

## Recommendation Systems - Part 1

### Topics covered so far



- Recommendation Systems
  - Introduction to the Recommendation Systems, specific metrics to measure the performance,
    sparsity of data, and time varying data
  - Examples of datasets
  - Modelling process and simple solutions
  - Improving solutions, Clustering
  - Collaborative Filtering
  - Singular Value Thresholding

### **Discussion questions**



- 1. Why are recommendation systems useful? Give some examples of recommendation systems.
- 2. How would you define popularity based recommendation systems?
- 3. What are the measures to find similarity among users/items in recommendation systems?
- 4. What are collaborative filtering based recommendation systems and its types?
- 5. What is matrix factorization technique that is used for recommendation systems?

## **Recommendation Systems**



Recommender systems aim to predict users' interests and recommend product items that quite likely are interesting for them.

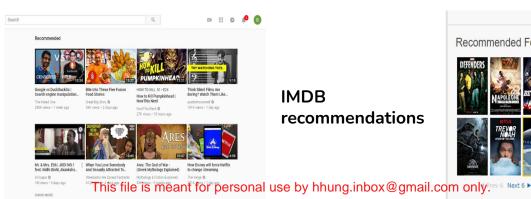
#### Why are they useful?

- Help user find item of their interest
- Help item provider deliver their items to right user
- Identify products most relevant to the user
- Personalized content
- Help website improve user engagement.

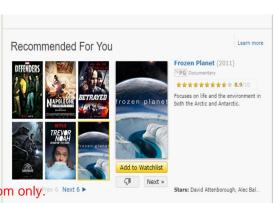
#### Some facts about recommendation systems

- Netflix 2/3 rented movies are from recommendation
- Google News 38% more click-through are due to recommendation
- Amazon 35% sales are from recommendation Source: (Celma & Lamere, ISMIR 2007)

Youtube recommendations



**IMDR** recommendations



## Popularity based recommendation systems



It is a type of recommendation systems which suggest products/items based on the popularity or trend. These systems check about the product or movie which are in trend or are most popular among the users and directly recommend those

#### Advantages:

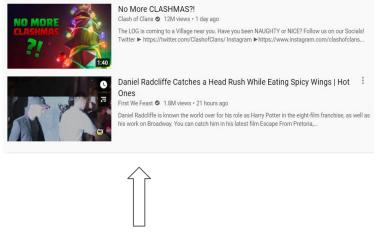
- No cold start problem
- No need for the user's historical data

#### **Disadvantages:**

- Not personalized to users
- Only takes popularity in account

#### **Examples:**

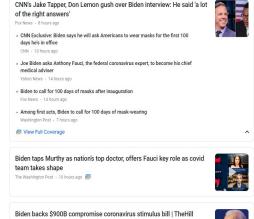
- 1. Google News
- 2. You tube trending videos





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YouTube



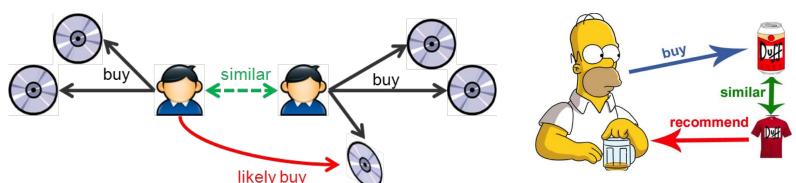
Pelosi and McConnell resume talks as Congress rushes to strike a Covid stimulus

CNBC - 15 hours ago

## **Collaborative Filtering**



- The main idea behind collaborative filtering is that **if a user's likes/dislikes are similar to another user's likes/dislikes, then their tastes are considered similar.** We can use this to recommend a product that other similar users liked.
- It is based on the assumption that if a person who liked something in past will also like it in future.
- It is of two types:
  - User-User collaborative filtering: It is based on the search of similar users from the user-item interaction matrix.
  - Item-Item collaborative filtering: It is based on the search of similar items from the user-item interaction matrix.



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Source: medium



## Advantages and Disadvantages of Collaborative Filtering

Advantages	Disadvantages
No domain knowledge needed	Cold start problem - can't handle new data
Personalized to users	Sparsity - Unable to compute ratings if there are a very less number of user preferences
Adaptive to the preferences changes over time	Scalability - Computationally expensive to scale

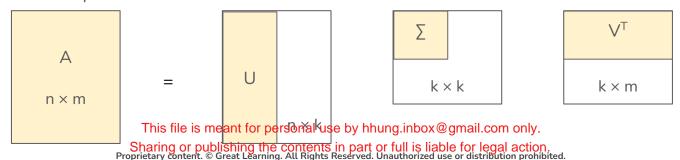
## **Matrix Factorization (SVD)**



- Sparsity and scalability can be the biggest two challenges with CF methods
- Matrix Factorization decomposes the original sparse matrix to low-dimensional matrices with latent features and less sparsity
- It gives us how much a user is aligned with a set of latent features, and how much a movie fits into this set of latent features
- It uses **Singular Value Decomposition** to factorize the matrix. For a user-movies  $n \times m$  matrix, it is given by

$$A = U \sum V^{T}$$

Where, U is an  $n \times k$  user-latent feature matrix,  $V^T$  is an  $k \times m$  movie-latent feature matrix, and  $\sum$  is a  $k \times k$  diagonal matrix containing the singular values of original matrix, simply representing how important a specific feature is to predict user preference.





# **Case Study**



**Happy Learning!** 

