Big Data Computing

Master's Degree in Computer Science

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Recap from Last Lectures

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- 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

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  - Searching/Filtering
  - Recommending

Why Do We Need Recommendation?

We are constantly moving from scarcity to abundance

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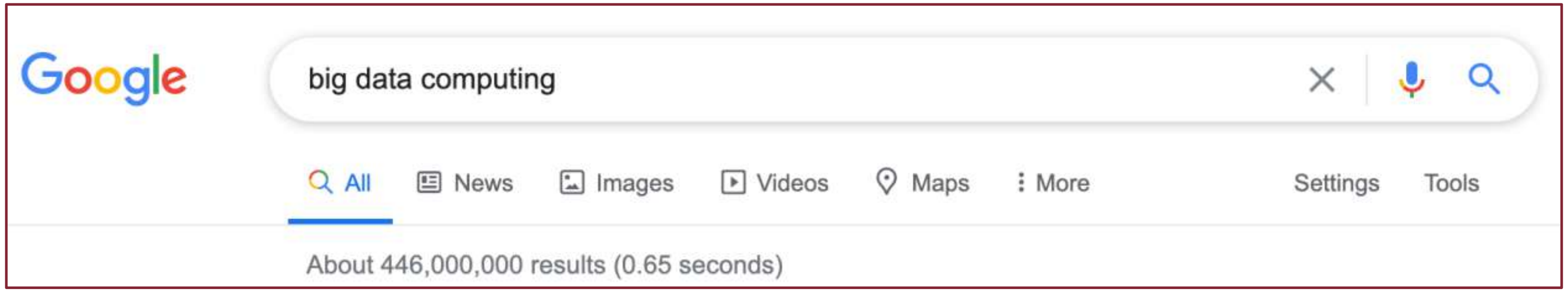

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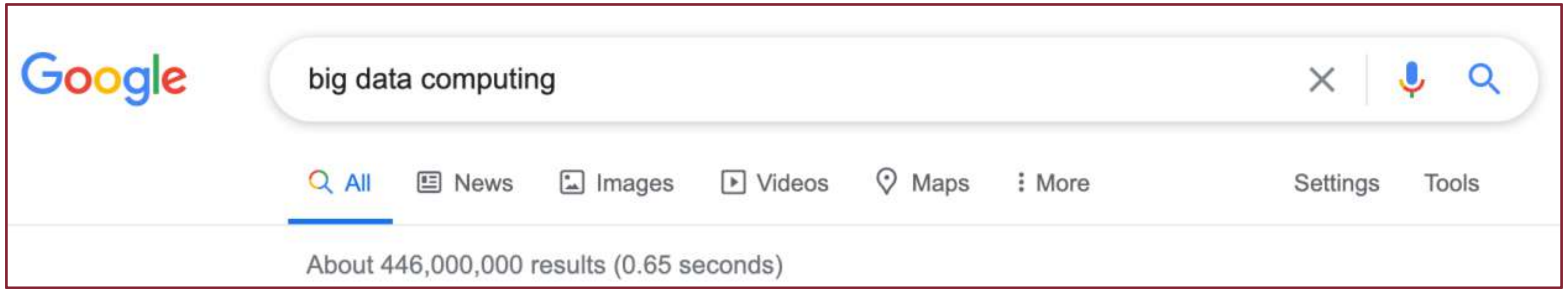

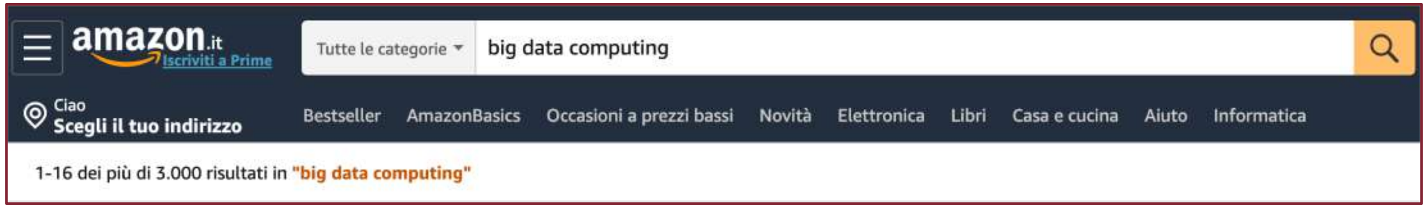

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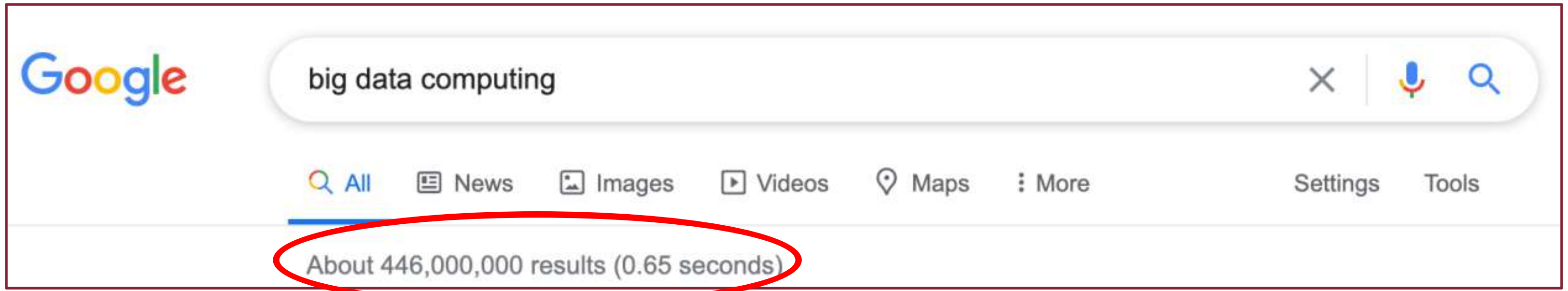

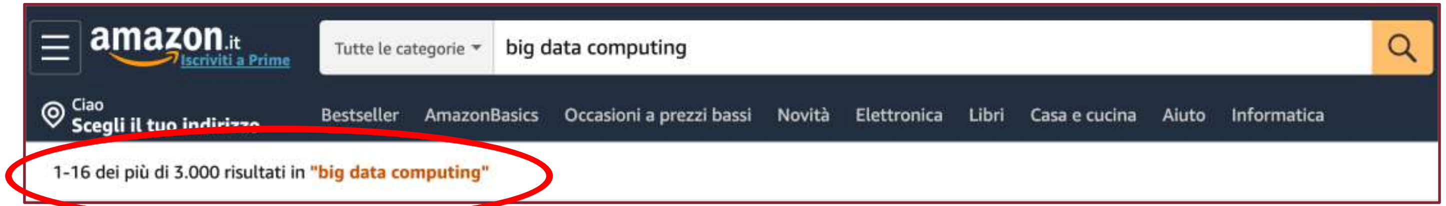

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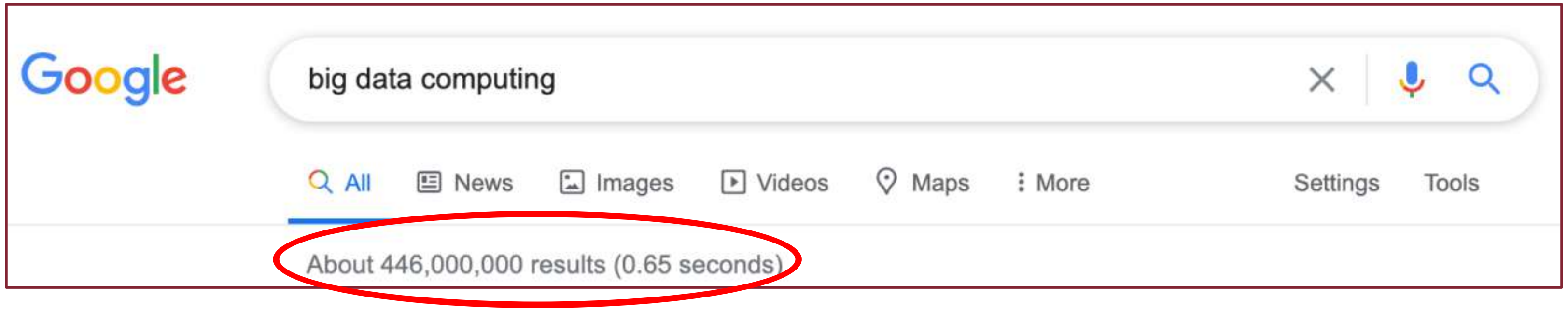

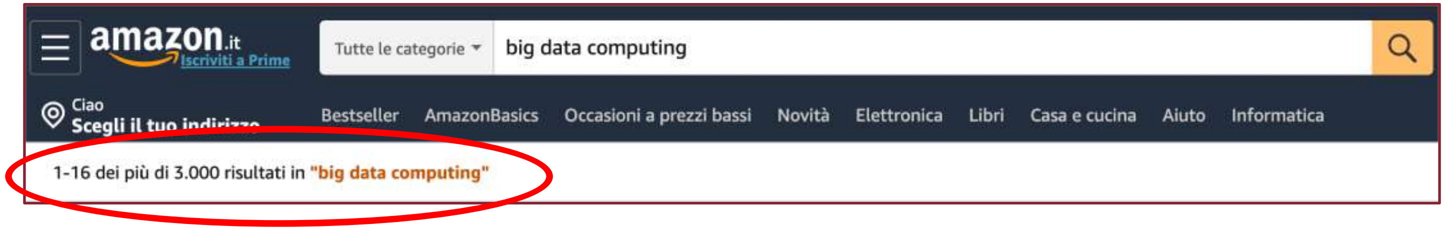

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How could we even possibly think of exhaustively explore all of them?

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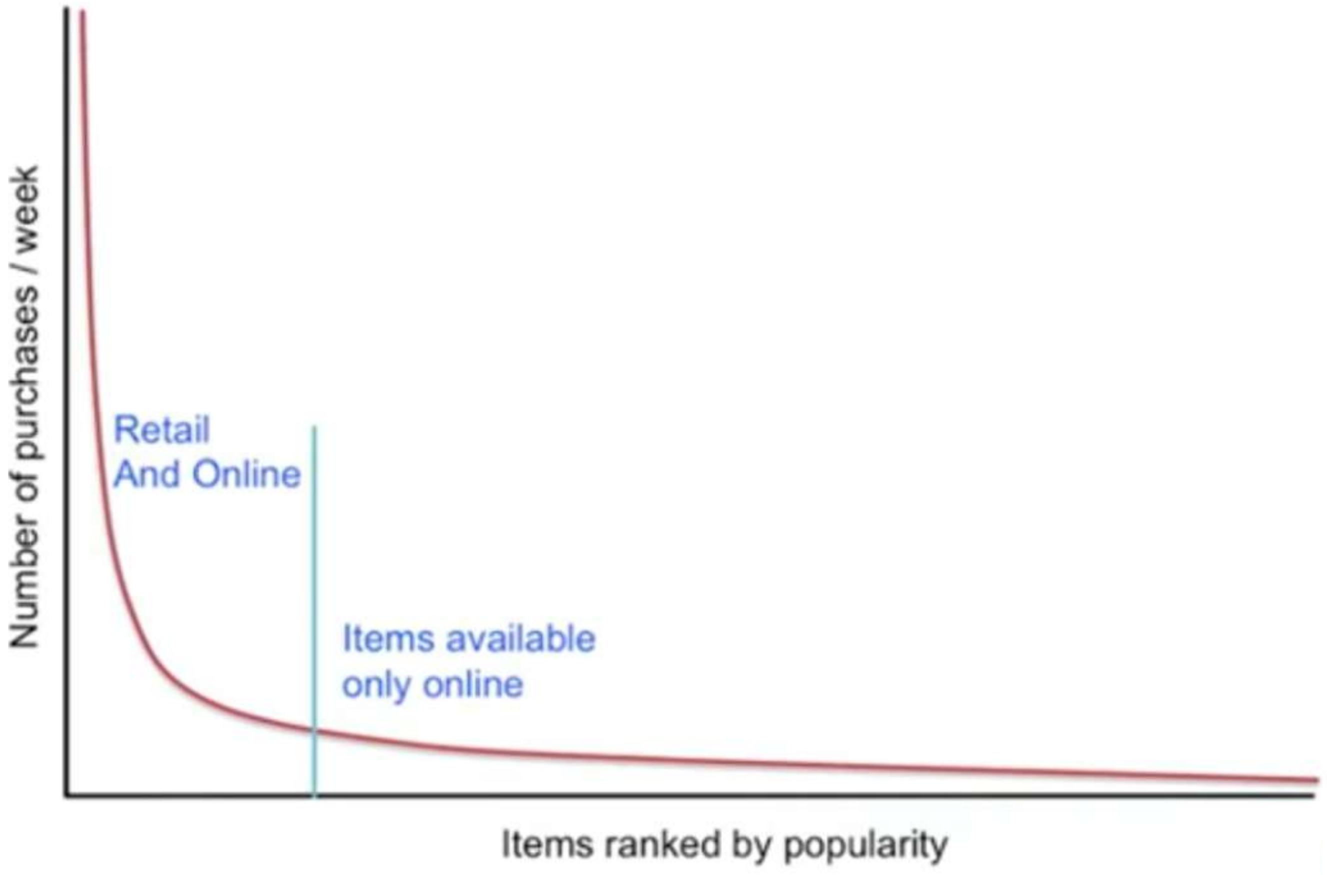
Recommender Systems

The Economics of Abundance: The Long Tail



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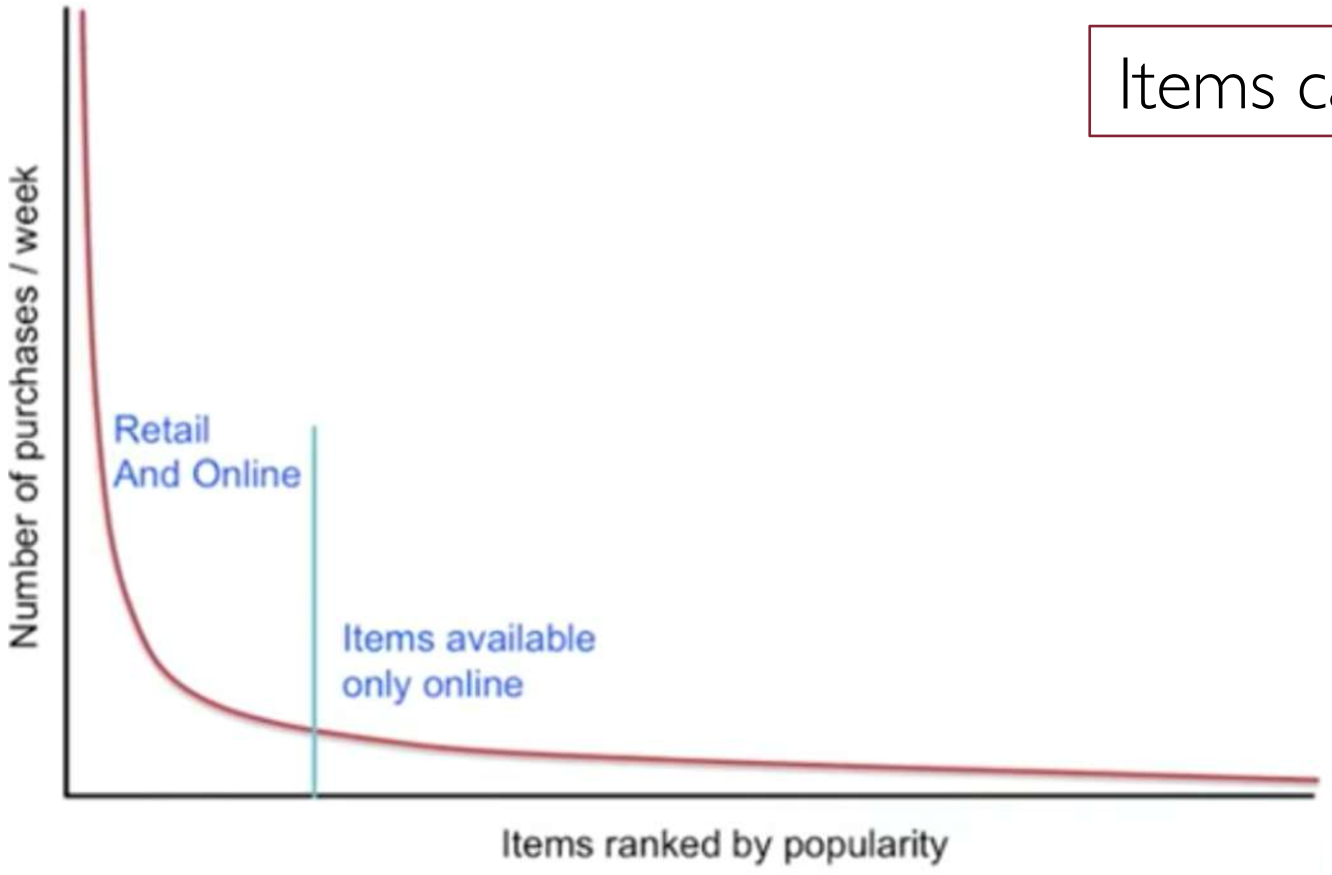

Items can be *anything*

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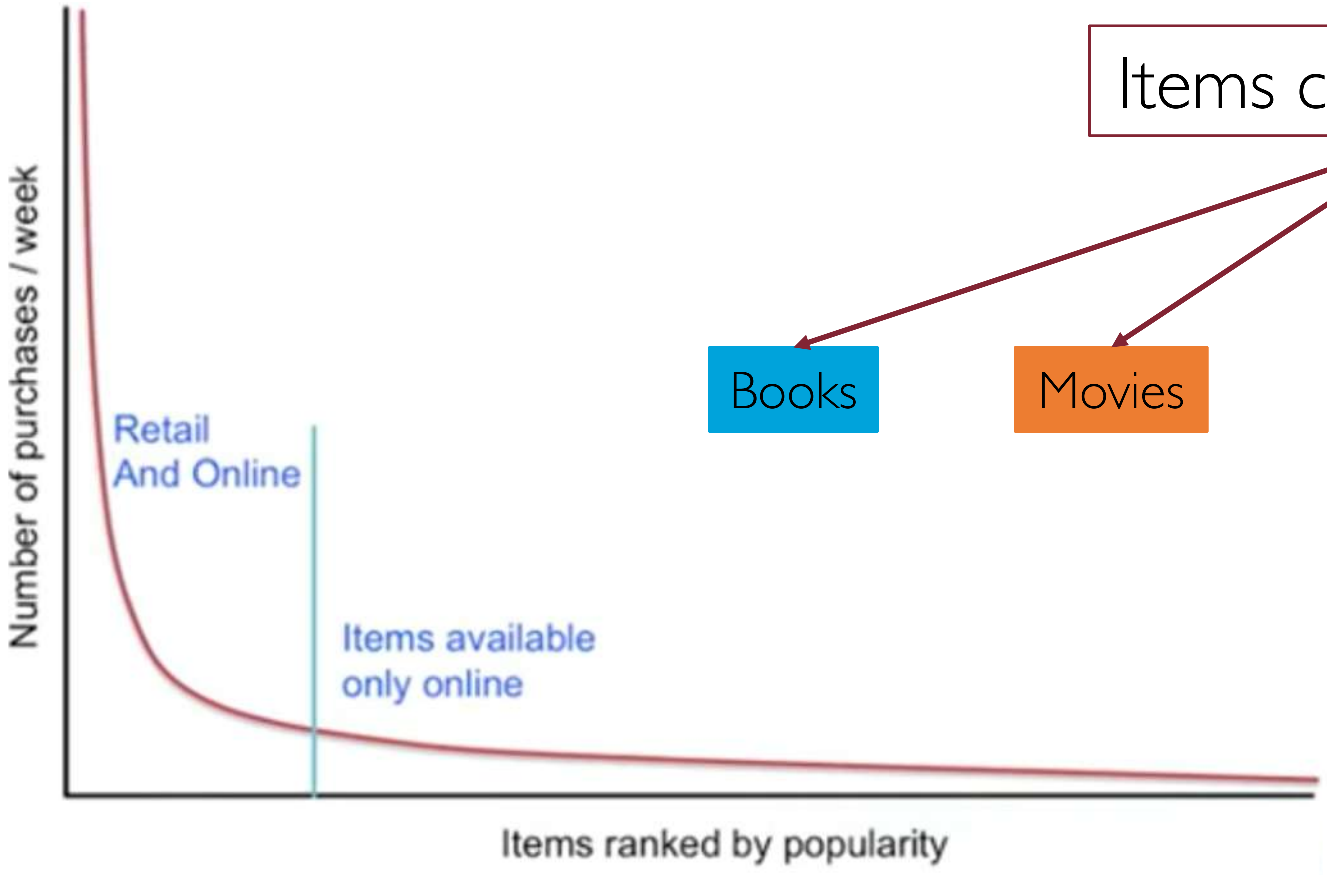

Items can be *anything*

Books | Movies | News Articles | … | Search Results

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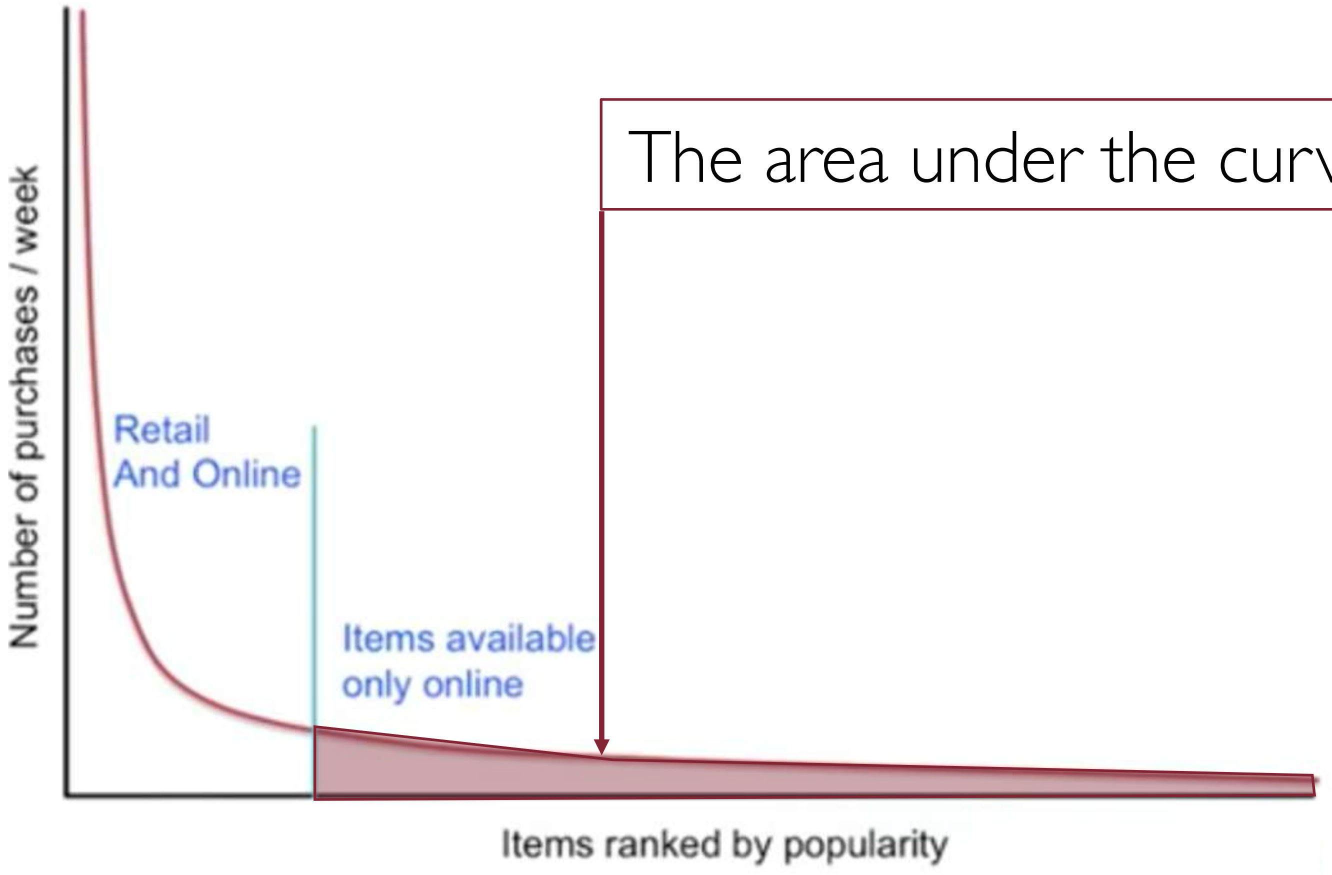

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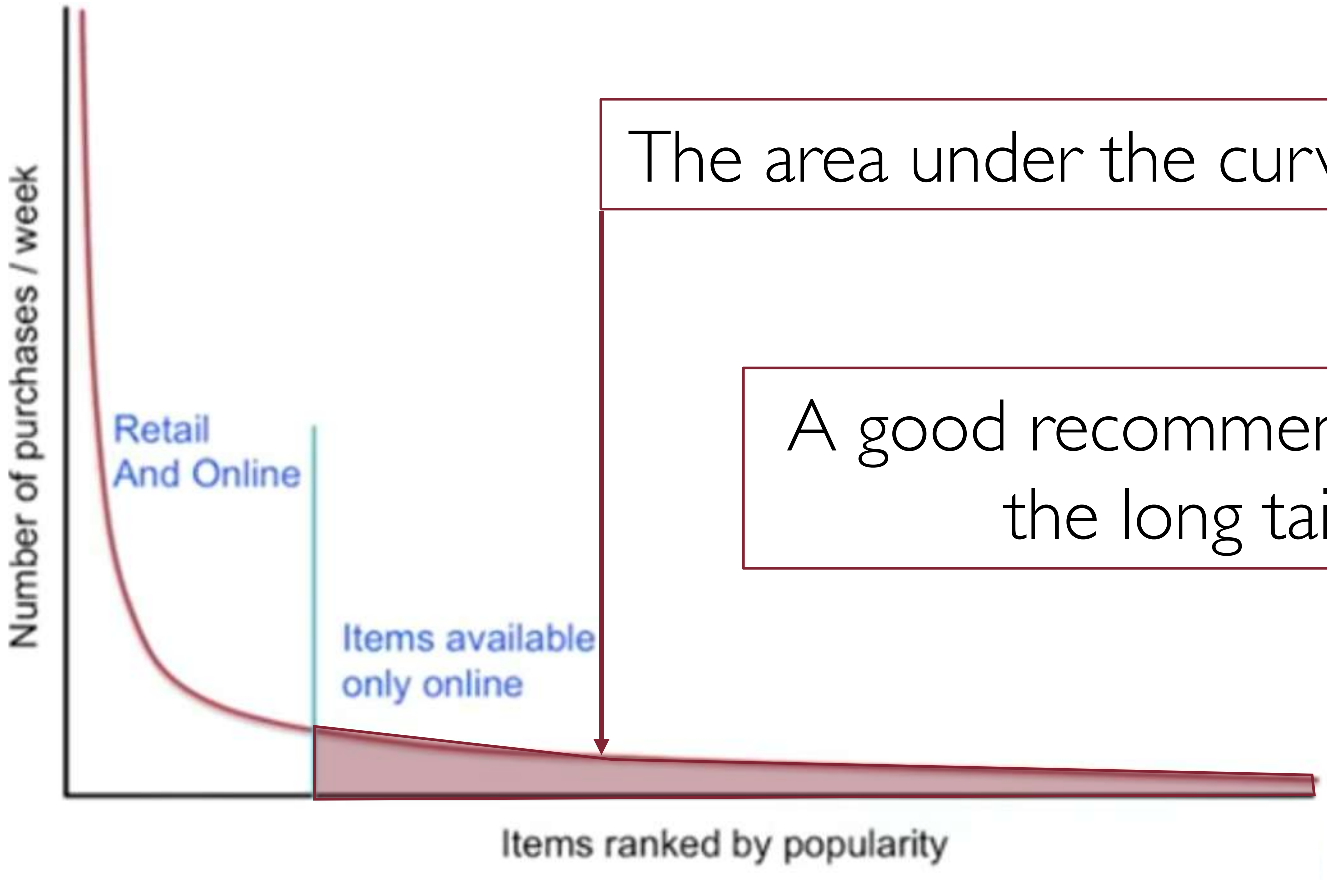

The area under the curve for the long tail is quite large!

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

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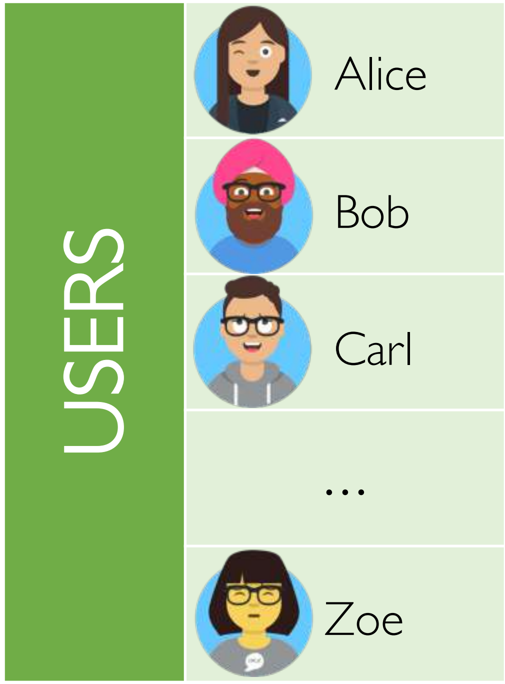
$\mathcal{R} \subseteq \mathbb{R}$ Set of ratings (totally ordered)

$\mathcal{R} = \{0, 1, \ldots, v-1\}$ 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

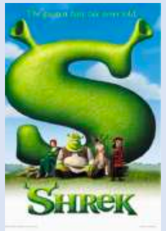
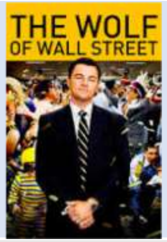
Bob

Carl

…

Zoe

The Utility Function (User-Item Matrix)

		MOVIES							
									
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	…	…	…	…	…	…	…	…	…
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The Utility Function (User-Item Matrix)

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Data Collection

Gathering known ratings to populate the utility matrix

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Extrapolate unknown ratings from the known ones

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Recommendation Evaluation

Measure the performance of recommender methods

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Explicit

Ask people to rate items

Doesn't scale: only few users leave ratings

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Implicit

Learn ratings from user actions

Click/purchases implies positive feedback
What about negative ones?

Rating Prediction

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The utility matrix R is sparse!

Most people have not rated most items

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Cold Start

New users/items have no history

Recommendation Evaluation

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Measure the performance of recommender methods

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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

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Content-based filtering

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Collaborative filtering

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(a.k.a. memory-based)

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

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

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3 approaches to recommender systems

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

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

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Steps

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

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

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

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Movies

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

Images/Videos

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

...

People

```
- Age
- Sex
- Job
- Friends
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Think of each profile as a vector of numerical/categorical features

Item Profile: Example

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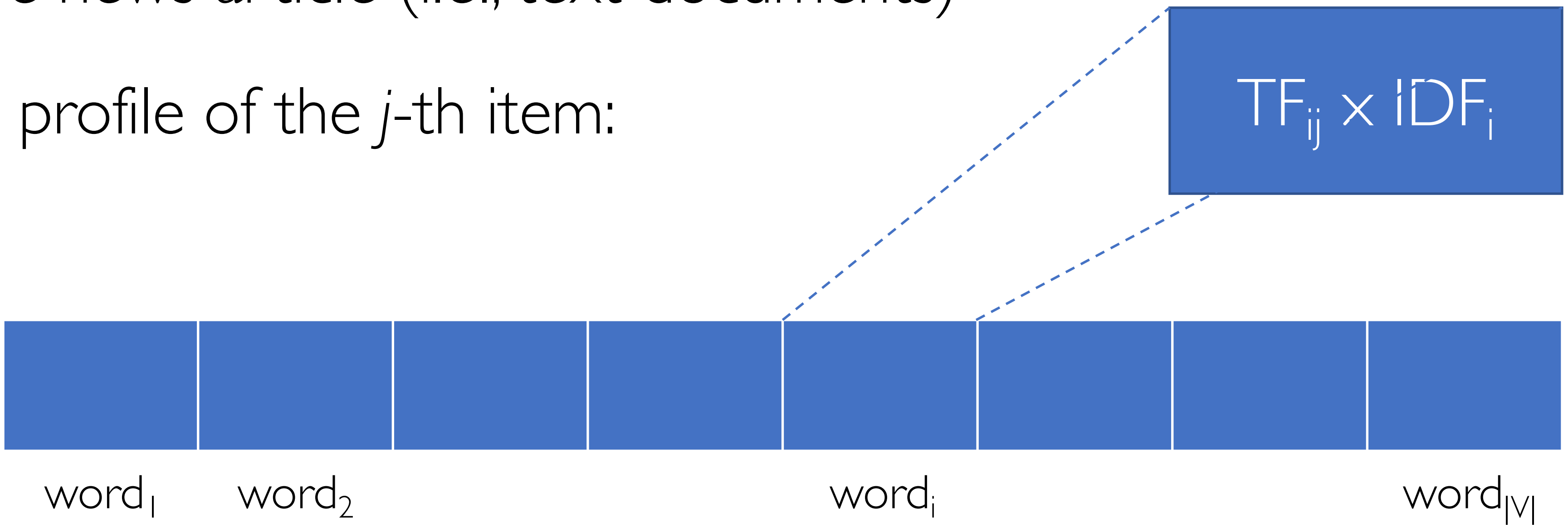

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The simplest solution to build the user profile is to take the average of item profiles rated

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

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

All the items are treated equally, independently of the rating

Simple User Profile: Example

Items = Movies

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Movie Profile = List of Actors

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j-th movie

Simple User Profile: Example

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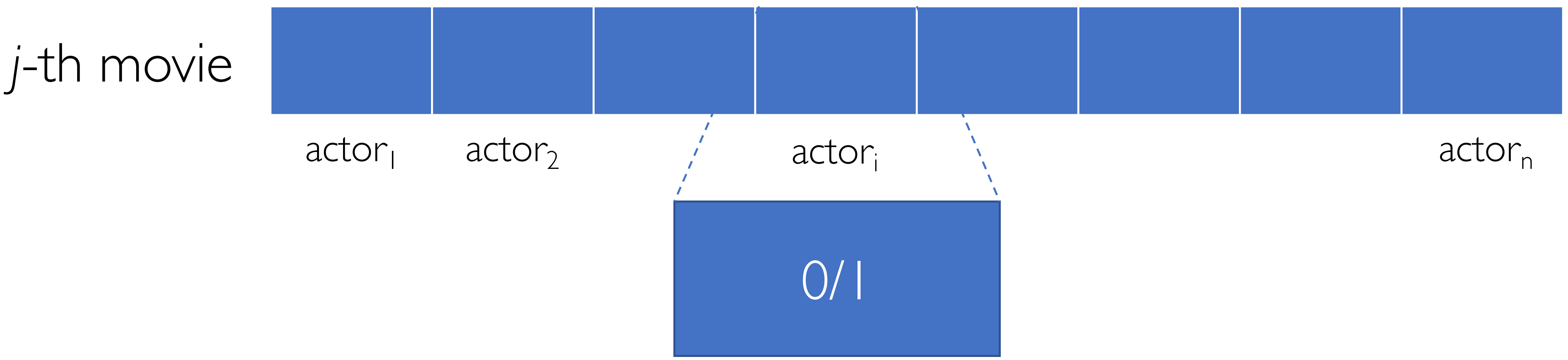
Movie Profile = List of Actors



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
$actor_1$	$actor_2$	$actor_1$	$actor_2$	$actor_1$	$actor_2$	$actor_1$	$actor_2$	$actor_1$	$actor_2$

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2 movies feature actor 1

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3 movies feature actor 2

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

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(1+1)/5

0.4	
$actor_1$	$actor_2$

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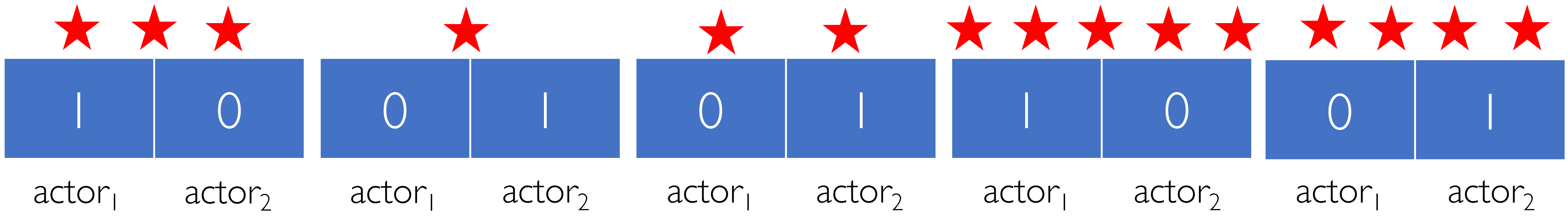
0.4	0.6
$actor_1$	$actor_2$

$(1+1+1)/5$

Simple User Profile: Example With Ratings

Suppose user u has watched (and rated) 5 movies



Normalize ratings by subtracting user's mean rating before

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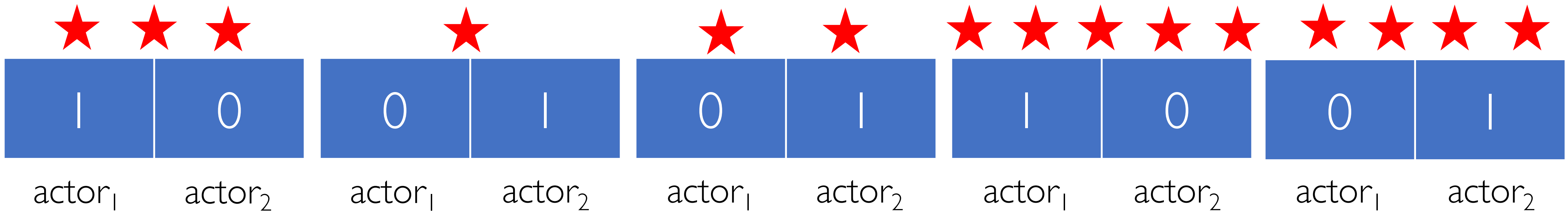

Normalize ratings by subtracting user's mean rating before

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

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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
$actor_1$	$actor_2$	$actor_1$	$actor_2$	$actor_1$	$actor_2$	$actor_1$	$actor_2$	$actor_1$	$actor_2$

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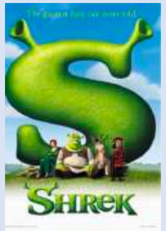
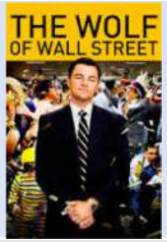
Normalize ratings by subtracting user's mean rating before

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

Building Predictions (from Item/User Profiles)

		MOVIES							
									
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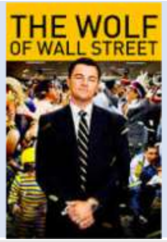
	 Bob	4	?	?	?	?	3	?	3
	 Carl	5	5	3	4	5	4		5
	…	…	…	…	…	…	…	…	…
	 Zoe		1	3				5	4

Building Predictions (from Item/User Profiles)

How to fill the "?"?

USERS	MOVIES							
								
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- 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*

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

Building Predictions (from Item/User Profiles)

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

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

Building Predictions (from Item/User Profiles)

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

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

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- Explainable recommendations using content features that caused an item to be recommended

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- May need to create average profiles and gradually improve them overtime

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- 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