# Big Data Computing

Master's Degree in Computer Science

2021-2022


Gabriele Tolomei

Department of Computer Science

Sapienza Università di Roma

tolomei@di.uniroma1.it


SAPIENZA UNIVERSITÀ DI ROMA

# Recap from Last Lectures

- So far, we have talked about 2 main tasks which are pretty common in the context of "Big Data":

# Recap from Last Lectures

- So far, we have talked about 2 main tasks which are pretty common in the context of "Big Data":
  - Clustering (unsupervised learning)

# Recap from Last Lectures

- So far, we have talked about 2 main tasks which are pretty common in the context of "Big Data":
  - Clustering (unsupervised learning)
  - Regression/Classification (supervised learning)

# Recap from Last Lectures

- So far, we have talked about 2 main tasks which are pretty common in the context of "Big Data":
  - Clustering (unsupervised learning)
  - Regression/Classification (supervised learning)
- We have discussed a number of techniques to solve those tasks:
  - K-means, PCA
  - Linear Regression, Logistic Regression, Decision Trees, and ensembles

# Information Overload

- With the explosion of content and services available on the Web, consumers are inundated with choices

# Information Overload

- With the explosion of content and services available on the Web, consumers are inundated with choices
- This phenomenon is usually referred to as information overload

# Information Overload

- With the explosion of content and services available on the Web, consumers are inundated with choices
- This phenomenon is usually referred to as information overload
- To actually take advantage of such a huge pile of information we need techniques that narrow down it to human-manageable figures:

# Information Overload

- With the explosion of content and services available on the Web, consumers are inundated with choices
- This phenomenon is usually referred to as information overload
- To actually take advantage of such a huge pile of information we need techniques that narrow down it to human-manageable figures:
  - Searching/Filtering

# Information Overload

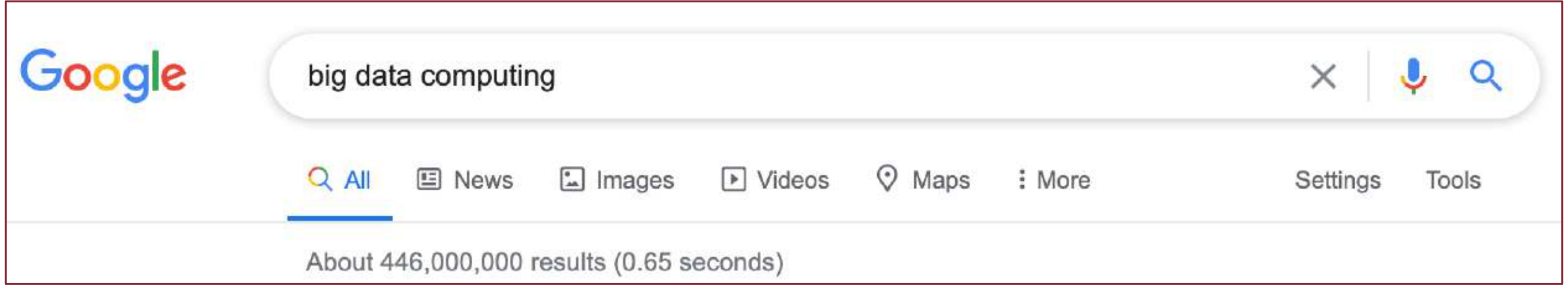
- With the explosion of content and services available on the Web, consumers are inundated with choices
- This phenomenon is usually referred to as information overload
- To actually take advantage of such a huge pile of information we need techniques that narrow down it to human-manageable figures:
  - Searching/Filtering
  - Recommending

# Why Do We Need Recommendation?

We are constantly moving from scarcity to abundance

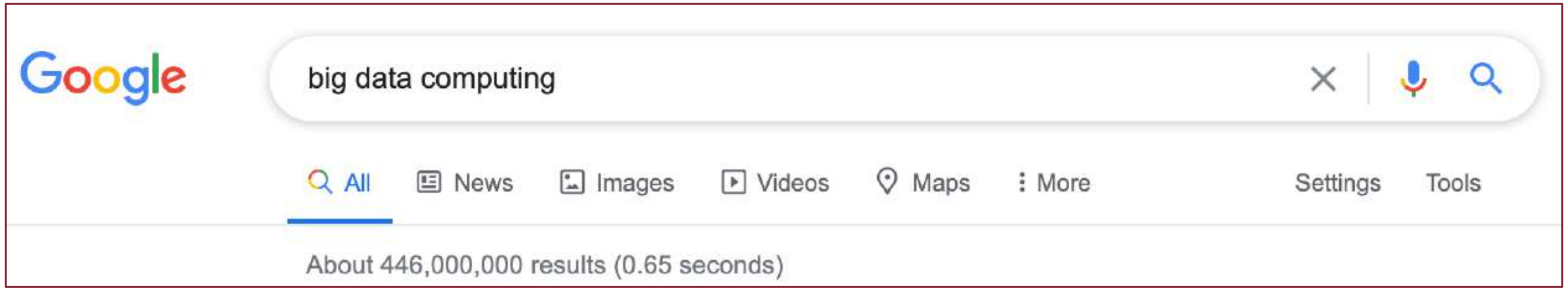
# Why Do We Need Recommendation?

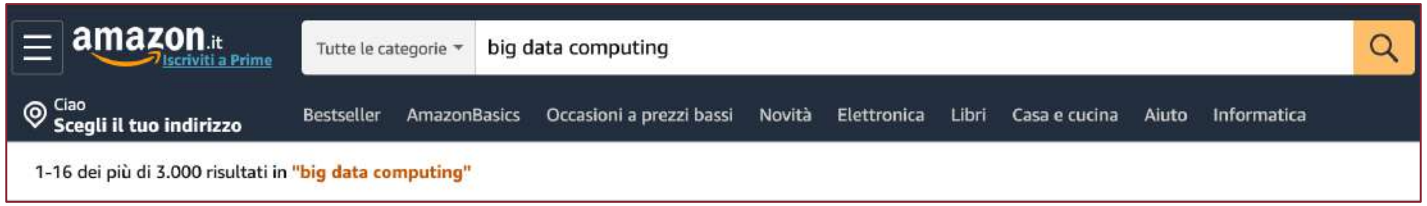
We are constantly moving from scarcity to abundance



# Why Do We Need Recommendation?

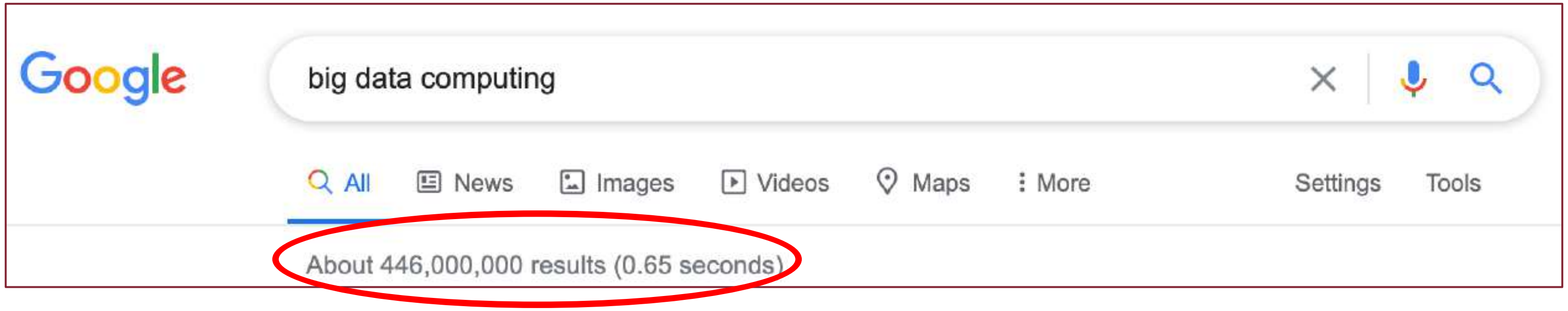
We are constantly moving from scarcity to abundance

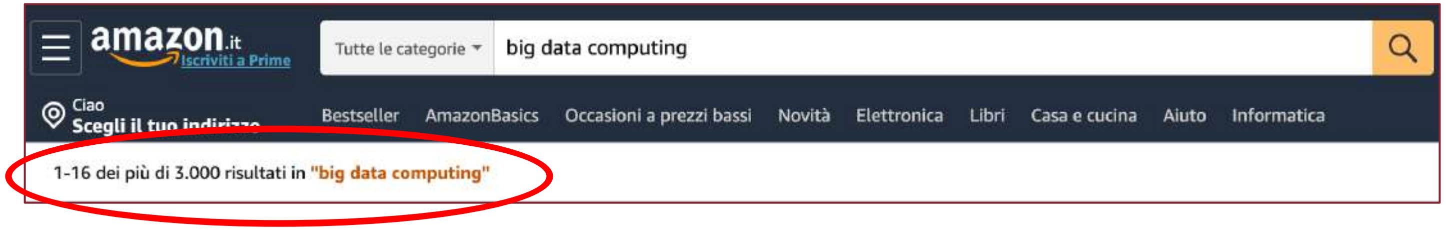


# Why Do We Need Recommendation?

We are constantly moving from scarcity to abundance

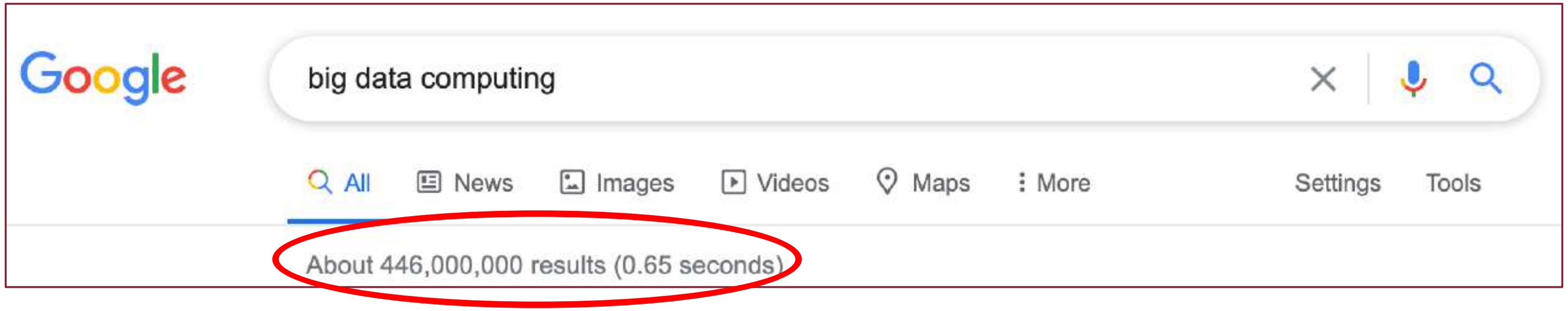


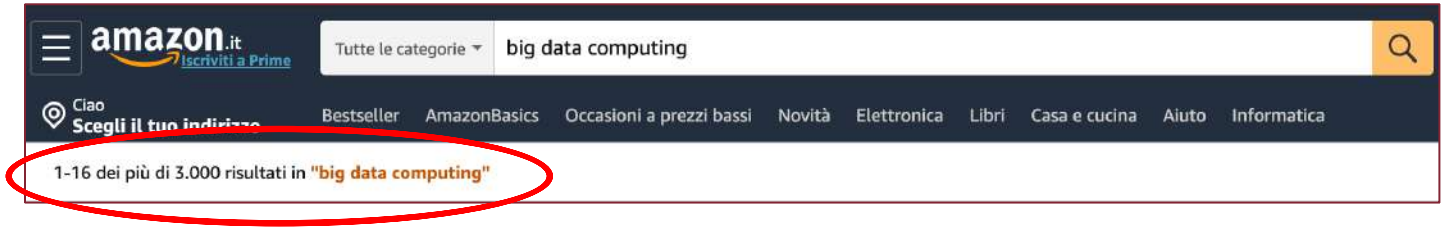




The number of relevant "items" of interest is huge

# Why Do We Need Recommendation?

We are constantly moving from scarcity to abundance




The number of relevant "items" of interest is huge

How could we even possibly think of exhaustively explore all of them?

# Why Do We Need Recommendation?

Compared to physical stores, online catalogs of product/services are almost unlimited

# Why Do We Need Recommendation?

Compared to physical stores, online catalogs of product/services are almost unlimited

Matching consumers with the most appropriate products/services is key to enhancing user satisfaction and loyalty

# Why Do We Need Recommendation?

Compared to physical stores, online catalogs of product/services are almost unlimited

Matching consumers with the most appropriate products/services is key to enhancing user satisfaction and loyalty

More choices need better filters!

# Why Do We Need Recommendation?

Compared to physical stores, online catalogs of product/services are almost unlimited

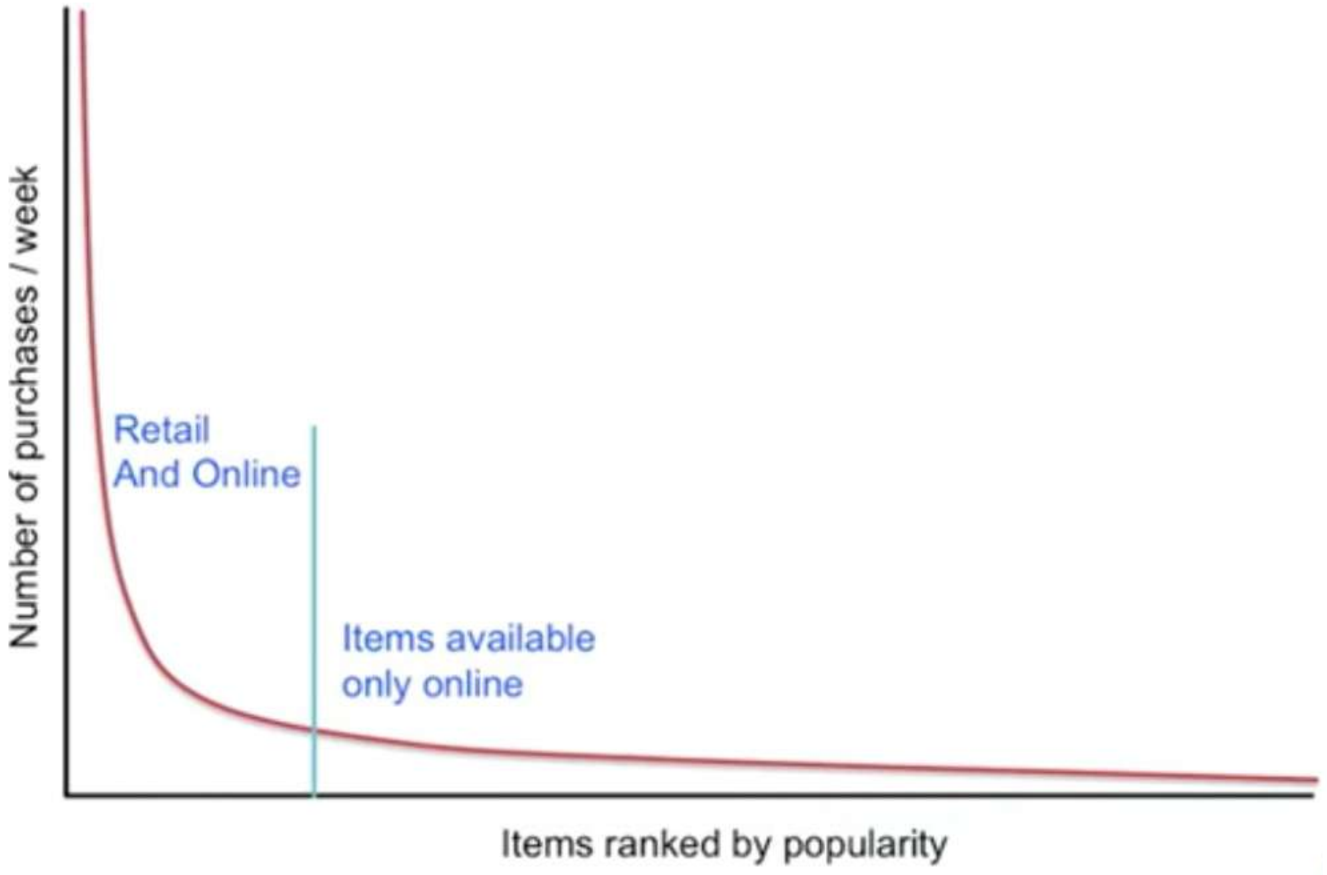
Matching consumers with the most appropriate products/services is key to enhancing user satisfaction and loyalty

More choices need better filters!

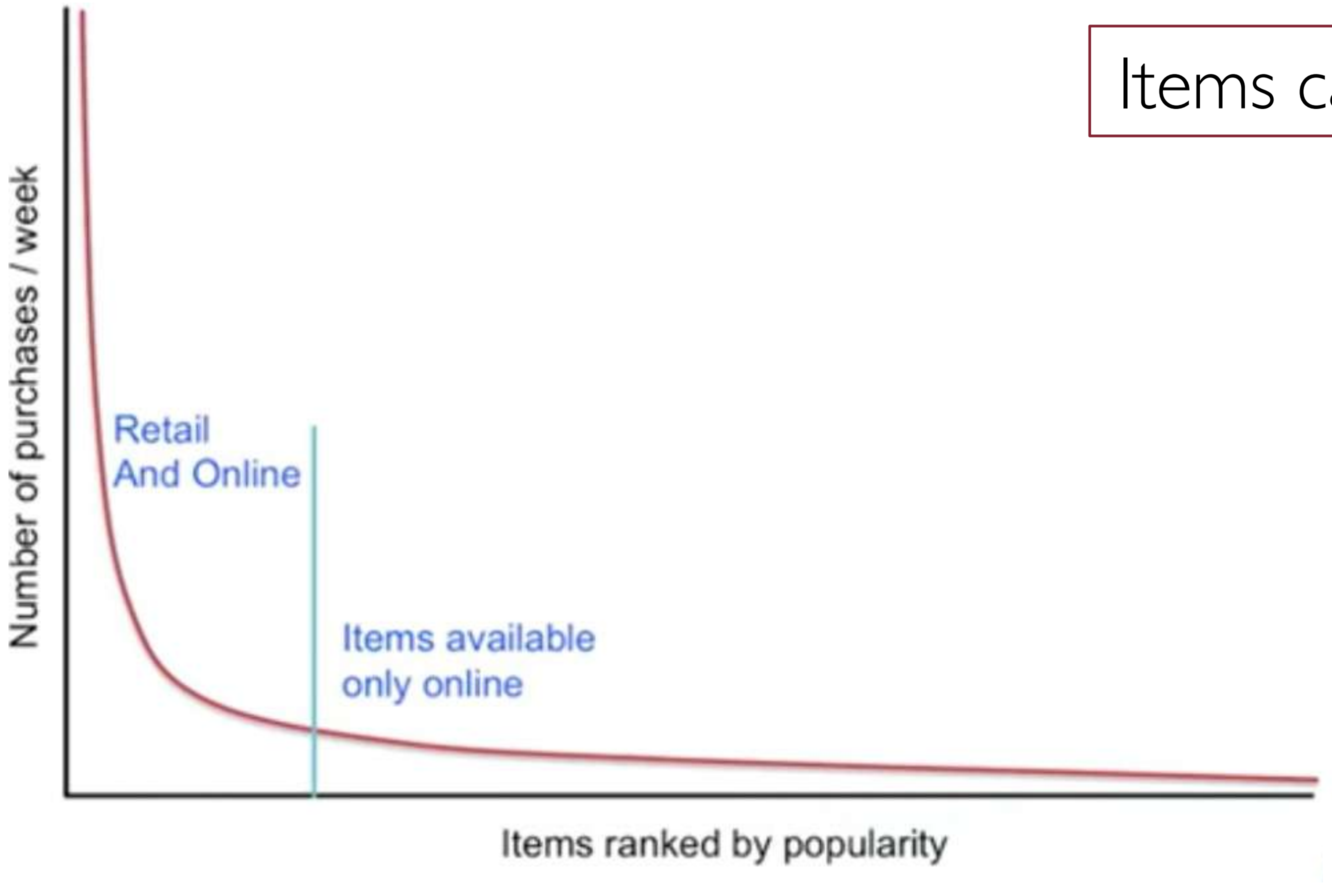
↓

**Recommender Systems**

# The Economics of Abundance: The Long Tail

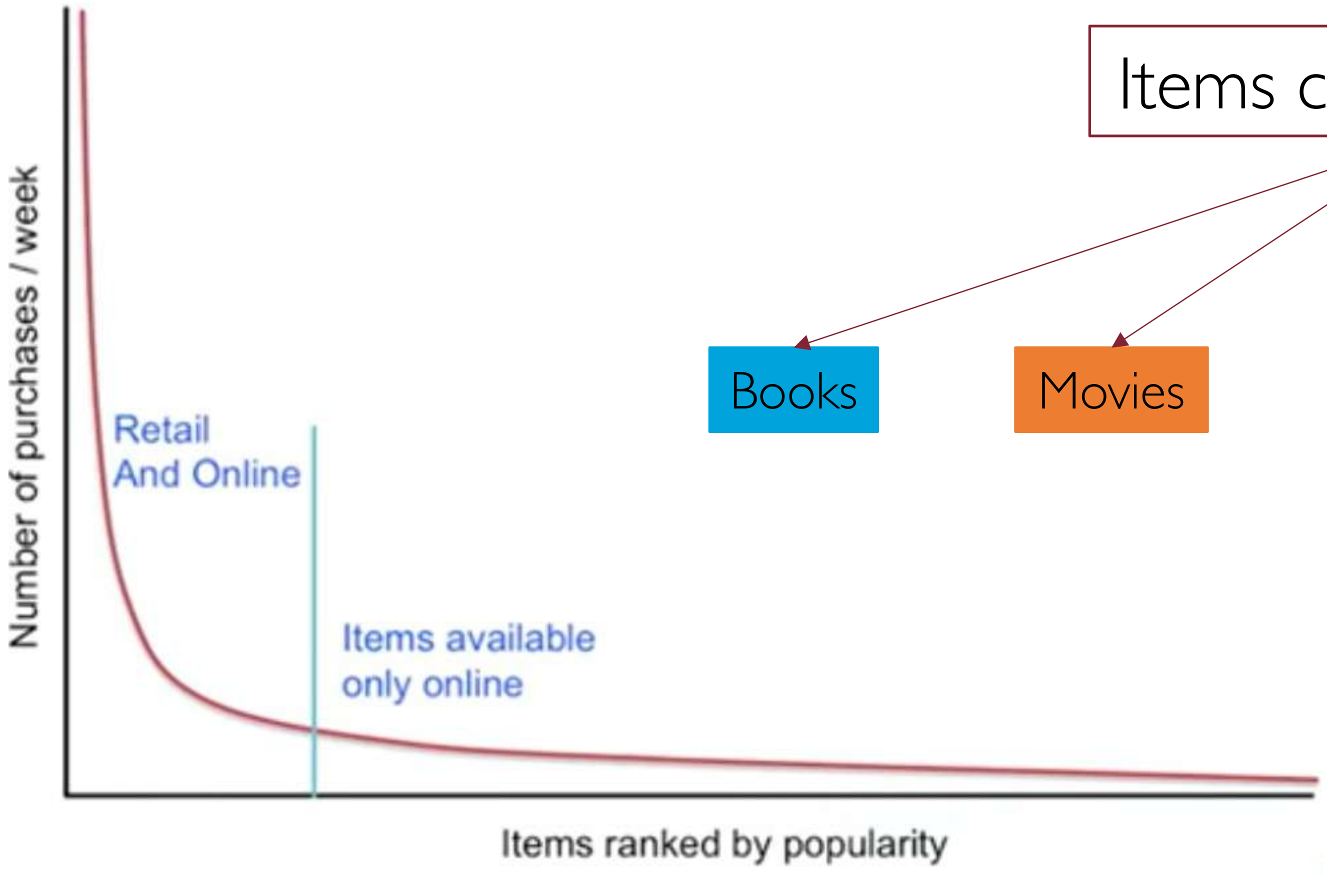


# The Economics of Abundance: The Long Tail




Items can be *anything*

# The Economics of Abundance: The Long Tail

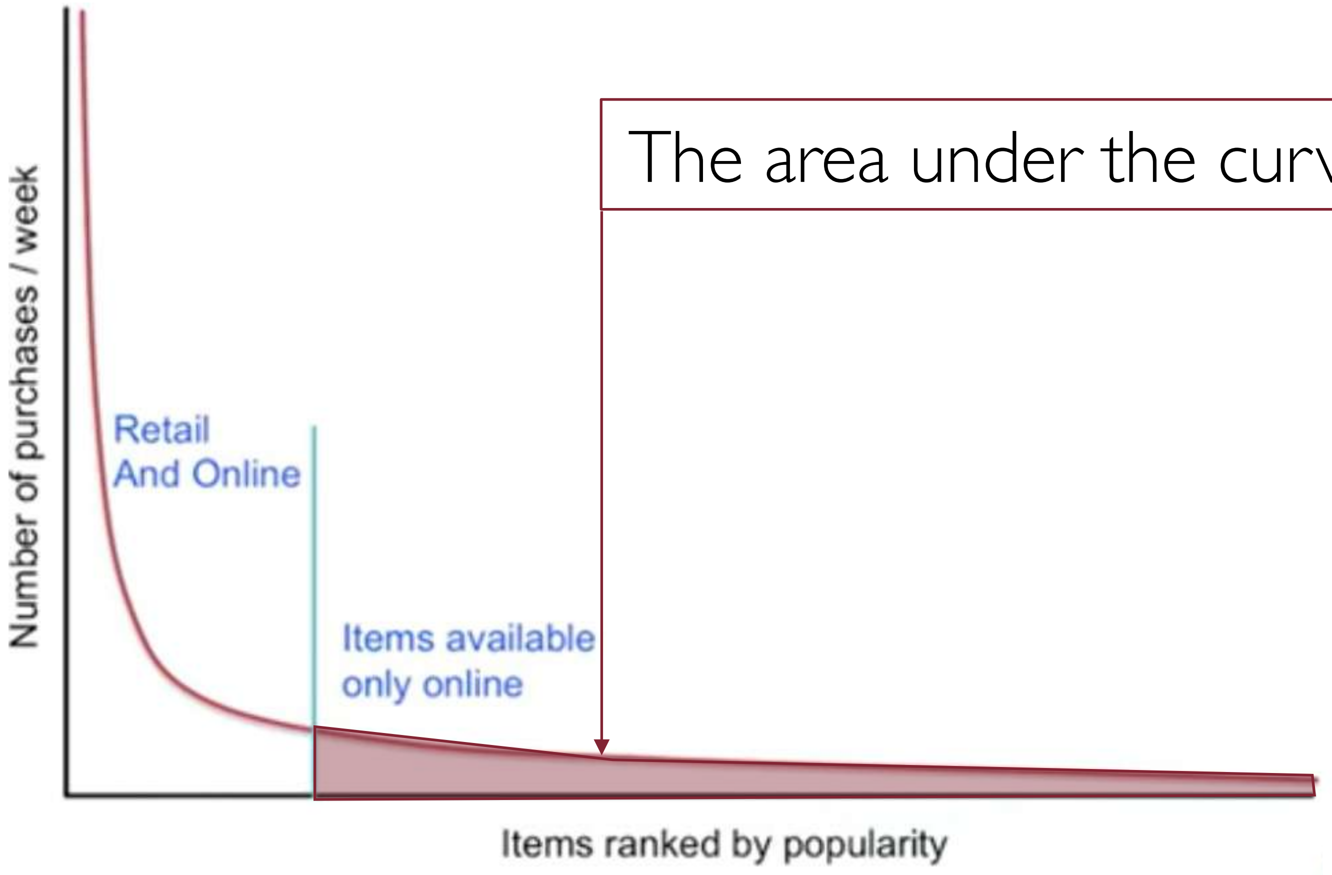



Items can be *anything*

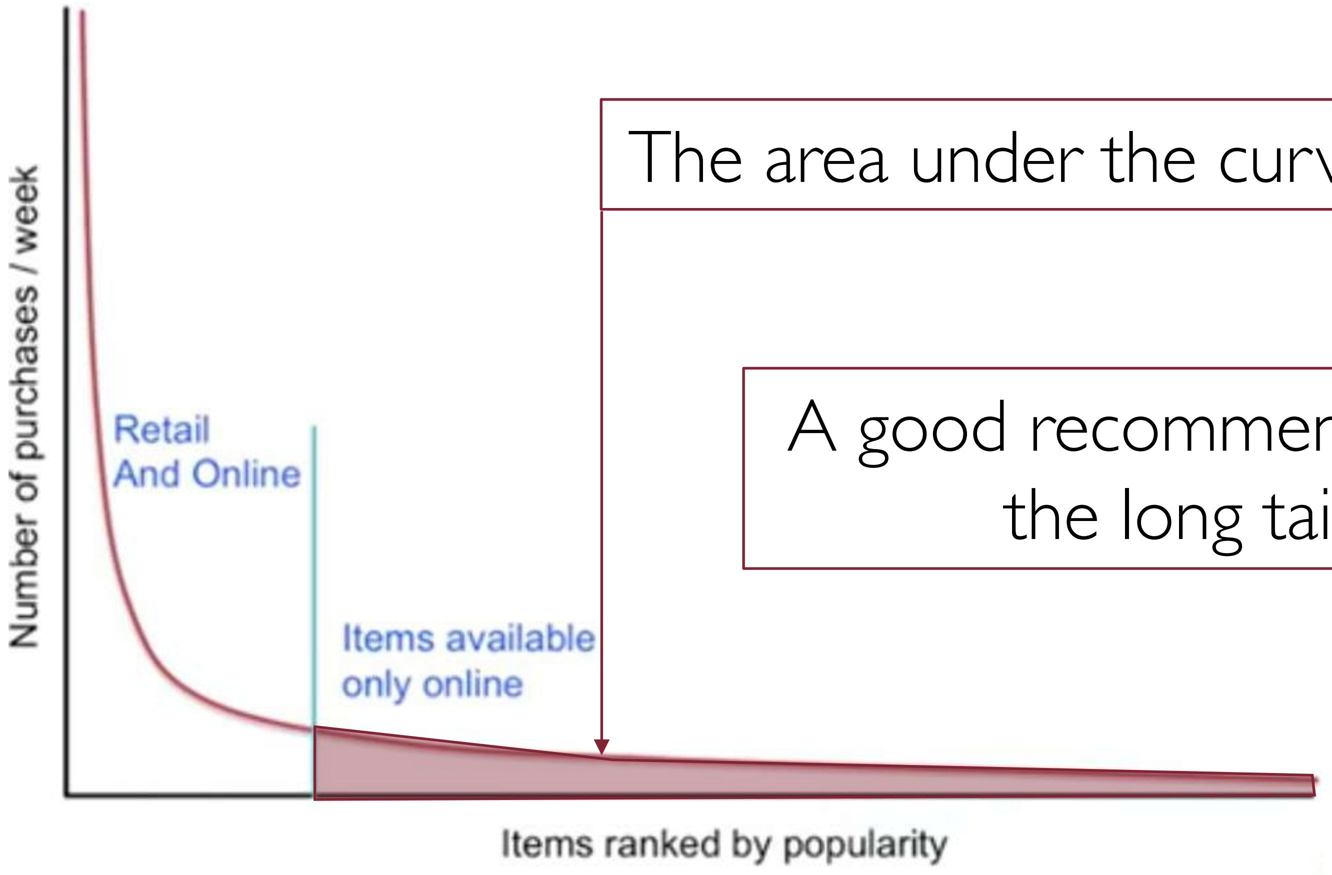
Books | Movies | News Articles | … | Search Results

# The Economics of Abundance: The Long Tail

The area under the curve for the long tail is quite large!



# The Economics of Abundance: The Long Tail




The area under the curve for the long tail is quite large!

A good recommendation system should expose the long tail/hidden items to users

# Recommender Systems: Formalism

$\mathcal{U} = \{u_1, \ldots, u_m\}$ Set of users

# Recommender Systems: Formalism

$$\mathcal{U} = \{u_1, \ldots, u_m\}$$ Set of users

$$\mathcal{I} = \{i_1, \ldots, i_n\}$$ Set of items

# Recommender Systems: Formalism

$\mathcal{U} = \{u_1, \ldots, u_m\}$ Set of users

$\mathcal{I} = \{i_1, \ldots, i_n\}$ Set of items

$r : \mathcal{U} \times \mathcal{I} \mapsto \mathcal{R}$ utility function (user-item matrix)

# Recommender Systems: Formalism

$\mathcal{U} = \{u_1, \ldots, u_m\}$ Set of users

$\mathcal{I} = \{i_1, \ldots, i_n\}$ Set of items

$r : \mathcal{U} \times \mathcal{I} \mapsto \mathcal{R}$ utility function (user-item matrix)

$\mathcal{R} \subseteq \mathbb{R}$ Set of ratings (totally ordered)

# Recommender Systems: Formalism

$\mathcal{U} = \{u_1, \ldots, u_m\}$ Set of users

$\mathcal{I} = \{i_1, \ldots, i_n\}$ Set of items

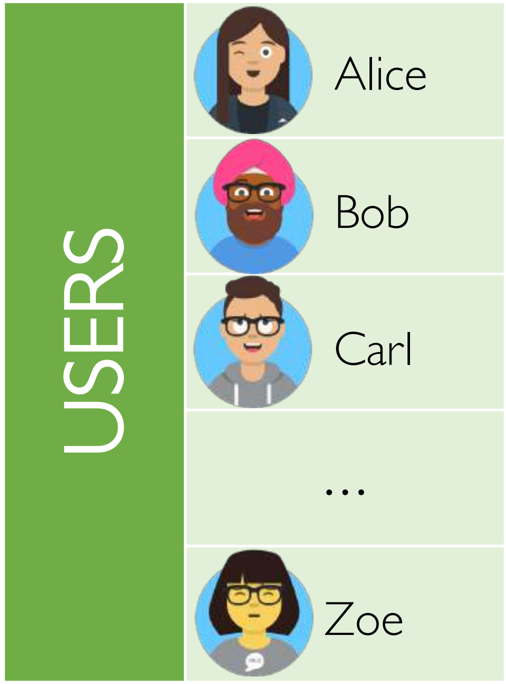
$r : \mathcal{U} \times \mathcal{I} \mapsto \mathcal{R}$ utility function (user-item matrix)

$\mathcal{R} \subseteq \mathbb{R}$ Set of ratings (totally ordered)

$\mathcal{R} = \{0, 1, \ldots, v - 1\}$ Discrete ratings (e.g., 0-5 stars)

$\mathcal{R} = [0, 1]$ Continuous ratings

# The Utility Function (User-Item Matrix)



# The Utility Function (User-Item Matrix)

MOVIES


USERS

Alice

Bob

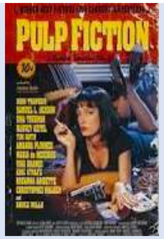
Carl

...

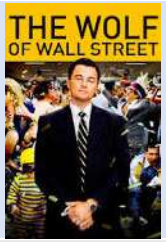
Zoe

# The Utility Function (User-Item Matrix)







| USERS | MOVIES | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Alice | 2 | | 5 | 4 | 5 | 4 | | 4 |
| Bob | 4 | | | | | 3 | | 3 |
| Carl | 5 | 5 | 3 | 4 | 5 | 4 | | 5 |
| … | … | … | … | … | … | … | … | … |
| Zoe | | 1 | 3 | | | | 5 | 4 |

# The Utility Function (User-Item Matrix)

3 key problems for a recommender system

# The Utility Function (User-Item Matrix)

3 key problems for a recommender system

**Data Collection**

Gathering known ratings to populate the utility matrix

# The Utility Function (User-Item Matrix)

3 key problems for a recommender system

## Data Collection

Gathering known ratings to populate the utility matrix

## Rating Prediction

Extrapolate unknown ratings from the known ones

# The Utility Function (User-Item Matrix)

3 key problems for a recommender system

### Data Collection

Gathering known ratings to populate the utility matrix

### Rating Prediction

Extrapolate unknown ratings from the known ones

### Recommendation Evaluation

Measure the performance of recommender methods

# Data Collection

**Data Collection**

Gathering known ratings to populate the utility matrix

# Data Collection

**Data Collection**

Gathering known ratings to populate the utility matrix

**Explicit**

Ask people to rate items

Doesn't scale: only few users leave ratings

# Data Collection

**Data Collection**

Gathering known ratings to populate the utility matrix

**Explicit**

Ask people to rate items

Doesn't scale: only few users leave ratings

**Implicit**

Learn ratings from user actions

Click/purchases implies positive feedback
What about negative ones?

# Rating Prediction

**Rating Prediction**

Extrapolate unknown ratings from the known ones

# Rating Prediction

**Rating Prediction**

Extrapolate unknown ratings from the known ones

The utility matrix R is sparse!

Most people have not rated most items

# Rating Prediction

## Rating Prediction

Extrapolate unknown ratings from the known ones

The utility matrix R is sparse!

Most people have not rated most items

Cold Start

New users/items have no history

# Recommendation Evaluation

**Recommendation Evaluation**

Measure the performance of recommender methods

# Recommendation Evaluation

**Recommendation Evaluation**

Measure the performance of recommender methods

- RMSE
- Mean Average Precision/Recall at K (MAP@K/MAR@K)
- Personalization
- Serendipity

# Recommendation Strategies

3 approaches to recommender systems

# Recommendation Strategies

3 approaches to recommender systems

Content-based filtering

# Recommendation Strategies

3 approaches to recommender systems

Content-based filtering

Collaborative filtering

# Recommendation Strategies

3 approaches to recommender systems

Content-based filtering

Collaborative filtering

Neighborhood-based
(a.k.a. memory-based)

# Recommendation Strategies

3 approaches to recommender systems

Content-based filtering

Collaborative filtering

- Neighborhood-based (a.k.a. memory-based)
- Latent-factor-based (a.k.a. model-based)

# Recommendation Strategies

3 approaches to recommender systems

Content-based filtering

Collaborative filtering

- Neighborhood-based (a.k.a. memory-based)
- Latent-factor-based (a.k.a. model-based)
- Hybrid (memory-model-based)

# Recommendation Strategies

3 approaches to recommender systems

Content-based filtering

Collaborative filtering

Hybrid

Neighborhood-based
(a.k.a. memory-based)

Latent-factor-based
(a.k.a. model-based)

Hybrid
(memory-model-based)

# CONTENT-BASED FILTERING

# Content-based Filtering

**Idea**

Recommend items to user *u* similar to previous items rated highly by *u*

# Content-based Filtering

**Idea**

Recommend items to user *u* similar to previous items rated highly by *u*

Core concept: Item/User **Profiles**

# Content-based Filtering

**Idea**

Recommend items to user *u* similar to previous items rated highly by *u*

Core concept: Item/User **Profiles**

**Steps**

1. Build item profiles (i.e., a description of items using metadata information)

# Content-based Filtering

**Idea**

Recommend items to user *u* similar to previous items rated highly by *u*

Core concept: Item/User **Profiles**

**Steps**

1. Build item profiles (i.e., a description of items using metadata information)
2. Based on the item profiles, build user profiles: user profile says what the user likes

# Content-based Filtering

**Idea**

Recommend items to user *u* similar to previous items rated highly by *u*

Core concept: Item/User **Profiles**

**Steps**

1. Build item profiles (i.e., a description of items using metadata information)
2. Based on the item profiles, build user profiles: user profile says what the user likes
3. Match the user profile with the item catalog

# Building Item Profiles

Goal

For each item $i$ create a profile, i.e., a set of features

# Building Item Profiles

**Goal**

For each item *i* create a profile, i.e., a set of features

**Movies**

- Author
- Title
- Director
- Genre

…

**Images/Videos**

- Width
- Height
- Framerate
- Tags

…

…

**People**

- Age
- Sex
- Job
- Friends

…

# Building Item Profiles

**Goal**

For each item *i* create a profile, i.e., a set of features

**Movies**

```
- Author
- Title
- Director
- Genre
```
…

**Images/Videos**

```
- Width
- Height
- Framerate
- Tags
```
…

…

**People**

```
- Age
- Sex
- Job
- Friends
```
…

Think of each profile as a vector of numerical/categorical features

# Item Profile: Example

- Suppose we want to build a news recommender system

# Item Profile: Example

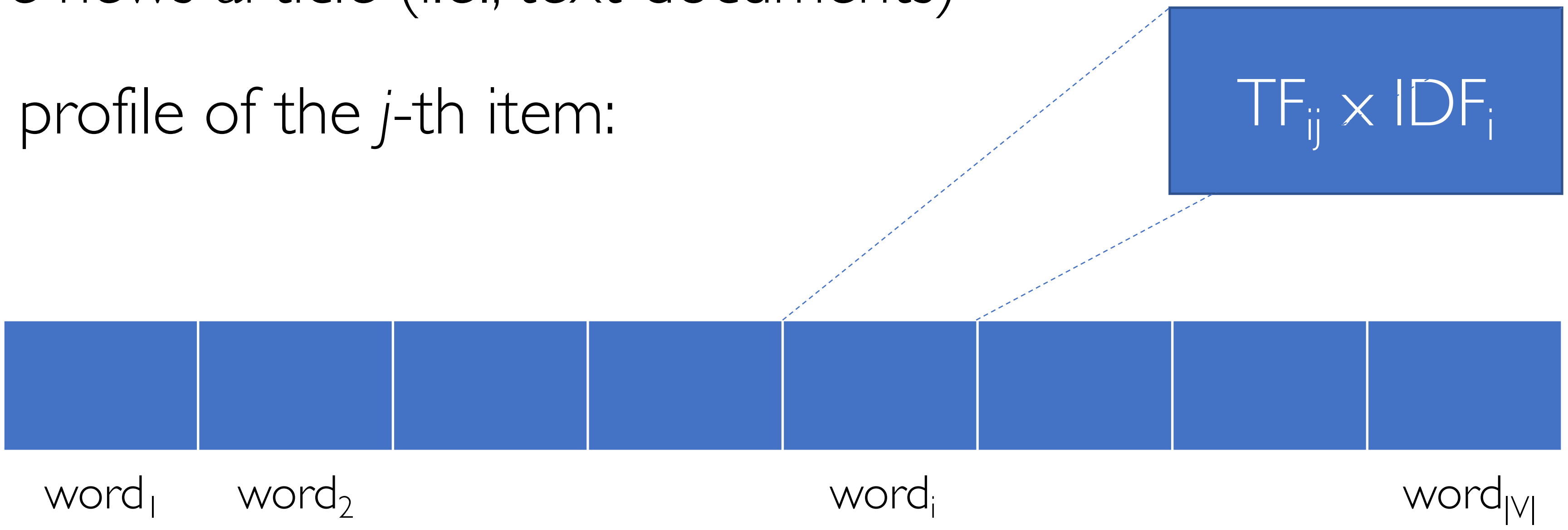
- Suppose we want to build a news recommender system
- Items are news article (i.e., text documents)

# Item Profile: Example

- Suppose we want to build a news recommender system
- Items are news article (i.e., text documents)
- Possible profile of the *j*-th item:

# Item Profile: Example

- Suppose we want to build a news recommender system
- Items are news article (i.e., text documents)
- Possible profile of the *j*-th item:



# Building User Profiles

**Goal**

For each user $u$ create a profile, from the profiles of the items she rated

# Building User Profiles

**Goal**

For each user *u* create a profile, from the profiles of the items she rated

$\mathcal{I}_u \subseteq \mathcal{I}$ The set of items rated by user *u*

# Building User Profiles

**Goal**

For each user $u$ create a profile, from the profiles of the items she rated

$\mathcal{I}_u \subseteq \mathcal{I}$ The set of items rated by user $u$

$\mathbf{i}_j$ The vector profile of item $j$

# Building User Profiles

**Goal**

For each user *u* create a profile, from the profiles of the items she rated

$\mathcal{I}_u \subseteq \mathcal{I}$ The set of items rated by user *u*

$\mathbf{i}_j$ The vector profile of item *j*

The simplest solution to build the user profile is to take the average of item profiles rated

$$\mathbf{u}_i = \frac{1}{|\mathcal{I}_u|} \sum_{\mathbf{i}_j \in \mathcal{I}_u} \mathbf{i}_j$$

# Building User Profiles

**Goal**

For each user *u* create a profile, from the profiles of the items she rated

$\mathcal{I}_u \subseteq \mathcal{I}$ The set of items rated by user *u*

$\mathbf{i}_j$ The vector profile of item *j*

The simplest solution to build the user profile is to take the average of item profiles rated

$$\mathbf{u}_i = \frac{1}{|\mathcal{I}_u|} \sum_{\mathbf{i}_j \in \mathcal{I}_u} \mathbf{i}_j$$

All the items are treated equally, independently of the rating

# Simple User Profile: Example

Items = Movies

# Simple User Profile: Example

Items = Movies

Movie Profile = List of Actors

# Simple User Profile: Example

Items = Movies

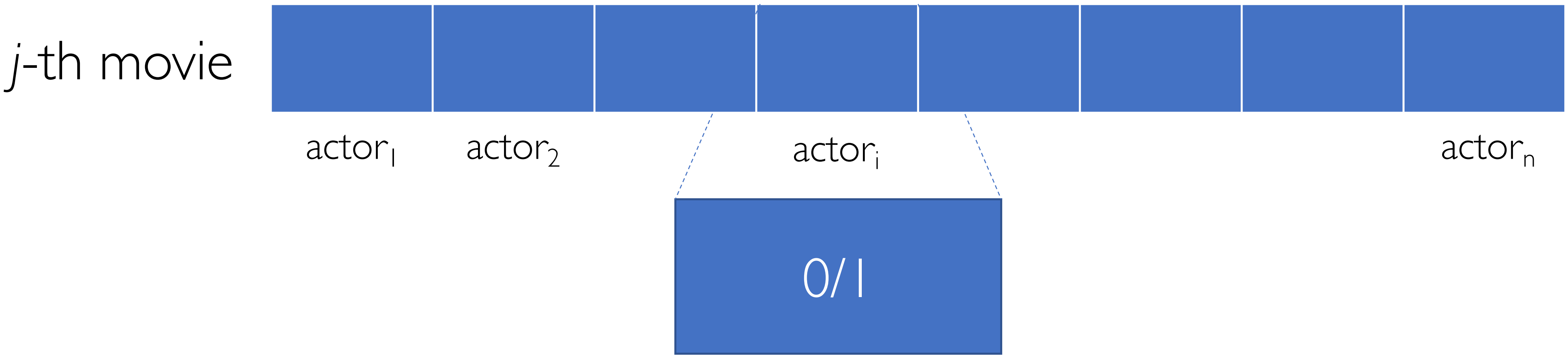
Movie Profile = List of Actors

*j*-th movie

# Simple User Profile: Example

Items = Movies

Movie Profile = List of Actors




Binary feature indicating if actor$_i$ appears in movie$_j$

# Simple User Profile: Example

Suppose user u has watched 5 movies, each movie represented by 2 actors

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| 1 | 0 | 0 | 1 | 0 | 1 | 1 | 0 | 0 | 1 |
| $actor_1$ | $actor_2$ | $actor_1$ | $actor_2$ | $actor_1$ | $actor_2$ | $actor_1$ | $actor_2$ | $actor_1$ | $actor_2$ |

# Simple User Profile: Example

Suppose user u has watched 5 movies, each movie represented by 2 actors

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| 1 | 0 | 0 | 1 | 0 | 1 | 1 | 0 | 0 | 1 |
| $actor_1$ | $actor_2$ | $actor_1$ | $actor_2$ | $actor_1$ | $actor_2$ | $actor_1$ | $actor_2$ | $actor_1$ | $actor_2$ |

2 movies feature actor 1

# Simple User Profile: Example

Suppose user u has watched 5 movies, each movie represented by 2 actors

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| 1 | 0 | 0 | 1 | 0 | 1 | 1 | 0 | 0 | 1 |
| $actor_1$ | $actor_2$ | $actor_1$ | $actor_2$ | $actor_1$ | $actor_2$ | $actor_1$ | $actor_2$ | $actor_1$ | $actor_2$ |

3 movies feature actor 2

# Simple User Profile: Example

Suppose user u has watched 5 movies, each movie represented by 2 actors

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| 1 | 0 | 0 | 1 | 0 | 1 | 1 | 0 | 0 | 1 |
| $actor_1$ | $actor_2$ | $actor_1$ | $actor_2$ | $actor_1$ | $actor_2$ | $actor_1$ | $actor_2$ | $actor_1$ | $actor_2$ |

User profile is the **mean** of item profiles

# Simple User Profile: Example

Suppose user u has watched 5 movies, each movie represented by 2 actors

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| 1 | 0 | 0 | 1 | 0 | 1 | 1 | 0 | 0 | 1 |
| $actor_1$ | $actor_2$ | $actor_1$ | $actor_2$ | $actor_1$ | $actor_2$ | $actor_1$ | $actor_2$ | $actor_1$ | $actor_2$ |

User profile is the **mean** of item profiles

$(1+1)/5$

| | |
|---|---|
| 0.4 | |
| $actor_1$ | $actor_2$ |

# Simple User Profile: Example

Suppose user u has watched 5 movies, each movie represented by 2 actors

| 1 | 0 | 0 | 1 | 0 | 1 | 1 | 0 | 0 | 1 |
|---|---|---|---|---|---|---|---|---|---|
| $actor_1$ | $actor_2$ | $actor_1$ | $actor_2$ | $actor_1$ | $actor_2$ | $actor_1$ | $actor_2$ | $actor_1$ | $actor_2$ |

User profile is the **mean** of item profiles

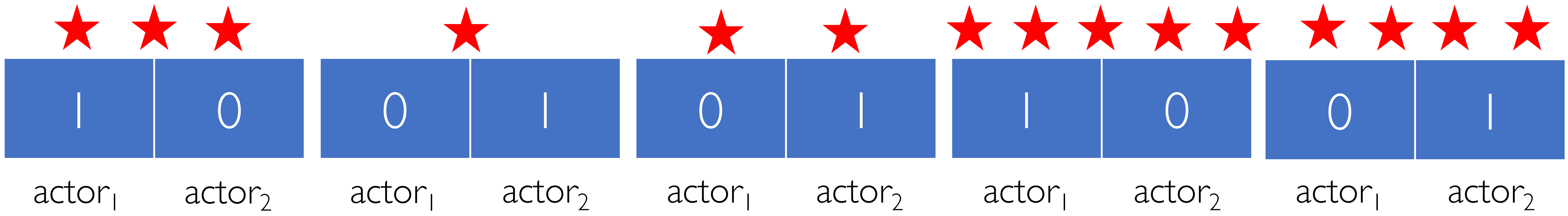
$(1+1)/5$

| 0.4 | 0.6 |
|---|---|
| $actor_1$ | $actor_2$ |

$(1+1+1)/5$

# Simple User Profile: Example With Ratings

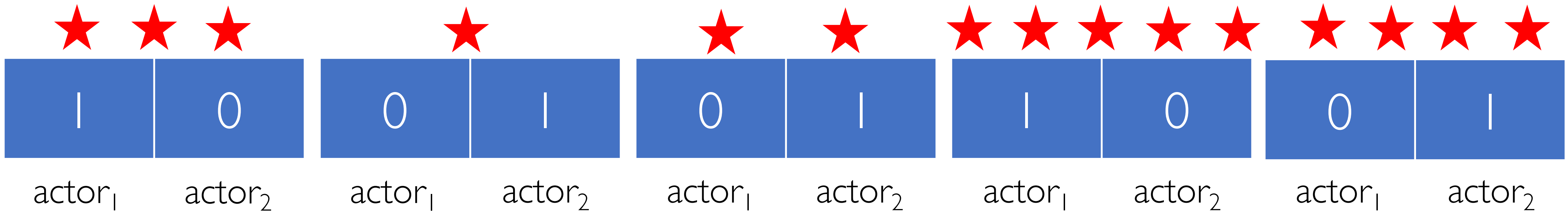
Suppose user *u* has watched (and rated) 5 movies




Normalize ratings by subtracting user's mean rating before

# Simple User Profile: Example With Ratings

Suppose user $u$ has watched (and rated) 5 movies




Normalize ratings by subtracting user's mean rating before

Avg. User Rating = (3 + 1 + 2 + 5 + 4)/5 = 3

# Simple User Profile: Example With Ratings

Suppose user *u* has watched (and rated) 5 movies

| 3-3 = 0 | | 1-3 = -2 | | 2-3 = -1 | | 5-3 = 2 | | 4-3 = 1 | |
|---|---|---|---|---|---|---|---|---|---|
| 1 | 0 | 0 | 1 | 0 | 1 | 1 | 0 | 0 | 1 |
| $actor_1$ | $actor_2$ | $actor_1$ | $actor_2$ | $actor_1$ | $actor_2$ | $actor_1$ | $actor_2$ | $actor_1$ | $actor_2$ |

Normalize ratings by subtracting user's mean rating before

Avg. User Rating = (3 + 1 + 2 + 5 + 4)/5 = 3

# Simple User Profile: Example With Ratings

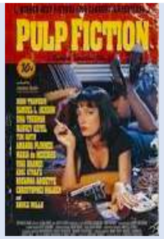
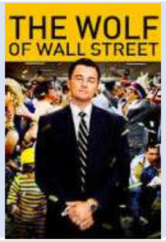
Suppose user $u$ has watched (and rated) 5 movies

| 0 | | -2 | | -1 | | 2 | | 1 | |
|---|---|---|---|---|---|---|---|---|---|
| 1 | 0 | 0 | 1 | 0 | 1 | 1 | 0 | 0 | 1 |
| $actor_1$ | $actor_2$ | $actor_1$ | $actor_2$ | $actor_1$ | $actor_2$ | $actor_1$ | $actor_2$ | $actor_1$ | $actor_2$ |

Normalize ratings by subtracting user's mean rating before

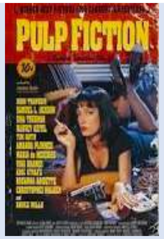
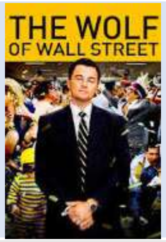
| (0+2)/2 | 1 | -2/3 | [-2+(-1)+1]/3 |
|---|---|---|---|
| | $actor_1$ | $actor_2$ | |

# Building Predictions (from Item/User Profiles)

| | | MOVIES | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | |   |   |   |   |   |   |   |   |
| USERS |  Alice | 2 | | 5 | 4 | 5 | 4 | | 4 |
| |  Bob | 4 | ? | ? | ? | ? | 3 | ? | 3 |
| |  Carl | 5 | 5 | 3 | 4 | 5 | 4 | | 5 |
| | … | … | … | … | … | … | … | … | … |
| |  Zoe | | 1 | 3 | | | | 5 | 4 |

# Building Predictions (from Item/User Profiles)

How to fill the "?"?

| | | MOVIES | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | |   |   |   |   |   |   |   |   |
| USERS |  Alice | 2 | | 5 | 4 | 5 | 4 | | 4 |
| |  Bob | 4 | ? | ? | ? | ? | 3 | ? | 3 |
| |  Carl | 5 | 5 | 3 | 4 | 5 | 4 | | 5 |
| | … | … | … | … | … | … | … | … | … |
| |  Zoe | | 1 | 3 | | | | 5 | 4 |

# Building Predictions (from Item/User Profiles)

- Given user profile **u** we can estimate the missing entries of the utility matrix for *u* (i.e., the ratings *u* would give to unrated items)

# Building Predictions (from Item/User Profiles)

- Given user profile **u** we can estimate the missing entries of the utility matrix for *u* (i.e., the ratings *u* would give to unrated items)
- For each item unrated by *u*, compute the cosine similarity (or Pearson's correlation) between *u* and the corresponding item profile vectors

# Building Predictions (from Item/User Profiles)

- Given user profile **u** we can estimate the missing entries of the utility matrix for *u* (i.e., the ratings *u* would give to unrated items)
- For each item unrated by *u*, compute the cosine similarity (or Pearson's correlation) between *u* and the corresponding item profile vectors
- Finally, we pick the top-*k* items with the highest similarity score, and we recommend those to *u*

# Building Predictions (from Item/User Profiles)

$$A^0 = \emptyset$$

# Building Predictions (from Item/User Profiles)

$$A^0 = \emptyset$$
$$A^1 = \text{argmax}_i \{\text{sim}(\mathbf{u}, \mathbf{i}) : i \in \mathcal{I} - \mathcal{I}_u - A^0\}$$

# Building Predictions (from Item/User Profiles)

$$A^0 = \emptyset$$
$$A^1 = \text{argmax}_i\{\text{sim}(\mathbf{u}, \mathbf{i}) : i \in \mathcal{I} - \mathcal{I}_u - A^0\}$$
$$A^2 = \text{argmax}_i\{\text{sim}(\mathbf{u}, \mathbf{i}) : i \in \mathcal{I} - \mathcal{I}_u - A^0 - A^1\}$$

# Building Predictions (from Item/User Profiles)

$$A^0 = \emptyset$$
$$A^1 = \text{argmax}_i\{\text{sim}(\mathbf{u}, \mathbf{i}) : i \in \mathcal{I} - \mathcal{I}_u - A^0\}$$
$$A^2 = \text{argmax}_i\{\text{sim}(\mathbf{u}, \mathbf{i}) : i \in \mathcal{I} - \mathcal{I}_u - A^0 - A^1\}$$
$$\ldots$$
$$A^k = \text{argmax}_i\{\text{sim}(\mathbf{u}, \mathbf{i}) : i \in \mathcal{I} - \mathcal{I}_u - A^0 - A^1 - \ldots - A^{k-1}\}$$

# Building Predictions (from Item/User Profiles)

$$A^0 = \emptyset$$
$$A^1 = \text{argmax}_i \{\text{sim}(\mathbf{u}, \mathbf{i}) : i \in \mathcal{I} - \mathcal{I}_u - A^0\}$$
$$A^2 = \text{argmax}_i \{\text{sim}(\mathbf{u}, \mathbf{i}) : i \in \mathcal{I} - \mathcal{I}_u - A^0 - A^1\}$$
$$\ldots$$
$$A^k = \text{argmax}_i \{\text{sim}(\mathbf{u}, \mathbf{i}) : i \in \mathcal{I} - \mathcal{I}_u - A^0 - A^1 - \ldots - A^{k-1}\}$$

$$\boxed{R_{u,k} = \bigcup_{j=1}^{k} A^j = \bigcup_{j=1}^{k} \text{argmax}_i \left\{\text{sim}(\mathbf{u}, \mathbf{i}) : i \in \mathcal{I} - \mathcal{I}_u - \{\cup_{l=0}^{j-1} A^l\}\right\}}$$

# Content-based Filtering: PROs

- No need for data on other users: only the user and the items rated by her/him are needed

# Content-based Filtering: PROs

- No need for data on other users: only the user and the items rated by her/him are needed
- No item cold start problem: when the item is new or unpopular (i.e., no one has rated yet) it can still be recommended to users with highest profile similarity

# Content-based Filtering: PROs

- No need for data on other users: only the user and the items rated by her/him are needed
- No item cold start problem: when the item is new or unpopular (i.e., no one has rated yet) it can still be recommended to users with highest profile similarity
- Explainable recommendations using content features that caused an item to be recommended

# Content-based Filtering: CONs

- Finding the appropriate item features is hard

# Content-based Filtering: CONs

- Finding the appropriate item features is hard
- Overspecialization: never recommends items outside user's profile

# Content-based Filtering: CONs

- Finding the appropriate item features is hard
- Overspecialization: never recommends items outside user's profile
- Unable to exploit quality judgments of other users

# Content-based Filtering: CONs

- Finding the appropriate item features is hard
- Overspecialization: never recommends items outside user's profile
- Unable to exploit quality judgments of other users
- Cold start problem for new users: If the user hasn't rated any items, then there's no user profile

# Content-based Filtering: CONs

- Finding the appropriate item features is hard
- Overspecialization: never recommends items outside user's profile
- Unable to exploit quality judgments of other users
- Cold start problem for new users: If the user hasn't rated any items, then there's no user profile
- May need to create average profiles and gradually improve them overtime

# Take-Home Message of Today

- Recommender systems as tools for dealing with information overload

# Take-Home Message of Today

- Recommender systems as tools for dealing with information overload
- The main goal of recommender systems is to select items that are likely of interest to users

# Take-Home Message of Today

- Recommender systems as tools for dealing with information overload
- The main goal of recommender systems is to select items that are likely of interest to users
- They make use of either explicit (e.g., ratings) or implicit (e.g., clicks) feedback to build a user-item utility matrix

# Take-Home Message of Today

- Recommender systems as tools for dealing with information overload
- The main goal of recommender systems is to select items that are likely of interest to users
- They make use of either explicit (e.g., ratings) or implicit (e.g., clicks) feedback to build a user-item utility matrix
- Content-based recommender systems make use of item and user profiles (built in the item space) to come up with top-*k* suggestions