

INTRODUCTION TO DATA SCIENCE

This lecture is
based on course by E. Fox and C. Guestrin, Univ of Washington

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WFAiS UJ, Informatyka Stosowana
I stopień studiów

Recommending system: films

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Machine learning:
recommending system

□ Personalizacja

You Tube

100 Hours a Minute
What do I care about?

Information overload



Browsing is "history"
– Need new ways
to discover content

Personalization: Connects *users & items*

viewers

videos

Recomending system:

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Connect users with movies they may want to watch

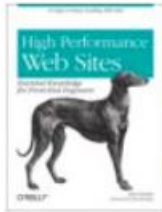
Recomending system:

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amazon.com

[Help](#) | [Close window](#)

Recommended for You



**High Performance Web Sites:
Essential Knowledge for
Front-End Engineers**
by Steve Souders (Author)
Our Price: \$19.79
Used & new from \$16.24

[Add to Cart](#)

[Add to Wish List](#)

Because you purchased...

**Programming Collective Intelligence: Building
Smart Web 2.0 Applications** (Paperback)
by Toby Segaran (Author)



Today's Recommendations For You

Here's a daily sample of items recommended for you. Click here to [see all recommendations](#)

Even Faster Web Sites: Performance... (Paperback) by Steve Souders
★★★★☆ (7) \$23.10
[Fix this recommendation](#)

Simply JavaScript (Paperback) by Kevin Yank
★★★★☆ (19) \$26.37
[Fix this recommendation](#)

The Art & Science of Java (Paperback)
★★★★☆ (5)
[Fix this recommendation](#)

[Any Category](#) Algorithms Boxed Sets Business & Culture Java
Networking Networks, Protocols & APIs SQL

Recommendations combine
global & session interests

Recommending system: popularity?

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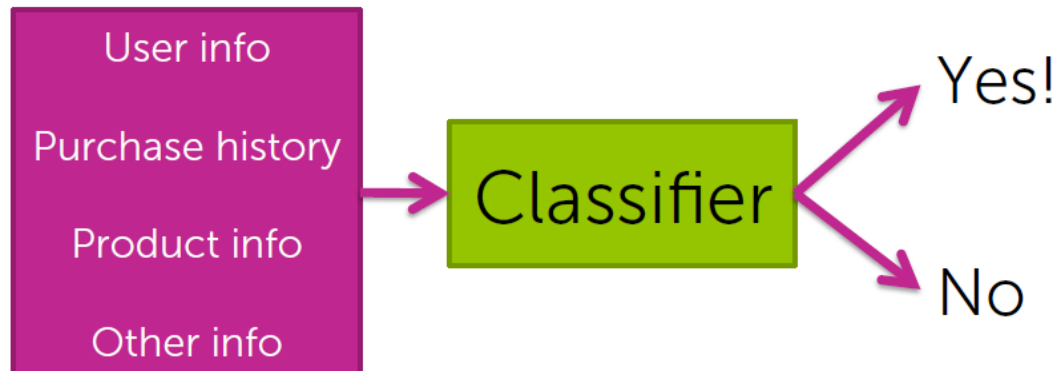
- **Popularność?**
 - ▣ **Ranking wg. liczba oglądań**
 - ▣ **Nie ma personalizacji**

Recommending system: classification

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□ Classification?

- ▣ What is probability that I will buy this product?
- ▣ Personalisation: purchase history, monthly and yearly trends, etc.



Recommending system: correlations

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- **Analyse correlations. Customers who bought product A also bought product B**
 - ▣ **Correlation matrix**

User  purchased *diapers*

1. Look at *diapers* row of matrix
2. Recommend other items with largest counts
 - *baby wipes, milk, baby food,...*

Recommending system: correlations
















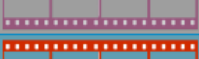


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- **Analyse correlations. Customers who bought product A also bought product B**
 - ▣ **Should we normalise correlation matrix?**
 - ▣ **How to quantify that products are „products“?**
- **Limitation of correlations:**
 - ▣ **It is not looking at the purchasing history (trends in time)**
 - ▣ **How to add a new customer (no info on correlations)?**

Recommending system: films

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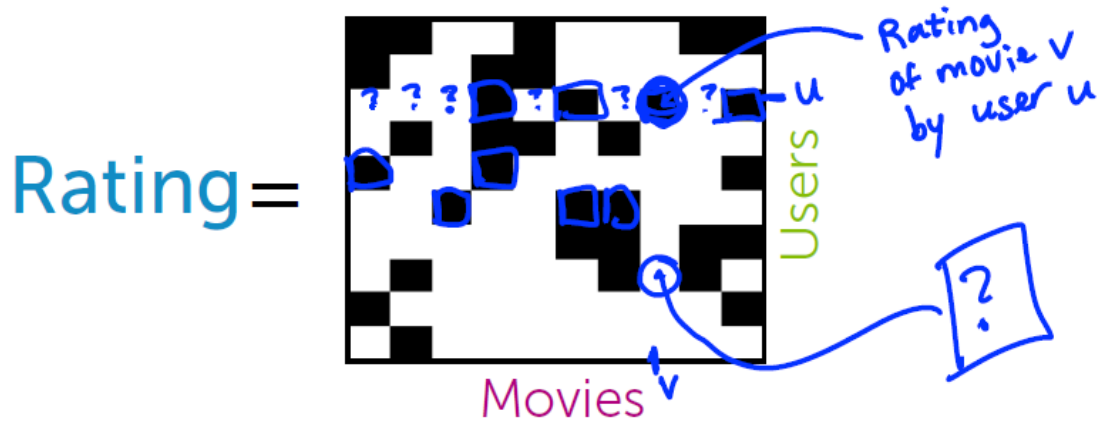
- Users watch movies and rate them

User	Movie	Rating
		★★★★☆
		★★★★★
		★★★☆☆
		★★★☆☆
		★★★★☆
		★★★☆☆
		★★★★☆
		★★★★★
		★★★★☆

Each user only watches a few of the available movies

Recommending system: films

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- **Data:** Users score some movies

$Rating(u,v)$ known for black cells
 $Rating(u,v)$ unknown for white cells

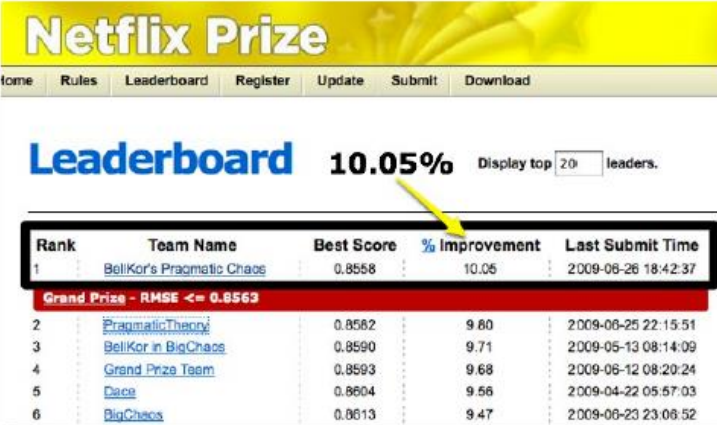
- **Goal:** Filling missing data?



Recommending system: optimisation

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- Squeezing last bit of accuracy by blending models
- Netflix Prize 2006-2009
 - 100M ratings
 - 17,770 movies
 - 480,189 users
 - Predict 3 million ratings to highest accuracy
 - **Winning team blended over 100 models**



The screenshot shows the Netflix Prize Leaderboard interface. At the top, there is a yellow banner with the text "Netflix Prize". Below the banner is a navigation menu with links for "Home", "Rules", "Leaderboard", "Register", "Update", "Submit", and "Download". The main heading is "Leaderboard" in blue, followed by "10.05%" in black, and "Display top 20 leaders." in grey. A yellow arrow points to the "10.05%" value. Below this is a table with the following columns: Rank, Team Name, Best Score, % Improvement, and Last Submit Time. The table is bordered in black. A red banner below the table reads "Grand Prize - RMSE <= 0.8563".

Rank	Team Name	Best Score	% Improvement	Last Submit Time
1	BellKor's Pragmatic Chaos	0.8558	10.05	2009-06-26 18:42:37
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	Dase	0.8604	9.56	2009-04-22 05:57:03
6	BigChaos	0.8613	9.47	2009-06-23 23:08:52

Recommending system: how effective?

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The world of all baby products



Recommending system: how effective?

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How many liked items were recommended?

The image displays a variety of baby products. Items circled in blue include a wooden high chair, a baby monitor, a car seat, a hanging mobile, and a pair of baby shoes. Items crossed out with blue X's include a crib, a pair of baby shoes, a set of baby bottles, and a baby bottle. Items enclosed in pink boxes include a baby stroller, a baby monitor, a box of Kirkland Baby Wipes, a baby stroller, a baby bottle, and two rubber ducks. A purple stick figure stands in the center of the collection.

Recall
$$\frac{\# \text{ liked \& shown}}{\# \text{ liked}} = \frac{3}{5}$$

Recommending system: how effective?

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How many recommended items were liked?

Precision
$$\frac{\# \text{ liked \& shown}}{\# \text{ shown}}$$

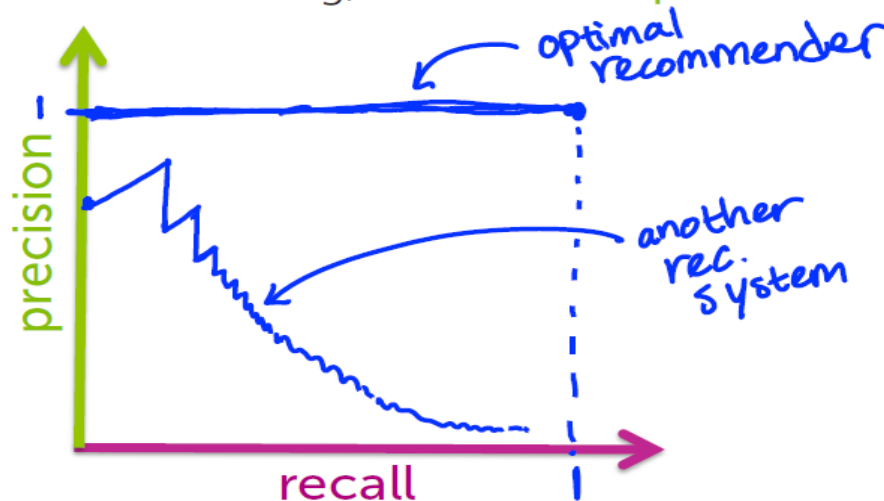
$$= \frac{3}{11}$$

Recommending system: how effective?

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Precision-recall curve

- **Input:** A specific recommender system
- **Output:** Algorithm-specific precision-recall curve
- To draw curve, vary threshold on # items recommended
 - For each setting, calculate the precision and recall

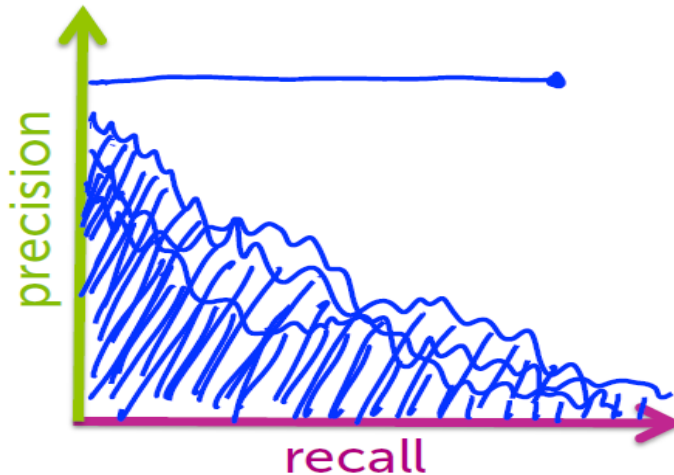


Recommending system: how effective?

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Which Algorithm is Best?

- For a given **precision**, want **recall** as large as possible (or vice versa)
- One metric: largest **area under the curve (AUC)** ★
- Another: set desired recall and maximize precision (precision at k)



Recommending system

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Models

- Collaborative filtering
- Matrix factorization
- PCA

Algorithms

- Coordinate descent
- Eigen decomposition
- SVD

Concepts

- Matrix completion, eigenvalues, random projections, cold-start problem, diversity, scaling up