Microsoft Movie Market Analysis

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Part 1, Introduction

Microsoft, the client, has tasked our firm with the analysis of film industry da
trends and provide insights into their movie making ventures. All analysis ar
recommendations will be key to their initial efforts at penetrating the market.

Let's first pull in the data and took a look at it.

In [2]:

```
#import libraries
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
# import sqlite3

# current issues - 1. there are duplicate titles, as many as 4 duplicates for
```

In [3]:

```
#initial pull of data with pandas read of title basics csv to get a feel for
dfbscs = pd.read_csv(r"C:\Users\josep\Desktop\CourseWork\phase_1\Phase1\Movie
pd.options.display.float_format = '{:.3f}'.format # to remove the scientific
```

We've imported our first data and formated any float objects moving forward. What does a quick look at the first five row

imdb.title.basics.csv gives us access to the titles of the mov as well as runtime and start year.

In [4]:

```
dfbscs.head()
```

	tconst	primary_title	original_title	start_year	runtime_min
0	tt0063540	Sunghursh	Sunghursh	2013	175.000
1	tt0066787	One Day Before the Rainy Season	Ashad Ka Ek Din	2019	114.000
2	tt0069049	The Other Side of the Wind	The Other Side of the Wind	2018	122.000
3	tt0069204	Sabse Bada Sukh	Sabse Bada Sukh	2018	nan
4	tt0100275	The Wandering Soap Opera	La Telenovela Errante	2017	80.000

In [5]:

```
# Let's pull in the other two recommended databases to take a look at what is
dfrtngs = pd.read_csv(r"C:\Users\josep\Desktop\CourseWork\phase_1\Phase1\Movi
dfgrss = pd.read_csv(r"C:\Users\josep\Desktop\CourseWork\phase_1\Phase1\Movie
```

In [6]:

```
# And get some info on each of them while taking a look at their size and da
# tconst column will be a key between basics and ratings, while title will b
# of a key between basics and movie gross dataframes
dfbscs.info()
dfrtngs.info()
dfgrss.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
<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
<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
```

Some of these dataFrames have a lot of rows of data, som There's a lot going on here, but let's first make sure that we data that will be used to provide insights and make recomm Microsoft.

In [7]:

```
dfbscs.head()
```

	tconst	primary_title	original_title	start_year	runtime_min
0	tt0063540	Sunghursh	Sunghursh	2013	175.000
1	tt0066787	One Day Before the Rainy Season	Ashad Ka Ek Din	2019	114.000
2	tt0069049	The Other Side of the Wind	The Other Side of the Wind	2018	122.000
3	tt0069204	Sabse Bada Sukh	Sabse Bada Sukh	2018	nan
4	tt0100275	The Wandering Soap Opera	La Telenovela Errante	2017	80.000

In [8]:

```
dfrtngs.head()
```

	tconst	averagerating	numvotes
0	tt10356526	8.300	31
1	tt10384606	8.900	559
2	tt1042974	6.400	20
3	tt1043726	4.200	50352
4	tt1060240	6.500	21

In [9]:

```
dfgrss.head()
```

	title	studio	domestic_gross	foreign_gross	year
0	Toy Story 3	BV	415000000.000	652000000	2010
1	Alice in Wonderland (2010)	BV	334200000.000	691300000	2010
2	Harry Potter and the Deathly Hallows Part 1	WB	296000000.000	664300000	2010
3	Inception	WB	292600000.000	535700000	2010
4	Shrek Forever After	P/DW	238700000.000	513900000	2010

In [10]:

```
df_ratings = pd.merge(dfbscs,dfrtngs, on='tconst') # titles without ratings a
df_ratings
# quick check to see if numbers fall in reasonable parameters
print(df_ratings['averagerating'].max()) # = 10
print(df_ratings['averagerating'].min()) # = 1.0
print(df_ratings['start_year'].max()) # = 2019
print(df_ratings['start_year'].min()) # = 2010
# merging data allows for a single consolidated list and removes any titles t
# average rating or numvotes
# can then merge the new df with dfgrss to get gross amounts
# but have to change the column headings on dfbscs first to title from primar
```

```
10.0
1.0
2019
2010
```

In [11]:

```
# create a new df, df_clean that can merge on column 'title' after renaming 
df_clean = df_ratings.rename(columns = {'primary_title':'title'})
df_clean = df_clean.sort_values(by=['numvotes'],axis=0,ascending=False,ignor
df_clean = df_clean.drop_duplicates(subset='title') # after deleting duplica
print(len(df_clean))
# check for duplicate titles, verify that "The Door" has multiple entries

# *****want to remove duplicate titles with the least numvotes this is temp 
#
# duplicates = df_clean[df_clean.duplicated(subset='title')]
# print(len(duplicates))
# print(duplicates.head())
# for x in df_clean['title']:
#     if x=='The Door':
#         print(x)
# *****

df_ratings_and_gross = pd.merge(df_clean,dfgrss, on='title')
# we now have two sets of data - one 3027 (df_ratings_and_gross) rows long t
# and domestic and foreign gross. The other data set has 73856 records, (df_
# can still provide data on overall ratings.
# There is still some data cleaning to do before we begin visualizing the da
# additionally, one set contains foreign gross which is set to a sting datat
# to be converted to a float object

# since there are duplicates in the data, I want to sort the df and have the

df_ratings_and_gross = df_ratings_and_gross.sort_values(by=['numvotes'],axis
# now we can utilize .drop_duplicates on the titles column in order to remov
print(df_ratings_and_gross)
df_ratings_and_gross = df_ratings_and_gross.drop_duplicates(subset='title')
print(df_ratings_and_gross) # note that rows have decreased to 2598 from 302
```

```
69993
        tconst                    title           original_title  start_year  \
0    tt1375666                Inception                Inception        2010
1    tt1345836    The Dark Knight Rises    The Dark Knight Rises        2012
2    tt0816692             Interstellar             Interstellar        2014
3    tt1853728         Django Unchained         Django Unchained        2012
4    tt0993846  The Wolf of Wall Street  The Wolf of Wall Street        2013
...        ...                      ...                      ...         ...
```

```
2594  tt8851190                  Red                   Red        2018
2595  tt1666555          Anchor Baby           Anchor Baby        2010
2596  tt1692325       Eyes Wide Open        Eyes Wide Open        2010
2597  tt3436064     The Last Station     La última estación        2012
2598  tt2713406             Meerkats              Meerkats        2011

      runtime_minutes                   genres  averagerating  numvotes  \
0             148.000  Action,Adventure,Sci-Fi          8.800   1841066
1             164.000          Action,Thriller          8.400   1387769
2             169.000   Adventure,Drama,Sci-Fi          8.600   1299334
3             165.000            Drama,Western          8.400   1211405
4             180.000    Biography,Crime,Drama          8.200   1035358
...               ...                      ...            ...       ...
2594           90.000                    Drama          8.100        26
2595           95.000           Drama,Thriller          7.000        25
2596          110.000      Documentary,History          8.700        17
2597           90.000              Documentary          7.600        10
2598           40.000              Documentary          7.400         7

     studio  domestic_gross foreign_gross  year
0        WB   292600000.000     535700000  2010
1        WB   448100000.000     636800000  2012
2      Par.   188000000.000     489400000  2014
3     Wein.   162800000.000     262600000  2012
4      Par.   116900000.000     275100000  2013
...     ...             ...           ...   ...
2594   Sum.    90400000.000     108600000  2010
2595    AGF       15800.000        161000  2011
2596    NAV       26300.000        250000  2010
2597    SPC     6600000.000       6900000  2010
2598    NGE      778000.000        482000  2012

[2599 rows x 12 columns]
         tconst                    title          original_title  start_year  \
0     tt1375666                Inception               Inception        2010
1     tt1345836    The Dark Knight Rises   The Dark Knight Rises        2012
2     tt0816692             Interstellar            Interstellar        2014
3     tt1853728         Django Unchained        Django Unchained        2012
4     tt0993846  The Wolf of Wall Street  The Wolf of Wall Street        2013
...         ...                      ...                     ...         ...
2594  tt8851190                      Red                     Red        2018
2595  tt1666555              Anchor Baby             Anchor Baby        2010
2596  tt1692325           Eyes Wide Open          Eyes Wide Open        2010
2597  tt3436064         The Last Station      La última estación        2012
2598  tt2713406                 Meerkats                Meerkats        2011

      runtime_minutes                   genres  averagerating  numvotes  \
0             148.000  Action,Adventure,Sci-Fi          8.800   1841066
1             164.000          Action,Thriller          8.400   1387769
2             169.000   Adventure,Drama,Sci-Fi          8.600   1299334
3             165.000            Drama,Western          8.400   1211405
4             180.000    Biography,Crime,Drama          8.200   1035358
...               ...                      ...            ...       ...
2594           90.000                    Drama          8.100        26
2595           95.000           Drama,Thriller          7.000        25
2596          110.000      Documentary,History          8.700        17
2597           90.000              Documentary          7.600        10
```

```
2598          40.000             Documentary         7.400         7

     studio  domestic_gross foreign_gross  year
0        WB   292600000.000     535700000  2010
1        WB   448100000.000     636800000  2012
2      Par.   188000000.000     489400000  2014
3     Wein.   162800000.000     262600000  2012
4      Par.   116900000.000     275100000  2013
...     ...             ...           ...   ...
2594   Sum.    90400000.000     108600000  2010
2595    AGF       15800.000        161000  2011
2596    NAV       26300.000        250000  2010
2597    SPC     6600000.000       6900000  2010
2598    NGE      778000.000        482000  2012

[2598 rows x 12 columns]
```

In [12]:

```
# change foreign gross to a float obj
df_ratings_and_gross['foreign_gross'] = pd.to_numeric(df_ratings_and_gross['
# in this ~3000 records dataset, we need to look for outliers or invalid dat
# for max, mins in float data. nothing stands out
print(df_ratings_and_gross['averagerating'].max()) # = 9.2
print(df_ratings_and_gross['averagerating'].min()) # = 1.6
print(df_ratings_and_gross['year'].max()) # = 2018
print(df_ratings_and_gross['year'].min()) # = 2010
print(df_ratings_and_gross['start_year'].max()) # = 2019
print(df_ratings_and_gross['start_year'].min()) # = 2010
```

```
8.8
1.6
2018
2010
2019
2010
```

I want to also make sure that all NaN values are ignored when proceeding w
mind that there are NaN values still present in the data, let's move forward
and answer some questions about the data and what it means.

Part 2, Question 1

Does a longer runtime indicate a lower average rating? Should Microsoft ha
range for their projects?

In [13]:

```
# For this initial question, we need to ignore NaN values in average rating.
# NaN values, there are some movies with high or low ratings but very few vo
# that the average ratings are higher or lower than they would otherwise be w
# For that reason, I will exclude data with 10 votes or fewer when comparing
```

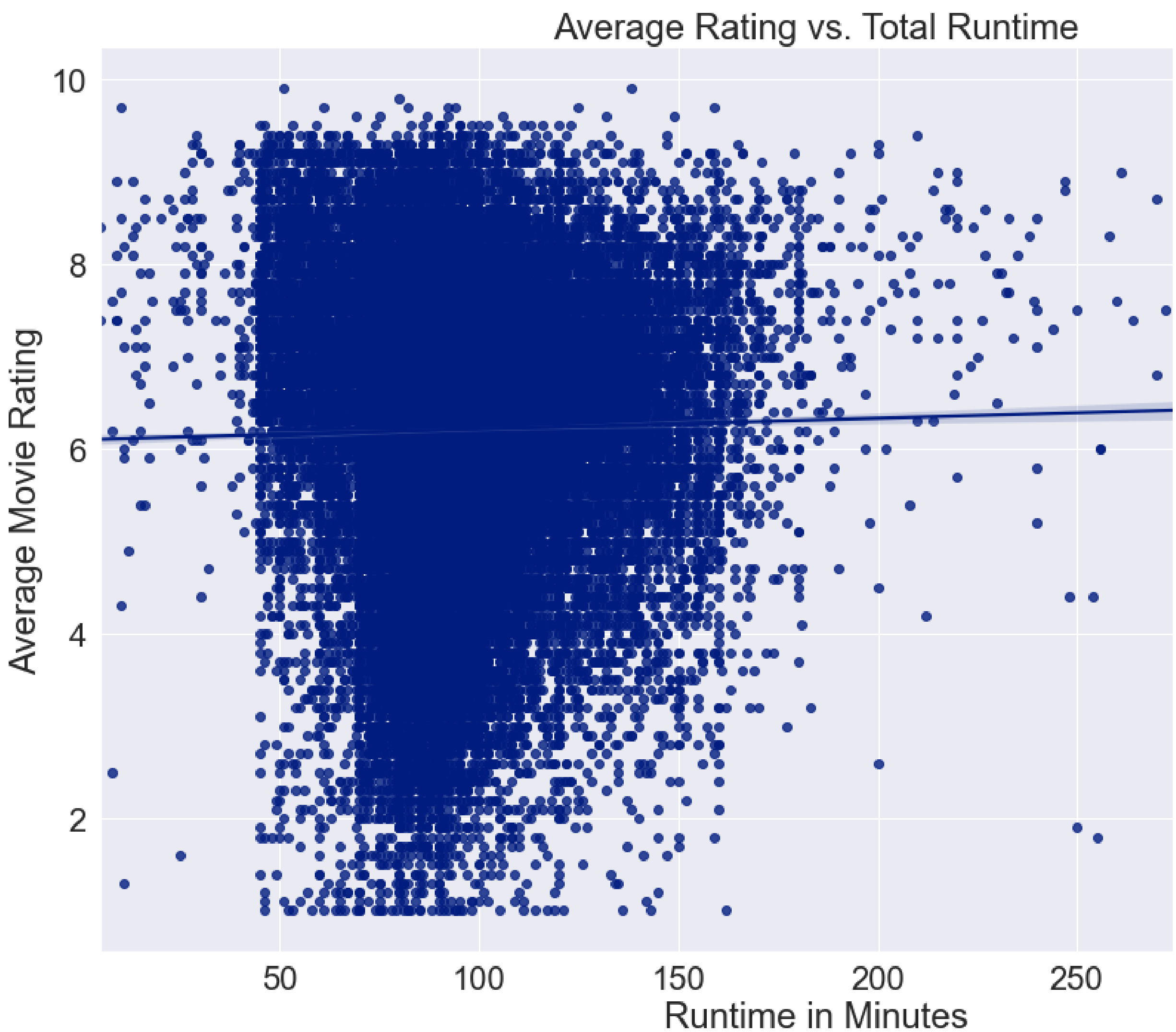
In [14]:

```
# create new df to call for lmplot
data_df = df_clean[['runtime_minutes','averagerating','numvotes']]
# filter for numvotes less than 10
df_over_ten = data_df[data_df.numvotes > 10]
# filter for movie outliers with ridiculous lengths
df_over_ten = df_over_ten[df_over_ten.runtime_minutes <= 400]
df_over_ten = df_over_ten.dropna()
# we have removed all rows with a NaN present. Additionally, we can see that
# excluded data that has less than 6 votes that are contributing to the rati
print(df_over_ten)
# count values to take another look at the data
df_over_ten['runtime_minutes'].value_counts().sort_values()
print(df_over_ten.corr())
# also standard deviation for runtime minutes to figure out a good range for
df_over_ten.mean()
df_over_ten.std()
# 68% of movies are produced within 22 minutes of a 95 minute average.
```

```
       runtime_minutes  averagerating  numvotes
2387           148.000          8.800   1841066
2241           164.000          8.400   1387769
280            169.000          8.600   1299334
12072          165.000          8.400   1211405
325            143.000          8.100   1183655
...                ...            ...       ...
30670           85.000          6.500        11
30560           45.000          5.900        11
11947          102.000          6.300        11
11502           89.000          7.600        11
34460          240.000          8.500        11

[52456 rows x 3 columns]
                 runtime_minutes  averagerating  numvotes
runtime_minutes            1.000          0.018     0.125
averagerating              0.018          1.000     0.066
numvotes                   0.125          0.066     1.000


runtime_minutes      22.422
averagerating         1.431
numvotes          35847.867
dtype: float64
```

In [15]:

```
# drop numvotes column from df_over_five and create an lmplot in seaborn
df_plot1 = df_over_ten.drop(columns=['numvotes'])
# plot lmplot
sns.set(font_scale=2)
sns.set_style("darkgrid")
palette = sns.set_palette("dark")
ax = sns.lmplot(x='runtime_minutes',y='averagerating',data=df_plot1,height=1(
ax.set(xlabel="Runtime in Minutes",ylabel="Average Movie Rating")
plt.title('Average Rating vs. Total Runtime')
plt.show()
```



Question 1 Insights

There is no readily apparent correlation between total runtime and the avera
based on the information in the data tables. Microsoft should focus on makir
standard deviation (+/- 22 minutes) of the mean of 95 minutes.

In [16]:

```
df_plot1.corr()
# as we can see, there is no correlation between runtime_minutes and averager
```

	runtime_minutes	averagerating
runtime_minutes	1.000	0.018
averagerating	0.018	1.000

Part 3, Question 2

What can we learn by looking at the correlation between total gross and the
rating of a movie? Put slightly differently, does a higher quality movie demar
money at the BO?

In [17]:

```
# just as a reminder, here is what the table we will be working with for ques
df_ratings_and_gross.info()
```

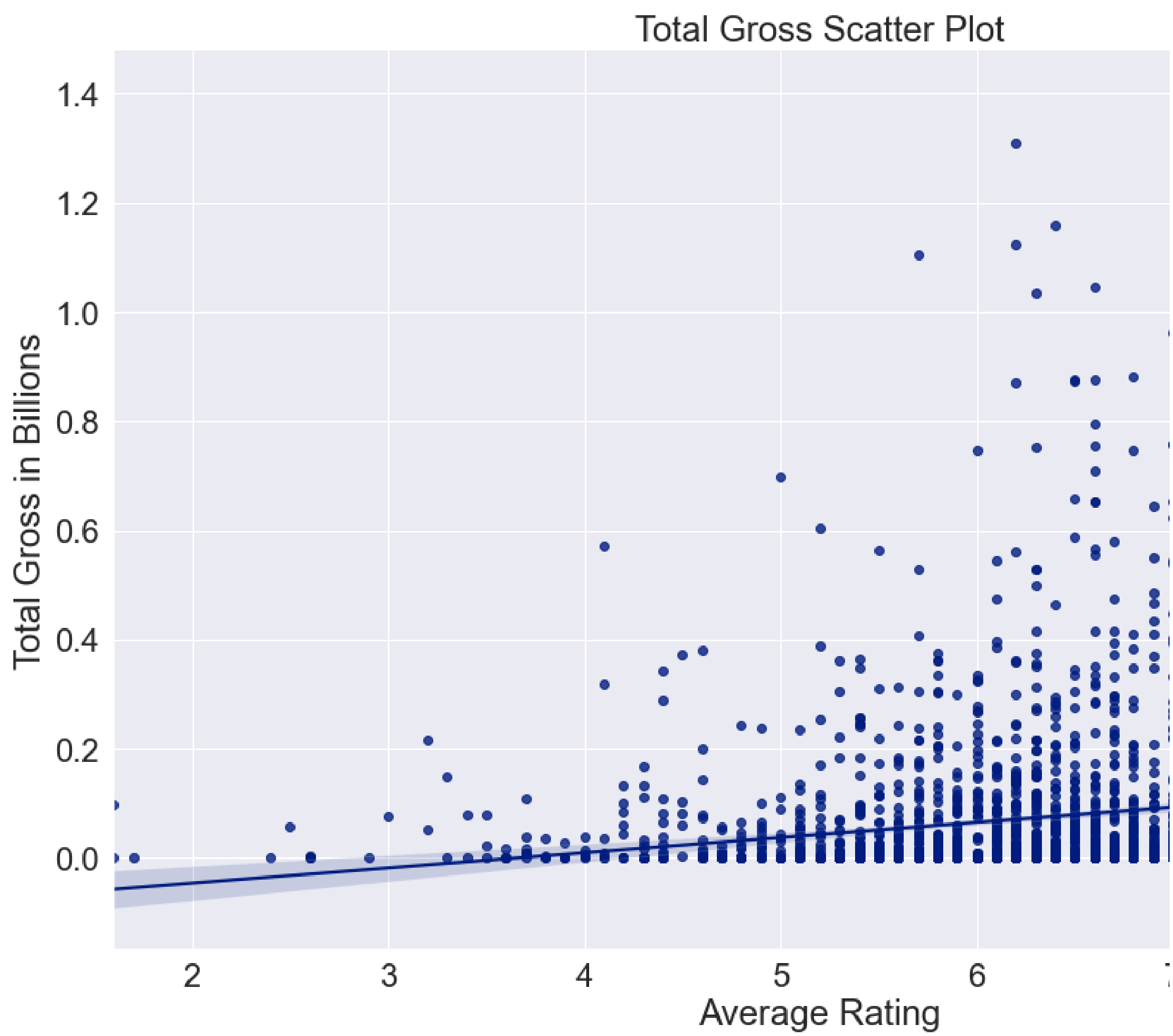
```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 2598 entries, 0 to 2598
Data columns (total 12 columns):
 #   Column           Non-Null Count  Dtype  
---  ------           --------------  -----  
 0   tconst           2598 non-null   object 
 1   title            2598 non-null   object 
 2   original_title   2598 non-null   object 
 3   start_year       2598 non-null   int64  
 4   runtime_minutes  2598 non-null   float64
 5   genres           2598 non-null   object 
 6   averagerating    2598 non-null   float64
 7   numvotes         2598 non-null   int64  
 8   studio           2595 non-null   object 
 9   domestic_gross   2581 non-null   float64
 10  foreign_gross    1554 non-null   float64
 11  year             2598 non-null   int64  
dtypes: float64(4), int64(3), object(5)
memory usage: 263.9+ KB
```

In [18]:

```
# For this question, we will look at a graphical representation of the averag
# plotted agains the total gross (domestic_gross + foreign_gross)
# sum foreign and domestic into new column, ignoring NaN values of which ther
df_ratings_and_gross['total_gross'] = df_ratings_and_gross['domestic_gross']
df_ratings_and_gross # but how many of the total gross are 0 after adding a N
# domestic/foreign columns
df_ratings_and_gross.isna().sum()
df_ratings_and_gross['total_gross'].value_counts()
df_ratings_and_gross['total_gross']=df_ratings_and_gross['total_gross']/10000
# great, we can see that total gross has 0 elements that show NaN, as predict
# If a movie had NaN in both domestic and foreign gross then it is showing a
# after checking for value counts == 0 we can see that we have only good data
# assuming that all NaN's were meant to be 0's. For domestic gross, that is l
# be unusual but not impossible for a movie to make money abroad but not in t
```

In [19]:

```
# plot graph of average rating vs total gross
sns.set(font_scale=2)
sns.set_style("darkgrid")
palette = sns.set_palette("dark")
ax = sns.lmplot(x='averagerating',y=('total_gross'),data=df_ratings_and_gros
ax.set(xlabel="Average Rating",ylabel="Total Gross in Billions")
plt.ticklabel_format(style='plain',axis='y')
plt.title('Total Gross Scatter Plot')
plt.show()
# issue here is y axis label with 1e9 top left, make it prettier
df_plot2 = df_ratings_and_gross.drop(columns=['start_year','runtime_minutes'
```



Question 2 Insights

As seen in the graph above and the correlation table below, there is only a s
average rating and the total gross of a movie. The higher quality a movie is,

gross more at the box office. We still haven't hit on a truly valuable insight fo

In [20]:

```
df_plot2.corr()
```

	averagerating	domestic_gross	foreign_gross	total_gross
averagerating	1.000	0.154	0.186	0.147
domestic_gross	0.154	1.000	0.826	0.920
foreign_gross	0.186	0.826	1.000	0.978
total_gross	0.147	0.920	0.978	1.000

Part 4, Question 3

What genre of films gross the most at the box office (BO)? What other insights can v
this?

In [21]:

```
# We will need to break out the genres and list them separately for all films
# are multiple genres listed.
# df_ratings_and_gross has total gross in it from our previous exercise
len(df_ratings_and_gross['genres'].unique())
# let's separate these out
```

```
296
```

In [22]:

```
df_ratings_and_gross.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 2598 entries, 0 to 2598
Data columns (total 13 columns):
 #   Column           Non-Null Count  Dtype
---  ------           --------------  -----
 0   tconst           2598 non-null   object
 1   title            2598 non-null   object
 2   original_title   2598 non-null   object
 3   start_year       2598 non-null   int64
 4   runtime_minutes  2598 non-null   float64
 5   genres           2598 non-null   object
 6   averagerating    2598 non-null   float64
 7   numvotes         2598 non-null   int64
 8   studio           2595 non-null   object
 9   domestic_gross   2581 non-null   float64
 10  foreign_gross    1554 non-null   float64
 11  year             2598 non-null   int64
 12  total_gross      2598 non-null   float64
dtypes: float64(5), int64(3), object(5)
memory usage: 284.2+ KB
```

In [23]:

```
# need to separate genres out into a list and count total occurences
# see above for list of unique genre combinations - there are too many to pu
# histogram with.
#genres_list = df_ratings_and_gross['genres'].dropna().str.lower().str.split
#g_list = []

#for genre_list in genres_list:
#    try:
#        g_list.extend(genre_list)
#    except:
#        continue
```

In [24]:

```
# Raf dummify genres example
# df_example = pd.get_dummies(df_ratings_and_gross['genres'].str.split(',').
```

Lets group our data by genres, including those where genre look at what the averages of the data can show us.

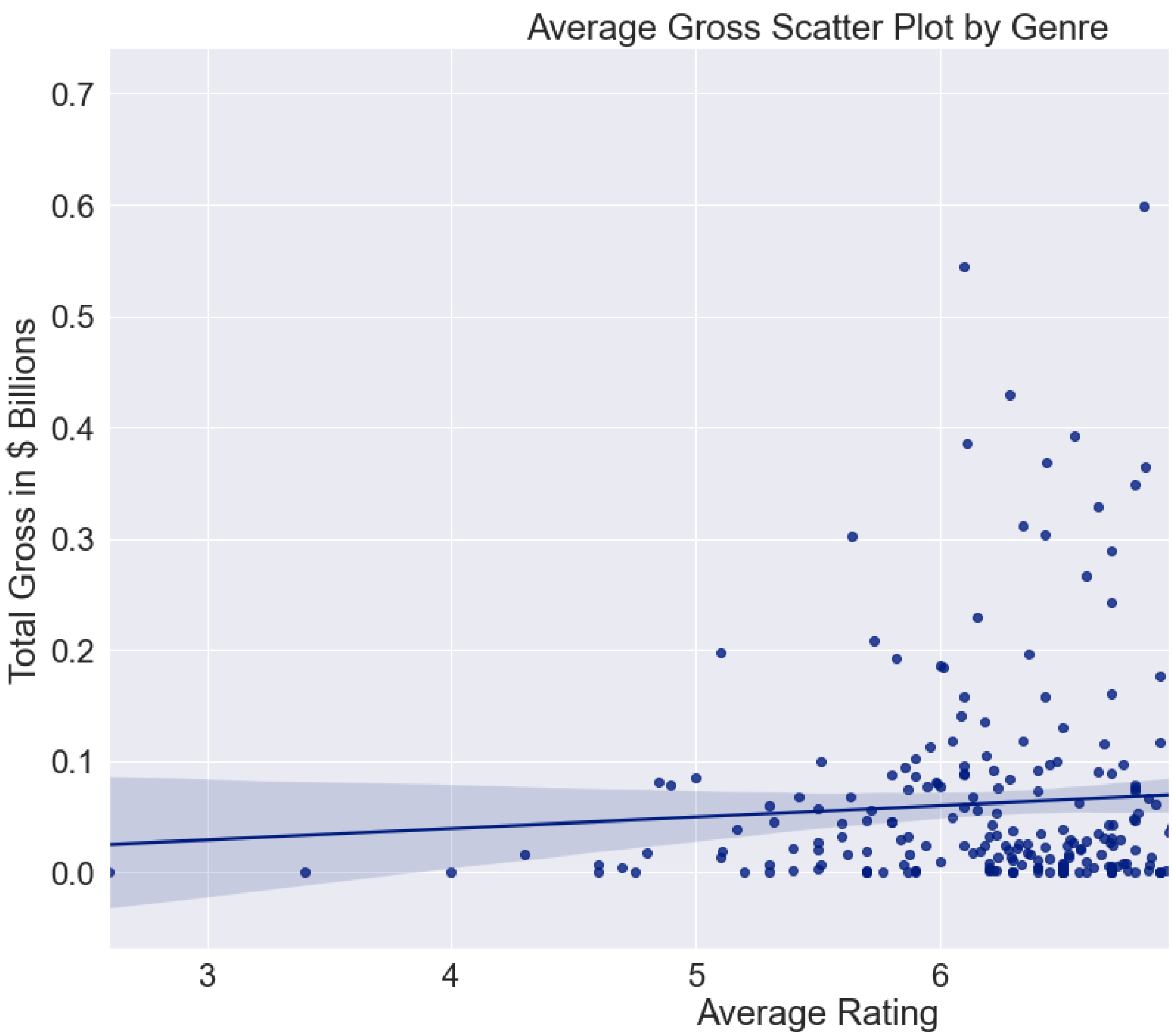
In [25]:

```
df_genres = df_ratings_and_gross.groupby(df_ratings_and_gross['genres']).mear
# let's graph the top 20 of
# this for total_gross and single out some genres (and genre combinations) tl
# successful.
df_genres2 = df_genres.sort_values('total_gross',axis=0,ascending=False).rese
df_genres2.head(15) # we can see hear the top 15 grossing genres or combinat
```

	index	genres	start_year	runtime_minutes	averagerating	numvote
0	106	Adventure,Fantasy	2013.333	139.667	7.167	375770.3
1	101	Adventure,Drama,Sci-Fi	2014.500	156.500	8.300	989725.0
2	11	Action,Adventure,Sci-Fi	2013.978	131.370	6.833	428425.1
3	30	Action,Comedy,Mystery	2018.000	121.000	6.100	1250.000
4	148	Biography,Drama,Musical	2017.000	105.000	7.600	199663.0
5	8	Action,Adventure,Fantasy	2015.065	117.903	6.287	250437.6
6	110	Adventure,Mystery,Sci-Fi	2012.000	124.000	7.000	538720.0
7	12	Action,Adventure,Thriller	2013.750	125.000	6.550	224555.0
8	104	Adventure,Family,Fantasy	2015.125	120.000	6.113	164708.6
9	72	Action,Sci-Fi	2014.000	113.000	7.900	546284.0
10	75	Adventure,Animation,Comedy	2014.200	94.453	6.439	107169.0
11	96	Adventure,Drama,Fantasy	2013.400	118.800	6.840	254748.0
12	68	Action,Mystery,Sci-Fi	2014.000	113.000	6.800	387038.0
13	45	Action,Drama,Family	2010.500	133.500	6.650	214967.5
14	4	Action,Adventure,Comedy	2015.355	112.806	6.342	187106.8

In [26]:

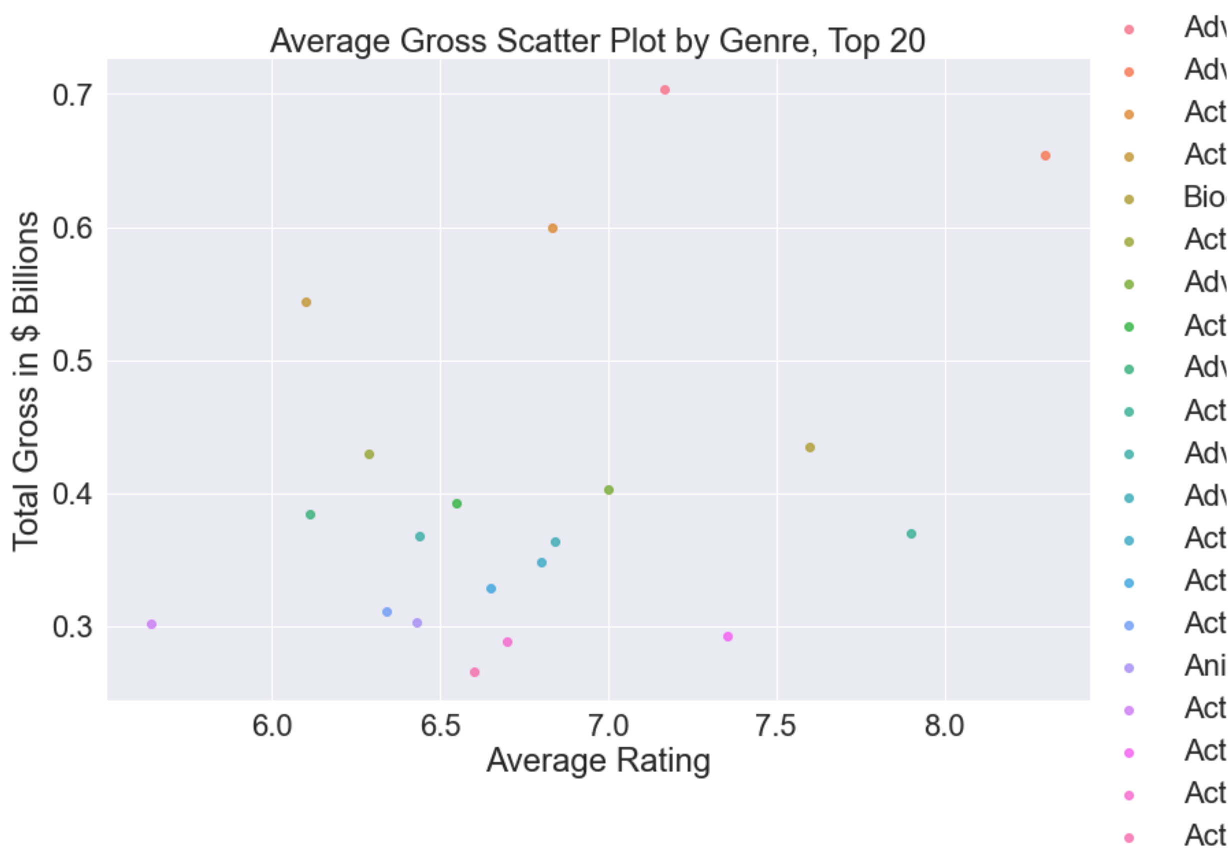
```
# graph represents the average per genre rating and the average per genre to
sns.set(font_scale=2)
sns.set_style("darkgrid")
palette = sns.set_palette("dark")
ax = sns.lmplot(x='averagerating',y='total_gross',data=df_genres2,height=10,a
ax.set(xlabel="Average Rating",ylabel="Total Gross in $ Billions")
plt.ticklabel_format(style='plain',axis='y')
plt.title('Average Gross Scatter Plot by Genre')
plt.show()
df_genres2.corr()
```



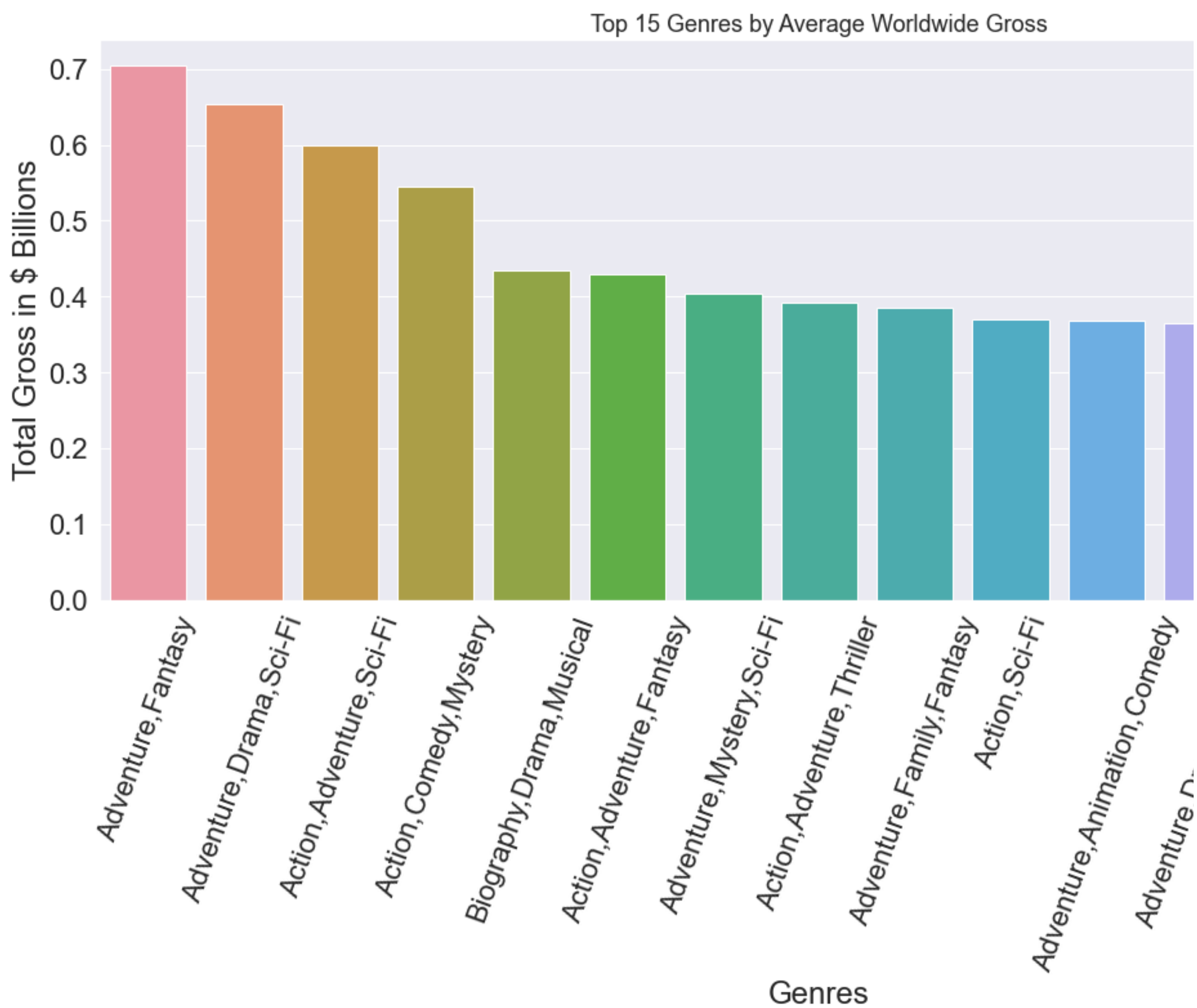
	index	start_year	runtime_minutes	averagerating	numvotes	domestic_
index	1.000	0.011	-0.165	0.069	-0.155	-0.236
start_year	0.011	1.000	0.098	0.169	-0.021	0.048
runtime_minutes	-0.165	0.098	1.000	0.052	0.282	0.220
averagerating	0.069	0.169	0.052	1.000	0.189	0.050
numvotes	-0.155	-0.021	0.282	0.189	1.000	0.788
domestic_gross	-0.236	0.048	0.220	0.050	0.788	1.000
foreign_gross	-0.311	0.253	0.324	0.108	0.646	0.763
year	0.018	0.954	0.076	0.215	-0.088	-0.026
total_gross	-0.298	0.107	0.266	0.075	0.761	0.906

In [27]:

```
# one scatter plot for the highest 15 grossing genres and have average ratin
sns.set(font_scale=2)
sns.set_style("darkgrid")
palette = sns.set_palette("dark")
ax = sns.lmplot(x='averagerating',y='total_gross',data=df_genres2.head(20),hu
ax.set(xlabel="Average Rating",ylabel="Total Gross in $ Billions")
plt.ticklabel_format(style='plain',axis='y')
plt.title('Average Gross Scatter Plot by Genre, Top 20')
plt.show()
```



In [28]:
```
# one bar chart with genres on x axis, total gross on y axis
fig_dims = (20,8)
fig, ax = plt.subplots(figsize=fig_dims)
sns.set(font_scale=1.5)
sns.set_style("darkgrid")
palette = sns.set_palette("dark")
ax = sns.barplot(x=df_genres2.head(15)['genres'], y=df_genres2.head(15)['tota
ax.set(xlabel="Genres",ylabel="Total Gross in $ Billions")
plt.ticklabel_format(style='plain',axis='y')
plt.xticks(rotation=70)
plt.title('Top 15 Genres by Average Worldwide Gross')
plt.show()
```



Question 3 Insights

Adventure, Action, Fantasy, and Sci-Fi movies are all heavily featured as th
Microsoft should begin by focusing on some of these more popular genres i

market, even if there is low ROI up front. Creating good cornerstone conten
foundation for creating profits in the future.

Part 5, Question 4

What Genres of film provides the highest ROI?

In [29]:

```
dfrtmovie = pd.read_csv(r"C:\Users\josep\Desktop\CourseWork\phase_1\Phase1\Mo
dfbudgets = pd.read_csv(r"C:\Users\josep\Desktop\CourseWork\phase_1\Phase1\Mo
```

In [30]:

```
dfbudgets = dfbudgets.rename(columns = {'movie':'title'})
dfbudgets_merge = pd.merge(df_ratings_and_gross,dfbudgets, on='title') # merg
# # movies with extremely low production budgets are going to create some out
dfbudgets_2 = dfbudgets_merge.drop(columns=['domestic_gross_y','domestic_gros
dfbudgets_2['production_budget'] = dfbudgets_2['production_budget'].str.repla
dfbudgets_2['production_budget'] = dfbudgets_2['production_budget'].str.repla
dfbudgets_2['production_budget'] = dfbudgets_2['production_budget'].astype('-
avebudget = dfbudgets_2['production_budget'].mean()
stdevbudget = dfbudgets_2['production_budget'].std()
# # I want to remove the outlier data outside of 2 standard deviations with p
# # miraculous movies like Paranormal Activity that had a huge ROI. This shou
lower_bound = avebudget - (stdevbudget * 2)
higher_bound = avebudget + (stdevbudget * 2)
```

In [31]:

```
dfbudgets_2 = dfbudgets_2[dfbudgets_2.production_budget >= lower_bound]
dfbudgets_2 = dfbudgets_2[dfbudgets_2.production_budget <= higher_bound]
print(dfbudgets_2.info()) # check to see if 5% of data removed - verified
dfbudgets_2['production_budget'] = dfbudgets_2['production_budget']/1000000
dfbudgets_2['worldwide_gross'] = dfbudgets_2['worldwide_gross'].str.replace('
dfbudgets_2['worldwide_gross'] = dfbudgets_2['worldwide_gross'].str.replace('
dfbudgets_2['worldwide_gross'] = dfbudgets_2['worldwide_gross'].astype('float
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 1087 entries, 0 to 1165
Data columns (total 15 columns):
 #   Column             Non-Null Count  Dtype  
---  ------             --------------  -----  
 0   tconst             1087 non-null   object 
 1   title              1087 non-null   object 
 2   original_title     1087 non-null   object 
 3   start_year         1087 non-null   int64  
 4   runtime_minutes    1087 non-null   float64
 5   genres             1087 non-null   object 
 6   averagerating      1087 non-null   float64
 7   numvotes           1087 non-null   int64  
 8   studio             1087 non-null   object 
 9   year               1087 non-null   int64  
 10  total_gross        1087 non-null   float64
 11  id                 1087 non-null   int64  
 12  release_date       1087 non-null   object 
 13  production_budget  1087 non-null   float64
 14  worldwide_gross    1087 non-null   object 
dtypes: float64(4), int64(4), object(7)
memory usage: 135.9+ KB
None
```

In [32]:

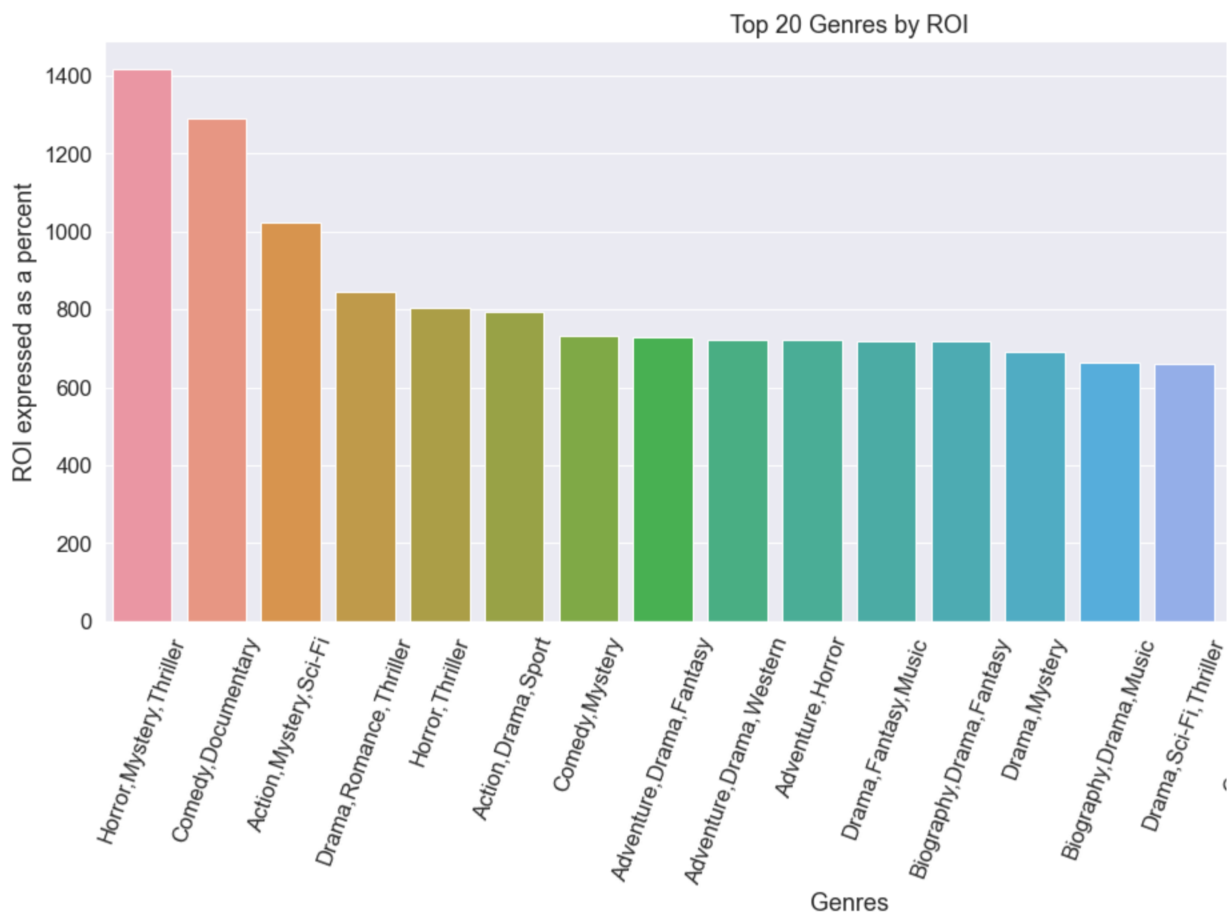
```
# for the purposes of the question we will be looking at total_gross divided

dfbudgets_2 = dfbudgets_2.groupby(dfbudgets_2['genres']).mean().reset_index(
dfbudgets_2['ROI'] = (dfbudgets_2['total_gross']/(dfbudgets_2['production_bud
dfbudgets_2_sorted = dfbudgets_2.sort_values('ROI',axis=0,ascending=False).re
```

In [33]:
```
dfbudgets_2_sorted.head(20)
```

	index	genres	start_year	runtime_minutes	averagerating	numvotes
0	180	Horror,Mystery,Thriller	2014.192	93.769	5.500	93775.654
1	99	Comedy,Documentary	2013.000	75.000	6.800	7880.000
2	49	Action,Mystery,Sci-Fi	2014.000	113.000	6.800	387038.000
3	165	Drama,Romance,Thriller	2015.333	115.000	5.100	140024.667
4	182	Horror,Thriller	2014.176	98.706	5.571	90904.059
5	39	Action,Drama,Sport	2016.000	170.000	7.100	33371.000
6	120	Comedy,Mystery	2011.000	102.000	6.500	432800.000
7	69	Adventure,Drama,Fantasy	2012.750	116.750	6.875	283280.250
8	73	Adventure,Drama,Western	2010.000	110.000	7.600	284034.000
9	76	Adventure,Horror	2013.000	100.000	5.300	33239.000
10	145	Drama,Fantasy,Music	2014.000	107.000	6.800	107625.000
11	86	Biography,Drama,Fantasy	2018.000	99.000	5.400	24351.000
12	159	Drama,Mystery	2010.000	100.000	7.200	127751.000
13	88	Biography,Drama,Music	2014.600	123.400	6.680	87972.400
14	168	Drama,Sci-Fi,Thriller	2011.500	92.500	7.050	397175.000
15	113	Comedy,Fantasy	2012.500	97.500	5.750	188033.500
16	153	Drama,Horror,Mystery	2014.900	101.100	6.130	83364.000
17	33	Action,Drama,Family	2010.333	135.667	6.500	192112.000
18	47	Action,Horror,Sci-Fi	2015.333	100.500	5.733	80642.500
19	179	Horror,Mystery,Sci-Fi	2013.000	84.500	5.200	44551.000

In [35]:

```
# one bar chart with genres on x axis, total gross on y axis
fig_dims = (20,8)
fig, ax = plt.subplots(figsize=fig_dims)
sns.set(font_scale=1.5)
sns.set_style("darkgrid")
palette = sns.set_palette("dark")
ax = sns.barplot(x=dfbudgets_2_sorted.head(20)['genres'], y=dfbudgets_2_sorte
ax.set(xlabel="Genres",ylabel="ROI expressed as a percent")
plt.ticklabel_format(style='plain',axis='y')
plt.xticks(rotation=70)
plt.title('Top 20 Genres by ROI')
plt.show()
```



Question 4 Insights

There are some extremely high ROI's for certain combinations of genres. Af
foundation of quality content and a user base supportive of that content, we
utilize less than the average for production budgets while diversifying conte
finding material to develop in the Horror, Thriller, Mystery, and Sci-Fi will pro
in the long run. The worst thing Microsoft could do is throw money at projec
underperform without first establishing quality original content.

```
In [ ]:
```