LECTURE 8 RECOMMENDER SYSTEM

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OUTLINE

Introduction

Similarity Measures

Introduction to Collaborative Filtering

User-based Collaborative Filtering (UBCF)

Item-based Collaborative Filtering (IBCF)

INTRODUCTION

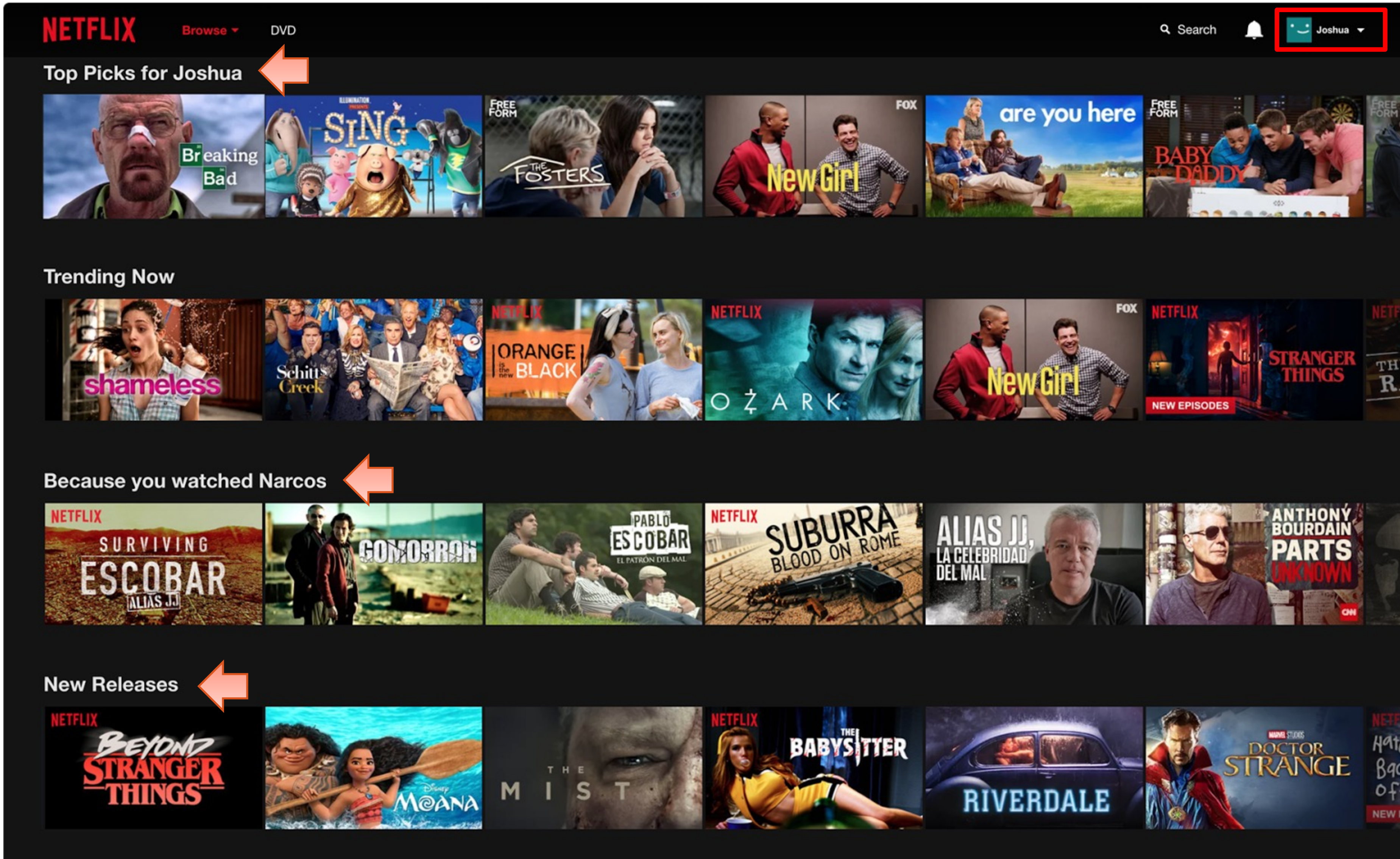
Introduction → Similarity Measures → Introduction to CF → User-based CF → Item-based CF

EXAMPLE OF RECOMMENDER SYSTEMS

amazon

Nuby Ice Gel Teether Keys

NETFLIX PERSONALIZATION



MANY OTHER RECOMMENDER SYSTEMS ONLINE

RECOMMENDER SYSTEMS

Recommender systems aim to:

- provide information that is relevant and useful
- make systems smarter and provide better user experience
- help businesses encourage more purchases

TYPES OF RECOMMENDATIONS

Editorial and hand curated

- Product of the Week
- Staff's favorites
- etc

Simple Aggregates

- Most popular, Top rated

Tailored to individual users

- Personalized recommendations

Will focus on this approach

THE RECOMMENDATION PROBLEM

U **= set of Users**

S **= set of Items**

Utility function ***: U*** **x** ***S*** $\rightarrow$ ***R***

- ***R*** = set of ratings
- E.g. **1-5** stars, real number in **[0,1]**

UTILITY MATRIX

Objective:
Make use of existing data to predict the utility value of each item ***s*** ($\in S$) to each user ***u*** ($\in U$)

Then recommend the top ***k*** items to ***u***

Items

	X-Men	Antman	Frozen	Cinderella	Annabelle
Alice			5	5	2
Bob	4	5		1	
Charlie	3	2			5
…	…	…	…	…	…

Users

PREDICTION

2 common types of predictions:

Rating prediction

- Predict the rating score that a user is likely to give to an item (that is not seen)
- Recommendation is the unseen items with highest ratings

Item prediction

- Predict a ranked list of items that a user is likely to buy or use

KEY CHALLENGES

1. How to gather the ratings?

2. How to derive the unknown ratings?

	X-Men	Antman	Frozen	Cinderella	Annabelle
Alice			5	5	2
Bob	4	5		1	
Charlie	3	2			5
…	…	…	…	…	…

1. GATHER RATINGS

Explicit

- Ask users to rate items
- Doesn’t work well in practice – people can’t be bothered ☹

Implicit

- Learn ratings from user actions
  - E.g. purchase implies high rating
- What about low ratings?

2. DERIVE UNKNOWN RATINGS

Key Problem: Utility matrix is sparse

- Most of the entries are empty
- **Cold start** problem
    - New items have no ratings
    - New users have no history

SIMILARITY MEASURES

Introduction → Similarity Measures → Introduction to CF → User-based CF → Item-based CF

SIMILARITY MEASURES

To find movies similar to a user's interest, there are a few similarity measures that can be adopted:

- Euclidean Distance
- Cosine Similarity
- Correlation
- Jaccard Similarity

User similarity:

- **u** = target user
- **v** = another user
- Each user is represented by their ratings of movies
- Want to find sim(**u**, **v**)
- Then recommend movies watched by similar users

Rating of **u** for movie i

EUCLIDEAN DISTANCE

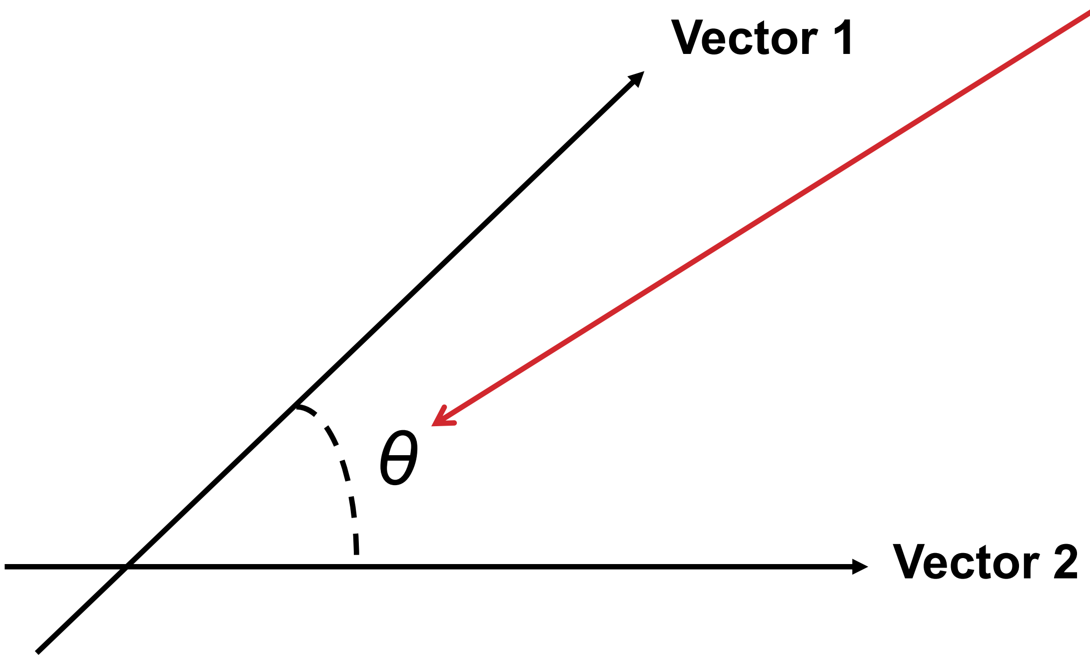
Euclidean distance is the square root of square differences in the components

$$d(\mathbf{u},\mathbf{v}) = \sqrt{(r_{\mathbf{u},1} - r_{\mathbf{v},1})^2 + \ldots + (r_{\mathbf{u},i} - r_{\mathbf{v},i})^2 + \ldots + (r_{\mathbf{u},n} - r_{\mathbf{v},n})^2}$$

	X-Men	Antman	Frozen	Cinderella	Annabelle
Alice			5	5	2
Bob	4	5		1	
…	…	…	…	…	…

COSINE SIMILARITY

Cosine similarity is a measure of similarity between 2 non-zero vectors



Smaller the angle means that they are more similar

Why is **cosine** function is used?

Think about the cosine graph

COSINE SIMILARITY

Cosine similarity is a measure of similarity between 2 non-zero vectors

$$cos(\theta) = cos(\mathbf{u}, \mathbf{v}) = \frac{\vec{r}_u . \vec{r}_v}{||\vec{r}_u||. ||\vec{r}_v||} = \frac{\sum_i r_{\mathbf{u},i} r_{\mathbf{v},i}}{\sqrt{\sum_i^n {r_{\mathbf{u},i}}^2} \sqrt{\sum_i^n {r_{\mathbf{v},i}}^2}}$$

Consider every item. If a user has not rated the item, the rating is 0

Only consider common items where both **u** and **v** have rating

CORRELATION

The Pearson's Correlation Coefficient is another common similarity measure

$$cor(\mathbf{u},\mathbf{v}) = \frac{\sum_{i\in C}(r_{\mathbf{u},i}-\bar{r}_{\mathbf{u}})(r_{\mathbf{v},i}-\bar{r}_{\mathbf{v}})}{\sqrt{\sum_{i\in C}(r_{\mathbf{u},i}-\bar{r}_{\mathbf{u}})^2}\sqrt{\sum_{i\in C}(r_{\mathbf{v},i}-\bar{r}_{\mathbf{v}})^2}}$$

Note: regarding the **mean** value, there seems to be differing opinions whether it is average over all items rated by the user u or just average over items common items
We will stick with the former (i.e. all items rated by user u)

$$cor(\mathbf{u},\mathbf{v}) = \frac{\sum_{i \in C}(r_{\mathbf{u},i} - \bar{r}_{\mathbf{u}})(r_{\mathbf{v},i} - \bar{r}_{\mathbf{v}})}{\sqrt{\sum_{i \in C}\left(r_{\mathbf{u},i} - \bar{r}_{\mathbf{u}}\right)^2}\sqrt{\sum_{i \in C}\left(r_{\mathbf{v},i} - \bar{r}_{\mathbf{v}}\right)^2}}$$

CORRELATION

	X-Men	Antman	Frozen	Cinderella	Annabelle
Alice			5	5	2
Bob	4	5		1	
…	…	…	…	…	…

$$\bar{r}_{\text{Alice}} = (5 + 5 + 2\,)/3 = 4$$

$$\bar{r}_{\text{Bob}} = (4 + 5 + 1\,)/3 = 3.333$$

$$cor(\textbf{Alice},\textbf{Bob}) = \frac{(5 - \bar{r}_{\textbf{Alice}})(1 - \bar{r}_{\textbf{Bob}})}{\sqrt{\left(5 - \bar{r}_{\textbf{Alice}}\right)^2}\sqrt{\left(1 - \bar{r}_{\textbf{Bob}}\right)^2}} = \frac{(1)(-2.333)}{\sqrt{(1)^2}\sqrt{(-2.333)^2}} = -1$$

JACCARD SIMILARITY

Jaccard similarity is a method of finding portion of intersection

$$J(A,B) = \frac{|A \cap B|}{|A \cup B|}$$

E.g. ***A*** = [watching, tv, and, reading, book]

B = [reading, LOTR]

J(***A***,***B***) = 1 / 6

$$J(A, B) = \frac{|A \cap B|}{|A \cup B|}$$

JACCARD SIMILARITY

Unlike previous measures, it does not consider the actual rating in the formula

How to calculate Jaccard similarity for users?

- Possible strategies:
- Convert utility matrix into Boolean flags (1 if rated, 0 if not rated)
- Or
- Treat ratings (3,4,5) as 1 and (1,2,blank) as 0

HANDS-ON: SIMILARITY MEASURES

Download and access:
[Similarity Measures.ipynb]

jupyter Similarity Measures Last Checkpoint: an hour ago (autosaved)

Logout

File Edit View Insert Cell Kernel Widgets Help

Trusted | Python 3

Run Code

Similarity Measure

In [1]:
```
import numpy as np
import pandas as pd
```

In [2]:
```
utility_matrix = pd.DataFrame([[np.nan, np.nan, 5, 5, 2],
                               [4, 5, np.nan, 1, np.nan]],
                    columns = ["x-men", "antman", "frozen", "cinderalla", "annabelle"],
                    index = ["alice", "bob"])
utility_matrix
```

Out[2]:

	x-men	antman	frozen	cinderalla	annabelle
alice	NaN	NaN	5.0	5	2.0
bob	4.0	5.0	NaN	1	NaN

Euclidean Distance

In [3]:
```
alice_rating = utility_matrix.loc["alice"]
alice_rating
```

Out[3]:
```
x-men         NaN
antman        NaN
frozen        5.0
cinderalla    5.0
annabelle     2.0
Name: alice, dtype: float64
```

INTRODUCTION TO COLLABORATIVE FILTERING

Introduction
Similarity Measures
Introduction to CF
User-based CF
Item-based CF

RECALL: UTILITY MATRIX

So far we have not make use of information of the different users and their ratings to aid in the recommendation

Items

	X-Men	Antman	Frozen	Cinderella	Annabelle
Alice			5	5	2
Bob	4	5		1	
Charlie	3	2			5
…	…	…	…	…	…

Users

COLLABORATIVE FILTERING

Collaborative Filtering (CF) make use of the ratings of other users to make the recommendations

The unique thing about CF compared to other approaches is that we do not need content information about the items

- Why is this a benefit?
- The recommender system can work for any items
- We do not need to handcraft different features for different domains

COLLABORATIVE FILTERING

2 main kinds of Collaborative Filtering approaches:

- User-based Collaborative Filtering
    - Making recommendation based on similarity between users
- Item-based Collaborative Filtering
    - Making recommendation based on similarity between items

USER-BASED COLLABORATIVE FILTERING

Introduction → Similarity Measures → Introduction to CF → **User-based CF** → Item-based CF

USER-BASED COLLABORATIVE FILTERING

Strategy:

User x

Compare preferences

All users

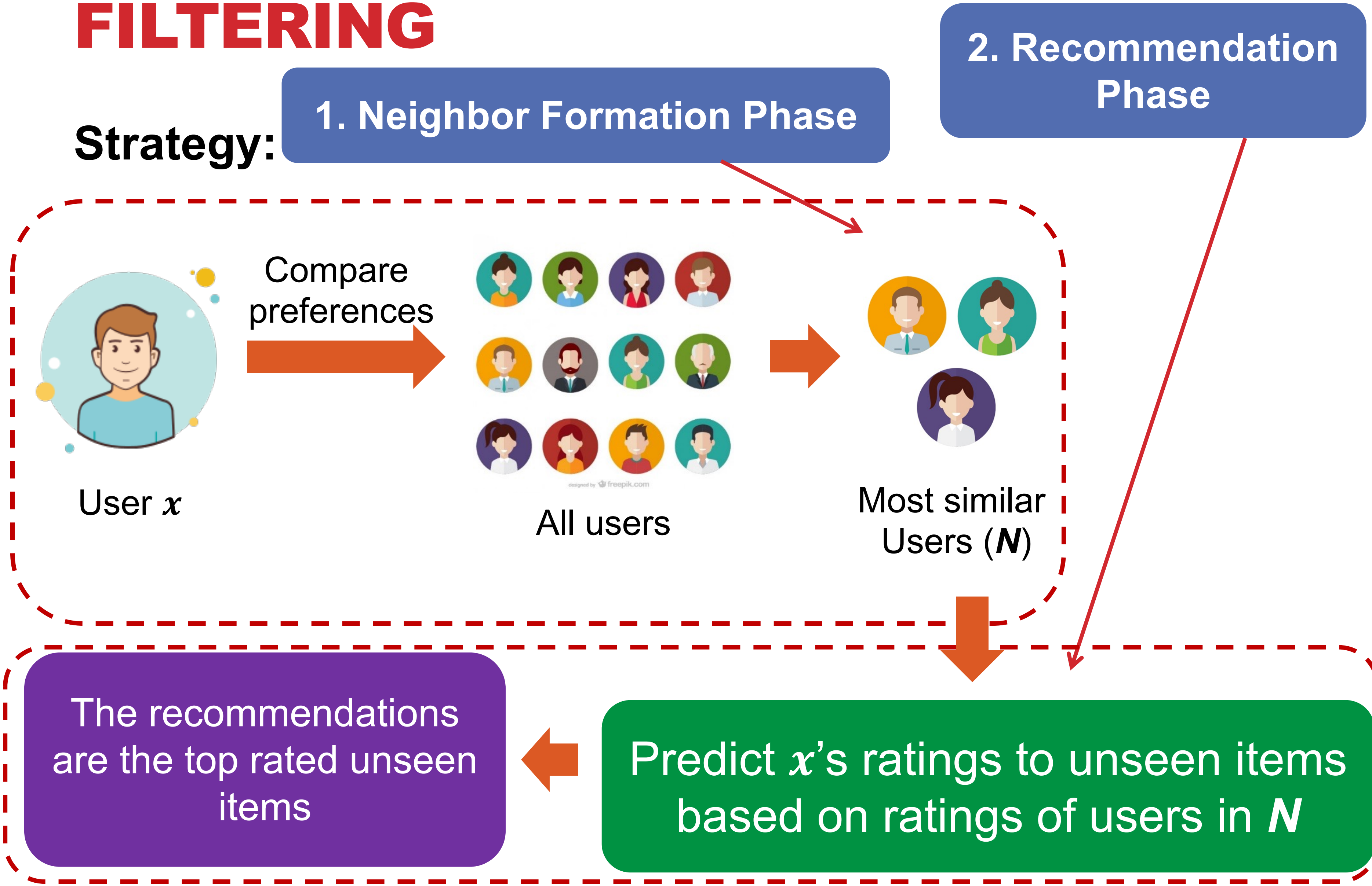
Most similar Users (***N***)

Predict x's ratings to unseen items based on ratings of users in ***N***

The recommendations are the top rated unseen items

USER-BASED COLLABORATIVE FILTERING

Strategy:



NEIGHBORHOOD FORMATION PHASE

	X-Men	Antman	Frozen	Cinderella	Annabelle
Alice		?	5	5	2
Charlie	1		1	2	4
Dave		2	5		1
…	…	…	…	…	…

Suppose we want to predict what **Alice** is likely to give as rating for **Antman**

Find the set of users who have also watched **Antman** and determine the set of most similar users denoted as ***N***

NEIGHBORHOOD FORMATION PHASE

How to calculate the similarity between users?

- Have discussed the common similarity measures:
  - Euclidean Distance
  - Cosine Similarity
  - Correlation
  - Jaccard Similarity

SIMILARITY BETWEEN USERS

	X-Men	Antman	Frozen	Cinderella	Annabelle
Alice			5	5	2
Charlie	1		1	2	4
Dave		2	5		1
…	…	…	…	…	…

Given the above utility matrix, intuitively we want:

- sim(**Alice**, **Charlie**) < sim(**Alice**, **Dave**)
- Using Jaccard Similarity:
  - J(**Alice**, **Charlie**) = 3/4, J(**Alice**, **Dave**) = 2/4
  - J(**Alice**, **Charlie**) $\nless$ J(**Alice**, **Dave**)

SIMILARITY BETWEEN USERS

	X-Men	Antman	Frozen	Cinderella	Annabelle
Alice			5	5	2
Charlie	1		1	2	4
Dave		2	5		1
…	…	…	…	…	…

Given the above utility matrix, intuitively we want:

- sim(**Alice**, **Charlie**) < sim(**Alice**, **Dave**)
- Using Cosine Similarity:
  - cos(**Alice**, **Charlie**) = 0.667, cos(**Alice**, **Dave**) = 0.671
  - cos(**Alice**, **Charlie**) < cos(**Alice**, **Dave**)
  - But very close, so not so ideal

SIMILARITY BETWEEN USERS

	X-Men	Antman	Frozen	Cinderella	Annabelle
Alice			5	5	2
Charlie	1		1	2	4
Dave		2	5		1
…	…	…	…	…	…

Given the above utility matrix, intuitively we want:

- sim(**Alice**, **Charlie**) < sim(**Alice**, **Dave**)
- Using Pearson Correlation Coefficient:
  - cor(**Alice**, **Charlie**) = -0.912, cor(**Alice**, **Dave**) = 0.883
  - cor(**Alice**, **Charlie**) < cor(**Alice**, **Dave**)
  - Much better!

NEIGHBORHOOD FORMATION PHASE

Once we have all the similarity value between Alice and other users, we need to determine *N* (the set of most similar users)

- How to determine ***N***?
- 2 common approaches:
  - Rank the similarity values and choose ***k*** users with the highest similarity value
  - Choose all users with similarity value higher than a threshold

This is effectively doing the K-Nearest Neighbor (kNN) algorithm

- kNN is typically for classification, but now it can be used as part of the process to predict the rating of an unseen movie

RECOMMENDATION PHASE: RATING PREDICTION

Next step is to combine ratings of *N* to make a rating prediction

- How to combine the rating?
- Let $r_{x,i}$ be the rating prediction of movie $\boldsymbol{i}$ for user $\boldsymbol{x}$
  - $\hat{r}_{x,i} = \frac{1}{k}\sum_{y \in N} r_{y,i}$
  - or
  - $\hat{r}_{x,i} = \frac{\sum_{y \in N} sim(x,y) \cdot r_{y,i}}{\sum_{y \in N} sim(x,y)}$

Average rating for i based on *N*

Weightage average rating

RECOMMENDATION PHASE: RATING PREDICTION

The previous 2 approaches does not take into account x's average rating

Could also generate the rating prediction based on the average rating of x ($\bar{r}_x$):

- $\hat{r}_{x,i} = \bar{r}_x + \frac{\sum_{y \in N} sim(x,y) \cdot (r_{y,i} - \bar{r}_x)}{\sum_{y \in N} |sim(x,y)|}$

RECOMMENDATION PHASE: RATING PREDICTION

Example:

Current user : ***x*** , unseen movie : ***i***

N = *3* users : ***a***, ***b***, ***c***

Ratings of users for movie ***i*** **:** $r_{\boldsymbol{a},i}$= 4, $r_{\boldsymbol{b},i}$= 3, $r_{\boldsymbol{c},i}$= 5

sim($\boldsymbol{x}$, ***a***) = 0.9, sim($\boldsymbol{x}$, ***b***) = 0.8, sim($\boldsymbol{x}$, ***c***) = 0.7

Average ratings $\boldsymbol{x}$ gave for any movies: $\overline{r_x}$ = 2

Approach 1

$$\hat{r}_{x,i} = \frac{1}{k}\sum_{y\in N} r_{y,i} = \frac{1}{3}(4+3+5) = 4$$

Approach 2

$$\hat{r}_{x,i} = \frac{\sum_{y\in N} sim(x,y)\cdot r_{y,i}}{\sum_{y\in N} sim(x,y)} = \frac{0.9*4+0.8*3+0.7*5}{0.9+0.8+0.7} = 3.96$$

Notice that if we do not consider a user's average rating, the prediction can differ by quite a bit

Approach 3

$$\hat{r}_{x,i} = \bar{r}_x + \frac{\sum_{y\in N} sim(x,y)\cdot(r_{y,i}-\bar{r}_x)}{\sum_{y\in N}|sim(x,y)|} = 2 + \frac{0.9*(4-2)+0.8*(3-2)+0.7*(5-2)}{3} = 3.56$$

RECOMMENDATION PHASE: MAKING RECOMMENDATIONS

After obtaining the x's rating predictions of all the unseen items, the next step is to make recommendations

Note that most of the time we are more interested in the recommendation results rather than the rating prediction

- How do we make recommendations?
- Rank movies by highest ratings and choose top ***m*** movies with the highest rating
- Or choose movies above a certain rating threshold

ITEM-BASED COLLABORATIVE FILTERING

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PROBLEM WITH USER-BASED CF

User-based CF has a scalability issue

- When the number of users of a site increases tremendously, pairwise similarity comparison between users in the site becomes computationally expensive

To address this issue, Amazon.com proposed Item-based Collaborative Filtering

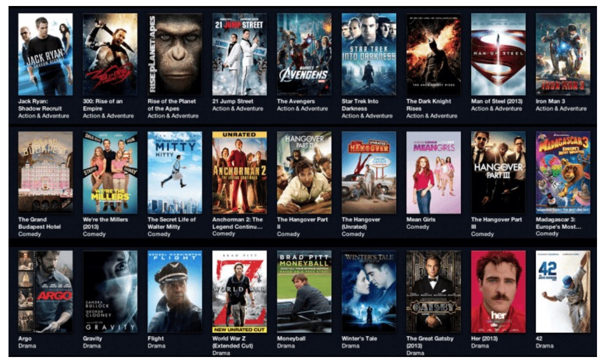
- To predict the rating value of items, Item-based CF compares the similarity between items instead of users

ITEM-BASED COLLABORATIVE FILTERING

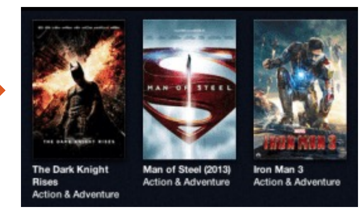
Strategy:

User x
Unseen movie i

Compare similarity



Movies rated by x



Most similar movies ($N(i;x)$)

Predict x's rating to i based on ratings of movies in $N(i;x)$

The recommendations are the top rated unseen items

ITEM-BASED COLLABORATIVE FILTERING

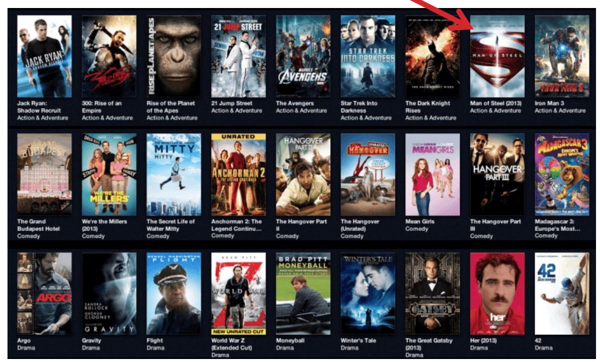
Strategy:

1. Neighbor Formation Phase

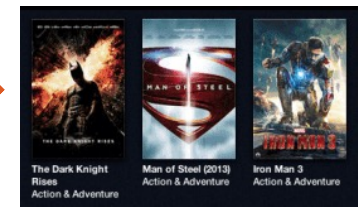
2. Recommendation Phase

User x
Unseen movie i

Compare similarity



Movies rated by x



Most similar movies ($N(i; x)$)

Predict x's rating to i based on ratings of movies in $N(i; x)$

The recommendations are the top rated unseen items

NEIGHBORHOOD FORMATION PHASE

How to calculate the similarity between items?

- Can use any of the previously discussed similarity measures
- But typically, we use **adjusted cosine similarity**:

$$acos(i,j) = \frac{\sum_{u \in U} (r_{u,i} - \bar{r}_u).(r_{u,j} - \bar{r}_u)}{\sqrt{\sum_{u \in U} (r_{u,i} - \bar{r}_u)^2} \sqrt{\sum_{u \in U} (r_{u,j} - \bar{r}_u)^2}}$$

items i and j

For all users

Average rating of user u

NEIGHBORHOOD FORMATION PHASE

$$cos(i,j) = \frac{\sum_{u \in U} r_{u,i} . r_{u,j}}{\sqrt{\sum_{u \in U} {r_{u,i}}^2} \sqrt{\sum_{u \in U} {r_{u,j}}^2}}$$

$acos(i,j)$ similar to $cos(i,j)$ except that we first deduct each rating value by the **mean of that user** first before calculating the cosine similarity

$$acos(i,j) = \frac{\sum_{u \in U} (r_{u,i} - \bar{r}_u) . (r_{u,j} - \bar{r}_u)}{\sqrt{\sum_{u \in U} (r_{u,i} - \bar{r}_u)^2} \sqrt{\sum_{u \in U} (r_{u,j} - \bar{r}_u)^2}}$$

RECOMMENDATION PHASE

To compute the rating prediction of movie i for user x, we can do something similar to the user−based CF

- $\hat{r}_{x,i} = \frac{\sum_{j \in N(i;x)} sim(i,j) \cdot r_{x,j}}{\sum_{j \in N(i;x)} sim(i,j)}$

Similarity between an item in $N(i;x)$ and i (use adjusted cosine similarity here)

Set of items rated by x that are similar to i

The recommendation selection process is the same as User-based CF

EXAMPLE

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

EXAMPLE

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**

EXAMPLE

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**

Calculate the mean rating of each **user**

$$acos(i,j) = \frac{\sum_{u \in U} (r_{u,i} - \bar{r}_u).(r_{u,j} - \bar{r}_u)}{\sqrt{\sum_{u \in U} (r_{u,i} - \bar{r}_u)^2} \sqrt{\sum_{u \in U} (r_{u,j} - \bar{r}_u)^2}}$$

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	

$\bar{r}_1$ =(1+2+1)/3=4/3
$\bar{r}_2$ =(4+2)/2=3
$\bar{r}_3$ =(3+5+4+4+3)/5=19/5
$\bar{r}_4$ =(4+1+3)/3=8/3
$\bar{r}_5$ =(2+5+4+3)/4=14/4
$\bar{r}_6$ =(5+2)/2=7/2
$\bar{r}_7$ =(4+3)/2=7/2
$\bar{r}_8$ =(4+2)/2=3
$\bar{r}_9$ =(5+4)/2=9/2
$\bar{r}_{10}$ =(2+3)/2=5/2
$\bar{r}_{11}$ =(4+1+5+2+2+4)/6=3
$\bar{r}_{12}$ =(3+5)/2=4

Sum of rating for each user is now **0**

After adjustment by mean rating of users

users

movies	1	2	3	4	**5**	6	7	8	9	10	11	12
1	-1/3		-0.8		?	1.5			0.5		1	
2			1.2	4/3			0.5			-0.5	-2	-1
3	2/3	1		-5/3	-1.5		-0.5		-0.5	0.5	2	
4		-1	0.2		1.5			1			-1	
5			0.2	1/3	0.5	-1.5					-1	1
6	-1/3		-0.8		-0.5			-1			1	

$\bar{r}_1$ =(1+2+1)/3=4/3
$\bar{r}_2$ =(4+2)/2=3
$\bar{r}_3$ =(3+5+4+4+3)/5=19/5
$\bar{r}_4$ =(4+1+3)/3=8/3
$\bar{r}_5$ =(2+5+4+3)/4=14/4
$\bar{r}_6$ =(5+2)/2=7/2
$\bar{r}_7$ =(4+3)/2=7/2
$\bar{r}_8$ =(4+2)/2=3
$\bar{r}_9$ =(5+4)/2=9/2
$\bar{r}_{10}$ =(2+3)/2=5/2
$\bar{r}_{11}$ =(4+1+5+2+2+4)/6=3
$\bar{r}_{12}$ =(3+5)/2=4

EXAMPLE

Now apply the normal cosine similarity formula (treating missing values as 0)

users

movies	1	2	3	4	**5**	6	7	8	9	10	11	12
1	-1/3		-0.8		?	1.5			0.5		1	
2			1.2	4/3			0.5			-0.5	-2	-1
3	2/3	1		-5/3	-1.5		-0.5		-0.5	0.5	2	
4		-1	0.2		1.5			1			-1	
5			0.2	1/3	0.5	-1.5					-1	1

$$acos(m1, m3) = \frac{\left(-\frac{1}{3} * \frac{2}{3}\right) + \left(\frac{1}{2} * -\frac{1}{2}\right) + (1 * 2)}{\sqrt{\left(-\frac{1}{3}\right)^2 + 0.8^2 + 1.5^2 + 0.5^2 + 1} * \sqrt{\left(\frac{2}{3}\right)^2 + 1 + \left(-\frac{5}{3}\right)^2 + (-1.5)^2 + (-0.5)^2 + (-0.5)^2 + (0.5)^2 + 2^2}} = 0.22$$

EXAMPLE

Suppose we want the **2** most similar movies (i.e. k = 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		0.22
4		2	4		5			4			2		
5			4	3	4	2					2	5	
6	1		3		3			2			4		0.49

$$N(i = 1; x = 5) = [movie3, movie6]$$

EXAMPLE

$$\hat{r}_{x,i} = \frac{\sum_{j \in N(i;x)} sim(i,j) \cdot r_{x,j}}{\sum_{j \in N(i;x)} sim(i,j)}$$

users

movies	1	2	3	4	**5**	6	7	8	9	10	11	12	sim(1,m)
1	1		3		2.69	5			5		4		1.00
2			5	4			4			2	1	3	
<u>3</u>	2	4		1	2		3		4	3	5		0.22
4		2	4		5			4			2		
5			4	3	4	2					2	5	
<u>6</u>	1		3		3			2			4		0.49

$$\hat{r}_{1,5} = \frac{0.22*2+0.49*3}{0.22+0.49} = 2.69$$

USER-BASED CF VS ITEM-BASED CF

In theory, the 2 CF approaches are similar

Item-based CF is faster than User-based CF

- Recall: User-based CF has a scalability issue
- Need to perform pairwise similarity comparison between users in the site and this can only be perform at real time
- Whereas, for Item-based CF, we could pre-compute the item similarity matrix
- Thus the prediction time of item-based CF is much faster

WHY CAN'T WE PRE-COMPUTE THE SIMILARITY MATRIX FOR USER-BASED CF?

	Spiderman	Toy Story
Alice	1→5	1
Bob	2	2
Charlie	2	5
Dave	4	4
Emily	1	3
Fabian	4	2
Gary	2	5

Usually number of users is much larger than number of items

Suppose Alice's rating of Spiderman changes from 1 to 5, the set of *N* will change drastically

Whereas, for the similarity between 2 movies is not so much affected

USER-BASED CF VS ITEM-BASED CF

Apart from speed, in practice, item-based CF usually also works better than user-based CF

- Items are simpler, while users might have multiple tastes
  - Items usually belong to a category whereas users might have different preferences
  - Furthermore, users taste can also change over time

SUMMARY

Types of Recommendations

The Recommendation Problem

- Utility Matrix

Making Recommendations using Aggregates

Similarity Measures

Collaborative Filtering Recommender Systems