notebook

March 12, 2023

1 Microsoft Movie Data Analysis

1.1 Problem Overview

The purpose of this EDA is to determine the types or genres of movies that are most in demand and are performing best in the market in order to come up with actionable insights for the company's stake holders.

1.2 Business Understanding

Big companies have been recently flooding into the home entertainment industry of which movies are a big part. In this analysis we are going to look at data from sources such as IMDB the popular movie review site. We are looking to determine: * Trend in how much movies gross over the years * Most popular genres of movies * Which genres gross the most domestically * Which genres gross the most worldwide * Trend in movie ratings over time

1.3 Data Understanding

The first thing we shall do is import the necessary libraries and store our data in some pandas dataframes. From there we can use some descriptive methods to understand our data.

NB: The project directory contains a folder Data which contains the data files. Some files that are too large to push to github shall

be left compressed to be uncompressed when running this notebook

[34]:
```
#modules for uncompressing some data files
import zipfile
import os

#path to compressed file
zip_file_imdb = 'Data/im.db.zip'

#path to extracted file
extracted_file_imdb = 'Data/im.db'

#check if extracted file already exists
if not os.path.isfile(extracted_file_imdb):
```

```
    #extract compressed file
    with zipfile.ZipFile(zip_file_imdb, 'r') as zip_reference:
        zip_reference.extractall('Data')
```

[35]:
```
!cd Data && ls -a && cd ..
```

```
.                         im.db                   rt.reviews.tsv.gz
..                        im.db.zip               tmdb.movies.csv.gz
bom.movie_gross.csv.gz    rt.movie_info.tsv.gz    tn.movie_budgets.csv.gz
```

[36]:
```
import pandas as pd
import numpy as np
import sqlite3

#connection and cursor to database
conn = sqlite3.connect('Data/im.db')
cursor = conn.cursor()
```

Lets see what tables are in our im.db database.

[37]:
```
pd.read_sql("SELECT name FROM sqlite_master WHERE type='table';", conn)
```

[37]:
```
            name
0   movie_basics
1      directors
2      known_for
3     movie_akas
4  movie_ratings
5        persons
6     principals
7        writers
```

[38]:
```
movie_basics = pd.read_sql("SELECT * FROM movie_basics;", conn)
print("shape:", movie_basics.shape)
movie_basics.head()
```

```
shape: (146144, 6)
```

[38]:
```
    movie_id                    primary_title              original_title  \
0  tt0063540                        Sunghursh                   Sunghursh
1  tt0066787  One Day Before the Rainy Season             Ashad Ka Ek Din
2  tt0069049       The Other Side of the Wind  The Other Side of the Wind
3  tt0069204                  Sabse Bada Sukh             Sabse Bada Sukh
4  tt0100275         The Wandering Soap Opera       La Telenovela Errante

   start_year  runtime_minutes                genres
0        2013            175.0    Action,Crime,Drama
1        2019            114.0       Biography,Drama
2        2018            122.0                 Drama
3        2018              NaN          Comedy,Drama
```

```
4        2017             80.0  Comedy,Drama,Fantasy
```

[39]:
```python
movie_ratings = pd.read_sql("SELECT * FROM movie_ratings;", conn)
print("shape:", movie_ratings.shape)
movie_ratings.head(3)
```

```
shape: (73856, 3)
```

[39]:
```
     movie_id  averagerating  numvotes
0  tt10356526            8.3        31
1  tt10384606            8.9       559
2   tt1042974            6.4        20
```

The cells above read necessary tables from the database into dataframes.

[40]:
```python
movie_gross = pd.read_csv('Data/bom.movie_gross.csv.gz')
print("shape:", movie_gross.shape)
movie_gross.head(3)
```

```
shape: (3387, 5)
```

[40]:
```
                                         title studio  domestic_gross  \
0                                  Toy Story 3     BV     415000000.0
1                   Alice in Wonderland (2010)     BV     334200000.0
2  Harry Potter and the Deathly Hallows Part 1     WB     296000000.0

  foreign_gross  year
0     652000000  2010
1     691300000  2010
2     664300000  2010
```

[41]:
```python
movie_budgets = pd.read_csv('Data/tn.movie_budgets.csv.gz')
print("shape:", movie_budgets.shape)
movie_budgets.head(3)
```

```
shape: (5782, 6)
```

[41]:
```
   id  release_date                                        movie  \
0   1  Dec 18, 2009                                       Avatar
1   2  May 20, 2011  Pirates of the Caribbean: On Stranger Tides
2   3   Jun 7, 2019                                 Dark Phoenix

  production_budget domestic_gross worldwide_gross
0      $425,000,000   $760,507,625  $2,776,345,279
1      $410,600,000   $241,063,875  $1,045,663,875
2      $350,000,000    $42,762,350    $149,762,350
```

Ok. We have our dataframes: `movie_basics` `movie_gross` `movie_ratings` `movie_budgets`

1.4 Data Preparation

1.4.1 Data Cleaning

1.Lets normalize column names This will make merging easier

[42]:
```python
movie_gross.rename(columns={'title':'primary_title'}, inplace=True)
movie_gross.columns
```

[42]:
```
Index(['primary_title', 'studio', 'domestic_gross', 'foreign_gross', 'year'],
dtype='object')
```

[43]:
```python
movie_budgets.rename(columns={'movie':'primary_title'}, inplace=True)
movie_budgets.columns
```

[43]:
```
Index(['id', 'release_date', 'primary_title', 'production_budget',
       'domestic_gross', 'worldwide_gross'],
      dtype='object')
```

2.Missing Values.

[44]:
```python
print("movie_basics nulls:\n", movie_basics.isna().sum().loc[movie_basics.
 ↪isna().sum()>0])
print("movie_ratings nulls:\n", movie_ratings.isna().sum().loc[movie_ratings.
 ↪isna().sum()>0])
print("movie_gross nulls:\n", movie_gross.isna().sum().loc[movie_gross.isna().
 ↪sum()>0])
print("movie_budgets nulls:\n", movie_budgets.isna().sum().loc[movie_budgets.
 ↪isna().sum()>0])
```

```
movie_basics nulls:
 original_title        21
runtime_minutes    31739
genres              5408
dtype: int64
movie_ratings nulls:
 Series([], dtype: int64)
movie_gross nulls:
 studio               5
domestic_gross      28
foreign_gross     1350
dtype: int64
movie_budgets nulls:
 Series([], dtype: int64)
```

[45]:
```python
#fill null values in 'runtime_minutes' column with the mean value
movie_basics['runtime_minutes'].fillna(movie_basics['runtime_minutes'].mean(),␣
 ↪inplace=True)
#Remove all remaining rows with null values
movie_basics.dropna(axis=0, inplace=True)
```

```
movie_basics.isna().sum()
```

[45]:
```
movie_id           0
primary_title      0
original_title     0
start_year         0
runtime_minutes    0
genres             0
dtype: int64
```

For the `movie_gross` dataframe, we are going to create two subsets of the dataframe so that one contains only domestic movie grossing and the other contains foreign grossing with null values eliminated.

[46]:
```
movie_domestic_gross =  movie_gross.loc[:, movie_gross.columns !=␣
↪'foreign_gross']
movie_foreign_gross = movie_gross.loc[:, movie_gross.columns !=␣
↪'domestic_gross']
print("domestic_null:\n", movie_domestic_gross.isna().sum(),"\nforeign_null:
↪\n", movie_foreign_gross.isna().sum())
```

```
domestic_null:
 primary_title      0
studio            5
domestic_gross    28
year              0
dtype: int64
foreign_null:
 primary_title       0
studio             5
foreign_gross    1350
year               0
dtype: int64
```

[47]:
```
movie_domestic_gross.dropna(inplace=True)
movie_foreign_gross.dropna(inplace=True)
print("domestic:", movie_domestic_gross.shape)
print("foreign:", movie_foreign_gross.shape)
```

```
domestic: (3356, 4)
foreign: (2033, 4)

<ipython-input-47-50876856e023>:1: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  movie_domestic_gross.dropna(inplace=True)
<ipython-input-47-50876856e023>:2: SettingWithCopyWarning:
```

```
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  movie_foreign_gross.dropna(inplace=True)
```

3.Duplicates

[48]:
```
print("movie_basics dups:\n", movie_basics.duplicated().sum())
print("movie_ratings dups:\n", movie_ratings.duplicated().sum())
print("movie_domestic_gross dups:\n", movie_domestic_gross.duplicated().sum())
print("movie_foreign_gross dups:\n", movie_foreign_gross.duplicated().sum())
print("movie_budgets dups:\n", movie_budgets.duplicated().sum())
```

```
movie_basics dups:
 0
movie_ratings dups:
 0
movie_domestic_gross dups:
 0
movie_foreign_gross dups:
 0
movie_budgets dups:
 0
```

4.Outliers

[49]:
```
movie_basics =␣
 ↪movie_basics[movie_basics['runtime_minutes']<movie_basics['runtime_minutes'].
 ↪quantile(0.99)]
movie_basics
```

[49]:
```
         movie_id                                 primary_title  \
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
5       tt0111414                                  A Thin Life
...           ...                                          ...
146138  tt9916428                         The Secret of China
146139  tt9916538                         Kuambil Lagi Hatiku
146140  tt9916622  Rodolpho Teóphilo - O Legado de um Pioneiro
146141  tt9916706                              Dankyavar Danka
146143  tt9916754               Chico Albuquerque - Revelações

                                    original_title  start_year  \
1                                 Ashad Ka Ek Din        2019
2                      The Other Side of the Wind        2018
3                                 Sabse Bada Sukh        2018
```

```
4                           La Telenovela Errante        2017
5                                     A Thin Life        2018
...                                           ...         ...
146138                        The Secret of China        2019
146139                        Kuambil Lagi Hatiku        2019
146140  Rodolpho Teóphilo - O Legado de um Pioneiro        2015
146141                            Dankyavar Danka        2013
146143              Chico Albuquerque - Revelações        2013

        runtime_minutes                genres
1            114.000000       Biography,Drama
2            122.000000                 Drama
3             86.187247          Comedy,Drama
4             80.000000  Comedy,Drama,Fantasy
5             75.000000                Comedy
...                 ...                   ...
146138        86.187247  Adventure,History,War
146139       123.000000                 Drama
146140        86.187247           Documentary
146141        86.187247                Comedy
146143        86.187247           Documentary

[139278 rows x 6 columns]
```

`movie_basics` has the year column represented in an abnormal way. Lets clean that up.

[50]:
```python
movie_basics.rename(columns={'start_year':'year'}, inplace=True)
movie_basics.head()
```

[50]:
```
    movie_id                    primary_title              original_title  \
1  tt0066787  One Day Before the Rainy Season             Ashad Ka Ek Din
2  tt0069049       The Other Side of the Wind  The Other Side of the Wind
3  tt0069204                  Sabse Bada Sukh             Sabse Bada Sukh
4  tt0100275         The Wandering Soap Opera       La Telenovela Errante
5  tt0111414                      A Thin Life                 A Thin Life

   year  runtime_minutes                genres
1  2019       114.000000       Biography,Drama
2  2018       122.000000                 Drama
3  2018        86.187247          Comedy,Drama
4  2017        80.000000  Comedy,Drama,Fantasy
5  2018        75.000000                Comedy
```

Finally lets clean values in `movie_budgets` to contain integers and remove the '$' and ','

[51]:
```python
# Function that converts values in monetary terms to int.
def dollars_to_int(money_df):
    for column in money_df.columns:
#         print(type(column))
#Note ...dtype == 'object' checks if column contains strings
```

```
        if money_df[column].dtype == 'object' and money_df[column].values[0].
 ↪startswith('$'):
            money_df[column] = money_df[column].str.replace('$', '').str.
 ↪replace(',', '').astype(int)
dollars_to_int(movie_budgets)
movie_budgets.head()
```

[51]:
```
   id  release_date                                primary_title  \
0   1  Dec 18, 2009                                       Avatar
1   2  May 20, 2011  Pirates of the Caribbean: On Stranger Tides
2   3   Jun 7, 2019                                 Dark Phoenix
3   4   May 1, 2015                      Avengers: Age of Ultron
4   5  Dec 15, 2017            Star Wars Ep. VIII: The Last Jedi

   production_budget  domestic_gross  worldwide_gross
0          425000000       760507625       2776345279
1          410600000       241063875       1045663875
2          350000000        42762350        149762350
3          330600000       459005868       1403013963
4          317000000       620181382       1316721747
```

[52]:
```
movie_df_names=[movie_basics, movie_ratings, movie_domestic_gross,␣
 ↪movie_foreign_gross, movie_budgets]
```

[53]:
```
# a function to print out head()'s in our dfs
def print_heads(df_names):
    for df in df_names:
        print(str(df.columns), "\n", df.head(2), "\n\n")
print_heads(movie_df_names)
```

```
Index(['movie_id', 'primary_title', 'original_title', 'year',
       'runtime_minutes', 'genres'],
      dtype='object')
    movie_id                    primary_title              original_title  \
1  tt0066787  One Day Before the Rainy Season             Ashad Ka Ek Din
2  tt0069049       The Other Side of the Wind  The Other Side of the Wind

   year  runtime_minutes              genres
1  2019            114.0  Biography,Drama
2  2018            122.0            Drama


Index(['movie_id', 'averagerating', 'numvotes'], dtype='object')
      movie_id  averagerating  numvotes
0  tt10356526            8.3        31
1  tt10384606            8.9       559


Index(['primary_title', 'studio', 'domestic_gross', 'year'], dtype='object')
```

```
                primary_title studio  domestic_gross  year
0                 Toy Story 3     BV     415000000.0  2010
1  Alice in Wonderland (2010)     BV     334200000.0  2010


Index(['primary_title', 'studio', 'foreign_gross', 'year'], dtype='object')
                primary_title studio foreign_gross  year
0                 Toy Story 3     BV     652000000  2010
1  Alice in Wonderland (2010)     BV     691300000  2010


Index(['id', 'release_date', 'primary_title', 'production_budget',
       'domestic_gross', 'worldwide_gross'],
      dtype='object')
   id  release_date                                primary_title  \
0   1  Dec 18, 2009                                       Avatar
1   2  May 20, 2011  Pirates of the Caribbean: On Stranger Tides

   production_budget  domestic_gross  worldwide_gross
0          425000000       760507625       2776345279
1          410600000       241063875       1045663875
```

[54]:
```
movie_basics.to_json('CleanData/clean_movie_basics.json')
movie_ratings.to_json('CleanData/clean_movie_ratings.json')
movie_domestic_gross.to_json('CleanData/clean_movie_domestic_gross.json')
movie_foreign_gross.to_json('CleanData/clean_movie_foreign_gross.json')
movie_budgets.to_json('CleanData/clean_movie_budgets.json')
```

[55]:
```
!cd CleanData && ls -alh && cd ..
```

```
total 22M
drwxrwxr-x 2 josh josh 4.0K Mac 10 18:12 .
drwxrwxr-x 7 josh josh 4.0K Mac 12 08:44 ..
-rw-rw-r-- 1 josh josh  18M Mac 12 08:46 clean_movie_basics.json
-rw-rw-r-- 1 josh josh 577K Mac 12 08:46 clean_movie_budgets.json
-rw-rw-r-- 1 josh josh 221K Mac 12 08:46 clean_movie_domestic_gross.json
-rw-rw-r-- 1 josh josh 135K Mac 12 08:46 clean_movie_foreign_gross.json
-rw-rw-r-- 1 josh josh 3.1M Mac 12 08:46 clean_movie_ratings.json
```

The two cells above store our dataframes in clean files in a folder CleanData.

1.5 Analysis

[56]:
```
#import vis libraries
import matplotlib.pyplot as plt
import seaborn as sns

%matplotlib inline

#reloading our dataset
movie_basics = pd.read_json('CleanData/clean_movie_basics.json')
movie_ratings = pd.read_json('CleanData/clean_movie_ratings.json')
movie_budgets = pd.read_json('CleanData/clean_movie_budgets.json')
movie_domestic_gross = pd.read_json('CleanData/clean_movie_domestic_gross.json')
movie_foreign_gross = pd.read_json('CleanData/clean_movie_foreign_gross.json')

#seaborn styles
sns.set_style('whitegrid')
```

1.5.1 1.Most common Genres

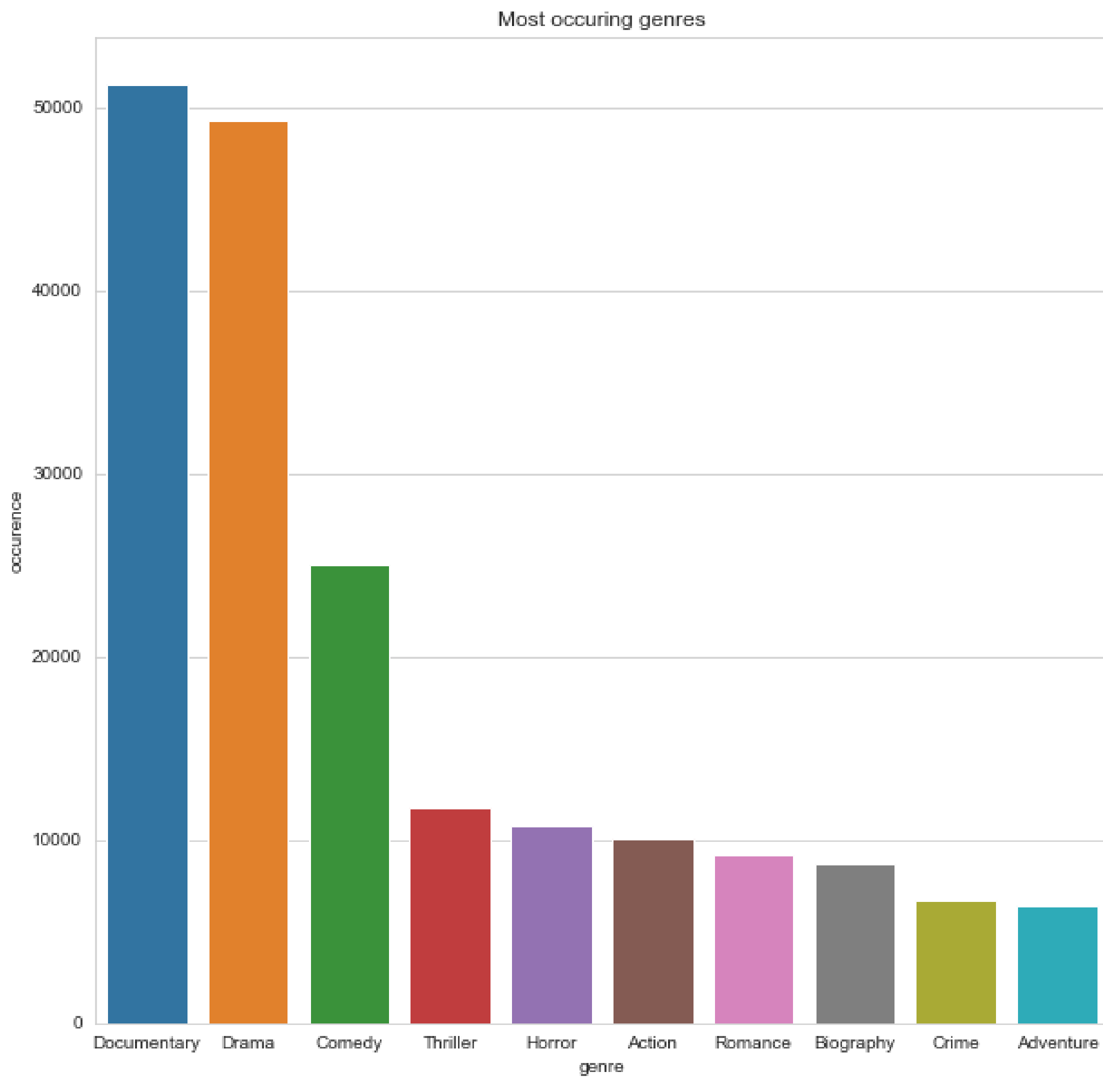
Lets plot a bar chart showing the top 10 most occuring genre of movies in our `movie_basics` df

[57]:
```
#figure and axes for top_10_genres_plot
top_10_genres_fig, top_10_genres_ax = plt.subplots(figsize=(10,10))

#loop to populate a list with unique genre names
genre_name_list = []

for current_movie_genres in movie_basics.genres:
    curr_mov_genre_list = current_movie_genres.split(',')
    for genre in curr_mov_genre_list:
        if genre in genre_name_list:
            continue;
        elif genre not in genre_name_list:
            genre_name_list.append(genre)
#Dict to store genre name and count
genre_counts_dict = {}
for genre in genre_name_list:
    genre_counts_dict[genre] = movie_basics[movie_basics['genres'].str.
 ↪contains(genre)].shape[0]
genre_counts_df = pd.DataFrame.from_dict(dict(sorted(genre_counts_dict.items(),
                                                     key=lambda item:item[1],
                                                     reverse=True)),␣
 ↪orient='index')
#plot
top_10_genres = genre_counts_df.reset_index().rename(columns={'index':'genre',␣
 ↪0:'occurence'})[:10]
```

```
top_10_genres_plot = sns.barplot(data=top_10_genres, x='genre', y='occurence',␣
↪ax=top_10_genres_ax)
top_10_genre_names = list(top_10_genres.genre)
top_10_genres_ax.set_title('Most occuring genres')
top_10_genres_fig.savefig('./images/top_10_genres.png');
```



From the plot it seems most movies produced are classified as **Documentary**, **Drama** and some falling under **Comedy**. Althought there is a large disparity between the first two genres and the third.

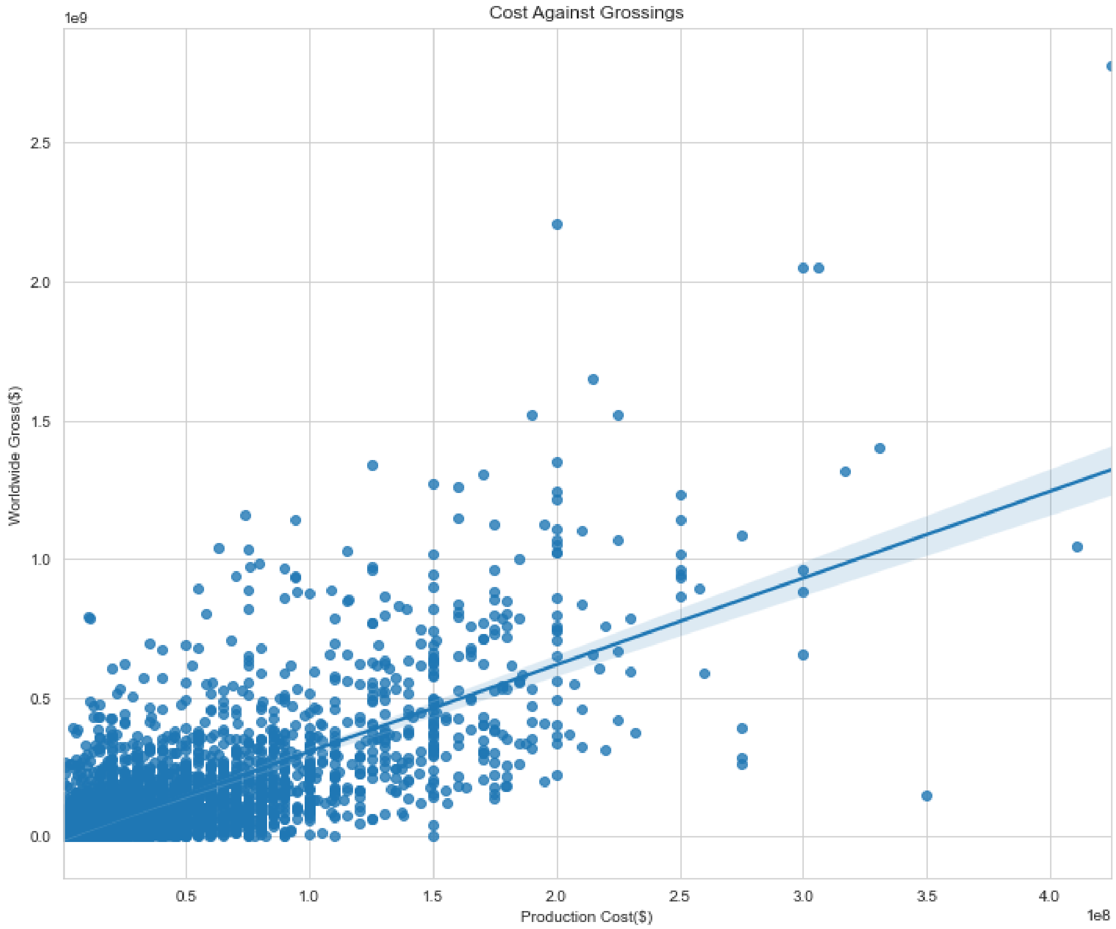
1.5.2 2.Relationship between production cost and worldwide gross.

[59]:
```
movie_budgets.head(10)
```

[59]:
```
    id  release_date                               primary_title  \
0    1  Dec 18, 2009                                      Avatar
1    2  May 20, 2011  Pirates of the Caribbean: On Stranger Tides
2    3   Jun 7, 2019                                 Dark Phoenix
3    4   May 1, 2015                      Avengers: Age of Ultron
4    5  Dec 15, 2017            Star Wars Ep. VIII: The Last Jedi
5    6  Dec 18, 2015         Star Wars Ep. VII: The Force Awakens
6    7  Apr 27, 2018                       Avengers: Infinity War
7    8  May 24, 2007   Pirates of the Caribbean: At WorldâĂŹs End
8    9  Nov 17, 2017                               Justice League
9   10   Nov 6, 2015                                      Spectre

   production_budget  domestic_gross  worldwide_gross
0          425000000       760507625       2776345279
1          410600000       241063875       1045663875
2          350000000        42762350        149762350
3          330600000       459005868       1403013963
4          317000000       620181382       1316721747
5          306000000       936662225       2053311220
6          300000000       678815482       2048134200
7          300000000       309420425        963420425
8          300000000       229024295        655945209
9          300000000       200074175        879620923
```

[60]:
```
#scatterplot
movie_budgets['release_date'] = pd.to_datetime(movie_budgets['release_date'],␣
 ↪format='%b %d, %Y')
cost_gross_fig, cost_gross_ax = plt.subplots(figsize=(12,10))
sns.regplot(x=movie_budgets['production_budget'],␣
 ↪y=movie_budgets['worldwide_gross'])
cost_gross_ax.set_title('Cost Against Grossings')
cost_gross_ax.set_xlabel('Production Cost($)')
cost_gross_ax.set_ylabel('Worldwide Gross($)')
cost_gross_fig.savefig('./images/cost_gross.png');
```



From the scatter plot above, we can tell clearly using the regression line that a relationship exists between the **production_cost** of a movie and its **grossing**

1.5.3 3.Trend in movie ratings over time per genre

A lineplot showing how movie ratings have changed over the year. This can be useful in understanding consumer reception.

[63]:
```
#df to store merged basic and rating dataframes
basics_and_ratings = pd.merge(movie_basics, movie_ratings, on='movie_id',
 ↪how='right').dropna()
basics_and_ratings.tail()
```

[63]:
```
        movie_id                                     primary_title  \
73851  tt9805820                                             Caisa
73852  tt9844256  Code Geass: Lelouch of the Rebellion - Glorifi...
73853  tt9851050                                           Sisters
73854  tt9886934                                  The Projectionist
73855  tt9894098                                            Sathru
```

```
                                        original_title    year  \
73851                                            Caisa  2018.0
73852  Code Geass: Lelouch of the Rebellion Episode III  2018.0
73853                                          Sisters  2019.0
73854                                  The Projectionist  2019.0
73855                                           Sathru  2019.0

       runtime_minutes                     genres  averagerating  numvotes
73851        84.000000                Documentary            8.1        25
73852       120.000000  Action,Animation,Sci-Fi            7.5        24
73853        86.187247               Action,Drama            4.7        14
73854        81.000000                Documentary            7.0         5
73855       129.000000                   Thriller            6.3       128
```

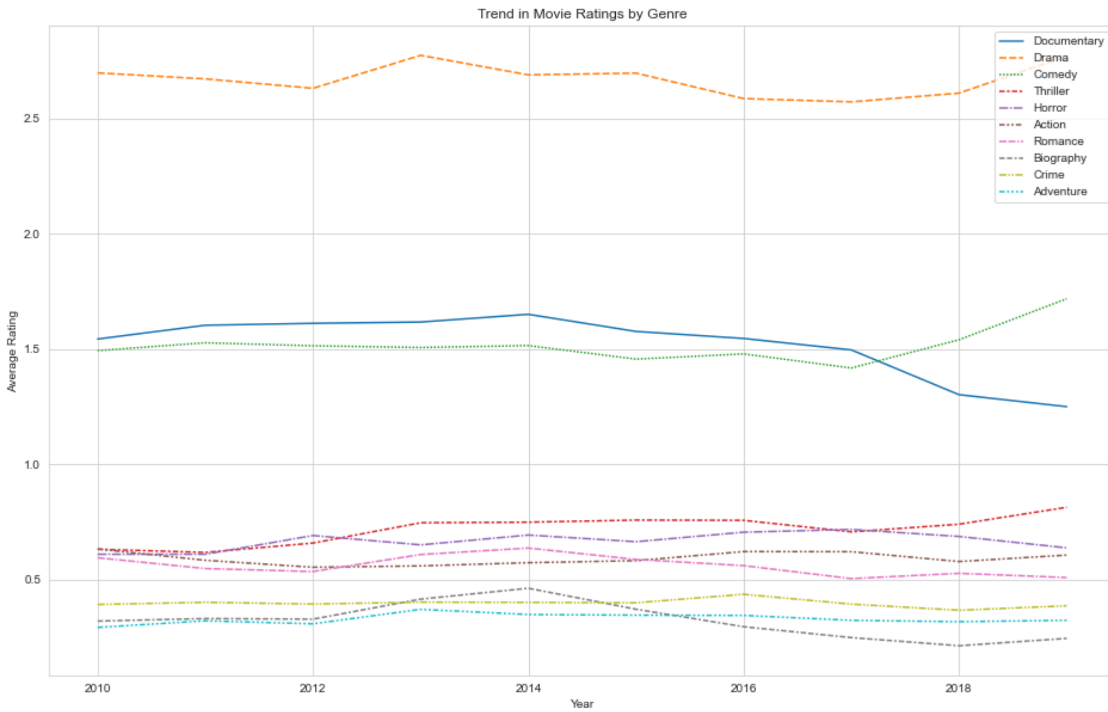
[64]:

```
#get a df of binary indicators for genres per movie
genres_bin_df = basics_and_ratings['genres'].str.get_dummies(sep=',')
basics_ratings_genrewise = pd.concat([basics_and_ratings, genres_bin_df],␣
↪axis=1)

#group by year and get mean rating per year
basics_ratings_year_avg = basics_ratings_genrewise.groupby(['year']).mean()
#multiply avg binary values for each genre by the year average.
for genre in top_10_genre_names:
    basics_ratings_year_avg[genre] = basics_ratings_year_avg[genre] *␣
↪basics_ratings_year_avg['averagerating']

#seaborn plot
rating_trend_fig, rating_trend_ax = plt.subplots(figsize=(16,10))

sns.lineplot(data=basics_ratings_year_avg[top_10_genre_names],␣
↪ax=rating_trend_ax)
#plot details
rating_trend_ax.set_title('Trend in Movie Ratings by Genre')
rating_trend_ax.set_xlabel('Year')
rating_trend_ax.set_ylabel('Average Rating');
rating_trend_fig.savefig('./images/rating_trend.png');
```

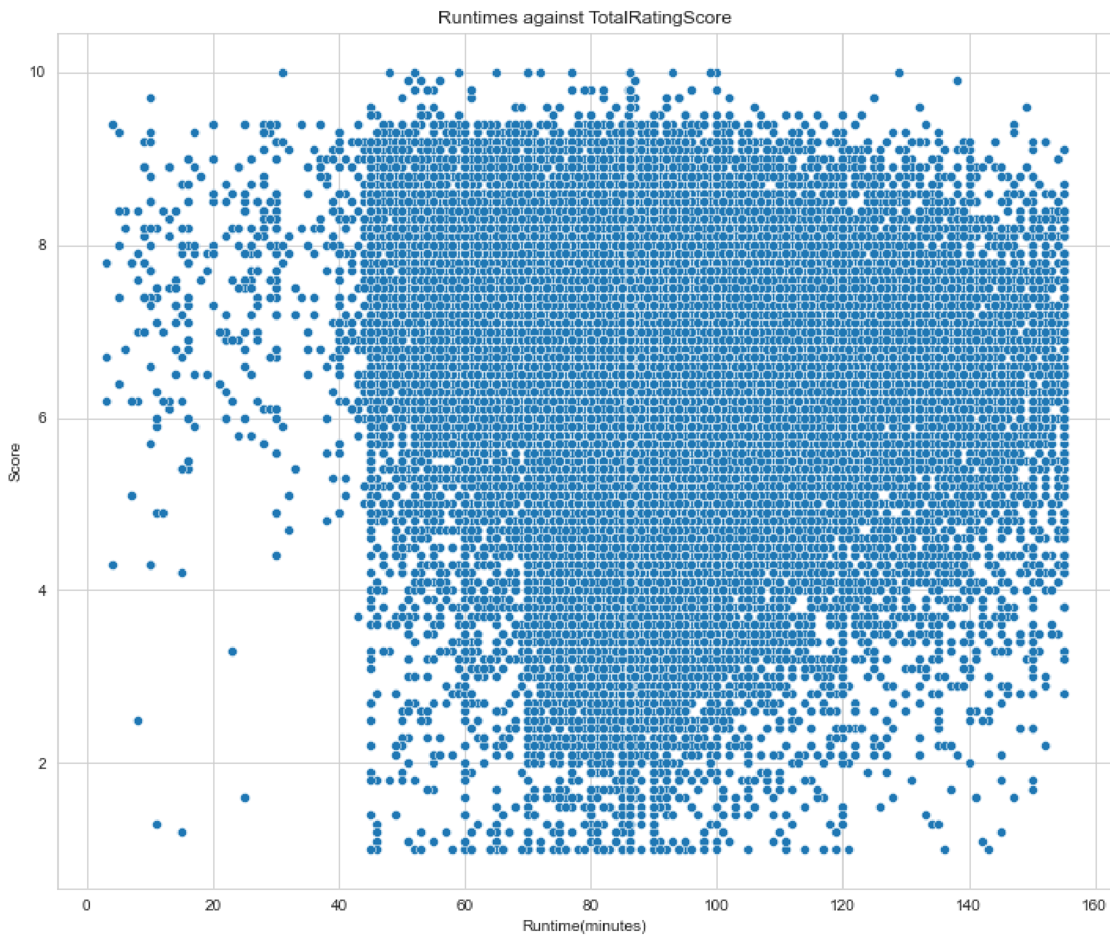


From the plot we can decipher that of the top most common genres of movies, the **Documentaries** have been on a steady decline in ratings over the past 2-3 years. **Drama** seems to be maintaining high review scores. **Comedy** has been staedily increasing in ratings over the past few years surpasssing Documentaries in a ratings around 2017.

1.5.4 4.Relationship between runtime and rating

We can use a scatterplot to show the relationship between *runtime* and *rating* for all movies

[62]:
```
# Scatterplot
runtime_ratings_fig, runtime_ratings_ax = plt.subplots(figsize=(12,10))
basics_and_ratings['ratescore'] = basics_and_ratings['averagerating'] *␣
 ↪basics_and_ratings['numvotes']
basics_and_ratings
sns.scatterplot(x=basics_and_ratings['runtime_minutes'],␣
 ↪y=basics_and_ratings['averagerating'], ax=runtime_ratings_ax)
runtime_ratings_ax.set_title('Runtimes against TotalRatingScore')
runtime_ratings_ax.set_xlabel('Runtime(minutes)')
runtime_ratings_ax.set_ylabel('Score')
runtime_ratings_fig.savefig('./images/runtime_rating.png')
# plt.show();
```



There doesnt seem to be any clear relationship between runtime and rating.

1.5.5 5. Which genres gross the most

[65]:
```python
#Above and Beyond
import this
```

```
The Zen of Python, by Tim Peters

Beautiful is better than ugly.
Explicit is better than implicit.
Simple is better than complex.
Complex is better than complicated.
Flat is better than nested.
Sparse is better than dense.
Readability counts.
Special cases aren't special enough to break the rules.
Although practicality beats purity.
```

```
Errors should never pass silently.
Unless explicitly silenced.
In the face of ambiguity, refuse the temptation to guess.
There should be one-- and preferably only one --obvious way to do it.
Although that way may not be obvious at first unless you're Dutch.
Now is better than never.
Although never is often better than *right* now.
If the implementation is hard to explain, it's a bad idea.
If the implementation is easy to explain, it may be a good idea.
Namespaces are one honking great idea -- let's do more of those!
```

1.6 Summary

The most commonly produced genres of movies are: * Documentary * Drama * Comedy

Drama ratings have maintained over the years. However **Documentary** Ratings have been declining in recent years. **Comedy** ratings have been on the steady incline, surpassing **documentaries**

The is a relationship between **production cost** of a movie and how much the movie **grosses**. It seems to be a positive covariant relationship.

1.7 Conclusion.

-It would be advisable to Invest resources in one of the three most common genres. **Comedy** movies would be a good start as they are popular and seem to be on the rise in terms of ratings. **Drama** movies are good as a less risky investment as they seem to maintain their ratings. They are also rated significantly higher than most other genres. The production cost seems to be a good indicatior of the movies potential success.

1.8 Next Steps

Further analysisi would be helpful in determining: * cost per genre to produce * most highly rated writers for each movie and each genre etc.
These are but a few of the extra steps that might be taken to get more insights.