Recommender Systems

Data Science Dojo

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Overview

- What are Recommender Systems?
- How do they work?
  - Collaborative Recommendation
  - Content-Based Recommendation
- How do we evaluate them?
- Example using Azure ML

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Recommender Systems

- What are Recommender Systems?
  - To solve information overload problem
  - Automated systems to filter and recommend products based on users' interest and taste.

Example: Retail

Related to Items You've Viewed See more

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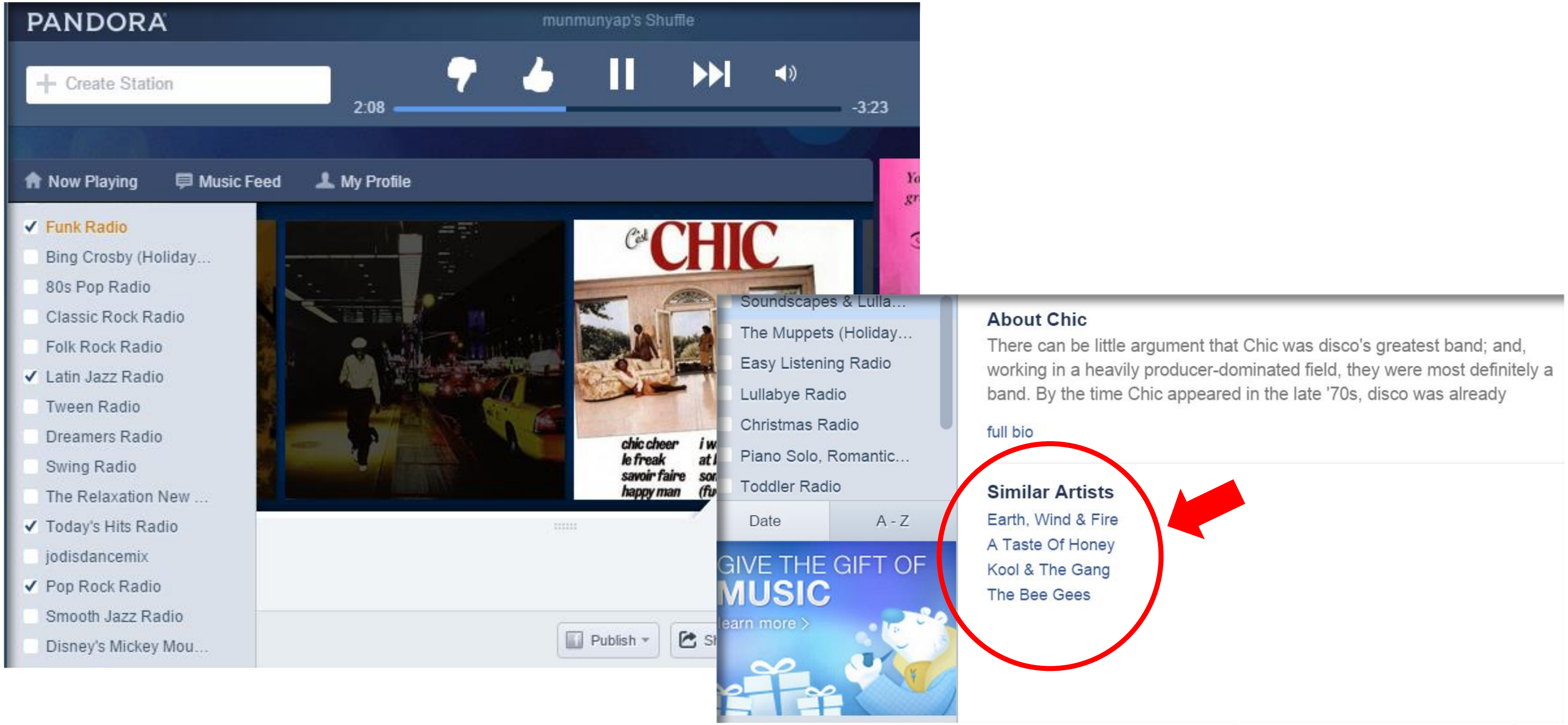
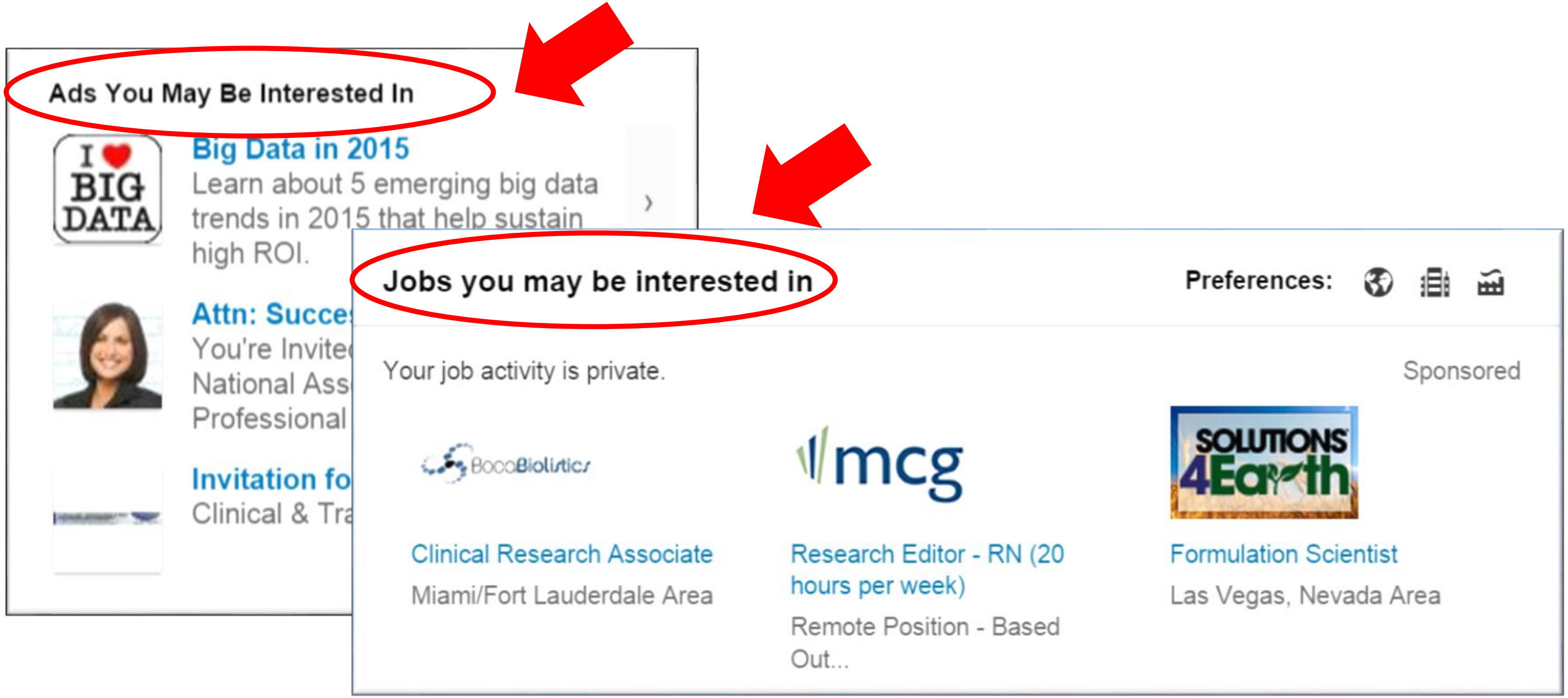
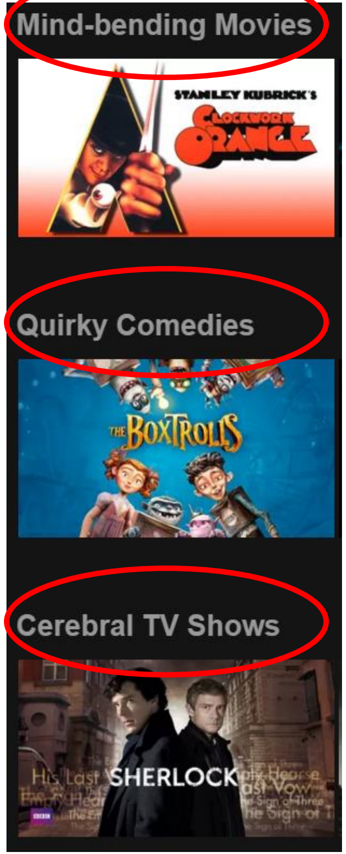
Example: Entertainment

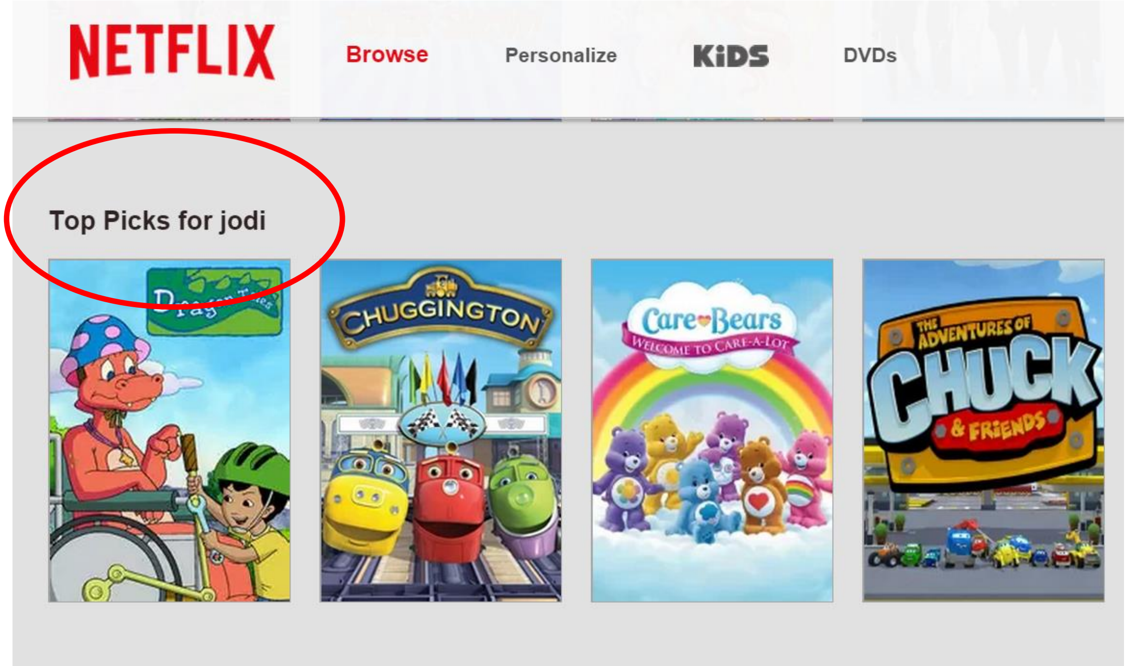


Example: Social Media



Example: Netflix





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Why recommendation systems?

For customer

- Narrow down the set of choices
- Discover new things
- Find things that are interesting
- Save time

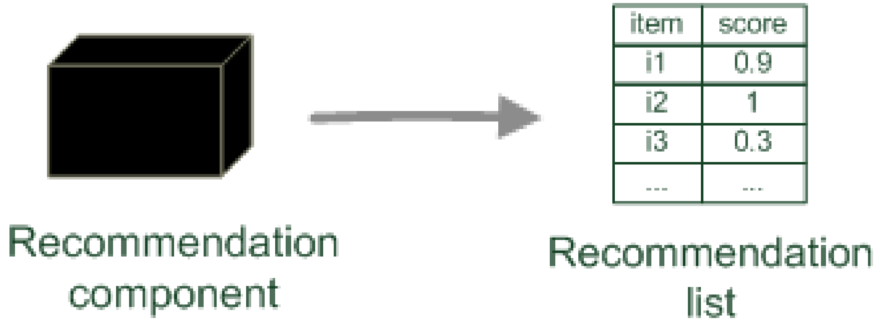
Why recommendation systems?

For businesses

- Increase the number of items sold
- Sell more diverse items
- Increase the user satisfaction
- Better understand what the user wants

Recommender Systems

Recommender systems reduce information overload by estimating relevance



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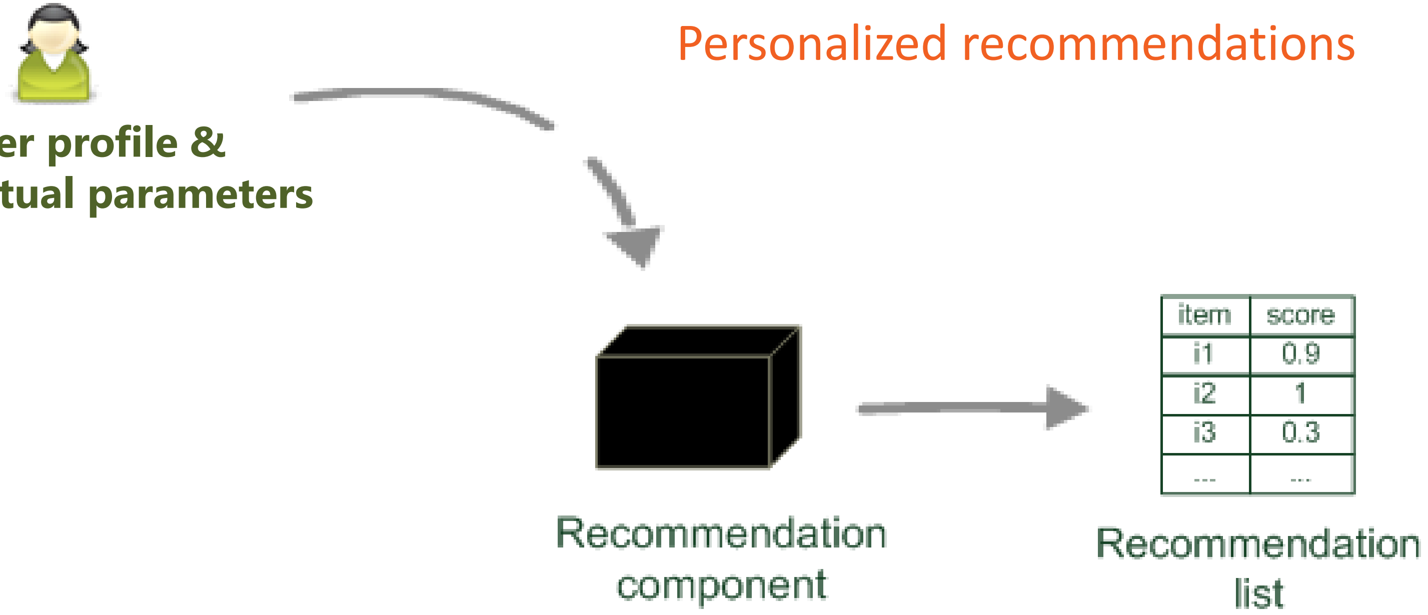
Recommender Systems

Personalized recommendations



item	score
i1	0.9
i2	1
i3	0.3
...	...

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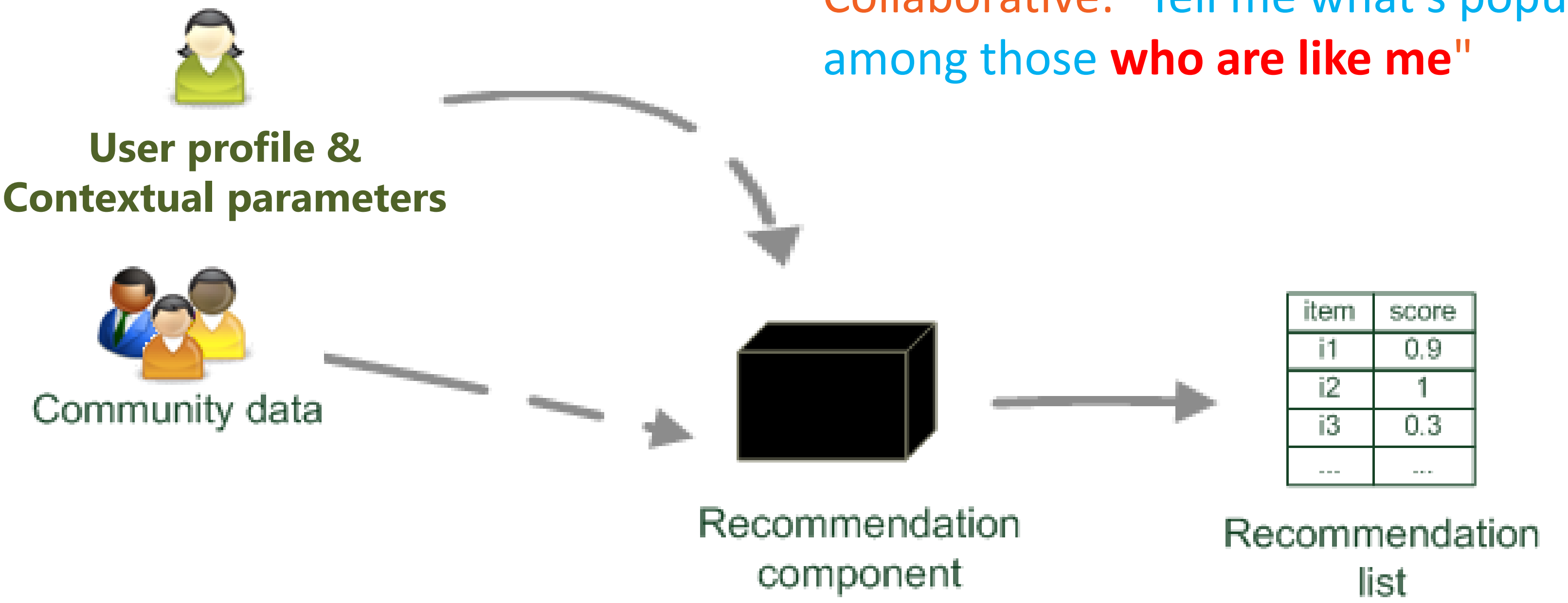
Collaborative Filtering

- Maintain a database of many users' ratings of a variety of items.
- For a given user, find other similar users whose ratings strongly correlate with the current user.
- Recommend items rated highly by these similar users, but not rated by the current user.

Collaborative Filtering (CF)

Collaborative: "Tell me what's popular among those **who are like me**"



Collaborative Filtering

- Most popular recommendation algorithm
  - Used by large, commercial e-commerce sites
  - Well-understood, variety of algorithms
  - Applicable to many domain (books, movies, songs,…)

- Approach: borrow the "wisdom of the crowd" to recommend items

Collaborative Filtering

- Assumption:
  - Users give ratings to items
  - Users who has similar tastes in the past, have similar tastes in the future.
- User-based collaborative
- Item-based collaborative

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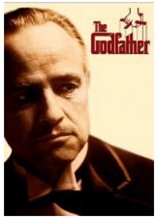
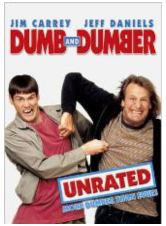
Movie Rating Example





Alice	5	3	4	4	?
Bob	3	1	2	3	3
Chris	4	3	4	3	5
Donna	3	3	1	5	4
Evi	1	5	5	2	1

Movie Rating Example

Goal: Given Alice is an "active" user, we want to predict the rating of movie *i* Alice hasn't seen before.

- Find set of users who liked the same items as Alice in the past and also had rated movie *i*
- Predict Alice's rating on movie *i*
- Repeat for all items Alice has not seen and recommend the best rated.

User-Based collaborative filtering

- How do we define similarity?
- How many neighbor should we include?
- How to generate prediction from neighbors' ratings?

User-Based collaborative filtering

- **Nearest neighbors**
  - **Pearson correlation**

j : Alice
k: Bob
P: set of items, rated by Alice and Bob

j,k : users

$r_{j,p}$: *rating of user j for item p*

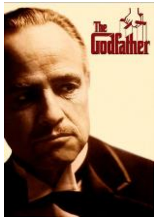
$\bar{r}_j$ *and* $\bar{r}_k$ *are the average ratings of user j and user k over all items*

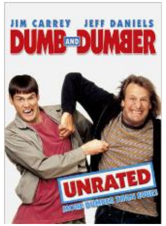
P: set of items, rated both by j and k

Possible similarity values between -1 and 1

$$\boldsymbol{sim(j,k)} = \frac{\sum_{p\,\in \boldsymbol{P}} (\boldsymbol{r}_{j,p} - \bar{\boldsymbol{r}}_j)(\boldsymbol{r}_{k,p} - \bar{\boldsymbol{r}}_k)}{\sqrt{\sum_{p\,\in \boldsymbol{P}} (\boldsymbol{r}_{j,p} - \bar{\boldsymbol{r}}_j)^2}\sqrt{\sum_{\boldsymbol{p}\,\in \boldsymbol{P}} (\boldsymbol{r}_{k,p} - \bar{\boldsymbol{r}}_k)^2}}$$

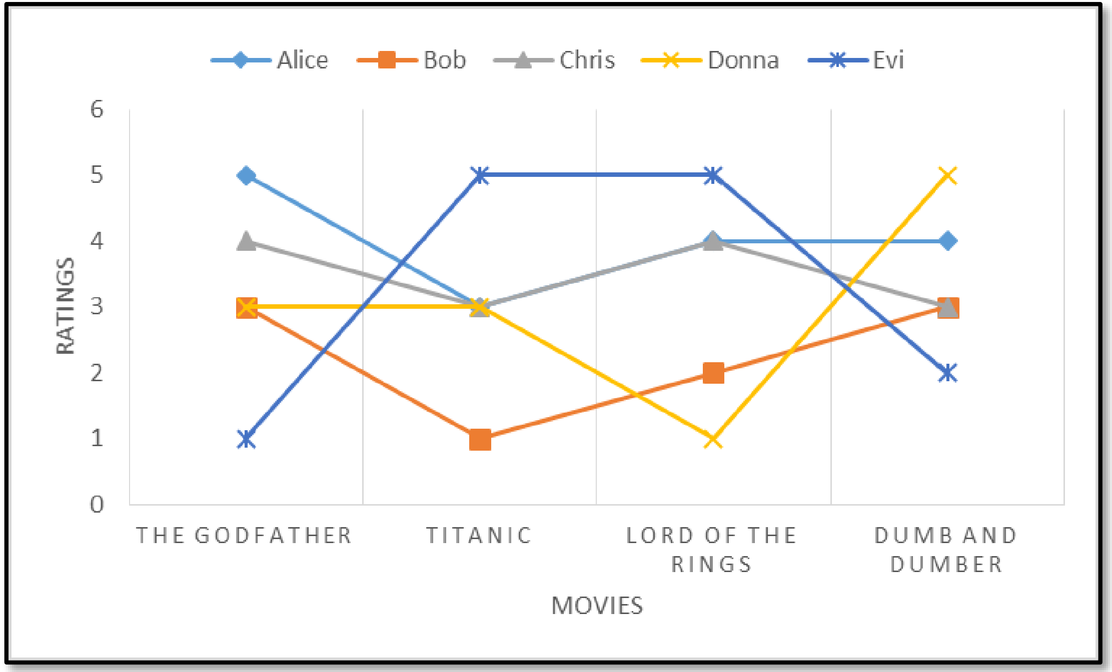
Pearson Correlation





Alice	5	3	4	4	?	
Bob	3	1	2	3	3	sim=0.85
Chris	4	3	4	3	5	sim=0.90
Donna	3	3	1	5	4	sim=0.70
Evi	1	5	5	2	1	sim=0.79

Pearson Correlation



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Making recommendations

- Making predictions is typically not the ultimate goal
- Usual approach
  - Rank items based on their predicted ratings
- However
  - This might lead to the inclusion of (only) niche items
- Better approach
  - Optimize according to a given rank evaluation metric

Collaborative Filtering

- Assumption:
  - Users give ratings to items
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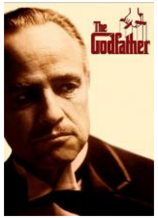
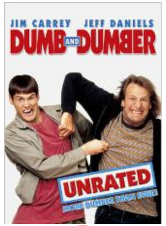
- User-based collaborative
- **Item-based collaborative**

Item-based collaborative filtering

- Basic idea:
  - Use the similarity between items (and not users) to make predictions
- Example:
  - Look for movies that are similar to movie 5
  - Take Alice's ratings for these items to predict the rating for movie 5

Movie Rating Example





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Item-based Similarity Measurements

- cosine similarity

$$sim(\vec{a},\vec{b}) = \frac{\vec{a}\cdot\vec{b}}{|\vec{a}| * |\vec{b}|}$$

- Adjusted cosine similarity

$$sim(\vec{a},\vec{b}) = \frac{\sum_{u\in U}(r_{u,a}-\overline{r_u})(r_{u,b}-\overline{r_u})}{\sqrt{\sum_{u\in U}(r_{u,a}-\overline{r_u})^2}\sqrt{\sum_{u\in U}(r_{u,b}-\overline{r_u})^2}}$$

Collaborative Filtering Pros

- well-understood and proven
- works well in many domains
- no knowledge engineering required
- serendipity of results

Collaborative Filtering Cons

Data sparsity: New user needs to indicate preferences for sufficient number of items before getting recommendations

Scalability: Millions of customers (M) and millions of items (N).

Grey Sheep and Black Sheep: Grey sheep are users with inconsistent recommendations. Black sheep are the users with idiosyncratic preferences.

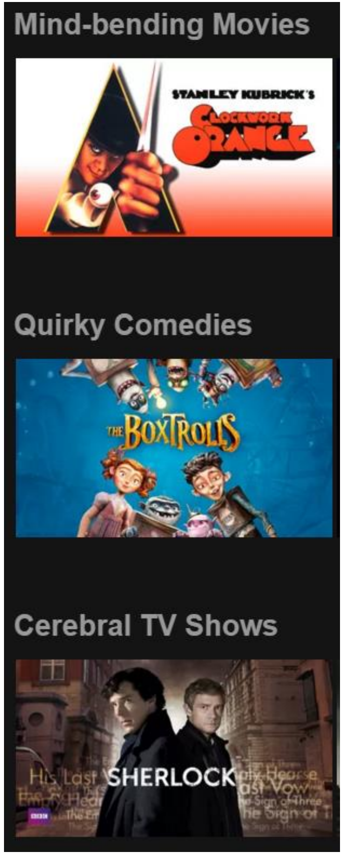
Collaborative Filtering Cons

Shilling: Intentional manipulation of ratings of your own products and competitors products

Diversity and Long Tail: Rich get richer.

Cold Start: Need initial customer/rating database

Example: Netflix



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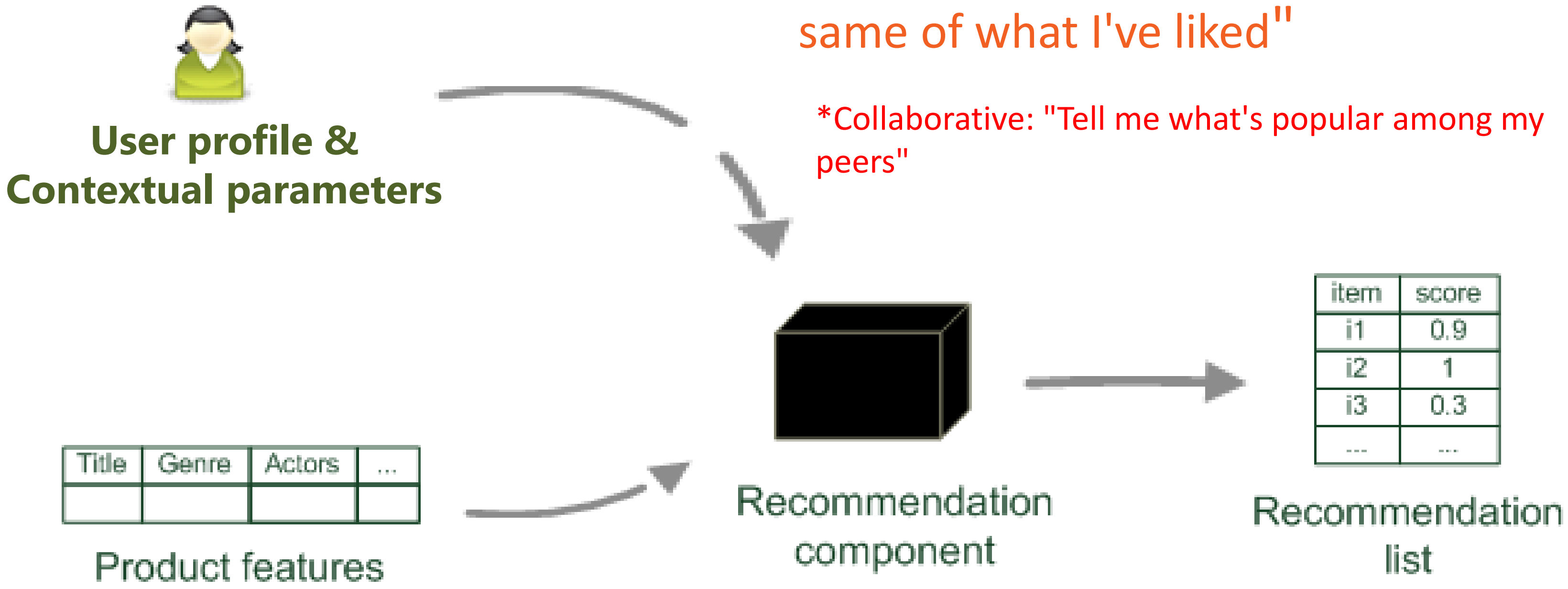
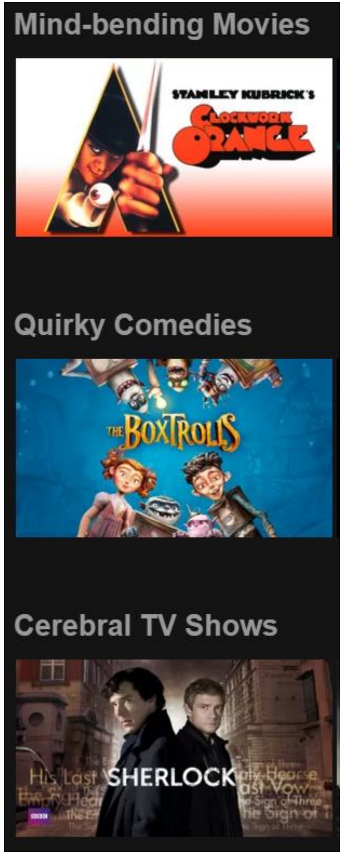
Content-based recommendation

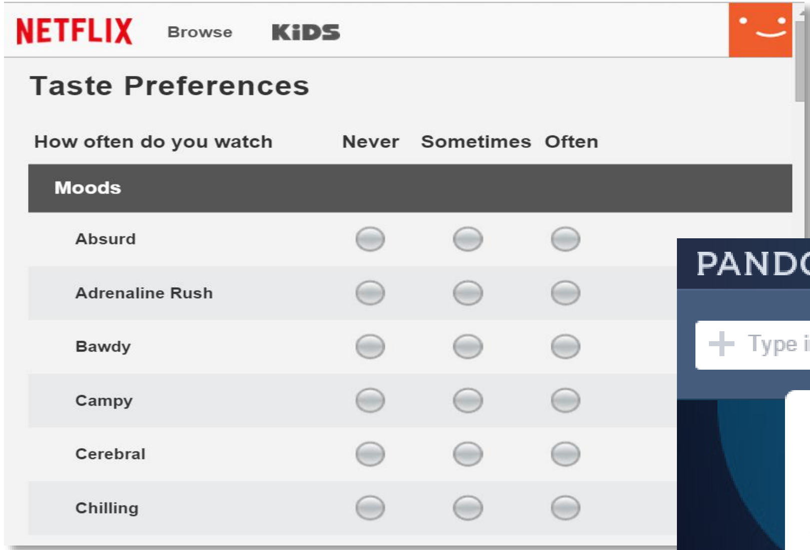
Content-based: "Show me more of the same of what I've liked"

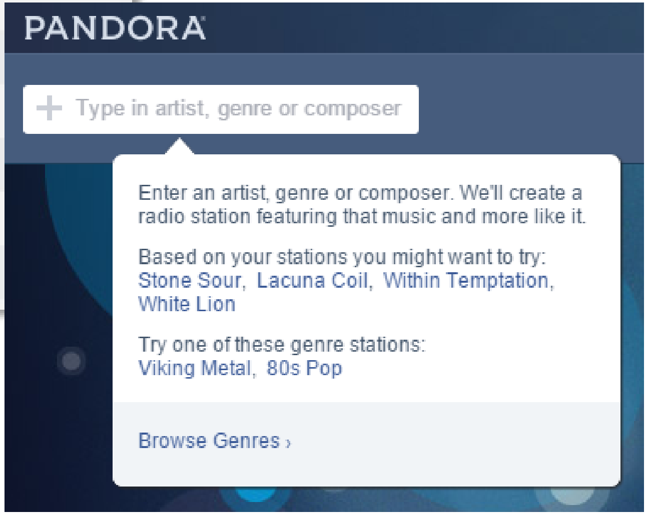
*Collaborative: "Tell me what's popular among my peers"



Content-based recommendation







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Content-based recommendation

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Overview - History - Domain specific interests - Criticism

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Content-based recommendation

Recommend items that are “similar” to the user preferences

What do we need:

- Item Profiles: content of the items
- User profiles: preferences of the user.
  - User specified or based on item ratings

Item Profile Strategies

- **Expert Labeling**
  - Assign keywords based on content
  - Good for songs, movies, etc
  - May be provided by creators/distributors
  - Crowd sourcing?

Content-based recommendation

- **Information Retrieval (IR)**
  - Used for text documents (web pages, books, tweets)
  - Based on word content of document set
  - No expert knowledge involved
  - Can be keyword or full dictionary based

Content-based recommendation

- **Prediction: Simple approach**
  - Compute the similarity of an item and user profile based on keyword overlap
  - $\text{sim}(b_i, b_j) = \dfrac{2 * |keywords(b_i) \cap keywords(b_j)|}{|keywords(b_i)| + |keywords(b_j)|}$

Simple approach: drawbacks

- Not every word has similar importance
- Longer documents have a higher chance to have an overlap with the user profile
- Automated extraction particularly problematic

TF-IDF

- Common Solution: TF-IDF
  - **Term Frequency:** Measures, how often a term appears (density in a document)
    - Assuming that important terms appear more often
    - Normalization has to be done in order to take document length into account
  - **Inverse Document Frequency:** Aims to reduce the weight of terms that appear in all documents

Term Frequency

- **Term frequency (TF)**
  - Let *freq(t,d)* number of occurrences of keyword *t* in document *d*
  - Let *max{freq(w,d)}* denote the highest number of occurrences of another keyword of *d*
  - $TF(t,d) = \frac{freq(t,d)}{\max\{freq(w,d) : w \in d\}}$

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Inverse Document Frequency

- **Inverse Document Frequency (IDF)**
  - N: number of all recommendable documents
  - n(t): number of documents in which keyword t appears
  - $IDF(t) = log\frac{N}{n(t)}$

TF-IDF

- Compute the overall importance of keywords
  - Given a keyword *t* and a document *d*

$$TF\text{-}IDF\,(t,d) = TF(t,d) * IDF(t)$$

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TF-IDF Exercise

- http://lsirwww.epfl.ch/courses/dis/2006ws/exercises/IR/Exercise8.htm
- http://lsirwww.epfl.ch/courses/dis/2006ws/exercises/IR/Exercise%208%20solution%202007.pdf

Recommending items

- Simple method: nearest neighbors
  - Given a set of documents D already rated by the user (like/dislike, ratings)
    - Find the n nearest neighbors of a not-yet-seen item *i* in D
    - Take these ratings to predict a rating/vote for *i*

Example taken from http://informationretrieval.org

Recommending items

- Query-based retrieval: Rocchio's method
- Probabilistic methods
- linear classification/regression algorithms
- etc

Example taken from http://informationretrieval.org

Content-based recommenders

Advantages

- No community required: Only need the items and a single user profile for recommendation.
- Transparency: CB models can tell you why they recommend an item, not subject to vagaries of human taste
- No cold start: new items can be suggested before being rated by a substantial number of users.

Content-based recommenders

Disadvantages

- Limited content analysis: requires well annotated content for good recommendations.
- Over-specialization
- New users: limited user information results in bad recommendations.

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Evaluating Recommendation

- Metrics measure error rate
  - **Mean Absolute Error (*MAE*)** computes the deviation between predicted ratings and actual ratings

$$MAE = \frac{1}{n}\sum_{i=1}^{n} | p_i - r_i |$$

  - **Root Mean Square Error (*RMSE*)** is similar to *MAE*, but places more emphasis on larger deviation

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n} (p_i - r_i)^2}$$

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Metrics

- Order matters, not exact ranking value
- Discounted cumulative gain (DCG)
  - Logarithmic reduction factor

$$DCG_{pos} = rel_1 + \sum_{i=2}^{pos} \frac{rel_i}{\log_2 i}$$

Where:

- *pos* denotes the position up to which relevance is accumulated
- rel_i returns the relevance of recommendation at position *i*

Metrics

- **Ideal discounted cumulative gain (IDCG)**
  - Assumption that items are ordered by decreasing relevance

$$IDCG_{pos} = rel_1 + \sum_{i=2}^{|h|-1} \frac{rel_i}{\log_2 i}$$

- **Normalized discounted cumulative gain (nDCG)**

$$nDCG_{pos} = \frac{DCG_{pos}}{IDCG_{pos}}$$

  - Normalized to the interval [0..1]

QUESTIONS

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