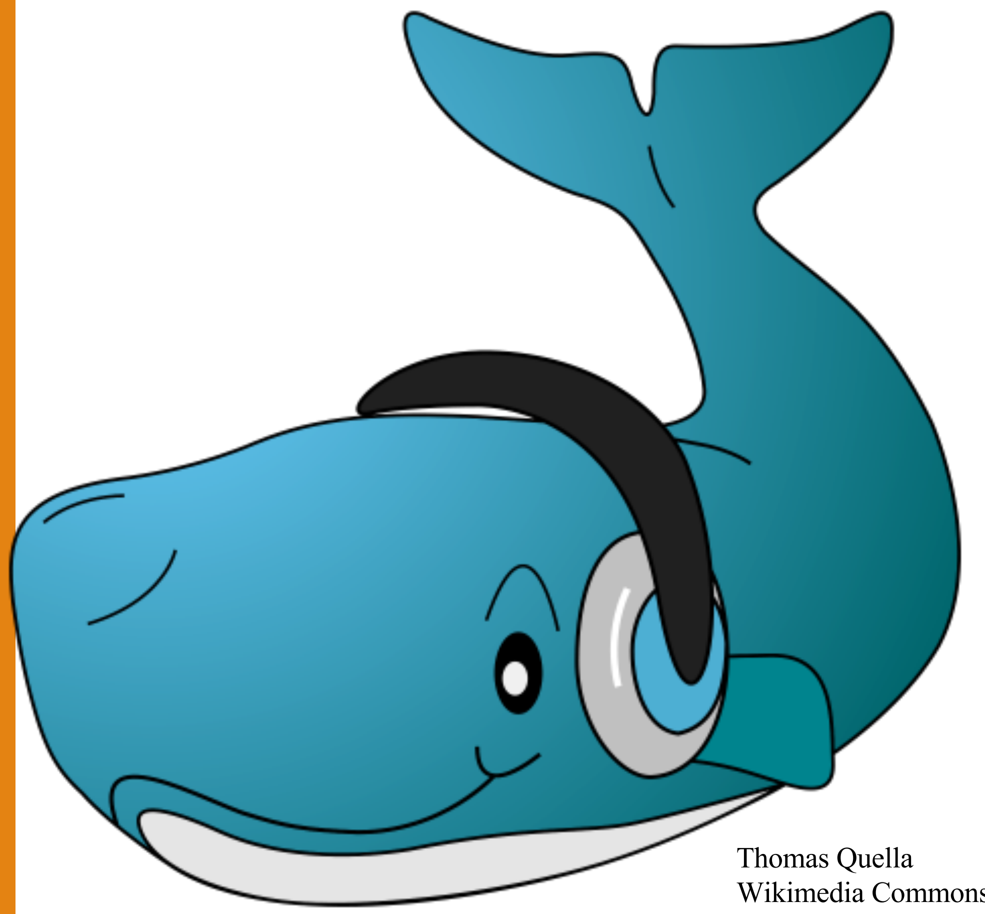
# Recommender Systems and Collaborative Filtering

## Introduction to Recommender Systems

# Recommender systems: The task



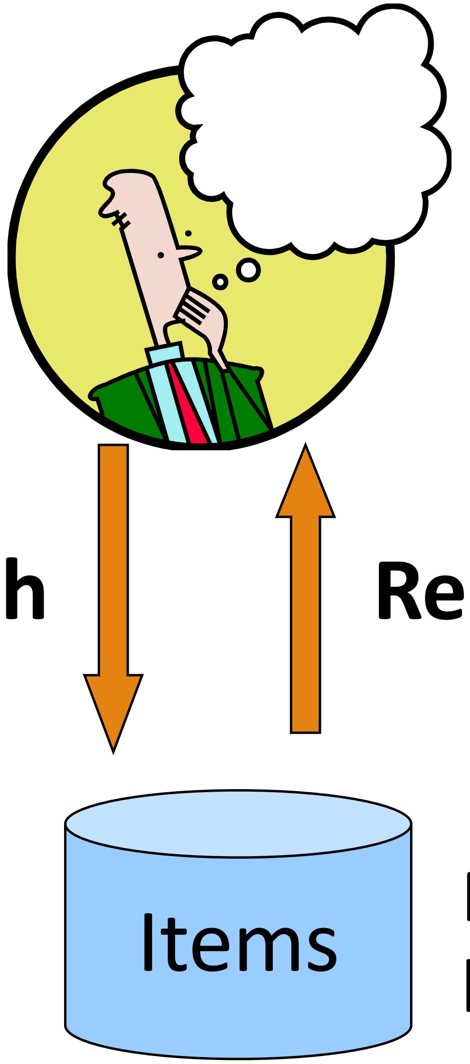
Thomas Quella
Wikimedia Commons

Plays an Ella Fitzgerald song
What should we recommend next?

**Customer W**

# Recommendations

Search




Recommendations

Products, web sites, blogs, news items, …

# Types of Recommendations

## Editorial and hand curated

- List of favorites
- Lists of “essential” items

## Simple aggregates

- Top 10, Most Popular, Recent Uploads

## Tailored to individual users

- Amazon, Netflix, Apple Music…

Today's class

# Knowing how personalized recommendations work

Relevant for building practical news or product recommenders.

# Relevant for understanding how misinformation spreads

**QAnon Supporters And Anti-Vaxxers Are Spreading a Hoax That Bill Gates Created the Coronavirus**

It has no basis in reality, but that hasn't slowed its spread across Facebook and Twitter

The Guardian

Las Vegas survivors furious as YouTube promotes clips calling shooting a hoax

**'Fiction is outperforming reality': how YouTube's algorithm distorts truth**

THE WALL STREET JOURNAL

**How YouTube Drives People to the Internet's Darkest Corners**

Google's video site often recommends divisive or misleading material, despite recent changes designed to fix the problems

# Formal Model

$\boldsymbol{X}$ = set of **Users**

$\boldsymbol{S}$ = set of **Items**

**Utility function** $\boldsymbol{u}: \boldsymbol{X} \times \boldsymbol{S} \rightarrow \boldsymbol{R}$

- $\boldsymbol{R}$ = set of ratings
- $\boldsymbol{R}$ is a totally ordered set
- e.g., **1-5** stars, real number in **[0,1]**

# Utility Matrix

| | | | Harry Potter | | | Twilight | | Star Wars | |
|---|---|---|---|---|---|---|---|---|---|
| | | | HP1 | HP2 | HP3 | TW | SW1 | SW2 | SW3 |
| Anita | $A$ | | 4 | | | 5 | 1 | | |
| Beyonce | $B$ | | 5 | 5 | 4 | | | | |
| Calvin | $C$ | | | | | 2 | 4 | 5 | |
| David | $D$ | | | 3 | | | | | 3 |

# Key Problems

1. **Gathering "known" ratings for matrix**
   - How to collect the data in the utility matrix

2. **Extrapolate unknown ratings from known ones**
   - Mainly interested in high unknown ratings
   - We are not interested in knowing what you don't like but what you like

3. **Evaluating extrapolation methods**
   - How to measure performance of recommendation methods

# (1) Gathering Ratings

**Explicit**

- Ask people to rate items
- Doesn’t work well in practice – people can't be bothered
- Crowdsourcing: Pay people to label items

**Implicit**

- Learn ratings from user actions
  - E.g., purchase (or watch video, or read article) implies high rating

# (2) Extrapolating Utilities

**Key problem:** Utility matrix ***U*** is **sparse**

- Most people have not rated most items

- **The "Cold Start" Problem:**
  - New items have no ratings
  - New users have no history

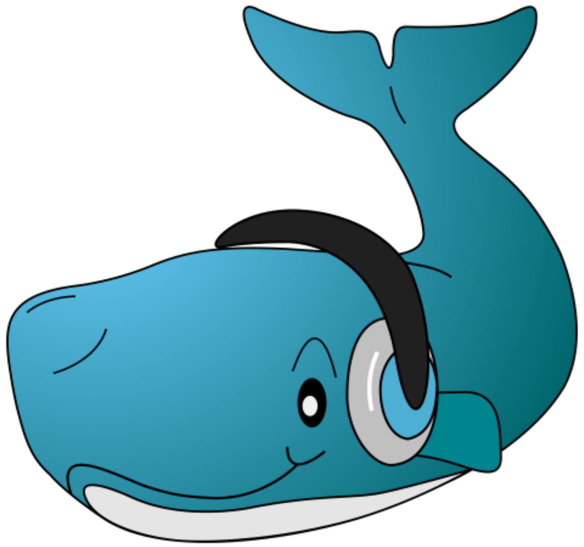
# (2) Extrapolating Utilities

**Three approaches to recommender systems:**

1. Content-based
2. Collaborative Filtering
3. Latent factor (Neural embedding) based

**This lecture!**

# Content-based vs. Collaborative Filtering



Thomas Quella
Wikimedia Commons

## Database

- Ella Fitzgerald: Jazz, Mid-20th century, vocal legend, famous duets, …
- Louis Armstrong: Jazz, Mid-20th century, vocal legend, famous duets, …

Content-based

Suggest Louis Armstrong

Collaborative filtering

## Customer W

- Plays Ella Fitzgerald
- What should we recommend next?

Photographer: Paul Stafford for www.travelmag.com
https://www.flickr.com/photos/113306963@N05/33886542421

## Customer D

- Plays Ella Fitzgerald
- Plays Louis Armstrong

Recommender Systems and Collaborative Filtering

# Introduction to Recommender Systems

Recommender Systems and Collaborative Filtering

# Content-based Recommender Systems

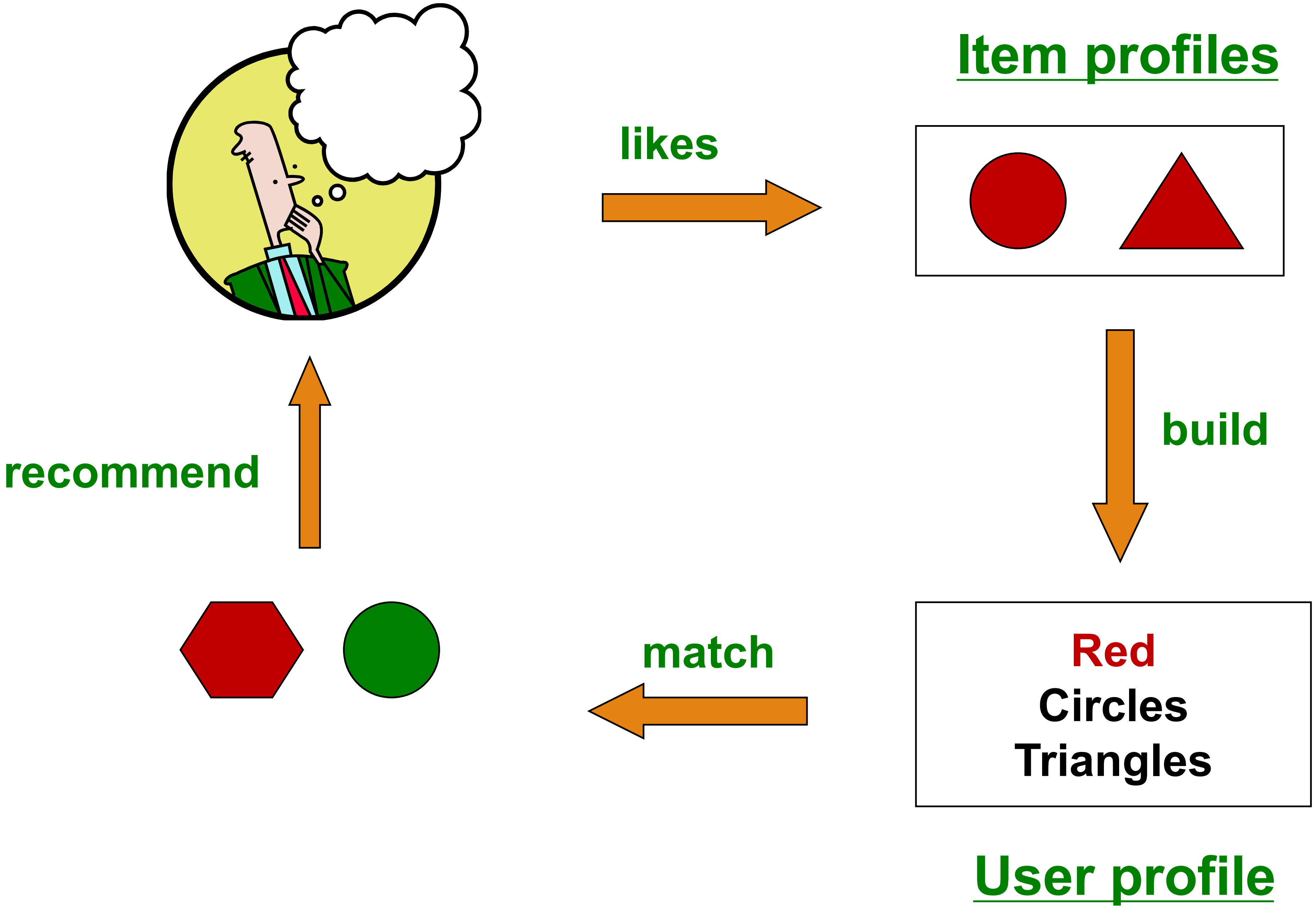
# Content-based Recommendations

**Main idea:** Recommend items to customer ***x*** similar to previous items rated highly by ***x***

**Movie recommendations**
- Recommend movies with same actor(s), director, genre, …

**Websites, blogs, news**
- Recommend other sites with similar types or words

# Plan of Action



# Item Profiles

For each item, create an **item profile**

**Profile is a set (vector) of features**

- **Movies:** genre, director, actors, year…
- **Text:** Set of "important" words in document

**How to pick important features?**

- **TF-IDF** (Term frequency * Inverse Doc Frequency)
- For example use all words whose tf-idf > threshold, normalized for document length

# Content-based Item Profiles

| | Melissa McCarthy | Actor A | Actor B | … | Johnny Depp | Comic Genre | Spy Genre | Pirate Genre |
|---|---|---|---|---|---|---|---|---|
| **Movie X** | 0 | 1 | 1 | 0 | 1 | 1 | 0 | 1 |
| **Movie Y** | 1 | 1 | 0 | 1 | 0 | 1 | 1 | 0 |

But what if we want to have real or ordinal features too?

# Content-based Item Profiles

| | Melissa McCarthy | Actor A | Actor B | … | Johnny Depp | Comic Genre | Spy Genre | Pirate Genre | Avg Rating |
|---|---|---|---|---|---|---|---|---|---|
| **Movie X** | 0 | 1 | 1 | 0 | 1 | 1 | 0 | 1 | 3 |
| **Movie Y** | 1 | 1 | 0 | 1 | 0 | 1 | 1 | 0 | 4 |

For example "average rating"

Maybe we want a scaling factor α between binary and numeric features

# Content-based Item Profiles

| | Melissa McCarthy | Actor A | Actor B | … | Johnny Depp | Comic Genre | Spy Genre | Pirate Genre | Avg Rating |
|---|---|---|---|---|---|---|---|---|---|
| **Movie X** | 0 | 1 | 1 | 0 | 1 | 1 | 0 | 1 | 3α |
| **Movie Y** | 1 | 1 | 0 | 1 | 0 | 1 | 1 | 0 | 4α |

Scaling factor α between binary and numeric features

$$\text{Cosine(Movie X, Movie Y)} = \frac{2+12\alpha^2}{\sqrt{5+9\alpha^2}\sqrt{5+16\alpha^2}}$$

$\alpha = 1$: 0.82 $\alpha = 2$: 0.94 $\alpha = 0.5$: 0.69

# User Profiles

**Want a vector with the same components/dimensions as items**

- Could be 1s representing user purchases
- Or arbitrary numbers from a rating

**User profile is aggregate of items:**

- Weighted average of rated item profiles

# Sample user profile

- Items are movies
- Utility matrix has 1 if user has seen movie
- 20% of the movies user U has seen have Melissa McCarthy
- U["Melissa McCarthy"] = 0.2

| | Melissa McCarthy | Actor A | Actor B | … | |
|---|---|---|---|---|---|
| User U | 0.2 | .005 | 0 | 0 | … |

# Prediction

- Users and items have the same dimensions!

| | Melissa McCarthy | Actor A | Actor B | … | |
|---|---|---|---|---|---|
| Movie i | 0 | 1 | 1 | 0 | … |
| User x | 0.2 | .005 | 0 | 0 | 0 |

- So just recommend the items whose vectors are most similar to the user vector!

- Given user profile $\boldsymbol{x}$ and item profile $\boldsymbol{i}$,
- estimate $u(\boldsymbol{x}, \boldsymbol{i}) = \cos(\boldsymbol{x}, \boldsymbol{i}) = \frac{\boldsymbol{x} \cdot \boldsymbol{i}}{||\boldsymbol{x}|| \cdot ||\boldsymbol{i}||}$

# Pros: Content-based Approach

**+: No need for data on other users**

- No user sparsity problems

**+: Able to recommend to users with unique tastes**

**+: Able to recommend new & unpopular items**

- No first-rater problem

**+: Able to provide explanations**

- Just list the content-features that caused an item to be recommended

# Cons: Content-based Approach

- **Finding the appropriate features is hard**
  - E.g., images, movies, music
- **Recommendations for new users**
  - **How to build a user profile?**
- **Overspecialization**
  - Never recommends items outside user's content profile
  - People might have multiple interests
  - **Unable to exploit quality judgments of other users**

# Content-based Recommender Systems

# Collaborative Filtering: User-User

# Collaborative filtering

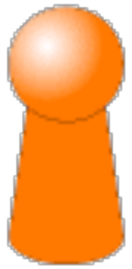
Instead of using content features of items to determine what to recommend

Find similar users and recommend items that they like!

# Collaborative Filtering
## Version 1: "User-User" Collaborative Filtering

Consider user ***x***

and unrated item ***i***




Find set ***N*** of other users whose ratings are "**similar**" to ***x***'s ratings

Estimate ***x***'s ratings for ***i*** based on ratings for ***i*** of users in ***N***

# Collaborative filtering

Find similar users and recommend items that they like:

- Represent users by their rows in the **utility matrix**
- Two users are similar if their vectors are similar!

| | Harry Potter | | | Twilight | Star Wars | | |
|---|---|---|---|---|---|---|---|
| | HP1 | HP2 | HP3 | TW | SW1 | SW2 | SW3 |
| $A$ | 4 | | | 5 | 1 | | |
| $B$ | 5 | 5 | 4 | | | | |
| $C$ | | | | 2 | 4 | 5 | |
| $D$ | | 3 | | | | | 3 |

# Finding Similar Users

Let $\boldsymbol{r_x}$ be the vector of user $\boldsymbol{x}$'s ratings

$\boldsymbol{r_x}$ = [*, _, _, *, ***]
$\boldsymbol{r_y}$ = [*, _, **, **, _]

$\boldsymbol{r_x}$ = {1, 0, 0, 1, 3}
$\boldsymbol{r_y}$ = {1, 0, 2, 2, 0}

**Cosine similarity measure**

- sim($\boldsymbol{x}$, $\boldsymbol{y}$) = cos($\boldsymbol{r_x}$, $\boldsymbol{r_y}$) = $\frac{r_x \cdot r_y}{||r_x||\,||r_y||}$

**Problem:** This representation leads to unintuitive results

# Problems with raw utility matrix cosine

| | Harry Potter | | | Twilight | Star Wars | | |
|---|---|---|---|---|---|---|---|
| | HP1 | HP2 | HP3 | TW | SW1 | SW2 | SW3 |
| $A$ | 4 | | | 5 | 1 | | |
| $B$ | 5 | 5 | 4 | | | | |
| $C$ | | | | 2 | 4 | 5 | |
| $D$ | | 3 | | | | | 3 |

**Intuitively we want: sim(*A*, *B*) > sim(*A*, *C*)**

$$\text{sim(A,B)} = \frac{4 \times 5}{\sqrt{4^2 + 5^2 + 1^2}\sqrt{5^2 + 5^2 + 4^2}} = 0.380$$

$$\text{sim(A,C)} = \frac{5 \times 2 + 1 \times 4}{\sqrt{4^2 + 5^2 + 1^2}\sqrt{2^2 + 4^2 + 5^2}} = 0.322$$

Yes, 0.380 > 0.322

But only barely works…

# Problem with raw cosine

| | HP1 | HP2 | HP3 | TW | SW1 | SW2 | SW3 |
|---|---|---|---|---|---|---|---|
| $A$ | 4 | | | 5 | 1 | | |
| $B$ | 5 | 5 | 4 | | | | |
| $C$ | | | | 2 | 4 | 5 | |
| $D$ | | 3 | | | | | 3 |

- Problem with cosine:
  - C really loves SW
  - A hates SW
  - B just hasn’t seen it
- Another problem: we’d like to normalize the raters
  - D rated everything the same; not very useful

# Mean-Centered Utility Matrix: subtract the means of each row

| | HP1 | HP2 | HP3 | TW | SW1 | SW2 | SW3 |
|---|---|---|---|---|---|---|---|
| $A$ | 4 | | | 5 | 1 | | |
| $B$ | 5 | 5 | 4 | | | | |
| $C$ | | | | 2 | 4 | 5 | |
| $D$ | | 3 | | | | | 3 |

| | HP1 | HP2 | HP3 | TW | SW1 | SW2 | SW3 |
|---|---|---|---|---|---|---|---|
| $A$ | $2/3$ | | | $5/3$ | $-7/3$ | | |
| $B$ | $1/3$ | $1/3$ | $-2/3$ | | | | |
| $C$ | | | | $-5/3$ | $1/3$ | $4/3$ | |
| $D$ | | 0 | | | | | 0 |

- Now a 0 means no information
- And negative ratings means viewers with opposite ratings will have vectors in opposite directions!

# Modified Utility Matrix: subtract the means of each row

| | HP1 | HP2 | HP3 | TW | SW1 | SW2 | SW3 |
|---|---|---|---|---|---|---|---|
| $A$ | $2/3$ | | | $5/3$ | $-7/3$ | | |
| $B$ | $1/3$ | $1/3$ | $-2/3$ | | | | |
| $C$ | | | | $-5/3$ | $1/3$ | $4/3$ | |
| $D$ | | $0$ | | | | | $0$ |

$$\text{Cos(A,B)} = \frac{(2/3)\times(1/3)}{\sqrt{(2/3)^2+(5/3)^2+(-7/3)^2}\sqrt{(1/3)^2+(1/3)^2+(-2/3)^2}} = 0.092$$

$$\text{Cos(A,C)} = \frac{(5/3)\times(-5/3)+(-7/3)\times(1/3)}{\sqrt{(2/3)^2+(5/3)^2+(-7/3)^2}\sqrt{(-5/3)^2+(1/3)^2+(4/3)^2}} = -0.559$$

Now A and C are (correctly) way further apart than A,B

Terminological Note: subtracting the mean is **mean-centering**, not **normalizing**

(normalizing is dividing by a norm to turn something into a probability), but the textbook (and common usage) sometimes overloads the term “normalize”

# Finding similar users with overlapping-item mean-centering

Let $\boldsymbol{r_x}$ be the vector of user ***x***'s ratings

$\boldsymbol{r_x}$ = {1, 0, 0, 1, 3}

$\boldsymbol{r_y}$ = {1, 0, 2, 2, 0}

$\boldsymbol{r_x}$ = [*, _, _, *, ***]

$\boldsymbol{r_y}$ = [*, _, **, **, _]

**Mean-centering:**

- For each user x, let $\overline{r_x}$ be mean of $r_x$ (ignoring missing values)
- $\overline{r_x}$ = (1 + 1 + 3)/3 = 5/3 $\overline{r_y}$ = (1 + 2 + 2)/3 = 5/3
- Subtract this average from each of their ratings
  - (but do nothing to the "missing values"; they stay "null").
  - mean centered $r_x$ = {-2/3, 0, 0, -2/3, 4/3}

**One new idea: Keep only items they both rate (unlike 2 slides ago)**

$\boldsymbol{r_x}$ = {-2/3, , , -2/3, }

$\boldsymbol{r_y}$ = {-2/3, , , 1/3, }

$\boldsymbol{r_x}$ = {-2/3, -2/3}

$\boldsymbol{r_y}$ = {-2/3, 1/3}

**Now take cosine:**

- Now compute cosine between user vectors
  - cos([-2/3, -2/3], [-2/3, 1/3])

# Mean-centered overlapping-item cosine similarity

Let $\boldsymbol{r_x}$ be the vector of user $\boldsymbol{x}$'s ratings,and $\overline{r_x}$ be its mean (ignoring missing values)

**Instead of basic cosine similarity measure**

- sim($\boldsymbol{x}$, $\boldsymbol{y}$) = cos($\boldsymbol{r_x}$, $\boldsymbol{r_y}$) = $\frac{r_x \cdot r_y}{||r_x||\ ||r_y||}$

**Mean-centered overlapping-item cosine similarity**

(Variant of Pearson correlation)

- $\boldsymbol{S_{xy}}$ = items rated by both users $\boldsymbol{x}$ and $\boldsymbol{y}$

$$\boldsymbol{sim(x,y)} = \frac{\sum_{s \in S_{xy}} (\boldsymbol{r_{xs}} - \overline{\boldsymbol{r_x}})(\boldsymbol{r_{ys}} - \overline{\boldsymbol{r_y}})}{\sqrt{\sum_{s \in S_{xy}} (\boldsymbol{r_{xs}} - \overline{\boldsymbol{r_x}})^2} \sqrt{\sum_{s \in S_{xy}} (\boldsymbol{r_{ys}} - \overline{\boldsymbol{r_y}})^2}}$$

# Rating Predictions

**From similarity metric to recommendations for an unrated item *i*:**

Let $\boldsymbol{r_x}$ be the vector of user ***x***'s ratings

Let ***N*** be the set of ***k*** users most similar to ***x*** who have rated item ***i***

**Prediction for item *i* of user *x*:**

- Rate i as the mean of what k-people-like-me rated i

$$r_{xi} = \frac{1}{k} \sum_{y \in N} r_{yi}$$

- Even better: Rate i as the mean weighted by their similarity to me …

$$r_{xi} = \frac{\sum_{y \in N} s_{xy}\, r_{yi}}{\sum_{y \in N} s_{xy}}$$

**Shorthand:**

$$\boldsymbol{s_{xy} = sim(x, y)}$$

- **Many other tricks possible…**

Recommender Systems and Collaborative Filtering

# Collaborative Filtering: User-User

# Collaborative Filtering: Item-Item

# Collaborative Filtering Version 2: Item-Item Collaborative Filtering

**So far: User-user collaborative filtering**

**Alternate view that often works better: Item-item**

- For item ***i***, find other similar items
- Estimate rating for item ***i*** based on ratings for those similar items
- Can use same similarity metrics and prediction functions as in user-user model
- "Rate i as the mean of my ratings for other items, weighted by their similarity to i"

$$\boxed{r_{xi} = \frac{\sum_{j \in N(i;x)} s_{ij} \; r_{xj}}{\sum_{j \in N(i;x)} s_{ij}}}$$

***N(i;x)***…set of items rated by ***x*** *and* similar to ***i***
$s_{ij}$… similarity of items ***i*** and ***j***
$r_{xj}$…rating of user ***x*** on item ***j***

# Item-Item CF (|N|=2)

users

| movies | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 1 | | 3 | | | 5 | | | 5 | | 4 | |
| 2 | | | 5 | 4 | | | 4 | | | 2 | 1 | 3 |
| 3 | 2 | 4 | | 1 | 2 | | 3 | | 4 | 3 | 5 | |
| 4 | | 2 | 4 | | 5 | | | 4 | | | 2 | |
| 5 | | | 4 | 3 | 4 | 2 | | | | | 2 | 5 |
| 6 | 1 | | 3 | | 3 | | | 2 | | | 4 | |

- unknown rating

- rating between 1 to 5

# Item-Item CF (|N|=2)

**users**

| movies | 1 | 2 | 3 | 4 | **5** | 6 | 7 | 8 | 9 | 10 | 11 | 12 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 1 | | 3 | | ? | 5 | | | 5 | | 4 | |
| 2 | | | 5 | 4 | | | 4 | | | 2 | 1 | 3 |
| 3 | 2 | 4 | | 1 | 2 | | 3 | | 4 | 3 | 5 | |
| 4 | | 2 | 4 | | 5 | | | 4 | | | 2 | |
| 5 | | | 4 | 3 | 4 | 2 | | | | | 2 | 5 |
| 6 | 1 | | 3 | | 3 | | | 2 | | | 4 | |

- estimate rating of movie **1** by user **5**

# Item-Item CF (|N|=2)

users

| movies | 1 | 2 | 3 | 4 | **5** | 6 | 7 | 8 | 9 | 10 | 11 | 12 | sim(1,m) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 1 | | 3 | | ? | 5 | | | 5 | | 4 | | 1.00 |
| 2 | | | 5 | 4 | | | 4 | | | 2 | 1 | 3 | .. |
| **3** | 2 | 4 | | 1 | 2 | | 3 | | 4 | 3 | 5 | | ? |
| 4 | | 2 | 4 | | 5 | | | 4 | | | 2 | | .. |
| 5 | | | 4 | 3 | 4 | 2 | | | | | 2 | 5 | .. |
| **6** | 1 | | 3 | | 3 | | | 2 | | | 4 | | |

**Neighbor selection:**
Identify movies similar to movie **1**, **rated by user 5**

**Here we use mean centered item-overlap cosine as similarity:**
**1)** Subtract mean rating $m_i$ from each movie $i$ between rows
**2)** Compute (item-overlapping) cosine similarities

# Item-Item CF (|N|=2)

users

movies

| | 1 | 2 | 3 | 4 | **5** | 6 | 7 | 8 | 9 | 10 | 11 | 12 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 1 | | 3 | | ? | 5 | | | 5 | | 4 | |

Subtract mean rating $\boldsymbol{m_i}$ from each movie $\boldsymbol{i}$

$$\boldsymbol{m_1} = (1+3+5+5+4)/5 = 18/5$$

| | **1** | **2** | **3** | **4** | **5** | **6** | **7** | **8** | **9** | **10** | **11** | **12** |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **1** | -13/5 | | -3/5 | | ? | 7/5 | | | 7/5 | | 2/5 | |
| **3** | -1 | 1 | | -2 | -1 | | 0 | | 1 | 0 | 2 | |
| **6** | -8/5 | | 2/5 | | 2/5 | | | -3/5 | | | 7/5 | |

Showing computation only for #3 and #6

**Neighbor selection:**
Identify movies similar to movie **1**, **rated by user 5**

**Here we use mean centered item-overlap cosine as similarity:**
**1)** Subtract mean rating $\boldsymbol{m_i}$ from each movie $\boldsymbol{i}$
**2)** Compute (item-overlapping) cosine similarities between rows

# Item-Item CF (|N|=2)

users

| movies | 1 | 2 | 3 | 4 | **5** | 6 | 7 | 8 | 9 | 10 | 11 | 12 | sim(1,m) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | -13/5 | | -3/5 | | ? | 7/5 | | | 7/5 | | 2/5 | | 1.00 |
| 2 | | | 5 | 4 | | | 4 | | | 2 | 1 | 3 | .. |
| **3** | -1 | 1 | | -2 | -1 | | 0 | | 1 | 0 | 2 | | ? |
| 4 | | 2 | 4 | | 5 | | | 4 | | | 2 | | .. |
| 5 | | | 4 | 3 | 4 | 2 | | | | | 2 | 5 | .. |
| **6** | -8/5 | | 2/5 | | 2/5 | | | -3/5 | | | 7/5 | | ? |

**Neighbor selection:**
Identify movies similar to movie **1**, **rated by user 5**

**Here we use mean centered item-overlap cosine as similarity:**
**1)** Subtract mean rating $m_i$ from each movie $i$
**2)** Compute (item-overlapping) cosine similarities between rows

# Compute Cosine Similarity:

For rows 1 and 3, they both have values for users 1, 9 and 11.

$$\text{sim}(1, 3) = \frac{(-13/5)(-1)+(7/5)(1)+(2/5)(2)}{\sqrt{(-13/5)^2+(7/5)^2+(2/5)^2}\cdot\sqrt{(-1)^2+(1)^2+(2)^2}} \approx 0.658$$

For rows 1 and 6, they both have values for users 1, 3 and 11.

$$\text{sim}(1, 6) = \frac{(-13/5)(-8/5)+(-3/5)(2/5)+(2/5)(7/5)}{\sqrt{(-13/5)^2+(-3/5)^2+(2/5)^2}\cdot\sqrt{(-8/5)^2+(2/5)^2+(7/5)^2}} \approx 0.768$$

# Item-Item CF (|N|=2)

users

| movies | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | sim(1,m) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 1 | | 3 | | ? | 5 | | | 5 | | 4 | | 1.000 |
| 2 | | | 5 | 4 | | | 4 | | | 2 | 1 | 3 | .. |
| **3** | 2 | 4 | | 1 | 2 | | 3 | | 4 | 3 | 5 | | .658 |
| 4 | | 2 | 4 | | 5 | | | 4 | | | 2 | | .. |
| 5 | | | 4 | 3 | 4 | 2 | | | | | 2 | 5 | .. |
| **6** | 1 | | 3 | | 3 | | | 2 | | | 4 | | .768 |

**Compute similarity weights:**

**$s_{1,3}$=.658, $s_{1,6}$=.768** (we compute $s_{1,2}$, $s_{1,4}$, $s_{1,5}$ too; let's assume those are smaller)

# Item-Item CF (|N|=2)
# Approximate rating with weighted mean

users

| movies | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | sim(1,m) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 1 | | 3 | | **2.54** | 5 | | | 5 | | 4 | | 1.000 |
| 2 | | | 5 | 4 | | | 4 | | | 2 | 1 | 3 | .. |
| 3 | 2 | 4 | | 1 | 2 | | 3 | | 4 | 3 | 5 | | .658 |
| 4 | | 2 | 4 | | 5 | | | 4 | | | 2 | | .. |
| 5 | | | 4 | 3 | 4 | 2 | | | | | 2 | 5 | .. |
| 6 | 1 | | 3 | | 3 | | | 2 | | | 4 | | .768 |

**Predict by taking weighted average:**

$r_{1,5}$ = (0.658*2 + 0.768*3) / (0.658+0.768) = 2.54

$$r_{ix} = \frac{\sum_{j \in N(i;x)} s_{ij}\, r_{jx}}{\sum s_{ij}}$$

# Item-Item vs. User-User

- **In practice, <u>item-item</u> often works better than user-user**
- **Why?** Items are simpler, users have multiple tastes
  - (People are more complex than objects)

# Pros/Cons of Collaborative Filtering

**+ Works for any kind of item**

- No feature selection needed

**- Cold Start:**

- Need enough users in the system to find a match

**- Sparsity:**

- The user/ratings matrix is sparse
- Hard to find users that have rated the same items

**- First rater:**

- Cannot recommend an item that has not been previously rated

**- Popularity bias:**

- Cannot recommend items to someone with unique taste
- Tends to recommend popular items

**- Ethical and social issues:**

- Can lead to filter bubbles and radicalization spirals

Recommender Systems and Collaborative Filtering

# Collaborative Filtering: Item-Item

Recommender Systems and Collaborative Filtering

# Simplified item-item similarity computation for our tiny PA6 dataset

# Simplified item-item for our tiny PA6 dataset

First, assume you've converted all the values to

+1 (like),

0 (no rating)

−1 (dislike)

users

| movies | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 1 | | 3 | | | 5 | | | 5 | | 4 | |
| 2 | | | 5 | 4 | | | 4 | | | 2 | 1 | 3 |
| 3 | 2 | 4 | | 1 | 2 | | 3 | | 4 | 3 | 5 | |
| 4 | | 2 | 4 | | 5 | | | 4 | | | 2 | |
| 5 | | | 4 | 3 | 4 | 2 | | | | | 2 | 5 |
| 6 | 1 | | 3 | | 3 | | | 2 | | | 4 | |

# Simplified item-item for our tiny PA6 dataset

First, assume you've converted all the values to

+1 (like),

0 (no rating)

–1 (dislike)

users

| movies | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | -1 | | 1 | | | 1 | | | 1 | | 1 | |
| 2 | | | 1 | 1 | | | 1 | | | -1 | -1 | 1 |
| 3 | -1 | 1 | | -1 | -1 | | 1 | | 1 | 1 | 1 | |
| 4 | | -1 | 1 | | 1 | | | 1 | | | -1 | |
| 5 | | | 1 | 1 | 1 | -1 | | | | | -1 | 1 |
| 6 | -1 | | 1 | | 1 | | | -1 | | | 1 | |

# Simplified item-item for our tiny PA6 dataset

Assume you've **binarized**, i.e. converted all the values to

- +1 (like), 0 (no rating) –1 (dislike)

For this binary case, some tricks that the TAs recommend:

- **Don't mean-center users, just keep the raw +1,0,-1**
- **Don't normalize (i.e. don't divide the product by the sum)**
- **i.e., instead of this:**

$$r_{xi} = \frac{\sum_{j \in N(i;x)} s_{ij}\, r_{xj}}{\sum_{j \in N(i;x)} s_{ij}}$$

- **Just do this:**

$$r_{xi} = \sum_{j \in N(i;x)} s_{ij}\, r_{xj}$$

***$s_{ij}$***… similarity of items ***i*** and ***j***
***$r_{xj}$***…rating of user ***x*** on item ***j***
***N(i;x)***…set of items rated by ***x***

- **Don't use mean-centered item-overlap cosine to compute $s_{ij}$**
  - **Just use cosine**

# Simplified item-item for our tiny PA6 dataset

1. binarize, i.e. convert all values to
   - +1 (like), 0 (no rating) −1 (dislike)
2. The user x gives you (say) ratings for 2 movies m1 and m2
   - $r_{xj}$…rating of user ***x*** on item ***j***
3. For each movie *i* in the dataset
   - $r_{xi} = \sum_{j \in (m1,m2)} s_{ij}\, r_{xj}$
   - Where $s_{ij}$… cosine between vectors for movies ***i*** and ***j***
4. Recommend the movie *i* with max $r_{xi}$

Recommender Systems and Collaborative Filtering

# Simplified item-item similarity computation for our tiny PA6 dataset

# Recommender Systems and Collaborative Filtering

## Evaluation and Implications

# YouTube's Recommendation Algorithm

Covington, Adams, Sargin 2016. Deep Neural Networks for YouTube Recommendations

1. Represent each video and user as an embedding
2. Train a huge neural net classifier (softmax over millions of possible videos) to predict the next video the user will watch
3. Input features:
   - User's watch history (video ids)
   - User's recent queries (word embeddings)
   - Date, popularity, virality of video
4. Learn **embeddings** for **videos** and **users** in training

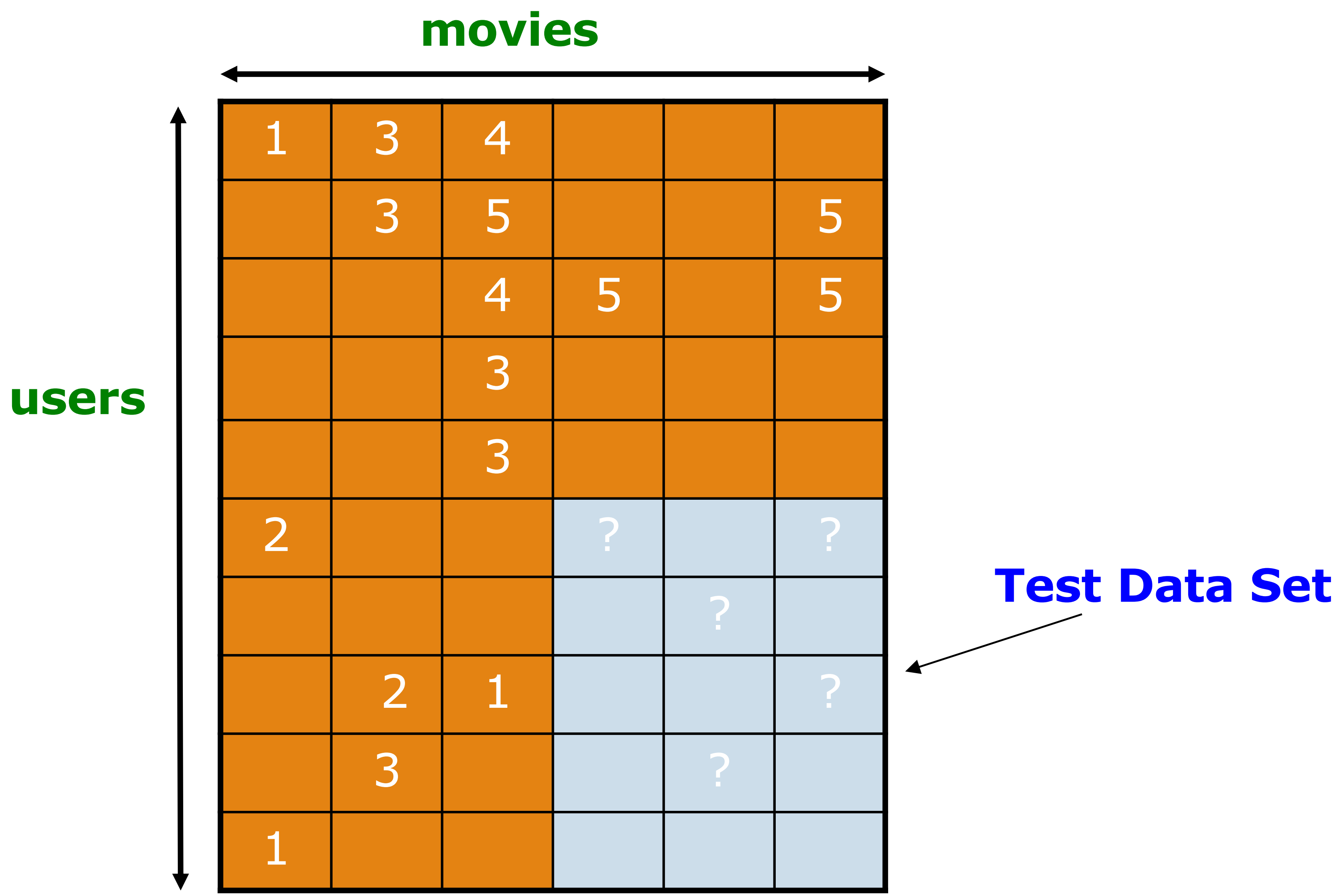
# Evaluation

**movies**

**users**

| | | | | | |
|---|---|---|---|---|---|
| 1 | 3 | 4 | | | |
| | 3 | 5 | | | 5 |
| | | 4 | 5 | | 5 |
| | | 3 | | | |
| | | 3 | | | |
| 2 | | | 2 | | 2 |
| | | | | 5 | |
| | 2 | 1 | | | 1 |
| | 3 | | | 3 | |
| 1 | | | | | |

# Evaluation



# Evaluating Predictions

**Compare predictions with known ratings**

- **Root-mean-square error** (RMSE)
  - $\sqrt{\frac{\sum_{xi}\left(r_{xi}-r_{xi}^{*}\right)^{2}}{N}}$
  - where $\boldsymbol{r_{xi}}$ is predicted, $\boldsymbol{r_{xi}^{*}}$ is the true rating of $\boldsymbol{x}$ on $\boldsymbol{i}$
- **Rank Correlation**:
  - Spearman's *correlation* between system's and user's complete rankings

# But is predicting watching the right loss function?

# What could go wrong? Ethical and societal implications in recommendation engines.

Milano, Silvia, Mariarosaria Taddeo, and Luciano Floridi. "Recommender systems and their ethical challenges." *AI & SOCIETY* 35, no. 4 (2020): 957-967.

- Spread of misinformation and propaganda
- Filter bubbles
- Inappropriate or unethical content
- Opacity
- Violating user privacy

# What could go wrong? Ethical and societal implications

Howard, Ganesh, Lioustiou. 2019. The IRA, Social Media, and Political Polarization in the United States, 2012-2018

## Propaganda campaigns

- Russia Internet Research Agency (IRA)
  - attack on the United States 2013-2018
  - computational propaganda on YouTube, Facebook, Instagram, to misinform/polarize US voters.
  - Goal: induce African American, Mexican American voters to boycott elections

# Ethical and societal implications: Filter bubbles

THE WALL STREET JOURNAL

**How YouTube Drives People to the Internet's Darkest Corners**

Google's video site often recommends divisive or misleading material, despite recent changes designed to fix the problems

“I realized really fast that YouTube’s recommendation was putting people into filter bubbles,” Chaslot said. “There was no way out. **If a person was into Flat Earth conspiracies, it was bad for watch-time to recommend anti-Flat Earth videos, so it won’t even recommend them**.”

"The question before us is the ethics of leading people down hateful rabbit holes full of misinformation and lies at scale just because it works to increase the time people spend on the site – and it does work"

- – Zeynep Tufekci

# Open research questions

What would algorithms look like that could recommend but also include these social costs?

Recommender Systems and Collaborative Filtering

# Evaluation and Implications