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Recommender Systems: Latent Factor Models

CS547 Machine Learning for Big Data

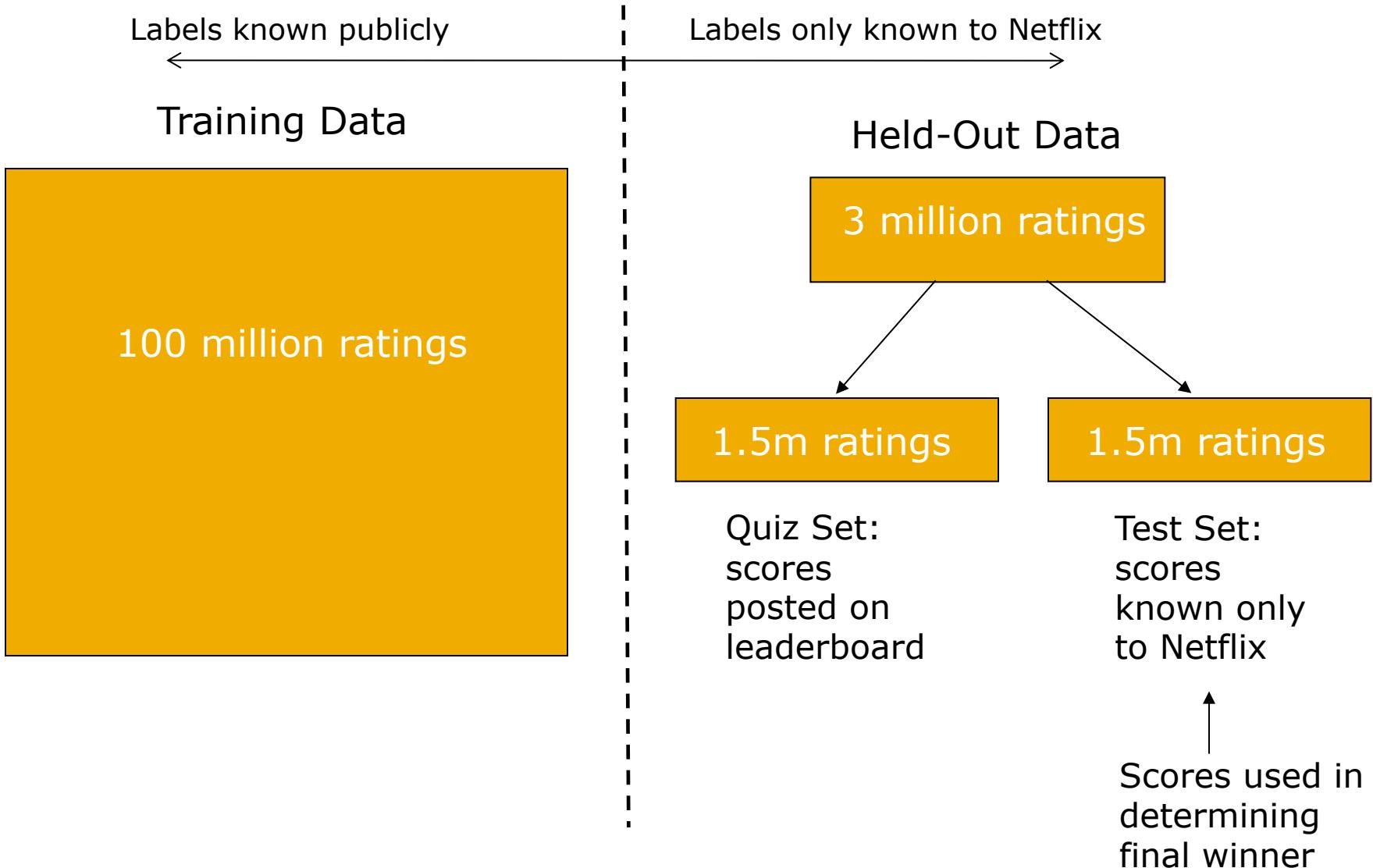
Tim Althoff

W PAUL G. ALLEN SCHOOL
OF COMPUTER SCIENCE & ENGINEERING

The Netflix Prize

- **Training data**
 - 100 million ratings, 480,000 users, 17,770 movies
 - 6 years of data: 2000-2005
- **Test data**
 - Last few ratings of each user (2.8 million)
 - **Evaluation criterion:** Root Mean Square Error (RMSE) =
$$\sqrt{\frac{1}{|R|} \sum_{(i,x) \in R} (\hat{r}_{xi} - r_{xi})^2}$$
 - **Netflix's system RMSE: 0.9514**
- **Competition**
 - 2,700+ teams
 - **\$1 million prize for 10% improvement on Netflix**

Competition Structure



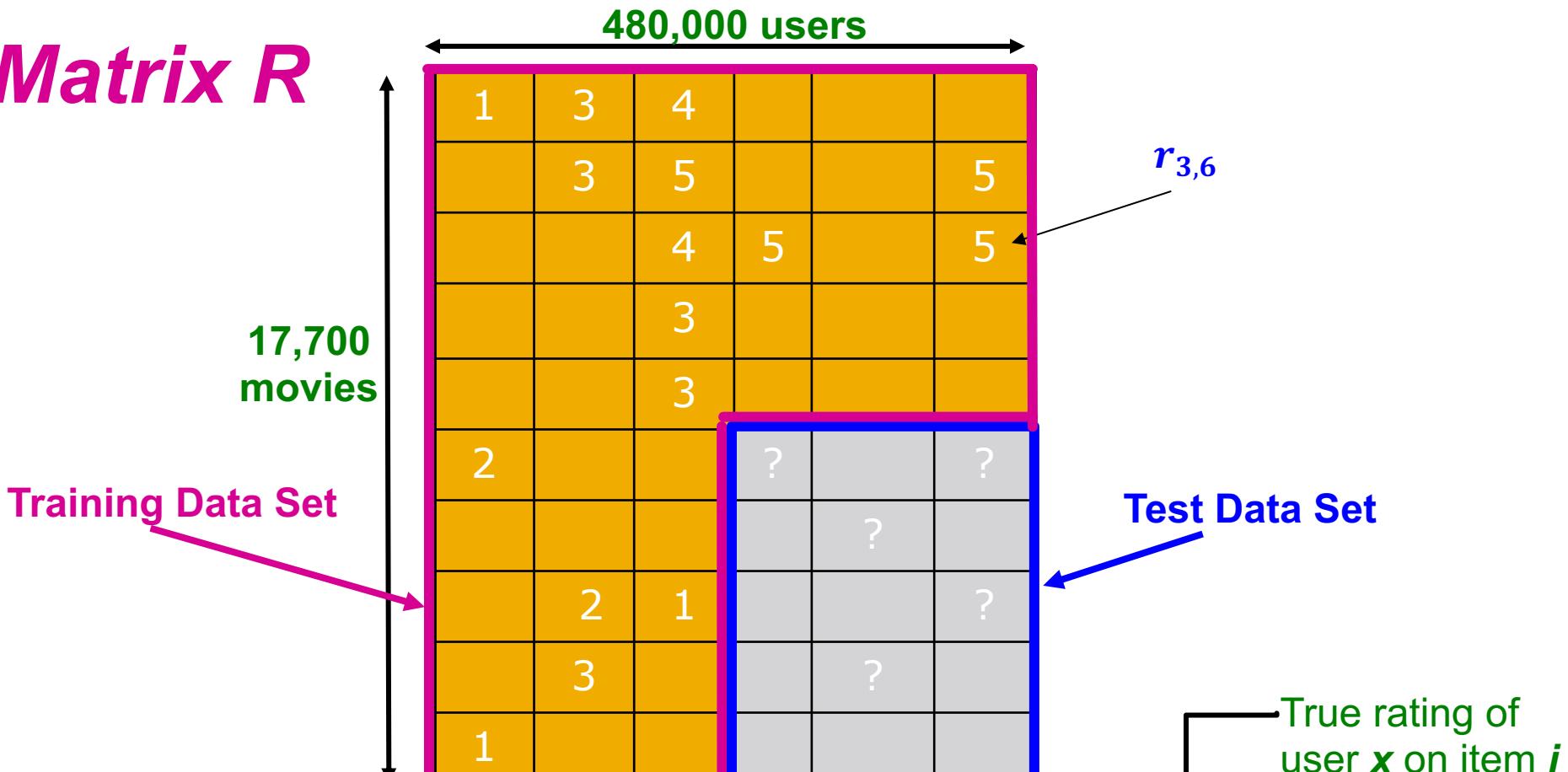
The Netflix Utility Matrix R

Matrix R

480,000 users					
17,700 movies	1	3	4		
		3	5		5
			4	5	
			3		
			3		
	2			2	2
					5
		2	1		1
		3			3
	1				

Utility Matrix R : Evaluation

Matrix R



$$\text{RMSE} = \frac{1}{|R|} \sqrt{\sum_{(i,x) \in R} (\hat{r}_{xi} - r_{xi})^2}$$

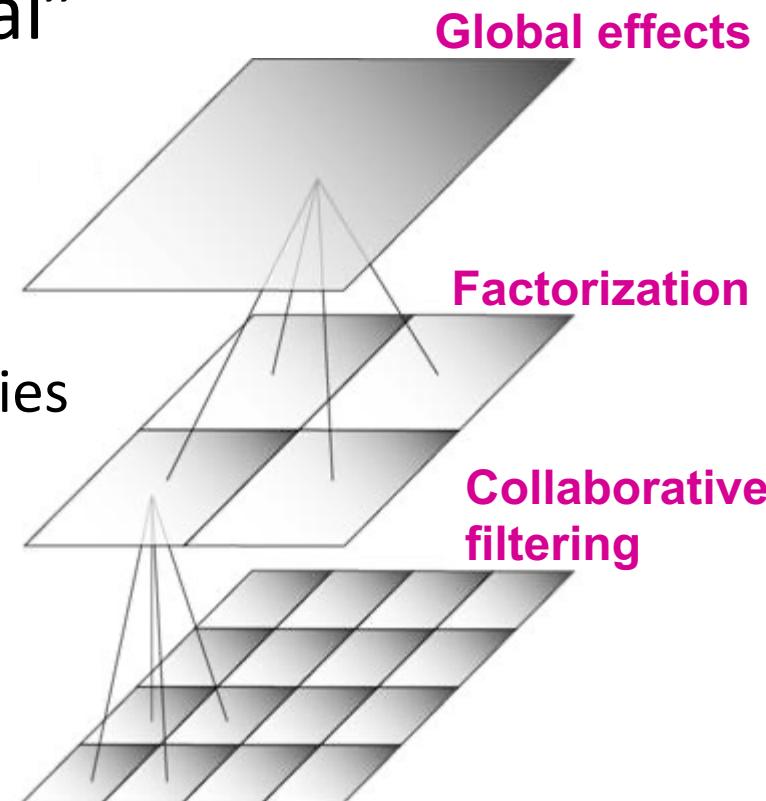
↑
Predicted rating

BellKor Recommender System

- The winner of the Netflix Challenge
- Multi-scale modeling of the data:

Combine top level, “regional” modeling of the data, with a refined, local view:

- Global:
 - Overall deviations of users/movies
- Factorization:
 - Addressing “regional” effects
- Collaborative filtering:
 - Extract local patterns



Modeling Local & Global Effects

■ Global:

- Mean movie rating: **3.7 stars**
- *The Sixth Sense* is **0.5 stars** above avg.
- Joe rates **0.2 stars** below avg.



→ **Baseline estimation:**

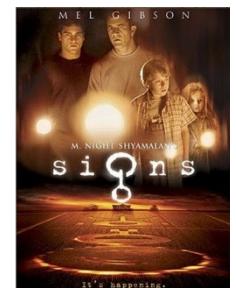
Joe will rate *The Sixth Sense* 4 stars

- That is $4 = 3.7 + 0.5 - 0.2$

■ Local neighborhood (CF/NN):

- Joe didn't like related movie *Signs*
- → **Final estimate:**

Joe will rate *The Sixth Sense* 3.8 stars



Recap: Collaborative Filtering (CF)

- The earliest and the most popular **collaborative filtering method**
- Derive unknown ratings from those of “similar” movies (item-item variant)
- Define **similarity metric** s_{ij} of items i and j
- Select k -nearest neighbors, compute the rating
 - $N(i; x)$: items most similar to i that were rated by x

$$\hat{r}_{xi} = \frac{\sum_{j \in N(i; x)} s_{ij} \cdot r_{xj}}{\sum_{j \in N(i; x)} s_{ij}}$$

s_{ij} ... similarity of items i and j
 r_{xj} ... rating of user x on item j
 $N(i; x)$... set of items similar to item i that were rated by x

Modeling Local & Global Effects

- In practice we get better estimates if we model deviations:

$$\hat{r}_{xi} = b_{xi} + \frac{\sum_{j \in N(i;x)} s_{ij} \cdot (r_{xj} - b_{xj})}{\sum_{j \in N(i;x)} s_{ij}}$$

baseline estimate for r_{xi}

$$b_{xi} = \mu + b_x + b_i$$

μ = overall mean rating

b_x = rating deviation of user x

= (avg. rating of user x) – μ

b_i = (avg. rating of movie i) – μ

Problems/Issues:

- Similarity metrics are “arbitrary”
- Pairwise similarities neglect interdependencies among users
- Taking a weighted average can be restricting

Solution: Instead of s_{ij} use w_{ij} that we estimate directly from data

Idea: Interpolation Weights w_{ij}

- Use a **weighted sum** rather than **weighted avg.**:

$$\widehat{r}_{xi} = b_{xi} + \sum_{j \in N(i; x)} w_{ij} (r_{xj} - b_{xj})$$

- **A few notes:**

- $N(i; x)$... set of movies rated by user x that are similar to movie i
- w_{ij} is the **interpolation weight** (some real number)
 - Note, we allow: $\sum_{j \in N(i; x)} w_{ij} \neq 1$
- w_{ij} models interaction between pairs of movies (it does not depend on user x)

Idea: Interpolation Weights w_{ij}

- $\hat{r}_{xi} = b_{xi} + \sum_{j \in N(i,x)} w_{ij} (r_{xj} - b_{xj})$
- How to set w_{ij} ?
 - Remember, error metric is: $\frac{1}{|R|} \sqrt{\sum_{(i,x) \in R} (\hat{r}_{xi} - r_{xi})^2}$
or equivalently SSE: $\sum_{(i,x) \in R} (\hat{r}_{xi} - r_{xi})^2$
 - Find w_{ij} that minimize SSE on training data!
 - Models relationships between item i and its neighbors j
 - w_{ij} can be learned/estimated based on x and all other users that rated i

Why is this a good idea?

Recommendations via Optimization

- **Goal: Make good recommendations**
 - Quantify goodness using **RMSE**:
Lower RMSE --> better recommendations
 - Really want to make good recommendations on items that user has not yet seen. **Can't really do this!**
 - **Let's set build a system such that it works well on known (user, item) ratings (generalization)**
And **hope** the system will also predict well the **unknown ratings**

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

Recommendations via Optimization

- Idea: Let's set values w such that they work well on known (user, item) ratings
- How to find such values w ?
- Idea: Define an objective function and solve the optimization problem
- Find w_{ij} that minimize SSE on training data!

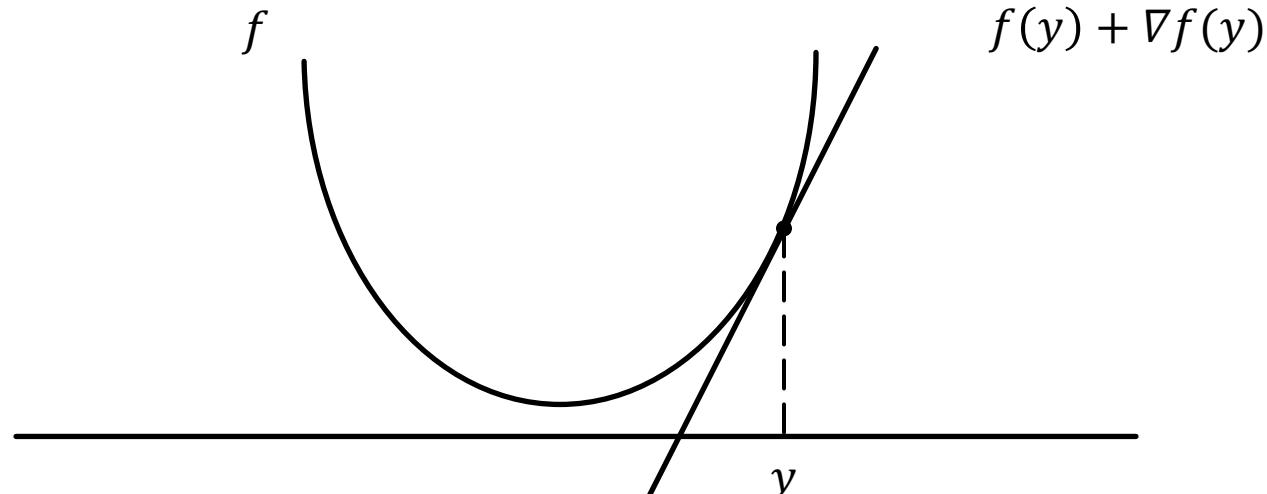
$$J(w) = \sum_{x,i \in R} \left(\underbrace{\left(b_{xi} + \sum_{j \in N(i;x)} w_{ij}(r_{xj} - b_{xj}) \right)}_{\text{Predicted rating}} - r_{xi} \right)^2$$

True rating

- Think of w as a vector of numbers

Detour: Minimizing a function

- A simple way to minimize a function $f(x)$:
 - Compute the derivative $\nabla f(x)$
 - Start at some point y and evaluate $\nabla f(y)$
 - Make a step in the reverse direction of the gradient: $y = y - \nabla f(y)$
 - Repeat until convergence



Interpolation Weights

- We have the optimization problem, now what?
- Gradient descent:

■ Iterate until convergence: $w \leftarrow w - \eta \nabla_w J$ η ... learning rate

where $\nabla_w J$ is the gradient (derivative evaluated on data):

$$\nabla_w J = \left[\frac{\partial J(w)}{\partial w_{ij}} \right] = 2 \sum_{x,i \in R} \left(\left[b_{xi} + \sum_{k \in N(i;x)} w_{ik} (r_{xk} - b_{xk}) \right] - r_{xi} \right) (r_{xj} - b_{xj})$$

for $j \in \{N(i; x), \forall i, \forall x\}$

else $\frac{\partial J(w)}{\partial w_{ij}} = 0$

- Note: We fix movie i , go over all r_{xi} , for every movie $j \in N(i; x)$, we compute $\frac{\partial J(w)}{\partial w_{ij}}$

while $|w_{new} - w_{old}| > \epsilon$:

$w_{old} = w_{new}$

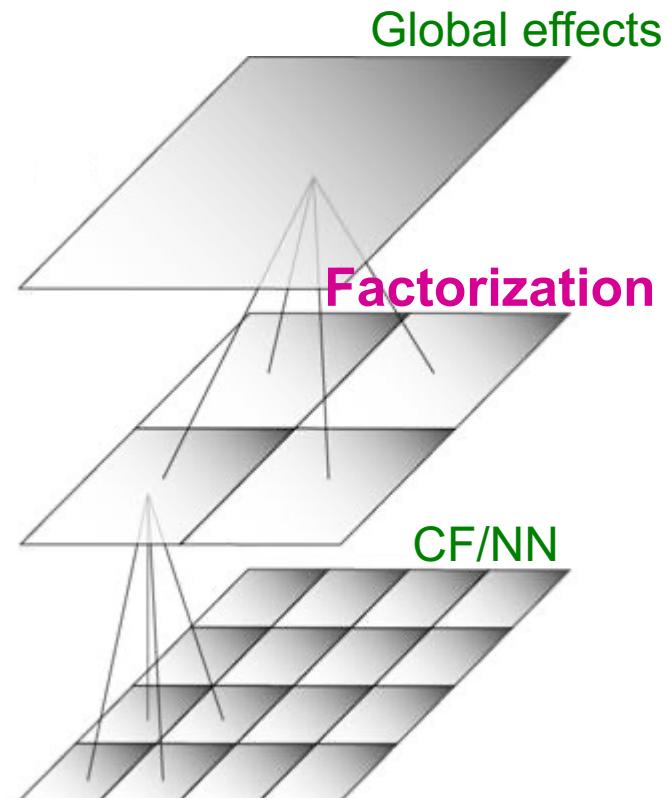
$w_{new} = w_{old} - \eta \cdot \nabla w_{old}$

Interpolation Weights

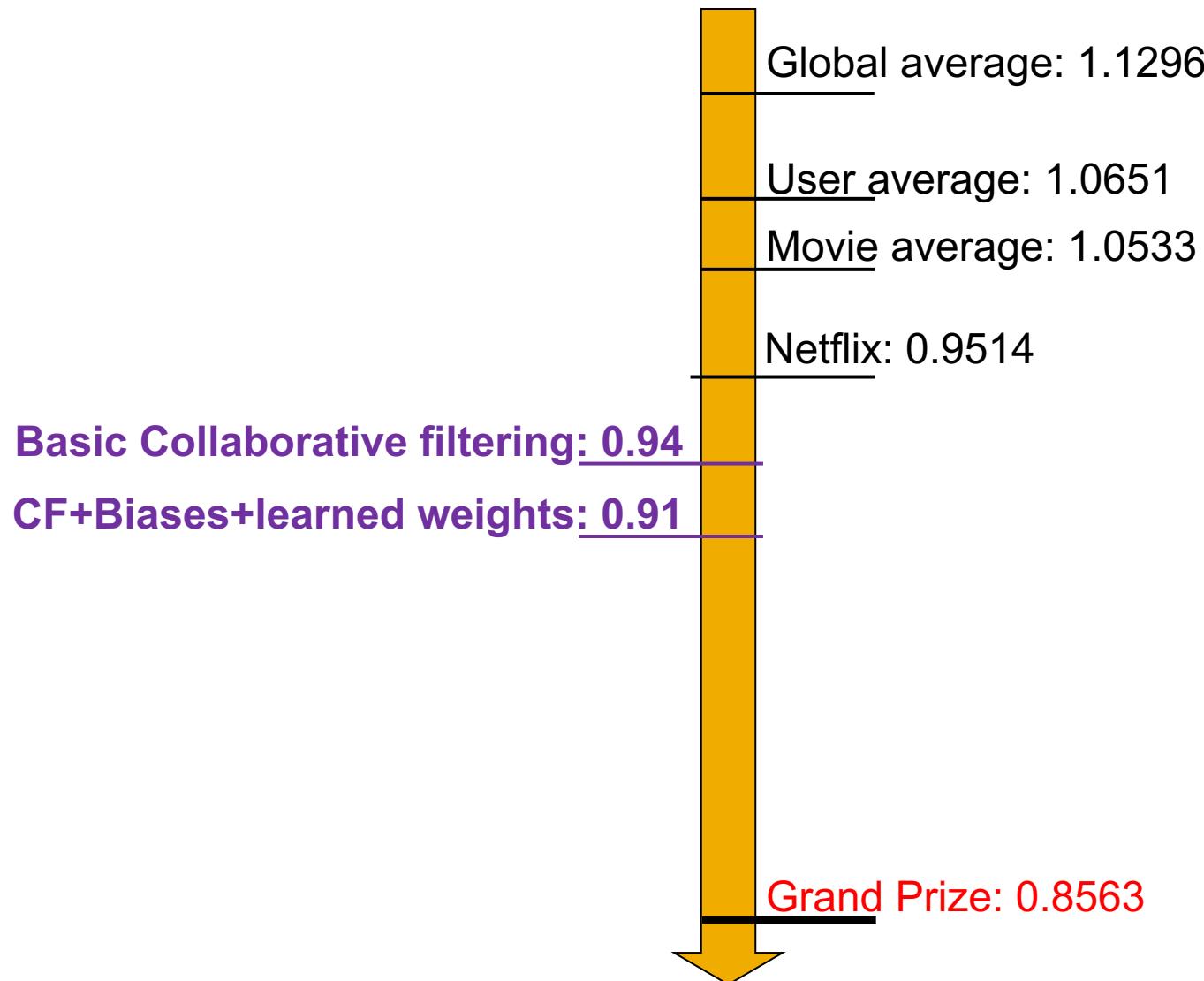
- So far: $\widehat{r}_{xi} = b_{xi} + \sum_{j \in N(i;x)} w_{ij}(r_{xj} - b_{xj})$

- Weights w_{ij} derived based on their roles; **no use of an arbitrary similarity metric** ($w_{ij} \neq s_{ij}$)
- Explicitly account for interrelationships among the neighboring movies

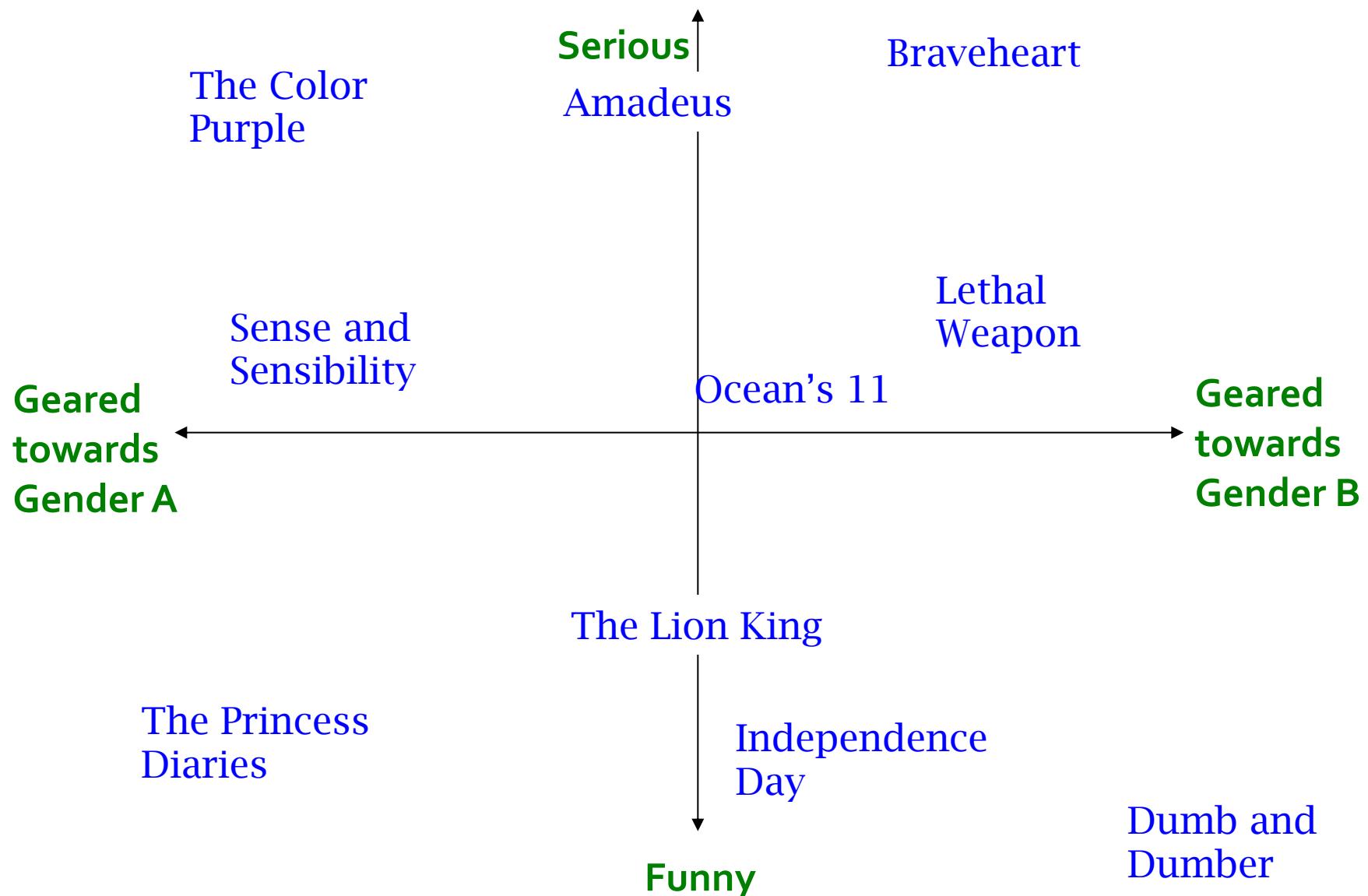
- **Next: Latent factor model**
 - Extract “regional” correlations



Performance of Various Methods



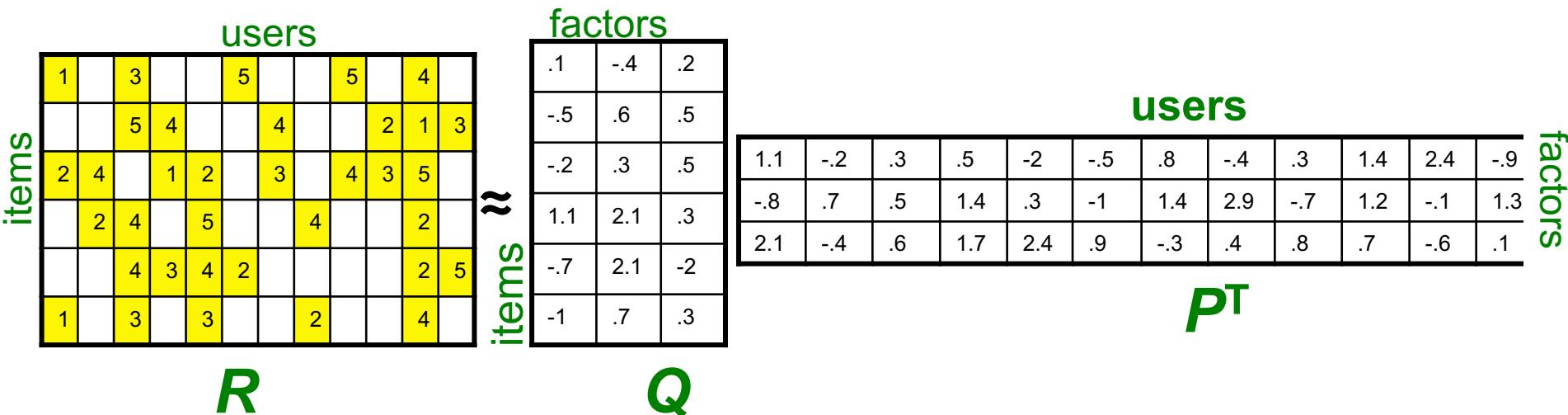
Latent Factor Models (e.g., SVD)



Latent Factor Models

$$\text{SVD: } A = U \Sigma V^T$$

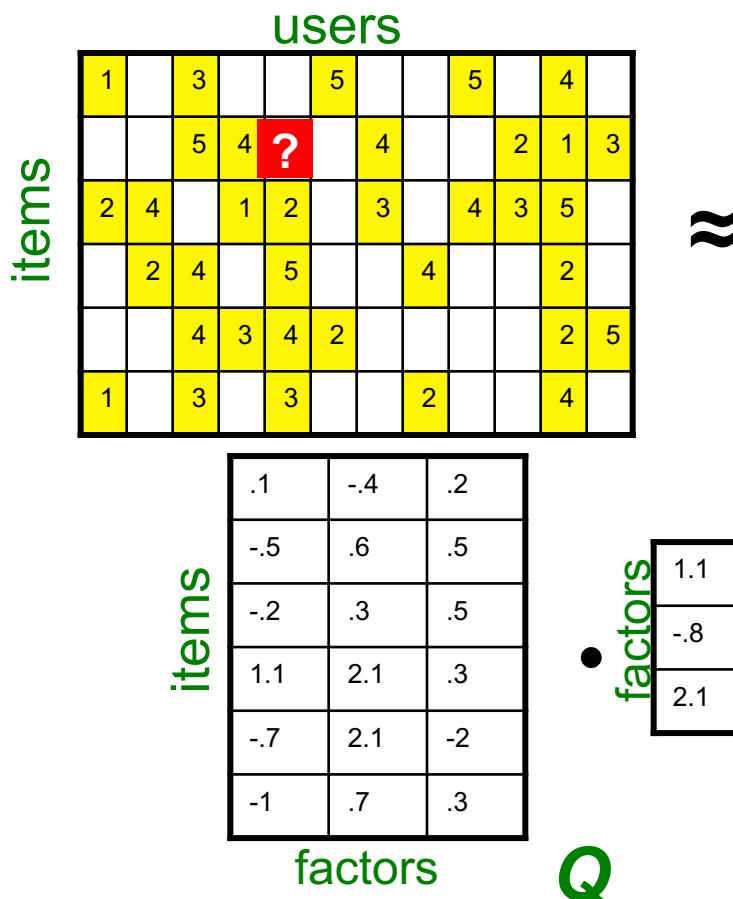
- “SVD” on Netflix data: $R \approx Q \cdot P^T$



- For now let's assume we can approximate the rating matrix R as a product of “thin” $Q \cdot P^T$
 - R has missing entries but let's ignore that for now!
 - Basically, we want the reconstruction error to be small on known ratings and we don't care about the values on the missing ones

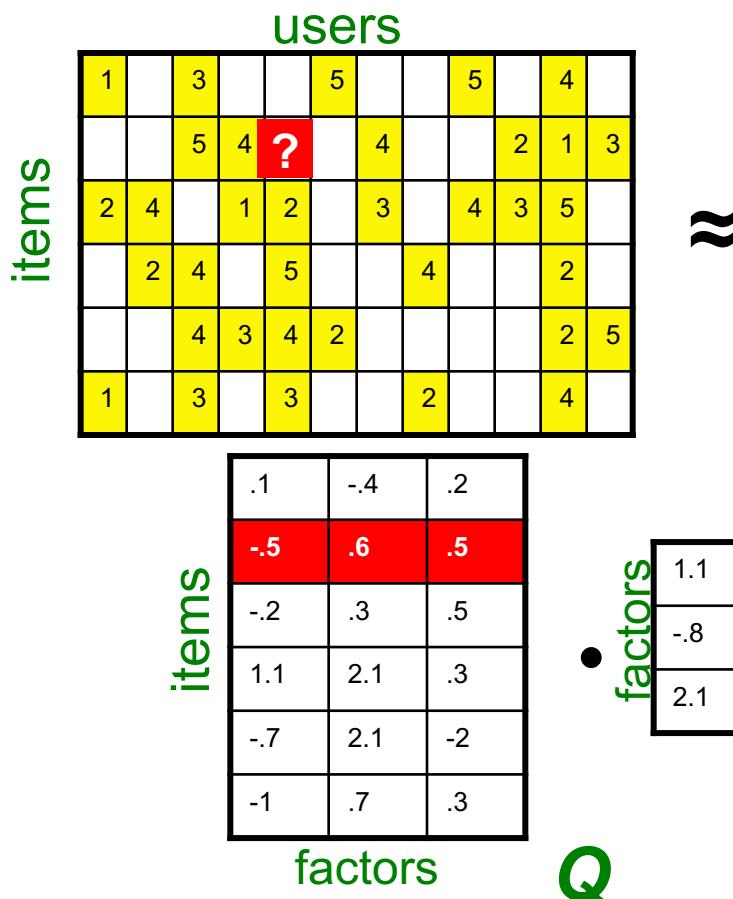
Ratings as Products of Factors

- How to estimate the missing rating of user x for item i ?



Ratings as Products of Factors

- How to estimate the missing rating of user x for item i ?



$$\hat{r}_{xi} = q_i \cdot p_x$$
$$= \sum_f q_{if} \cdot p_{xf}$$

q_i = row i of Q
 p_x = column x of P^T

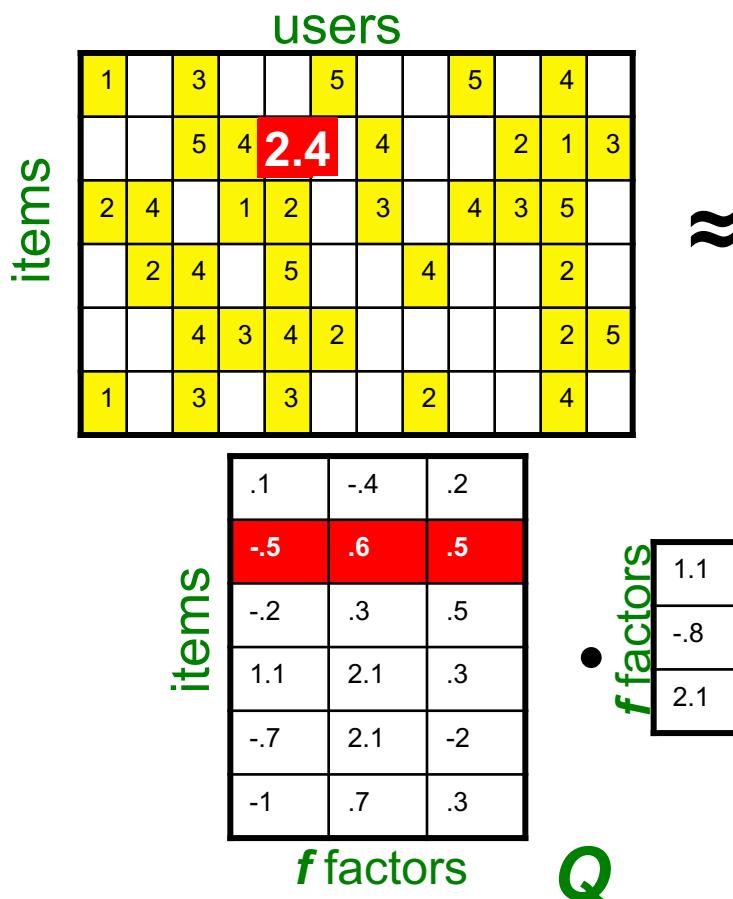
users

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

P^T

Ratings as Products of Factors

- How to estimate the missing rating of user x for item i ?

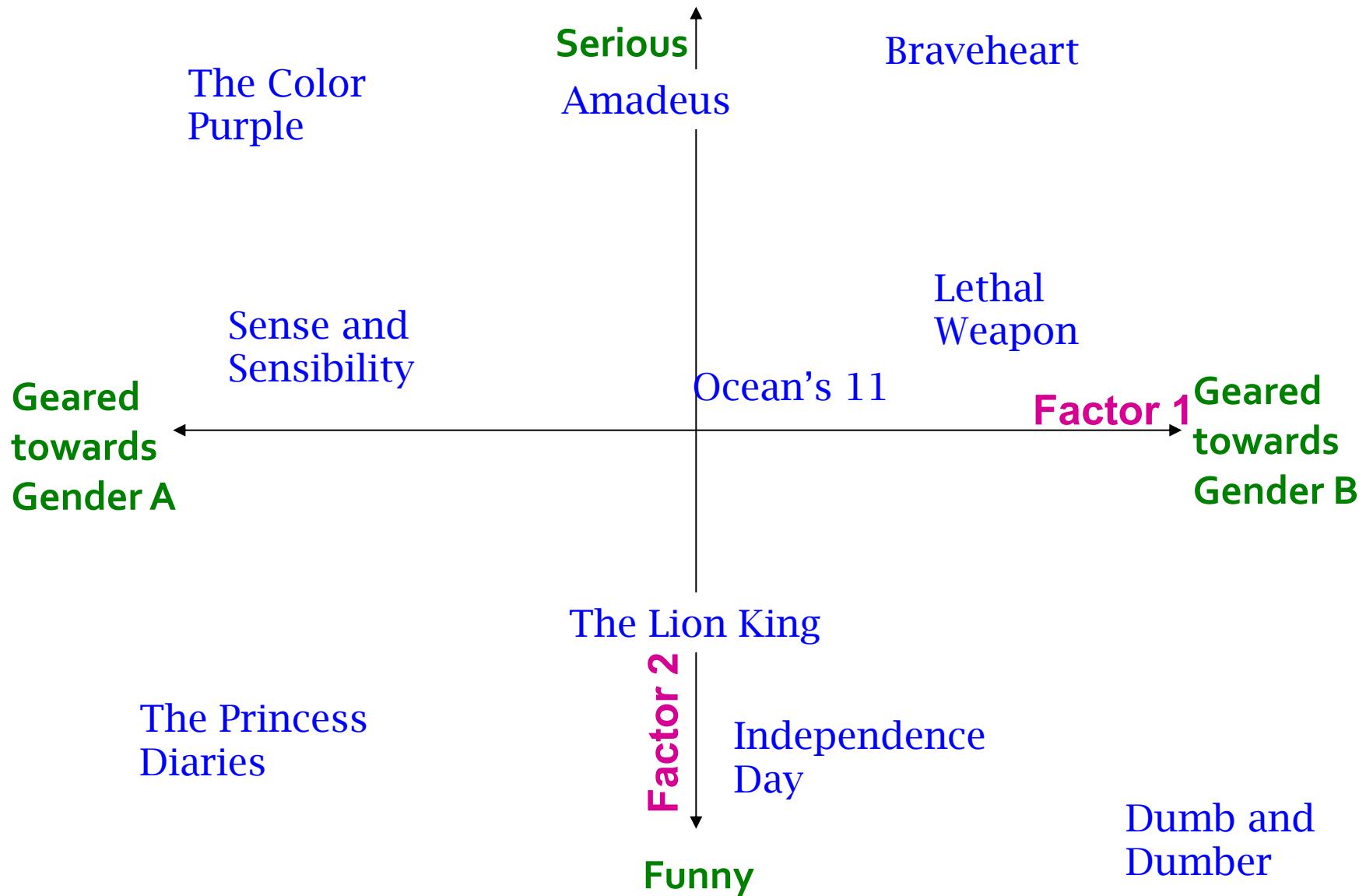


users

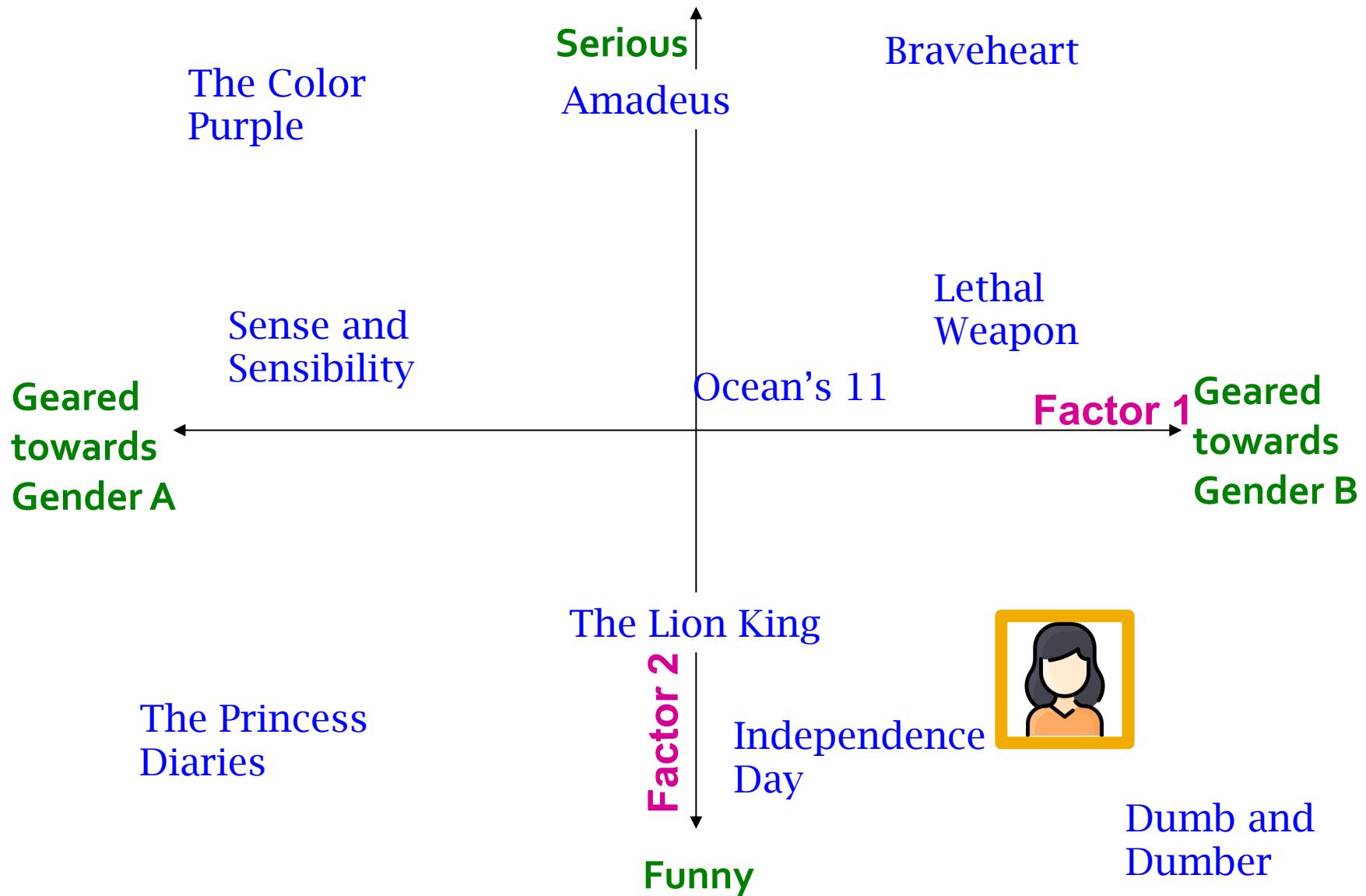
P^T

.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	

Latent Factor Models

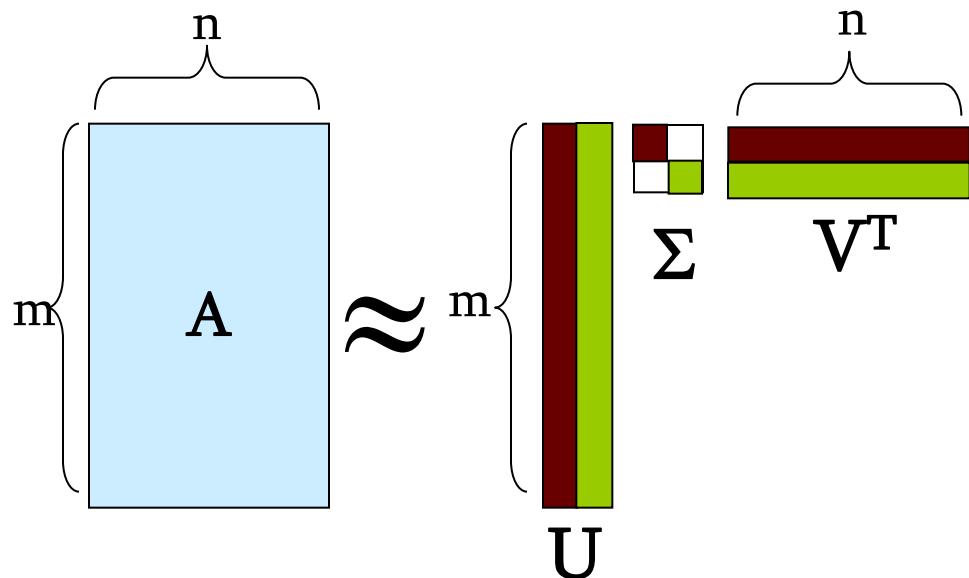


Latent Factor Models



Recap: SVD

- Remember SVD:
 - A : Input data matrix
 - U : Left singular vecs
 - V^T : Right singular vecs
 - Σ : Singular values



- So in our case:

“SVD” on Netflix data: $R \approx Q \cdot P^T$

$$A = R, \quad Q = U, \quad P^T = \Sigma \quad V^T$$

$$\hat{r}_{xi} = q_i \cdot p_x$$

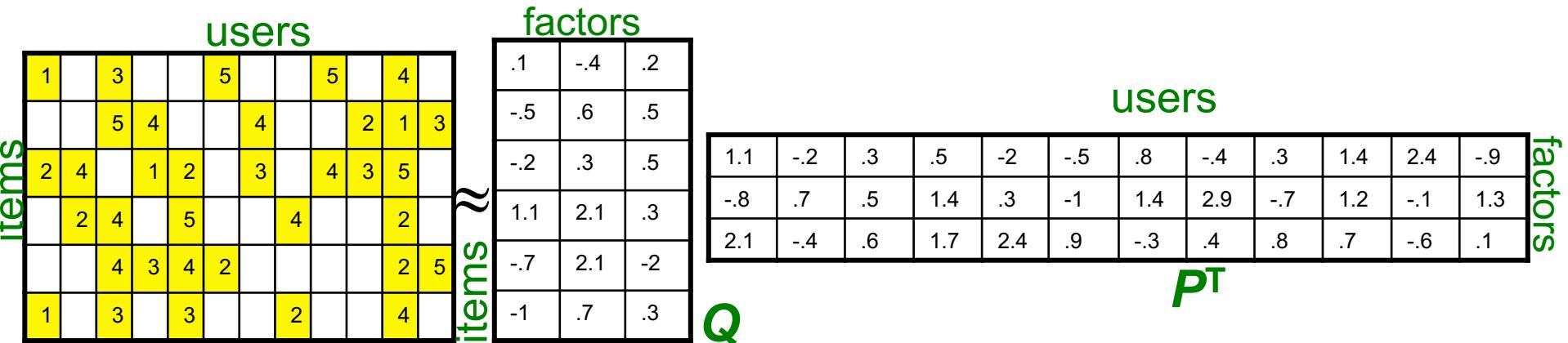
SVD: More good stuff

- We already know that SVD gives minimum reconstruction error (Sum of Squared Errors):

$$\min_{U,V,\Sigma} \sum_{ij \in A} (A_{ij} - [U\Sigma V^T]_{ij})^2$$

- Note two things:
 - SSE and RMSE are monotonically related:
 - $RMSE = \frac{1}{c} \sqrt{SSE}$ Great news: SVD is minimizing RMSE!
 - Complication: The sum in SVD error term is over all entries (no-rating is interpreted as zero-rating). But our R has missing entries!

Latent Factor Models



- SVD isn't defined when entries are missing!
- Use specialized methods to find P, Q

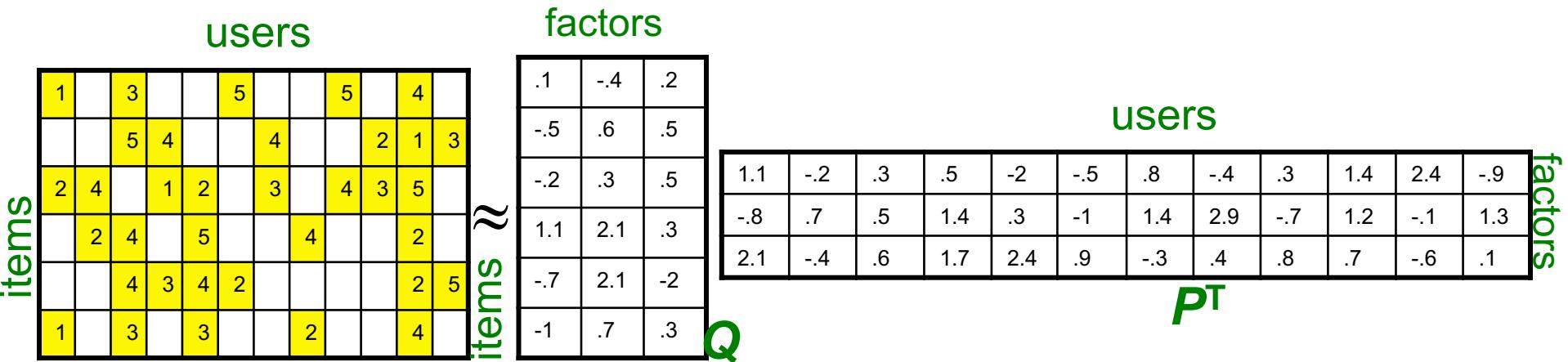
- $\min_{P,Q} \sum_{(i,x) \in R} (r_{xi} - q_i \cdot p_x)^2 \quad \hat{r}_{xi} = q_i \cdot p_x$
- Note:
 - We don't require cols of P, Q to be orthogonal/unit length
 - P, Q map users/movies to a latent space
 - This was the most popular model among Netflix contestants

Finding the Latent Factors

Latent Factor Models

- Our goal is to find P and Q such that:

$$\min_{P,Q} \sum_{(i,x) \in R} (r_{xi} - q_i \cdot p_x)^2$$



Back to Our Problem

- Want to minimize SSE for unseen test data
- Idea: Minimize SSE on training data
 - Want large k (# of factors) to capture all the signals
 - But, SSE on test data begins to rise for $k > 2$
- This is a classical example of **overfitting**:
 - With too much freedom (too many free parameters) the model starts fitting noise
 - That is, the model fits too well the training data and is thus **not generalizing** well to unseen test data

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

Dealing with Missing Entries

- To solve overfitting we introduce regularization:

- Allow rich model where there is sufficient data
- Shrink aggressively where data is scarce

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

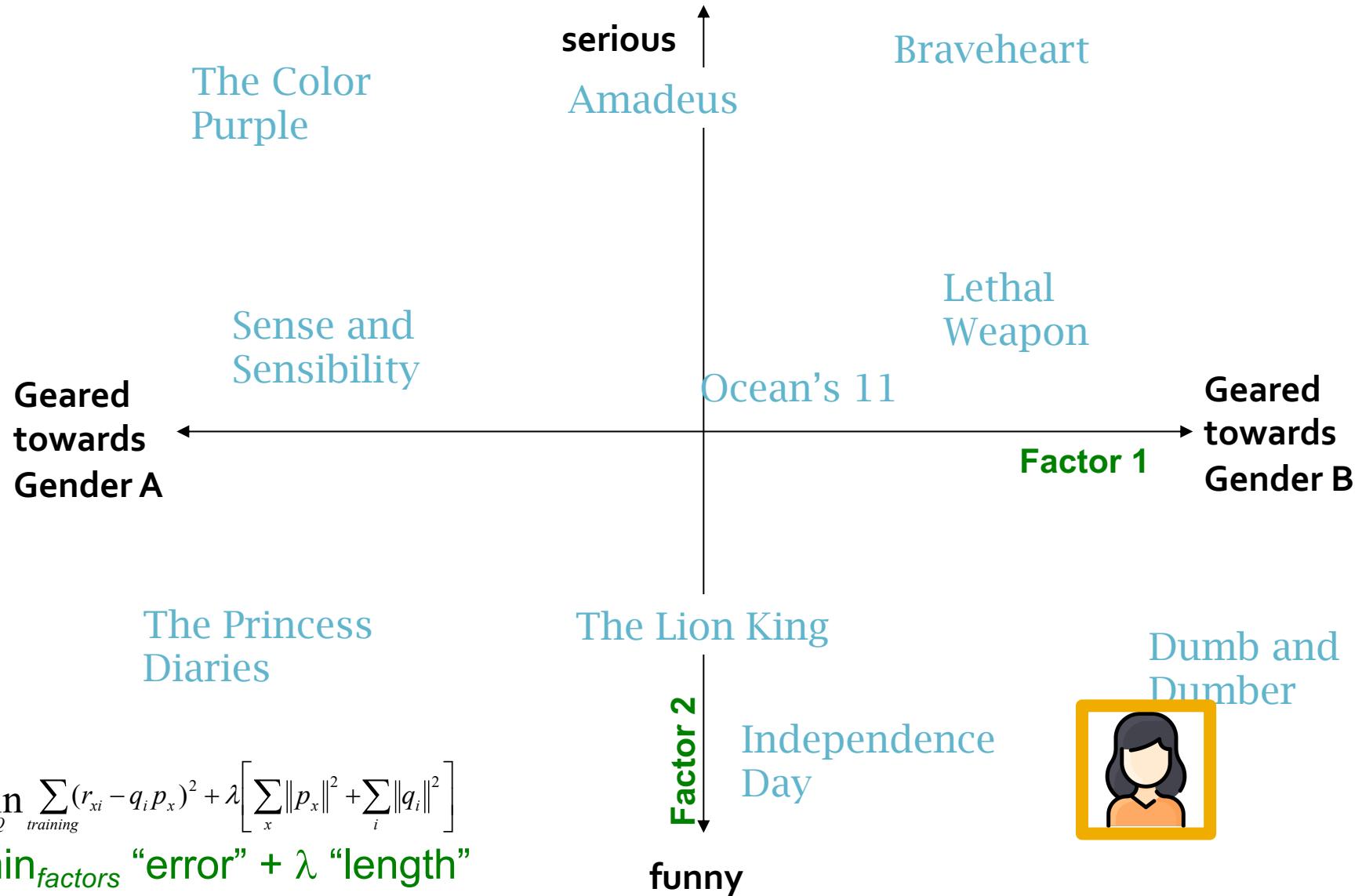
$$\min_{P,Q} \sum_{\text{training}} (r_{xi} - q_i p_x)^2 + \left[\lambda_1 \sum_x \|p_x\|^2 + \lambda_2 \sum_i \|q_i\|^2 \right]$$

“error” “length”

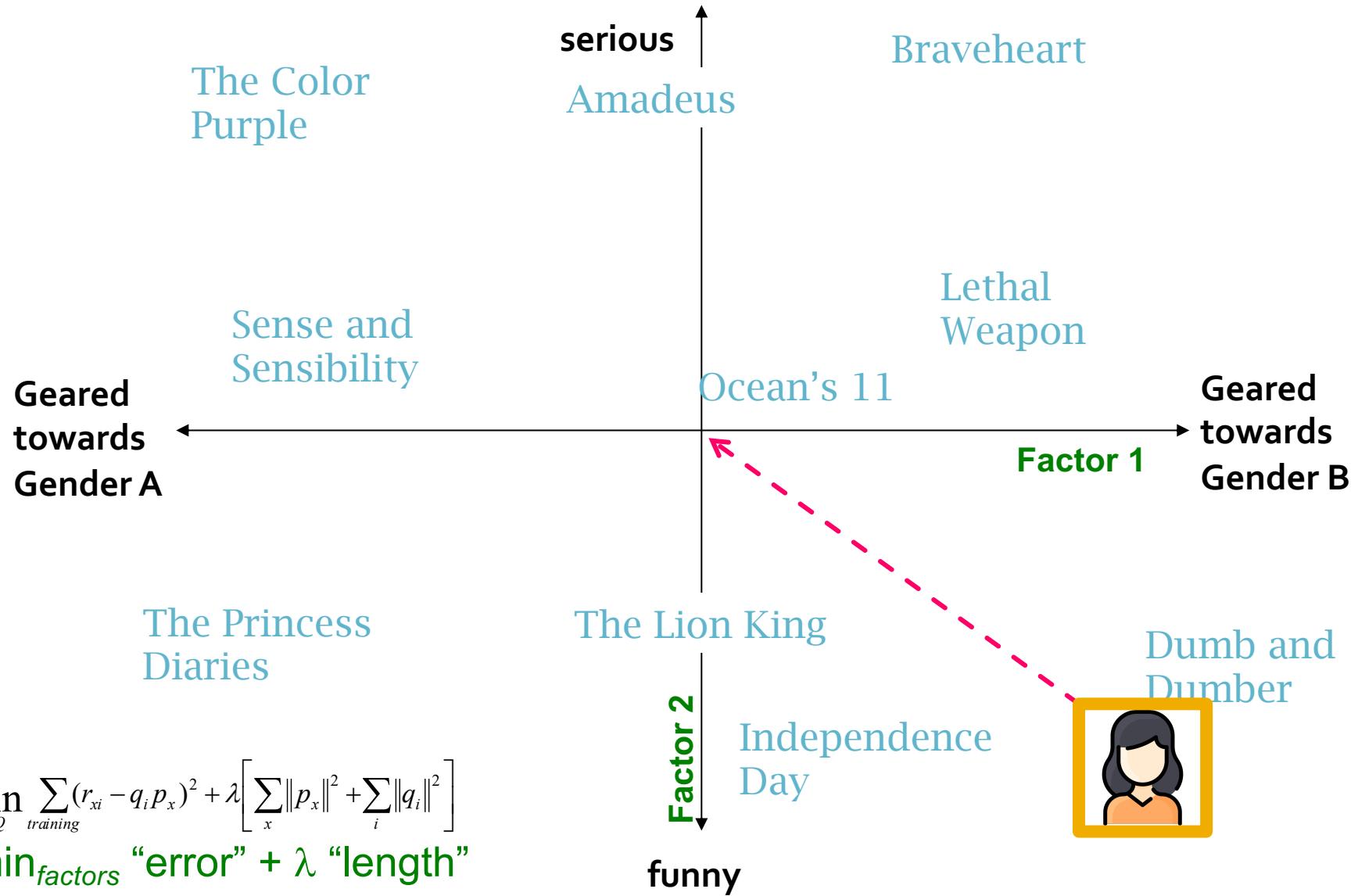
$\lambda_1, \lambda_2 \dots$ user set regularization parameters

Note: We do not care about the absolute (“raw”) value of the objective function, but we care about P,Q that achieve the minimum of the objective

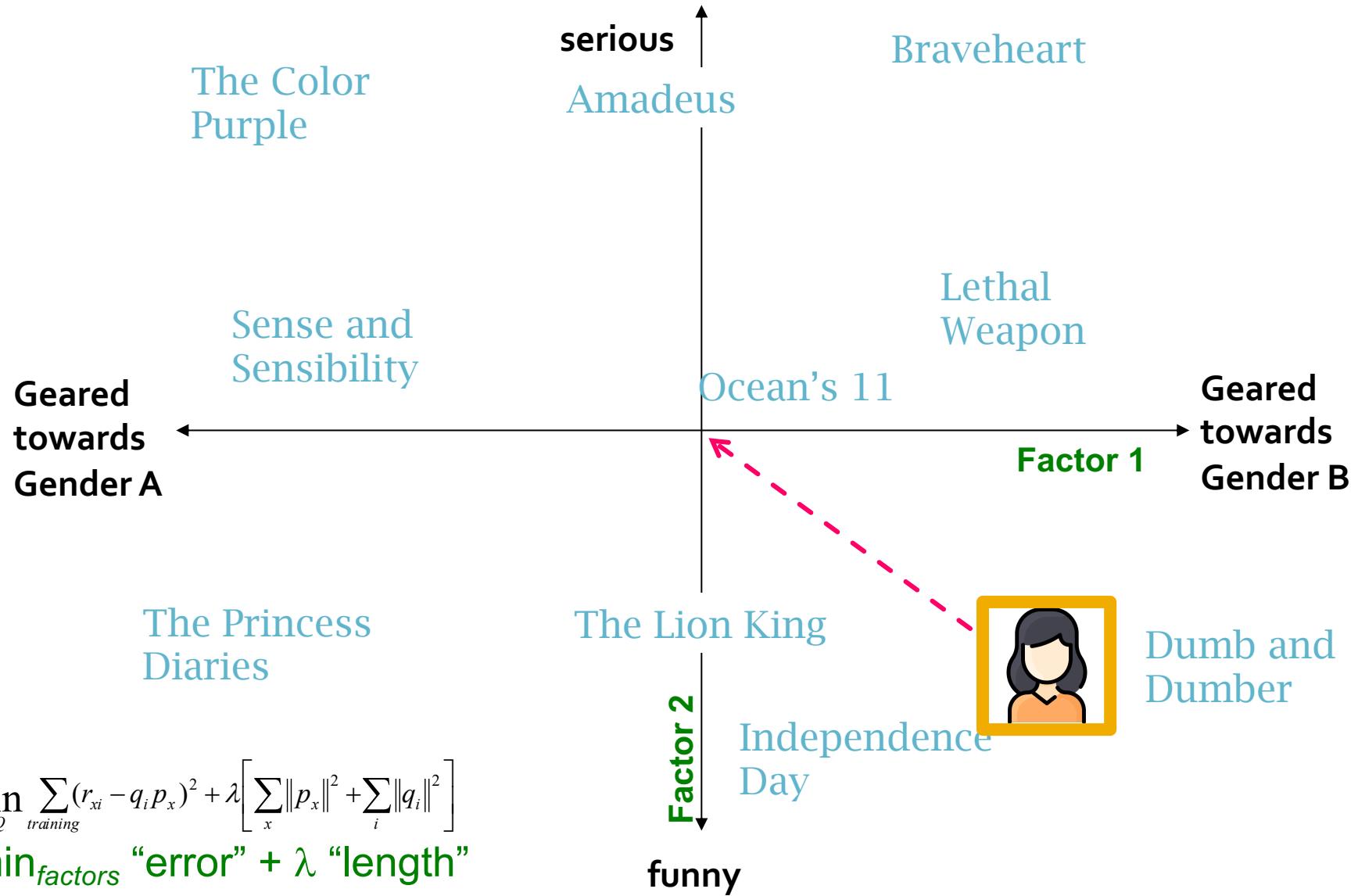
The Effect of Regularization



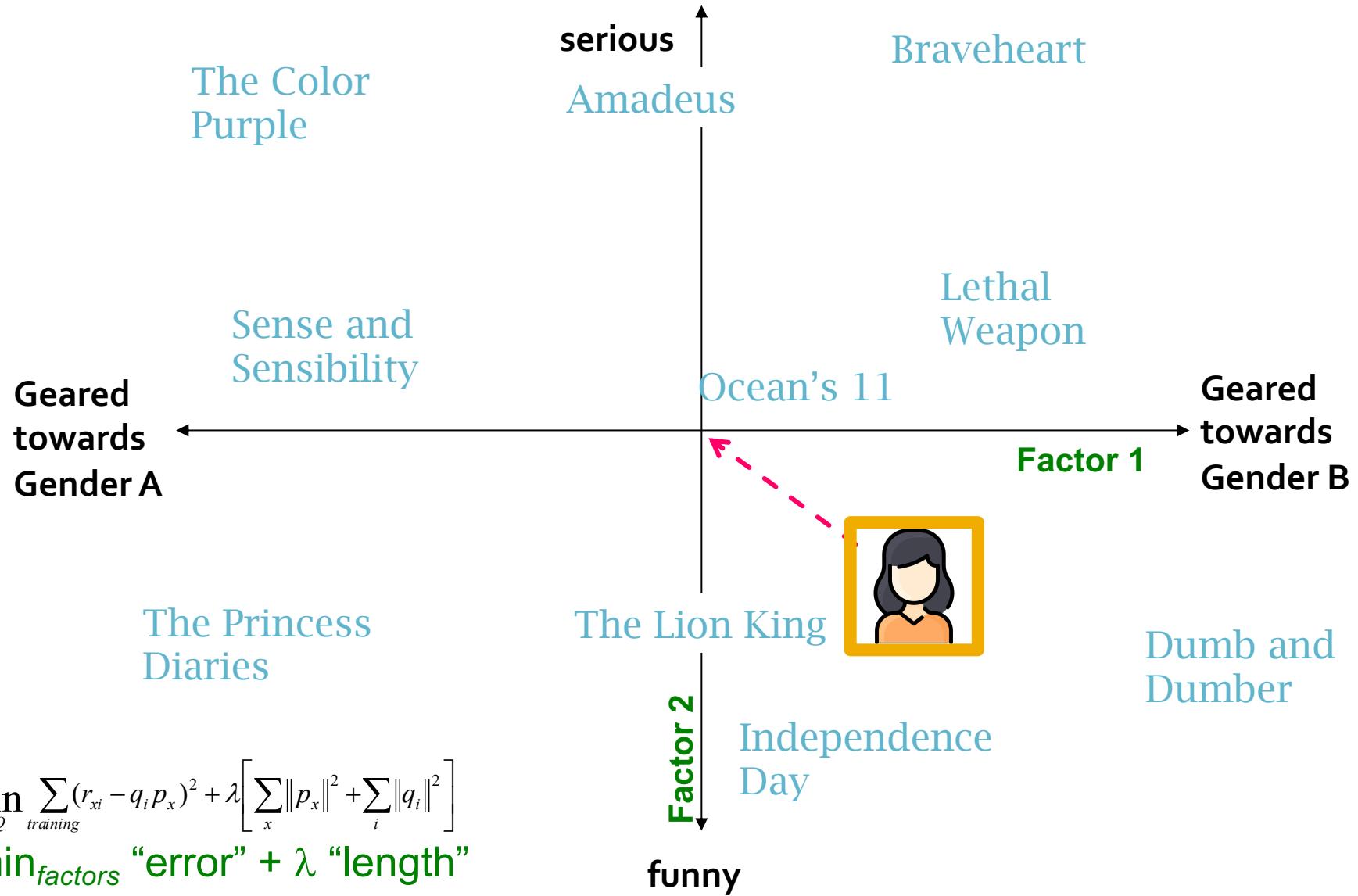
The Effect of Regularization



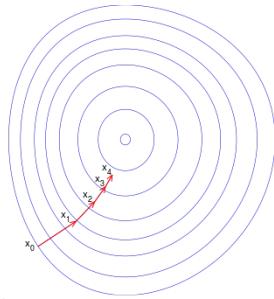
The Effect of Regularization



The Effect of Regularization



Stochastic Gradient Descent



- Want to find matrices P and Q :

$$\min_{P,Q} \sum_{\text{training}} (r_{xi} - q_i p_x)^2 + \left[\lambda_1 \sum_x \|p_x\|^2 + \lambda_2 \sum_i \|q_i\|^2 \right]$$

- Gradient descent:

- Initialize P and Q (using SVD, pretend missing ratings are 0)

- Do gradient descent:

- $P \leftarrow P - \eta \cdot \nabla P$

- $Q \leftarrow Q - \eta \cdot \nabla Q$

- where ∇Q is gradient/derivative of matrix Q :

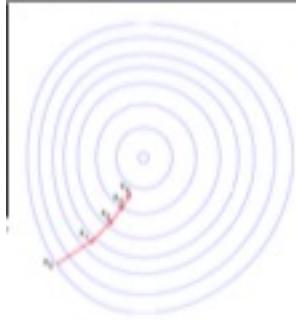
$$\nabla Q = [\nabla q_{if}] \text{ and } \nabla q_{if} = \sum_{x,i} -2(r_{xi} - q_i p_x) p_{xf} + 2\lambda_2 q_{if}$$

- Here q_{if} is entry f of row q_i of matrix Q

How to compute gradient of a matrix?
Compute gradient of every element independently!

- Observation: Computing gradients is slow!

Stochastic Gradient Descent



■ Gradient Descent (GD) vs. Stochastic GD

- **Observation:** $\nabla Q = [\nabla q_{if}]$ where

$$\nabla q_{if} = \sum_{x,i} -2(r_{xi} - q_{if} p_{xf}) p_{xf} + 2\lambda q_{if} = \sum_{x,i} \nabla Q(r_{xi})$$

- Here q_{if} is entry f of row q_i of matrix Q

- $Q \leftarrow Q - \eta \nabla Q = Q - \eta [\sum_{x,i} \nabla Q(r_{xi})]$

- **Idea:** Instead of evaluating gradient over all ratings evaluate it for each individual rating and make a step

- **GD:** $Q \leftarrow Q - \eta [\sum_{r_{xi}} \nabla Q(r_{xi})]$

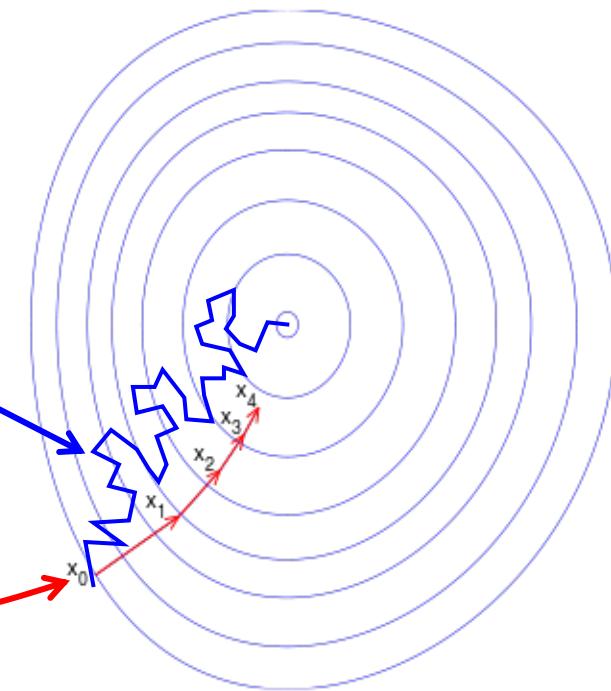
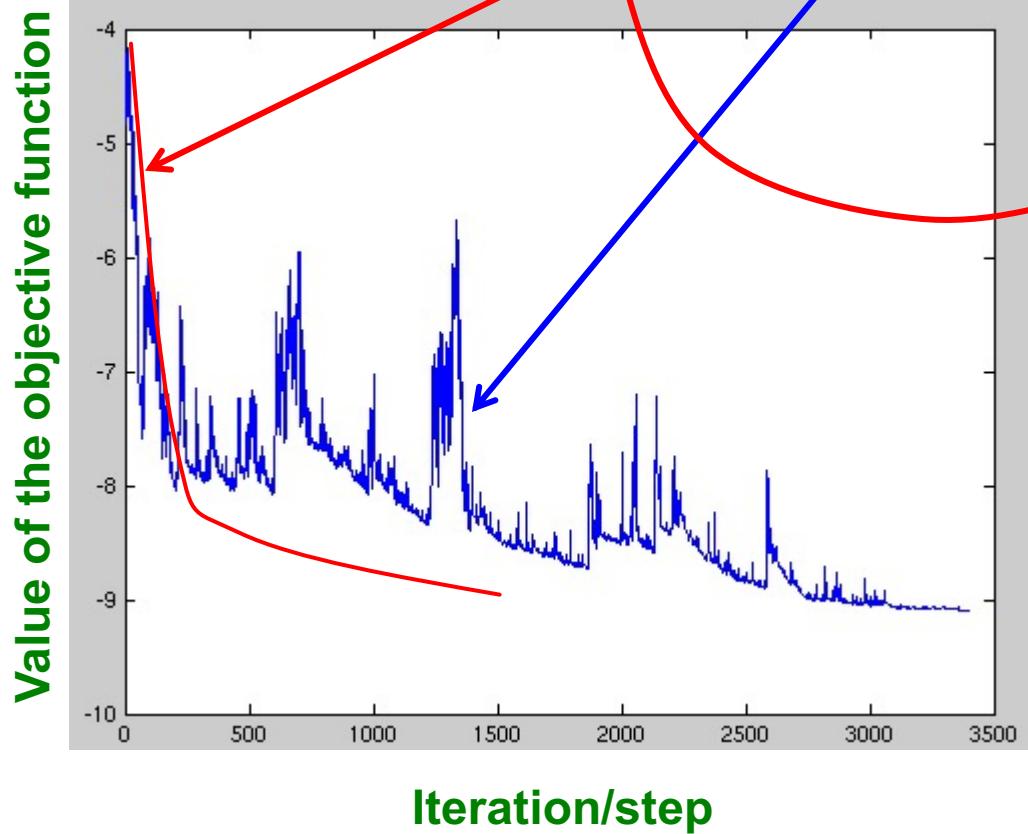
- **SGD:** $Q \leftarrow Q - \mu \nabla Q(r_{xi})$

- **Faster convergence!**

- Need more steps but each step is computed much faster

SGD vs. GD

Convergence of **GD** vs. **SGD**

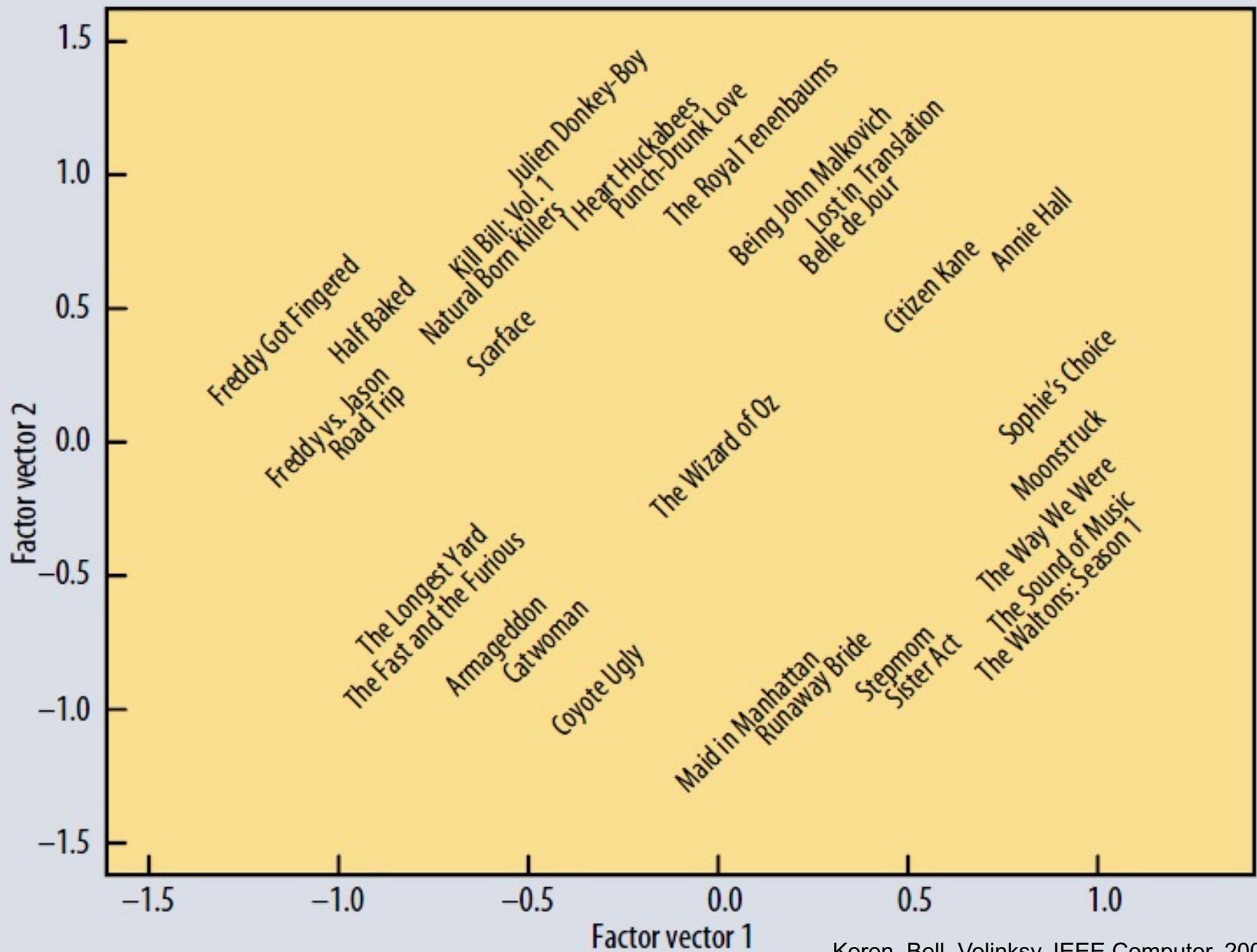


GD improves the value of the objective function at every step.

SGD improves the value but in a “noisy” way.

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

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



Extending Latent Factor Model to Include Biases

Modeling Biases and Interactions

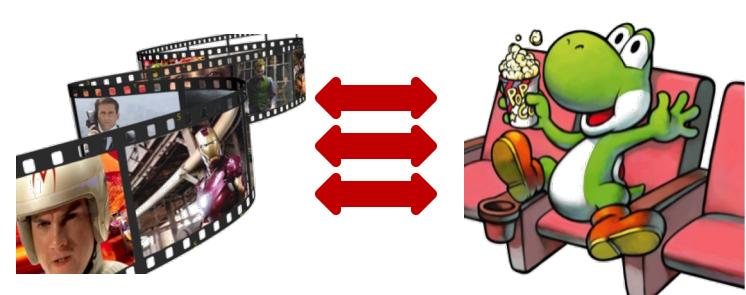
user bias



movie bias



user-movie interaction



Global: Baseline predictor

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

Local: User-Movie interaction

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

- μ = overall mean rating
- b_x = bias of user x
- b_i = bias of movie i

Baseline Predictor

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



- Rating scale of user x
- 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”)

Putting It All Together

$$r_{xi} = \mu + b_x + b_i + q_i \cdot p_x$$

Overall mean rating Bias for user x Bias for movie i User-Movie interaction

■ Example:

- Mean rating: $\mu = 3.7$
- You are a critical reviewer: your mean rating is 1 star lower than the mean: $b_x = -1$
- Star Wars gets a mean rating of 0.5 higher than average movie: $b_i = +0.5$
- Predicted rating for you on Star Wars:
 $= 3.7 - 1 + 0.5 = 3.2$ (*before user movie interaction*)

Fitting the New Model

- **Solve:**

$$\min_{Q,P} \sum_{(x,i) \in R} (r_{xi} - (\mu + b_x + b_i + q_i p_x))^2$$

goodness of fit

$$+ \left(\lambda_1 \sum_i \|q_i\|^2 + \lambda_2 \sum_x \|p_x\|^2 + \lambda_3 \sum_x \|b_x\|^2 + \lambda_4 \sum_i \|b_i\|^2 \right)$$

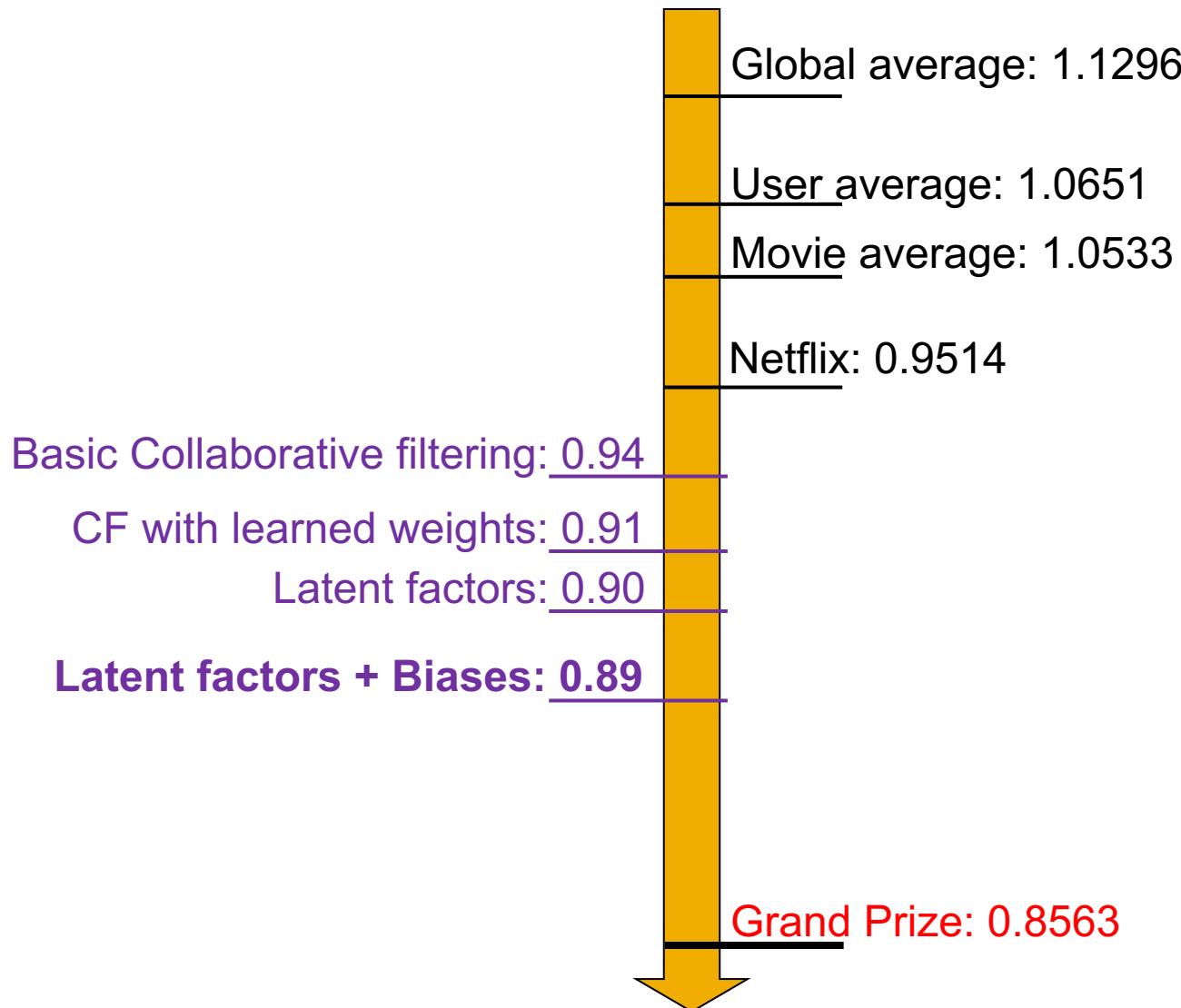
regularization

λ is selected via grid-search on a validation set

- **Stochastic gradient decent to find parameters**

- **Note:** Both biases b_x, b_i as well as interactions q_i, p_x are treated as parameters (and we learn them)

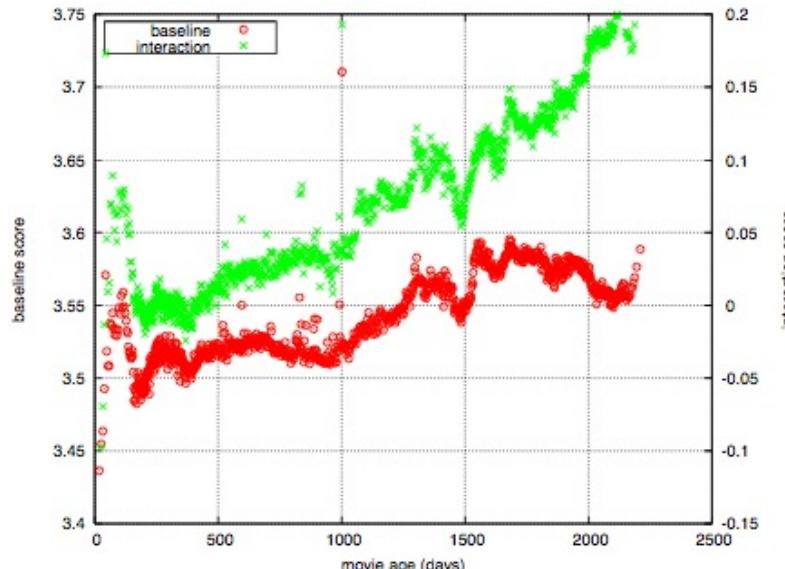
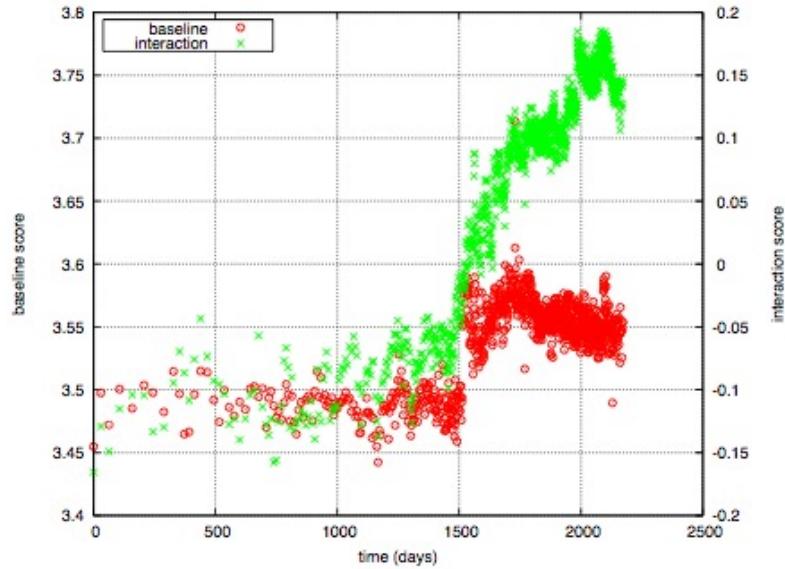
Performance of Various Methods



The Netflix Challenge: 2006-09

Temporal Biases Of Users

- **Sudden rise in the average movie rating (early 2004)**
 - Improvements in Netflix
 - GUI improvements
 - Meaning of rating changed
- **Movie age**
 - Users prefer new movies without any reasons
 - Older movies that are rated seem inherently better than newer ones



[Y. Koren, Collaborative filtering with temporal dynamics, KDD '09]

Temporal Biases & Factors

- **Original model:**

$$r_{xi} = \mu + b_x + b_i + q_i \cdot p_x$$

- **Add time dependence to biases:**

$$r_{xi} = \mu + b_x(t) + b_i(t) + q_i \cdot p_x$$

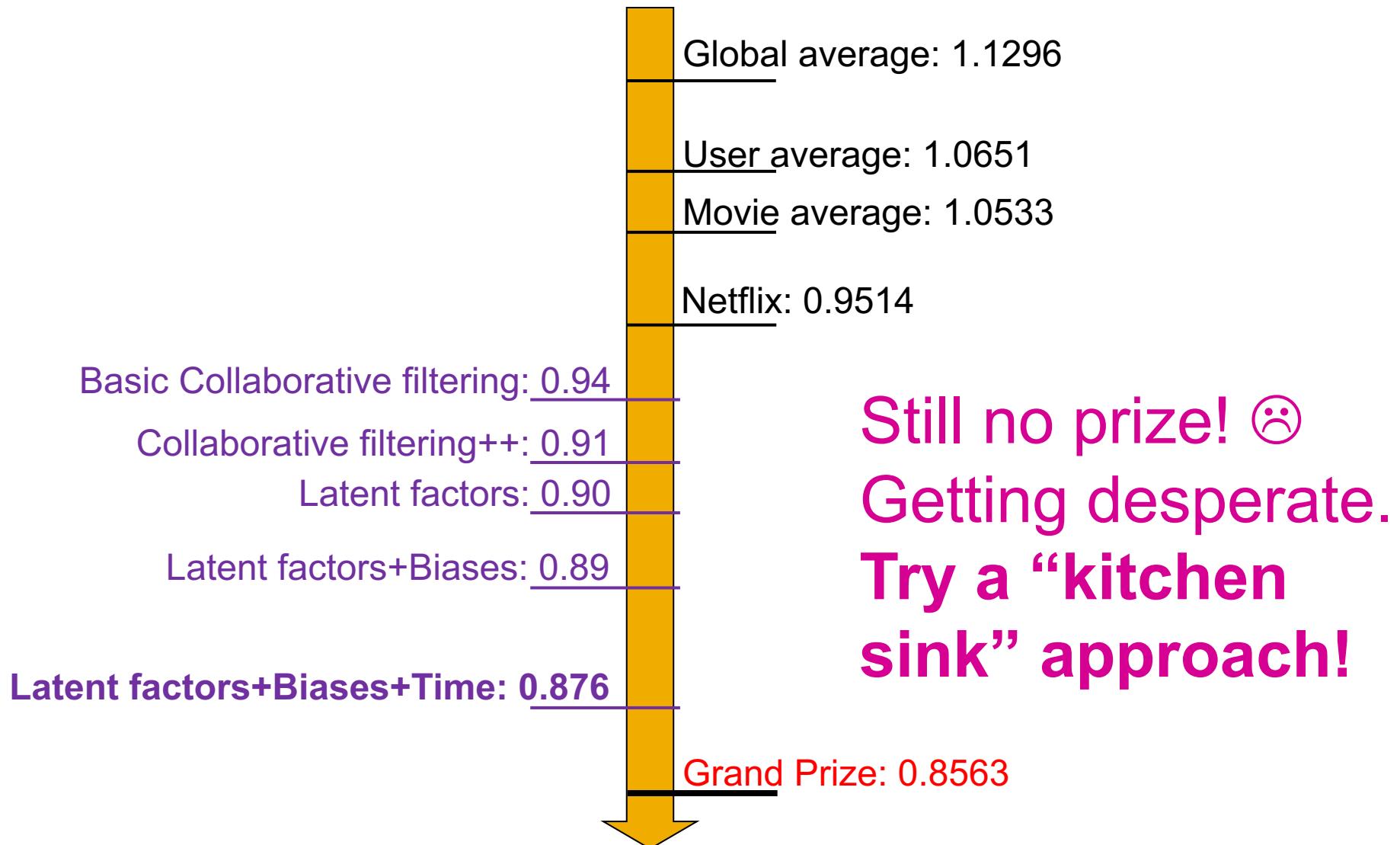
- Make parameters b_x and b_i to depend on time
- (1) Parameterize time-dependence by linear trends
(2) Each bin corresponds to 10 consecutive weeks

$$b_i(t) = b_i + b_{i,\text{Bin}(t)}$$

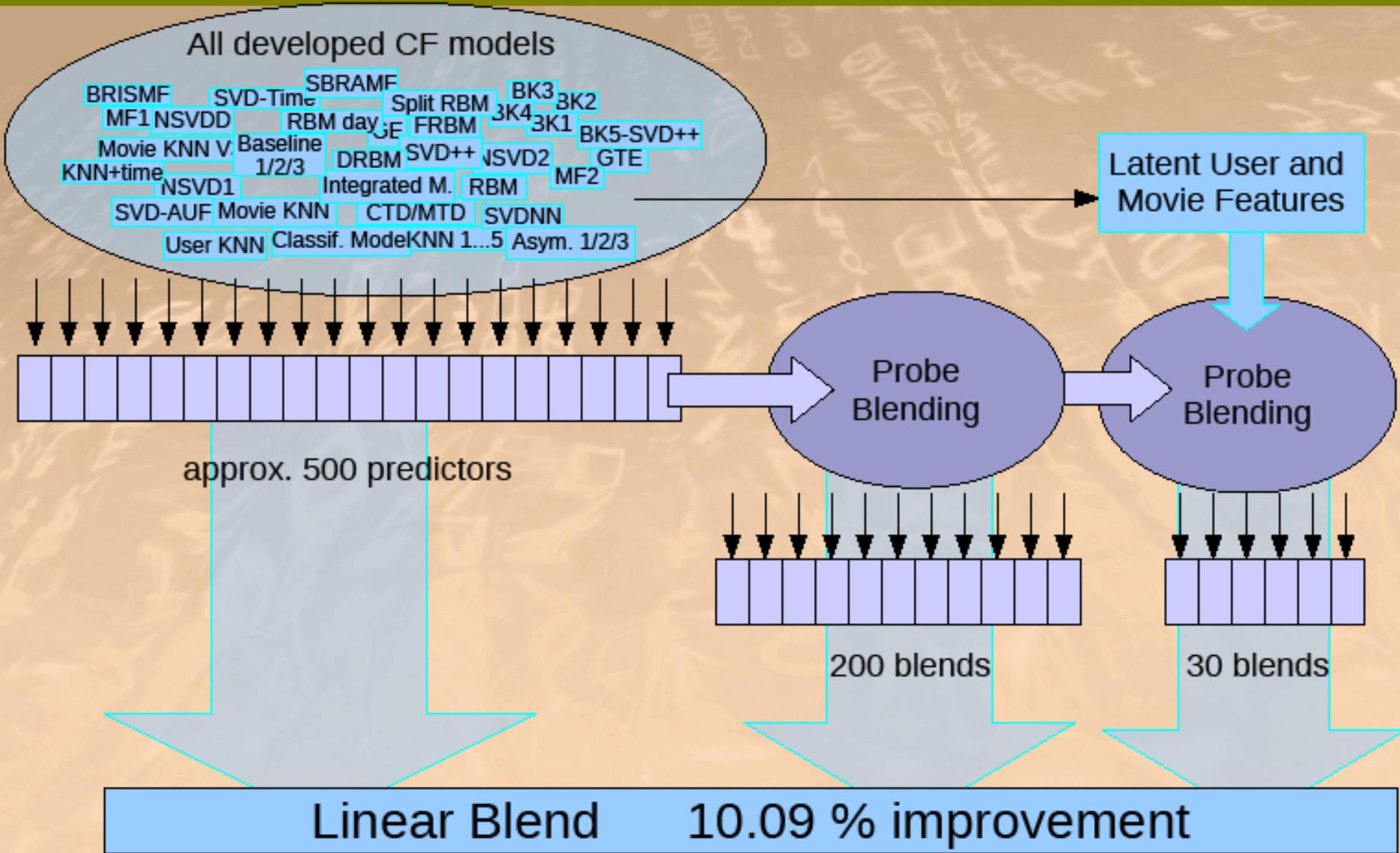
- **Add temporal dependence to factors**

- $p_x(t)$... user preference vector on day t

Performance of Various Methods



The big picture Solution of BellKor's Pragmatic Chaos



Standing on June 26th 2009

The screenshot shows the Netflix Prize Leaderboard page. At the top, there's a yellow banner with the text "Netflix Prize" and some decorative stars. Below the banner is a navigation bar with links: Home, Rules, Leaderboard, Register, Update, Submit, and Download. The main title "Leaderboard" is displayed prominently in blue. To the right of the title is a text box that says "Display top 20 leaders." A horizontal line separates the header from the table.

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

June 26th submission triggers 30-day “last call”

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 get small improvements in their scores
 - Realize they are in direct competition with team **Ensemble**
- **Strategy**
 - Both teams carefully monitoring the leader board
 - 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**
 - Only 1 final submission could be made in the last 24h
- **24 hours before deadline...**
 - **BellKor** team member in Austria notices (by chance) that **Ensemble** posts a score that is slightly better than BellKor's
- **Frantic last 24 hours for both teams**
 - Much computer time on final optimization
 - 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....

COMPLETED

Netflix Prize

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Leaderboard

Showing Test Score. [Click here to show quiz score](#)Display top leaders.

Rank	Team Name	Best Test Score	% Improvement	Best Submit Time
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	9.98	2009-07-16 21:27:40
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

Grand Prize - RMSE = 0.8567 - Winning Team: BellKor's Pragmatic Chaos				
Rank	Team Name	Best Test Score	% Improvement	Best Submit Time
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
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Progress Prize 2008 - RMSE = 0.8627 - Winning Team: BellKor in BigChaos				
Rank	Team Name	Best Test Score	% Improvement	Best Submit Time
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

Million \$ Awarded Sept 21st 2009



**What's the moral of
the story?**

Submit early! ☺

Acknowledgments

- Some slides and plots borrowed from Yehuda Koren, Robert Bell and Padhraic Smyth, Jure Leskovec
- **Further reading:**
 - Y. Koren, Collaborative filtering with temporal dynamics, KDD '09
- <https://web.archive.org/web/20141130213501/http://www2.research.att.com/~volinsky/netflix/bpc.html>
- <https://web.archive.org/web/20141227110702/http://www.the-ensemble.com/>

Please give us feedback 😊
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