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In [2]: import numpy as np

In [3]: import pandas as pd

In [4]: import difflib

In [5]: from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.metrics.pairwise import cosine_similarity

In [6]: # loading the data from the csv file to apandas dataframe
movies_data = pd.read_csv('D:\study\datasets\movies.csv')

In [6]: # first five rows of dataframe
movies_data.head()

```

Out[6]:

	index	budget	genres	homepage	id	keywords	original_language	original_title	overview	popu
0	0	237000000	Action Adventure Fantasy Science Fiction	http://www.avatarmovie.com/	19995	culture clash future space war space colony so...	en	Avatar	In the 22nd century, a paraplegic Marine is di...	150.4
1	1	300000000	Adventure Fantasy Action	http://disney.go.com/disneypictures/pirates/	285	ocean drug abuse exotic island east india trad...	en	Pirates of the Caribbean: At World's End	Captain Barbossa, long believed to be dead, ha...	139.0
2	2	245000000	Action Adventure Crime	http://www.sonypictures.com/movies/spectre/	206647	spy based on novel secret agent sequel mi6	en	Spectre	A cryptic message from Bond's past sends him o...	107.3
3	3	250000000	Action Crime Drama Thriller	http://www.thedarkknightises.com/	49026	dc comics crime fighter terrorist secret ident...	en	The Dark Knight Rises	Following the death of District Attorney Harve...	112.3
4	4	260000000	Action Adventure Science Fiction	http://movies.disney.com/john-carter	49529	based on novel mars medallion space travel pri...	en	John Carter	John Carter is a war-weary, former military ca...	43.9

5 rows × 24 columns

```

In [8]: # number of rows and coloumns
movies_data.shape

Out[8]: (4803, 24)

In [9]: # selecting the relevant features for recommendation

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

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

In [11]: # replacing null values
for feature in selected_features:
    movies_data[feature]=movies_data[feature].fillna('')

In [12]: # combining all the 5 selected features

combined_features = movies_data['genres']+' '+movies_data['keywords']+' '+movies_data['tagline']+' '+movies_data

In [13]: 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

```

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In [14]: #converting text data into feature vector
vectorizer = TfidfVectorizer()
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In [15]: feature_vectors = vectorizer.fit_transform(combined_features)
```

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In [16]: 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

```

```
In [17]: # similarity scores using cosine similarity
similarity = cosine_similarity(feature_vectors)
```

```
In [18]: 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.          ]]

```

```
In [19]: # getting movie name from the user
movie_name = input('enter your movie name : ')
```

enter your movie name : batman

```
In [21]: #creating list with all movie names
list_of_all_titles = movies_data['title'].tolist()

In [23]: # finding close match of movie
find_close_match = difflib.get_close_matches(movie_name, list_of_all_titles)

In [24]: print(find_close_match)

['Batman', 'Batman', 'Catwoman']

In [27]: close_match = find_close_match[0]
print(close_match)

Batman

In [30]: # finding 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)

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In [44]: # getting list of similar movies
similarity_score = list(enumerate(similarity[index_of_the_movie]))

In [45]: # sorting movies based on similarity scores
sorted_similar_movies = sorted(similarity_score, key = lambda x:x[1], reverse=True)

In [42]: 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 . Batman
2 . Batman Returns
3 . Batman & Robin
4 . The Dark Knight Rises
5 . Batman Begins
6 . The Dark Knight
7 . A History of Violence
8 . Superman
9 . Beetlejuice
10 . Bedazzled
11 . Mars Attacks!
12 . The Sentinel
13 . Planet of the Apes
14 . Man of Steel
15 . Suicide Squad
16 . The Mask
17 . Salton Sea
18 . Spider-Man 3
19 . The Postman Always Rings Twice
20 . Hang 'em High
21 . Spider-Man 2
22 . Dungeons & Dragons: Wrath of the Dragon God
23 . Superman Returns
24 . Jonah Hex
25 . Exorcist II: The Heretic
26 . Superman II
27 . Green Lantern
28 . Superman III
29 . Something's Gotta Give
```

Movies Recomendation System

```
In [43]: 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 : spiderman
 Movies suggested for you :

- 1 . Spider-Man
- 2 . Spider-Man 3
- 3 . Spider-Man 2
- 4 . The Notebook
- 5 . Seabiscuit
- 6 . Clerks II
- 7 . The Ice Storm
- 8 . Oz: The Great and Powerful
- 9 . Horrible Bosses
- 10 . The Count of Monte Cristo
- 11 . In Good Company
- 12 . Finding Nemo
- 13 . Clear and Present Danger
- 14 . Brothers
- 15 . The Good German
- 16 . Drag Me to Hell
- 17 . Bambi
- 18 . The Queen
- 19 . Charly
- 20 . Escape from L.A.
- 21 . Daybreakers
- 22 . The Life Aquatic with Steve Zissou
- 23 . Labor Day
- 24 . Wimbledon
- 25 . Cold Mountain
- 26 . Hearts in Atlantis
- 27 . Out of the Furnace
- 28 . Bullets Over Broadway
- 29 . The Purge: Election Year

In []:

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