Importing the dependencies

printing the first 5 rows of the dataframe

movies_data.head()

```
\verb"import numpy as np"
import pandas as pd
{\tt import\ difflib}
from \ sklearn.feature\_extraction.text \ import \ TfidfVectorizer
from sklearn.metrics.pairwise import cosine_similarity
Data Collection and Pre-Processing
# loading the data from the csv file to apandas dataframe
movies_data=pd.read_csv('/content/movies.csv', sep=',',
                header='infer',
                index_col=None,
                usecols=None,
                squeeze=False,
                engine='python',
                quotechar='"',
                error_bad_lines=False)
 /usr/local/lib/python3.8/dist-packages/IPython/core/interactiveshell.py:3326: FutureWarning: The error_bad_lines argument has been depr
       exec(code_obj, self.user_global_ns, self.user_ns)
     Skipping line 2868: unexpected end of data
```

```
index
                   budget
                             genres
                                                                  homepage
                                                                                id keywords
# number of rows and columns in the data frame
movies_data.shape
     (2866, 24)
                                                                                       colony
# selecting the relevant features for recommendation
selected_features = ['genres','keywords','tagline','cast','director']
print(selected_features)
     ['genres', 'keywords', 'tagline', 'cast', 'director']
                                                                                        4---4
# replacing the null valuess with null string
for feature in selected_features:
 movies_data[feature] = movies_data[feature].fillna('')
                              Crime
                                                                                        agent
# combining all the 5 selected features
combined_features = movies_data['genres']+' '+movies_data['keywords']+' '+movies_data['tagline']+' '+movies_data['cast']+' '+movies_data['dir
                                                                                       COITIICS
                              Action
print(combined_features)
             Action Adventure Fantasy Science Fiction cultu...
    0
    1
             Adventure Fantasy Action ocean drug abuse exot...
     2
             Action Adventure Crime spy based on novel secr...
             Action Crime Drama Thriller dc comics crime fi...
     3
             Action Adventure Science Fiction based on nove...
             Thriller Horror vampire dracula bite blood vla...
     2861
             Family Comedy based on novel job interview bad...
     2862
     2863
             Drama Romance bachelor beautiful prejudice sui...
             Science Fiction Drama Thriller artificial inte...
     2865
             Adventure scotland biography 18th century high...
    Length: 2866, dtype: object
# converting the text data to feature vectors
vectorizer = TfidfVectorizer()
feature_vectors = vectorizer.fit_transform(combined_features)
print(feature_vectors)
                     0.164314481344402
       (0, 1160)
       (0, 3832)
                     0.11640168863502841
       (0, 6403)
                     0.1925488727149144
       (0, 4991)
                     0.1600885757983711
       (0, 4292)
                     0.23685245608367106
       (0, 7188)
                     0.15633324481850083
       (0, 8188)
                     0.20689427986446918
       (0, 6899)
                     0.21112018541050012
       (0, 6535)
                     0.22480997625975965
       (0, 8510)
                     0.22480997625975965
       (0, 8384)
                     0.22159200163941709
       (0, 6552)
                     0.15062469049514243
       (0, 5620)
                     0.25574686386273904
       (0, 5462)
                     0.09212531261319962
       (0, 8380)
                     0.1201410067245958
       (0, 7514)
                     0.06809811150660568
       (0, 2420)
                     0.24821282829280872
       (0, 7011)
                     0.21112018541050012
                     0.23685245608367106
       (0, 1540)
       (0, 8143)
                     0.12153830316809083
       (0, 7062)
                     0.31538603933367
       (0, 2897)
                     0.16058878018527561
       (0, 1462)
                     0.24205707301347945
       (0, 1777)
                     0.25574686386273904
       (0, 2663)
                     0.09424689905578607
       (2865, 7217)
                     0.2000265312588519
       (2865, 1279) 0.18172252845298603
```

```
(2865, 4293) 0.18172252845298603
       (2865, 1308) 0.1710153731984597
       (2865, 2434) 0.12895862198915717
       (2865, 6455) 0.15888045974539744
       (2865, 4643) 0.4766413792361924
       (2865, 3467) 0.4083349271578864
       (2865, 815)
                    0.13386287212977616
       (2865, 3894) 0.12764891089858607
       (2865, 3538) 0.15059767508092572
       (2865, 1692) 0.1516333801429095
       (2865, 5309) 0.14864069888844816
       (2865, 4435) 0.13670508520461372
       (2865, 6675) 0.17331309081634544
       (2865, 3487) 0.10228590182314887
       (2865, 3934) 0.07802420392865589
(2865, 7586) 0.1181026939801353
       (2865, 3430) 0.11665932413817903
       (2865, 3621) 0.14200421513806746
       (2865, 3945) 0.11156529887913935
       (2865, 4696) 0.20863643855330283
       (2865, 4987) 0.08663768441385027
       (2865, 4377) 0.13922195008914895
       (2865, 126) 0.05801999176796022
Cosine Similarity
# getting the similarity scores using cosine similarity
similarity = cosine similarity(feature vectors)
print(similarity)
                  0.06233862 \ 0.0340665 \ \dots \ 0.00867704 \ 0.02835473 \ 0.00430406] 
      [0.06233862 1.
                      0.02687679 ... 0.09525828 0.
                                   ... 0.
      [0.0340665 0.02687679 1.
                                                                 0.0045218 1
                                       ... 1.
      [0.00867704 0.09525828 0.
                                                      0.00826616 0.
                                       ... 0.00826616 1. 0.13818532]
      [0.02835473 0.
                       0.
      [0.00430406 0.00769072 0.0045218 ... 0. 0.13818532 1.
                                                                           ]]
print(similarity.shape)
     (2866, 2866)
Getting the movie name from the user
# getting the movie name from the user
movie_name = input(' Enter your favourite movie name : ')
      Enter your favourite movie name : Batman
# 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 Rises', 'John Carter', 'Spider-Man 3', 'Tangled', 'A
# 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)
     ['Batman', 'Catwoman', 'Catwoman']
close_match = find_close_match[0]
print(close_match)
     Batman
```

```
# 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)
    1359
# getting a list of similar movies
similarity_score = list(enumerate(similarity[index_of_the_movie]))
print(similarity_score)
    len(similarity_score)
    2866
# 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)
    [(1359, 1.0), (1835, 1.0), (402, 0.1576604605019644), (738, 0.1576604605019644), (2791, 0.1448235067789417), (1691, 0.14124966612128542)]
# 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)
    Movies suggested for you :
    1 . Bulletproof Monk
    2 . Bulletproof Monk
    3 . The Rundown
    4 . The Rundown
    5 . Dragonball Evolution
    6 . Curse of the Golden Flower
    7 . Curse of the Golden Flower
    8 . Pirates of the Caribbean: At World's End
    9 . Anna and the King
    10 . Anna and the King
    11 . The Replacement Killers
    12 . Priest
    13 . Priest
    14 . The Hunted
    15 . The Hunted
    16 . Drillbit Taylor
    17 . Drillbit Taylor
    18 . Million Dollar Baby
    19 . The Pursuit of Happyness
    20 . The Pursuit of Happyness
    21 . DOA: Dead or Alive
    22 . Role Models
    23 . The Dukes of Hazzard
    24 . The Dukes of Hazzard
    25 . Cop Out
    26 . Cop Out
    27 . American Reunion
    28 . American Reunion
    29 . The Hobbit: The Desolation of Smaug
Movie Recommendation Sytem
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)
     Enter your favourite movie name : Avatar
    Movies suggested for you :
    1 . Avatar
    2 . Guardians of the Galaxy
    3 . Star Trek Into Darkness
    4 . Star Trek Beyond
    5 . Galaxy Quest
    6 . Galaxy Quest
    7 . Pocahontas
    8 . Pocahontas
    9 . Alien³
    10 . Alien³
    11 . Gravity
    12 . Gravity
    13 . Clash of the Titans
    14 . Clash of the Titans
    15 . Space Cowboys
    16 . Space Cowboys
    17 . Moonraker
    18 . Event Horizon
    19 . Event Horizon
    20 . The Book of Life
     21 . The Book of Life
    22 . Colombiana
    23 . Colombiana
    24 . Shadow Conspiracy
    25 . Shadow Conspiracy
    26 . Terminator Salvation
     27 . Star Trek
    28 . Alien: Resurrection
    29 . Alien: Resurrection
```

✓ 6s completed at 21:13

• ×