

Movie Recommendation Engine



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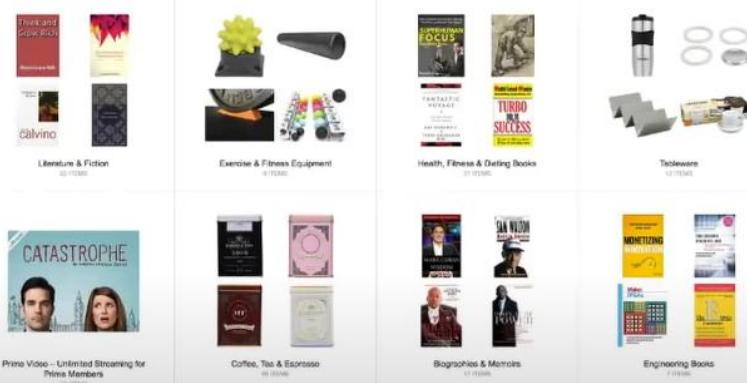
INTRODUCTION

“What movie should I watch this evening?”

What's Common?

1. Amazon

Recommended for you, Thomas



2. Netflix

Because you watched Marvel's Daredevil



Because you watched Bo Burnham: Make Happy



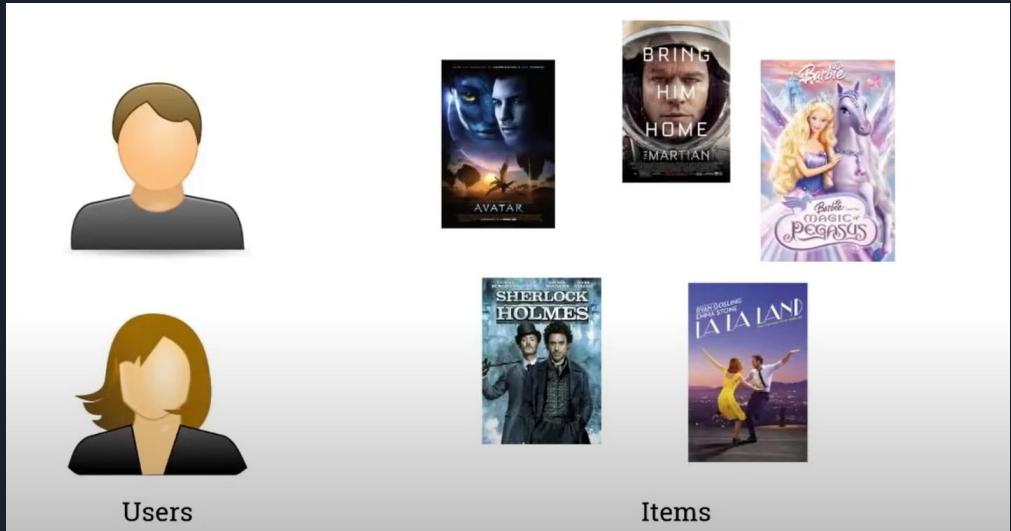


PROJECT OBJECTIVES

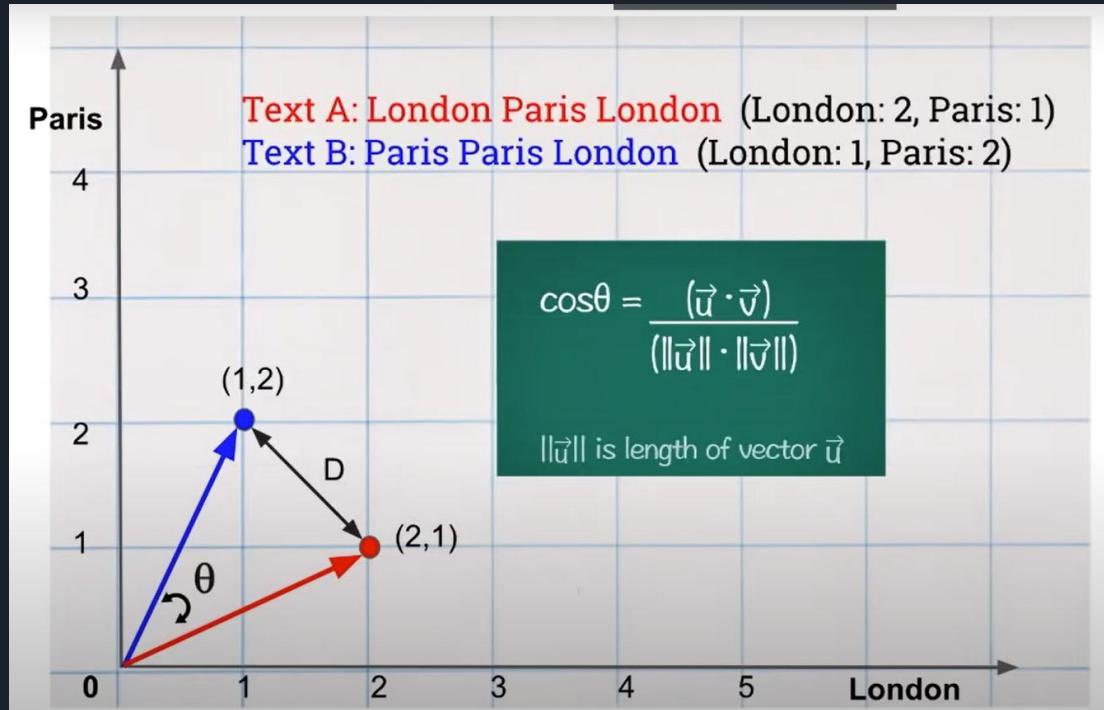
- Working on Algorithm for recommending movies.
- Working with a large datasets.
- Implement the processed data in the Algorithm.

NEED OF RECOMMENDATION ENGINE

- Customer Satisfaction
- Providing Reports
- Revenue Maximization



CONCEPT OF SIMILARITY FOR RECOMMENDATION



Continue...

```
In [1]: import pandas as pd
import numpy as np
from sklearn.feature_extraction.text import CountVectorizer
from sklearn.metrics.pairwise import cosine_similarity

In [2]: text = ["London Paris London", "Paris Paris London"]

In [3]: cv = CountVectorizer()
count_matrix = cv.fit_transform(text)

In [4]: print(cv.get_feature_names())
print(count_matrix.toarray())

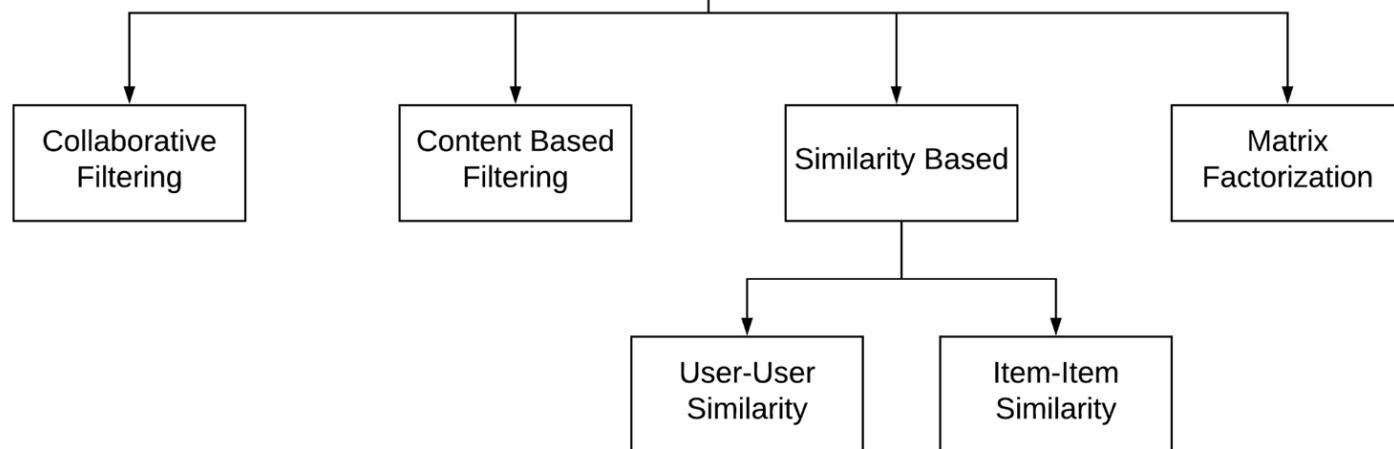
['london', 'paris']
[[2 1]
 [1 2]]

In [5]: similarity_scores = cosine_similarity(count_matrix)
print(similarity_scores)

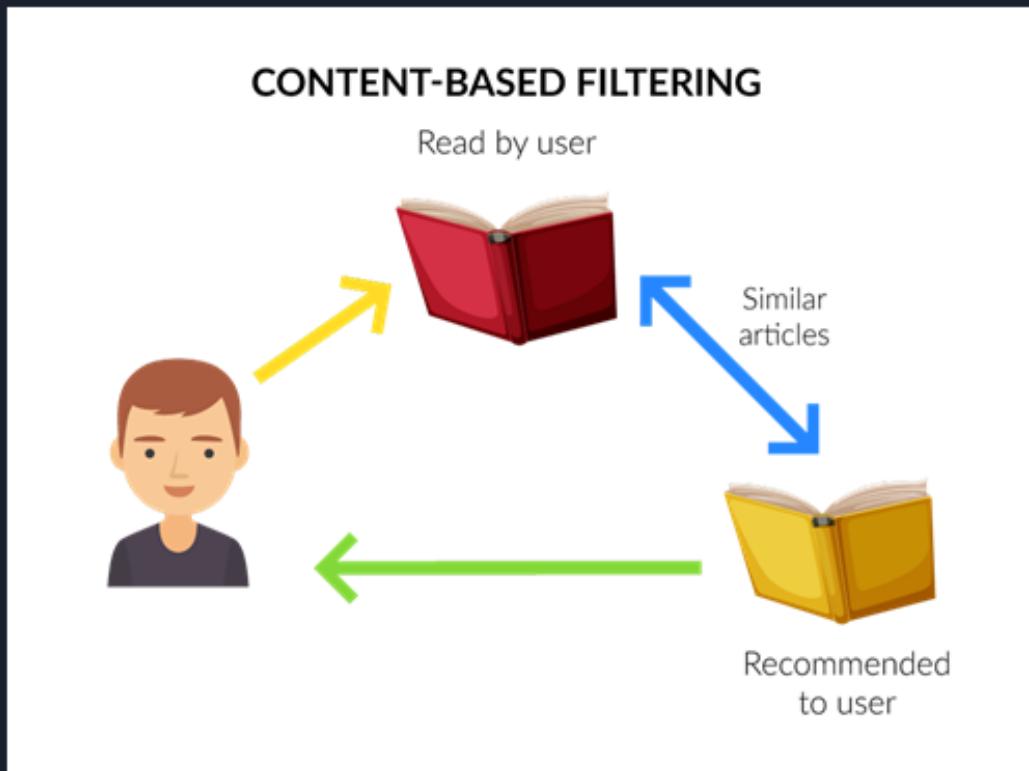
[[1.  0.8]
 [0.8 1. ]]
```

TYPES OF RECOMMENDATION ENGINE

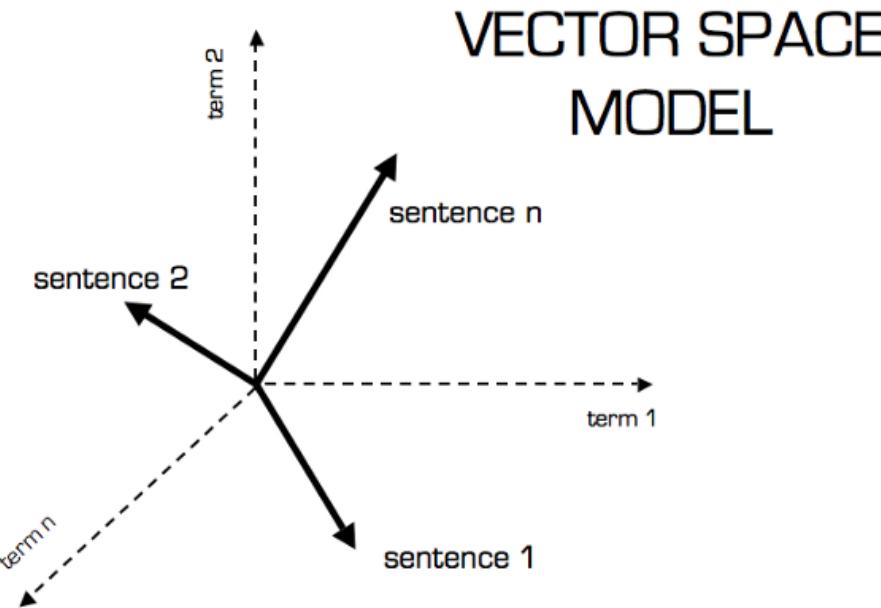
Types of Recommender Systems



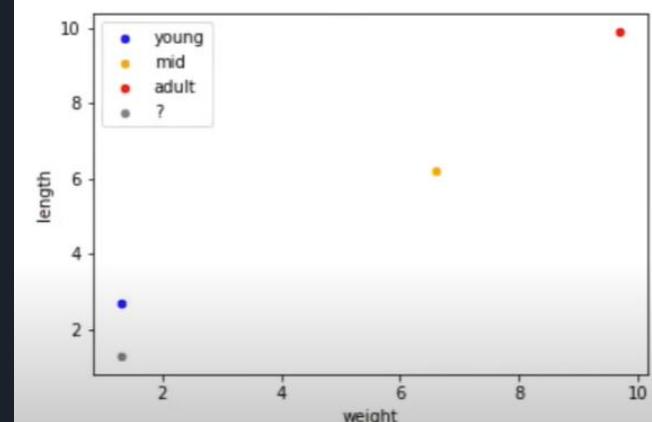
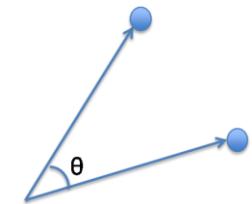
CONTENT BASED RECOMMENDATION ENGINE



CONCEPT OF CONTENT BASED RECOMMENDATION ENGINE



$$sim(A, B) = \cos(\theta) = \frac{A \cdot B}{\|A\| \|B\|}$$



Continue...

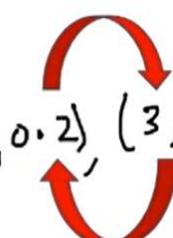
Movies →

	0	1	2	3	
0	1	0.8	0.2	0.5	①
1		1	0.3	0.6	
2			1	0.1	
3				1	
⋮					

→ $[1, 0.8, 0.2, 0.5]$

↓ ② $\left[(0, 1), (1, 0.8), (2, 0.2), (3, 0.5) \right]$

↓ ③ $\left[(0, 1), (1, 0.8), (3, 0.5), (2, 0.2) \right]$



IMPLEMENTING CONTENT BASED RECOMMENDATION ENGINE

```
✓ [17] movie_user_likes = "Interstellar"
0s     movie_index = get_index_from_title(movie_user_likes)
         similar_movies = list(enumerate(cosine_sim[movie_index])) #accessing the row corresponding to given movie to find all the similarity scores for

✓ [18] sorted_similar_movies = sorted(similar_movies,key=lambda x:x[1],reverse=True)[1:]

✓ [19] i=0
0s     print("Top 5 similar movies to "+movie_user_likes+" are:\n")
         for element in sorted_similar_movies:
             print(get_title_from_index(element[0]))
             i=i+1
             if i>5:
                 break

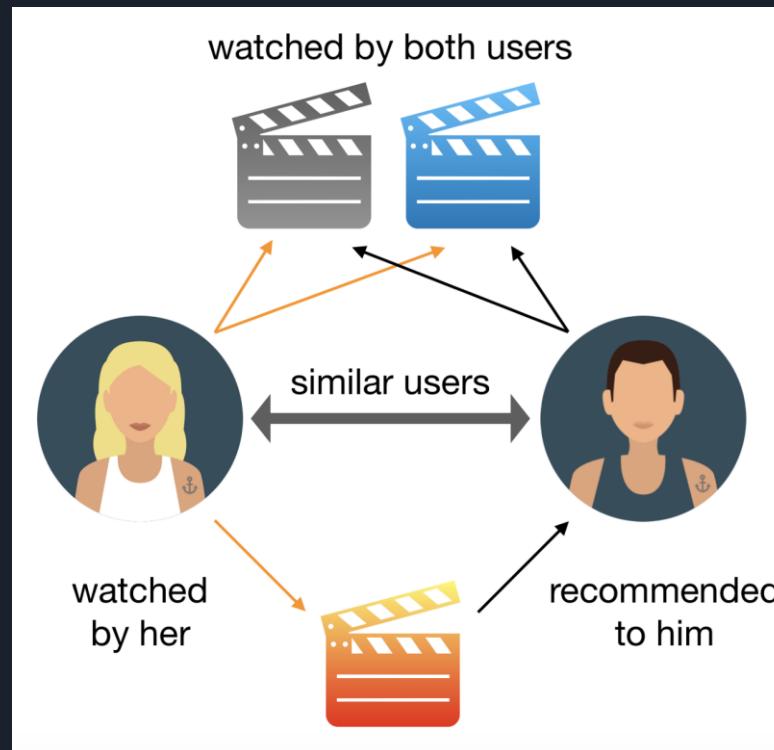
Top 5 similar movies to Interstellar are:

The Matrix Revolutions
Midnight Special
The Matrix Reloaded
The Martian
The Terminator
Armageddon
```

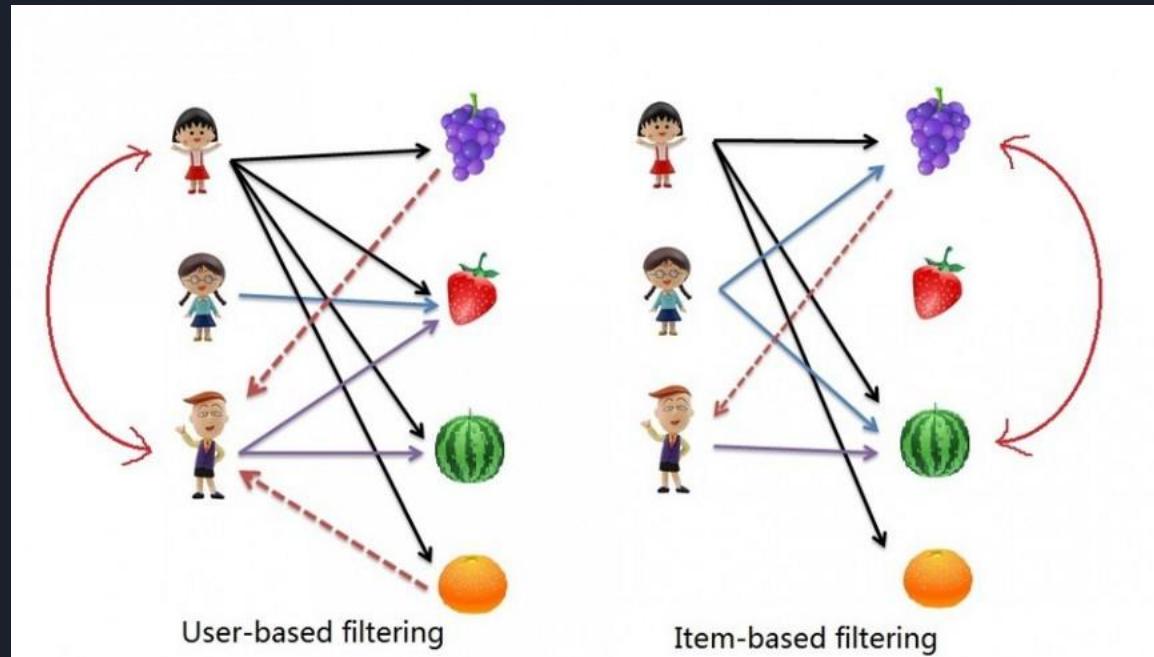
✓ 0s completed at 10:23 PM

00:56
10.11.21

COLLABORATIVE FILTERING RECOMMENDATION ENGINE



TYPES OF COLLABORATIVE FILTERING RECOMMENDATION ENGINE



Cont...

	User 1	User 2	User 3
Movie 1	5	2	4
Movie 2	3	4	3
Movie 3	1	4	1
Movie 4	2		??
Movie 5	5	2	??

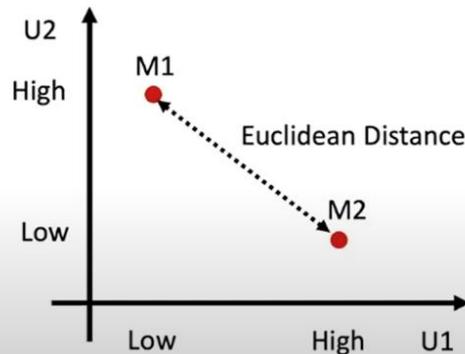
User-User Collaborative Filtering

	Movie 1	Movie 2	Movie 3	Movie 4	Movie 5
User 1	5	3	1	2	5
User 2	2	4	4		2
User 3	4	3	1	??	??

Item-Item Collaborative Filtering

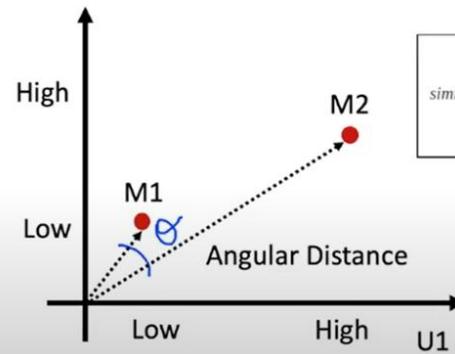
CONCEPT OF COLLABORATIVE FILTERING RECOMMENDATION ENGINE

Quantifying the Similarity



Dissimilar Users

Option 1: Cosine Distance
Option 2: Pearson Correlation



Similar Users

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

Continue...

	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	

sim(1,m)

1.00

-0.18

0.41

-0.10

-0.31

0.59

IMPLEMENTING COLLABORATIVE FILTERING BASED RECOMMENDATION ENGINE

```
action_lover = [("Amazing Spider-Man, The (2012"),5),("Mission: Impossible III (2006)",4),("Toy Story 3 (2010)",2),("2 Fast 2 Furious (Fast and similar_movies = pd.DataFrame()
for movie, rating in action_lover:
    similar_movies = similar_movies.append(get_similar(movie, rating), ignore_index = True)

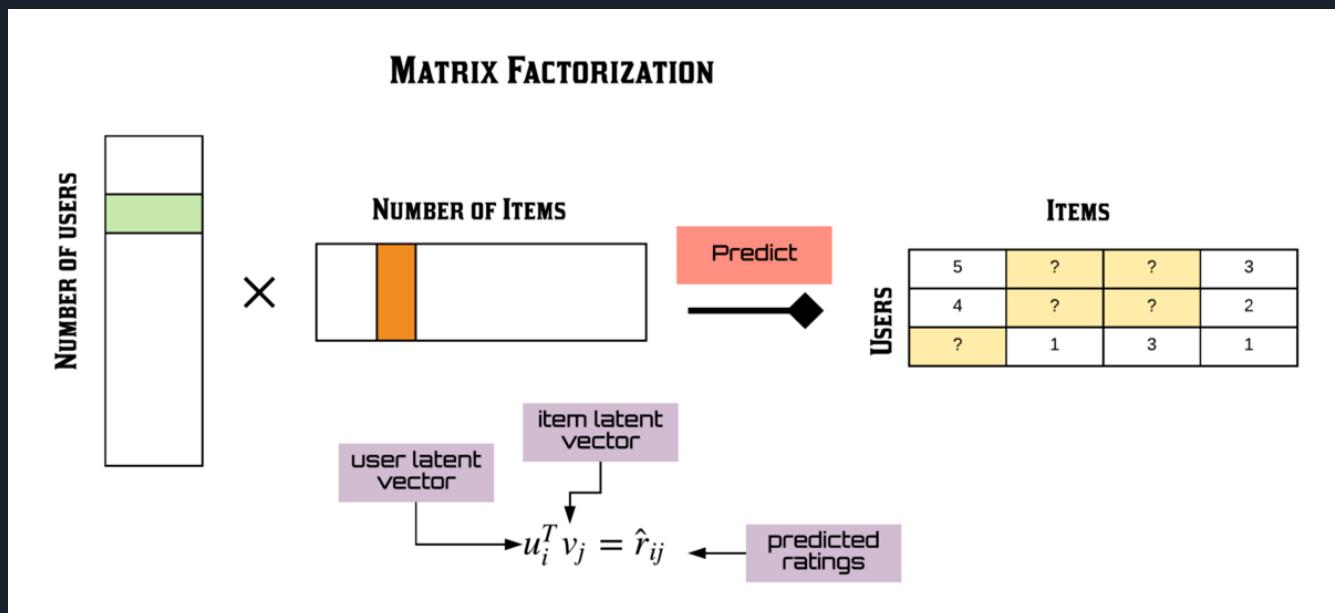
similar_movies.head(10)
similar_movies.sum().sort_values(ascending=False).head(20)
```

Movie Title	Score
Amazing Spider-Man, The (2012)	3.233134
Mission: Impossible III (2006)	2.874798
2 Fast 2 Furious (Fast and the Furious 2, The) (2003)	2.701477
Over the Hedge (2006)	2.229721
Crank (2006)	2.176259
Mission: Impossible - Ghost Protocol (2011)	2.159666
Hancock (2008)	2.156098
The Amazing Spider-Man 2 (2014)	2.153677
Hellboy (2004)	2.137518
Snakes on a Plane (2006)	2.137396
Jumper (2008)	2.129716
Chronicles of Riddick, The (2004)	2.121689
Tron: Legacy (2010)	2.111843
Fantastic Four (2005)	2.083022
X-Men: The Last Stand (2006)	2.077530
Wreck-It Ralph (2012)	2.067907
Kung Fu Hustle (Gong fu) (2004)	2.067457
Godzilla (2014)	2.061653
Incredible Hulk, The (2008)	2.050104
Quantum of Solace (2008)	2.016189

✓ 0s completed at 1:09 AM

MATRIX FACTORIZATION

- Need of Matrix Factorization
- Reasons to Reduce Dimensions
- Advantages of Reducing Dimensions



CONCEPT OF MATRIX FACTORIZATION

$$\mathbf{A}_{m \times n} = \mathbf{U}_{m \times m} \times \begin{matrix} & \text{red} \\ & \text{pink} \\ \text{white} & \end{matrix} \Sigma_{m \times n} \times \mathbf{V}_{n \times n}^T$$

$(m < n)$

$$\mathbf{A}_{m \times n} = \mathbf{U}_{m \times m} \times \begin{matrix} & \text{red} \\ & \text{pink} \\ \text{white} & \end{matrix} \Sigma_{m \times n} \times \mathbf{V}_{n \times n}^T$$

$(m > n)$

IMPLEMENTING MATRIX FACTORIZATION BASED RECOMMENDATION ENGINE

```
predictions = recommend_movies(preds, 1310, movies, ratings, 20)

predictions
```

	movie_id	title	genres
1618	1674	Witness (1985)	Drama Romance Thriller
1880	1961	Rain Man (1988)	Drama
1187	1210	Star Wars: Episode VI - Return of the Jedi (1983)	Action Adventure Romance Sci-Fi War
1216	1242	Glory (1989)	Action Drama War
1202	1225	Amadeus (1984)	Drama
1273	1302	Field of Dreams (1989)	Drama
1220	1246	Dead Poets Society (1989)	Drama
1881	1962	Driving Miss Daisy (1989)	Drama
1877	1957	Chariots of Fire (1981)	Drama
1938	2020	Dangerous Liaisons (1988)	Drama Romance
1233	1259	Stand by Me (1986)	Adventure Comedy Drama
3011	3098	Natural, The (1984)	Drama
2112	2194	Untouchables, The (1987)	Action Crime Drama
1876	1956	Ordinary People (1980)	Drama
1268	1296	Room with a View, A (1986)	Drama Romance
2267	2352	Big Chill, The (1983)	Comedy Drama
1278	1307	When Harry Met Sally... (1989)	Comedy Romance
1165	1186	Sex, Lies, and Videotape (1989)	Drama
1199	1222	Full Metal Jacket (1987)	Action Drama War
2833	2919	Year of Living Dangerously (1982)	Drama Romance



ISSUES ASSOCIATED WITH RECOMMENDER SYSTEMS

- Handling Unknown Users/Items (Cold Start Problem)
- Data Sparsity
- Scalability
- Dynamic Updates

CONCLUSION

- Recommendation Engine is for sure a companion and advisor to help us make the right choices by providing us tailored options and creating a personalized experience for us.
- It is beyond any doubt that recommendation engines are getting popular and critical in the new age of things.





REFERENCES

- <https://grouplens.org/datasets/movielens/>
- <https://www.kaggle.com/tmdb/tmdb-movie-metadata>
- <https://unsplash.com/s/photos/movie>

Thank you!