# Recommendation Systems

Data Science Dojo



### Overview

- Introduction
  - Collaborative vs Content-based
- How do they work?
  - Data structure
  - Ranking by similarity
  - Predicting
  - Evaluation
- Advantages/Disadvantages
- Example using Azure ML



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## **Recommendation Systems**

What are Recommendation Systems?

 Automated systems to filter and recommend products based on users' interest and taste.

Designed to solve the information overload problem

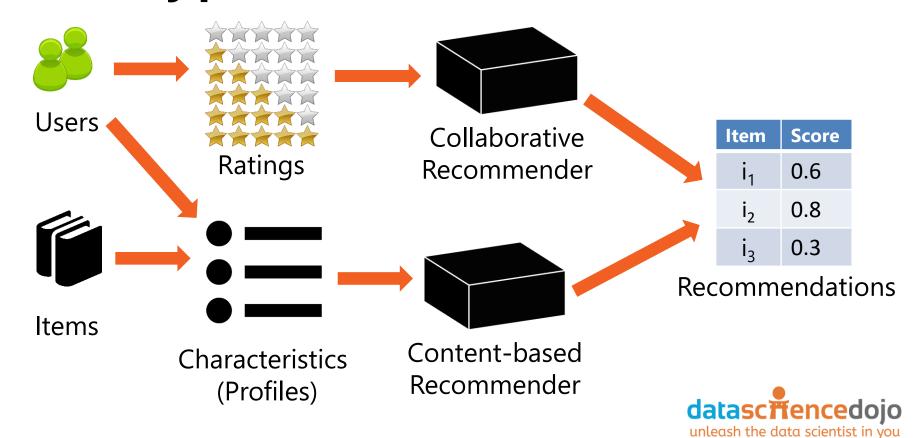


# Why recommendation systems?

- For Customers
  - Narrow down the set of choices
  - Discover new, interesting things
  - Save time
- For Business
  - Increase the number of items sold
  - Sell more diverse items
  - Better understand what the user wants



# Two Types of Recommenders



# Two Types of Recommenders

#### **Collaborative**

- 'Give me items that people like me enjoy'
- Wisdom of the crowds
- Widely applicable

#### **Content-Based**

- 'Give me items similar to items I like'
- Content analysis based
- Related to Information Retrieval



# Two Types of Recommenders

#### **Collaborative**

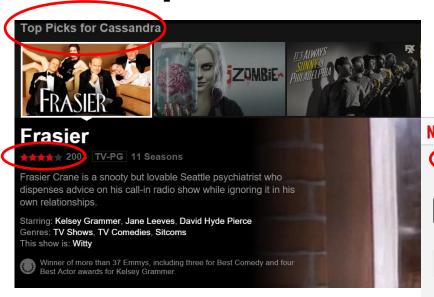
- Users, Items, & Ratings
- Use Ratings of similar Users to recommend unseen Items

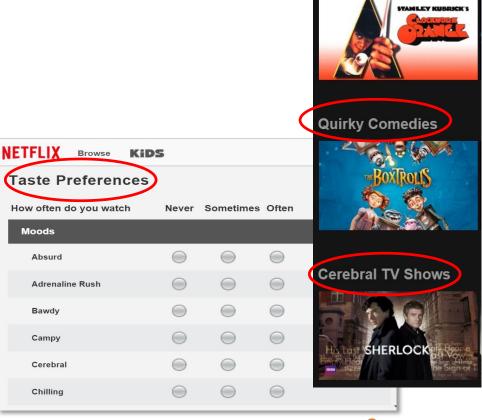
#### **Content-Based**

- User & Item profiles
- Use overlap of User and Item characteristics to recommend unseen items



## **Example: Netflix**

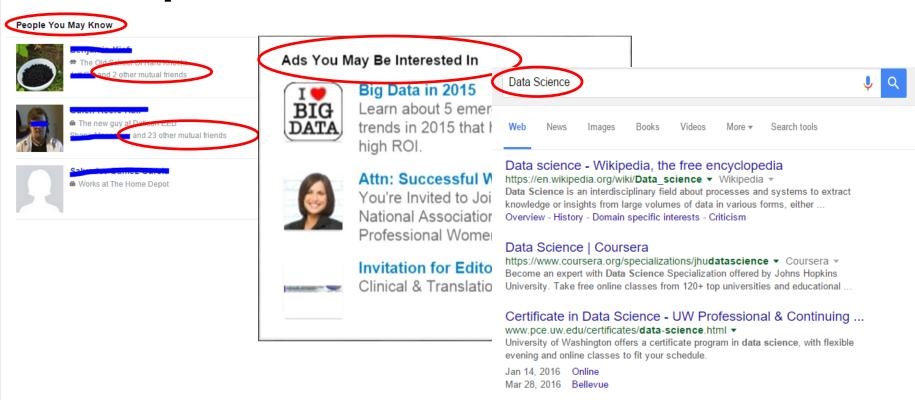






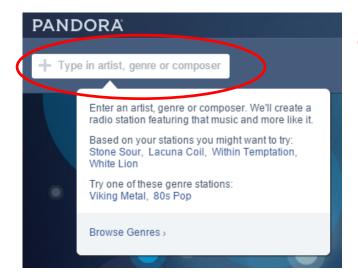
Mind-bending Movies

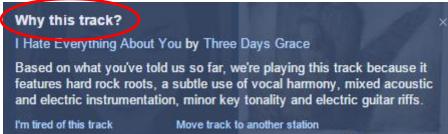
## **Example: Social Media & Search**





## **Example: Pandora**

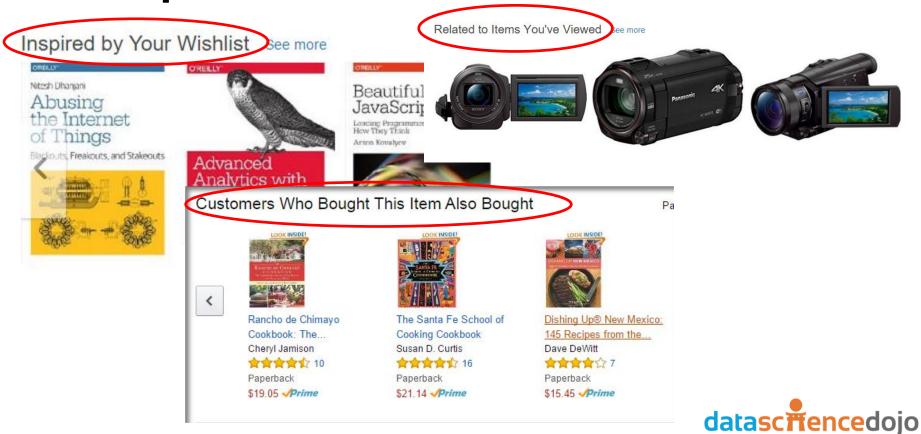








## **Example: Amazon**



unleash the data scientist in you

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### **Data Structure**

- What kind of data?
  - Collaborative
    - Ratings of Items by Users
  - Content-based
    - Characteristic profiles of Users and Items



## **Data Structure - Collaborative**











Alice	5	3	4	4	(5)
Bob	3	1	2	3	3
Chris	4	3	4	3	5
Donna	3	3	1	5	4
Evi	1	5	5	2	1



## Data Structure – Content-based









Item/User	Drama?	Comedy?	Adventure?	Romance?
The Godfather	5	1	2	1
Titanic	4	3	2	5
Lord of the Rings	4	2	5	1
Dumb & Dumber	1	5	2	2
Spirited Away	5	3	5	2
Alice	5	4	1	4
Bob	3	1	1	1
Chris	4	2	5	2



## **Content-based: User Profiles**

#### User Provided

- Ask for preferences
- Needs accounts
- Often low completion rates

#### Automated Generation

- Cookies follow behavior
- No user persistence (often)
- Loss in translation



### **Content-based: Item Profiles**

#### Expert Labeling

- Assign keywords based on content
- May be provided by creators/distributors
- Crowd sourcing?

### Automated Indexing

- Used for text documents
- Based on word content of document set
- No expert knowledge involved



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# **Similarity Measurements**

- Given two vectors  $\vec{x}$  and  $\vec{y}$  with n components each
  - Ratings of User x and User y
  - Ratings for Item x and Item y
  - Profiles of User x and Item y
- How similar are the Users/Items?



# **Similarity Measurements**

Pearson's Correlation

$$sim(\vec{x}, \vec{y}) = \frac{\sum_{i=1}^{n} (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n} (x_i - \bar{x})^2} \sqrt{\sum_{i=1}^{n} (y_i - \bar{y})^2}}$$

Cosine Similarity

$$sim(\vec{x}, \vec{y}) = \frac{\vec{x} \cdot \vec{y}}{|\vec{x}| * |\vec{y}|} = \frac{\sum_{i=1}^{n} x_i y_i}{\sqrt{\sum_{i=1}^{n} x_i^2} \sqrt{\sum_{i=1}^{n} y_i^2}}$$



### Collaborative: User-Based

- Goal: Predict User u's rating on a movie m they haven't seen
  - Find the N most similar Users to u who have seen m
  - Use their ratings to predict u's rating



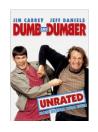
## Collaborative: User-based

Which metric should we use?



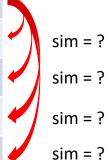






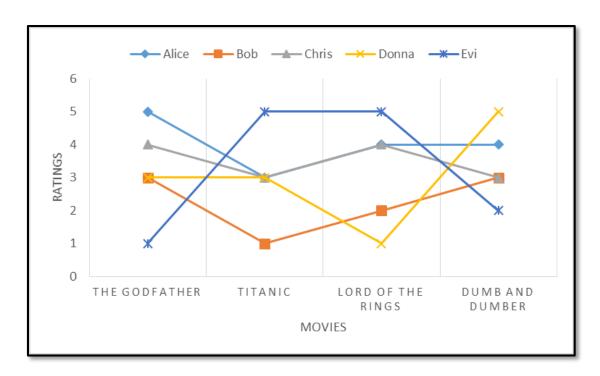


Alice	5	3	4	4	?
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Evi	1	5	5	2	1





## Collaborative: User-based





## Collaborative: User-based

Pearson's correlation corrects for varied baselines











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

sim=0.85 sim=0.90 sim=0.70 sim=0.79



### Collaborative: Item-based

- Alternate approach:
  - Use the similarity between items (and not users) to make predictions
  - Look for movies that are similar to movie m
  - Take **Alice**'s ratings for these items to predict the rating for movie m



## Collaborative: Item-based

Which metric should we use?











Alice	5	3	4	4	?
Bob	3	1	2	3	3
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Evi	1	5	5	2	1
				_	_

sim = ?

sim = ?

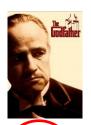
sim = ?

sim = ?



### Collaborative: Item-based

Cosine similarity allows for objective good/bad











Alice	5	3	4	4	?
Bob	3	1	2	3	3
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sim=0.99

sim=0.74

sim=0.72

sim=0.93

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# **Content-based: Similarity**

- Goal: Return a recommendation list of items for each user
  - Find similarity of each User to each Item
  - Order Items by similarity



# **Content-based: Similarity**





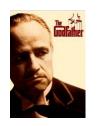




Item/User	Drama?	Comedy?	Adventure?	Romance?	
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Bob	3	1	1	1	
Chris	4	2	5	2	



# **Content-based: Similarity**











Alice	0.83	0.96	0.72	0.79	0.83
Bob	0.99	0.86	0.85	0.59	0.91
Chris	0.87	0.82	0.99	0.69	0.99

- Cosine similarity doesn't erase baselines
- Predict order, not exact rating



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## **Collaborative: Predictions**

- Use "Aggregation Function"
- Choose N nearest neighbors to User u
- Combine each neighbor j's rating on Item i  $(r_{j,i})$
- Simple

• 
$$r_{u,i} = \frac{1}{N} \sum_{j=1}^{N} r_{j,i}$$

- Weighted & Centered
  - $r_{u,i} = \overline{r_u} + \alpha \sum_{j=1}^{N} sim(j, u)(r_{j,i} \overline{r_j})$



### **Content-based: Predictions**

- Simple
  - Rank in order of similarity
- Information retrieval techniques
  - Well studied, wide diversity of models
  - Classification algorithms



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# **Evaluating Recommendation**

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

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



### **Metrics**

- Order matters, not exact ranking value
- Graded Relevance
  - Have humans assign scores to possible results
  - Ideal results will be ordered by relevance, high to low
- Discounted cumulative gain (DCG)
  - Logarithmic reduction factor

$$DCG_N = rel_1 + \sum_{i=2}^{N} \frac{rel_i}{\log_2 i}$$

#### Where:

- *N* is the length of the recommendation list
- $rel_i$  returns the relevance of recommendation at position  $i_{dat}$



### **Metrics**

- Ideal discounted cumulative gain (IDCG)
  - DCG value when items are ordered perfectly

$$IDCG_N = rel_1 + \sum_{i=2}^{N} \frac{rel_i}{\log_2 i}$$

Normalized discounted cumulative gain (nDCG)

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

Normalized to the interval [0..1]



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# Advantages

#### **Collaborative**

- Wide applicability
- Serendipity
- Simple

#### Content-based

- No community needed
- Transparency
- Good cold start



# Disadvantages

#### **Collaborative**

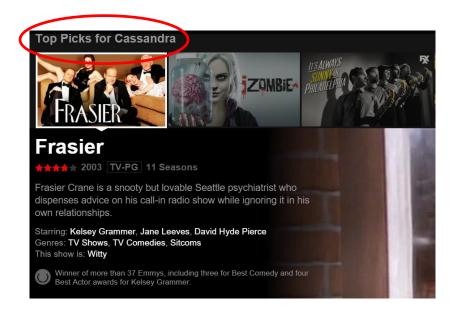
- Poor cold start
- Grey Sheep
  - Shared accounts
- Shilling
- Poor scaling

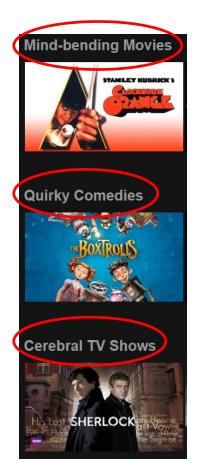
#### **Content-based**

- Limited profiles
  - New users
  - Cost of expert labeling
- Over-specialization
  - Lack of diversity



### **Back to Netflix**







## **QUESTIONS**



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