# 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?

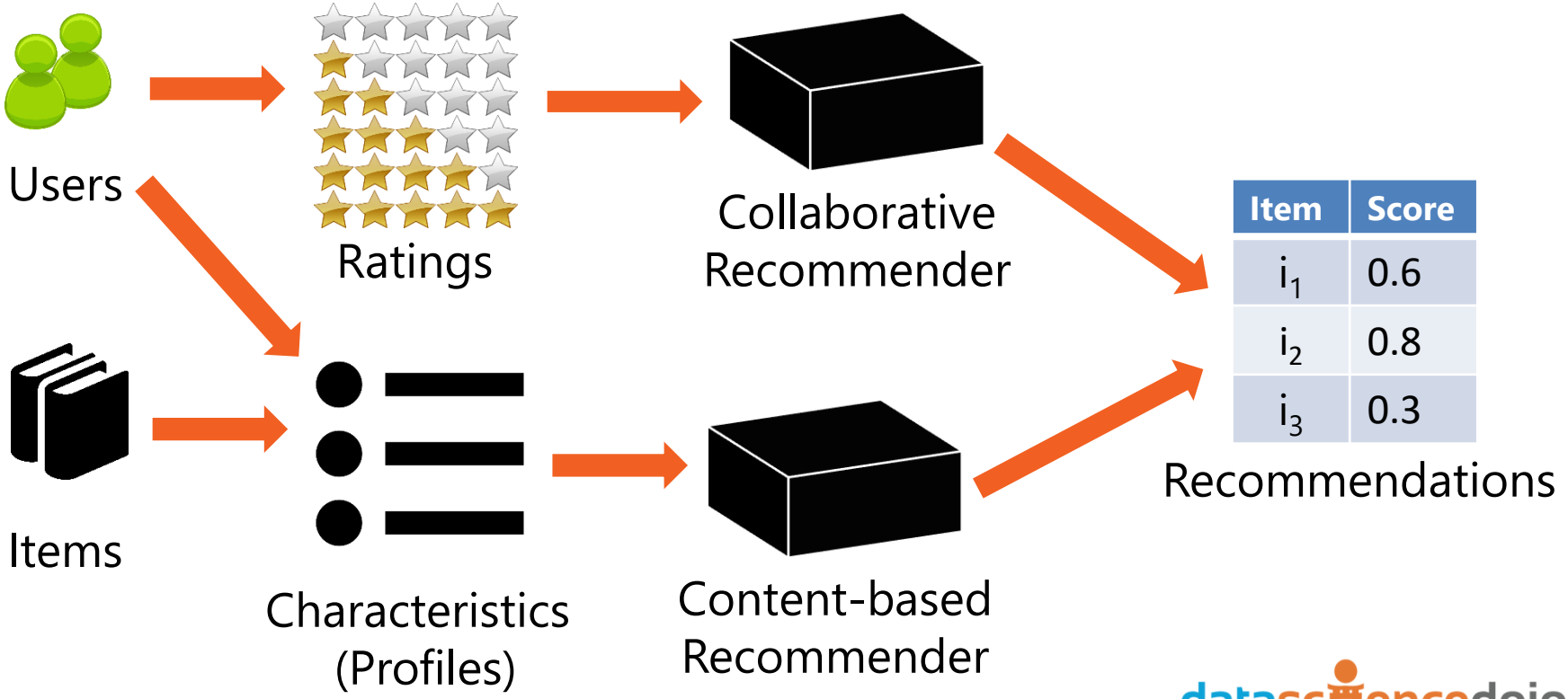
  - Automated systems to filter and recommend products based on users' interest and taste.

  - 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

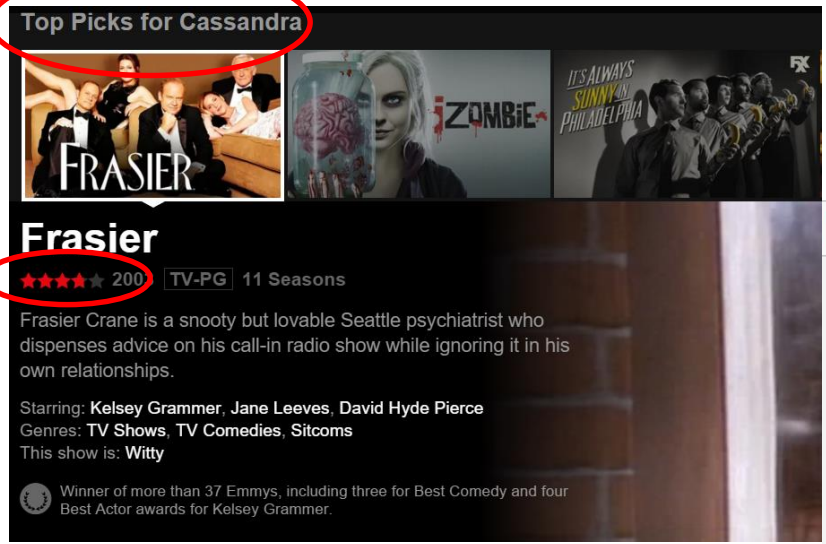
## Collaborative

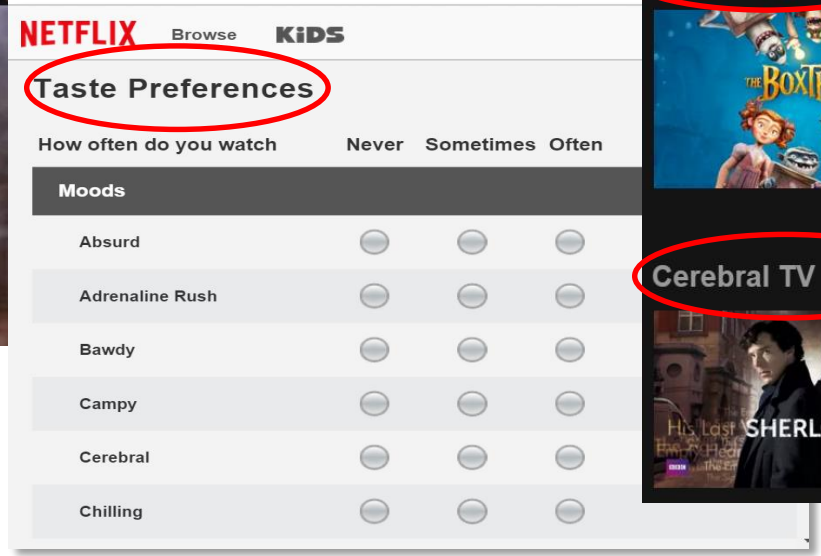
- Users, Items, & Ratings
- Use Ratings of similar Users to recommend unseen Items

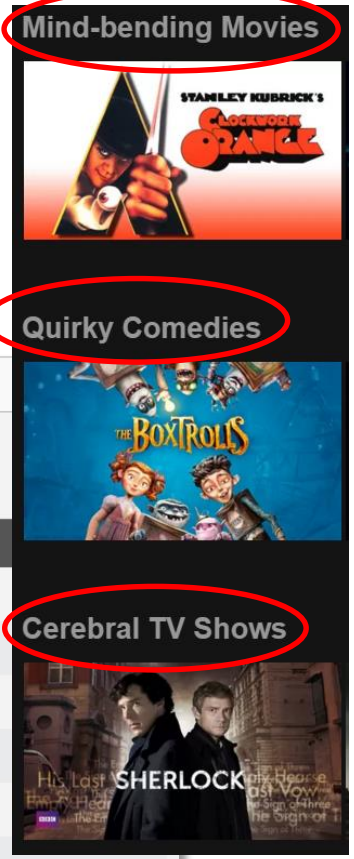
## Content-Based

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

# Example: Netflix

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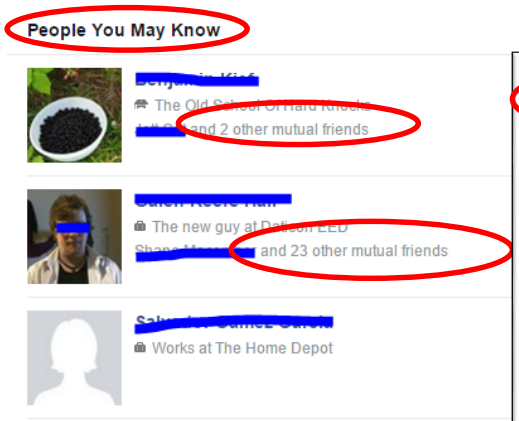
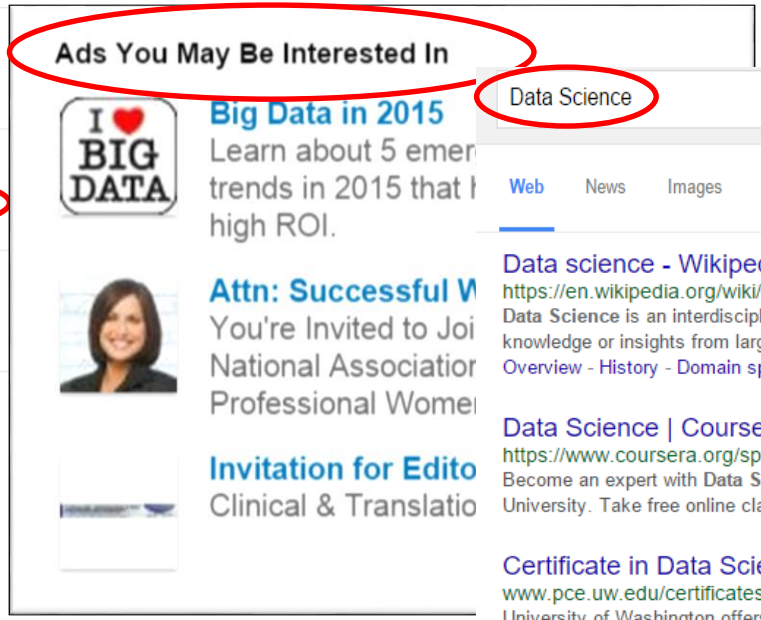
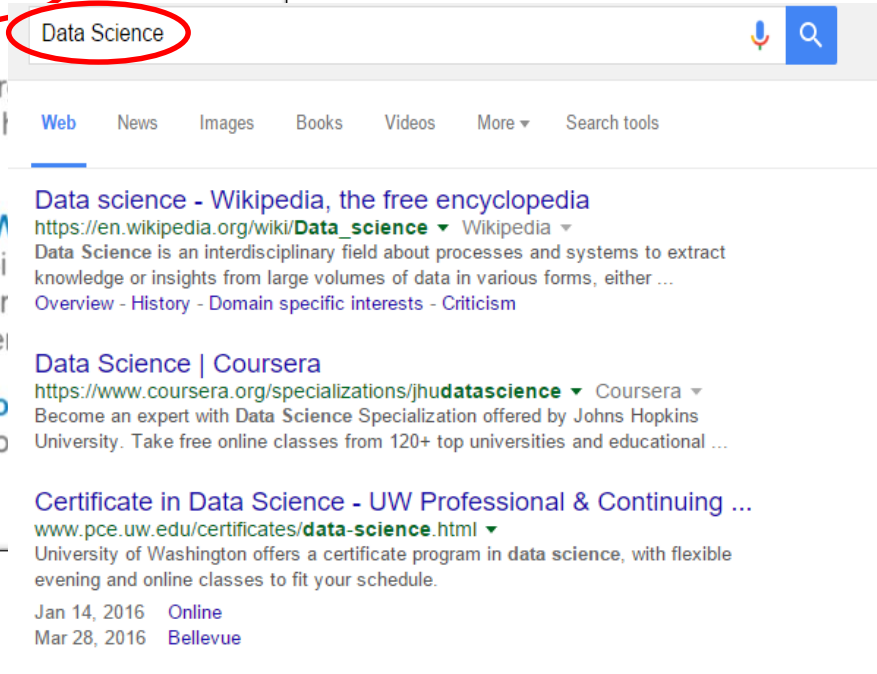
# Example: Social Media & Search

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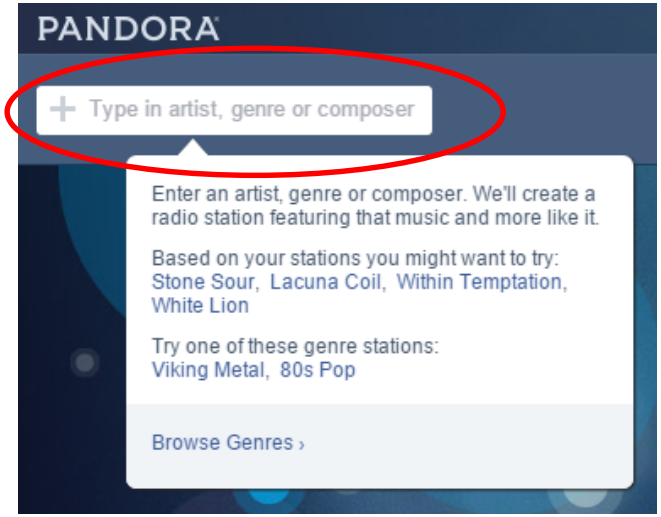
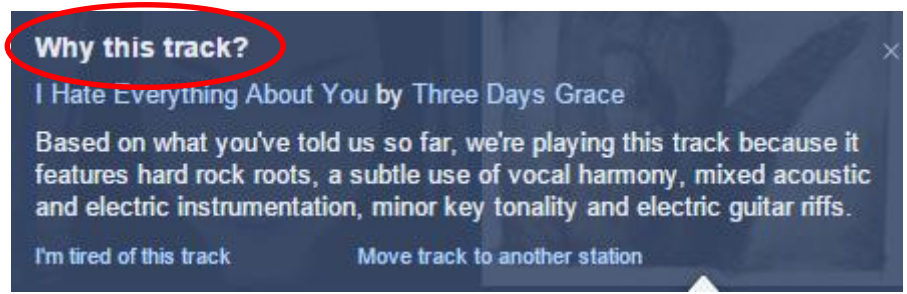
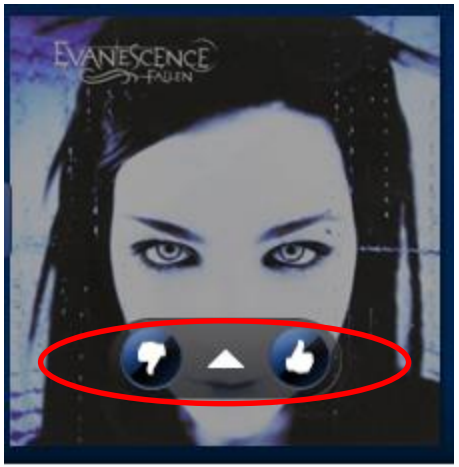
# Example: Pandora

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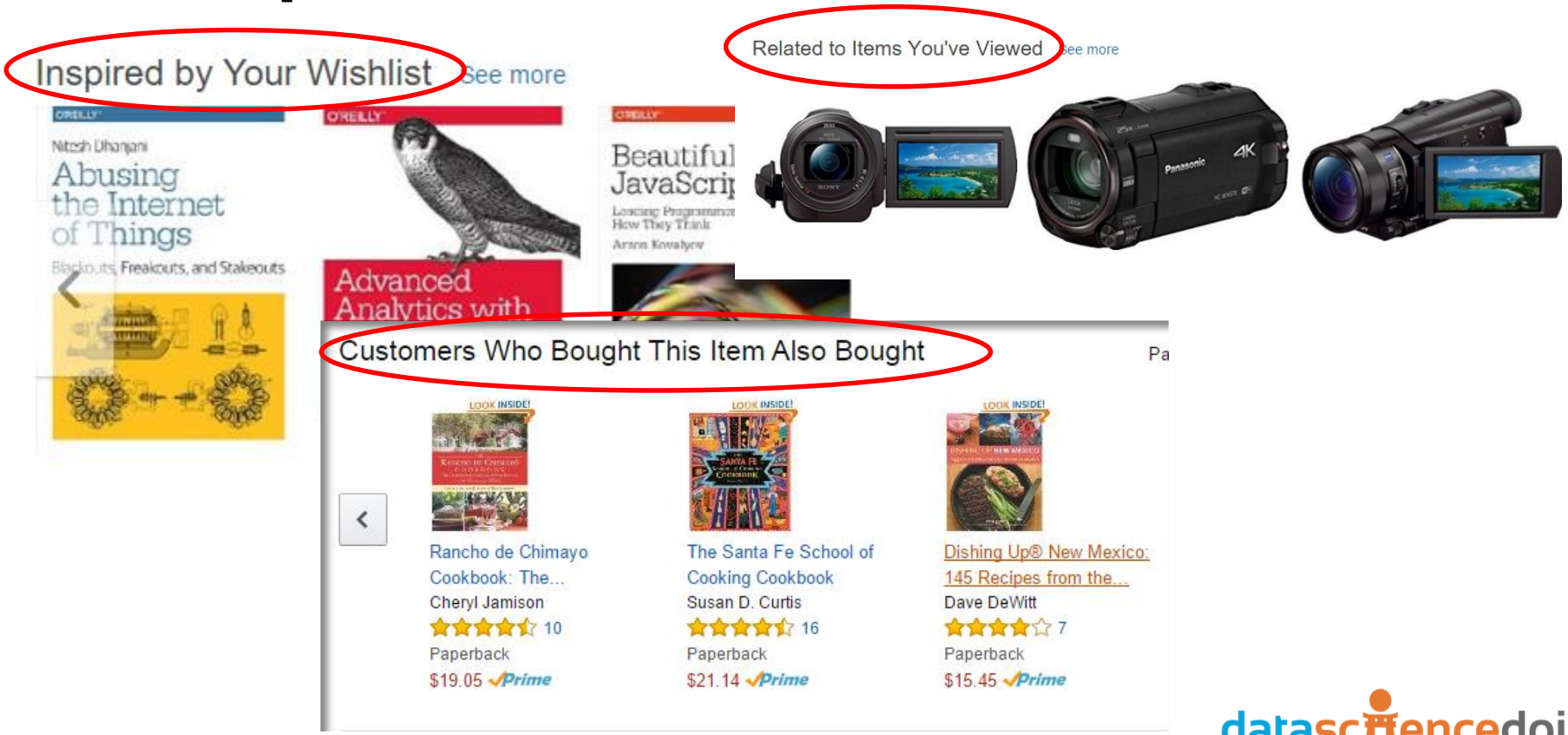
# Example: Amazon

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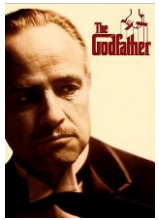
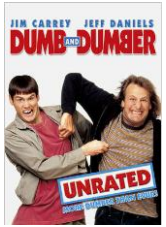
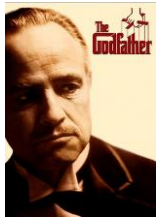
# Data Structure

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

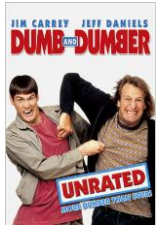
# Data Structure - Collaborative

| |  |  |  |  |  |
|---|---|---|---|---|---|
| Alice | 5 | 3 | 4 | 4 | ? |
| 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

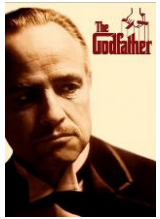
$$sim(\vec{x}, \vec{y}) = \frac{\vec{x} \cdot \vec{y}}{|\vec{x}| * |\vec{y}|} = \frac{\sum_{i=1}^{n} x_i y_i}{\sqrt{\sum_{i=1}^{n} x_i^2}\sqrt{\sum_{i=1}^{n} y_i^2}}$$

# Collaborative: User-Based

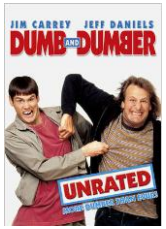
- Goal: Predict User $u$'s rating on a movie $m$ they haven't seen
  - Find the N most similar Users to $u$ who have seen $m$
  - Use their ratings to predict $u$'s rating

# Collaborative: User-based

## Which metric should we use?



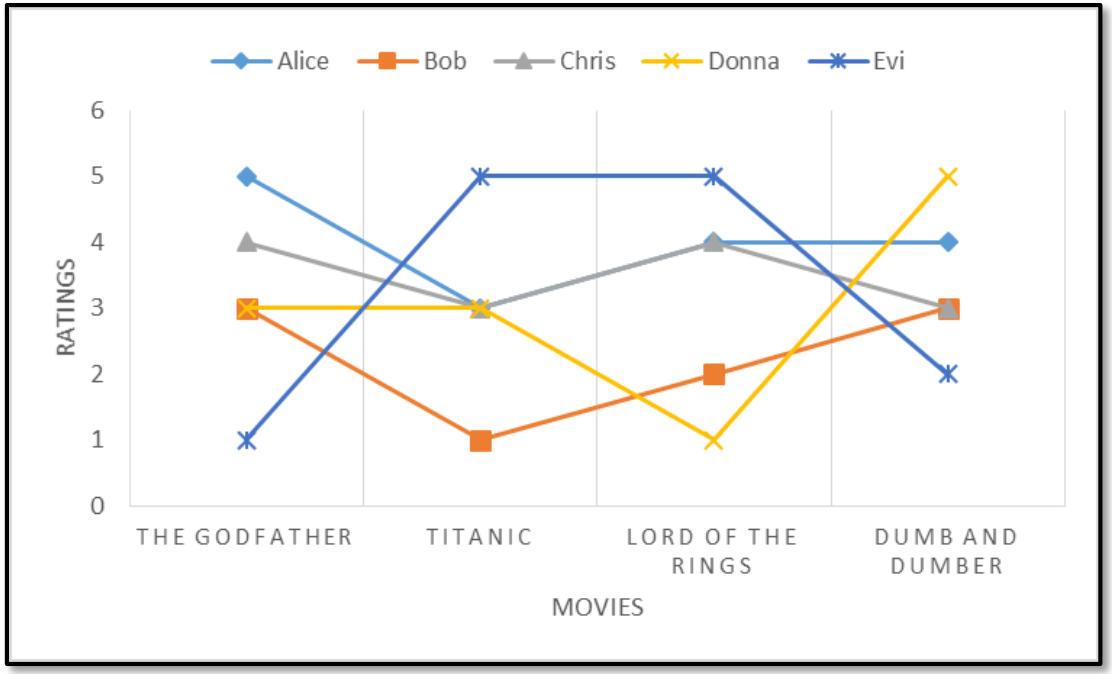




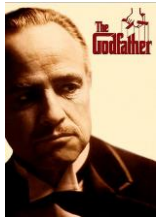
| | | | | | | |
|---|---|---|---|---|---|---|
| Alice | 5 | 3 | 4 | 4 | ? | |
| Bob | 3 | 1 | 2 | 3 | 3 | sim = ? |
| Chris | 4 | 3 | 4 | 3 | 5 | sim = ? |
| Donna | 3 | 3 | 1 | 5 | 4 | sim = ? |
| Evi | 1 | 5 | 5 | 2 | 1 | sim = ? |

# Collaborative: User-based

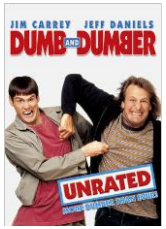


# Collaborative: User-based

## Pearson's correlation corrects for varied baselines







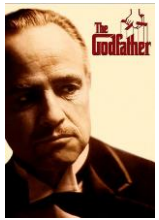
| | | | | | | |
|---|---|---|---|---|---|---|
| Alice | 5 | 3 | 4 | 4 | ? | |
| Bob | 3 | 1 | 2 | 3 | 3 | sim=0.85 |
| Chris | 4 | 3 | 4 | 3 | 5 | sim=0.90 |
| Donna | 3 | 3 | 1 | 5 | 4 | sim=0.70 |
| Evi | 1 | 5 | 5 | 2 | 1 | sim=0.79 |

# Collaborative: Item-based

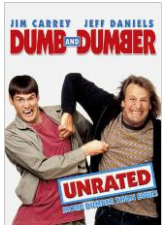
- Alternate approach
  - Use the similarity between items (and not users) to make predictions
  - Look for movies that are similar to movie $m$
  - Take **Alice**'s ratings for these items to predict the rating for movie $m$

# Collaborative: Item-based

Which metric should we use?







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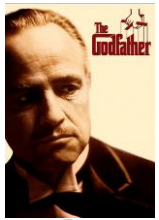
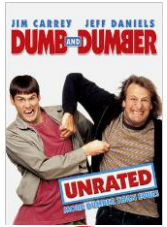
sim = ? sim = ? sim = ? sim = ?

# Collaborative: Item-based

Cosine similarity allows for objective good/bad







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

sim=0.99 sim=0.74 sim=0.72 sim=0.93

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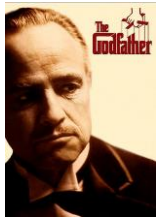
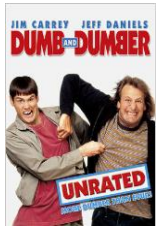
# Content-based: Similarity

- 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







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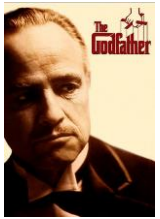
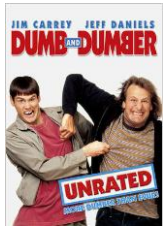
| *Dumb & Dumber* | 1 | 5 | 2 | 2 |
| *Spirited Away* | 5 | 3 | 5 | 2 |
| **Alice** | 5 | 4 | 1 | 4 |
| **Bob** | 3 | 1 | 1 | 1 |
| **Chris** | 4 | 2 | 5 | 2 |

# Content-based: 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
  - $r_{u,i} = \overline{\boldsymbol{r}_u} + \alpha \sum_{j=1}^{N} sim(j,u)(r_{j,i} - \overline{r_j})$

# Content-based: Predictions

- Simple
  - Rank in order of similarity
- Information retrieval techniques
  - Well studied, wide diversity of methods
  - 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 $i$

# 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

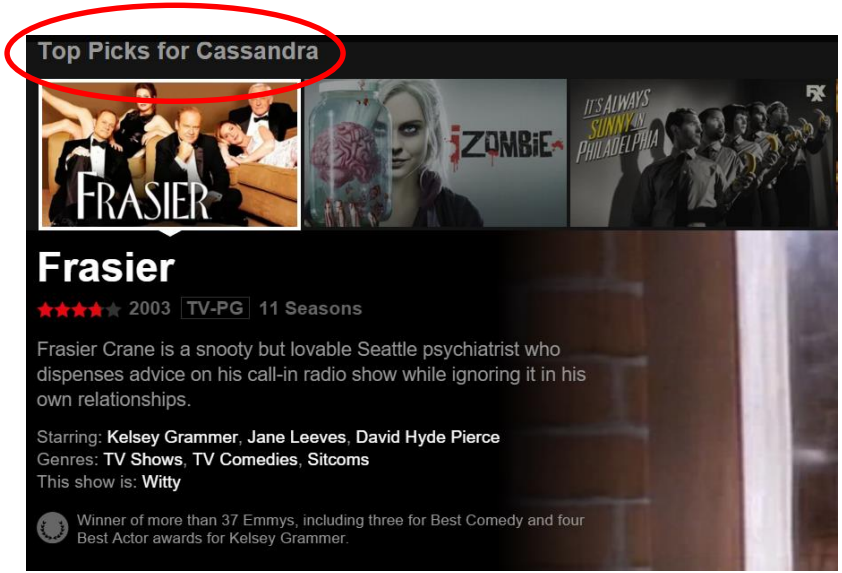
## Collaborative

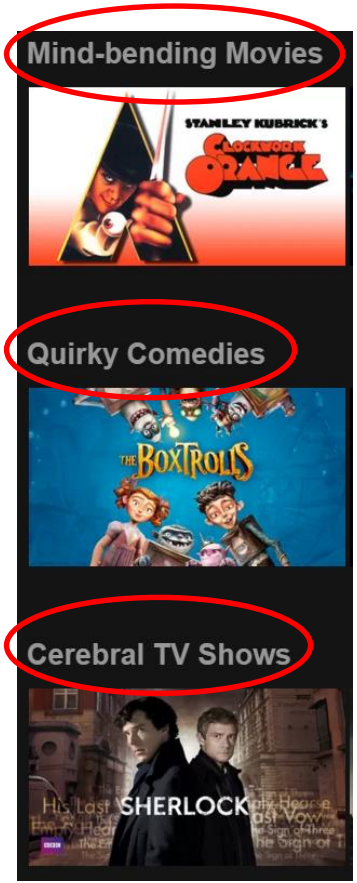
- Poor cold start
- Grey Sheep
  - Shared accounts
- Shilling
- Poor scaling

## Content-based

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

# Back to Netflix

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# QUESTIONS

# Overview

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