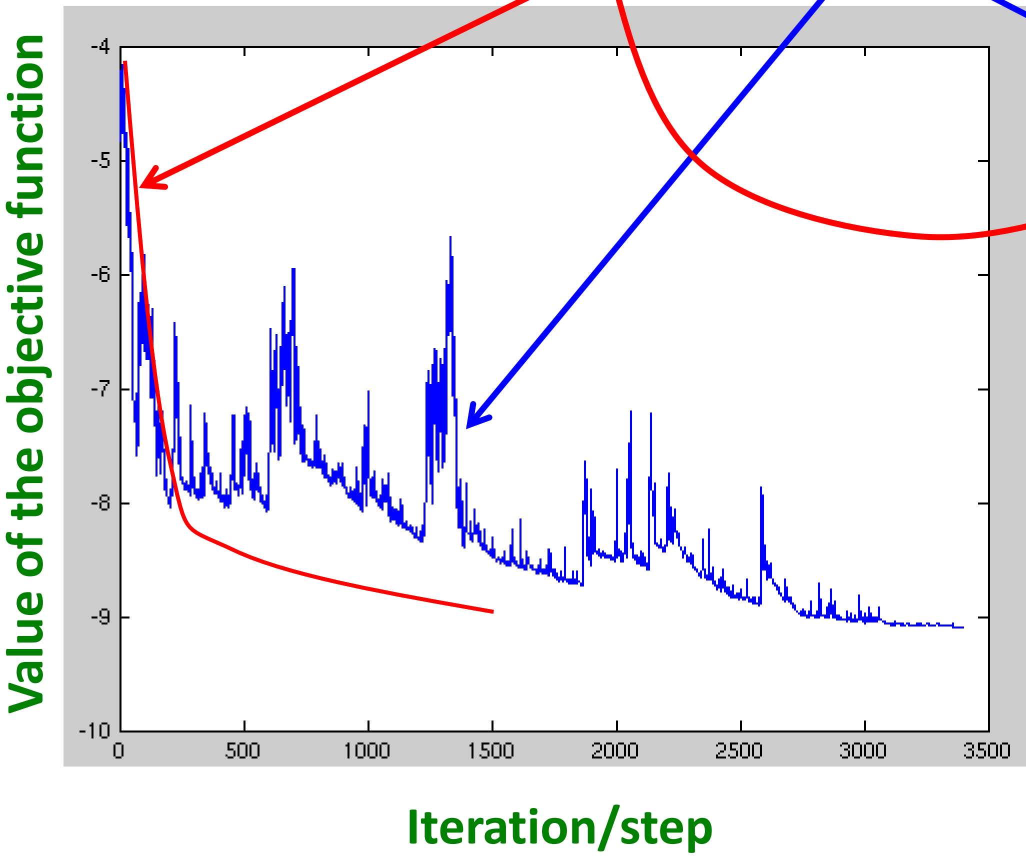
Each update is computationally cheap.

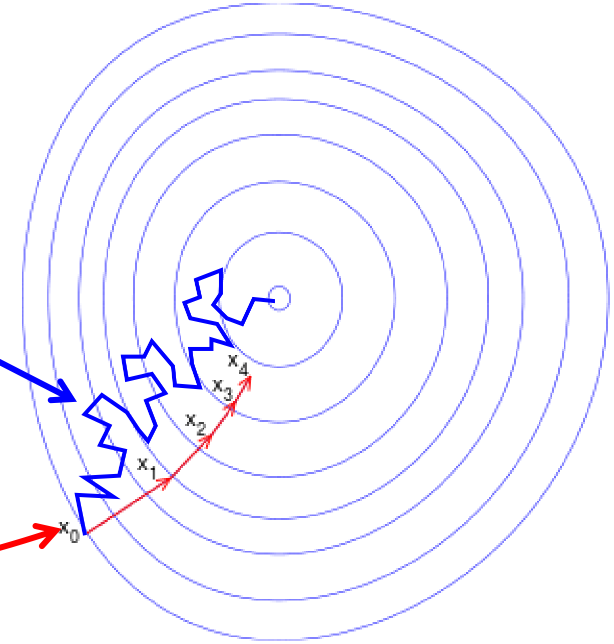
So we update the parameters R times per iteration compared to conventional gradient descent (e.g., $R = 100$ million ratings for Netflix) and take a lot of noisy/cheap steps in parameter space

Empirically, we can often converge to a solution much faster with stochastic gradient than with the full gradient.

SG vs GD

Convergence of GD vs. SG





GD improves the value of the objective function at every step.

SG improves the value but in a "noisy" way.

GD takes fewer steps to converge but each step takes much longer to compute.

In practice, **SG** is much faster!

Learning the (Latent) Matrix Factors

We can use the same idea of (stochastic) gradient descent to learn our factors.

Recall that:

$$\hat{r}_{ui} = \mu + b_u + b_i + q_i^t p_u$$

where q_i and p_u are the k-dimensional factor vectors for item i and user u respectively.

We can treat these factors as an additional set of $k(N+M)$ parameters to learn and use gradient descent to learn them.

Update equations for the factors (for stochastic gradient):

$$\begin{aligned} p_u^{\text{new}} &= p_u^{\text{old}} + \gamma e_{u,i} q_i \\ q_i^{\text{new}} &= q_i^{\text{old}} + \gamma e_{u,i} p_u \end{aligned}$$

Regularizing the Parameters

As discussed earlier, it is often useful to regularize and add a penalty term to penalize large parameter values.

This gives a modified objective function of the form

$$E = \sum_{u,i} \left(r_{u,i} - \hat{r}_{u,i} \right)^2 + \lambda \sum_{u,i} b_i^2 + b_u^2 + ||q_i||^2 + ||p_u||^2$$

Now we get modified gradient terms and our update equations change accordingly, e.g.,

$$\begin{aligned} p_u^{\text{new}} &= p_u^{\text{old}} + \gamma(e_{u,i} q_i^{\text{old}} - \lambda p_u^{\text{old}}) \\ q_i^{\text{new}} &= q_i^{\text{old}} + \gamma(e_{u,i} p_u^{\text{old}} - \lambda q_i^{\text{old}}) \end{aligned}$$

In the Netflix competition the winning team used $\gamma = 0.005, \lambda = 0.02$ (determined by extensive experimentation on validation data)

Adding "Content" Features for Items and/or Users

Say we also have features for the items (will just do items here, same math for features for users)

Let $\mathbf{x_i}$ be a d-dimensional feature vector for item i

We can use include the features in the prediction model, weighted by parameters $\alpha_j, j = 1, \ldots, d$

$$\hat{r}_{ui} = \mu + b_u + b_i + q_i^t p_u + \sum_{j=1}^{d} \alpha_j x_{ij}$$

where x_{ij} is the jth feature value for item i.

Note that this is like a generalized form of linear regression, where we have bias and latent factor terms in the prediction as well as the more typical weighted sum of feature values.

5%

8%

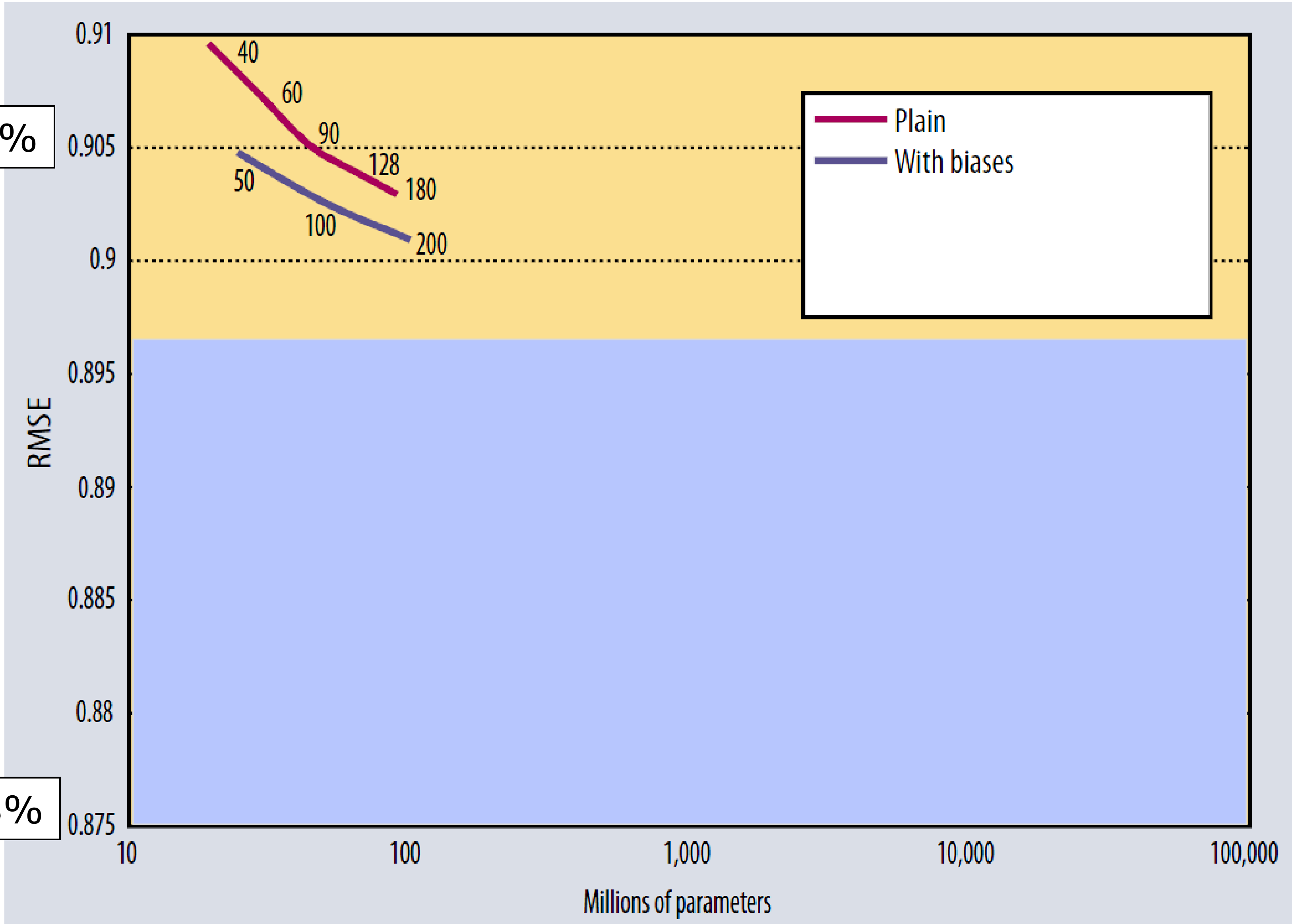
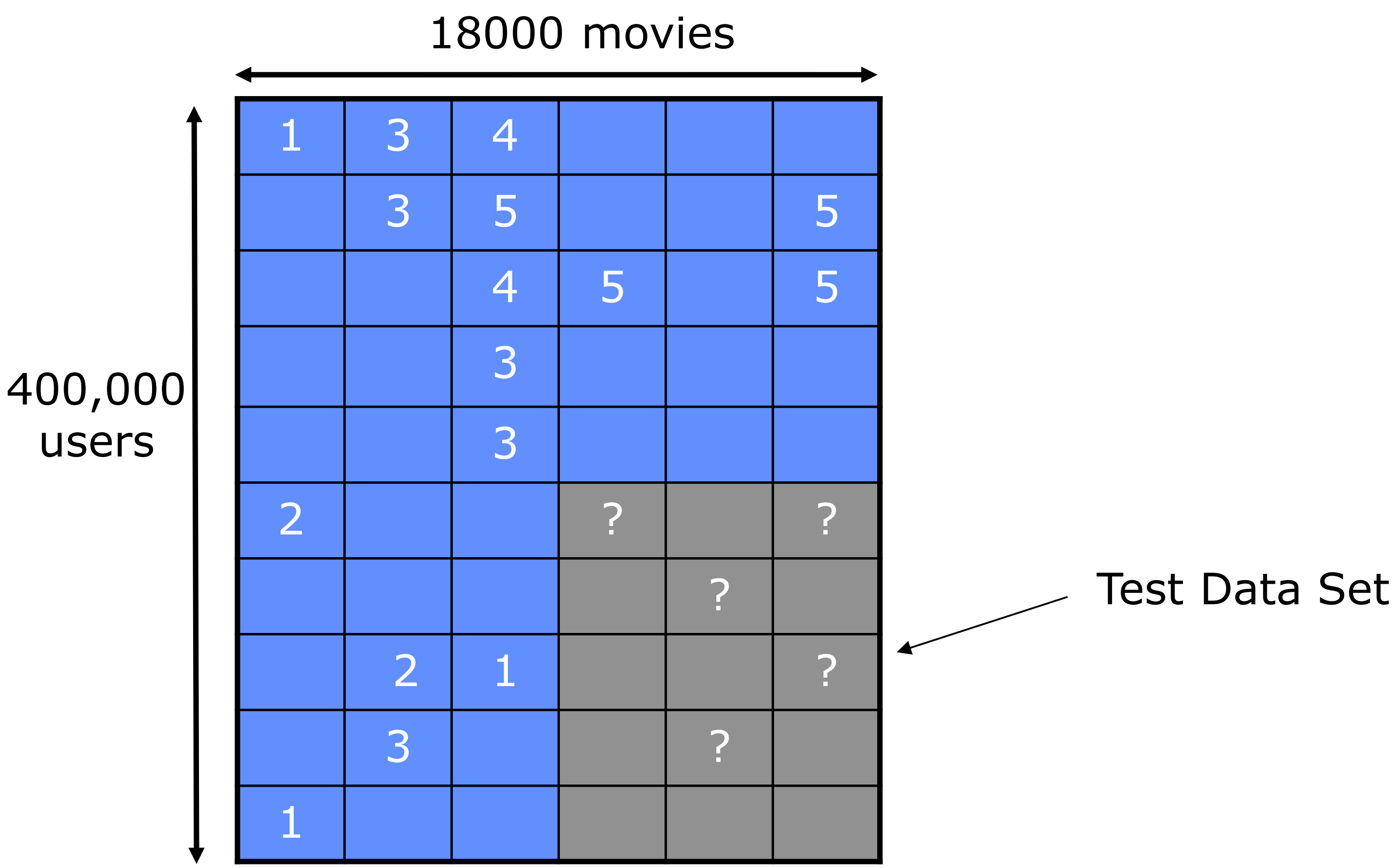
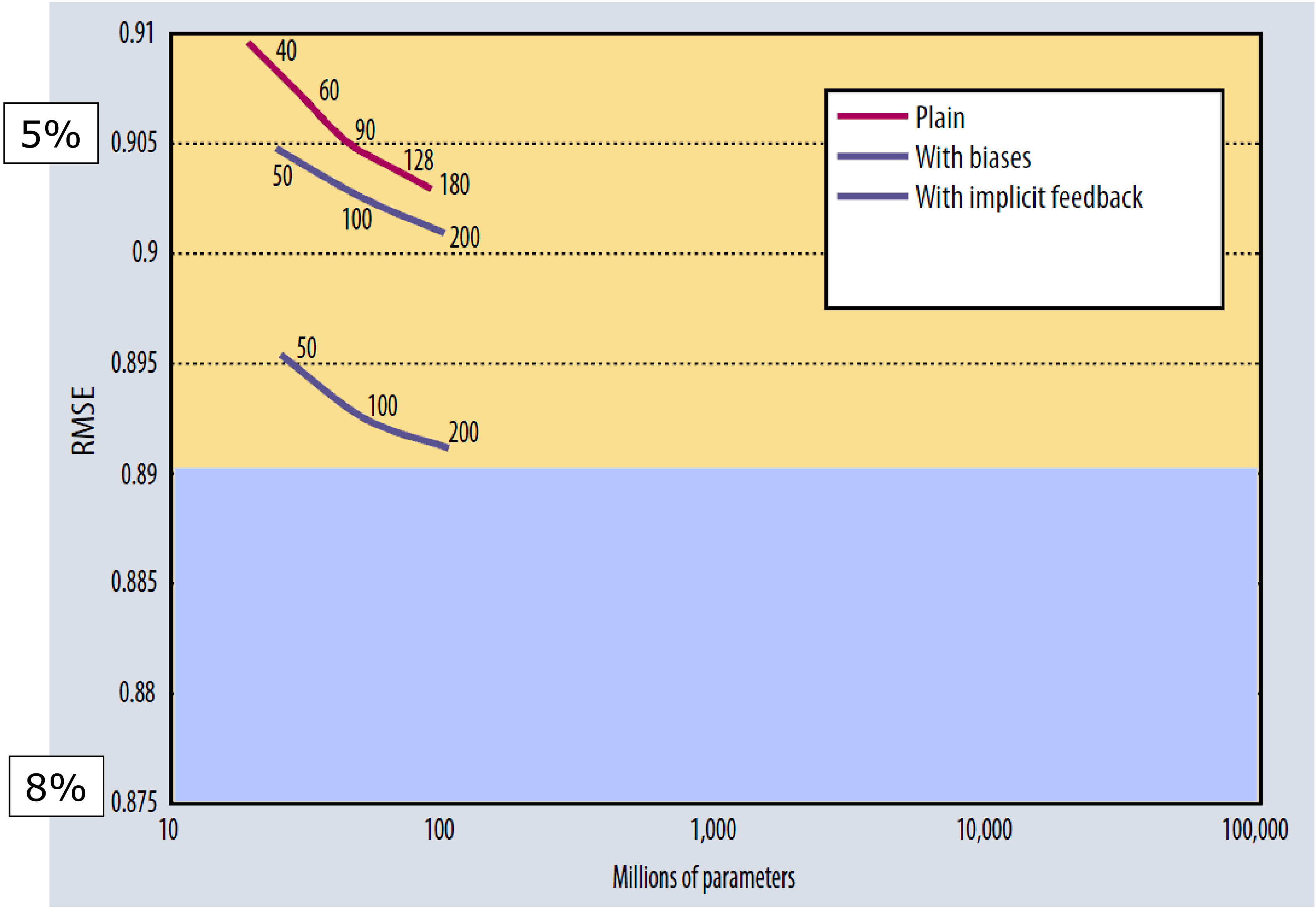


Figure from Koren, Bell, Volinksy, IEEE Computer, 2009

Adding Implicit Information





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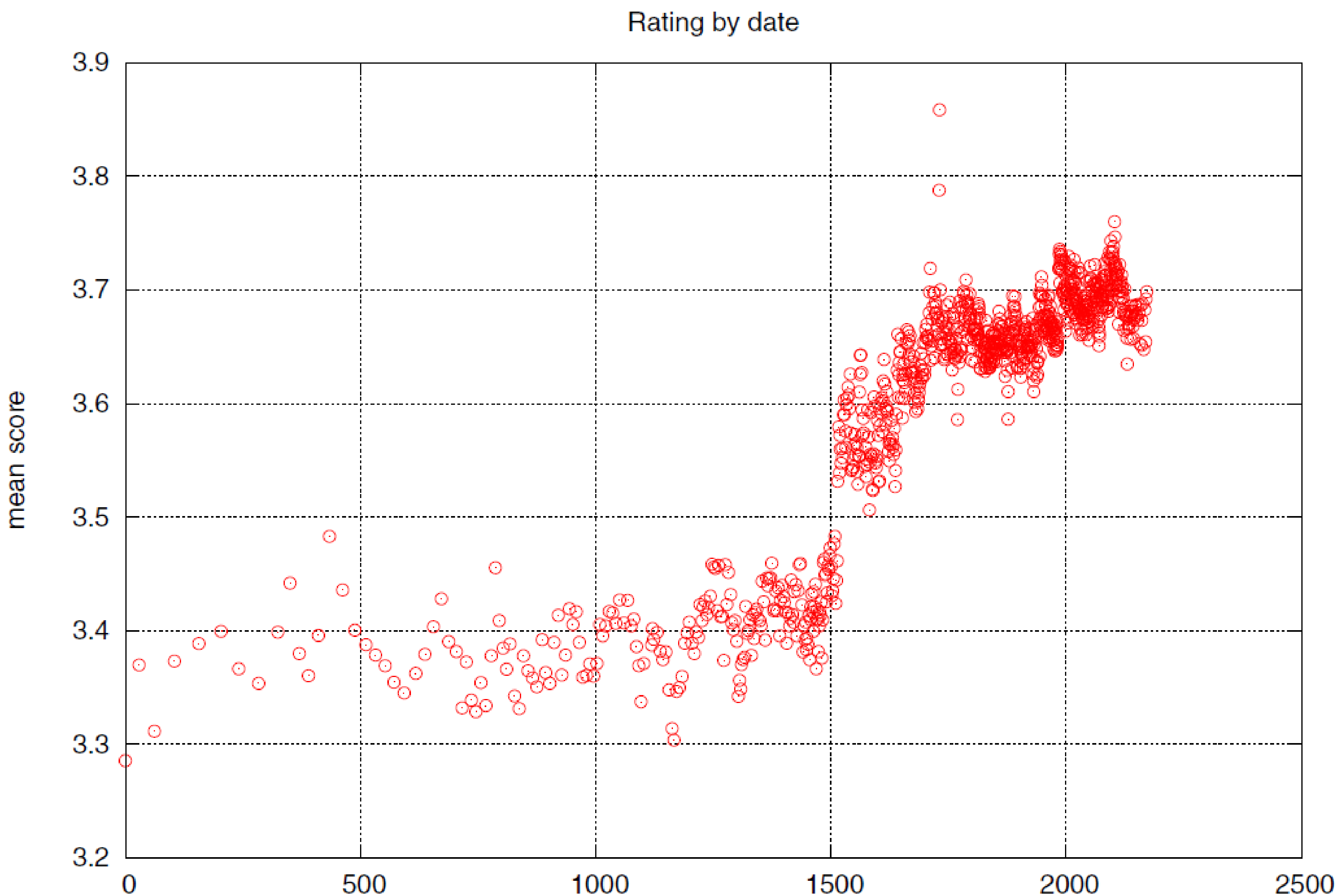
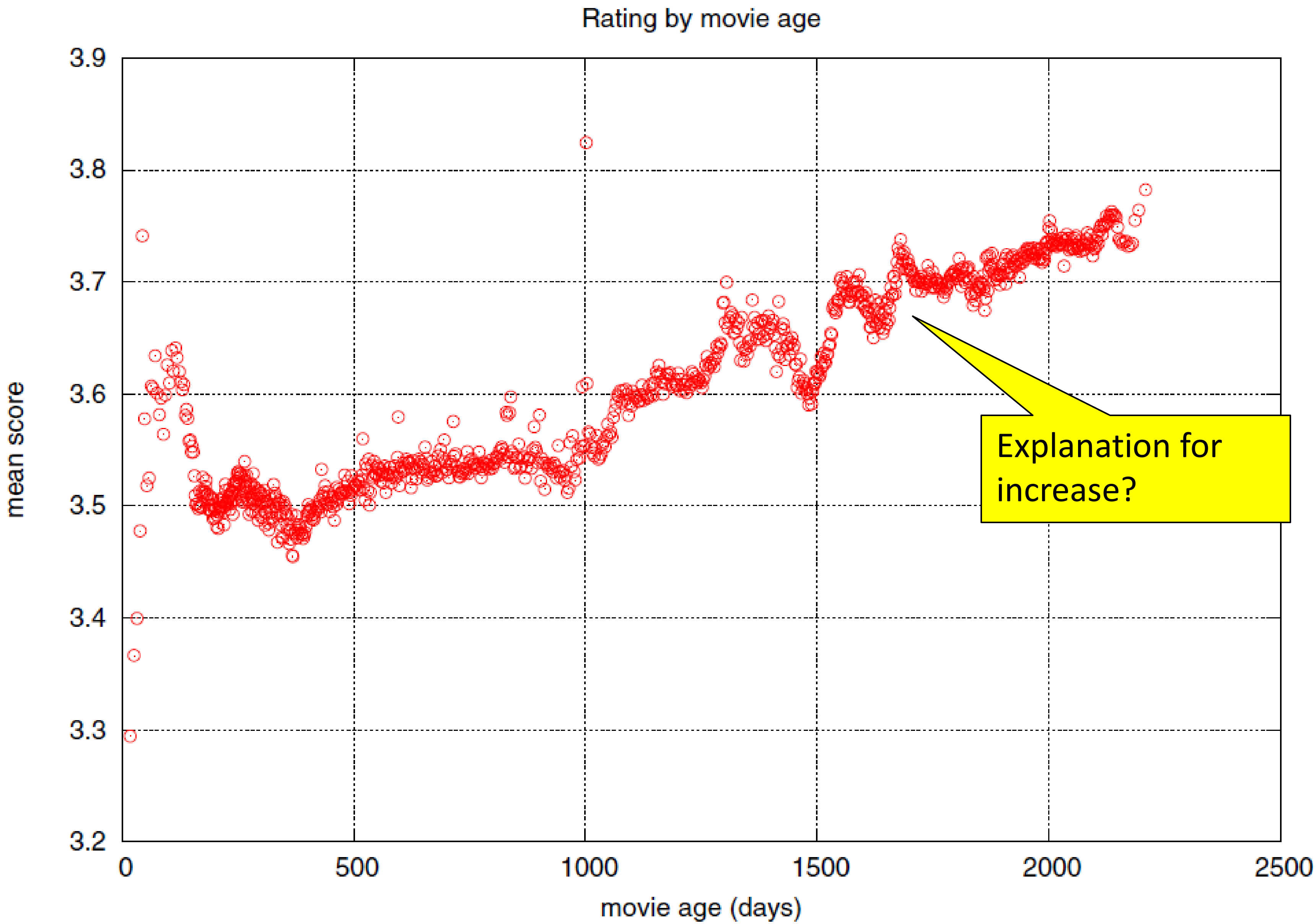


Rating by date
mean score
3.9
3.8
3.7
3.6
3.5
3.4
3.3
3.2
0
500
1000
1500
2000
2500


Rating by movie age
3.9
3.8
3.7
3.6
3.5
3.4
3.3
3.2
mean score
0
500
1000
1500
2000
2500
movie age (days)
Explanation for increase?

Adding Time Effects

$$r_{ui} \approx \mu + b_u + b_i + \text{user-movie interactions}$$

Add time dependence
to biases

$$r_{ui} \approx \mu + b_u(t) + b_i(t) + \text{user-movie interactions}$$

Time-dependence parametrized by linear trends, binning, and other methods

For details see
Y. Koren, Collaborative filtering with temporal dynamics, ACM SIGKDD Conference 2009

Adding Time Effects

$$r_{ui} \approx \mu + b_u(t) + b_i(t) + q^t_i \, p_u(t)$$

Add time dependence to user "factor weights"

Models the fact that user's interests over "genres" (the q's) may change over time

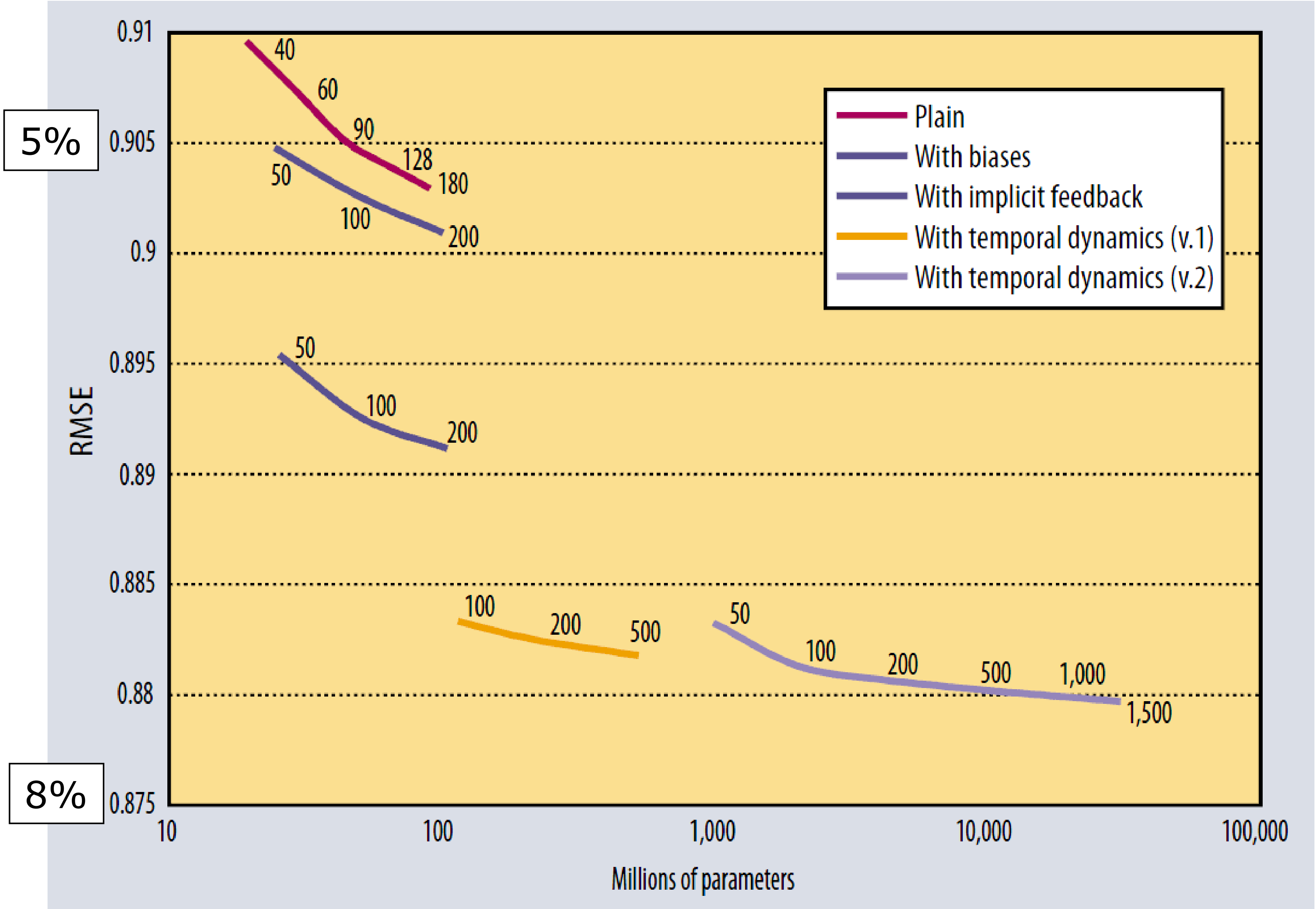


Figure from Koren, Bell, Volinksy, IEEE Computer, 2009

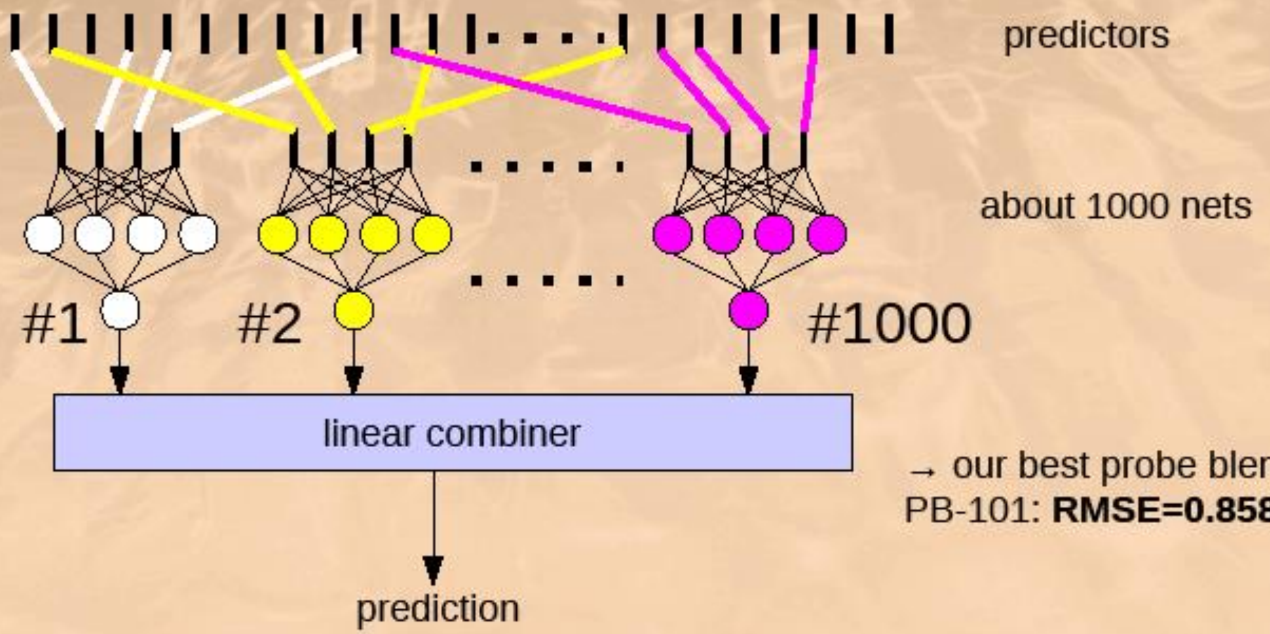
The Kitchen Sink Approach….

- Many options for modeling
  - Variants of the ideas we have seen so far
    - Different numbers of factors
    - Different ways to model time
    - Different ways to handle implicit information
    - ….
  - Other models (not described here)
    - Nearest-neighbor models
    - Restricted Boltzmann machines

- Model averaging was useful in the Netflix competition….
  - Linear model combining
  - Neural network combining
  - Gradient boosted decision tree combining
  - Note: combining weights learned on validation set ("stacking")

Ensemble NNBlend

- Train many small NN's (>1000) on a random subset
  - Per net: 20..40 weights
- Combine them linearly



→ our best probe blend:
PB-101: **RMSE=0.8584**

Michael Jahrer / Andreas Töscher – Team BigChaos – September 21, 2009

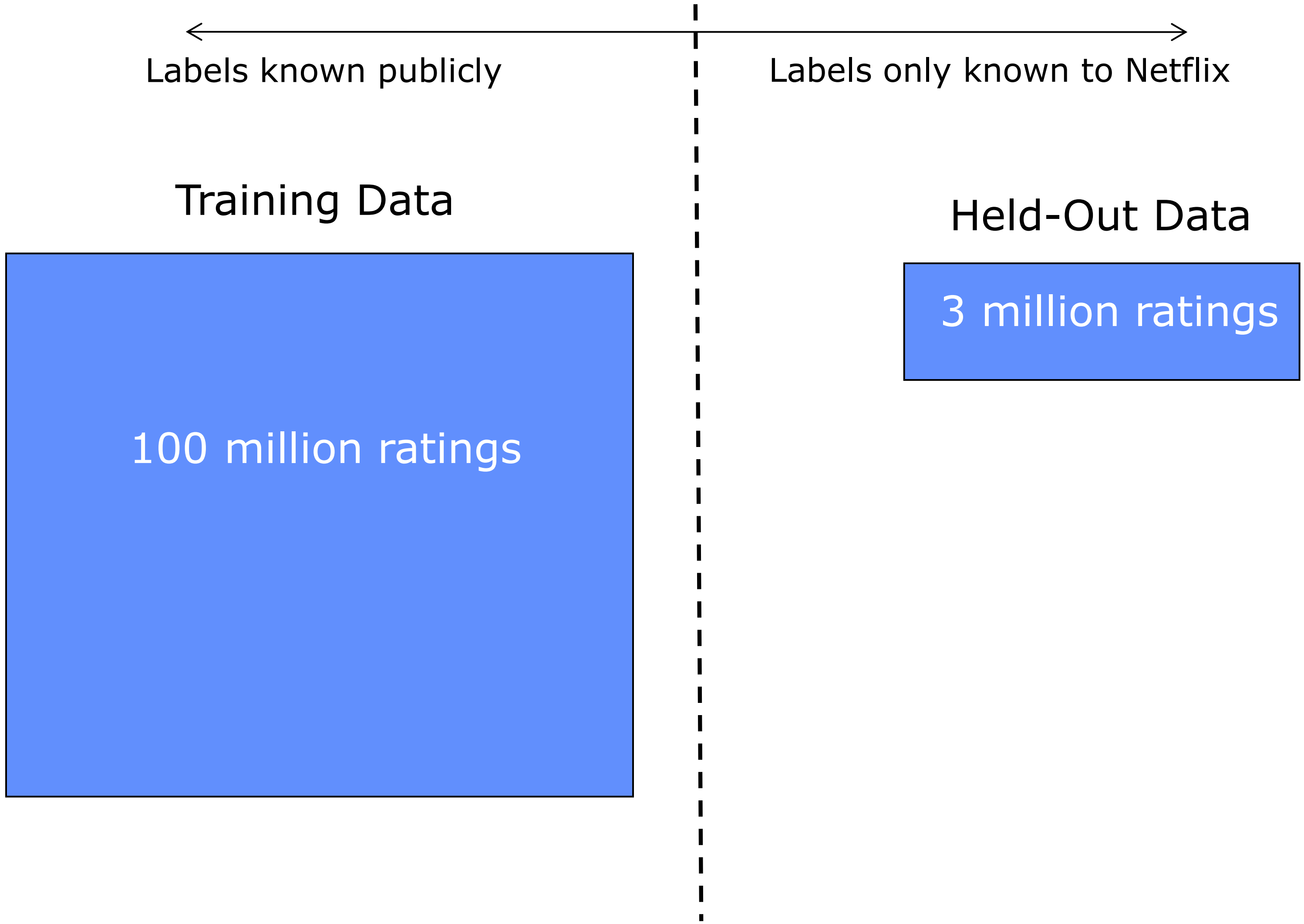
Other Aspects of Model Building

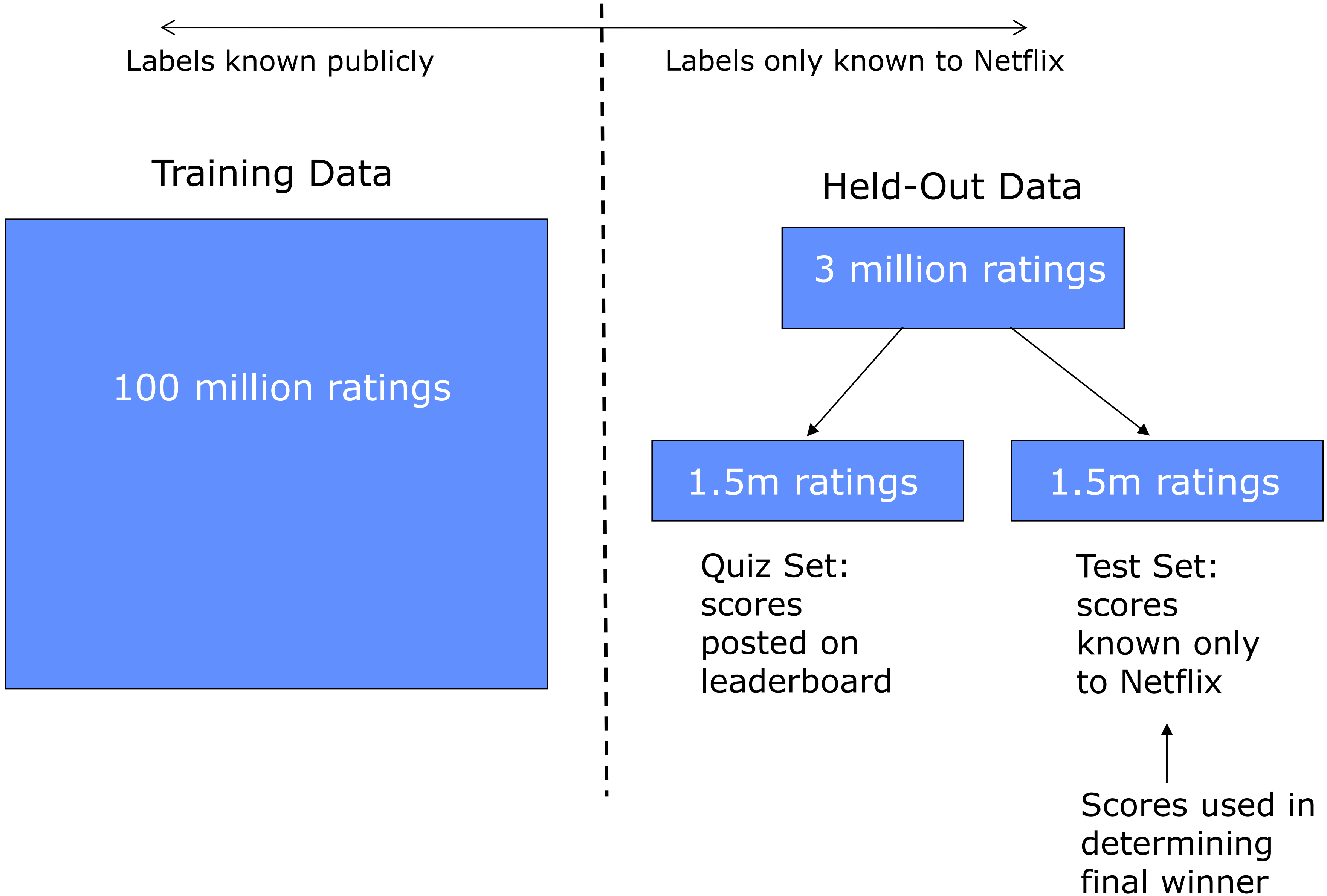
- Automated parameter tuning
  - Using a validation set, and grid search, various parameters such as learning rates, regularization parameters, etc., can be optimized

- Memory requirements
  - Memory: can fit within roughly 1 Gbyte of RAM

- Training time
  - Order of days: but achievable on commodity hardware rather than a supercomputer
  - Some parallelization used

The Netflix Competition: 2006-2009


Labels known publicly
Labels only known to Netflix
Training Data
100 million ratings
Held-Out Data
3 million ratings


Labels known publicly
Labels only known to Netflix
Training Data
100 million ratings
Held-Out Data
3 million ratings
1.5m ratings
1.5m ratings
Quiz Set: scores posted on leaderboard
Test Set: scores known only to Netflix
Scores used in determining final winner

Structure of Competition

- Register to enter at Netflix site
- Download training data of 100 million ratings
  - 480k users x 17.7k movies
  - Anonymized
- Submit predictions for 3 million ratings in "test set"
  - True ratings are known only to Netflix
- Can submit multiple times (limit of once/day)
- Prize
  - $1 million dollars if error is 10% lower than Netflix current system
  - Annual progress prize of $50,000 to leading team each year

RMSE Baseline Scores on Test Data

1.054 - just predict the mean user rating for each movie

0.953 - Netflix's own system (Cinematch) as of 2006

0.941 - nearest-neighbor method using correlation

0.857 - required 10% reduction to win $1 million

Other Aspects of Rules

- Rights
  - Software + non-exclusive license to Netflix
  - Algorithm description to be posted publicly

- Final prize details
  - If public score of any contestant is better than 10%, this triggers a 30-day final competition period
  - Anyone can submit scores in this 30-day period
  - Best score at the end of the 30-day period wins the $1 million prize

- Competition not open to entrants in North Korea, Iran, Libya, Cuba….and Quebec

Why did Netflix do this?

- Customer satisfaction/retention is key to Netflix – they would really like to improve their recommender systems
- Progress with internal system (Cinematch) was slow
- Initial prize idea from CEO Reed Hastings
- $1 million would likely easily pay for itself
- Potential downsides
  - Negative publicity (e.g., privacy)
  - No-one wins the prize (conspiracy theory)
  - The prize is won within a day or 2
  - Person-hours at Netflix to run the competition
  - Algorithmic solutions are not useful operationally

Setting up and Launching…

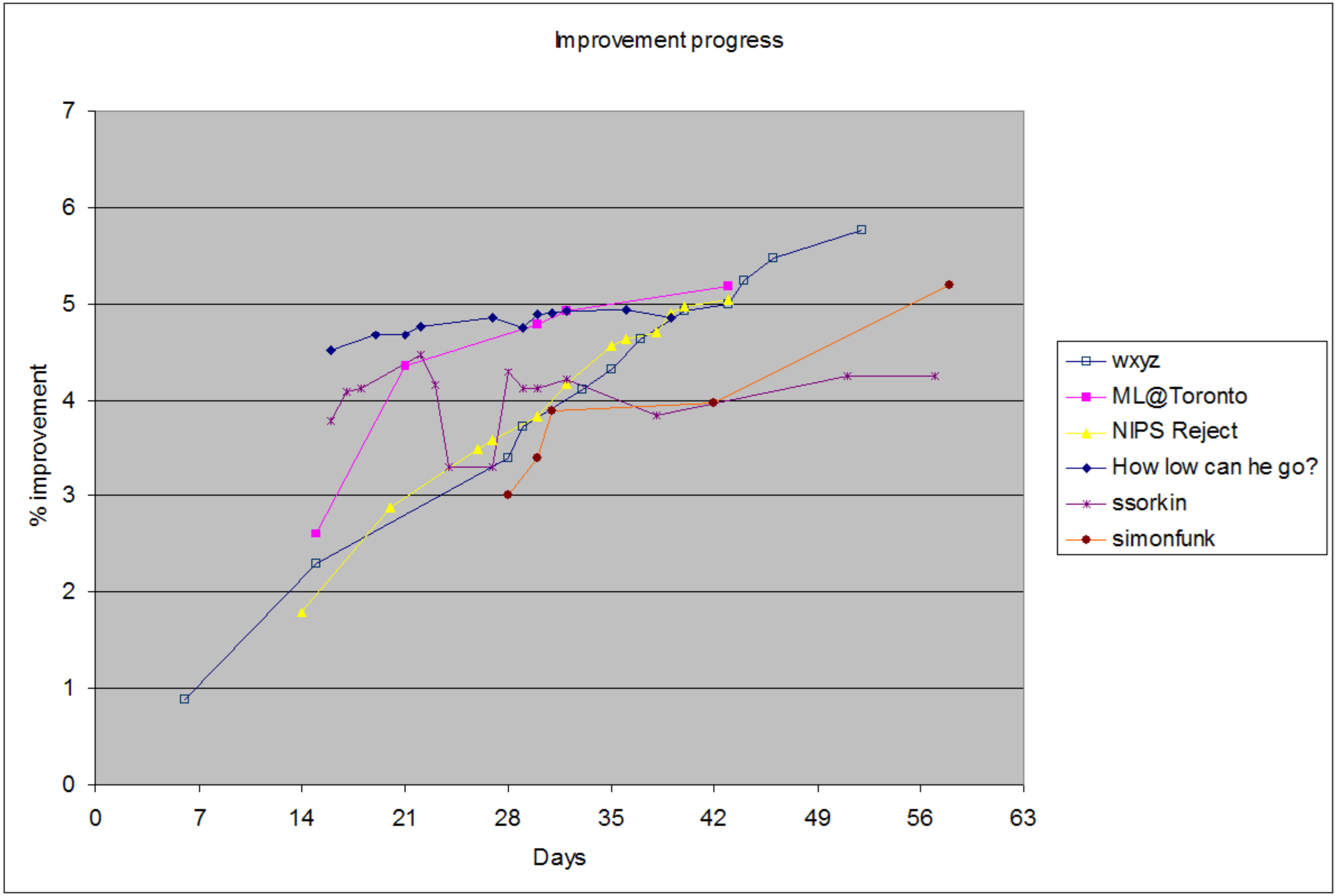
- Summer 2006
  - Email from Netflix about large monetary award
  - Is this real?
  - Apparently so: serious and well-organized
  - Spent summer carefully designing data set and rules

- Official Launch, Oct 2nd 2006
  - Email lists, conferences, press releases, etc
  - Significant initial interest in research community, blogs, etc
    - 40,000 teams (eventually) from over 150 countries.
  - Number of initial registrants significantly exceeded expectations

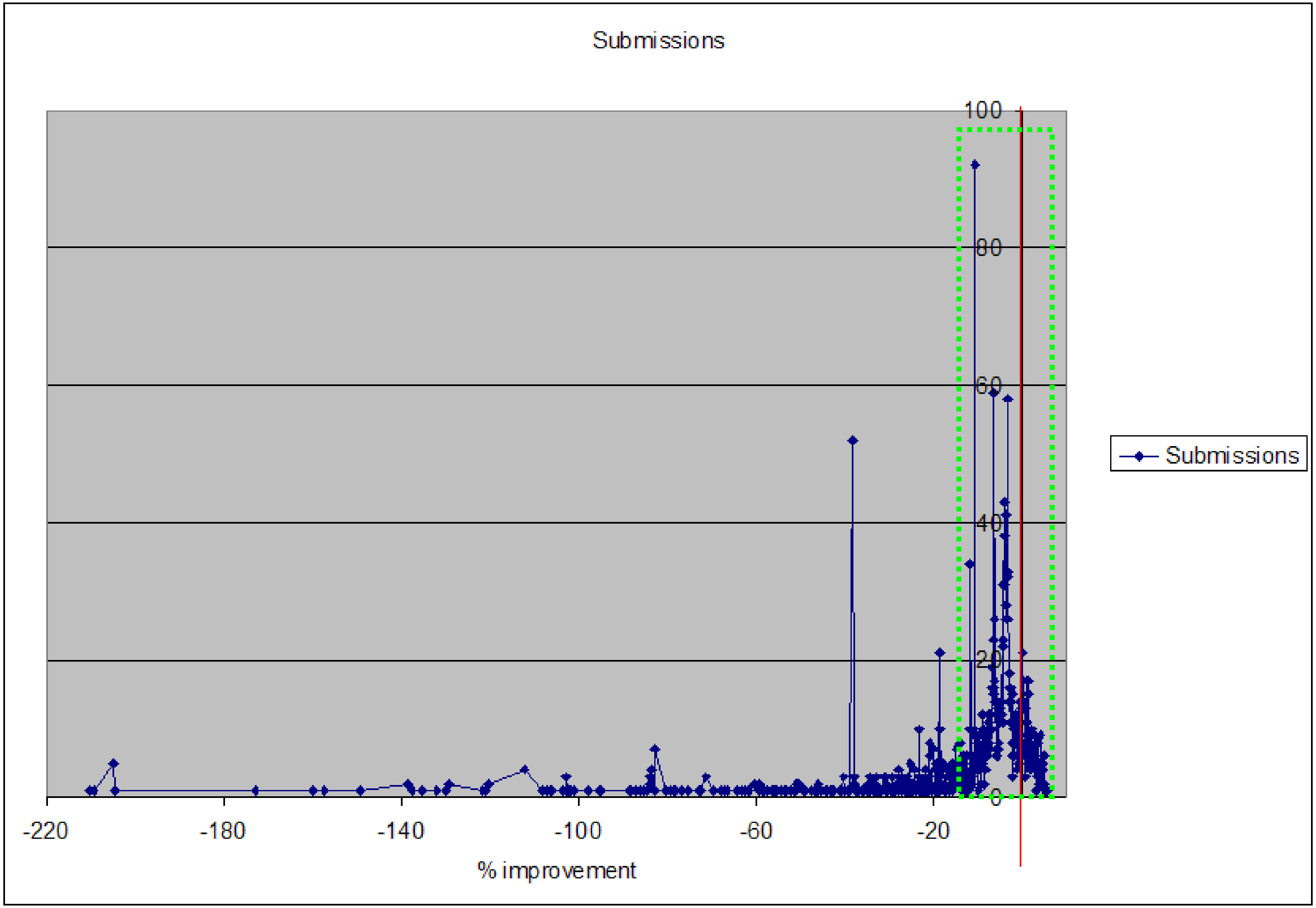
Progress in first 3 months

Oct 2, 2006	Launch of competition
Oct 8, 2006	WXY Consulting already better than Cinematch score
Oct 15, 2006	3 teams above Cinematch, one with 1.06% improvement (qualifying for $50k progress prize)
Dec, 2006:	Jim Bennett from Netflix describes progress so far during an invited talk at NIPS

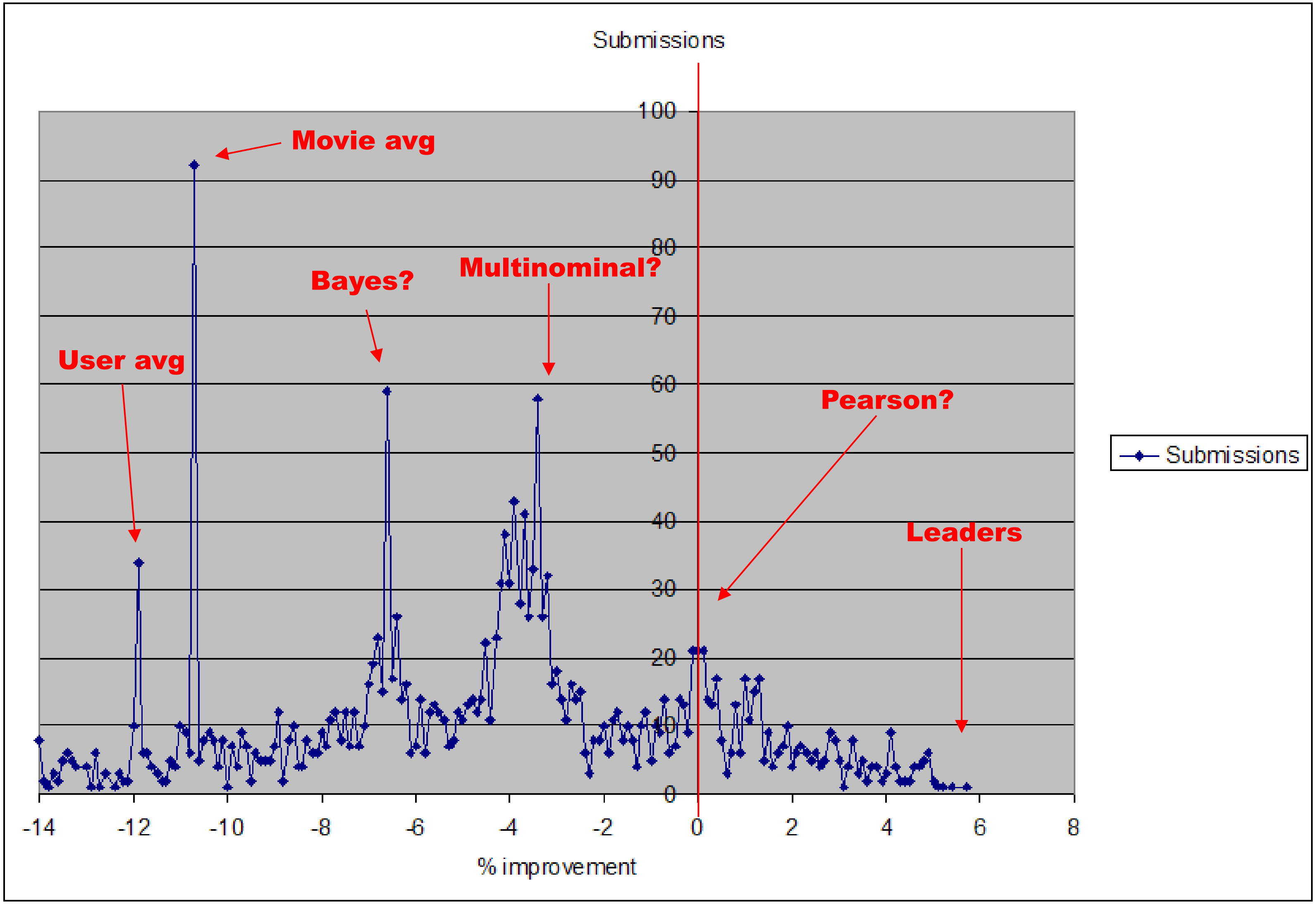
Prize Progress



Prize Submissions



Prize Submissions



The 13th International Conference on Knowledge Discovery and Data Mining
San Jose, California • Aug 12-15, 2007

Home
Program
KDD Cup
Registration
Travel
Organizers

KDD Cup

Co-organized by ACM SIGKDD and Netflix

KDD Cup is the first and the oldest data mining competition, and is an integral part of the annual ACM SIGKDD International Conference on Knowledge Discovery and Data Mining (KDD). This year's KDD Cup will be related to (but different from) the current Netflix Prize competition (**http://www.netflixprize.com/**). There will also be a workshop at the KDD-07 conference, where the participants of both the KDD Cup and the current Netflix Prize competition will present their papers and exchange ideas.

There are 2 parallel options for participating:*

1. The KDD Cup competition (open to all)
2. Workshop paper submissions (open to Netflix prize participants only)

Full details are provided at the KDD Cup and Workshop 2007 website:

http://www.cs.uic.edu/Netflix-KDD-Cup-2007

If you have any comments and suggestions, please email *liub@cs.uic.edu* .

Organizing Committee

- Jim Bennett, Neflix, USA
- Charles Elkan, University of California, San Diego, USA
- Bing Liu (Chair), University of Illinois at Chicago, USA
- Padhraic Smyth, University of California, Irvine, USA
- Domonkos Tikk, Budapest University of Technology and Economics, Hungary

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First Progress Prize, October 2007

Progress prize: $50k annually awarded to leading team provided there is at least 1% improvement over previous year

Sept 2nd	First progress prize "30 day" last call
Oct 2nd	Leaders were BellKor, 8.4% improvement (Yehuda Koren, Bob Bell, Chris Volinksy, AT&T Research)

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Sept 2nd	First progress prize "30 day" last call
Oct 2nd	Leaders were BellKor, 8.4% improvement (Yehuda Koren, Bob Bell, Chris Volinksy, AT&T Research)
Oct/Nov	Code and documentation submitted for judging
	Complicated methods: primarily relying on factor models
Nov 13	Winners officially declared and BellKor documentation published on Netflix Web site

Progress in 2008…

Progress slows down…improvements are incremental

Many of the leading prize contenders publishing their methods and techniques at academic conferences (2nd KDD workshop in August)

Much speculation on whether the prize would ever be won – is 10% even attainable?

Many initial participants had dropped out – too much time and effort to seriously compete

But leaderboard and forum still very active

Progress Prize 2008

Sept 2nd	Only 3 teams qualify for 1% improvement over previous year
Oct 2nd	Leading team has 9.4% overall improvement
Oct/Nov	Code/documentation reviewed and judged

Progress Prize 2008

Sept 2nd	Only 3 teams qualify for 1% improvement over previous year
Oct 2nd	Leading team has 9.4% overall improvement
Oct/Nov	Code/documentation reviewed and judged

Progress prize ($50,000) awarded to BellKor team of 3 AT&T researchers (same as before) plus 2 Austrian graduate students, Andreas Toscher and Martin Jahrer

Key winning strategy: clever "blending" of predictions from models used by both teams

Speculation that 10% would be attained by mid-2009

Example of Predictor Specifications....

OB-42 rmse=0.8998
MovieKNNV3, Residual: OB-39, Pearson correlation, $K = 13$, $\alpha = 658$, $\beta = 2480$, $\gamma = -2.6$, $\delta = 7.5$

OB-43 rmse=0.8971
SVD-AUF, Residual: OB-30, adaptiveUserFactorMode=KRR, kernelType=extended-polynomial, $\lambda = 4.78376$, $\alpha = 0.657533$, $\gamma = 0.720031$, $\beta = 3.27554$

OB-44 rmse=0.9245
GE, Residual: OB-35, 16 effects, $\alpha_1 = 374.977$, $\alpha_2 = 8.90702e-05$, $\alpha_3 = 2535.9$, $\alpha_4 = 900.414$, $\alpha_5 = 1.04115e-05$, $\alpha_6 = 2087.92$, $\alpha_7 = 131.291$, $\alpha_8 = 3173.84$, $\alpha_9 = 1.45471e-06$, $\alpha_{10} = 6.40823e-08$, $\alpha_{11} = 4451.15$, $\alpha_{12} = 274.423$, $\alpha_{13} = 1020.64$, $\alpha_{14} = 0.00758424$, $\alpha_{15} = 3858.57$, $\alpha_{16} = 0.00346888$

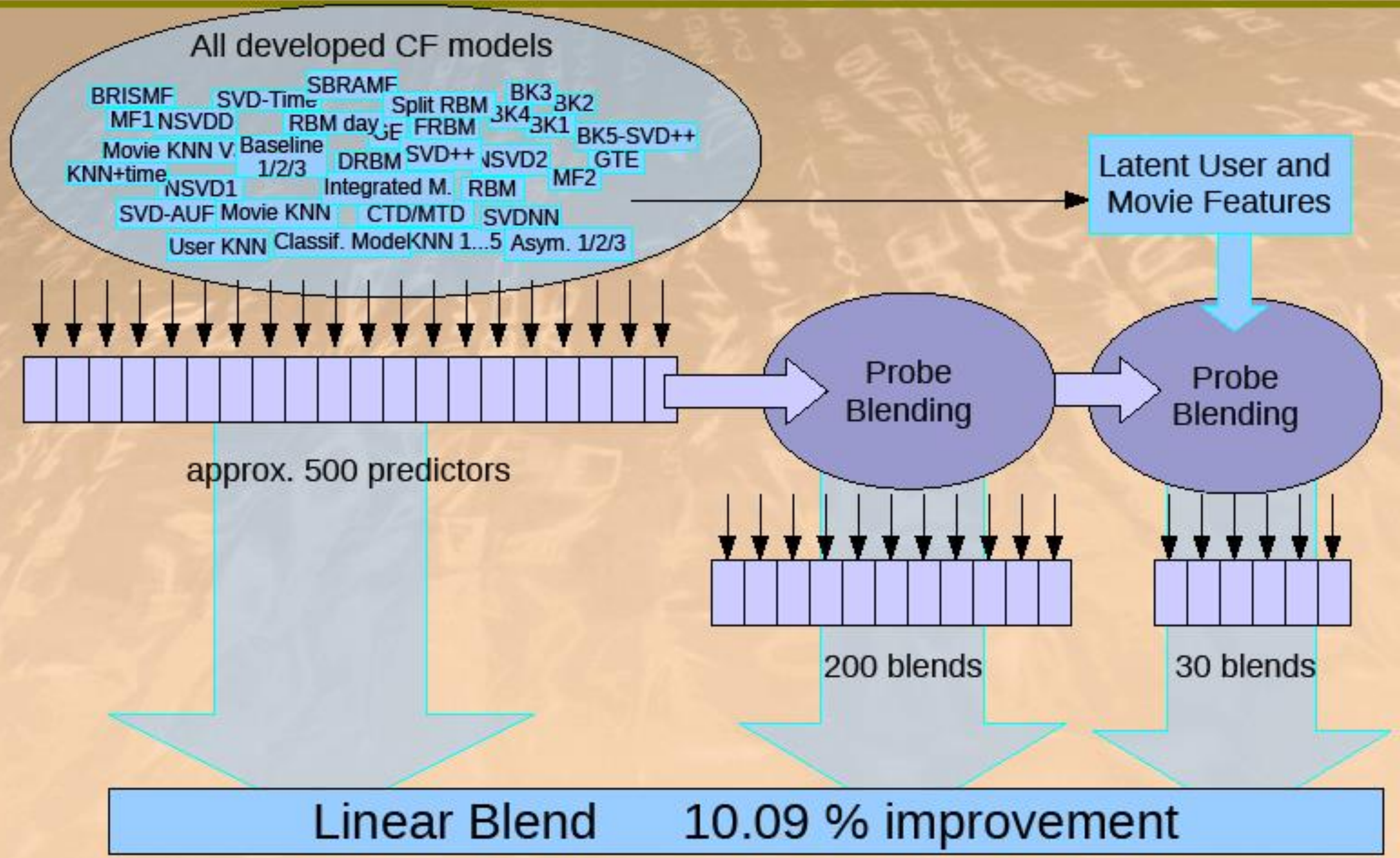
OB-45 rmse=0.8998
MovieKNNV3, Residual: OB-40, Spearman's rank correlation, $K = 38$, $\alpha = 667.6$, $\beta = 255.5$, $\gamma = -1.39$, $\delta = 3.3$

OB-46 rmse=0.8958
MovieKNNV3, Residual: OB-41, Pearson correlation, $K = 60$, $\alpha = 804$, $\beta = 231$, $\gamma = -2.6$, $\delta = 17$

OB-47 rmse=0.9777
NSVD2, Residual: no, $k = 50$, $\eta_i = 2e-3$, $\eta_u = 2e-3$, $\eta_{\mu_i} = 2e-3$, $\eta_{\mu_u} = 2e-3$, $\lambda_i = 5e-4$, $\lambda_u = 5e-4$, $\lambda_{\mu_i} = 1e-4$, $\lambda_{\mu_u} = 1e-4$, 3 epochs

The big picture

Solution of BellKor's Pragmatic Chaos



June 26th 2009: after 1000 Days and nights…

NETFLIX

Netflix Prize

Home | Rules | Leaderboard | Register | Update | Submit | Download

Leaderboard

Display top 20 leaders.

Rank	Team Name	Best Score	% Improvement	Last Submit Time
1	BellKor's Pragmatic Chaos	0.8558	10.05	2009-06-26 18:42:37
Grand Prize - RMSE <= 0.8563				
2	PragmaticTheory	0.8582	9.80	2009-06-25 22:15:51
3	BellKor in BigChaos	0.8590	9.71	2009-05-13 08:14:09
4	Grand Prize Team	0.8593	9.68	2009-06-12 08:20:24
5	Dace	0.8604	9.56	2009-04-22 05:57:03
6	BigChaos	0.8613	9.47	2009-06-23 23:06:52
Progress Prize 2008 - RMSE = 0.8616 - Winning Team: BellKor in BigChaos				
7	BellKor	0.8620	9.40	2009-06-24 07:16:02
8	Gravity	0.8634	9.25	2009-04-22 18:31:32
9	Opera Solutions	0.8638	9.21	2009-06-26 23:18:13
10	BruceDengDaoCiYiYou	0.8638	9.21	2009-06-27 00:55:55
11	pengpengzhou	0.8638	9.21	2009-06-27 01:06:43
12	xlvector	0.8639	9.20	2009-06-26 13:49:04
13	xiangliang	0.8639	9.20	2009-06-26 07:47:34
14	Feeds2	0.8641	9.18	2009-06-26 22:51:55
15	Ces	0.8642	9.17	2009-06-24 14:34:14

The Leading Team

- BellKorPragmaticChaos
  - BellKor:
    - Yehuda Koren (now Yahoo!), Bob Bell, Chris Volinsky, AT&T
  - BigChaos:
    - Michael Jahrer, Andreas Toscher, 2 grad students from Austria
  - Pragmatic Theory
    - Martin Chabert, Martin Piotte, 2 engineers from Montreal (Quebec)

- June 26th submission triggers 30-day "last call"

- Submission timed purposely to coincide with vacation schedules

The Last 30 Days

- Ensemble team formed
  - Group of other teams on leaderboard forms a new team
  - Relies on combining their models
  - Quickly also get a qualifying score over 10%

- BellKor
  - Continue to eke out small improvements in their scores
  - Realize that they are in direct competition with Ensemble

- Strategy
  - Both teams carefully monitoring the leaderboard
  - Only sure way to check for improvement is to submit a set of predictions
    - This alerts the other team of your latest score

24 Hours from the Deadline

- Submissions limited to 1 a day
  - So only 1 final submission could be made by either team in the last 24 hours
- 24 hours before deadline…
  - BellKor team member in Austria notices (by chance) that Ensemble posts a score that is slightly better than BellKor's
  - Leaderboard score disappears after a few minutes (rule loophole)
- Frantic last 24 hours for both teams
  - Much computer time on final optimization
  - run times carefully calibrated to end about an hour before deadline
- Final submissions
  - BellKor submits a little early (on purpose), 40 mins before deadline
  - Ensemble submits their final entry 20 mins later
  - ….and everyone waits….

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Netflix Prize

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Leaderboard

Display top 20 leaders.

Rank	Team Name	Best Score	% Improvement	ast Submit Time
1	The Ensemble	0.8553	10.10	2009-07-26 18:38:22
2	BellKor's Pragmatic Chaos	0.8554	10.09	009-07-26 18:18:28
Grand Prize - RMSE <= 0.8563				
3	Grand Prize Team	0.8571	9.91	2009-07-24 13:07:49
4	Opera Solutions and Vandelay United	0.8573	9.89	2009-07-25 20:05:52
5	Vandelay Industries !	0.8579	9.83	2009-07-26 02:49:53
6	PragmaticTheory	0.8582	9.80	2009-07-12 15:09:53
7	BellKor in BigChaos	0.8590	9.71	2009-07-26 12:57:25
8	Dace_	0.8603	9.58	2009-07-24 17:18:43
9	Opera Solutions	0.8611	9.49	2009-07-26 18:02:08
10	BellKor	0.8612	9.48	2009-07-26 17:19:11
11	BigChaos	0.8613	9.47	2009-06-23 23:06:52
12	Feeds2	0.8613	9.47	2009-07-24 20:06:46
Progress Prize 2008 - RMSE = 0.8616 - Winning Team: BellKor in BigChaos				
13	xiangliang	0.8633	9.26	2009-07-21 02:04:40
14	Gravity	0.8634	9.25	2009-07-26 15:58:34
15	Ces	0.8642	9.17	2009-07-25 17:42:38
16	Invisible Ideas	0.8644	9.14	2009-07-20 03:26:12
17	Just a guy in a garage	0.8650	9.08	2009-07-22 14:10:42
18	Craig Carmichael	0.8656	9.02	2009-07-25 16:00:54
19	J Dennis Su	0.8658	9.00	2009-03-11 09:41:54
20	acmehill	0.8659	8.99	2009-04-16 06:29:35
Progress Prize 2007 - RMSE = 0.8712 - Winning Team: KorBell				

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20	acmehill	0.8659	8.99	2009-04-16 06:29:35
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Training Data

100 million ratings

Held-Out Data

3 million ratings

1.5m ratings

Quiz Set:
scores
posted on
leaderboard

1.5m ratings

Test Set:
scores
known only
to Netflix

Scores used in
determining
final winner

Netflix Scoring and Judging

- Leaders on test set are contacted and submit their code and documentation (mid-August)

- Judges review documentation and inform winners that they have won $1 million prize (late August)

- Considerable speculation in press and blogs about which team has actually won

- News conference scheduled for Sept 21st in New York to announce winner and present $1 million check

NETFLIX

Netflix Prize

COMPLETED

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Leaderboard

Showing Test Score. Click here to show quiz score

Display top 20 leaders.

Rank	Team Name	Best Test Score	% Improvement	Best Submit Time
Grand Prize - RMSE = 0.8567 - Winning Team: BellKor's Pragmatic Chaos				
1	BellKor's Pragmatic Chaos	0.8567	10.06	2009-07-26 18:18:28
2	The Ensemble	0.8567	10.06	2009-07-26 18:38:22
3	Grand Prize Team	0.8582	9.90	2009-07-10 21:24:40
4	Opera Solutions and Vandelay United	0.8588	9.84	2009-07-10 01:12:31
5	Vandelay Industries !	0.8591	9.81	2009-07-10 00:32:20
6	PragmaticTheory	0.8594	9.77	2009-06-24 12:06:56
7	BellKor in BigChaos	0.8601	9.70	2009-05-13 08:14:09
8	Dace_	0.8612	9.59	2009-07-24 17:18:43
9	Feeds2	0.8622	9.48	2009-07-12 13:11:51
10	BigChaos	0.8623	9.47	2009-04-07 12:33:59
11	Opera Solutions	0.8623	9.47	2009-07-24 00:34:07
12	BellKor	0.8624	9.46	2009-07-26 17:19:11
Progress Prize 2008 - RMSE = 0.8627 - Winning Team: BellKor in BigChaos				
13	xiangliang	0.8642	9.27	2009-07-15 14:53:22
14	Gravity	0.8643	9.26	2009-04-22 18:31:32
15	Ces	0.8651	9.18	2009-06-21 19:24:53
16	Invisible Ideas	0.8653	9.15	2009-07-15 15:53:04
17	Just a guy in a garage	0.8662	9.06	2009-05-24 10:02:54
18	J Dennis Su	0.8666	9.02	2009-03-07 17:16:17
19	Craig Carmichael	0.8666	9.02	2009-07-25 16:00:54
20	acmehill	0.8668	9.00	2009-03-21 16:20:50
Progress Prize 2007 - RMSE = 0.8723 - Winning Team: KorBell				

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Netflix Prize

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Leaderboard

Showing Test Score. Click here to show quiz score

Display top 20 leaders.

Rank	Team Name	Best Test Score	% Improvement	Best Submit Time
Grand Prize - RMSE = 0.8567 - Winning Team: BellKor's Pragmatic Chaos				
1	BellKor's Pragmatic Chaos	0.8567	10.06	2009-07-26 18:18:28
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3	Grand Prize Team	[illegible]	[illegible]	[illegible]
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9	Feeds2	0.8622	9.48	2009-07-12 13:11:51
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20	acmehill	0.8668	9.00	2009-03-21 16:20:50
Progress Prize 2007 - RMSE = 0.8723 - Winning Team: KorBell				

Million Dollars Awarded Sept 21st 2009

Lessons Learned

Lessons Learned

- Scale is important
  - e.g., stochastic gradient descent on sparse matrices
- Latent factor models work well on this problem
  - Previously had not been explored for recommender systems
- Understanding your data is important, e.g., time-effects
- Combining models works surprisingly well
  - But final 10% improvement can probably be achieved by judiciously combining about 10 models rather than 1000's
  - This is likely what Netflix will do in practice
- Surprising amount of collaboration among participants

The New York Times

Netflix Competitors Learn the Power of Teamwork

By STEVE LOHR
Published: July 27, 2009

A contest set up by Netflix, which offered a $1 million prize to anyone who could significantly improve its movie recommendation system, ended on Sunday with two teams in a virtual dead heat, and no winner to be declared until September.

Enlarge This Image

Ozier Muhammad/The New York Times

Chris Volinsky, a scientist at AT&T Research, left, is on a high-ranking team in a Netflix contest. With him is Robert Bell.

Related

The Screens Issue: If You Liked This, You're Sure to Love That (November 23, 2008)

Times Topics: Netflix Inc.

But the contest, which began in October 2006, has already produced an impressive legacy. It has shaped careers, spawned at least one start-up company and inspired research papers. It has also changed conventional wisdom about the best way to build the automated systems that increasingly help people make online choices about movies, books, clothing, restaurants, news and other goods and services.

These so-called recommendation engines are computing models that predict what a person might enjoy based on statistical scoring of that person's stated preferences, past consumption patterns and similar choices made by many others — all made possible by the ease of data collection and tracking on the Web.

Why Collaboration?

Openness of competition structure

- Rules stated that winning solutions would be published
  - Non-exclusive license of winning software to Netflix
  - “Description of algorithm to be posted on site”
- Research workshops sponsored by Netflix
- Leaderboard was publicly visible: “it was addictive….”

Netflix Prize: Forum

Forum for discussion about the Netflix Prize and dataset.

You are not logged in.

Announcement

Congratulations to team "BellKor's Pragmatic Chaos" for being awarded the $1M Grand Prize on September 21, 2009. Stay tuned for details of the next contest, Netflix Prize 2.

Administrivia

Forum	Topics	Posts	Last post
Important Announcements	5	151	Today 04:29:38 by YehudaKoren
Registration Problems	1	1	2006-10-05 08:37:53 by prizemaster
Administrivia Administrative notes from the maintainers	3	43	2009-06-22 09:23:04 by dale5351
Prize and Forum FAQ	15	18	2009-03-24 10:18:36 by prizemaster
Request for new Category or Forum Want to add a new high-level Category or Forum? This is the place to ask or comment.	18	40	2008-04-29 20:50:19 by filmmakershelp

Awarded Prizes

Forum	Topics	Posts	Last post
Grand Prize	1	14	2009-10-09 12:18:23 by statistician
Progress Prize 2008	2	17	2009-03-18 02:40:53 by CS1
Progress Prize 2007	5	29	2008-10-06 06:51:51 by dinc3r

Questions (and answers)

Forum	Topics	Posts	Last post

Why Collaboration?

Development of Online Community

- Active Netflix prize forum + other blogs
- Quickly acquired "buzz"
- Forum was well-moderated by Netflix
- Attracted discussion from novices and experts alike
- Early posting of code and solutions
- Early self-identification (links via leaderboard)

Why Collaboration?

Academic/Research Culture

- Nature of competition was technical/mathematical
- Attracted students, hobbyists, researchers
- Many motivated by fundamental interest in producing better algorithms - $1 million would be a nice bonus
- History in academic circles of being open, publishing, sharing

Why Collaboration?

Technical Reasons

- Realization that combining many different models and techniques always produced small but systematic improvements

  (Statistical theory supports this….)

- “Teaming” was strategically attractive

- Particularly for the “end-game” (summer 2009), teaming was quite critical in terms of who won the competition

Questions

- Does reduction in squared error metric correlate with real improvements in user satisfaction?

- Are these competitions good for scientific research?
  - Should researchers be solving other more important problems?

- Are competitions a good strategy for companies?

Law Blog

WSJ on the cases, trends and personalities of interest to the business community.

« On Congress, the Estate Tax and the Constitution

Are Too Man
Pressured In
Guilty?

DECEMBER 18, 2009, 4:32 PM ET

Did Netflix Violate Subscribers' Privacy? Lawsuit Says Yes

By Ashby Jones

A potentially very interesting lawsuit was filed in San Jose, Calif., on Thursday concerning a closeted lesbian's privacy and Netflix, the movie rental company.

The woman, an Ohio resident who, for purposes of the lawsuit has requested anonymity, sued Netflix alongside others hoping to sue on behalf of a potential class, claiming that the company divulged personal information which allowed thousands to discern her sexual preference. Click here for the story, from Wired; here for the complaint.

Here's the backstory. In 2006, Netflix initiated a contest in which it would pay $1 million to the first person or team of people to make certain improvements to its recommendation system —

Links to additional information

- Netflix prize page (FAQs, rules, forum, etc)

  http://www.netflixprize.com/

- Page with links to articles, blogs, etc

  http://www.research.att.com/~volinsky/netflix/bpc.html