Photo by Jiangnan_Photography

Project Overview

This project analyzes datasets containing data on movies and helps identify the key things needed when starting a movie studio.

Business Problem

Microsoft sees all the big companies creating original video content and they want to get in on the fun. To create a new movie studio, they'll have to know the type of movies being currently watched and how they perform financialy. Doing this will help them get an edge on the competition.

Data

Tmdb and im.db databases have a long listing of relevant data needed. Each having data on the genre, title and ratings of various movies produced over the years. The datasets also provided other data such as the writers and directors.

Data Understanding

From leading review and rating databases and sites, relevant data is obtained and compiled.

```
# importing the most used libraries for the project
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
%matplotlib inline
```

IMDB data

```
# To import relevant library for sql
import sqlite3
conn = sqlite3.connect('Data/im.db')

# To know the tables in the database
table_name_query = """SELECT name
                      AS 'Table Names'
                      FROM sqlite_master
                      WHERE type='table';"""
pd.read_sql(table_name_query,conn)
```

	Table Names
0	movie_basics
1	directors
2	known_for
3	movie_akas
4	movie_ratings
5	persons
6	principals
7	writers

To know what movie_ratings table contains we query through the table as shown below.

```
first_query = """
SELECT *
  FROM movie_ratings;
"""
pd.read_sql(first_query,conn)
```

	movie_id	averagerating	numvotes
0	tt10356526	8.3	31
1	tt10384606	8.9	559
2	tt1042974	6.4	20
3	tt1043726	4.2	50352
4	tt1060240	6.5	21
...	...	...	...

```
73851   tt9805820           8.1         25
73852   tt9844256           7.5         24
73853   tt9851050           4.7         14
73854   tt9886934           7.0          5
73855   tt9894098           6.3        128

[73856 rows x 3 columns]
```

To know what movie_basics table contains we query through the table as shown below.

```
second_query = """
SELECT *
  FROM movie_basics;
"""
pd.read_sql(second_query,conn)
```

```
         movie_id                                primary_title  \
0       tt0063540                                    Sunghursh
1       tt0066787              One Day Before the Rainy Season
2       tt0069049                   The Other Side of the Wind
3       tt0069204                              Sabse Bada Sukh
4       tt0100275                     The Wandering Soap Opera
...           ...                                          ...
146139  tt9916538                          Kuambil Lagi Hatiku
146140  tt9916622  Rodolpho Teóphilo - O Legado de um Pioneiro
146141  tt9916706                              Dankyavar Danka
146142  tt9916730                                       6 Gunn
146143  tt9916754               Chico Albuquerque - Revelações

                                     original_title  start_year  \
0                                         Sunghursh        2013
1                                   Ashad Ka Ek Din        2019
2                        The Other Side of the Wind        2018
3                                   Sabse Bada Sukh        2018
4                             La Telenovela Errante        2017
...                                             ...         ...
146139                          Kuambil Lagi Hatiku        2019
146140  Rodolpho Teóphilo - O Legado de um Pioneiro        2015
146141                              Dankyavar Danka        2013
146142                                       6 Gunn        2017
146143               Chico Albuquerque - Revelações        2013

        runtime_minutes                genres
0                 175.0    Action,Crime,Drama
1                 114.0       Biography,Drama
2                 122.0                 Drama
3                   NaN          Comedy,Drama
4                  80.0  Comedy,Drama,Fantasy
...                 ...                   ...
```

```
146139          123.0                 Drama
146140            NaN           Documentary
146141            NaN                Comedy
146142          116.0                  None
146143            NaN           Documentary

[146144 rows x 6 columns]
```

```
# To know the 20 most recent movies to be produced
third_query = """
SELECT primary_title, start_year, genres
  FROM movie_basics
ORDER BY start_year DESC
LIMIT 20;

"""
pd.read_sql(third_query,conn)
```

```
                                  primary_title  start_year  \
0                                     100 Years        2115
1                                      Avatar 5        2027
2                        Untitled Star Wars Film        2026
3                                      Avatar 4        2025
4                        Untitled Star Wars Film        2024
5      Fantastic Beasts and Where to Find Them 5        2024
6                        Untitled Marvel Project        2023
7           Untitled Disney Live-Action Project        2023
8                                      Avatar 3        2023
9             Wraith of the Umbra and Eidolon II        2023
10  Untitled Illumination Entertainment Project        2023
11                   Untitled Disney Marvel Film        2022
12                   Untitled Disney Marvel Film        2022
13              The Hunchback of the Lighthouse        2022
14                         Corazones en Llamas 5        2022
15                            The Weary Traveler        2022
16               Untitled Pixar Animation Project       2022
17              Untitled Disney Animation Project       2022
18                       Untitled Star Wars Film        2022
19                           Mi Asesino Favorito        2022

                       genres
0                       Drama
1   Action,Adventure,Fantasy
2                     Fantasy
3   Action,Adventure,Fantasy
4                        None
5   Adventure,Family,Fantasy
6                      Action
7                        None
8     Action,Adventure,Drama
```

```
9    Adventure,Drama,Fantasy
10                      None
11                    Action
12                    Action
13                     Drama
14                    Action
15                    Horror
16                      None
17                      None
18                      None
19              Comedy,Crime
```

Now that we know what the movie_ratings and movie_basics tables contain it is easy to obtain the data we want.

```
# Code below joins the movie_ratings and movie_basics tables and filters data
#based on number of votes a movie has and orders the data based on averagerating
fourth_query = """
SELECT *
  FROM movie_basics
       INNER JOIN movie_ratings
       ON movie_basics.'movie_id' = movie_ratings.'movie_id'
 WHERE numvotes > 100
 ORDER BY averagerating DESC
 LIMIT 40;

"""
pd.read_sql(fourth_query,conn)
```

```
      movie_id                                       primary_title  \
0    tt9537008                                   Gini Helida Kathe
1    tt7131622                      Once Upon a Time ... in Hollywood
2    tt8718580                                          Eghantham
3    tt9680166                          Yeh Suhaagraat Impossible
4    tt9343826                                Ananthu V/S Nusrath
5    tt6058226                                Ekvtime: Man of God
6    tt4131686                                    I Want to Live
7    tt9760512                                   D/O Parvathamma
8    tt9417594                     Kosovo: A Moment In Civilization
9    tt5963218                                     Aloko Udapadi
10   tt6842524  Hare Krishna! The Mantra, the Movement and the...
11   tt8866064                          10 Days Before the Wedding
12   tt8354112                                              Mosul
13   tt8063272                          Uninvited: Marcelo Burlon
14   tt7738784                                            Peranbu
15   tt8203706                                American Deep State
16   tt9390200                                       Dokyala Shot
```

```
17   tt2264978                          Harvesting the High Plains
18   tt5858514                             The Children of Genghis
19   tt3746274                              Mama's Heart. Gongadze
20   tt6693242                                          3 Wheeling
21  tt10084190                      Chandigarh amritsar chandigarh
22   tt2185170                                        Jurisdiction
23   tt5624252                                  That Vitamin Movie
24   tt7562038                                      Butcher Angels
25   tt6859280     The Nagano Tapes: Rewound, Replayed & Reviewed
26   tt5813916                                     The Mountain II
27   tt5354160                                            Aynabaji
28  tt10380266                                      Adutha Chodyam
29   tt2357748  Rock and Roll's Greatest Failure: Otway the Movie
30   tt8176142                                 Oru Kadhai Sollatuma
31   tt4450674                                           Druglawed
32   tt2170667                                              Wheels
33   tt5759506                                        Avec l'amour
34   tt4126322                                         The Ataxian
35   tt5375100                                        Paint Drying
36   tt5593384                                   Truth and Justice
37   tt7214598                              Land of Hope and Glory
38   tt6487784                                   Generation Freedom
39   tt5773402                                            Dominion

                                        original_title  start_year  \
0                                    Gini Helida Kathe        2019
1                     Once Upon a Time ... in Hollywood        2019
2                                            Eghantham        2018
3                             Yeh Suhaagraat Impossible        2019
4                                   Ananthu V/S Nusrath        2018
5                                   Ekvtime: Man of God        2018
6                                        I Want to Live        2015
7                                       D/O Parvathamma        2019
8                      Kosovo: A Moment In Civilization        2017
9                                        Aloko Udapadi        2017
10  Hare Krishna! The Mantra, the Movement and the...        2017
11                           10 Days Before the Wedding        2018
12                                                Mosul        2019
13                            Uninvited: Marcelo Burlon        2017
14                                              Peranbu        2018
15                                  American Deep State        2019
16                                         Dokyala Shot        2019
17                           Harvesting the High Plains        2012
18                                  Chingisiin huuhduud        2017
19                               Mama's Heart. Gongadze        2017
20                                           3 Wheeling        2017
21                       Chandigarh amritsar chandigarh        2019
22                                         Jurisdiction        2012
23                                   That Vitamin Movie        2016
```

```
24                              Fereshtegan-e ghassab        2013
25     The Nagano Tapes: Rewound, Replayed & Reviewed        2018
26                                             Dag II        2016
27                                           Aynabaji        2016
28                                     Adutha Chodyam        2019
29  Rock and Roll's Greatest Failure: Otway the Movie        2013
30                               Oru Kadhai Sollatuma        2019
31                                          Druglawed        2015
32                                             Wheels        2014
33                                      Avec l'amour        2017
34                                        The Ataxian        2015
35                                       Paint Drying        2016
36                                      Tõde ja õigus        2019
37                           Land of Hope and Glory        2017
38                                 Generation Freedom        2019
39                                           Dominion        2018

    runtime_minutes                          genres    movie_id  \
0             138.0                           Drama   tt9537008
1             159.0                    Comedy,Drama   tt7131622
2             125.0                           Drama   tt8718580
3              92.0                          Comedy   tt9680166
4             149.0             Comedy,Drama,Family   tt9343826
5             132.0         Biography,Drama,History   tt6058226
6             106.0  Adventure,Biography,Documentary   tt4131686
7               NaN                          Action   tt9760512
8              46.0                     Documentary   tt9417594
9             113.0                   Drama,History   tt5963218
10             90.0                     Documentary   tt6842524
11            120.0            Comedy,Drama,Musical   tt8866064
12             86.0                     Documentary   tt8354112
13             83.0                     Documentary   tt8063272
14            147.0                           Drama   tt7738784
15             62.0                     Documentary   tt8203706
16            122.0                        Thriller   tt9390200
17             67.0                     Documentary   tt2264978
18            101.0                Adventure,Family   tt5858514
19            100.0      Biography,Crime,Documentary   tt3746274
20            101.0               Documentary,Sport   tt6693242
21            107.0            Comedy,Drama,Romance  tt10084190
22             50.0       Action,Comedy,Documentary   tt2185170
23             86.0                     Documentary   tt5624252
24              NaN                       Drama,War   tt7562038
25             73.0                     Documentary   tt6859280
26            135.0                Action,Drama,War   tt5813916
27            147.0          Crime,Mystery,Thriller   tt5354160
28            112.0                           Drama  tt10380266
29             97.0                     Documentary   tt2357748
30            102.0                           Drama   tt8176142
```

31	100.0	Crime,Documentary,History	tt4450674
32	115.0	Drama	tt2170667
33	67.0	Comedy,Documentary,Drama	tt5759506
34	81.0	Adventure,Documentary,Drama	tt4126322
35	607.0	Documentary	tt5375100
36	165.0	Drama	tt5593384
37	48.0	Documentary	tt7214598
38	98.0	Documentary	tt6487784
39	120.0	Documentary	tt5773402

	averagerating	numvotes
0	9.9	417
1	9.7	5600
2	9.7	639
3	9.6	624
4	9.6	808
5	9.6	2604
6	9.6	1339
7	9.6	427
8	9.5	140
9	9.5	6509
10	9.5	829
11	9.5	354
12	9.5	617
13	9.5	349
14	9.4	9629
15	9.4	500
16	9.4	816
17	9.4	132
18	9.4	797
19	9.4	500
20	9.4	104
21	9.4	952
22	9.4	114
23	9.4	927
24	9.4	251
25	9.4	192
26	9.3	100568
27	9.3	18470
28	9.3	587
29	9.3	411
30	9.3	532
31	9.3	122
32	9.3	17308
33	9.3	180
34	9.3	197
35	9.3	218
36	9.3	1220
37	9.2	140

```
38             9.2       227
39             9.2      1096
```

```python
fifth_query = """
SELECT genres,COUNT(genres) AS main_genres, runtime_minutes,
averagerating, numvotes
  FROM movie_basics
       JOIN movie_ratings
       ON movie_basics.'movie_id' = movie_ratings.'movie_id'
 WHERE numvotes > 100
 GROUP BY genres
 ORDER BY averagerating DESC
 LIMIT 50
;
"""
im_df = pd.read_sql(fifth_query,conn)

# Top 50 genres by averagerating
im_df
```

	genres	main_genres	runtime_minutes	\
0	Documentary,Music,Sport	3	96.0	
1	Documentary,Music,War	1	95.0	
2	Documentary	1771	87.0	
3	Comedy,Music,Musical	4	110.0	
4	Adventure,Drama,War	1	90.0	
5	Drama,Family,Musical	4	120.0	
6	Adventure,Documentary,Sport	5	46.0	
7	Documentary,History,War	17	99.0	
8	Comedy,Crime,Thriller	28	135.0	
9	Adventure,Documentary,History	3	103.0	
10	Drama,Mystery,War	6	131.0	
11	Drama,Fantasy,Horror	69	104.0	
12	Crime,Documentary,Mystery	8	107.0	
13	Comedy,History,Musical	1	134.0	
14	Animation,History	1	135.0	
15	Romance,Thriller,War	1	125.0	
16	Documentary,History,Thriller	5	77.0	
17	Documentary,History,News	33	125.0	
18	Documentary,Fantasy,Horror	1	60.0	
19	Documentary,Family,History	7	80.0	
20	Comedy,Musical,Western	1	120.0	
21	Animation,Documentary,Mystery	1	93.0	
22	Animation,Crime,Mystery	1	116.0	
23	Documentary,History,Music	17	85.0	
24	Animation,Comedy,Drama	23	163.0	
25	Adventure,Drama,Fantasy	23	130.0	
26	Documentary,Drama,Romance	4	86.0	
27	Comedy,Crime,Documentary	1	87.0	
28	Animation,Fantasy,Mystery	1	109.0	

29	Animation,Crime,Documentary	1	82.0
30	Adventure,Animation,Horror	3	106.0
31	Adventure,Animation,Family	60	90.0
32	Action,Drama,Sport	21	160.0
33	Action,Adventure,Biography	12	156.0
34	Fantasy,Musical,Sci-Fi	1	172.0
35	Drama,Musical,Thriller	4	130.0
36	Documentary,Sport,Thriller	1	120.0
37	Documentary,History,Mystery	2	90.0
38	Comedy,Documentary,Musical	2	NaN
39	Comedy,Documentary,Drama	25	85.0
40	Animation,Romance	1	50.0
41	Documentary,News	45	97.0
42	Documentary,Family,Music	7	105.0
43	Comedy,History,War	1	90.0
44	Biography,Drama,Thriller	19	134.0
45	Animation,Drama,Mystery	2	90.0
46	Animation,Drama,History	4	94.0
47	Animation,Biography,Crime	2	94.0
48	Action,Documentary,Sport	5	111.0
49	Action,Adventure,Documentary	12	77.0

	averagerating	numvotes
0	9.1	170
1	8.9	742
2	8.9	559
3	8.9	198
4	8.9	658
5	8.7	351
6	8.5	434
7	8.4	15612
8	8.4	7279
9	8.4	115
10	8.3	124156
11	8.3	14128
12	8.3	116
13	8.3	172
14	8.3	7451
15	8.2	165
16	8.2	343
17	8.2	3894
18	8.2	405
19	8.2	127
20	8.2	186
21	8.2	1014
22	8.2	526
23	8.1	369
24	8.1	5406
25	8.1	691835

```
26             8.0       512
27             8.0     58721
28             8.0      1038
29             8.0      6552
30             8.0       311
31             8.0       283
32             8.0      3839
33             8.0    621193
34             7.9       539
35             7.9      5279
36             7.9     28979
37             7.9       122
38             7.9       252
39             7.9      1418
40             7.9       195
41             7.8      2553
42             7.8       130
43             7.8       445
44             7.8    387402
45             7.8      4640
46             7.8      2345
47             7.8     39737
48             7.8      2059
49             7.8       180
```

Tmdb Data

```
df_tmdb = pd.read_csv('Data/tmdb.movies.csv',index_col=0)
df_tmdb.columns
```

```
Index(['genre_ids', 'id', 'original_language', 'original_title',
'popularity',
       'release_date', 'title', 'vote_average', 'vote_count'],
      dtype='object')
```

```
df_tmdb.head()
```

```
             genre_ids     id original_language  \
0      [12, 14, 10751]  12444                en
1  [14, 12, 16, 10751]  10191                en
2        [12, 28, 878]  10138                en
3      [16, 35, 10751]    862                en
4        [28, 878, 12]  27205                en

                                 original_title  popularity
release_date  \
0  Harry Potter and the Deathly Hallows: Part 1      33.533   2010-11-
19
```

```
1                       How to Train Your Dragon      28.734   2010-03-
26
2                                     Iron Man 2      28.515   2010-05-
07
3                                      Toy Story      28.005   1995-11-
22
4                                      Inception      27.920   2010-07-
16

                                          title  vote_average
vote_count
0  Harry Potter and the Deathly Hallows: Part 1           7.7
10788
1                       How to Train Your Dragon           7.7
7610
2                                     Iron Man 2           6.8
12368
3                                      Toy Story           7.9
10174
4                                      Inception           8.3
22186
```

```
df_tmdb.tail()
```

```
             genre_ids      id original_language
original_title  \
26512         [27, 18]  488143                en  Laboratory
Conditions
26513         [18, 53]  485975                en
_EXHIBIT_84xxx_
26514     [14, 28, 12]  381231                en           The Last
One
26515  [10751, 12, 28]  366854                en           Trailer
Made
26516         [53, 27]  309885                en             The
Church

       popularity release_date                 title  vote_average  \
26512         0.6   2018-10-13  Laboratory Conditions           0.0
26513         0.6   2018-05-01        _EXHIBIT_84xxx_           0.0
26514         0.6   2018-10-01           The Last One           0.0
26515         0.6   2018-06-22           Trailer Made           0.0
26516         0.6   2018-10-05             The Church           0.0

       vote_count
26512           1
26513           1
26514           1
26515           1
26516           1
```

```
df_tmdb.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 26517 entries, 0 to 26516
Data columns (total 9 columns):
 #   Column             Non-Null Count  Dtype  
---  ------             --------------  -----  
 0   genre_ids          26517 non-null  object 
 1   id                 26517 non-null  int64  
 2   original_language  26517 non-null  object 
 3   original_title     26517 non-null  object 
 4   popularity         26517 non-null  float64
 5   release_date       26517 non-null  object 
 6   title              26517 non-null  object 
 7   vote_average       26517 non-null  float64
 8   vote_count         26517 non-null  int64  
dtypes: float64(2), int64(2), object(5)
memory usage: 2.0+ MB
```

Data Preparation

This involves ordering, filtering and dropping the data for analysis.

We first check for missing values in the columns.

```
df_tmdb.isnull().sum()
```

```
genre_ids            0
id                   0
original_language    0
original_title       0
popularity           0
release_date         0
title                0
vote_average         0
vote_count           0
dtype: int64
```

```
# Here we drop columns that are irrelevant
df_tmdb = df_tmdb.drop(columns = ['original_language','title','id'])

# To confirm the changes we run the variable
df_tmdb
```

```
                 genre_ids
original_title  \
0           [12, 14, 10751]  Harry Potter and the Deathly Hallows: Part
1
1       [14, 12, 16, 10751]                         How to Train Your
Dragon
```

```
2              [12, 28, 878]                                    Iron Man
2
3             [16, 35, 10751]                                    Toy
Story
4              [28, 878, 12]
Inception
...                       ...                                          .
..
26512               [27, 18]                         Laboratory
Conditions
26513               [18, 53]
_EXHIBIT_84xxx_
26514           [14, 28, 12]                                    The Last
One
26515         [10751, 12, 28]                                    Trailer
Made
26516               [53, 27]                                      The
Church

       popularity release_date  vote_average  vote_count
0          33.533   2010-11-19           7.7       10788
1          28.734   2010-03-26           7.7        7610
2          28.515   2010-05-07           6.8       12368
3          28.005   1995-11-22           7.9       10174
4          27.920   2010-07-16           8.3       22186
...           ...          ...           ...         ...
26512       0.600   2018-10-13           0.0           1
26513       0.600   2018-05-01           0.0           1
26514       0.600   2018-10-01           0.0           1
26515       0.600   2018-06-22           0.0           1
26516       0.600   2018-10-05           0.0           1

[26517 rows x 6 columns]
```

```
# Here we filter the data to remain with data with over 1000 votes
df_tmdb = df_tmdb.loc[df_tmdb['vote_count']>1000]

# Here we filter the data again to remain with data with over a rating
of 8
df_tmdb=df_tmdb.loc[df_tmdb['vote_average']>8]

df_tmdb
```

```
                     genre_ids
original_title  \
4                [28, 878, 12]
Inception
19              [18, 53, 9648]                                    Shutter
Island
43                 [35, 10749]                                  Some Like
```

```
It Hot
180          [18, 10752, 9648]
Incendies
2471           [10751, 14, 12]  Harry Potter and the Deathly Hallows:
Part 2
2472           [10751, 16, 18]                                   The
Lion King
2485                      [18]                               Good Will
Hunting
2511                  [18, 35]
Intouchables
2552                      [18]
The Help
5201                  [18, 80]                    Once Upon a Time in
America
5423        [16, 10751, 10749]
Paperman
7971       [16, 18, 10751, 14]                                    おおか
みこどもの雨と雪
11026      [36, 18, 53, 10752]                               The
Imitation Game
11031              [18, 10402]
Whiplash
11032            [12, 18, 878]
Interstellar
11142                     [18]
Mommy
14173          [16, 10751, 14]                                        千
と千尋の神隠し
14199                 [18, 53]
Room
17389          [10749, 16, 18]
君の名は。
17396          [18, 36, 10752]                                   Hacksaw
Ridge
17402           [9648, 80, 53]
Contratiempo
17407                 [18, 53]
Room
17429                     [18]
Lion
17466          [53, 18, 10749]
ㅇㅏ가ㅆㅣ
20626          [16, 10751, 14]                                        千
と千尋の神隠し
20632          [10749, 16, 18]
君の名は。
20635  [16, 10751, 35, 12, 14]
Coco
```

```
20643          [18, 36, 10752]                                 Hacksaw
Ridge
20659           [9648, 80, 53]
Contratiempo
20660              [10749, 18]                          Call Me by
Your Name
20662              [18, 10751]
Wonder
20673                 [80, 18]     Three Billboards Outside Ebbing,
Missouri
20677                     [18]
Lion
20743          [18, 16, 10749]
聲の形
20857           [16, 18, 9648]                                Loving
Vincent
23811             [12, 28, 14]                        Avengers:
Infinity War
23812    [28, 12, 16, 878, 35]             Spider-Man: Into the
Spider-Verse
23825              [18, 10402]                             Bohemian
Rhapsody
23827                 [18, 35]
Green Book
23859  [16, 10751, 35, 12, 14]
Coco
23861          [18, 36, 10752]
Schindler's List
23865          [14, 16, 10751]
となりのトトロ
23896              [10749, 18]                          Call Me by
Your Name
23903              [18, 10751]
Wonder
23922                 [80, 18]     Three Billboards Outside Ebbing,
Missouri
23970          [35, 18, 10749]                                 Love,
Simon
24000              [35, 10749]                            Some Like
It Hot
24169           [16, 18, 9648]                                Loving
Vincent
24231                     [18]                            Sulla mia
pelle
24268                 [14, 18]                           Det sjunde
inseglet

       popularity release_date  vote_average  vote_count
4          27.920   2010-07-16           8.3       22186
```

19	18.060	2010-02-18	8.1	12625
43	14.200	1959-03-18	8.2	1562
180	8.973	2010-09-04	8.1	1034
2471	29.206	2011-07-15	8.1	11567
2472	28.583	1994-06-23	8.2	10160
2485	18.013	1997-12-05	8.1	5764
2511	15.013	2011-11-02	8.2	9940
2552	12.598	2011-08-10	8.1	3944
5201	17.717	1984-06-01	8.4	2243
5423	7.606	2012-11-02	8.1	1125
7971	12.316	2013-11-26	8.2	1056
11026	33.078	2014-12-19	8.1	10396
11031	28.784	2014-10-10	8.4	7908
11032	28.440	2014-11-05	8.2	18597
11142	11.095	2014-08-29	8.3	1399
14173	32.043	2002-09-20	8.5	7424
14199	20.000	2015-10-16	8.1	5494
17389	28.238	2017-04-07	8.6	4161
17396	24.074	2016-11-04	8.1	6608
17402	21.087	2016-09-22	8.2	1673
17407	20.000	2015-10-16	8.1	5494
17429	17.216	2016-11-25	8.1	3833
17466	14.374	2016-10-21	8.3	1213
20626	32.043	2002-09-20	8.5	7424
20632	28.238	2017-04-07	8.6	4161
20635	25.961	2017-11-22	8.2	8669
20643	24.074	2016-11-04	8.1	6608
20659	21.087	2016-09-22	8.2	1673
20660	20.504	2017-11-24	8.3	4957
20662	20.101	2017-11-17	8.2	3959
20673	17.808	2017-11-10	8.2	5432
20677	17.216	2016-11-25	8.1	3833
20743	13.187	2017-10-20	8.3	1034
20857	10.025	2017-09-22	8.2	1200
23811	80.773	2018-04-27	8.3	13948
23812	60.534	2018-12-14	8.4	4048
23825	37.197	2018-11-02	8.1	7629
23827	36.284	2018-11-16	8.3	3499
23859	25.961	2017-11-22	8.2	8669
23861	25.334	1993-12-15	8.5	8065
23865	25.068	2018-12-11	8.1	3267
23896	20.504	2017-11-24	8.3	4957
23903	20.101	2017-11-17	8.2	3959
23922	17.808	2017-11-10	8.2	5432
23970	15.608	2018-03-16	8.2	3165
24000	14.200	1959-03-18	8.2	1562
24169	10.025	2017-09-22	8.2	1200
24231	9.161	2018-09-12	8.2	1078
24268	8.693	1958-10-13	8.2	1163

```python
# The data is being grouped according to the vote average and sorted according to the day of release
df_tmdb.groupby(['vote_average'])
df_tmdb.sort_values('release_date')
df_tmdb
```

```
                     genre_ids
original_title  \
4                [28, 878, 12]
Inception
19              [18, 53, 9648]                                    Shutter
Island
43                 [35, 10749]                                  Some Like
It Hot
180          [18, 10752, 9648]
Incendies
2471          [10751, 14, 12]  Harry Potter and the Deathly Hallows:
Part 2
2472          [10751, 16, 18]                                        The
Lion King
2485                      [18]                                  Good Will
Hunting
2511                  [18, 35]
Intouchables
2552                      [18]
The Help
5201                  [18, 80]                          Once Upon a Time in
America
5423        [16, 10751, 10749]
Paperman
7971       [16, 18, 10751, 14]                                      おおか
みこどもの雨と雪
11026      [36, 18, 53, 10752]                                   The
Imitation Game
11031              [18, 10402]
Whiplash
11032            [12, 18, 878]
Interstellar
11142                     [18]
Mommy
14173         [16, 10751, 14]                                         千
と千尋の神隠し
14199                 [18, 53]
Room
17389         [10749, 16, 18]
君の名は。
17396         [18, 36, 10752]                                    Hacksaw
Ridge
17402           [9648, 80, 53]
```

```
Contratiempo
17407                 [18, 53]
Room
17429                     [18]
Lion
17466          [53, 18, 10749]
아가씨
20626          [16, 10751, 14]                                        千
と千尋の神隠し
20632          [10749, 16, 18]
君の名は。
20635  [16, 10751, 35, 12, 14]
Coco
20643          [18, 36, 10752]                                   Hacksaw
Ridge
20659           [9648, 80, 53]
Contratiempo
20660              [10749, 18]                              Call Me by
Your Name
20662              [18, 10751]
Wonder
20673                 [80, 18]     Three Billboards Outside Ebbing,
Missouri
20677                     [18]
Lion
20743          [18, 16, 10749]
聲の形
20857           [16, 18, 9648]                                    Loving
Vincent
23811             [12, 28, 14]                                Avengers:
Infinity War
23812    [28, 12, 16, 878, 35]             Spider-Man: Into the
Spider-Verse
23825              [18, 10402]                                 Bohemian
Rhapsody
23827                 [18, 35]
Green Book
23859  [16, 10751, 35, 12, 14]
Coco
23861          [18, 36, 10752]
Schindler's List
23865          [14, 16, 10751]
となりのトトロ
23896              [10749, 18]                              Call Me by
Your Name
23903              [18, 10751]
Wonder
23922                 [80, 18]     Three Billboards Outside Ebbing,
Missouri
```

```
23970           [35, 18, 10749]                                              Love,
Simon
24000               [35, 10749]                                         Some Like
It Hot
24169            [16, 18, 9648]                                           Loving
Vincent
24231                      [18]                                          Sulla mia
pelle
24268                  [14, 18]                                      Det sjunde
inseglet
```

```
       popularity release_date  vote_average  vote_count
4          27.920   2010-07-16           8.3       22186
19         18.060   2010-02-18           8.1       12625
43         14.200   1959-03-18           8.2        1562
180         8.973   2010-09-04           8.1        1034
2471       29.206   2011-07-15           8.1       11567
2472       28.583   1994-06-23           8.2       10160
2485       18.013   1997-12-05           8.1        5764
2511       15.013   2011-11-02           8.2        9940
2552       12.598   2011-08-10           8.1        3944
5201       17.717   1984-06-01           8.4        2243
5423        7.606   2012-11-02           8.1        1125
7971       12.316   2013-11-26           8.2        1056
11026      33.078   2014-12-19           8.1       10396
11031      28.784   2014-10-10           8.4        7908
11032      28.440   2014-11-05           8.2       18597
11142      11.095   2014-08-29           8.3        1399
14173      32.043   2002-09-20           8.5        7424
14199      20.000   2015-10-16           8.1        5494
17389      28.238   2017-04-07           8.6        4161
17396      24.074   2016-11-04           8.1        6608
17402      21.087   2016-09-22           8.2        1673
17407      20.000   2015-10-16           8.1        5494
17429      17.216   2016-11-25           8.1        3833
17466      14.374   2016-10-21           8.3        1213
20626      32.043   2002-09-20           8.5        7424
20632      28.238   2017-04-07           8.6        4161
20635      25.961   2017-11-22           8.2        8669
20643      24.074   2016-11-04           8.1        6608
20659      21.087   2016-09-22           8.2        1673
20660      20.504   2017-11-24           8.3        4957
20662      20.101   2017-11-17           8.2        3959
20673      17.808   2017-11-10           8.2        5432
20677      17.216   2016-11-25           8.1        3833
20743      13.187   2017-10-20           8.3        1034
20857      10.025   2017-09-22           8.2        1200
23811      80.773   2018-04-27           8.3       13948
23812      60.534   2018-12-14           8.4        4048
```

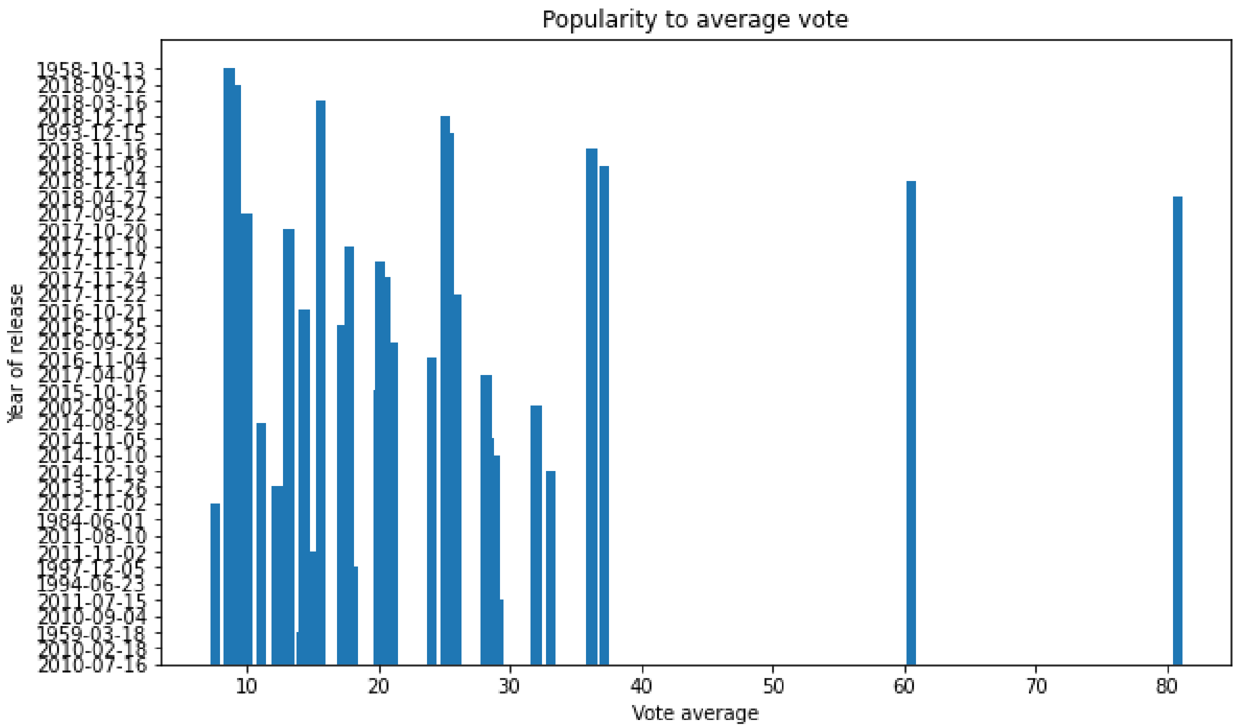
```
23825      37.197   2018-11-02          8.1         7629
23827      36.284   2018-11-16          8.3         3499
23859      25.961   2017-11-22          8.2         8669
23861      25.334   1993-12-15          8.5         8065
23865      25.068   2018-12-11          8.1         3267
23896      20.504   2017-11-24          8.3         4957
23903      20.101   2017-11-17          8.2         3959
23922      17.808   2017-11-10          8.2         5432
23970      15.608   2018-03-16          8.2         3165
24000      14.200   1959-03-18          8.2         1562
24169      10.025   2017-09-22          8.2         1200
24231       9.161   2018-09-12          8.2         1078
24268       8.693   1958-10-13          8.2         1163
```

Data Analysis

This involves plotting graphs to show relationship between the data.

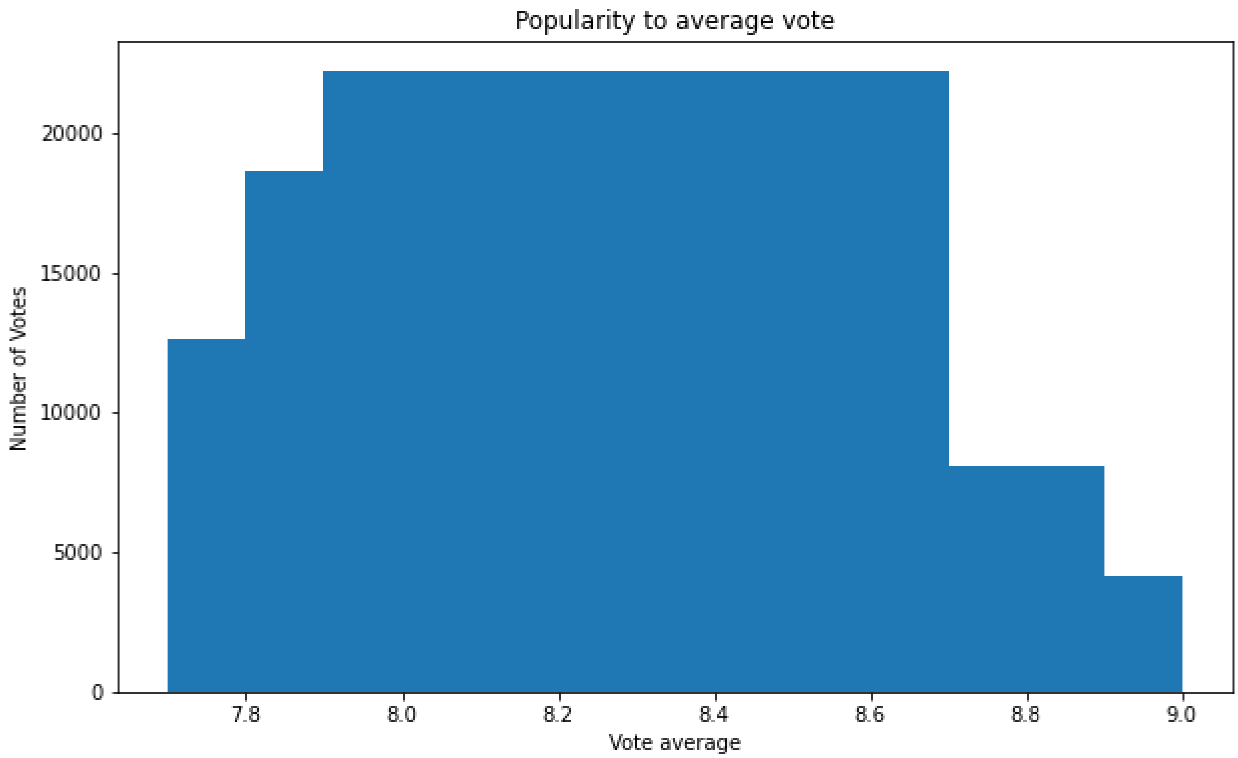
```
tmdb_figure, ax = plt.subplots(figsize=(10,6))
y = df_tmdb['release_date']
x = df_tmdb['popularity']

ax.bar(x,y)
ax.set_title("Popularity to average vote")
ax.set_xlabel('Vote average')
ax.set_ylabel('Year of release')
plt.show()
```




```
tmdb_figure, ax = plt.subplots(figsize=(10,6))
x = df_tmdb['vote_average']
y = df_tmdb['vote_count']

ax.bar(x,y)
ax.set_title("Popularity to average vote")
ax.set_xlabel('Vote average')
ax.set_ylabel('Number of Votes')
plt.show()
```



Conclusion

The analysis leads to the following recomendations;

1. On the genre of movie we can first release:
    a. Documentary,Music,Sport
    b. Documentary,Music,War
    c. Documentary
    d. Comedy,Music,Musical
    e. Adventure,Drama,War
    f. Drama,Family,Musical as per data from im.db database
2. That ratings generated depended on the number of people that voted and as such data with high number of votes and a high rating were considered in the analysis.
3. Apart from the two year in the 90s most of the recent movies were also popular and thus indicated that there are still people that watch movies.

Next step

Further analysis could help in identifying:

1. Best time for a movie to be released by the studio.This could use data from the box office to know period that movies are watched alot.
2. Predict revenue that can be made from the box office after release of the movie. This could help inform or change the approach used in advertising or promoting the movie.