Final Project Submission

Please fill out:

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- Scheduled project review date/time: 10/7/2022
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- Blog post URL: https://medium.com/@sjeanat3/skyes-phase-i-blog-post-e159f949f39b (https://medium.com/@sjeanat3/skyes-phase-i-blog-post-e159f949f39b)

Microsoft Movie Studios Business Strategy Proposal

Overview

This project seeks to recommend Microsoft a business strategy related to launching a movie production studio. Due to the lack of Microsoft's industry knowledge, the below data analysis will interpret the available data to recommend (i) the top movie production companies to replicate, (ii) movie genres to invest in and (iii) target budgets and return on investments. Microsoft will be able to ultimately use this analysis to identify the necessary investment strategies to apply to their first productions.

Business Problem

Microsoft's business problem largely involves entering the large, global industry of film and lack of experience in the movie production industry. Although Microsoft itself is a substantial firm with numerous resources, the film industry has many barriers of industry heavily dependent on industry experience and scale. Microsoft currently offers rental movies on its site for users but has never produced a film. It is crucial for Microsoft to selectively choose what films to produce as this could make or break the program.

Data Understanding

For purposes of this analysis we will be utilizing IMDB's data set which provides for movie genres, Box Office Mojo's data set (powered by IMDB Pro) which provides production studio data, and The Numbers data set which gives access to worldwide gross sales data and release years.

In [1]:
```
import pandas as pd
import sqlite3
import matplotlib.pyplot as plt
%matplotlib inline
from plotly.subplots import make_subplots
import plotly.express as px
```

First, we will import any libraries necessary for this analysis and open the relevant files.

The files loaded below contain a various amount of information regarding movies which include movie titles, production studios, production budgets, gross sales data (worldwide and domestic), ratings data and more.

In [2]:
```
#Utilizing pd.read_csv to open the CSV file
df_bow = pd.read_csv("zippedData/bom.movie_gross.csv.gz")
df_bow.head()
```

Out[2]:

	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

In [3]:
```
#Utilizing pd.read_csv to open the CSV file
df_tn = pd.read_csv("zippedData/tn.movie_budgets.csv.gz")
df_tn.head()
```

Out[3]:

	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

In [4]:
```
#Utilizing sqlite to open the db
conn = sqlite3.connect('zippedData/im.db')
df_imdb_movie_basics = pd.read_sql("""SELECT * FROM movie_basics;""", conn)
df_imdb_movie_basics.head()
```

Out[4]:

	movie_id	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 [5]:
```
#Utilizing pd.read_sql to open the SQL file
df_imdb_movie_ratings = pd.read_sql("""SELECT * FROM movie_ratings;""", conn)
df_imdb_movie_ratings.head()
```

Out[5]:

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

Data Preparation

The below data preparations include creating various data frames from three of the files that were opened (Box Office Mojo, The Numbers, and IMDB). Here, I've made three separate data frames that highlight the top 8 studios by volume of movie production combined with the production budget from The Numbers data set, as well as creating a data set of the combined IMDB data. Ultimately, the IMDB data frame will be combined with the 'Top 8 Studios' and 'The Numbers' data frames to create one large, aggregated data frame.

Combining this data in all one data frame will help with visualizing the available data in one place and ultimately aid with the data cleaning process.

Create a Dataframe of the Top 8 Studios with the Most Movies Produced

In [6]:
```
#Create a list of the top 8 production studios through .value_counts()
list(df_bow['studio'].value_counts().head(8).index)
```

Out[6]:
```
['IFC', 'Uni.', 'WB', 'Fox', 'Magn.', 'SPC', 'Sony', 'BV']
```

In [7]:
```
#Utilize the above list and.loc[] to create a data frame only including our top 8 production studios
top_studios_df = df_bow.loc[(df_bow['studio'] == 'IFC') | (df_bow['studio'] == 'Uni.') | \
(df_bow['studio'] == 'WB') | (df_bow['studio'] == 'Magn.') | (df_bow['studio'] == 'Fox') | \
(df_bow['studio'] == 'SPC') | (df_bow['studio'] == 'Sony') | (df_bow['studio'] == 'BV')]

#Use .groupby() to organize the data frame by production studio
top_studios_df.groupby('studio').count()
```

Out[7]:

studio	title	domestic_gross	foreign_gross	year
BV	106	106	104	106
Fox	136	136	134	136
IFC	166	166	68	166
Magn.	136	136	55	136
SPC	123	123	59	123
Sony	110	109	106	110
Uni.	147	147	144	147
WB	140	140	130	140

Create a Dataframe of the Numbers Data (Production Budget, Sales)

In [8]:
```
#Utilize .str.split to split the release_date column to seperate 'month_date' and 'year' columns
df_time_tn = df_tn['release_date'].str.split(",", expand=True)
df_time_tn = df_time_tn.rename(columns = {0 : 'month_date'})
df_time_tn = df_time_tn .rename(columns = {1 : 'year'})
```

In [9]:
```
#Join the separated month_date, year data frame with our original 'the numbers' data frame
df_tn = df_tn.join(df_time_tn, how = 'outer')

#Drop columns that woon't be used
df_tn = df_tn.drop(['id', 'release_date', 'month_date'], axis = 1)

#Rename the 'movie' column name to 'title'
df_tn = df_tn.rename(columns = {'movie' : 'title'})
```

In [10]:
```
#Define a function that will convert a string containing '$' and commas to an integer
def change(L):
    char_to_replace= {'$': '', ',': ''}
    for key, value in char_to_replace.items():
        L = L.replace(key, value)
    t = int(L)
    return t
```

In [11]:
```
#Apply the above function to the columns that need to be converted to integers
df_tn['production_budget'] = df_tn['production_budget'].map(change)
df_tn['domestic_gross']= df_tn['domestic_gross'].map(change)
df_tn['worldwide_gross']= df_tn['worldwide_gross'].map(change)
df_tn[['year']] = df_tn[['year']].apply(pd.to_numeric)
```

Combine Top 5 Studios DF with Numbers Data

In [12]:
```
#Use .drop() to remove any unnecessary columns
top_studios_df = top_studios_df.drop(['domestic_gross', 'foreign_gross'], axis = 1)

#Use .merge() to combine our top_studios data frame and numbers data frame based on 'title' and 'year'
top_studios_tn_df = pd.merge(top_studios_df, df_tn, how = 'right', on = ['title', 'year'])

#Identify any N/A values
top_studios_tn_df.isna().sum()

#Drop any N/As that are found in the 'studio' column
top_studios_tn_df = top_studios_tn_df.dropna(subset = ['studio'])

#Check if there are any N/A values after dropping
top_studios_tn_df.isna().sum()
```

Out[12]:
```
title                0
studio               0
year                 0
production_budget    0
domestic_gross       0
worldwide_gross      0
dtype: int64
```

Join the Two IMDB Data Frames

In [13]:
```
#Create a SQL query to combine the two IMDB data frames

q = """
SELECT *
FROM movie_basics
JOIN movie_ratings
    ON movie_basics.movie_id = movie_ratings.movie_id
;
"""

imdb_movie_agg_df = pd.read_sql(q, conn)
```

In [14]:
```
#Drop the irrelevant columns
imdb_movie_agg_df = imdb_movie_agg_df.drop(['original_title', 'movie_id'], axis=1)

#Rename 'primary_title' to 'title' and 'start_year' to 'year' so that this matches our other dataframes
imdb_movie_agg_df = imdb_movie_agg_df.rename(columns = {'primary_title' : 'title'})
imdb_movie_agg_df = imdb_movie_agg_df.rename(columns = {'start_year' : 'year'})

#Preview the dataset
imdb_movie_agg_df.head()
```

Out[14]:

	title	year	runtime_minutes	genres	averagerating	numvotes
0	Sunghursh	2013	175.0	Action,Crime,Drama	7.0	77
1	One Day Before the Rainy Season	2019	114.0	Biography,Drama	7.2	43
2	The Other Side of the Wind	2018	122.0	Drama	6.9	4517
3	Sabse Bada Sukh	2018	NaN	Comedy,Drama	6.1	13
4	The Wandering Soap Opera	2017	80.0	Comedy,Drama,Fantasy	6.5	119

Join the IMDB Data Frame and Top Studios w/ Numbers

In [15]:
```python
#Merge our aggregated IMDB data frame and top studios with numbers data frame
imdb_studios_tn_df = pd.merge(imdb_movie_agg_df, top_studios_tn_df, how = 'inner', \
                              on = ['title', 'year'])

#Check this joined data frame's info
imdb_studios_tn_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 486 entries, 0 to 485
Data columns (total 10 columns):
 #   Column             Non-Null Count  Dtype  
---  ------             --------------  -----  
 0   title              486 non-null    object 
 1   year               486 non-null    int64  
 2   runtime_minutes    485 non-null    float64
 3   genres             485 non-null    object 
 4   averagerating      486 non-null    float64
 5   numvotes           486 non-null    int64  
 6   studio             486 non-null    object 
 7   production_budget  486 non-null    int64  
 8   domestic_gross     486 non-null    int64  
 9   worldwide_gross    486 non-null    int64  
dtypes: float64(2), int64(5), object(3)
memory usage: 41.8+ KB
```

Data Cleaning

Thus far, we have created and joined three separate data frames. Now, we will begin the cleaning process. Given our above .info() check did not show any 'null' values, we can now check if there are any repeat inputs by movie title and remove any duplicates.

Identify/Remove Duplicate Movies

In [16]:
```
#Utilize a function which concates a data frame of movie titles with duplicate entries
pd.concat(g for _, g in imdb_studios_tn_df.groupby("title") if len(g) > 1)
```

Out[16]:

	title	year	runtime_minutes	genres	averagerating	numvotes	studio	production_budget	domestic_gross	worldwide_gros
349	Coco	2017	105.0	Adventure,Animation,Comedy	8.4	277194	BV	175000000	209726015	79800810
350	Coco	2017	98.0	Horror	7.4	35	BV	175000000	209726015	79800810
92	Leap Year	2010	100.0	Comedy,Romance	6.5	86125	Uni.	19000000	25918920	3261892
93	Leap Year	2010	94.0	Drama,Romance	5.9	2211	Uni.	19000000	25918920	3261892
58	The Bounty Hunter	2010	110.0	Action,Comedy,Romance	5.6	112444	Sony	45000000	67061228	13580883
59	The Bounty Hunter	2010	NaN	None	6.3	29	Sony	45000000	67061228	13580883

In [17]:
```
#Remove the duplicates based on their location
imdb_studios_tn_df = imdb_studios_tn_df.drop(labels=93, axis=0)
imdb_studios_tn_df = imdb_studios_tn_df.drop(labels=350, axis=0)
imdb_studios_tn_df = imdb_studios_tn_df.drop(labels=59, axis=0)

imdb_studios_tn_df.shape
```

Out[17]: (483, 10)

Since our analysis will ultimately review each movie's genre, we will now separate the 'genres' column by three separate classifications and check if there are any genre names that can be aggregated under one classification. We then can check if all three genre columns are necessary, or if any could be removed.

Our analysis will also need to analyze each movie's return on investment (ROI). Therefor, we will add an ROI column which runs a formula based on the worldwide gross sales and production budget data that is available.

Edit Genres, Organize into Main Genres vs. Sub Genres

In [18]:
```
#Utilize .str.split() so that we can separate the 'genres' column to its own data frame
test_df = imdb_studios_tn_df['genres'].str.split(",", expand=True)
test_df = test_df.rename(columns = {0 : 'genre_1'})
test_df = test_df.rename(columns = {1 : 'genre_2'})
test_df = test_df.rename(columns = {2 : 'genre_3'})
test_df
```

Out[18]:

	genre_1	genre_2	genre_3
0	Adventure	Comedy	Drama
1	Action	Crime	Drama
2	Action	Adventure	Sci-Fi
3	Comedy	Family	None
4	Adventure	Animation	Comedy
...	...	...	...
481	Horror	Thriller	None
482	Biography	Drama	Thriller
483	Biography	Comedy	Drama
484	Documentary	None	None
485	Crime	Drama	Thriller

483 rows × 3 columns

In [19]:
```
#Join this genres data frame with our original datafrme
imdb_studios_tn_df = imdb_studios_tn_df.join(test_df, how = 'outer')
```

In [20]:
```
#Fill any N/As in the 'gennre_2' column with the input that is in genre_1
imdb_studios_tn_df['genre_2'] = imdb_studios_tn_df['genre_2'].fillna(imdb_studios_tn_df['genre_1'])
```

Replace All 'Biography' with 'Documentary'

In [21]:
```
#Conform the 'Biography' genres in each column to all clasify as 'Documentary'
imdb_studios_tn_df.loc[(imdb_studios_tn_df['genre_1'] == 'Biography'),'genre_1']='Documentary'
imdb_studios_tn_df.loc[(imdb_studios_tn_df['genre_2'] == 'Biography'),'genre_2']='Documentary'
imdb_studios_tn_df.loc[(imdb_studios_tn_df['genre_3'] == 'Biography'),'genre_3']='Documentary'
```

In [22]:
```
#Conform the 'Music' genres in each column to all clasify as 'Musical'
imdb_studios_tn_df.loc[(imdb_studios_tn_df['genre_2'] == 'Music'),'genre_2']='Musical'
imdb_studios_tn_df.loc[(imdb_studios_tn_df['genre_3'] == 'Music'),'genre_3']='Musical'
```

In [23]:
```
#If the 'genre_2' genre is the same as 'genre 1', replace the 'genre 2' genre with '-'
imdb_studios_tn_df.loc[(imdb_studios_tn_df['genre_2'] == imdb_studios_tn_df['genre_1']),'genre_2']='-'
imdb_studios_tn_df = imdb_studios_tn_df.drop('genre_3', axis = 1)

#Drop our 'genres' column
imdb_studios_tn_df = imdb_studios_tn_df.drop(['genres'], axis = 1)

#Create a new 'genres' column that concatenates our new 'genre_1' with 'genre_2'
imdb_studios_tn_df['genres'] = imdb_studios_tn_df['genre_1'] + ', ' + imdb_studios_tn_df['genre_2']
```

Add a Column of ROIs

Source for calculating ROI: https://www.linkedin.com/pulse/how-can-one-calculate-roi-when-investing-movies-sharad-patel/ (https://www.linkedin.com/pulse/how-can-one-calculate-roi-when-investing-movies-sharad-patel/)

In [24]:

```
#Add a new ROI(percentage) column that is based on the formula described in the above article
imdb_studios_tn_df['ROI_(percentage)'] = (imdb_studios_tn_df['worldwide_gross'] \
                                          /imdb_studios_tn_df['production_budget'])* 100
imdb_studios_tn_df.head()
```

Out[24]:

	title	year	runtime_minutes	averagerating	numvotes	studio	production_budget	domestic_gross	worldwide_gross	genre_1	genre_2
0	The Secret Life of Walter Mitty	2013	114.0	7.3	275300	Fox	91000000	58236838	187861183	Adventure	Comedy
1	A Walk Among the Tombstones	2014	114.0	6.5	105116	Uni.	28000000	26017685	62108587	Action	Crime
2	Jurassic World	2015	124.0	7.0	539338	Uni.	215000000	652270625	1648854864	Action	Adventure
3	The Three Stooges	2012	92.0	5.1	28570	Fox	30000000	44338224	54052249	Comedy	Family
4	Tangled	2010	100.0	7.8	366366	BV	260000000	200821936	586477240	Adventure	Animation

Data Analysis

Show Top 10 Studios by Number of Movies Produced

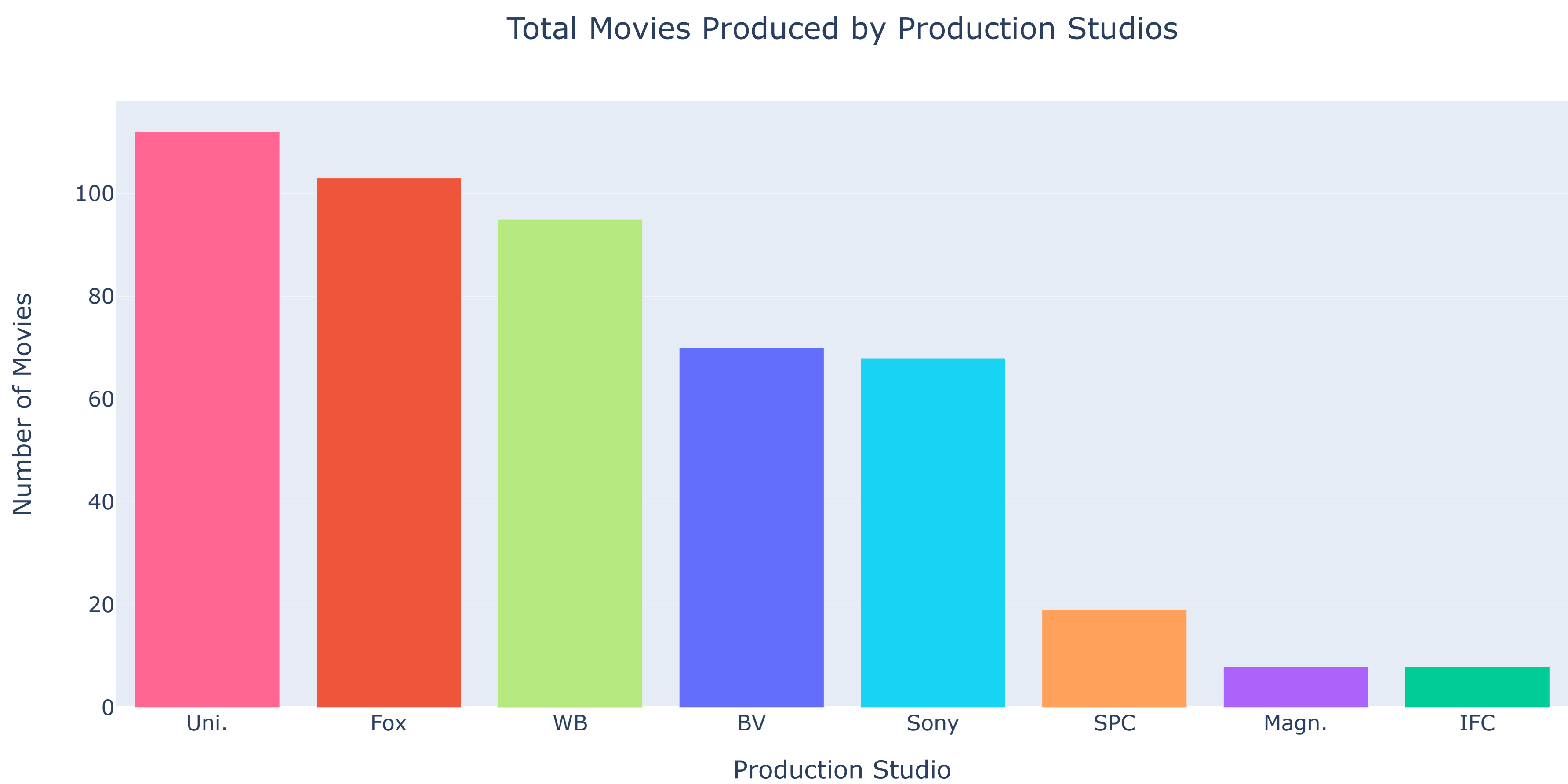
The below data frame groups our data frame by production studio in order to analyze the top eight production studios based on total movies produced through a Plotly bar chart.

In [25]:
```
#Create a top 10 Studios data frame, grouped by studio and showing the movie counts
top_10_studios = imdb_studios_tn_df.groupby('studio').count()
top_10_studios
```

Out[25]:

studio	title	year	runtime_minutes	averagerating	numvotes	production_budget	domestic_gross	worldwide_gross	genre_1	genre_2	genres	ROI_(p
BV	70	70	70	70	70	70	70	70	70	70	70	
Fox	103	103	103	103	103	103	103	103	103	103	103	
IFC	8	8	8	8	8	8	8	8	8	8	8	
Magn.	8	8	8	8	8	8	8	8	8	8	8	
SPC	19	19	19	19	19	19	19	19	19	19	19	
Sony	68	68	68	68	68	68	68	68	68	68	68	
Uni.	112	112	112	112	112	112	112	112	112	112	112	
WB	95	95	95	95	95	95	95	95	95	95	95	

In [26]:
```
#Create a bar chart using plotly to show case the top 10 studios by movie count
fig = px.bar(top_10_studios, x = list(top_10_studios.iloc[:, 0].index),  y = 'title',
             title = "Total Movies Produced by Production Studios",
             labels = {'title': 'Number of Movies', 'x': 'Production Studio'},
             color_discrete_sequence=[px.colors.qualitative.Plotly])
fig.update_layout(
    title={
        'y':0.9,
        'x':0.5,
        'xanchor': 'center',
        'yanchor': 'top'},
    barmode='stack', xaxis={'categoryorder':'total descending'})
fig.update_layout()
fig.show()
```



Show Top 10 Studios by Median ROI

The below data frame also groups our data frame by production studio but now, will be used to analyze the top eight production studios based on the production studios' median return on investment through a Plotly bar chart.

In [27]:
```
#Create a data frame of the top 10 studios by median in order to create the below graph
top_10_studios_mean = imdb_studios_tn_df.groupby('studio').median()
top_10_studios_mean
```

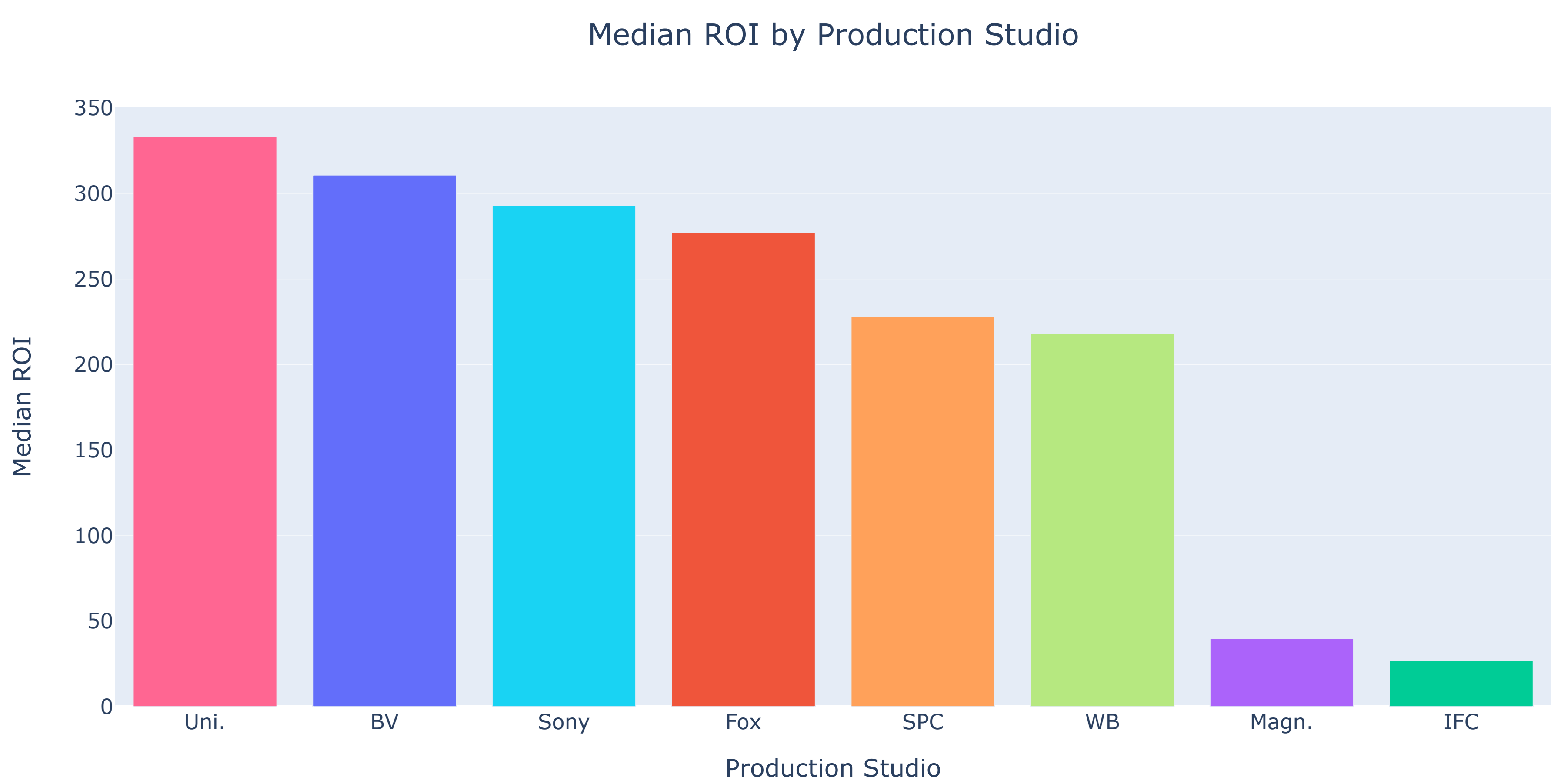
Out[27]:

	year	runtime_minutes	averagerating	numvotes	production_budget	domestic_gross	worldwide_gross	ROI_(percentage)
studio								
BV	2014.0	117.0	7.1	206168.5	150000000.0	140451743.5	279853106.0	310.769105
Fox	2014.0	106.0	6.4	95318.0	58000000.0	65014513.0	165720921.0	277.242173
IFC	2013.5	100.0	6.3	25595.5	2500000.0	391642.5	923687.5	26.785371
Magn.	2010.0	99.0	6.4	39193.5	5750000.0	278293.0	1045462.0	39.809127
SPC	2011.0	109.0	7.3	65304.0	8000000.0	4033574.0	20005613.0	228.318773
Sony	2013.0	104.0	6.3	106103.0	55000000.0	78398803.0	191678378.0	293.098748
Uni.	2014.0	108.0	6.3	115787.5	40000000.0	63775337.5	125970792.5	333.119747
WB	2014.0	113.0	6.6	123955.0	58000000.0	60457138.0	130673154.0	218.282005

In [28]:
```
#Create a bar chart using plotly to show case the top 10 studios by median ROI
fig = px.bar(top_10_studios_mean, x = list(top_10_studios_mean.iloc[:, 0].index),  y = 'ROI_(percentage)',
             title = "Median ROI by Production Studio",
             labels = {'ROI_(percentage)': 'Median ROI', 'x': 'Production Studio'},
             color_discrete_sequence=[px.colors.qualitative.Plotly])

fig.update_layout(
    title={
        'y':0.9,
        'x':0.5,
        'xanchor': 'center',
        'yanchor': 'top'},
    barmode='stack', xaxis={'categoryorder':'total descending'})

fig.update_layout()
fig.show()
```



Show Top 5 Studios by Number of Movies Produced

The below data frame groups our data frame by the top five production companies previously identified and is also grouped by genre. The data frame will ultimately be used through a bar chart that visualizes how many movies were produced and classified by genre and the production studio.

In [29]:
```
#Creat a top 5 studios data frame
top_5_studios = imdb_studios_tn_df.loc[(imdb_studios_tn_df['studio'] == 'Uni.') | \
(imdb_studios_tn_df['studio'] == 'WB') | (imdb_studios_tn_df['studio'] == 'Fox') | \
(imdb_studios_tn_df['studio'] == 'Sony') | (imdb_studios_tn_df['studio'] == 'BV')]

#Groupby studio and genre_1 and take the count
top_5_studios_group = top_5_studios.groupby(['studio', 'genre_1']).count()

#Reset the index so we can accurately graph the below data frame
top_5_studios_genre_chart = top_5_studios_group.reset_index()
top_5_studios_genre_chart.head()
```

Out[29]:

	studio	genre_1	title	year	runtime_minutes	averagerating	numvotes	production_budget	domestic_gross	worldwide_gross	genre_2	genres
0	BV	Action	26	26	26	26	26	26	26	26	26	26
1	BV	Adventure	23	23	23	23	23	23	23	23	23	23
2	BV	Animation	1	1	1	1	1	1	1	1	1	1
3	BV	Comedy	8	8	8	8	8	8	8	8	8	8
4	BV	Documentary	7	7	7	7	7	7	7	7	7	7

In [30]:
```
#Utilize ther above data frame for when we graph just the top 5 studios by count
top_5_studios_bar_chart = top_5_studios.groupby('studio').count()
top_5_studios_bar_chart
```

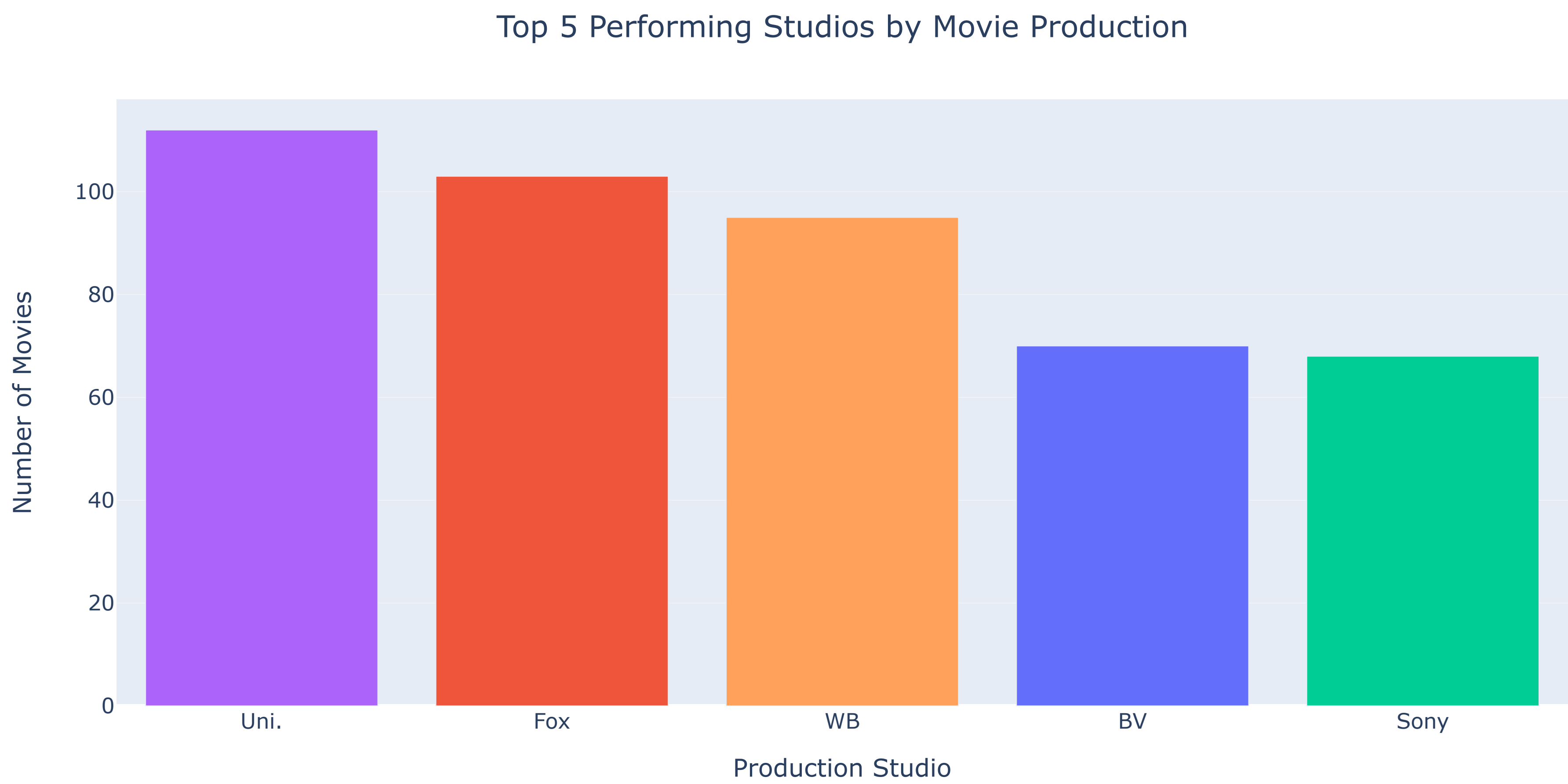
Out[30]:

	title	year	runtime_minutes	averagerating	numvotes	production_budget	domestic_gross	worldwide_gross	genre_1	genre_2	genres	ROI_(p
studio												
BV	70	70	70	70	70	70	70	70	70	70	70	
Fox	103	103	103	103	103	103	103	103	103	103	103	
Sony	68	68	68	68	68	68	68	68	68	68	68	
Uni.	112	112	112	112	112	112	112	112	112	112	112	
WB	95	95	95	95	95	95	95	95	95	95	95	

In [31]:
```
#Graph the top 5 studios by count
fig = px.bar(top_5_studios_bar_chart, x = list(top_5_studios_bar_chart.iloc[:, 0].index),  y = 'title',
             title = "Top 5 Performing Studios by Movie Production",
             labels = {'x': 'Production Studio', 'title': 'Number of Movies'},
             color_discrete_sequence=[px.colors.qualitative.Plotly])

fig.update_layout(
    title={
        'y':0.9,
        'x':0.5,
        'xanchor': 'center',
        'yanchor': 'top'},
         barmode='stack', xaxis={'categoryorder':'total descending'})

fig.show()
```



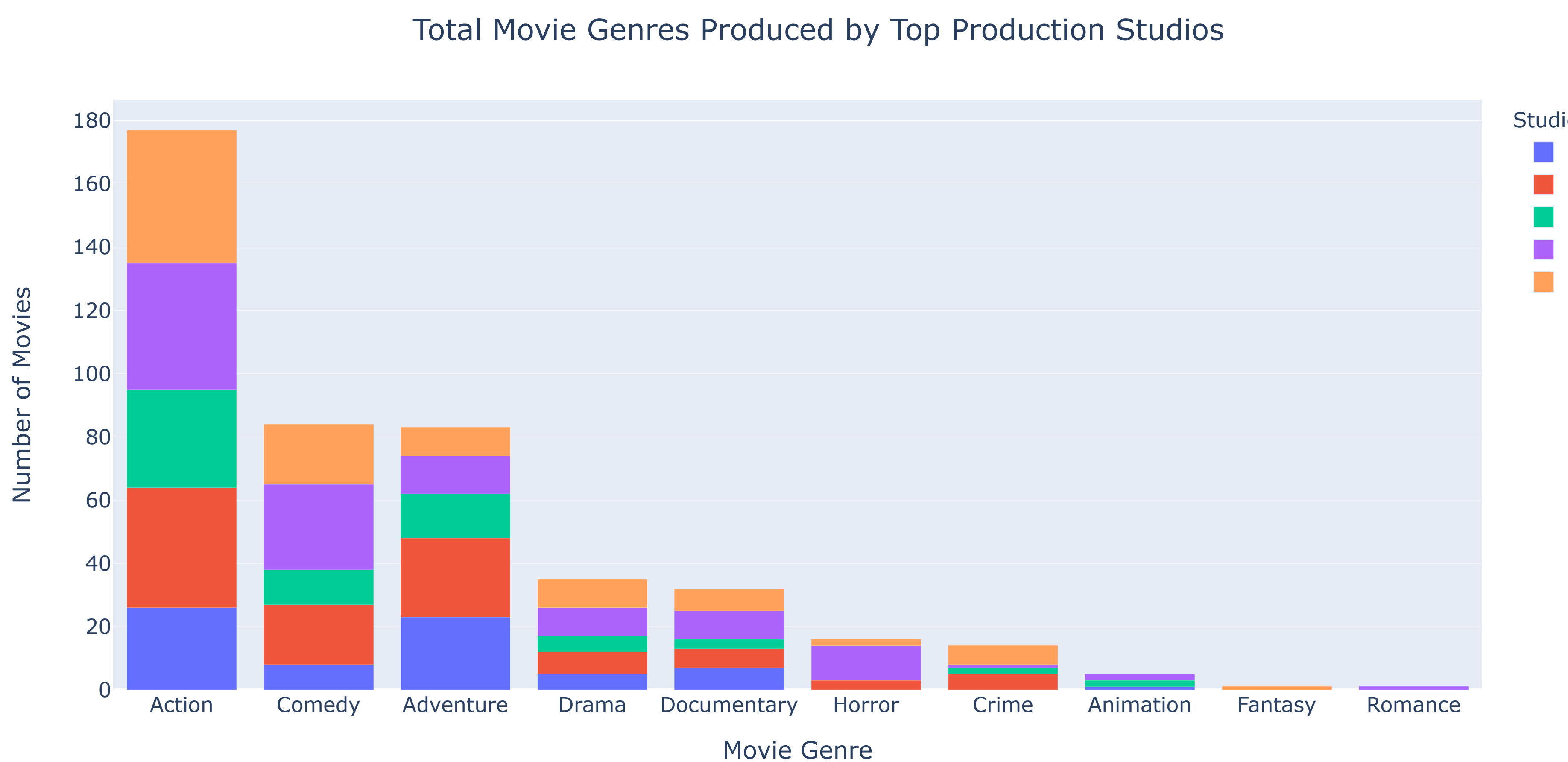
Show Top 5 Studios by Production and Genre

The below data frame groups our data frame by the top five production companies previously identified and is also grouped by genre. The data frame will ultimately be used through a bar chart that visualize how many movies were produced classified by genre and the production studio.

In [32]:
```python
#Create a bar chart which highlights the number of movies produced by movie genre and top 5 studios
fig = px.bar(top_5_studios_genre_chart, x = 'genre_1',  y = 'title', color = 'studio',
             title = "Total Movie Genres Produced by Top Production Studios",
             labels = {'genre_1': 'Movie Genre', 'title': 'Number of Movies', 'studio': "Studio"})

fig.update_layout(
    title={
        'y':0.9,
        'x':0.5,
        'xanchor': 'center',
        'yanchor': 'top'},
        barmode='stack', xaxis={'categoryorder':'total descending'})

fig.show()
```



Show Top Production Studios and Genres by Distribution of Movie Budget

The below data frame now groups our data frame by the top five production companies previously identified, the top three genres, and the distribution of movie budgets. The data frame will be visualized through a box chart.

In [33]:
```
#Create a data frame of the top 5 studios by median in order to create the below graph
top_genres = top_5_studios.loc[(top_5_studios['genre_1'] == 'Action') | (top_5_studios['genre_1'] == 'Adventure'
                                (top_5_studios['genre_1'] == 'Comedy')]
```

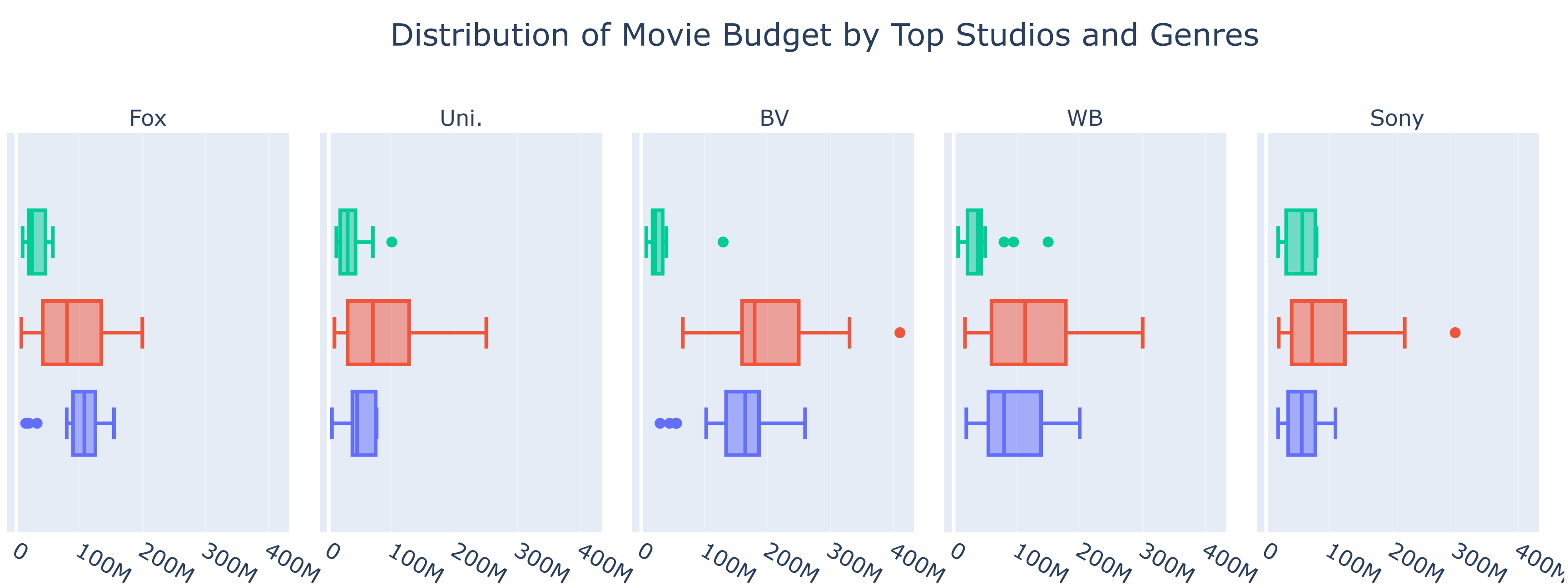
In [34]:
```python
#Create a box plot with Ploty which highlights the distribution of movie budget \
#produced by top genres and top studios

fig = px.box(data_frame = top_genres, x= 'production_budget', color = 'genre_1', facet_col = 'studio',
                title = "Distribution of Movie Budget by Top Studios and Genres",
                width=1060, height=400, facet_col_wrap=5,
                labels = {'production_budget': 'Production Budget', 'production_budget': 'Production Budget',
                          'production_budget': 'Production Budget', 'genre_1': 'Movie Genre'})

fig.for_each_annotation(lambda a: a.update(text=a.text.split("=")[1]))
fig.update_layout(xaxis_title='Production Budget',
    title={
        'y':0.9,
        'x':0.5,
        'xanchor': 'center',
        'yanchor': 'top'})

fig['layout']['xaxis1']['title']['text'] = ''
fig['layout']['xaxis2']['title']['text'] = ''
fig['layout']['xaxis4']['title']['text'] = ''
fig['layout']['xaxis5']['title']['text'] = ''


fig.show()
```



Production Budget

Show Top Production Studios and Genres by Distribution of Movie ROI

Similar to the graph above, we are grouping our data frame by the top five production companies, the top three genres, and now by the distribution of movie ROIs. This data frame will also be visualized through a box chart.

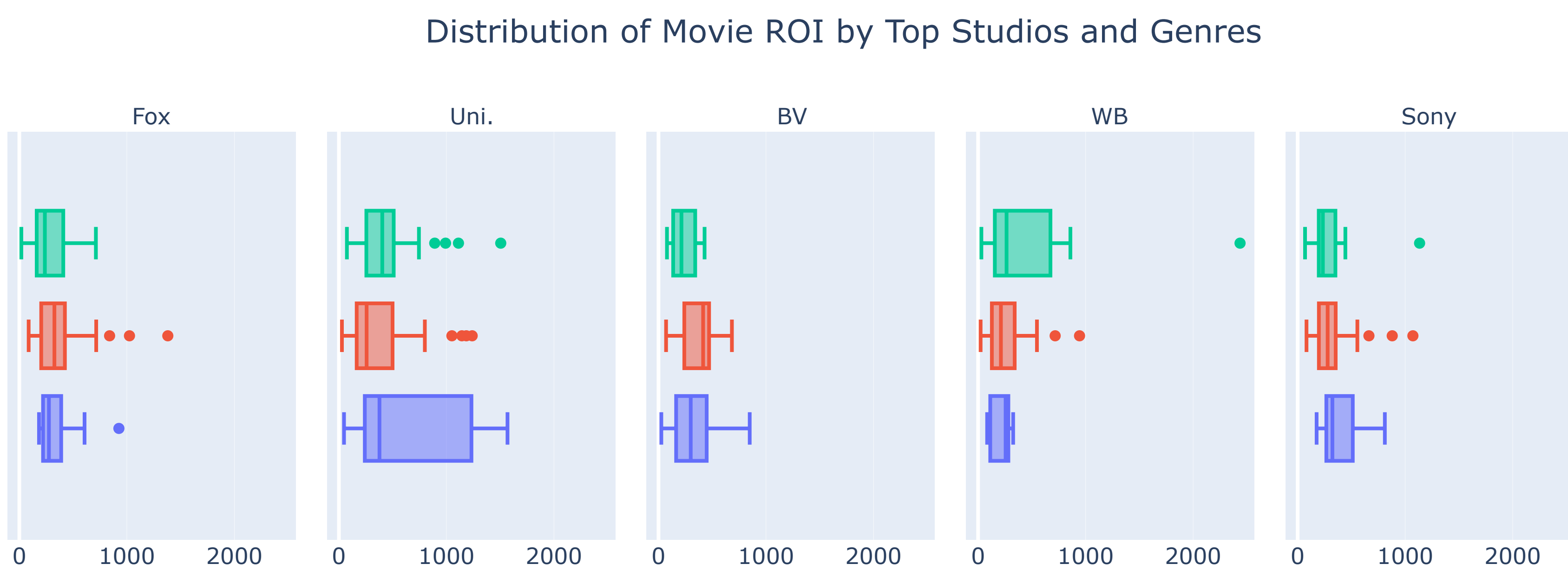
In [35]:
```python
#Create a box plot with Ploty which highlights the distribution of ROI
#produced by top genres and top studios

fig = px.box(data_frame = top_genres, x= 'ROI_(percentage)', color = 'genre_1', facet_col = 'studio',
             title = "Distribution of Movie ROI by Top Studios and Genres",
             width=1060, height=400, facet_col_wrap=5,
             labels = {'ROI_(percentage)': 'ROI (percentage)', 'ROI_(percentage)': 'ROI (percentage)',
                       'ROI_(percentage)': 'ROI (percentage)', 'genre_1': 'Movie Genre'})

fig.for_each_annotation(lambda a: a.update(text=a.text.split("=")[1]))
fig.update_layout(xaxis_title='ROI (percentage)',
    title={
        'y':0.9,
        'x':0.5,
        'xanchor': 'center',
        'yanchor': 'top'})

fig['layout']['xaxis1']['title']['text'] = ''
fig['layout']['xaxis2']['title']['text'] = ''
fig['layout']['xaxis4']['title']['text'] = ''
fig['layout']['xaxis5']['title']['text'] = ''


fig.show()
```



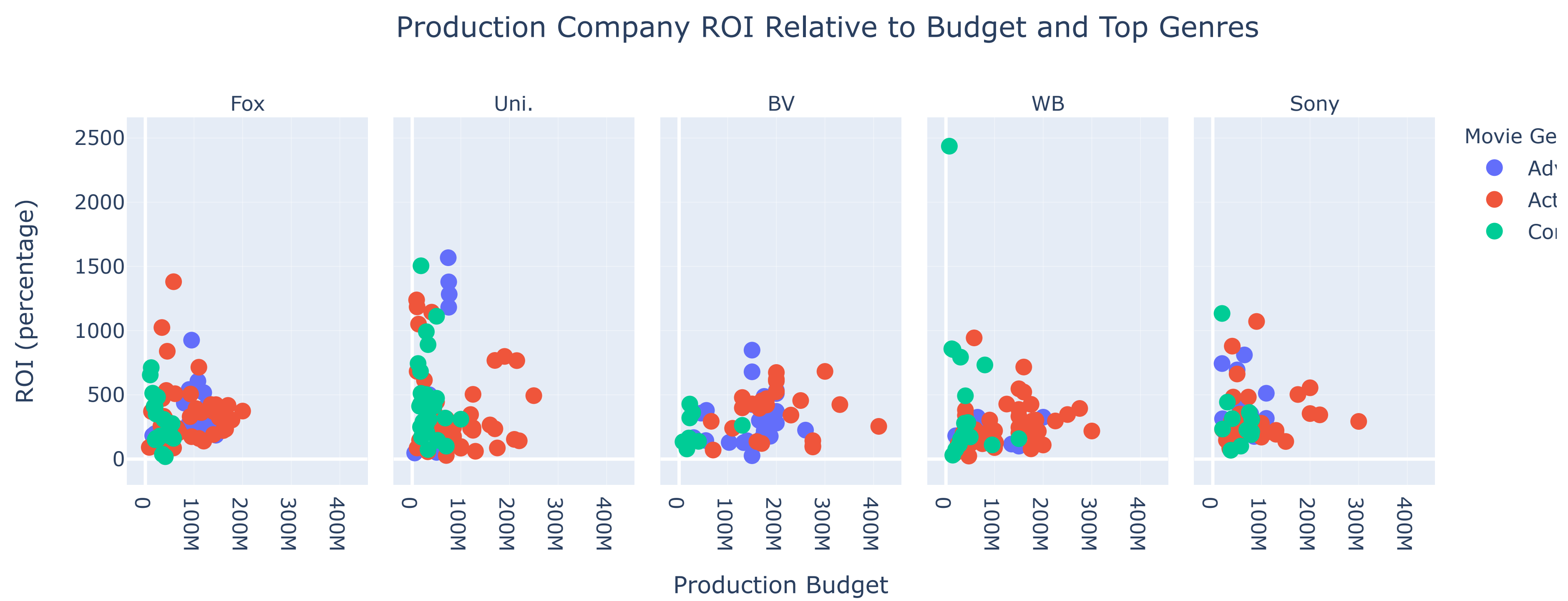
ROI (percentage)

Show Top Production Studios and Genres by the Relationship between Movie Budget and ROI

The last visualization will be a scatter plot. To create the visual will again utilize our top_genres data frame but will now visualize the top production companies, the top genres, and the relationship between movie budgets and ROIs.

In [36]:

```
#Create a scatter plot with Ploty which highlights the distribution of ROI and production budget
#produced by top genres and top studios
fig = px.scatter(data_frame = top_genres, x="production_budget", y="ROI_(percentage)", color='genre_1',
                facet_col = 'studio',
                title = "Production Company ROI Relative to Budget and Top Genres",
                width=1000, height=400, facet_col_wrap=5,
                labels = {'production_budget': 'Production Budget', 'production_budget': 'Production Budget',
                          'production_budget': 'Production Budget', 'ROI_(percentage)': 'ROI (percentage)',
                         'genre_1': 'Movie Genre'})
fig.for_each_annotation(lambda a: a.update(text=a.text.split("=")[1]))
fig.update_layout(
    title={
        'y':0.9,
        'x':0.5,
        'xanchor': 'center',
        'yanchor': 'top'})
fig['layout']['xaxis']['title']['text'] = ''
fig['layout']['xaxis2']['title']['text'] = ''
fig['layout']['xaxis4']['title']['text'] = ''
fig['layout']['xaxis5']['title']['text'] = ''
fig.update_traces(marker=dict(size=10),
                  selector=dict(mode='markers'))
fig.show()
```



Conclusion

This analysis leads to three recommendations for improving operations of Microsoft's Movie Studios:

- **Consider employing both BV (Disney's) and Universal Studio's business and production strategies.** Considering the volume of movies produced and median ROI, Disney and Universal Studio are consistently the front runner of the industry.
- **Mostly invest in action and comedy movies.** Given comedy tends to have a smaller distribution of production budgets and relatively consistently high ROI, Microsoft should produce comedy films as their first few projects. As productions are rolled-out, Microsoft can then produce more action films as these too have relatively higher ROIs but tend to have a wider distribution in terms of project budget.
- **Target low budgets and high ROIs.** Given there is no clear linear correlation related to project budget size and return on investment, Microsoft should consider producing projects with lower budgets (<$100m) as these tend to produce relatively high ROIs (~500%).

Next Steps

Further analyses could yield additional insights to further inform Microsoft's movie production strategy:

- **More recent data sets to analyze the most up-to-date movie production trends.** These insights rely upon movies that were released between 2010 and 2018. In order to analyze the most recent movie production projects, a more recent data set representing films released during 2019 or after could result in more accurate analyses.
- **More time to analyze which sub-genres are most invested in.** Given the time constraint of this presentation, an analysis of sub-genre investments by top production companies could further assist Microsoft in deciding, for example, which types of comedy films the firm should invest in.
- **Refined calculation of ROI. The analyses of ROI in this assumes a relatively simple calculation.** With a larger data set that include production budget breakdowns and expense line items could result in more accurate ROI representations.