Big Data Computing

Master's Degree in Computer Science

2019-2020

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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

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- 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?

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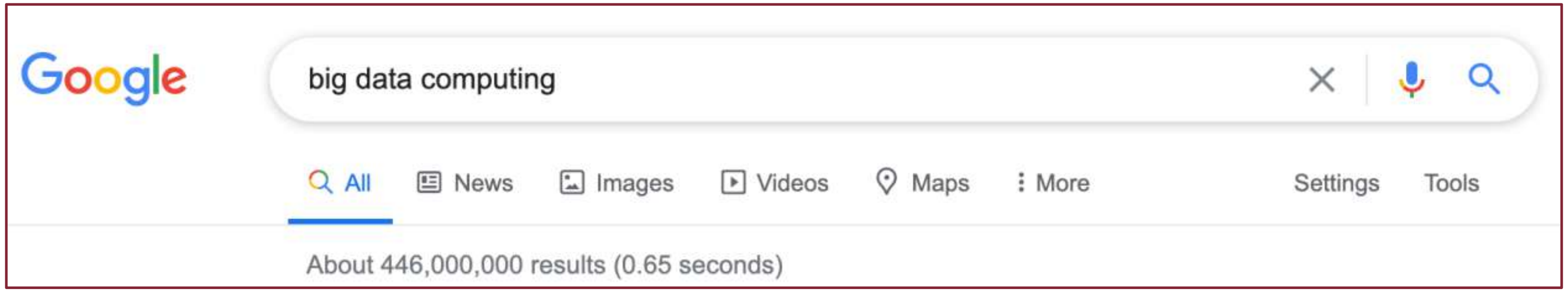

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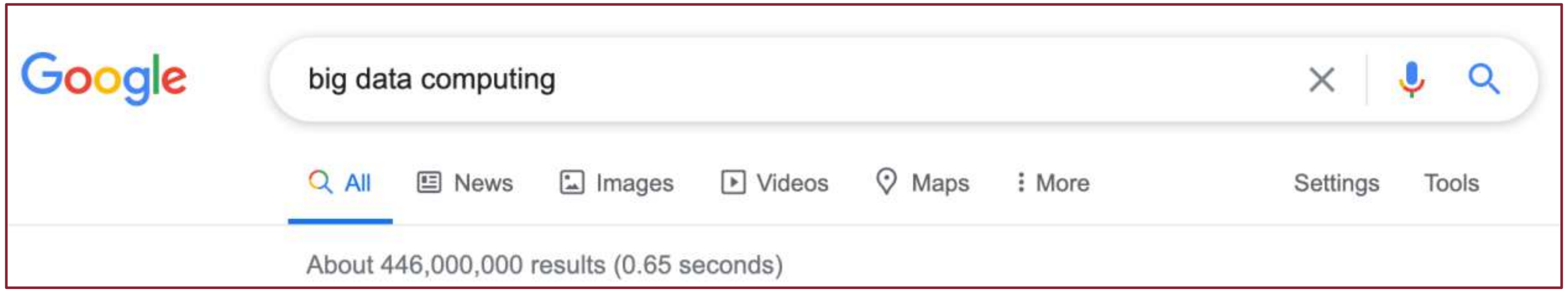

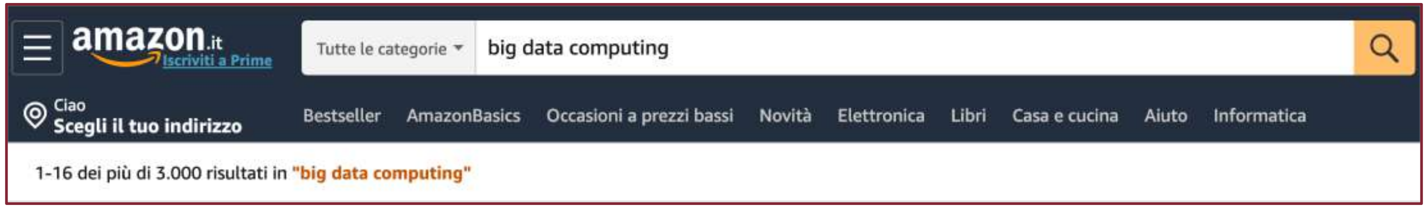

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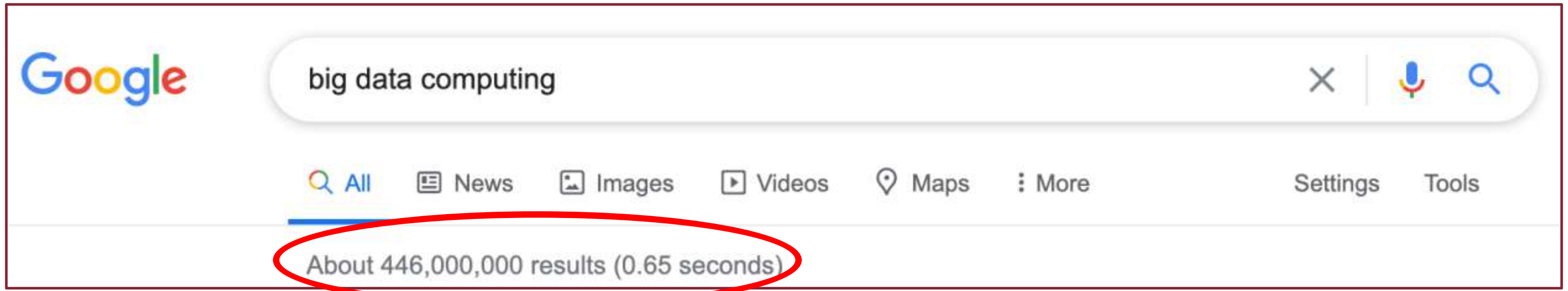

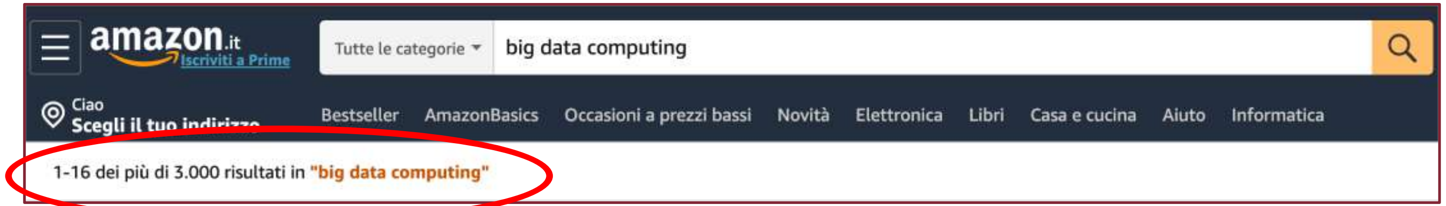

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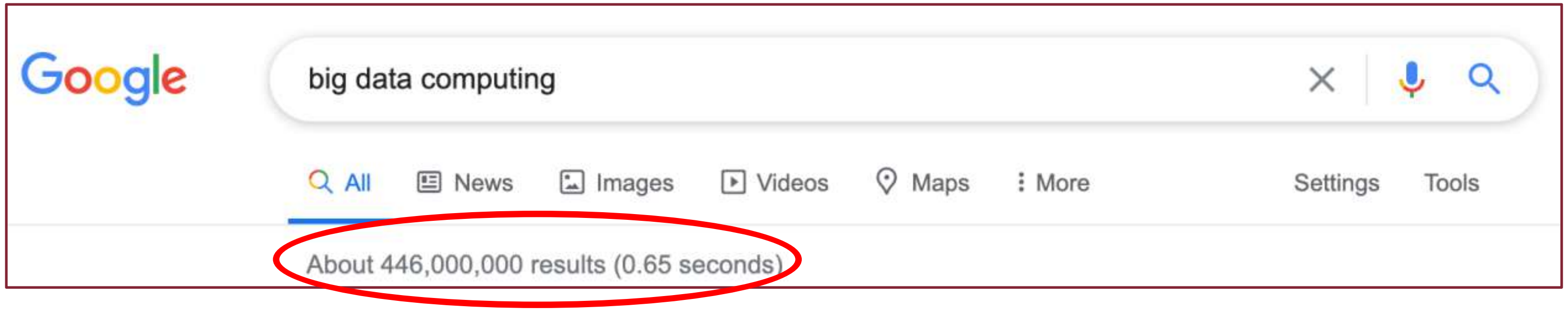

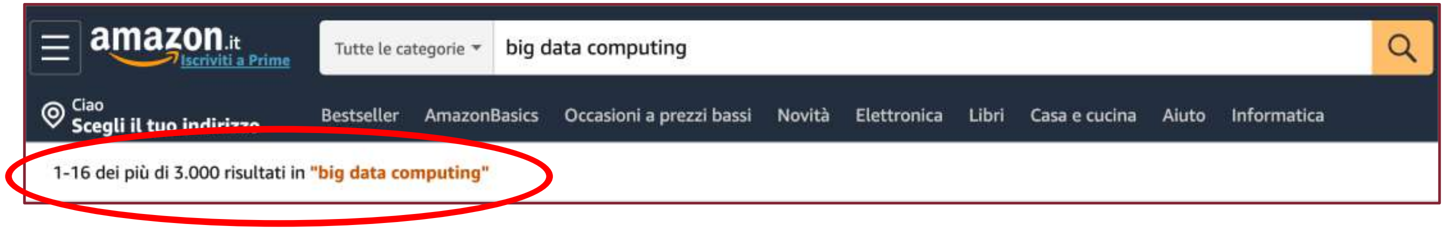

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How could we even possibly think of exhaustively explore all of them?

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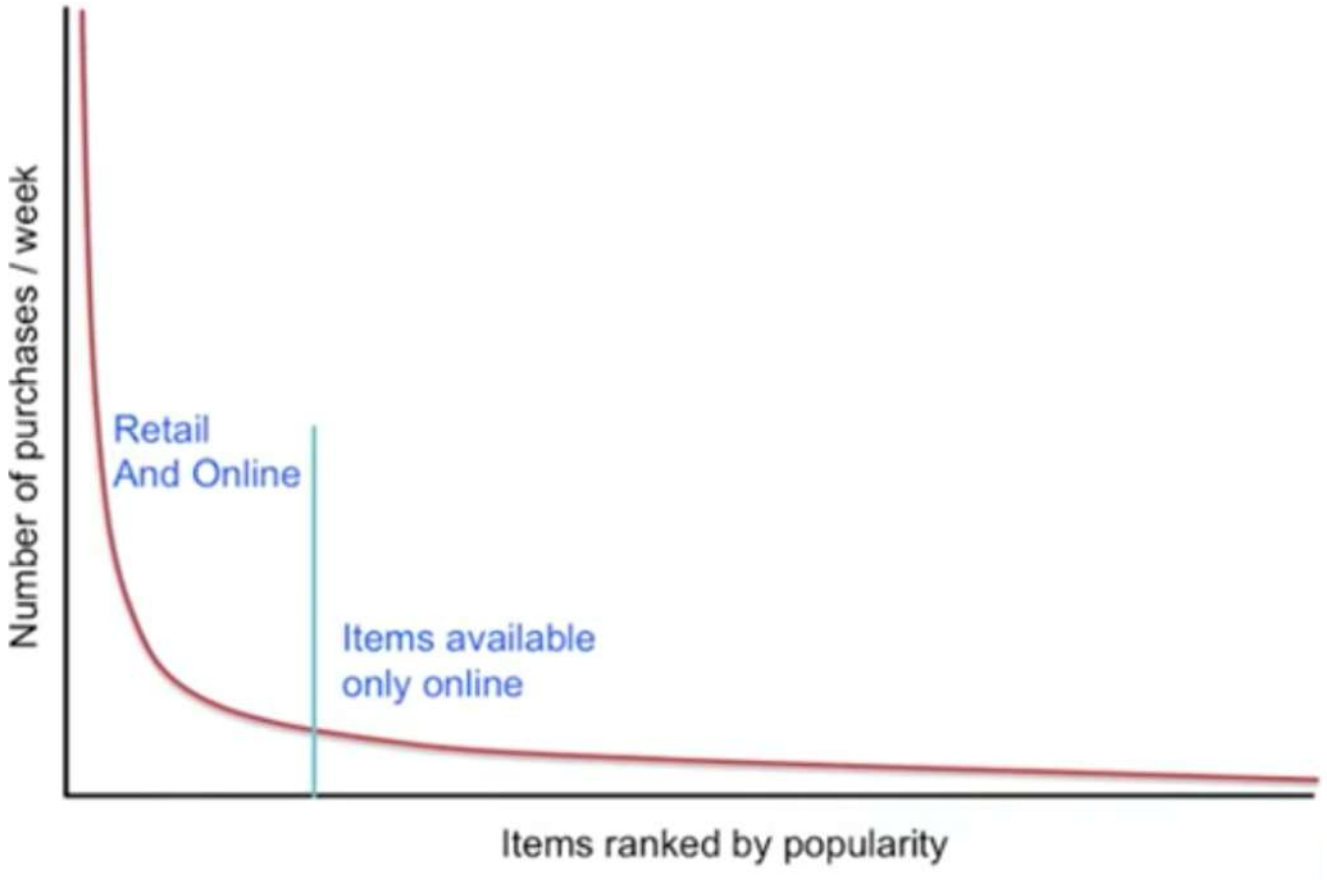
↓

Recommender Systems

The Economics of Abundance: The Long Tail



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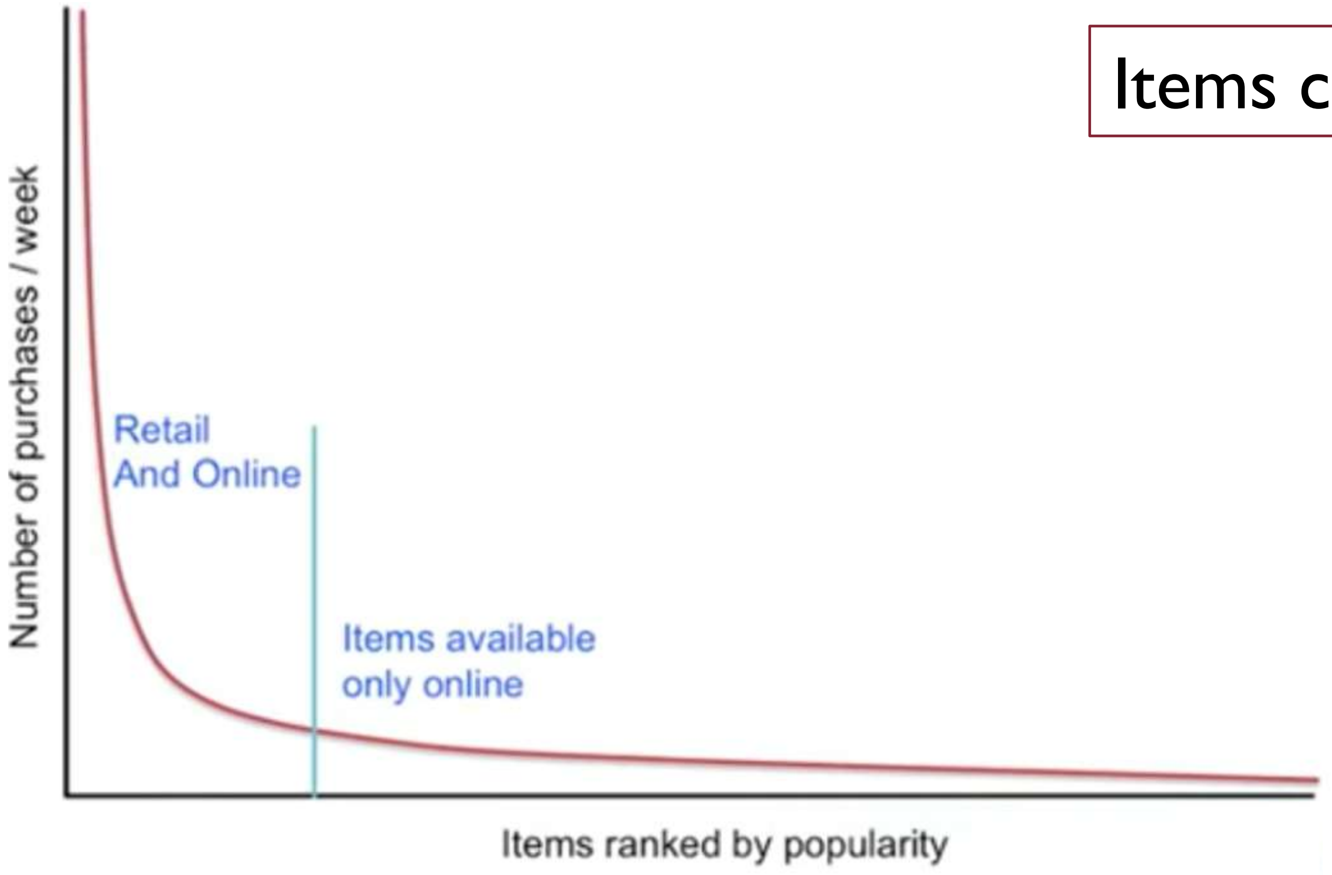

Items can be *anything*

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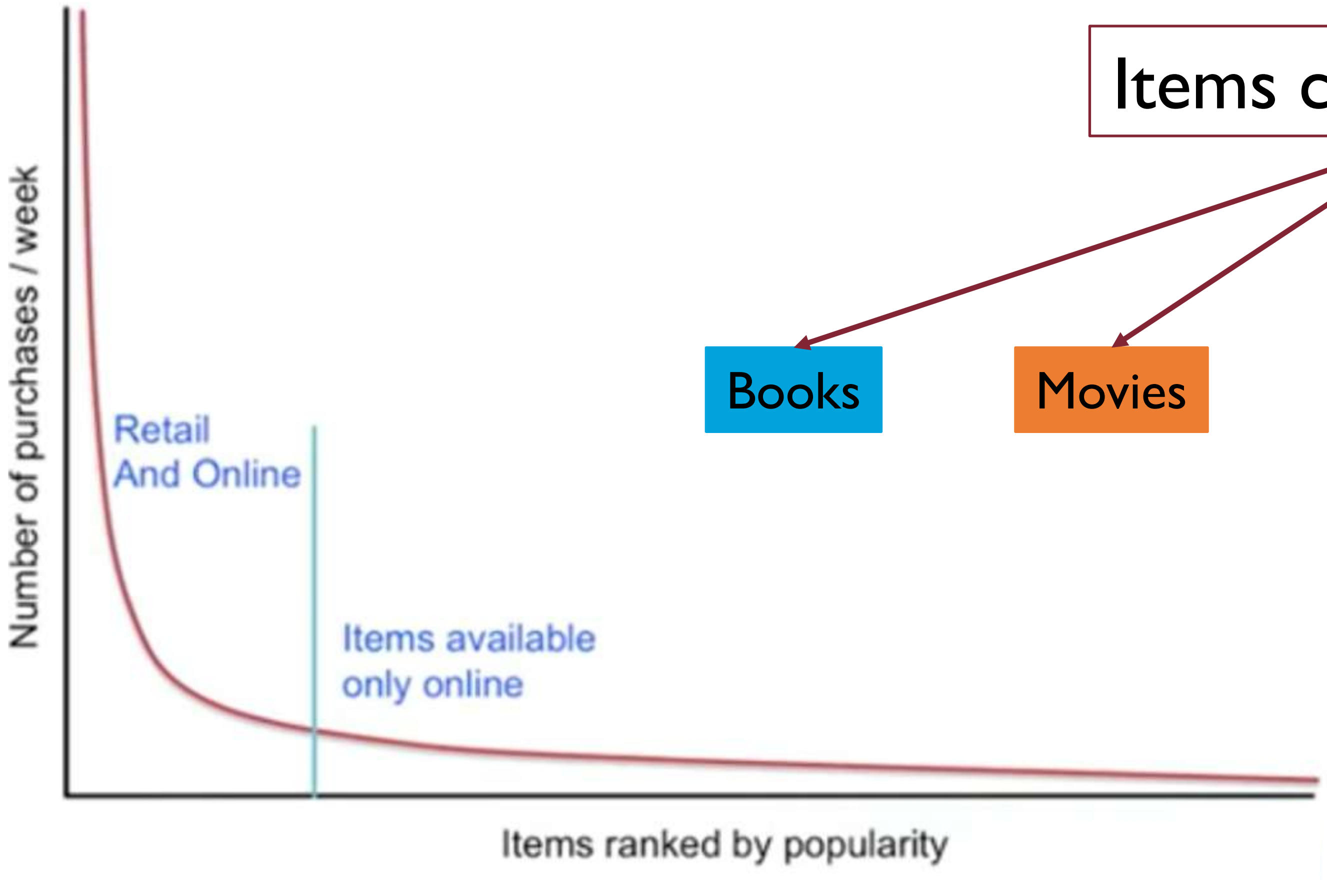

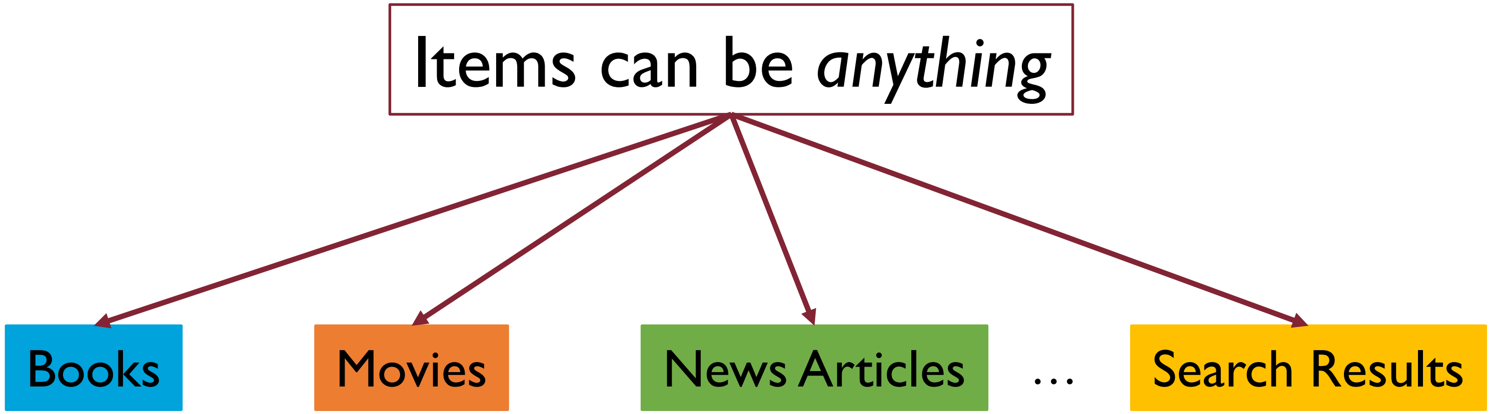

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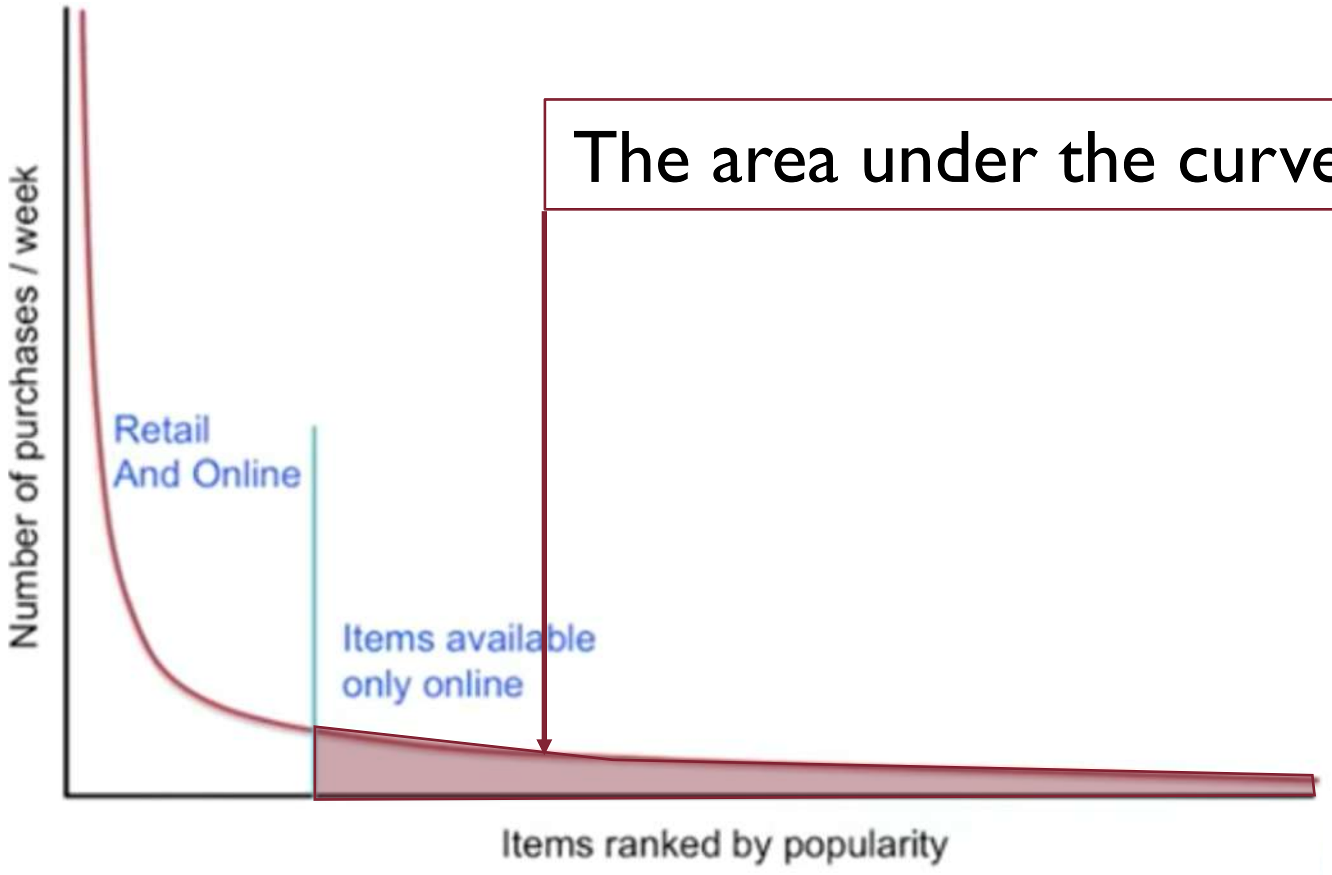
The area under the curve for the long tail is quite **large**!



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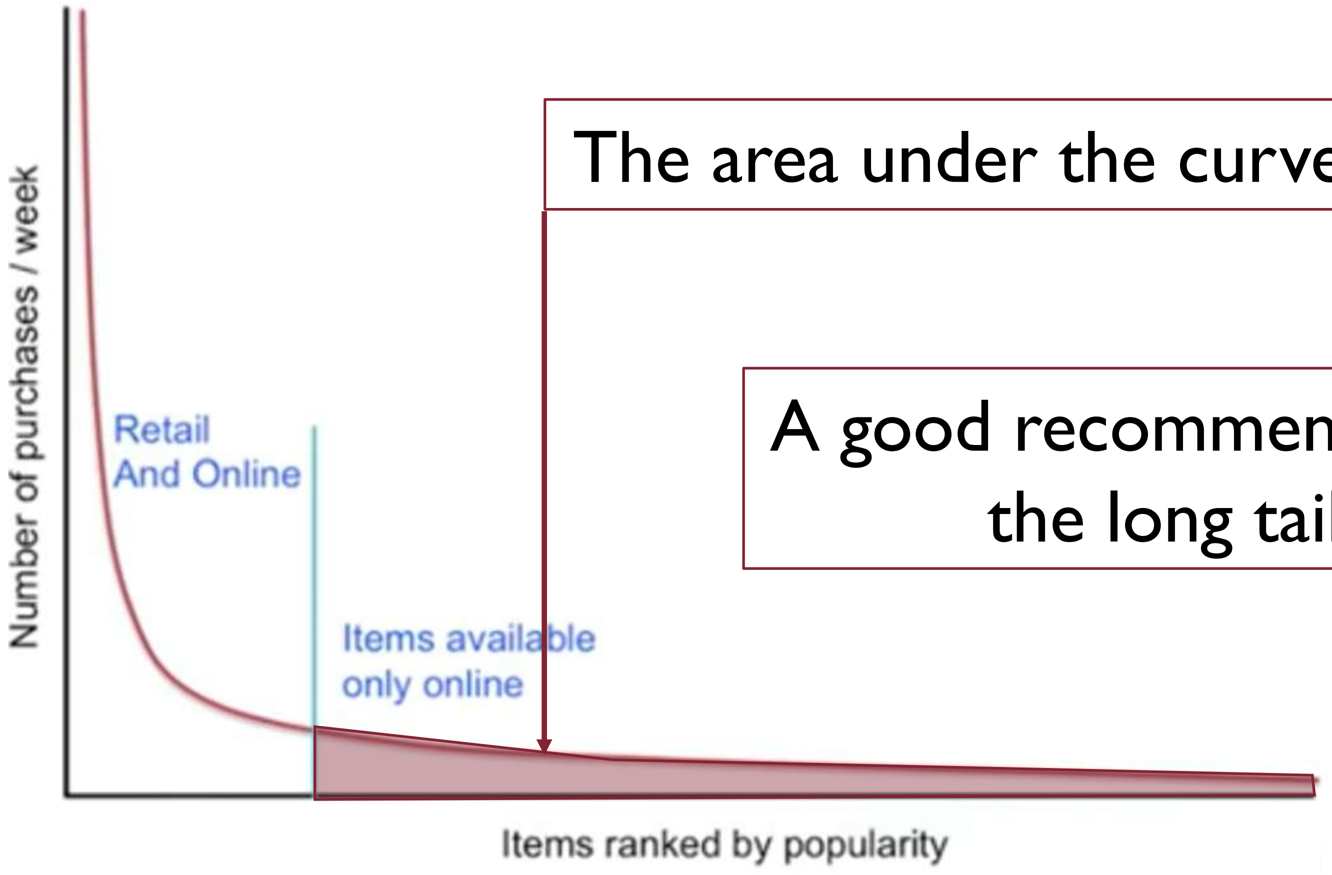

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A good recommendation system should expose the long tail/hidden items to users

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)

USERS	
	Alice
	Bob
	Carl
	…
	Zoe

The Utility Function (User-Item Matrix)

MOVIES

USERS

 Alice

 Bob

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						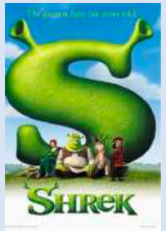		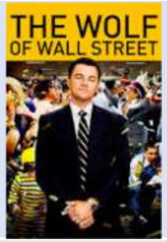	
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Recommendation Evaluation

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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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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(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

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

Item Profile: Example

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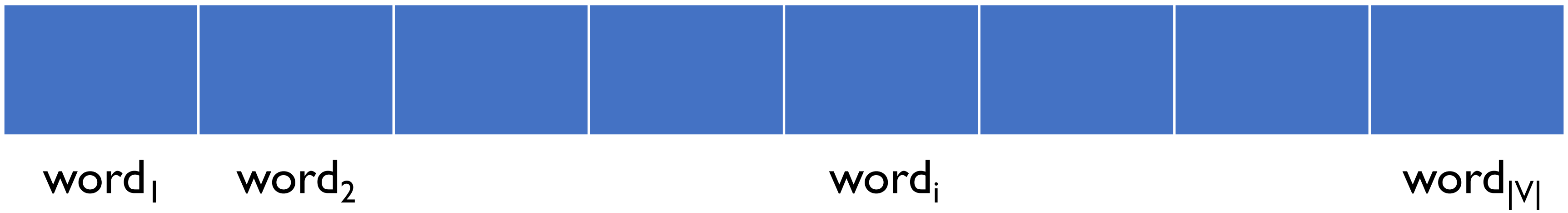

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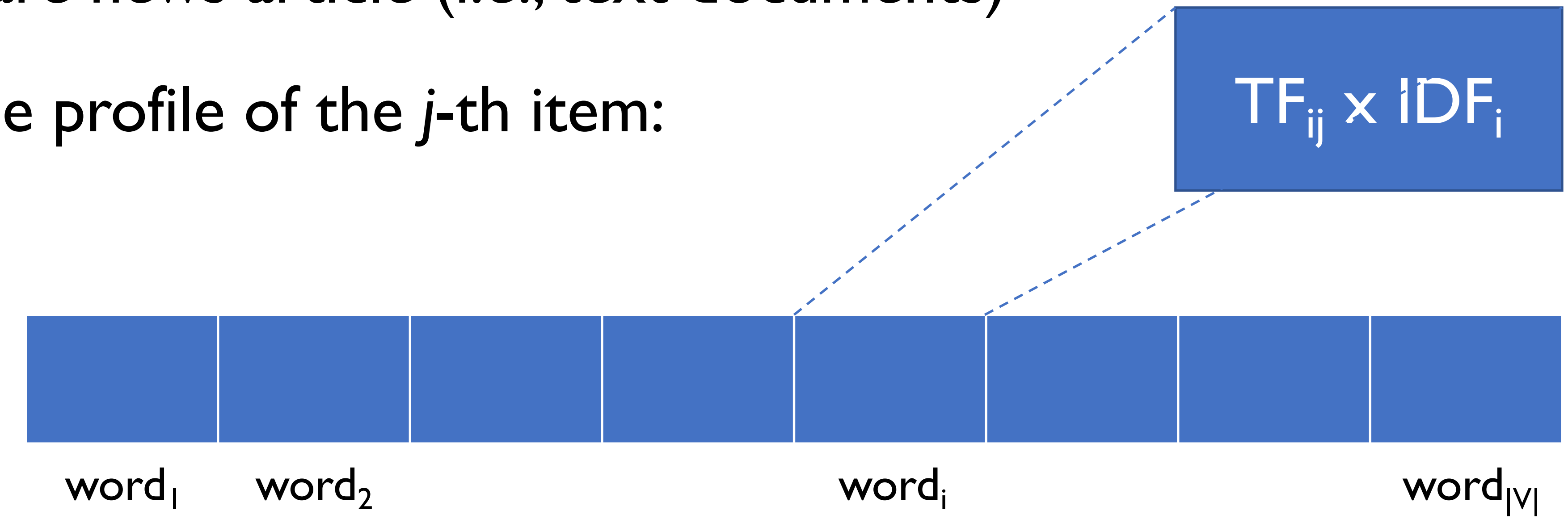

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The simplest solution to build the user profile is to take the average of item profiles rated

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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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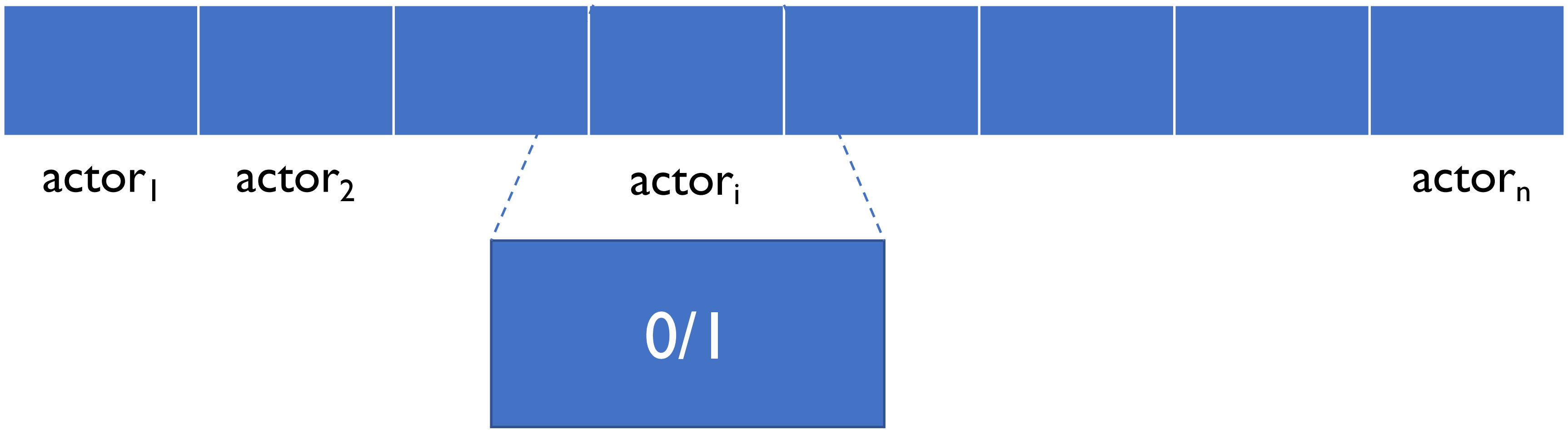

Binary feature indicating if $actor_i$ appears in $movie_j$

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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$(1+1)/5$

0.4	
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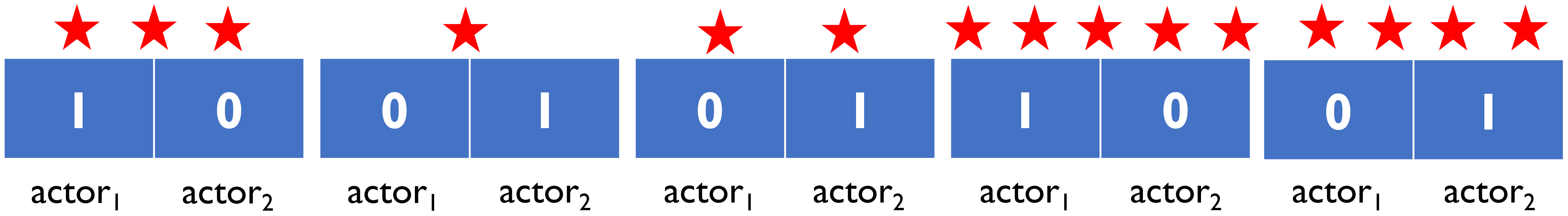
0.4	0.6
$actor_1$	$actor_2$

$(1+1+1)/5$

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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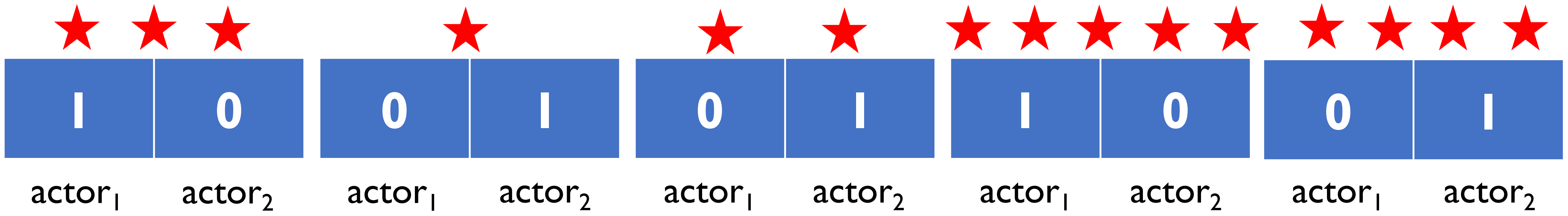

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Avg. User Rating = (3 + 1 + 2 + 5 + 4)/5 = 3

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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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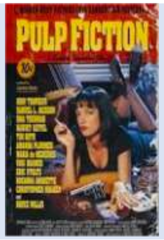
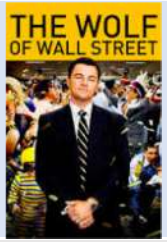
Normalize ratings by subtracting user's mean rating before

(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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How to fill the "?"?

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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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- 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