5. Social Information Filtering

Contents

Information Filtering

- Information Filtering is the process of monitoring large amounts of dynamically generated information and pushing to a user the subset of information likely to be of her/his interest (based on her/his information needs).

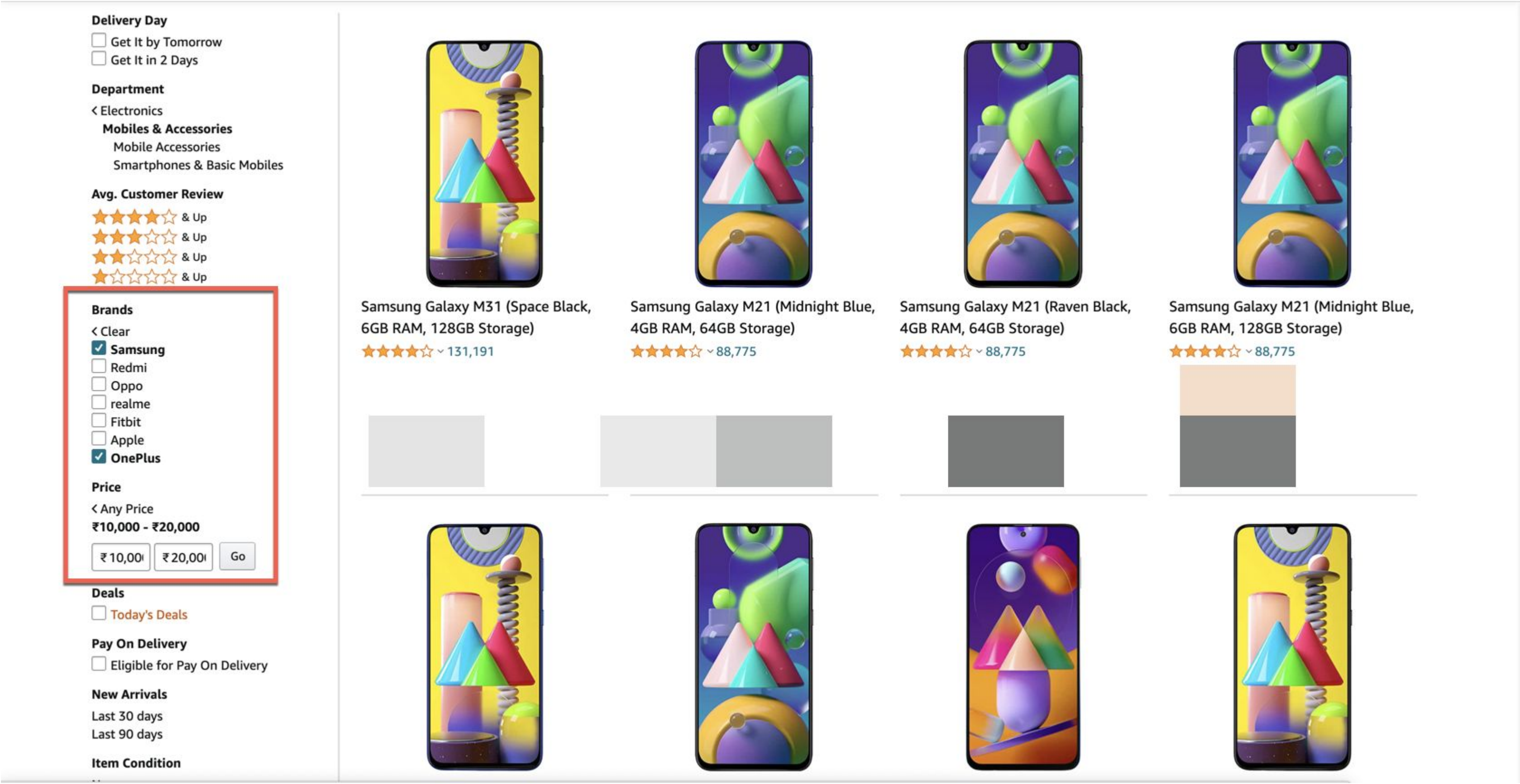
Information Filtering :

- Every store must have category-specific filtering. When starting out with **implementing product filtering, it's important to note that customers prefer category-specific options rather than generic parameters such as brands or product ratings.**

- **Few customers** actually start with a specific brand or rating in mind, but they do know the category they are looking in (when browsing) or a particular product (when on a mission to find it).

- Here, **category filtering works well because the parameters change based on the product.**

- For example, **a customer shopping for a dress may want to filter based on the size, price, color, length, and fabrics. Meanwhile, a customer shopping for a mobile phone might prefer to filter based on the amount of memory, size of the screen or battery, or perhaps the price.**


Delivery Day
Get It by Tomorrow
Get It in 2 Days
Department
‹ Electronics
Mobiles & Accessories
Mobile Accessories
Smartphones & Basic Mobiles
Avg. Customer Review
& Up
& Up
& Up
& Up
Brands
‹ Clear
Samsung
Redmi
Oppo
realme
Fitbit
Apple
OnePlus
Price
‹ Any Price
₹10,000 - ₹20,000
₹10,00
₹20,00
Go
Deals
Today's Deals
Pay On Delivery
Eligible for Pay On Delivery
New Arrivals
Last 30 days
Last 90 days
Item Condition
Samsung Galaxy M31 (Space Black, 6GB RAM, 128GB Storage)
131,191
Samsung Galaxy M21 (Midnight Blue, 4GB RAM, 64GB Storage)
88,775
Samsung Galaxy M21 (Raven Black, 4GB RAM, 64GB Storage)
88,775
Samsung Galaxy M21 (Midnight Blue, 6GB RAM, 128GB Storage)
88,775

Category

Price

Brands

RAM

- 1 GB 4
- 4 GB 5
- 6GB 8

Battery Capacity

Internal Storage

- 128 GB 2
- 16 GB 5
- 32 GB 4
- 64 GB 5
- 8 GB 4

Offers

Display

Colour

ReTrack Leather Zipper Headphone Pouch

★★★★☆

Rs.99.00 ~~Rs.499.00~~

Realme DL125 1 m Micro USB Cable

★☆☆☆☆

Rs.199.00

Mi 120 cm 1.2 m Micro USB Cable

★★☆☆☆

Rs.265.00

OPPO USB Data Cable 1 m Micro USB Cable

★★★★☆

Rs.119.00 ~~Rs.350.00~~

Apple MD820ZM/A Lightning to Micro USB Adapter Lightning Cable

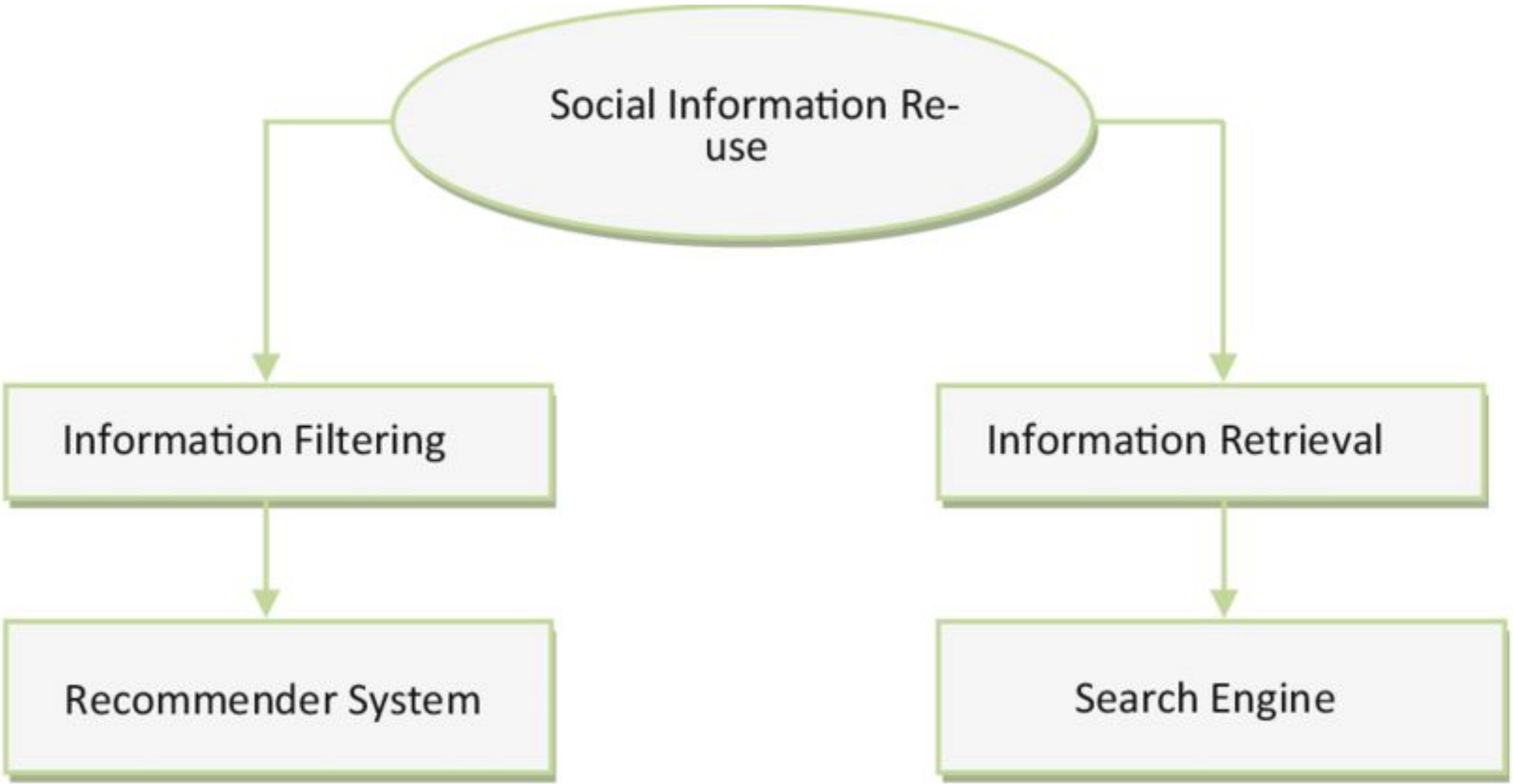
★★★★★

Rs.1,699.00

boAt Micro USB150 1.5 m Micro USB Cable

★★★☆☆

Rs.299.00 ~~Rs.499.00~~


Social Information Re-use
Information Filtering
Information Retrieval
Recommender System
Search Engine

Social Information Sharing

- Social information sharing refers to the **exchange of information, ideas, and content among individuals** within a social network or community.
- It can take place through various channels, such as **online social media platforms, messaging apps, forums, or in-person** conversations.
- Social information sharing can facilitate the **spread of information and ideas, and can help to build connections and relationships** among individuals.
- It can also have negative consequences, such as the **spread of misinformation** or the invasion of privacy.
- The use of algorithms and other technologies can facilitate social information sharing by suggesting content to users or by helping to connect individuals with similar interests.

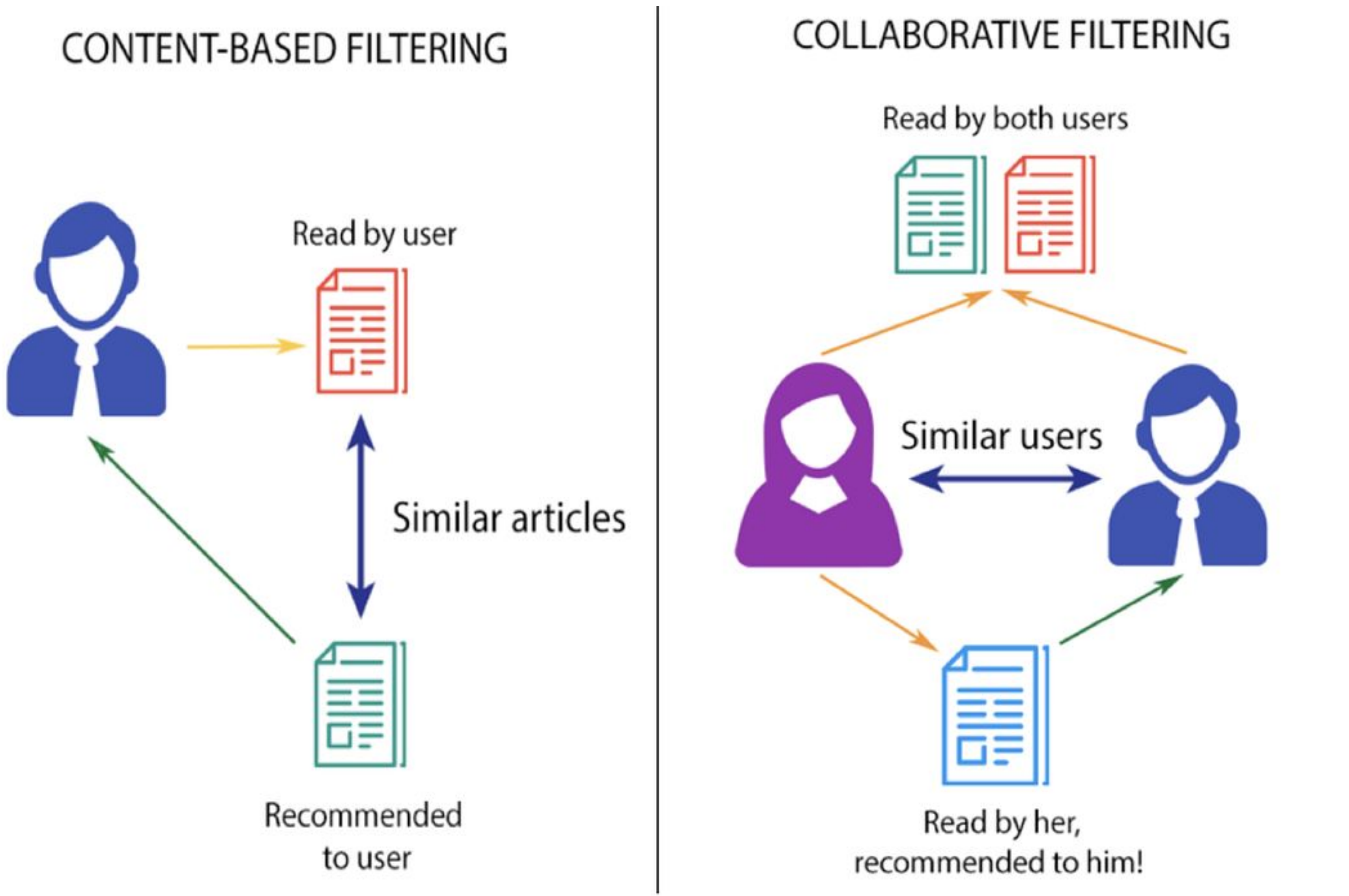
- **Social sharing websites like Reddit, Digg, are designed for people to share interesting content**
- The **community then votes the items up or down, and most interesting links are highlighted.**
- The reliance on large numbers of people to help complete a task like this is a type of **CrowdSourcing,** where **almost each person contributes a tiny amount of work by sharing or voting on the content, and aggregate results are a valuable contribution.**

Social Information Filtering

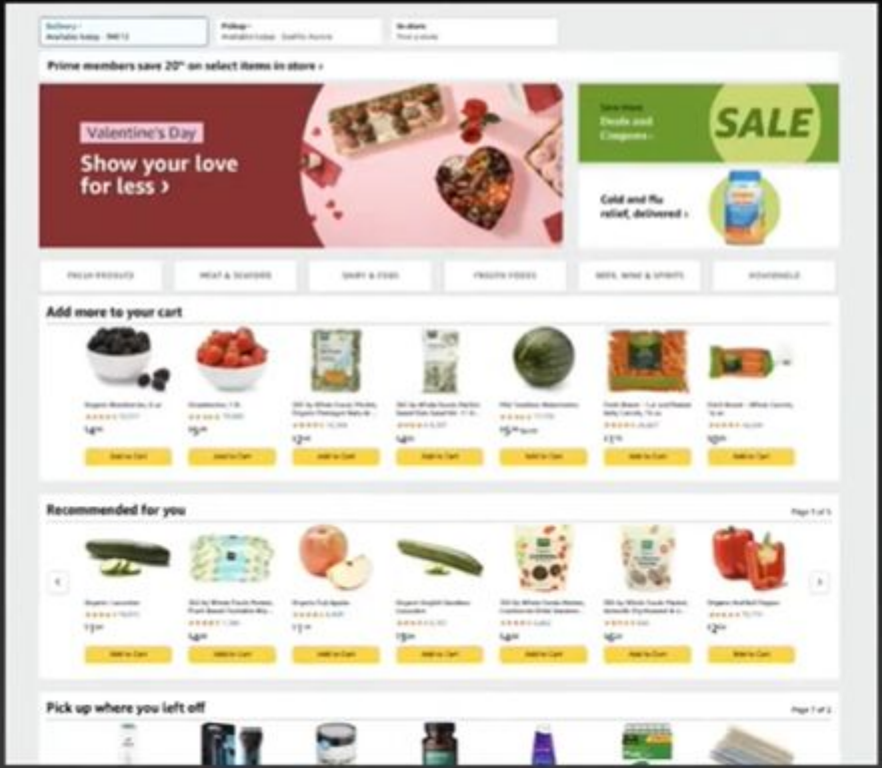
- Social information filtering is a **process for organizing and filtering information based on social connections and relationships.**
- It can involve the **use of algorithms and/or human judgment to identify relevant information.**
- It is used in a variety of contexts, including **online social networks, news aggregators, and recommendation systems.**
- It can be used to surface relevant content to users based on their social connections and interests.
- Two Types :
    - **Content Based Filtering**
    - **Collaborative Filtering**

Automated Recommendation System

- An automated recommendation system is a technology that **uses algorithms to suggest content, products, or other items** to **users** based on their interests and past behaviors.
- Recommendation systems can be used in a variety of contexts, such as **online retail, streaming services, and social media.**
- They **rely on data about the user**, such as their **past actions, preferences, and demographic information,** to make personalized recommendations.
- Recommendation systems can improve the user experience by **providing relevant and personalized recommendations.**
- However, they can also raise **concerns about privacy** and the potential for manipulation or bias in the recommendations.


CONTENT-BASED FILTERING
Read by user
Similar articles
Recommended
to user
COLLABORATIVE FILTERING
Read by both users
Similar users
Read by her,
recommended to him!

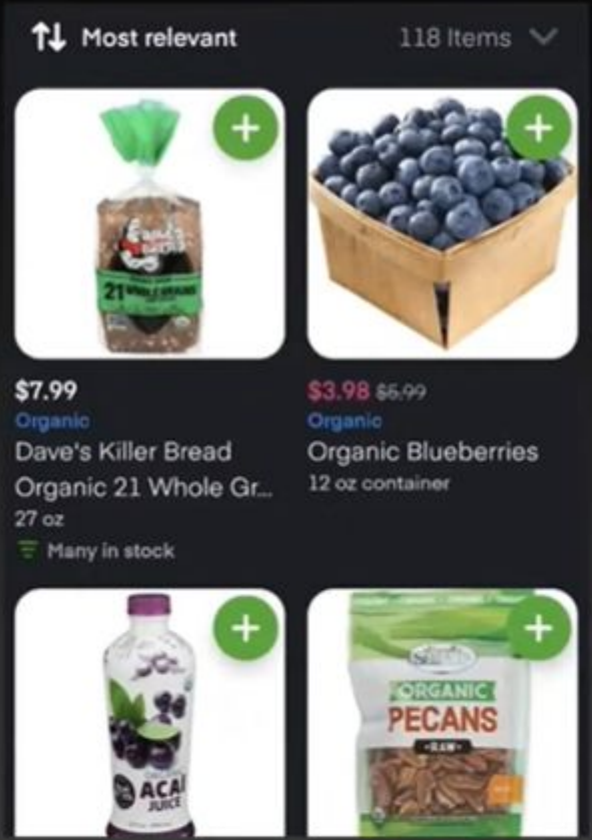
Amazon Recommendations



CAROUSEL BASED

Instacart Recommendations

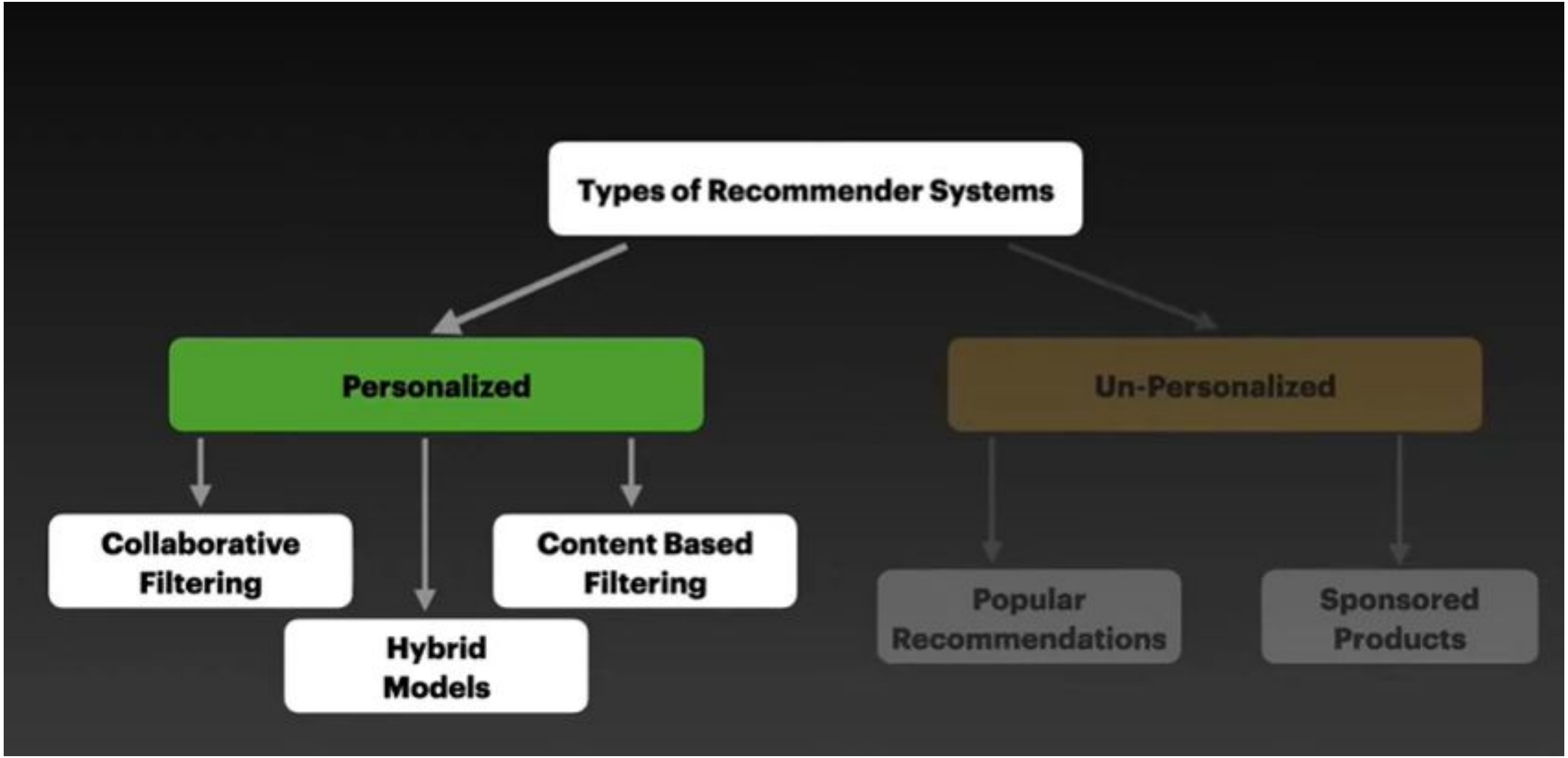
BUY IT AGAIN



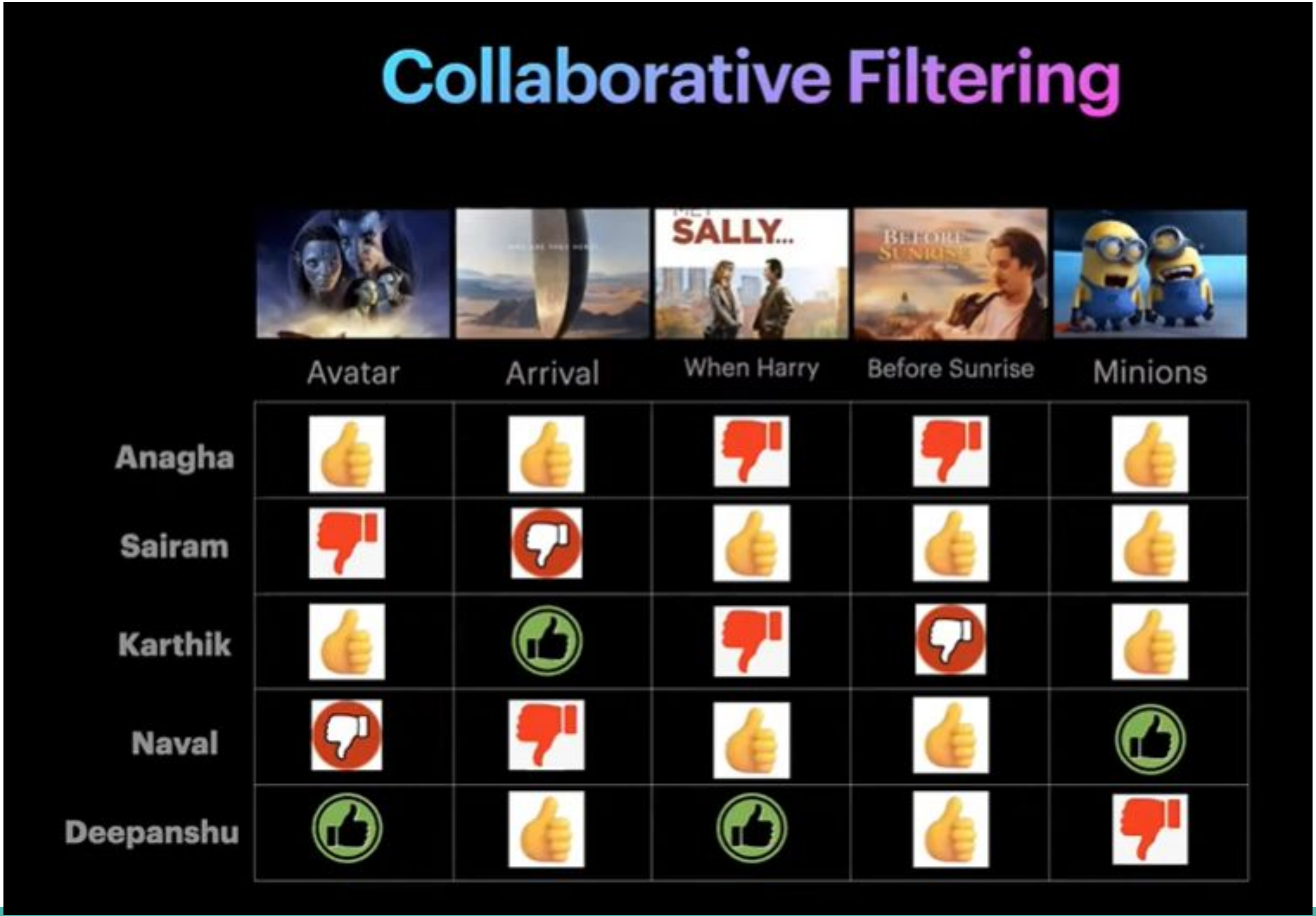
Netflix Recommendations

Why Recommender Systems?

- Save Time
- Surface Products that Are relevant
- Personalized
- Coverage

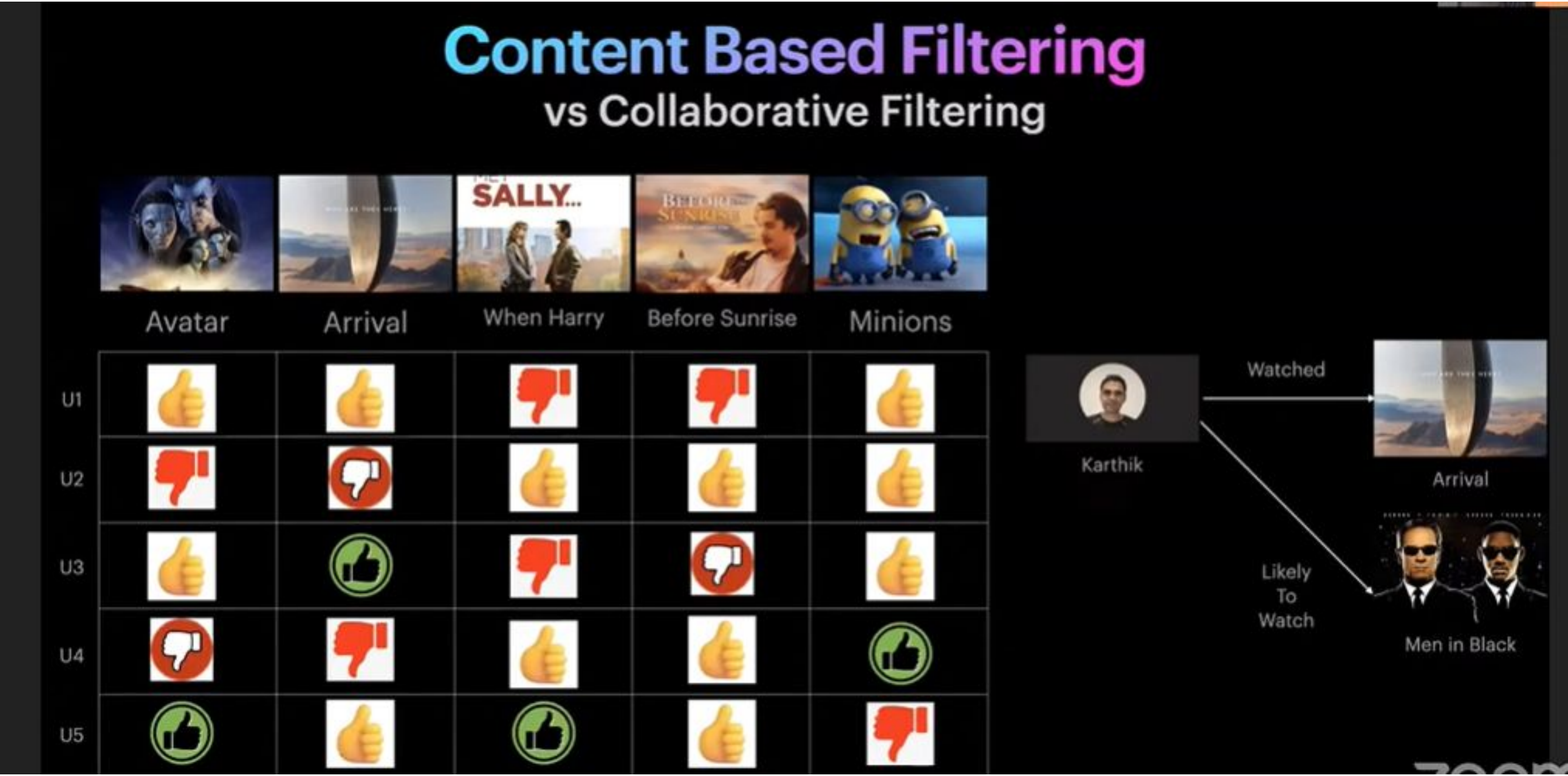


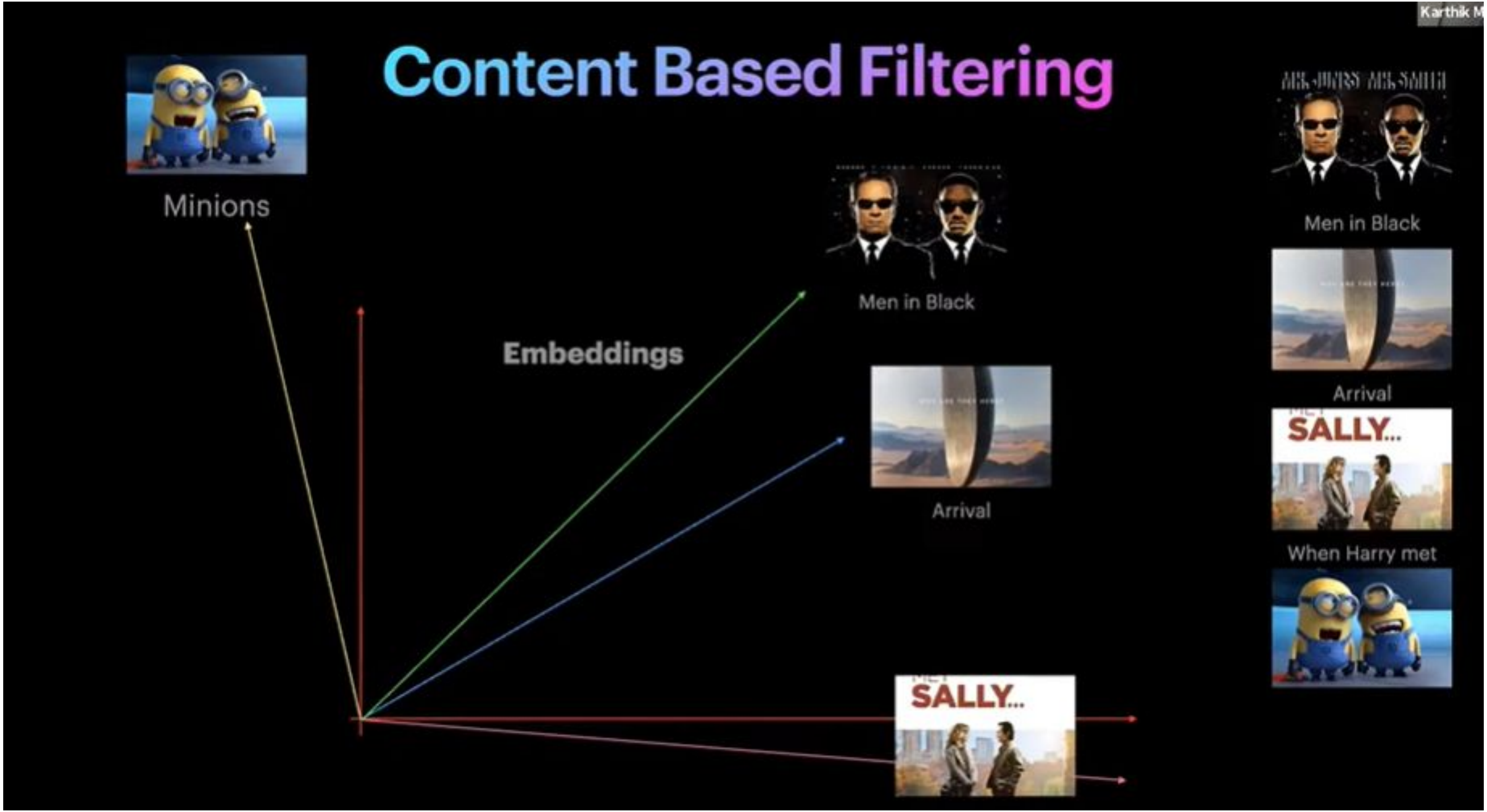
Types of Recommender Systems
Personalized
Un-Personalized
Collaborative Filtering
Content Based Filtering
Hybrid Models
Popular Recommendations
Sponsored Products


Collaborative Filtering
SALLY...
Avatar
Arrival
When Harry
Before Sunrise
Minions
Anagha
Sairam
Karthik
Naval
Deepanshu

Karthik Mohan

Collaborative Filtering


Content Based Filtering
vs Collaborative Filtering
Avatar
Arrival
When Harry
Before Sunrise
Minions
U1
U2
U3
U4
U5
Karthik
Watched
Arrival
Likely
To
Watch
Men in Black



Content Based Filtering
Minions
Embeddings
Men in Black
Arrival
SALLY...
Men in Black
Arrival
SALLY...
When Harry met
Karthik M

Collaborative Filtering vs Content Based Filtering

Collaborative Filtering

Pros

A. Fast train/inference
B. Can recommend variety of products
C. Takes in behavioral signals

Cons

A. Can't handle Cold-start users or Products
B. Doesn't use content signals

Content Based Filtering

Pros

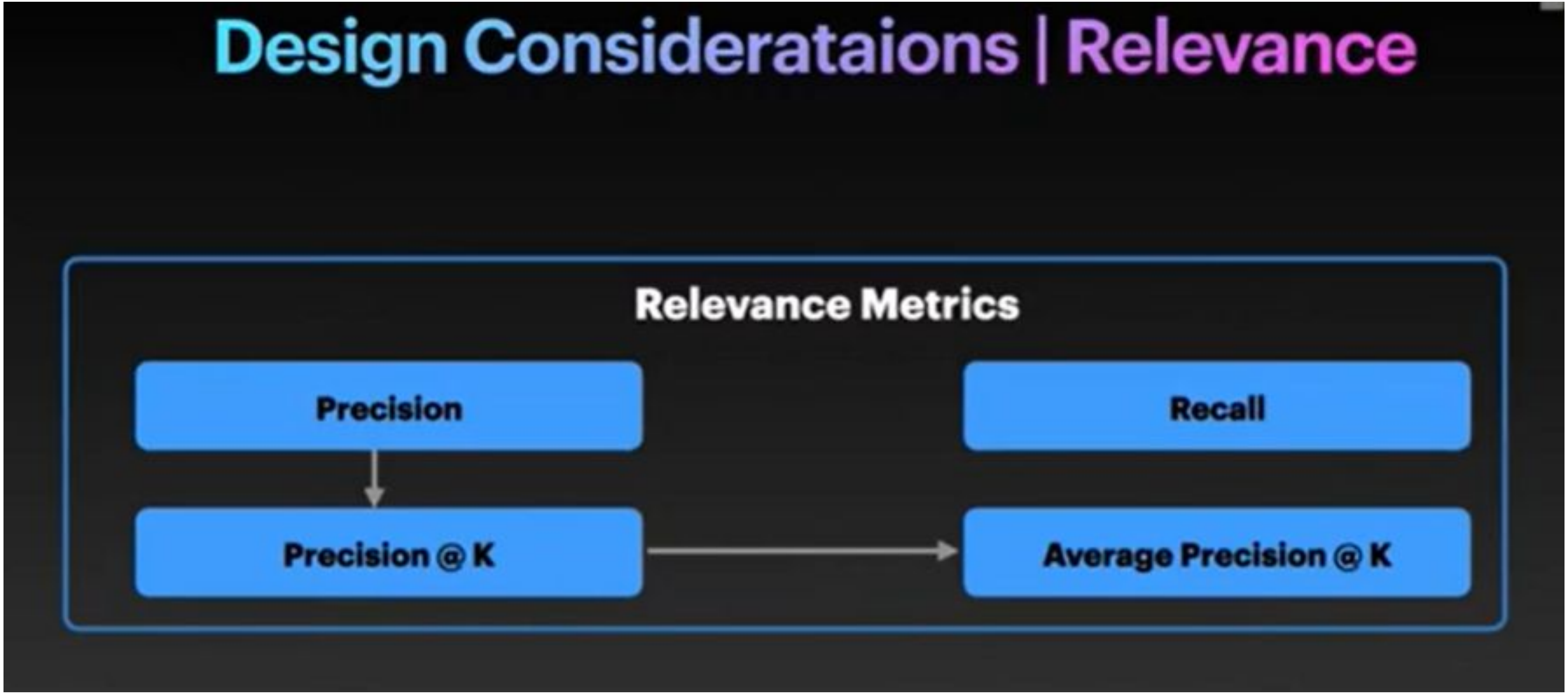
A. Cold-Start Recommendations
B. Recommend content similar to a given product or video

Cons

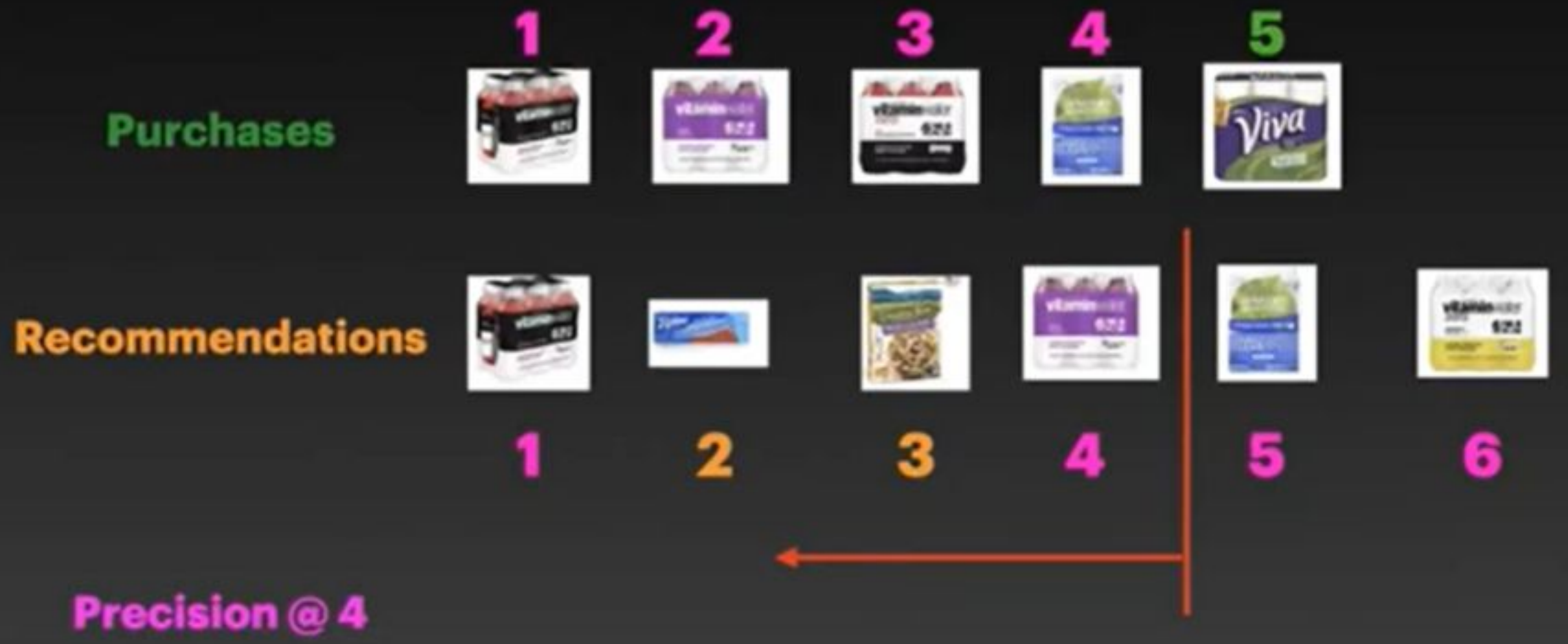
A. Slower training/inference
B. Doesn't take in user behavior signals
C. Less coverage

Design Considerations

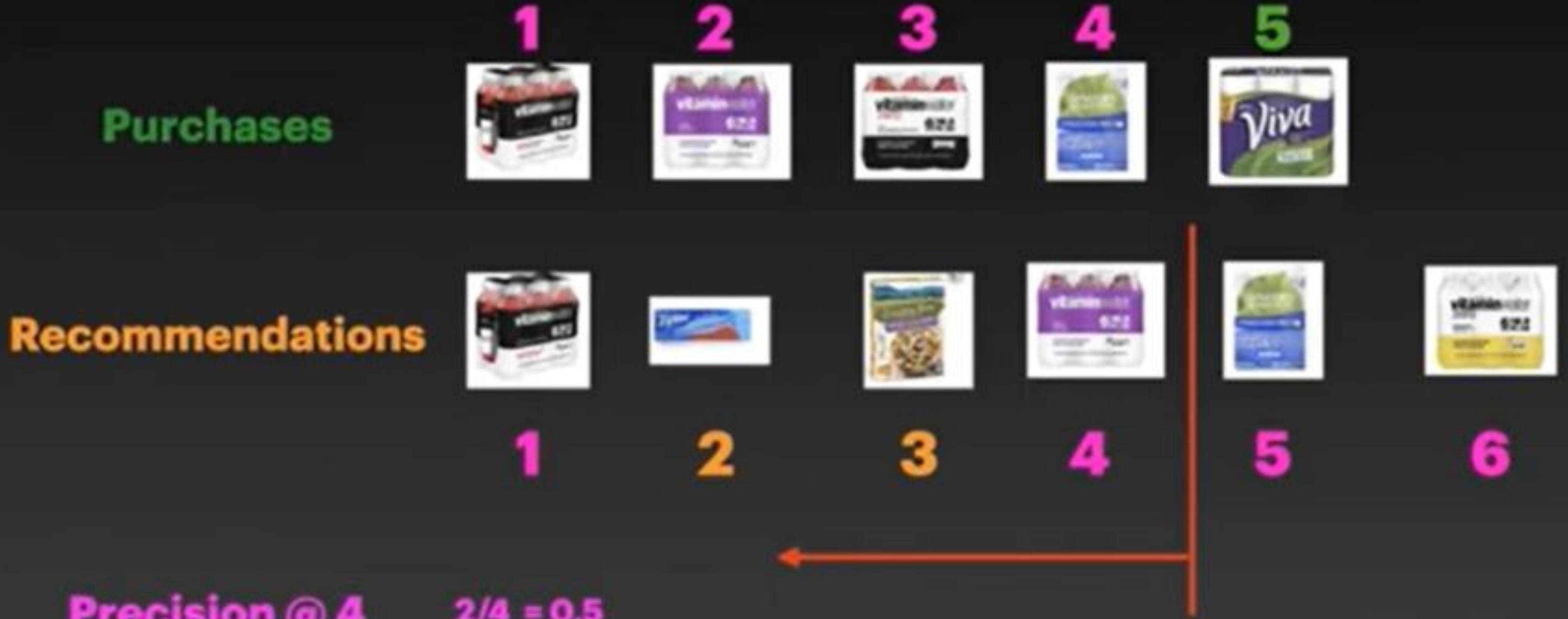
- Relevance
- Freshness
- Latency
- Scalability
- Cold-Start
- Diversity
- Fairness


Design Considerataions | Relevance
Relevance Metrics
Precision
Recall
Precision @ K
Average Precision @ K

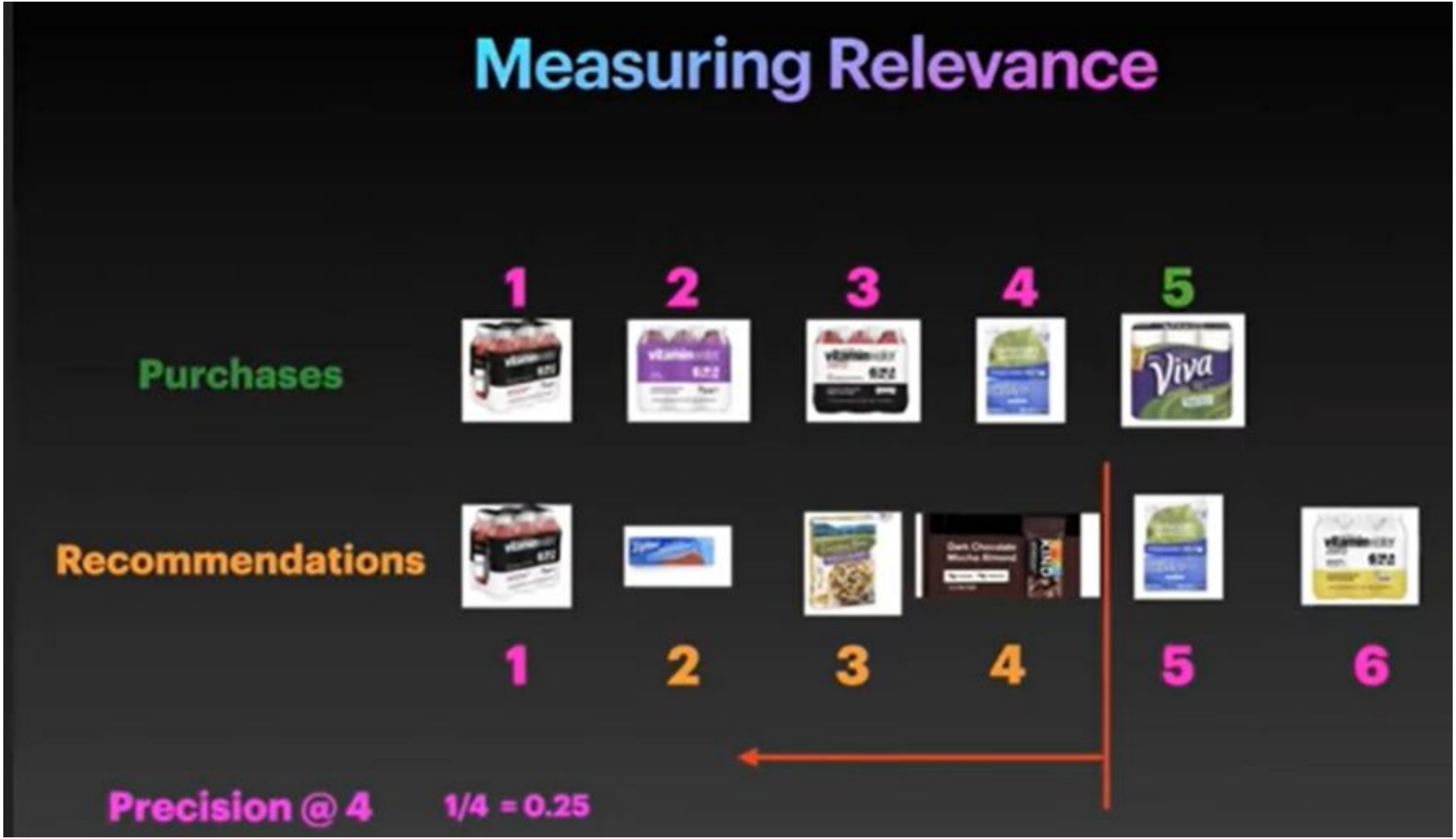
Measuring Relevance



Measuring Relevance

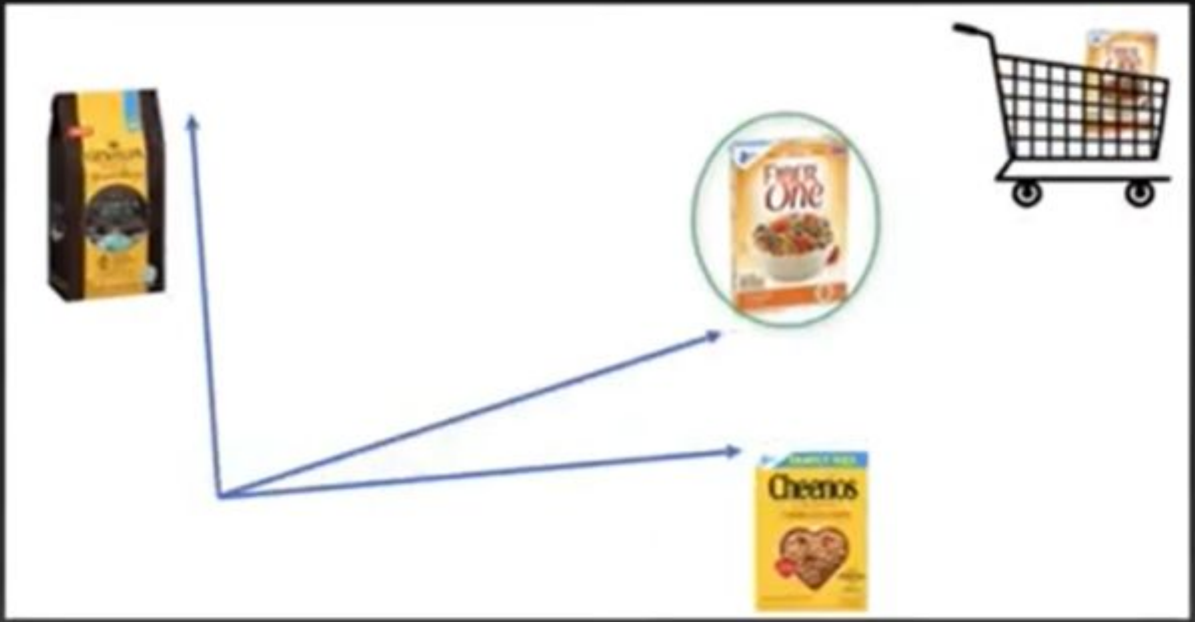


Precision @ 4 2/4 = 0.5


Measuring Relevance
1
2
3
4
5
Purchases
Viva
Recommendations
Dark Chocolate Mocha Almond
KIND
1
2
3
4
5
6
Precision @ 4
1/4 = 0.25

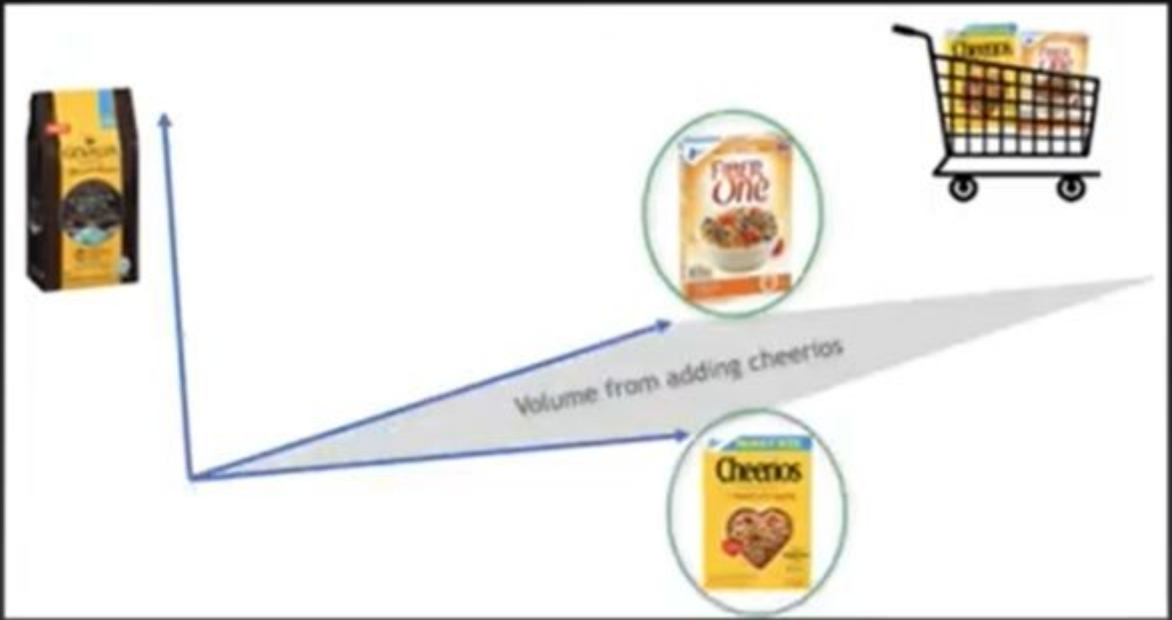
Design Considerations | Diversity

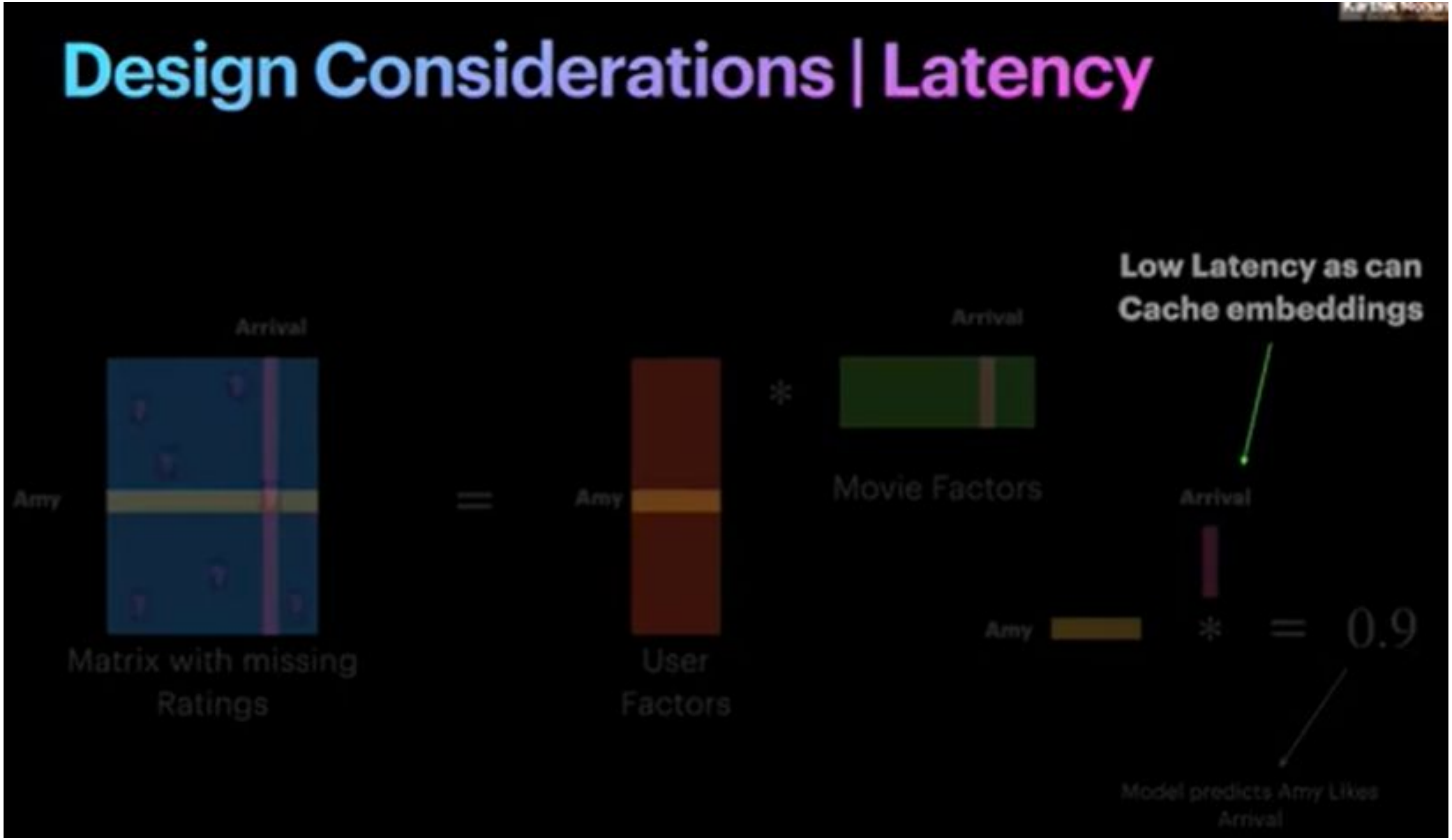
In Online Shopping



Design Considerations | Diversity

In Online Shopping




Design Considerations | Latency
Low Latency as can
Cache embeddings
Arrival
Amy
Matrix with missing
Ratings
=
Amy
User
Factors
*
Arrival
Movie Factors
Arrival
Amy
*
=
0.9
Model predicts Amy Likes
Arrival

Design Considerations | Scalability

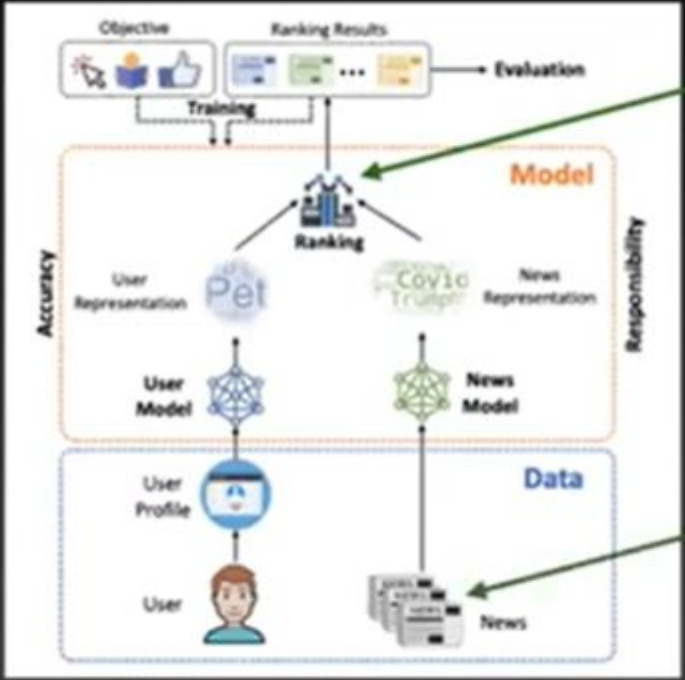
#Movies	Training	Prediction Time
$100K$	Easy	Low Latency
$1M$	Easy	Low Latency
$10M$	Complex	
$1B$	Complex	High Latency

Need a multi-stage approach

Karthik Mohan

Two Tower Architecture

A popular RecSys Architecture

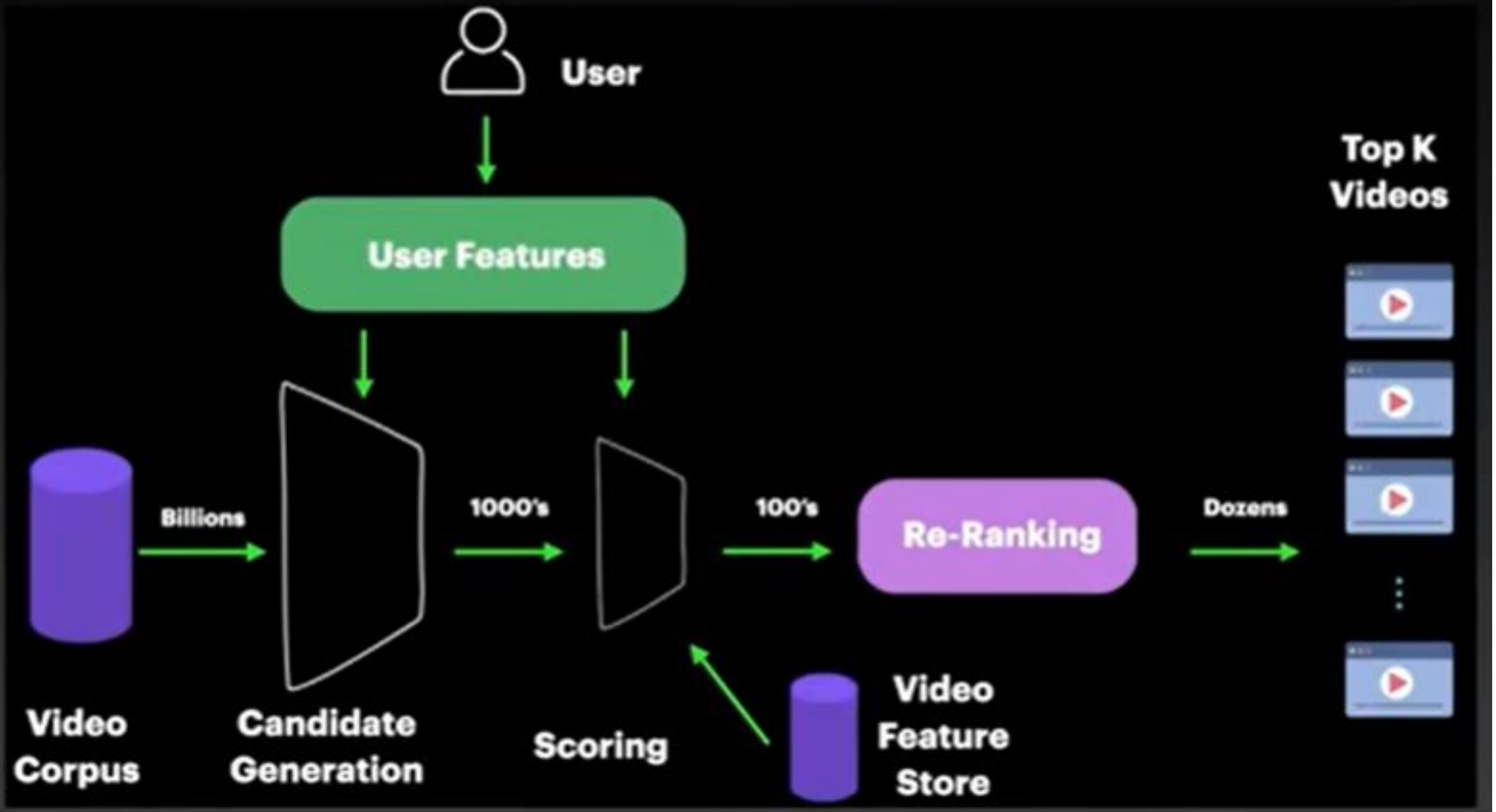


Collaborative
Filtering

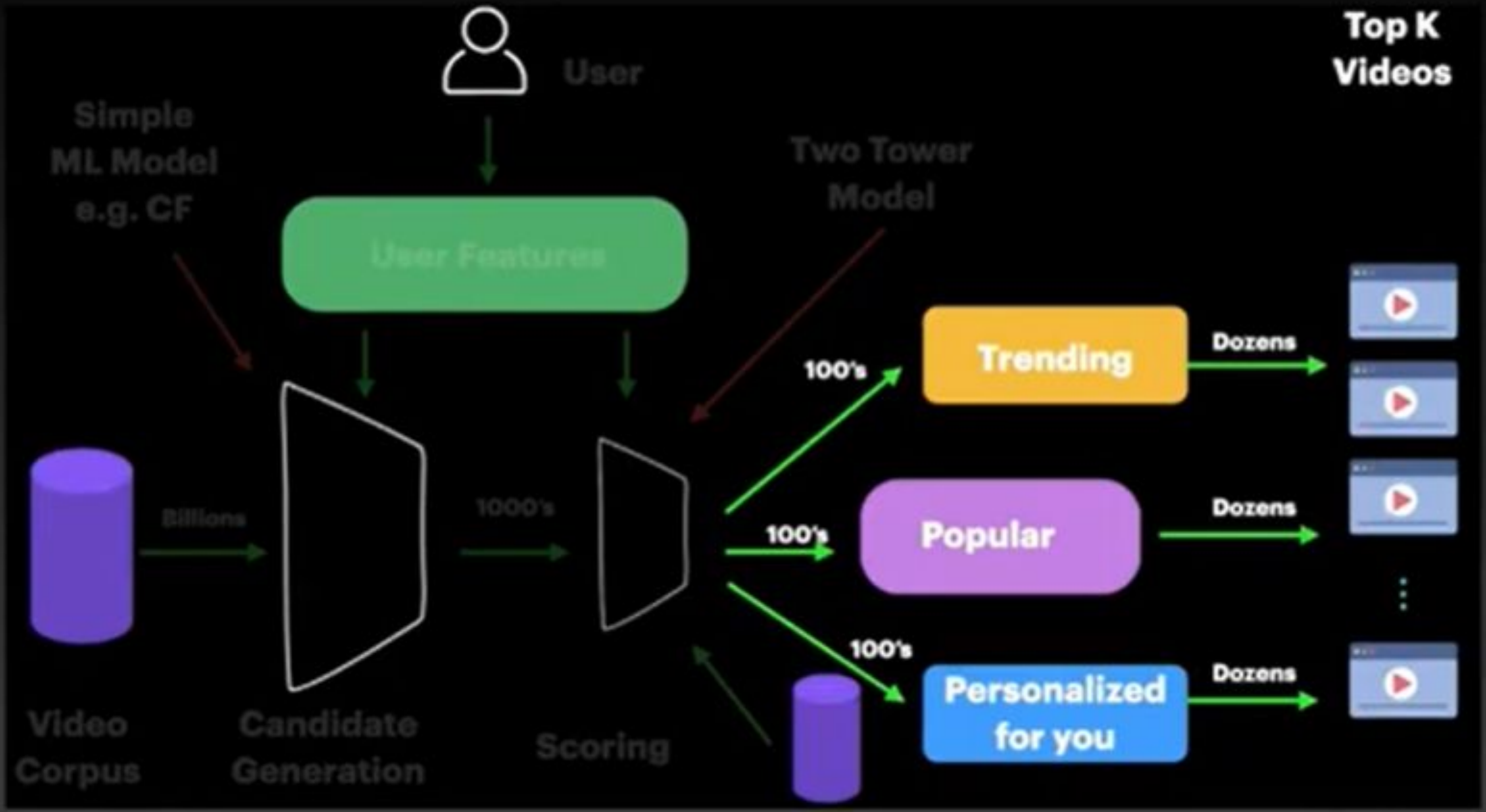
Hybrid Model

Content Based Filtering

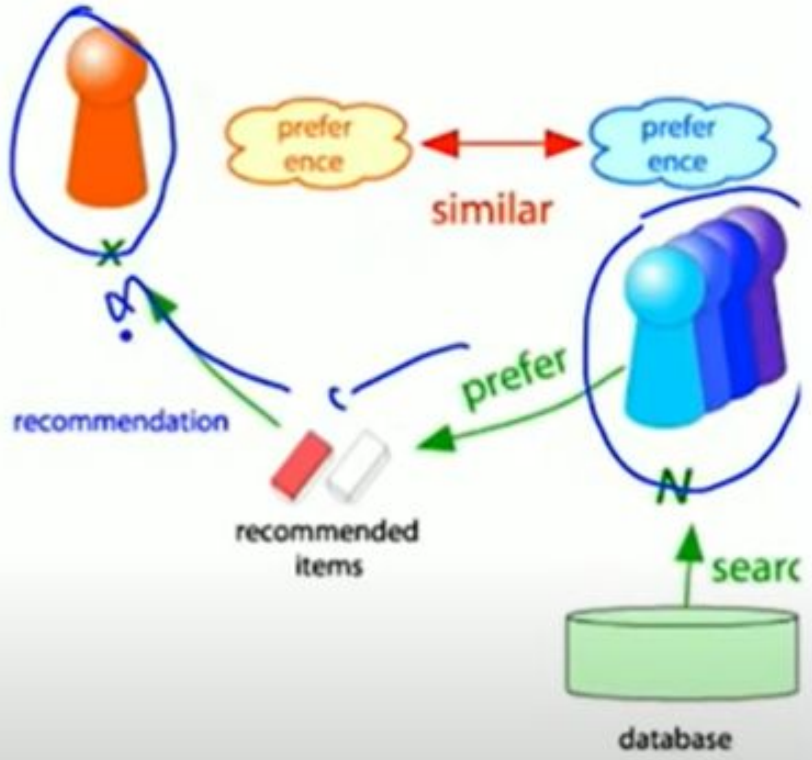
Scalable RecSys Design



Multi-channel Scalable RecSys Design



- 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***



Similar Users (1)

	HP1	HP2	HP3	TW	SW1	SW2	SW3
A	4			5	1		
B	5	5	4				
C				2	4	5	
D		3					3

- Consider users $\boldsymbol{x}$ and $\boldsymbol{y}$ with rating vectors $\boldsymbol{r}_x$ and $\boldsymbol{r}_y$
- We need a similarity metric sim($\boldsymbol{x}$, $\boldsymbol{y}$)
- Capture intuition that sim(A,B) > sim(A,C)

Option 1: Jaccard Similarity

	HP1	HP2	HP3	TW	SW1	SW2	SW3
A	4			5	1		
B	5	5	4				
C				2	4	5	
D		3					3

- sim(A,B) = $| r_A \cap r_B | / | r_A \cup r_B |$
- sim(A,B) = 1/5; sim(A,C) = 2/4
  - sim(A,B) < sim(A,C)
- Problem: Ignores rating values!

Option 2: Cosine similarity

	HP1	HP2	HP3	TW	SW1	SW2	SW3
A	4	0	0	5	1	0	0
B	5	5	4				
C				2	4	5	
D		3					3

- sim(A,B) = cos(r_A, r_B)
- sim(A,B) = 0.38, sim(A,C) = 0.32
  - sim(A,B) < sim(A,C), but not by much

$$\cos(\theta) = \frac{\mathbf{A} \cdot \mathbf{B}}{\|\mathbf{A}\|\|\mathbf{B}\|} = \frac{\sum_{i=1}^{n} A_i B_i}{\sqrt{\sum_{i=1}^{n} A_i^2}\sqrt{\sum_{i=1}^{n} B_i^2}}$$

Option 2: Cosine similarity

	HP1	HP2	HP3	TW	SW1	SW2	SW3
A	4	0	0	5	1	0	0
B	5	5	4	0	0	0	0
C				2	4	5	
D		3					3

- sim(A,B) = cos(r_A, r_B)
- sim(A,B) = 0.38, sim(A,C) = 0.32
  - sim(A,B) > sim(A,C), but not by much
- Problem: treats missing ratings as negative

Option 3: Centered cosine

- Normalize ratings by subtracting row mean

	HP1	HP2	HP3	TW	SW1	SW2	SW3
A	4			5	1		
B	5	5	4				
C				2	4	5	
D		3					3

	HP1	HP2	HP3	TW	SW1	SW2	SW3
A	$2/3$			$5/3$	$-7/3$		
B	$1/3$	$1/3$	$-2/3$				
C				$-5/3$	$1/3$	$4/3$	
D		0					0

Centered Cosine similarity (2)

	HP1	HP2	HP3	TW	SW1	SW2	SW3
A	$2/3$			$5/3$	$-7/3$		
B	$1/3$	$1/3$	$-2/3$				
C				$-5/3$	$1/3$	$4/3$	
D		0					0

- sim(A,B) = cos(r_A, r_B) = 0.09; sim(A,C) = -0.56
  - sim(A,B) > sim(A,C)
- Captures intuition better
  - Missing ratings treated as "average"
  - Handles "tough raters" and "easy raters"

Centered Cosine similarity (2)

	HP1	HP2	HP3	TW	SW1	SW2	SW3
A	$2/3$			$5/3$	$-7/3$		
B	$1/3$	$1/3$	$-2/3$				
C				$-5/3$	$1/3$	$4/3$	
D		0					0

- sim(A,B) = cos(r_A, r_B) = 0.09; sim(A,C) = -0.56
  - sim(A,B) > sim(A,C)
- Captures intuition better
  - Missing ratings treated as "average"
  - Handles "tough raters" and "easy raters"
- Also known as Pearson Correlation

Item-Item Collaborative Filtering

- **So far: User-user collaborative filtering**
- **Another view: Item-item**
  - 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-Item CF (|N|=2)

movies \ users	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-Item CF (|N|=2)

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-Item CF (|N|=2)

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

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

$m_1 = (1+3+5+5+4)/5 = 3.6$

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-Item CF (|N|=2)

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

Item-Item CF (|N|=2)

users

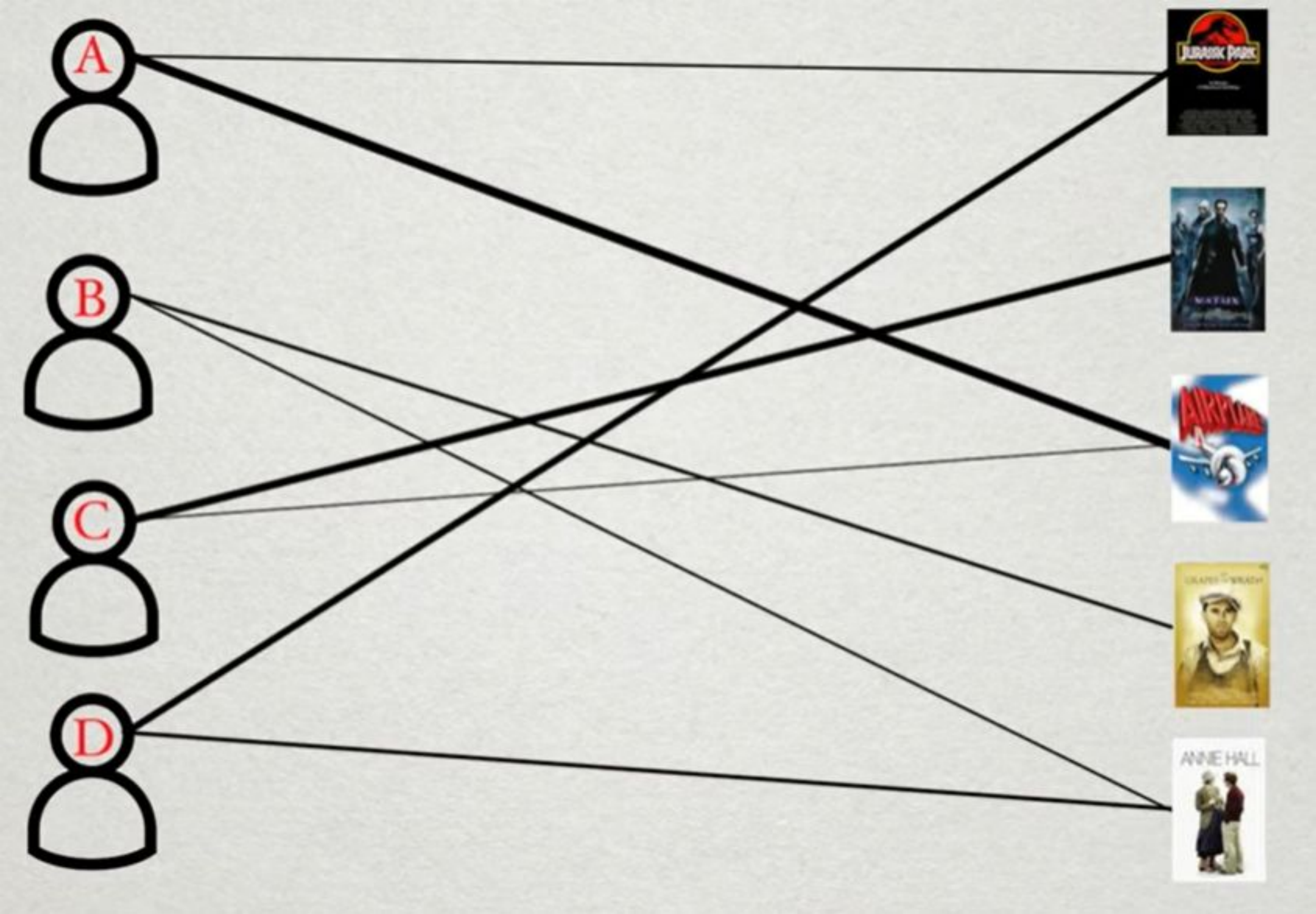
movies	1	2	3	4	5	6	7	8	9	10	11	12
1	1		3		2.6	5			5		4	
2			5	4			4			2	1	3
3	2	4		1	2		3		4	3	5	
4		2	4		5			4			2	
5			4	3	4	2					2	5
6	1		3		3			2			4	

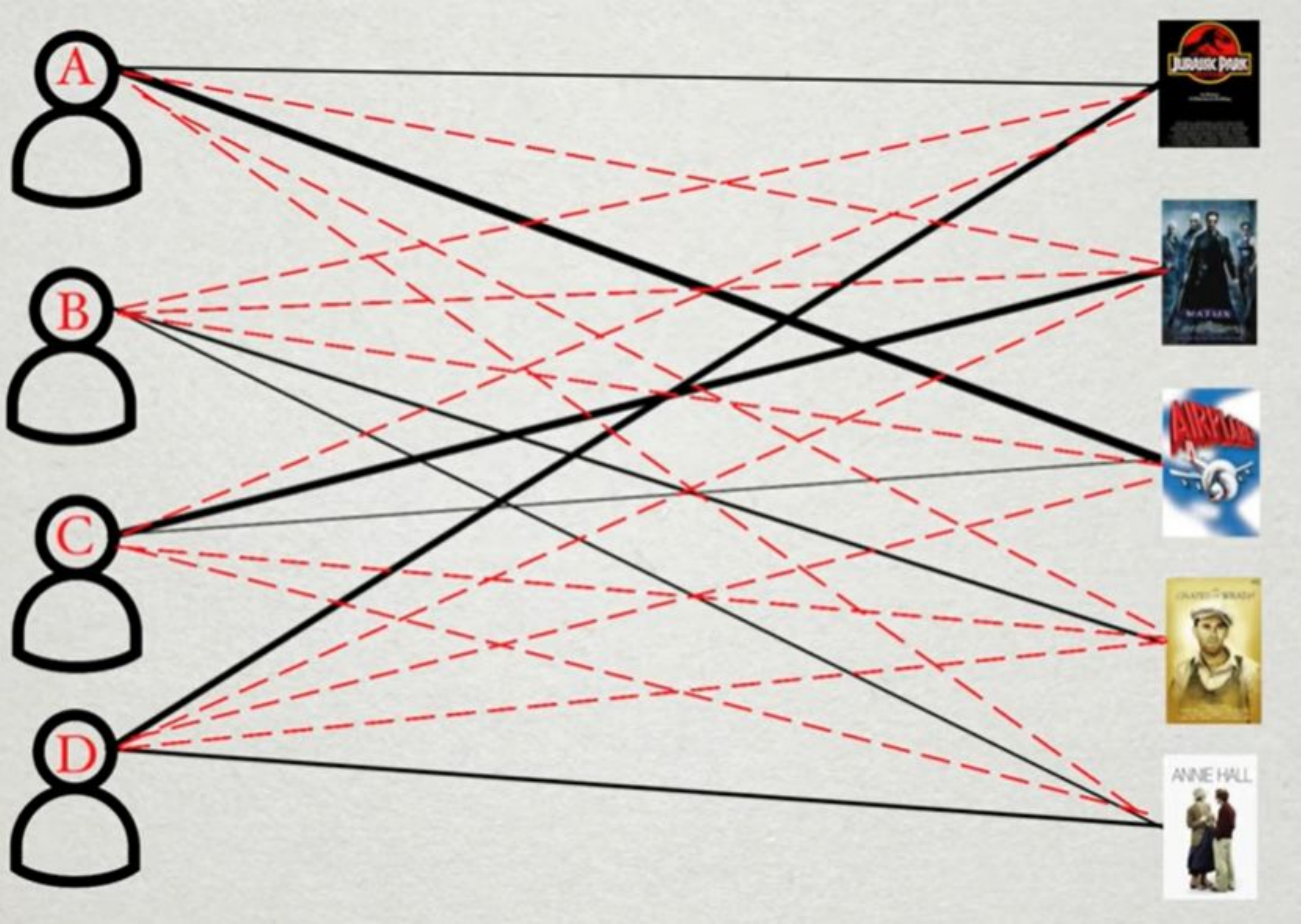
Predict by taking weighted average:

$r_{15} = (0.41*2 + 0.59*3) / (0.41+0.59) = 2.6$

Item-Item v. User-User

- In theory, user-user and item-item are dual approaches
- In practice, item-item outperforms user-user in many use cases
- Items are "simpler" than users
  - Items belong to a small set of "genres", users have varied tastes
  - Item Similarity is more meaningful than User Similarity

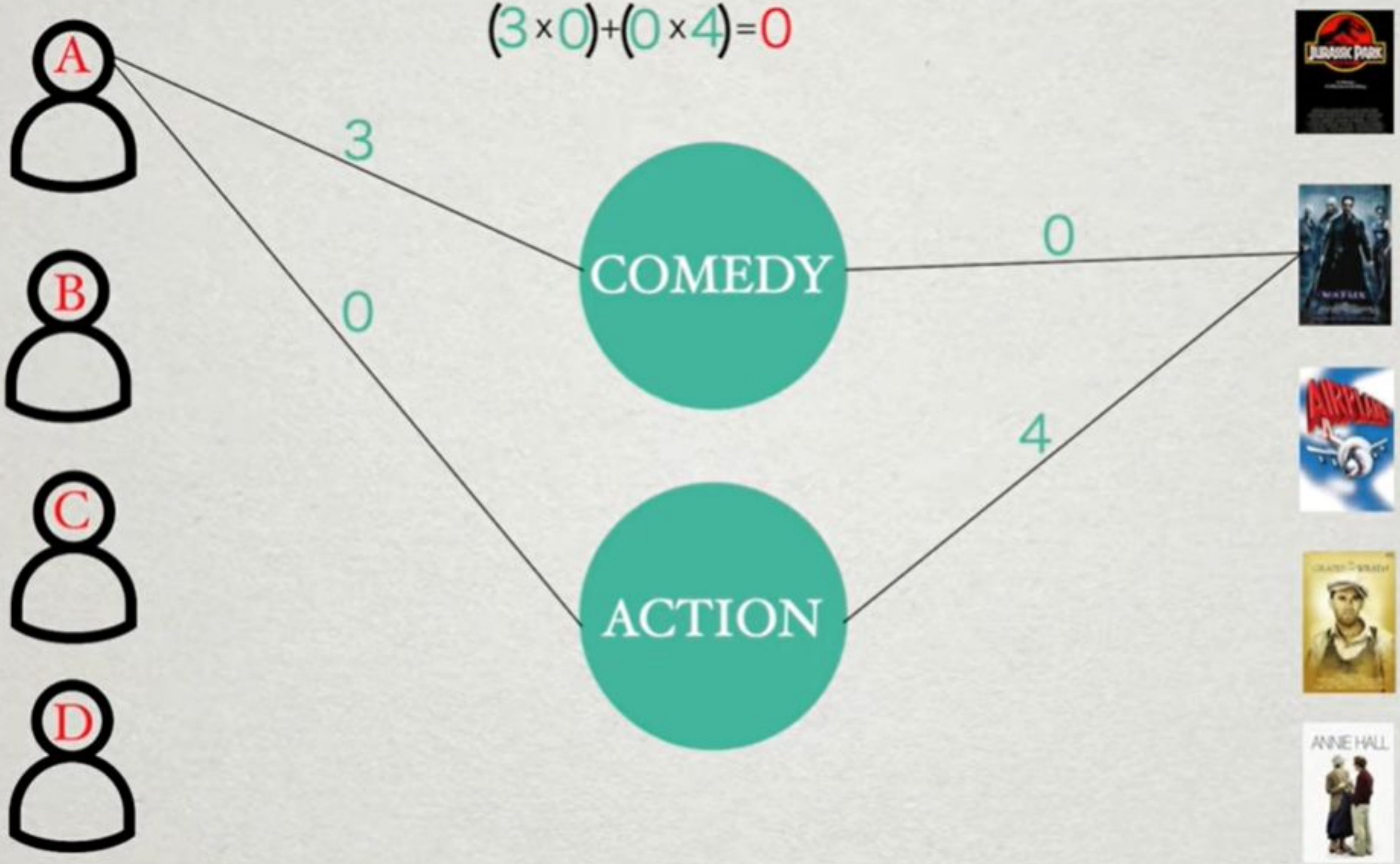

A
B
C
D
JURASSIC PARK
ANNIE HALL



A
B
C
D
JURASSIC PARK
MATRIX
AIRPLANE
ANNIE HALL

A	?	4	?	0	1
B	3	1	2	?	?
C	?	2	3	1	?
D	?	0	?	4	?

$$(3 \times 0) + (0 \times 4) = 0$$



COMEDY	1	0	4	1	4
ACTION	3	4	3	2	0

	COMEDY	ACTION
A	3	0
B	2	2
C	4	4
D	0	4

	COMEDY	ACTION
A	3	0
B	2	2
C	4	4
D	0	4

COMEDY	1	0	4	1	4
ACTION	3	4	3	2	0

A	3	0	12	3	12
B	8	8	14	6	8
C	16	16	28	12	16
D	12	16	12	8	0

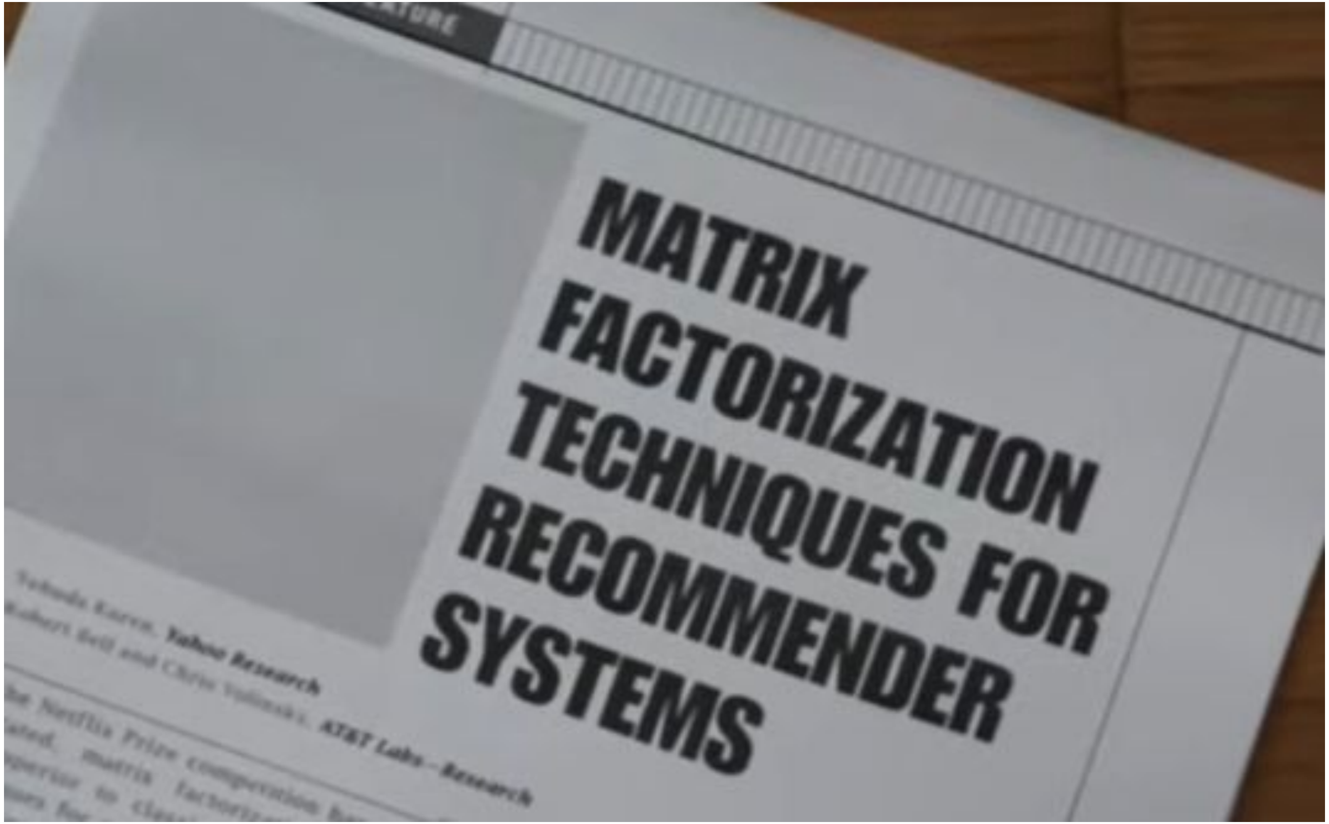
How old are you?

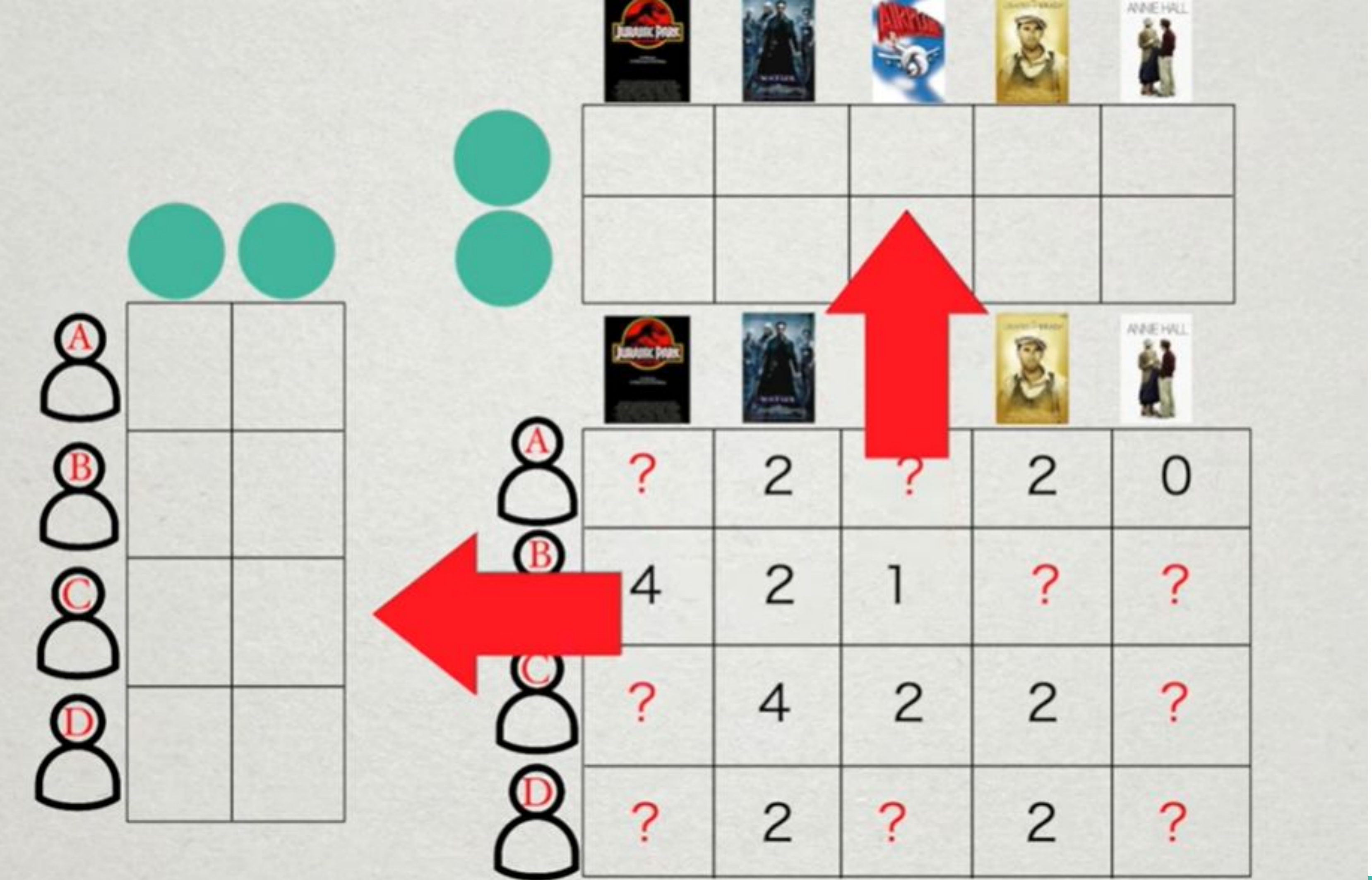
What is your highest level of education completion?

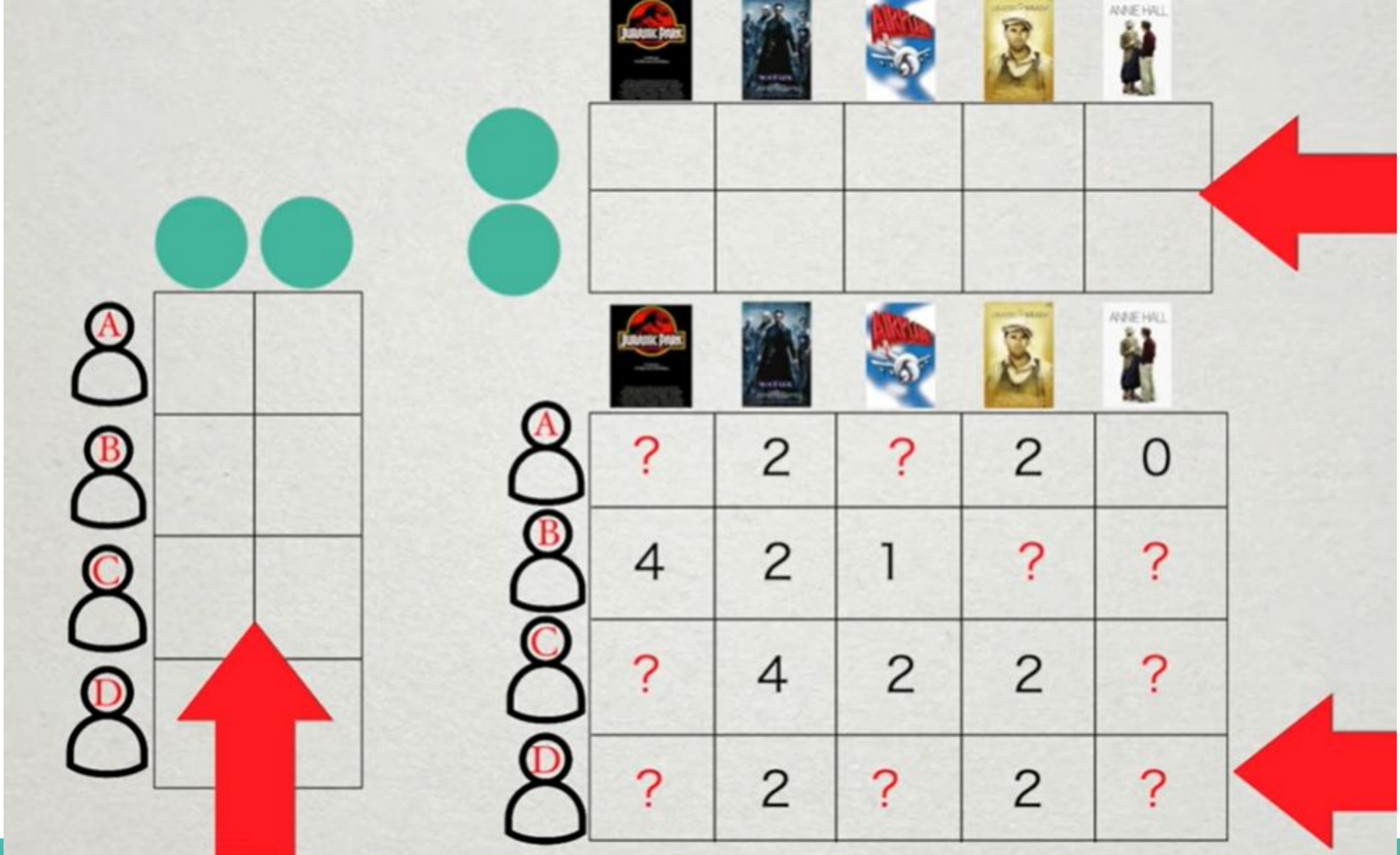
- Some high school
- High school
- Some college
- Two-year college program
- Four-year college program
- Some graduate school
- Graduate school
- Some doctorate school
- Doctorate school
- Other

In general, how much do you like watching movies from the following genres?

	Really dislike	Dislike	Neither like nor dislike	Like	Really like	Not sure of genre definition
Action	○	●	○	○	○	○
Adventure	○	○	●	○	○	○
Animation	○	○	○	○	●	○
Comedy	○	○	○	●	○	○
Crime/Gangster	○	●	○	○	○	○
Documentary	○	○	○	○	●	○
Drama	○	○	○	●	○	○
Fantasy	●	○	○	○	○	○
Film-Noir	●	○	○	○	○	○
Foreign	○	○	●	○	○	○
Horror	○	○	○	●	○	○
Indie	○	●	○	○	○	○
Musical	○	○	○	○	●	○
Mystery	○	○	○	○	○	○
Romance	○	○	○	○	○	○
Rom-Com	○	○	○	○	○	○
Sci-Fi	○	○	○	○	○	○
Sport	○	○	○	○	○	○
Thriller	○	○	○	○	○	○


MATRIX FACTORIZATION TECHNIQUES FOR RECOMMENDER SYSTEMS
Yehuda Koren, Yahoo Research
Robert Bell and Chris Volinsky, AT&T Labs—Research


A
B
C
D
ANNIE HALL
? 2 ? 2 0
4 2 1 ? ?
? 4 2 2 ?
? 2 ? 2 ?



	Jurassic Park	The Matrix	Airplane	(poster 4)	Annie Hall
A	?	2	?	2	0
B	4	2	1	?	?
C	?	4	2	2	?
D	?	2	?	2	?

A	0	2
B	1	0
C	2	0
D	0	2

3	2	1	1	2
0	1	2	1	0

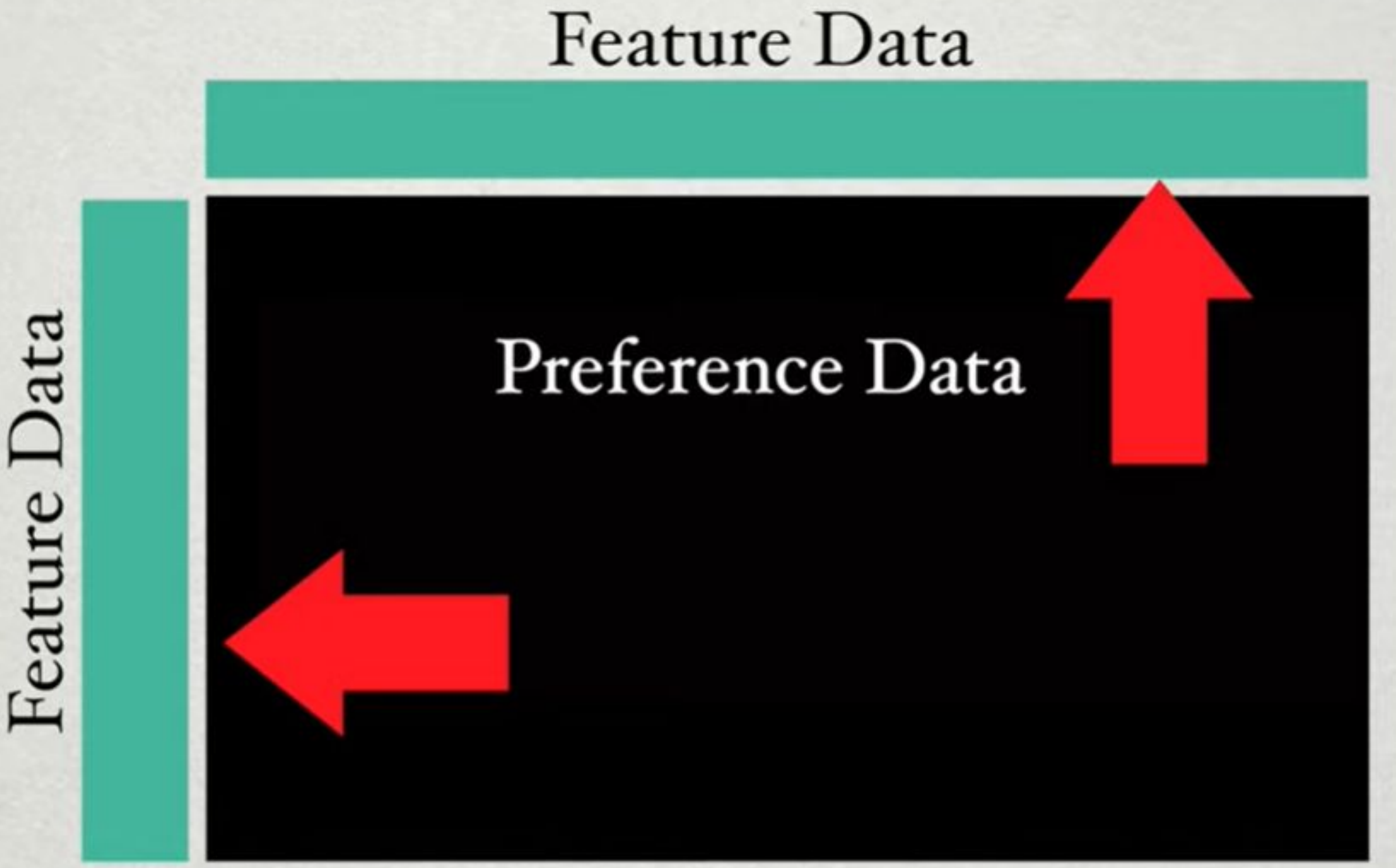
A	?	2	?	2	0
B	4	2	1	?	?
C	?	4	2	2	?
D	?	2	?	2	?

Latent Features

	?	?
A	0	2
B	1	0
C	2	0
D	0	2

?	3	2	1	1	2
?	0	1	2	1	0

A	0	2	4	2	0
B	4	2	1	1	2
C	8	4	2	2	4
D	0	2	4	2	0

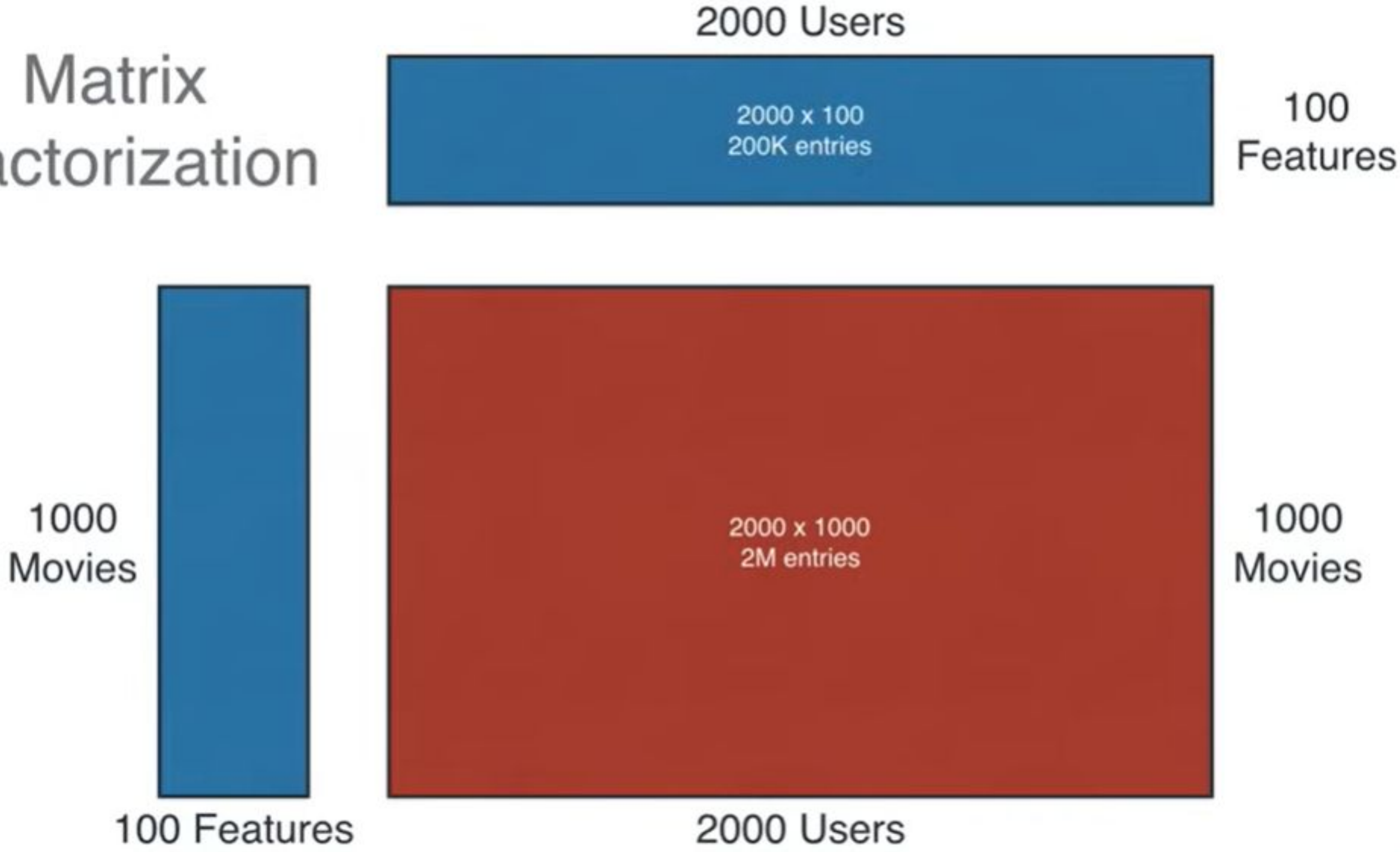

Feature Data
Feature Data
Preference Data

Matrix Factorization

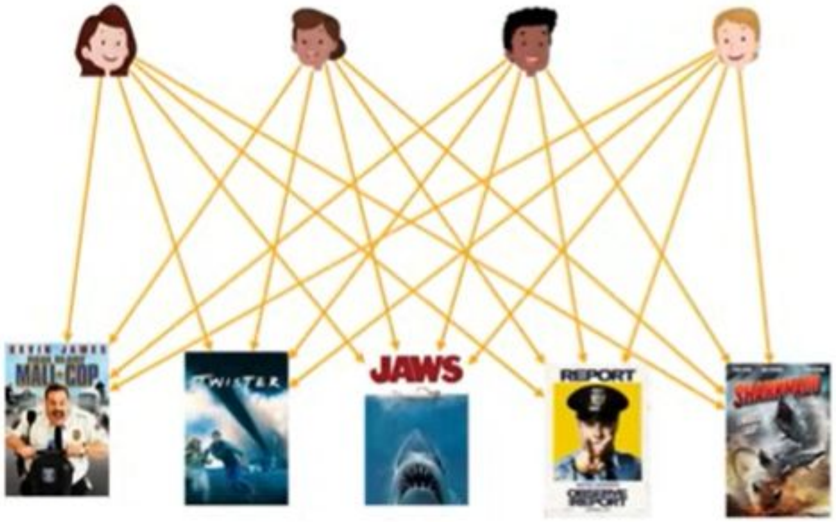
1000 Movies

2000 Users

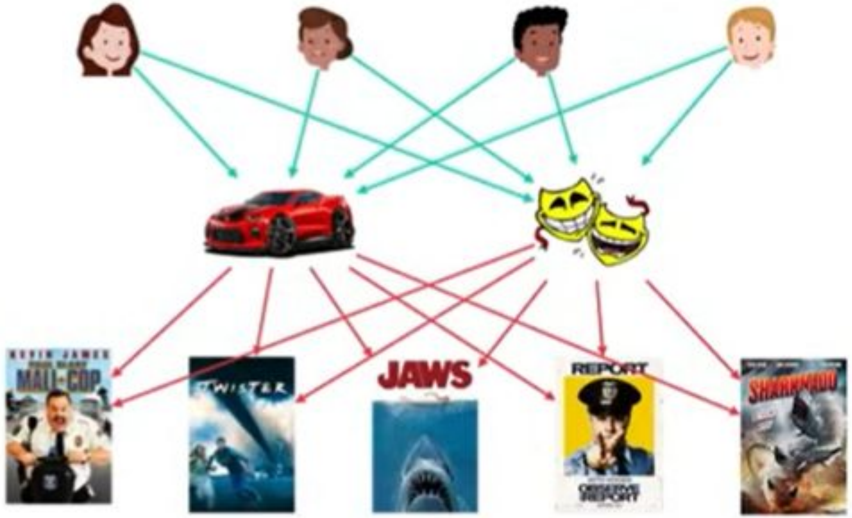
Matrix Factorization



Quiz: How many parameters (arrows)?

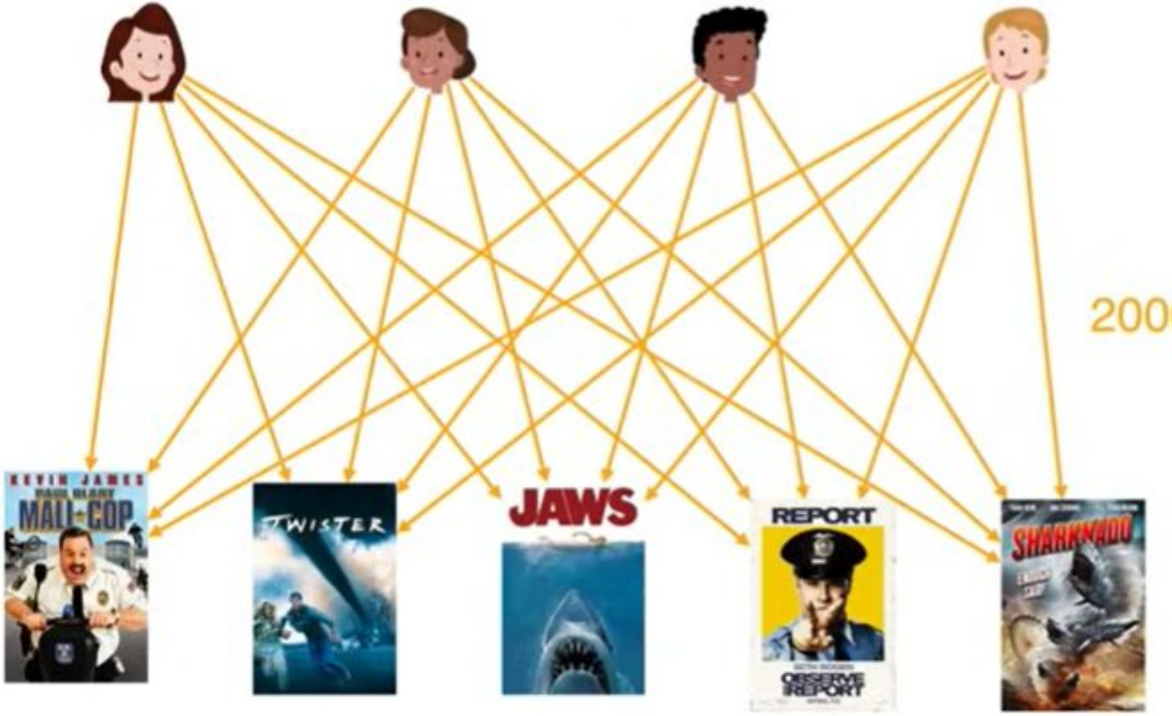


20 parameters



18 parameters

Quiz: How many parameters?

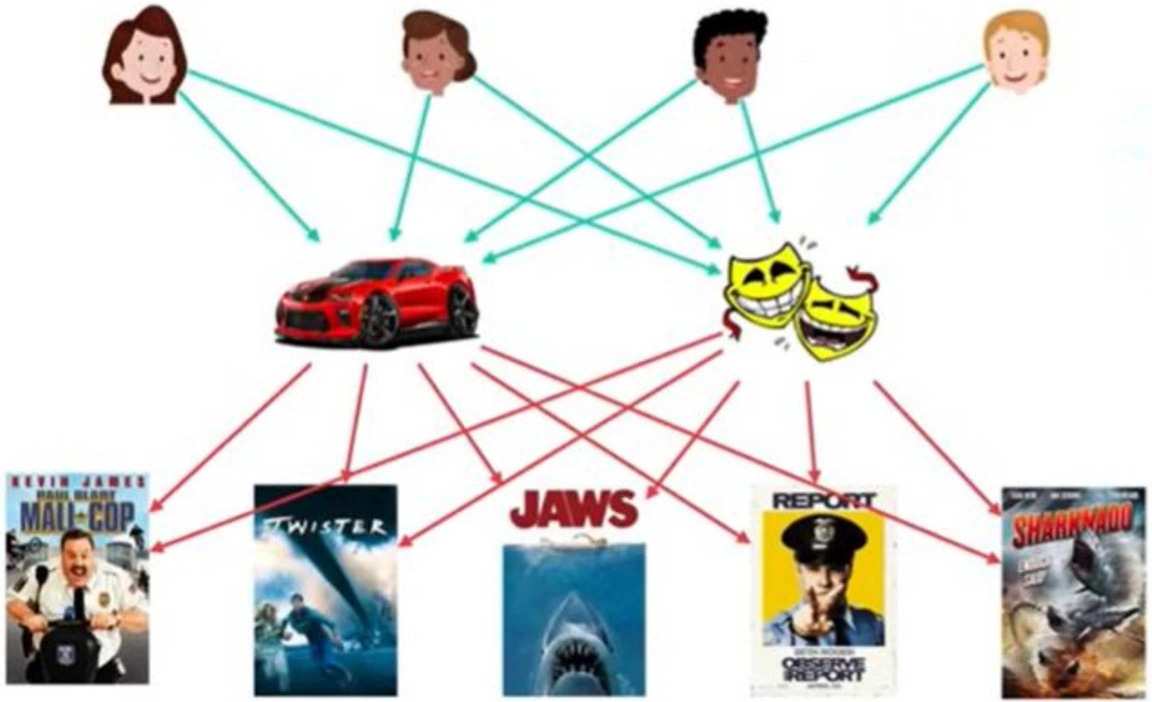


2000 users

2000 x 1000 = 2,000,000 parameters

1000 movies

Quiz: How many parameters?



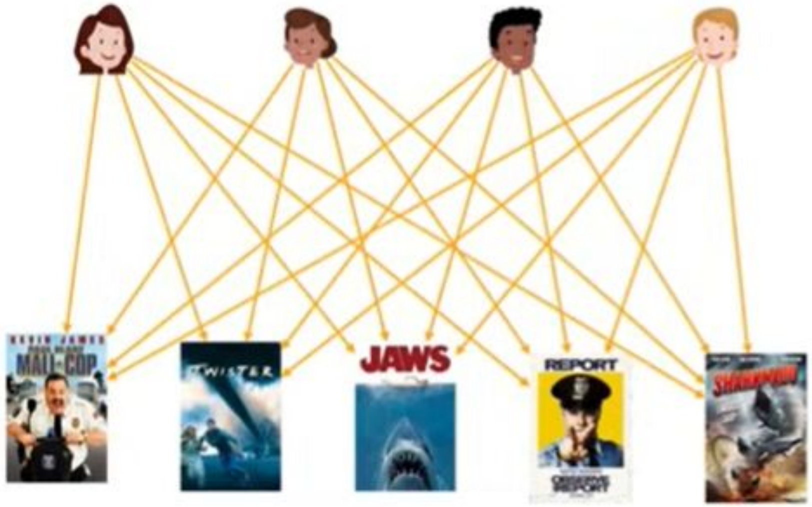
2000 users

2000x100 = 200,000 parameters

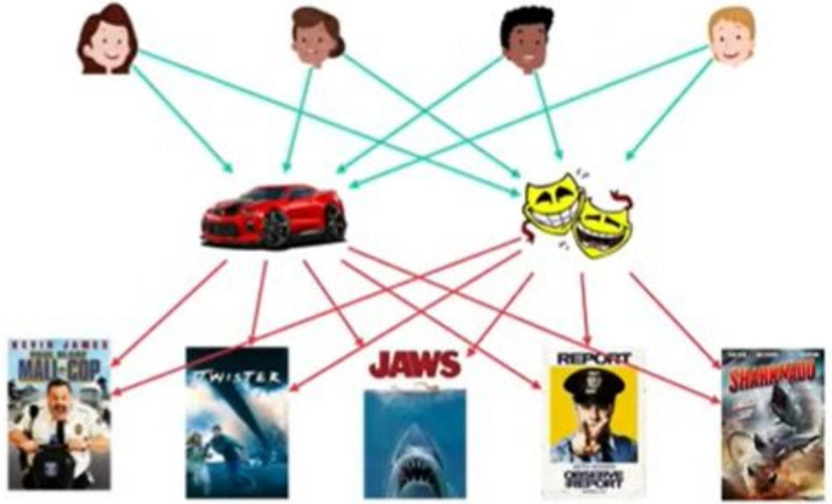
100 features

1000 movies

Storage?

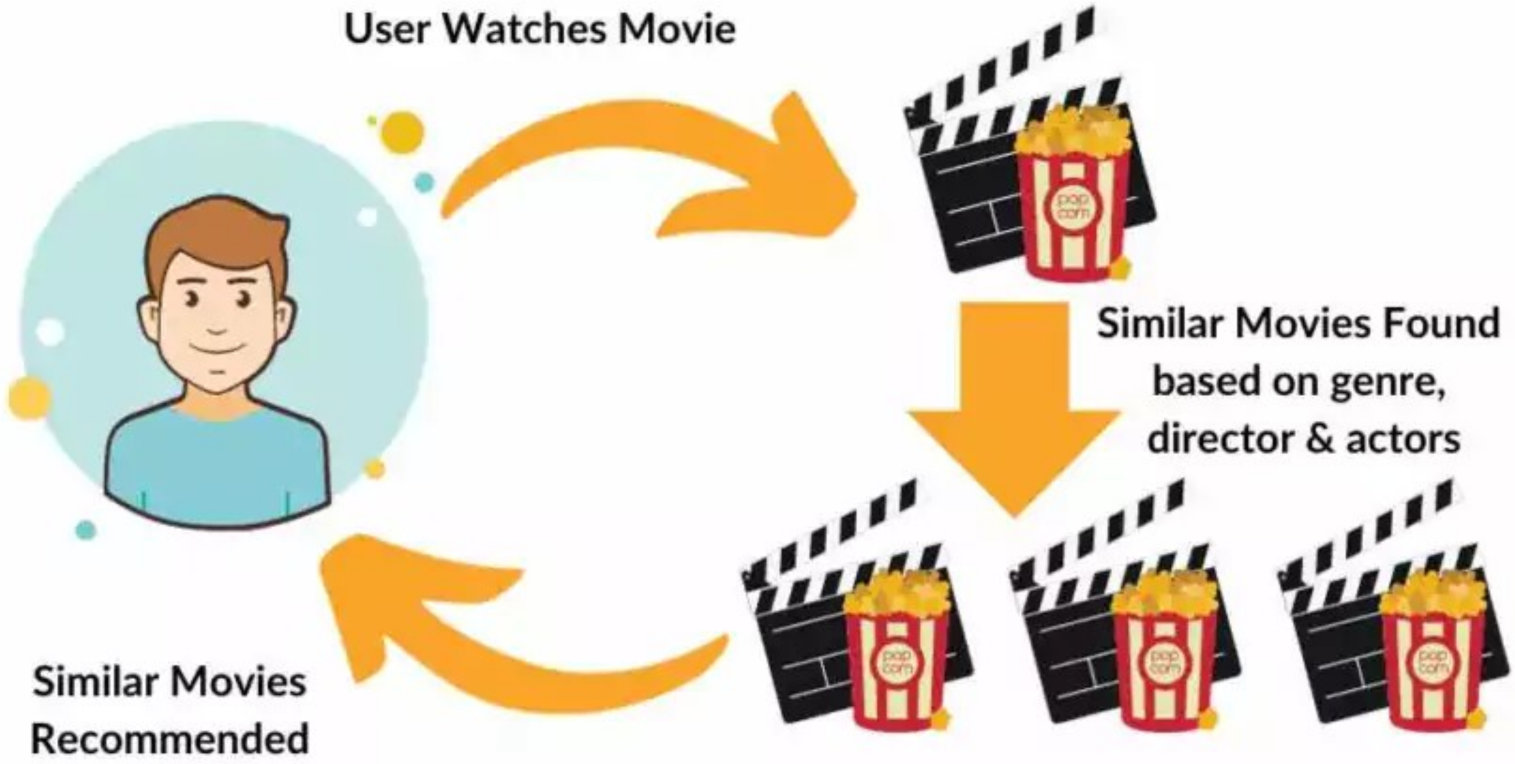


2M parameters



300K parameters

Content-Based Recommendation System



Content-based recommendation systems

Content-based recommendation systems are a popular and widely used approach to provide personalized recommendations to users. These systems are based on the idea that a user's preferences can be predicted based on their previous interactions with items, such as their viewing and purchasing history.

What is the difference between collaborative and content based recommendation system?

Content-based filtering is like recommending content based on the content of the movies you like. Collaborative filtering is like recommending content based on what other people with similar preferences have liked.

Advantages of content-based filtering are:

- No item cold-start problem. The system can recommend products before any users try them.
- It is adaptive. Captures changes in users' interests.
- Items recommended for one user do not depend on other users.
- Recommends unpopular products.

Working Mechanism of Content-Based Recommendation Systems

The heart of content-based recommendation systems lies the concept of similarity measures. Following similarity measures can be used-

Cosine Similarity: Cosine similarity, a widely used metric, quantifies the cosine of the angle between two vectors. In content-based systems, these vectors represent the user and item profiles. The closer the cosine similarity is to 1, the more similar the items are deemed to be in the feature space.

- **Jaccard Similarity:**

This is particularly useful for binary data. It measures the ratio of the intersection of feature sets to their union. Applied to user and item profiles, Jaccard similarity helps assess the overlap of preferences between users and the characteristics of items.

How does Cosine Similarity Work? A Simple Example

Representation of Items:

- Each item (e.g., movie, article) is represented as a vector in a multi-dimensional space.
- Each dimension corresponds to a feature or attribute of the item.

Feature Vector Construction:

- For instance, if you're recommending movies based on genres,
- you might represent each movie as a vector where each dimension corresponds to a genre.
- The value in each dimension indicates the strength or presence of that genre in the movie.

Movie A: `[1, 0, 1, 0, 1] # Action=1, Drama=0, Comedy=1, ...`

Movie B: `[0, 1, 1, 0, 0] # Action=0, Drama=1, Comedy=1, ...`

How does Cosine Similarity Work? A Simple Example

User Preferences:

- Similarly, user preferences are represented as a vector.
- Each dimension corresponds to the user’s choice for a particular feature.

User Preferences: `[1, 0, 0, 1, 0] # Prefers Action and Comedy`

Cosine Similarity Calculation:

The cosine similarity between two vectors A and B
is calculated using the formula:

`Cosine Similarity(A, B) = (A · B) / (||A|| * ||B||`

$A \cdot B$ is the dot product of vectors A and B.
$||A||$ and $||B||$ are the magnitudes
(or Euclidean norms) of vectors A and B.
The result is a similarity score between -1 and 1.
A score of 1 indicates perfect similarity,
0 means no similarity, and -1 indicates perfect dissimilarity.

Instagram Recommendation System (Collaborative Recommendations)

- The post you see as a suggested post on Instagram when you scroll through your feed is where Instagram uses a recommendation system to recommend posts that may interest you.

- The suggested posts you see on Instagram are recommended based on your activities on Instagram, such as:
  - What kind of accounts do you follow, and what kind of posts do you engage with
  - The caption of the posts that you engage with also plays a role in suggesting more similar posts
  - How do other users with similar interests as yours engage with the posts

Spotify (Content Based Recommendation)

- North American MUAs of Spotify spend the most time on the platform, averaging 140 minutes per day. \

- Additionally, the platform also trends younger: 55% of their users are between the ages of 18 – 34.

- With an active user base higher than Apple Music, YouTube Music, and Amazon Music, Spotify is clearly the most used music streaming platform to date.

What Does Spotify's Algorithm Determine?

- Except for their saved music, Spotify's algorithm affects almost everything a user sees when they use the application. With the help of its robust algorithm Spotify acts like a recommendation engine, suggesting content based on media users have already listened to, or saved for later listening.

- This is the core function of the Spotify recommendation engine, and that foundation determines what suggested content – podcasts, music, other audio content – a user will see when they open the app.

- Powered by AI, Spotify's algorithm analyzes three main features when **determining to recommend content: lyrical content and language, song features, and past listening habits. Additionally, songs are affected by users' interaction with songs, such as whether or not they have listened past the first thirty seconds or skipped, as well as inclusions in other playlists.**

Traditional Recommendation Systems

1. Traditional recommendation systems **rely on human judgment and expertise** to recommend items to users.
2. These systems can be used in a **variety of contexts, such as bookstores, libraries, and music stores.**
3. They may **rely on personal recommendations** from friends or trusted sources, or on reviews and ratings provided by other users.
4. They may be less efficient than automated systems, but they can also be more flexible and adaptable to the needs and preferences of individual users.

Case Study : Reddit Voting System

- **Reddit** is a social news website that **allows users to post links and vote** on them.
- The votes are used to rank articles and determine which ones appear on the front page.
- The **simple vote count method** can be biased towards older articles, as they have more time to gather votes and stay highlighted longer.
- This system adjusts after every vote and takes into account the total number of votes a post has received.
- Sorting options, such as "**Best,**" "**Top,**" "**New,**" "**Old,**" **and** "**Controversial,**" are important to Reddit users in order to navigate and make sense of the vast amount of content on the website.

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Case Study : Trust Based Movie Recommendation

- **FilmTrust** is a movie recommendation system that uses social networks and trust to make recommendations.
- Users can rate and review movies, view others' ratings and reviews, and make social connections with other users on the system.
- When creating a social connection, **users are asked to rate how much they trust the other person's opinion** about movies on a **scale from 1 to 10.**
- The **system estimates trust in other people's opinions** using a weighted average based on the trust ratings given by the user and their friends.
- **Trust values are used to adjust the average rating** of a movie and give more weight to ratings from users who are trusted more by the user receiving the recommendation.
- The system also takes the user's own ratings into account when making recommendations.