MODULE 5

Introduction to Machine Learning

Recommender Systems

Modules for this course

1. Overview: What is Machine learning
2. Categories of machine learning
3. Building a Classification Model
4. Machine Learning application approach
5. **Recommender Systems**
6. Building a Recommender Engine

Module 5

Recommender Systems

Objectives

Objectives

- What is a Recommender System
- What is the difference between content based and collaborative filtering Recommender systems
- Which limitations recommender systems frequently encounter
- How collaborative filtering can identify similar users and items

Outline

- What is a recommender system?
- Types of collaborative filtering
- Limitations of recommender systems
- Fundamental concepts
- Essential points
- Conclusion
- Hands-On Exercise: Implementing a Basic Recommender

What is a Recommender System?

NETFLIX

Types of Recommendations

1. **Content-based (CB)**

Analyze attributes of items for building user profiles

2. **Collaborative filtering (CF)**

Inspect rating patterns to find similar users/items

In general, CF performs **better** than CB

- CF fail to provide accurate predictions with insufficient ratings
- CB can alleviate the sparsity problem

Content-Based Recommendations

1. **Focus:**
   - Content-based systems recommend items to users based on the **attributes** and **characteristics** of the items themselves and the user's historical preferences for those attributes.
2. **User Profile:**
   - These systems create a user profile by analyzing the content or features of items the user has interacted with. The user profile captures the user's preferences for different attributes.
3. **Similarity Calculation:**
   - Recommendations are made by calculating the similarity between the user's profile and the attributes of different items.

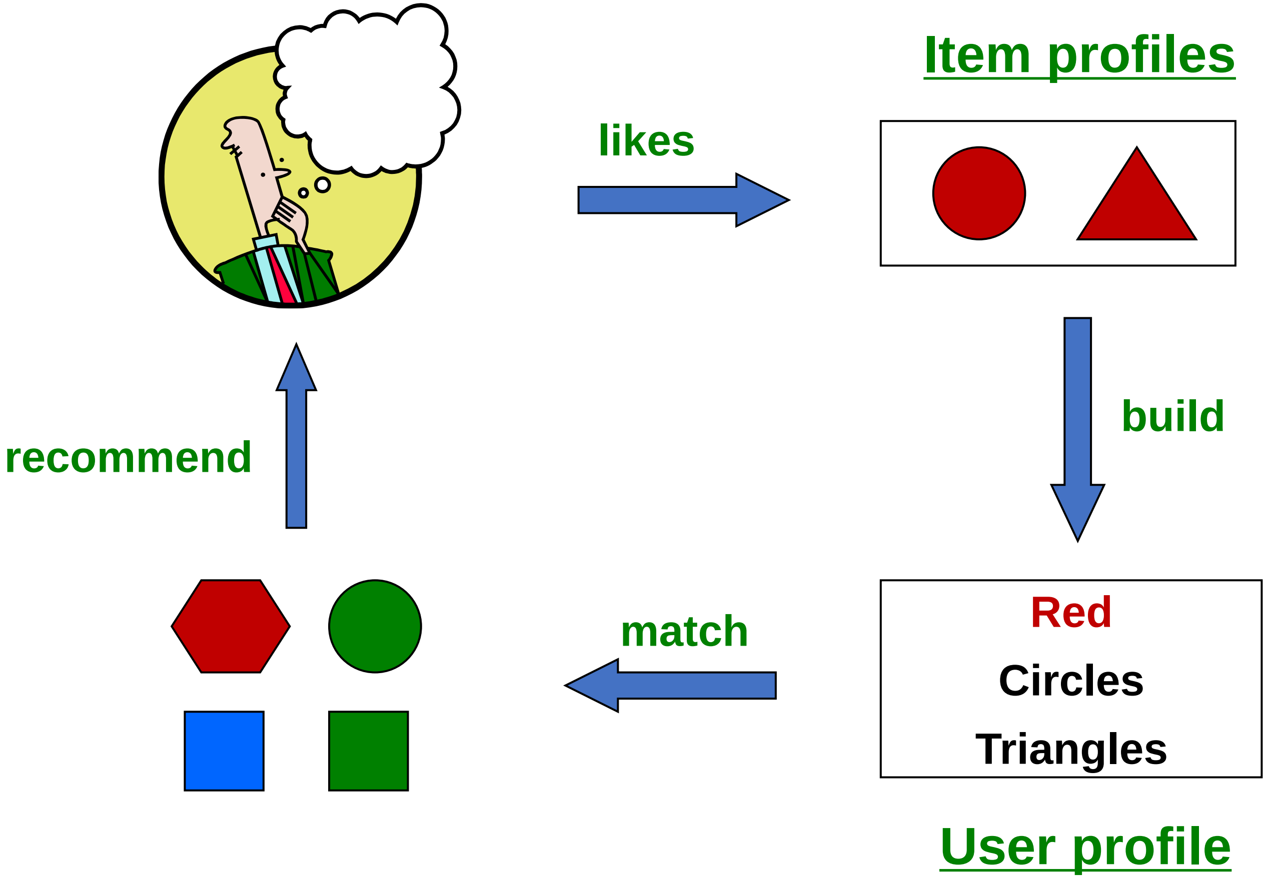
Content-Based Recommendations

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

Example:

- **Movie recommendations**
  - Recommend movies with same actor(s), director, genre, …
- **Websites, blogs, news**
  - Recommend other sites with “similar” content

Plan of Action



Items Profile

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

Profile is a set (vector) of features

- **Movies:** author, title, actor, director,…
- **Text:** Set of “important” words in document

How to pick important features?

- Usual heuristic from text mining is **TF-IDF** (Term frequency * Inverse Doc Frequency)
  - **Term … Feature**
  - **Document … Item**

Sidenote: TF-IDF

f_{ij} = frequency of term (feature) i in doc (item) j

$$TF_{ij} = \frac{f_{ij}}{\max_k f_{kj}}$$

Note: we normalize TF to discount for "longer" documents

n_i = number of docs that mention term i

N = total number of docs

$$IDF_i = \log \frac{N}{n_i}$$

TF-IDF score: $w_{ij} = TF_{ij} \times IDF_i$

Doc profile = set of words with highest **TF-IDF** scores, together with their scores

User Profiles and Prediction

- **User profile possibilities:**
  - Weighted average of rated item profiles
  - **Variation:** weight by difference from average rating for item
- **Prediction heuristic: Cosine similarity of user and item profiles)**
  - Given user profile ***x*** and item profile ***i***, estimate $u(\boldsymbol{x}, \boldsymbol{i}) = \cos(\boldsymbol{x}, \boldsymbol{i}) = \frac{\boldsymbol{x} \cdot \boldsymbol{i}}{||\boldsymbol{x}|| \cdot ||\boldsymbol{i}||}$
- **How do you quickly find items closest to x?**
  - Job for LSH!

Pros & Cons: Content-based Approach

1. **Advantages**:
   1. Can provide personalized recommendations even for new or less popular items, if their attributes are known.
   2. Less reliant on large user interaction data.
   3. Can handle the cold-start problem for new users.
2. **Limitations**:
   1. Limited to the features available for item descriptions.
   2. May not capture changes in a user's preferences over time.
   3. Tends to produce recommendations that are like past interactions.

Collaborative Filtering

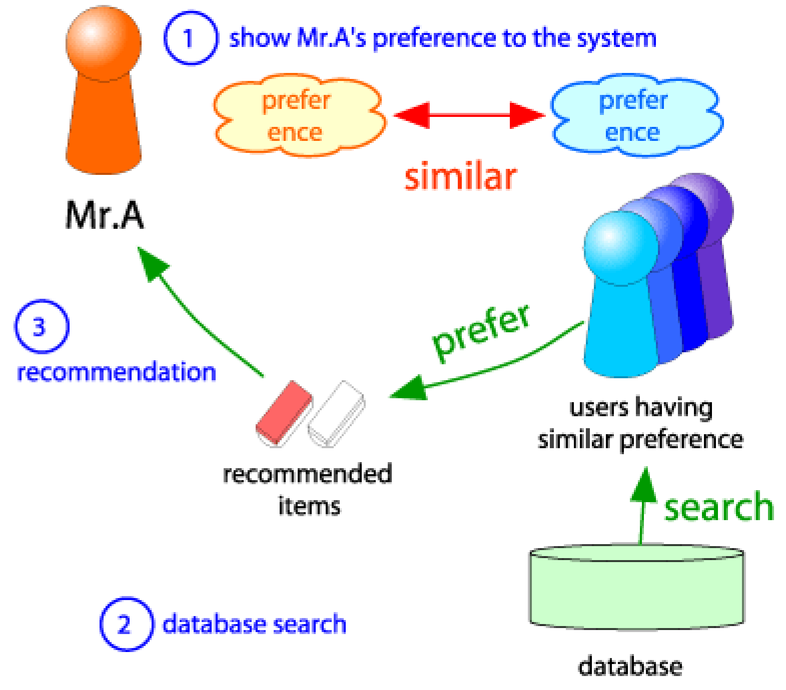
- **Principle**: Collaborative filtering recommends items to users based on the preferences and behaviors of other users. It assumes that users who agree in the past will agree in the future.
- **User-Item Matrix**: It creates a user-item interaction matrix where each entry represents the user's preference for an item (e.g., ratings, likes, purchase history).
- **User-Based vs. Item-Based**:
  - User-Based Collaborative Filtering: Recommends items to a user based on the preferences of similar users.
  - Item-Based Collaborative Filtering: Recommends items to a user based on the preferences of other items they have interacted with.

Types of Collaborative Filtering

- **Collaborative filtering can be subdivided into two main types**
- **User-based: “What do users similar to you like?”**
  - For a given user, find other people who have similar tastes
  - Then, recommend items based on past behavior of those users
- **Item-based: “What is similar to other items you like?”**
  - Given items that a user likes, determine which items are similar
  - Make recommendations to the user based on those items

User-Based Collaborative Filtering

- Consider user ***x***
- Find set ***N*** of other users whose ratings are "**similar**" to ***x***'s ratings
- Estimate ***x***'s ratings based on ratings of users in ***N***



Finding "Similar" Users

- Let $\boldsymbol{r_x}$ be the vector of user $\boldsymbol{x}$'s ratings
- **Jaccard similarity measure**
  - **Problem:** Ignores the value of the rating
- **Cosine similarity measure**
  - sim($\boldsymbol{x}$, $\boldsymbol{y}$) = cos($\boldsymbol{r_x}$, $\boldsymbol{r_y}$) = $\frac{r_x \cdot r_y}{||r_x|| \cdot ||r_y||}$
  - **Problem:** Treats some missing ratings as "negative"
- **Pearson correlation coefficient**
  - $\boldsymbol{S_{xy}}$ = items rated by both users $\boldsymbol{x}$ and $\boldsymbol{y}$

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

Rating Predictions

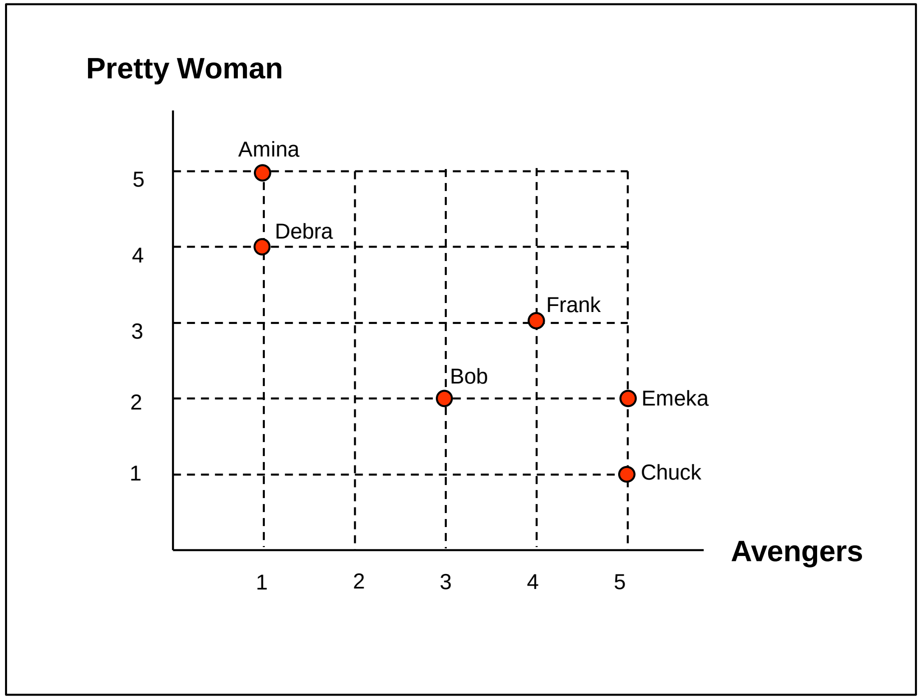
From similarity metric to recommendations:

- Let $\boldsymbol{r_x}$ be the vector of user $\boldsymbol{x}$'s ratings
- Let $\boldsymbol{N}$ be the set of $\boldsymbol{k}$ users most similar to $\boldsymbol{x}$ who have rated item $\boldsymbol{i}$
- **Prediction for item *i* of *user x*:**
  - $r_{xi} = \frac{1}{k} \sum_{y \in N} r_{yi}$
  - Or even better: $r_{xi} = \frac{\sum_{y \in N} s_{xy} \cdot r_{yi}}{\sum_{y \in N} s_{xy}}$

- **Many other tricks possible...**

User-Based Collaborative Filtering

- **User-based collaborative filtering is social**
  - It takes a “people first” approach, based on common interests
- **In this example, Amina and Debra have similar tastes**
  - Each is likely to enjoy a movie that the other rated highly



Pros & Cons: Collaborative Filtering

1. **Advantages**:
    1. Captures complex user behaviors and preferences.
    2. Can discover hidden patterns in user interactions.
2. **Limitations**:
    1. Can suffer from the cold-start problem for new items or users.
    2. Sensitive to sparsity in the user-item interaction matrix.

Item-Based Collaborative Filtering

- **So far: User-based collaborative filtering**
- **Another view: Item-based**
  - For item ***i***, find other similar items
  - Estimate rating for item ***i*** based on ratings for similar items
  - Can use same similarity metrics and prediction functions as in user-user model

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

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

Item-Based Collaborative Filtering

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-Based Collaborative Filtering

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-Based Collaborative Filtering

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	-0.18
3	2	4		1	2		3		4	3	5		<u>0.41</u>
4		2	4		5			4			2		-0.10
5			4	3	4	2					2	5	-0.31
6	1		3		3			2			4		<u>0.59</u>

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

Here we use Pearson correlation as similarity:
1) Subtract mean rating m_i from each movie i
$m_1 = (1+3+5+5+4)/5 = \mathbf{3.6}$
row 1: *[-2.6, 0, -0.6, 0, 0, 1.4, 0, 0, 1.4, 0, 0.4, 0]*
2) Compute cosine similarities between rows

Item-Based Collaborative Filtering

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	-0.18
3	2	4		1	2		3		4	3	5		0.41
4		2	4		5			4			2		-0.10
5			4	3	4	2					2	5	-0.31
6	1		3		3			2			4		0.59

Compute similarity weights:
$s_{1,3}$=0.41, $s_{1,6}$=0.59

Item-Based Collaborative Filtering

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	-0.18
3	2	4		1	2		3		4	3	5		0.41
4		2	4		5			4			2		-0.10
5			4	3	4	2					2	5	-0.31
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Compute similarity weights:

$s_{1,3}=0.41$, $s_{1,6}=0.59$

Summary

Recommendation systems use several different technologies. We can classify these systems into two broad groups.

- Content-based systems examine properties of the items recommended.
- Collaborative filtering systems recommend items based on similarity measures between users and/or items.

Questions