

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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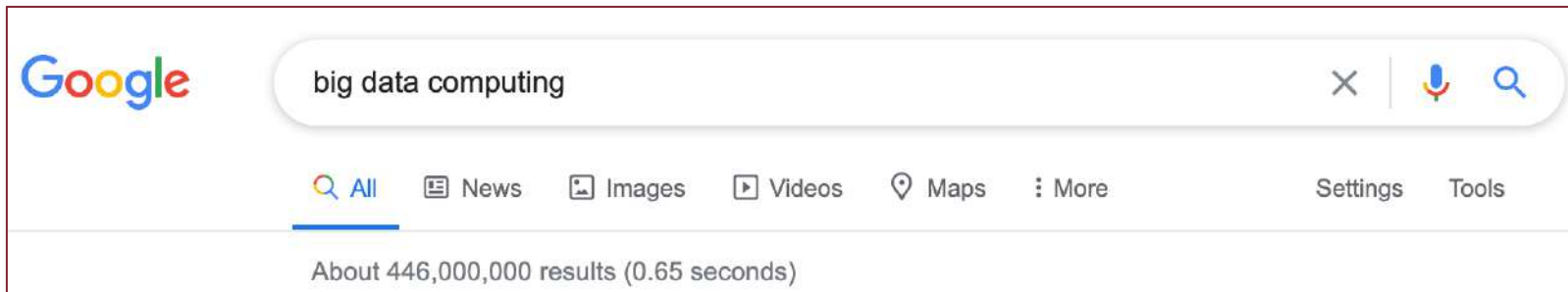
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- To actually take advantage of such a huge pile of information we need techniques that narrow down it to **human-manageable** figures:
 - **Searching/Filtering**
 - **Recommending**

Why Do We Need Recommendation?

We are constantly moving from scarcity to abundance

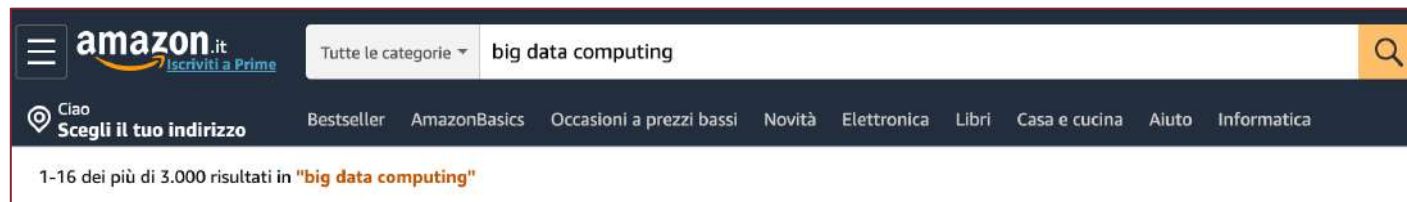
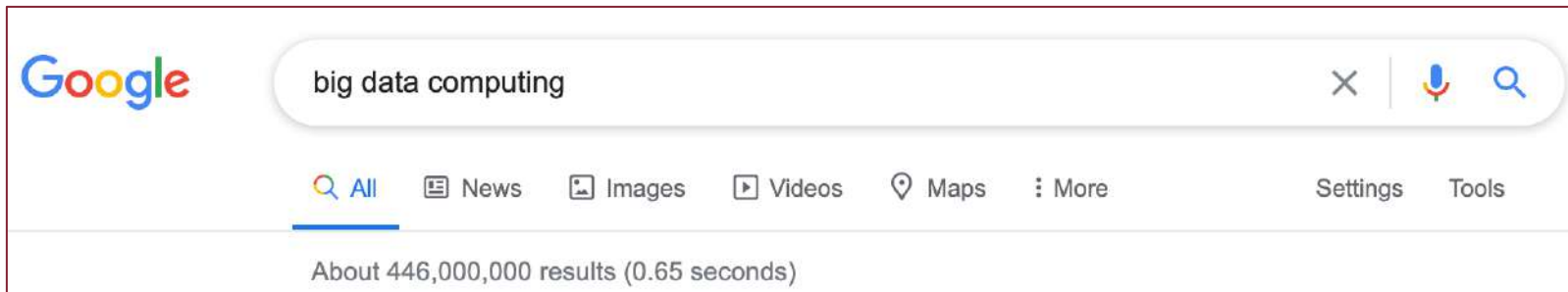
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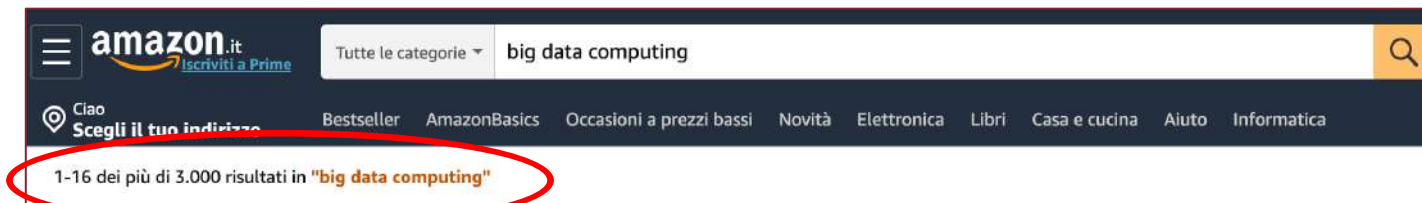
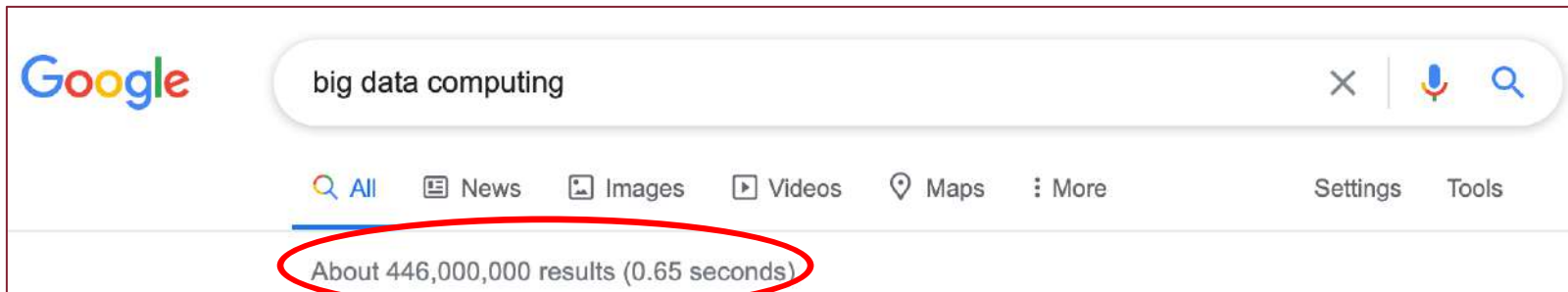
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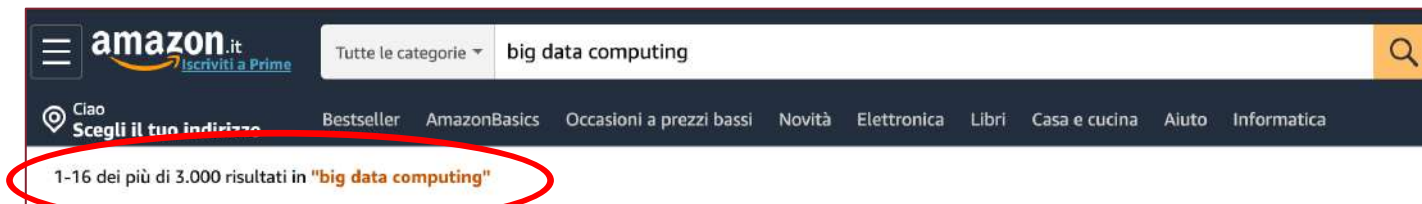
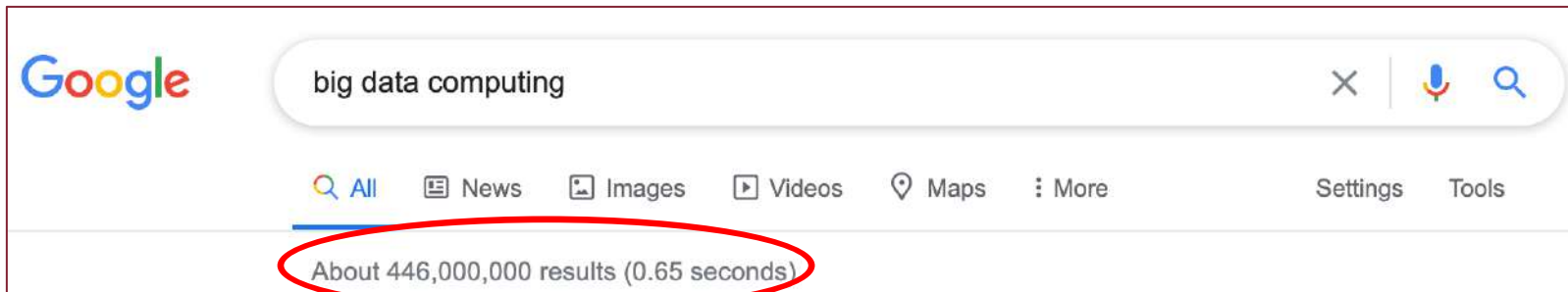
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The number of relevant "items" of interest is huge

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The number of relevant "items" of interest is huge

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

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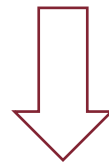
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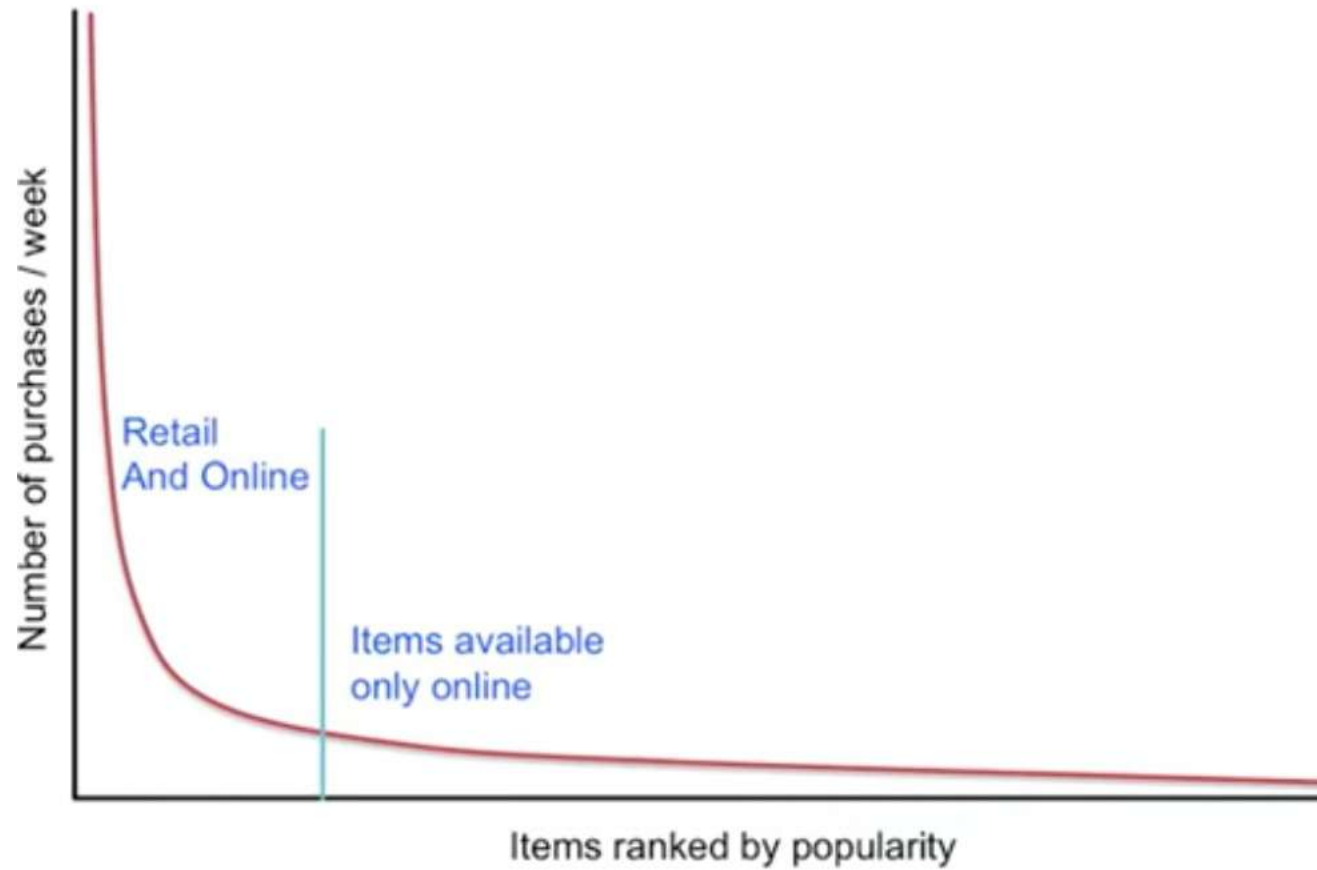
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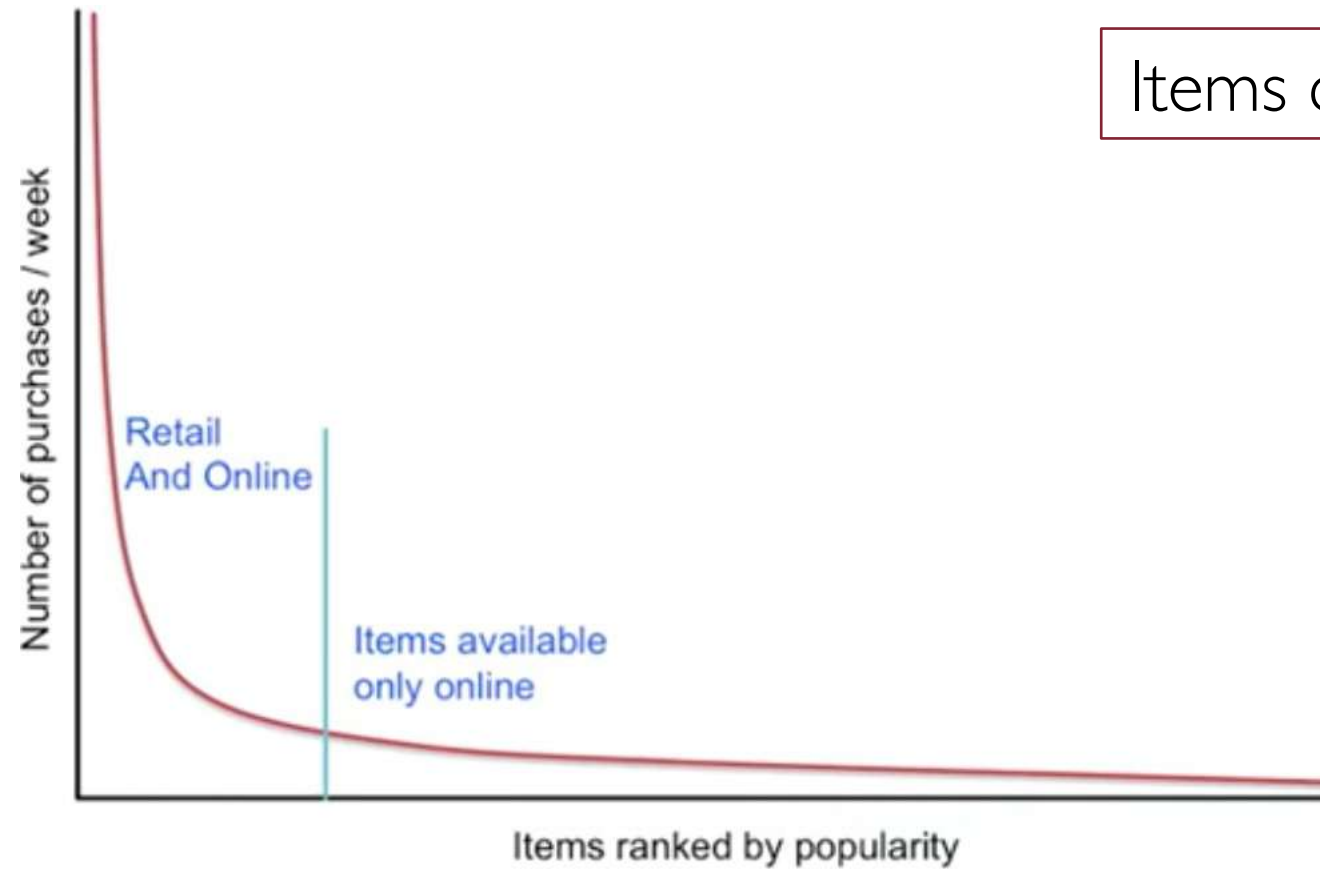


Recommender Systems

The Economics of Abundance: The Long Tail

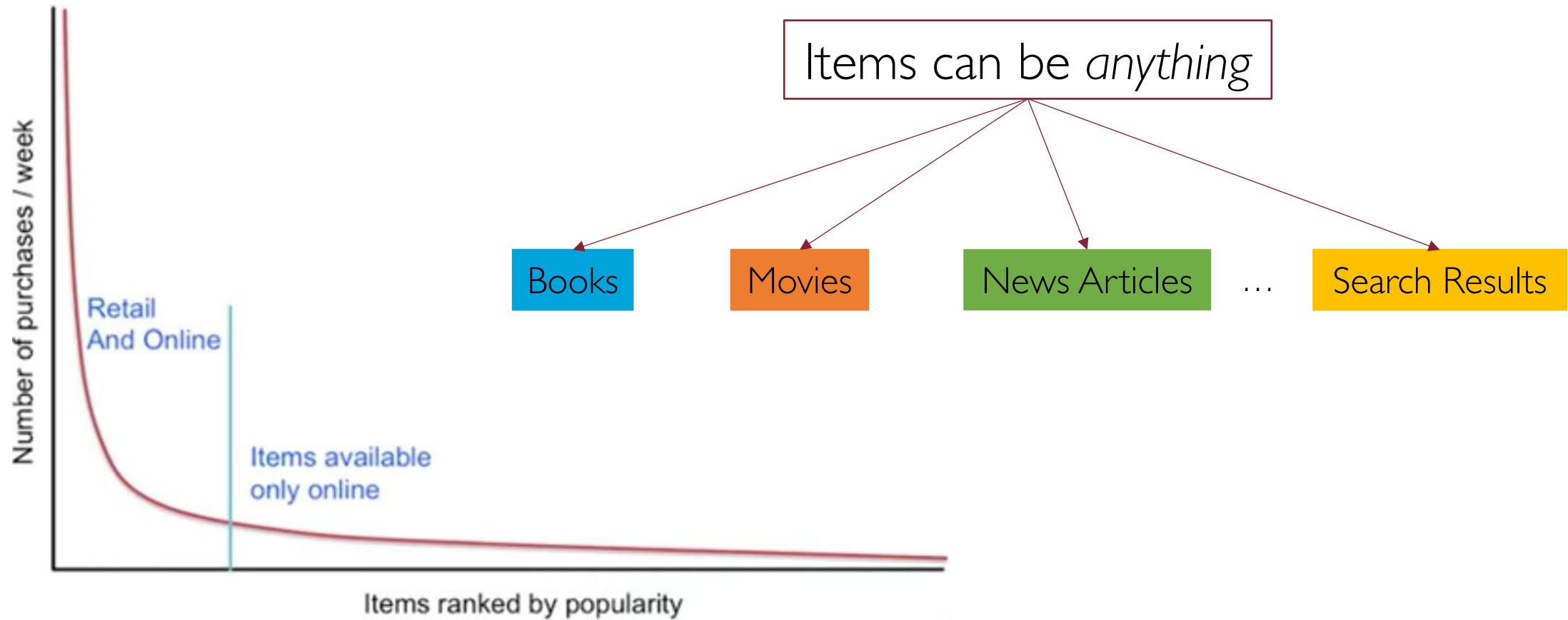


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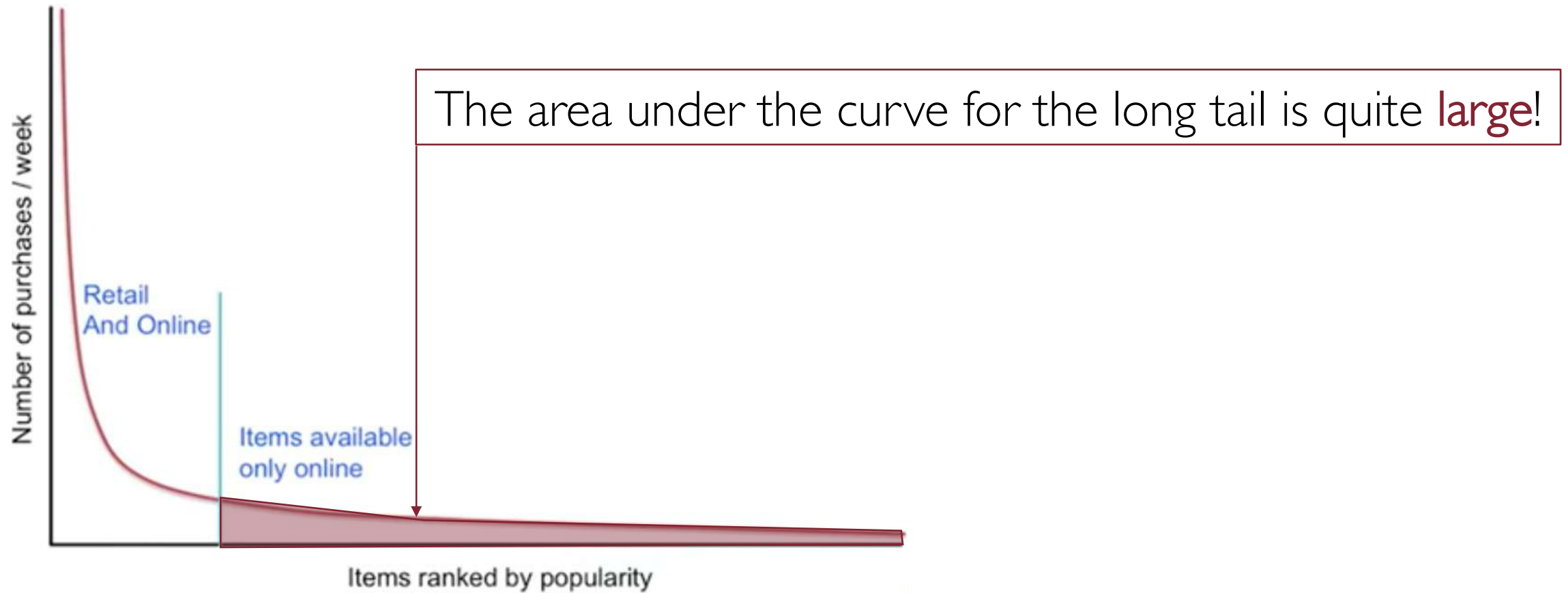


Items can be *anything*

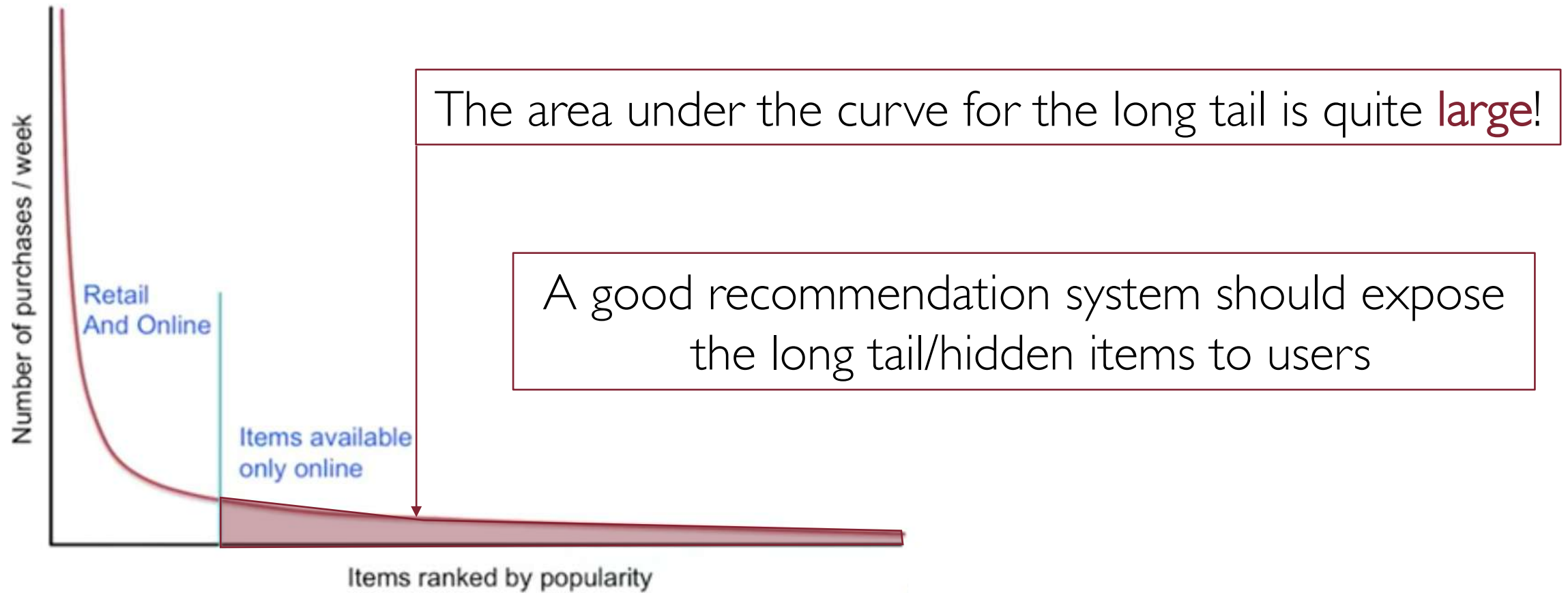
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Recommender Systems: Formalism

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

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


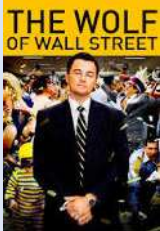

The Utility Function (User-Item Matrix)

USERS		Alice
		Bob
		Carl
	...	
		Zoe

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The Utility Function (User-Item Matrix)

		MOVIES							
									
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	 Bob	4					3		3
	 Carl	5	5	3	4	5	4		5

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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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Learn ratings from user actions

Click/purchases implies positive feedback
What about negative ones?

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Cold Start

New users/items have no history

Recommendation Evaluation

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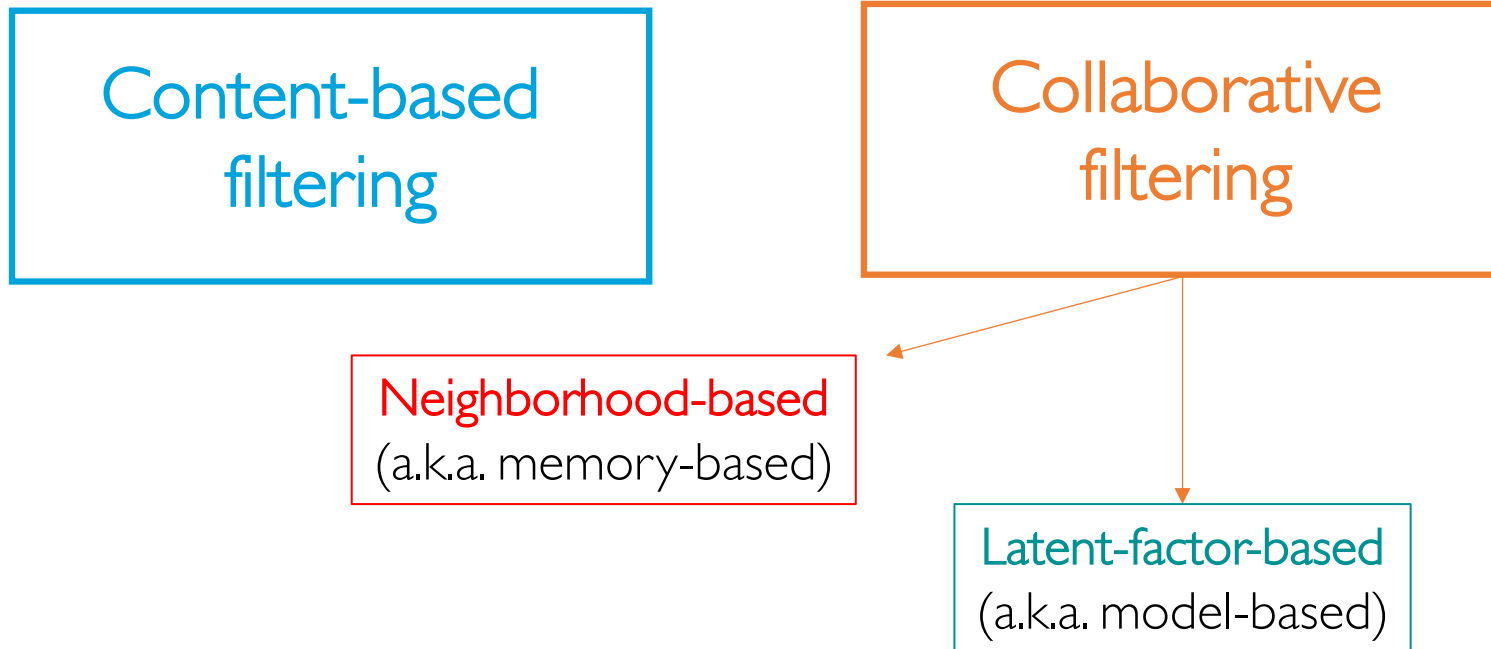
Collaborative
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Neighborhood-based
(a.k.a. memory-based)



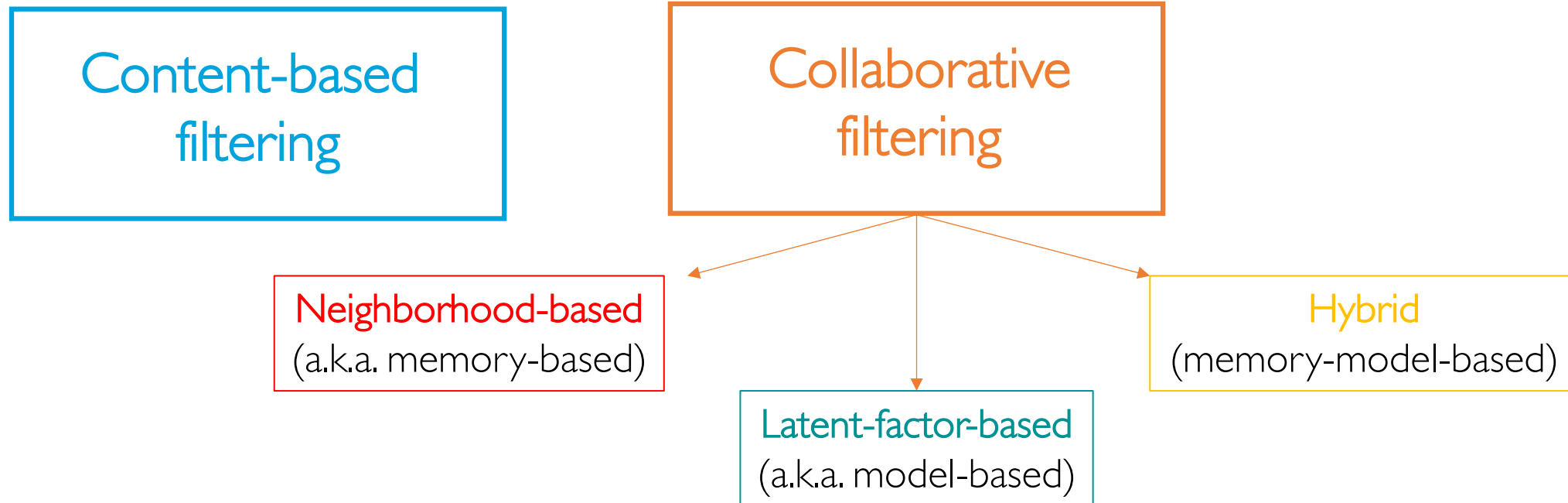
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3 approaches to recommender systems



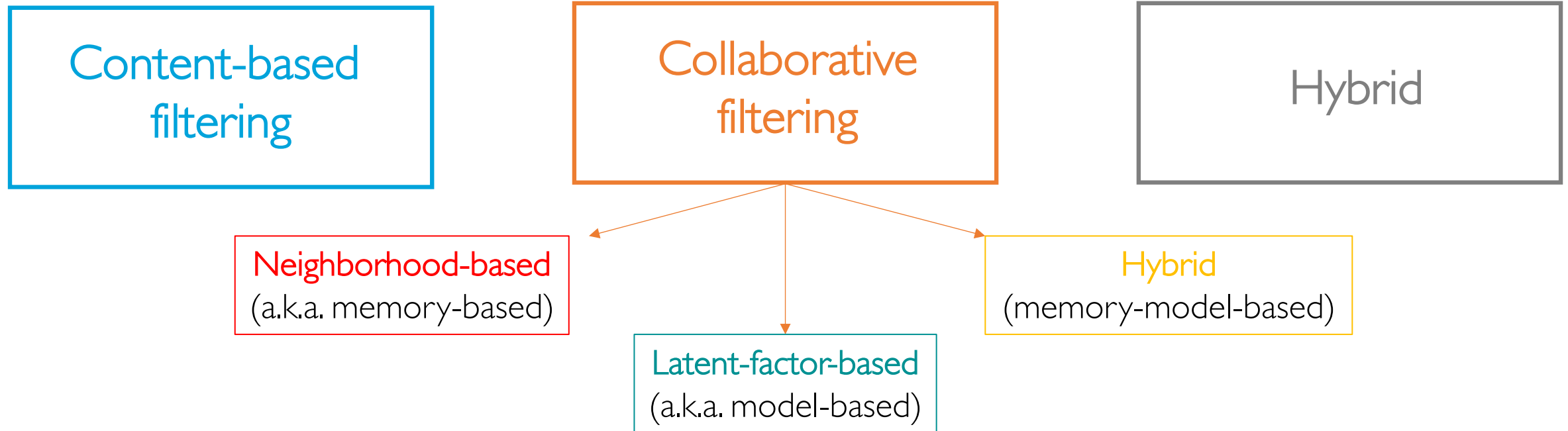
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CONTENT-BASED FILTERING

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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

- Suppose we want to build a news recommender system

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- Items are news article (i.e., text documents)

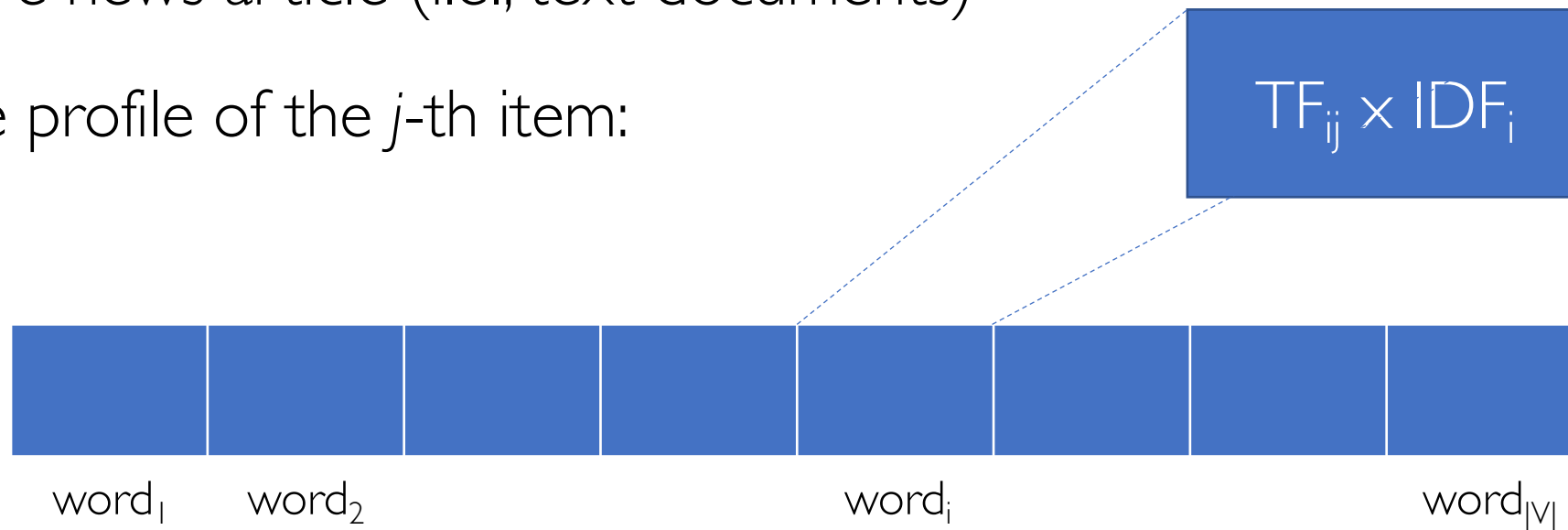
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The simplest solution to build the user profile is to take the average of item profiles rated

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All the items are treated equally,
independently of the rating

Simple User Profile: Example

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Movie Profile = List of Actors

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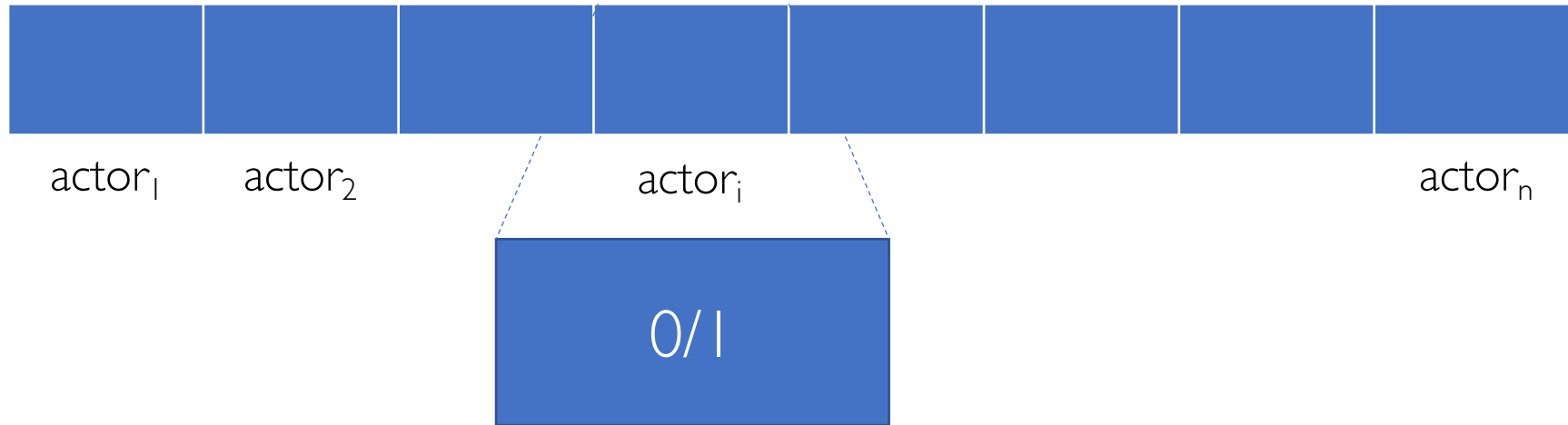


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Binary feature indicating if actor_i appears in movie j

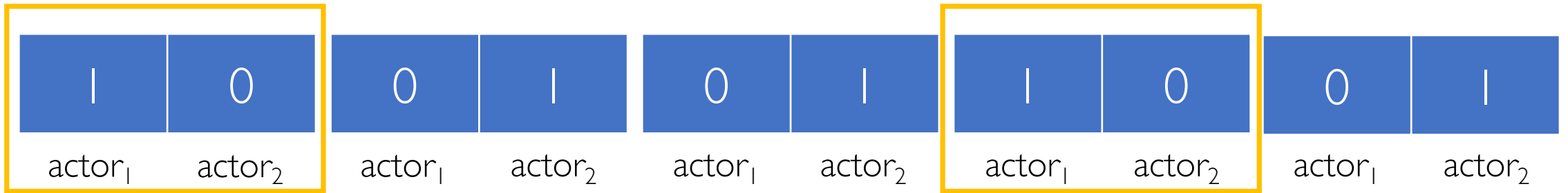
Simple User Profile: Example

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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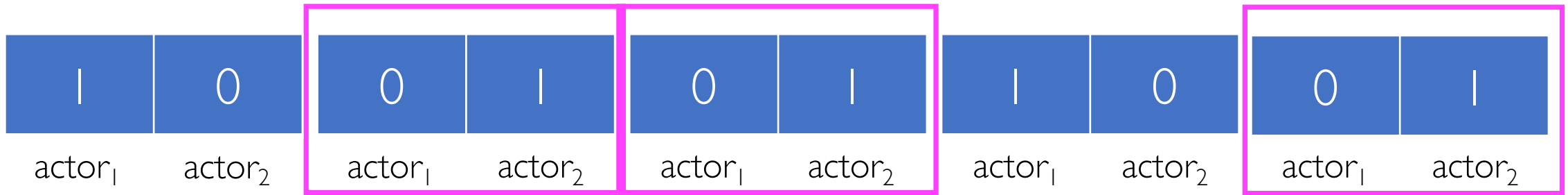
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2 movies feature actor 1

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3 movies feature actor 2

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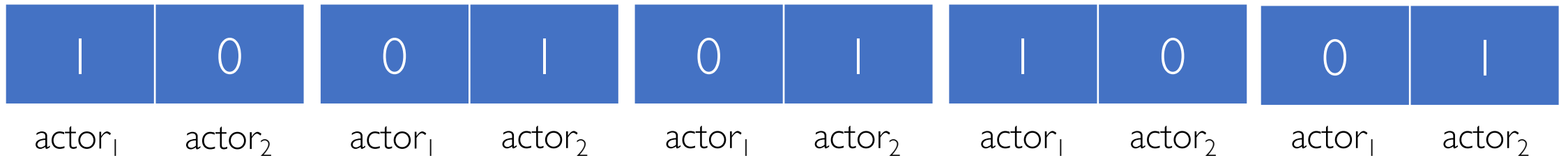
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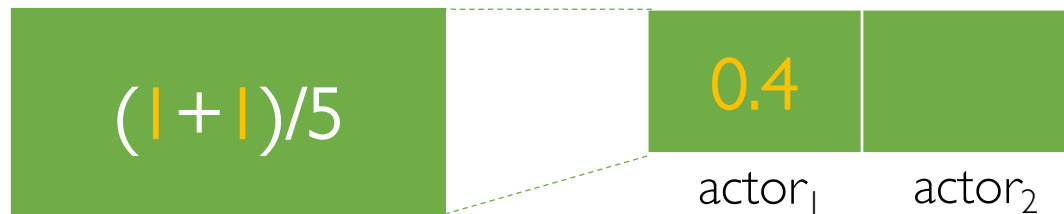
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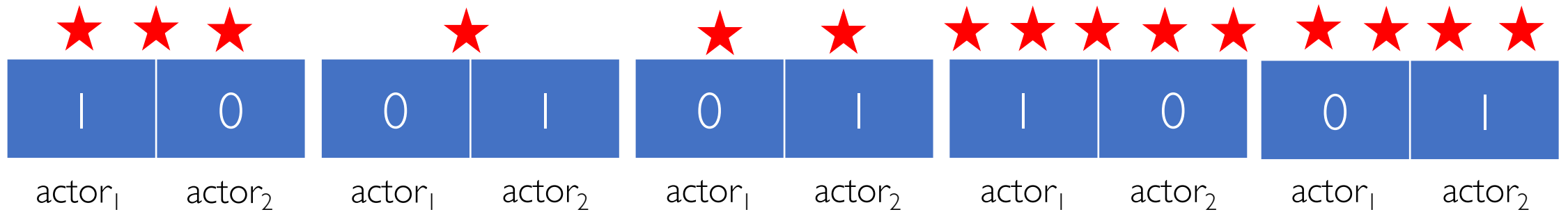


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Simple User Profile: Example With Ratings

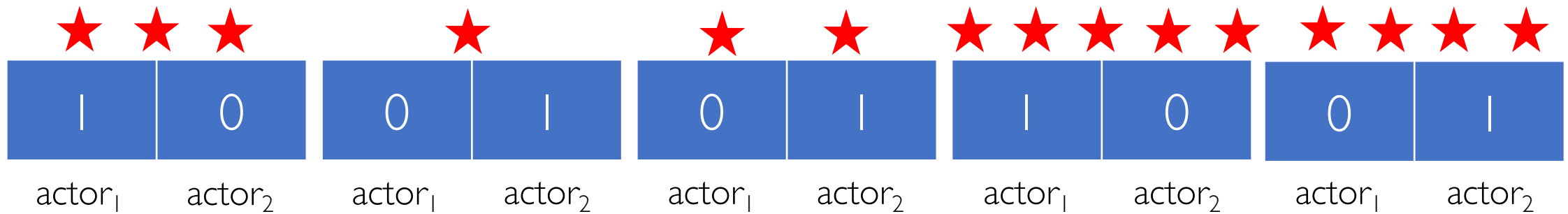
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Normalize ratings by subtracting user's mean rating before

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$$\text{Avg. User Rating} = (3 + 1 + 2 + 5 + 4)/5 = 3$$

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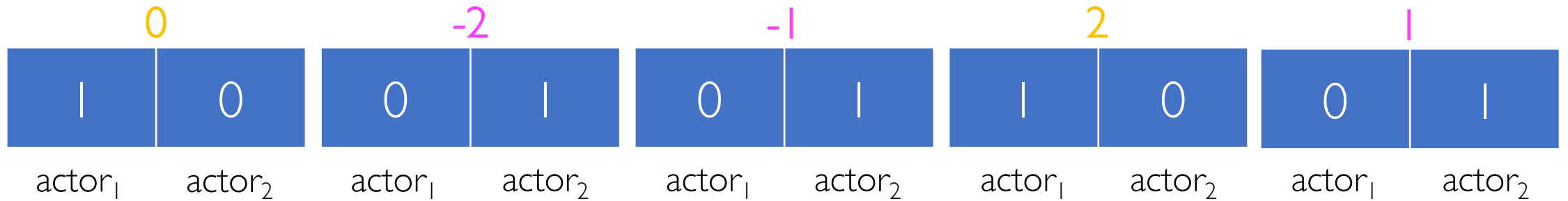
$3-3 = 0$		$1-3 = -2$		$2-3 = -1$		$5-3 = 2$		$4-3 = 1$	
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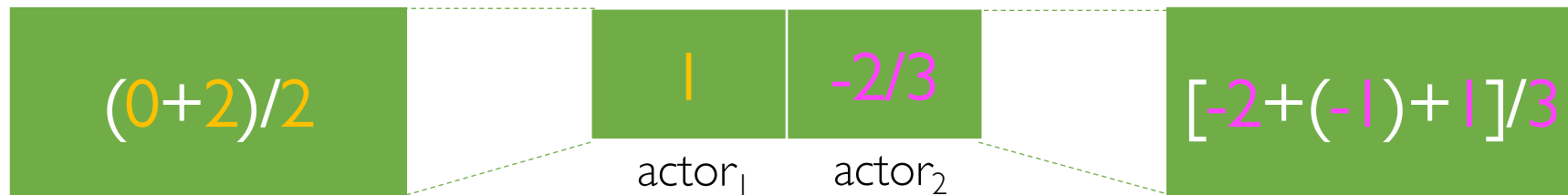
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Building Predictions (from Item/User Profiles)


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

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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

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- 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

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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