Microsoft Movie Analysis

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Overview

Business Problem

- Which genres are the most profitable and yield the highest ROI?
- What budget range in those genres yields the highest ROI?
- · Who are the top casts and directors in those genres that Microsoft should work with?

Data

When cleaning the data, we will drop all columns that we don't need for this project. We will clean up duplicates after we join the tables so that we can achieve the desirable output record at once.

- tn_movie_budgets
- imdb_name_basics
- · imdb title principals
- imdb_title_basics

Prepare Data

```
In [1]: #import libraries
   import datetime as dt
   import numpy as np
   import pandas as pd
   import matplotlib.pyplot as plt
%matplotlib inline
   import seaborn as sns
from scipy import stats
```

Clean Up tn_movie_budgets

In [2]: | ls zippedData

```
bom.movie_gross.csv.gz imdb.title.ratings.csv.gz 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 tn.movie_budgets.csv.gz imdb.title.principals.csv.gz
```

In [3]: #import the tn_movie_budgets and examine the data
tn_movie_budgets = pd.read_csv("zippedData/tn.movie_budgets.csv.gz")

#get summary of the DataFrame
tn_movie_budgets.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	<pre>production_budget</pre>	5782 non-null	object
4	domestic_gross	5782 non-null	object
5	worldwide_gross	5782 non-null	object
	1		

dtypes: int64(1), object(5)
memory usage: 271.2+ KB

- In [4]: #drop id since we don't need column, and domestic_gross column because we w
 tn_movie_budgets = tn_movie_budgets.drop(['id','domestic_gross'], axis = 1)
- In [5]: #convert release_date to datetime and add a release_year column
 tn_movie_budgets['release_date'] = pd.to_datetime(tn_movie_budgets['release
 tn_movie_budgets['release_year'] = tn_movie_budgets['release_date'].dt.year
 #check data
 tn_movie_budgets.head()

Out[5]:

	release_date	movie	production_budget	worldwide_gross	release_year
0	2009-12-18	Avatar	\$425,000,000	\$2,776,345,279	2009
1	2011-05-20	Pirates of the Caribbean: On Stranger Tides	\$410,600,000	\$1,045,663,875	2011
2	2019-06-07	Dark Phoenix	\$350,000,000	\$149,762,350	2019
3	2015-05-01	Avengers: Age of Ultron	\$330,600,000	\$1,403,013,963	2015
4	2017-12-15	Star Wars Ep. VIII: The Last Jedi	\$317,000,000	\$1,316,721,747	2017

In [6]: #check for missing values tn_movie_budgets.isna().sum()

Out[6]: release_date 0
movie 0
production_budget 0
worldwide_gross 0
release_year 0
dtype: int64

In [7]: #convert currency with \$ to integer
 tn_movie_budgets[tn_movie_budgets.columns[2:]] = tn_movie_budgets[tn_movie_
#check data
 tn_movie_budgets.head()

Out[7]:

	release_date	movie	production_budget	worldwide_gross	release_year
0	2009-12-18	Avatar	425000000	2776345279	2009
1	2011-05-20	Pirates of the Caribbean: On Stranger Tides	410600000	1045663875	2011
2	2019-06-07	Dark Phoenix	350000000	149762350	2019
3	2015-05-01	Avengers: Age of Ultron	330600000	1403013963	2015
4	2017-12-15	Star Wars Ep. VIII: The Last Jedi	317000000	1316721747	2017

In [8]: #examine the data if there are any rows with 0
 print(len(tn_movie_budgets[tn_movie_budgets['production_budget'] > 0]) / le
 print(len(tn_movie_budgets[tn_movie_budgets['worldwide_gross'] > 0]) / len(

1.0 0.936527153234175

In [9]: #drop rows with 0 in worldwide_gross column since 93.6% of data have associ
tn_movie_budgets = tn_movie_budgets[tn_movie_budgets['worldwide_gross'] > 0
#check data
tn_movie_budgets.head()

Out[9]:

	release_date	movie	production_budget	worldwide_gross	release_year
0	2009-12-18	Avatar	425000000	2776345279	2009
1	2011-05-20	Pirates of the Caribbean: On Stranger Tides	410600000	1045663875	2011
2	2019-06-07	Dark Phoenix	350000000	149762350	2019
3	2015-05-01	Avengers: Age of Ultron	330600000	1403013963	2015
4	2017-12-15	Star Wars Ep. VIII: The Last Jedi	317000000	1316721747	2017

```
In [10]: #calculate ROI and add the column
    def roi(budget, gross):
        return (gross - budget) / budget * 100
        tn_movie_budgets['ROI'] = roi(tn_movie_budgets['production_budget'], tn_mov
    #check data
    tn_movie_budgets
```

Out[10]:

	release_date	movie	production_budget	worldwide_gross	release_year	ROI
0	2009-12-18	Avatar	425000000	2776345279	2009	553.257713
1	2011-05-20	Pirates of the Caribbean: On Stranger Tides	410600000	1045663875	2011	154.667286
2	2019-06-07	Dark Phoenix	350000000	149762350	2019	-57.210757
3	2015-05-01	Avengers: Age of Ultron	330600000	1403013963	2015	324.384139
4	2017-12-15	Star Wars Ep. VIII: The Last Jedi	317000000	1316721747	2017	315.369636
5775	2006-05-26	Cavite	7000	71644	2006	923.485714
5776	2004-12-31	The Mongol King	7000	900	2004	-87.142857
5778	1999-04-02	Following	6000	240495	1999	3908.250000
5779	2005-07-13	Return to the Land of Wonders	5000	1338	2005	-73.240000
5781	2005-08-05	My Date With Drew	1100	181041	2005	16358.272727

5415 rows × 6 columns

Clean Up imdb_title_basics

In [11]: #import the file and examine the data imdb_title_basics = pd.read_csv("zippedData/imdb.title.basics.csv.gz") imdb_title_basics.head()

Out[11]:

	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

In [12]: #set tconst column as the index since it will be used as primary key/foreig
imdb_title_basics = imdb_title_basics.set_index('tconst')

#check data
imdb_title_basics.head()

Out[12]:

	primary_title	original_title	start_year	runtime_minutes	genres
tconst					
tt0063540	Sunghursh	Sunghursh	2013	175.0	Action,Crime,Drama
tt0066787	One Day Before the Rainy Season	Ashad Ka Ek Din	2019	114.0	Biography, Drama
tt0069049	The Other Side of the Wind	The Other Side of the Wind	2018	122.0	Drama
tt0069204	Sabse Bada Sukh	Sabse Bada Sukh	2018	NaN	Comedy,Drama
tt0100275	The Wandering Soap Opera	La Telenovela Errante	2017	80.0	Comedy, Drama, Fantasy

genres

genres

```
In [13]: #drop original_title and runtime_minutes columns as we don't need this data
imdb_title_basics = imdb_title_basics.drop(['original_title','runtime_minut

#check data
imdb_title_basics.head()
```

primary_title start_year

Out[13]:

tconst			
tt0063540	Sunghursh	2013	Action,Crime,Drama
tt0066787	One Day Before the Rainy Season	2019	Biography,Drama
tt0069049	The Other Side of the Wind	2018	Drama
tt0069204	Sabse Bada Sukh	2018	Comedy,Drama
tt0100275	The Wandering Soap Opera	2017	Comedy, Drama, Fantasy

```
In [14]: #check for missing values
imdb_title_basics.isna().sum()
```

```
Out[14]: primary_title 0 start_year 0 genres 5408 dtype: int64
```

```
In [15]: #examine genre column to determine whether we shoup drop N/As or replace th imdb_title_basics['genres'].isna().sum()/len(imdb_title_basics)
```

```
Out[15]: 0.037004598204510616
```

```
In [16]: #drop rows with N/A in genre column since only 3.7% of data shows N/A
imdb_title_basics = imdb_title_basics.dropna(subset = ['genres'])
```

```
In [17]: #convert genre to list
imdb_title_basics['genres'] = imdb_title_basics['genres'].map(lambda x: x.s
#check data
imdb_title_basics.head()
```

primary_title start_year

Out[17]:

J		• •=	
			tconst
[Action, Crime, Drama]	2013	Sunghursh	tt0063540
[Biography, Drama]	2019	One Day Before the Rainy Season	tt0066787
[Drama]	2018	The Other Side of the Wind	tt0069049
[Comedy, Drama]	2018	Sabse Bada Sukh	tt0069204
[Comedy, Drama, Fantasy]	2017	The Wandering Soap Opera	tt0100275

Clean Up imdb_title_principals

```
In [18]: #import the file and examine the data
imdb_title_principals = pd.read_csv("zippedData/imdb.title.principals.csv.g

#examine data
imdb_title_principals.head()
```

Out[18]:

	tconst	ordering	nconst	category	job	characters
0	tt0111414	1	nm0246005	actor	NaN	["The Man"]
1	tt0111414	2	nm0398271	director	NaN	NaN
2	tt0111414	3	nm3739909	producer	producer	NaN
3	tt0323808	10	nm0059247	editor	NaN	NaN
4	tt0323808	1	nm3579312	actress	NaN	["Beth Boothby"]

In [19]: #set tconst column as the index since it will be used as primary key/foreig
imdb_title_principals = imdb_title_principals.set_index('tconst')

#check data
imdb_title_principals.head()

Out[19]:

	ordering	nconst	category	job	characters
tconst					
tt0111414	1	nm0246005	actor	NaN	["The Man"]
tt0111414	2	nm0398271	director	NaN	NaN
tt0111414	3	nm3739909	producer	producer	NaN
tt0323808	10	nm0059247	editor	NaN	NaN
tt0323808	1	nm3579312	actress	NaN	["Beth Boothby"]

Out[20]:

nconst category

		tconst
actor	nm0246005	tt0111414
director	nm0398271	tt0111414
producer	nm3739909	tt0111414
editor	nm0059247	tt0323808
actress	nm3579312	110323808

```
In [21]: #check for missing values
         imdb_title_principals.isna().sum()
Out[21]: nconst
                      0
         category
         dtype: int64
In [22]: #examine the job titles and value counts in category column
         imdb_title_principals.category.value_counts()
Out[22]: actor
                                 256718
         director
                                 146393
         actress
                                 146208
         producer
                                 113724
         cinematographer
                                  80091
         composer
                                  77063
         writer
                                  74357
         self
                                  65424
         editor
                                  55512
         production designer
                                   9373
         archive_footage
                                   3307
         archive sound
                                     16
         Name: category, dtype: int64
In [23]: #replace 'actress' with 'actors'
         imdb_title_principals['category'] = imdb_title_principals.category.str.repl
         #check data
         imdb title principals.head()
Out[23]:
                     nconst category
```

		tconst
actor	nm0246005	tt0111414
director	nm0398271	tt0111414
producer	nm3739909	tt0111414
editor	nm0059247	tt0323808
actor	nm3579312	tt0323808

Clean Up imdb_name_basics

```
In [24]: #import the file and examine the data
   imdb_name_basics = pd.read_csv("zippedData/imdb.name.basics.csv.gz")

#examine data
   imdb_name_basics.head()
```

Out[24]:

primary_professio	death_year	birth_year	primary_name	nconst	
miscellaneous,production_manager,produce	NaN	NaN	Mary Ellen Bauder	nm0061671	0
composer,music_department,sound_departmen	NaN	NaN	Joseph Bauer	nm0061865	1
miscellaneous,actor,write	NaN	NaN	Bruce Baum	nm0062070	2
camera_department,cinematographer,art_departmen	NaN	NaN	Axel Baumann	nm0062195	3
production_designer,art_department,set_decorato	NaN	NaN	Pete Baxter	nm0062798	4

```
In [25]: #set nconst column as the index since it will be used as primary key/foreig
imdb_name_basics = imdb_name_basics.set_index('nconst')

#check data
imdb_name_basics.head()
```

Out[25]:

	primary_name	birth_year	death_year	primary_profession
nconst				
nm0061671	Mary Ellen Bauder	NaN	NaN	miscellaneous,production_manager,producer
nm0061865	Joseph Bauer	NaN	NaN	composer,music_department,sound_department
nm0062070	Bruce Baum	NaN	NaN	miscellaneous,actor,writer
nm0062195	Axel Baumann	NaN	NaN	camera_department,cinematographer,art_department
nm0062798	Pete Baxter	NaN	NaN	production_designer,art_department,set_decorator

```
In [26]: #drop birth_year, death_year, primary_profession, and 'known_for_titles' as
imdb_name_basics = imdb_name_basics.drop(['birth_year','death_year','primar
#check data
imdb_name_basics.head()
```

Out[26]:

primary_name

nconst	
nm0061671	Mary Ellen Bauder
nm0061865	Joseph Bauer
nm0062070	Bruce Baum
nm0062195	Axel Baumann
nm0062798	Pete Baxter

Join Datasets

Merge movie_budgets and title_basics as df

Combine movie_budget and title_basics DataFrame to create a new DataFrame called df. Since the column names are different, we are going to explicitly mention both the column names using 'left_on' and 'right_on' arguments. Then, we will remove the duplicate columns as a result of the merge, and reset the index to 'tconst' so that we can easily use the index as the primary key when joining with other tables for additional analyes.

Out[27]:

	genres	release_date	movie	production_budget	worldwide_gross	release_year
tconst						
tt0249516	[Action, Animation, Comedy]	2012-12-31	Foodfight!	45000000	73706	2012
tt0359950	[Adventure, Comedy, Drama]	2013-12-25	The Secret Life of Walter Mitty	91000000	187861183	2013
tt0365907	[Action, Crime, Drama]	2014-09-19	A Walk Among the Tombstones	28000000	62108587	2014
tt0369610	[Action, Adventure, Sci-Fi]	2015-06-12	Jurassic World	215000000	1648854864	2015
tt0376136	[Comedy, Drama]	2011-10-28	The Rum Diary	45000000	21544732	2011

Out[28]: (94, 7)

For higher accuracy and simplicity of this analysis project, we will remove duplicates from this DataFrame.

Out[29]:

	genres	release_date	movie	production_budget	worldwide_gross	release_year
tconst						
tt0249516	[Action, Animation, Comedy]	2012-12-31	Foodfight!	45000000	73706	2012
tt0359950	[Adventure, Comedy, Drama]	2013-12-25	The Secret Life of Walter Mitty	91000000	187861183	2013
tt0365907	[Action, Crime, Drama]	2014-09-19	A Walk Among the Tombstones	28000000	62108587	2014
tt0369610	[Action, Adventure, Sci-Fi]	2015-06-12	Jurassic World	215000000	1648854864	2015
tt0376136	[Comedy, Drama]	2011-10-28	The Rum Diary	45000000	21544732	2011

Join df with imdb_title_principals

Update the df DataFrame by joining imdb_title_principals using an inner join, and the output will automatically drop N/A values. There is no need to specify where the join will occur since we have already reset indices for this purpose when cleaning the data.

```
In [30]: #join df with imdb_title_principals
df = imdb_title_principals.join(df, how='inner')
df
```

Out[30]:

		nconst	category	genres	release_date	movie	production_budget	worldwide
	tconst							
•	tt0249516	nm0257258	producer	[Action, Animation, Comedy]	2012-12-31	Foodfight!	45000000	
	tt0249516	nm0240381	actor	[Action, Animation, Comedy]	2012-12-31	Foodfight!	45000000	
	tt0249516	nm0240380	actor	[Action, Animation, Comedy]	2012-12-31	Foodfight!	45000000	
	tt0249516	nm0000221	actor	[Action, Animation, Comedy]	2012-12-31	Foodfight!	45000000	
	tt0249516	nm0519456	actor	[Action, Animation, Comedy]	2012-12-31	Foodfight!	45000000	
	tt9024106	nm0465484	director	[Biography, Drama]	2019-03-29	Unplanned	6000000	18 [.]
	tt9024106	nm0813301	director	[Biography, Drama]	2019-03-29	Unplanned	6000000	18
	tt9024106	nm2445956	producer	[Biography, Drama]	2019-03-29	Unplanned	6000000	18
	tt9024106	nm7839151	producer	[Biography, Drama]	2019-03-29	Unplanned	6000000	18 ⁻
	tt9024106	nm0498920	producer	[Biography, Drama]	2019-03-29	Unplanned	6000000	18 [.]

13144 rows × 9 columns

```
In [31]: #Check for people who appears more than once in a movie
df.reset_index().duplicated(subset=['tconst', 'nconst']).sum()
```

Out[31]: 0

```
In [32]: df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 13144 entries, tt0249516 to tt9024106
Data columns (total 9 columns):
#
    Column
                       Non-Null Count
                                       Dtype
                        _____
 0
    nconst
                        13144 non-null object
 1
    category
                        13144 non-null
                                       object
 2
                       13144 non-null object
    genres
 3
    release_date
                        13144 non-null
                                       datetime64[ns]
 4
    movie
                        13144 non-null
                                       object
 5
    production budget 13144 non-null
                                       int64
 6
    worldwide_gross
                        13144 non-null int64
 7
    release year
                        13144 non-null int64
 8
    ROI
                        13144 non-null float64
dtypes: datetime64[ns](1), float64(1), int64(3), object(4)
memory usage: 1.0+ MB
```

Join df with imbd_name_basics

Out[33]:

	tconst	nconst	category	genres	release_date	movie	production_budget	wc
	0 tt0249516	nm0257258	producer	[Action, Animation, Comedy]	2012-12-31	Foodfight!	45000000	
	1 tt0249516	nm0240381	actor	[Action, Animation, Comedy]	2012-12-31	Foodfight!	45000000	
	2 tt0249516	nm0240380	actor	[Action, Animation, 2012-12-31 Foodfight! Comedy]		45000000		
	3 tt0249516	nm0000221	actor	[Action, Animation, 2012-12-31 Foodfight! Comedy]		45000000		
	4 tt0249516	nm0519456	actor	[Action, Animation, Comedy]	2012-12-31	Foodfight!	45000000	
								
1313	9 tt9024106	nm0478750	actor	[Biography, Drama]	2019-03-29	Unplanned	6000000	
1314	0 tt9024106	nm5237225	actor	[Biography, Drama]	2019-03-29	Unplanned	6000000	
1314	1 tt9024106	nm2445956	producer	[Biography, Drama]	2019-03-29	Unplanned	6000000	
1314	2 tt9024106	nm7839151	producer	[Biography, Drama]	2019-03-29	Unplanned	6000000	
1314	3 tt9024106	nm0498920	producer	[Biography, Drama]	2019-03-29	Unplanned	6000000	

13144 rows × 11 columns

Split Genres to Separate Rows

Use explode function to transform each element in a list in 'genres' column. This will allow us to easily run analysis by **genres**.

```
In [34]: df = df.explode('genres')
df.head()
```

Out[34]:

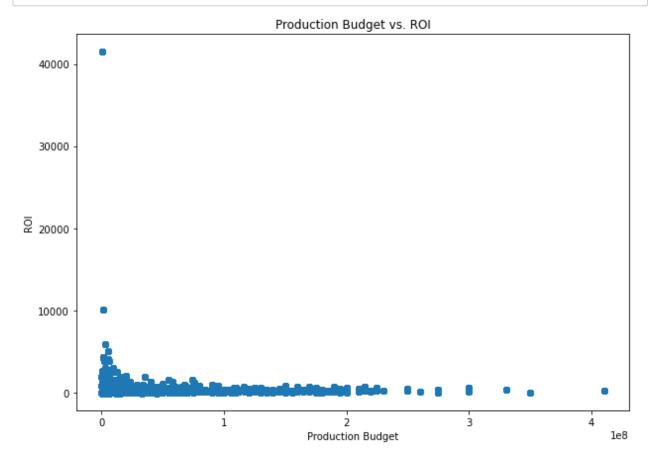
	tconst	nconst	category	genres	release_date	movie	production_budget	worldwid
0	tt0249516	nm0257258	producer	Action	2012-12-31	Foodfight!	45000000	
0	tt0249516	nm0257258	producer	Animation	2012-12-31	Foodfight!	45000000	
0	tt0249516	nm0257258	producer	Comedy	2012-12-31	Foodfight!	45000000	
1	tt0249516	nm0240381	actor	Action	2012-12-31	Foodfight!	45000000	
1	tt0249516	nm0240381	actor	Animation	2012-12-31	Foodfight!	45000000	

Identify and Remove Outliers

We have now completed cleaning up and joining the DataFrames that are required for this project. However, we need to further examine the data before we start data exploration to check if there are any outliers that should be removed.

First, we will examine the overall production_budget and ROI, and will create a fuction so that we can re-visualize the data after removing the outliers.

In [36]: scatter_plot(df)



Z Score Method

Using a z-score method

(https://www.ctspedia.org/do/view/CTSpedia/OutLier#:~:text=Any%20z%2Dscore%20greater%20th we will clean up the data by removing data points with z-score greater than 3. For this project, we can ignore checking data points with z-score less than 3 because ROI cannot be less than -100%.

```
In [37]: #calculate z-score on ROI and create a new column to show the z-score
df['ROI_zscore'] = stats.zscore(df['ROI'])

#remove rows with z-score greater than 3
df = df[df['ROI_zscore'] < 3]
df</pre>
```

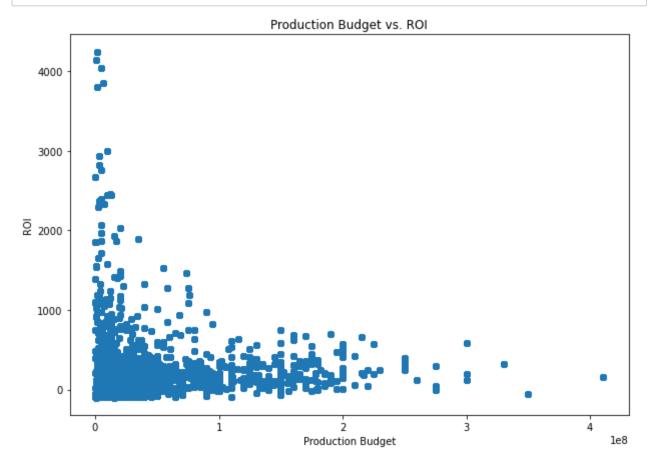
Out[37]:

	tconst	nconst	category	genres	release_date	movie	production_budget	now
0	tt0249516	nm0257258	producer	Action	2012-12-31	Foodfight!	45000000	
0	tt0249516	nm0257258	producer	Animation	2012-12-31	Foodfight!	45000000	
0	tt0249516	nm0257258	producer	Comedy	2012-12-31	Foodfight!	45000000	
1	tt0249516	nm0240381	actor	Action	2012-12-31	Foodfight!	45000000	
1	tt0249516	nm0240381	actor	Animation	2012-12-31	Foodfight!	45000000	
			•••					
13141	tt9024106	nm2445956	producer	Drama	2019-03-29	Unplanned	6000000	
13142	tt9024106	nm7839151	producer	Biography	2019-03-29	Unplanned	6000000	
13142	tt9024106	nm7839151	producer	Drama	2019-03-29	Unplanned	6000000	
13143	tt9024106	nm0498920	producer	Biography	2019-03-29	Unplanned	6000000	
13143	tt9024106	nm0498920	producer	Drama	2019-03-29	Unplanned	6000000	

34149 rows × 12 columns

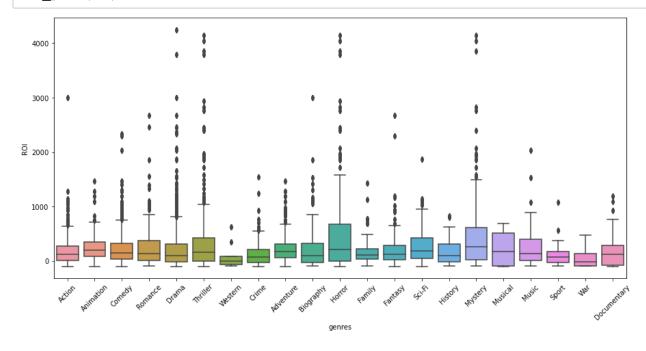
Now, vusualize the updated DataFrame after removing rows with z-score greater 3.

In [38]: scatter_plot(df)



The scatter plot looks so much better! Now that we have cleaned up the overall DataFrame with z-score calculation on ROI, we want to examine the data more thoroughly. Let's take a look at ROI by genre - create a box plot with outliers.

In [40]: box_plot(df)



1.5xIQR Rule

Here, we are going to use 1.5xIQR rule (https://www.khanacademy.org/math/statistics-probability/summarizing-quantitative-data/box-whisker-plots/a/identifying-outliers-iqr-rule#:~:text=A%20commonly%20used%20rule%20says,or%20below%20the%20first%20quartile.), which defines a data point as an outlier if it is more than '1.5 * IQR' above the thrid quartile or less than '1.5 * IQR' below the first quartile. We can ignore outliers less than '1.5 * IQR' because ROI cannot be less than -100%.

Let's create a new DataFrame called iqr to calculate the upper threshold that will be used to identify the high outliers.

```
In [41]: #create an empty DataFrame
    iqr = pd.DataFrame()

#calculate Quartile 1
    iqr['Q1'] = df.groupby('genres').ROI.quantile(.25)

#calculate Quartile 3
    iqr['Q3'] = df.groupby('genres').ROI.quantile(.75)

#calculate interquartile range
    iqr['IQR'] = iqr['Q3'] - iqr['Q1']

#calculate the upper threshold
    iqr['upper_threshold'] = iqr['Q3'] + 1.5*iqr['IQR']

#check data
    iqr
```

Out[41]:

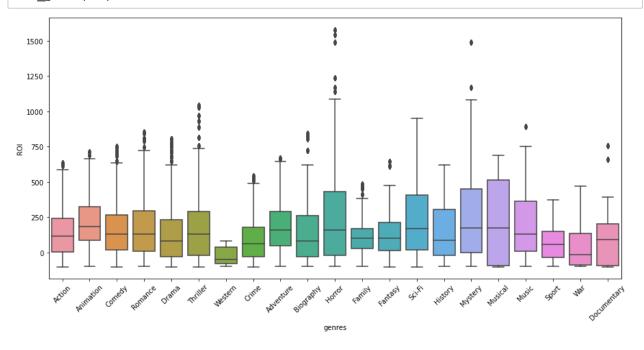
	Q1	Q3	IQR	upper_threshold
genres				
Action	12.515718	269.713673	257.197955	655.510605
Adventure	55.974192	306.801427	250.827235	683.042280
Animation	86.577085	345.300955	258.723870	733.386761
Biography	-26.218484	322.261705	348.480189	844.981989
Comedy	27.430332	319.246700	291.816368	756.971252
Crime	-26.138270	207.666667	233.804937	558.374072
Documentary	-79.944000	289.962850	369.906850	844.823125
Drama	-19.907396	311.539470	331.446865	808.709768
Family	32.972215	226.110043	193.137828	515.816785
Fantasy	16.348439	284.146742	267.798303	685.844196
History	-16.447875	306.539022	322.986897	791.019368
Horror	-11.086850	679.593740	690.680590	1715.614626
Music	13.301505	401.673606	388.372101	984.231757
Musical	-90.503464	512.379108	602.882573	1416.702968
Mystery	23.503274	613.105500	589.602226	1497.508839
Romance	12.515718	367.887600	355.371882	900.945423
Sci-Fi	42.489871	425.732893	383.243022	1000.597426
Sport	-32.963460	168.870141	201.833601	471.620543
Thriller	-2.476980	421.434029	423.911009	1057.300541
War	-89.894700	135.857985	225.752685	474.487013
Western	-72.948733	80.583507	153.532240	310.881867

```
In [42]: #create a new column in df to map the upper threshold
df['iqr_upper_threshold'] = df['genres'].map(iqr['upper_threshold'])
#remove rows with the upper outliers
df = df[df['ROI'] < df['iqr_upper_threshold']]
#check data
df.head()</pre>
```

Out[42]:

	tconst	nconst	category	genres	release_date	movie	production_budget	worldwid
0	tt0249516	nm0257258	producer	Action	2012-12-31	Foodfight!	45000000	
0	tt0249516	nm0257258	producer	Animation	2012-12-31	Foodfight!	45000000	
0	tt0249516	nm0257258	producer	Comedy	2012-12-31	Foodfight!	45000000	
1	tt0249516	nm0240381	actor	Action	2012-12-31	Foodfight!	45000000	
1	tt0249516	nm0240381	actor	Animation	2012-12-31	Foodfight!	45000000	

In [43]: box_plot(df)



There are still some outliers but this box plot looks much better after we cleaned up the DataFrame using 1.5xIQR rule.

Questions

Question 1: Which genres are the most profitable and yield the highest ROI?

Genre 1, Genre2, Genre3 win!

Question 2: What is the ideal budget range to yield the highest ROI?

Question 3: Who are the top casts and directors in those genres that Microsoft should work with?

Conclusions

Further Analysis

For More Information

In [6]: ls zippedData/

bom.movie_gross.csv.gz
imdb.name.basics.csv.gz
imdb.title.akas.csv.gz
imdb.title.basics.csv.gz
imdb.title.crew.csv.gz
imdb.title.principals.csv.gz

imdb.title.ratings.csv.gz
rt.movie_info.tsv.gz
rt.reviews.tsv.gz
tmdb.movies.csv.gz
tn.movie_budgets.csv.gz