# Advanced Analytical Theory and Methods: Recommendation System

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# Recommendation System

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Amazon’s 35% of the revenue comes from these recommendation engines.

# What is it?

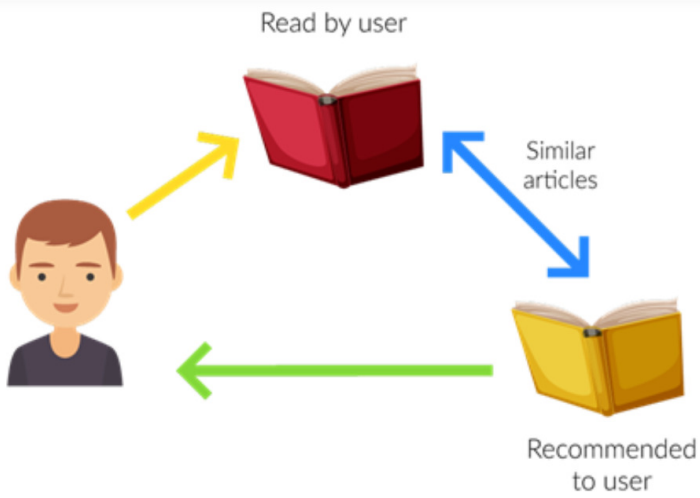
- It is a subclass of Information filtering Systems that seeks to predict the rating or the preference a user might give to an item.

**Information Filtering Systems:**
Removes redundant or unwanted information from an information stream

- Simply, it is an algorithm that suggests relevant items to users.
  - Netflix: which movie to watch
  - E-commerce: which product to buy, or
  - Kindle: which book to read, etc.

# Content Based Filtering (CBF)

- **Relevant items are shown using the content of the previously searched items by the users.** Here content refers to the attribute/tag of the product that the user likes.
- In this type of system, products are tagged using certain keywords, and then the system tries to understand what the user wants it looks in its database and finally tries to recommend different products that the user wants.




In a movie recommendation system, each film is tagged with genres. When a new user, User A, joins, the system initially suggests popular movies or gathers information through a user form. As User A rates movies over time, preferences emerge; for instance, if User A consistently rates action movies highly but rates anime movies poorly, the system recommends more action-oriented content. However, this doesn't imply a dislike for anime movies; further data collection is needed to refine recommendations accurately.

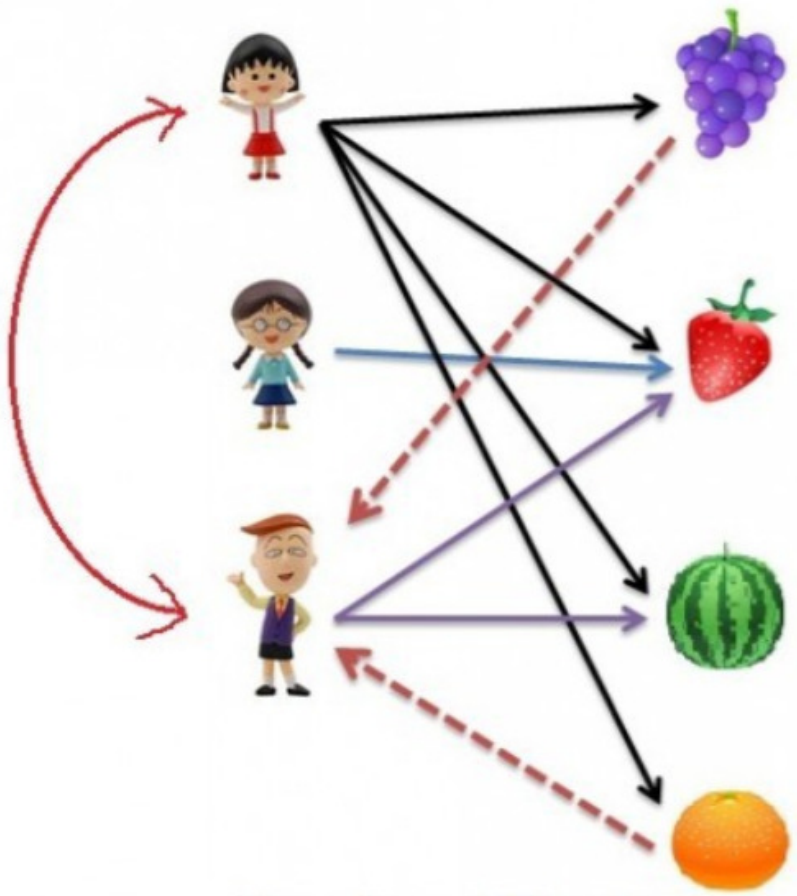
# Collaborative Filtering (CF)

- Recommending new items to users based on similar users' interests and preferences is collaborative-based filtering.
  - This approach addresses the limitations of content-based filtering and leverages user interactions, making it more robust.
  - By focusing on the historical performance of users, this recommendation system can predict future preferences with greater accuracy.

There are **2 types of collaborative filtering**:-

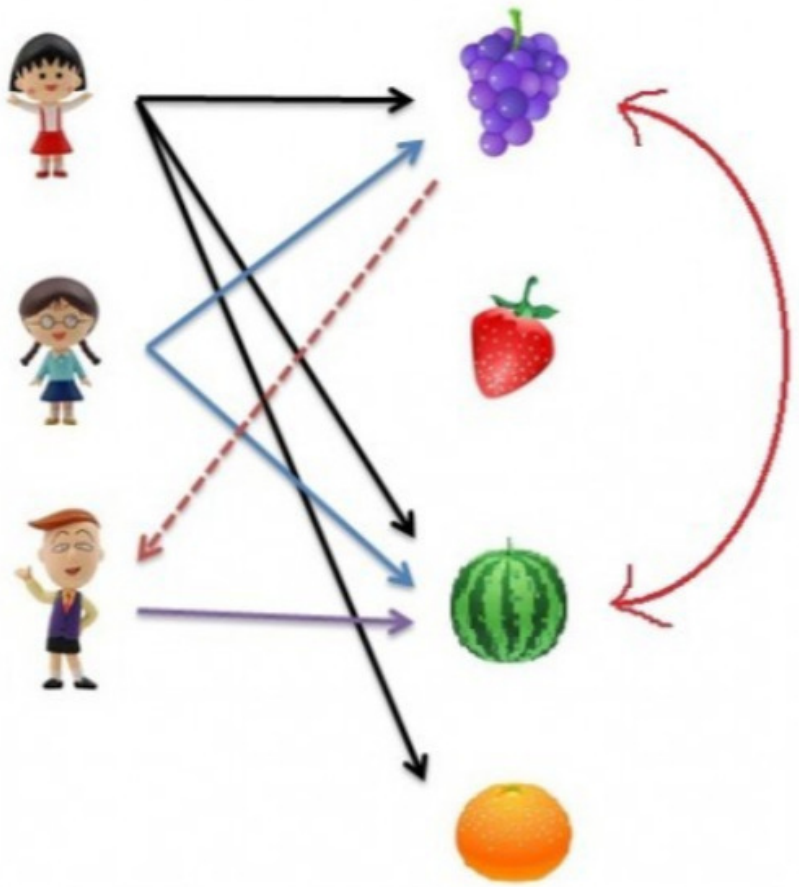
A. **User-Based Collaborative Filtering**
B. **Item-based Collaborative Filtering**

# User-Based Collaborative Filtering




- Rating of the item is done using the rating of neighboring users.
- In simple terms, it is based on **users' similarity.**

# Item-based Collaborative Filtering

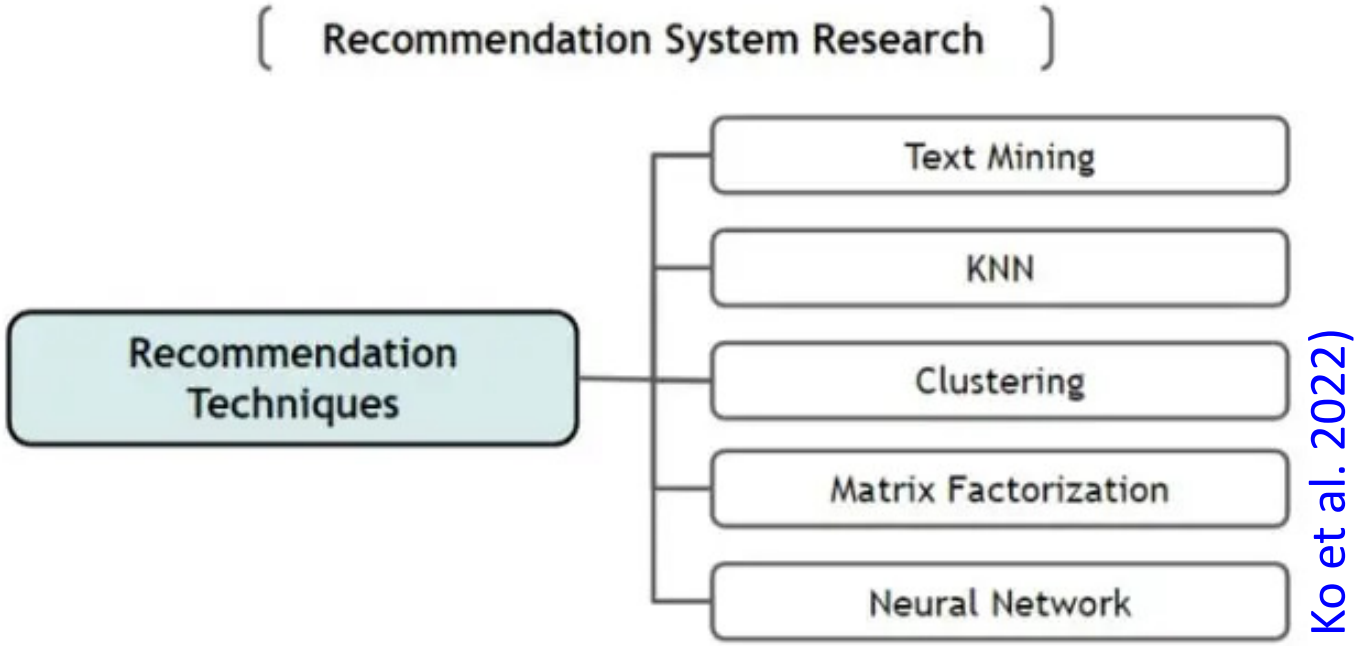


Item-based filtering

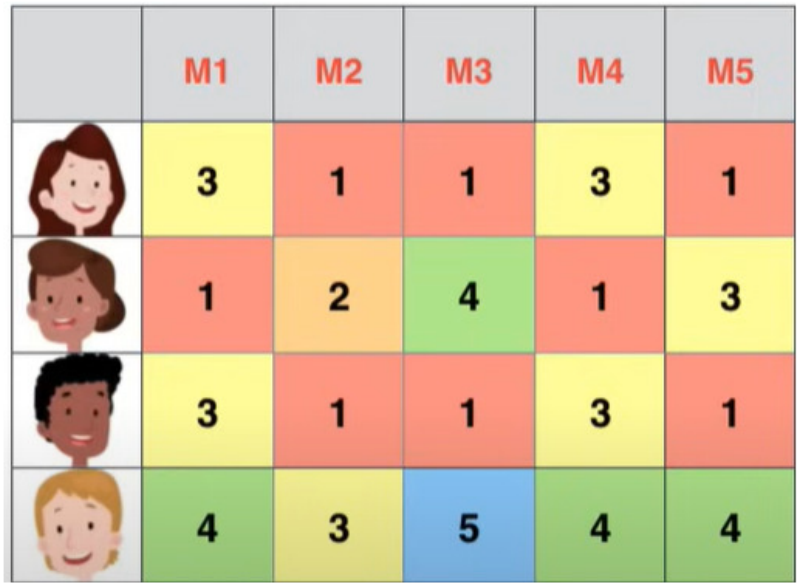
- The rating of the item is predicted using the user's rating on neighboring items.
- In simple words, it is based on the notion of item similarity.

# Recommendation Techniques

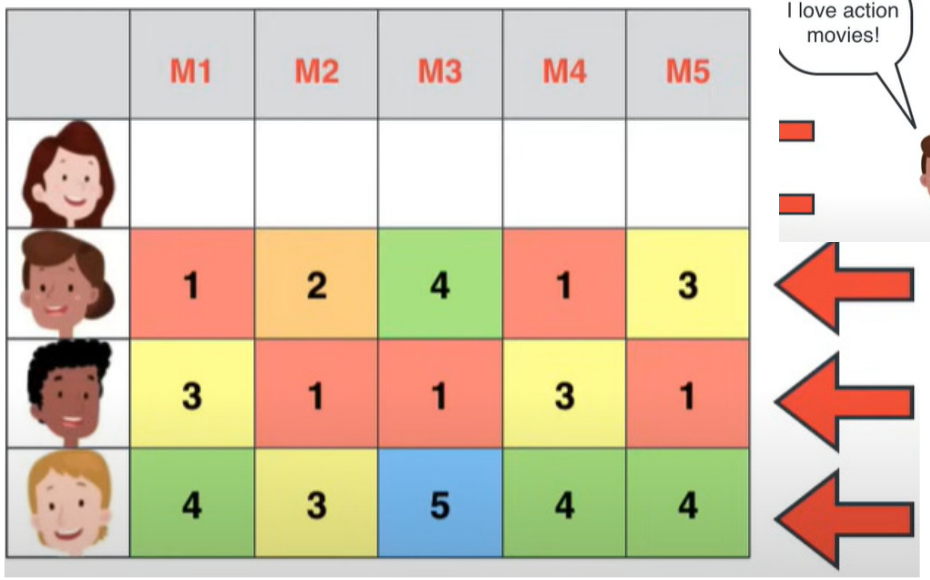
- Data mining techniques are precious for uncovering patterns and correlations within data.
- This information can then be used to make recommendations (e.g., suggesting similar items or grouping users with similar interests).



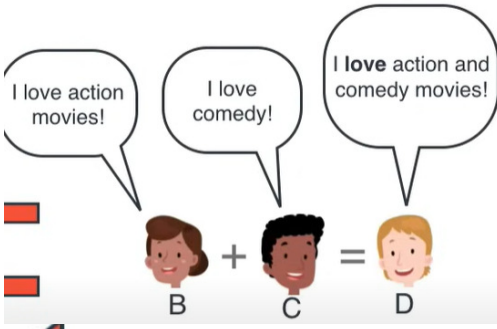
# Dependent Rows and Columns

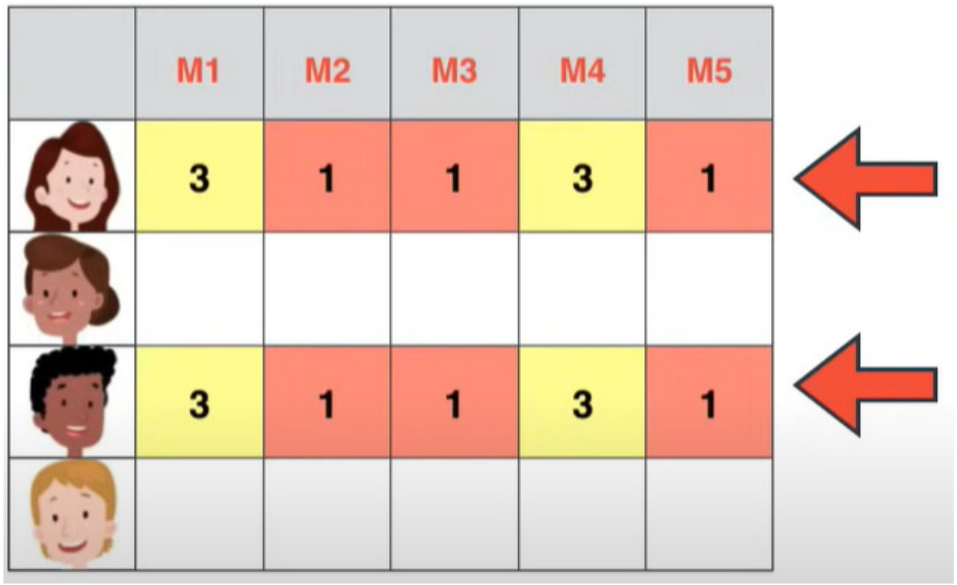


| | M1 | M2 | M3 | M4 | M5 |
|---|---|---|---|---|---|
| | 3 | 1 | 1 | 3 | 1 |
| | 1 | 2 | 4 | 1 | 3 |
| | 3 | 1 | 1 | 3 | 1 |
| | 4 | 3 | 5 | 4 | 4 |



| | M1 | M2 | M3 | M4 | M5 |
|---|---|---|---|---|---|
| | | | | | |
| | 1 | 2 | 4 | 1 | 3 |
| | 3 | 1 | 1 | 3 | 1 |
| | 4 | 3 | 5 | 4 | 4 |



| | M1 | M2 | M3 | M4 | M5 |
|---|---|---|---|---|---|
| | 3 | 1 | 1 | 3 | 1 |
| | | | | | |
| | 3 | 1 | 1 | 3 | 1 |
| | | | | | |

| | M1 | M2 | M3 | M4 | M5 |
|---|---|---|---|---|---|
| | 3 | | | 3 | |
| | 1 | | | 1 | |
| | 3 | | | 3 | |
| | 4 | | | 4 | |

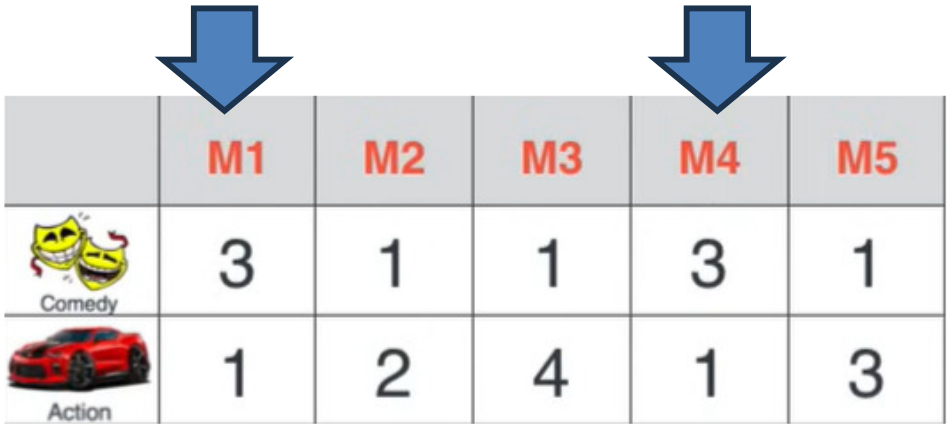
Question: How do we figure out all these depencencies?

## Matrix Factorization

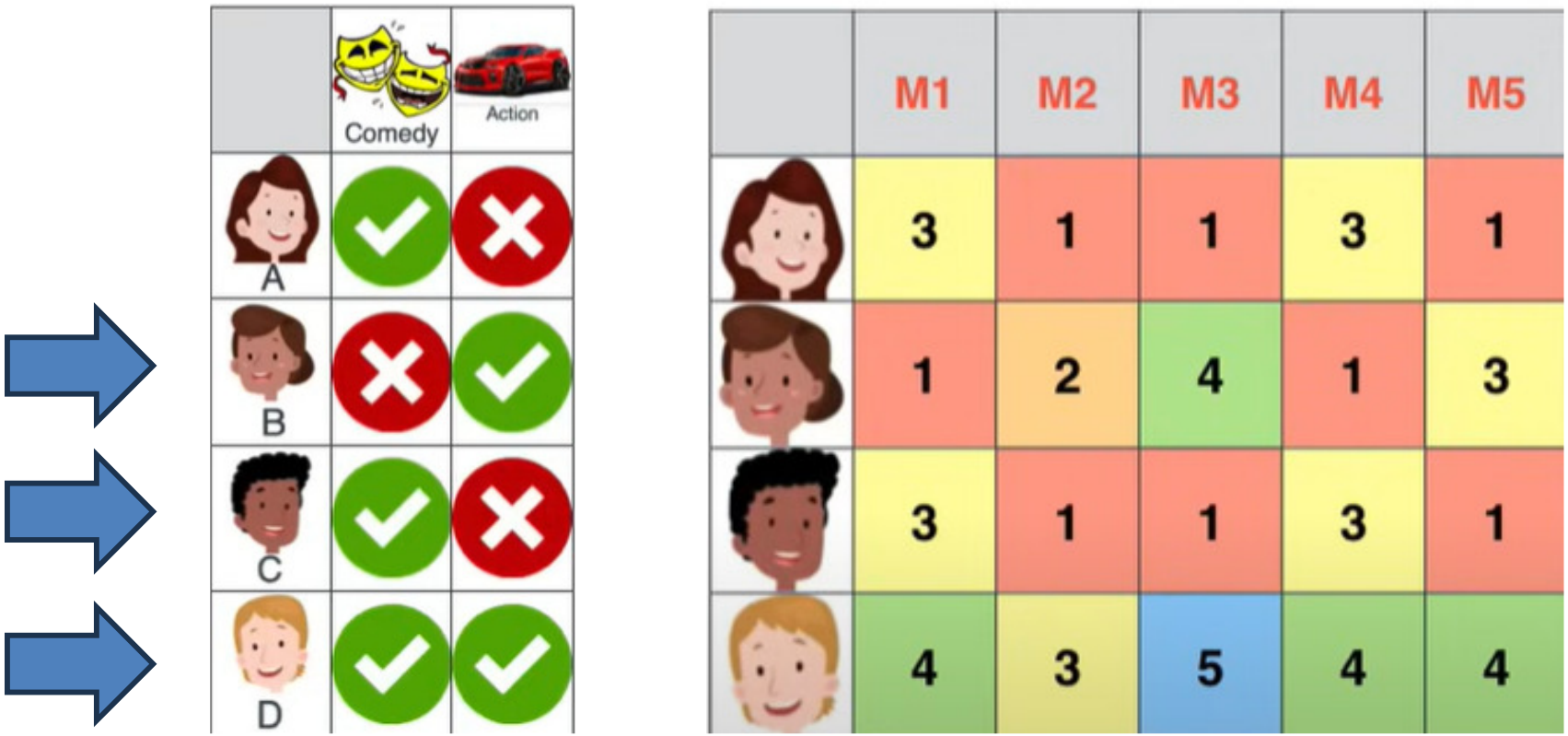
this x that =

| | M1 | M2 | M3 | M4 | M5 |
|---|---|---|---|---|---|
| | 3 | 1 | 1 | 3 | 1 |
| | 1 | 2 | 4 | 1 | 3 |
| | 3 | 1 | 1 | 3 | 1 |
| | 4 | 3 | 5 | 4 | 4 |

# Matrix Factorization



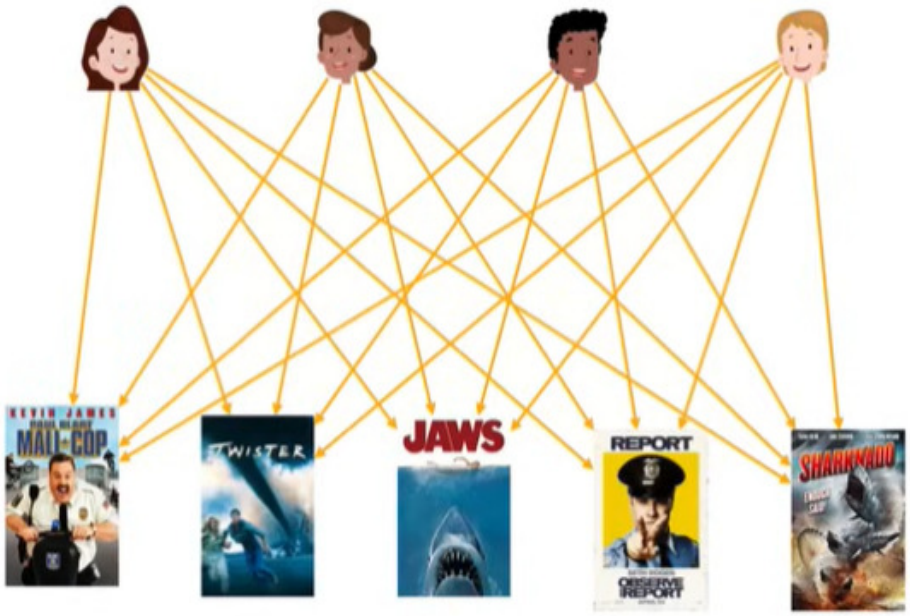
| | M1 | M2 | M3 | M4 | M5 |
|---|---|---|---|---|---|
| Comedy | 3 | 1 | 1 | 3 | 1 |
| Action | 1 | 2 | 4 | 1 | 3 |



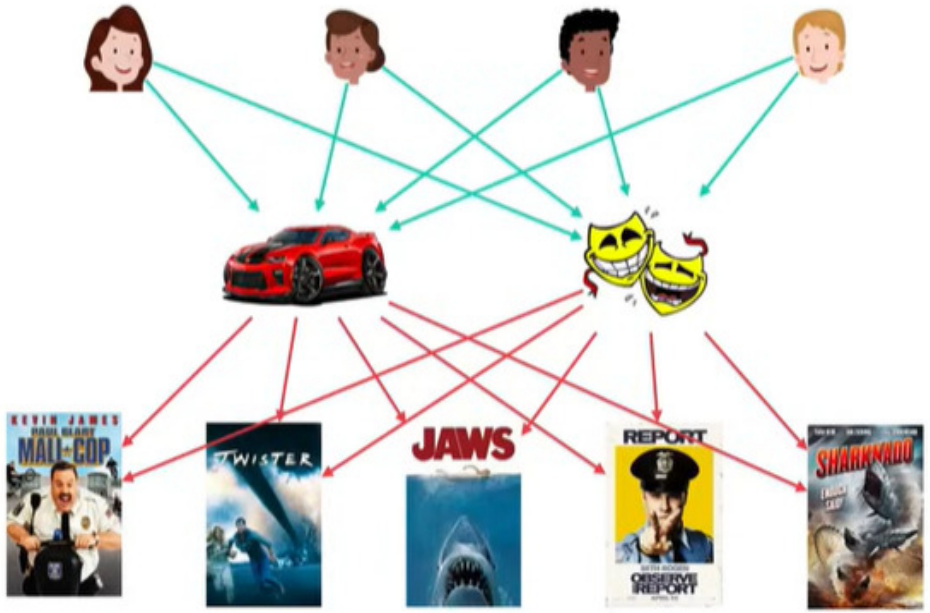
| | Comedy | Action |
|---|---|---|
| A | ✓ | ✗ |
| B | ✗ | ✓ |
| C | ✓ | ✗ |
| D | ✓ | ✓ |

| | M1 | M2 | M3 | M4 | M5 |
|---|---|---|---|---|---|
| A | 3 | 1 | 1 | 3 | 1 |
| B | 1 | 2 | 4 | 1 | 3 |
| C | 3 | 1 | 1 | 3 | 1 |
| D | 4 | 3 | 5 | 4 | 4 |

# How many parameters?




**20 Parameters**

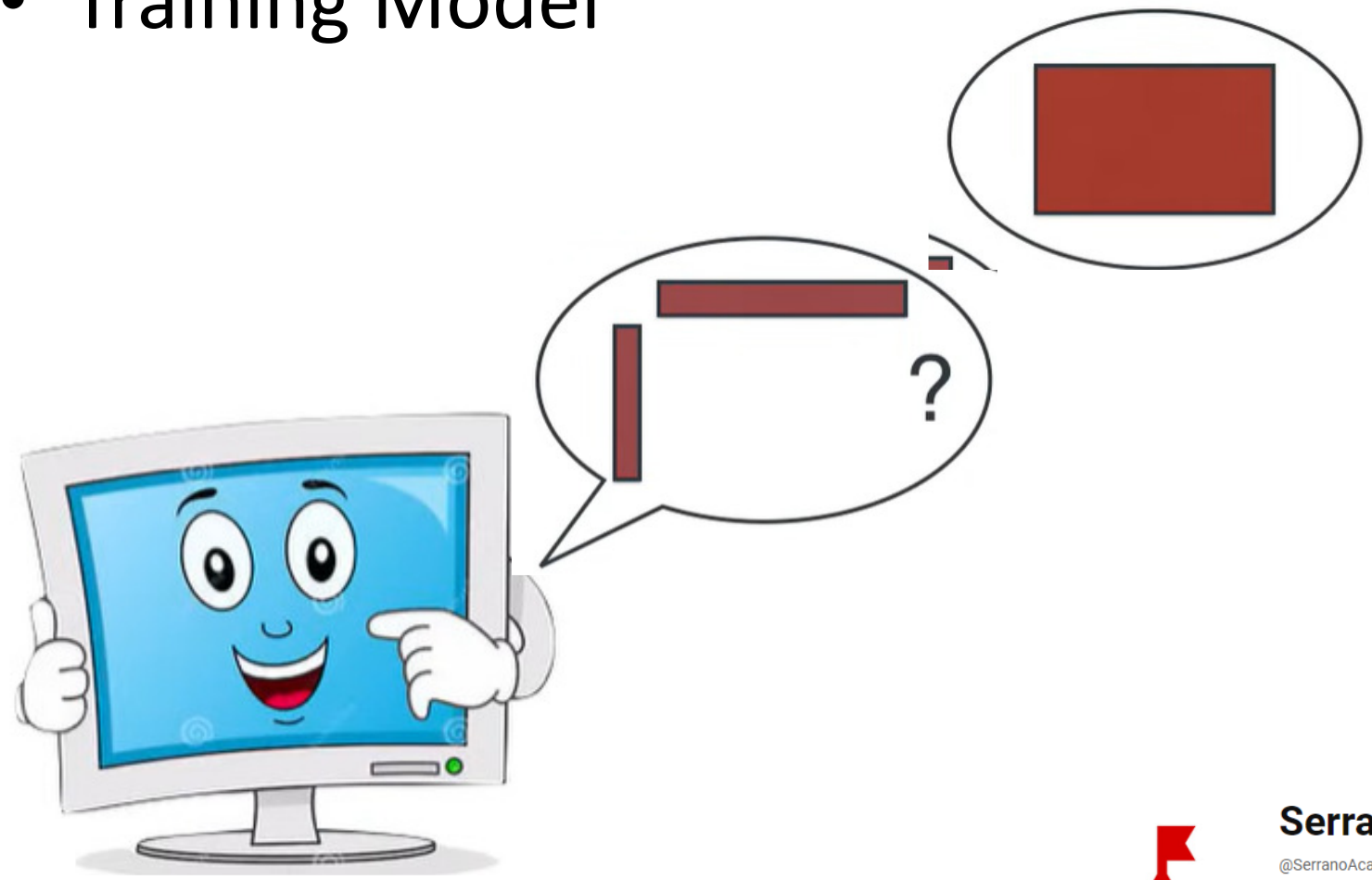



**18 Parameters**

- 2000 Users, 1000 Movies
- 2000000 Parameters vs 2000x100+100x1000=300K Parameters

# How to find right factorization?

- Training Model

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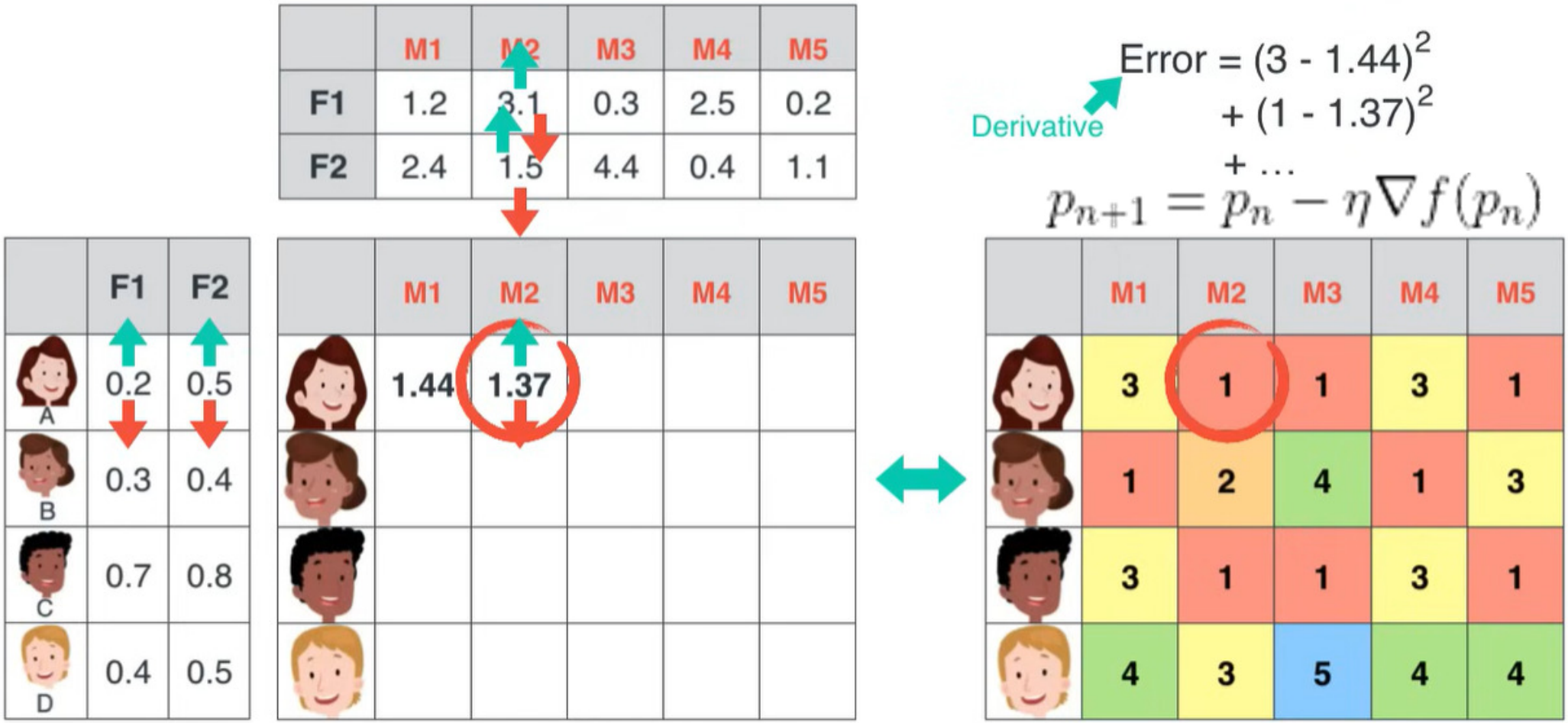
# Gradient Decent-Reduce Error

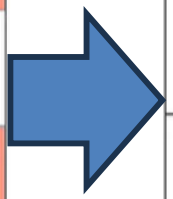


# How to use it?

| | M1 | M2 | M3 | M4 | M5 |
|---|---|---|---|---|---|
| F1 | 3 | 1 | 1 | 3 | 1 |
| F2 | 1 | 2 | 4 | 1 | 3 |

| | F1 | F2 |
|---|---|---|
| A | 1 | 0 |
| B | 0 | 1 |
| C | 1 | 0 |
| D | 1 | 1 |

| | M1 | M2 | M3 | M4 | M5 |
|---|---|---|---|---|---|
| A | 3 | | 1 | | 1 |
| B | 1 | | 4 | 1 | |
| C | 3 | 1 | | 3 | 1 |
| D | | 3 | | 4 | 4 |



| | M1 | M2 | M3 | M4 | M5 |
|---|---|---|---|---|---|
| A | 3 | 1 | 1 | 3 | 1 |
| B | 1 | 2 | 4 | 1 | 3 |
| C | 3 | 1 | 1 | 3 | 1 |
| D | 4 | 3 | 5 | 4 | 4 |