

Movie Recommendation by Prabhat

Importing the Library

```
In [3]: import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
```

```
In [7]: #Loading the Dataset
rating = pd.read_csv('ml-100k/u.data', sep='\t', names=['user_id', 'item_id',
print(rating)
```

	user_id	item_id	rating	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 x 4 columns]

```
In [25]: movies = pd.read_csv('ml-100k/u.item', sep='|', header=None, encoding='latin-1',
                                'unknown', 'Action', 'Adventure', 'Animation',
                                'Crime', 'Documentary', 'Drama', 'Fantasy', 'Fi
                                'Musical', 'Mystery', 'Romance', 'Sci-Fi', 'Thr
# print(movies)
```

	item_id	title	release_date	\
0	1	Toy Story (1995)	01-Jan-1995	
1	2	GoldenEye (1995)	01-Jan-1995	
2	3	Four Rooms (1995)	01-Jan-1995	
3	4	Get Shorty (1995)	01-Jan-1995	
4	5	Copycat (1995)	01-Jan-1995	
...
1677	1678	Mat' i syn (1997)	06-Feb-1998	
1678	1679	B. Monkey (1998)	06-Feb-1998	
1679	1680	Sliding Doors (1998)	01-Jan-1998	
1680	1681	You So Crazy (1994)	01-Jan-1994	
1681	1682	Scream of Stone (Schrei aus Stein) (1991)	08-Mar-1996	

	video_release_date	IMDb_URL
\		
0	NaN	http://us.imdb.com/M/title-exact?Toy%20Story%20(1995)
1	NaN	http://us.imdb.com/M/title-exact?GoldenEye%20(1995)
2	NaN	http://us.imdb.com/M/title-exact?Four%20Rooms%20(1995)
3	NaN	http://us.imdb.com/M/title-exact?Get%20Shorty%20(1995)
4	NaN	http://us.imdb.com/M/title-exact?Copycat%20(1995)
...
1677	NaN	http://us.imdb.com/M/title-exact?Mat%27+i+syn+(1997)
1678	NaN	http://us.imdb.com/M/title-exact?B%2E+Monkey+(1998)
1679	NaN	http://us.imdb.com/M/title-exact?Sliding+Doors+(1998)
1680	NaN	http://us.imdb.com/M/title-exact?You%20So%20Cr...
1681	NaN	http://us.imdb.com/M/title-exact?Schrei%20aus%...

	unknown	Action	Adventure	Animation	Children	...	Fantasy	\
0	0	0	0	1	1	...	0	
1	0	1	1	0	0	...	0	
2	0	0	0	0	0	...	0	
3	0	1	0	0	0	...	0	
4	0	0	0	0	0	...	0	
...
1677	0	0	0	0	0	...	0	
1678	0	0	0	0	0	...	0	
1679	0	0	0	0	0	...	0	
1680	0	0	0	0	0	...	0	
1681	0	0	0	0	0	...	0	

	Film-Noir	Horror	Musical	Mystery	Romance	Sci-Fi	Thriller	War	\
0	0	0	0	0	0	0	0	0	
1	0	0	0	0	0	0	1	0	
2	0	0	0	0	0	0	1	0	
3	0	0	0	0	0	0	0	0	
4	0	0	0	0	0	0	1	0	
...
1677	0	0	0	0	0	0	0	0	
1678	0	0	0	0	1	0	1	0	
1679	0	0	0	0	1	0	0	0	
1680	0	0	0	0	0	0	0	0	
1681	0	0	0	0	0	0	0	0	

	Western
0	0
1	0

```

2          0
3          0
4          0
...
1677       0
1678       0
1679       0
1680       0
1681       0

```

[1682 rows x 24 columns]

```
In [19]: users = pd.read_csv('ml-100k/u.user', sep='|', names = ['user_id', 'age', 'gender', 'occupation', 'zip-code'])
print(users)
```

```

   user_id  age gender occupation zip-code
0         1   24     M  technician   85711
1         2   53     F      other   94043
2         3   23     M    writer   32067
3         4   24     M  technician   43537
4         5   33     F      other   15213
..      ...  ...   ...      ...      ...
938      939   26     F    student   33319
939      940   32     M administrator   02215
940      941   20     M    student   97229
941      942   48     F   librarian   78209
942      943   22     M    student   77841

```

[943 rows x 5 columns]

```
In [31]: # Merging the movies with rating
merged = pd.merge(rating, movies[['item_id', 'title']], on='item_id')
print(merged)
```

```

   user_id  item_id  rating  timestamp                               title
0        196      242        3  881250949                      Kolya (1996)
1        186      302        3  891717742          L.A. Confidential (1997)
2         22      377        1  878887116          Heavyweights (1994)
3        244       51        2  880606923  Legends of the Fall (1994)
4        166      346        1  886397596          Jackie Brown (1997)
...      ...      ...      ...      ...
99995     880      476        3  880175444  First Wives Club, The (1996)
99996     716      204        5  879795543    Back to the Future (1985)
99997     276     1090        1  874795795                      Sliver (1993)
99998      13      225        2  882399156    101 Dalmatians (1996)
99999      12      203        3  879959583          Unforgiven (1992)

```

[100000 rows x 5 columns]

```
In [57]: ## Taking the input from the user for ratings
def get_user_rating():
    print("Rate the movie:\n")
    user_ratings = {}
    while True:
        movie_title = input("Enter the movie title or type 'done': ").strip()
        if movie_title.lower() == 'done':
            break
```

```
        ratings = input(f"Rate: {movie_title} on a scale of 1 to 5").strip()
        user_ratings[movie_title] = ratings
    return user_ratings
user_ratings = get_user_rating()
```

Rate the movie:

```
In [59]: ## similiarity calculation
from sklearn.metrics.pairwise import cosine_similarity

user_movie_matrix = merged.pivot_table(index = 'user_id', columns = 'title', v
similarity = cosine_similarity(user_movie_matrix)
similarity_df = pd.DataFrame(similarity, index=user_movie_matrix.index, colu
print(similarity_df.head(7))
```

user_id \ user_id	1	2	3	4	5	6	7
1	1.000000	0.168937	0.048388	0.064561	0.379670	0.429682	0.44309
7							
2	0.168937	1.000000	0.113393	0.179694	0.073623	0.242106	0.10860
4							
3	0.048388	0.113393	1.000000	0.349781	0.021592	0.074018	0.06742
3							
4	0.064561	0.179694	0.349781	1.000000	0.031804	0.068431	0.09150
7							
5	0.379670	0.073623	0.021592	0.031804	1.000000	0.238636	0.37473
3							
6	0.429682	0.242106	0.074018	0.068431	0.238636	1.000000	0.49352
9							
7	0.443097	0.108604	0.067423	0.091507	0.374733	0.493529	1.00000
0							

user_id \ user_id	8	9	10	...	934	935	936	\
1	0.320079	0.078385	0.377733	...	0.372213	0.119860	0.269860	
2	0.104257	0.162470	0.161273	...	0.147095	0.310661	0.363328	
3	0.084419	0.062039	0.066217	...	0.033885	0.043453	0.167140	
4	0.188060	0.101284	0.060859	...	0.054615	0.036784	0.133619	
5	0.248930	0.056847	0.201427	...	0.340183	0.080580	0.095284	
6	0.202514	0.184997	0.554851	...	0.384703	0.112464	0.187093	
7	0.285815	0.146092	0.488501	...	0.459442	0.114526	0.113190	

user_id \ user_id	937	938	939	940	941	942	94
3							
1	0.193343	0.197949	0.118722	0.315064	0.149086	0.181612	0.39943
2							
2	0.410725	0.322713	0.231096	0.228793	0.162911	0.175273	0.10673
2							
3	0.071288	0.126278	0.026758	0.164539	0.102899	0.136757	0.02699
0							
4	0.196561	0.146058	0.030202	0.196858	0.152041	0.171538	0.05875
2							
5	0.081053	0.148607	0.071612	0.239955	0.139595	0.153799	0.31394
1							
6	0.220179	0.138685	0.112729	0.354454	0.145268	0.312264	0.27761
2							
7	0.120105	0.153818	0.104394	0.330926	0.060175	0.285273	0.39556
0							

[7 rows x 943 columns]

Recommend Movie

```
In [61]: # Get the most similiar users
user_id = 1 # lets take this as example
similiar_user = similiarity_df[user_id].sort_values(ascending=False).iloc[1:]
# Get the top-rated movie
recommendations = user_movie_matrix.loc[similiar_user].mean(axis=0).sort_val
```

```
# Filter the movie ,the user has already rated
recommendations = recommendations[~recommendations.index.isin(user_ratings.index)]
print(recommendations.head(5))
```

```
title
Star Wars (1977)          5.0
Raiders of the Lost Ark (1981)  5.0
Aliens (1986)             4.8
Empire Strikes Back, The (1980)  4.8
Citizen Kane (1941)       4.8
dtype: float64
```

```
In [67]: # Visuals
top_movie = recommendations.head(7)
plt.figure(figsize=(8,6))
top_movie.plot(kind='bar',color='skyblue')
plt.title(f"Top five Movie Recommendation for user {user_id}")
plt.xlabel("Movie Titles")
plt.ylabel("Predicted Ratings")
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()
```

