LP3 Machine Learning Mini Project

Problem Statemet - To prepare a movie recommendation system which would recommend similar movies to the user according to the user interest. Dataset used - 'movies.csv'

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```
import numpy as np
import pandas as pd
import·difflib
from·sklearn.feature_extraction.text·import·TfidfVectorizer
from sklearn.metrics.pairwise import cosine_similarity
```

Data Collection and Preprocessing

```
movies_data = pd.read_csv('movies.csv')
```

```
# printing the first 5 rows of the dataframe
movies_data.head()
```

	index	budget	genres	homepage	id	keyword
0	0	237000000	Action Adventure Fantasy Science Fiction	http://www.avatarmovie.com/	19995	cultu cla futu spa w spa colo so
1	1	300000000	Adventure Fantasy Action	http://disney.go.com/disneypictures/pirates/	285	ocea dru abus exo islar east ind trad
			Action			sp based nov
			Action			comi
			Action			ma

```
# number of rows and columns in the data frame

movies_data.shape
```

```
(4803, 24)
```

```
# selecting the relevant features for recommendation

selected_features = ['genres','keywords','tagline','cast','director']
print(selected_features)
```

```
['genres', 'keywords', 'tagline', 'cast', 'director']
```

```
# replacing the null valuess with null string

for feature in selected_features:
  movies_data[feature] = movies_data[feature].fillna('')
```

5 rows × 24 columns

```
# combining all the 5 selected features

combined_features = movies_data['genres']+' '+movies_data['keywords']+' '+movies_data['tag
```

```
print(combined_features)
```

```
0       Action Adventure Fantasy Science Fiction cultu...
1       Adventure Fantasy Action ocean drug abuse exot...
2       Action Adventure Crime spy based on novel secr...
3       Action Crime Drama Thriller dc comics crime fi...
4       Action Adventure Science Fiction based on nove...
                              ...
4798    Action Crime Thriller united states\u2013mexic...
4799    Comedy Romance  A newlywed couple's honeymoon ...
```

```
4800    Comedy Drama Romance TV Movie date love at fir...
4801      A New Yorker in Shanghai Daniel Henney Eliza...
4802    Documentary obsession camcorder crush dream gi...
Length: 4803, dtype: object
```

```
# converting the text data to feature vectors

vectorizer = TfidfVectorizer()


feature_vectors = vectorizer.fit_transform(combined_features)


print(feature_vectors)
```

```
  (0, 2432)     0.17272411194153
  (0, 7755)     0.1128035714854756
  (0, 13024)    0.1942362060108871
  (0, 10229)    0.16058685400095302
  (0, 8756)     0.22709015857011816
  (0, 14608)    0.15150672398763912
  (0, 16668)    0.19843263965100372
  (0, 14064)    0.20596090415084142
  (0, 13319)    0.2177470539412484
  (0, 17290)    0.20197912553916567
  (0, 17007)    0.23643326319898797
  (0, 13349)    0.15021264094167086
  (0, 11503)    0.27211310056983656
  (0, 11192)    0.09049319826481456
  (0, 16998)    0.1282126322850579
  (0, 15261)    0.07095833561276566
  (0, 4945)     0.24025852494110758
  (0, 14271)    0.21392179219912877
  (0, 3225)     0.24960162956997736
  (0, 16587)    0.12549432354918996
  (0, 14378)    0.33962752210959823
  (0, 5836)     0.1646750903586285
  (0, 3065)     0.22208377802661425
  (0, 3678)     0.21392179219912877
  (0, 5437)     0.1036413987316636
  :     :
  (4801, 17266) 0.2886098184932947
  (4801, 4835)  0.24713765026963996
  (4801, 403)   0.17727585190343226
  (4801, 6935)  0.2886098184932947
  (4801, 11663) 0.21557500762727902
  (4801, 1672)  0.1564793427630879
  (4801, 10929) 0.13504166990041588
  (4801, 7474)  0.11307961713172225
  (4801, 3796)  0.3342808988877418
  (4802, 6996)  0.5700048226105303
  (4802, 5367)  0.22969114490410403
  (4802, 3654)  0.262512960498006
  (4802, 2425)  0.24002350969074696
  (4802, 4608)  0.24002350969074696
  (4802, 6417)  0.21753405888348784
  (4802, 4371)  0.1538239182675544
  (4802, 12989) 0.1696476532191718
  (4802, 1316)  0.1960747079005741
```

```
  (4802, 4528)  0.19504460807622875
  (4802, 3436)  0.21753405888348784
  (4802, 6155)  0.18056463596934083
  (4802, 4980)  0.16078053641367315
  (4802, 2129)  0.3099656128577656
  (4802, 4518)  0.16784466610624255
  (4802, 11161) 0.17867407682173203
```

Cosine Similarity

```
# getting the similarity scores using cosine similarity

similarity = cosine_similarity(feature_vectors)


print(similarity)
```

```
[[1.         0.07219487 0.037733   ... 0.         0.         0.        ]
 [0.07219487 1.         0.03281499 ... 0.03575545 0.         0.        ]
 [0.037733   0.03281499 1.         ... 0.         0.05389661 0.        ]
 ...
 [0.         0.03575545 0.         ... 1.         0.         0.02651502]
 [0.         0.         0.05389661 ... 0.         1.         0.        ]
 [0.         0.         0.         ... 0.02651502 0.         1.        ]]
```

```
print(similarity.shape)
```

```
(4803, 4803)
```

Getting Movie name

```
# getting the movie name from the user

movie_name = 'iron man'


# creating a list with all the movie names given in the dataset

list_of_all_titles = movies_data['title'].tolist()
print(list_of_all_titles)
```

```
['Avatar', "Pirates of the Caribbean: At World's End", 'Spectre', 'The Dark Knight Ri
```

```
# finding the close match for the movie name given by the user

find_close_match = difflib.get_close_matches(movie_name, list_of_all_titles)
print(find_close_match)
```

```
['Iron Man', 'Iron Man 3', 'Iron Man 2']
```

```
close_match = find_close_match[0]
```

```
print(close_match)
```

```
     Iron Man
```

```
# finding the index of the movie with title

index_of_the_movie = movies_data[movies_data.title == close_match]['index'].values[0]
print(index_of_the_movie)
```

```
     68
```

```
# getting a list of similar movies

similarity_score = list(enumerate(similarity[index_of_the_movie]))
print(similarity_score)
```

```
     [(0, 0.033570748780675445), (1, 0.0546448279236134), (2, 0.013735500604224323), (3, 0
```

```
len(similarity_score)
```

```
     4803
```

```
# sorting the movies based on their similarity score

sorted_similar_movies = sorted(similarity_score, key = lambda x:x[1], reverse = True)
print(sorted_similar_movies)
```

```
     [(68, 1.0000000000000002), (79, 0.40890433998005965), (31, 0.31467052449477506), (7,
```

```
# print the name of similar movies based on the index

print('Movies suggested for you : \n')

i = 1

for movie in sorted_similar_movies:
  index = movie[0]
  title_from_index = movies_data[movies_data.index==index]['title'].values[0]
  if (i<30):
    print(i, '.',title_from_index)
    i+=1
```

```
     Movies suggested for you :

     1 . Iron Man
     2 . Iron Man 2
     3 . Iron Man 3
     4 . Avengers: Age of Ultron
     5 . The Avengers
     6 . Captain America: Civil War
```

```
7 . Captain America: The Winter Soldier
8 . Ant-Man
9 . X-Men
10 . Made
11 . X-Men: Apocalypse
12 . X2
13 . The Incredible Hulk
14 . The Helix... Loaded
15 . X-Men: First Class
16 . X-Men: Days of Future Past
17 . Captain America: The First Avenger
18 . Kick-Ass 2
19 . Guardians of the Galaxy
20 . Deadpool
21 . Thor: The Dark World
22 . G-Force
23 . X-Men: The Last Stand
24 . Duets
25 . Mortdecai
26 . The Last Airbender
27 . Southland Tales
28 . Zathura: A Space Adventure
29 . Sky Captain and the World of Tomorrow
```

Movie Recommendation System

```
movie_name = input(' Enter your favourite movie name : ')

list_of_all_titles = movies_data['title'].tolist()

find_close_match = difflib.get_close_matches(movie_name, list_of_all_titles)

close_match = find_close_match[0]

index_of_the_movie = movies_data[movies_data.title == close_match]['index'].values[0]

similarity_score = list(enumerate(similarity[index_of_the_movie]))

sorted_similar_movies = sorted(similarity_score, key = lambda x:x[1], reverse = True)

print('Movies suggested for you : \n')

i = 1

for movie in sorted_similar_movies:
  index = movie[0]
  title_from_index = movies_data[movies_data.index==index]['title'].values[0]
  if (i<30):
    print(i, '.',title_from_index)
    i+=1
```

```
 Enter your favourite movie name : iron man
Movies suggested for you :

1 . Iron Man
```

```
2 . Iron Man 2
3 . Iron Man 3
4 . Avengers: Age of Ultron
5 . The Avengers
6 . Captain America: Civil War
7 . Captain America: The Winter Soldier
8 . Ant-Man
9 . X-Men
10 . Made
11 . X-Men: Apocalypse
12 . X2
13 . The Incredible Hulk
14 . The Helix... Loaded
15 . X-Men: First Class
16 . X-Men: Days of Future Past
17 . Captain America: The First Avenger
18 . Kick-Ass 2
19 . Guardians of the Galaxy
20 . Deadpool
21 . Thor: The Dark World
22 . G-Force
23 . X-Men: The Last Stand
24 . Duets
25 . Mortdecai
26 . The Last Airbender
27 . Southland Tales
28 . Zathura: A Space Adventure
29 . Sky Captain and the World of Tomorrow
```