

Recommendation Systems

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Recommendation Systems

- **Data**

items

users

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

- **Goal**

- Learn what a user might be interested in and recommend other items he might like

Ratings from 1 to 5



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

Compute Average Rating



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

3.25

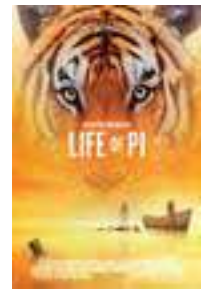
3.5

2.5

2.25

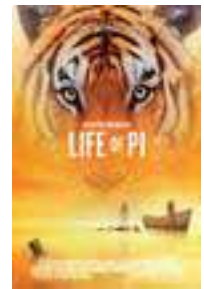
4

Subtract Average Rating



User 1	1.75	0.5	0.5	-1.25	-1
User 2	-2.25	-2.5	-0.5	2.75	0
User 3	-1.25	1.5	-1.5	-0.25	1
User 4	1.75	0.5	1.5	-1.25	?

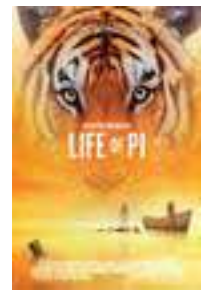
Computing Similarity



User 1	1.75	0.5	0.5	-1.25	-1
User 2	-2.25	-2.5	-0.5	2.75	0
User 3	-1.25	1.5	-1.5	-0.25	1
User 4	1.75	0.5	1.5	-1.25	?

Compute a similarity score between two users: The higher the score is, the more likely they enjoy the same movies

Pearson Correlation Measure

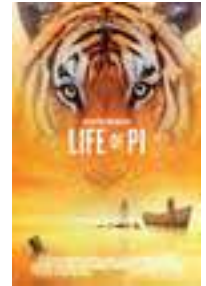


User 1	1.75	0.5	0.5	-1.25	-1
User 4	1.75	0.5	1.5	-1.25	?

$$\frac{1.75 \cdot 1.75 + 0.5 \cdot 0.5 + 0.5 \cdot 1.5 + (-1.25) \cdot (-1.25)}{\sqrt{1.75^2 + 0.5^2 + 0.5^2 + (-1.25)^2} \sqrt{1.75^2 + 0.5^2 + 1.5^2 + (-1.25)^2}}$$

$$= 0.9305$$

Computing New Rating



User 1	1.75	0.5	0.5	-1.25	-1
User 2	-2.25	-2.5	-0.5	2.75	0
User 3	-1.25	1.5	-1.5	-0.25	1
User 4	1.75	0.5	1.5	-1.25	?

User 1 & User 4: 0.9305 User 2 & User 4: -0.7904

User 3 & User 4: -0.4382



$$? = 4 + 0.9305 * (-1) + (-0.7904) * 0 + (-0.4382) * 1 = 2.6313$$

Investigating the Reasons behind “Likes” and “Dislikes”

- **Based on genres**
 - Bob likes comedy movies
 - “Dumb and Dumber” is a comedy movie, so Bob should like it
- **More factors**
 - Genre, cast, amount of actions, orientation to children, female or male
 - Depth of character development
 -

If We Scored All Factors for All the Movies

	Orientation to female	Amount of action	Character development	Happy ending	...
Movie 1	5	2	2	2	...
Movie 2	1	4	1	5	...
...

	Orientation to female	Amount of action	Character development	Happy ending	...
Mary	5	3	2	1	...



Example

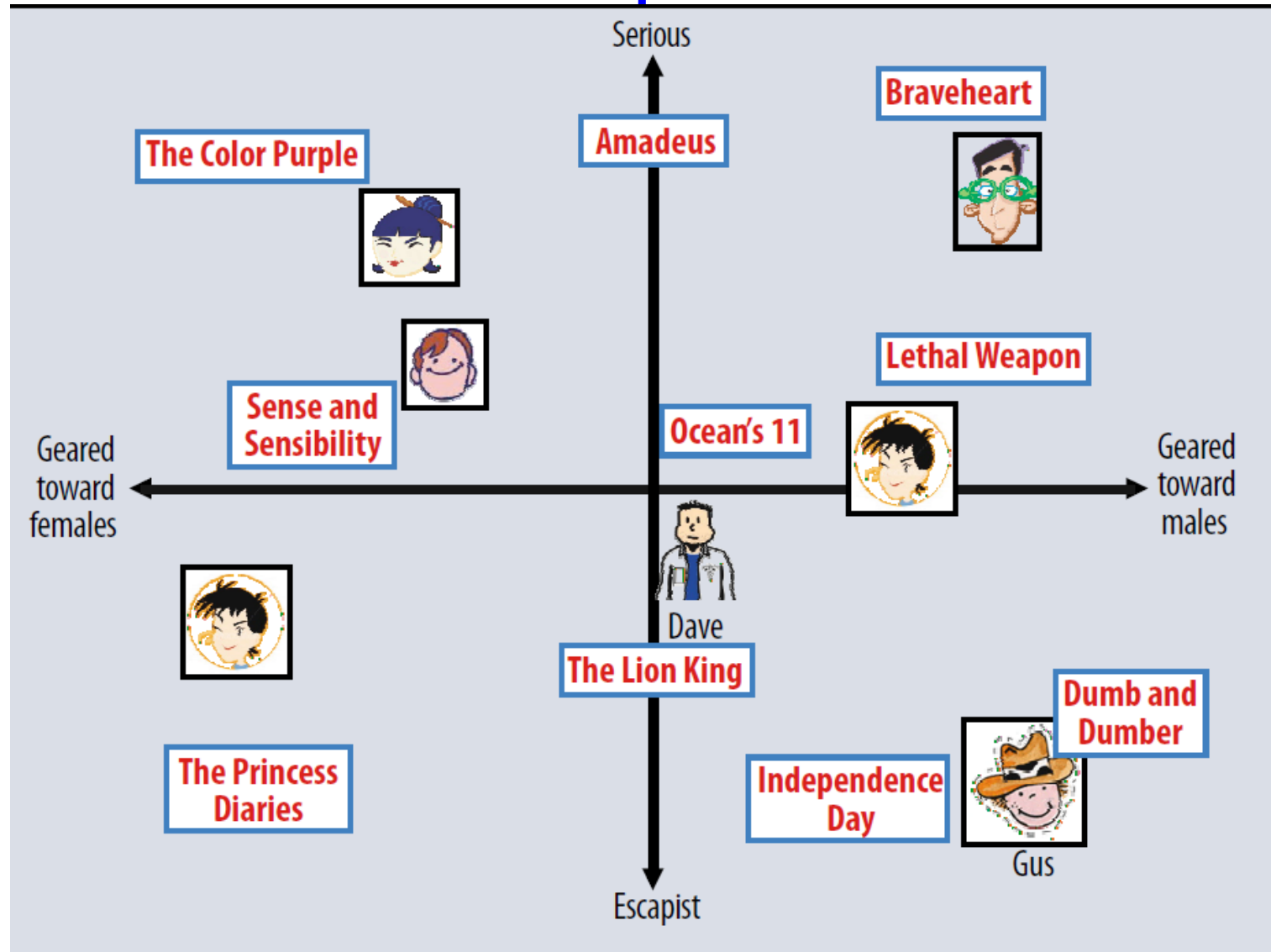


Figure 2. A simplified illustration of the latent factor approach, which characterizes both users and movies using two axes—male versus female and serious versus escapist.

What We Have—One Score Per User Per Movie

items

users

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

Modeling Systematic Biases

$$r_{ui} \approx m + b_u + b_i + q_i^t p_u$$

	overall average rating	+ average rating bias for user u	+ average rating bias for movie i	+ user-movie interaction bias
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Example:

Mean rating $m = 3.7$

You are a critical reviewer: your ratings are 1 lower than the average $\rightarrow b_u = -1$

Star Wars gets an average rating of 0.5 higher than average movie: $b_i = +0.5$

Based on various factors, your taste tend to prefer Star Wars with a degree $q_i^t p_u = +0.2$

Predicted rating for you on Star Wars = $3.7 - 1 + 0.5 + 0.2 = 3.4$

Infer Movie and User Scores from Known Ratings

$$\min_{q,p} \sum_{(u,i) \in R} (r_{ui} - (m + b_u + b_i + q_i^t p_u))^2$$

true rating
estimated rating

find the values for p and q which minimize the overall error

find the scoring patterns that minimize the difference between the true ratings and the predicted ratings!

Other Useful Techniques

- **Time factor**
 - A user's taste or rating scale may change over time
 - A movie's popularity may change over time
- **User or movie profiles**
 - Age, gender of users; genre, cast, plots of movies;
- **Ensemble techniques**
 - Design many recommender systems and take their votes
 - Highly effective in real practice

Netflix

- Movie rentals by DVD (mail) and online (streaming)
- 100k movies, 10 million customers
- Ships 1.9 million disks to customers each day
 - 50 warehouses in the US
 - Complex logistics problem
- Moving towards online delivery of content
- Significant interaction of customers with Web site

The \$1 Million Question

NETFLIX

Netflix Prize

Home
Rules
Leaderboard
Register
Update
Submit
Download

NETFLIX

Browse Recommendations Friends Queue Buy DVDs

Home Genres New Releases Previews Netflix Top 100 Crit

Movies For You

Randy, the following movies were chosen based on your interest in:
[Bowling for Columbine](#)
[Carnivale: Season 1](#)
[Fahrenheit 9/11](#)

The Big One

★★★★☆
 er subversive
 y from

Daniel Kraus
 rivetingly cre
 series cont
 document s
 ntures of a motley cre
 nies who've made the C
 stbow their ... [Read Mo](#)

You really liked it...

Now own it for just \$5.99

Shop as low

g - Original artv

Lewis Black: Pe
 and Scores

Add

★★★★☆ Not Interested

★★★★☆ Not Interested

Welcome!

The Netflix Prize seeks to substantially improve the accuracy of predictions about how much someone is going to love a movie based on their movie preferences. Improve it enough and you win one (or more) Prizes. Winning the Netflix Prize improves our ability to connect people to the movies they love.

Read the [Rules](#) to see what is required to win the Prizes. If you are interested in joining the quest, you should [register a team](#).

You should also read the [frequently asked questions](#) about the Prize. And check out how various teams are doing on the [Leaderboard](#).

Good luck and thanks for helping!

FAQ | Forum | [Netflix Home](#)

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Training Data

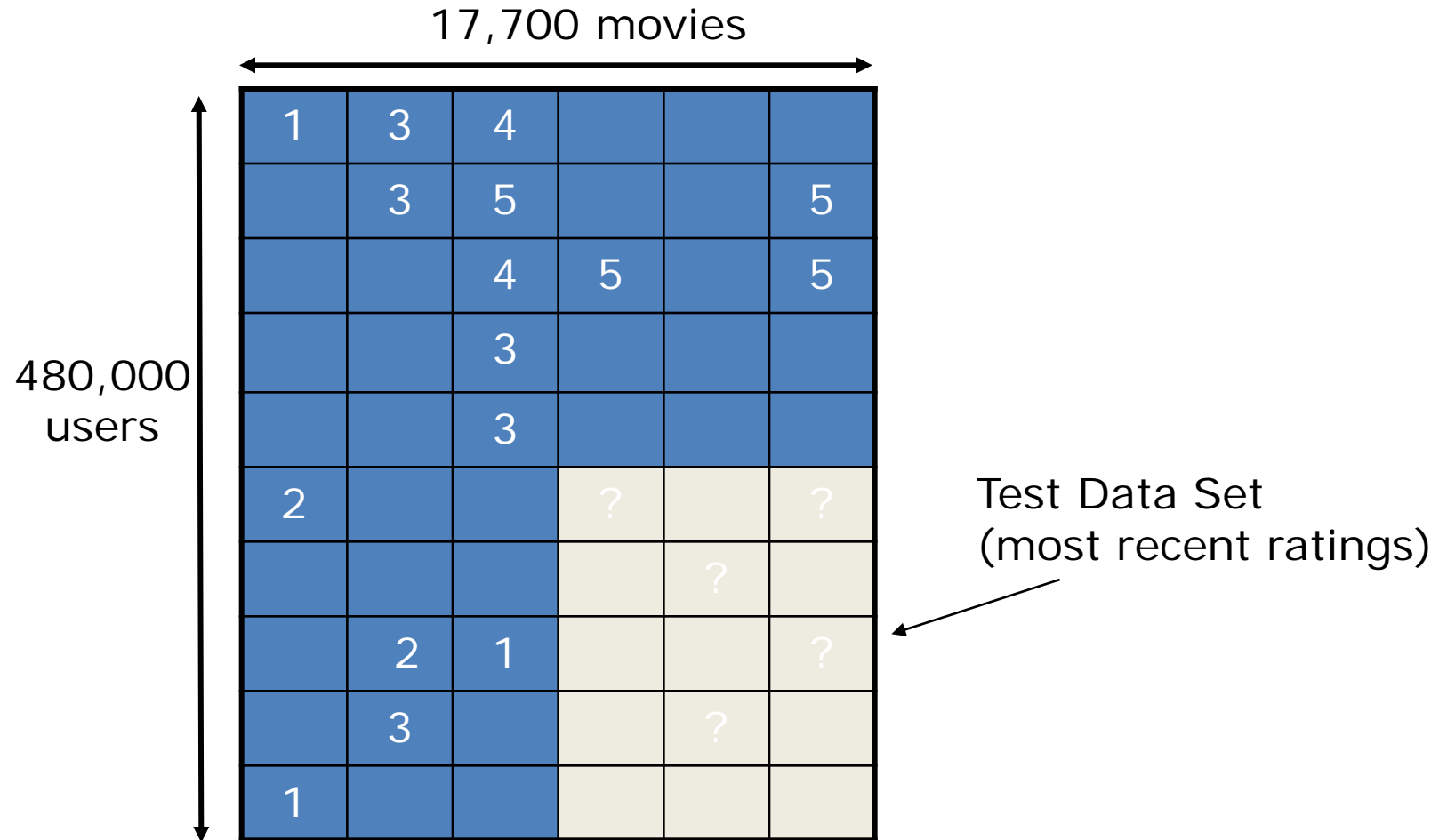
100 million ratings

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

Ratings Data



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

Evaluation Comparison

- 1.054 - just predict the average 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

Million Dollars Awarded Sept 21st 2009

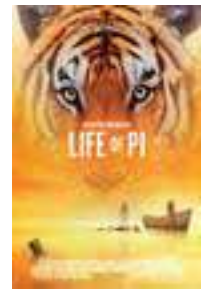


40,000 teams from over 150 countries

Other Rating Applications

- **Modeled as user-item pairs**
 - User-books, user-CDs, user-hotels, user-products, user-friends,
- **Consider unique characteristics of each application**

Implicit "Preference"



User 1	1	1	1	0	0
User 2	0	0	0	1	0
User 3	0	1	0	0	0
User 4	0	1	1	0	0

User check the movie webpage: 1

User did not check the movie webpage: 0

Implicitly Show Interests

- **All of our online activities are recorded:**
 - Which tweets we read
 - Which product description we browsed
 - Which advertisement we clicked
 - Which videos we viewed
 -
- **Recommendation is given based on our activities**
 - Preference may not be that strong compared with explicit ratings

Question

- **Youtube can gather the following types of implicit feedback**
 - Which videos each user viewed
 - Which videos each user liked
 - Which videos each user shared
 - Which videos each user commented
- **How to use all the information to recommend videos to users?**