Embeddings: Vector & Semantic Search

Applications | Concepts | Examples

January 23 2025 | Lecture at University of Washington, Seattle by Dr. Karthik Mohan

1. Introduction and Motivation



2. Semantic Search



NETFLIX



Trending Now >

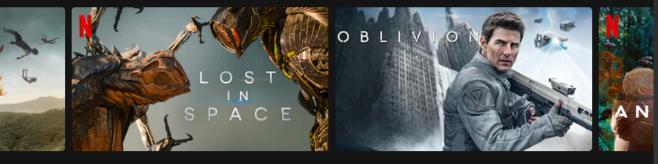


Futuristic Sci-Fi





MULTIPLE CAROUSELS



NETFLIX

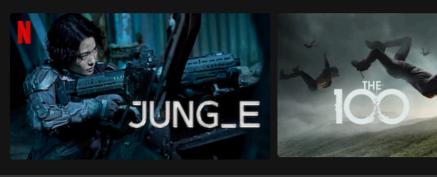
POPULAR yet PERSONALIZED

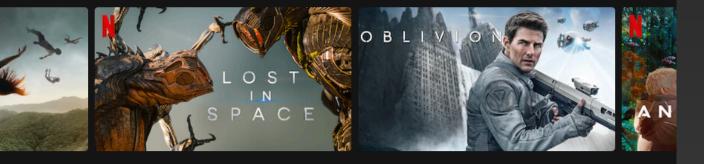


Trending Now >



Futuristic Sci-Fi





POPULAR yet

PERSONALIZED TRENDS

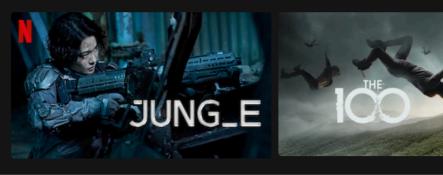
NETFLIX

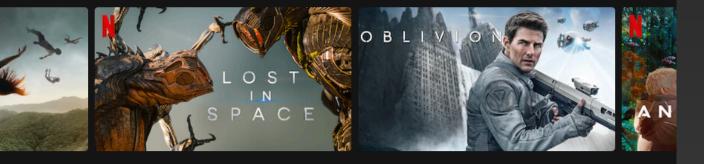


Trending Now >



Futuristic Sci-Fi





POPULAR yet

PERSONALIZED GENRE

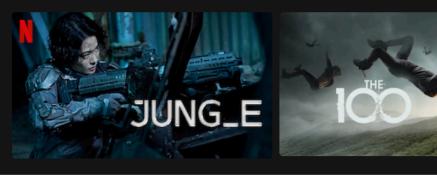


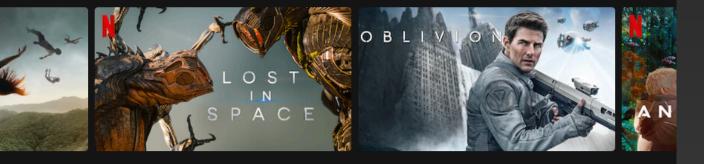


Trending Now >



Futuristic Sci-Fi





Netflix Million Dollar Prize!



Netflix Million Dollar Prize!

NETFLIX

Netflix Prize

Home Rules

Leaderboard

Register Update

Leaderboard

Rank	Team Name	Bes
- 1	No Grand Prize candidates yet	
Grand	<u> Prize</u> - RMSE <= 0.8563	
1	PragmaticTheory	0
2	BellKor in BigChaos	0
3	Grand Prize Team	0
4	Dace	0
5	BigChaos	0
Progr	<u>ess Prize 2008</u> - RMSE = 0.861	6 - Wini
6	BellKor	0
7	Gravity	0
8	Opera Solutions	0
9	xivector	0
10	BruceDengDaoCiYiYou	0
11	Ces	0
12	majia2	0
13	xiangliang	0
14	Feeds2	0
15	Just a quy in a garage	0
16	Team ESP	0
17	pengpengzhou	0
18	NewNetflixTeam	0
19	J Dennis Su	0

leaders.

st Score	% Improvement	Last Submit Time
	-	-
0.8584	9.78	2009-06-16 01:04:47
0.8590	9.71	2009-05-13 08:14:09
0.8593	9.68	2009-06-12 08:20:24
0.8604	9.56	2009-04-22 05:57:03
0.8613	9.47	2009-06-15 18:03:55
ning Tea	m: BellKor in BigCh	iaos
0.8620	9.40	2009-06-17 13:41:48
0.8634	9.25	2009-04-22 18:31:32
0.8640	9.19	2009-06-09 22:24:53
0.8640	9.19	2009-06-17 12:47:27
0.8641	9.18	2009-06-02 17:08:31
0.8642	9.17	2009-06-12 23:04:25
0.8642	9.17	2009-06-15 03:35:00
0.8642	9.17	2009-06-13 16:35:35
0.8647	9.11	2009-06-16 22:21:19
0.8650	9.08	2009-05-24 10:02:54
0.8653	9.05	2009-06-16 05:25:11
0.8654	9.04	2009-05-05 18:18:03
0.8657	9.01	2009-05-31 07:30:22
0.8658	9.00	2009-03-11 09:41:54

Display top 40



Rishi

Michael

Karthik

Roshin

Amy

Collaborative Filtering



Avatar

Arrival

Rishi

Michael

Karthik

Roshin

Amy

When Harry Before Sunrise



Avatar

Arrival

Rishi		
Michael		
Karthik		
Roshin		
Amy		

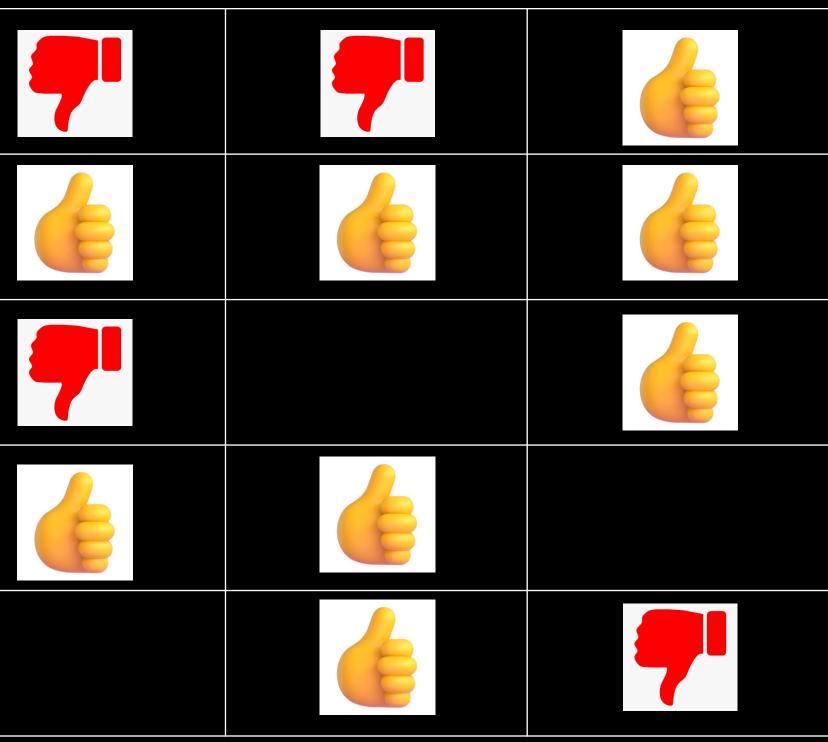






When Harry

Before Sunrise





Avatar

Arrival

When Harry

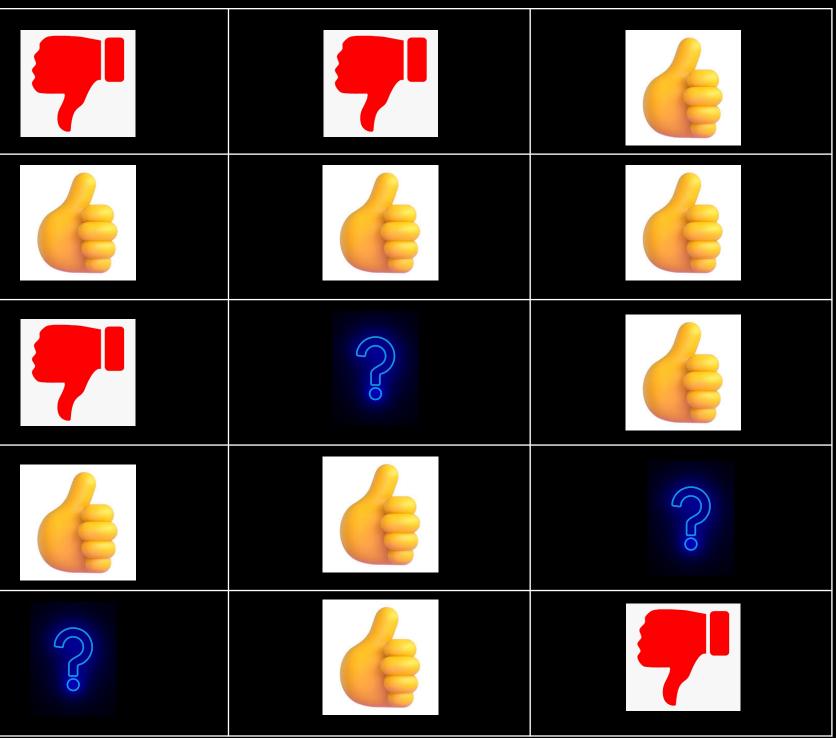
Rishi		
Michael		
Karthik		
Roshin		
Amy		













Avatar

Arrival

When Harry

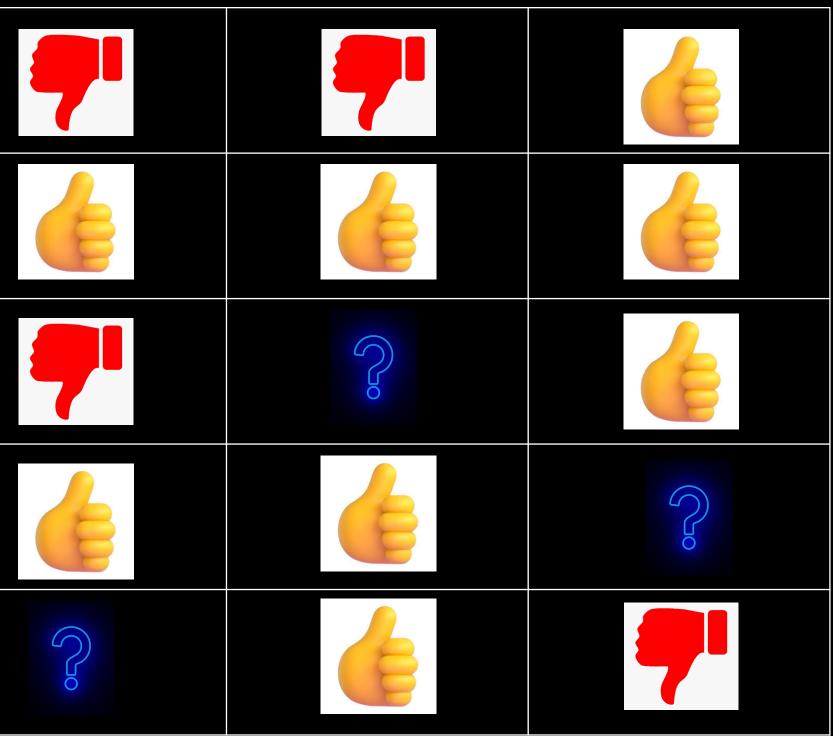
Rishi		
Michael		
Karthik		
Roshin		
Amy		













Avatar

Arrival

When Harry

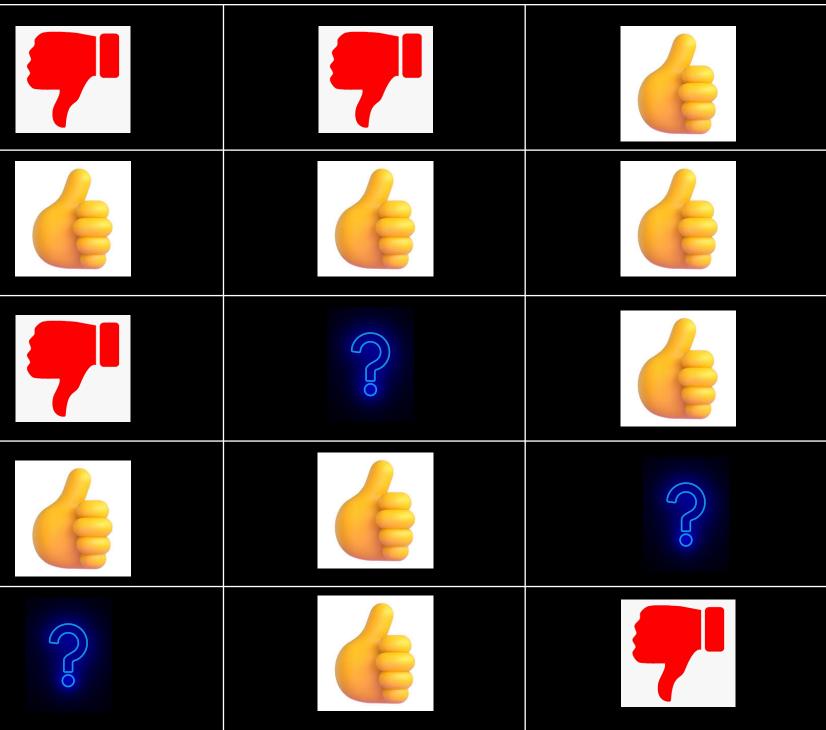
	Rishi		
	Michael		
and the second	Karthik		
	Roshin		
	Amy		







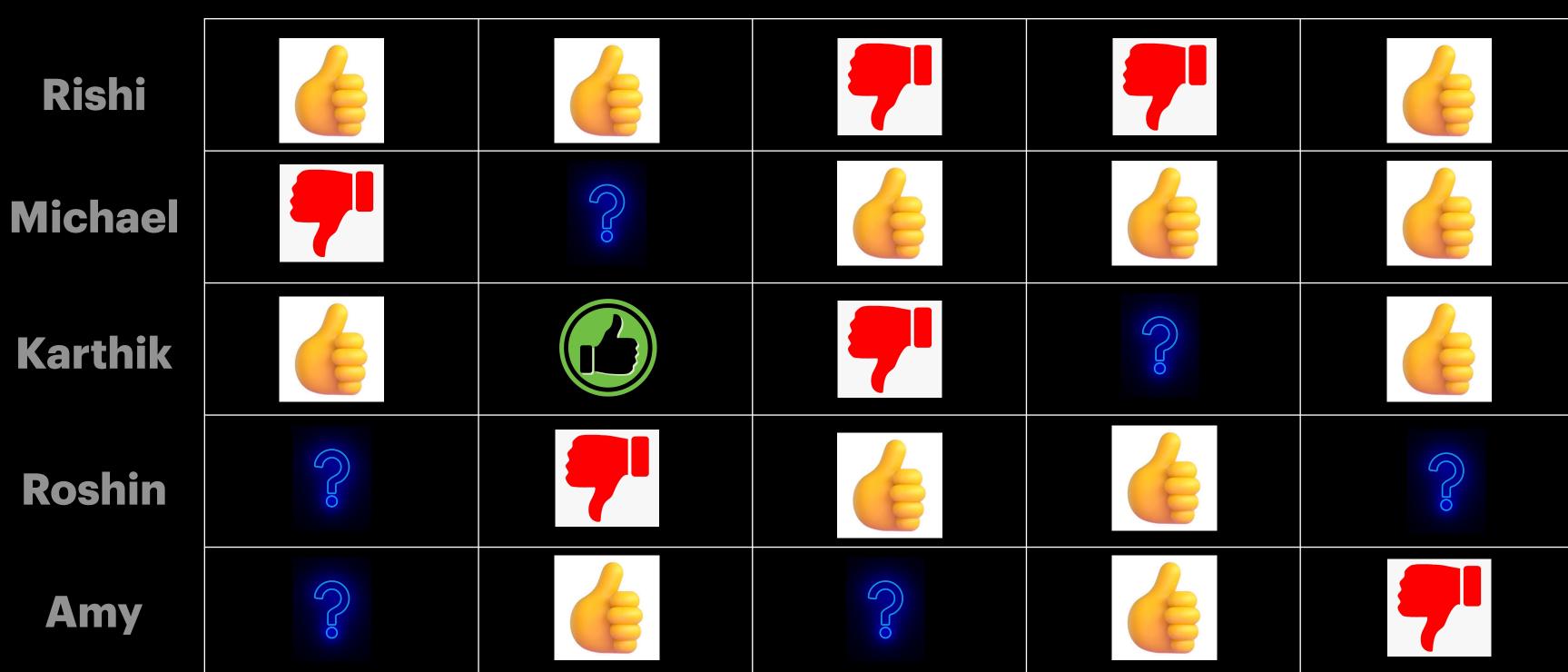






Avatar

Arrival





When Harry









Avatar

Arrival









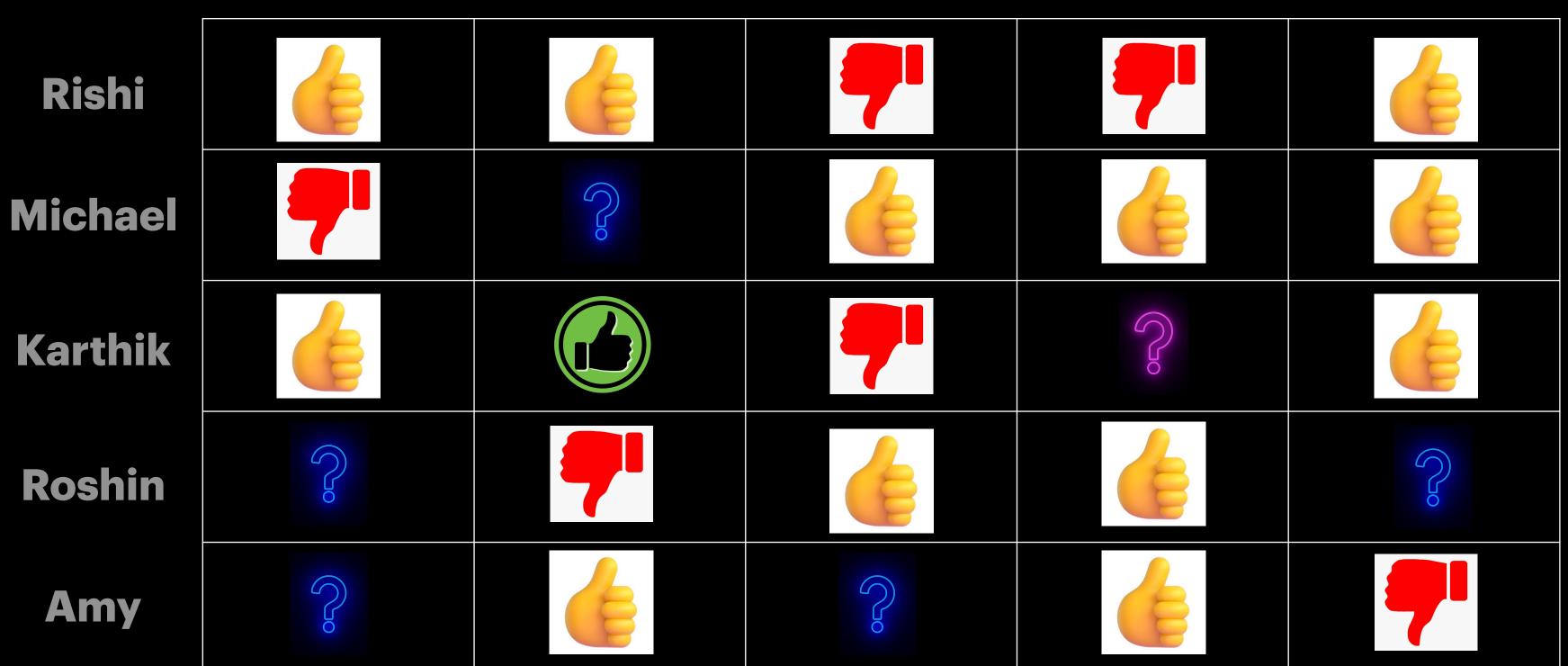
Before Sunrise





Avatar

Arrival









When Harry

Before Sunrise

Minions



Avatar

Arrival





When Harry









Avatar

Arrival





When Harry









Avatar

Arrival





When Harry



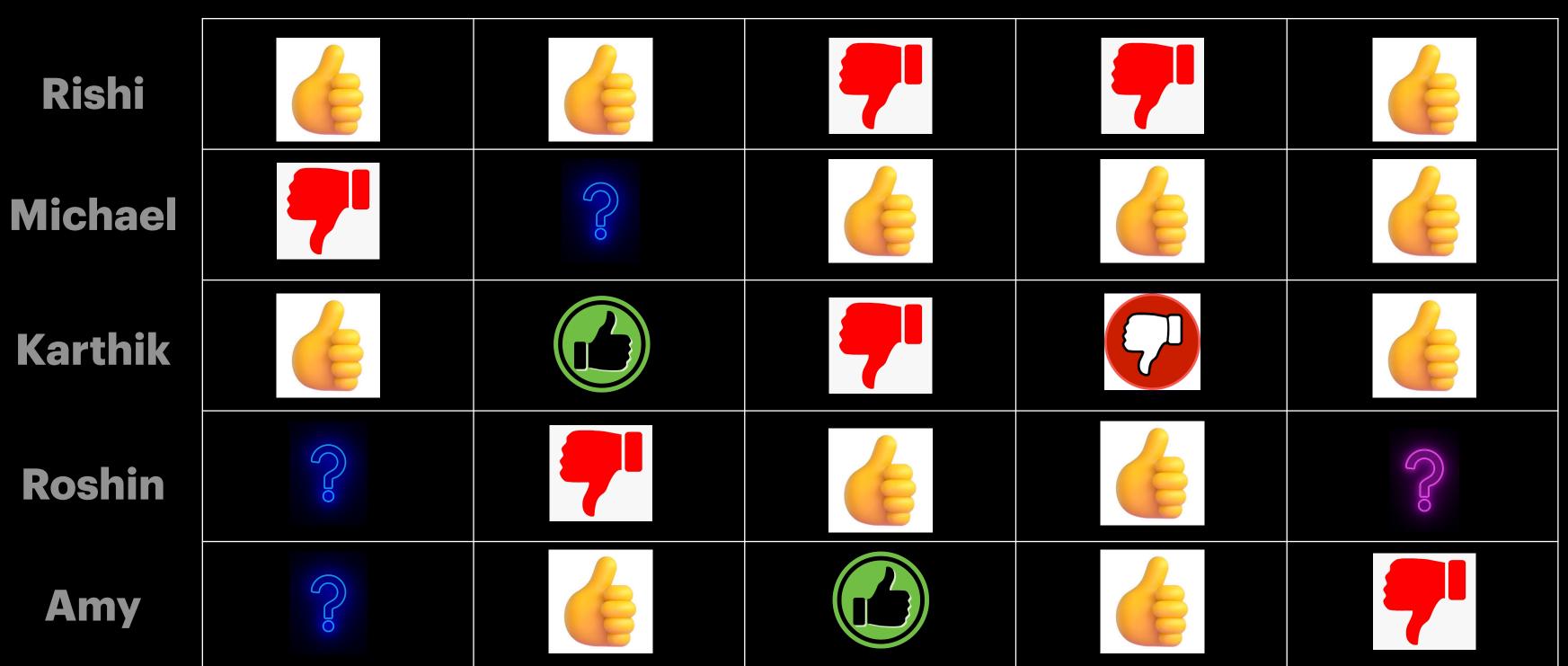






Avatar

Arrival







When Harry

Before Sunrise





Avatar

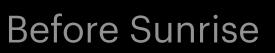
Arrival









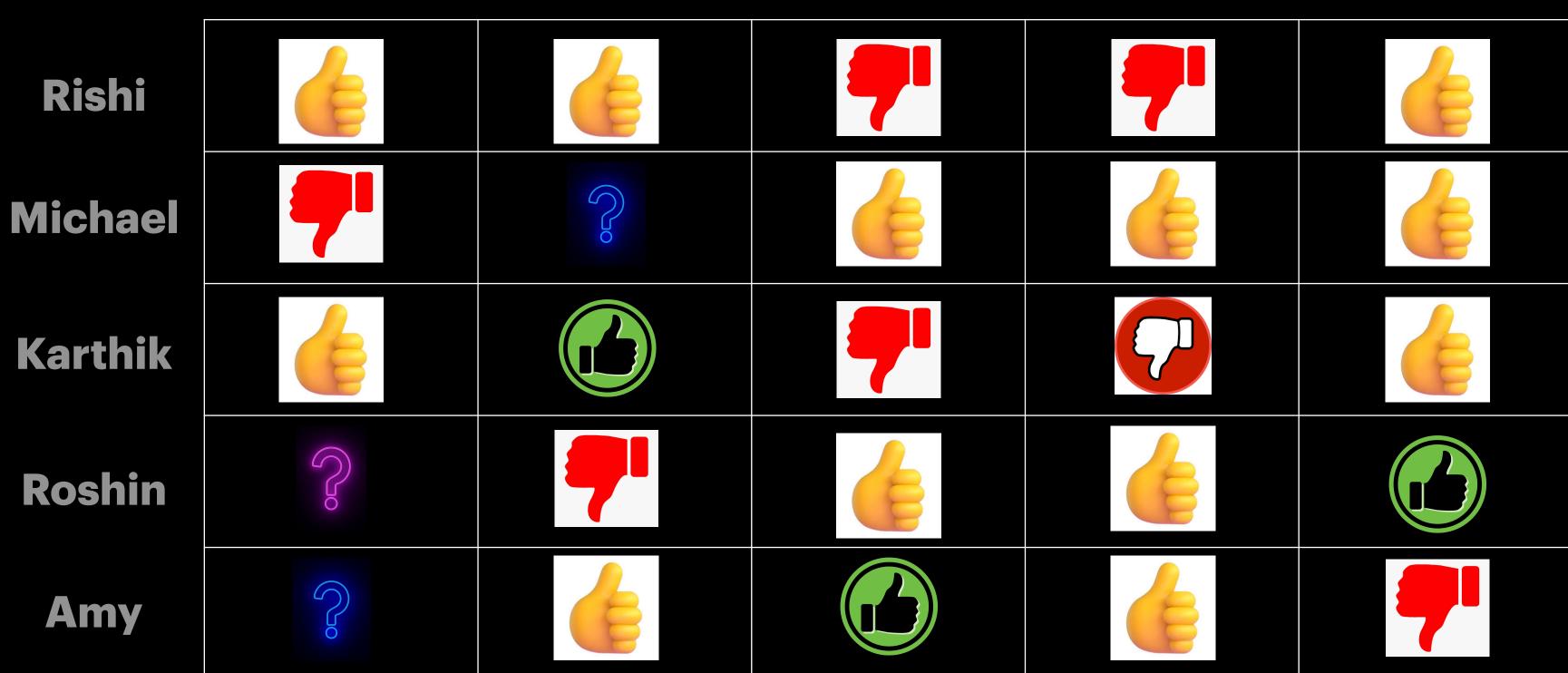






Avatar

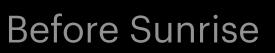
Arrival















Avatar

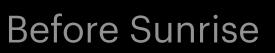
Arrival

Rishi		
Michael		
Karthik		
Roshin		
Amy		

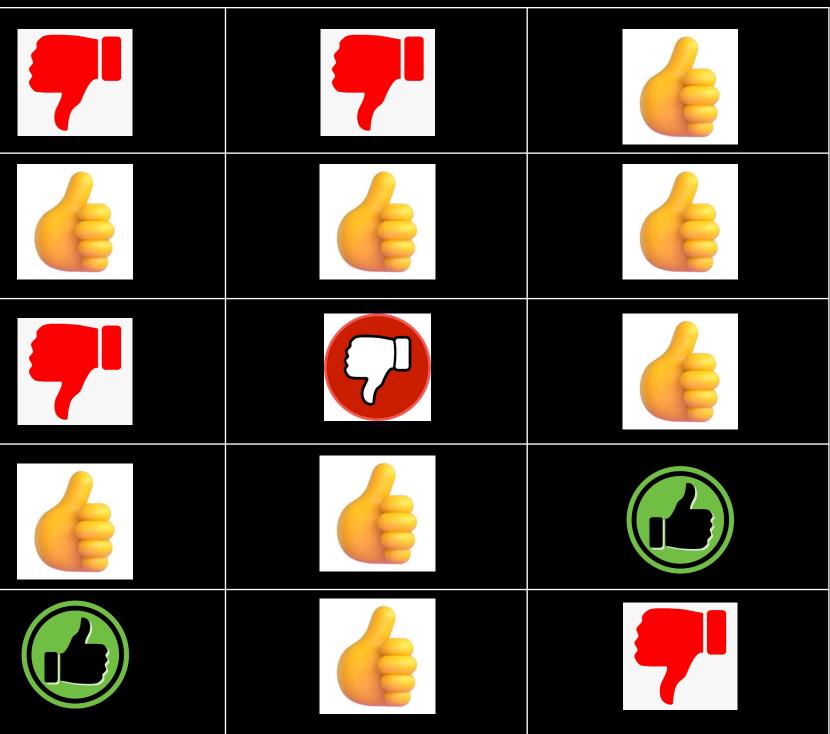














Avatar

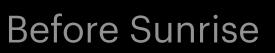
Arrival

Rishi		
Michael		
Karthik		
Roshin		
Amy		

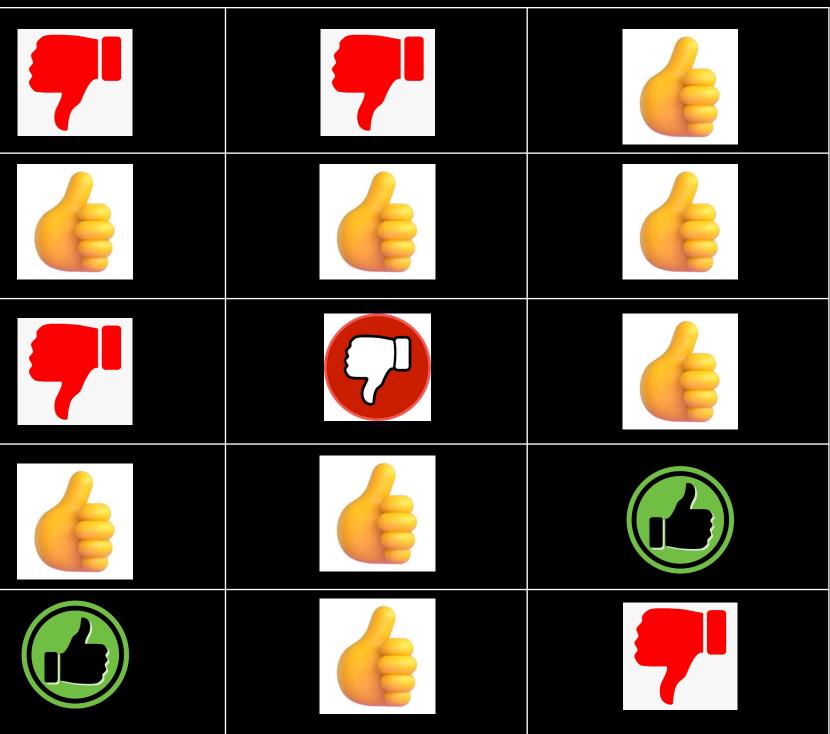














Avatar

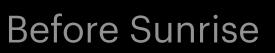
Arrival

Rishi		
Michael		
Karthik		
Roshin		
Amy		

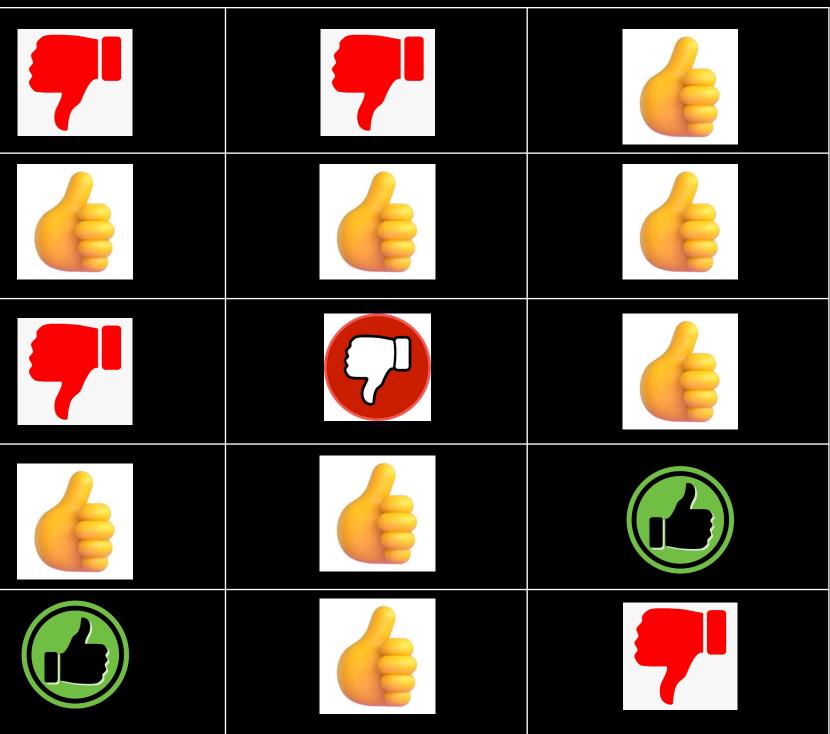














Avatar

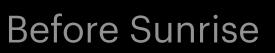
Arrival

Rishi		
Michael		
Karthik		
Roshin		
Amy		

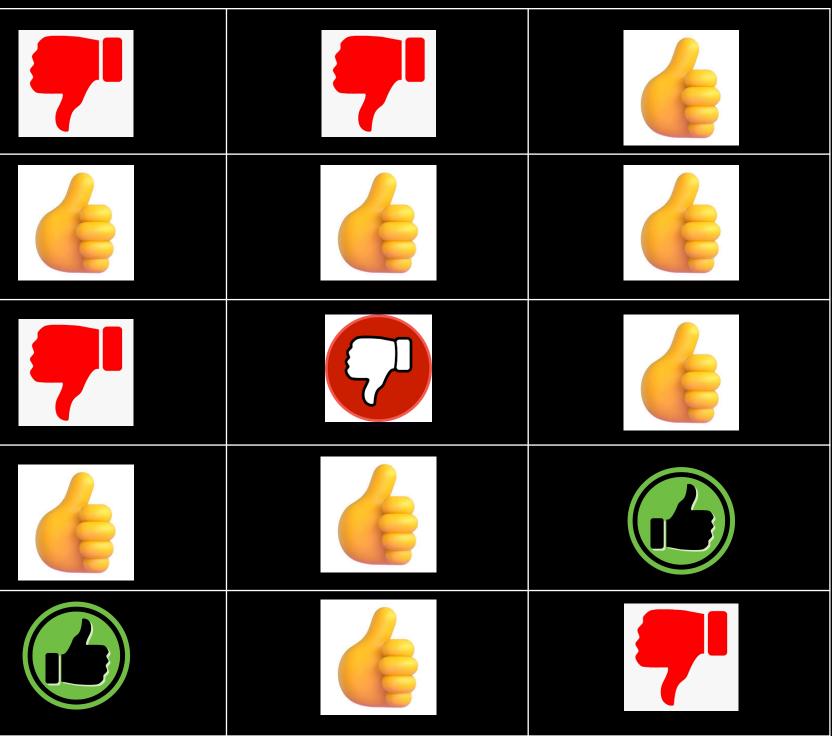














Avatar

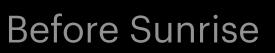
Arrival

Rishi		
Michael		
Karthik		
Roshin		
Amy		

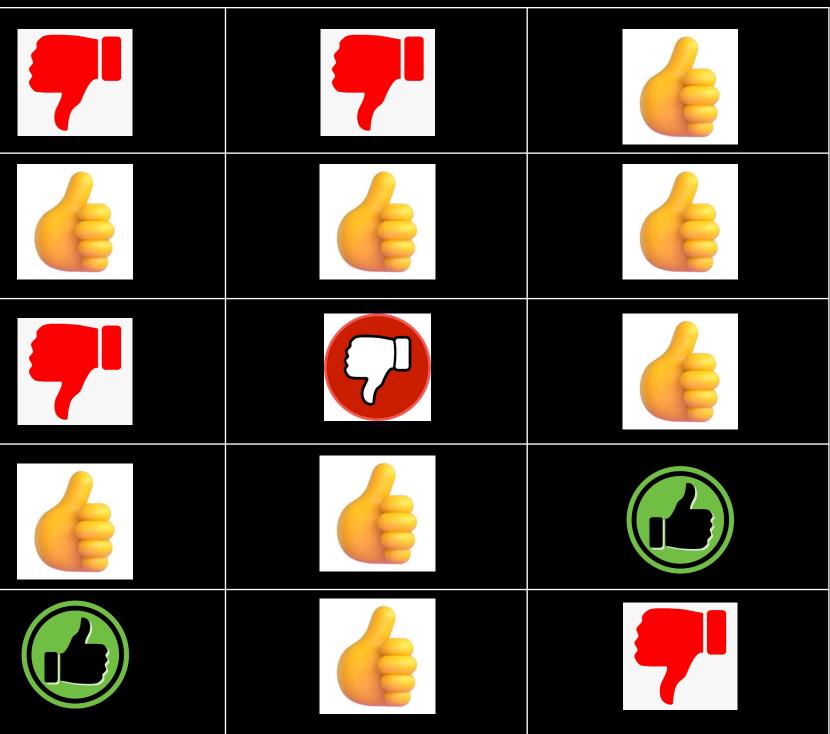


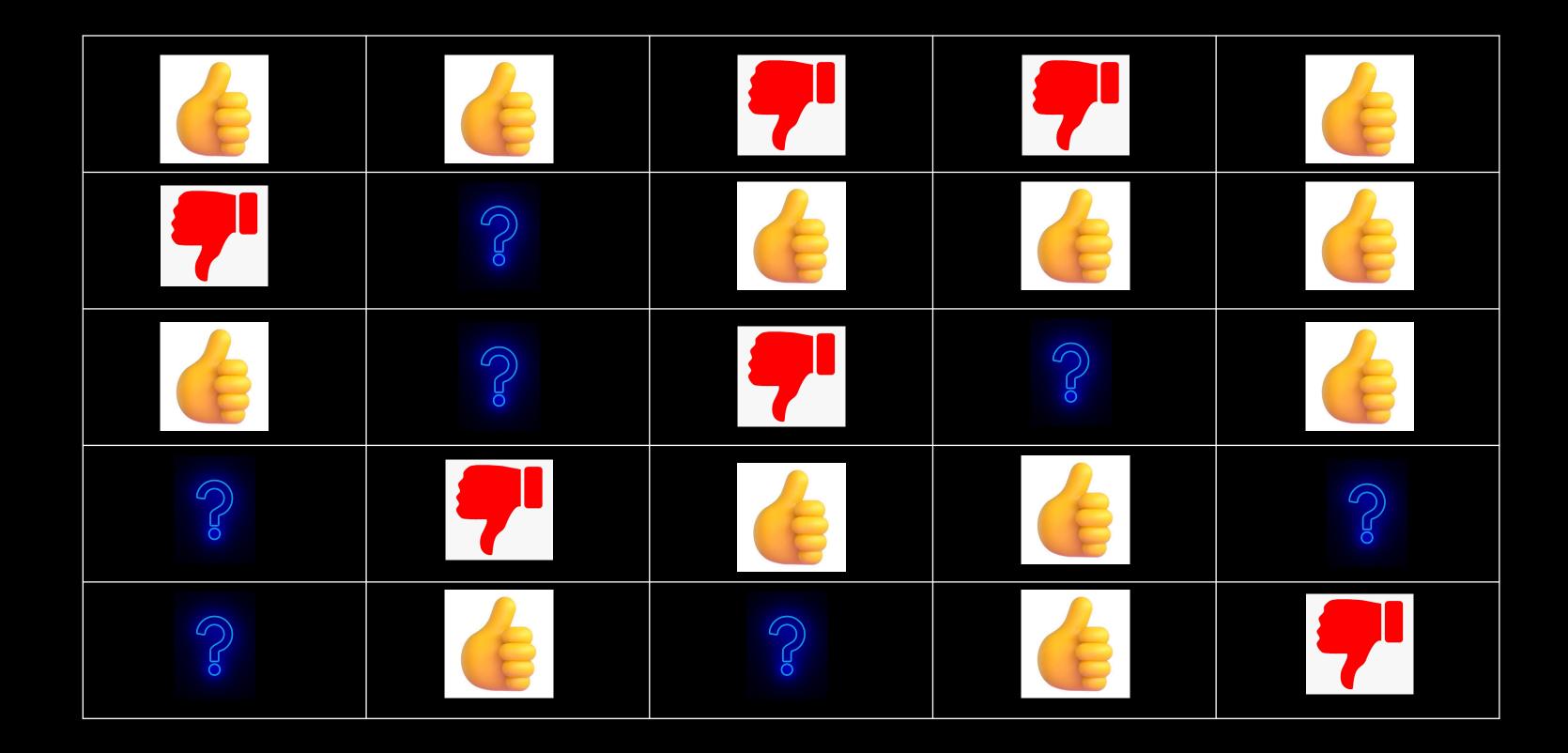


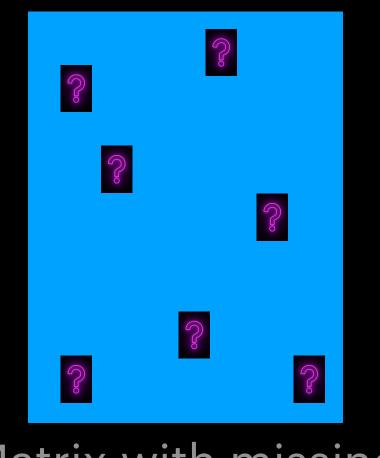






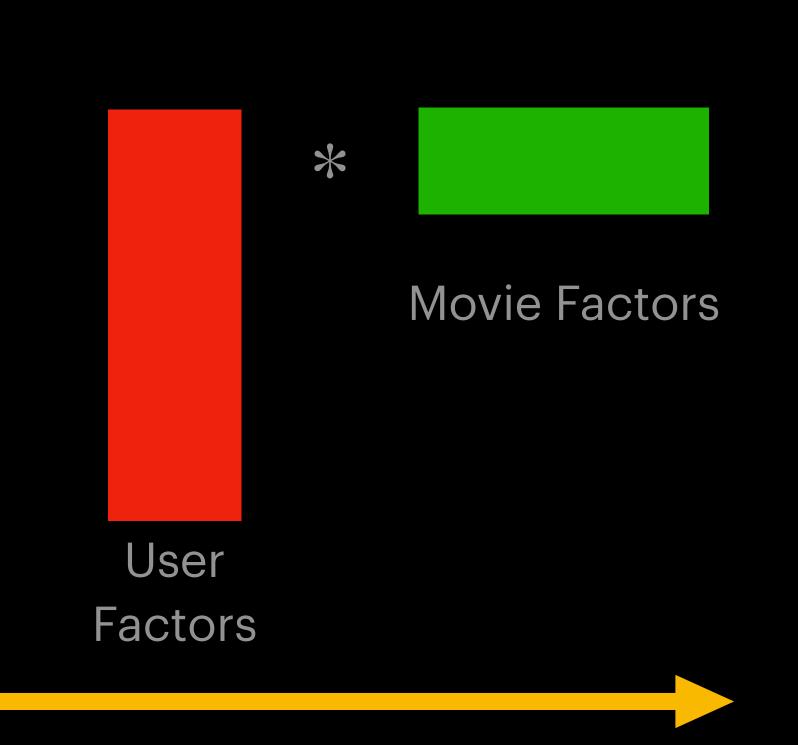


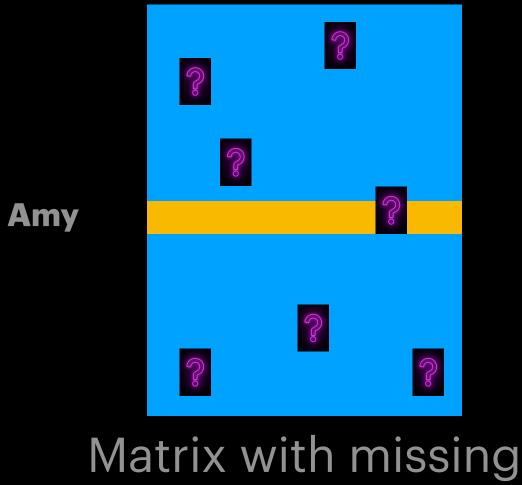




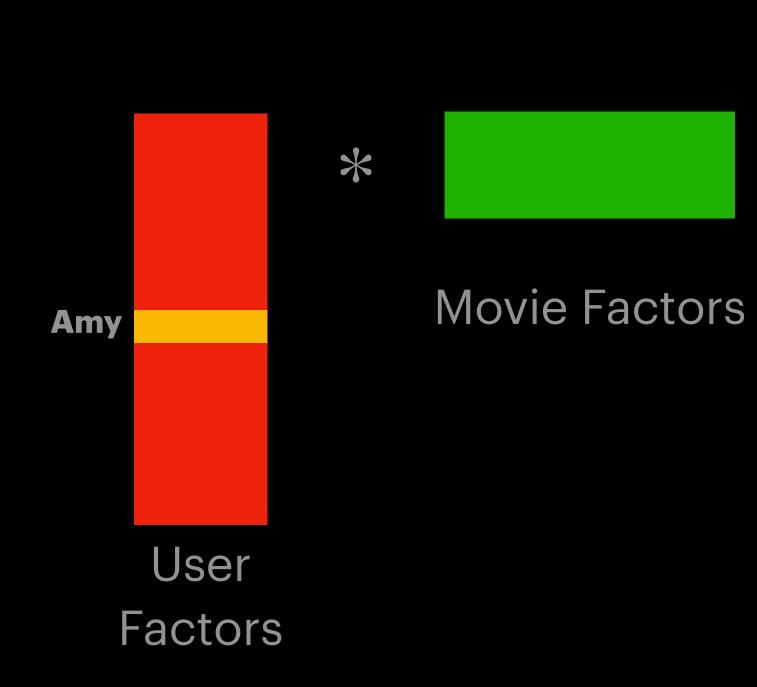
Matrix with missing Ratings

Machine Learning Algorithm for Matrix Completion

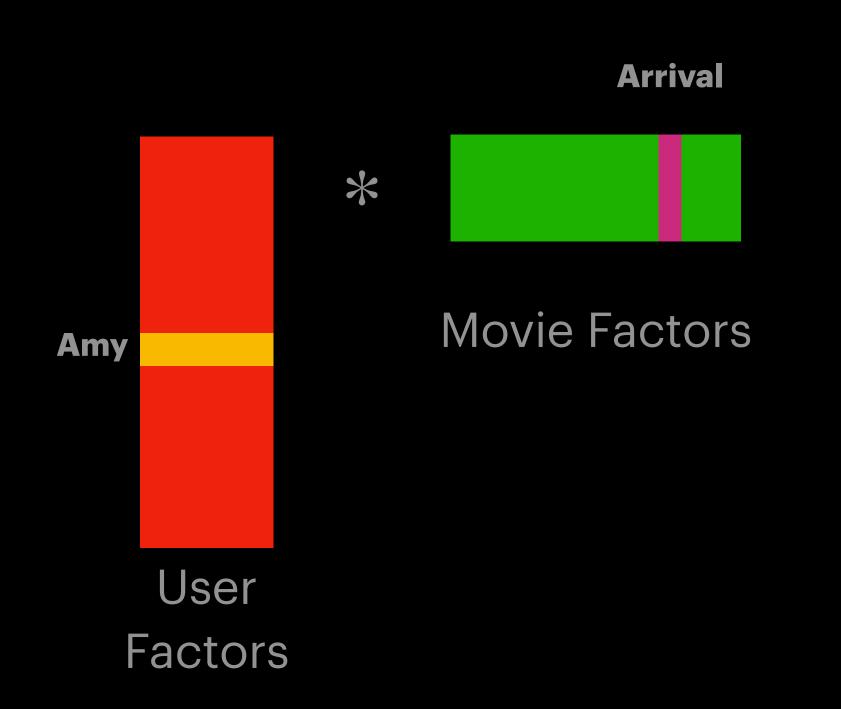




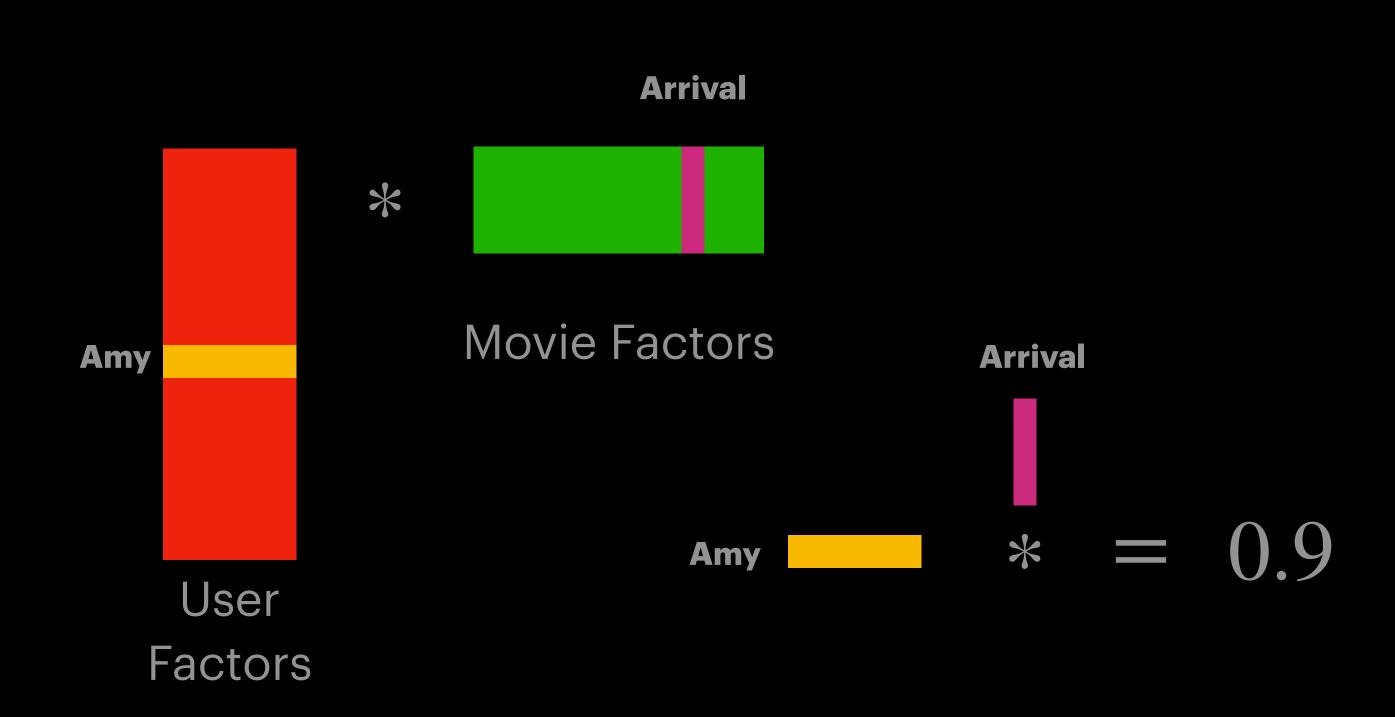
Ratings



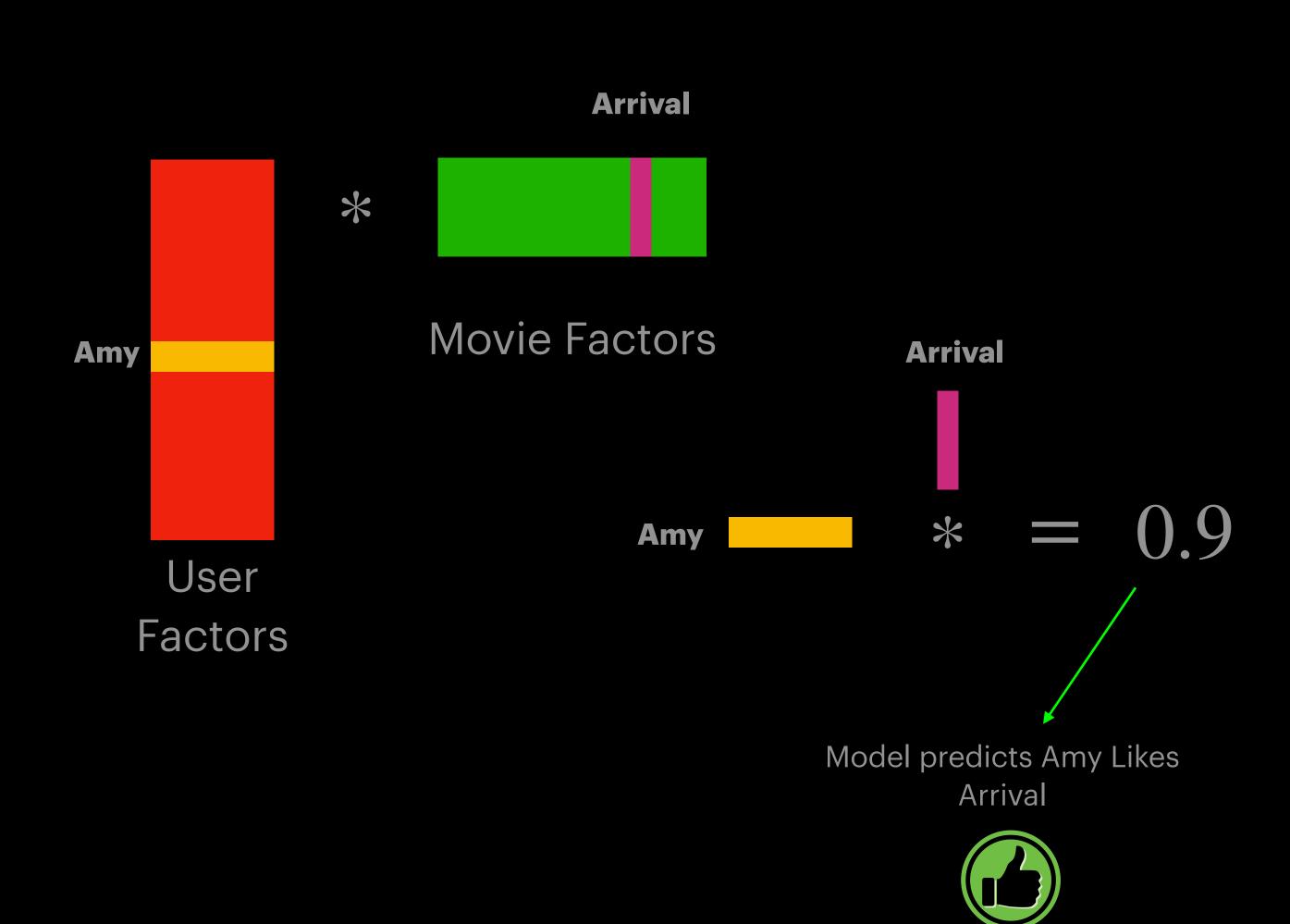


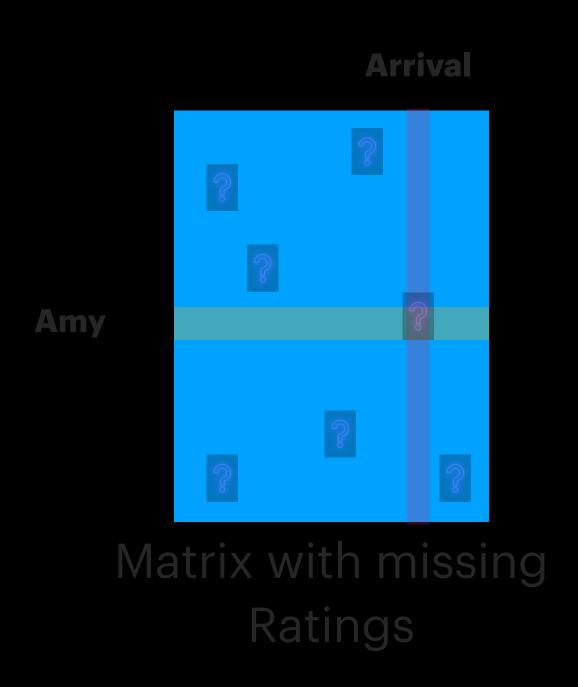




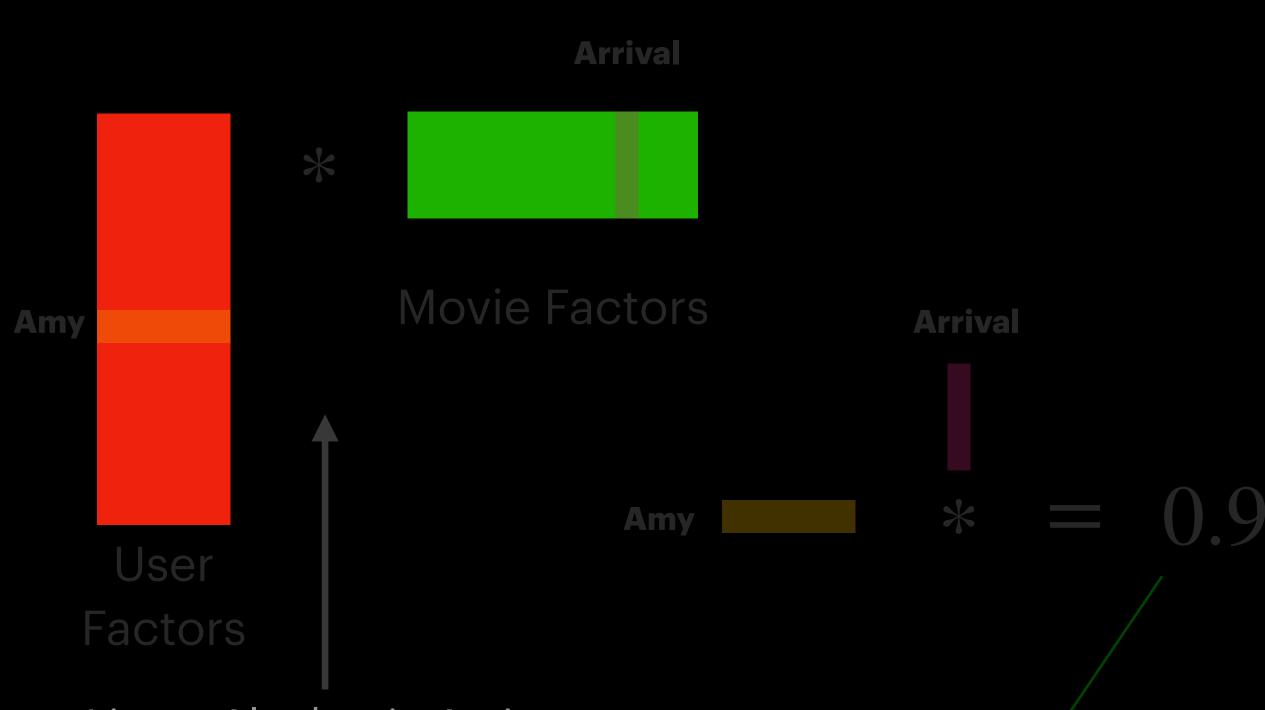






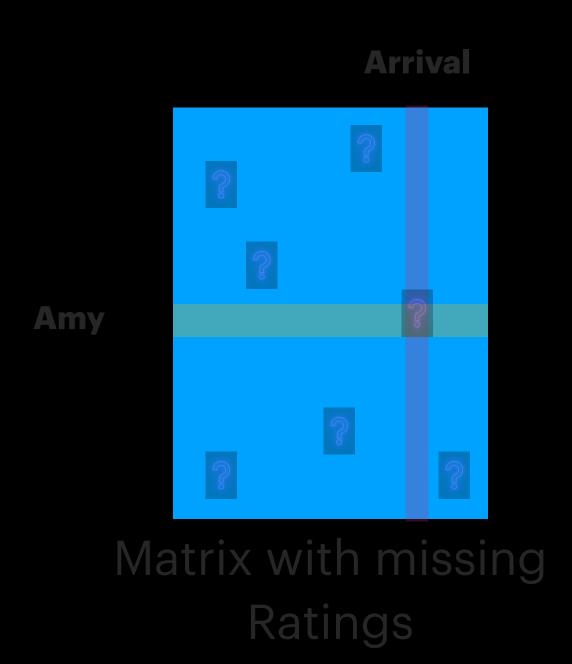


Linear Algebra in Action Q: What is the closest Linear Algebra method that looks similar to the above factorization?

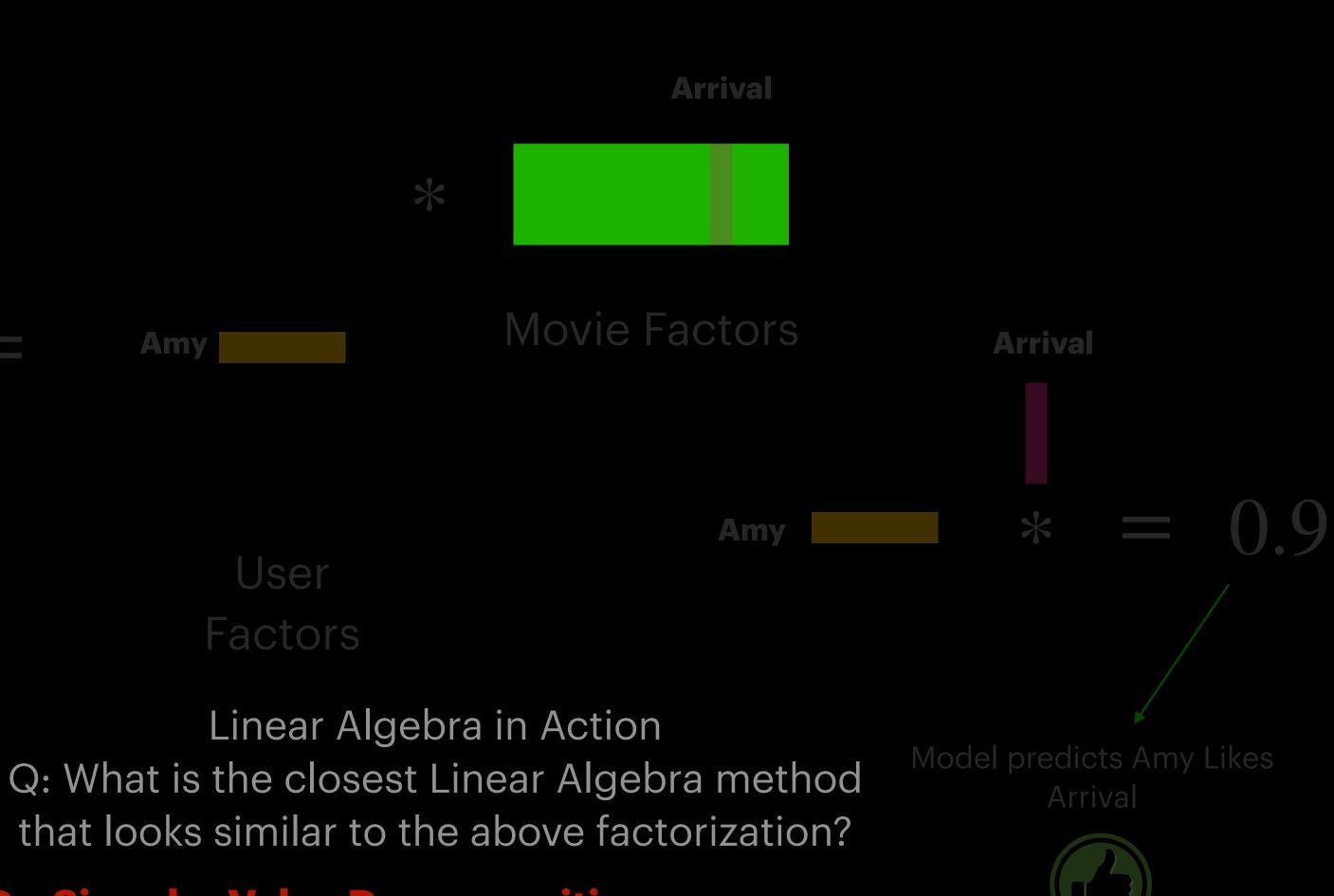


Model predicts Amy Like Arrival



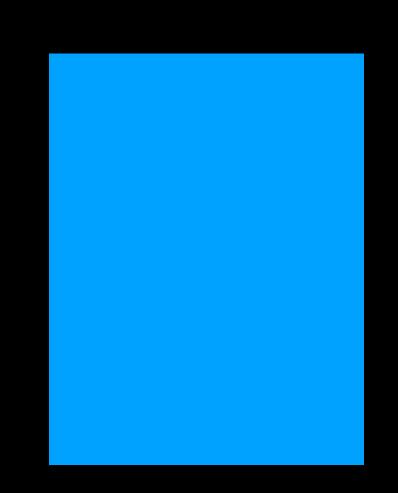


A: SVD = Singular Value Decomposition

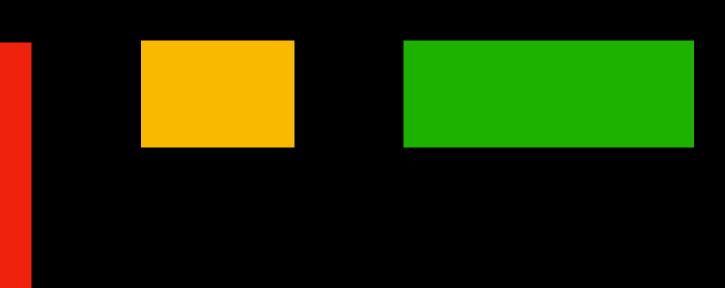












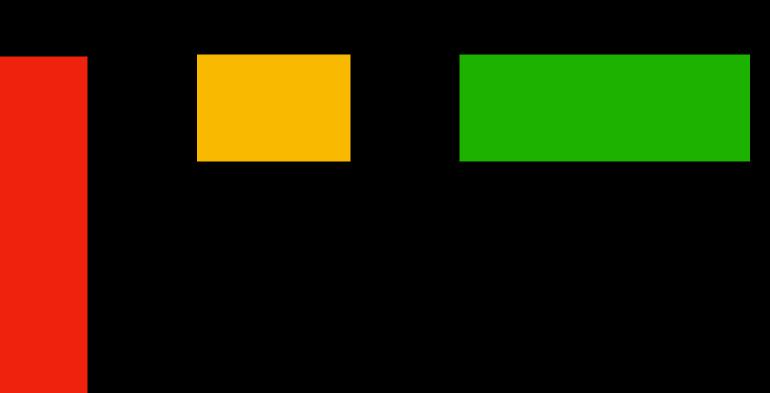












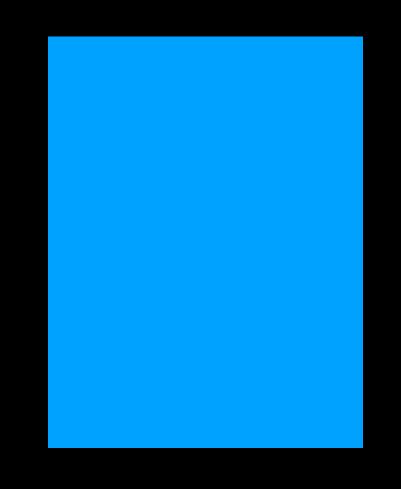








Every matrix has an SVD!









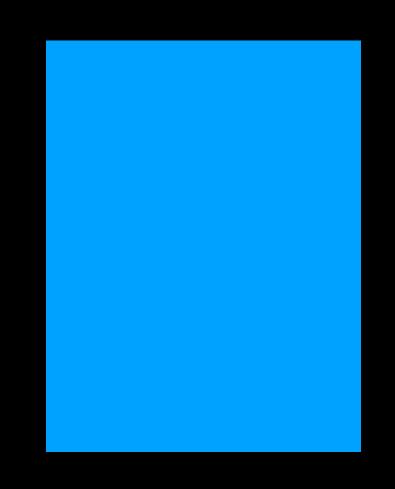






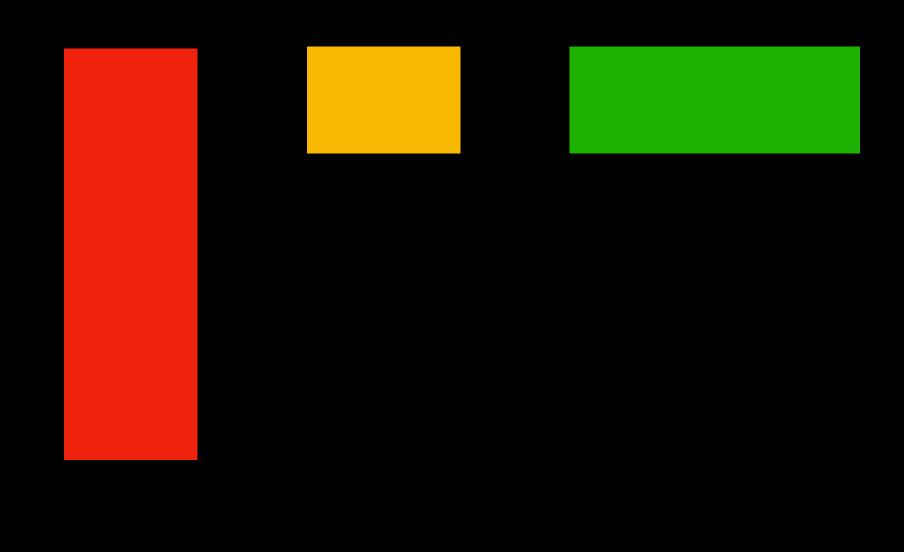


Hence: Data Matrix also has an SVD!







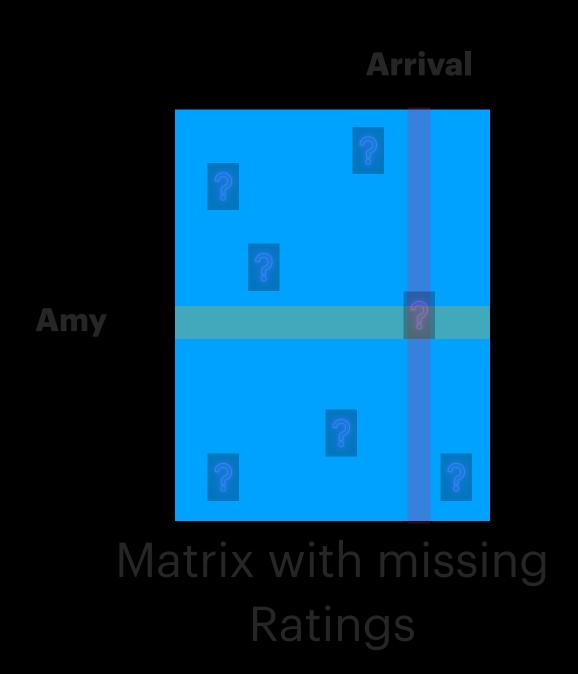


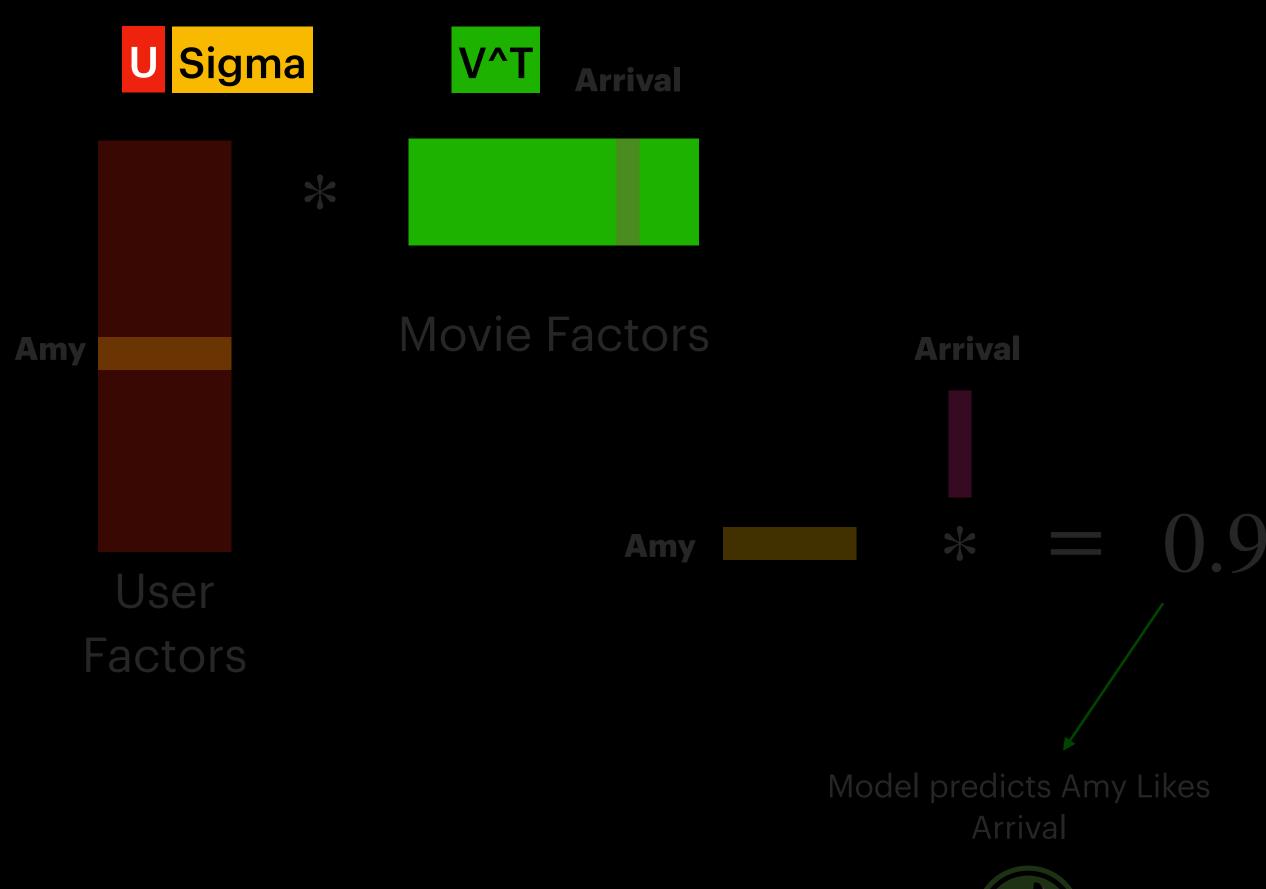






Collaborative Filtering Through Matrix Completion!





Collaborative Filtering: Advanced SVD method or Iterative SVD method



Collaborative Filtering

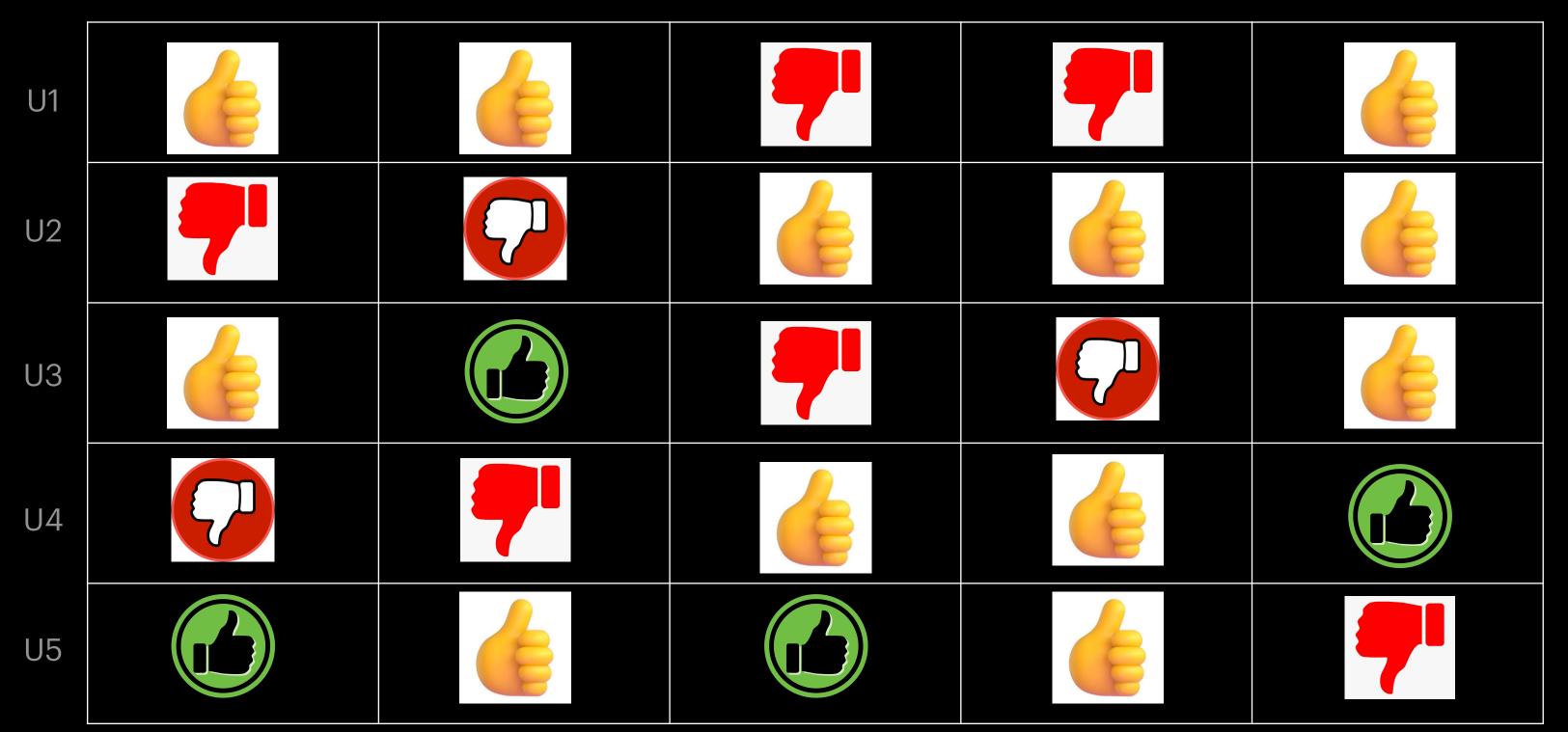


Avatar

Arrival

When Harry

Before Sunrise



nrise Minions



Men in Black

Collaborative Filtering

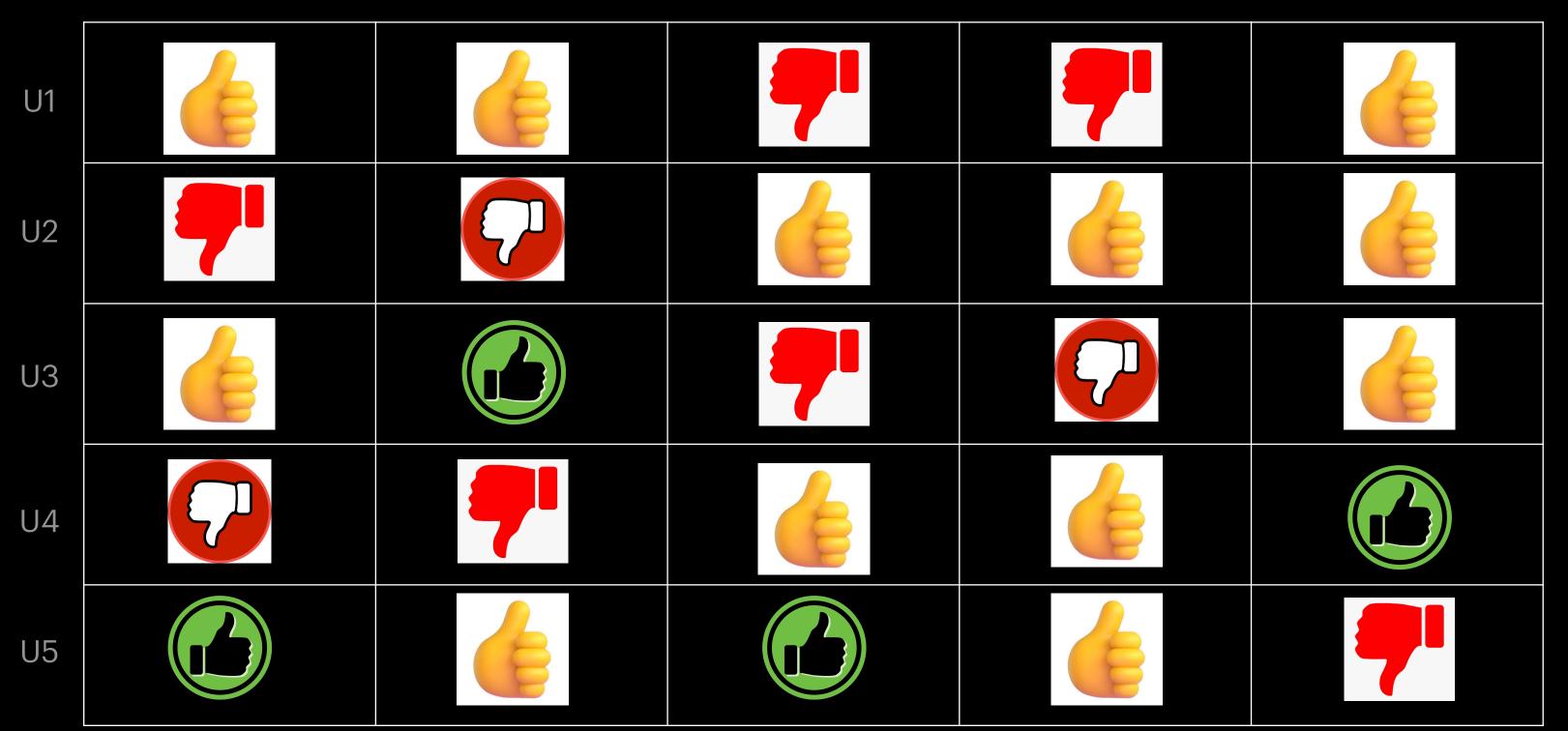


Avatar

Arrival

When Harry

Before Sunrise



Minions



Men in Black



Collaborative Filtering

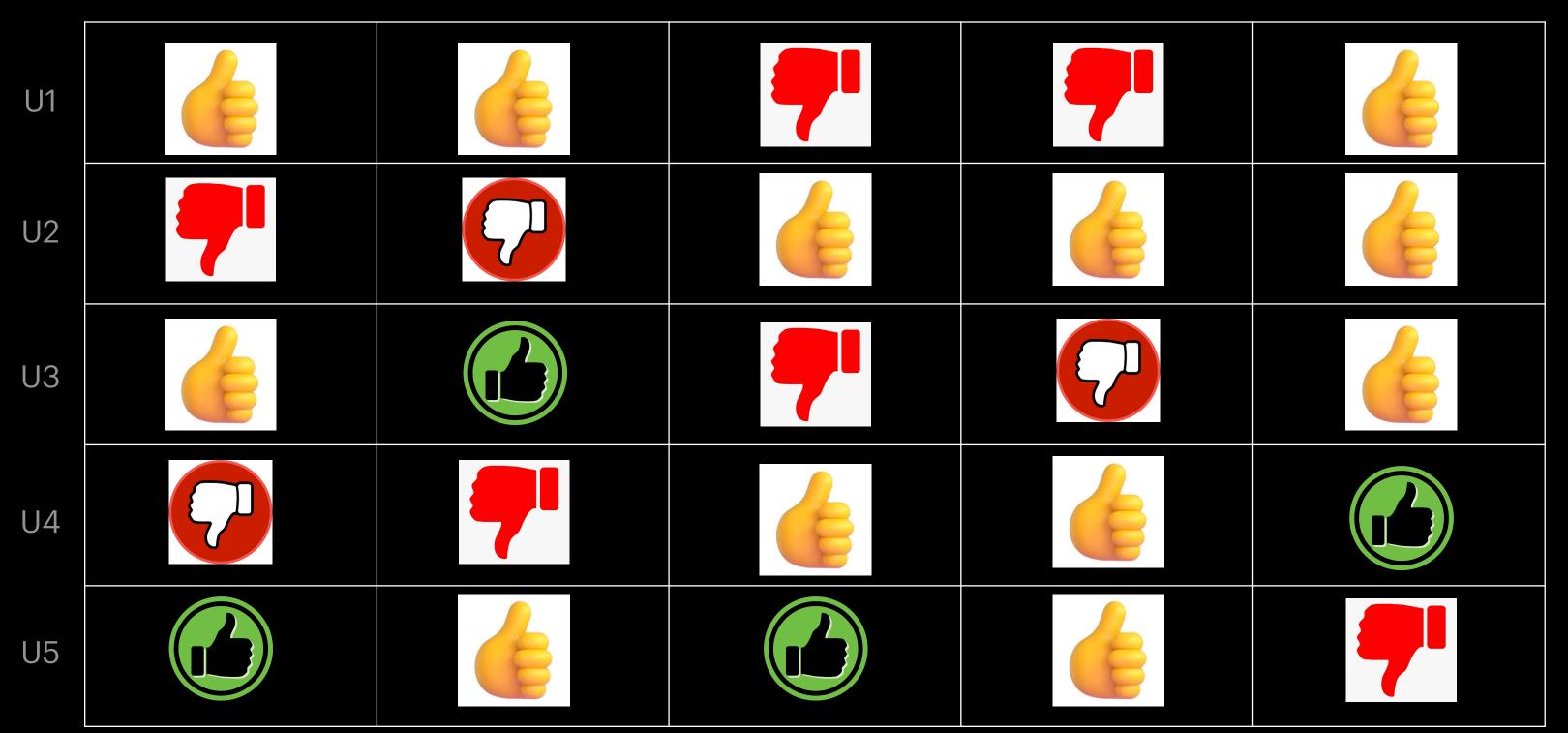


Avatar

Arrival

When Harry

Before Sunrise



Minions



Men in Black



 \bigcirc

 \bigcirc

020

Cold Start Problem



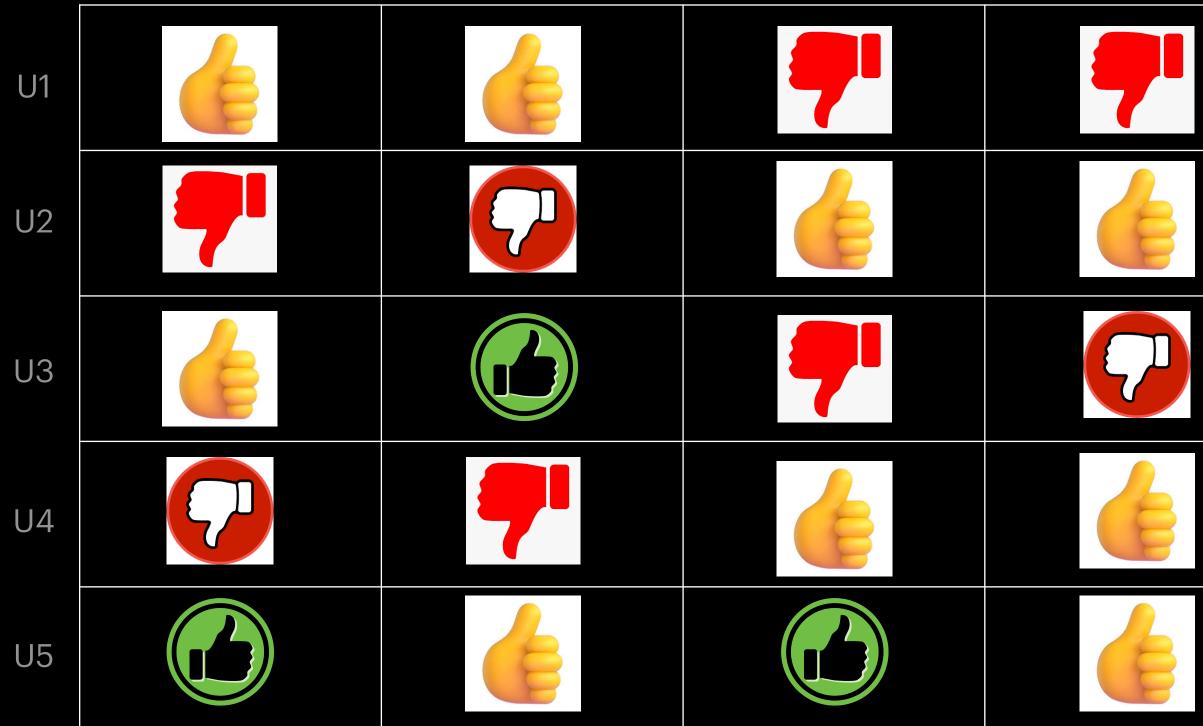


Avatar

Arrival

When Harry

Before Sunrise

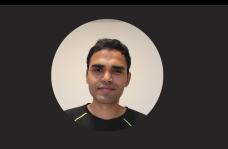


rise Minic





Men in Black



Karthik

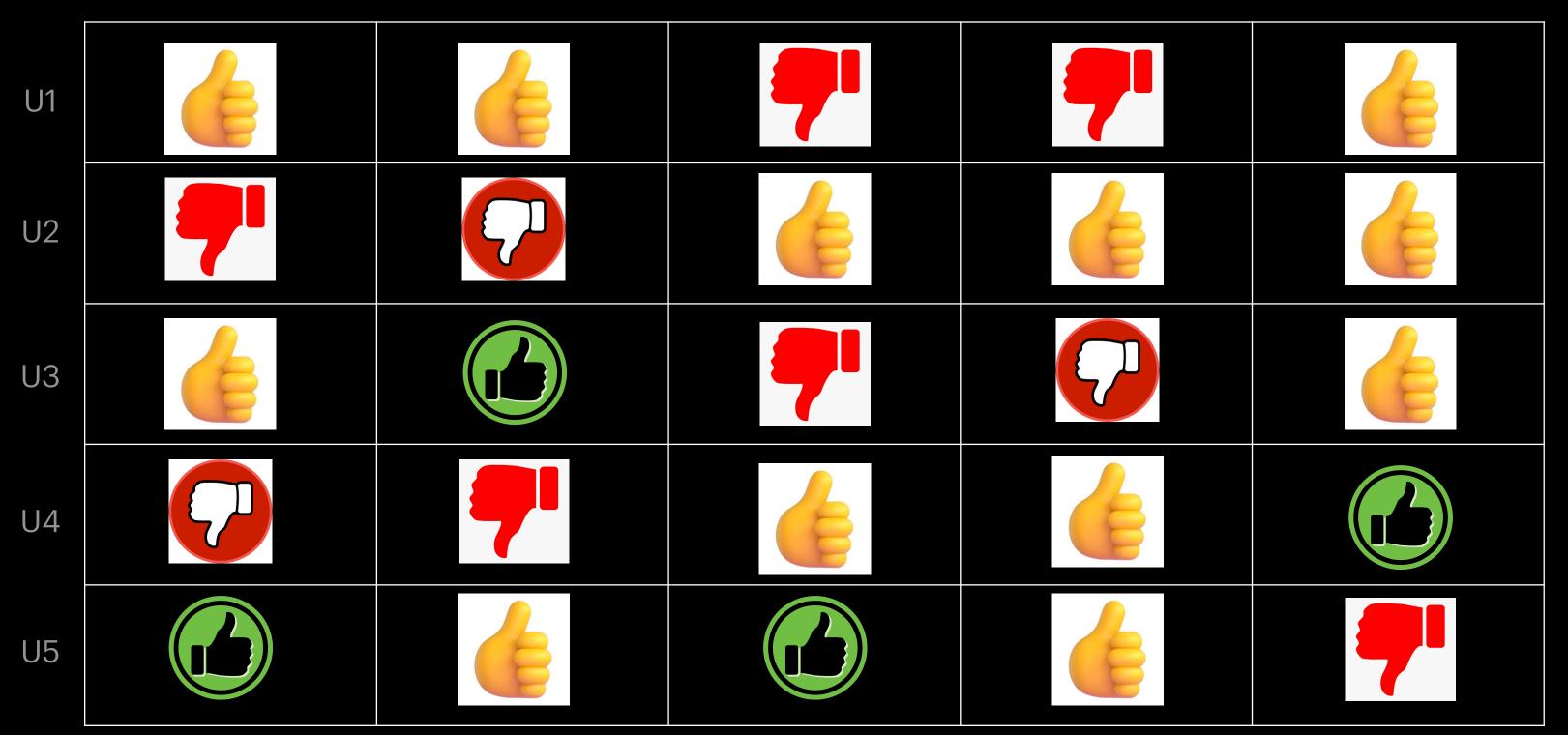


Avatar

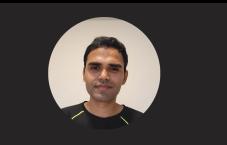
Arrival

When Harry

Before Sunrise



Minions



Karthik

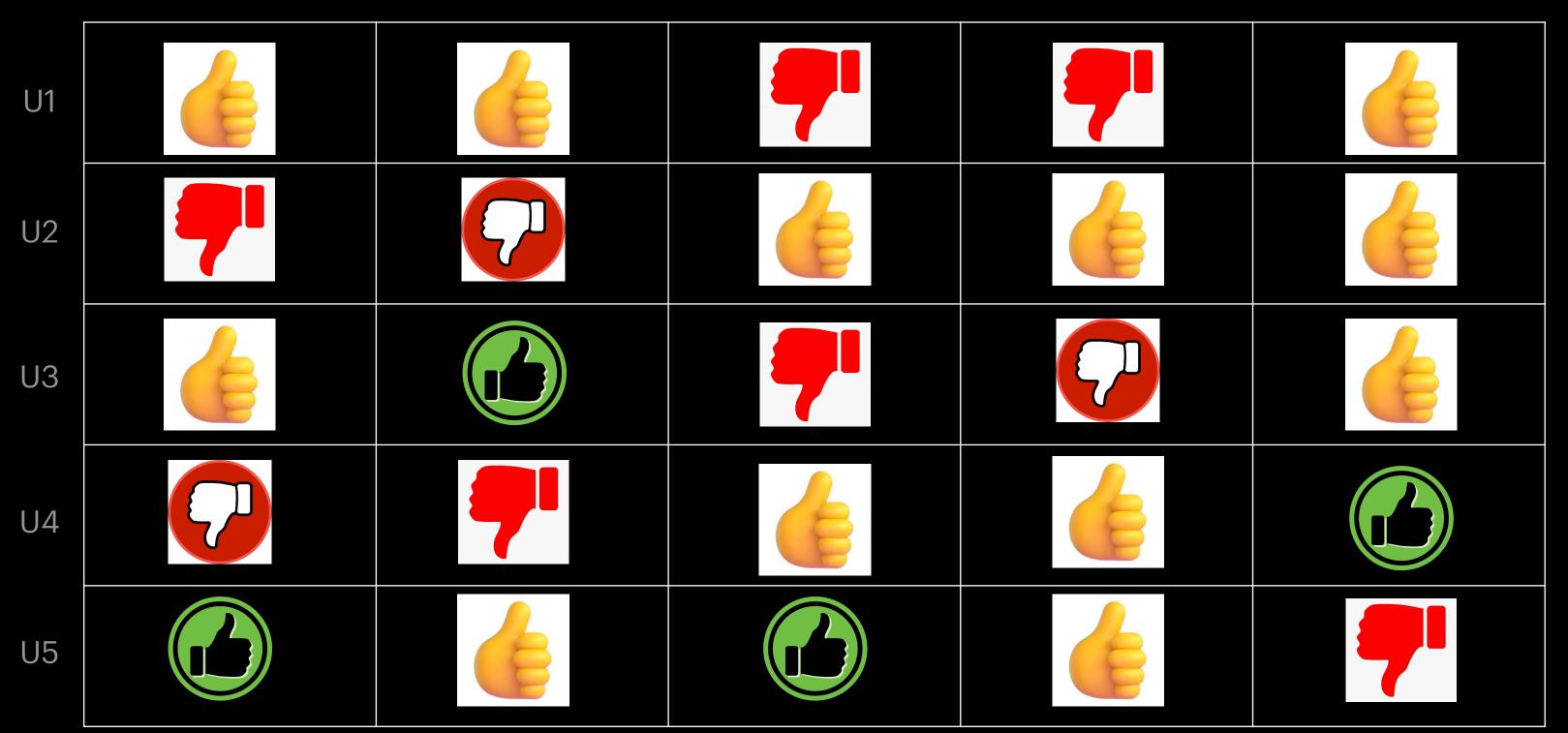


Avatar

Arrival

When Harry

Before Sunrise



Minions



Karthik

Watched



Arrival

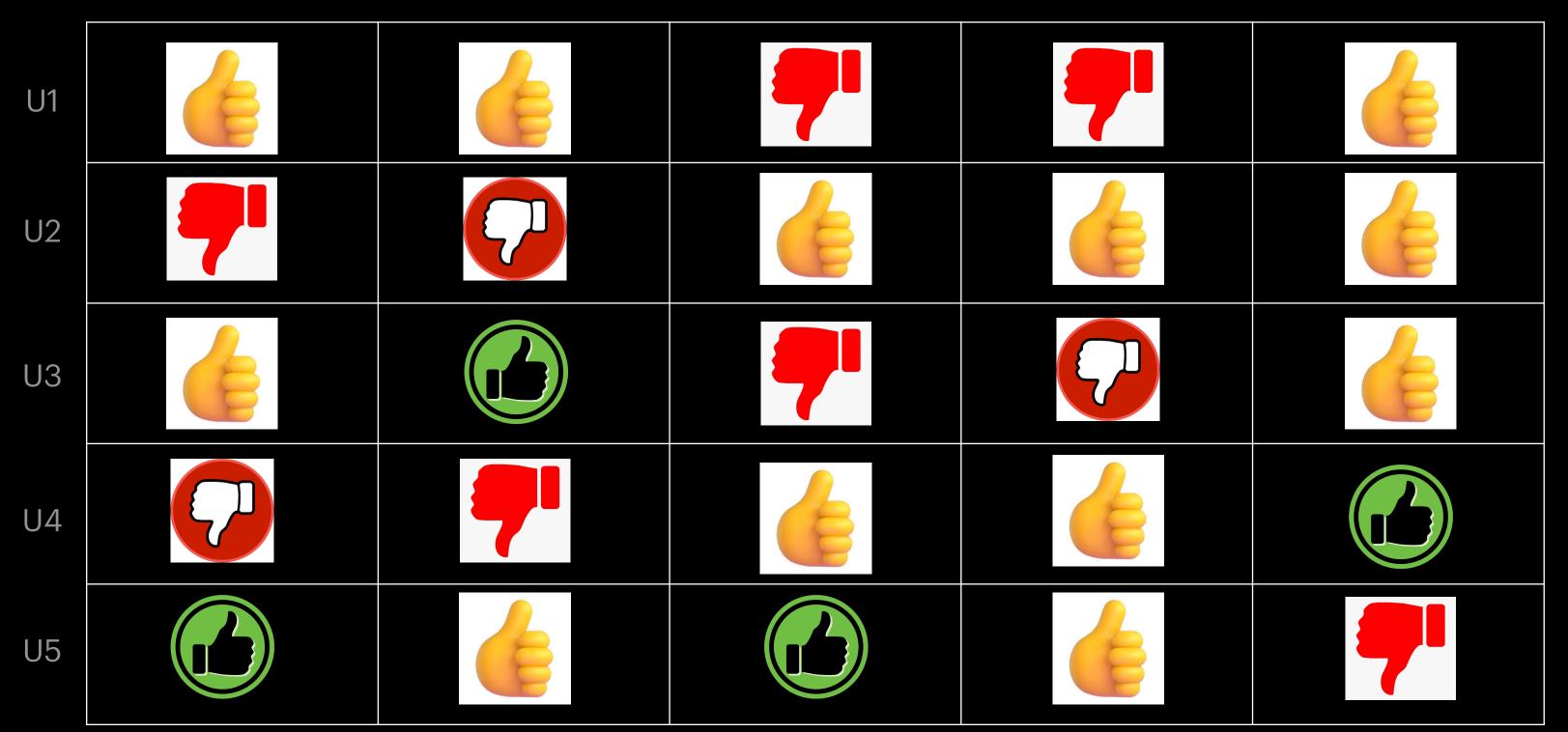


Avatar

Arrival

When Harry

Before Sunrise



Minions



Karthik

Watched





Arrival

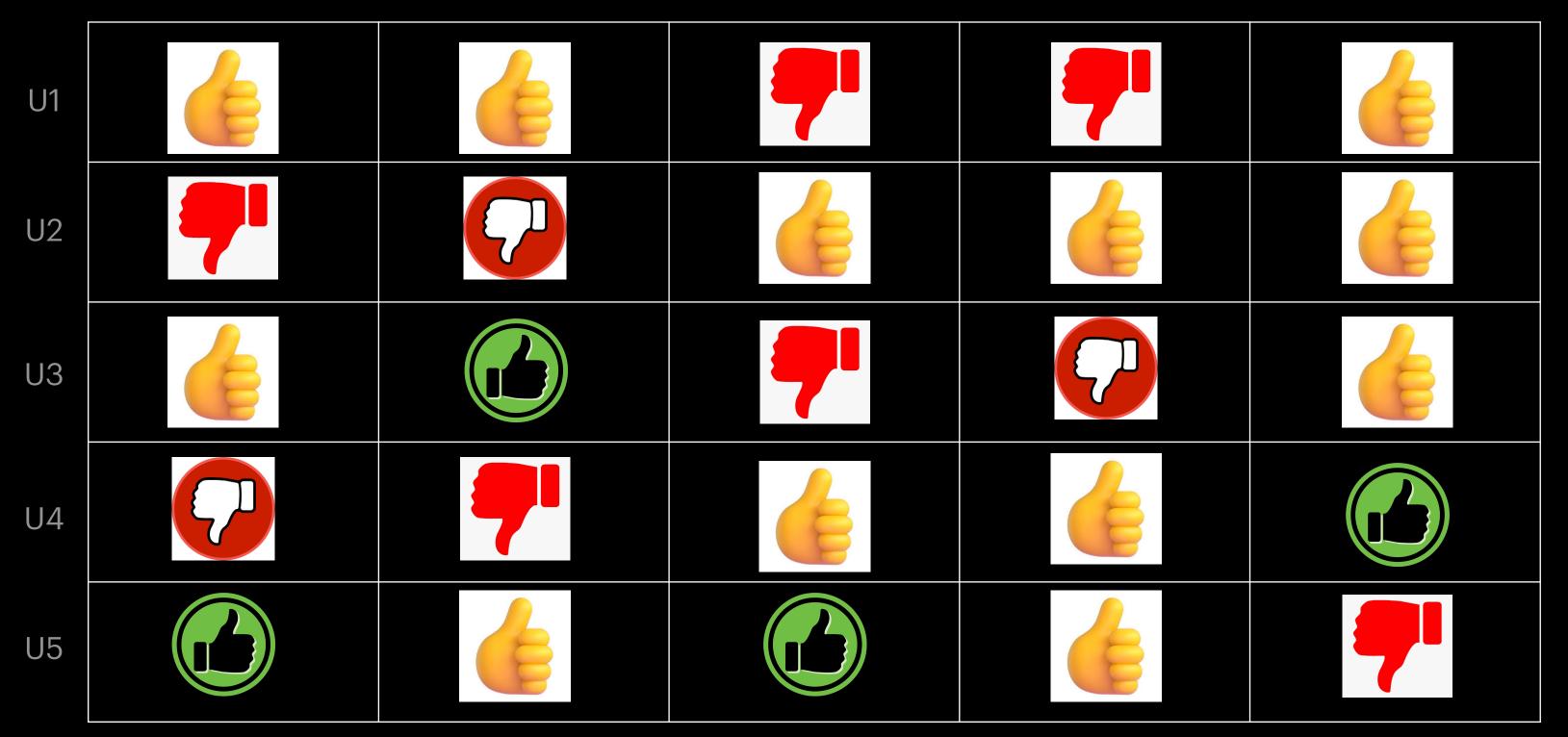


Avatar

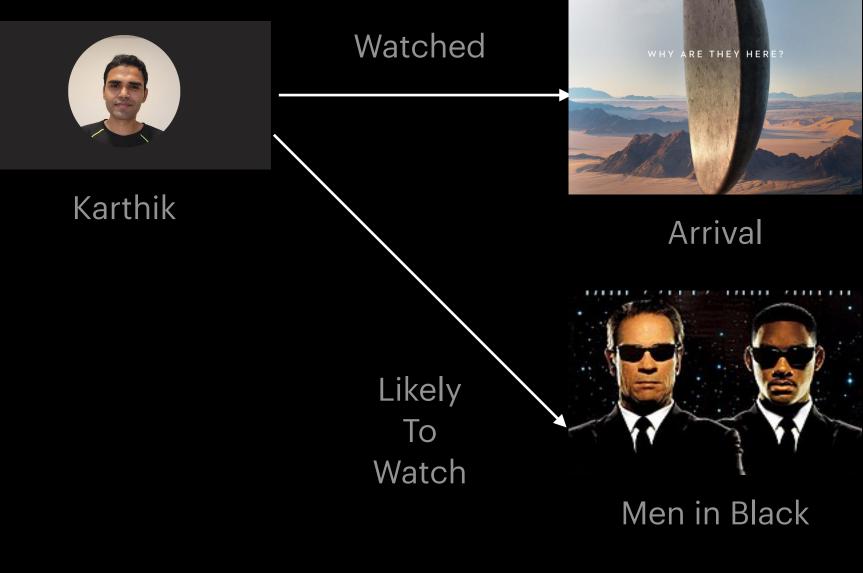
Arrival

When Harry

Before Sunrise



Minions





Minions

Embeddings



Men in Black



Arrival



Men in Black





When Harry met











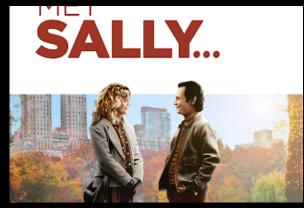
Embeddings



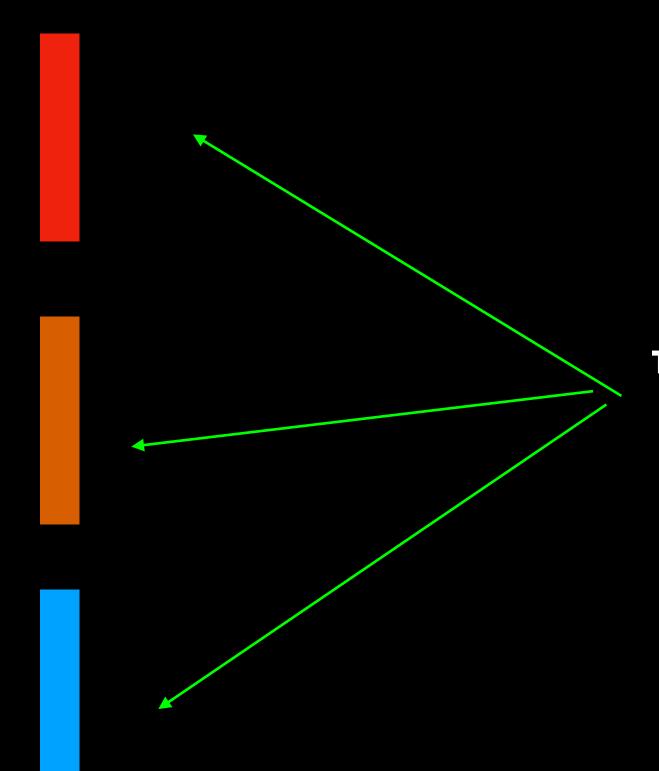
Men in Black



Arrival



When Harry met



Typically 128 or 256 latent dimensions

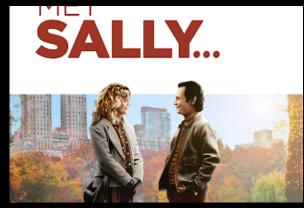
Embeddings



Men in Black



Arrival



When Harry met

How do we Obtain these embeddings?

Embeddings



Men in Black



Arrival



When Harry met

How do we Obtain these embeddings?

A: Through a DL model! Maybe last but one hidden layer activations

Embeddings Interpretation

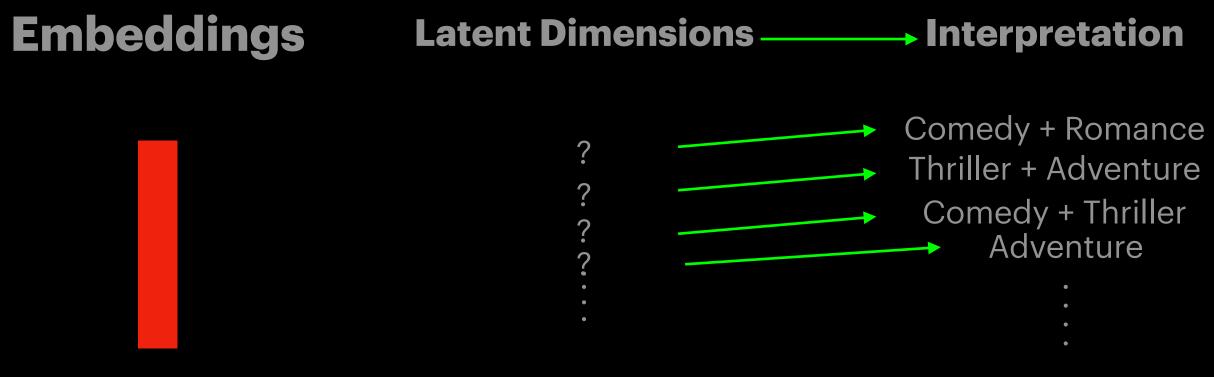


Men in Black



Arrival





Embeddings | Vector Representations

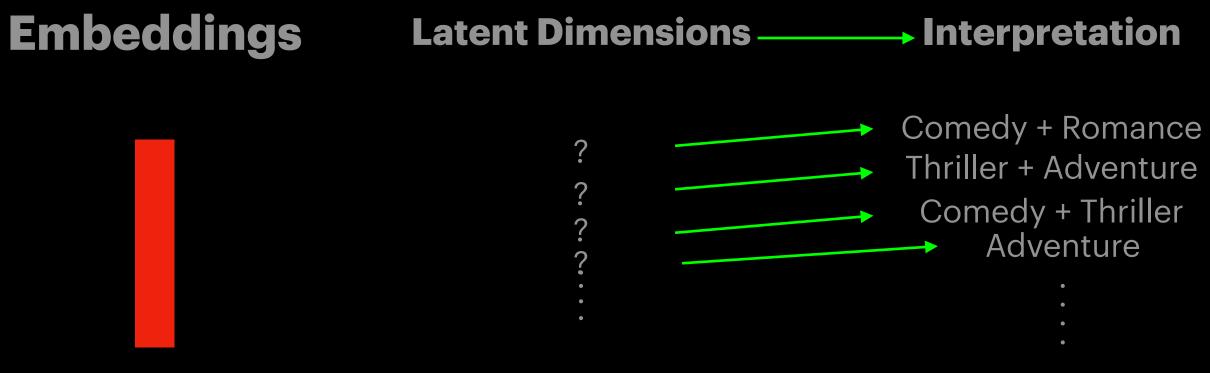


Men in Black



Arrival







Minions





Men in Black



Arrival



Men in Black





When Harry met













Minions





Men in Black



Arrival

High Cosine Similarity



When Harry met





Men in Black

















Minions





Men in Black



Arrival

High Cosine Similarity

Low Cosine Similarity



When Harry met

<u>ህዜ ግቢ</u> ተደረ ካዝ እስጠ በ



Men in Black











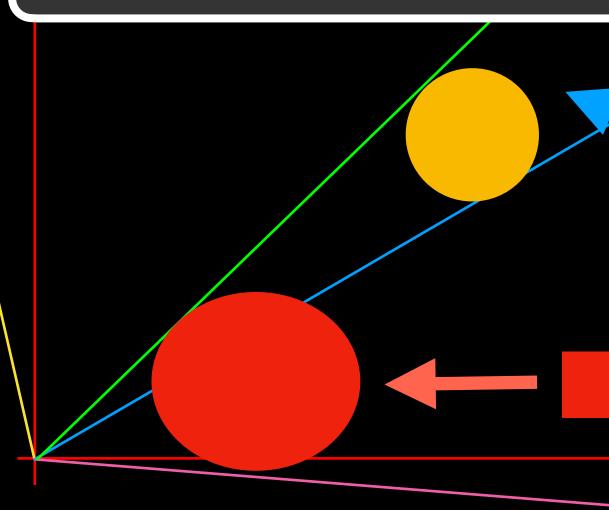






Minions

Smaller Angle = Higher Cosine Similarity Larger Angle = Lower Cosine Similarity





Men in Black

Arrival **High Cosine Similarity**

Low Cosine Similarity



When Harry met



Men in Black



Arrival SALLY.

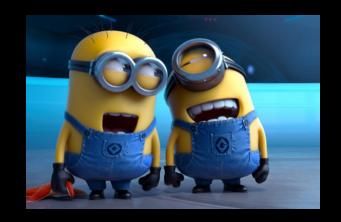












Minions

Embeddings

Smaller Angle = Higher Cosine Similarity Larger Angle = Lower Cosine Similarity





Men in Black

High Cosine Similarity

Low Cosine Similarity



Men in Black

















Minions

Embeddings

Smaller Angle = Higher Cosine Similarity Larger Angle = Lower Cosine Similarity





Men in Black

High Cosine Similarity

Low Cosine Similarity



Men in Black















Cauchy-Schwarz Inequality!

 $-1 \le CosineSimilarity(x, y) = \frac{x^T y}{||x||||y||} \le 1$

Cauchy-Schwarz Inequality

$-1 \leq CosineSimilarity(x,$

 $|x^T y| < = ||x||||y||$

$$y) = \frac{x^T y}{||x||||y||} \le 1$$

Cauchy-Schwarz Inequality

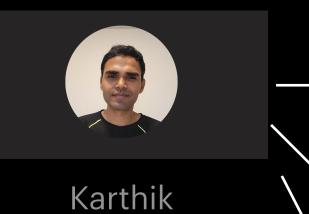
$-1 \leq CosineSimilarity(x,$

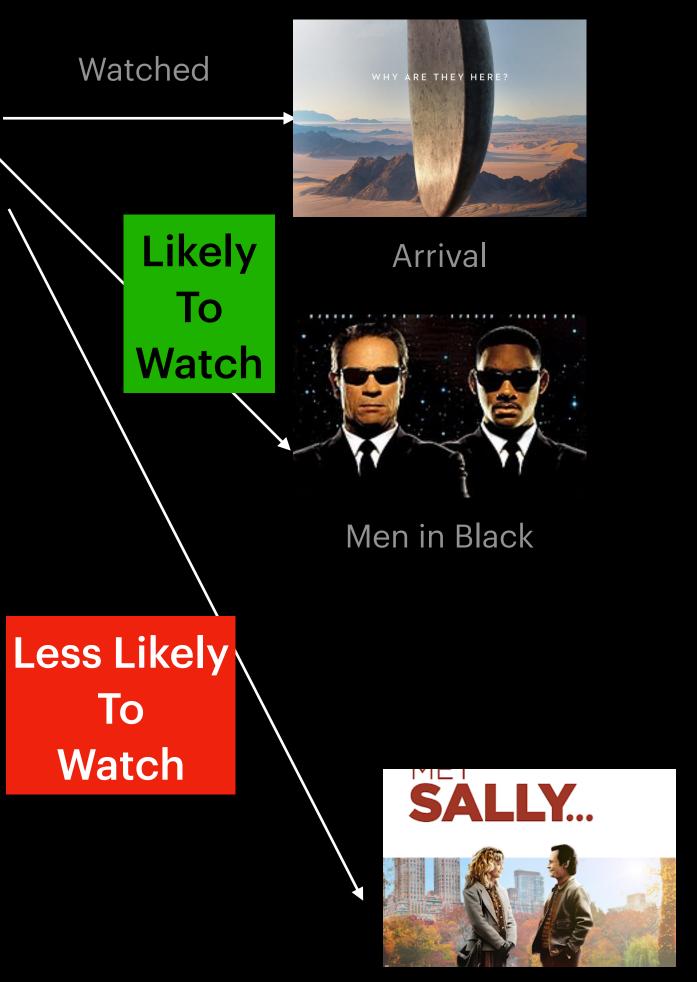
 $|x^T y| < = ||x|| ||y||$

 $\left\| x \right\|_{2}$

$$y) = \frac{x^T y}{||x||||y||} \le 1$$

Euclidean Norm of x





What if I like both sci-fi and romance?



Minions

Embeddings



Men in Black



Arrival





When Harry met



Men in Black















Embeddings

Can Embed both Movies and Users in Same space!

Minions



Men in Black



Arrival





When Harry met



Men in Black

















Minions





Men in Black



Arrival





When Harry met



Men in Black











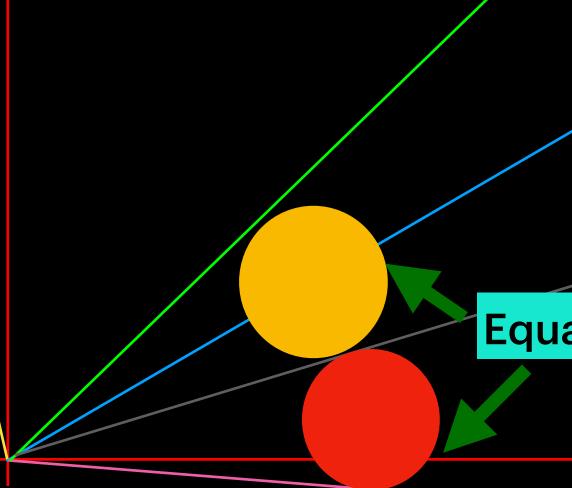






Minions



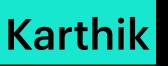




Men in Black



Arrival



Equal Cosine Similarity



When Harry met



Men in Black







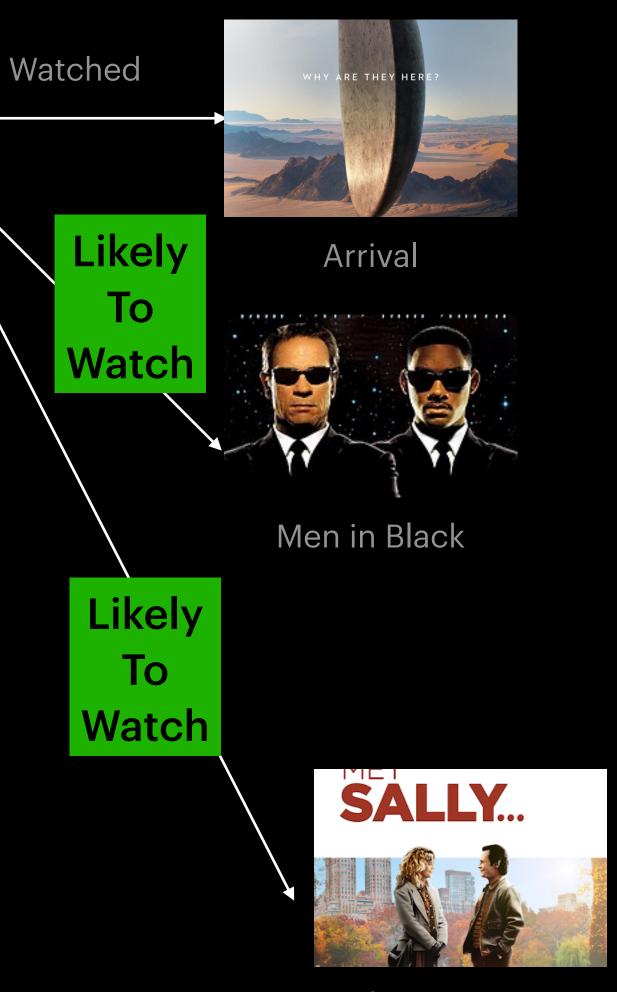




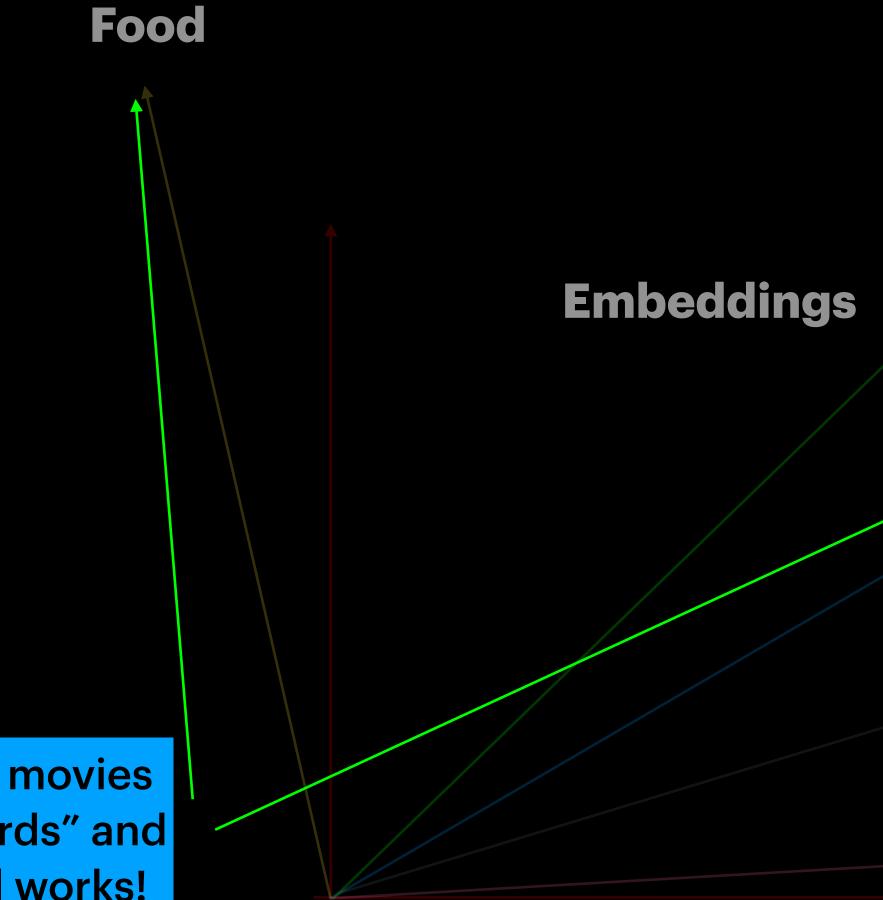


Like both Sci-fi and Romance









Replace movies with "words" and This still works!

Word Embeddings

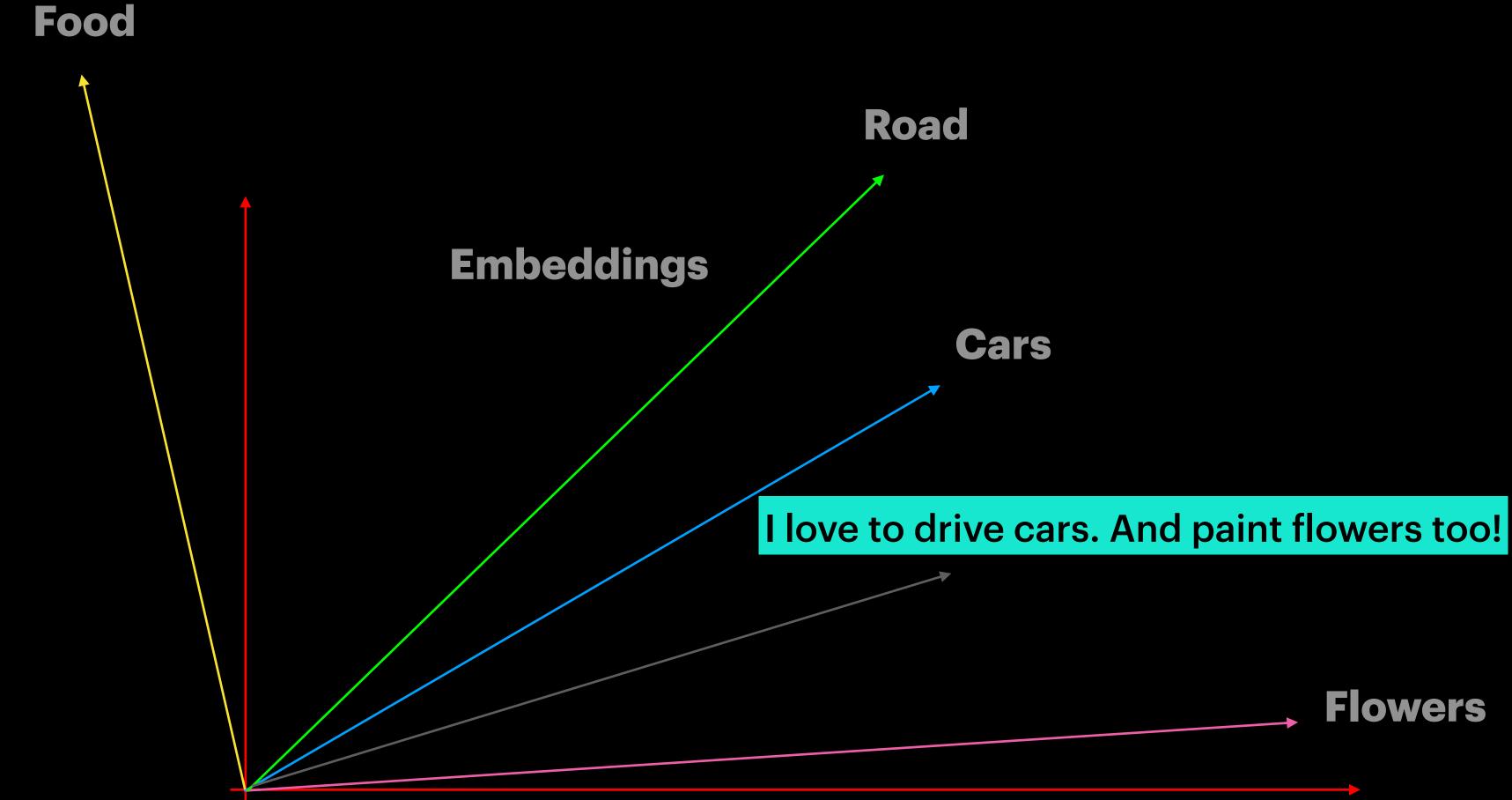


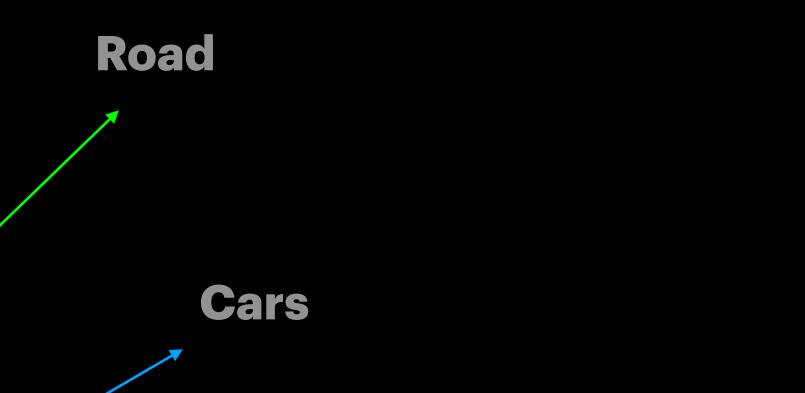
Cars

Karthik

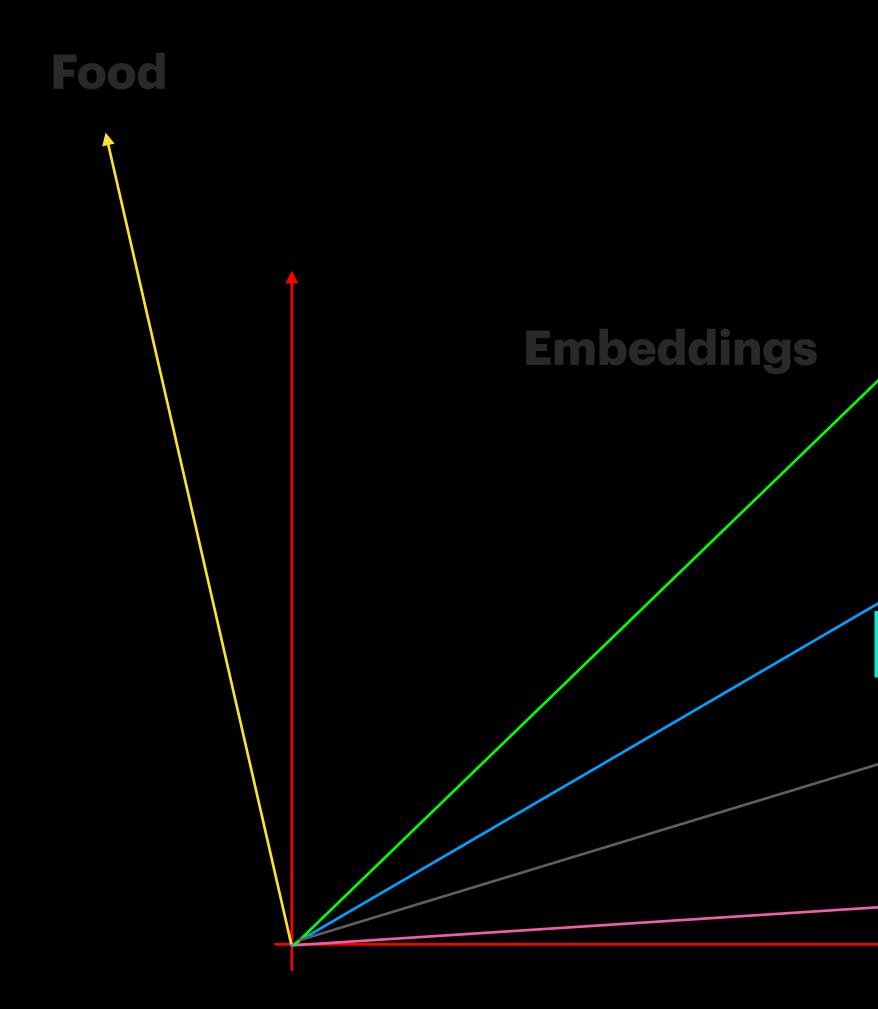


Word Embeddings





Word and Sentence Embeddings



This embeds a word



This embeds a sentence

Flowers

Cars

Word and Sentence Embeddings

How do we Obtain these embeddings?

A: Through a DL model! Maybe last but one hidden layer activations

Word and Sentence Embeddings

How do we Obtain these embeddings?

A: Through a DL model! Maybe last but one hidden layer activations

> Glove Embeddings Sentence BERT

We will cover Sentence BERT when we Get to Transformers!

Embeddings

Semantic Search: Enables us to find the closest category for A given sentence

Food

This embeds a word



This embeds a sentence

Flowers

Cars

Embeddings

Typical Search: Based on look-up. May Not handle semantics. Uses Trie Datastructure

Food

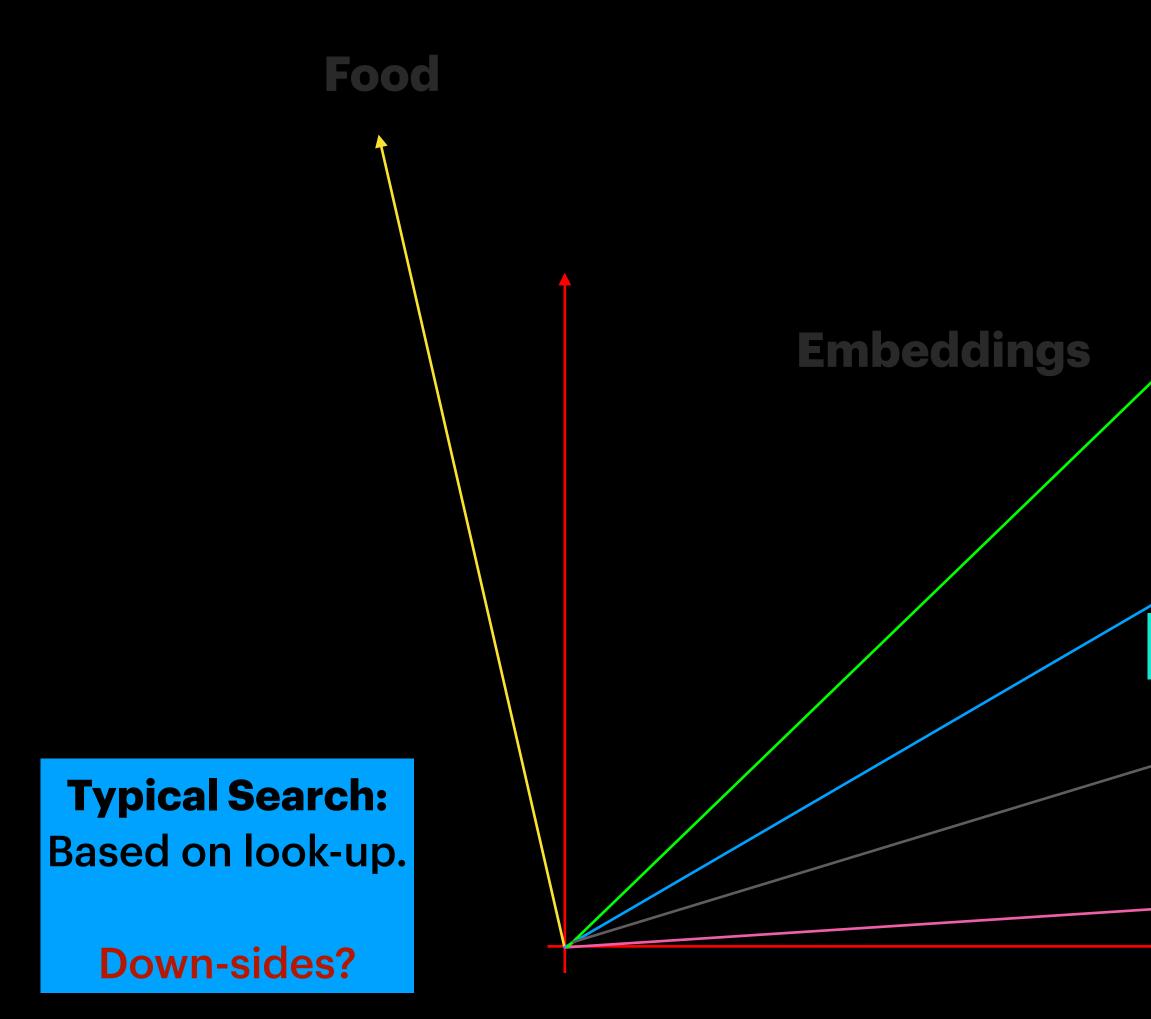
This embeds a word



This embeds a sentence

Howers

Cars



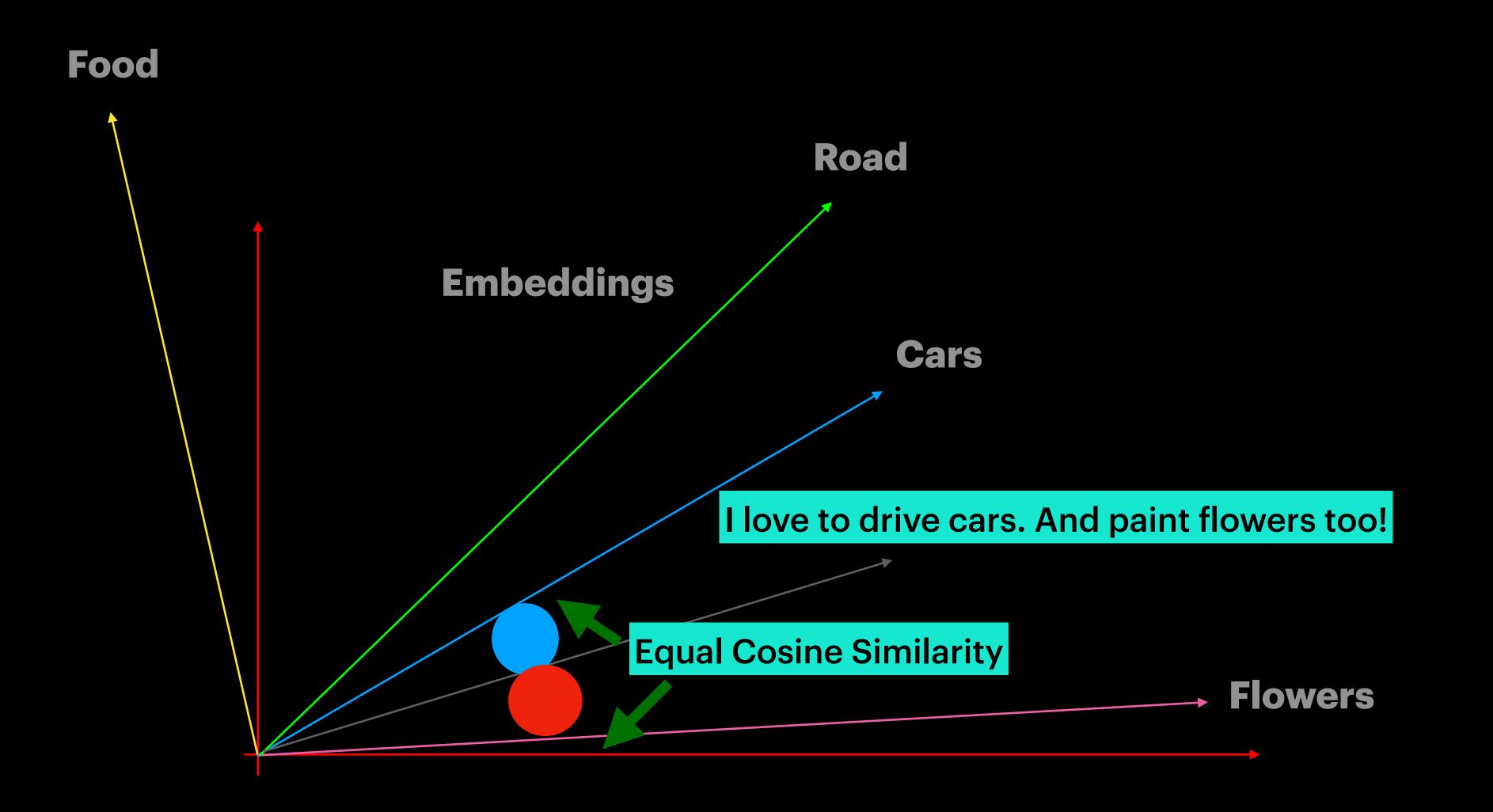
This embeds a word

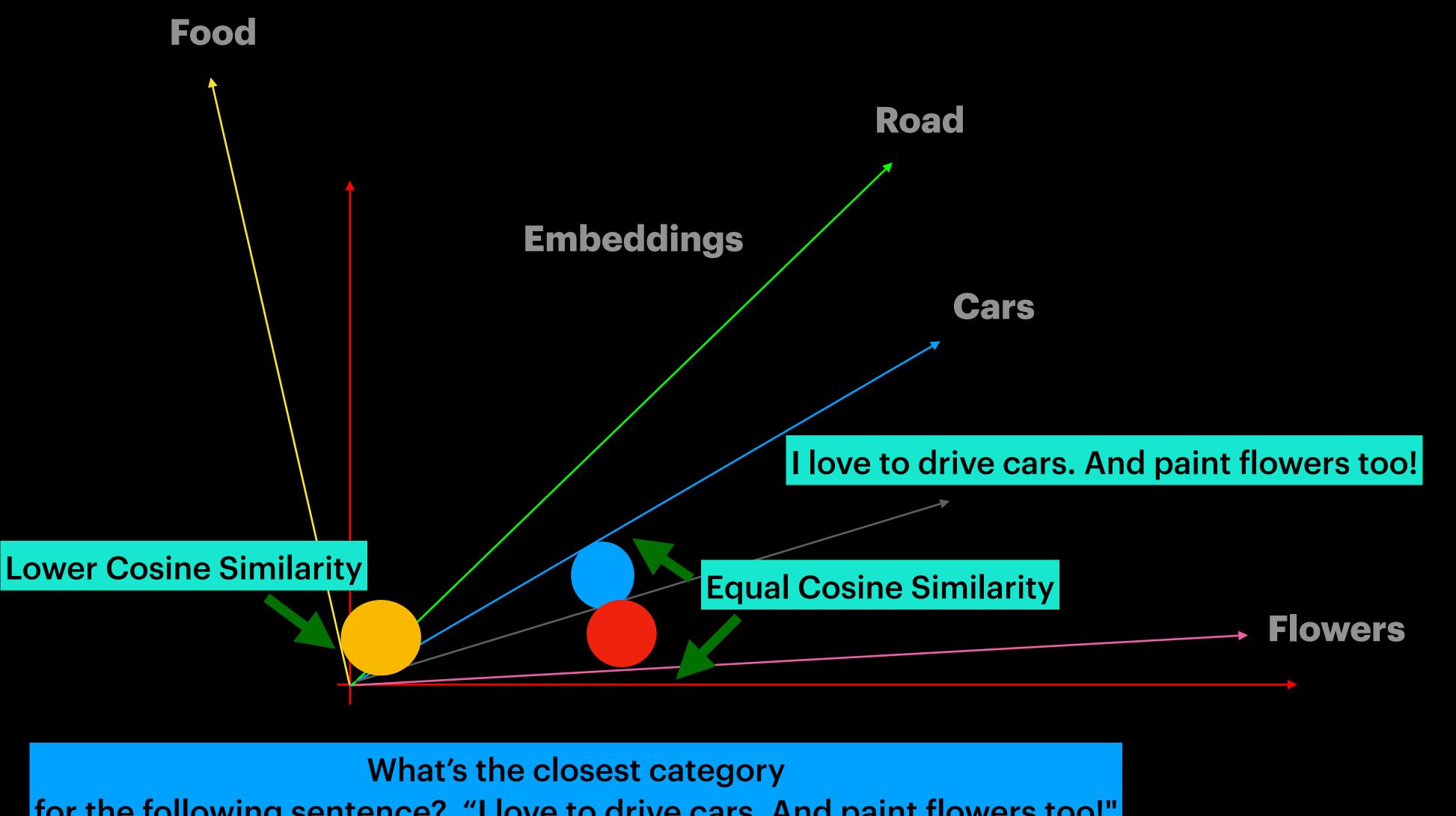


This embeds a sentence

Flowers

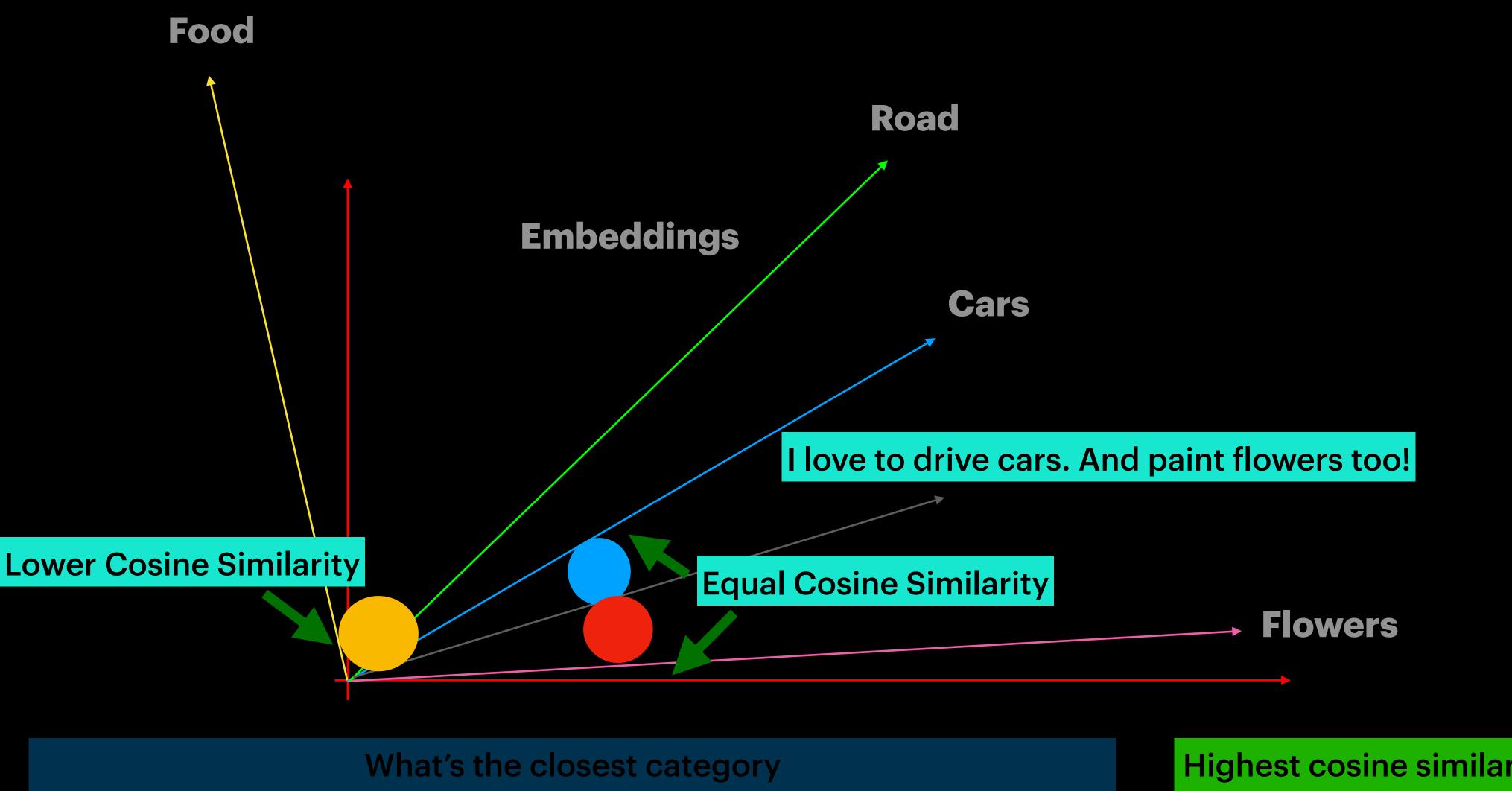
Cars





for the following sentence? "I love to drive cars. And paint flowers too!"





for the following sentence? "I love to drive cars. And paint flowers too!"

Semantic Search Vector Search

Highest cosine similarity based on vector search: Flowers and Cars





What is King - Man + Woman?

Vector Arithmetic!

Demo on Semantic Search