

RECOMMENDER SYSTEMS

Recommender Systems

- A **recommender system** (RS) helps users that have no sufficient competence or time to evaluate the, potentially overwhelming, number of alternatives offered by a web site.
 - In their simplest form, RSs recommend to their users personalized and **ranked lists**

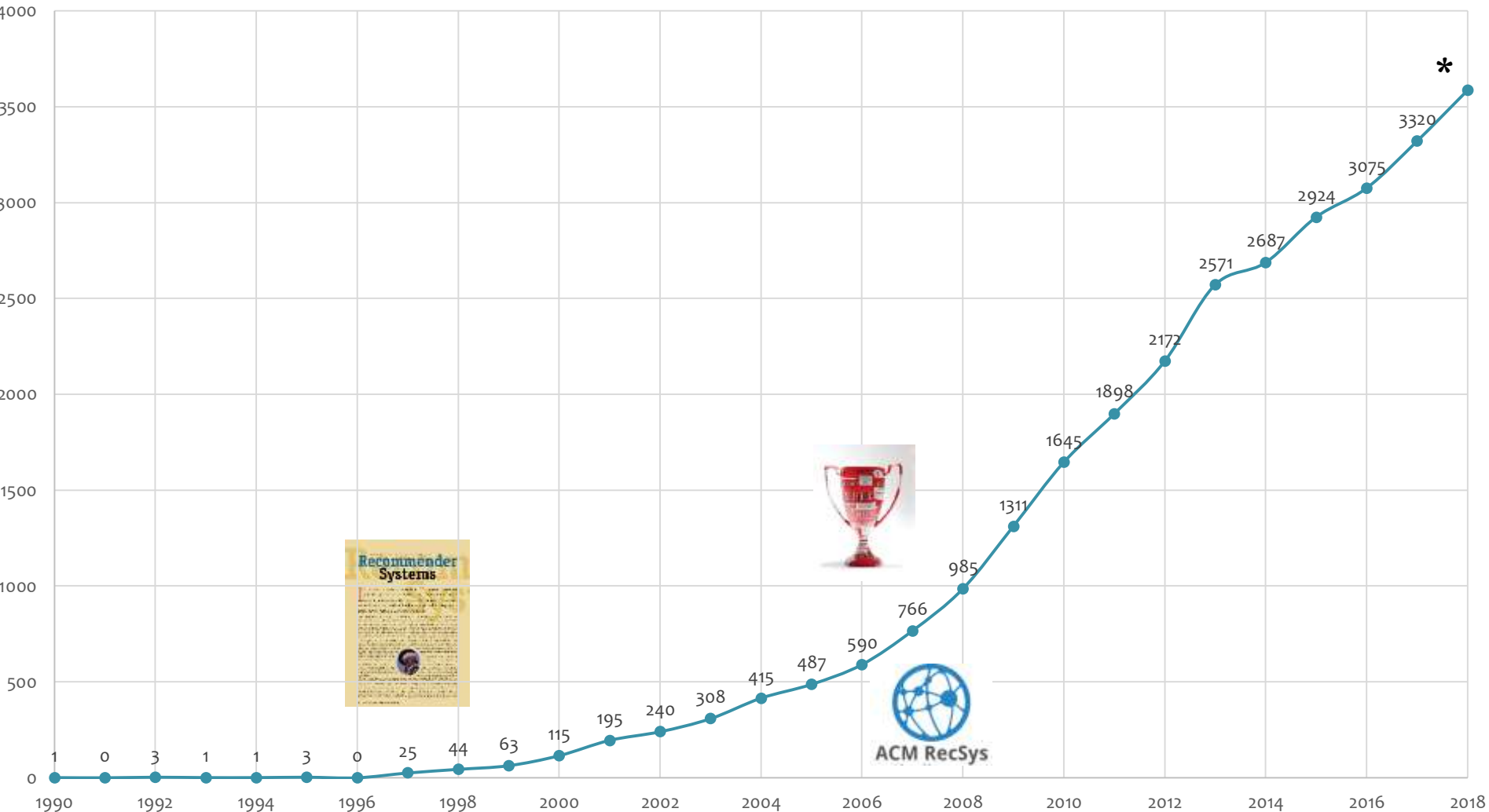


The Impact of RecSys

- 35% of the purchases on **Amazon** are the result of their recommender system, according to **McKinsey**.
- During the Chinese global shopping festival of November 11, 2016, **Alibaba** achieved growth of up to 20% of their conversion rate using personalized landing pages, according to **Alizila**.
- Recommendations are responsible for 70% of the time people spend watching videos on **YouTube**.
- 75% of what people are watching on **Netflix** comes from recommendations, according to **McKinsey**

The Rise of the Recommender System

Papers in Microsoft Academic




*2018-Estimated

Recommender Systems

A Common Challenge:


- Assume you're a company selling **items** of some sort: movies, songs, products, etc.
- Company collects millions of **ratings** from **users** of their **items**
- To maximize profit / user happiness, you want to **recommend** items that users are likely to want

Recommender Systems



NEW & INTERESTING FINDS ON AMAZON

EXPLORE




amazon Prime

All ▾


Q

CYBER MONDAY DEALS WEEK

Hello, Matt
Your Account ▾ Prime ▾ Lists ▾  Cart

Departments ▾ Browsing History ▾ Matt's Amazon.com Cyber Monday Gift Cards & Registry Sell Help

Your Amazon.com Your Browsing History Recommended For You Improve Your Recommendations Your Profile Learn More




Matt's Amazon

You could be seeing useful stuff here!
Sign in to get your order status, balances and rewards.


Sign In

Recommended for you, Matt




Buy It Again in Grocery

14 ITEMS



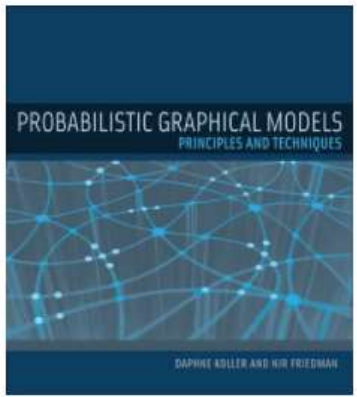
Buy It Again in Pets

6 ITEMS



Buy It Again in Baby Products

5 ITEMS



Engineering Books

86 ITEMS

NETFLIX

COMPLETED

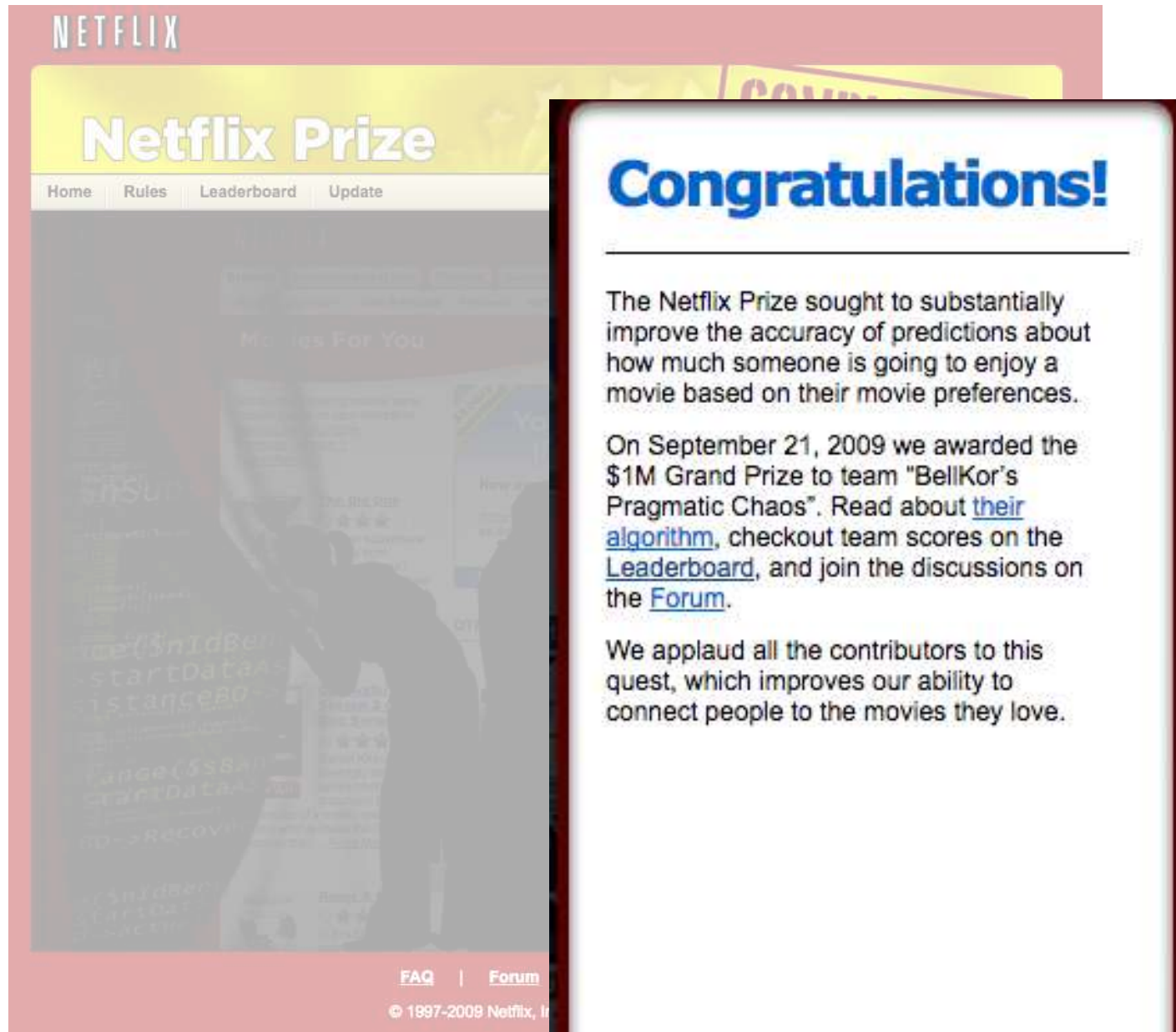
Congratulations!

On September 21, 2009 we awarded the \$1M Grand Prize to team "BellKor's Pragmatic Chaos". Read about [their algorithm](#), checkout team scores on the [Leaderboard](#), and join the discussions on the [Forum](#).

We applaud all the contributors to this quest, which improves our ability to connect people to the movies they love.

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Recommender Systems



The image shows a screenshot of the Netflix Prize website. The background is a faded view of the site's interface, including the 'Netflix Prize' header, navigation links like 'Home', 'Rules', 'Leaderboard', and 'Update', and a section titled 'Movies For You'. Overlaid on the right side of the screenshot is a white box with a dark red border containing a congratulatory message. The message is titled 'Congratulations!' in large blue text. Below the title, it explains the purpose of the Netflix Prize and announces the winner of the \$1M Grand Prize on September 21, 2009. It mentions the winning team 'BellKor's Pragmatic Chaos' and provides links to read about their algorithm, view team scores on the leaderboard, and join discussions on the forum. The message concludes by applauding all contributors.

NETFLIX

Netflix Prize

Home Rules Leaderboard Update

Congratulations!

The Netflix Prize sought to substantially improve the accuracy of predictions about how much someone is going to enjoy a movie based on their movie preferences.

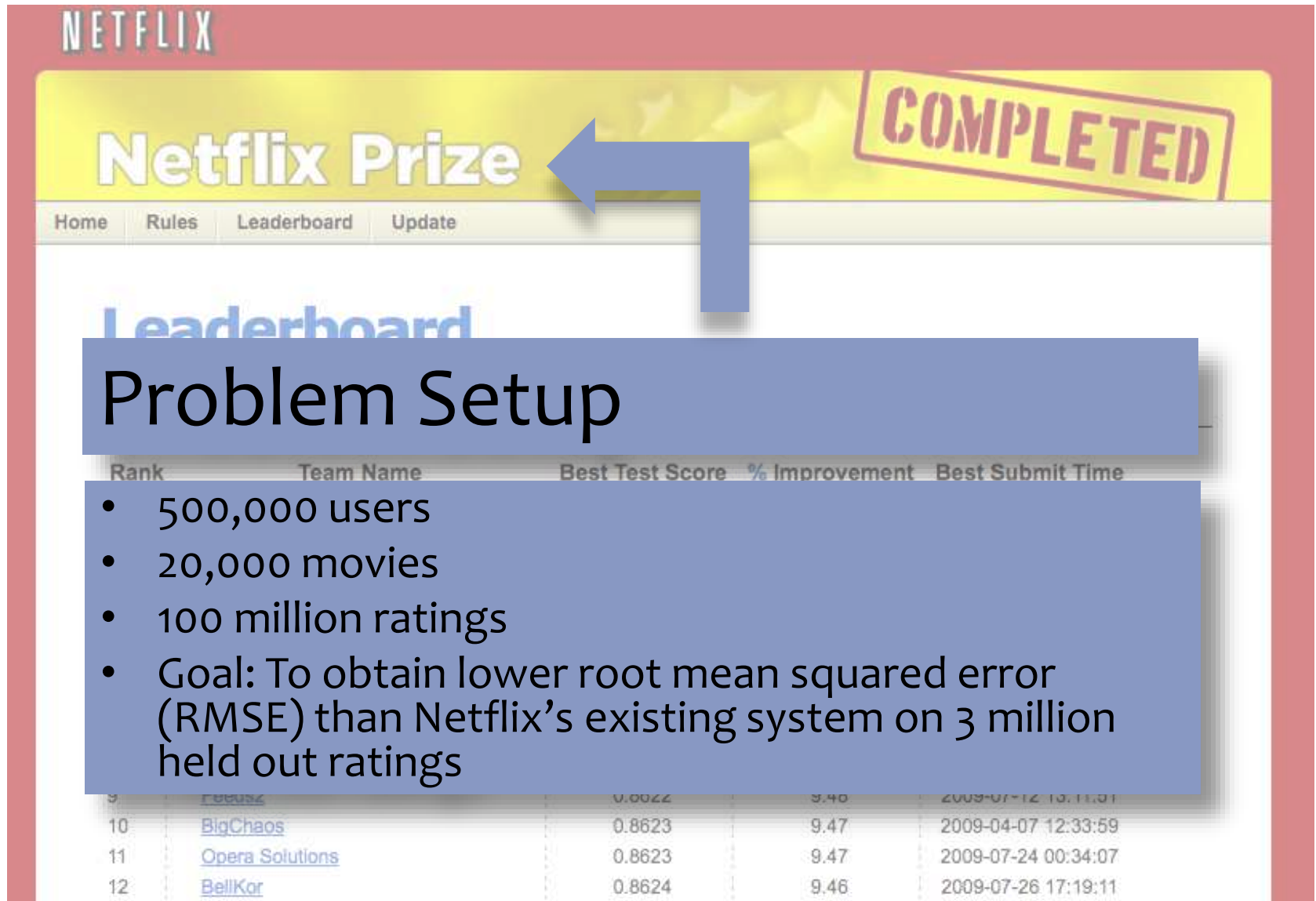
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FAQ | Forum

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Recommender Systems




The screenshot shows the Netflix Prize website interface. At the top, the 'NETFLIX' logo is on the left, and a yellow banner contains the text 'Netflix Prize' and a red 'COMPLETED' stamp. Below the banner is a navigation bar with links: 'Home', 'Rules', 'Leaderboard', and 'Update'. The 'Leaderboard' link is highlighted. A large blue arrow points from the 'COMPLETED' stamp towards the 'Netflix Prize' text. Below the navigation bar, the word 'Leaderboard' is displayed in a large, stylized font. A blue semi-transparent box is overlaid on the page, containing the text 'Problem Setup' and a bulleted list of details about the competition. Below this box, a table shows the top 12 teams on the leaderboard.

Problem Setup

- 500,000 users
- 20,000 movies
- 100 million ratings
- Goal: To obtain lower root mean squared error (RMSE) than Netflix's existing system on 3 million held out ratings

Rank	Team Name	Best Test Score	% Improvement	Best Submit Time
9	Feus2	0.8622	9.46	2009-07-12 15:11:01
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

Recommender Systems



NETFLIX

Netflix Prize

COMPLETED

Home Rules Leaderboard Update

Leaderboard

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

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
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Recommender Systems

- **Setup:**


- **Items:**
movies, songs, products, etc.
(often many thousands)
- **Users:**
watchers, listeners, purchasers, etc.
(often many millions)
- **Feedback:**
5-star ratings, not-clicking 'next',
purchases, etc.

- **Key Assumptions:**


- Can represent ratings numerically
as a user/item matrix
- Users only rate a small number of
items (the matrix is sparse)

	Doctor Strange	Star Trek: Beyond	Zootopia
Alice	1		5
Bob	3	4	
Charlie	3	5	2

Recommender Systems



Netflix Prize



[Home](#) [Rules](#) [Leaderboard](#) [Update](#)

Leaderboard

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

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Two Types of Recommender Systems

Content Filtering

- *Example:* **Pandora.com** music recommendations (Music Genome Project)
- **Con:** Assumes access to **side information** about items (e.g. properties of a song)
- **Pro:** Got a **new item** to add? No problem, just be sure to include the side information

Collaborative Filtering

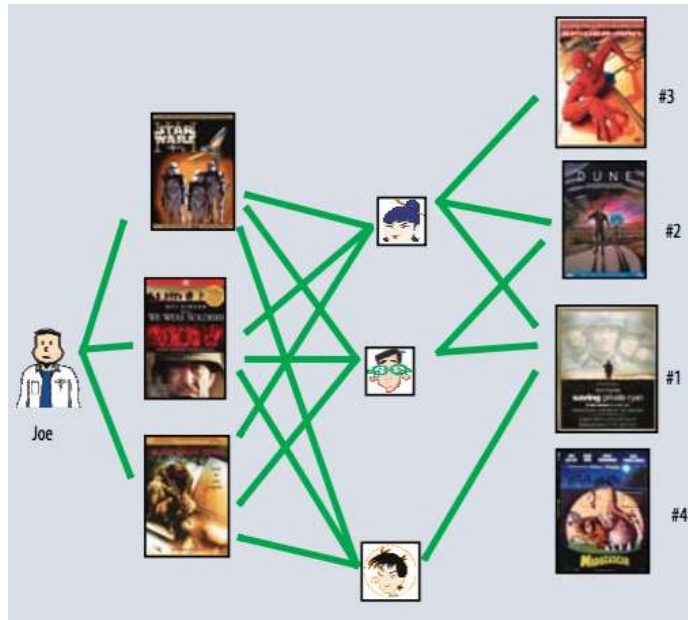
- *Example:* **Netflix** movie recommendations
- **Pro:** Does not assume access to **side information** about items (e.g. does not need to know about movie genres)
- **Con:** Does not work on **new items** that have no ratings

Collaborative Filtering

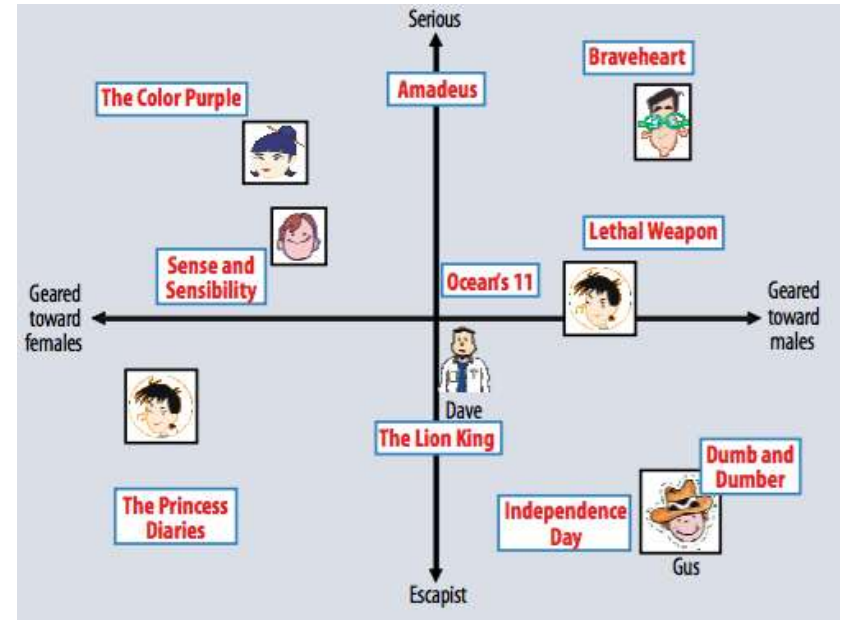
- **Everyday Examples of Collaborative Filtering...**
 - Bestseller lists
 - Top 40 music lists
 - The “recent returns” shelf at the library
 - Unmarked but well-used paths thru the woods
 - The printer room at work
 - “Read any good books lately?”
 - ...
- **Common insight:** personal tastes are correlated
 - If Alice and Bob both like X and Alice likes Y then Bob is more likely to like Y
 - especially (perhaps) if Bob knows Alice

Two Types of Collaborative Filtering

1. Neighborhood Methods

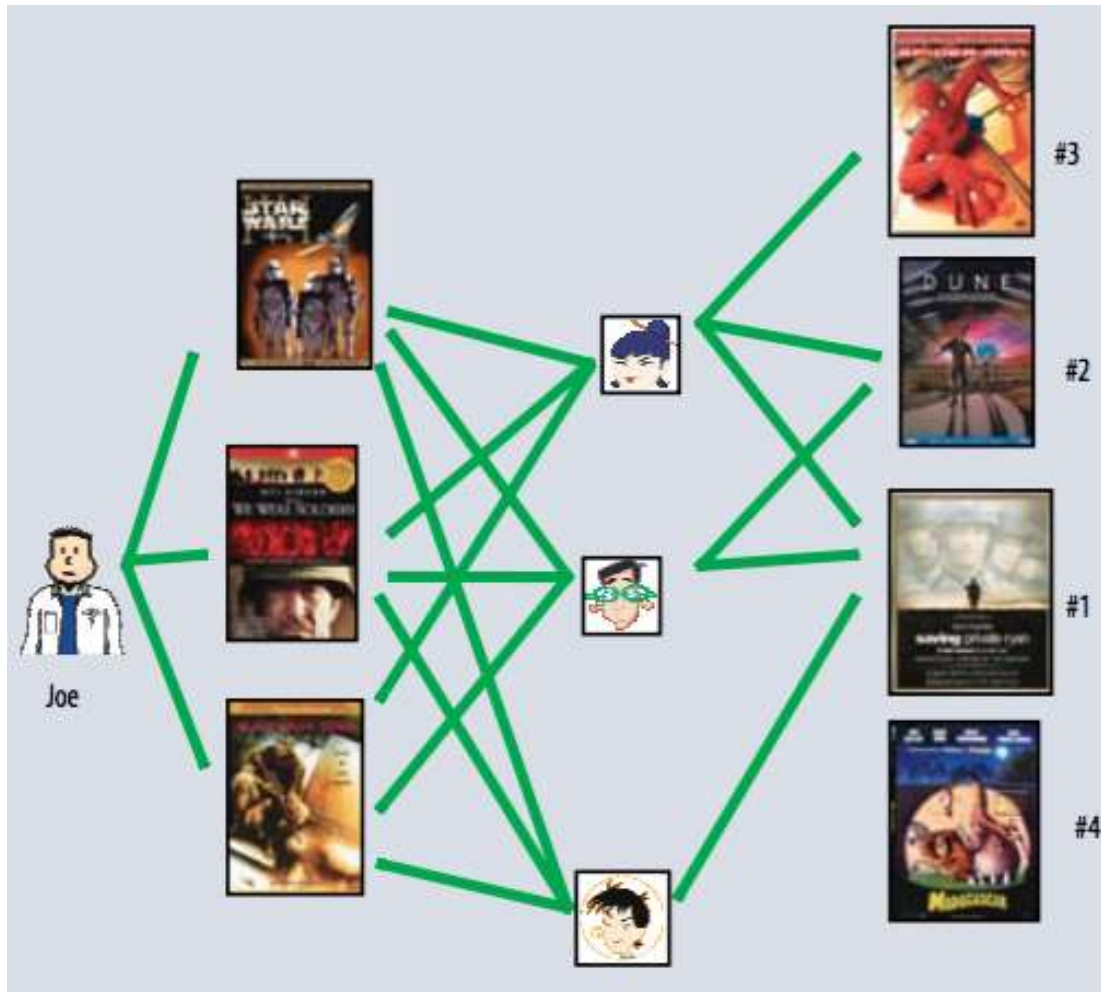


2. Latent Factor Methods



Two Types of Collaborative Filtering

1. Neighborhood Methods



In the figure, assume that a green line indicates the movie was **watched**

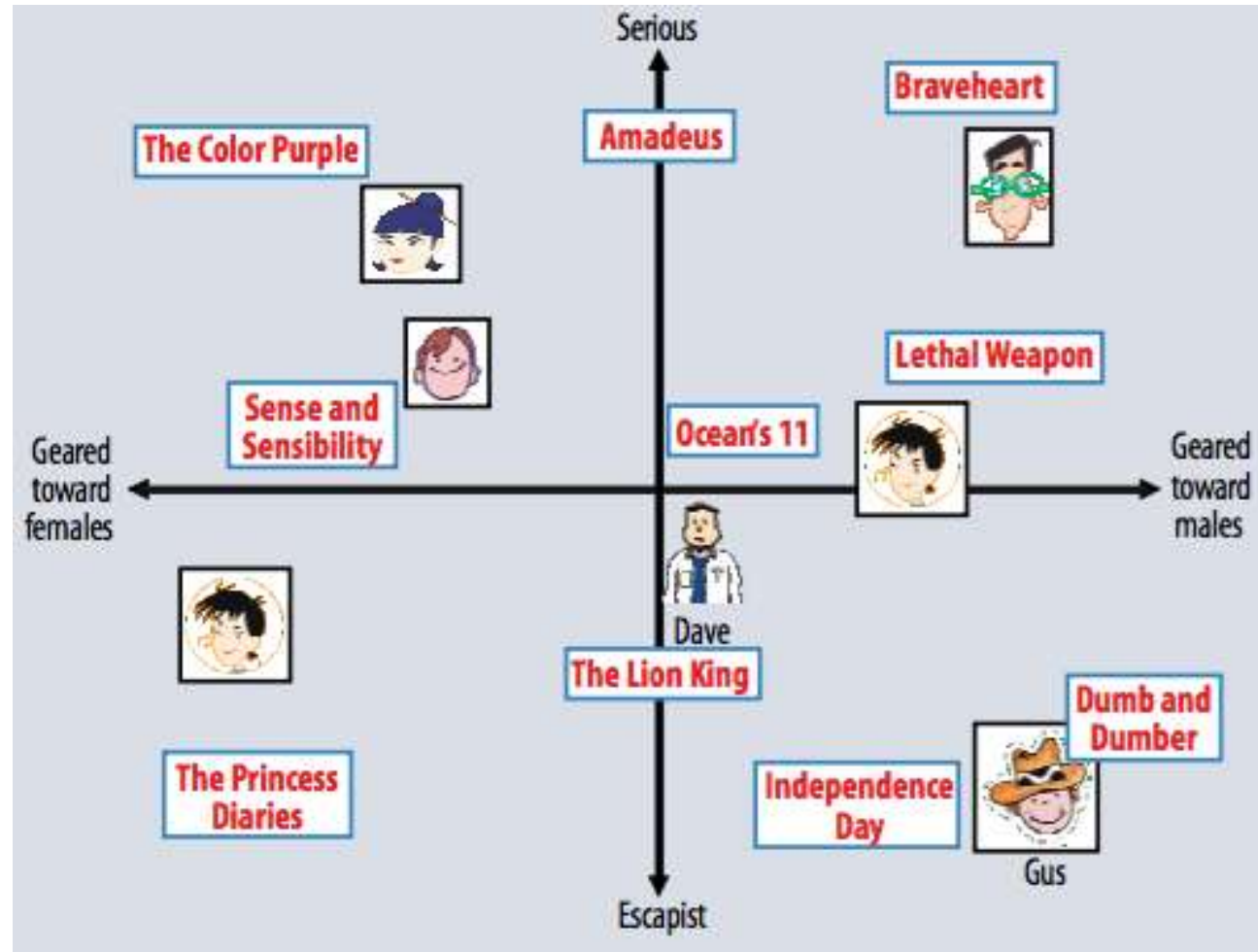
Algorithm:

1. **Find neighbors** based on similarity of movie preferences
2. **Recommend** movies that those neighbors watched

Two Types of Collaborative Filtering

2. Latent Factor Methods

- Assume that both movies and users live in some **low-dimensional space** describing their properties
- Recommend** a movie based on its **proximity** to the user in the latent space



MATRIX FACTORIZATION

Matrix Factorization (with matrices)

- User vectors:

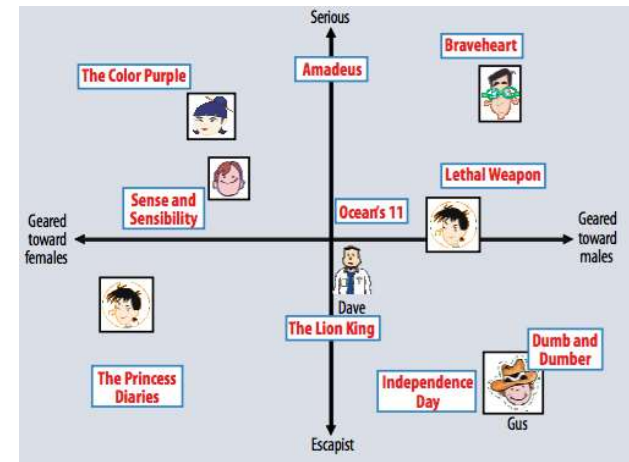
$$(W_{u*})^T \in \mathbb{R}^r$$

- Item vectors:

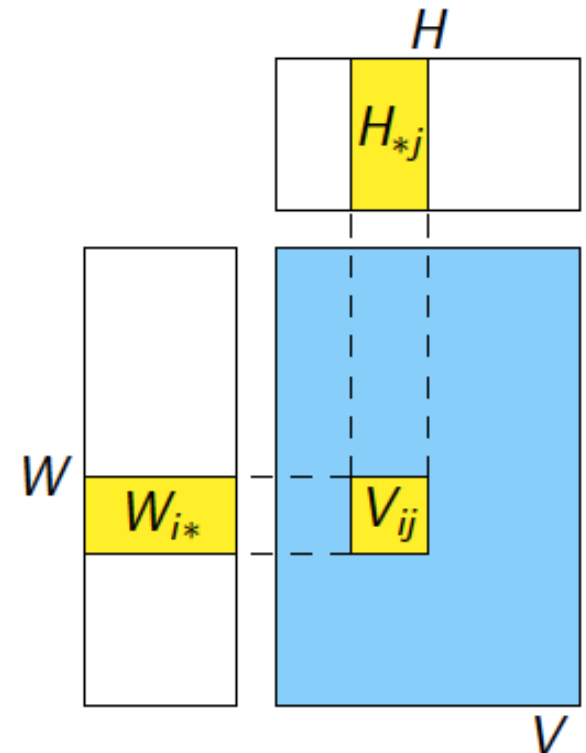
$$H_{*i} \in \mathbb{R}^r$$

- Rating prediction:

$$\begin{aligned} V_{ui} &= W_{u*} H_{*i} \\ &= [WH]_{ui} \end{aligned}$$



Figures from Koren et al. (2009)



Figures from Gemulla et al. (2011)₁₉

Matrix Factorization (with vectors)

- User vectors:

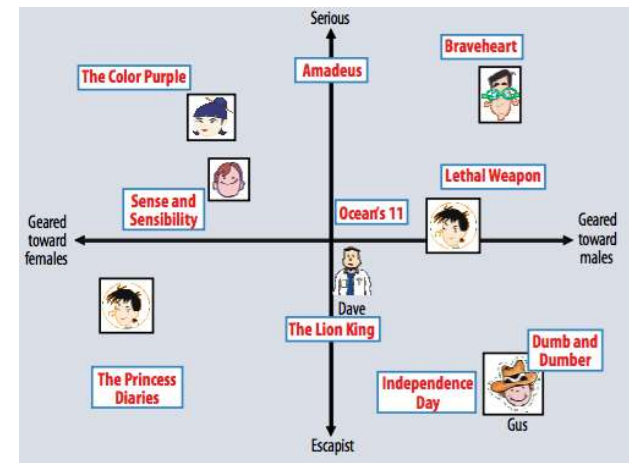
$$\mathbf{w}_u \in \mathbb{R}^r$$

- Item vectors:

$$\mathbf{h}_i \in \mathbb{R}^r$$

- Rating prediction:

$$v_{ui} = \mathbf{w}_u^T \mathbf{h}_i$$



Figures from Koren et al. (2009)

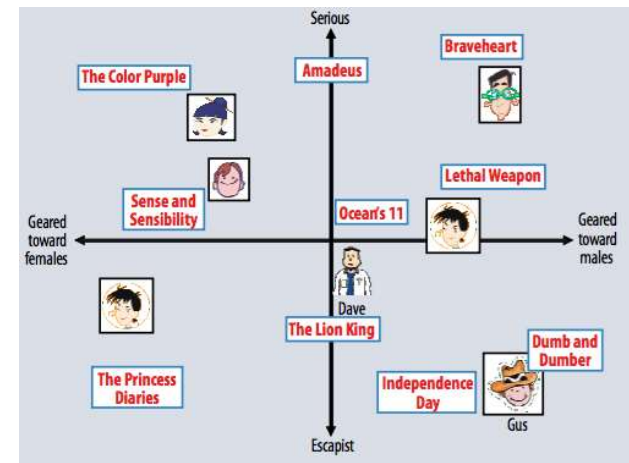
Matrix Factorization (with vectors)

- Set of non-zero entries:

$$\mathcal{Z} = \{(u, i) : v_{ui} \neq 0\}$$

- Objective:

$$\operatorname{argmin}_{\mathbf{w}, \mathbf{h}} \sum_{(u, i) \in \mathcal{Z}} (v_{ui} - \mathbf{w}_u^T \mathbf{h}_i)^2$$

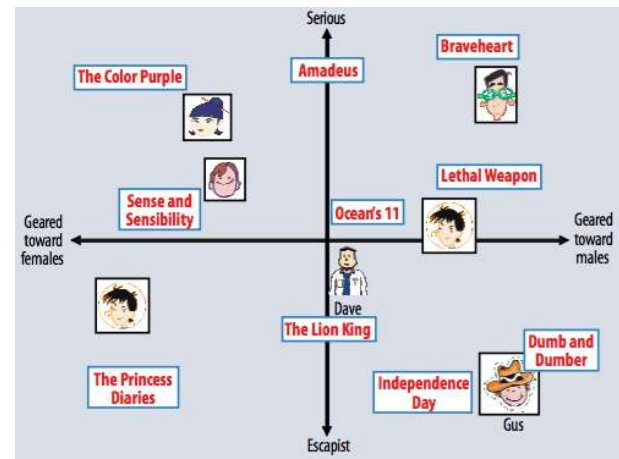


Figures from Koren et al. (2009)

Matrix Factorization (with vectors)

- Regularized Objective:

$$\begin{aligned} \operatorname{argmin}_{\mathbf{w}, \mathbf{h}} \sum_{(u,i) \in \mathcal{Z}} (v_{ui} - \mathbf{w}_u^T \mathbf{h}_i)^2 \\ + \lambda \left(\sum_i \|\mathbf{w}_i\|^2 + \sum_u \|\mathbf{h}_u\|^2 \right) \end{aligned}$$



Figures from Koren et al. (2009)

Matrix Factorization (with vectors)

- Regularized Objective:

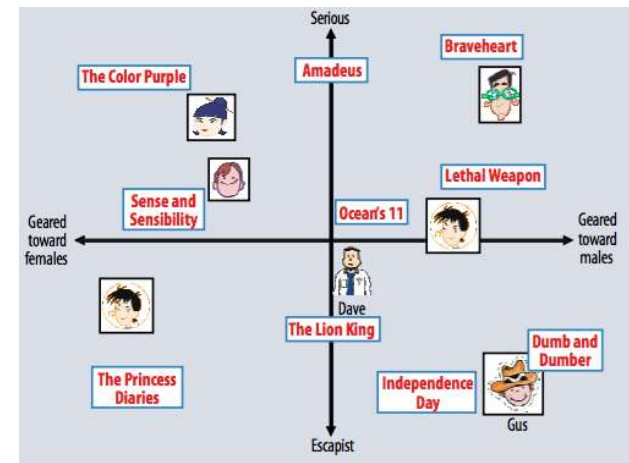
$$\begin{aligned} \operatorname{argmin}_{\mathbf{w}, \mathbf{h}} \sum_{(u,i) \in \mathcal{Z}} (v_{ui} - \mathbf{w}_u^T \mathbf{h}_i)^2 \\ + \lambda \left(\sum_i \|\mathbf{w}_i\|^2 + \sum_u \|\mathbf{h}_u\|^2 \right) \end{aligned}$$

- SGD update for random (u,i):

$$e_{ui} \leftarrow v_{ui} - \mathbf{w}_u^T \mathbf{h}_i$$

$$\mathbf{w}_u \leftarrow \mathbf{w}_u + \gamma(e_{ui} \mathbf{h}_i - \lambda \mathbf{w}_u)$$

$$\mathbf{h}_i \leftarrow \mathbf{h}_i + \gamma(e_{ui} \mathbf{w}_u - \lambda \mathbf{h}_i)$$



Figures from Koren et al. (2009)

Matrix Factorization (with matrices)

- User vectors:

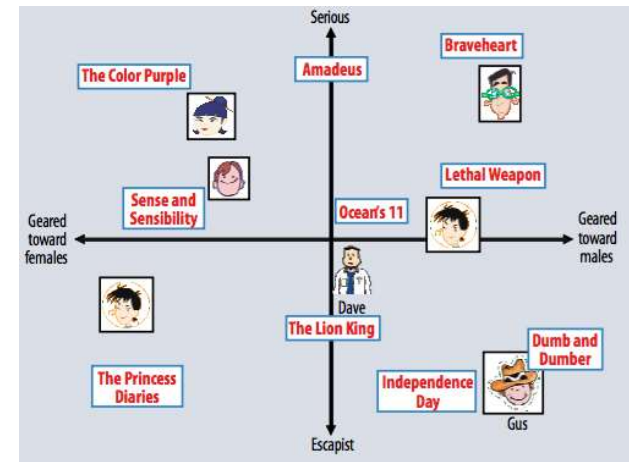
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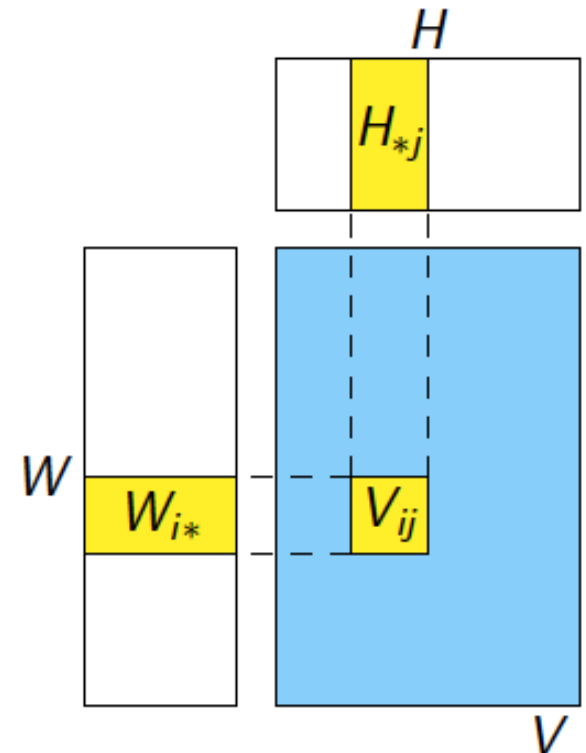
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- Rating prediction:

$$\begin{aligned} V_{ui} &= W_{u*} H_{*i} \\ &= [WH]_{ui} \end{aligned}$$



Figures from Koren et al. (2009)



Figures from Gemulla et al. (2011)₂₄

Matrix Factorization (with matrices)

- SGD

require that the loss can be written as

$$L = \sum_{(i,j) \in Z} l(\mathbf{V}_{ij}, \mathbf{W}_{i*}, \mathbf{H}_{*j})$$

Algorithm 1 SGD for Matrix Factorization

Require: A training set Z , initial values \mathbf{W}_0 and \mathbf{H}_0

while not converged **do** {step}

 Select a training point $(i, j) \in Z$ uniformly at random.

$\mathbf{W}'_{i*} \leftarrow \mathbf{W}_{i*} - \epsilon_n N \frac{\partial}{\partial \mathbf{W}_{i*}} l(\mathbf{V}_{ij}, \mathbf{W}_{i*}, \mathbf{H}_{*j})$

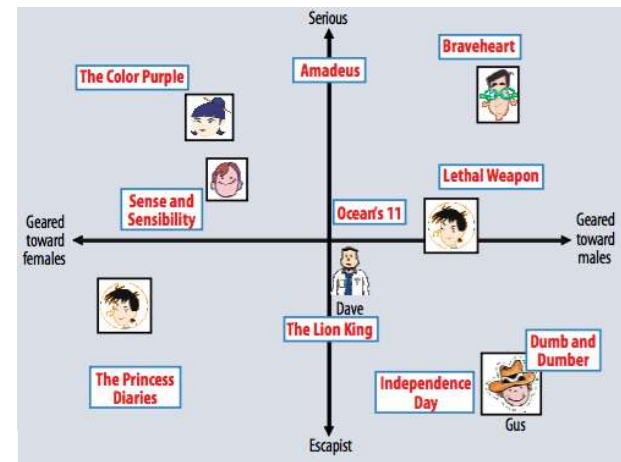
$\mathbf{H}_{*j} \leftarrow \mathbf{H}_{*j} - \epsilon_n N \frac{\partial}{\partial \mathbf{H}_{*j}} l(\mathbf{V}_{ij}, \mathbf{W}_{i*}, \mathbf{H}_{*j})$

$\mathbf{W}_{i*} \leftarrow \mathbf{W}'_{i*}$

end while

↖ step size

Figure from Gemulla et al. (2011)



Figures from Koren et al. (2009)

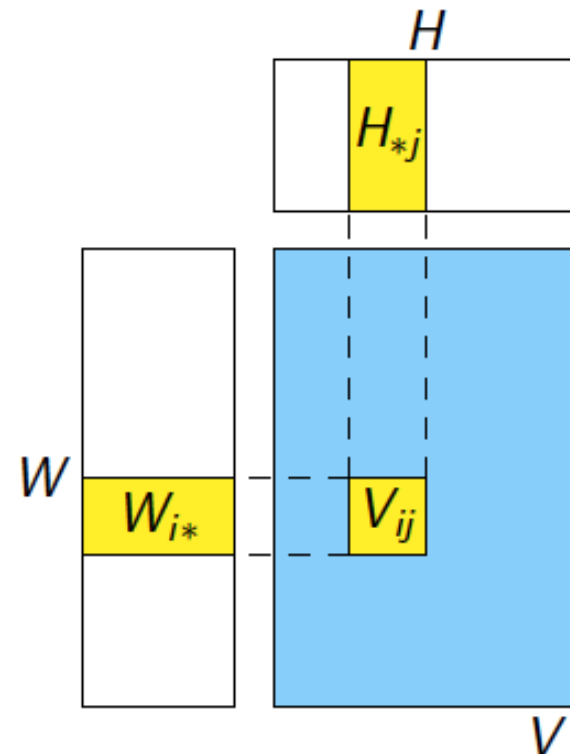


Figure from Gemulla et al. (2011)₂₅

Matrix Factorization

Example Factors

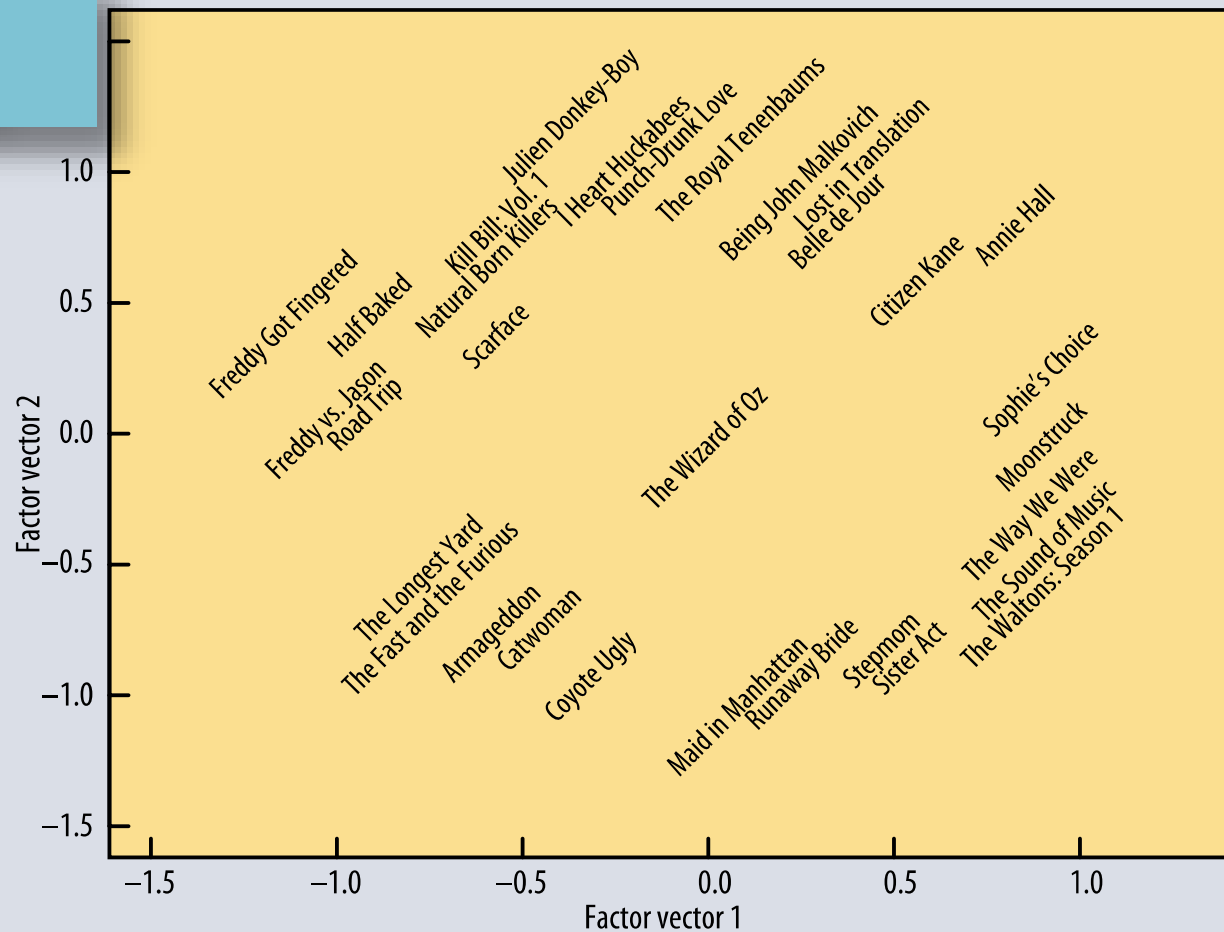
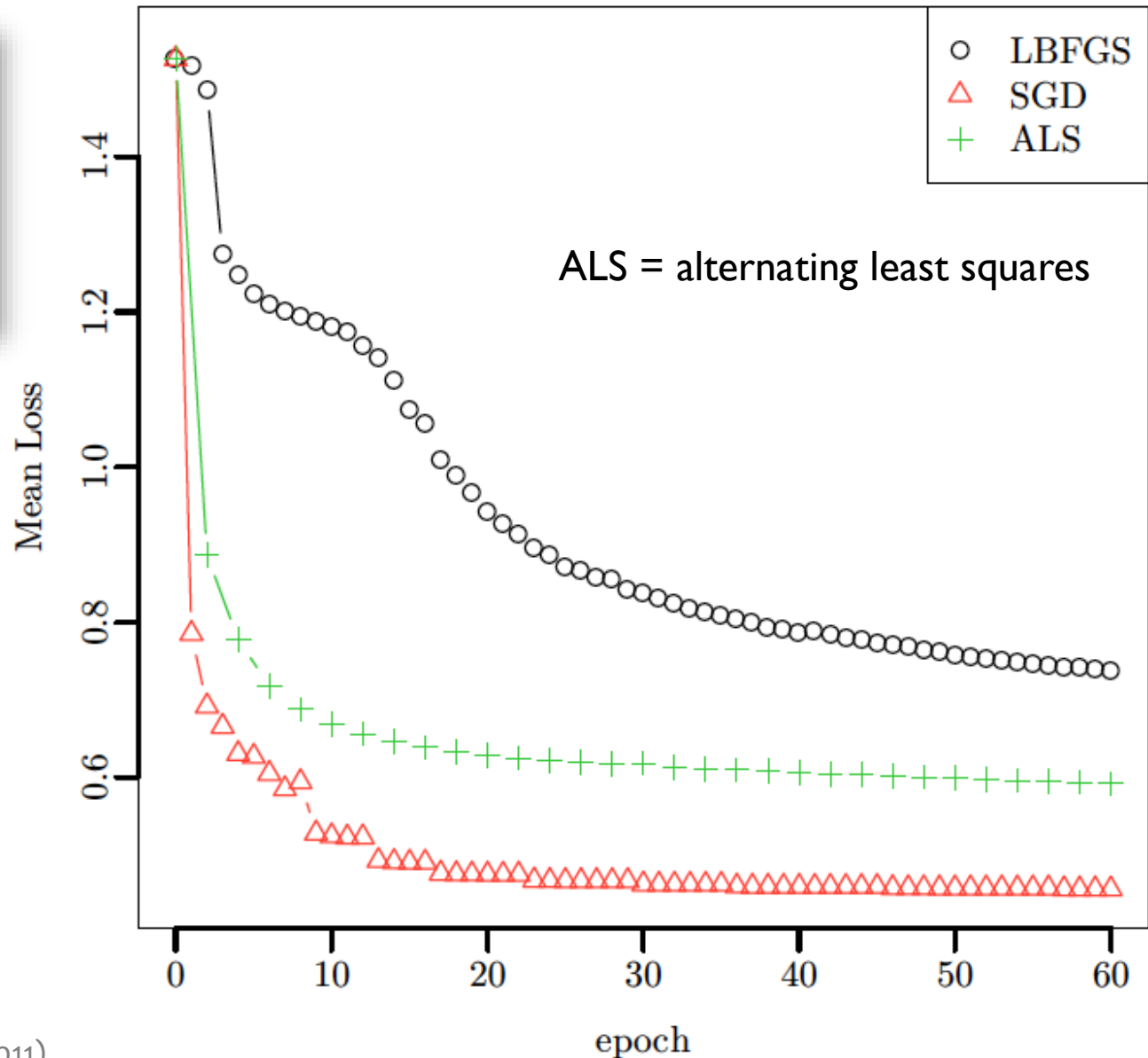


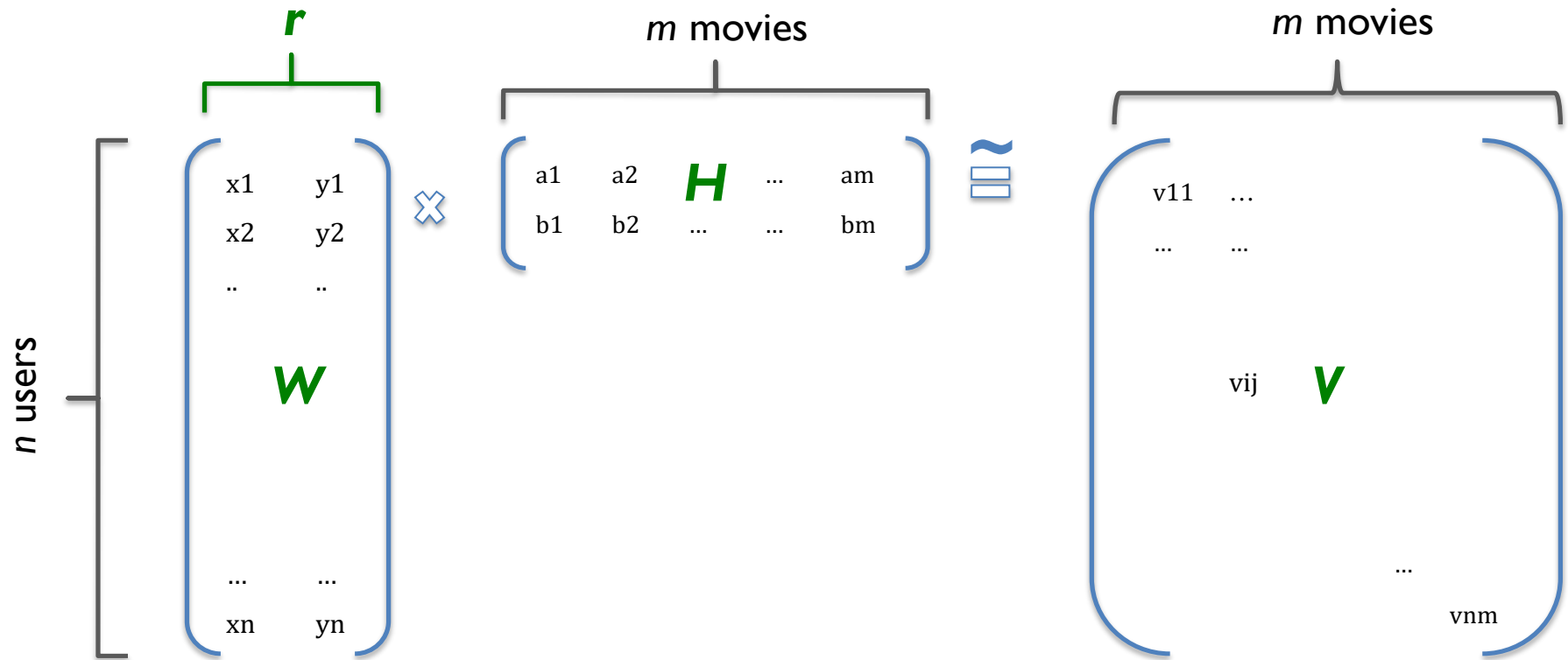
Figure 3. The first two vectors from a matrix decomposition of the Netflix Prize data. Selected movies are placed at the appropriate spot based on their factor vectors in two dimensions. The plot reveals distinct genres, including clusters of movies with strong female leads, fraternity humor, and quirky independent films.

Matrix Factorization

Comparison of Optimization Algorithms



MATRIX MULTIPLICATION IN MACHINE LEARNING

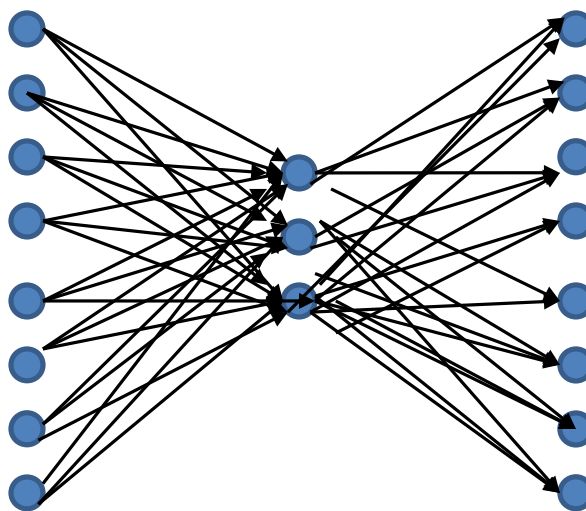


$V[i,j]$ = user i 's rating of movie j

... vs autoencoders & nonlinear PCA

- Assume we would like to learn the following (trivial?) output function:
- Using the following network:
- With *linear* hidden units, how do the weights match up to W and H ?

Input	Output
00000001	00000001
00000010	00000010
00000101	00000100
00001000	00001000
00010000	00010000
00100000	00100000
01000000	01000000
10000000	10000000



Summary

- Recommender systems solve many **real-world** (*large-scale) **problems**
- Collaborative filtering by Matrix Factorization (MF) is an **efficient** and **effective** approach
- MF is just another example of a **common recipe**:
 1. define a model
 2. define an objective function
 3. optimize with SGD