Movie Recommendation System

TML PROJECT

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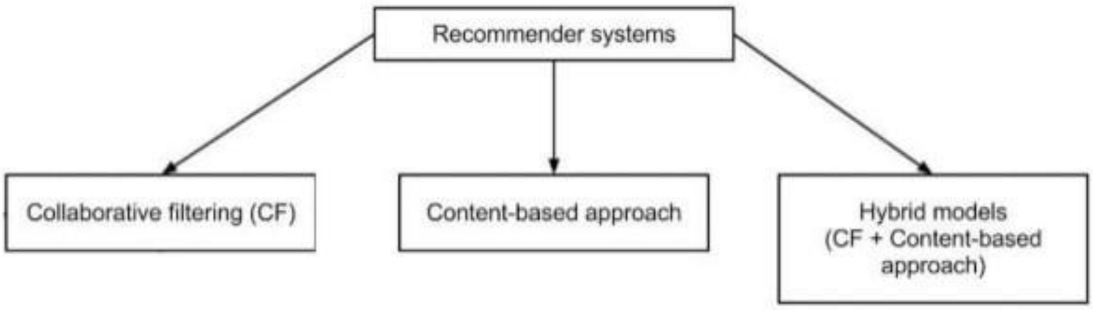
Why Do We Need Recommender Systems?

We now live in what some call the “era of abundance”. For any given product, there are sometimes thousands of options to choose from. Think of the examples above: streaming videos, social networking, online shopping; the list goes on. Recommender systems help to personalize a platform and help the user find something they like.

The easiest and simplest way to do this is to recommend the most popular items. However, to really enhance the user experience through personalized recommendations, we need dedicated recommender systems.

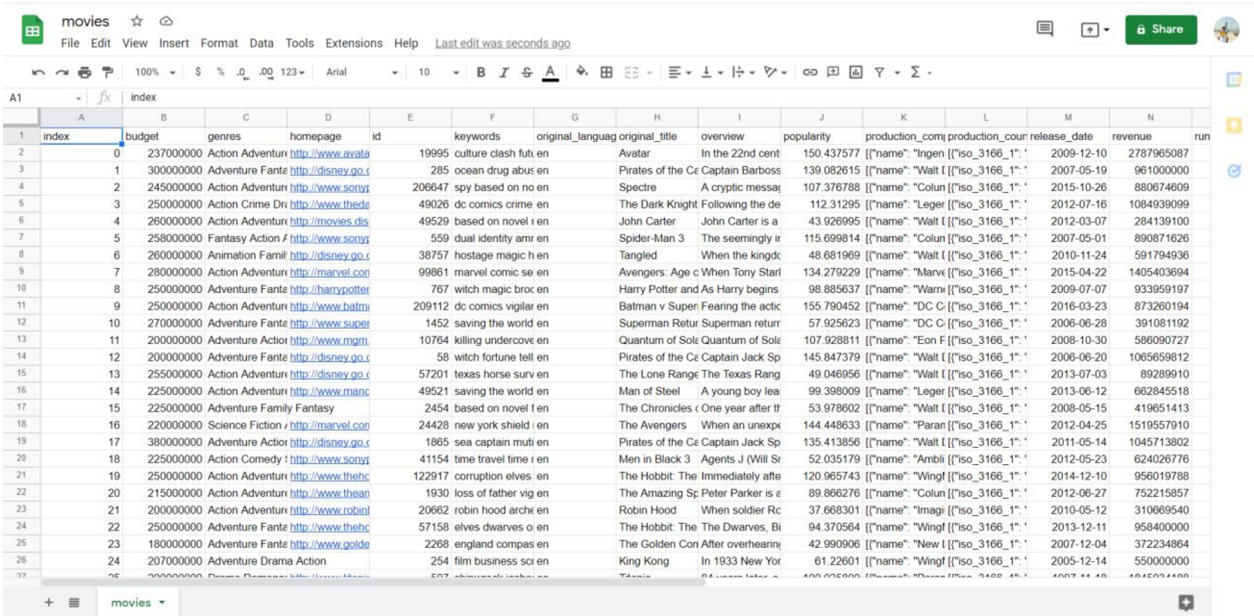
TYPES OF RECOMMENDER SYSTEMS



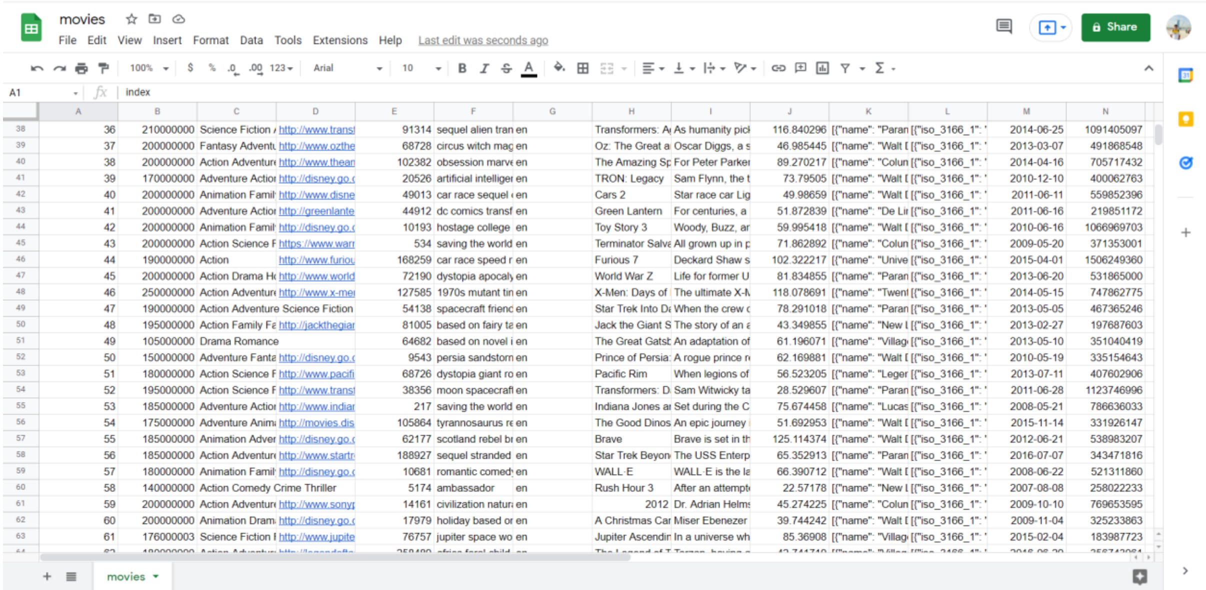
Designing our Movie Recommendation System

To obtain recommendations for our users, we will give them a suggested movies list they haven't watched yet based on their favourite movie. To do this, we will use similarities in movies such as genre, budget, popularity etc . At this point, it's worth mentioning that in the real world, we will likely encounter new users or movies without a history. Such situations are called cold start problems.

Our custom dataset:



index	budget	genres	homepage	id	keywords	original_languag	original_title	overview	popularity	production_comp	production_coun	release_date	revenue	run
0	237000000	Action Adventur	http://www.avata	19995	culture clash futu	en	Avatar	In the 22nd cent	150.437577	[{"name": "Ingen	[{"iso_3166_1": '	2009-12-10	2787965087	
1	300000000	Adventure Fanta	http://disney.go.c	285	ocean drug abus	en	Pirates of the Ca	Captain Barboss	139.082615	[{"name": "Walt I	[{"iso_3166_1": '	2007-05-19	961000000	
2	245000000	Action Adventur	http://www.sonyp	206647	spy based on no	en	Spectre	A cryptic messag	107.376788	[{"name": "Colun	[{"iso_3166_1": '	2015-10-26	880674609	
3	250000000	Action Crime Dra	http://www.theda	49026	dc comics crime	en	The Dark Knight	Following the de	112.31295	[{"name": "Leger	[{"iso_3166_1": '	2012-07-16	1084939099	
4	260000000	Action Adventur	http://movies.dis	49529	based on novel r	en	John Carter	John Carter is a	43.926995	[{"name": "Walt I	[{"iso_3166_1": '	2012-03-07	284139100	
5	258000000	Fantasy Action A	http://www.sonyp	559	dual identity amr	en	Spider-Man 3	The seemingly ir	115.699814	[{"name": "Colun	[{"iso_3166_1": '	2007-05-01	890871626	
6	260000000	Animation Famil	http://disney.go.c	38757	hostage magic h	en	Tangled	When the kingdo	48.681969	[{"name": "Walt I	[{"iso_3166_1": '	2010-11-24	591794936	
7	280000000	Action Adventur	http://marvel.con	99861	marvel comic se	en	Avengers: Age o	When Tony Starl	134.279229	[{"name": "Marve	[{"iso_3166_1": '	2015-04-22	1405403694	
8	250000000	Adventure Fanta	http://harrypotter	767	witch magic broc	en	Harry Potter and	As Harry begins	98.885637	[{"name": "Warn	[{"iso_3166_1": '	2009-07-07	933959197	
9	250000000	Action Adventur	http://www.batm	209112	dc comics vigilar	en	Batman v Super	Fearing the actic	155.790452	[{"name": "DC C	[{"iso_3166_1": '	2016-03-23	873260194	
10	270000000	Adventure Fanta	http://www.super	1452	saving the world	en	Superman Retur	Superman returr	57.925623	[{"name": "DC C	[{"iso_3166_1": '	2006-06-28	391081192	
11	200000000	Adventure Actior	http://www.mgm.	10764	killing undercove	en	Quantum of Sola	Quantum of Sola	107.928811	[{"name": "Eon F	[{"iso_3166_1": '	2008-10-30	586090727	
12	200000000	Adventure Fanta	http://disney.go.c	58	witch fortune tell	en	Pirates of the Ca	Captain Jack Sp	145.847379	[{"name": "Walt I	[{"iso_3166_1": '	2006-06-20	1065659812	
13	255000000	Action Adventur	http://disney.go.c	57201	texas horse surv	en	The Lone Range	The Texas Rang	49.046956	[{"name": "Walt I	[{"iso_3166_1": '	2013-07-03	89289910	
14	225000000	Action Adventur	http://www.manc	49521	saving the world	en	Man of Steel	A young boy lea	99.398009	[{"name": "Leger	[{"iso_3166_1": '	2013-06-12	662845518	
15	225000000	Adventure Family Fantasy		2454	based on novel t	en	The Chronicles c	One year after th	53.978602	[{"name": "Walt I	[{"iso_3166_1": '	2008-05-15	419651413	
16	220000000	Science Fiction A	http://marvel.con	24428	new york shield	en	The Avengers	When an unexpe	144.448633	[{"name": "Paran	[{"iso_3166_1": '	2012-04-25	1519557910	
17	380000000	Adventure Actior	http://disney.go.c	1865	sea captain muti	en	Pirates of the Ca	Captain Jack Sp	135.413856	[{"name": "Walt I	[{"iso_3166_1": '	2011-05-14	1045713802	
18	225000000	Action Comedy S	http://www.sonyp	41154	time travel time r	en	Men in Black 3	Agents J (Will Sr	52.035179	[{"name": "Ambli	[{"iso_3166_1": '	2012-05-23	624026776	
19	250000000	Action Adventur	http://www.thehc	122917	corruption elves	en	The Hobbit: The	Immediately afte	120.965743	[{"name": "Wingl	[{"iso_3166_1": '	2014-12-10	956019788	
20	215000000	Action Adventur	http://www.thean	1930	loss of father vig	en	The Amazing Sp	Peter Parker is a	89.866276	[{"name": "Colun	[{"iso_3166_1": '	2012-06-27	752215857	
21	200000000	Action Adventur	http://www.robinl	20662	robin hood arche	en	Robin Hood	When soldier Rc	37.668301	[{"name": "Imagi	[{"iso_3166_1": '	2010-05-12	310669540	
22	250000000	Adventure Fanta	http://www.thehc	57158	elves dwarves o	en	The Hobbit: The	The Dwarves, Bi	94.370564	[{"name": "Wingl	[{"iso_3166_1": '	2013-12-11	958400000	
23	180000000	Adventure Fanta	http://www.golde	2268	england compas	en	The Golden Con	After overhearin	42.990906	[{"name": "New L	[{"iso_3166_1": '	2007-12-04	372234864	
24	207000000	Adventure Drama Action		254	film business scr	en	King Kong	In 1933 New Yor	61.22601	[{"name": "Wingl	[{"iso_3166_1": '	2005-12-14	550000000	



	A	B	C	D	E	F	G	H	I	J	K	L	M	N
38	36	210000000	Science Fiction /	http://www.transf	91314	sequel alien tran	en	Transformers: A	As humanity pick	116.840296	[{"name": "Paran	[{"iso_3166_1": '	2014-06-25	1091405097
39	37	200000000	Fantasy Adventu	http://www.ozthe	68728	circus witch mag	en	Oz: The Great a	Oscar Diggs, a s	46.985445	[{"name": "Walt D	[{"iso_3166_1": '	2013-03-07	491868548
40	38	200000000	Action Adventure	http://www.thean	102382	obsession marve	en	The Amazing Sp	For Peter Parker	89.270217	[{"name": "Colun	[{"iso_3166_1": '	2014-04-16	705717432
41	39	170000000	Adventure Action	http://disney.go.c	20526	artificial intelliger	en	TRON: Legacy	Sam Flynn, the t	73.79505	[{"name": "Walt D	[{"iso_3166_1": '	2010-12-10	400062763
42	40	200000000	Animation Family	http://www.disne	49013	car race sequel (	en	Cars 2	Star race car Lig	49.98659	[{"name": "Walt D	[{"iso_3166_1": '	2011-06-11	559852396
43	41	200000000	Adventure Action	http://greenlante	44912	dc comics transf	en	Green Lantern	For centuries, a	51.872839	[{"name": "De Lir	[{"iso_3166_1": '	2011-06-16	219851172
44	42	200000000	Animation Family	http://disney.go.c	10193	hostage college	en	Toy Story 3	Woody, Buzz, ar	59.995418	[{"name": "Walt D	[{"iso_3166_1": '	2010-06-16	1066969703
45	43	200000000	Action Science F	https://www.warr	534	saving the world	en	Terminator Salva	All grown up in p	71.862892	[{"name": "Colun	[{"iso_3166_1": '	2009-05-20	371353001
46	44	190000000	Action	http://www.furiou	168259	car race speed r	en	Furious 7	Deckard Shaw s	102.322217	[{"name": "Unive	[{"iso_3166_1": '	2015-04-01	1506249360
47	45	200000000	Action Drama Ho	http://www.world	72190	dystopia apocaly	en	World War Z	Life for former U	81.834855	[{"name": "Paran	[{"iso_3166_1": '	2013-06-20	531865000
48	46	250000000	Action Adventure	http://www.x-mer	127585	1970s mutant tin	en	X-Men: Days of	The ultimate X-M	118.078691	[{"name": "Twent	[{"iso_3166_1": '	2014-05-15	747862775
49	47	190000000	Action Adventure Science Fiction		54138	spacecraft friend	en	Star Trek Into Da	When the crew c	78.291018	[{"name": "Paran	[{"iso_3166_1": '	2013-05-05	467365246
50	48	195000000	Action Family Fa	http://jackthegiar	81005	based on fairy ta	en	Jack the Giant S	The story of an a	43.349855	[{"name": "New L	[{"iso_3166_1": '	2013-02-27	197687603
51	49	105000000	Drama Romance		64682	based on novel i	en	The Great Gatsb	An adaptation of	61.196071	[{"name": "Villag	[{"iso_3166_1": '	2013-05-10	351040419
52	50	150000000	Adventure Fanta	http://disney.go.c	9543	persia sandstorm	en	Prince of Persia:	A rogue prince r	62.169881	[{"name": "Walt D	[{"iso_3166_1": '	2010-05-19	335154643
53	51	180000000	Action Science F	http://www.pacifi	68726	dystopia giant ro	en	Pacific Rim	When legions of	56.523205	[{"name": "Leger	[{"iso_3166_1": '	2013-07-11	407602906
54	52	195000000	Action Science F	http://www.transf	38356	moon spacecraft	en	Transformers: D	Sam Witwicky ta	28.529607	[{"name": "Paran	[{"iso_3166_1": '	2011-06-28	1123746996
55	53	185000000	Adventure Action	http://www.indiar	217	saving the world	en	Indiana Jones ar	Set during the C	75.674458	[{"name": "Lucas	[{"iso_3166_1": '	2008-05-21	786636033
56	54	175000000	Adventure Anima	http://movies.dis	105864	tyrannosaurus re	en	The Good Dinos	An epic journey	51.692953	[{"name": "Walt D	[{"iso_3166_1": '	2015-11-14	331926147
57	55	185000000	Animation Adver	http://disney.go.c	62177	scotland rebel br	en	Brave	Brave is set in th	125.114374	[{"name": "Walt D	[{"iso_3166_1": '	2012-06-21	538983207
58	56	185000000	Action Adventure	http://www.startr	188927	sequel stranded	en	Star Trek Beyon	The USS Enterp	65.352913	[{"name": "Paran	[{"iso_3166_1": '	2016-07-07	343471816
59	57	180000000	Animation Family	http://disney.go.c	10681	romantic comedy	en	WALL·E	WALL·E is the la	66.390712	[{"name": "Walt D	[{"iso_3166_1": '	2008-06-22	521311860
60	58	140000000	Action Comedy Crime Thriller		5174	ambassador	en	Rush Hour 3	After an attempt	22.57178	[{"name": "New L	[{"iso_3166_1": '	2007-08-08	258022233
61	59	200000000	Action Adventure	http://www.sonyp	14161	civilization natura	en	2012	Dr. Adrian Helms	45.274225	[{"name": "Colun	[{"iso_3166_1": '	2009-10-10	769653595
62	60	200000000	Animation Drama	http://disney.go.c	17979	holiday based or	en	A Christmas Car	Miser Ebenezer	39.744242	[{"name": "Walt D	[{"iso_3166_1": '	2009-11-04	325233863
63	61	176000003	Science Fiction F	http://www.jupite	76757	jupiter space wo	en	Jupiter Ascendin	In a universe wh	85.36908	[{"name": "Villag	[{"iso_3166_1": '	2015-02-04	183987723

To view the complete dataset:

https://docs.google.com/spreadsheets/d/1jnMDWDckQBxwDKcM4pSEEZBXlx0HWndUNj7NN91Cfvg/edit?usp=sharing

Final Output:

```
 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
```

TML Project : Movie Reccomendation System

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In [5]:

```
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 Pre-Processing

In [6]:

```
# loading the data from the csv file to apandas dataframe
movies_data = pd.read_csv('/movies.csv')
```

printing the first 5 rows of the dataframe

In [7]:

```
movies_data.head()
```

Out[7]:

	index	budget	genres	homepage	id	keywords	ori
0	0	237000000	Action Adventure Fantasy Science Fiction	http://www.avatarmovie.com/	19995	culture clash future space war space colony so...	
1	1	300000000	Adventure Fantasy Action	http://disney.go.com/disneypictures/pirates/	285	ocean drug abuse exotic island east india trad...	
2	2	245000000	Action Adventure Crime	http://www.sonypictures.com/movies/spectre/	206647	spy based on novel secret agent sequel mi6	
3	3	250000000	Action Crime Drama Thriller	http://www.thedarkknightrises.com/	49026	dc comics crime fighter terrorist secret ident...	
4	4	260000000	Action Adventure Science Fiction	http://movies.disney.com/john-carter	49529	based on novel mars medallion space travel pri...	

In [8]:

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

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 [10]:

```
# replacing the null valuess with null string

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

In [11]:

```
# combining all the 5 selected features

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

In [12]:

```
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
```

In [13]:

```
# converting the text data to feature vectors

vectorizer = TfidfVectorizer()
```

In [14]:

```
feature_vectors = vectorizer.fit_transform(combined_features)
```

In [15]:

```
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

In [16]:

```
# getting the similarity scores using cosine similarity

similarity = cosine_similarity(feature_vectors)
```

In [ ]:

```
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 [17]:

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

```
(4803, 4803)
```

Getting the movie name from the user

In [18]:

```
# getting the movie name from the user

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

```
 Enter your favourite movie name : Iron Man
```

In [19]:

```python
# 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 Dar
k Knight Rises', 'John Carter', 'Spider-Man 3', 'Tangled', 'Avengers: Age
of Ultron', 'Harry Potter and the Half-Blood Prince', 'Batman v Superman:
Dawn of Justice', 'Superman Returns', 'Quantum of Solace', "Pirates of the
Caribbean: Dead Man's Chest", 'The Lone Ranger', 'Man of Steel', 'The Chro
nicles of Narnia: Prince Caspian', 'The Avengers', 'Pirates of the Caribbe
an: On Stranger Tides', 'Men in Black 3', 'The Hobbit: The Battle of the F
ive Armies', 'The Amazing Spider-Man', 'Robin Hood', 'The Hobbit: The Deso
lation of Smaug', 'The Golden Compass', 'King Kong', 'Titanic', 'Captain A
merica: Civil War', 'Battleship', 'Jurassic World', 'Skyfall', 'Spider-Man
2', 'Iron Man 3', 'Alice in Wonderland', 'X-Men: The Last Stand', 'Monster
s University', 'Transformers: Revenge of the Fallen', 'Transformers: Age o
f Extinction', 'Oz: The Great and Powerful', 'The Amazing Spider-Man 2',
'TRON: Legacy', 'Cars 2', 'Green Lantern', 'Toy Story 3', 'Terminator Salv
ation', 'Furious 7', 'World War Z', 'X-Men: Days of Future Past', 'Star Tr
ek Into Darkness', 'Jack the Giant Slayer', 'The Great Gatsby', 'Prince of
Persia: The Sands of Time', 'Pacific Rim', 'Transformers: Dark of the Moo
n', 'Indiana Jones and the Kingdom of the Crystal Skull', 'The Good Dinosa
ur', 'Brave', 'Star Trek Beyond', 'WALL·E', 'Rush Hour 3', '2012', 'A Chri
```

In [20]:

```python
# 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']
```

In [21]:

```python
close_match = find_close_match[0]
print(close_match)
```

```
Iron Man
```

In [22]:

```python
# 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
```

In [23]:

```python
# 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, 0.013735500604224
323), (3, 0.006468756104392058), (4, 0.03268943310073386), (5, 0.013907256
685755473), (6, 0.07692837576335507), (7, 0.23944423963486405), (8, 0.0078
82387851851008), (9, 0.07599206098164225), (10, 0.07536074882460438), (11,
0.01192606921174529), (12, 0.013707618139948929), (13, 0.012376074925089967), (14, 0.09657127116284188), (15, 0.007286271383816743), (16, 0.22704403
782296803), (17, 0.013112928084103857), (18, 0.04140526820609594), (19, 0.
07883282546834255), (20, 0.07981173664799915), (21, 0.011266873271064948),
(22, 0.006892575895462364), (23, 0.006599097891242659), (24, 0.01266520812
2549737), (25, 0.0), (26, 0.2156624109683154), (27, 0.030581282093826635), (28, 0.06107440221966537 6), (29, 0.014046184258938898), (30, 0.0807734
659476981), (31, 0.31467052449477506), (32, 0.02878209913426701), (33, 0.1
3089810941050173), (34, 0.0), (35, 0.03535009067486559 5), (36, 0.031853252
69937555), (37, 0.008024326882532318), (38, 0.1126182690487113), (39, 0.08
902766481306311), (40, 0.008086007019135987), (41, 0.06454289714171595),
(42, 0.0), (43, 0.05431669251894044 6), (44, 0.006244741632576977), (45, 0.
023530724758699103), (46, 0.14216268867232237), (47, 0.03716851751705058),
(48, 0.013755725647812333), (49, 0.0), (50, 0.012978759995781826), (51, 0.
027557058720715163), (52, 0.03032640708636649), (53, 0.022454895898373586
```

In [24]:

```python
len(similarity_score)
```

Out[24]:

```
4803
```

In [25]:

```python
# 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, 0.3146705244947
7506), (7, 0.23944423963486405), (16, 0.22704403782296803), (26, 0.2156624
1096831154), (85, 0.20615862984665329), (182, 0.19573956139611606), (511,
0.16702973947860686), (3623, 0.1609246088135586), (64, 0.1529992413944514
5), (203, 0.14818667948665118), (174, 0.1471993120942043), (4401, 0.145059
71470107848), (101, 0.14401677581826294), (46, 0.14216268867232237), (169,
0.1380947013224906), (1740, 0.13624382641690763), (94, 0.136168195790290
1), (788, 0.1330589507422922), (126, 0.13263982780511066), (131, 0.1313769
8586006535), (33, 0.13089810941050173), (2487, 0.12309731939910507), (783,
0.12162995562040377), (138, 0.11846458075866884), (2442, 0.117255123354833
21), (661, 0.11719294096248463), (607, 0.11387063493435637), (38, 0.112618
2690487113), (2651, 0.1121878787373205), (353, 0.1116846512704428), (122,
0.10850296033661253), (1553, 0.1079782217151326), (1451, 0.10784939497470
7), (242, 0.10630339022327012), (618, 0.1025469263536857), (720, 0.1008756
5815879387), (2390, 0.10006436988307142), (1210, 0.09911415072466837), (34
43, 0.09877044853778177), (954, 0.0986387254713941), (2235, 0.098295721499
18514), (3385, 0.09760018407279153), (14, 0.09657127116284188), (870, 0.09
574351274416697), (1406, 0.09571953277826747), (2875, 0.0957179952078477),
(2880, 0.09551596914906027), (800, 0.09503280362598002), (1368, 0.09403221
```

In [26]:

```
# 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 Sytem

In [28]:

```
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
```

In [ ]:

```

```