Movie_wyq

June 30, 2022

[1]:
```
# load packages
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from datetime import datetime
```

1 Data Exploration

[2]:
```
# load two csv files
credit = pd.read_csv('./movie/tmdb_5000_credits.csv')
movie = pd.read_csv('./movie/tmdb_5000_movies.csv')
```

[3]:
```
credit.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 4803 entries, 0 to 4802
Data columns (total 4 columns):
 #   Column    Non-Null Count  Dtype 
---  ------    --------------  ----- 
 0   movie_id  4803 non-null   int64 
 1   title     4803 non-null   object
 2   cast      4803 non-null   object
 3   crew      4803 non-null   object
dtypes: int64(1), object(3)
memory usage: 150.2+ KB
```

[4]:
```
credit.head(5)
```

[4]:

	movie_id	title	cast	\
0	19995	Avatar		
1	285	Pirates of the Caribbean: At World's End		
2	206647	Spectre		
3	49026	The Dark Knight Rises		
4	49529	John Carter		

```
0  [{"cast_id": 242, "character": "Jake Sully", "…
1  [{"cast_id": 4, "character": "Captain Jack Spa…
2  [{"cast_id": 1, "character": "James Bond", "cr…
3  [{"cast_id": 2, "character": "Bruce Wayne / Ba…
4  [{"cast_id": 5, "character": "John Carter", "c…

                                                crew
0  [{"credit_id": "52fe48009251416c750aca23", "de…
1  [{"credit_id": "52fe4232c3a36847f800b579", "de…
2  [{"credit_id": "54805967c3a36829b5002c41", "de…
3  [{"credit_id": "52fe4781c3a36847f81398c3", "de…
4  [{"credit_id": "52fe479ac3a36847f813eaa3", "de…
```

From the first 5 rows of credit table, we found that some variables are lists. We need to extract useful variables from those lists.

[5]:
```
movie.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 4803 entries, 0 to 4802
Data columns (total 20 columns):
 #   Column                Non-Null Count  Dtype
---  ------                --------------  -----
 0   budget                4803 non-null   int64
 1   genres                4803 non-null   object
 2   homepage              1712 non-null   object
 3   id                    4803 non-null   int64
 4   keywords              4803 non-null   object
 5   original_language     4803 non-null   object
 6   original_title        4803 non-null   object
 7   overview              4800 non-null   object
 8   popularity            4803 non-null   float64
 9   production_companies  4803 non-null   object
 10  production_countries  4803 non-null   object
 11  release_date          4802 non-null   object
 12  revenue               4803 non-null   int64
 13  runtime               4801 non-null   float64
 14  spoken_languages      4803 non-null   object
 15  status                4803 non-null   object
 16  tagline               3959 non-null   object
 17  title                 4803 non-null   object
 18  vote_average          4803 non-null   float64
 19  vote_count            4803 non-null   int64
dtypes: float64(3), int64(4), object(13)
memory usage: 750.6+ KB
```

[6]:
```
movie.head(5)
```

[6]:

	budget	genres	homepage	id	keywords	original_language	original_title	overview	popularity	production_companies	production_countries	release_date	revenue
0	237000000	[{"id": 28, "name": "Action"}, {"id": 12, "nam…	http://www.avatarmovie.com/	19995	[{"id": 1463, "name": "culture clash"}, {"id":…	en	Avatar	In the 22nd century, a paraplegic Marine is di…	150.437577	[{"name": "Ingenious Film Partners", "id": 289…	[{"iso_3166_1": "US", "name": "United States o…	2009-12-10	2787965087
1	300000000	[{"id": 12, "name": "Adventure"}, {"id": 14, "…	http://disney.go.com/disneypictures/pirates/	285	[{"id": 270, "name": "ocean"}, {"id": 726, "na…	en	Pirates of the Caribbean: At World's End	Captain Barbossa, long believed to be dead, ha…	139.082615	[{"name": "Walt Disney Pictures", "id": 2}, {"…	[{"iso_3166_1": "US", "name": "United States o…	2007-05-19	961000000
2	245000000	[{"id": 28, "name": "Action"}, {"id": 12, "nam…	http://www.sonypictures.com/movies/spectre/	206647	[{"id": 470, "name": "spy"}, {"id": 818, "name…	en	Spectre	A cryptic message from Bond’s past sends him o…	107.376788	[{"name": "Columbia Pictures", "id": 5}, {"nam…	[{"iso_3166_1": "GB", "name": "United Kingdom"…	2015-10-26	880674609
3	250000000	[{"id": 28, "name": "Action"}, {"id": 80, "nam…	http://www.thedarkknightrises.com/	49026	[{"id": 849, "name": "dc comics"}, {"id": 853,…	en	The Dark Knight Rises	Following the death of District Attorney Harve…	112.312950	[{"name": "Legendary Pictures", "id": 923}, {"…	[{"iso_3166_1": "US", "name": "United States o…	2012-07-16	1084939099
4	260000000	[{"id": 28, "name": "Action"}, {"id": 12, "nam…	http://movies.disney.com/john-carter	49529	[{"id": 818, "name": "based on novel"}, {"id":…	en	John Carter	John Carter is a war-weary, former military ca…	43.926995	[{"name": "Walt Disney Pictures", "id": 2}]			

```
4  [{"iso_3166_1": "US", "name": "United States o…   2012-03-07   284139100

   runtime                                  spoken_languages    status  \
0    162.0  [{"iso_639_1": "en", "name": "English"}, {"iso…  Released
1    169.0           [{"iso_639_1": "en", "name": "English"}]  Released
2    148.0  [{"iso_639_1": "fr", "name": "Fran\u00e7ais"},…  Released
3    165.0           [{"iso_639_1": "en", "name": "English"}]  Released
4    132.0           [{"iso_639_1": "en", "name": "English"}]  Released

                                      tagline  \
0                    Enter the World of Pandora.
1  At the end of the world, the adventure begins.
2                          A Plan No One Escapes
3                               The Legend Ends
4           Lost in our world, found in another.

                                  title  vote_average  vote_count
0                                Avatar           7.2       11800
1  Pirates of the Caribbean: At World's End           6.9        4500
2                               Spectre           6.3        4466
3                The Dark Knight Rises           7.6        9106
4                           John Carter           6.1        2124
```

Observing 5 rows of movie table, we need to split genres and drop irrelevant columns.

2 Data Cleaning

2.1 merge two table on movie id

[7]:
```
movie = movie.rename(columns={"id":"movie_id"})
```

[8]:
```
# merge two dataset with their common column
raw_df = pd.merge(movie, credit, on = 'movie_id')
raw_df.head()
```

[8]:
```
      budget                                             genres  \
0  237000000  [{"id": 28, "name": "Action"}, {"id": 12, "nam…
1  300000000  [{"id": 12, "name": "Adventure"}, {"id": 14, "…
2  245000000  [{"id": 28, "name": "Action"}, {"id": 12, "nam…
3  250000000  [{"id": 28, "name": "Action"}, {"id": 80, "nam…
4  260000000  [{"id": 28, "name": "Action"}, {"id": 12, "nam…

                                    homepage  movie_id  \
0                http://www.avatarmovie.com/     19995
1  http://disney.go.com/disneypictures/pirates/       285
2   http://www.sonypictures.com/movies/spectre/    206647
3           http://www.thedarkknightrises.com/     49026
```

```
4          http://movies.disney.com/john-carter     49529

                                              keywords original_language  \
0  [{"id": 1463, "name": "culture clash"}, {"id":…                en
1  [{"id": 270, "name": "ocean"}, {"id": 726, "na…                en
2  [{"id": 470, "name": "spy"}, {"id": 818, "name…                en
3  [{"id": 849, "name": "dc comics"}, {"id": 853,…                en
4  [{"id": 818, "name": "based on novel"}, {"id":…                en

                            original_title  \
0                                   Avatar
1  Pirates of the Caribbean: At World's End
2                                  Spectre
3                    The Dark Knight Rises
4                               John Carter

                                              overview  popularity  \
0  In the 22nd century, a paraplegic Marine is di…  150.437577
1  Captain Barbossa, long believed to be dead, ha…  139.082615
2  A cryptic message from Bond’s past sends him o…  107.376788
3  Following the death of District Attorney Harve…  112.312950
4  John Carter is a war-weary, former military ca…   43.926995

                                production_companies  … runtime  \
0  [{"name": "Ingenious Film Partners", "id": 289…  …   162.0
1  [{"name": "Walt Disney Pictures", "id": 2}, {"…  …   169.0
2  [{"name": "Columbia Pictures", "id": 5}, {"nam…  …   148.0
3  [{"name": "Legendary Pictures", "id": 923}, {"…  …   165.0
4        [{"name": "Walt Disney Pictures", "id": 2}]  …   132.0

                                     spoken_languages    status  \
0  [{"iso_639_1": "en", "name": "English"}, {"iso…  Released
1           [{"iso_639_1": "en", "name": "English"}]  Released
2  [{"iso_639_1": "fr", "name": "Fran\u00e7ais"},…  Released
3           [{"iso_639_1": "en", "name": "English"}]  Released
4           [{"iso_639_1": "en", "name": "English"}]  Released

                                        tagline  \
0                    Enter the World of Pandora.
1  At the end of the world, the adventure begins.
2                          A Plan No One Escapes
3                               The Legend Ends
4            Lost in our world, found in another.

                                     title_x vote_average vote_count  \
0                                     Avatar          7.2      11800
1  Pirates of the Caribbean: At World's End          6.9       4500
```

```
2                                    Spectre          6.3       4466
3                      The Dark Knight Rises          7.6       9106
4                                 John Carter          6.1       2124

                                      title_y  \
0                                      Avatar
1  Pirates of the Caribbean: At World's End
2                                    Spectre
3                      The Dark Knight Rises
4                                 John Carter

                                                  cast  \
0  [{"cast_id": 242, "character": "Jake Sully", "…
1  [{"cast_id": 4, "character": "Captain Jack Spa…
2  [{"cast_id": 1, "character": "James Bond", "cr…
3  [{"cast_id": 2, "character": "Bruce Wayne / Ba…
4  [{"cast_id": 5, "character": "John Carter", "c…

                                                  crew
0  [{"credit_id": "52fe48009251416c750aca23", "de…
1  [{"credit_id": "52fe4232c3a36847f800b579", "de…
2  [{"credit_id": "54805967c3a36829b5002c41", "de…
3  [{"credit_id": "52fe4781c3a36847f81398c3", "de…
4  [{"credit_id": "52fe479ac3a36847f813eaa3", "de…

[5 rows x 23 columns]
```

[9]:
```
raw_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 4803 entries, 0 to 4802
Data columns (total 23 columns):
 #   Column                Non-Null Count  Dtype
---  ------                --------------  -----
 0   budget                4803 non-null   int64
 1   genres                4803 non-null   object
 2   homepage              1712 non-null   object
 3   movie_id              4803 non-null   int64
 4   keywords              4803 non-null   object
 5   original_language     4803 non-null   object
 6   original_title        4803 non-null   object
 7   overview              4800 non-null   object
 8   popularity            4803 non-null   float64
 9   production_companies  4803 non-null   object
 10  production_countries  4803 non-null   object
 11  release_date          4802 non-null   object
 12  revenue               4803 non-null   int64
```

```
 13  runtime               4801 non-null   float64
 14  spoken_languages      4803 non-null   object
 15  status                4803 non-null   object
 16  tagline               3959 non-null   object
 17  title_x               4803 non-null   object
 18  vote_average          4803 non-null   float64
 19  vote_count            4803 non-null   int64
 20  title_y               4803 non-null   object
 21  cast                  4803 non-null   object
 22  crew                  4803 non-null   object
dtypes: float64(3), int64(4), object(16)
memory usage: 900.6+ KB
```

[10]:
```
movie.shape, credit.shape, raw_df.shape
```

[10]:
```
((4803, 20), (4803, 4), (4803, 23))
```

From the statistics information above, we have 4803 observations of 23 variables. We also acquire the data type of each factor.

2.2 Handle Json Columns

There are 6 variables which are list type. We use convert function to split and extract useful information from them.

[11]:
```
json_cols = ['genres', 'keywords',␣
 ↪'production_companies','production_countries',
            'spoken_languages','cast', 'crew']
raw_df[json_cols].head()
```

[11]:
```
                                              genres  \
0  [{"id": 28, "name": "Action"}, {"id": 12, "nam…
1  [{"id": 12, "name": "Adventure"}, {"id": 14, "…
2  [{"id": 28, "name": "Action"}, {"id": 12, "nam…
3  [{"id": 28, "name": "Action"}, {"id": 80, "nam…
4  [{"id": 28, "name": "Action"}, {"id": 12, "nam…

                                            keywords  \
0  [{"id": 1463, "name": "culture clash"}, {"id":…
1  [{"id": 270, "name": "ocean"}, {"id": 726, "na…
2  [{"id": 470, "name": "spy"}, {"id": 818, "name…
3  [{"id": 849, "name": "dc comics"}, {"id": 853,…
4  [{"id": 818, "name": "based on novel"}, {"id":…

                                production_companies  \
0  [{"name": "Ingenious Film Partners", "id": 289…
1  [{"name": "Walt Disney Pictures", "id": 2}, {"…
2  [{"name": "Columbia Pictures", "id": 5}, {"nam…
```

```
3  [{"name": "Legendary Pictures", "id": 923}, {"…
4        [{"name": "Walt Disney Pictures", "id": 2}]

                                production_countries  \
0  [{"iso_3166_1": "US", "name": "United States o…
1  [{"iso_3166_1": "US", "name": "United States o…
2  [{"iso_3166_1": "GB", "name": "United Kingdom"…
3  [{"iso_3166_1": "US", "name": "United States o…
4  [{"iso_3166_1": "US", "name": "United States o…

                                   spoken_languages  \
0  [{"iso_639_1": "en", "name": "English"}, {"iso…
1           [{"iso_639_1": "en", "name": "English"}]
2  [{"iso_639_1": "fr", "name": "Fran\u00e7ais"},…
3           [{"iso_639_1": "en", "name": "English"}]
4           [{"iso_639_1": "en", "name": "English"}]

                                               cast  \
0  [{"cast_id": 242, "character": "Jake Sully", "…
1  [{"cast_id": 4, "character": "Captain Jack Spa…
2  [{"cast_id": 1, "character": "James Bond", "cr…
3  [{"cast_id": 2, "character": "Bruce Wayne / Ba…
4  [{"cast_id": 5, "character": "John Carter", "c…

                                               crew
0  [{"credit_id": "52fe48009251416c750aca23", "de…
1  [{"credit_id": "52fe4232c3a36847f800b579", "de…
2  [{"credit_id": "54805967c3a36829b5002c41", "de…
3  [{"credit_id": "52fe4781c3a36847f81398c3", "de…
4  [{"credit_id": "52fe479ac3a36847f813eaa3", "de…
```

[12]:
```
import ast
```

[13]:
```
raw_df.genres[0]
```

[13]:
```
'[{"id": 28, "name": "Action"}, {"id": 12, "name": "Adventure"}, {"id": 14,
"name": "Fantasy"}, {"id": 878, "name": "Science Fiction"}]'
```

[14]:
```
def convert(data):
    result = []
    for i in ast.literal_eval(data):
        result.append(i['name'])
    return result
```

[15]:
```
raw_df['genres'] = raw_df['genres'].apply(convert)
raw_df['genres'].head()
```

[15]:
```
0    [Action, Adventure, Fantasy, Science Fiction]
1                      [Adventure, Fantasy, Action]
2                        [Action, Adventure, Crime]
3                  [Action, Crime, Drama, Thriller]
4              [Action, Adventure, Science Fiction]
Name: genres, dtype: object
```

[16]:
```
raw_df['keywords'] = raw_df['keywords'].apply(convert)
raw_df['production_companies'] = raw_df['production_companies'].apply(convert)
raw_df['production_countries'] = raw_df['production_countries'].apply(convert)
```

2.3 Preserve top 4 cast and the director from the cast list

[17]:
```
# extract top 4 cast
def top4_cast(data):
    cnt = 0
    result = []
    for i in ast.literal_eval(data ):
        if cnt<4:
            result.append(i['name'])
            cnt = cnt+1
        if cnt>4:
            break

    return result
```

[18]:
```
raw_df['cast'] = raw_df['cast'].apply(top4_cast )
```

[19]:
```
raw_df['cast'][0]
```

[19]:
```
['Sam Worthington', 'Zoe Saldana', 'Sigourney Weaver', 'Stephen Lang']
```

[20]:
```
# extract director from the cast
def director(data):
    for i in ast.literal_eval(data):
        if i['job'] == 'Director':
            return i['name']
```

[21]:
```
raw_df['Director'] = raw_df['crew'].apply(director)
raw_df['Director'].head()
```

[21]:
```
0        James Cameron
1       Gore Verbinski
2           Sam Mendes
3    Christopher Nolan
4       Andrew Stanton
Name: Director, dtype: object
```

2.4 Handle Missing Values

[22]:
```
raw_df.isnull().sum().sort_values(ascending=False)
```

[22]:
```
homepage                3091
tagline                  844
Director                  30
overview                   3
runtime                    2
release_date               1
spoken_languages           0
crew                       0
cast                       0
title_y                    0
vote_count                 0
vote_average               0
title_x                    0
status                     0
budget                     0
genres                     0
production_countries       0
production_companies       0
popularity                 0
original_title             0
original_language          0
keywords                   0
movie_id                   0
revenue                    0
dtype: int64
```

The table above shows the missing values in the table. Homepage, tagline, and overview are not helpful for our data analysis. So we dropped them. title_x and title_y are duplicated by selecting one of them and removing the other one. The unknown release_date is made today and the missing value of runtime is filled with the median.

[23]:
```
raw_df.drop(['homepage' , 'tagline', 'overview','title_x'] , axis = 1 , inplace␣
↪= True)
raw_df = raw_df.rename(columns={'title_y':'title'})
```

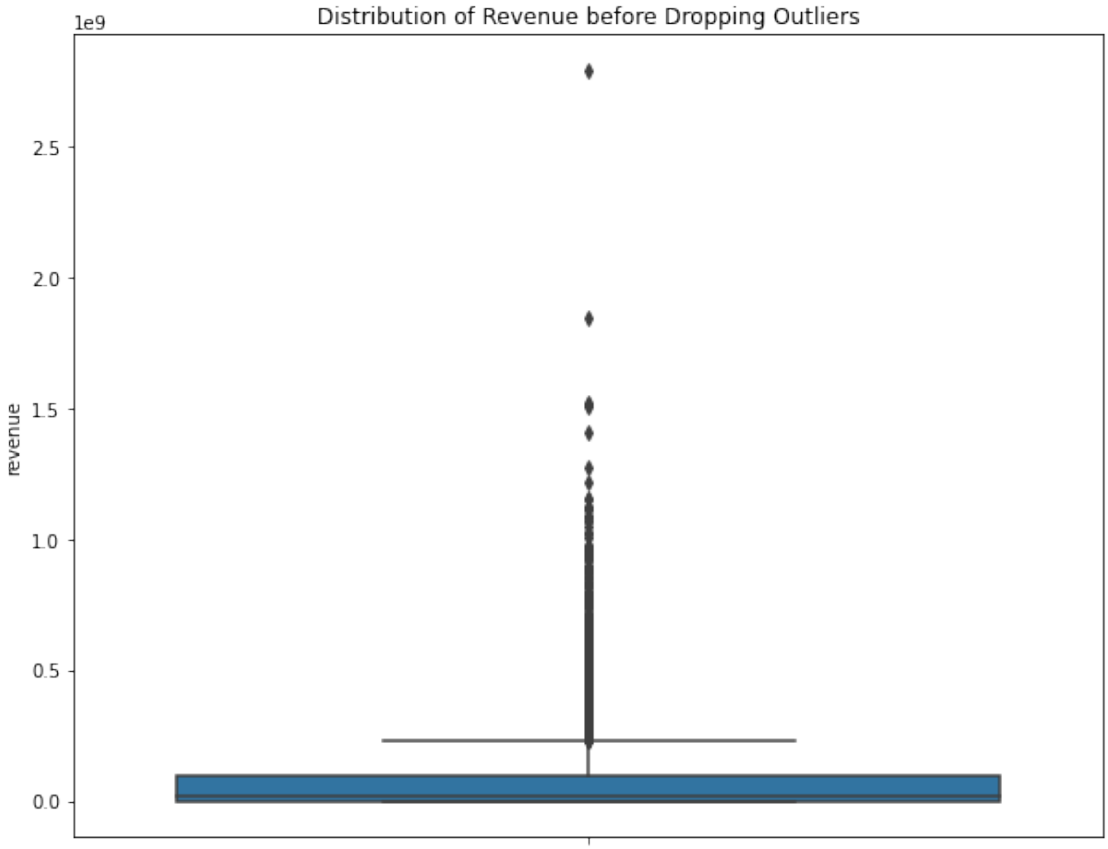
[24]:
```
raw_df['release_date'].fillna(datetime.today().strftime('%m/%d/%Y'),␣
↪inplace=True)
```

[25]:
```
raw_df['runtime'].fillna(raw_df['runtime'].median(), inplace=True)
```

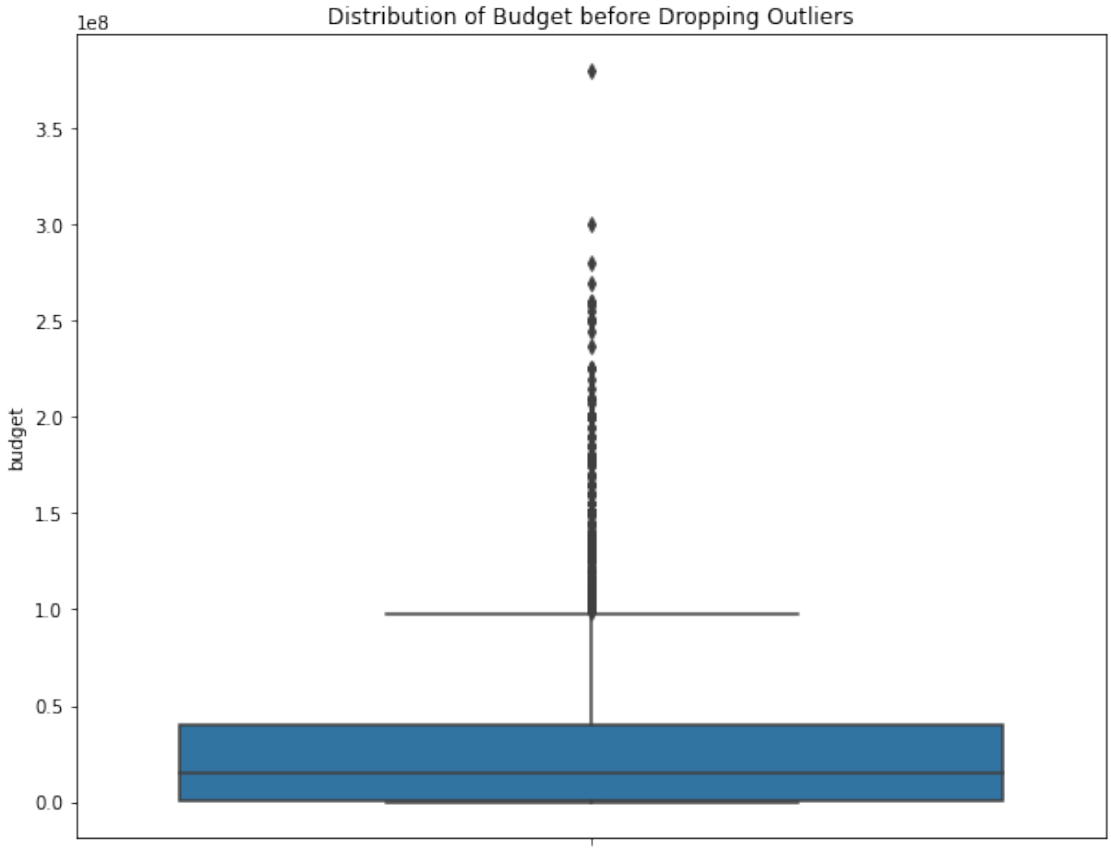
2.5 Handle Outliers

In this dataset, revenue is the target variable and budget is an important factor. So we draw distribution of the revenue and budget to check if there are outliers.

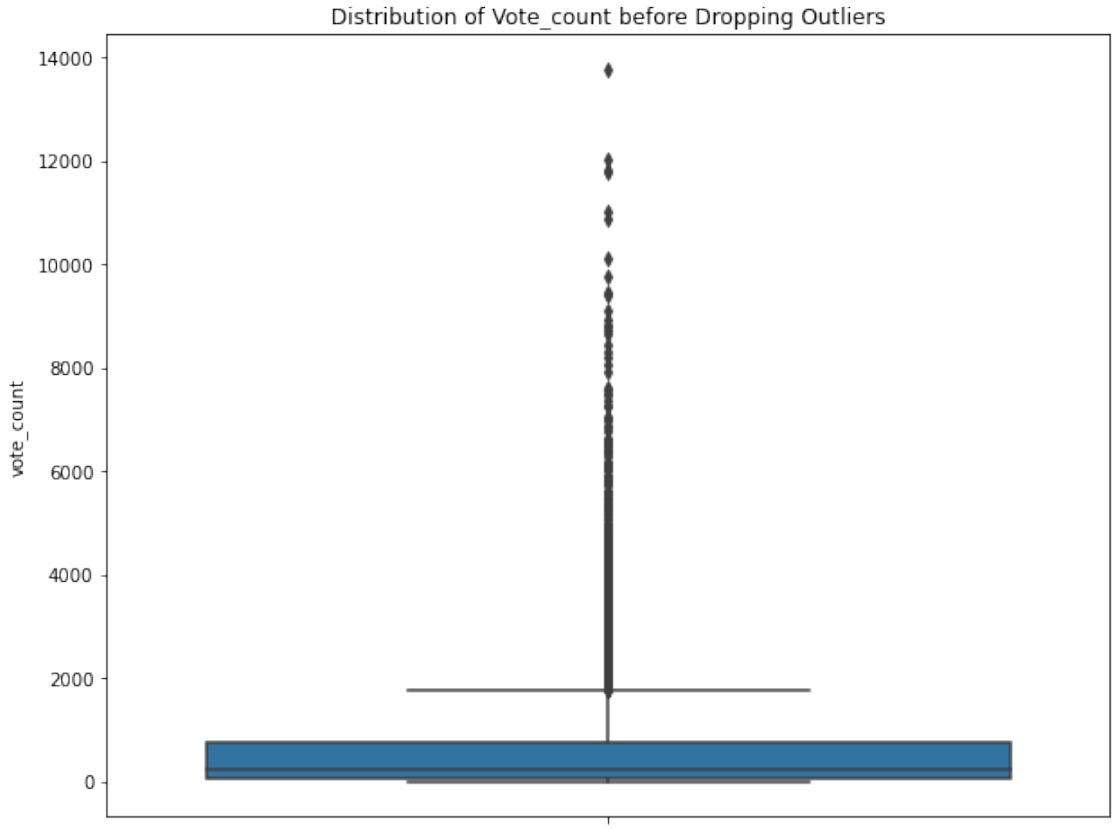
[26]:
```
plt.figure(figsize=(10,8))
sns.boxplot(y=raw_df['revenue'])
plt.title('Distribution of Revenue before Dropping Outliers')
plt.show()
```



[27]:
```
plt.figure(figsize=(10,8))
sns.boxplot(y=raw_df['budget'])
plt.title('Distribution of Budget before Dropping Outliers')
plt.show()
```



[28]:
```
plt.figure(figsize=(10,8))
sns.boxplot(y=raw_df['vote_count'])
plt.title('Distribution of Vote_count before Dropping Outliers')
plt.show()
```

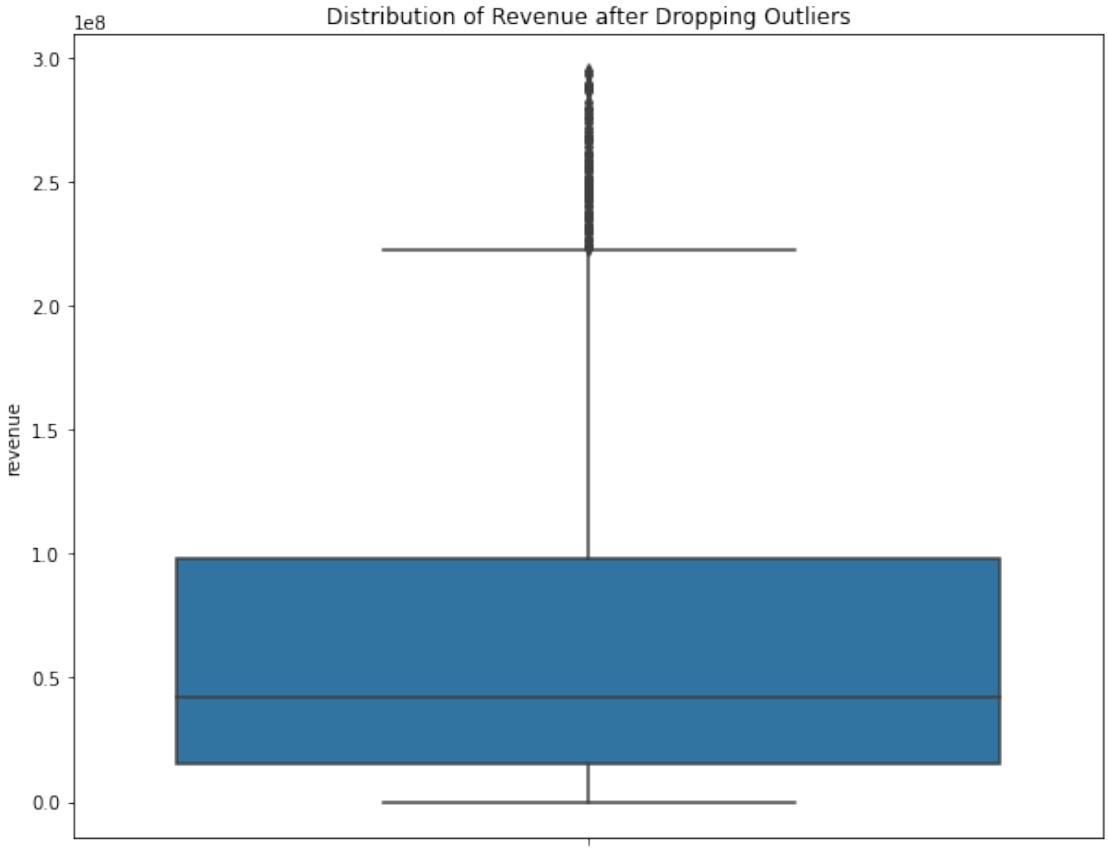


Two figures above show that most of revenue and budget of movies are under 500,000,000 and 100,000,000. However there are many outliers need to be dropped. So, we determined that the value higher than 95% and lower than 5% are outliers.

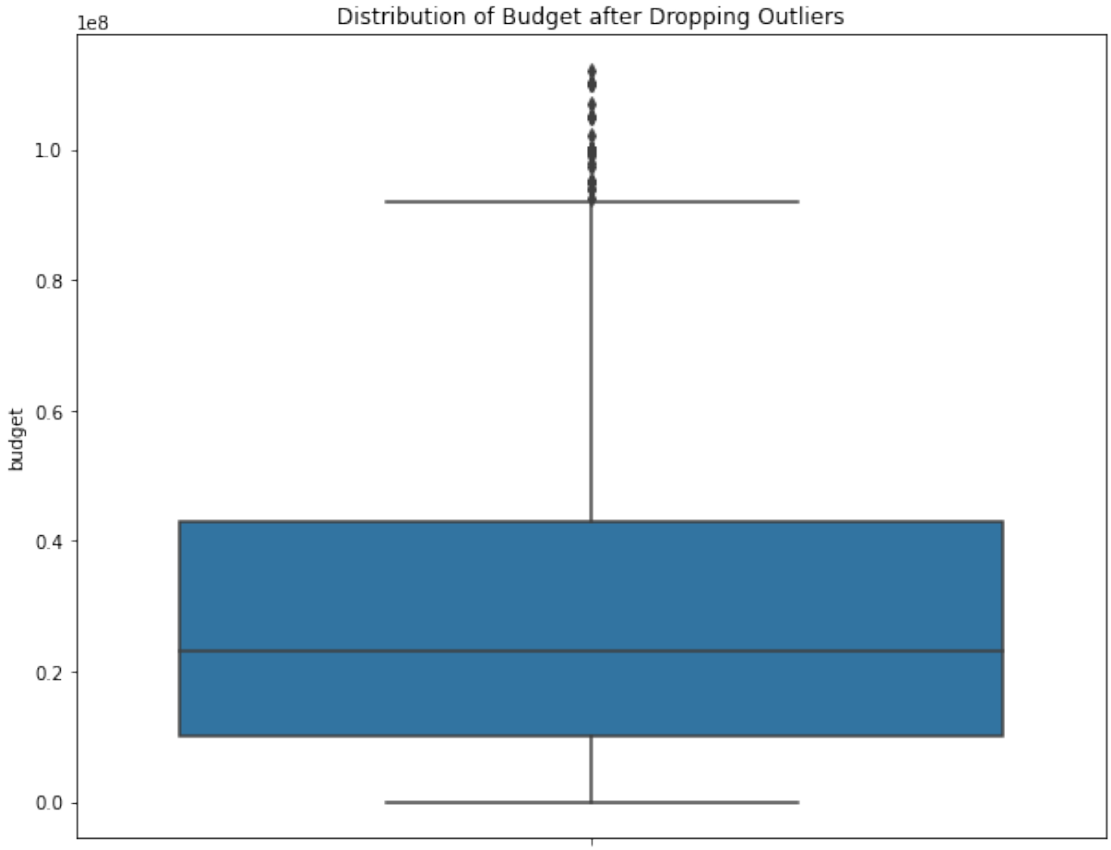
[29]:
```
def outlier(df, cname):
    maxthresold = df[cname].quantile(0.95)
    minthresold = df[cname].quantile(0.05)
    df = df[(df[cname]<maxthresold) & (df[cname]>minthresold)]
    return df
```

[30]:
```
for i in ['budget', 'revenue', 'vote_count']:
    raw_df = outlier(raw_df, i)
```

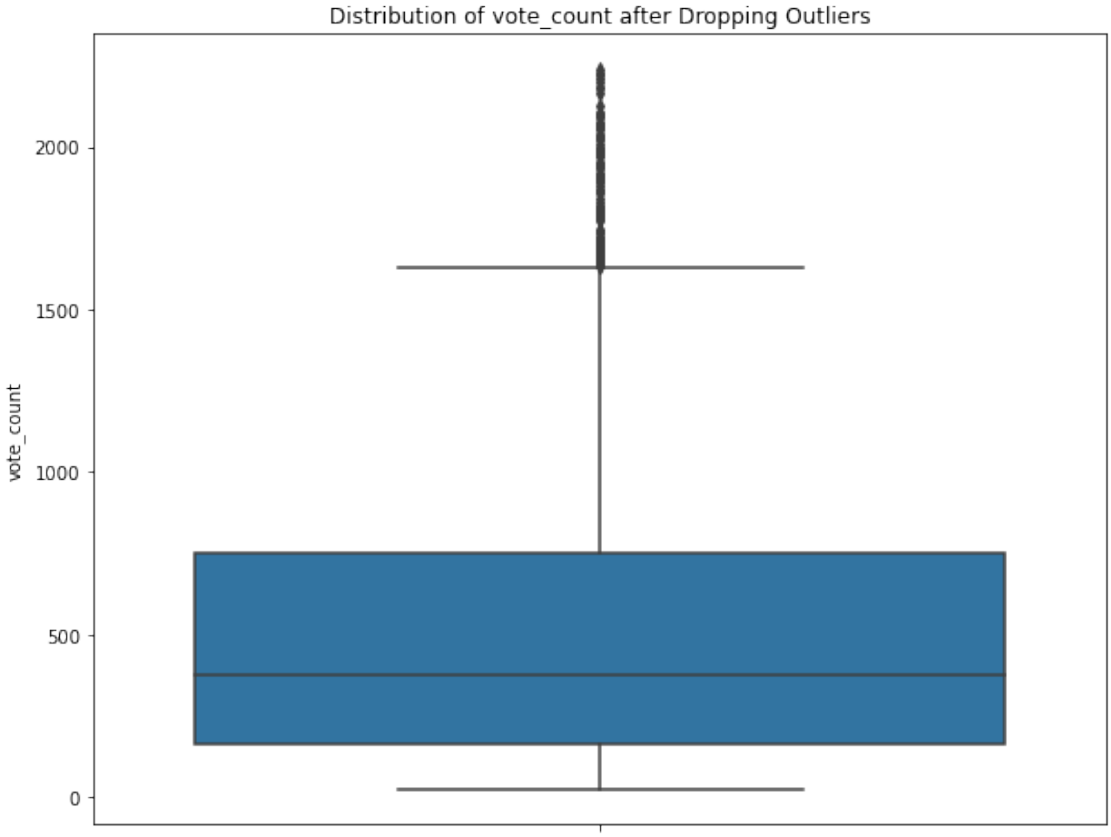
[31]:
```
plt.figure(figsize=(10,8))
sns.boxplot(y=raw_df['revenue'])
plt.title('Distribution of Revenue after Dropping Outliers')
plt.show()
```



[32]:
```
plt.figure(figsize=(10,8))
sns.boxplot(y=raw_df['budget'])
plt.title('Distribution of Budget after Dropping Outliers')
plt.show()
```



[33]:
```
plt.figure(figsize=(10,8))
sns.boxplot(y=raw_df['vote_count'])
plt.title('Distribution of vote_count after Dropping Outliers')
plt.show()
```



After dropping outliers, there only have less outlier which are acceptable. Make a copy of our cleaned data.

[34]:
```
data = raw_df.copy()
```

Now, we get the cleaned data.

3 Data Visualization

3.1 Release Date

We want to split release date into its year, month and day. Such that, we could count the number of movies released by day of week, month and year.

[35]:
```
data['release_date'].head()
```

[35]:
```
97     2016-07-29
151    2007-11-05
155    2005-12-21
188    2010-07-21
207    1990-06-01
```

```
Name: release_date, dtype: object
```

[36]:
```
data['release_date'] = pd.to_datetime(data['release_date'])
lst = ['year','month','weekday']
for i in lst:
    data[i] = getattr(data['release_date'].dt, i).astype('int')
data.head()
```

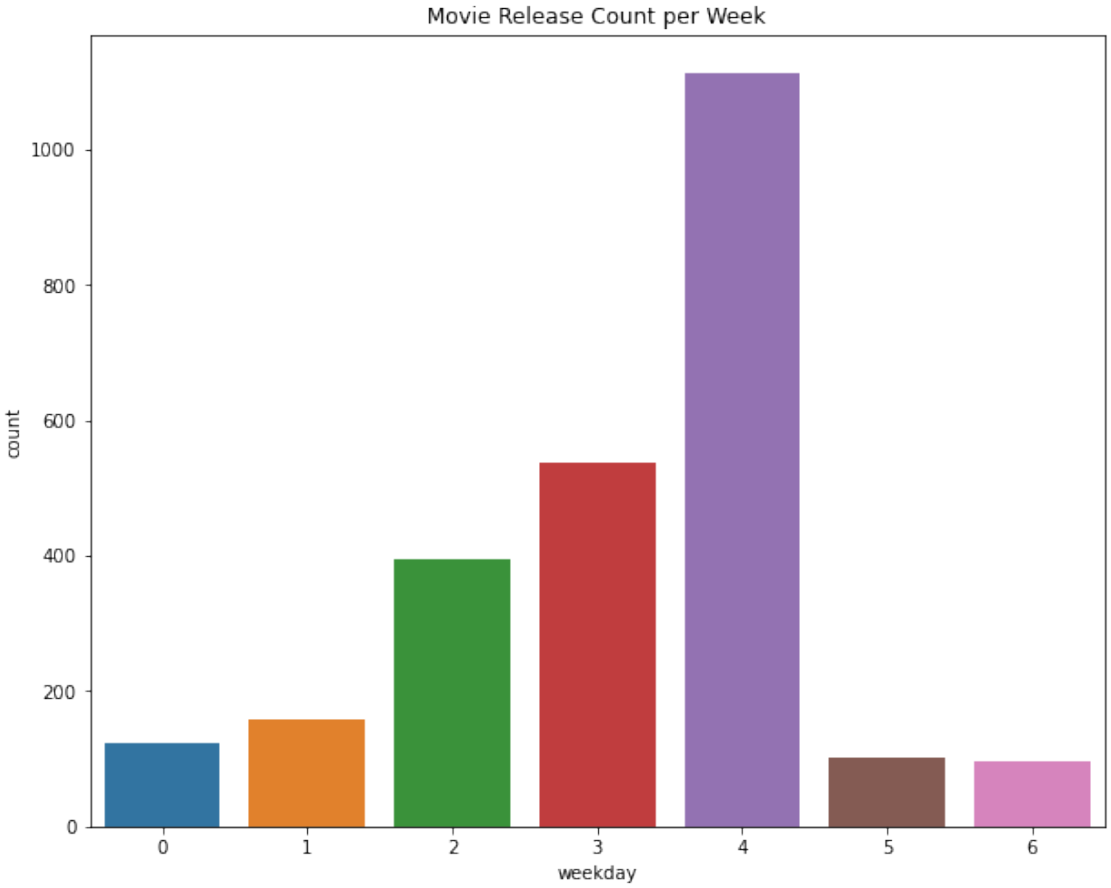
[36]:

	budget	genres	movie_id	keywords	original_language	original_title	popularity	production_companies	production_countries	release_date	…	status	vote_average	vote_count	title
97	15000000	[Action, Adventure, Drama, Horror, Science Fic…	315011	[monster, godzilla, giant monster, destruction…	ja		9.476999	[Cine Bazar, Toho Pictures]	[Japan]	2016-07-29	…	Released	6.5	143	Shin Godzilla
151	70000000	[Adventure, Action, Animation]	2310	[denmark, nordic mythology, lie, pride and van…	en	Beowulf	35.601665	[Paramount Pictures, Shangri-La Entertainment,…	[United States of America]	2007-11-05	…	Released	5.5	841	Beowulf
155	100000000	[Comedy]	7552	[based on novel, desperation, robber, hold-up …	en	Fun with Dick and Jane	25.159168	[Imagine Entertainment, Columbia Pictures Corp…	[United States of America]	2005-12-21	…	Released	5.9	627	Fun with Dick and Jane
188	110000000	[Action, Mystery, Thriller]	27576	[assassination, spy, cia, kidnapping, cold war…	en	Salt	48.829437	[Columbia Pictures, Di Bonaventura Pictures, R…	[United States of America]	2010-07-21	…	Released	6.2		
207	65000000	[Action, Adventure, Science Fiction]	861	[oxygen, falsely accused, resistance, mars, do…	en	Total Recall	43.129703	[TriStar Pictures, Carolco Pictures, Carolco I…	[United States of America]	1990-06-01	…	Released	7.1		

```
188       2093                     Salt
207       1710            Total Recall

                                                  cast  \
97   [Hiroki Hasegawa, Yutaka Takenouchi, Satomi Is…
151  [Ray Winstone, Angelina Jolie, Anthony Hopkins…
155  [Jim Carrey, Téa Leoni, Alec Baldwin, Richard …
188  [Angelina Jolie, Liev Schreiber, Chiwetel Ejio…
207  [Arnold Schwarzenegger, Sharon Stone, Rachel T…

                                                  crew         Director  year  \
97   [{"credit_id": "5921d321c3a368799b05933f", "de…     Hideaki Anno  2016
151  [{"credit_id": "52fe434cc3a36847f8049c1b", "de…  Robert Zemeckis  2007
155  [{"credit_id": "56757f0192514179d2002f80", "de…     Dean Parisot  2005
188  [{"credit_id": "536b7b400e0a2647c800c203", "de…    Phillip Noyce  2010
207  [{"credit_id": "52fe4283c3a36847f8024ec5", "de…   Paul Verhoeven  1990

    month weekday
97      7       4
151    11       0
155    12       2
188     7       2
207     6       4

[5 rows x 23 columns]
```

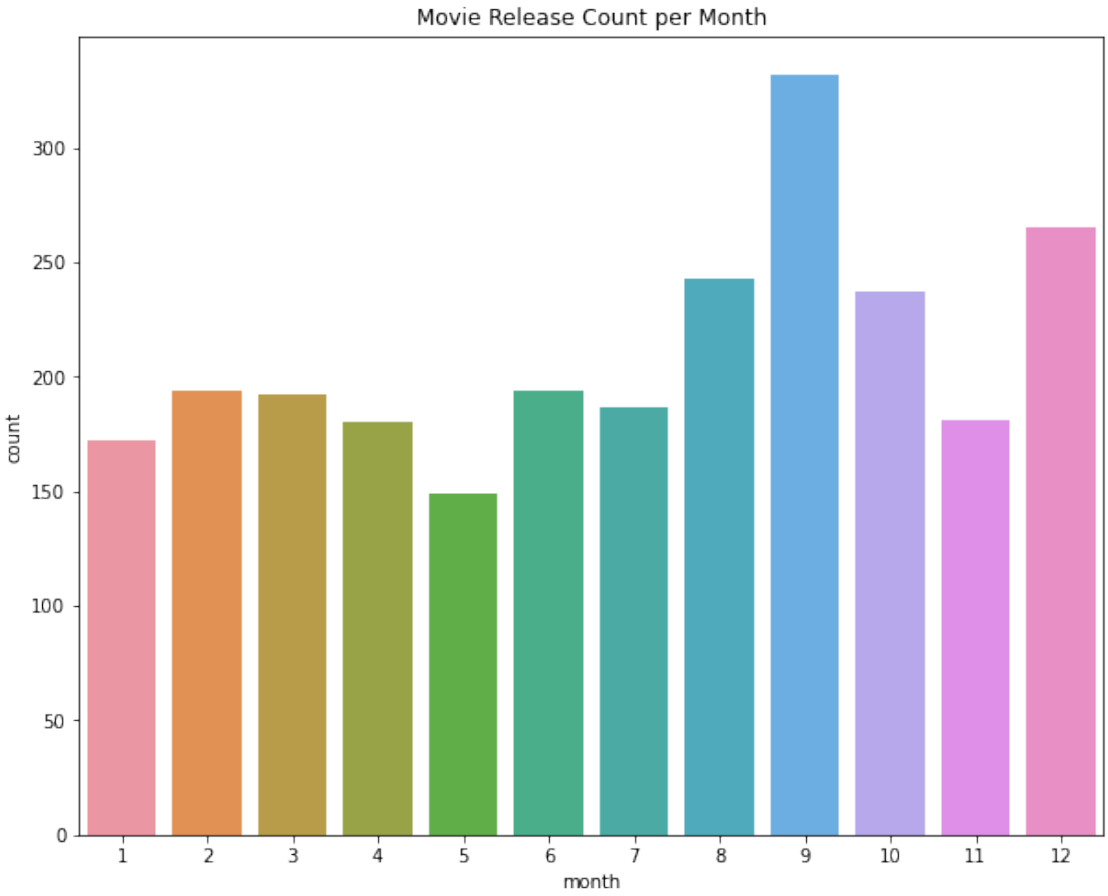
3.1.1 Movie Release Count per Week

[37]:
```
plt.figure(figsize = (10,8))
sns.countplot(x='weekday', data = data)
plt.title("Movie Release Count per Week")
plt.show()
```



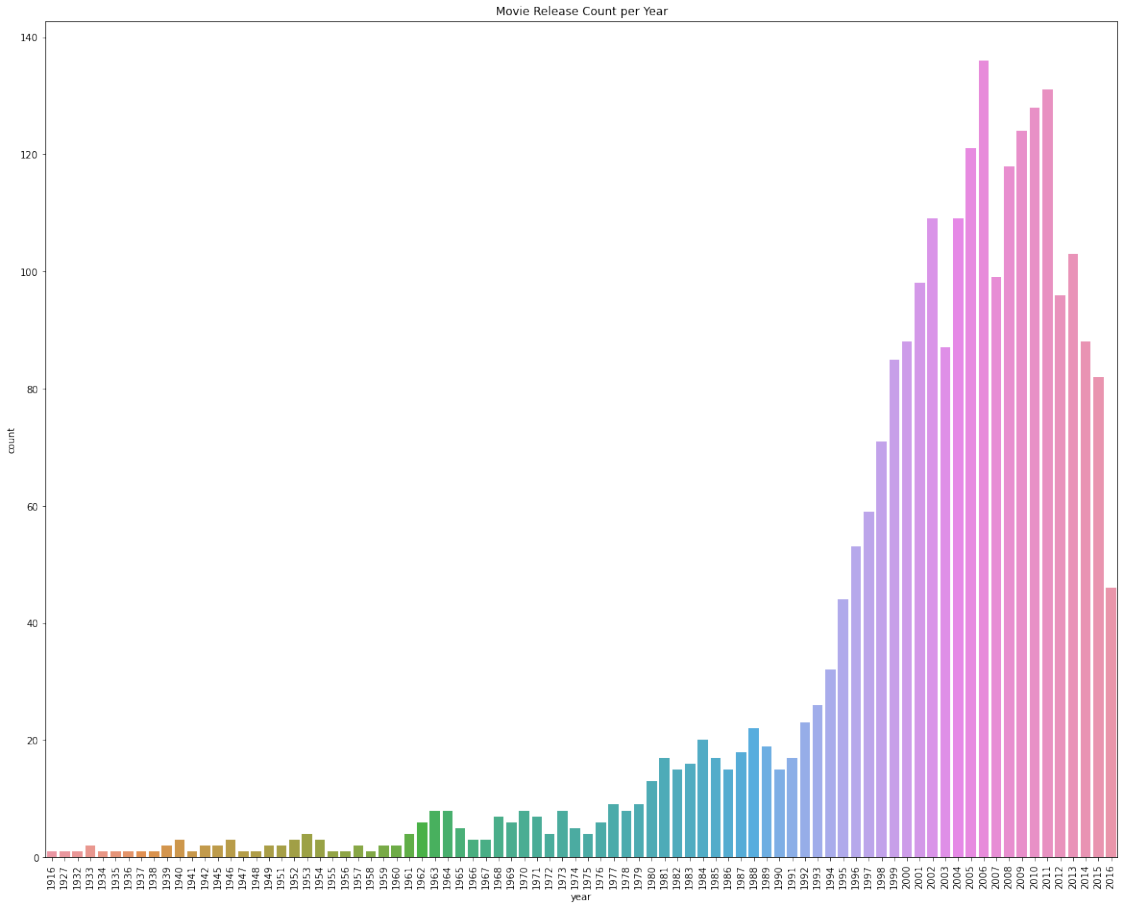
From the distribution of the movies release per week, we can find the most films released on Friday. This is followed by Thursdays and Wednesdays. Saturday and Sunday, on the contrary, have the least released movies.

[38]:
```
plt.figure(figsize = (10,8))
sns.countplot(x='month', data = data)
plt.title("Movie Release Count per Month")
plt.show()
```



From the monthly movie release distribution chart, we can see that the most movies were released in September while the least movies were released in May.

[39]:
```
plt.figure(figsize = (20,16))
sns.countplot(x='year', data = data)
plt.title("Movie Release Count per Year")
plt.xticks(rotation = 'vertical')
plt.show()
```

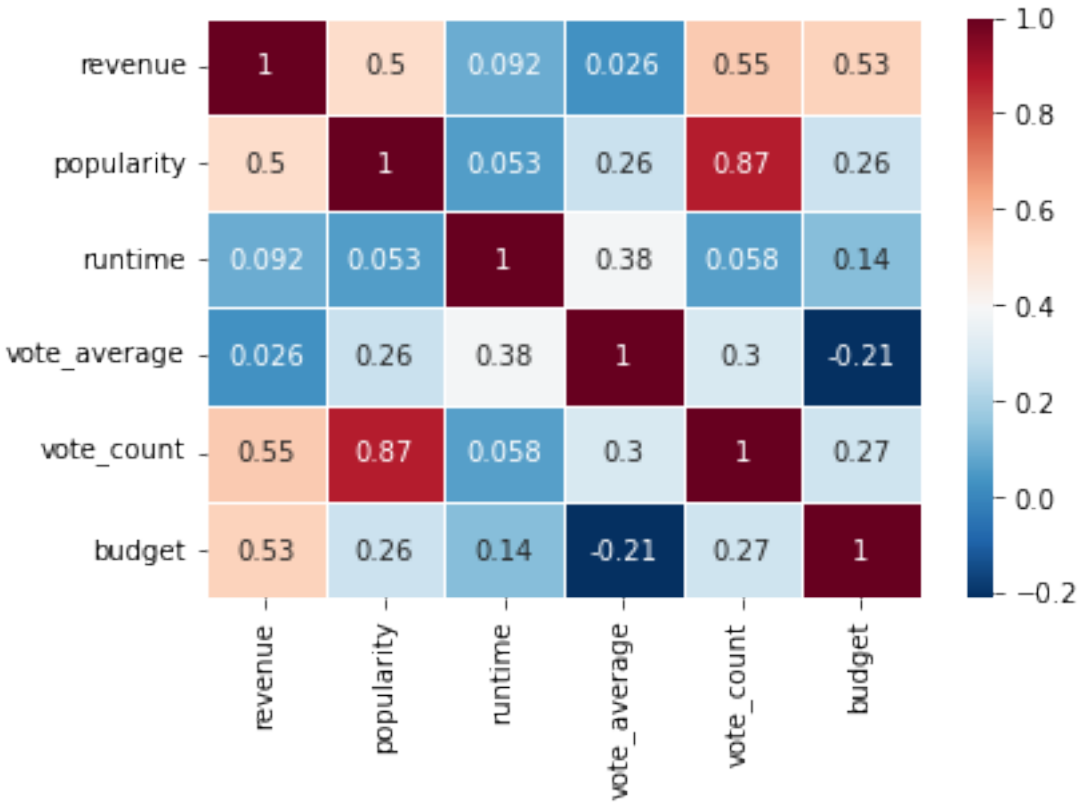


The annual distribution of movie releases illustrates that the earliest movie release recorded in the dataset was in 1916. There have been a small number of movie releases since then. It was not until after 1980 that the film industry came to a booming period. The number of movie releases increased dramatically. In the 21st century, the number of movie releases exploded even more, with as many as 150 movies released worldwide in a year.

3.1.2 Correlation Heatmap

[40]:
```
pearsoncorr = data.loc[:
  ↪,['revenue','popularity','runtime','vote_average','vote_count','budget']].
  ↪corr(method='pearson')
sns.heatmap( pearsoncorr,
             xticklabels=pearsoncorr.columns,
             yticklabels=pearsoncorr.columns,
             cmap='RdBu_r',
             annot=True,
             linewidth=0.5 )
```

[40]: <AxesSubplot:>



From the heatmap of the Pearson correlation, we could find that the budget has the most positive correlation. It indicates that the higher budget the movie input, the higher revenue the movie will get. Vote average has the least positive correlation with the revenue.

3.1.3 Genre Trend Shifting Patterns

[41]:
```
genres_df = data['genres'].apply(pd.Series)
genres_df.head()
```

[41]:

	0	1	2	3	4	5	6
97	Action	Adventure	Drama	Horror	Science Fiction	NaN	NaN
151	Adventure	Action	Animation	NaN	NaN	NaN	NaN
155	Comedy	NaN	NaN	NaN	NaN	NaN	NaN
188	Action	Mystery	Thriller	NaN	NaN	NaN	NaN
207	Action	Adventure	Science Fiction	NaN	NaN	NaN	NaN

[42]:
```
stacked_genres = genres_df.stack()
stacked_genres.head()
```

[42]:
```
97  0            Action
    1         Adventure
```

```
    2              Drama
    3             Horror
    4    Science Fiction
dtype: object
```

[43]:
```
raw_dummies = pd.get_dummies(stacked_genres)
raw_dummies.head()
```

[43]:

		Action	Adventure	Animation	Comedy	Crime	Documentary	Drama	Family	\
97	0	1	0	0	0	0	0	0	0	
	1	0	1	0	0	0	0	0	0	
	2	0	0	0	0	0	0	1	0	
	3	0	0	0	0	0	0	0	0	
	4	0	0	0	0	0	0	0	0	

		Fantasy	History	Horror	Music	Mystery	Romance	Science Fiction	\
97	0	0	0	0	0	0	0	0	
	1	0	0	0	0	0	0	0	
	2	0	0	0	0	0	0	0	
	3	0	0	1	0	0	0	0	
	4	0	0	0	0	0	0	1	

		Thriller	War	Western
97	0	0	0	0
	1	0	0	0
	2	0	0	0
	3	0	0	0
	4	0	0	0

[44]:
```
genres_dummies = raw_dummies.sum(level=0)
genres_dummies.head(3)
```

```
/var/folders/5n/xdbycb5n3dx6rxxjnkh477y00000gn/T/ipykernel_67136/568268698.py:1:
FutureWarning: Using the level keyword in DataFrame and Series aggregations is
deprecated and will be removed in a future version. Use groupby instead.
df.sum(level=1) should use df.groupby(level=1).sum().
  genres_dummies = raw_dummies.sum(level=0)
```

[44]:

	Action	Adventure	Animation	Comedy	Crime	Documentary	Drama	Family	\
97	1	1	0	0	0	0	1	0	
151	1	1	1	0	0	0	0	0	
155	0	0	0	1	0	0	0	0	

	Fantasy	History	Horror	Music	Mystery	Romance	Science Fiction	\
97	0	0	1	0	0	0	1	
151	0	0	0	0	0	0	0	
155	0	0	0	0	0	0	0	

```
     Thriller  War  Western
97          0    0        0
151         0    0        0
155         0    0        0
```

[45]:
```
genres_dummies['year'] = data['year']
genres_dummies.head(3)
```

[45]:
```
     Action  Adventure  Animation  Comedy  Crime  Documentary  Drama  Family  \
97        1          1          0       0      0            0      1       0
151       1          1          1       0      0            0      0       0
155       0          0          0       1      0            0      0       0

     Fantasy  History  Horror  Music  Mystery  Romance  Science Fiction  \
97         0        0       1      0        0        0                1
151        0        0       0      0        0        0                0
155        0        0       0      0        0        0                0

     Thriller  War  Western  year
97          0    0        0  2016
151         0    0        0  2007
155         0    0        0  2005
```

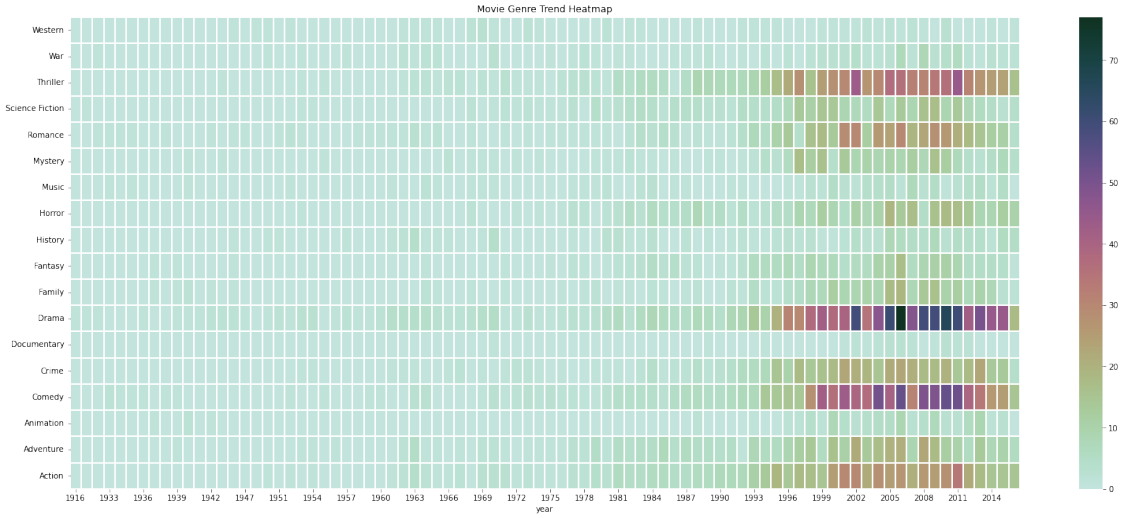
[46]:
```
grouped = genres_dummies.groupby('year')
groupedCnt = grouped.agg(np.sum).transpose()
groupedCnt
```

[46]:
```
year             1916  1927  1932  1933  1934  1935  1936  1937  1938  1939  \
Action              0     0     0     0     0     0     0     0     0     0
Adventure           0     0     0     0     0     0     0     0     0     1
Animation           0     0     0     0     0     0     0     1     0     0
Comedy              0     0     0     2     1     1     1     0     1     1
Crime               0     0     0     0     0     0     0     0     0     0
Documentary         0     0     0     0     0     0     0     0     0     0
Drama               1     1     1     0     0     0     1     0     0     1
Family              0     0     0     0     0     0     0     1     0     1
Fantasy             0     0     0     0     0     0     0     1     0     1
History             0     0     0     0     0     0     0     0     0     0
Horror              0     0     0     0     0     0     0     0     0     0
Music               0     0     0     1     0     1     0     0     0     0
Mystery             0     0     0     0     0     0     0     0     0     0
Romance             0     0     1     1     1     1     0     0     1     0
Science Fiction     0     1     0     0     0     0     0     0     0     0
Thriller            0     0     0     0     0     0     0     0     0     0
War                 0     0     1     0     0     0     0     0     0     0
Western             0     0     0     0     0     0     0     0     0     0
```

```
year                …  2007  2008  2009  2010  2011  2012  2013  2014  2015  \
Action              …    21    26    25    28    34    22    18    15    15
Adventure           …     9    23    18    12    10     6    13     8    10
Animation           …     3     4     7     3     3     6     9     2     3
Comedy              …    31    49    49    53    52    39    34    26    25
Crime               …    21    18    18    20    14    18    23    13    13
Documentary         …     2     0     1     3     2     2     0     0     0
Drama               …    48    59    59    66    60    42    50    44    44
Family              …     8    14    16    10    12     7    10     8     3
Fantasy             …     6     9    11    11     9     5     5     5     4
History             …     5     4     7     3     5     4     4     2     6
Horror              …    17     5    16    18    17    14     9     9    12
Music               …     7     3     5     1     3     4     5     2     5
Mystery             …    12     8    16    12     7     4     3     5     7
Romance             …    19    23    28    26    21    18    15    12    11
Science Fiction     …     9    16    17     9    13     8     6     5     3
Thriller            …    32    31    34    36    44    31    27    25    24
War                 …     2     8     3     4     6     2     1     3     2
Western             …     2     1     0     3     0     0     0     1     0

year             2016
Action             15
Adventure           6
Animation           0
Comedy             15
Crime               4
Documentary         0
Drama              18
Family              2
Fantasy             1
History             5
Horror             10
Music               0
Mystery             4
Romance             4
Science Fiction     4
Thriller           16
War                 2
Western             1

[18 rows x 84 columns]
```

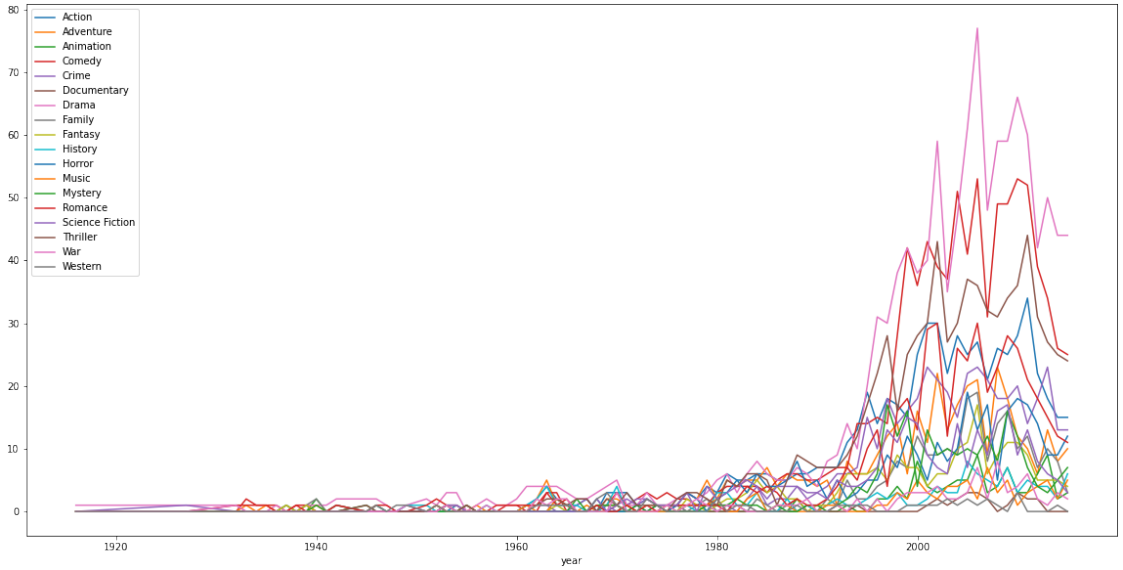
[47]:
```
plt.figure(figsize=(27,11))
cmap = sns.cubehelix_palette(start=1.5, rot=1.5, as_cmap=True)
sns.heatmap(groupedCnt, xticklabels=3, cmap=cmap, linewidths=0.05).
 ↪invert_yaxis()
```

```
plt.title('Movie Genre Trend Heatmap')
plt.show()
```



[48]:
```
groupedCnt.T.sort_index()[:-1].plot.line(figsize = (20,10))
```

[48]: <AxesSubplot:xlabel='year'>



From the heatmap, we could easily find the five most popular generes which are ‘Drama’, ‘Comedy’, ‘Thriller’, ‘Action’ and ‘Romance’. From the line graph we can see that ‘Drama’ has been a popular category since movies first appeared and all types of movies have shown a growth trend.

4 Modeling

4.1 Choose Features

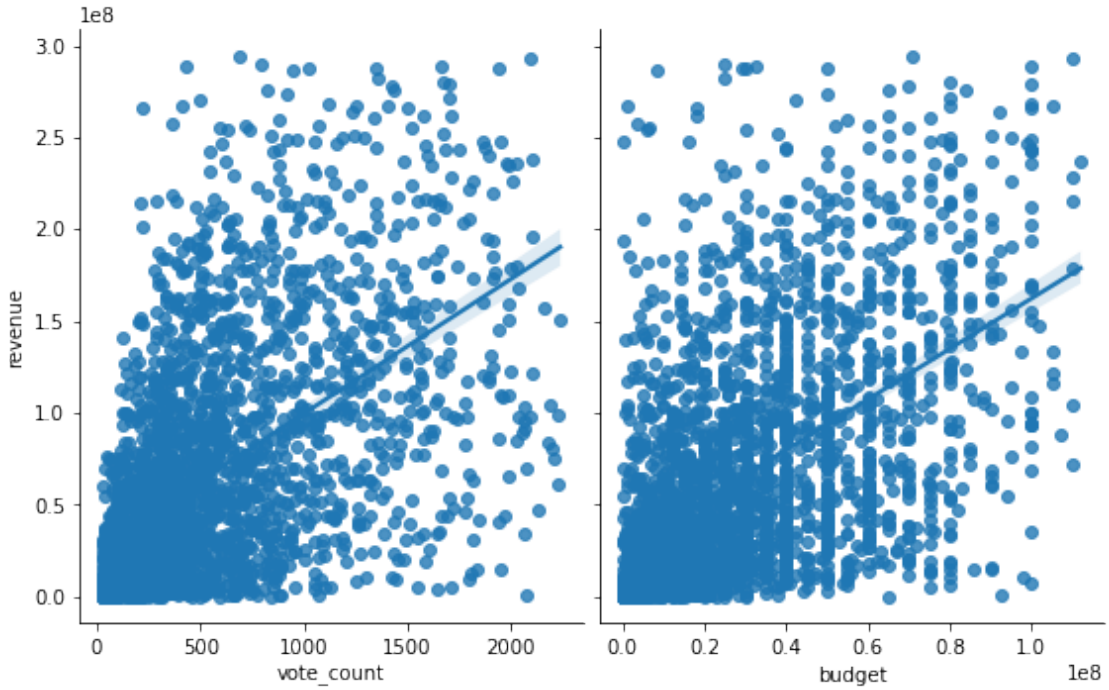
According to the correlation matrix above, we found that budget, popularity and vote_count have a higher correlation with the revenue. However, the correlation of vote_count and popularity is too high. Hence, we only choose vote_count and budget in the following models.

[49]:
```
data[['revenue', 'budget', 'vote_count']].describe()
```

[49]:

	revenue	budget	vote_count
count	2.526000e+03	2.526000e+03	2526.000000
mean	6.554095e+07	2.947258e+07	534.114410
std	6.404430e+07	2.488870e+07	481.765619
min	5.000000e+00	1.000000e+00	26.000000
25%	1.563141e+07	1.000000e+07	163.250000
50%	4.235547e+07	2.300000e+07	373.500000
75%	9.831186e+07	4.300000e+07	750.000000
max	2.944566e+08	1.120000e+08	2237.000000

[82]:
```
sns.pairplot(data, x_vars=['vote_count','budget'], y_vars='revenue',kind="reg",␣
↪height=5, aspect=0.8)
plt.show()
```



4.2 Feature Scaling

The description of the data shows enormous gaps between the largest/smallest and median values. It means no coefficient can use the feature without blowing up on big values. Thus, we replace such features x with log(x).

[50]:
```
data["logre"] = data['revenue'].map(lambda x:np.log(x+1))
data["logbud"] = data['budget'].map(lambda x:np.log(x+1))
data["logvote"]=data['vote_count'].map(lambda x:np.log(x+1))
```

4.3 Implement Models

[51]:
```
import math
def RSE(y_true, y_predicted):
    """
    - y_true: Actual values
    - y_predicted: Predicted values
    """
    y_true = np.array(y_true)
    y_predicted = np.array(y_predicted)
    RSS = np.sum(np.square(y_true - y_predicted))

    rse = math.sqrt(RSS / (len(y_true) - 2))
    return rse
```

4.3.1 Linear Regression

After data processing, we made prediction of revenue based on vote_count and budget multi-linear regression. In the graph on the right, the X-axis represents vote_count and budget, and the Y-axis represents revenue. According to the previous Heatmap of the Pearson correlation, it can be seen that popularity, vote_count and budget are most correlated with revenue. I chose vote_count and budget because popularity and Vote_count have a strong correlation of 0.87. If I put three variables there, then the collinear phenomena may occur. Since the variables of the X-axis are highly correlated, they will affect the prediction, and other variables cannot be fixed, so the real relationship between X and Y cannot be found.

[83]:
```
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
dfm1 = data[["logre","logbud","logvote"]]
```

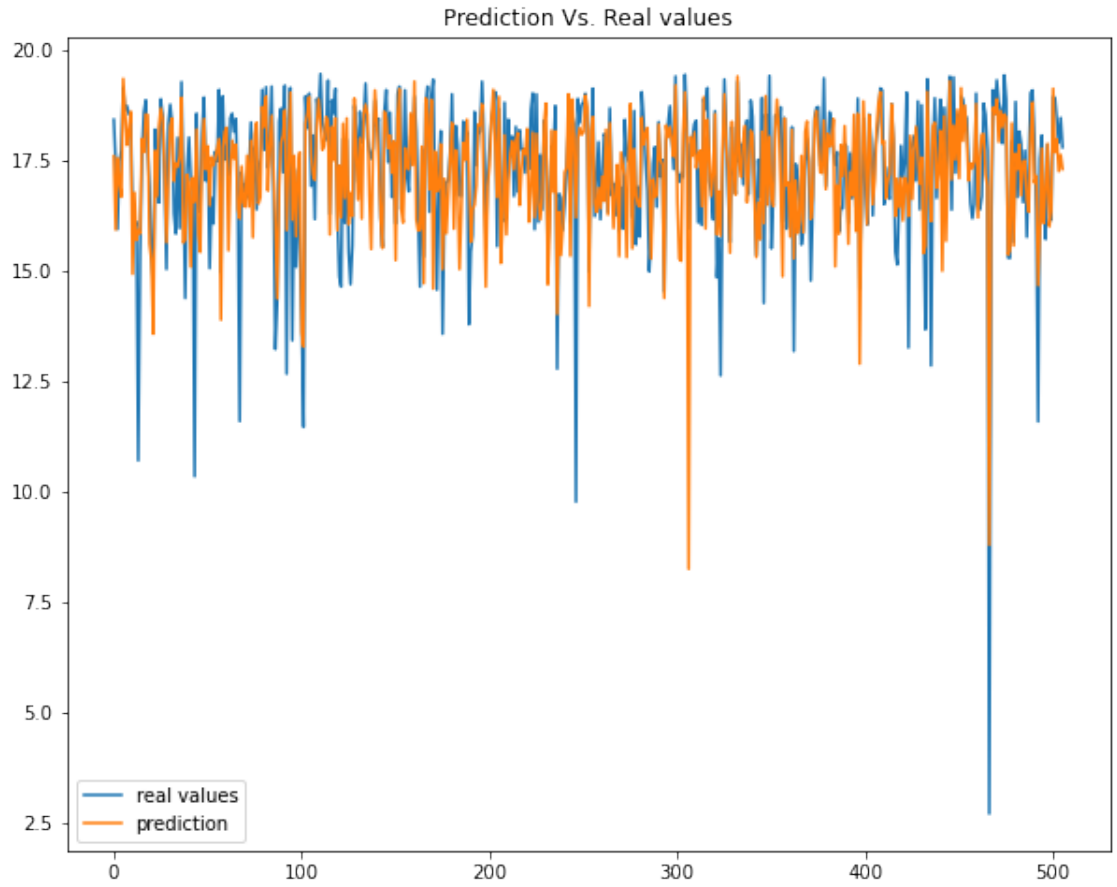
[84]:
```
X = dfm1[["logbud","logvote"]].values
y = dfm1.logre.values
```

[85]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
 ↪random_state=0)
md1 = LinearRegression()
md1.fit(X_train, y_train)
```

[85]:
```
LinearRegression()
```

[86]:
```
y_pred = md1.predict(X_test)
```

[87]:
```
acc = y_test
pre = y_pred
plt.figure(figsize = (10,8))
plt.plot(acc,label = 'real values')
plt.plot(pre, label = 'prediction')
plt.legend()
plt.title('Prediction Vs. Real values')
plt.show()
```



[88]:
```
from sklearn.metrics import mean_absolute_error
from sklearn.metrics import mean_squared_error
print('Mean Absolute Error:', mean_absolute_error(y_test, y_pred))
print('Mean Squared Error:', mean_squared_error(y_test, y_pred))
print('Root Mean Squared Error:', np.sqrt(mean_squared_error(y_test, y_pred)))
```

```
Mean Absolute Error: 0.781572673634959
Mean Squared Error: 1.3484192347888506
Root Mean Squared Error: 1.161214551574708
```

When making predictions, the mean absolute error between the predicted and observed values is 0.78, I think it's good, because it represents the absolute difference between the actual value and the forecast value.

Mean Squared error is 1.35, there is no overfit in this group of predictions. Because MSE equals 0 is theoretically the best, the closer you get to 0, the better prediction you get. However, if the MSE is too small, it may indicate that the model is overfit; if the MSE is too large, it may indicate that the model is underfit.

The root mean squared error is 1.16. This means it fits the data fairly well, because it's close to zero.

[89]:
```
from sklearn.model_selection import cross_val_score
scores = -cross_val_score(md1, X_train, y_train, cv=5,␣
 ↪scoring='neg_mean_absolute_error')
print(scores)
print(scores.mean())
```

```
[0.88057459 0.89725257 0.80694632 0.87003787 0.86942442]
0.8648471547682235
```

We separate the training data into 5 groups to make cross-validation and this is the mean value of five scores. This process is used to estimate the skill of the model on new data and overcome the overfitting and underfitting problems. Now, the cross validation score shows a good performance of the multiple linear regression model in other data sets not only in the train and test data set. But, we still need to compare this model with the rest two models.

[90]:
```
print(RSE(y_test, y_pred))
```

```
1.1635162675133388
```

This is the residual standard error of the multi-linear regression. It is close to 0 which means the model is accuracy.

4.4 Logistic Regression

[91]:
```
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression

dfm2 = data[["logre","logbud","logvote"]]

for index, row in dfm2.iterrows():
    if row["logbud"] >= row["logre"]:
        dfm2.loc[index, "Target"] = 0
    else:
        dfm2.loc[index, "Target"] = 1
dfm2.Target = dfm2.Target.astype(int)
```

```
/var/folders/5n/xdbycb5n3dx6rxxjnkh477y00000gn/T/ipykernel_67136/3790494380.py:1
0: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  dfm2.loc[index, "Target"] = 1
/var/folders/5n/xdbycb5n3dx6rxxjnkh477y00000gn/T/ipykernel_67136/3790494380.py:1
1: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  dfm2.Target = dfm2.Target.astype(int)
```

[92]:
```
X = dfm2[["logbud", "logvote"]].values
y = dfm2.Target
```

[93]:
```
x_train, x_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
↪random_state=0)
```

[94]:
```
md2 = LogisticRegression()
md2.fit(x_train, y_train)
```

[94]:
```
LogisticRegression()
```

[95]:
```
predictions = md2.predict(x_test)
```

[96]:
```
print(RSE(y_test, predictions))
```

```
0.45206756062017917
```

This is the residual standard error of the logistic regression. It shows a larger value than the residual standard error of the multiple linear regression. Hence, multiple linear regression is better

than logistic regression in the test data set.

[97]:
```
scores = cross_val_score(md2, X_train, y_train, cv=5, scoring='accuracy')
print(scores)
print(scores.mean())
```

```
[0.77227723 0.77722772 0.78465347 0.73267327 0.75      ]
0.7633663366336634
```

The mean value of the cross validation score is 0.76. It shows a decrease in the score compared to the mean score of multiple linear regression cross validation. This indicates that the logistic regression model shows a lower accuracy.

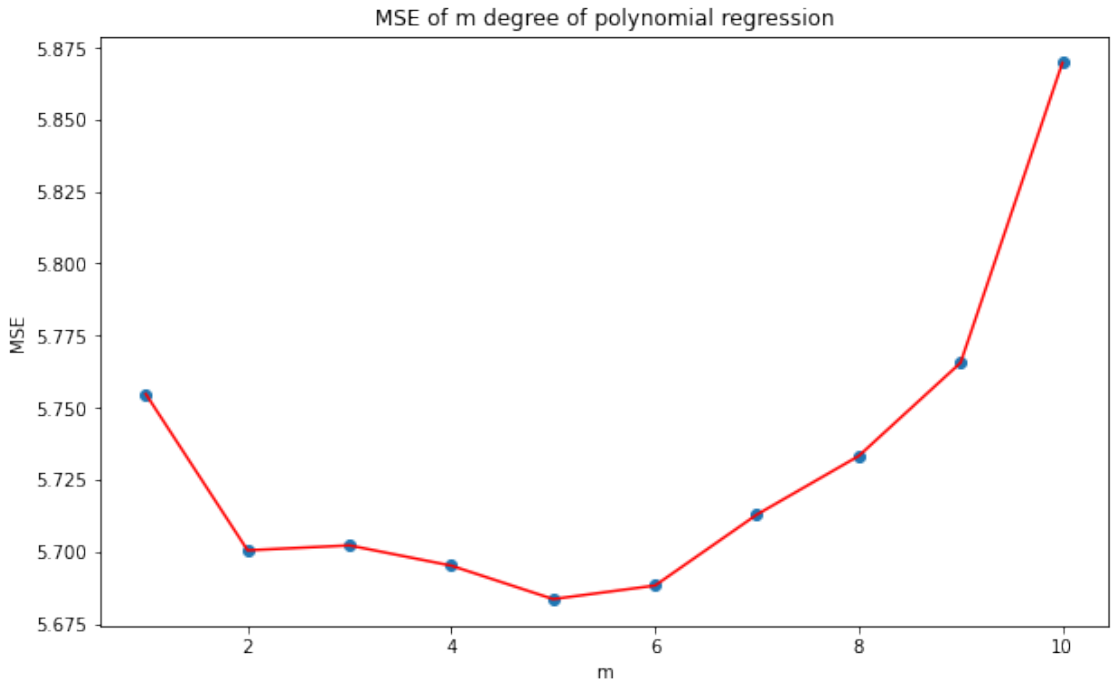
4.5 Polynomial Regression

Polynomial Regression is a form of linear regression in which the relationship between the independent variable x and dependent variable y is modeled as an nth degree polynomial.

[98]:
```
train_df = data[:int(len(data)*0.8)]
test_df = data[int(len(data)*0.8):]
```

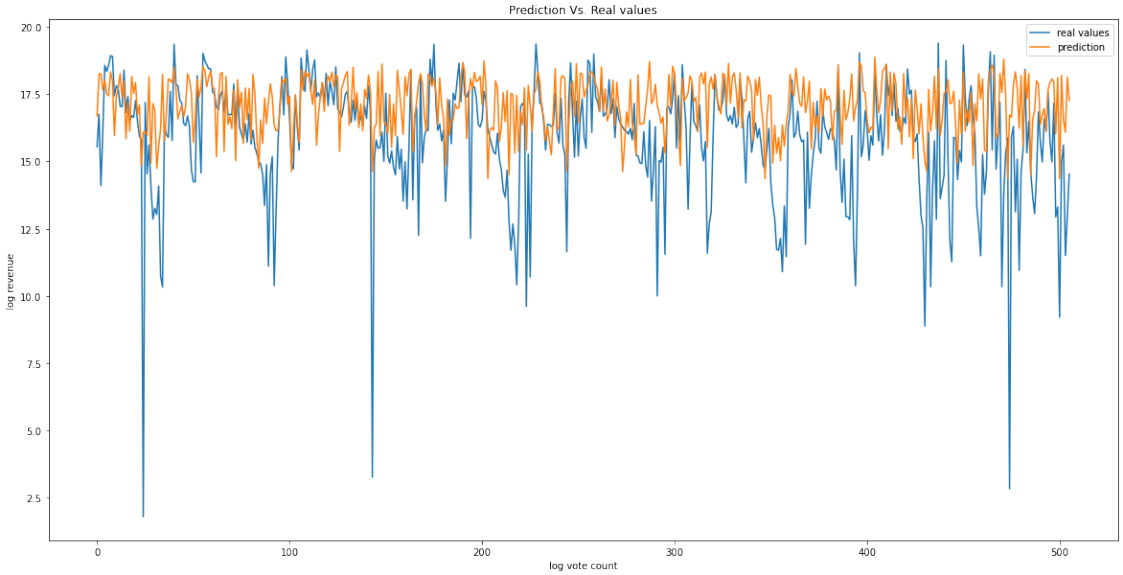
[99]:
```
train_x = train_df[['logvote']].values
train_y = train_df['revenue'].apply(np.log1p).values
test_x = test_df['logvote'].values
test_y = test_df['revenue'].apply(np.log1p).values
```

[100]:
```
from sklearn.preprocessing import PolynomialFeatures
from sklearn.pipeline import make_pipeline
mse = []
m = 1
m_max = 10
train_x = train_x.reshape(len(train_x),1)
test_x = test_x.reshape(len(test_x),1)
train_y = train_y.reshape(len(train_y),1)
while m<=m_max:
    model = make_pipeline(PolynomialFeatures(m,␣
 ↪include_bias=False),LinearRegression())
    model.fit(train_x,train_y)
    pre_y = model.predict(test_x)
    mse.append(mean_squared_error(test_y, pre_y.flatten()))
    m = m+1
plt.figure(figsize=(10,6))
plt.plot([i for i in range(1, m_max+1)], mse, 'r')
plt.scatter([i for i in range(1, m_max+1)], mse)
plt.title('MSE of m degree of polynomial regression')
plt.xlabel('m')
plt.ylabel('MSE')
plt.show()
```



In Polynomial Regression, I first set degree of polynomial regression from 1 to 10. Then, I record the mean square error for each time. From the graph above, we can see that when the degree equals to 5 the mean square error be the least. So, we decided the degree of polynomial regression is 5.

[101]:
```
model = make_pipeline(PolynomialFeatures(5,␣
  ↪include_bias=False),LinearRegression())
model.fit(train_x,train_y)
pre_y = model.predict(test_x)
acc = test_y
pre = pre_y
plt.figure(figsize = (20,10))
plt.plot(acc,label = 'real values')
plt.plot(pre, label = 'prediction')
plt.xlabel('log vote count')
plt.ylabel('log revenue')
plt.legend()
plt.title('Prediction Vs. Real values')
plt.show()
```



[102]:
```
print(RSE(test_y, pre_y))
```

```
61.58304906404056
```

This is the residual standard error of the polynomial regression. We could easily find that this number is much larger than the residual standard error of the multiple linear regression. Hence, the multiple linear regression model is much better than the polynomial regression model in the test data set.

[103]:
```
from sklearn.metrics import mean_absolute_error
from sklearn.metrics import mean_squared_error
print("polynomial regression mean absolute error: ",␣
 ↪mean_absolute_error(test_y,pre_y.flatten()))
print("polynomial regression mean squared error: ",␣
 ↪mean_squared_error(test_y,pre_y.flatten()))
print('Root Mean Squared Error:', np.sqrt(mean_squared_error(y_test, y_pred)))
```

```
polynomial regression mean absolute error:  1.6290956840608994
polynomial regression mean squared error:  5.683510728153394
Root Mean Squared Error: 16.54425549041142
```

The mean absolute error between the predicted and observed values is 1.63. It is higher than the mean absolute error than multiple linear regression. It indicates the error between true value and predict value is larger.

Mean Squared error is 5.68 which indicates that this model is not fitter than the multiple linear regression.

This is the root mean square error of polynomial regression. It indicates that the model do not fit the data well since the value of RMSE is too large.

[104]:
```
from sklearn.model_selection import cross_val_score
scores = -cross_val_score(model, train_x, train_y, cv=5,␣
 ↪scoring='neg_mean_absolute_error')
print(scores)
print(scores.mean())
```

```
[0.76341057 0.65232188 0.74835349 0.85855298 1.08719215]
0.8219662124365467
```

This is the mean value of the five cross validation scores. This value is larger than the value of logistic regression but lower than the multiple linear regression. Only discussing the cross validation score, the polynomial regression model shows a better performance in new datasets than the logistic regression.

5 Conclusion

From the exploration data analysis, we could conclude that more movie producers prefer release movies on Fridays or summer.

It was not until after 1980 that the film industry came to a booming period.

'Drama' has been a popular category since movies first appeared and all types of movies have shown a growth trend from about 1990. Between 2005 and 2010, most genre films reached their peak. And after 2010, there was a certain degree of decline.

Vote_count is the most correlated factor in predicting the revenue of the movie, while vote average is the least correlated factor.

According to the residual standard error and the mean cross validation score, the multiple linear regression gives the best performance compared to the rest two models.

It has the least residual standard error which indicates that it is the most accuracy in the test data set. Meanwhile, it has the highest mean cross validation score which indicates that it also have a good performance in the new datasets rather than the train and test dataset.

Besides, we suppose that the polynomial regression is better than the logistic regression. Firstly, the polynomial regression is a numeric prediction model while the logistic regression is a classification prediction model. Then, the logistic regression has the worst performance in new datasets. It will give inaccuracy prediction if we use this model to make a prediction of the movie revenue.