

```
import pandas as pd
```

```
import numpy as np
```

```
df=pd.read_csv(r'https://raw.githubusercontent.com/YBI-Foundation/Dataset/main/Movies%20Re
```

```
df.head()
```

	Movie_ID	Movie_Title	Movie_Genre	Movie_Language	Movie_Budget	Movie_Popularity
0	1	Four Rooms	Crime Comedy	en	4000000	22.876230
1	2	Star Wars	Adventure Action Science Fiction	en	11000000	126.393695
2	3	Finding Nemo	Animation Family	en	94000000	85.688789
3	4	Forrest Gump	Comedy Drama Romance	en	55000000	138.133331
4	5	American Beauty	Drama	en	15000000	80.878605

Saved successfully!



5 rows × 21 columns

```
df.info()
```

✓ 19s completed at 6:55 PM



<class 'pandas.core.frame.DataFrame'>

RangeIndex: 4760 entries, 0 to 4759

Data columns (total 21 columns):

#	Column	Non-Null Count	Dtype
0	Movie_ID	4760 non-null	int64
1	Movie_Title	4760 non-null	object
2	Movie_Genre	4760 non-null	object
3	Movie_Language	4760 non-null	object
4	Movie_Budget	4760 non-null	int64
5	Movie_Popularity	4760 non-null	float64
6	Movie_Release_Date	4760 non-null	object
7	Movie_Revenue	4760 non-null	int64
8	Movie_Runtime	4758 non-null	float64
9	Movie_Vote	4760 non-null	float64
10	Movie_Vote_Count	4760 non-null	int64
11	Movie_Homepage	1699 non-null	object
12	Movie_Keywords	4373 non-null	object
13	Movie_Overview	4757 non-null	object
14	Movie_Production_House	4760 non-null	object
15	Movie_Production_Country	4760 non-null	object
16	Movie_Spoken_Language	4760 non-null	object
17	Movie_Tagline	3942 non-null	object
18	Movie_Cast	4733 non-null	object
19	Movie_Crew	4760 non-null	object
20	Movie_Director	4738 non-null	object

dtypes: float64(3), int64(4), object(14)

memory usage: 781.1+ KB

df.describe()

	Movie_ID	Movie_Budget	Movie_Popularity	Movie_Revenue	Movie_Runtime	Movie_Vote
count	4760.000000	4.760000e+03	4760.000000	4.760000e+03	4758.000000	4760.000000
mean	2380.500000	1.500000e+07	13.119058	1.944716e+07	104.000000	104.000000
min	1.000000	0.000000e+00	0.000372	0.000000e+00	0.000000	0.000000
25%	1190.750000	9.257500e+05	4.807074	0.000000e+00	94.000000	94.000000
50%	2380.500000	1.500000e+07	13.119058	1.944716e+07	104.000000	104.000000
75%	3572.250000	4.000000e+07	28.411929	9.341276e+07	118.000000	118.000000
max	4788.000000	3.800000e+08	875.581305	2.787965e+09	338.000000	110.000000

Saved successfully!



```
df.shape
```

```
(4760, 21)
```

```
df.columns
```

```
Index(['Movie_ID', 'Movie_Title', 'Movie_Genre', 'Movie_Language',
      'Movie_Budget', 'Movie_Popularity', 'Movie_Release_Date',
      'Movie_Revenue', 'Movie_Runtime', 'Movie_Vote', 'Movie_Vote_Count',
      'Movie_Homepage', 'Movie_Keywords', 'Movie_Overview',
      'Movie_Production_House', 'Movie_Production_Country',
      'Movie_Spoken_Language', 'Movie_Tagline', 'Movie_Cast', 'Movie_Crew',
      'Movie_Director'],
      dtype='object')
```

Get Feture Selection

```
df_features = df[['Movie_Genre', 'Movie_Keywords', 'Movie_Tagline', 'Movie_Cast', 'Movie_Director']]
```

selected five existing feature to recommend movies .it may very form one project to another like one can add vote count budget language etc

```
df_features.shape
```

```
(4760, 5)
```

```
df_features
```

	Movie_Genre	Movie_Keywords	Movie_Tagline	Movie_Cast	Movie_Director
0	Crime Comedy	not a new year's eve witch bet hotel room	Twelve outrageous guests. Four scandalous requ...	Tim Roth Antonio Banderas Jennifer Beals Madon...	Allison Anders
1	Adventure Action Science Fiction	android galaxy hermit death star lightsaber	A long time ago in a galaxy far, far away...	Mark Hamill Harrison Ford Carrie Fisher Peter ...	George Lucas
2	Animation Family	father son relationship harbor underwater fish...	There are 3.7 trillion fish in the ocean, they...	Albert Brooks Ellen DeGeneres Alexander Gould ...	Andrew Stanton

3	Comedy Drama Romance	vietnam veteran hippie mentally disabled runni...	The world will never be the same, once you've ...	Tom Hanks Robin Wright Gary Sinise Mykelti Wil...	Robert Zemeckis
4	Drama	male nudity female nudity adultery midlife cri...	Look closer.	Kevin Spacey Annette Bening Thora Birch Wes Be...	Sam Mendes
...
4755	Horror		The hot spot where Satan's waitin'.	Lisa Hart Carroll Michael Des Barres Paul Drak...	Pece Dingo
4756	Comedy Family Drama		It's better to stand out than to fit in.	Roni Akurati Brighton Sharbino Jason Lee Anjul...	Frank Lotito
4757	Thriller Drama	christian film sex trafficking	She never knew it could happen to her...	Nicole Smolen Kim Baldwin Ariana Stephens Brys...	Jaco Booyens
4758	Family				
4759	Documentary	music actors legendary performer classic hollyw...		Tony Oppedisano	Simon Napier- Bell

4760 rows × 5 columns



```
df_features['Movie_Concept'] = df_features['Movie_Keywords'] + ' ' + df_features['Movie_Tagline']
```

Saved successfully!



x

```

0      Crime Comedyhotel new year's eve witch bet hot...
1      Adventure Action Science Fictionandroid galaxy...
2      Animation Familyfather son relationship harbor...
3      Comedy Drama Romancevietnam veteran hippie men...
4      Dramamale nudity female nudity adultery midlif...
...
4755   HorrorThe hot spot where Satan's waitin'.Lisa ...
4756   Comedy Family DramaIt's better to stand out th...
4757   Thriller Dramachristian film sex traffickingSh...
4758                                     Family
4759   Documentarymusic actors legendary performer cla...
Length: 4760, dtype: object

```

Get feature Text Conversion to Token

```
from sklearn.feature_extraction.text import TfidfVectorizer
```

```
tfidf=TfidfVectorizer()
```

```
x=tfidf.fit_transform(x)
```

```
x.shape
```

```
(4760, 27466)
```

```
print(x)
```

```
(0, 1028)      0.16196019146631543
(0, 24785)     0.1954632929283795
(0, 15844)     0.14205053053187272
(0, 15553)     0.17099186675469502
(0, 2132)      0.18002354204307464
(0, 13312)     0.09914387783149516
(0, 1887)      0.14106037409792174
(0, 1216)      0.13920306109638164
(0, 21158)     0.14205053053187272
(0, 24701)     0.11357423942624927
(0, 14943)     0.091376722056839
(0, 18098)     0.06200430666985742
(0, 26738)     0.175053052455033
(0, 9790)      0.08712552095655665
(0, 26675)     0.1116831168780693
(0, 13401)     0.13748876529263096
(0, 996)       0.0996
(0, 2372)      0.2372
(0, 3885)      0.3885
(0, 9626)      0.11757910435818826
(0, 11960)     0.20134029899961134
(0, 12801)     0.1530338818199682
(0, 2292)      0.1954632929283795
(0, 15172)     0.1537691763994982
(0, 18196)     0.08579029869987485
:              :
(4757, 1839)   0.19327629083107672
(4757, 5410)   0.19734759150400596
(4757, 11350)  0.21582294886514122
(4757, 22017)  0.1646400247918531
(4757, 17789)  0.18881341937258544
(4757, 9484)   0.1411164779725638
(4757, 14176)  0.2330831990045816
(4757, 11762)  0.17321388936472645
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```
(4757, 14052) 0.1776312353410007
(4757, 24232) 0.10947784435203887
(4757, 24746) 0.09744940789814222
(4757, 13079) 0.12400374714145113
(4757, 17721) 0.1489085353667712
(4758, 8651) 1.0
(4759, 18229) 0.33527342183765224
(4759, 22434) 0.33527342183765224
(4759, 18841) 0.33527342183765224
(4759, 6950) 0.33527342183765224
(4759, 345) 0.31978160936741457
(4759, 14742) 0.31978160936741457
(4759, 12139) 0.2778063685558062
(4759, 4446) 0.282306565154911
(4759, 17552) 0.3087899934962816
(4759, 9955) 0.21805075638656476
(4759, 2285) 0.21465229435984196
```

Get Similarity Score using Cosine Similarity

cosine_similarity compute the l2-normalized dot product of vector Euclidean(L2)normalization projects the vector onto the unit sphere and their dot product is then the cosine of the angle between the point denoted by the vector

```
from sklearn.metrics.pairwise import cosine_similarity
```

```
similarity_score=cosine_similarity(x)
```

```
similarity_score
```

Saved successfully!

```
0.03807033, ..., 0.    , 0.    ,
[0.01438634, 1.    , 0.00844858, ..., 0.    , 0.    ,
 0.    ],
[0.03807033, 0.00844858, 1.    , ..., 0.    , 0.    ,
 0.    ],
...,
[0.    , 0.    , 0.    , ..., 1.    , 0.    ,
 0.    ],
[0.    , 0.    , 0.    , ..., 0.    , 1.    ,
 0.    ],
[0.    , 0.    , 0.    , ..., 0.    , 0.    ,
 1.    ]])
```

```
similarity_score.shape
```

```
(4760, 4760)
```

```
(4/00, 4/00)
```

Get movies name as input from user and validate for closest Spelling

```
Favourite_Movie_Name=input('Enter your favorite movies name')
```

```
Enter your favorite movies nameavtaar
```

```
All_Movies_Title_List=df['Movie_Title'].tolist()
```

```
import difflib
```

```
Movies_Recommendation=difflib.get_close_matches(Favourite_Movie_Name,All_Movies_Title_List)
print(Movies_Recommendation)
```

```
['Avatar', 'Gattaca']
```

```
Close_Match=Movies_Recommendation[0]
print(Close_Match)
```

```
Avatar
```

```
Index_of_Close_Match_Movie=df[df.Movie_Title == Close_Match]['Movie_ID'].values[0]
print(Index_of_Close_Match_Movie)
```

```
2692
```

Saved successfully!



movies

```
Recommendation_score=list(enumerate(similarity_score[Index_of_Close_Match_Movie]))
print(Recommendation_score)
```

```
[(0, 0.011030833064862307), (1, 0.0), (2, 0.0), (3, 0.008556266387176359), (4, 0.0),
```

```
len(Recommendation_score)
```

```
4760
```

get All Movies Sort Based on Recommendation Score wrt Favourite Movies

```
# sorting the movies based on the similarity score
Sorted_similar_movies = sorted(Recommendation_score, key = lambda x:x[1], reverse = True)
print(Sorted_similar_movies)
```

```
[(2692, 1.0000000000000007), (110, 0.08195740486074782), (1994, 0.08144186697343063),
```

```
# print the similer movies based on the index
print('top 30 movies suggested for you :\n')
i=1
for movies in Sorted_similar_movies:
    ..index==movies[0]
    ..title_from_index=df[df.index==index]['Movie_Title'].values[0]
    ..if(i<31):
    ....print(i, '.', title_from_index)
    ....i+=1
```

📄 top 30 movies suggested for you :

```
1 . Niagara
2 . Some Like It Hot
3 . The Kentucky Fried Movie
4 . The Juror
5 . Enough
6 . Duel in the Sun
7 . Superman III
8 . Eye for an Eye
9 . The Misfits
10 . Beyond the Black Rainbow
11 . Brokeback Mountain
12 . All That Jazz
13 . Tora! Tora! Tora!
14 . Master and Commander: The Far Side of the World
15 . To Kill a Mockingbird
```

Saved successfully!

```
16 . Running with Scissors
17 . Edge of Darkness
18 . Man on Wire
19 . The Odd Life of Timothy Green
20 . Intolerable Cruelty
21 . The Curse of Downers Grove
22 . The Great Gatsby
23 . Mad Max 2: The Road Warrior
24 . Source Code
25 . Song One
26 . The Longest Yard
27 . The Boy Next Door
28 . The Lazarus Effect
```


Top 10 Movies Recommendation System

```
Movie_name = input('Enter your favourite movies name : ')
list_of_all_title = df['Movie_Title'].tolist()
Find_Close_Match = difflib.get_close_matches(Movie_name, list_of_all_title)
Close_Match = Find_Close_Match[0]
Index_of_Movie = df[df.Movie_Title == Close_Match]['Movie_ID'].values[0]
Recommendation_score= list(enumerate(similarity_score[Index_of_Movie]))
sorted_similear_movies= sorted(Recommendation_score,key = lambda x:x[1], reverse = True)
print('Top 10 movies suggested for you :\n ')
```

```
i=1
for movies in Sorted_similar_movies:
    index = movies[0]
    title_from_index=df[df.index == index]['Movie_Title'].values[0]
    if(i<11):
        print(i,'.',title_from_index)
        i+=1
```

Enter your favourite movies name : avtaar
Top 10 movies suggested for you :

- 1 . Niagara
- 2 . Some Like It Hot
- 3 . The Kentucky Fried Movie
- 4 . The Juror
- 5 . Enough
- 6 . Duel in the Sun
- 7 . Superman III
- 8 . Eye for an Eye
- 9 . The Misfits
- 10 . Beyond the Black Rainbow

Saved successfully!



Saved successfully!

