

Week 9 Report

Recommendation System

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I did not do much in this week's work. Just follow the contents taught in the class. When I selected the movie, I chose to see the most popular and highly rated ones ahead. The code and the result are as shown in Figure 1.

```
print(ratings_average.sort_values(by = ['ratings_count', 'rating'], ascending = False))
```

title	rating	ratings_count
Forrest Gump (1994)	4.164134	329
Shawshank Redemption, The (1994)	4.429022	317
Pulp Fiction (1994)	4.197068	307
Silence of the Lambs, The (1991)	4.161290	279
Matrix, The (1999)	4.192446	278
...
Wasp Woman, The (1959)	0.500000	1
While the City Sleeps (1956)	0.500000	1
Wizards of the Lost Kingdom II (1989)	0.500000	1
Yongary: Monster from the Deep (1967)	0.500000	1
Zombie Strippers! (2008)	0.500000	1

Figure 1. The most popular and highly rated movies

Great! The Matrix! That's it! The recommendation code is as shown in Figure 2 and the result is as shown in Figure 3.

```

1  import matplotlib.pyplot as pyplot
2  import numpy as numpy
3  import pandas as pd
4
5  ratings = pd.read_csv('D:/code/school/Introduction to Machine Learning/Week09_exercise/ml-latest-small/ratings.csv')
6  movies = pd.read_csv('D:/code/school/Introduction to Machine Learning/Week09_exercise/ml-latest-small/movies.csv')
7
8  data = pd.merge(ratings, movies, on = 'movieId')
9
10 ratings_average = pd.DataFrame(data.groupby('title')['rating'].mean())
11 ratings_average['ratings_count'] = pd.DataFrame(data.groupby('title')['rating'].count())
12
13 ratings_matrix = data.pivot_table(index='userId', columns='title', values='rating')
14
15 # print(ratings_average.sort_values('ratings_count', ascending=False).head(10))
16 # print(ratings_matrix.head(10))
17
18 ## find user rating for a Movie
19 # favorite_movie_ratings = ratings_matrix['Aladdin (1992)']
20 favorite_movie_ratings = ratings_matrix['Matrix, The (1999)']
21
22 #print(favorite_movie_ratings.head(10))
23
24 ##Finding similar movies
25 similar_movies = ratings_matrix.corrwith(favorite_movie_ratings)
26 # print(similar_movies.head(10))
27
28 ##Remove empty values
29 correlation = pd.DataFrame(similar_movies, columns=['Correlation'])
30 correlation.dropna(inplace=True)
31
32 # print(correlation.sort_values('Correlation', ascending=False).head(10))
33 ## Add Rating counts
34 correlation = correlation.join(ratings_average['ratings_count'])
35 # print(correlation.sort_values('Correlation', ascending=False).head(10))
36
37 ##See the recommendations
38 recommendation = correlation[correlation['ratings_count']>100].sort_values('Correlation', ascending=False)
39 # print(recommendation.head(10))
40
41 ##Confirm the recommendation Quality
42 recommendation = recommendation.merge(movies, on='title')
43 print(recommendation.head(10))
44
45 # print(ratings_average.sort_values(by = ['ratings_count', 'rating'], ascending = False))

```

Figure 2. Recommendation code

	title	Correlation	ratings_count	movieId	genres
0	Matrix, The (1999)	1.000000	278	2571	Action Sci-Fi Thriller
1	Die Hard (1988)	0.544466	145	1036	Action Crime Thriller
2	Inception (2010)	0.514767	143	79132	Action Crime Drama Mystery Sci-Fi Thriller IMAX
3	Braveheart (1995)	0.496045	237	110	Action Drama War
4	Aliens (1986)	0.470865	126	1200	Action Adventure Horror Sci-Fi
5	Lion King, The (1994)	0.444932	172	364	Adventure Animation Children Drama Musical IMAX
6	Monsters, Inc. (2001)	0.441205	132	4886	Adventure Animation Children Comedy Fantasy
7	Batman Begins (2005)	0.440338	116	33794	Action Crime IMAX
8	Jurassic Park (1993)	0.427936	238	480	Action Adventure Sci-Fi Thriller
9	Fight Club (1999)	0.417196	218	2959	Action Crime Drama Thriller

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Figure 3. Recommendation results

So I would recommend 'Die hard', or 'Inception' is also a good choice.