Movie Data Exploration

Author: Titilayo Amuwo

Overview

This project analyze different types of movie titles that is currently doing the best at the box office and how it relates to Profit.

Business Problem

Microsoft sees all the big companies creating original video content and wanted to get in on the fun. They have decided to create a new movie studio, but they don't know anything about creating movies. I need to explore what types of films are currently doing the best at the box office, and then translate those findings into actionable insights that the head of Microsoft's new movie studio can use to make a decision. Below I will analyze the data given to understand different movies and their ratings and it's relationship to profits.

Data Understanding

Let's import the libraries we may need for our analysis and import the dataframes as well.

In [461]:
```
#importing tools needed to work on data.
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from scipy.stats import pearsonr

%matplotlib inline
```

In [462]:
```
!ls zippedData/
```

```
bom.movie_gross.csv.gz       imdb.title.ratings.csv.gz
cleaned_movies_title_df.csv  movies_ranked_df.csv
imdb.name.basics.csv.gz      rt.movie_info.tsv.gz
imdb.title.akas.csv.gz       rt.reviews.tsv.gz
imdb.title.basics.csv.gz     tmdb.movies.csv.gz
imdb.title.crew.csv.gz       tn.movie_budgets.csv.gz
imdb.title.principals.csv.gz
```

In [463]:
```
#read the movie datas.
bom = pd.read_csv('zippedData/bom.movie_gross.csv.gz')
imdb_basics = pd.read_csv('zippedData/imdb.title.basics.csv.gz')
tn_movie = pd.read_csv('zippedData/tn.movie_budgets.csv.gz')
imdb_ratings = pd.read_csv ('zippedData/imdb.title.ratings.csv.gz')
```

Now that we have read the files we need, let's preview the info of each data frames to know the columns and datatype.

In [464]:
```
# retrieving the infomation of Bom to get the data type.
bom.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3387 entries, 0 to 3386
Data columns (total 5 columns):
 #   Column          Non-Null Count  Dtype  
---  ------          --------------  -----  
 0   title           3387 non-null   object 
 1   studio          3382 non-null   object 
 2   domestic_gross  3359 non-null   float64
 3   foreign_gross   2037 non-null   object 
 4   year            3387 non-null   int64  
dtypes: float64(1), int64(1), object(3)
memory usage: 132.4+ KB
```

In [465]:
```
# retrieving the info of imdb basics to get the data type.
imdb_basics.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 146144 entries, 0 to 146143
Data columns (total 6 columns):
 #   Column           Non-Null Count   Dtype  
---  ------           --------------   -----  
 0   tconst           146144 non-null  object 
 1   primary_title    146144 non-null  object 
 2   original_title   146123 non-null  object 
 3   start_year       146144 non-null  int64  
 4   runtime_minutes  114405 non-null  float64
 5   genres           140736 non-null  object 
dtypes: float64(1), int64(1), object(4)
memory usage: 6.7+ MB
```

In [466]:
```
tn_movie.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5782 entries, 0 to 5781
Data columns (total 6 columns):
 #   Column             Non-Null Count  Dtype 
---  ------             --------------  ----- 
 0   id                 5782 non-null   int64 
 1   release_date       5782 non-null   object
 2   movie              5782 non-null   object
 3   production_budget  5782 non-null   object
 4   domestic_gross     5782 non-null   object
 5   worldwide_gross    5782 non-null   object
dtypes: int64(1), object(5)
memory usage: 271.2+ KB
```

In [467]:
```
imdb_ratings.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 73856 entries, 0 to 73855
Data columns (total 3 columns):
 #   Column         Non-Null Count  Dtype  
---  ------         --------------  -----  
 0   tconst         73856 non-null  object 
 1   averagerating  73856 non-null  float64
 2   numvotes       73856 non-null  int64  
dtypes: float64(1), int64(1), object(1)
memory usage: 1.7+ MB
```

Let' look at the shape of the data to get the size of the index and columns.

In [468]:
```
bom.shape, imdb_basics.shape ,tn_movie.shape, imdb_ratings.shape
```

Out[468]:
```
((3387, 5), (146144, 6), (5782, 6), (73856, 3))
```

Here, let's look at the statistics summary of each data before cleaning the data

In [469]:
```
#using the describe method to generate summary statistics of the
#numerical data of Bom movies.

bom.describe()
```

Out[469]:

	domestic_gross	year
count	3.359000e+03	3387.000000
mean	2.874585e+07	2013.958075
std	6.698250e+07	2.478141
min	1.000000e+02	2010.000000
25%	1.200000e+05	2012.000000
50%	1.400000e+06	2014.000000
75%	2.790000e+07	2016.000000
max	9.367000e+08	2018.000000

In [470]:
```
imdb_basics.describe()
```

Out[470]:

	start_year	runtime_minutes
count	146144.000000	114405.000000
mean	2014.621798	86.187247
std	2.733583	166.360590
min	2010.000000	1.000000
25%	2012.000000	70.000000
50%	2015.000000	87.000000
75%	2017.000000	99.000000
max	2115.000000	51420.000000

In [471]:
```
tn_movie.describe()
```

Out[471]:

	id
count	5782.000000
mean	50.372363
std	28.821076
min	1.000000
25%	25.000000
50%	50.000000
75%	75.000000
max	100.000000

In [472]:
```
imdb_ratings.describe()
```

Out[472]:

	averagerating	numvotes
count	73856.000000	7.385600e+04
mean	6.332729	3.523662e+03
std	1.474978	3.029402e+04
min	1.000000	5.000000e+00
25%	5.500000	1.400000e+01
50%	6.500000	4.900000e+01
75%	7.400000	2.820000e+02
max	10.000000	1.841066e+06

In [473]:
```
#getting the label of the columns in order to combine / merge.
bom.columns, imdb_basics.columns ,tn_movie.columns, imdb_ratings.columns
```

Out[473]:
```
(Index(['title', 'studio', 'domestic_gross', 'foreign_gross', 'year'], dt
ype='object'),
 Index(['tconst', 'primary_title', 'original_title', 'start_year',
        'runtime_minutes', 'genres'],
       dtype='object'),
 Index(['id', 'release_date', 'movie', 'production_budget', 'domestic_gro
ss',
        'worldwide_gross'],
       dtype='object'),
 Index(['tconst', 'averagerating', 'numvotes'], dtype='object'))
```

In [474]:
```
#getting the first 10 rows of the Bom movies dataframe.
bom.head(10)
```

Out[474]:

	title	studio	domestic_gross	foreign_gross	year
0	Toy Story 3	BV	415000000.0	652000000	2010
1	Alice in Wonderland (2010)	BV	334200000.0	691300000	2010
2	Harry Potter and the Deathly Hallows Part 1	WB	296000000.0	664300000	2010
3	Inception	WB	292600000.0	535700000	2010
4	Shrek Forever After	P/DW	238700000.0	513900000	2010
5	The Twilight Saga: Eclipse	Sum.	300500000.0	398000000	2010
6	Iron Man 2	Par.	312400000.0	311500000	2010
7	Tangled	BV	200800000.0	391000000	2010
8	Despicable Me	Uni.	251500000.0	291600000	2010
9	How to Train Your Dragon	P/DW	217600000.0	277300000	2010

It is always a good practice to check the duplicate of each dataset before merging and after merging.

In [475]:
```
#Check duplicate for bom movie dataframe
bom.duplicated(subset=['title','year']).sum()
```

Out[475]: 0

In [476]:
```
#getting the first 10 rows of the imdb basics dataframe.
imdb_basics.head(10)
```

Out[476]:

	tconst	primary_title	original_title	start_year	runtime_minutes	genres
0	tt0063540	Sunghursh	Sunghursh	2013	175.0	Action,Crime,Drama
1	tt0066787	One Day Before the Rainy Season	Ashad Ka Ek Din	2019	114.0	Biography,Drama
2	tt0069049	The Other Side of the Wind	The Other Side of the Wind	2018	122.0	Drama
3	tt0069204	Sabse Bada Sukh	Sabse Bada Sukh	2018	NaN	Comedy,Drama
4	tt0100275	The Wandering Soap Opera	La Telenovela Errante	2017	80.0	Comedy,Drama,Fantasy
5	tt0111414	A Thin Life	A Thin Life	2018	75.0	Comedy
6	tt0112502	Bigfoot	Bigfoot	2017	NaN	Horror,Thriller
7	tt0137204	Joe Finds Grace	Joe Finds Grace	2017	83.0	Adventure,Animation,Comedy
8	tt0139613	O Silêncio	O Silêncio	2012	NaN	Documentary,History
9	tt0144449	Nema aviona za Zagreb	Nema aviona za Zagreb	2012	82.0	Biography

In [477]:
```
#check the duplicate of Imbd basic dataframe
imdb_basics.duplicated(subset=['tconst','primary_title','start_year']).su
```

Out[477]: 0

In [478]:
```
tn_movie.head(10)
```

Out[478]:

	id	release_date	movie	production_budget	domestic_gross	worldwide_gross
0	1	Dec 18, 2009	Avatar	$425,000,000	$760,507,625	$2,776,345,279
1	2	May 20, 2011	Pirates of the Caribbean: On Stranger Tides	$410,600,000	$241,063,875	$1,045,663,875
2	3	Jun 7, 2019	Dark Phoenix	$350,000,000	$42,762,350	$149,762,350
3	4	May 1, 2015	Avengers: Age of Ultron	$330,600,000	$459,005,868	$1,403,013,963
4	5	Dec 15, 2017	Star Wars Ep. VIII: The Last Jedi	$317,000,000	$620,181,382	$1,316,721,747
5	6	Dec 18, 2015	Star Wars Ep. VII: The Force Awakens	$306,000,000	$936,662,225	$2,053,311,220
6	7	Apr 27, 2018	Avengers: Infinity War	$300,000,000	$678,815,482	$2,048,134,200
7	8	May 24, 2007	Pirates of the Caribbean: At Worldâ€ s End	$300,000,000	$309,420,425	$963,420,425
8	9	Nov 17, 2017	Justice League	$300,000,000	$229,024,295	$655,945,209
9	10	Nov 6, 2015	Spectre	$300,000,000	$200,074,175	$879,620,923

In [479]:
```
#check the duplicate of tn movies dataframe
tn_movie.duplicated(subset=['movie','release_date']).sum()
```

Out[479]: 0

In [480]:
```
imdb_ratings.head(10)
```

Out[480]:

	tconst	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
5	tt1069246	6.2	326
6	tt1094666	7.0	1613
7	tt1130982	6.4	571
8	tt1156528	7.2	265
9	tt1161457	4.2	148

In [481]:
```
#checking the duplicate of imdb rating dataframe
imdb_ratings.duplicated(subset='tconst').sum()
```

Out[481]: 0

Data Preparation and Cleaning

Before working on tn movie I had to remove the dollar sign and also convert it to numerical values because the index was an object and without conversion, I will not be able to work with it as an a float. After that we are going to be cleaning each data in order to generate the samples for our analysis.

In [482]:
```
#Remove dollar signs from worldwide_gross column
tn_movie['worldwide_gross']=tn_movie['worldwide_gross'].replace({'\$':'',
```

In [483]:
```
#convert the index to numerical values
tn_movie['worldwide_gross']=pd.to_numeric(tn_movie['worldwide_gross'],err
```

In [484]:
```
#Remove dollar signs from production_budget column
tn_movie['production_budget']=tn_movie['production_budget'].replace({'\$'
```

In [485]:
```
tn_movie['production_budget']=pd.to_numeric(tn_movie['production_budget']
```

In [486]:
```
##Remove dollar signs from domestic_gross column
tn_movie['domestic_gross']=tn_movie['domestic_gross'].replace({'\$':'',',
```

In [487]:
```
#convert the index to numerical values
tn_movie['domestic_gross']=pd.to_numeric(tn_movie['domestic_gross'],error
```

In [488]:
```
#split the movie release date by year and create a new column for year.
tn_movie['year']= tn_movie['release_date'].map(lambda x: x[7:])
tn_movie.head()
```

Out[488]:

	id	release_date	movie	production_budget	domestic_gross	worldwide_gross	year
0	1	Dec 18, 2009	Avatar	425000000	760507625	2776345279	2009
1	2	May 20, 2011	Pirates of the Caribbean: On Stranger Tides	410600000	241063875	1045663875	2011
2	3	Jun 7, 2019	Dark Phoenix	350000000	42762350	149762350	2019
3	4	May 1, 2015	Avengers: Age of Ultron	330600000	459005868	1403013963	2015
4	5	Dec 15, 2017	Star Wars Ep. VIII: The Last Jedi	317000000	620181382	1316721747	2017

In [489]:
```
tn_movie.tail()
```

Out[489]:

	id	release_date	movie	production_budget	domestic_gross	worldwide_gross	year
5777	78	Dec 31, 2018	Red 11	7000	0	0	2018
5778	79	Apr 2, 1999	Following	6000	48482	240495	1999
5779	80	Jul 13, 2005	Return to the Land of Wonders	5000	1338	1338	2005
5780	81	Sep 29, 2015	A Plague So Pleasant	1400	0	0	2015
5781	82	Aug 5, 2005	My Date With Drew	1100	181041	181041	2005

In [490]:
```
#Drop the columns that I will not use for my analysis.
tn_df =tn_movie.drop(labels=['release_date','worldwide_gross','id'], axis
```

In [491]:
```
#rename movie column to title for uniformity
tn_df=tn_df.rename(columns = {'movie':'title'})
```

In [492]:
```
tn_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5782 entries, 0 to 5781
Data columns (total 4 columns):
 #   Column             Non-Null Count  Dtype 
---  ------             --------------  ----- 
 0   title              5782 non-null   object
 1   production_budget  5782 non-null   int64 
 2   domestic_gross     5782 non-null   int64 
 3   year               5782 non-null   object
dtypes: int64(2), object(2)
memory usage: 180.8+ KB
```

In [493]:
```
#drop the foreign_grosss column
bom_df = bom.drop('foreign_gross',axis = 1)
bom_df
```

0	Toy Story 3	BV	415000000.0	2010
1	Alice in Wonderland (2010)	BV	334200000.0	2010
2	Harry Potter and the Deathly Hallows Part 1	WB	296000000.0	2010
3	Inception	WB	292600000.0	2010
4	Shrek Forever After	P/DW	238700000.0	2010
...	...	...	...	...
3382	The Quake	Magn.	6200.0	2018
3383	Edward II (2018 re-release)	FM	4800.0	2018
3384	El Pacto	Sony	2500.0	2018
3385	The Swan	Synergetic	2400.0	2018
3386	An Actor Prepares	Grav.	1700.0	2018

3387 rows × 4 columns

In [494]:
```
#convert year from int to str
bom_df['year'] = bom_df['year'].astype(str)
bom_df.head()
```

Out[494]:

	title	studio	domestic_gross	year
0	Toy Story 3	BV	415000000.0	2010
1	Alice in Wonderland (2010)	BV	334200000.0	2010
2	Harry Potter and the Deathly Hallows Part 1	WB	296000000.0	2010
3	Inception	WB	292600000.0	2010
4	Shrek Forever After	P/DW	238700000.0	2010

In [495]:
```
tn_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5782 entries, 0 to 5781
Data columns (total 4 columns):
 #   Column             Non-Null Count  Dtype 
---  ------             --------------  ----- 
 0   title              5782 non-null   object
 1   production_budget  5782 non-null   int64 
 2   domestic_gross     5782 non-null   int64 
 3   year               5782 non-null   object
dtypes: int64(2), object(2)
memory usage: 180.8+ KB
```

In [496]:
```
bom_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3387 entries, 0 to 3386
Data columns (total 4 columns):
 #   Column          Non-Null Count  Dtype  
---  ------          --------------  -----  
 0   title           3387 non-null   object 
 1   studio          3382 non-null   object 
 2   domestic_gross  3359 non-null   float64
 3   year            3387 non-null   object 
dtypes: float64(1), object(3)
memory usage: 106.0+ KB
```

In [497]:
```
#merge bom and tn_movies on 'title' and 'year' columns.
bom_and_tn_df = bom_df.merge(tn_df, how='outer', on =['title','year','dom
bom_and_tn_df
```

0	Toy Story 3	BV	415000000.0	2010	NaN
1	Alice in Wonderland (2010)	BV	334200000.0	2010	NaN
2	Harry Potter and the Deathly Hallows Part 1	WB	296000000.0	2010	NaN
3	Inception	WB	292600000.0	2010	NaN
4	Shrek Forever After	P/DW	238700000.0	2010	NaN
...	...	...	...	...	...
9164	Red 11	NaN	0.0	2018	7000.0
9165	Following	NaN	48482.0	1999	6000.0
9166	Return to the Land of Wonders	NaN	1338.0	2005	5000.0
9167	A Plague So Pleasant	NaN	0.0	2015	1400.0
9168	My Date With Drew	NaN	181041.0	2005	1100.0

9169 rows × 5 columns

In [498]:
```
bom_and_tn_df.duplicated(subset=['title','year']).sum()
```

Out[498]: 318

In [499]:
```
bom_and_tn_df.drop_duplicates(subset= ['title','year'])
```

Out[499]:

	title	studio	domestic_gross	year	production_budget
0	Toy Story 3	BV	415000000.0	2010	NaN
1	Alice in Wonderland (2010)	BV	334200000.0	2010	NaN
2	Harry Potter and the Deathly Hallows Part 1	WB	296000000.0	2010	NaN
3	Inception	WB	292600000.0	2010	NaN
4	Shrek Forever After	P/DW	238700000.0	2010	NaN
...	...	...	...	...	...
9164	Red 11	NaN	0.0	2018	7000.0
9165	Following	NaN	48482.0	1999	6000.0
9166	Return to the Land of Wonders	NaN	1338.0	2005	5000.0
9167	A Plague So Pleasant	NaN	0.0	2015	1400.0
9168	My Date With Drew	NaN	181041.0	2005	1100.0

8851 rows × 5 columns

In [500]:
```
bom_and_tn_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 9169 entries, 0 to 9168
Data columns (total 5 columns):
 #   Column             Non-Null Count  Dtype  
---  ------             --------------  -----  
 0   title              9169 non-null   object 
 1   studio             3382 non-null   object 
 2   domestic_gross     9141 non-null   float64
 3   year               9169 non-null   object 
 4   production_budget  5782 non-null   float64
dtypes: float64(2), object(3)
memory usage: 429.8+ KB
```

In [501]:
```
imdb_basics
```

0	tt0063540	Sunghursh	Sunghursh	2013	175.0	Action,Crime,Drama
1	tt0066787	One Day Before the Rainy Season	Ashad Ka Ek Din	2019	114.0	Biography,Drama
2	tt0069049	The Other Side of the Wind	The Other Side of the Wind	2018	122.0	Drama
3	tt0069204	Sabse Bada Sukh	Sabse Bada Sukh	2018	NaN	Comedy,Drama
4	tt0100275	The Wandering Soap Opera	La Telenovela Errante	2017	80.0	Comedy,Drama,Fantasy
...	...	...	...	...	...	...
146139	tt9916538	Kuambil Lagi Hatiku	Kuambil Lagi Hatiku	2019	123.0	Drama
146140	tt9916622	Rodolpho Teóphilo - O	Rodolpho Teóphilo - O	2015	NaN	Documentary

In [502]:
```
#drop original_title column
imdb_basics_df = imdb_basics.drop('original_title',axis = 1)
imdb_basics_df
```

Out[502]:

	tconst	primary_title	start_year	runtime_minutes	genres
0	tt0063540	Sunghursh	2013	175.0	Action,Crime,Drama
1	tt0066787	One Day Before the Rainy Season	2019	114.0	Biography,Drama
2	tt0069049	The Other Side of the Wind	2018	122.0	Drama
3	tt0069204	Sabse Bada Sukh	2018	NaN	Comedy,Drama
4	tt0100275	The Wandering Soap Opera	2017	80.0	Comedy,Drama,Fantasy
...	...	...	...	...	...
146139	tt9916538	Kuambil Lagi Hatiku	2019	123.0	Drama
146140	tt9916622	Rodolpho Teóphilo - O Legado de um Pioneiro	2015	NaN	Documentary
146141	tt9916706	Dankyavar Danka	2013	NaN	Comedy
146142	tt9916730	6 Gunn	2017	116.0	NaN
146143	tt9916754	Chico Albuquerque - Revelações	2013	NaN	Documentary

146144 rows × 5 columns

In [503]:
```
#Rename the columns so i can merge with imdb ratings dataframe.
imdb_basics_df = imdb_basics_df.rename(columns = {'primary_title':'title'
imdb_basics_df
```

Out[503]:

	tconst	title	year	runtime_minutes	genres
0	tt0063540	Sunghursh	2013	175.0	Action,Crime,Drama
1	tt0066787	One Day Before the Rainy Season	2019	114.0	Biography,Drama
2	tt0069049	The Other Side of the Wind	2018	122.0	Drama
3	tt0069204	Sabse Bada Sukh	2018	NaN	Comedy,Drama
4	tt0100275	The Wandering Soap Opera	2017	80.0	Comedy,Drama,Fantasy
...	...	...	...	...	...
146139	tt9916538	Kuambil Lagi Hatiku	2019	123.0	Drama
146140	tt9916622	Rodolpho Teóphilo - O Legado de um Pioneiro	2015	NaN	Documentary
146141	tt9916706	Dankyavar Danka	2013	NaN	Comedy
146142	tt9916730	6 Gunn	2017	116.0	NaN

In [504]:
```
imdb_basics_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 146144 entries, 0 to 146143
Data columns (total 5 columns):
 #   Column           Non-Null Count   Dtype  
---  ------           --------------   -----  
 0   tconst           146144 non-null  object 
 1   title            146144 non-null  object 
 2   year             146144 non-null  int64  
 3   runtime_minutes  114405 non-null  float64
 4   genres           140736 non-null  object 
dtypes: float64(1), int64(1), object(3)
memory usage: 5.6+ MB
```

In [505]:
```
imdb_ratings.head()
```

Out[505]:

	tconst	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

In [506]:
```
imdb_df = imdb_basics_df.merge(imdb_ratings, on ='tconst')
imdb_df
```

Out[506]:

	tconst	title	year	runtime_minutes	genres	averagerating	numvot
0	tt0063540	Sunghursh	2013	175.0	Action,Crime,Drama	7.0	
1	tt0066787	One Day Before the Rainy Season	2019	114.0	Biography,Drama	7.2	
2	tt0069049	The Other Side of the Wind	2018	122.0	Drama	6.9	45
3	tt0069204	Sabse Bada Sukh	2018	NaN	Comedy,Drama	6.1	
4	tt0100275	The Wandering Soap Opera	2017	80.0	Comedy,Drama,Fantasy	6.5	1
...	...	...	...	...	...	...	
73851	tt9913084	Diabolik sono io	2019	75.0	Documentary	6.2	
73852	tt9914286	Sokagin Çocuklari	2019	98.0	Drama,Family	8.7	1
73853	tt9914642	Albatross	2017	NaN	Documentary	8.5	
73854	tt9914942	La vida sense la Sara Amat	2019	NaN	NaN	6.6	
73855	tt9916160	Drømmeland	2019	72.0	Documentary	6.5	

73856 rows × 7 columns

In [507]:
```
imdb_df.duplicated(subset= 'tconst').sum()
```

Out[507]: 0

In [508]:
```
imdb_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 73856 entries, 0 to 73855
Data columns (total 7 columns):
 #   Column           Non-Null Count  Dtype  
---  ------           --------------  -----  
 0   tconst           73856 non-null  object 
 1   title            73856 non-null  object 
 2   year             73856 non-null  int64  
 3   runtime_minutes  66236 non-null  float64
 4   genres           73052 non-null  object 
 5   averagerating    73856 non-null  float64
 6   numvotes         73856 non-null  int64  
dtypes: float64(2), int64(2), object(3)
memory usage: 4.5+ MB
```

In [509]:
```
imdb_df.rename(columns = {"tconst": "id"})
```

Out[509]:

	id	title	year	runtime_minutes	genres	averagerating	numvote
0	tt0063540	Sunghursh	2013	175.0	Action,Crime,Drama	7.0	7
1	tt0066787	One Day Before the Rainy Season	2019	114.0	Biography,Drama	7.2	4
2	tt0069049	The Other Side of the Wind	2018	122.0	Drama	6.9	451
3	tt0069204	Sabse Bada Sukh	2018	NaN	Comedy,Drama	6.1	1
4	tt0100275	The Wandering Soap Opera	2017	80.0	Comedy,Drama,Fantasy	6.5	11
...	...	...	...	...	...	...	...
73851	tt9913084	Diabolik	2019	75.0	Documentary	6.2	

In [510]:
```
#Change the 'year' datatype from int to string.
imdb_df['year']=imdb_df['year'].astype(str)
```

In [511]:
```
bom_and_tn_df
```

Out[511]:

	title	studio	domestic_gross	year	production_budget
0	Toy Story 3	BV	415000000.0	2010	NaN
1	Alice in Wonderland (2010)	BV	334200000.0	2010	NaN
2	Harry Potter and the Deathly Hallows Part 1	WB	296000000.0	2010	NaN
3	Inception	WB	292600000.0	2010	NaN
4	Shrek Forever After	P/DW	238700000.0	2010	NaN
...	...	...	...	...	...
9164	Red 11	NaN	0.0	2018	7000.0
9165	Following	NaN	48482.0	1999	6000.0
9166	Return to the Land of Wonders	NaN	1338.0	2005	5000.0
9167	A Plague So Pleasant	NaN	0.0	2015	1400.0
9168	My Date With Drew	NaN	181041.0	2005	1100.0

9169 rows × 5 columns

In [512]:
```
#Using the .merge() method to combine Bom movies with imbd movies.
#create a new variable name for the combined movies
movies_title_df = bom_and_tn_df.merge(imdb_df, on = ['title','year'])
movies_title_df
```

	title	studio	domestic_gross	year	production_budget	tconst	runtime_minutes	genres	averagerating	numvotes
0	Toy Story 3	BV	415000000.0	2010	NaN	tt0435761	103.0	Adven		
1	Inception	WB	292600000.0	2010	NaN	tt1375666	148.0			
2	Shrek Forever After	P/DW	238700000.0	2010	NaN	tt0892791	93.0	Adven		
3	The Twilight Saga: Eclipse	Sum.	300500000.0	2010	NaN	tt1325004	124.0	Ad		
4	Iron Man 2	Par.	312400000.0	2010	NaN	tt1228705	124.0			
...	...	...	...	...	...	...	...			
2231	Heroes of Dirt	NaN	0.0	2015	175000.0	tt1934172	98.0			
2232	Aroused	NaN	0.0	2013	150000.0	tt2403815	66.0			
2233	The Dirties	NaN	0.0	2013	55000.0	tt2334896	83.0			

In [513]:
```
movies_title_df.duplicated().sum()
```

Out[513]: 0

In [514]:
```
movies_title_df.shape
```

Out[514]: (2236, 10)

In [515]:
```
movies_title_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 2236 entries, 0 to 2235
Data columns (total 10 columns):
 #   Column             Non-Null Count  Dtype  
---  ------             --------------  -----  
 0   title              2236 non-null   object 
 1   studio             1845 non-null   object 
 2   domestic_gross     2226 non-null   float64
 3   year               2236 non-null   object 
 4   production_budget  389 non-null    float64
 5   tconst             2236 non-null   object 
 6   runtime_minutes    2232 non-null   float64
 7   genres             2234 non-null   object 
 8   averagerating      2236 non-null   float64
 9   numvotes           2236 non-null   int64  
dtypes: float64(4), int64(1), object(5)
memory usage: 192.2+ KB
```

Data Analysis

Here we are going to Analyze the data that we have cleaned and sort it to get the accurate data needed to produce visuals to represent each recommendations.

In [516]:
```
#Calculating my Profit.
#Formulae  Profit = Total Revenue - Total Cost
movies_title_df['profit'] = movies_title_df['domestic_gross'] - movies_ti
movies_title_df
```

Out[516]:

	title	studio	domestic_gross	year	production_budget	tconst	runtime_minutes	
0	Toy Story 3	BV	415000000.0	2010	NaN	tt0435761	103.0	Adven
1	Inception	WB	292600000.0	2010	NaN	tt1375666	148.0	
2	Shrek Forever After	P/DW	238700000.0	2010	NaN	tt0892791	93.0	Adven
3	The Twilight Saga: Eclipse	Sum.	300500000.0	2010	NaN	tt1325004	124.0	Ad
4	Iron Man 2	Par.	312400000.0	2010	NaN	tt1228705	124.0	
...	...	...	...	...	...	...	...	
2231	Heroes of Dirt	NaN	0.0	2015	175000.0	tt1934172	98.0	

In [517]:

```
#Calculating my Return On Investment.
#Formulae = ROI = Profit / cost * 100
movies_title_df['roi'] = movies_title_df['profit']/movies_title_df['produ
movies_title_df
```

Out[517]:

	title	studio	domestic_gross	year	production_budget	tconst	runtime_minutes	
0	Toy Story 3	BV	415000000.0	2010	NaN	tt0435761	103.0	Adve
1	Inception	WB	292600000.0	2010	NaN	tt1375666	148.0	
2	Shrek Forever After	P/DW	238700000.0	2010	NaN	tt0892791	93.0	Adve
3	The Twilight Saga: Eclipse	Sum.	300500000.0	2010	NaN	tt1325004	124.0	A
4	Iron Man 2	Par.	312400000.0	2010	NaN	tt1228705	124.0	
...	...	...	...	...	...	...	...	
2231	Heroes of Dirt	NaN	0.0	2015	175000.0	tt1934172	98.0	
2232	Aroused	NaN	0.0	2013	150000.0	tt2403815	66.0	
2233	The Dirties	NaN	0.0	2013	55000.0	tt2334896	83.0	
2234	Exeter	NaN	0.0	2015	25000.0	tt1945044	91.0	
2235	Dutch Kills	NaN	0.0	2015	25000.0	tt2759066	90.0	

2236 rows × 12 columns

In [518]:
```
movies_profit_df = movies_title_df.loc[movies_title_df['profit'] > 0]
movies_profit_df
```

Out[518]:

	title	studio	domestic_gross	year	production_budget	tconst	runtime_minutes	
5	Iron Man 2	NaN	312433331.0	2010	170000000.0	tt1228705	124.0	A
8	Despicable Me	NaN	251513985.0	2010	69000000.0	tt1323594	95.0	Ani
15	Black Swan	NaN	106954678.0	2010	13000000.0	tt0947798	108.0	
17	Megamind	NaN	148415853.0	2010	130000000.0	tt1001526	95.0	Act
32	The Social Network	NaN	96962694.0	2010	40000000.0	tt1285016	120.0	
...	...	...	...	...	...	...	...	
2212	Grace Unplugged	NaN	2507159.0	2013	1700000.0	tt2349460	102.0	
2224	Meet the Blacks	NaN	9097072.0	2016	900000.0	tt4191580	94.0	
2225	Kevin Hart: Laugh at My Pain	NaN	7706436.0	2011	750000.0	tt1999192	89.0	
2226	Columbus	NaN	1017107.0	2017	700000.0	tt5990474	104.0	
2227	Sholem Aleichem: Laughing in the Darkness	NaN	1131261.0	2011	500000.0	tt1976608	93.0	

207 rows × 12 columns

In [519]:
```
movies_ranked_df = movies_title_df.sort_values(by=['roi'],ascending=False
movies_ranked_df
```

Out[519]:

	title	studio	domestic_gross	year	production_budget	tconst	runtime_minutes	
549	The Devil Inside	NaN	53262945.0	2012	1000000.0	tt1560985	83.0	
799	The Purge	NaN	64473115.0	2013	3000000.0	tt2184339	85.0	
1867	A Ghost Story	NaN	1594798.0	2017	100000.0	tt6265828	92.0	Dr
980	Annabelle	NaN	84273813.0	2014	6500000.0	tt3322940	99.0	
839	Kevin Hart: Let Me Explain	NaN	32244051.0	2013	2500000.0	tt2609912	75.0	
...	...	...	...	...	...	...	...	
2105	Helicopter Eela	Eros	72000.0	2018	NaN	tt8427036	135.0	
2106	Girls vs Gangsters	WGUSA	37100.0	2018	NaN	tt7870578	120.0	
2107	A Paris Education	KL	21600.0	2018	NaN	tt6593240	137.0	
2108	The Quake	Magn.	6200.0	2018	NaN	tt6523720	106.0	
2109	An Actor Prepares	Grav.	1700.0	2018	NaN	tt5718046	97.0	

2236 rows × 12 columns

In [520]:
```
movies_ranked_df
```

Out[520]:

	title	studio	domestic_gross	year	production_budget	tconst	runtime_minutes	
549	The Devil Inside	NaN	53262945.0	2012	1000000.0	tt1560985	83.0	
799	The Purge	NaN	64473115.0	2013	3000000.0	tt2184339	85.0	
1867	A Ghost Story	NaN	1594798.0	2017	100000.0	tt6265828	92.0	Dr
980	Annabelle	NaN	84273813.0	2014	6500000.0	tt3322940	99.0	
839	Kevin Hart: Let Me Explain	NaN	32244051.0	2013	2500000.0	tt2609912	75.0	
...	...	...	...	...	...	...	...	
2105	Helicopter Eela	Eros	72000.0	2018	NaN	tt8427036	135.0	
2106	Girls vs Gangsters	WGUSA	37100.0	2018	NaN	tt7870578	120.0	
2107	A Paris Education	KL	21600.0	2018	NaN	tt6593240	137.0	
2108	The Quake	Magn.	6200.0	2018	NaN	tt6523720	106.0	
2109	An Actor Prepares	Grav.	1700.0	2018	NaN	tt5718046	97.0	

2236 rows × 12 columns

In [521]:
```
#getting the summary statistics of movies profit dataframe.
movies_profit_df.describe()
```

Out[521]:

	domestic_gross	production_budget	runtime_minutes	averagerating	numvotes	pr
count	2.070000e+02	2.070000e+02	207.000000	207.000000	2.070000e+02	2.070000e
mean	1.002225e+08	5.124831e+07	108.048309	6.657005	1.922260e+05	4.897424e
std	1.097864e+08	6.140446e+07	16.550235	0.905183	2.197955e+05	6.395659e
min	1.017107e+06	1.000000e+05	75.000000	4.000000	6.000000e+00	2.056160e
25%	2.988107e+07	1.150000e+07	95.000000	6.050000	3.891350e+04	8.981124e
50%	5.461190e+07	2.400000e+07	105.000000	6.700000	1.156240e+05	2.505578e
75%	1.370569e+08	6.100000e+07	118.000000	7.400000	2.858155e+05	5.763658e
max	6.232795e+08	3.306000e+08	169.000000	8.600000	1.299334e+06	3.982795e

In [522]:
```
movies_profit_df['roi'].describe()
```

Out[522]:
```
count     207.000000
mean      215.724228
std       442.150841
min         0.451083
25%        37.151528
50%       104.496136
75%       219.558672
max      5226.294500
Name: roi, dtype: float64
```

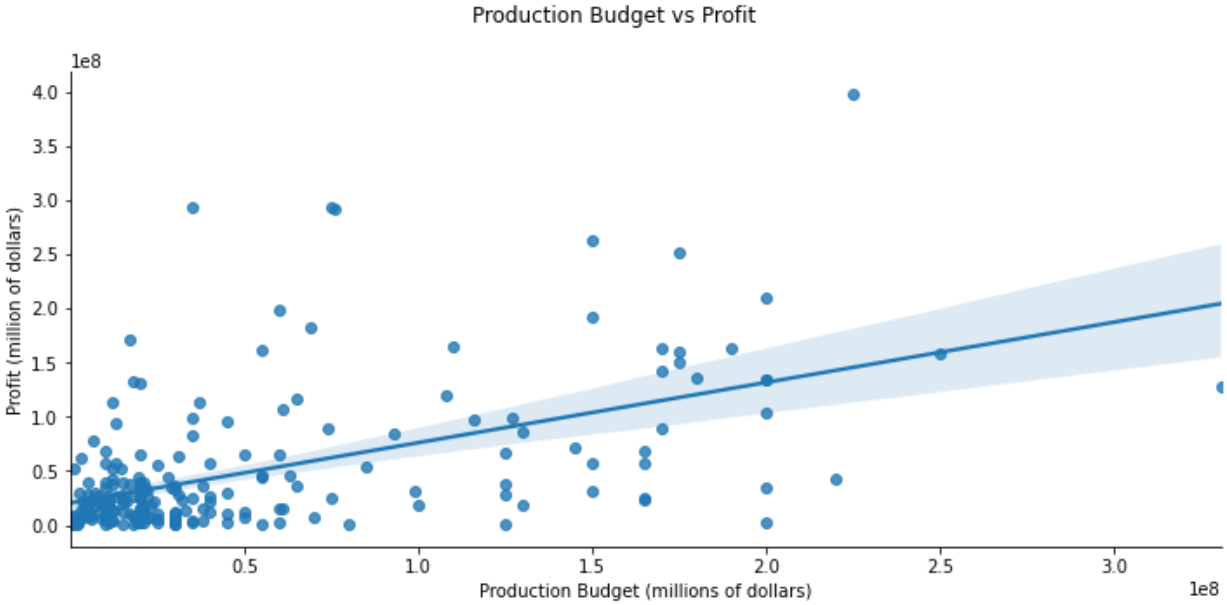
In [523]:
```
movies_profit_df['profit'].describe()
```

Out[523]:
```
count    2.070000e+02
mean     4.897424e+07
std      6.395659e+07
min      2.056160e+05
25%      8.981124e+06
50%      2.505578e+07
75%      5.763658e+07
max      3.982795e+08
Name: profit, dtype: float64
```

In [524]:
```
movies_profit_df.loc[0:35, 'production_budget'].describe()
```

Out[524]:
```
count    5.000000e+00
mean     8.440000e+07
std      6.463977e+07
min      1.300000e+07
25%      4.000000e+07
50%      6.900000e+07
75%      1.300000e+08
max      1.700000e+08
Name: production_budget, dtype: float64
```

In [525]:
```
graph=sns.lmplot(x ='production_budget', y='profit',data = movies_profit_
graph.set_axis_labels(x_var='Production Budget (millions of dollars)', y_
fig=graph.fig
fig.suptitle('Production Budget vs Profit')
plt.tight_layout()
plt.show()
fig.savefig('ProductionBudgetVSProfit.png')
```



In [526]:
```
#Saving my cleaned data
movies_title_df.to_csv('./ZippedData/cleaned_movies_title_df.csv')
```

In [527]:

```
#Create a genres Table
movies_title_df['genres'] = movies_title_df['genres'].str.split(',')
movies_title_df = movies_title_df.explode('genres')
movies_title_df
```

Out[527]:

	title	studio	domestic_gross	year	production_budget	tconst	runtime_minutes	ge
0	Toy Story 3	BV	415000000.0	2010	NaN	tt0435761	103.0	Adve
0	Toy Story 3	BV	415000000.0	2010	NaN	tt0435761	103.0	Anim
0	Toy Story 3	BV	415000000.0	2010	NaN	tt0435761	103.0	Cor
1	Inception	WB	292600000.0	2010	NaN	tt1375666	148.0	A
1	Inception	WB	292600000.0	2010	NaN	tt1375666	148.0	Adve
...	...	...	...	...	...	...	...	
2234	Exeter	NaN	0.0	2015	25000.0	tt1945044	91.0	My
2234	Exeter	NaN	0.0	2015	25000.0	tt1945044	91.0	Th
2235	Dutch Kills	NaN	0.0	2015	25000.0	tt2759066	90.0	C
2235	Dutch Kills	NaN	0.0	2015	25000.0	tt2759066	90.0	D
2235	Dutch Kills	NaN	0.0	2015	25000.0	tt2759066	90.0	Th

5563 rows × 12 columns

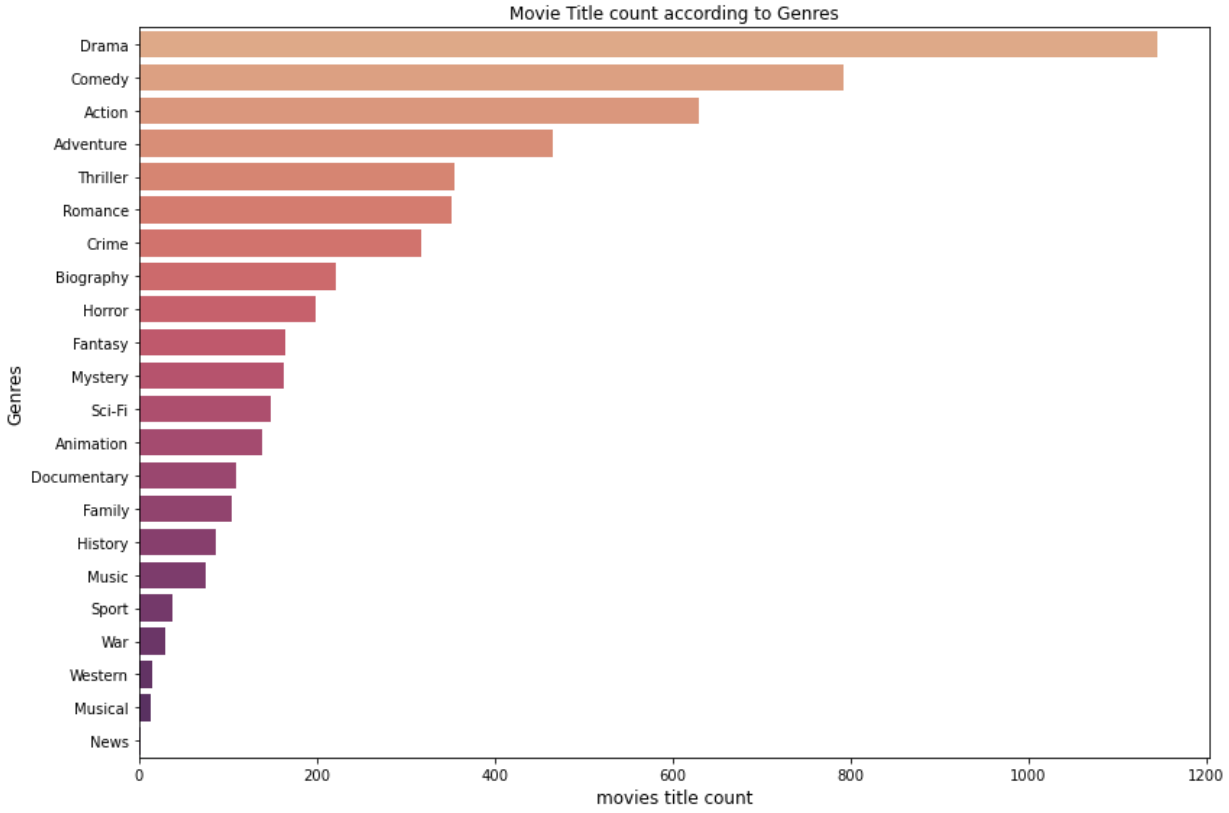
In [528]:
```
#counting each genres by movie titles
movies_genres_df = movies_title_df.groupby('genres',as_index=False)['titl
movies_genres_df.reset_index(inplace=True)
movies_genres_df
```

Out[528]:

	index	genres	title
0	7	Drama	1146
1	4	Comedy	792
2	0	Action	630
3	1	Adventure	465
4	19	Thriller	354
5	16	Romance	352
6	5	Crime	318
7	3	Biography	221
8	11	Horror	199
9	9	Fantasy	165
10	14	Mystery	162
11	17	Sci-Fi	148
12	2	Animation	138
13	6	Documentary	109
14	8	Family	105
15	10	History	86
16	12	Music	75
17	18	Sport	38
18	20	War	29
19	21	Western	15
20	13	Musical	13
21	15	News	1

In [529]:

```
plt.figure(figsize=(12,8))
graph = sns.barplot(x=movies_genres_df['title'], y =movies_genres_df['gen
fig=graph.get_figure()
graph.set_xlabel(xlabel='movies title count', fontsize=12)
graph.set_ylabel(ylabel='Genres', fontsize=12)
graph.set_title('Movie Title count according to Genres')
plt.tight_layout()
plt.show()
fig.savefig('Genres.png');
```



In [530]:
```
roi_genres_df=movies_title_df.groupby('genres',as_index=False)[['producti
roi_genres_df.reset_index(inplace=True)
roi_genres_df
```

Out[530]:

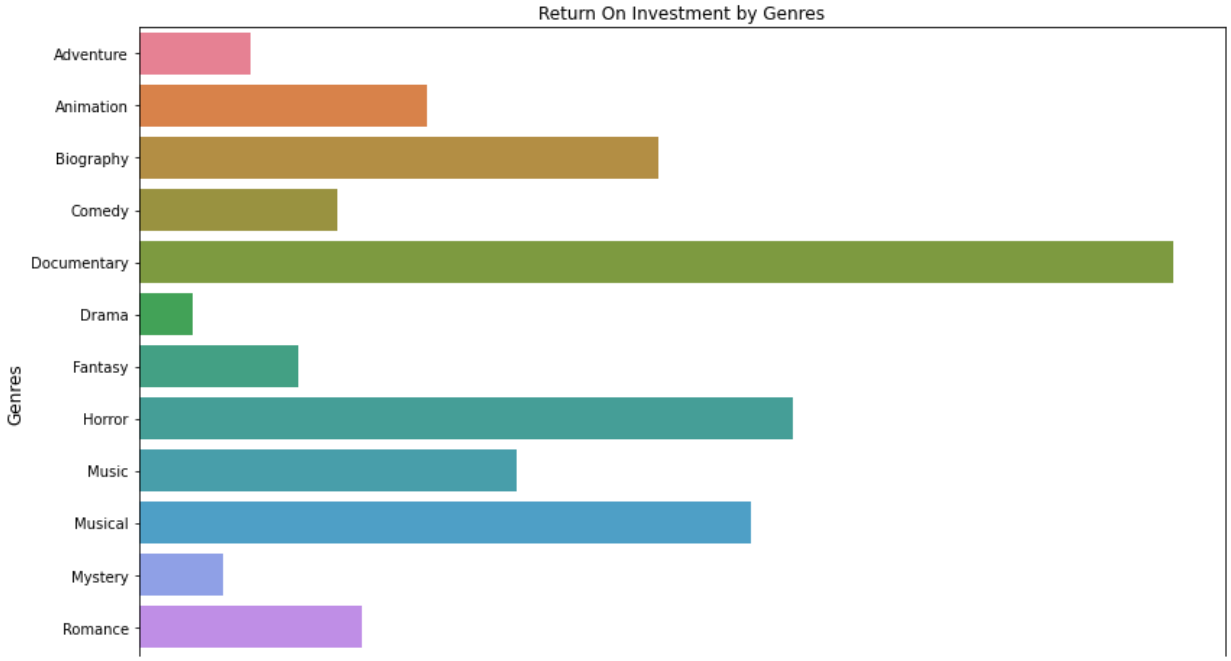
	index	genres	production_budget	profit	roi
0	0	Action	60000000.0	-2000000.0	-10.157111
1	1	Adventure	105500000.0	3605952.0	12.271350
2	2	Animation	75000000.0	28707064.0	31.493344
3	3	Biography	18000000.0	6068926.0	56.865574
4	4	Comedy	22000000.0	5608245.0	21.705542
5	5	Crime	22000000.0	-55000.0	-8.180506
6	6	Documentary	2250000.0	1471547.5	113.321146
7	7	Drama	15000000.0	478094.5	5.875551
8	8	Family	50000000.0	-1950368.0	-5.047100
9	9	Fantasy	42000000.0	1494798.0	17.385498
10	10	History	11500000.0	-3062651.5	-16.034922

In [531]:
```
roi_genres_df = roi_genres_df[roi_genres_df['roi'] > 0]
roi_genres_df
```

3	3	Biography	18000000.0	6068926.0	56.865574
4	4	Comedy	22000000.0	5608245.0	21.705542
6	6	Documentary	2250000.0	1471547.5	113.321146
7	7	Drama	15000000.0	478094.5	5.875551
9	9	Fantasy	42000000.0	1494798.0	17.385498
11	11	Horror	8000000.0	8197072.0	71.709725
12	12	Music	18000000.0	8080225.0	41.334077
13	13	Musical	200000000.0	134191110.0	67.095555
14	14	Mystery	11750000.0	2482887.5	9.207298
16	16	Romance	19000000.0	3260957.0	24.493317
17	17	Sci-Fi	120000000.0	23017894.0	63.233740
19	19	Thriller	17500000.0	2836826.5	10.079777

In [532]:

```
plt.figure(figsize=(12,8))
graph = sns.barplot(x=roi_genres_df['roi'], y =roi_genres_df['genres'], pa
fig=graph.get_figure()
graph.set_xlabel(xlabel='Return on Investment (Million of Dollars)', fonts
graph.set_ylabel(ylabel='Genres', fontsize=12)
graph.set_title('Return On Investment by Genres')
plt.tight_layout()
plt.show()
fig.savefig('Roi.png');
```



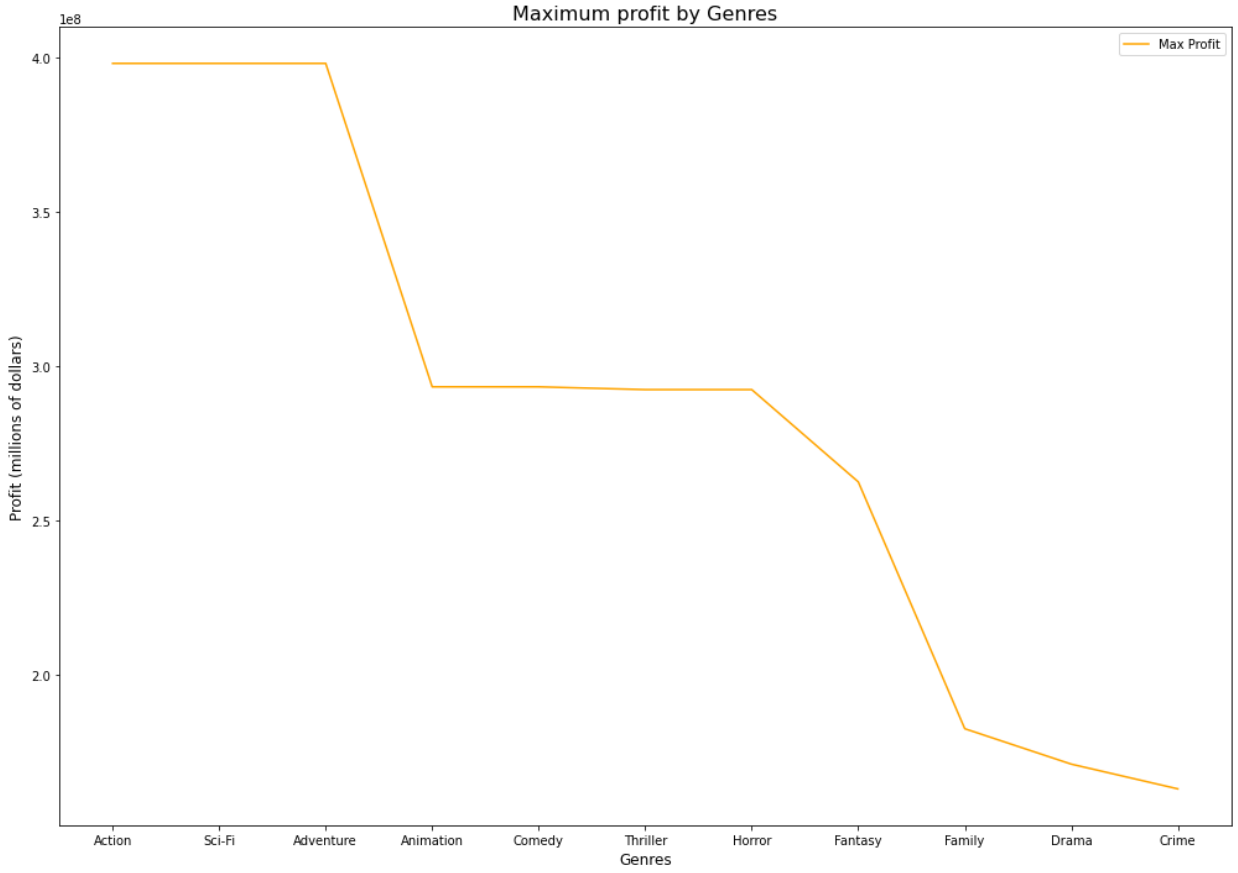
In [533]:
```
my movietitle dataframe by genres, return on investment and profit
he agg()method to get the maximum value and then sort it by profit
get the the first eleven genres with high profit and ROI
_max_df = movies_title_df.groupby(['genres'], as_index=False)[['roi','profit
_max_df=profit_max_df.iloc[0:11]
_max_df
```

Out[533]:

	genres	roi	profit
0	Action	690.424400	398279547.0
17	Sci-Fi	1006.025653	398279547.0
1	Adventure	391.179107	398279547.0
2	Animation	391.179107	293384330.0
4	Comedy	1189.762040	293384330.0
19	Thriller	2049.103833	292481748.0
11	Horror	5226.294500	292481748.0
9	Fantasy	1494.798000	262563408.0
8	Family	264.513022	182513985.0
7	Drama	1494.798000	171024361.0
5	Crime	306.470592	163007020.0

In [534]:

```
#Line graph showing maximum profit by genres
fig =plt.figure(figsize=(14,10))
graph=sns.lineplot(x= 'genres', y='profit',data=profit_max_df, color = 'o
fig=graph.get_figure()
graph.set_xlabel(xlabel='Genres', fontsize=12)
graph.set_ylabel(ylabel='Profit (millions of dollars)',fontsize =12)
graph.set_title('Maximum profit by Genres', fontsize=16)
plt.tight_layout()
plt.show()
fig.savefig('MaximumProfitbyGenres.png');
```



In [535]:
```
ping the dataframe by runtime and profit to get the maximum value of profit
t_runtime_df = movies_title_df.groupby(['runtime_minutes'], as_index=False)
t_runtime_df
```

Out[535]:

	runtime_minutes	profit
82	143.0	398279547.0
26	87.0	293384330.0
74	135.0	292481748.0
37	98.0	292065385.0
80	141.0	262563408.0
...	...	...
112	177.0	NaN
113	180.0	NaN
114	184.0	NaN
115	186.0	NaN
116	189.0	NaN

117 rows × 2 columns

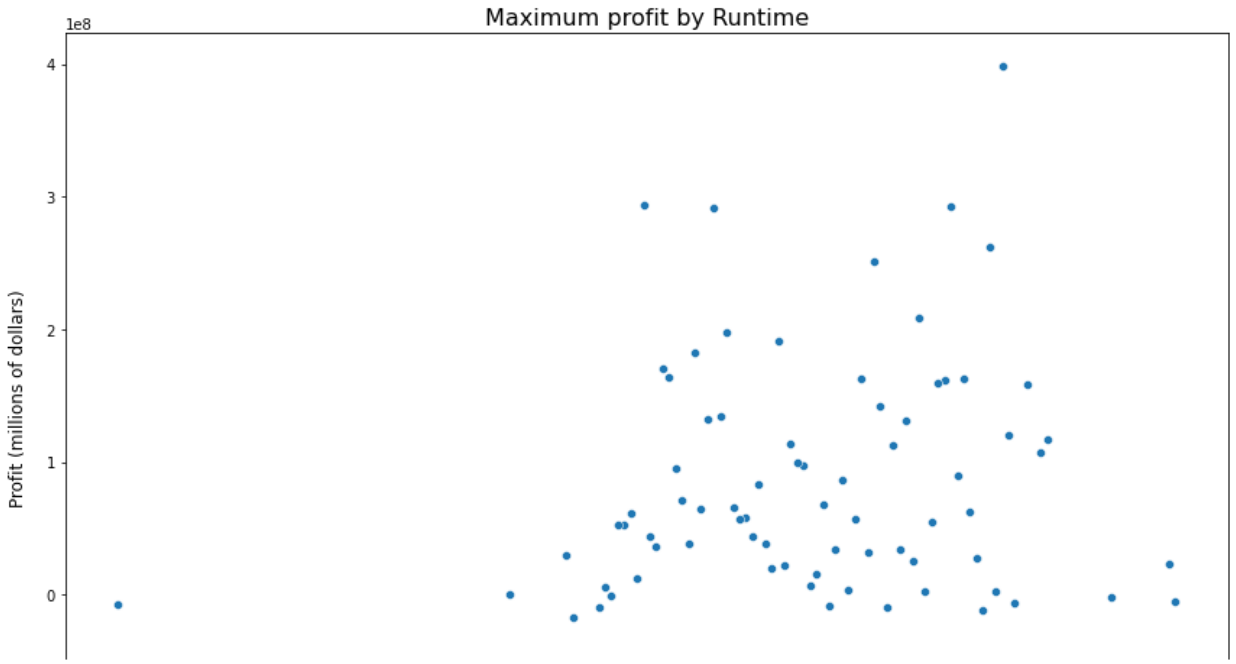
In [536]:
```
#In order to get the accurate information I went further to look at Top 80
profit_runtime_df=profit_runtime_df.iloc[0:80].sort_values('runtime_minutes
profit_runtime_df[profit_runtime_df['profit'] > 0]
```

Out[536]:

	runtime_minutes	profit
107	169.0	23017894.0
89	150.0	117207973.0
88	149.0	106767189.0
86	147.0	158084349.0
83	144.0	120433663.0
...	...	...
24	85.0	61473115.0
23	84.0	52575175.0
22	83.0	52262945.0
20	81.0	5542576.0
14	75.0	29744051.0

65 rows × 2 columns

In [537]:
```
#scatter plot showing the maximum profit by movies runtime in minutes.
plt.figure(figsize=(12,8))
graph=sns.scatterplot(data=profit_runtime_df, x='runtime_minutes', y='pro
plt.xlabel(xlabel='Runtime(Minutes)', fontsize=12)
plt.ylabel(ylabel='Profit (millions of dollars)',fontsize =12)
plt.title('Maximum profit by Runtime', fontsize=16)
plt.tight_layout()
plt.show()
plt.savefig('Runtime and Profit.png')
```



Conclusion

My recommendation for Microsoft is to look into production budget between $82,000,000 and 91,200,000 which correlates with a very high percentage of Return on Investment.

When choosing genres for the movie, I will suggest for Microsoft to look into the title with Average counts. For example, if you look at Adventure and Action genres, they have more than average counts and that can yield to high profit and return on Investment.

If Microsoft wishes to produce the best movies to make a higher profit they also need to look into the movie runtime. The average runtime for the top five genres is 102.00 minutes. This need to be considered when producing the movie.

My Analysis shows that 69 percent of the total net profits across all genres come from just the top five genres which are; Action, Adventure, Sci-Fi, comedy, Animation. I would recommend Microsoft to focus on Action, Adventure and Sci-Fi for high median net profits.

In [ ]: