

Big Data Computing

Master's Degree in Computer Science

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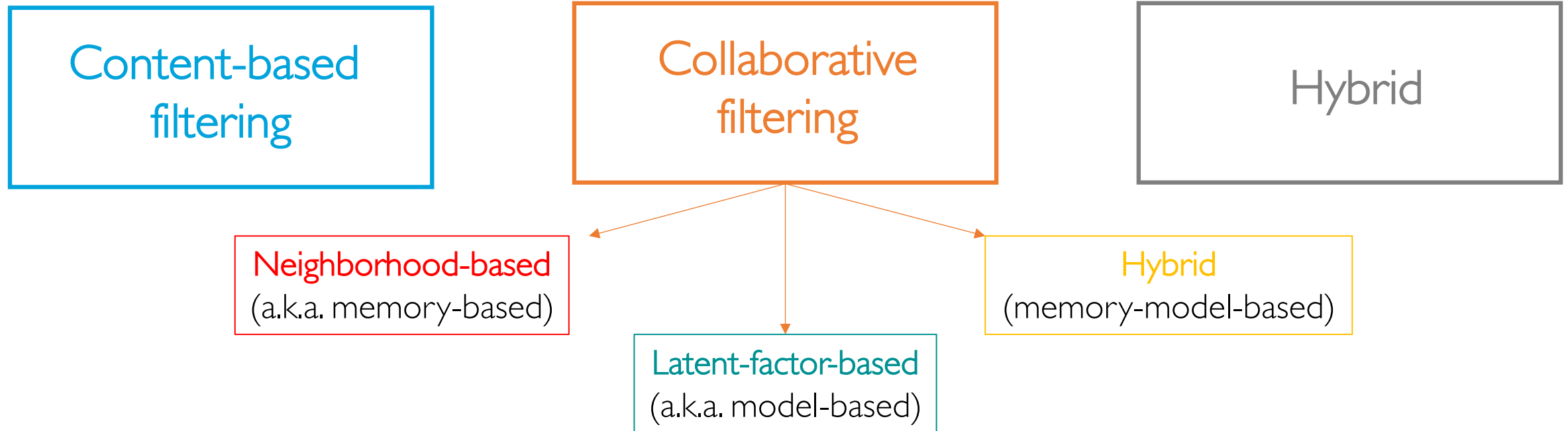
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SAPIENZA
UNIVERSITÀ DI ROMA

Recommendation Strategies

3 approaches to recommender systems



COLLABORATIVE FILTERING

Collaborative Filtering (CF)

Idea

Recommend items to user u based on preferences of other users similar to u

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Core concept:

User-to-User or Item-to-Item similarity

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Recommend items to user u based on preferences of other users similar to u

Core concept:

User-to-User or Item-to-Item similarity

No need for explicit creation of user/item profiles

Collaborative Filtering: Approaches

3 main approaches to collaborative filtering

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

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3 main approaches to collaborative filtering

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

Collaborative Filtering: Approaches

3 main approaches to collaborative filtering

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

Hybrid
(memory-model-based)

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

Neighborhood-based (Memory-based) CF

Compute the relationship between **users** or **items**

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User-based

Evaluates a user's preference for an item based on ratings of "neighboring" users for that item

Neighborhood-based (Memory-based) CF

Compute the relationship between **users** or **items**

User-based

Evaluates a user's preference for an item based on ratings of "neighboring" users for that item

Item-based

Evaluates a user's preference for an item based on ratings of "neighboring" items by the same user

USER-BASED COLLABORATIVE FILTERING

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Given a user u and an item i not rated by u , we want to estimate $r(u, i)$

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extract a subset of k **neighbours** of u

k -neighborhood of u is found on the basis of the similarity between user ratings
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Estimate $r(u, i)$ based on the ratings of users in the k -neighborhood of u

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In theory, rating prediction $r(u,i)$ could be defined on **any** item i **not rated** by u

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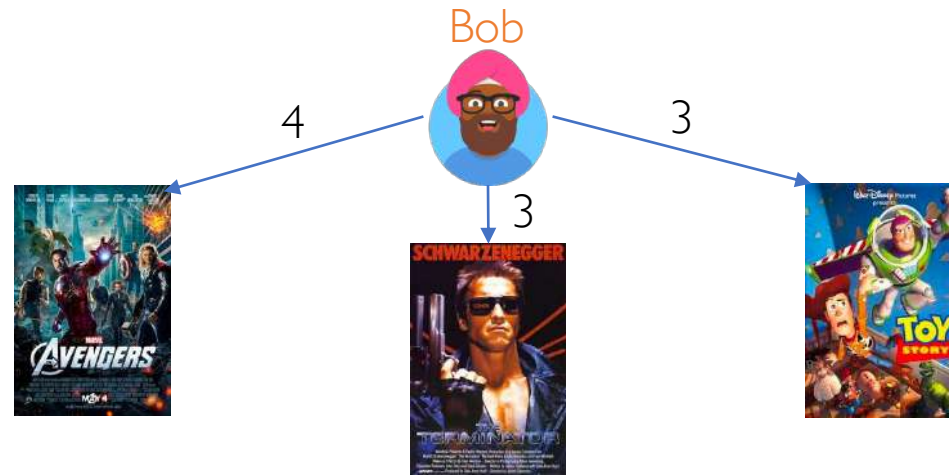
In other words, the u 's k -neighborhood must be computed first to narrow down the set of items which we must predict the rating of

User-based Neighborhood: Example

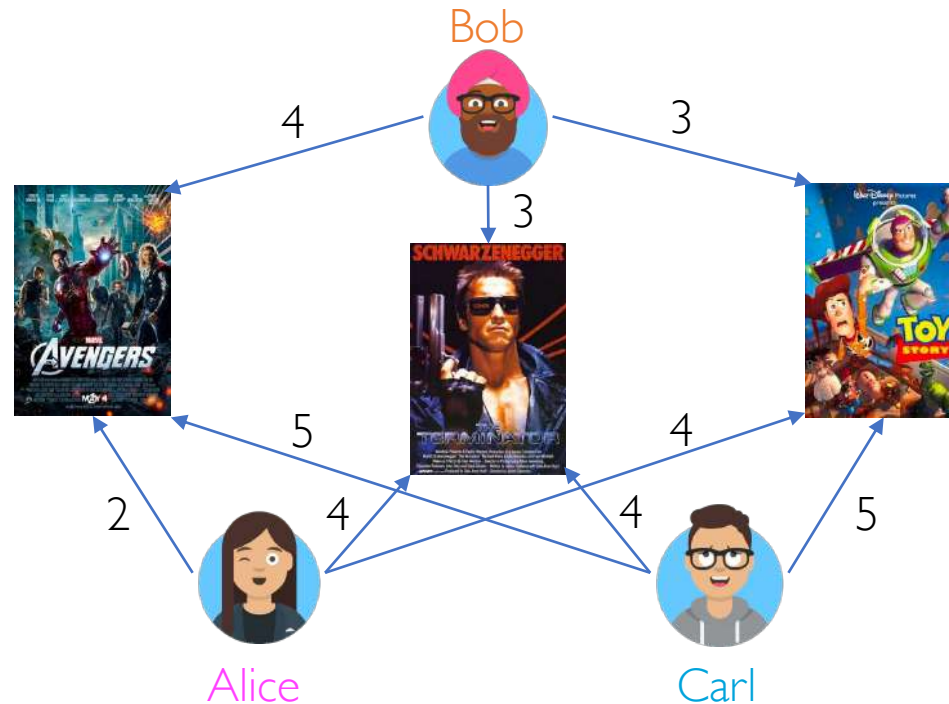
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USERS	 Alice	2		5	4	5	4		4
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	 Carl	5	5	3	4	5	4		5

	 Zoe		1	3				5	4

User-based Neighborhood: Example

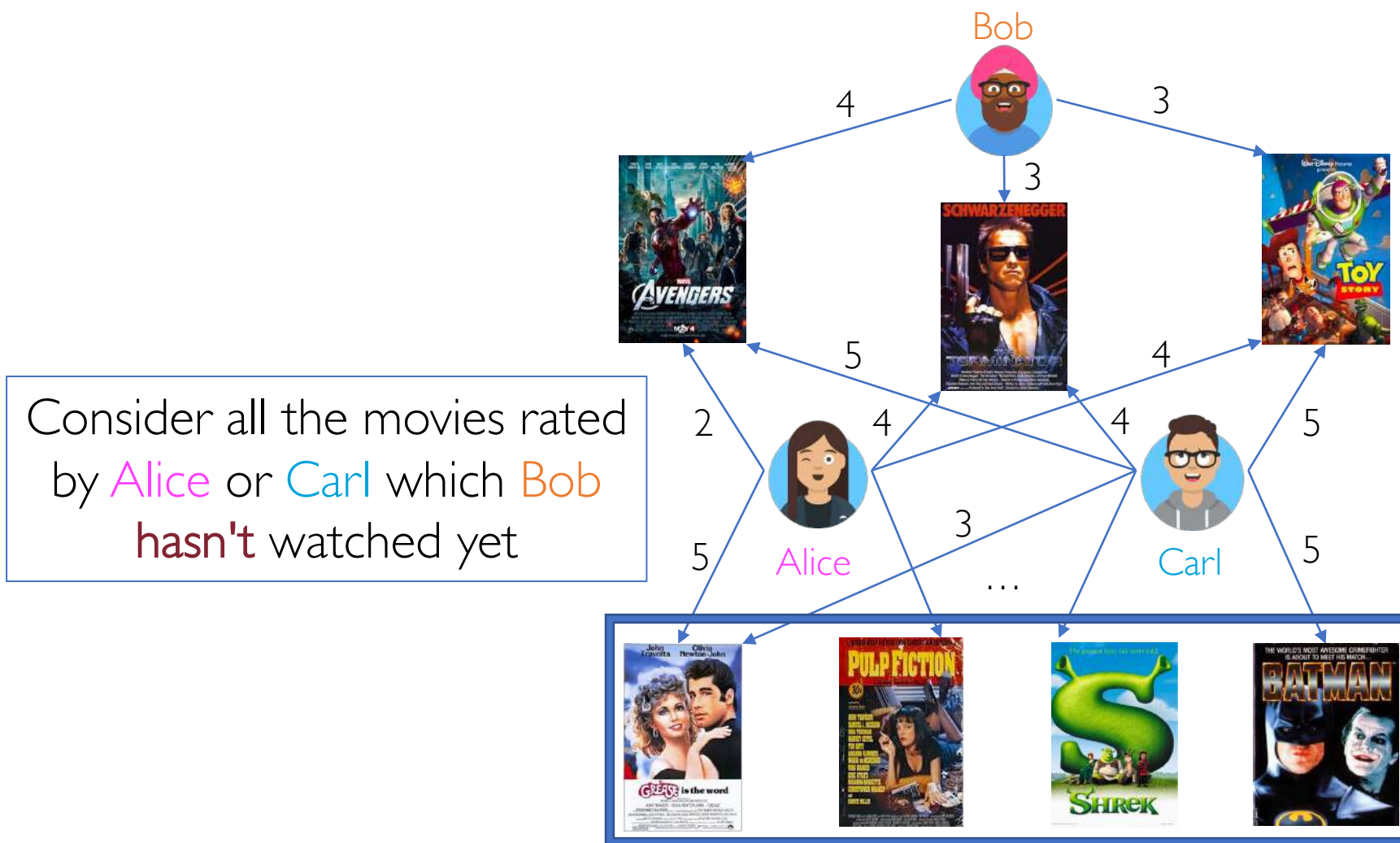


User-based Neighborhood: Example



Alice and Carl are the 2-nearest neighbours of Bob
if we look at their rating behaviours

User-based Neighborhood: Example



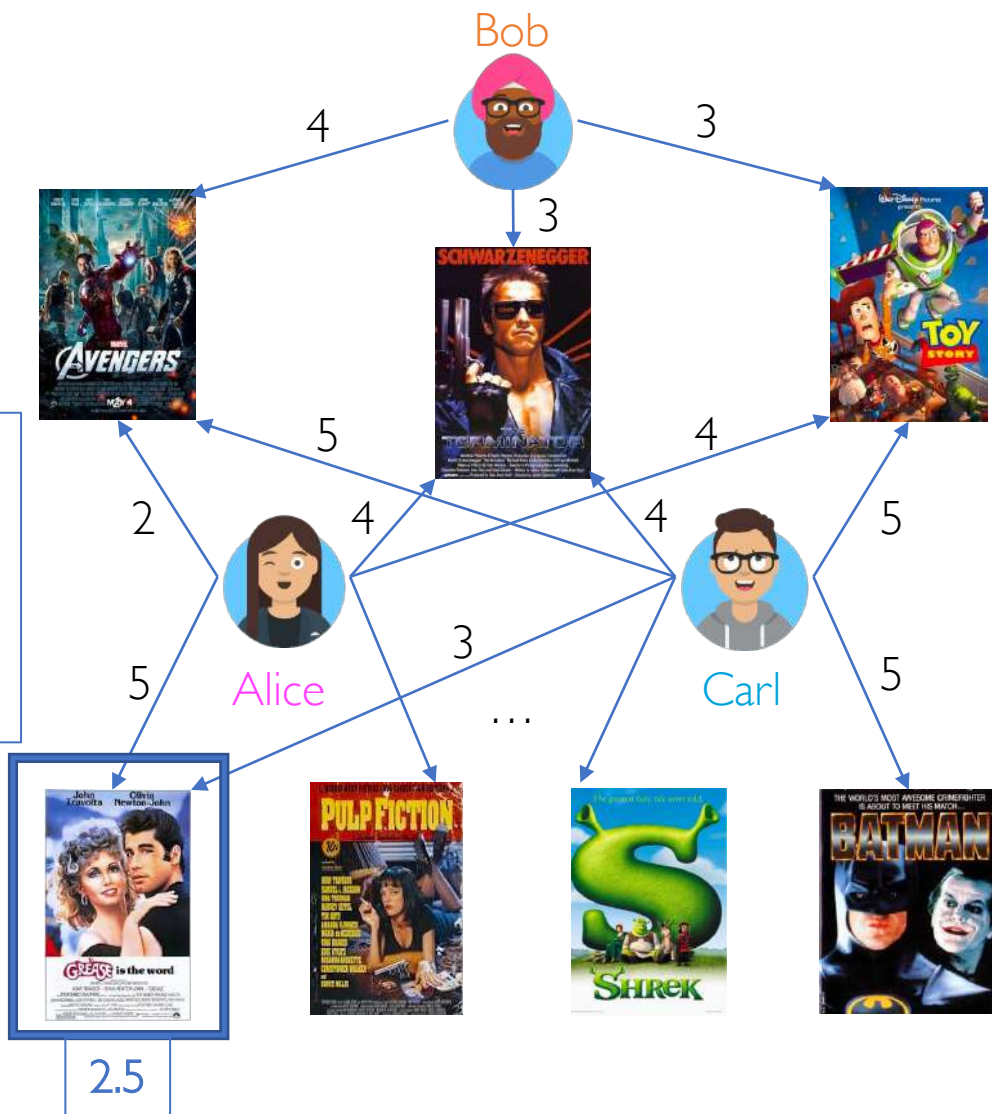
User-based Neighborhood: Example

Predict the rating that **Bob** would give to each of those movies on the basis of **Alice**'s and **Carl**'s ratings



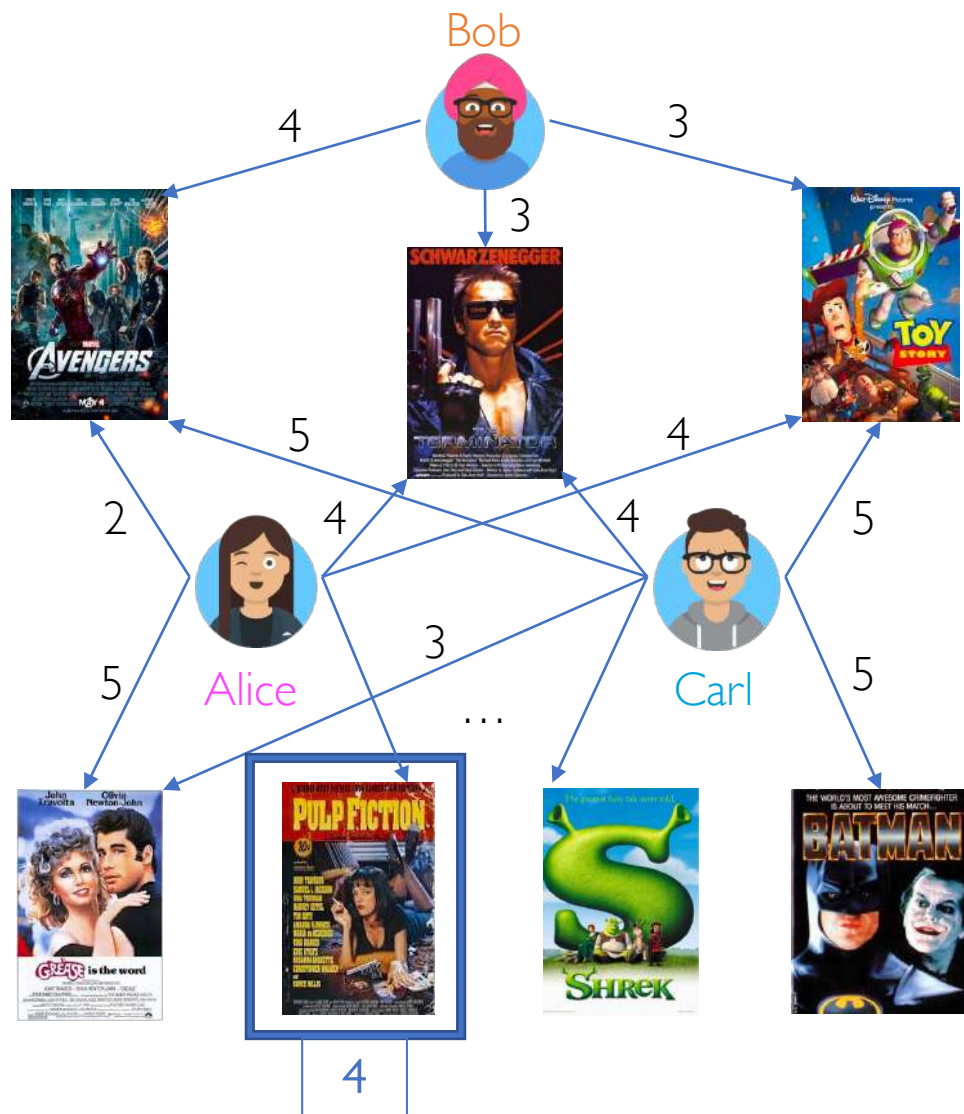
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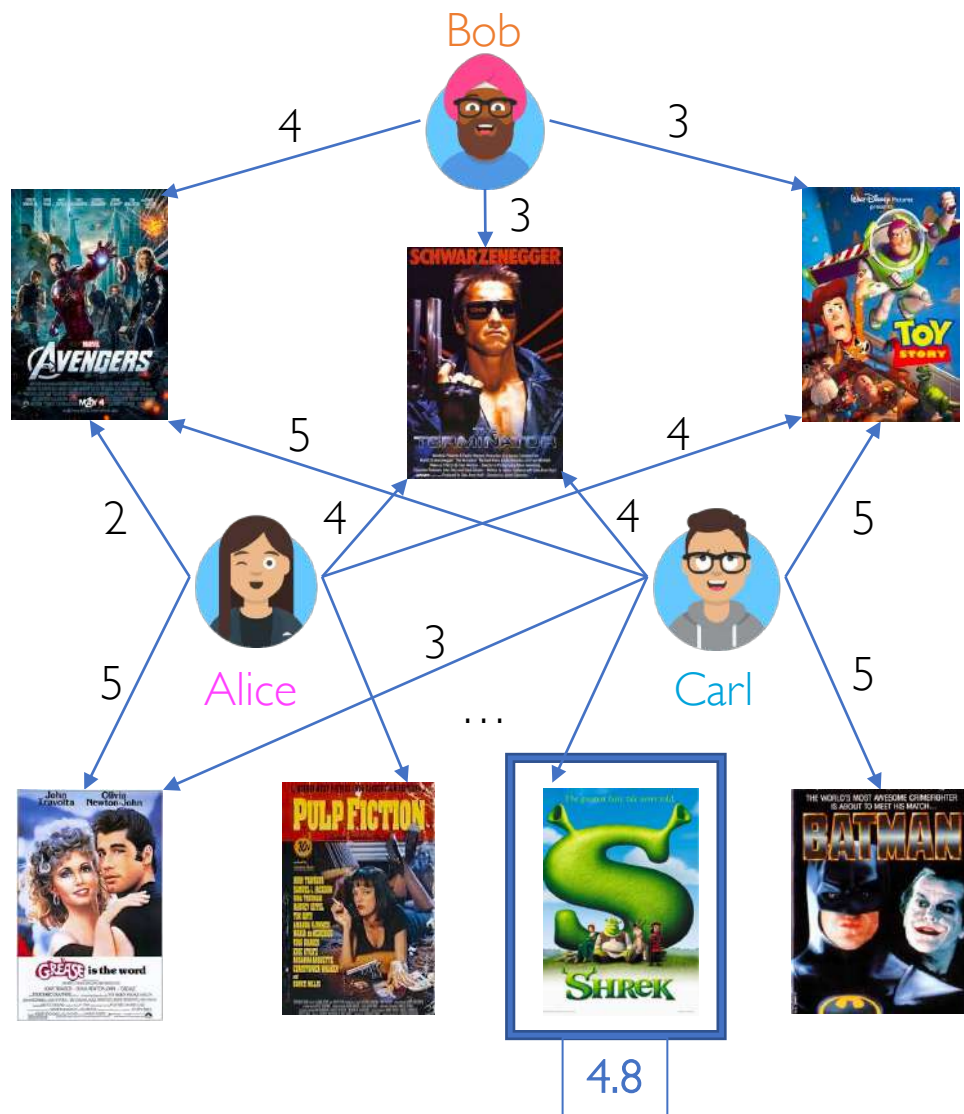
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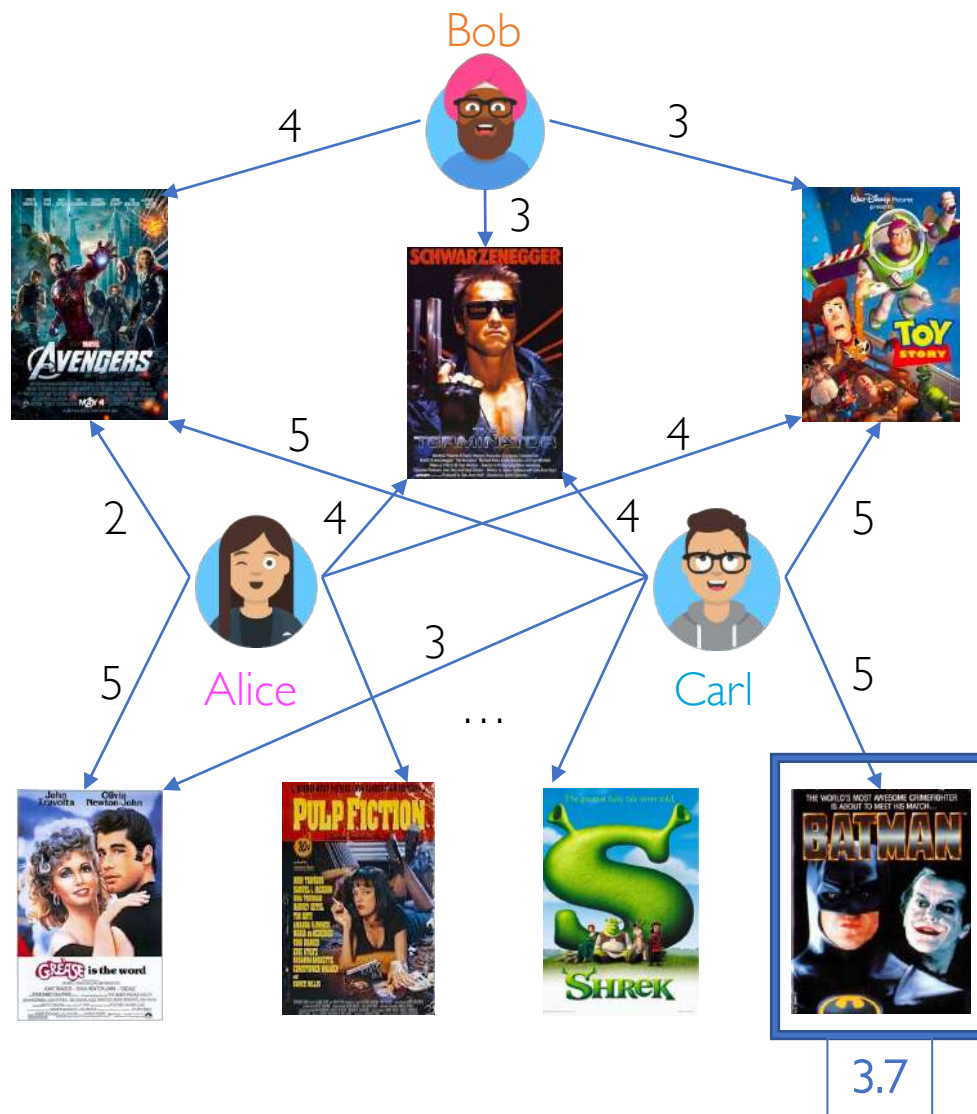
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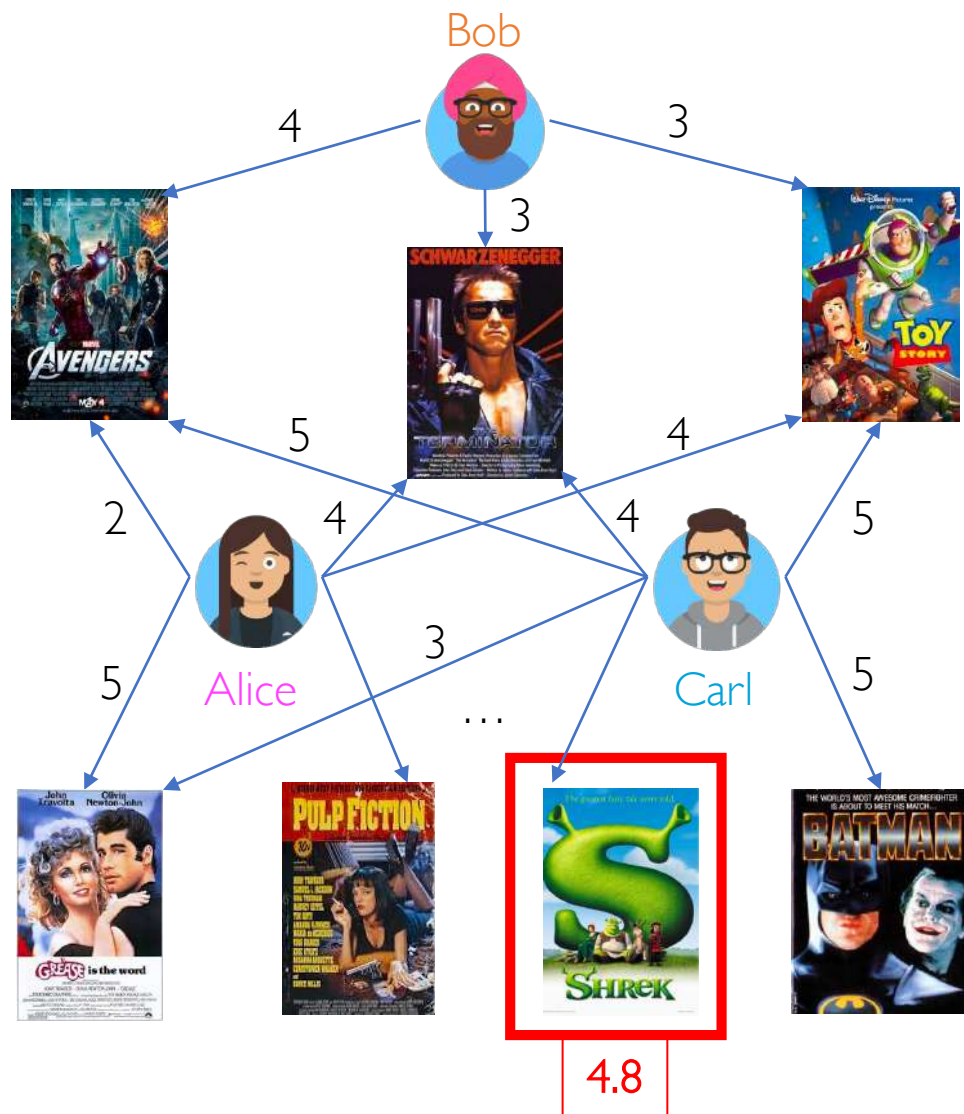
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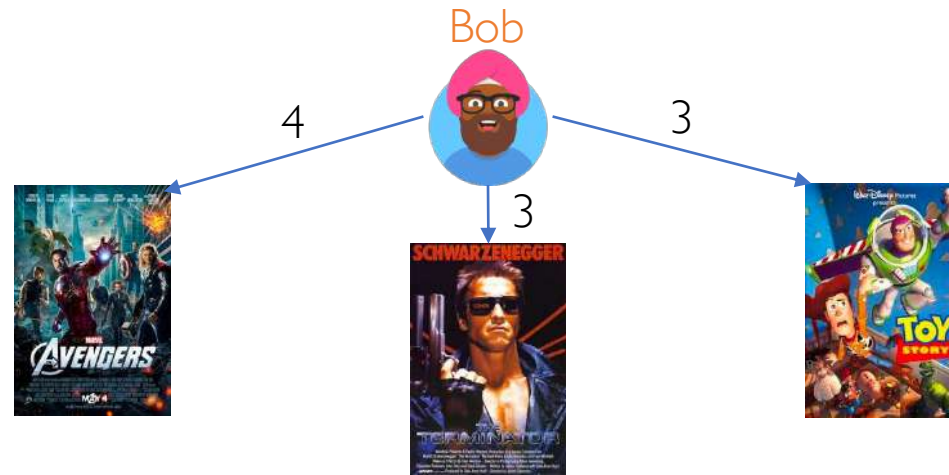


User-based Neighborhood: Example

Recommend the highest rated movie(s) to **Bob**!



User-based Neighborhood: Example



There is no point in predicting the rating of a movie which has only been rated by a user (Zoe) who is **not** in the Bob's neighborhood



User-to-User Similarity

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- Each user represented by her/his rating vector and similarity between them is measured in the item (rating) space

User-to-User Similarity










$\text{sim}(u, v)$ Similarity metric between any pair of users


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Must capture the intuition that $\underbrace{\text{sim}(\text{Alice}, \text{Carl})}_{\text{red}} > \underbrace{\text{sim}(\text{Alice}, \text{Bob})}_{\text{yellow}}$

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\mathbf{r}_{Bob}

User-to-User Similarity: Jaccard Similarity












$$\text{sim}(u, v) = J(\mathbf{r}_u, \mathbf{r}_v) = \frac{|\mathbf{r}_u \cap \mathbf{r}_v|}{|\mathbf{r}_u \cup \mathbf{r}_v|}$$


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$$\begin{aligned} \text{sim}(\text{Alice}, \text{Bob}) &= \frac{|\mathbf{r}_{\text{Alice}} \cap \mathbf{r}_{\text{Bob}}|}{|\mathbf{r}_{\text{Alice}} \cup \mathbf{r}_{\text{Bob}}|} \\ &= \frac{3}{6} = 0.5 \end{aligned}$$

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Problem!
Jaccard ignores rating values

User-to-User Similarity: Cosine Similarity

$$\text{sim}(u, v) = \text{cosine}(\mathbf{r}_u, \mathbf{r}_v) = \frac{\mathbf{r}_u \cdot \mathbf{r}_v}{\|\mathbf{r}_u\| \|\mathbf{r}_v\|}$$











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$$= \frac{102}{\sqrt{102} \sqrt{141}} \approx 0.85$$

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Problem!

Missing rating values are treated as 0s and have a negative effect

User-to-User Similarity: Pearson Correlation

$$\text{sim}(u, v) = \text{Pearson}(\mathbf{r}_u, \mathbf{r}_v) = \frac{(\mathbf{r}_u - \bar{\mathbf{r}}_u) \cdot (\mathbf{r}_v - \bar{\mathbf{r}}_v)}{\sqrt{(\mathbf{r}_u - \bar{\mathbf{r}}_u)^T \cdot (\mathbf{r}_u - \bar{\mathbf{r}}_u)} \times \sqrt{(\mathbf{r}_v - \bar{\mathbf{r}}_v)^T \cdot (\mathbf{r}_v - \bar{\mathbf{r}}_v)}}$$

		MOVIES							
									
USERS	 Alice	-2		1	0	1	0		0
	 Bob	2/3					-1/3		-1/3
	 Carl	4/7	4/7	-10/7	-3/7	4/7	-3/7		4/7

	 Zoe		-9/4	-1/4				7/4	-1/4

Solution:
Normalize ratings by
subtracting the mean rating

Now 0 means neutral, and if we treat missing ratings as 0, it doesn't mean it's negative

User-to-User Similarity: Pearson Correlation

$$\mathbf{r}'_u = \mathbf{r}_u - \bar{\mathbf{r}}_u \quad \text{mean-scaled rating vector of } u$$

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$$= \frac{(\mathbf{r}_u - \bar{\mathbf{r}}_u) \cdot (\mathbf{r}_v - \bar{\mathbf{r}}_v)}{\sqrt{(\mathbf{r}_u - \bar{\mathbf{r}}_u)^T \cdot (\mathbf{r}_u - \bar{\mathbf{r}}_u)} \times \sqrt{(\mathbf{r}_v - \bar{\mathbf{r}}_v)^T \cdot (\mathbf{r}_v - \bar{\mathbf{r}}_v)}} = \text{Pearson}(\mathbf{r}_u, \mathbf{r}_v)$$

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Top- k most "similar" users to u

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Set of items rated by u 's neighbors

$$\mathcal{I}^k = \{i \in \mathcal{I} : \mathbf{r}_{u',i} = \downarrow \wedge u' \in \mathcal{U}^k\}$$

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Predicted rating given by user u to item i

$$\mathbf{r}_u[i] = r(u, i) = r_{u,i}$$

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$$r_{u,i} = \frac{1}{k} \sum_{u' \in \mathcal{U}^k} \text{sim}(u, u') \cdot r_{u',i}$$

weighted average

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Aging

user profiles changed
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system model had to be
recomputed

ITEM-BASED COLLABORATIVE FILTERING

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- The model doesn't suffer from aging and therefore it does not need to be recomputed frequently

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Estimate $r(u, i)$ based on the ratings of items in the k -neighborhood of i

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$\mathbf{r}_{\text{Shrek}}$

Item-based Neighborhood: Example

Let's consider again Bob!

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Item-based Neighborhood: Example











Suppose we want to predict the rating **Bob** would give to **Shrek**


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USERS	 Alice	2		5	4	5	4		4
	 Bob	4				?	3		3
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Item-based Neighborhood: Example

We first extract the subset of k most similar items to Shrek which have been rated by Bob












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$\mathbf{r}_{\text{Shrek}}$

Item-based Neighborhood: Example

Suppose those are: The Avengers and The Terminator









		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

For example, item similarity is measured using Pearson's correlation

Item-based Neighborhood: Example

The predicted rating is computed as an **aggregating function** of the ratings that **Bob** gave to the k most similar movies to Shrek

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Predicted rating given by user u to item i

$$\mathbf{r}_u[i] = r(u, i) = r_{u,i}$$

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plain average

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In general, **item-based** works better than **user-based** CF

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 - Locality-Sensitive Hashing (LSH) approximation



Take-Home Message of Today

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 - In large scale systems, this must be pre-computed offline
 - At inference time, make use of ad hoc data structures (e.g., k-d trees) to efficiently compute the set of (approximated) nearest neighbors for a query user/item