Big Data Computing

Master's Degree in Computer Science

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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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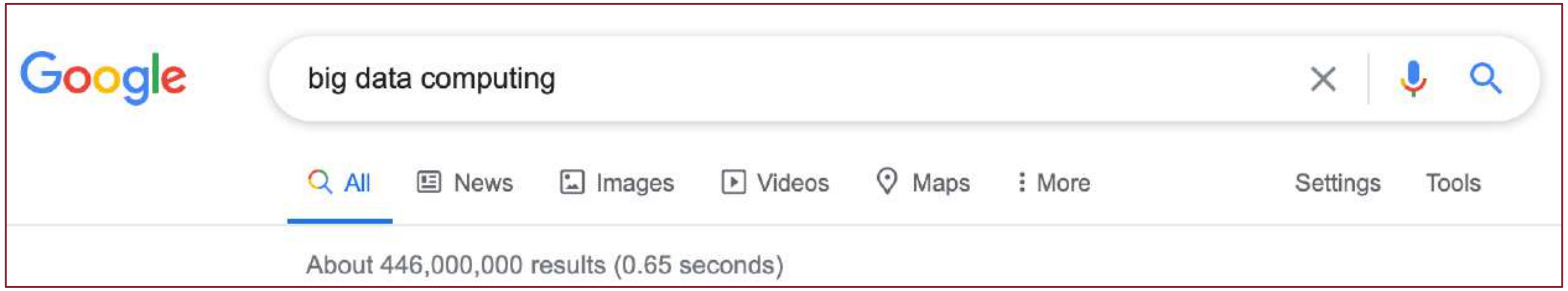

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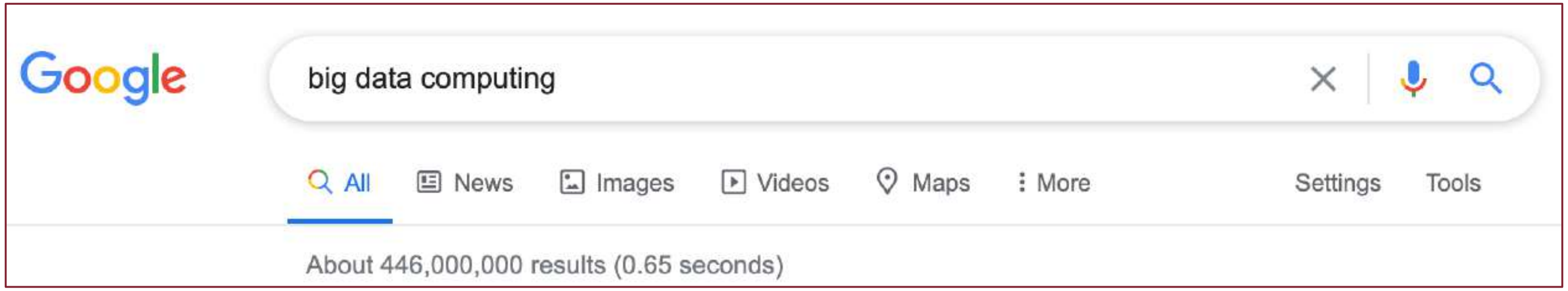

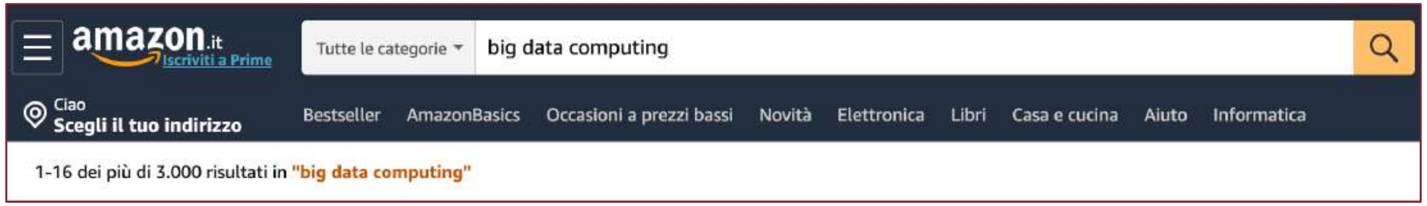

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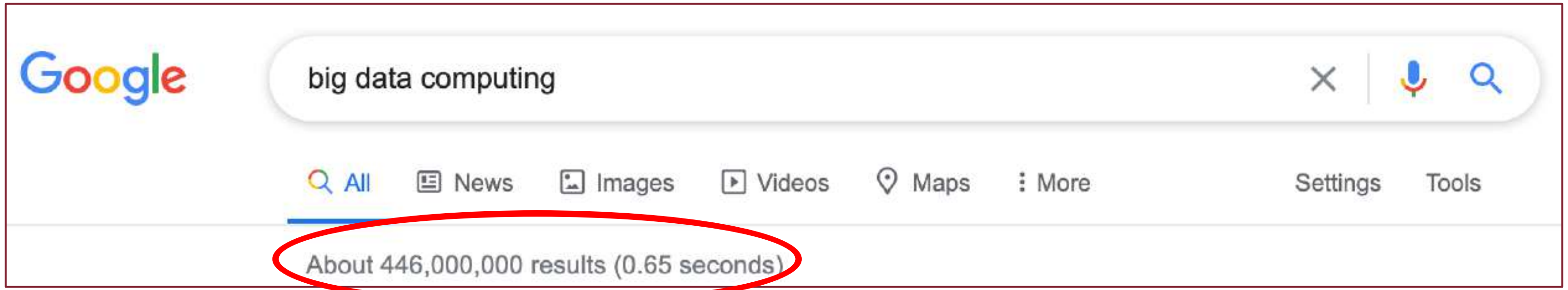

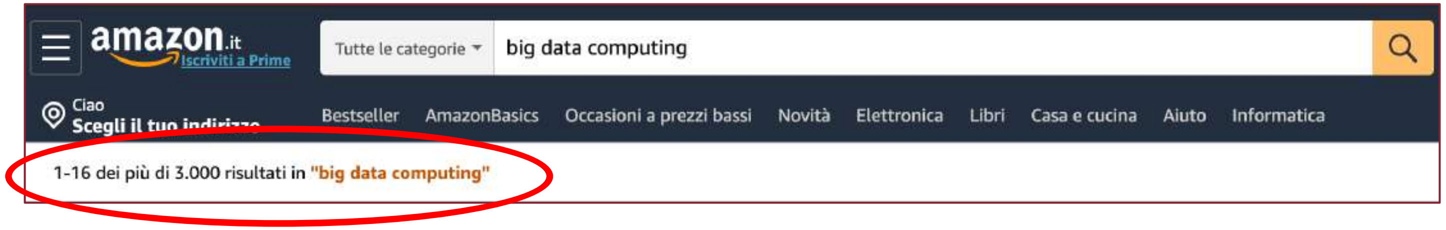

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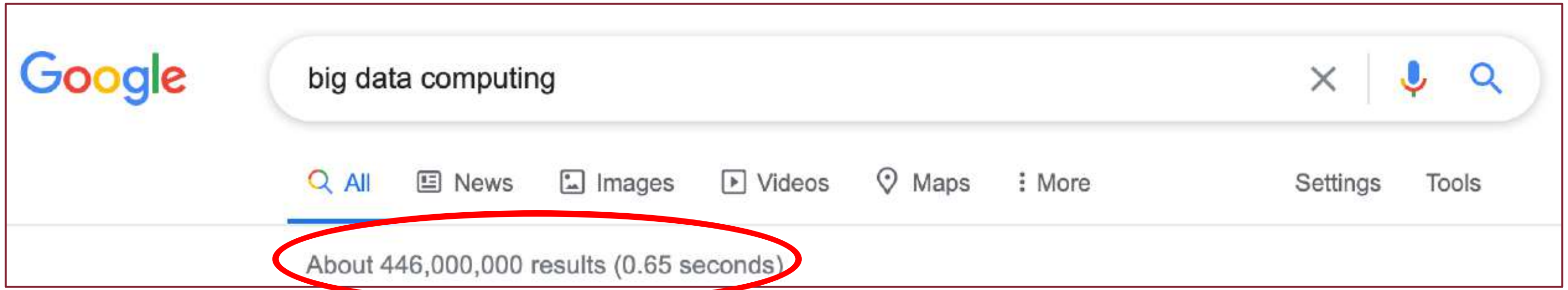

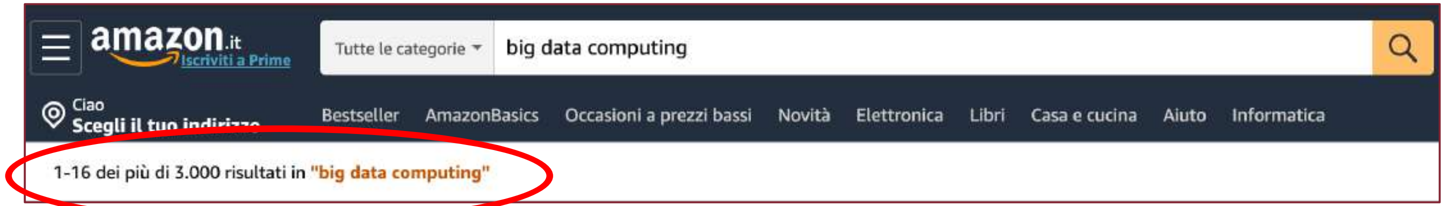

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How could we even think of exhaustively explore all of them?

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

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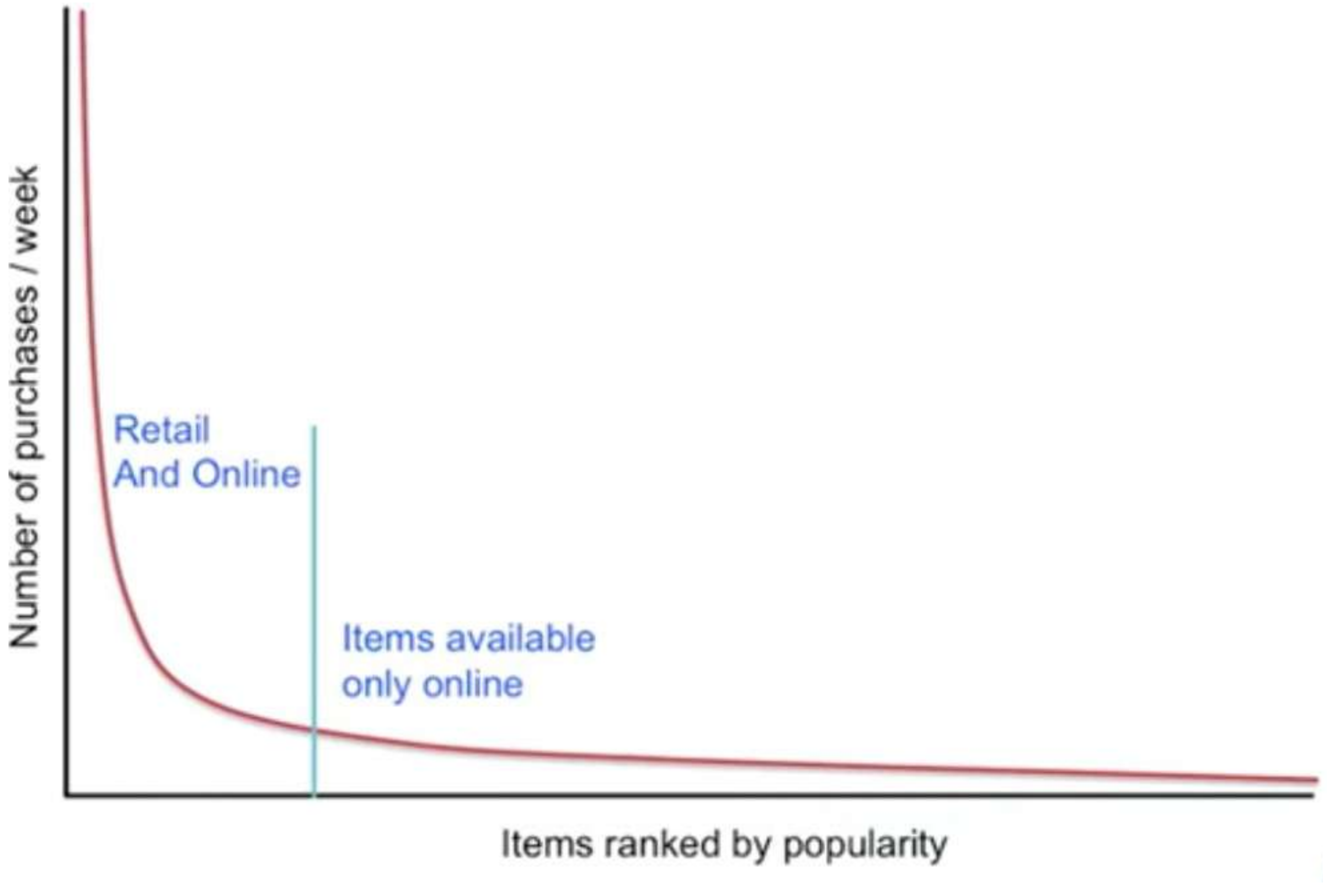
↓

Recommender Systems

The Economics of Abundance: The Long Tail



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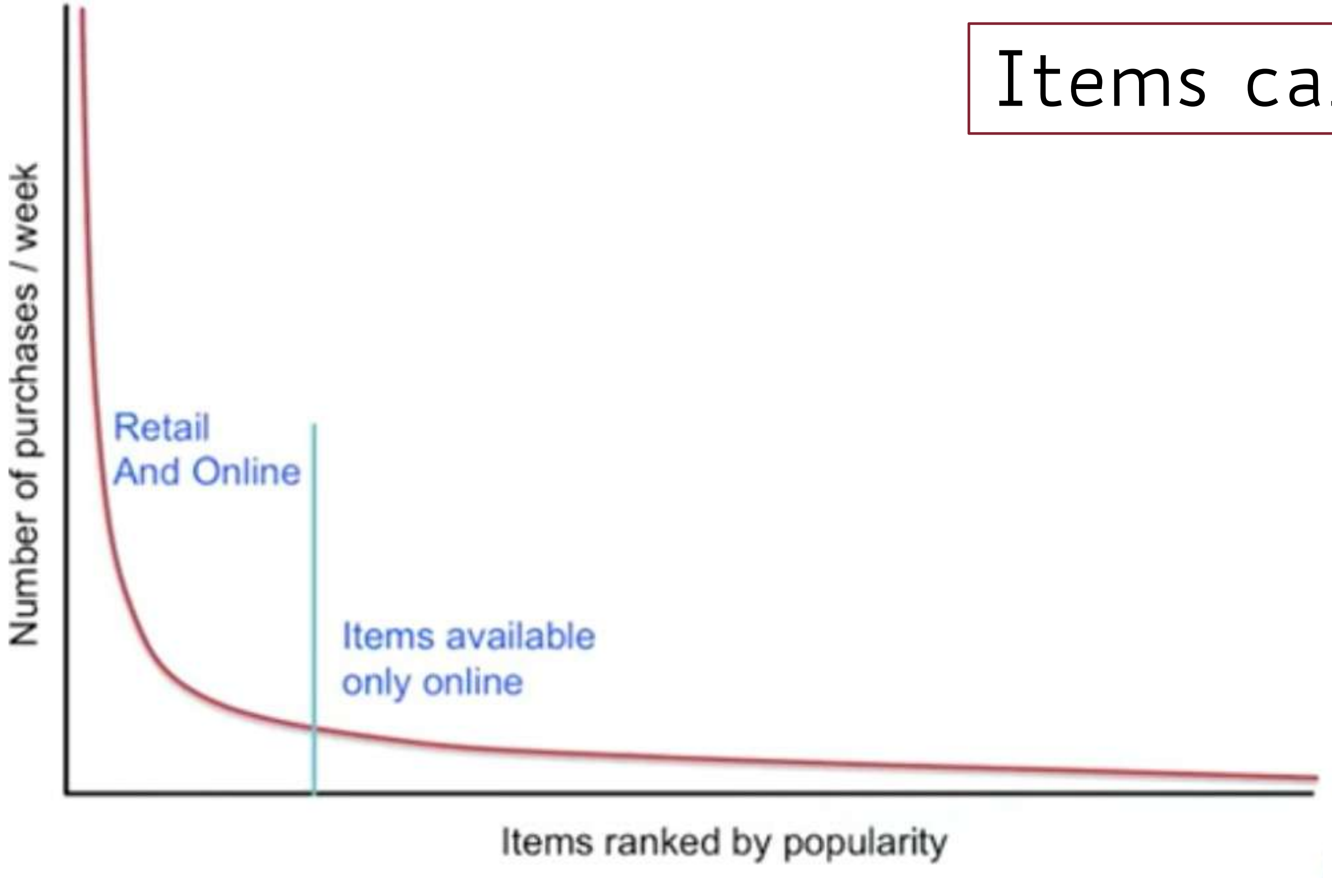
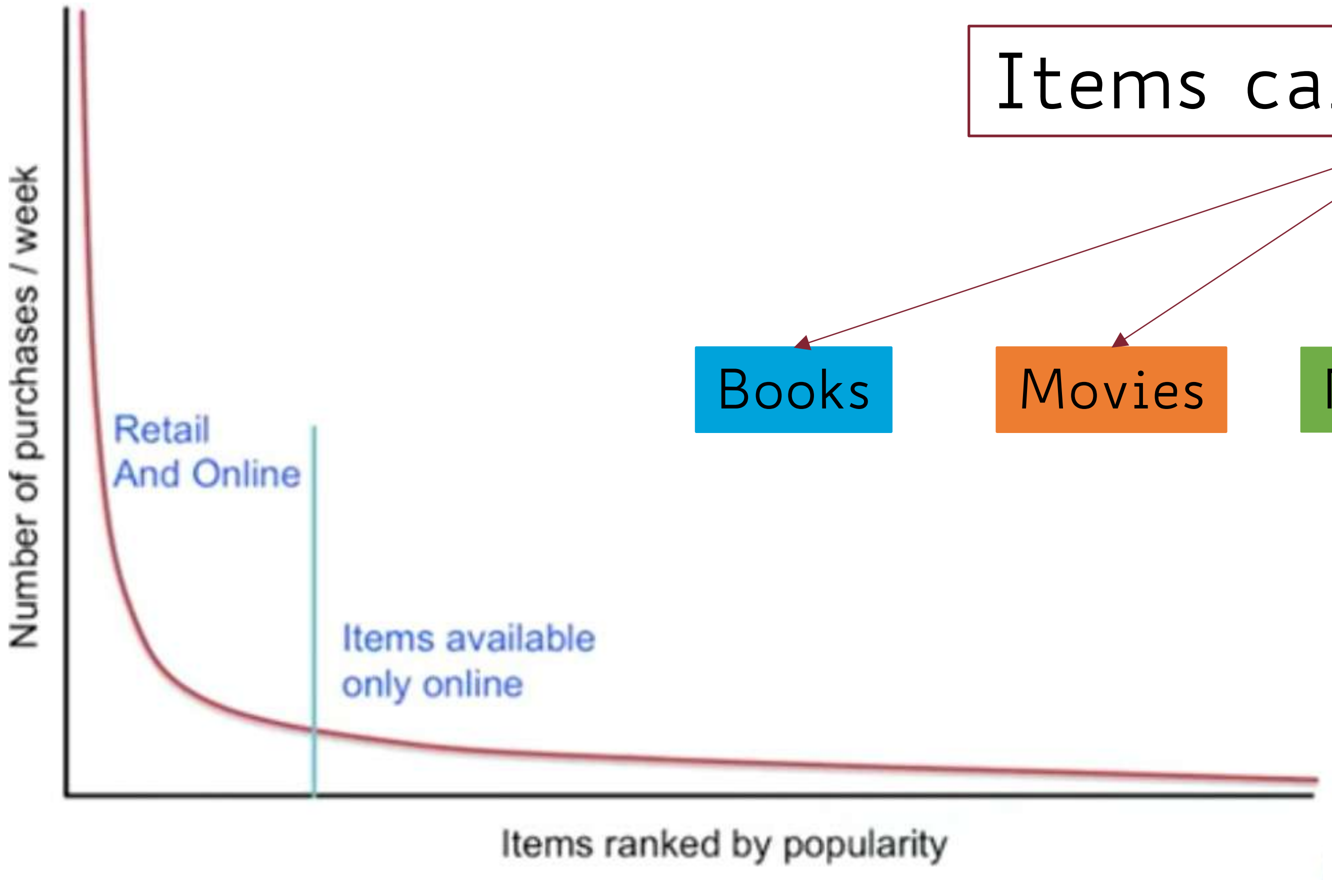
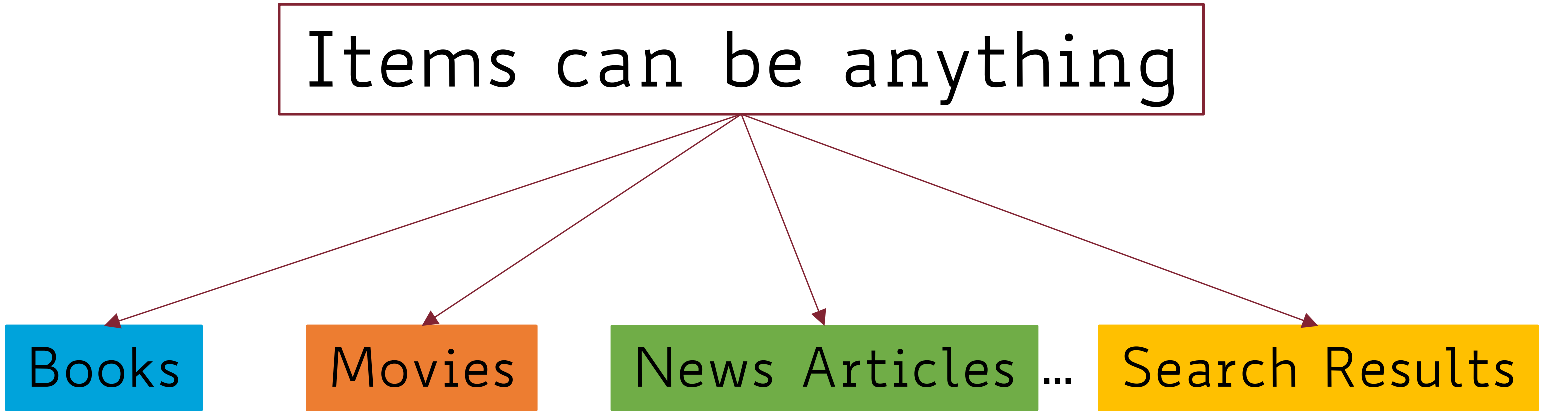


Items can be anything

The Economics of Abundance: The Long Tail





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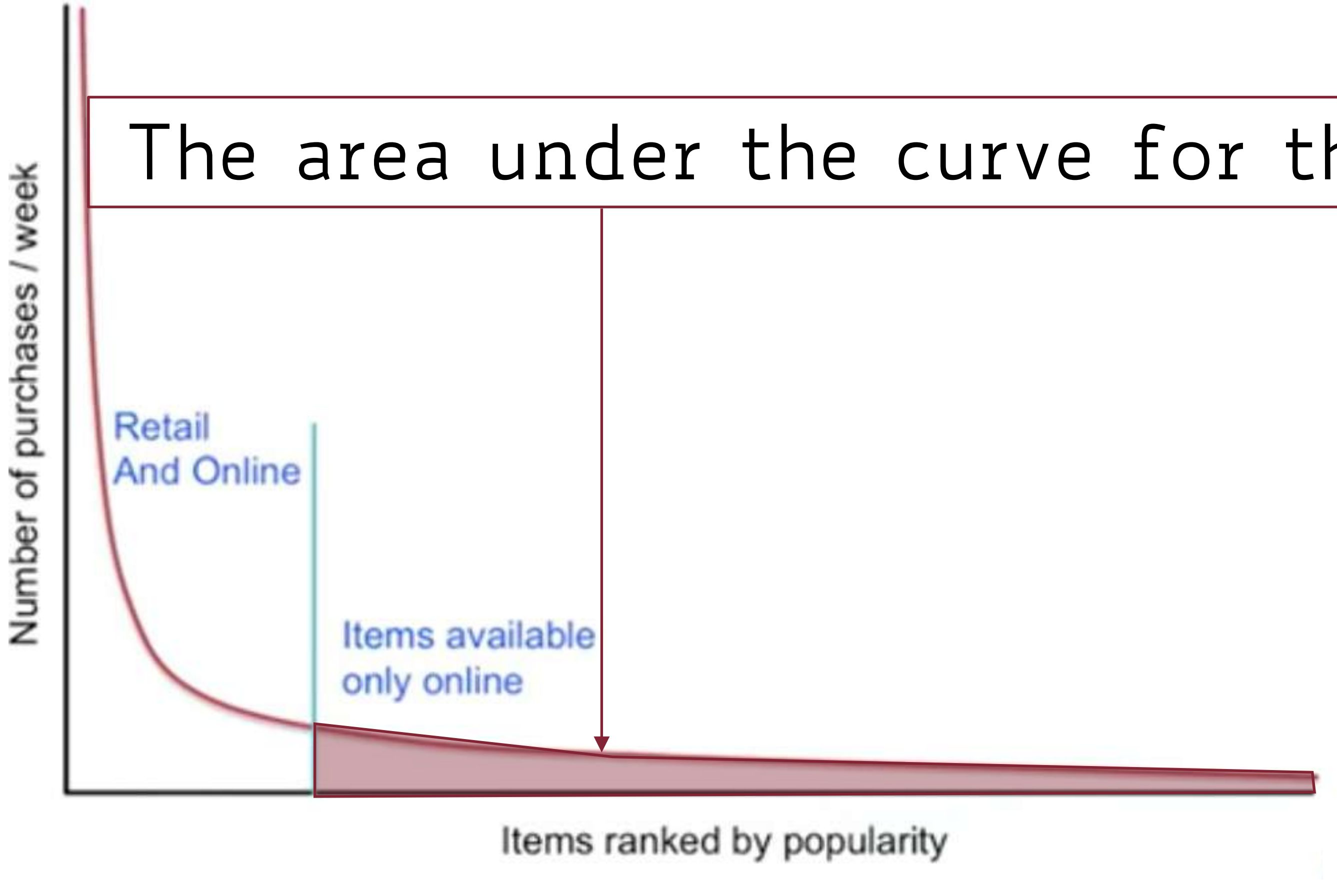
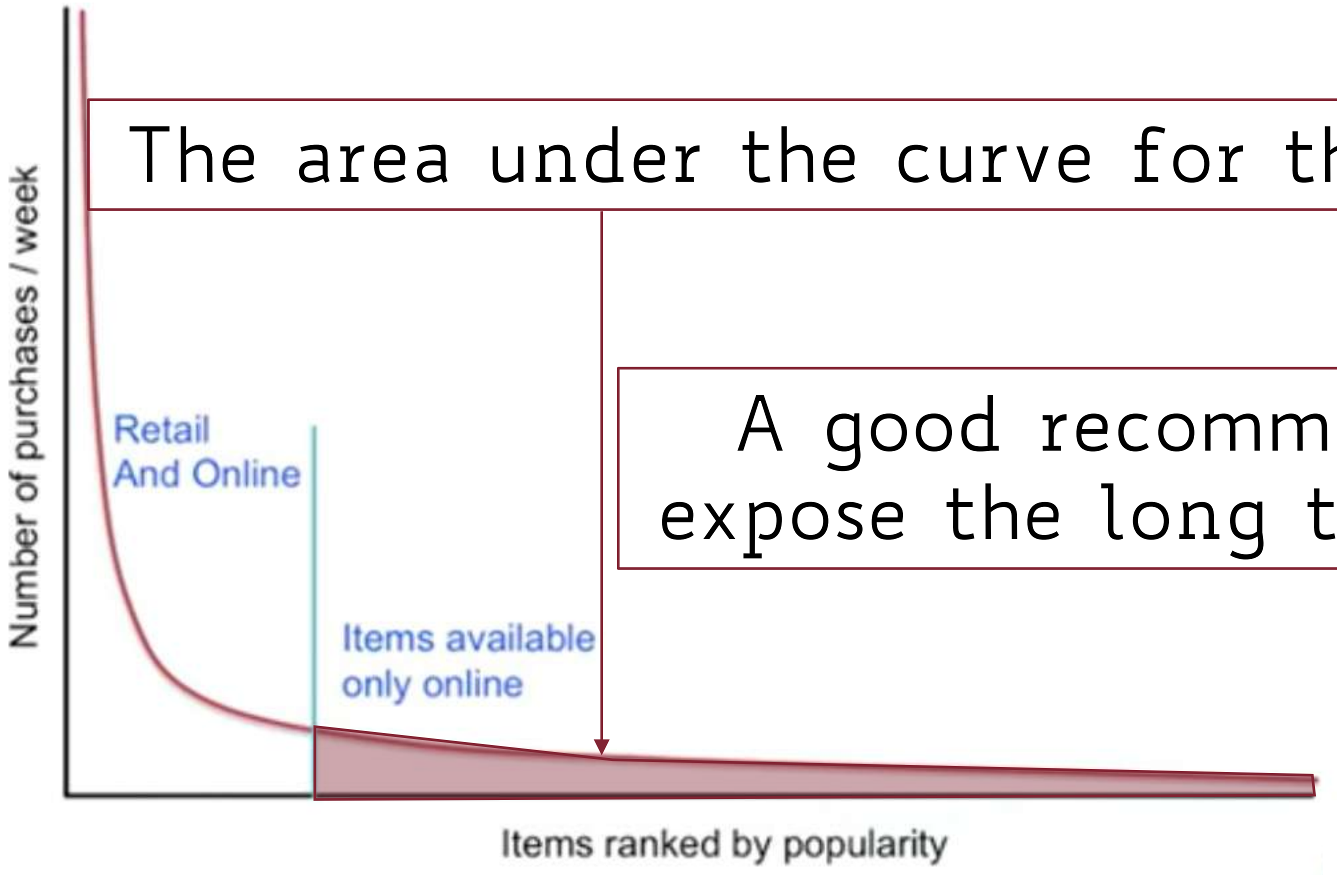


The Economics of Abundance: The Long Tail

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

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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


Carl

...


Zoe

The Utility Function (User-Item Matrix)

MOVIES

USERS								
 Alice	2		5	4	5	4		4
 Bob	4					3		3
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…	…	…	…	…	…	…	…	…
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3 key problems for a recommender system

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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

RMSE

Personalization

Serendipity

Mean Average Precision/Recall at K (MAP@K/MAR@K)

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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Hybrid (memory-model-based)

Recommendation Strategies

3 approaches to recommender systems

Content-based filtering

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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)

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Steps

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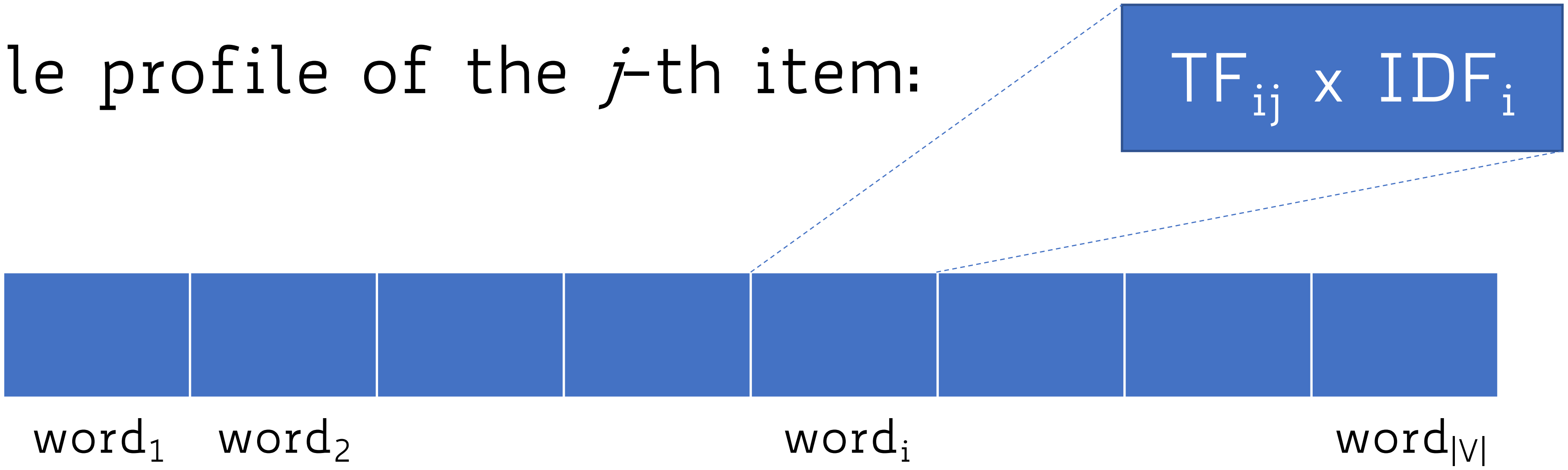

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The simplest solution to build the user profile is to take the average of item profiles rated

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

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All the items are treated equally, independently of the rating

Simple User Profile: Example

$\boxed{\text{Items = Movies}}$

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Items = Movies

Movie Profile = List of Actors

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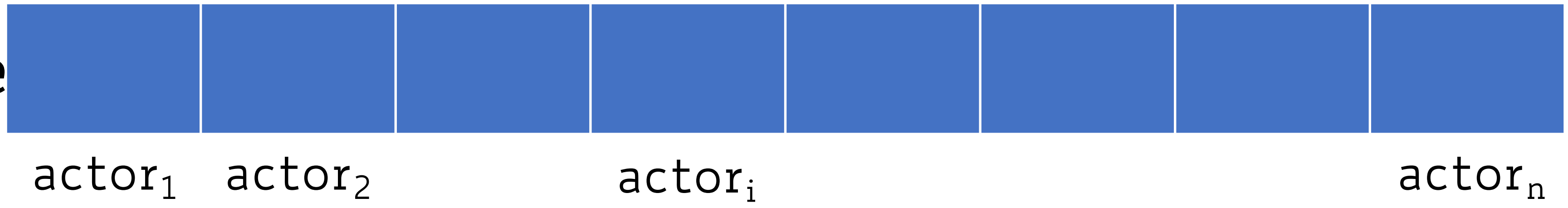
j-th movie



Simple User Profile: Example

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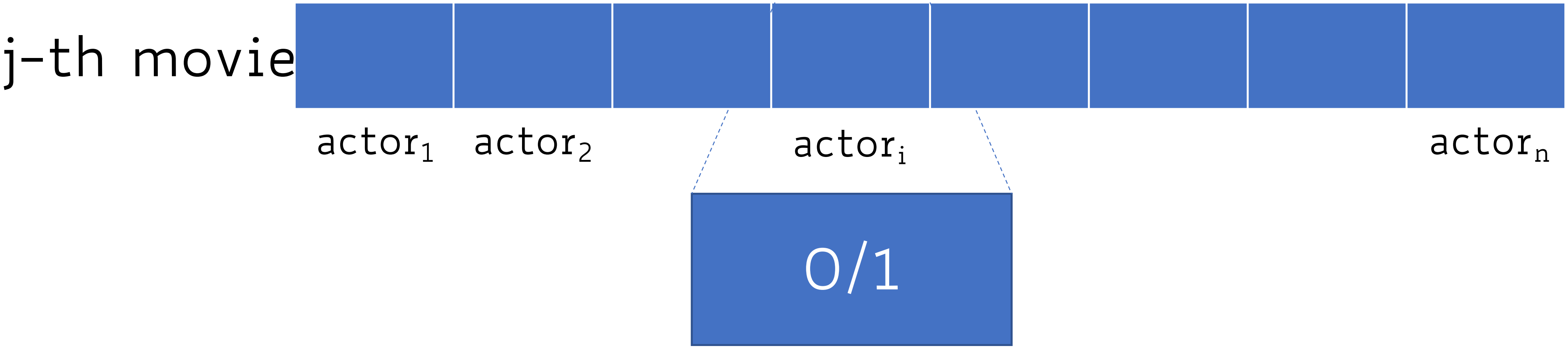

Binary feature indicating if actor$_i$ appears in movie$_j$

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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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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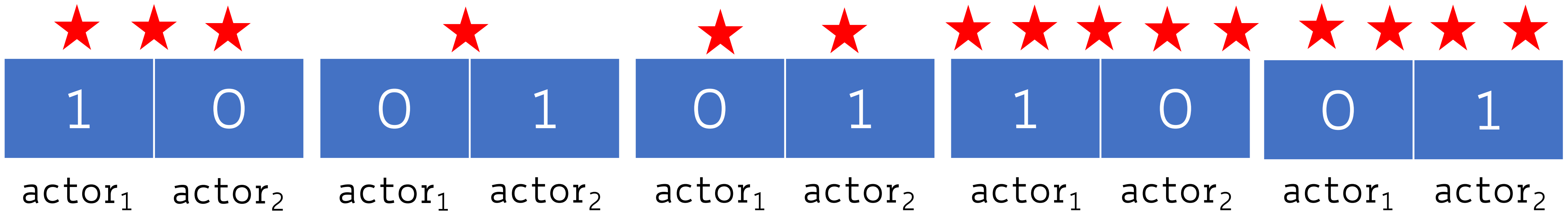
User profile is the mean of item profiles

(1+1)/5	0.4	0.6	(1+1+1)/5
	$actor_1$	$actor_2$	

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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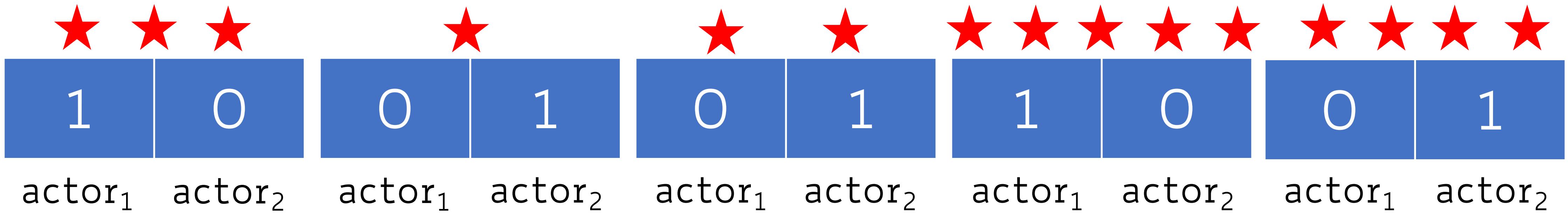

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Avg. User Rating = (3 + 1 + 2 + 5 + 4)/5 = 3

Simple User Profile: Example With Ratings

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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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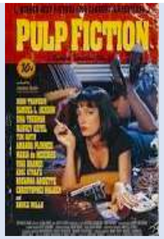
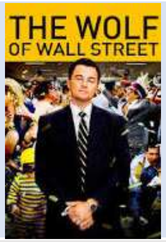
Rating	$actor_1$	$actor_2$
0	1	0
-2	0	1
-1	0	1
2	1	0
1	0	1

Normalize ratings by subtracting user's mean rating before

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

Building Predictions (from Item/User Profiles)

		MOVIES							
									
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	…	…	…	…	…	…	…	…	…
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How to fill the "?"?

MOVIES

USERS

Alice	2		5	4	5	4		4
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- Finally, we pick the top-k items with the **highest** similarity score, and we recommend those to u

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

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

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- 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

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- Overspecialization: never recommends items outside user's profile

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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