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**ROLL NO : TEAD21225**

**SUBJECT : SL III**

**CLASS : TE**

**BRANCH : AI&DS**

## Mini Project

**Problem Statment :** Develop a movie recommendation model using the scikit-learn library in python.

## Code & Output:

```
Click here to ask Blackbox to help you code faster
import numpy as np
import pandas as pd
import difflib
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.metrics.pairwise import cosine_similarity
```

[4] Python

## Data Collection and Pre-Processing

```
Click here to ask Blackbox to help you code faster
#Loading Data from the csv file
movies_data= pd.read_csv('movie_dataset.csv')
```

[9] Python

```
> Click here to ask Blackbox to help you code faster
#printing first 5 rows of dataset
movies_data.head()
```

[18] Python

	index	budget	genres	homepage	id	keywords	original_language	original_title	overview	popularity	...	runtime	spoken_languages	status	tagline	title	vote_average	vote_count
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...	150.437577	...	162.0	[[{"iso_639_1": "en", "name": "English"}, {"iso...	Released	Enter the World of Pandora.	Avatar	7.2	11800
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...	139.082615	...	169.0	[[{"iso_639_1": "en", "name": "English"}]]	Released	At the end of the world, the adventure begins.	Pirates of the Caribbean: At World's End	6.9	4500

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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...	139.082615	...	169.0	[{"iso_639_1": "en", "name": "English"}]	Released	At the end of the world, the adventure begins.	Pirates of the Caribbean: At World's End	6.9	4500
2	2	245000000	Action Adventure Crime	http://www.sonypictures.com/movies/spectre/	206647	spy based on novel secret agent sequel m16	en	Spectre	A cryptic message from Bond's past sends him o...	107.376788	...	148.0	[{"iso_639_1": "fr", "name": "Fran\u00e7ais"},...	Released	A Plan No One Escapes	Spectre	6.3	4466
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...	112.312950	...	165.0	[{"iso_639_1": "en", "name": "English"}]	Released	The Legend Ends	The Dark Knight Rises	7.6	9106
4	4	260000000	Action Adventure Science Fiction	http://movies.disney.com/john-carter	49529	based on novel mars medallion space travel pr...	en	John Carter	John Carter is a war- weary, former military ca...	43.926995	...	132.0	[{"iso_639_1": "en", "name": "English"}]	Released	Lost in our world, found in another.	John Carter	6.1	2124

5 rows \times 24 columns

```
#No. of Rows & Columns
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 values with null string
for feature in selected_features:
    movies_data[feature] = movies_data[feature].fillna('')

movies_data.isnull().sum()

index      0
budget      0
genres      0
homepage    3091
id          0
keywords    0
original_language  0
original_title  0
overview    3
popularity  0
production_companies  0
production_countries  0
release_date  1
revenue     0
runtime     2
```

```
cast          0
crew          0
director      0
dtype: int64
```

```
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# combining all the 5 selected features
combined_features = movies_data['genres']+' '+movies_data['keywords']+' '+movies_data['tagline']+' '+movies_data['cast']+' '+movies_data['director']
```

[21]

```
Click here to ask Blackbox to help you code faster
print(combined_features)
```

[22]

```
... 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
```

```
Click here to ask Blackbox to help you code faster
# converting the text data to feature vectors
```

```
vectorizer = TfidfVectorizer()
```

[23]

```
Click here to ask Blackbox to help you code faster
feature_vectors = vectorizer.fit_transform(combined_features)
```

[24]

```
Click here to ask Blackbox to help you code faster
feature_vectors = vectorizer.fit_transform(combined_features)
```

[24]

```
Click here to ask Blackbox to help you code faster
print(feature_vectors)
```

[25]

```
... (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
     ...
     (4802, 4980)   0.16078053641367315
     (4802, 2129)   0.3099656128577656
     (4802, 4518)   0.16784466610624255
     (4802, 11161) 0.17867407682173203
```

## Cosine Similarity

Click here to ask Blackbox to help you code faster  
#getting the similarity scores using cosine similarity

```
similarity = cosine_similarity(feature_vectors)
```

[26]

Click here to ask Blackbox to help you code faster  
print(similarity)

[27]

```
... [[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.          ]]
```

Click here to ask Blackbox to help you code faster  
similarity.shape

[30]

```
... (4803, 4803)
```

## Getting Movie Name from the user

Click here to ask Blackbox to help you code faster  
movie\_name = input('Enter your favourite movie name : ')

[31]

```
... Enter your favourite movie name : batman
```

> v

Click here to ask Blackbox to help you code faster  
#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)
```

[32]

```
... ['Avatar', 'Pirates of the Caribbean: At World's End', 'Spectre', 'The Dark Knight Rises', 'John Carter'
```

Click here to ask Blackbox to help you code faster  
# 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)
```

[33]

```
... ['Batman', 'Batman', 'Catwoman']
```

Click here to ask Blackbox to help you code faster  
close\_match = find\_close\_match[0]  
print(close\_match)

[34]

```
... Batman
```

Click here to ask Blackbox to help you code faster  
# 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)
```

[35]

```
... 1359
```

$$[(0, 0.02531512269737111), (1, 0.04983293064399152), (2, 0.013599520029326722), (3, 0.20438773732168222), (4, 0.024929726723526918), (5, 0.11533013884014888), (6, 0.0), (7, 0.0)]$$

4803

$$[(1359, 1.0), (428, 0.4311643836232694), (210, 0.25737999820859625), (3, 0.20438773732168222), (119, 0.19262528757150407), (65, 0.1775581506611392), (1512, 0.14705162654306444]$$

... Movies suggested for you :

**i = 1**

**i = 1**

```

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<=20):
        print(i, '.',title_from_index)
        i+=1

```

[47]

```

... Enter your favourite movie name : pirates
Movies suggested for you :

```

- 1 . Vampires
- 2 . Contact
- 3 . BloodRayne
- 4 . Dudley Do-Right
- 5 . Priest
- 6 . Ghosts of Mississippi
- 7 . Julia
- 8 . Stranded
- 9 . Me and Orson Welles
- 10 . The Shadow
- 11 . Wal-Mart: The High Cost of Low Price
- 12 . The Girl with the Dragon Tattoo
- 13 . Salvador
- 14 . The Lord of the Rings: The Two Towers
- 15 . xXx
- 16 . High Anxiety
- 17 . Vampire in Brooklyn
- 18 . The Black Hole
- 19 . How to Be Single
- 20 . Judgment at Nuremberg