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# Collaborative Filtering

EECS 349 Machine Learning

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# What is Collaborative Filtering?

- Recommendation system
  - Amazon recommends items based on your purchase history and ratings

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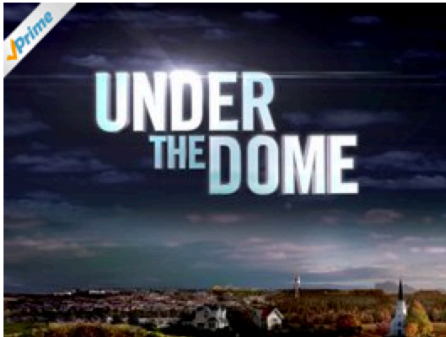
# What is Collaborative Filtering?

- Recommendation system
  - Amazon recommends items based on your purchase history and ratings

## View history

### Related to Titles You've Watched

You watched



## Recommendation

Customers who watched this also watched



# What is Collaborative Filtering?

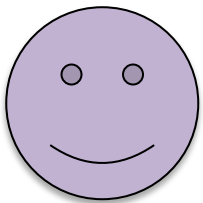
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- Task: How do I predict what you'll like?
- Two approaches
  - User-based: You will like *item A* because users who are similar to you like *item A*.
  - Item-based: You will like *item A* because you like items that are similar to *item A*.

# User-Based Collaborative Filtering

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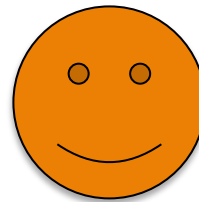
- Find users that is similar to you and you might like the item the user likes



**A**

I like..

- Star wars
- Star Trek
- Mission Impossible



**B**

I like..

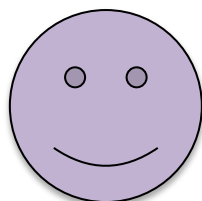
- Star wars
- Star Trek
- Mission Impossible
- X-men

***B** is a user who has similar preference to **A**.  
So **A** would like “X-men” too !!*

# Item-Based Collaborative Filtering

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- You might like items that are similar to items you already like



**A**

**I like Star wars !**

*“Star Trek” is a movie similar to Star Wars because it has “star” in the name. Then, **A** would like “Star Trek” too!*

*Do you think **A** would also like “Dancing with the Star”?*

# Feature Selection

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- Measuring similarity (of users or items) requires measuring their features.
  - implicit features
    - number of clicks
    - number of followers...
- Which features should I measure?
- Are there features that are (relatively) insensitive to the particulars of the recommendation tasks?
  - explicit features
    - user ratings
    - review
    - purchase history...
- User ratings to items or their purchase history is one of the explicit features to measure user preference

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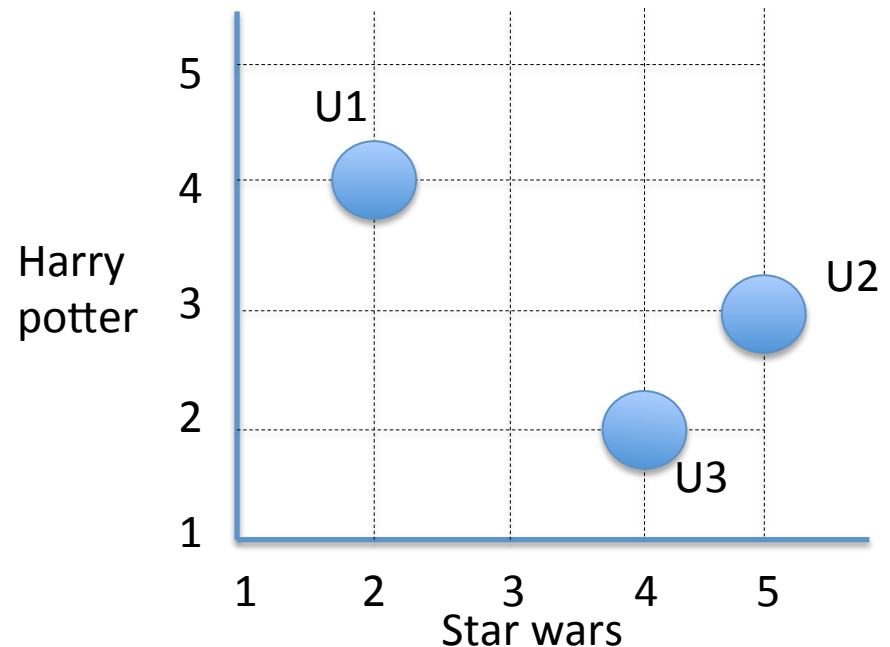
# **USER-BASED COLLABORATIVE FILTERING**



# How do we find a user who is similar?

- Distance (or similarity) measure
  - N-dimensional space
- Example: movie ratings of 3 users
  - Ratings from 1 (dislike) to 5 (like)

	U1	U2	U3
Harry Potter	4	3	2
Star Wars	2	5	4



# Which similarity measure to use?

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- p-norm
  - Manhattan
  - Euclidian
- Pearson Correlation
- Cosine Similarity
- Etc..

# Who is the most similar to John?

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## Example #1

	Inception	Begin again	Once
Brian	5	2	2
Bob	1	4	4
Cathy	2	3	3
John	5	1	2

- Manhattan Distance:

$$(\text{John, Brian}) = 0 + 1 + 0 = 1$$

$$(\text{John, Bob}) = 4 + 3 + 2 = 9$$

$$(\text{John, Cathy}) = 3 + 2 + 1 = 6$$

Q: Does Manhattan Distance measure similarities properly in this data set?

yes

# Who is the most similar to Adam?

---

## Example #2

	Inception	Begin again	Once	Star wars
Bill	2	3	3	2
Brian	5	1	1	5
Adam	3	2	2	3

- Manhattan Distance:

$$(\text{Adam, Bill}) = 1 + 1 + 1 + 1 = 4$$

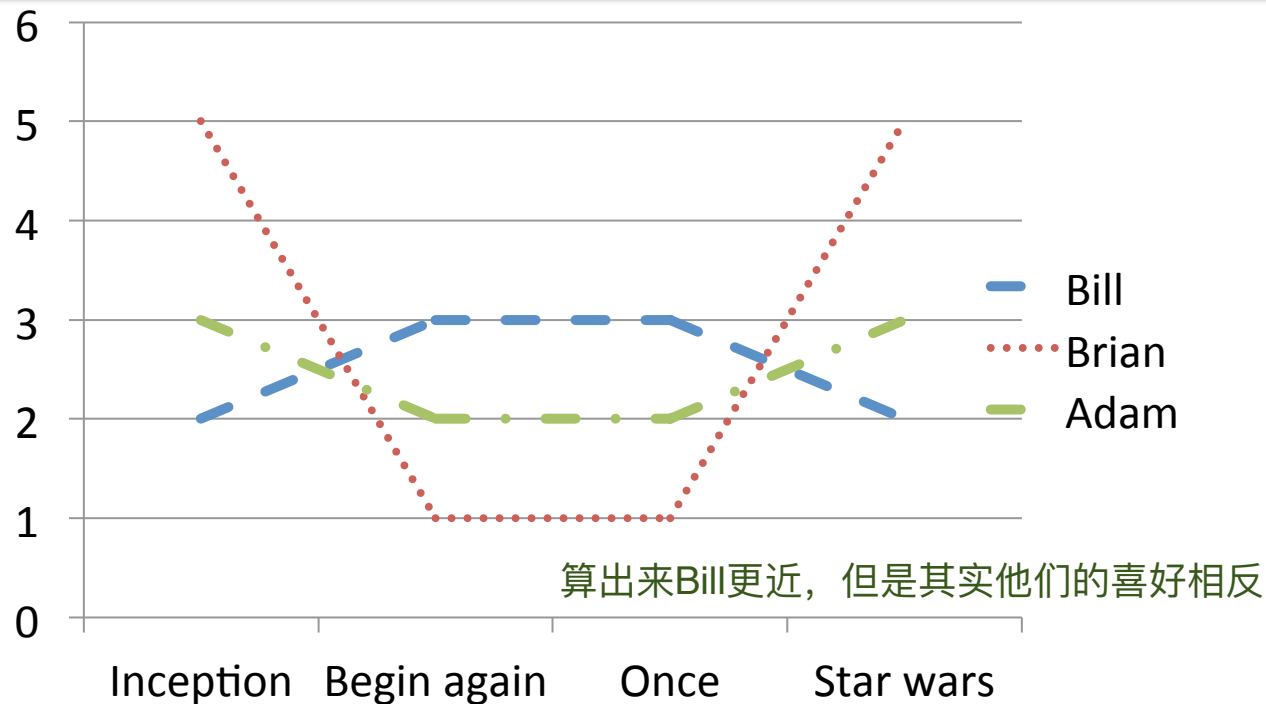
$$(\text{Adam, Brian}) = 2 + 1 + 1 + 2 = 6$$

Q: Does Manhattan Distance measure similarities properly in this data set?

no

Different users may use different rating scales

# Who is the most similar to Adam?



- Manhattan Distance:

$$(\text{Adam, Bill}) = 1 + 1 + 1 + 1 = 4$$

$$(\text{Adam, Brian}) = 2 + 1 + 1 + 2 = 6$$

Q: Does Manhattan Distance measure similarities properly in this data set?

Different users may use different rating scales

# Pearson Correlation

- Measure of correlation between two variables
- Pearson correlation coefficient
  - Range (-1, 1)
  - A perfect positive correlation: 1
  - A perfect negative correlation: -1

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

In Python,

```
>> import scipy.stats
```

```
>> scipy.stats.pearsonr(array1, array2)
```

# Cosine Similarity

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- Measure of similarity between two vectors
  - Range from -1 (opposite) to 1 (same)
- Cosine similarity between vector  $a$  and  $b$ :

$$\text{sim}(a, b) = \frac{a \cdot b}{|a| * |b|}$$

# Who is the most similar to Adam?

---

## Example #2

	Inception	Begin again	Once	Star wars
Bill	2	3	3	2
Brian	5	1	1	5
Adam	3	2	2	3

- Pearson Correlation:

$$(\text{Adam}, \text{Bill}) = -1$$

$$(\text{Adam}, \text{Brian}) = 1$$

Q: Does Pearson Correlation measure similarities properly in this data set?



# How to predict ratings to unrated items

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- User-based K- Nearest Neighbor Collaborative Filtering

recommendation: items you might like, is presents top k items

- 1) Define a similarity measure

prediction: how much you will like items,using some rating scale

- 2) Pick k users that had similar preferences to those of current user

- 3) Compute a prediction from a weighted average of k nearest neighbors' ratings (*see the next slide*)

*You need to do experiments to find optimal k value.*

# How to predict ratings to unrated items

- Prediction for the rating of user *a* for item *p*.

$$pred(a, p) = \bar{r}_a + \frac{\sum_{b \in k} sim(a, b) * (r_{b,p} - \bar{r}_b)}{\sum_{b \in k} sim(a, b)}$$

Rating of user *b* for item *p*

User *a*'s average rating

Similarity between user *a* and user *b*

# Let's practice user-based k-NN CF


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- In this practice and our homework, we will use much simpler way to compute a prediction of rating
  - 1) Define a similarity measure
  - 2) Pick k users that had similar preferences to those of current user
  - 3) 不用计算 Pick the **mode** of the top k nearest neighbors as the predicted rating
    - ex) If you pick 3 neighbors and their ratings to the target item are (2, 2, 3), then the prediction will be 2.

# Practice: User-based k-NN CF (k=1)

**Example #1: How would John rate Star wars?**

	Inception	Begin again	Once	Star wars
Brian	5	2	2	4
Bob	1	4	4	2
Cathy	2	3	3	1
John	5	1	2	?



Manhattan Distance:

$$(John, Brian) = 0 + 1 + 0 = 1$$

$$(John, Bob) = 4 + 3 + 2 = 9$$

$$(John, Cathy) = 3 + 2 + 1 = 6$$



The nearest neighbor: Brian  
John's rating to Star wars: 4

# Practice: User-based k-NN CF (k=1)

**Example #2: How would John rate Avatar?**

	Inception	Begin again	Once	Star wars	Avatar
Brian	2	3	3	1	4
Bob	5	1	1	5	2
Cathy	5	1	2	4	1
John	3	2	2	3	?

Manhattan Distance:

$$(\text{John, Brian}) = 1 + 1 + 1 + 2 = 5$$

$$(\text{John, Bob}) = 2 + 1 + 1 + 2 = 6$$

$$(\text{John, Cathy}) = 1 + 1 + 1 + 1 = 4$$



The nearest neighbor: Cathy  
John's rating to Avatar: 1

Pearson Correlation Coefficient

$$(\text{John, Brian}) = -0.90$$

$$(\text{John, Bob}) = 1.0$$

$$(\text{John, Cathy}) = 0.95$$



The nearest neighbor: Bob  
John's rating to Avatar: 2

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# **ITEM-BASED COLLABORATIVE FILTERING**

# How to predict ratings to unrated items

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- **Item-based K- Nearest Neighbor Collaborative Filtering**
  - 1) Define a similarity measure between **items**
  - 2) Pick k items rated by the current user similar to the target item
  - 3) Compute a prediction from a weighted average of the k similar items' ratings

# Let's practice **item-based** k-NN CF

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- In this practice and our homework, we will use much simpler way to compute a prediction of rating
  - 1) Define a similarity measure between **items**
  - 2) Pick k items rated by the current user similar to the target item
  - 3) **Pick the mode of the top k nearest neighbors as the predicted rating**
- ex) If you picked 3 items and current user's ratings to the 3 items are (2, 2, 3), then the prediction will be 2.



# Practice: Item-based k-NN CF (k=1)

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## Example #1

	Inception	Begin again	Once	Star wars
Brian	5	2	2	4
Bob	1	4	4	2
Cathy	2	3	3	1
John	5	1	2	?

Manhattan Distance:

$$(\text{Star wars}, \text{Inception}) = 1 + 1 + 1 = 3$$

$$(\text{Star wars}, \text{Begin again}) = 1 + 2 + 2 = 5$$

$$(\text{Star wars}, \text{Once}) = 2 + 2 + 2 = 6$$

The most similar item to Star wars: Inception  
John's rating to Star wars: 5

# The Cold Start Problem

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- What if this user has never rated anything before?
- What if nobody has rated this item before?
- Additional information. For example,
  - Ask users to rate some initial items
  - 人口学的 Demographic information for users
  - Content analysis or 元数据 metadata for items

# Missing values

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- Missing values in user-rating matrix
  - What if two users have rated different sets of things? How do we compare them?
  - What if two items have been rated by disjoint sets of users? How do we compare them?

# Dealing with missing values

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## Example

	Inception	Begin again	Once	Star wars	Avatar
Brian	2	?	3	?	4
Bob	5	1	1	5	2
Cathy	5	?	2	2	1
John	5	?	2	3	?

# Dealing with missing values

---

## Example

	Inception	Begin again	Once	Star wars	Avatar
Brian	2	0	3	0	4
Bob	5	1	1	5	2
Cathy	5	0	2	2	1
John	5	0	2	3	?

# Dealing with missing values

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- Discarding the person/item from comparison?
  - It does not solve cold start problem
  - What if the data set is so sparse<sup>稀少</sup>?
- Putting in a crazy number (-1000) for missing values?
- Putting in a random number?
- Putting in a mean (median) value?
  - Mean value of what set?
- Other advanced imputation technique?

# Make a decision

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- Which similarity (or distance) measure to use?
- How many neighbors to pick?
- How to weight neighbors chosen?
- User-based or item-based?
- How to deal with missing values?