

COMP6237 Data Mining

Lecture 1: Recommendation Systems

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Lecture slides available here:

<http://comp6237.ecs.soton.ac.uk/jon.html>

(Thanks to Prof. Jonathon Hare and Dr. Jo Grundy for providing the lecture materials used to develop the slides.)

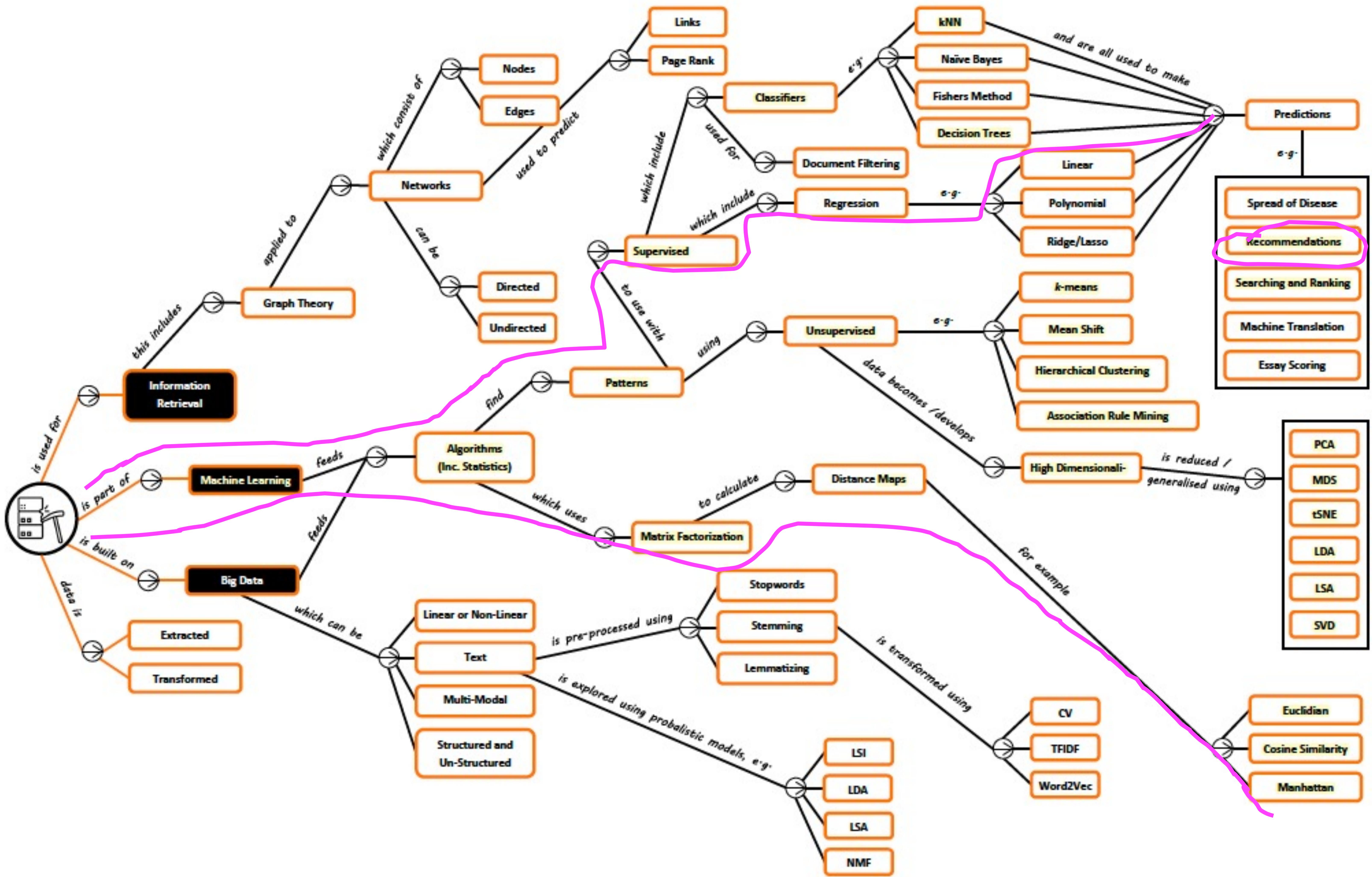
My Lectures

26-Feb	5	Zhiwu	Making Recommendations
27-Feb		Zhiwu	Finding Groups
29-Feb		Zhiwu	Covariance
04-Mar	6	Zhiwu	Embedding Data
05-Mar		Zhiwu	Search
07-Mar		Zhiwu	Document filtering
11-Mar	7	Zhiwu	Modelling with decision trees
12-Mar		Zhiwu	Modelling Prices & Nearest Neighbours
14-Mar		Zhiwu	Market Basket Analysis
18-Mar	8	Zhiwu & Shoaib & Markus	<i>Group coursework presentations</i>
19-Mar		Zhiwu & Shoaib & Markus	<i>Group coursework presentations</i>
21-Mar		Zhiwu & Shoaib & Markus	<i>Group coursework presentations</i>
22-Mar		Zhiwu & Shoaib & Markus	<i>Group coursework presentations</i>
Easter			
22-Apr	9	Zhiwu	Semantic Spaces & Latent Semantics
23-Apr		Zhiwu	Topic Modelling
25-Apr		Zhiwu	Outlier Detection

Four Key Slides for each lecture:

Roadmap + Textbook + Overview + Learning Outcomes (Exercise/Exam)

Recommendation Systems – Roadmap



Recommendation Systems – Textbook

Chapter 9

Recommendation Systems

There is an extensive class of Web applications that involve predicting user responses to options. Such a facility is called a *recommendation system*. We shall begin this chapter with a survey of the most important examples of these systems. However, to bring the problem into focus, two good examples of recommendation systems are:

1. Offering news articles to on-line newspaper readers, based on a prediction of reader interests.
2. Offering customers of an on-line retailer suggestions about what they might like to buy, based on their past history of purchases and/or product searches.

► **Mining of Massive Datasets J. Leskovec et al**

Recommendation Systems – Overview (1/4)



The image shows a screenshot of the IMDb movie page for "Migration". At the top right, there are navigation links: Cast & crew · User reviews · Trivia · FAQ | IMDbPro | All topics | Share. Below that, the movie's title "Migration" is displayed in large letters, followed by the release year "2023 · PG · 1h 23m". To the right, the IMDb rating is shown as 6.7/10 (16K votes), a user rating of 9/10, and a popularity score of 49. A large thumbnail image of the movie's characters (three ducks) is centered. Below the thumbnail, a "Play trailer 2:25" button is visible. To the left of the thumbnail is the movie's poster, which features a large crowd of yellow rubber ducks and the title "ILLUMINATION PRESENTS MIGRATION Only In Theaters This Holiday". Below the poster, genre tags are listed: Animation, Adventure, Comedy. A plot summary follows: "A family of ducks try to convince their overprotective father to go on the vacation of a lifetime." On the right side, there are sections for "IN THEATERS" (with a ticket icon and "see showtimes") and "Add to Watchlist" (with a plus sign and "Added by 34.6K users"). At the bottom, there are links for "Directors" (Benjamin Renner, Guylo Homsy), "Writers" (Mike White, Benjamin Renner), and "Stars" (Kumail Nanjiani, Tresi Gazal, Elizabeth Banks).

Recommendation Systems – Overview (2/4)

★ 10/10

Great for adults and kids - clean and entertaining family film

m_al_saeed 16 December 2023

The animation is colorful, action starts relatively early and is well spaced-out. The jokes were appropriate. My kids are aged 10 and 14, they both enjoyed it. There were kids of all ages in the theatre and I could hear laughs all the time. Perfect for the holidays and also has a great soundtrack.

The storyline is obvious in the title, but the journey was full of surprises enough to keep you on the edge. There were useful lessons to be learned and a morale to the story.

The last film I had seen at the cinema was Super Mario and "Migration" has delivered the same clean family entertainment that we have been missing.

Highly recommended.

40 out of 53 found this helpful. Was this review helpful?

[Report this](#) | [Permalink](#)

★ 2/10

Unoriginal and boring

sjo-15 5 February 2024

There was little here to keep my interest.

David Mitchell was funny and well cast. He really was like a tonic when he came along.

Otherwise, seen it all done before and better.

The story was formulaic, short on laughs and predictable.

Felt long at 90 minutes. Judging by the amount of phones I saw being looked at I wasn't the only adult wondering why they spent their money on this.

<https://www.imdb.com/title/tt6495056/>

Recommendation Systems – Overview (3/4)

Top picks >

TV shows and movies just for you



★ 7.1 

Wonka

[Watch options](#)

▶ Trailer 



★ 6.0 

Trolls Band Together

[Watch options](#)

▶ Trailer 



★ 7.0 

Elemental

[Watch options](#)

▶ Trailer 



★ 7.2 

Percy Jackson and the Olympians

 [Watchlist](#)

▶ Trailer 

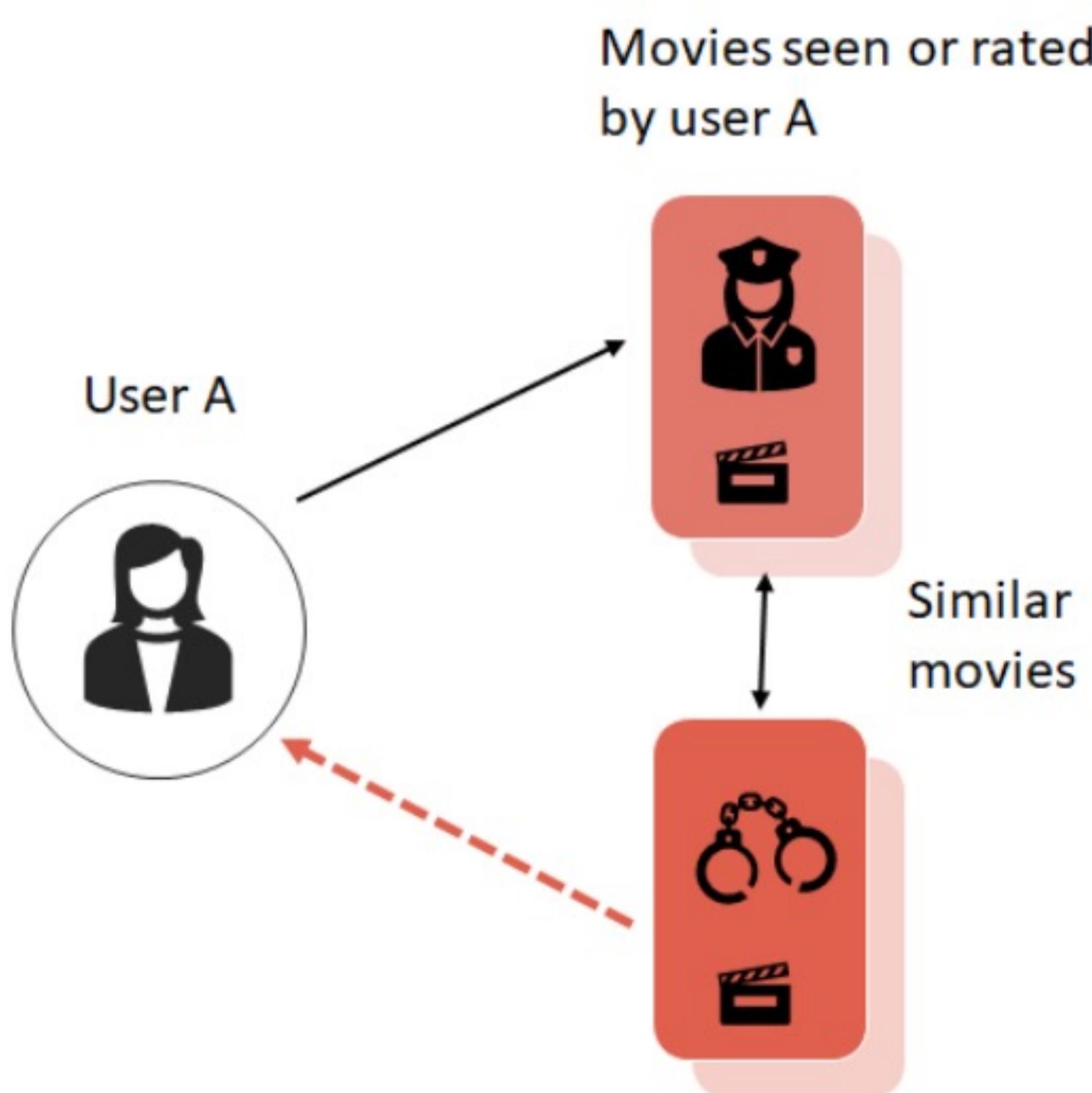
Recommendation Systems – Overview (4/4)

Film	Alice	Bob	Carol	Dave
Love Really	4	1		4
Deadly Weapon		1	4	5
Fast and Cross	5		5	4
Star Battles	1	5		
Dark Knight			5	?



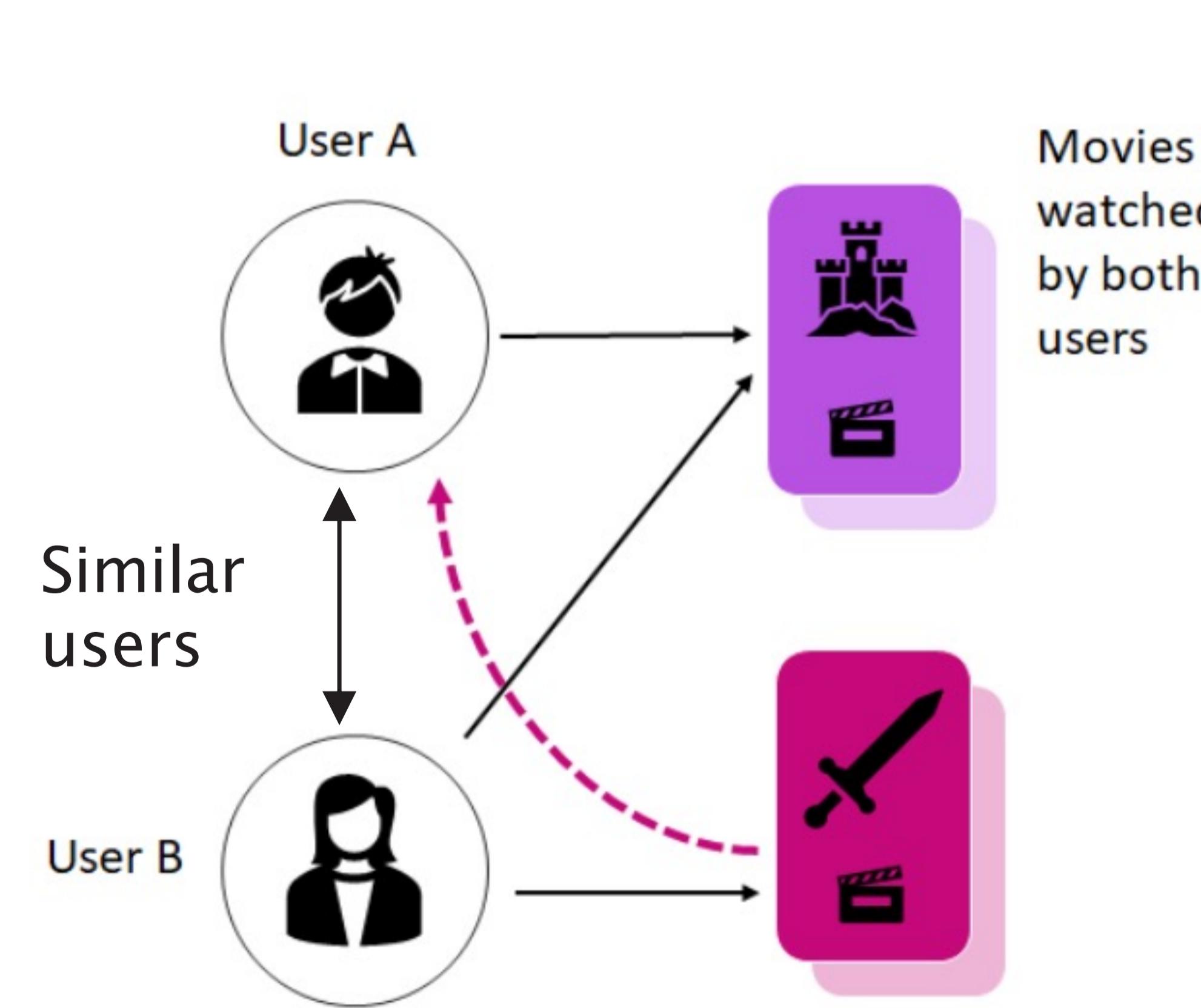
Content-based Filtering

Movie recommendations to user A



Collaborative Filtering

Movies watched by user A are recommended to user B



Left problems:

- How to represent the item/user data?
- How to save the data?
- How to compare the data (user/item)?

Recommendation Systems – Learning Outcomes

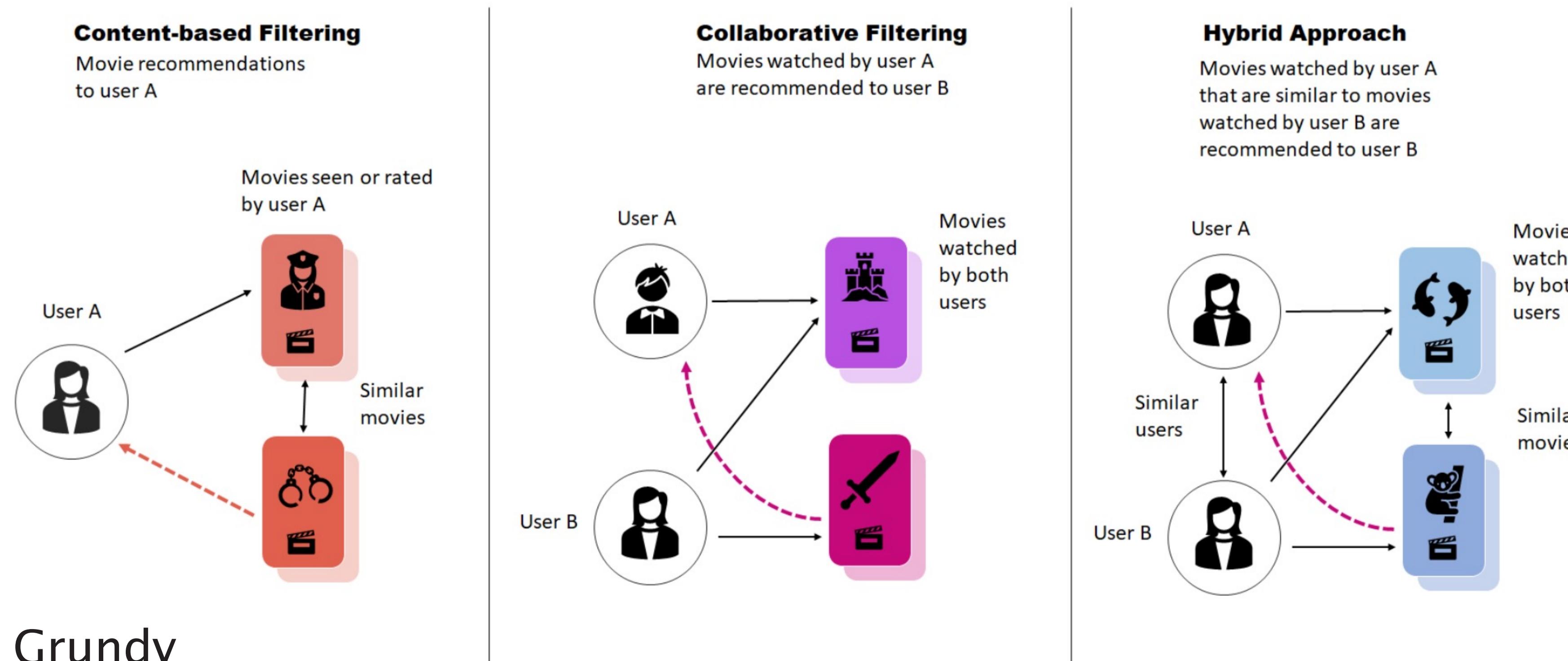
- LO1: Mastering fundamental concepts and mathematical calculations of content-based and user-based/item-based collaborative filtering approaches, such as (exam)
 - ❖ Measuring distances/similarities between users or items
 - ❖ Computing the resulting matrix using Compressed Row/Column Storage
 - ❖ Predicting the missing rating using content-based approach
 - ❖ Calculating the predicted rating with user-based/item-based collaborative filtering approach
- LO2: Implement basic algorithms using Python (coursework)

Assessment hints: Multi-choice Questions (single answer: concepts, calculation etc)

- *Textbook Exercises: textbooks (Programming + Mining)*
- *Other Exercises: <https://www-users.cse.umn.edu/~kumar001/dmbook/sol.pdf>*
- *ChatGPT or other AI-based techs*

Recommendation Systems – Algorithms

- **Content-based systems** (e.g., Netflix) **examine properties of the items recommended**. For instance, if a Netflix user has watched many cowboy movies, then recommend a movie classified in the database as having the “cowboy” genre.
- **Collaborative filtering systems** (e.g., Facebook Amazon) **recommend items based on similarity measures between users and/or items**. The items recommended to a user are those preferred by similar users.
- **Hybrid recommender systems** (e.g., Netflix) **Uses combinations of different approaches**



We will learn Content-based and collaborative filtering systems in this lecture

Recommendation Systems- Content based approach

Can use a vector of features for each film, eg romance, action *Content-based Features/data*

Film	Alice	Bob	Carol	Dave	x_1 romance	x_2 action
Love Really	4	1		4	1	0.1
Deadly Weapon		1	4	5	0.1	1
Fast and Cross	5		5	4	0.2	0.9
Star Fight	1	5			0.1	1

Each film can be described by the vector $X = [1 \quad x_1 \quad x_2]$ (1 is for the bias term)

Learn 2D parameter vector θ , where $\theta^T X$ gives the number of stars for each user.

$\theta = [0 \quad 5 \quad 0]$ for someone who really likes romance films

Recommendation Systems- Content based approach

Use **Linear Regression** to find user parameter vector θ where m is the number of films rated by that user

$$\min_{\theta} \frac{1}{m} \sum_{i=1}^m (\theta^T X_i - y)^2 \quad (1)$$

Can also use Bayesian classifiers, MLPs, etc.

Recommendation Systems- Content based approach

Linear Regression

Can use a vector of features for each film, eg romance, action

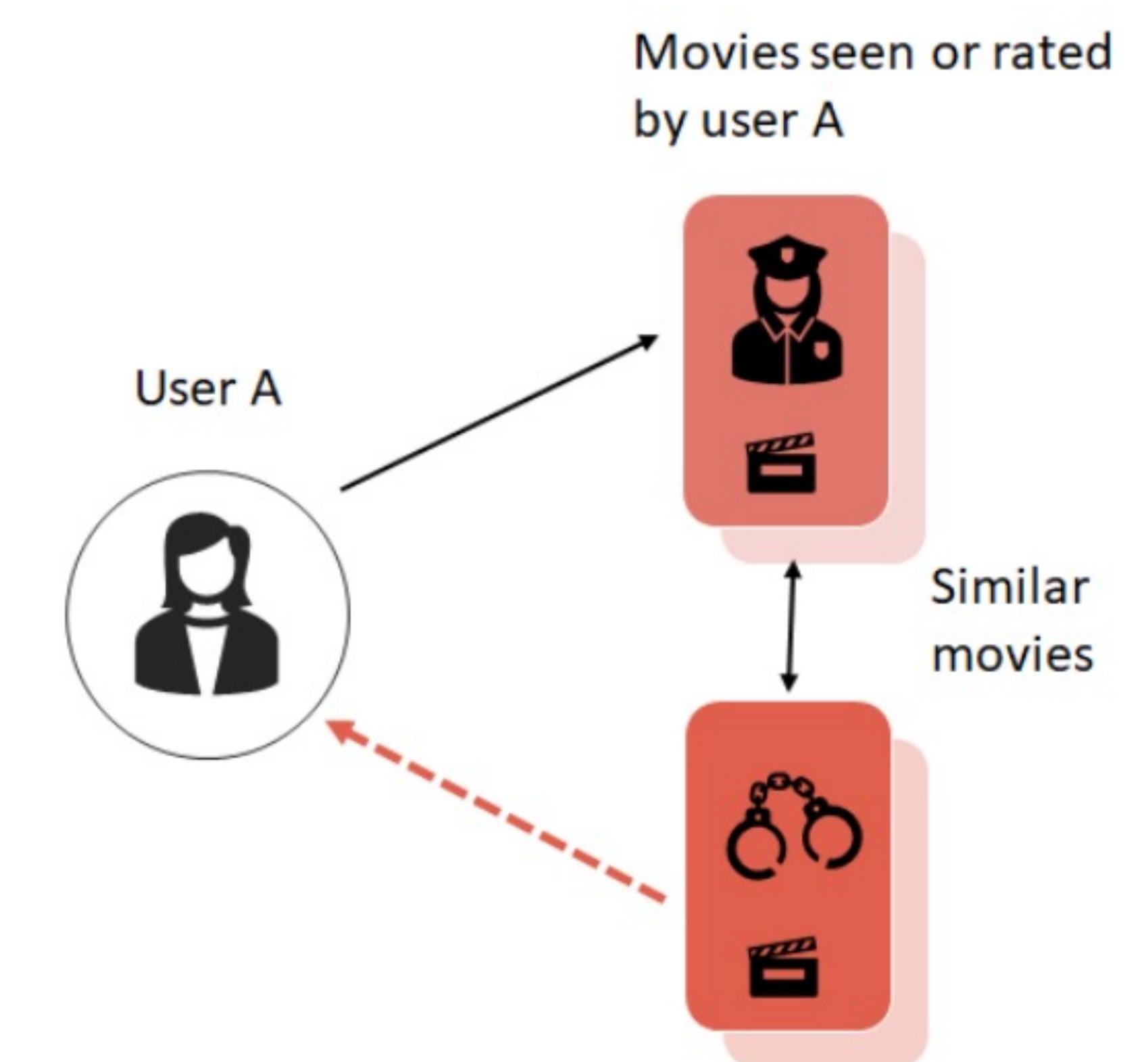
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Take the user 'Alice' as an example

$$y_1 = 4, y_3 = 5, y_4 = 1$$

$$X_1 = [1, x_1, x_2] = [1, 1, 0.1], X_3 = [1, 0.2, 0.9], X_4 = [1, 0.1, 1],$$

$\theta = [b, w_1, w_2]$, what about y_2 for 'Alice'?



Recommendation Systems- Content based approach

Linear Regression $\min_{\theta} \frac{1}{m} \sum_{i=1}^m (\theta^T X_i - y)^2$ (1)

Can use a vector of features for each film, eg romance, action

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$\theta = [b, w_1, w_2]$, what about y_2 for ‘Alice’?

Least Squares $\frac{1}{3} [(\theta^T X_1 - y_3) + (\theta^T X_2 - y_3) + (\theta^T X_4 - y_4)] = \min_{\theta} \frac{1}{3} (b + w^T X_1 - y_1)$

Recommendation Systems- Content based approach

Linear Regression $\min_{\theta} \frac{1}{m} \sum_{i=1}^m (\theta^T X_i - y)^2$ (1)

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- Data Mining and Machine Learning: Fundamental Concepts *Chapter 23, Page 589-593* and Algorithms M. L. Zaki and W. Meira

Recommendation Systems- Content based approach

Linear Regression $\min_{\theta} \frac{1}{m} \sum_{i=1}^m (\theta^T X_i - y)^2$ (1)

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$\theta = [b, w_1, w_2]$, what about y_2 for 'Alice'?

Least Squares: $SSE = \frac{1}{3} [(\theta^T X_1 - y_3) + (\theta^T X_2 - y_3) + (\theta^T X_4 - y_4)] = \min_{\theta} \frac{1}{3} (b + w^T X_1 - y_1)$

Gradient Decent:

Differentiate it with respect to b and set the result to 0

$$\frac{\partial}{\partial b} SSE = -2 \sum_{i=1}^n (y_i - b - w \cdot x_i) = 0 \quad \frac{\partial}{\partial w} SSE = -2 \sum_{i=1}^n x_i (y_i - b - w \cdot x_i) = 0$$

$$\begin{aligned} \Rightarrow \sum_{i=1}^n b &= \sum_{i=1}^n y_i - w \sum_{i=1}^n x_i \\ \Rightarrow b &= \frac{1}{n} \sum_{i=1}^n y_i - w \cdot \frac{1}{n} \sum_{i=1}^n x_i \end{aligned} \quad \begin{aligned} \Rightarrow \sum_{i=1}^n x_i \cdot y_i - b \sum_{i=1}^n x_i - w \sum_{i=1}^n x_i^2 &= 0 \end{aligned}$$

Recommendation Systems- Content based approach

Linear Regression $\min_{\theta} \frac{1}{m} \sum_{i=1}^m (\theta^T X_i - y)^2$ (1)

Can use a vector of features for each film, eg romance, action

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Least Squares $\frac{1}{3} [(\theta^T X_1 - y_3) + (\theta^T X_2 - y_3) + (\theta^T X_4 - y_4)] = \min_{\theta} \frac{1}{3} (b + w^T X_1 - y_1)$

Gradient Decent:

$$b = \mu_Y - w \cdot \mu_X$$

$$w = \frac{\sum_{i=1}^n (x_i - \mu_X)(y_i - \mu_Y)}{\sum_{i=1}^n (x_i - \mu_X)^2} = \frac{\sigma_{XY}}{\sigma_X^2} = \frac{\text{cov}(X, Y)}{\text{var}(X)}$$

Recommendation Systems- Content based approach

Use **Linear Regression** to find user parameter vector θ where m is the number of films rated by that user

$$\min_{\theta} \frac{1}{m} \sum_{i=1}^m (\theta^T X_i - y)^2 \quad (1)$$

Can also use Bayesian classifiers, MLPs, etc.

Problems?

requires hand coded knowledge of film

not easy to scale up

user may not have rated many films

Can use a vector of features for each film, eg romance, action

Film	Alice	Bob	Carol	Dave	x_1 romance	x_2 action
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Recommendation Systems – Collaborative Filtering

Collaborative Filtering example:

Alice likes Dr Who, Star Wars and Star Trek

Bob likes Dr Who and Star Trek

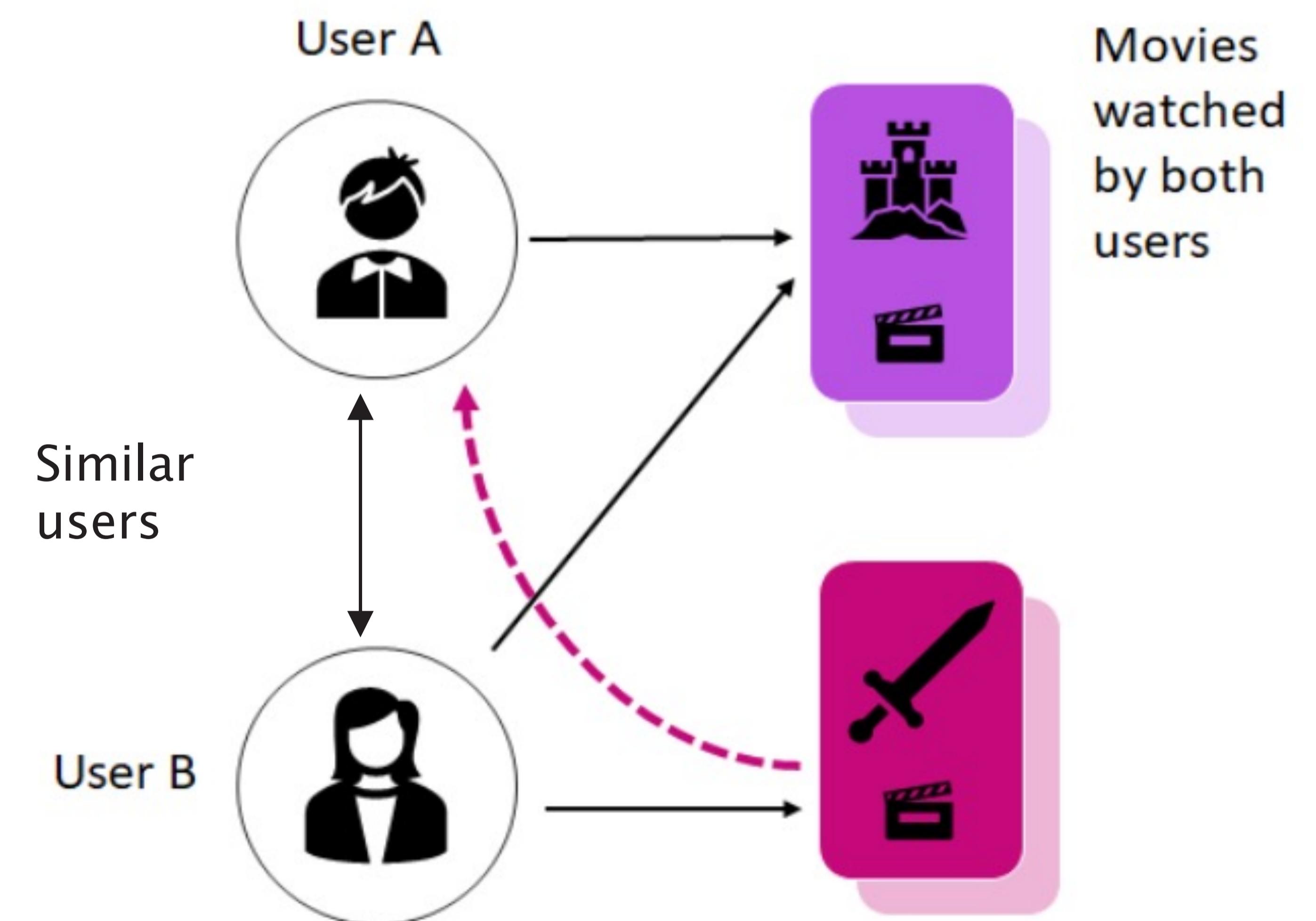
A recommender system would correlate the likes, and suggest that Bob might like Star Wars too.

Personal preferences can be correlated.

Task: Discover patterns in observed behaviour across a community of users

- ▶ Purchase history
- ▶ Item ratings
- ▶ Click counts

Predict new preferences based on those patterns



Recommendation Systems – Collaborative Filtering

Collaborative filtering uses a range of approaches to accomplish this task

- ▶ Neighbourhood based approach
- ▶ Model based approach
- ▶ Hybrid (Neighbourhood and model) based approach

This lecture will cover the Neighborhood based approach

Recommendation Systems – Collaborative Filtering

Measure user preferences. Eg. Film recommendation

Users rate films between 0 and 5 stars

	Life is Beautiful	Seven Samurai	Joker	Schindler's List	The Pianist	City of God
Lee	2.5	3.5	3.0	3.5	3.0	2.5
Sofia	3.0	3.5	1.5	5.0	3.0	3.5
Miley	2.5	3.0		3.5	4.0	
Justina		3.5	3.0	4.0	4.5	2.5
Donald	3.0	4.0	2.0	3.0	3.0	2.0
Mikey	3.0	4.0		5.0	3.0	3.5
Tristan		4.5		4.0		1.0

The data is **sparse**, there are missing values

Collaborative Filtering – Sparsity

Sparsity can be taken advantage of to speed up computations

Most libraries that do matrix algebra are based on LAPACK,
written in Fortan90

Computation is done by calls to the Basic Linear Algebra
Subprograms (BLAS).

This is how the Python numpy library does its linear algebra.

Collaborative Filtering – Sparsity

Compressed Row Storage (CRS)¹

Matrix specified by three arrays: *val*, *col_ind* and *row_ptr*

val stores the non zero values

col_ind stores column indices of each element in *val*

row_ptr stores the index of the elements in *val* which start a row

E.g. What matrix would this give?

val = [1, 2, 9, 8, 2, -1, 4, 5, 2, 7]

col_ind = [1, 2, 4, 3, 4, 1, 2, 4, 2, 3]

row_ptr = [1, 4, 6, 9]

¹Harwell-Boeing sparse matrix format, Duff et al, ACM Trans. Math. Soft.,

15 (1989), pp. 1-14.

Collaborative Filtering – Sparsity

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col_ind = [1, 2, 4, 3, 4, 1, 2, 4, 2, 3]

row_ptr = [1, 4, 6, 9]

$$\begin{bmatrix} 1 & 2 & 9 \\ & & 8 & 2 \\ -1 & 4 & 5 \\ & 2 & 7 \end{bmatrix}$$

¹Harwell-Boeing sparse matrix format, Duff et al, ACM Trans. Math. Soft., 15 (1989), pp. 1-14.

Collaborative Filtering – Sparsity

Analogously, there is also Compressed Column Storage (CCS)

Matrix specified by three arrays: *val*, *row_ind* and *col_ptr*

val stores the non zero values

row_ind stores row indices of each element in *val*

col_ptr stores the index of the elements in *val* which start a column

E.g. What matrix would this give?

val = [2,2,5,3,1,4]

row_ind = [1,4,3,1,2,1]

col_ptr = [1,3,4,6]

Collaborative Filtering – Sparsity

Analogously, there is also Compressed Column Storage (CCS)

Matrix specified by three arrays: *val*, *row_ind* and *col_ptr*

val stores the non zero values

row_ind stores row indices of each element in *val*

col_ptr stores the index of the elements in *val* which start a column

E.g. What matrix would this give?

val = [2,2,5,3,1,4]

row_ind = [1,4,3,1,2,1]

col_ptr = [1,3,4,6]

$$\begin{bmatrix} 2 & & 3 & 4 \\ & 1 & & \\ & & 5 & \\ 2 & & & \end{bmatrix}$$

The CCS is the CRS of A^T

Collaborative Filtering – Sparsity

Also Block Compressed Row Format (BSR) :

val stores the non zero blocks

col_ind stores column indices of each element in *val*

row_ptr stores the index of the elements in *val* which start a row

$$val = \begin{bmatrix} 2 \\ 3 & 1 \end{bmatrix} \begin{bmatrix} 4 & 7 \\ 3 & 1 \end{bmatrix} \begin{bmatrix} 4 & 5 \\ 3 & \end{bmatrix} \begin{bmatrix} 1 \\ 1 \end{bmatrix}$$

$$col_ind = [1, 2, 3, 1]$$

$$row_ptr = [1, 2, 4]$$

Collaborative Filtering – Sparsity

Also Block Compressed Row Format (BSR) :

val stores the non zero blocks

col_ind stores column indices of each element in *val*

row_ptr stores the index of the elements in *val* which start a row

$$val = \begin{bmatrix} 2 \\ 3 & 1 \end{bmatrix} \begin{bmatrix} 4 & 7 \\ 3 & 1 \end{bmatrix} \begin{bmatrix} 4 & 5 \\ 3 & \end{bmatrix} \begin{bmatrix} 1 \\ 1 \end{bmatrix}$$

$$col_ind = [1, 2, 3, 1]$$

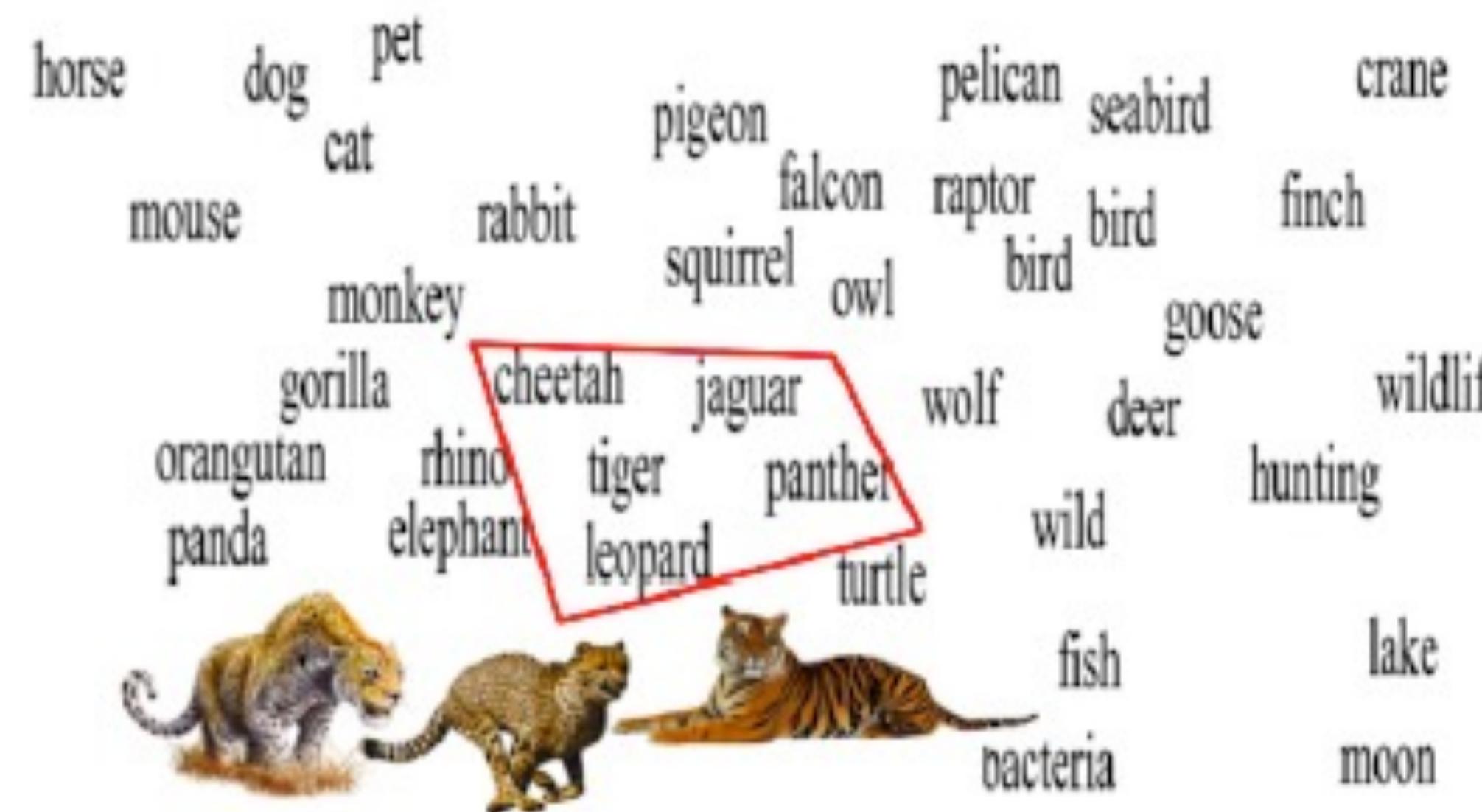
$$row_ptr = [1, 2, 4]$$

$$\begin{bmatrix} 2 \\ 3 & 1 \\ & 4 & 7 & 4 & 5 \\ & 3 & 1 & 3 \\ 1 \\ & 1 \end{bmatrix}$$

Collaborative Filtering – Feature Extraction

Features are stored in a 'feature vector', a fixed length list of numbers.

- ▶ The length of this vector is the number of dimensions
- ▶ Each vector represents a point and a direction in the featurespace.
- ▶ Each vector must have the same dimensionality



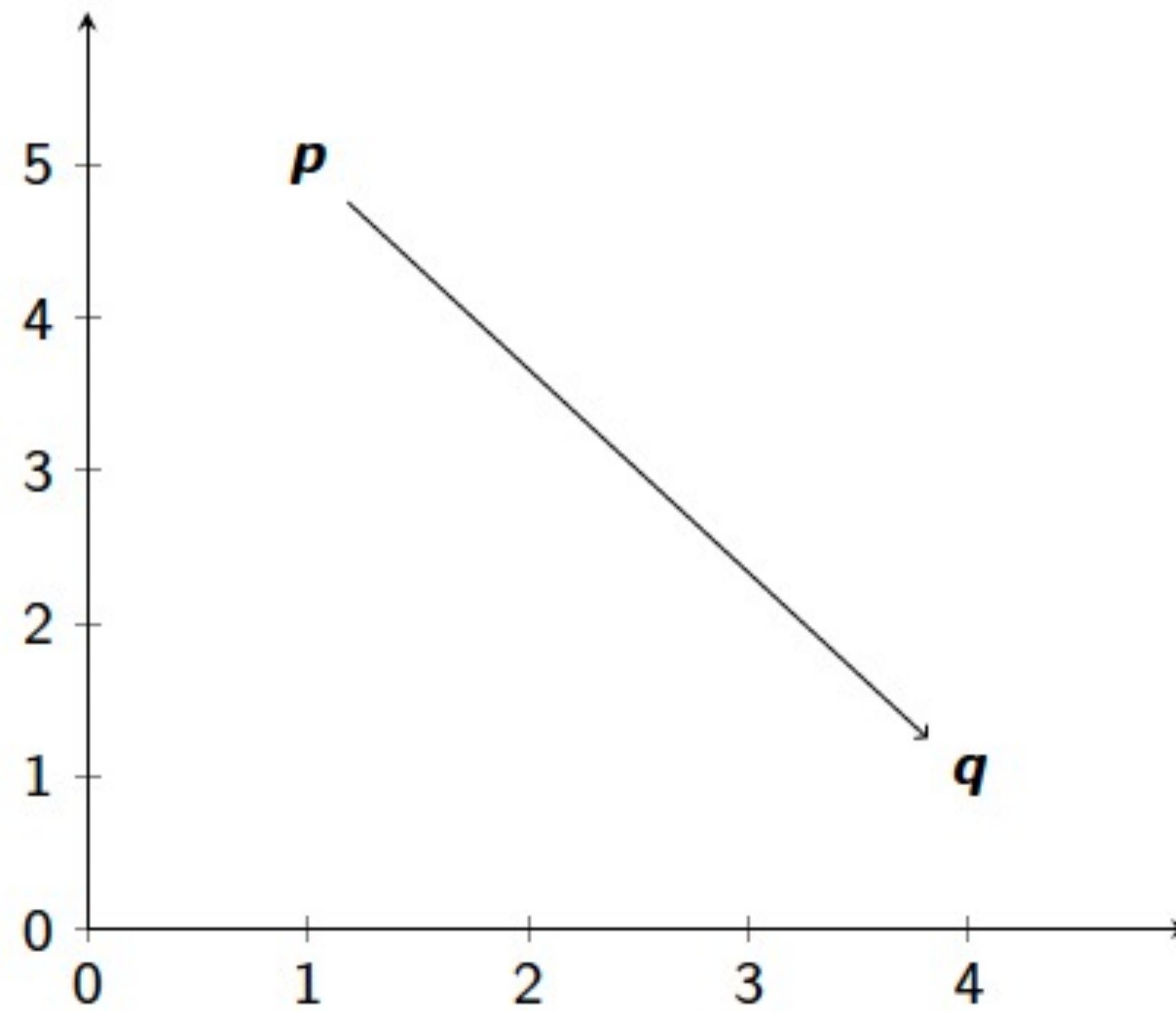
A projection of encoded word vectors shows that similar words are close to each other in feature space.

We say two things are *similar* if they have similar feature vectors, i.e. are close to each other in featurespace.

Collaborative Filtering – Distance

There are a number of ways to measure distance in feature space:

- ▶ Euclidean Distance:



p and **q** are N-dimensional feature vectors,

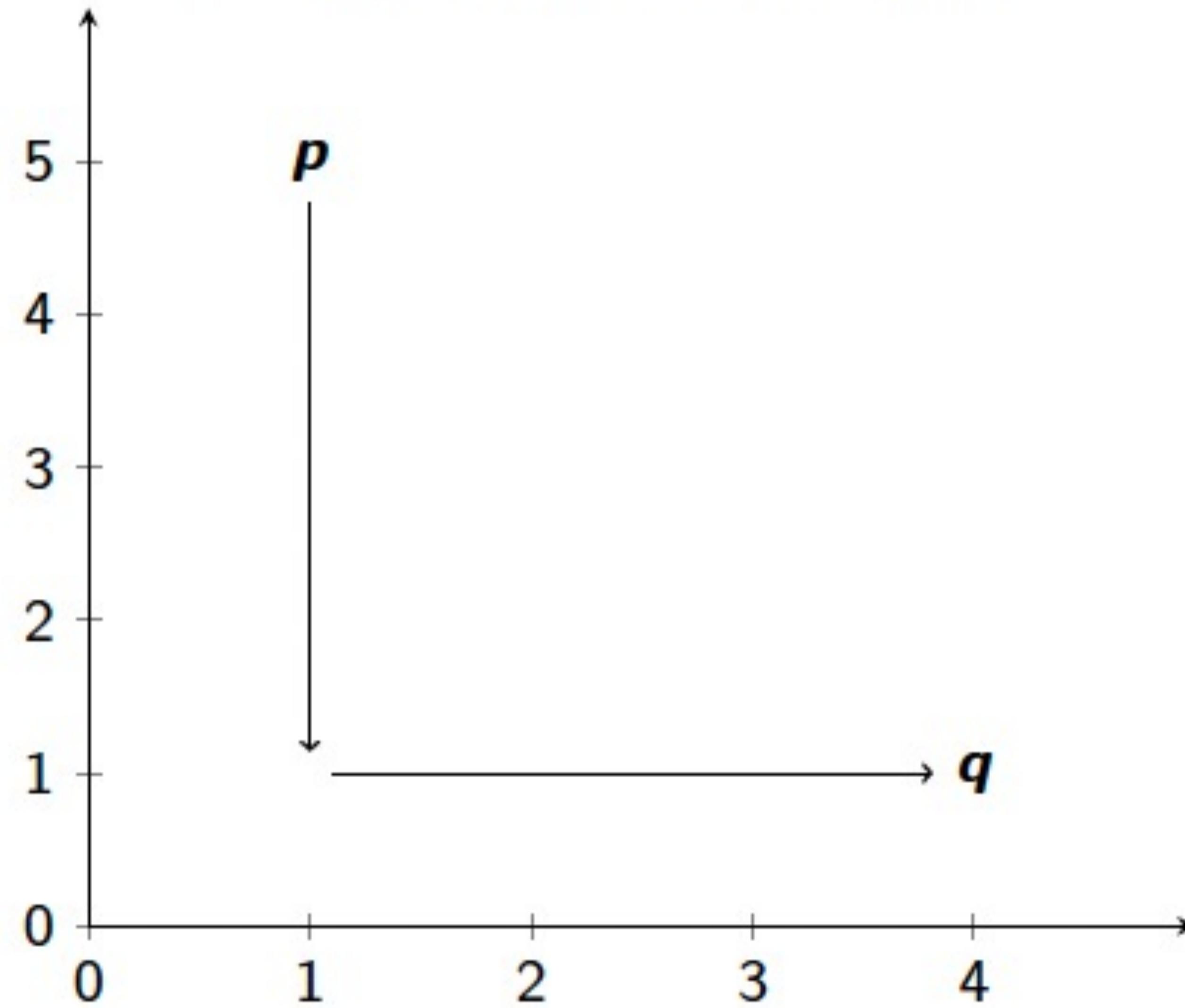
$$\begin{aligned}\mathbf{p} &= [p_1, p_2, \dots, p_N], \\ \mathbf{q} &= [q_1, q_2, \dots, q_N]\end{aligned}$$

Euclidean distance:

$$\|\mathbf{p} - \mathbf{q}\| = \sqrt{\sum_{i=1}^N (q_i - p_i)^2}$$

Collaborative Filtering – Distance

- Manhattan Distance:



p and **q** are N-dimensional feature vectors,

$$\mathbf{p} = [p_1, p_2, \dots, p_N],$$

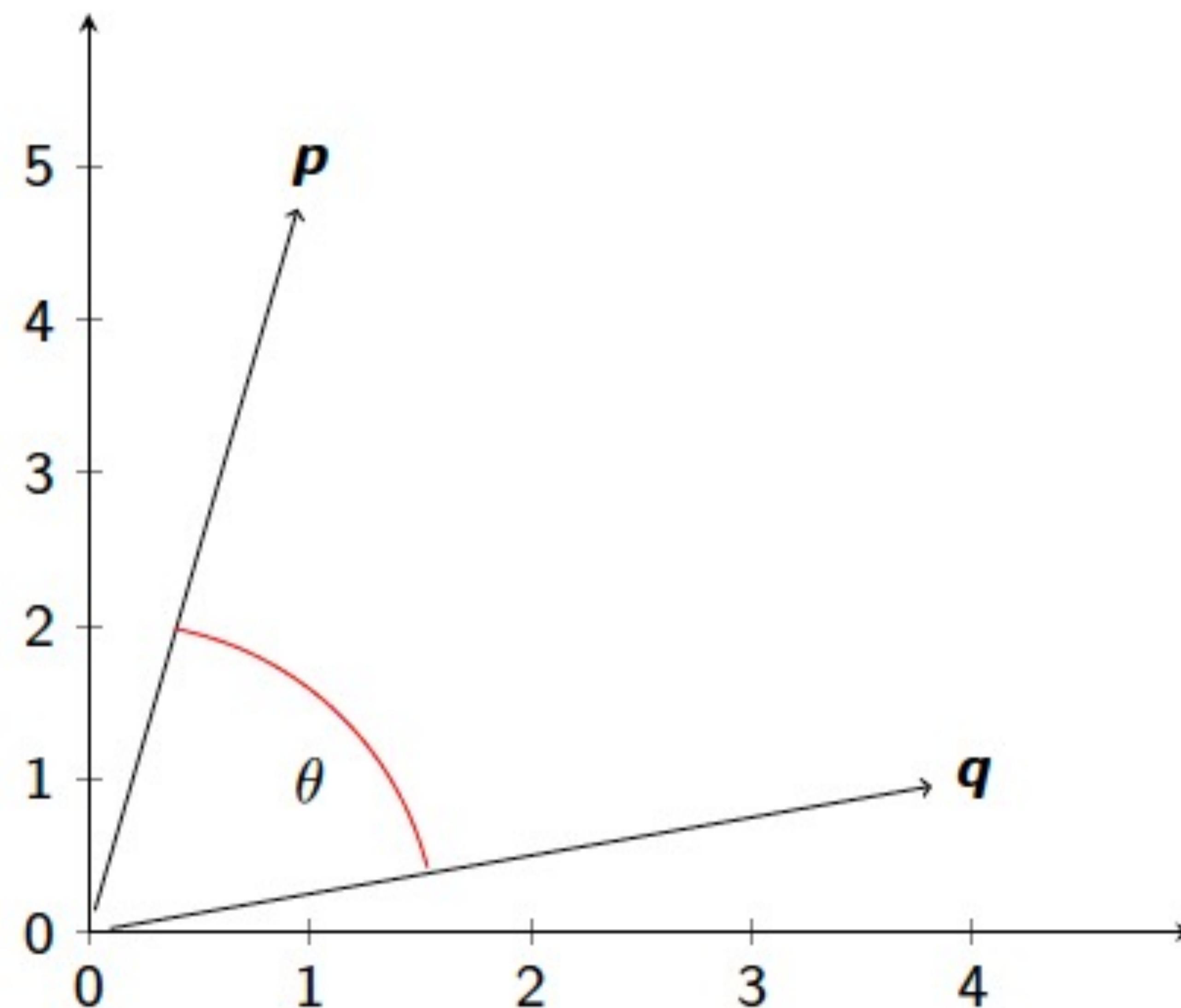
$$\mathbf{q} = [q_1, q_2, \dots, q_N]$$

Manhattan distance:

$$\|\mathbf{p} - \mathbf{q}\|_1 = \sum_{i=1}^N |q_i - p_i|$$

Collaborative Filtering – Distance

► Cosine Similarity



Only measures direction, not magnitude of vector.

\mathbf{p} and \mathbf{q} are N-dimensional feature vectors,

$$\mathbf{p} = [p_1, p_2, \dots, p_N],$$

$$\mathbf{q} = [q_1, q_2, \dots, q_N]$$

Cosine Similarity:

$$\cos(\theta) = \frac{\mathbf{p} \cdot \mathbf{q}}{|\mathbf{p}| |\mathbf{q}|}$$

$$= \frac{\sum_{i=1}^N p_i q_i}{\sqrt{\sum_{i=1}^N p_i^2} \sqrt{\sum_{i=1}^N q_i^2}}$$

Collaborative Filtering – User Similarity

Need to define a similarity score, based on the idea that similar users have similar tastes, i.e. like the same movies.)

Needs to take in to account sparsity, not all users have seen all movies.

Typically between 0 and 1, where 1 is the same, and 0 is totally different

Can visualise the users in feature space, using two dimensions at a time

Visualisation of users in film space ipynb

Film	Alice	Bob	Carol	Dave
Love Really	4	1		4
Deadly Weapon		1	4	5
Fast and Cross	5		5	4
Star Battles	1	5		

Collaborative Filtering – User Similarity

There are many ways to compute similarity based on Euclidean distance

We *could* chose:

$$sim_{L2}(x, y) = \frac{1}{1 + \sqrt{\sum_{i \in I_{xy}} (r_{x,i} - r_{y,i})^2}}$$

where $r_{x,i}$ is the rating from user x for item i
 I_{xy} is set of items rated by both x and y

i.e. when the distance is 0, the similarity is 1, but when the distance is large, similarity $\rightarrow 0$

Collaborative Filtering – User Similarity

Alternatively, calculate correlation of users, based on ratings they share

Using Pearson's Correlation: standard measure of dependence between two related variables.

$$sim_{Pearson}(x, y) = \frac{\sum_{i \in I_{xy}} (r_{x,i} - \bar{r}_x)(r_{y,i} - \bar{r}_y)}{\sqrt{\sum_{i \in I_{xy}} (r_{x,i} - \bar{r}_x)^2 \sum_{i \in I_{xy}} (r_{y,i} - \bar{r}_y)^2}}$$

Where \bar{r}_x is average rating user x gave for all items in I_{xy}

Correlation between users in ipynb

Collaborative Filtering – User Similarity

Can also use cosine similarity

$$sim_{cos}(x, y) = \frac{\sum_{i \in I_{xy}} r_{xi} r_{yi}}{\sqrt{\sum_{i \in I_{xy}} r_{xi}^2} \sqrt{\sum_{i \in I_{xy}} r_{yi}^2}}$$

Only performed over the items which are rated by both users

Collaborative Filtering – User Similarity

Users are inconsistent. Some users always give out 5s to films they like, whereas some are more picky.

For example, look at Lisa and Jill, both rank the films in the same order, but give different ratings.

Pearson correlation corrects for this, but Euclidean similarity doesn't.

Data normalisation and mean centering can overcome this.]

Data standardisation

Collaborative Filtering – User Filtering

We now have a set of measures for computing the similarity between users

Produce a ranked list of best matches to a target user. Typically want the top- N users

May only want to consider a subset of users, i.e. those who rated a particular item.

Ranking users by similarity ipynb

Collaborative Filtering – Recommending

Now we have a list of similar users, how can we recommend items?

Predict rating $r_{u,i}$ of item i by user u as an aggregation of the ratings of item i by users similar to u

$$r_{u,i} = \text{aggr}_{\hat{u} \in U}(r_{\hat{u},i})$$

Where U is the set of *top* users most similar to u that rated item i

Multiply the score by the similarity of the user

Normalise by sum of similarities (otherwise items rated more often will dominate)

$$r_{u,i} = \frac{\sum_{\hat{u} \in U} \text{sim}(u, \hat{u}) r_{\hat{u},i}}{\sum_{\hat{u} \in U} |\text{sim}(u, \hat{u})|}$$

This is *User Based Filtering*

Demo: User based recommendation

Collaborative Filtering – User Based Filtering

Can also aggregate by computing average over similar users

$$r_{u,i} = \frac{1}{N} \sum_{\hat{U} \in U} r_{\hat{U},i}$$

Or by subtracting the average user rating score for all the items they scored, this is to compensate for people that judge generously or meanly.

$$r_{u,i} = \bar{r}_u + \frac{\sum_{\hat{U} \in U} sim(u, \hat{U})(r_{\hat{U},i} - \bar{r}_{\hat{U}})}{\sum_{\hat{U} \in U} |sim(u, \hat{U})|}$$

Collaborative Filtering – Item Based Filtering

We can also compute similarity between items, using the same method.

This provides a *fuzzy* basis for recommending alternative items.

There are more structured ways of identifying what products people buy together using "Market Basket Analysis"

Demo: Item Item Similarity

Film	Alice	Bob	Carol	Dave
Love Really	4	1		4
Deadly Weapon		1	4	5
Fast and Cross	5		5	4
Star Battles	1	5		

Collaborative Filtering – Item Based Filtering

Problems?

- ▶ Need to compute the similarity against every user.
- ▶ Doesn't scale up to millions of users.
- ▶ Computationally hard
- ▶ With many items, may be little overlap, making the similarity calculation hard

Film	Alice	Bob	Carol	Dave
Love Really	4	1		4
Deadly Weapon		1	4	5
Fast and Cross	5		5	4
Star Battles	1	5		

Collaborative Filtering – Item Based Filtering

The comparisons between items will not change as frequently as comparisons between users

So?

- ▶ Precompute and store the most similar items for each item

To make a recommendation for a user:

- ▶ Look at top rated items
- ▶ Aggregate similar items using precomputed similarities

These similarities will change with new ratings, but will change **slowly**

Demo: Precomputing Item Similarity

Collaborative Filtering – Item Based Filtering

To compute recommendations using this approach:

Estimate the rating for unrated item \hat{i} that has a top-N similarity to a rated item i :

$$r_{u,\hat{i}} = \frac{\sum_{i \in I} sim(\hat{i}, i) r_{u,i}}{\sum_{i \in I} sim(\hat{i}, i)}$$

Where I is the subset of all N items similar to \hat{i}

Demo: Item based recommendation

Collaborative Filtering – Comparing User Item Based Filtering

User Based Filtering:

- ▶ Easier to implement
- ▶ No maintenance of comparisons
- ▶ Deals well with datasets that frequently change
- ▶ Deals well with small dense datasets

Item Based Filtering:

- ▶ Maintenance of comparison data necessary
- ▶ Deals well with small dense datasets
- ▶ Also deals well with larger sparse datasets
- ▶ Deals well with frequently changing users

Collaborative Filtering – Problem?

The 'cold start' problem

Collaborative filtering will not work for a new user, or new item.



Collaborative Filtering – Problem?

The 'cold start' problem

Collaborative filtering will not work for a new user, or new item.

For new items: Hybrid approach

- ▶ Use content based features to find similar items
- ▶ Bootstrap ratings for the new item by averaging the ratings users gave to similar items

Collaborative Filtering – Problem?

The 'cold start' problem

Collaborative filtering will not work for a new user, or new item.

For new users: Harder

- ▶ Bootstrap user profile from 'cookies'
- ▶ Ask new users questions

Recommendation Systems – Summary

Recommender systems are worth millions

Collaborative Filtering:

- ▶ Uses peoples behaviour to gather information
- ▶ Doesn't need content based features

User based Neighbourhood approach:

- ▶ Computes similarities between users
- ▶ Predicts unseen item weights using ratings of similar users

Item based Neighbourhood approach:

- ▶ Precomputes similarities between items
- ▶ Predicts unseen user ratings using ratings of similar items