Final Project Submission

Please fill out:

- Student name:
- Student pace: self paced / part time / full time
- Scheduled project review date/time:
- Instructor name:
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A. Business understanding

1. Does a studio or production company matters much in terms of Box office and the general revenue of a film?
2. Every film has a genre. How are different film genres contributing to a box office of a film?
3. Films differ in terms of quality. Production budget of a film has a direct influence on the quality of the movie. I will be seeking to answer the question on whether the production budget affects the box office of a film.
4. Does the presence of stars from another field like sports, music or even from the film industry affect the box office of a film?
5. There are top film producers. Do we have to use them in order to ensure our movies/ films travels up to the international level which will in turn increase the box office? Relationship between film producers and the box office of a movie.
6. Does the rating of a movie affects the box office?
7. How is the run-time of film related to gross income of a film/movie?
8. What are the top 5 movie genres that have high box office?
9. How is the original language from which the movie/ film is drawn affects the popularity?
10. What are the correlations between the given attributes of the datasets? Of interest is between the other attributes to box office/ revenue generated

We have to import the following libraries to aid in our code writing and visualizations.

In [ ]:
```
import pandas as pd
import numpy as np
import seaborn as sns
import sqlite3
import matplotlib.pyplot as plt
%matplotlib inline
```

We are interested with the top performing films in terms of gross income. We will therefore filter our data to the films generating gross income from above $100,000,000

In [ ]:
```
bom_df = pd.read_csv('bom.movie_gross.csv.gz') # Load the csv file and assign it to

bom_df = bom_df[bom_df['domestic_gross'] > 100000000] # filtering the dataset to onl
bom_df
```

Out[ ]:

	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
...	...	...	...	...	...
3116	Crazy Rich Asians	WB	174500000.0	64000000	2018
3119	Creed II	MGM	115700000.0	98300000	2018
3121	The Equalizer 2	Sony	102100000.0	88300000	2018
3123	The Mule	WB	103800000.0	68700000	2018
3129	A Wrinkle in Time	BV	100500000.0	32200000	2018

284 rows × 5 columns

Remove all the characters from our values in the dataset.

In [ ]:
```
bom_df['foreign_gross'].replace('\W', '', regex=True, inplace= True) # foreign_gross
                                                                      # a float we ha
```

Foreign gross is an object, we have to change it to a float now that we've removed characters from it.

In [ ]:
```
# .astype() method is used to change a data type to a prefered one. Here we are chan
bom_df.foreign_gross = bom_df.foreign_gross.astype(float)
```

Checking if there are null values.

In [ ]:
```
bom_df.isna().sum()# isna() is used to check for null values. And sum() sums the nul
```

Out[ ]:
```
title             0
studio            0
domestic_gross    0
foreign_gross     0
year              0
dtype: int64
```

From the above analysis, the dataframe has no null values.

In [ ]:
```
bom_df.info() # prints out the information of a dataframe
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 284 entries, 0 to 3129
Data columns (total 5 columns):
 #   Column          Non-Null Count  Dtype  
---  ------          --------------  -----  
 0   title           284 non-null    object 
 1   studio          284 non-null    object 
 2   domestic_gross  284 non-null    float64
 3   foreign_gross   284 non-null    float64
 4   year            284 non-null    int64  
dtypes: float64(2), int64(1), object(2)
memory usage: 13.3+ KB
```

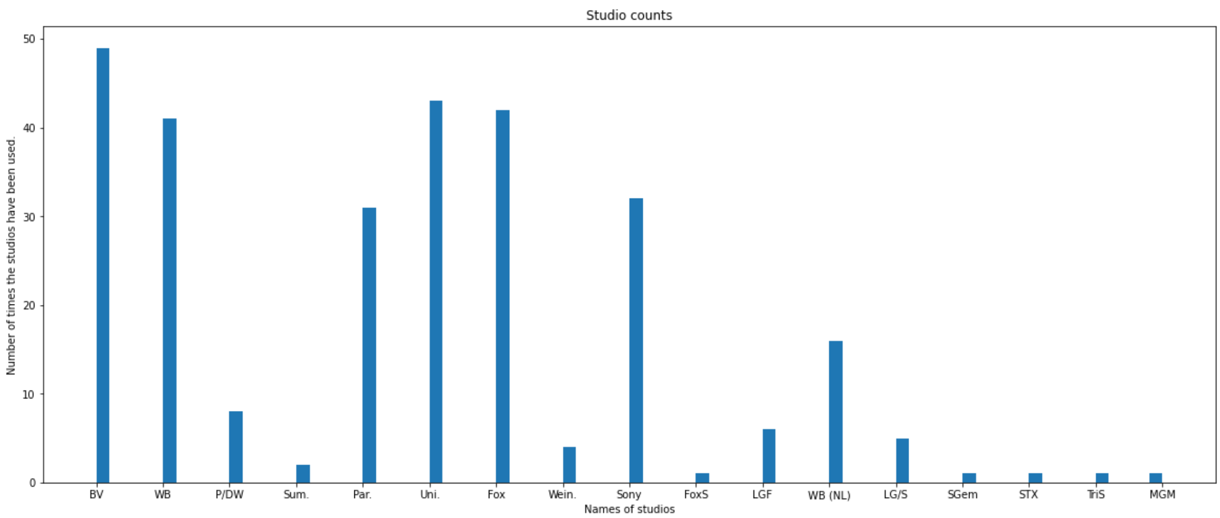
We want to know the studios that have been used most in production of films that have both domestic and foreign gross above $ 100,000,000. This will help us in identifying the qualities of those studios which makes them favorable for productions.

In [ ]:
```
# count of the studios used in production of films with their gross above $100000000
bom_df.studio.value_counts()
```

Out[ ]:
```
BV         49
Uni.       43
Fox        42
WB         41
Sony       32
Par.       31
WB (NL)    16
P/DW        8
LGF         6
LG/S        5
Wein.       4
Sum.        2
TriS        1
FoxS        1
STX         1
MGM         1
SGem        1
Name: studio, dtype: int64
```

Histogram showing the frequency of the studios in the movie production

In [ ]:
```
fig, ax = plt.subplots(figsize = (20,8))
ax.hist(bom_df.studio, bins = 80)
ax.set_xlabel('Names of studios')
ax.set_ylabel('Number of times the studios have been used.')
ax.set_title('Studio counts');
```



From the above analysis; The top movie/film studios are BV.(Buernos Vista), Uni.(Univeral pictures), WB.(Warner Bros), Sony and Par.(Paramount). I would recommend microsoft to look at what these studios are doing that makes them mostly prefered. Microsoft can perform a benchmark from these studios.

Finding the relationship between studio and the box_office(sum of domestic gross and foreign gross)

In [ ]:
```
# code on creation of a new column called box office which is the sum of domestic gr
bom_df['box_office'] =( bom_df.domestic_gross) + (bom_df.foreign_gross)
bom_df
```

Out[ ]:

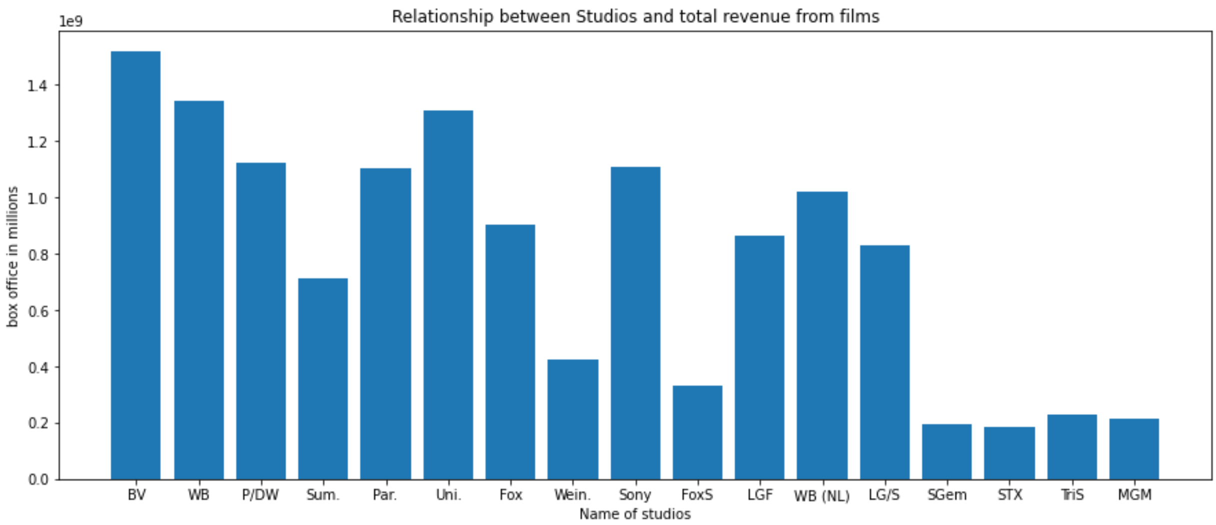
	title	studio	domestic_gross	foreign_gross	year	box_office
0	Toy Story 3	BV	415000000.0	652000000.0	2010	1.067000e+09
1	Alice in Wonderland (2010)	BV	334200000.0	691300000.0	2010	1.025500e+09
2	Harry Potter and the Deathly Hallows Part 1	WB	296000000.0	664300000.0	2010	9.603000e+08
3	Inception	WB	292600000.0	535700000.0	2010	8.283000e+08
4	Shrek Forever After	P/DW	238700000.0	513900000.0	2010	7.526000e+08
...	...	...	...	...	...	...
3116	Crazy Rich Asians	WB	174500000.0	64000000.0	2018	2.385000e+08
3119	Creed II	MGM	115700000.0	98300000.0	2018	2.140000e+08
3121	The Equalizer 2	Sony	102100000.0	88300000.0	2018	1.904000e+08
3123	The Mule	WB	103800000.0	68700000.0	2018	1.725000e+08
3129	A Wrinkle in Time	BV	100500000.0	32200000.0	2018	1.327000e+08

284 rows × 6 columns

Bar graph showing the relationship between studios and box offfice.

In [ ]:

```
fig, ax = plt.subplots(figsize=(15,6))
plt.bar( x= bom_df.studio, height= bom_df.box_office)
plt.xlabel('Name of studios')
plt.ylabel('box office in millions')
plt.title('Relationship between Studios and total revenue from films')
plt.show()
```



From the above analysis, We can see that Bv studio has the highest box office, followed by WB. BV(Buerno Vista), WB, Uni.(Univeral pictures) are most sorted after and produces films that have among the highest box office. Microsoft studio should match this top studios

2. For the below dataset, we are much interested in the top performing films in terms of box office.

We will use a sample of 20 films in our analysis as this will give us full information on the type of films that Microsoft should adopt.

In [ ]:

```
# Loading data and assigning it to rottent_df variable.
rottent_df = pd.read_csv('rotten_tomatoes_top_movies.csv', index_col = 0)
# we extract the columns that are needed for our analysis
rottent_df = rottent_df.loc[:,['title','year','critic_score','type','rating','genre'
# Arrange the rows in a descending order for easy extraction of top performing films
rottent_df.sort_values(by='box_office_(gross_usa)', ascending= False)
```

Out[ ]:

	title	year	critic_score	type	rating	genre	producer	box_of
1	Avengers: Endgame	2019	94	Action & Adventure	PG-13 (Sequences of Sci-Fi Violence|Action|Som...	sci fi, adventure, action, fantasy	Kevin Feige	
0	Black Panther	2018	96	Action & Adventure	PG-13 (Sequences of Action Violence|A Brief Ru...	adventure, action, fantasy	Kevin Feige	
10	Star Wars: The Last Jedi	2017	90	Action & Adventure	PG-13 (Violence|Sequences of Sci-Fi Action)	action, sci fi, adventure, fantasy	Kathleen Kennedy, Ram Bergman	
15	Incredibles 2	2018	93	Action & Adventure	PG (Some Brief Mild Language|Action Sequences)	comedy, animation, action, kids and family, ad...	John Walker, Nicole Paradis Grindle	
5	Wonder Woman	2017	93	Action & Adventure	PG-13 (Sequences of Violence|Action|Some Sugge...	adventure, fantasy, action	Charles Roven, Deborah Snyder, Zack Snyder, Ri...	
14	Spider-Man: Far From Home	2019	90	Action & Adventure	PG-13 (Sci-Fi Action Violence|Brief Suggestive...	action, comedy, fantasy, adventure	Kevin Feige, Amy Pascal	
18	Spider-Man: Homecoming	2017	92	Action & Adventure	PG-13 (Sci-Fi Action Violence|Brief Suggestive...	adventure, fantasy, action, comedy	Kevin Feige, Amy Pascal	
8	Thor: Ragnarok	2017	93	Action & Adventure	PG-13 (Brief Suggestive Material|Action|Intens...	comedy, fantasy, sci fi, action, adventure	Kevin Feige	

	title	year	critic_score	type	rating	genre	producer	box_of
9	Logan	2017	93	Action & Adventure	R (Language Throughout|Brief Nudity|Strong Bru...	adventure, action, fantasy	Hutch Parker, Simon Kinberg, Lauren Shuler Donner	
2	Mission: Impossible -- Fallout	2018	97	Action & Adventure	PG-13 (Intense Sequences of Action|Brief Stron...	action, mystery and thriller, adventure	Tom Cruise, Christopher McQuarrie, Jake Myers,...	
7	Coco	2017	97	Action & Adventure	PG (Thematic Elements)	comedy, music, animation, kids and family, adv...	Darla K. Anderson	
4	Spider-Man: Into the Spider-Verse	2018	97	Action & Adventure	PG (Mild Language|Frenetic Action Violence|The...	action, adventure, fantasy, comedy, kids and f...	Avi Arad, Amy Pascal, Phil Lord, Christopher M...	
6	Dunkirk	2017	92	Action & Adventure	PG-13 (Some Language|Intense War Experience)	drama, history, war	Emma Thomas, Christopher Nolan	
3	Mad Max: Fury Road	2015	97	Action & Adventure	R (Intense Sequences of Violence|Disturbing Im...	adventure, action	Doug Mitchell, George Miller, P.J. Voeten	
17	War for the Planet of the Apes	2017	94	Action & Adventure	PG-13 (Sequences of Sci-Fi Violence|Action|Som...	sci fi, adventure, action	Peter Chernin, Dylan Clark, Rick Jaffa, Amanda...	
11	Star Wars: The Force Awakens	2015	93	Action & Adventure	PG-13 (Sci-Fi Action Violence)	action, sci fi, adventure, fantasy	Kathleen Kennedy, J.J. Abrams, Bryan Burk	
19	Baby Driver	2017	92	Action & Adventure	R (Violence|Language Throughout)	mystery and thriller, action	Nira Park, Tim Bevan, Eric Fellner	
12	The Adventures	1938	100	Action & Adventure	PG	action, adventure	Hal B. Wallis	

	title	year	critic_score	type	rating	genre	producer	box_of
	of Robin Hood							
13	King Kong	1933	98	Action & Adventure	NaN	adventure, fantasy	Merian C. Cooper, Ernest B. Schoedsack	
16	Zootopia	2016	98	Action & Adventure	PG (Rude Humor|Action|Some Thematic Elements)	kids and family, comedy, adventure, animation	Clark Spencer	

Cleaning the dataset

In [ ]:
```
rottent_df.shape
```

Out[ ]:
```
(20, 10)
```

Check for missing values in the top 20 rows in all the columns.

In [ ]:
```
rottent_df.isna().sum()
```

Out[ ]:
```
title                    0
year                     0
critic_score             0
type                     0
rating                   1
genre                    0
producer                 0
box_office_(gross_usa)   3
runtime                  0
crew                     0
dtype: int64
```

We will back fill the missing values in box*office*(gross_usa) column.

In [ ]:
```
rottent_df['box_office_(gross_usa)'].fillna(method = 'bfill', inplace= True)
rottent_df
```

Out[ ]:

	title	year	critic_score	type	rating	genre	producer	box_of
0	Black Panther	2018	96	Action & Adventure	PG-13 (Sequences of Action Violence|A Brief Ru...	adventure, action, fantasy	Kevin Feige	
1	Avengers: Endgame	2019	94	Action & Adventure	PG-13 (Sequences of Sci-Fi Violence|Action|Som...	sci fi, adventure, action, fantasy	Kevin Feige	
2	Mission: Impossible -- Fallout	2018	97	Action & Adventure	PG-13 (Intense Sequences of Action|Brief Stron...	action, mystery and	Tom Cruise, Christopher McQuarrie,	

	title	year	critic_score	type	rating	genre	producer	box_of
						thriller, adventure	Jake Myers,...	
3	Mad Max: Fury Road	2015	97	Action & Adventure	R (Intense Sequences of Violence|Disturbing Im...	adventure, action	Doug Mitchell, George Miller, P.J. Voeten	
4	Spider-Man: Into the Spider-Verse	2018	97	Action & Adventure	PG (Mild Language|Frenetic Action Violence|The...	action, adventure, fantasy, comedy, kids and f...	Avi Arad, Amy Pascal, Phil Lord, Christopher M...	
5	Wonder Woman	2017	93	Action & Adventure	PG-13 (Sequences of Violence|Action|Some Sugge...	adventure, fantasy, action	Charles Roven, Deborah Snyder, Zack Snyder, Ri...	
6	Dunkirk	2017	92	Action & Adventure	PG-13 (Some Language|Intense War Experience)	drama, history, war	Emma Thomas, Christopher Nolan	
7	Coco	2017	97	Action & Adventure	PG (Thematic Elements)	comedy, music, animation, kids and family, adv...	Darla K. Anderson	
8	Thor: Ragnarok	2017	93	Action & Adventure	PG-13 (Brief Suggestive Material|Action|Intens...	comedy, fantasy, sci fi, action, adventure	Kevin Feige	
9	Logan	2017	93	Action & Adventure	R (Language Throughout|Brief Nudity|Strong Bru...	adventure, action, fantasy	Hutch Parker, Simon Kinberg, Lauren Shuler Donner	
10	Star Wars: The Last Jedi	2017	90	Action & Adventure	PG-13 (Violence|Sequences of Sci-Fi Action)	action, sci fi, adventure, fantasy	Kathleen Kennedy, Ram Bergman	
11	Star Wars: The Force Awakens	2015	93	Action & Adventure	PG-13 (Sci-Fi Action Violence)	action, sci fi, adventure, fantasy	Kathleen Kennedy, J.J. Abrams, Bryan Burk	

	title	year	critic_score	type	rating	genre	producer	box_of
12	The Adventures of Robin Hood	1938	100	Action & Adventure	PG	action, adventure	Hal B. Wallis	
13	King Kong	1933	98	Action & Adventure	NaN	adventure, fantasy	Merian C. Cooper, Ernest B. Schoedsack	
14	Spider-Man: Far From Home	2019	90	Action & Adventure	PG-13 (Sci-Fi Action Violence|Brief Suggestive...	action, comedy, fantasy, adventure	Kevin Feige, Amy Pascal	
15	Incredibles 2	2018	93	Action & Adventure	PG (Some Brief Mild Language|Action Sequences)	comedy, animation, action, kids and family, ad...	John Walker, Nicole Paradis Grindle	
16	Zootopia	2016	98	Action & Adventure	PG (Rude Humor|Action|Some Thematic Elements)	kids and family, comedy, adventure, animation	Clark Spencer	
17	War for the Planet of the Apes	2017	94	Action & Adventure	PG-13 (Sequences of Sci-Fi Violence|Action|Som...	sci fi, adventure, action	Peter Chernin, Dylan Clark, Rick Jaffa, Amanda...	
18	Spider-Man: Homecoming	2017	92	Action & Adventure	PG-13 (Sci-Fi Action Violence|Brief Suggestive...	adventure, fantasy, action, comedy	Kevin Feige, Amy Pascal	
19	Baby Driver	2017	92	Action & Adventure	R (Violence|Language Throughout)	mystery and thriller, action	Nira Park, Tim Bevan, Eric Fellner	

We have a missing value in rating column. We can drop the row with missing value since it will have a little impact on our dataset.

In [ ]:
```
rottent_df.dropna(axis = 0, inplace=True)

rottent_df.sort_values(by='box_office_(gross_usa)', ascending= False)
```

Out[ ]:

	title	year	critic_score	type	rating	genre	producer	box_of
1	Avengers: Endgame	2019	94	Action & Adventure	PG-13 (Sequences of Sci-Fi Violence|Action|Som...	sci fi, adventure, action, fantasy	Kevin Feige	
0	Black Panther	2018	96	Action & Adventure	PG-13 (Sequences of Action Violence|A Brief Ru...	adventure, action, fantasy	Kevin Feige	
10	Star Wars: The Last Jedi	2017	90	Action & Adventure	PG-13 (Violence|Sequences of Sci-Fi Action)	action, sci fi, adventure, fantasy	Kathleen Kennedy, Ram Bergman	
15	Incredibles 2	2018	93	Action & Adventure	PG (Some Brief Mild Language|Action Sequences)	comedy, animation, action, kids and family, ad...	John Walker, Nicole Paradis Grindle	
5	Wonder Woman	2017	93	Action & Adventure	PG-13 (Sequences of Violence|Action|Some Sugge...	adventure, fantasy, action	Charles Roven, Deborah Snyder, Zack Snyder, Ri...	
14	Spider-Man: Far From Home	2019	90	Action & Adventure	PG-13 (Sci-Fi Action Violence|Brief Suggestive...	action, comedy, fantasy, adventure	Kevin Feige, Amy Pascal	
12	The Adventures of Robin Hood	1938	100	Action & Adventure	PG	action, adventure	Hal B. Wallis	
18	Spider-Man: Homecoming	2017	92	Action & Adventure	PG-13 (Sci-Fi Action Violence|Brief Suggestive...	adventure, fantasy, action, comedy	Kevin Feige, Amy Pascal	
8	Thor: Ragnarok	2017	93	Action & Adventure	PG-13 (Brief Suggestive Material|Action|Intens...	comedy, fantasy, sci fi, action, adventure	Kevin Feige	

	title	year	critic_score	type	rating	genre	producer	box_of
9	Logan	2017	93	Action & Adventure	R (Language Throughout|Brief Nudity|Strong Bru...	adventure, action, fantasy	Hutch Parker, Simon Kinberg, Lauren Shuler Donner	
2	Mission: Impossible -- Fallout	2018	97	Action & Adventure	PG-13 (Intense Sequences of Action|Brief Stron...	action, mystery and thriller, adventure	Tom Cruise, Christopher McQuarrie, Jake Myers,...	
7	Coco	2017	97	Action & Adventure	PG (Thematic Elements)	comedy, music, animation, kids and family, adv...	Darla K. Anderson	
4	Spider-Man: Into the Spider-Verse	2018	97	Action & Adventure	PG (Mild Language|Frenetic Action Violence|The...	action, adventure, fantasy, comedy, kids and f...	Avi Arad, Amy Pascal, Phil Lord, Christopher M...	
6	Dunkirk	2017	92	Action & Adventure	PG-13 (Some Language|Intense War Experience)	drama, history, war	Emma Thomas, Christopher Nolan	
3	Mad Max: Fury Road	2015	97	Action & Adventure	R (Intense Sequences of Violence|Disturbing Im...	adventure, action	Doug Mitchell, George Miller, P.J. Voeten	
16	Zootopia	2016	98	Action & Adventure	PG (Rude Humor|Action|Some Thematic Elements)	kids and family, comedy, adventure, animation	Clark Spencer	
17	War for the Planet of the Apes	2017	94	Action & Adventure	PG-13 (Sequences of Sci-Fi Violence|Action|Som...	sci fi, adventure, action	Peter Chernin, Dylan Clark, Rick Jaffa, Amanda...	
11	Star Wars: The Force Awakens	2015	93	Action & Adventure	PG-13 (Sci-Fi Action Violence)	action, sci fi, adventure, fantasy	Kathleen Kennedy, J.J. Abrams, Bryan Burk	

	title	year	critic_score	type	rating	genre	producer	box_of
19	Baby Driver	2017	92	Action & Adventure	R (Violence|Language Throughout)	mystery and thriller, action	Nira Park, Tim Bevan, Eric Fellner	

Next we check for duplicates.

In [ ]:
```
rottent_df.duplicated()
```

Out[ ]:
```
0     False
1     False
2     False
3     False
4     False
5     False
6     False
7     False
8     False
9     False
10    False
11    False
12    False
14    False
15    False
16    False
17    False
18    False
19    False
dtype: bool
```

Well, there are no duplicates. We then look at the data types of each column features.

In [ ]:
```
rottent_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 19 entries, 0 to 19
Data columns (total 10 columns):
 #   Column                  Non-Null Count  Dtype 
---  ------                  --------------  ----- 
 0   title                   19 non-null     object
 1   year                    19 non-null     int64 
 2   critic_score            19 non-null     int64 
 3   type                    19 non-null     object
 4   rating                  19 non-null     object
 5   genre                   19 non-null     object
 6   producer                19 non-null     object
 7   box_office_(gross_usa)  19 non-null     object
 8   runtime                 19 non-null     object
 9   crew                    19 non-null     object
dtypes: int64(2), object(8)
memory usage: 1.6+ KB
```

box*office*(gross_usa) is of object type instead of float. We then have to change it to float.

In [ ]:
```
rottent_df['box_office_(gross_usa)'] = rottent_df['box_office_(gross_usa)'].replace(
rottent_df['box_office_(gross_usa)'] = rottent_df['box_office_(gross_usa)'].replace(

rottent_df['box_office_(gross_usa)'] = rottent_df['box_office_(gross_usa)'].astype(f
```

In [ ]:
```
rottent_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 19 entries, 0 to 19
Data columns (total 10 columns):
 #   Column                 Non-Null Count  Dtype  
---  ------                 --------------  -----  
 0   title                  19 non-null     object 
 1   year                   19 non-null     int64  
 2   critic_score           19 non-null     int64  
 3   type                   19 non-null     object 
 4   rating                 19 non-null     object 
 5   genre                  19 non-null     object 
 6   producer               19 non-null     object 
 7   box_office_(gross_usa)  19 non-null     float64
 8   runtime                19 non-null     object 
 9   crew                   19 non-null     object 
dtypes: float64(1), int64(2), object(7)
memory usage: 1.6+ KB
```

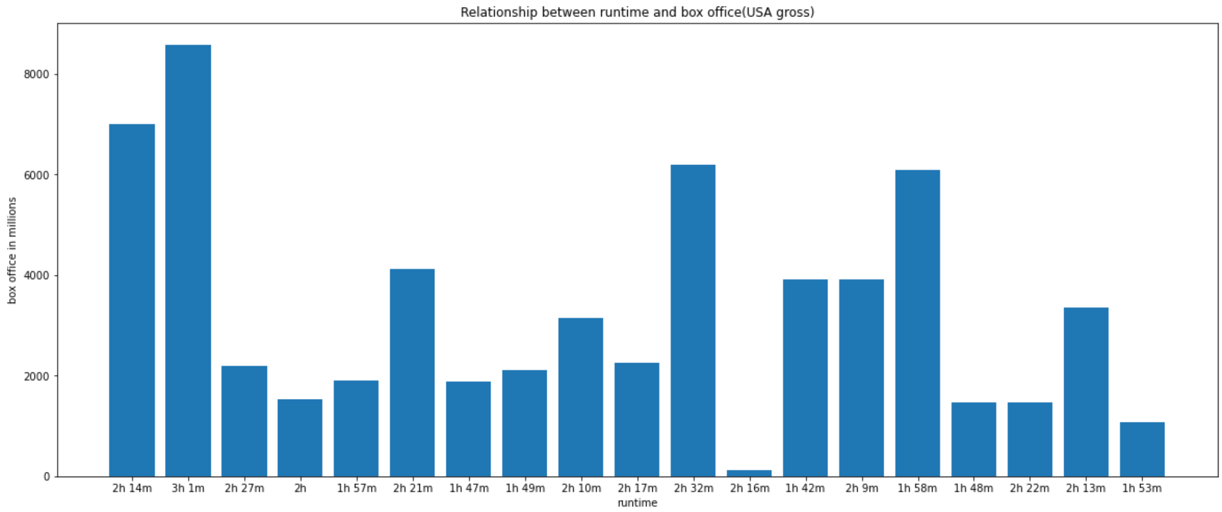
Look at the runtime of films top performing films then visualize the data.

In [ ]:
```
rottent_df.runtime
```

Out[ ]:
```
0      2h 14m
1       3h 1m
2      2h 27m
3          2h
4      1h 57m
5      2h 21m
6      1h 47m
7      1h 49m
8      2h 10m
9      2h 17m
10     2h 32m
11     2h 16m
12     1h 42m
14      2h 9m
15     1h 58m
16     1h 48m
17     2h 22m
18     2h 13m
19     1h 53m
Name: runtime, dtype: object
```

A bar graph showing the relationship between runtime and box office of a film. Does it affect the selling of the movie?

In [ ]:
```
fig, ax = plt.subplots(figsize = (20,8))
ax.bar(x = rottent_df['runtime'], height= rottent_df['box_office_(gross_usa)'])
ax.set_xlabel('runtime')
ax.set_ylabel('box office in millions')
ax.set_title('Relationship between runtime and box office(USA gross)');
```



From the visualization above, there is no clear relationship between runtime and box office as even films with a runtime of less than 2 hrs perfomed well in terms of box office in usa gross. I think the performance of a movie/film is dependent on factors like genres, the crews etc no the runtime. A movie/ film can have be long but 'boring'. I would advice Microsoft not to worry much about the runtime of the movie/film.

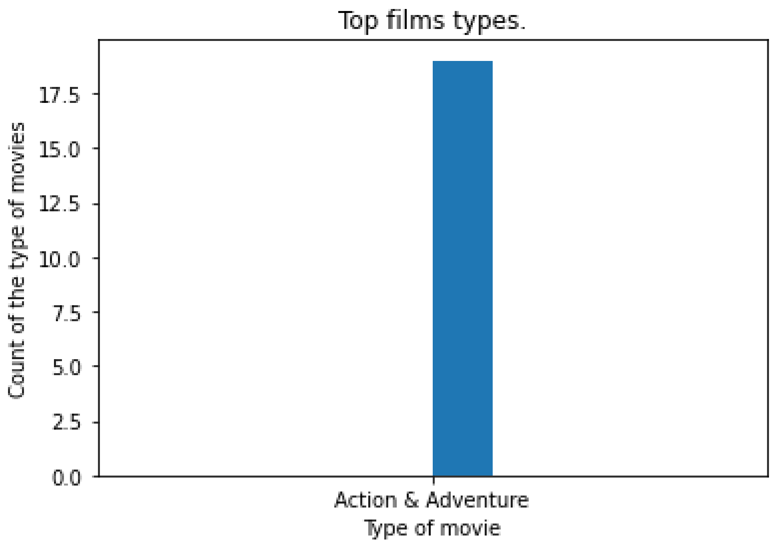
Look at the types of films and how they relate to box office of the top performing films.

In [ ]:
```
rottent_df.type.value_counts()
```

Out[ ]:
```
Action & Adventure    19
Name: type, dtype: int64
```

Histogram showing the leading type of movies among the top performing films.

In [ ]:
```
fig, ax = plt.subplots()
plt.hist(rottent_df.type)
ax.set_xlabel('Type of movie')
ax.set_ylabel('Count of the type of movies')
ax.set_title('Top films types.');
```

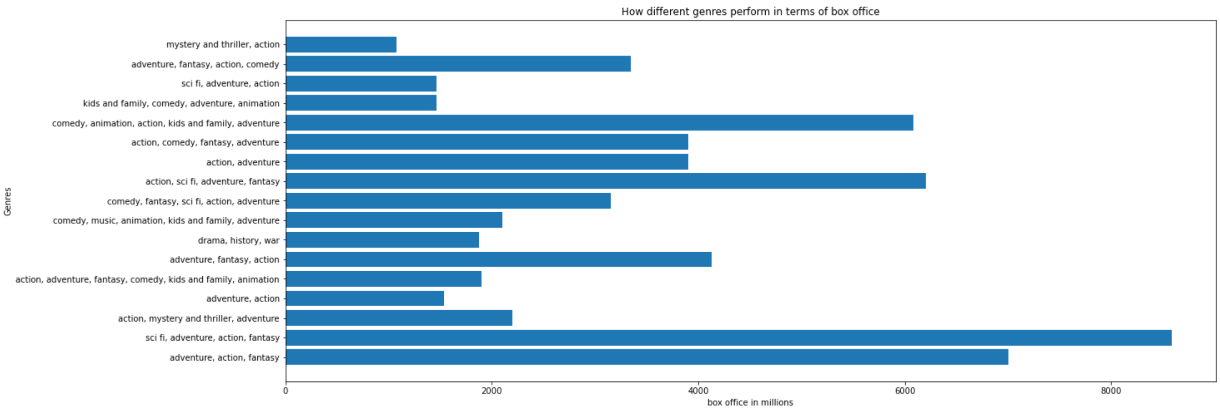


From the above visualization, we can see that the type of the top performing films is Action & Adventure. I would them recommend the creation of films that are of this(Action&Adventure) type.

Genres

Horizontal bar graph showing the relationship between genre and the box office of a movie. Which genre is mostly used in the production of these films?

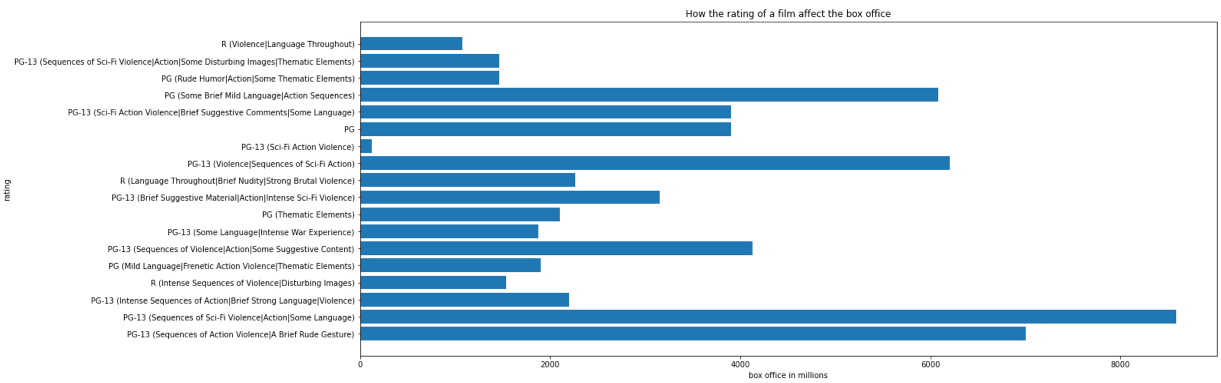
In [ ]:
```
fig, ax = plt.subplots(figsize=(20,8))
plt.barh(rottent_df['genre'], width= rottent_df['box_office_(gross_usa)'])
ax.set_title('How different genres perform in terms of box office')
ax.set_ylabel('Genres')
ax.set_xlabel('box office in millions');
```



From the above visualization, sci fi, adventure, action, fantasy genre performed top in terms of box office. Also, (comedy, animation, action, kids and family, adventure) genre and (adventure, action, fantasy) genre does well. I would recommend Microsoft studio films be centered on these kinds of genres.

We also will have to look at the rating of the top films since it will determine a lot when settling on the type of film to recommend to Microsoft.

In [ ]:
```
fig, ax = plt.subplots(figsize=(20,8))
plt.barh(rottent_df.rating,width=rottent_df['box_office_(gross_usa)'])
ax.set_ylabel('rating')
ax.set_xlabel('box office in millions')
ax.set_title('How the rating of a film affect the box office');
```



Also, the sample is of top performing films. The rating from the visualization above matters less in terms of box office. We can see the movies rated PG performing highly and also in some titles are performing not that highly.

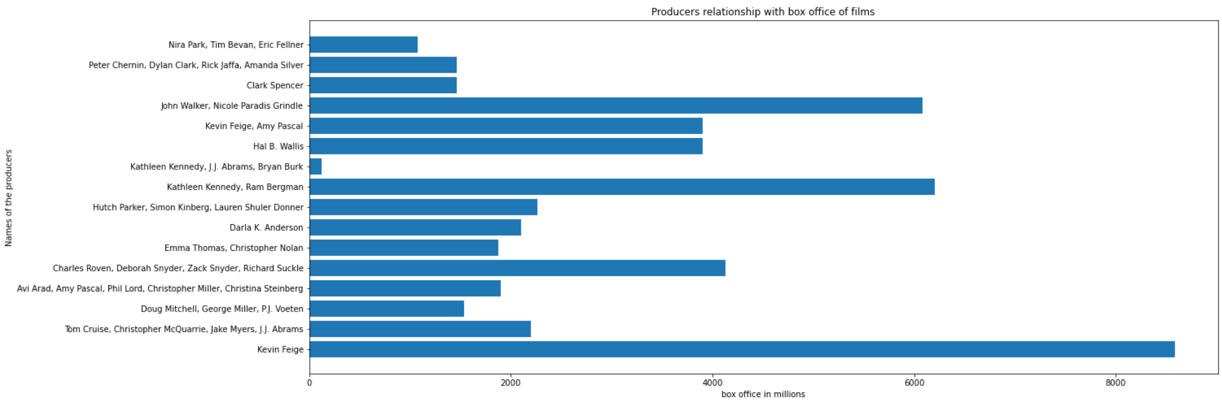
We then look at producers of these performing films. Who are the most sort after producers?

In [ ]:
```
rottent_df.producer.value_counts()
```

Out[ ]:
```
Kevin Feige                                                              3
Kevin Feige, Amy Pascal                                                  2
Kathleen Kennedy, J.J. Abrams, Bryan Burk                                1
Peter Chernin, Dylan Clark, Rick Jaffa, Amanda Silver                    1
Avi Arad, Amy Pascal, Phil Lord, Christopher Miller, Christina Steinberg    1
Tom Cruise, Christopher McQuarrie, Jake Myers, J.J. Abrams               1
Doug Mitchell, George Miller, P.J. Voeten                                1
John Walker, Nicole Paradis Grindle                                      1
Clark Spencer                                                            1
Kathleen Kennedy, Ram Bergman                                            1
Nira Park, Tim Bevan, Eric Fellner                                       1
Charles Roven, Deborah Snyder, Zack Snyder, Richard Suckle               1
Hutch Parker, Simon Kinberg, Lauren Shuler Donner                        1
Emma Thomas, Christopher Nolan                                           1
Darla K. Anderson                                                        1
Hal B. Wallis                                                            1
Name: producer, dtype: int64
```

A horizontal bar graph of box office against producers. We seek to find the top producers in the production of the best performing films.

In [ ]:
```
fig, ax = plt.subplots(figsize = (20,8))
ax.barh( rottent_df.producer, width= rottent_df['box_office_(gross_usa)'])
ax.set_xlabel('box office in millions')
ax.set_ylabel('Names of the producers')
ax.set_title('Producers relationship with box office of films');
```



Kevin Feige is the top film producer. I recommend microsoft to hire him to train the producers they intend to employ. This will ensure that the new producers are achieving the quality to which Kevin Feige produces films. If possible, Microsoft can hire him. ALso among the top 3 producers are Kathleen Kennedy and Ram Bergman.

3. To discover the relationship between production budget and box office, we sourced for a dataset containing this information for our analysis.

In [ ]:
```
# Loading dataset.
budget_df = pd.read_csv('tn.movie_budgets.csv', index_col = 0)
budget_df.head(10)# extracting the top 10 movies.
```

Out[ ]:

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

Cleaning the dataset.

In [ ]:
```
budget_df.shape
```

Out[ ]:
```
(5782, 5)
```

We first check for the information of this dataset using .info()

In [ ]:
```
budget_df.info()# gives us the information of the dataset
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 5782 entries, 1 to 82
Data columns (total 5 columns):
 #   Column             Non-Null Count  Dtype 
---  ------             --------------  ----- 
 0   release_date       5782 non-null   object
 1   movie              5782 non-null   object
 2   production_budget  5782 non-null   object
 3   domestic_gross     5782 non-null   object
 4   worldwide_gross    5782 non-null   object
dtypes: object(5)
memory usage: 271.0+ KB
```

From the above information, our dataset has no missing values. All columns have 5782 entries which is the shape of the entire dataset.

We then check if there are duplicates in our dataset.

In [ ]:
```
budget_df.duplicated().sum()# checking for duplicates and summing them up.
```

Out[ ]:
```
0
```

Well, our dataset seems to have no duplicates. We proceed to examine the data types of the various column entries. Production budget, domestic gross, wordwide gross and box office should all be in float data type

In [ ]:
```
budget_df['worldwide_gross'] = budget_df['worldwide_gross'].str.replace('[$,]','')#

budget_df['worldwide_gross'] = budget_df['worldwide_gross'].astype(float)#  changing
```

In [ ]:
```
budget_df['production_budget'] = budget_df['production_budget'].str.replace('[$,]','

budget_df['production_budget'] = budget_df['production_budget'].astype(float)
budget_df
```

Out[ ]:

id	release_date	movie	production_budget	domestic_gross	worldwide_gross
1	Dec 18, 2009	Avatar	425000000.0	$760,507,625	2.776345e+09
2	May 20, 2011	Pirates of the Caribbean: On Stranger Tides	410600000.0	$241,063,875	1.045664e+09
3	Jun 7, 2019	Dark Phoenix	350000000.0	$42,762,350	1.497624e+08
4	May 1, 2015	Avengers: Age of Ultron	330600000.0	$459,005,868	1.403014e+09
5	Dec 15, 2017	Star Wars Ep. VIII: The Last Jedi	317000000.0	$620,181,382	1.316722e+09
...	...	...	...	...	...
78	Dec 31, 2018	Red 11	7000.0	$0	0.000000e+00
79	Apr 2, 1999	Following	6000.0	$48,482	2.404950e+05
80	Jul 13, 2005	Return to the Land of Wonders	5000.0	$1,338	1.338000e+03
81	Sep 29, 2015	A Plague So Pleasant	1400.0	$0	0.000000e+00
82	Aug 5, 2005	My Date With Drew	1100.0	$181,041	1.810410e+05

5782 rows × 5 columns

In [ ]:
```
budget_df.info()# Givesus the information about the dataset
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 5782 entries, 1 to 82
Data columns (total 5 columns):
 #   Column             Non-Null Count  Dtype  
---  ------             --------------  -----  
 0   release_date       5782 non-null   object 
 1   movie              5782 non-null   object 
 2   production_budget  5782 non-null   float64
 3   domestic_gross     5782 non-null   object 
 4   worldwide_gross    5782 non-null   float64
dtypes: float64(2), object(3)
memory usage: 271.0+ KB
```

We are interested with the top performing films and so we extract the data of those films that have a worldwide gross of above $ 100000000.

In [ ]:
```
budget_df = budget_df[budget_df['worldwide_gross'] > 100000000]
budget_df.head(10)
```

Out[ ]:

id	release_date	movie	production_budget	domestic_gross	worldwide_gross
1	Dec 18, 2009	Avatar	425000000.0	$760,507,625	2.776345e+09

id	release_date	movie	production_budget	domestic_gross	worldwide_gross
2	May 20, 2011	Pirates of the Caribbean: On Stranger Tides	410600000.0	$241,063,875	1.045664e+09
3	Jun 7, 2019	Dark Phoenix	350000000.0	$42,762,350	1.497624e+08
4	May 1, 2015	Avengers: Age of Ultron	330600000.0	$459,005,868	1.403014e+09
5	Dec 15, 2017	Star Wars Ep. VIII: The Last Jedi	317000000.0	$620,181,382	1.316722e+09
6	Dec 18, 2015	Star Wars Ep. VII: The Force Awakens	306000000.0	$936,662,225	2.053311e+09
7	Apr 27, 2018	Avengers: Infinity War	300000000.0	$678,815,482	2.048134e+09
8	May 24, 2007	Pirates of the Caribbean: At Worldâ s End	300000000.0	$309,420,425	9.634204e+08
9	Nov 17, 2017	Justice League	300000000.0	$229,024,295	6.559452e+08
10	Nov 6, 2015	Spectre	300000000.0	$200,074,175	8.796209e+08

Check on the relationship between production budget and worldwide gross

Plotting a correlation matrix of production_budget and worldwide gross.

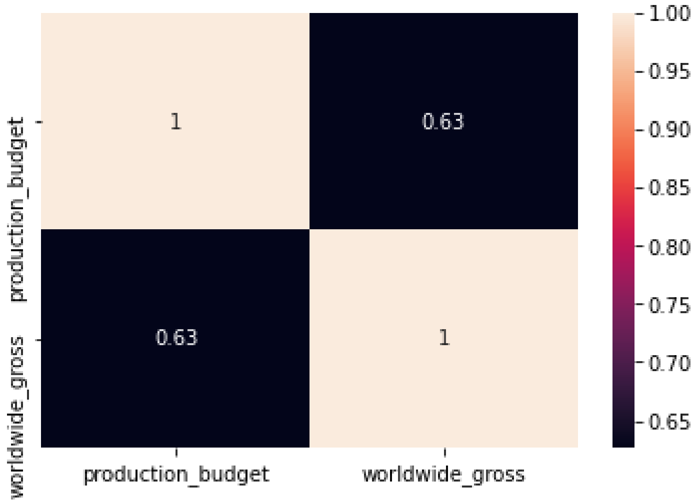
In [ ]:
```
correlation = budget_df.corr()
correlation. style. background_gradient (cmap = 'BrBG')
```

Out[ ]:

	production_budget	worldwide_gross
production_budget	1.000000	0.626202
worldwide_gross	0.626202	1.000000

Heatmap using seaborn of production budget and wordwide gross to aid in visualization.

In [ ]:
```
sns. heatmap (correlation, annot=True);
```



From the above correlation matrix, we can see that there is a high correlation of 0.63 between production budget and worldwide gross. The higher the production budget then the probability of a huge worldwide gross is high. I would therefore recommend Microsoft studio to invest more in the production of their films as this will see a high worldwide gross of the films.