

7.

Recommendation System

Recommendation Engine

Home

Fawn Qiu: Easy DIY projects for kid engineers

TED TV
7:03 • Jul 2016

RECOMMENDED BY YOUR APPS

Prime RECOMMENDED MOVIES

Prime RECENTLY ADDED TV

Types of recommendation Engine

Collaborative Recommendation System

- User based/Memory Based System
- Item Based

Content Based Recommendation System

Popularity Based Recommendation System

Overview about RS

Collaborative Recommendation System
↔
User based/Memory Based System



↓
Similar User



Overview about RS

Collaborative Recommendation System



User based/Memory Based System

User-Based Collaborative Filtering



Collaborative Recommendation System



User based/Memory Based System

Little Deeper How this
overview works

Little Deeper How this overview works

Collaborative Recommendation System

User based/Memory Based System

Dataset

	user_id	movie_id	rating	unix_timestamp
0	196	242	3	881250949
1	186	302	3	891717742
2	22	377	1	878887116
3	244	51	2	880606923
4	166	346	1	886397596
...
99995	880	476	3	880175444
99996	716	204	5	879795543
99997	276	1090	1	874795795
99998	13	225	2	882399156
99999	12	203	3	879959583

100000 rows × 4 columns

Little Deeper How this overview works

Collaborative Recommendation System

User based/Memory Based System

Pivot Table

Little Deeper How this overview works

Collaborative Recommendation System

User based/Memory Based System

Similarity Table(Cosine)

	0	1	2	3	4	5	6	7	8	9	...	933	934	935	936
0	2.22044e-15	0.833069	0.952540	0.935642	6.215248e-01	0.569761	0.559633	0.680928	0.921862	0.623456	...	0.630473	0.880518	0.725124	0.810295
1	8.330690e-01	0.000000	0.889409	0.821879	9.270210e-01	0.754157	0.892672	0.896656	0.838952	0.840138	...	0.843014	0.692058	0.641211	0.575954
2	9.525405e-01	0.889409	0.000000	0.655849	9.787555e-01	0.927585	0.933863	0.916940	0.938960	0.934849	...	0.968125	0.957247	0.836171	0.930962
3	9.356422e-01	0.821879	0.655849	0.000000	9.681958e-01	0.931956	0.908770	0.811940	0.898716	0.939141	...	0.947893	0.963216	0.866885	0.806529
4	6.215248e-01	0.927021	0.978755	0.968196	1.110223e-16	0.762714	0.626400	0.751070	0.943153	0.798573	...	0.661206	0.919420	0.905076	0.920221
...
938	8.819047e-01	0.771417	0.973729	0.969862	9.285415e-01	0.888148	0.892973	0.904102	0.960148	0.928540	...	0.933961	0.568846	0.741979	0.773551
939	6.859280e-01	0.773210	0.838110	0.803142	7.600453e-01	0.647551	0.670075	0.753117	0.879505	0.657039	...	0.672847	0.892976	0.812464	0.818683
940	8.513831e-01	0.838515	0.898757	0.847959	8.604049e-01	0.855554	0.940007	0.853855	0.856755	0.909695	...	0.953048	0.796699	0.711682	0.765789
941	8.204921e-01	0.827732	0.866584	0.829914	8.475026e-01	0.682672	0.717997	0.824678	0.907503	0.787670	...	0.773560	0.926487	0.910412	0.870446
942	6.018253e-01	0.894202	0.973444	0.941248	6.860592e-01	0.723958	0.605636	0.700191	0.924383	0.778140	...	0.736209	0.789237	0.856747	0.922207

943 rows x 943 columns

Little Deeper How this overview works



Prediction Table

movie_id	1	2	3	4	5	6	7	8	9	10	...
user_id											
1	5.0	3.0	4.0	3.0	3.0	5.0	4.0	1.0	5.0	3.0	...
2	4.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	2.0	...
3	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...
4	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...
5	4.0	3.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...
...
939	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	5.0	0.0	...
940	0.0	0.0	0.0	2.0	0.0	0.0	4.0	5.0	3.0	0.0	...
941	5.0	0.0	0.0	0.0	0.0	0.0	4.0	0.0	0.0	0.0	...
942	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...

	Star Wars	Hoop Dreams	Contact	Titanic
Joe	5	2	5	4
John	2	5	3	2
Al	2	2	4	2
Nathan	5	1	5	?

Joe [5,2,5]
John [2,5,2]
Al [2,2,4]
Nathan [5,1,5]

cos (Nathan,Joe) 0.99
cos (Nathan,John) 0.64
cos (Nathan,Al) 0.91

↖ ↘

Little Deeper How this overview works



Prediction Table

	Star Wars	Hoop Dreams	Contact	Titanic
Joe	5	2	5	4
John	2	5		3
Al	2	2	4	2
Nathan	5	1	5	?

	Star Wars	Hoop Dreams	Contact	Titanic
Joe	5	2	5	4
John	2	5		3
Al	2	2	4	2
Nathan	5	1	5	?

Joe [5,2,5]
John [2,5,2,5]
Al [2,2,4]
Nathan [5,1,5]

cos (Nathan,Joe) 0.99
cos (Nathan,John) 0.64
cos (Nathan,Al) 0.91

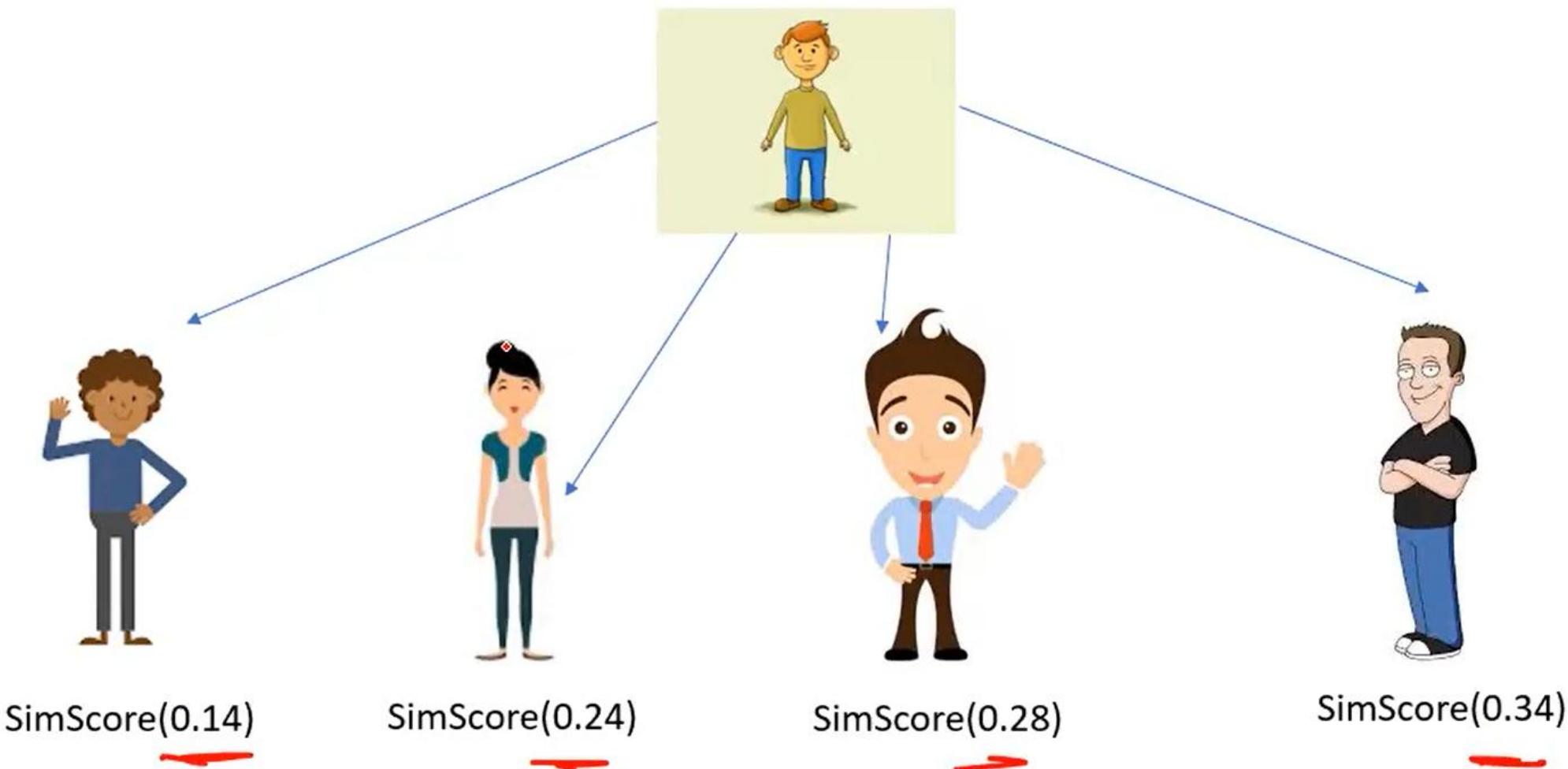
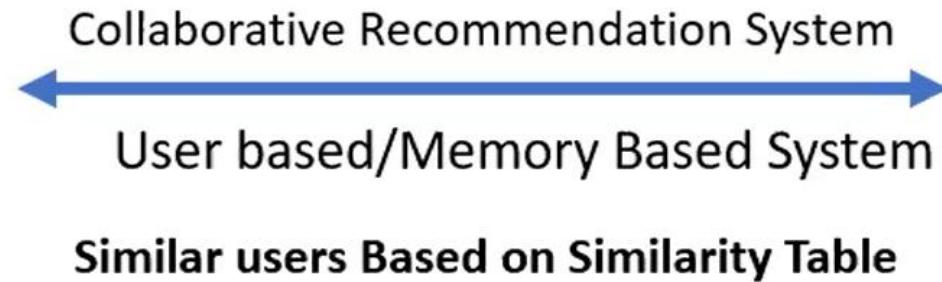


cos (Nathan,Joe) 0.99
cos (Nathan,John) 0.64
cos (Nathan,Al) 0.91

$$\frac{(0.99 \cdot 4 + 0.64 \cdot 3 + 0.91 \cdot 2)}{(0.99 + 0.64 + 0.91)}$$

? = 3.03

Little Deeper How this overview works



Little Deeper How this overview works

Collaborative Recommendation System
User based/Memory Based System
User_Input movie Id



Movie_Id

34

45

67

93

57

83

98

89

100



Movie_Id

34

45

89

673

876

893



Movie_Id

34

56

67

78

89

93



Movie_Id

67

83

56

83

86

90



Movie_Id

67

83

53

87

86

90

Collaborative Recommendation System



User based/Memory Based System

Highest Rated Movie_id

Movie_Id	Prediction Value
50	0.99
78	0.89
87	0.75
90	0.74
673	0.45
876	0.37
893	0.25

Threshold=0.7

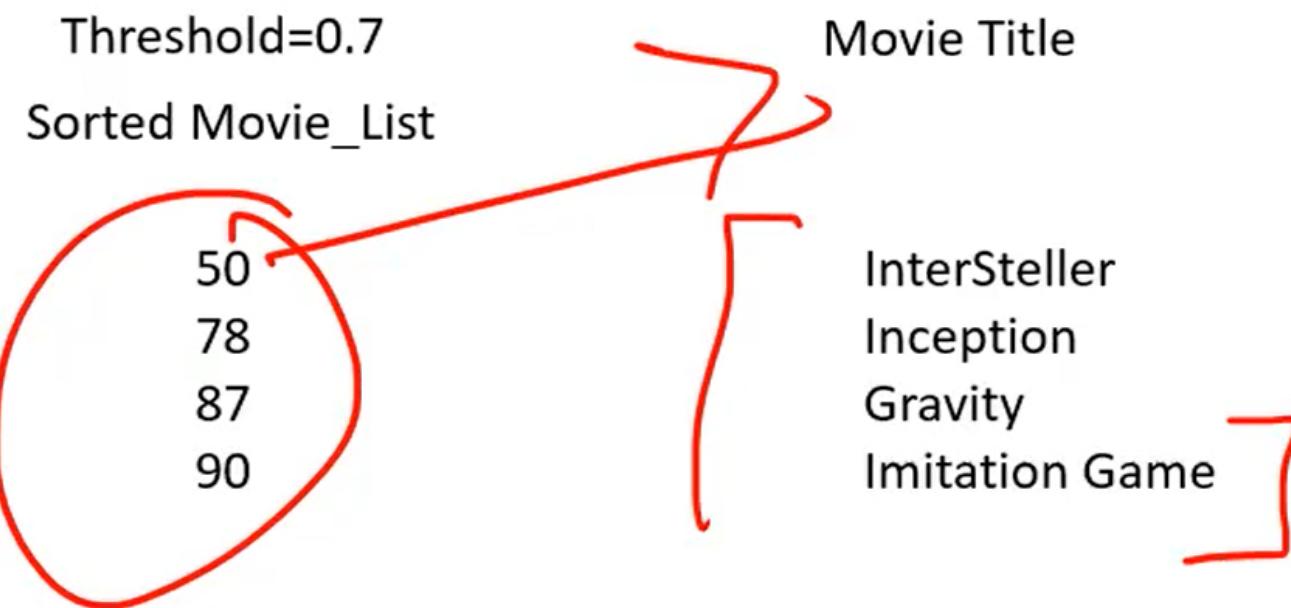
Sorted Movie_List

P 50
78
87
90 - .

Little Deeper How this overview works



Retrieve the Movie Title using
Highest rated movieid





STEPS FOR USER BASED RECOMMENDATION SYSTEM

Step1: Create Pivot Table , values as rating

Step2: Create similarity table between Users using
Pivot → Cosine Decision

Step3: Predict the non filled rating for the users using
formula*(This helps to find the not watched film)

Step4: Select the user_input

Step5: For the user_input select the similar user using
similarity Table(Minimum Distance is the similar)

Step6: Create a list of movie id for similar user



Step7: Create a list of movie id for user_input

Step8: Filter the movieid of user_input which is not present in similar user

Step9: Filtered movieid have to check with Prediction table(step3 Answer) because of filtered movieid list are the recommended list



STEPS FOR USER BASED RECOMMENDATION SYSTEM

Step10: But we have to select only the highest rated movie of the filtered list.

Step11: With help of threshold value we can select the highest rated movie(Completely using predicted table)

Step12: Now we have only the highest rated movieid list of important user.

Step13: Now load the movie tile table

Step14: Using movie title table we can retrieve the highest rated movie list of the user_input(Final Recommendation Title.)

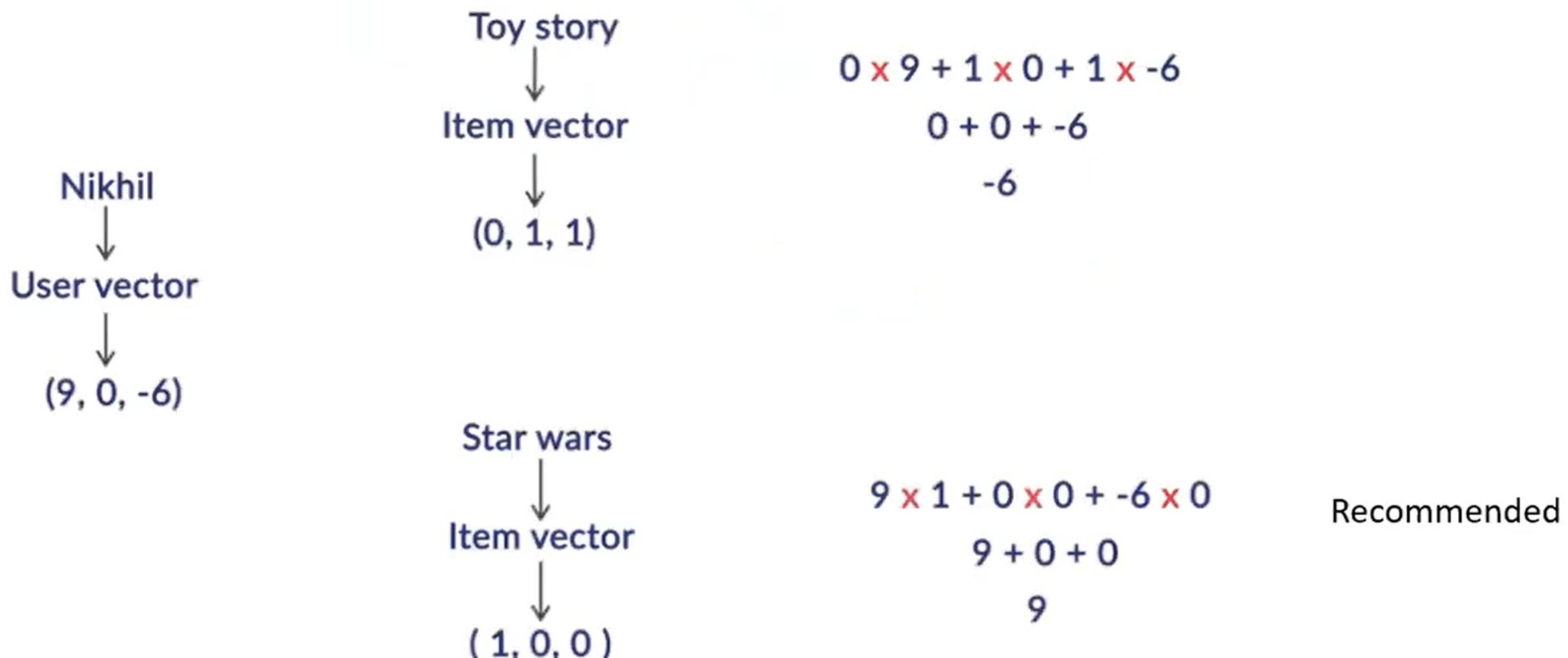
```
In [156]: #def userbased(input_user,user_similarity,user_predictions,similar_user_count,similar_user_movieid_count,thres):  
Recommended_movie=userbased(5,user_similarity,user_pred,2,0.8)  
  
['Twelve Monkeys (1995)']  
['Richard III (1995)']  
['Postino, Il (1994)']  
['Cold Comfort Farm (1995)']  
['Lone Star (1996)']  
['Swingers (1996)']  
['When the Cats Away (Chacun cherche son chat) (1996)']  
['Chasing Amy (1997)']  
['Heat (1995)']  
['Sense and Sensibility (1995)']  
['Secrets & Lies (1996)']  
['Donnie Brasco (1997)']  
["Ulee's Gold (1997)"]  
['Mother (1996)']  
['Cop Land (1997)']  
The common Movie in Recom & User: []
```

```
In [153]: len(Recommended_movie)
```

• Out[153]: 12

Content Based Recommendation

Overview



Content Based Recommendation

Movie Vector

	1	2	3	4	5	6	7	8	9	10	...	1673	1674	1675	1676	1677	1678	1679	1680	1681	1682
Action	0	1	0	1	0	0	0	0	0	0	...	1	0	0	0	0	0	0	0	0	0
Adventure	0	1	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0	0	0
Animation	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0	0	0
Children's	0	0	0	0	0	0	0	1	0	0	...	0	0	0	0	0	0	0	0	0	0
Comedy	0	0	1	0	0	0	1	0	0	0	...	0	0	0	0	0	0	0	0	1	0
Crime	0	0	0	0	1	0	0	0	0	0	...	0	0	0	0	0	0	0	0	0	0
Documentary	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0	0	0
Drama	0	0	0	1	1	1	1	1	1	1	...	0	1	1	1	1	1	0	1	0	1
Fantasy	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0	0	0
Film-Noir	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0	0	0
Horror	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0	0	0
Musical	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0	0	0
Mystery	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0	0	0
Romance	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	1	1	0	0
Sci-Fi	0	0	0	0	0	0	1	0	0	0	...	0	0	0	0	0	0	0	0	0	0
Thriller	0	1	1	0	1	0	0	0	0	0	...	1	0	0	0	0	0	1	0	0	0
War	0	0	0	0	0	0	0	0	0	1	...	0	0	0	0	0	0	0	0	0	0
Western	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0	0	0

18 rows × 1682 columns

Content Based Recommendation

↔

How to create User Vector

Step1: Pivot Table

movie_id	1	2	3	4	5	6	7	8	9	10	...	1673	1674	1675	1676	1677	1678	1679	1680	1681	1682
user_id																					
1	5.0	3.0	4.0	3.0	3.0	5.0	4.0	1.0	5.0	3.0	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
2	4.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	2.0	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
3	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
4	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
5	4.0	3.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
...
939	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	5.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
940	0.0	0.0	0.0	2.0	0.0	0.0	4.0	5.0	3.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
941	5.0	0.0	0.0	0.0	0.0	0.0	4.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
942	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
943	0.0	5.0	0.0	0.0	0.0	0.0	0.0	0.0	3.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0

943 rows × 1682 columns

