# Teaching Session | RecSys

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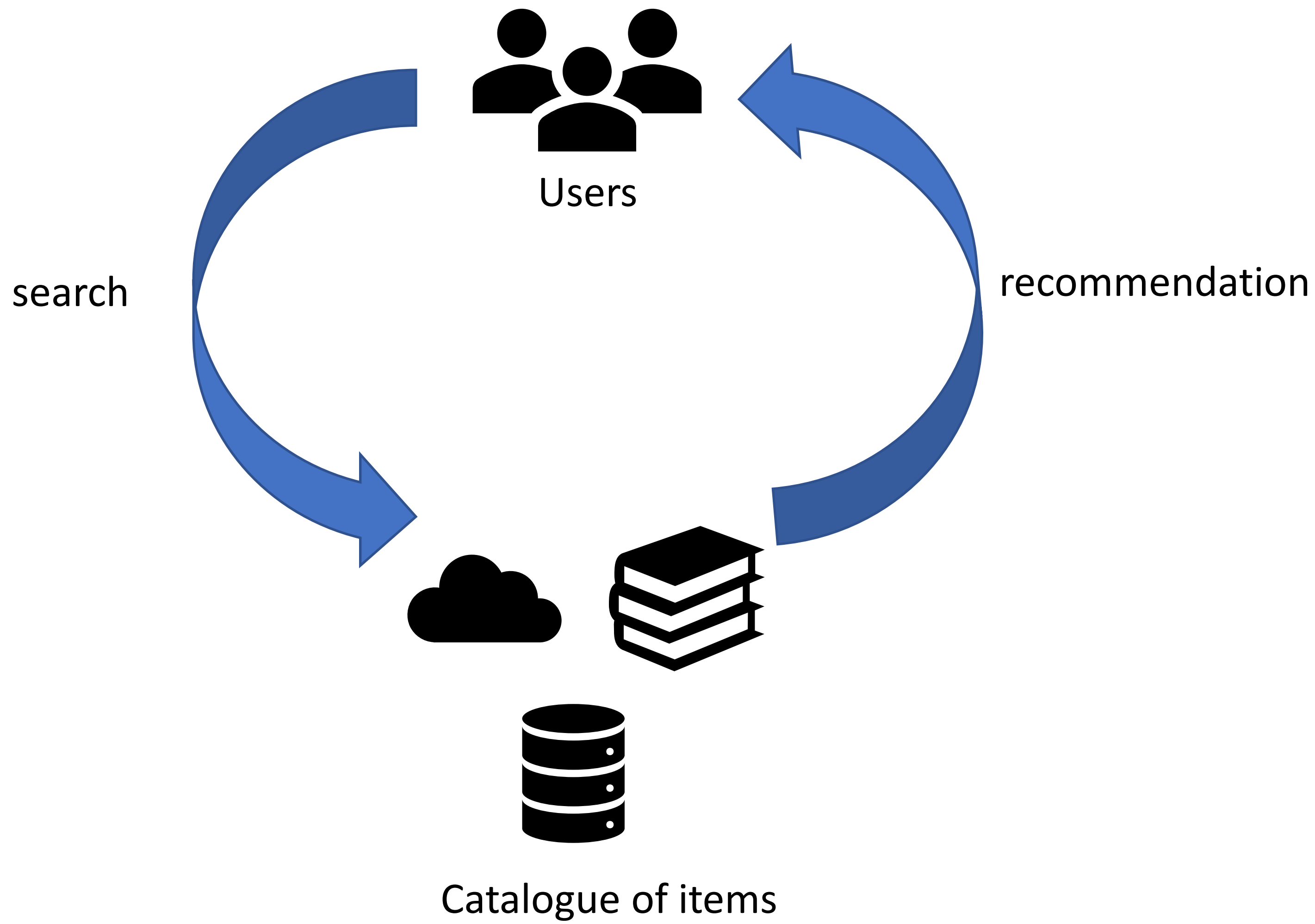
# Agenda

- Introduction
  - Why
  - Formal Math
- Collaborative Filtering
  - Theory
    - User-User
    - Item-Item
  - Drawbacks
- Latent Factor Model
  - Theory
  - Drawbacks
- Content Based Filtering
  - Theory
  - Caveats

# Introduction to RecSys

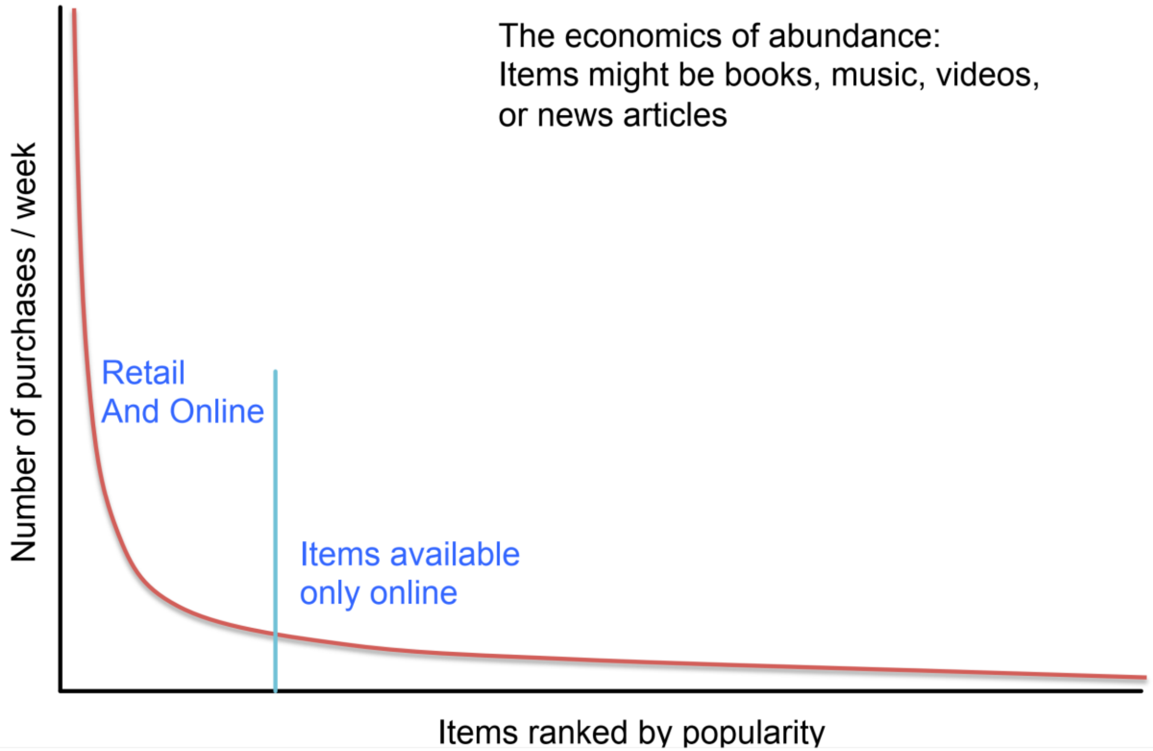
# Introduction to RecSys | What



# Introduction to RecSys | Why

- Brick and mortar stores did not need large scale recommendation systems
  - Lesser number of unique products
  - Lesser number of unique customer preferences
  - High cost of storage of inventory

- The internet brought with itself twin abilities
  - Low cost of dessimination of information of items
  - Larger access to number of unique customer preferences



# Introduction to RecSys | Formal Math

$C$ : Set of all customers
$S$ : Set of all items
$R$ : Set of ratings

$u$ : Utility function (often matrix) that maps each combination of customer-item to the set of ratings $R$

That is

$$u : C \times S \to R$$

## Utility Matrix

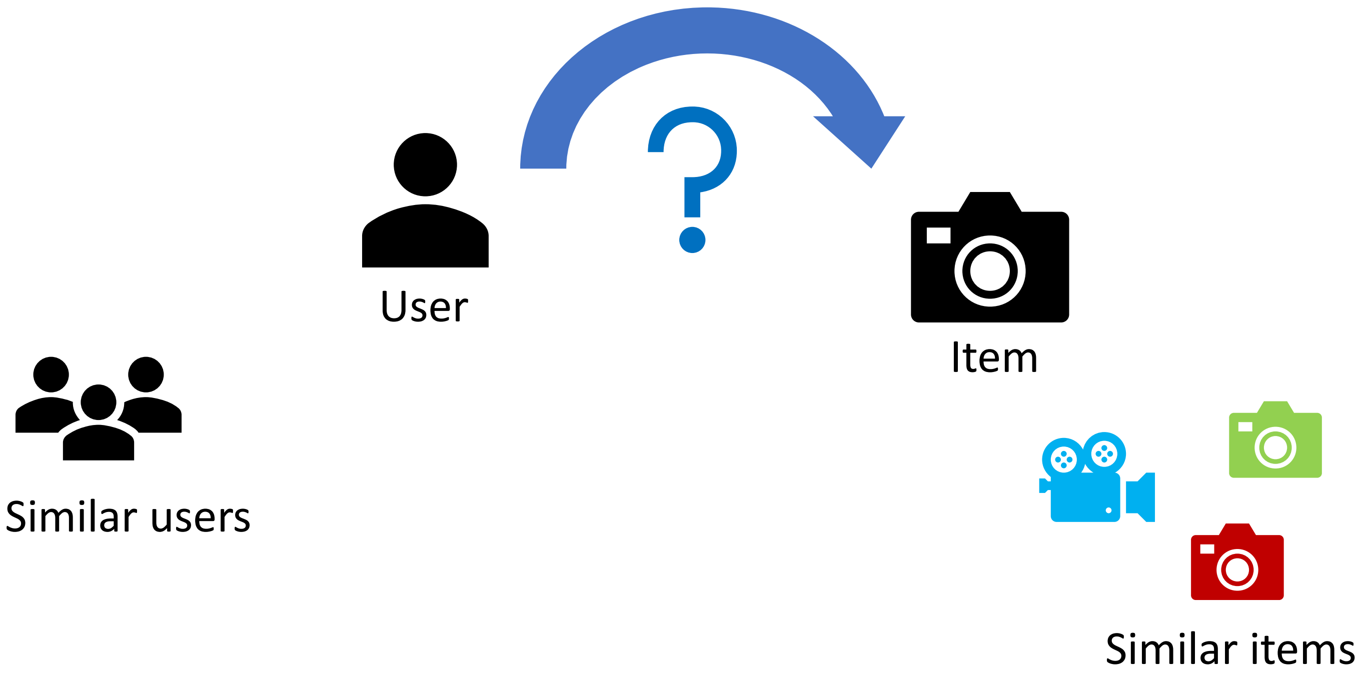
| | M1 | M2 | M3 | M4 | M5 |
|---|---|---|---|---|---|
| **Ali** | 3 | 1 | 1 | 3 | 1 |
| **Brad** | 1 | 2 | 4 | 1 | 3 |
| **Carol** | 3 | 1 | 1 | 3 | 1 |
| **Dany** | 4 | 3 | 5 | 4 | 4 |

- Usually is sparse, contains many missing values
- Rows are not completely independent, groups of users have similar preferences
- Columns are not completely independent, groups of items share similar attributes
- Missing values can have important implication

# Collaborative Filtering

# Collaborative Filtering | Theory

- A user's affinity for a particular item depends on
  - Aggregate affinity towards that item by a similar group of users (user – user)
  - Aggregate affinity towards a similar set of items by all users (item - item)



# Collaborative Filtering | Measuring Similarity

- We can define similarity between items by using various distance measures
  - Jaccard Index
    - Takes into account prescence or absence of ratings
    - Does NOT take magnitude of ratings into account
  - Cosine Similarity
    - Takes into account magnitude of ratings into account
    - Personal rating biases can cause misleading results
  - Mean Adjusted Cosine Similarity
    - Handles biases in ratings, for example consistent high or low raters

- The next step involves selecting top N similar entities, either users or items

# Collaborative Filtering | User - User

- Given a utility matrix $U = \{u_{ij}\}$, we want to find $u_{pq}$, that is, the rating of product $q$ as rated by user $p$
- We find $N$ users most similar to user $p$ by using the vector of ratings $r_p$ for user $p$ and calculating the mean centred cosine distance with other users' ratings vector
- We can also find top $N$ similar users to user $p$ by using unsupervised ML models such as K Nearest Neighbours
- The top $N$ similar users' ratings for product $q$ are taken and aggregated
- There are different ways to aggregate, simple average or similarity weighted average
- The aggregation forms the estimate of the rating of the product $q$ as rated by user $p$

# Collaborative Filtering | User - User

## What is the rating of movie 1 by user 5?

Users

Movies

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | S(1,m) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **1** | 1 | | 3 | | | 5 | | | 5 | | 4 | | 1 |
| **2** | | | 5 | 4 | | | 4 | | | 2 | 1 | 3 | -0.178 |
| **3** | 2 | 4 | | 1 | 2 | | 3 | | 4 | 3 | 5 | | 0.414 |
| **4** | | 2 | 4 | | 5 | | | 4 | | | 2 | | -0.101 |
| **5** | | | 4 | 3 | 4 | 2 | | | | | 2 | 5 | -0.312 |
| **6** | 1 | | 3 | | 3 | | | 2 | | | 4 | | 0.587 |

$$\frac{2+3}{2} = 2.5$$

$$\frac{2 \times 0.414 + 3 \times 0.587}{0.414 + 0.587} = 2.586$$

# Collaborative Filtering | Item - Item

What is the rating of movie 1 by user 5?

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 | |

| S(5,u) | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|

# Collaborative Filtering | Caveats

- In theory, user-user and item-item approaches should be complimentary to one another

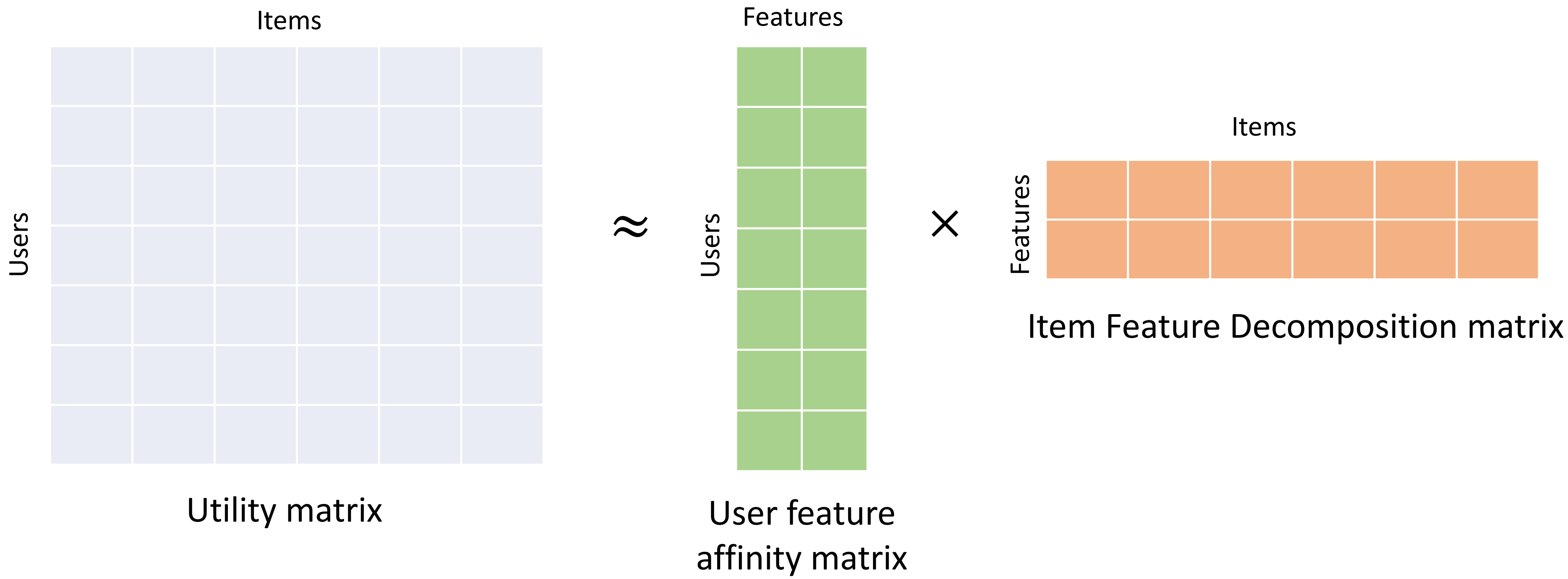
- In practice, we see that item-item collaborative filtering is much more powerful

- Items are more ‘simpler and invariant’ than users
  - Items’ attributes do not change with time
  - Users’ attributes and preferences change with time

# Latent Factor Models

# Latent Factor Models | Theory

- The utility matrix is a result of interaction of users with items
- Each item can be decomposed into several attributes
- Each person has a particular affinity towards each of the attributes



# Latent Factor Models | Theory

- We wish to decompose the utility matrix as a product of two separate matrices
- The decomposed product should approximate the original utility matrix as much as possible
- We choose an appropriate number of features based on
  - Domain knowledge
  - Reconstruction error threshold
- Each item is broken down into combination of one or more features, represented by the item feature decomposition matrix
- Each person has certain affinity towards certain features, represented by the user feature affinity matrix

# Latent Factor Models | Theory

- We wish to find matrices $P$ and $Q$ such that

$$\underset{\mathrm{P,Q}}{\arg\min} \left|\left|U - PQ^T\right|\right|_2^2$$

- This can be solved by minimizing the reconstruction loss $\left|U - PQ^T\right|_2^2$ using gradient descent

- Since we have to find optimum value of two matrices, we need to alternate between the two matrices to achieve the minima

- The matrix estimation can be made more robust by introducing regularisation in the loss function

# Latent Factor Models | Theory

Pseudo Code to minimise reconstruction error and find the optimal $P.Q$ matrices

- Choose appropriate hyperparameters, step size and regularization constant
- For each element in the utility matrix
  - Compute prediction error
    - Update $p_u$, the user vector
    - Use the updated $p_u$ vector to update $q_i$, the item vector
    - Stop if convergence criteria satisfied

# Latent Factor Models | Caveats

- Estimating $P, Q$ matrices to minimise reconstruction loss can be done by performing Singular Value Decomposition
- Theoretically, SVD ensures decomposition with minimum loss
- This is advantageous as it overcomes the drawbacks of the gradient descent approach
- These models also require orders of magnitude less resources to store and save the data
- They eliminate the cold start problem and popularity bias problem encountered in collaborative filtering

# Content Based Filtering

# Content Based Filtering | Theory

- We wish to recommend a customer only those items which are similar to the items that the customer has highly rated
- This involves extracting features from the items, using various techniques
  - TF-IDF
  - Word embeddings
- The item features and user likes are used to build a user profile
- The user profile is then matched with each item in the catalogue, and the highest scored items are served as recommendations

# Content Based Filtering | Caveats

- No need for data on other users
- Captures unique preferences of user groups
- Able to recommend new and unpopular items
- Explanations for recommended items available, since features are available for items
- Finding appropriate features is hard
- Rabbit holed recommendations, no surprise in recommendations
- Susceptible to cold start problem

# Q & A