

# Microsoft Movie Analysis

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## Overview

This EDA gives insight on what successful movie studios are doing well and what specific actions Microsoft can do to achieve similar aims.

## Business Problem

Microsoft sees all the big companies creating original video content and they want to get in on the fun. They have decided to create a new movie studio, but they don't know anything about creating movies. You are charged with exploring what types of films are currently doing the best at the box office. You must then translate those findings into actionable insights that the head of Microsoft's new movie studio can use to help decide what type of films to create.

**Question 1: How many films have the top studios made from 2010-2019, and which studio brings in the most earnings? In other words, what are the studios that will be Microsoft's biggest competition?**

**Question 2: Is there a positive correlation between film length and domestic gross?**

**Question 3: What are the most popular movie genres?**

## Data Understanding

Three sets of data were collected to answer these questions - box office mojo movie gross data, imdb title basics data, and imdb title ratings data.

In [1]:

```
# Import standard packages
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline
```

```
/Users/marissabush/opt/anaconda3/envs/learn-env/lib/python3.6/site-packages/statsmodels/t
ools/_testing.py:19: FutureWarning: pandas.util.testing is deprecated. Use the functions
in the public API at pandas.testing instead.
    import pandas.util.testing as tm
```

In [2]:

```
# Load csv files
bom_mg_df = pd.read_csv('data/zippedData/bom.movie_gross.csv.gz')
imdb_tr_df = pd.read_csv('data/zippedData/imdb.title.ratings.csv.gz')
imdb_tb_df = pd.read_csv('data/zippedData/imdb.title.basics.csv.gz')
```

## BOM Movie Gross Data

In [3]:

```
# Function to get data frame info
```

```
def df_scope(bom_mg_df):
    #print name, .shape, .info, .describe
    for name, df in bom_mg_df.items():
        print('=' * 100)
        print(name)
        print(bom_mg_df.shape, '\n')
        print(bom_mg_df.info(), '\n')
        print(bom_mg_df.describe(include='all'))
df_scope(bom_mg_df)
```

=====

=====

title  
(3387, 5)

<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  
None

	title	studio	domestic_gross	foreign_gross	year
count	3387	3382	3.359000e+03	2037	3387.000000
unique	3386	257	NaN	1204	NaN
top	Bluebeard	IFC	NaN	1200000	NaN
freq	2	166	NaN	23	NaN
mean	NaN	NaN	2.874585e+07	NaN	2013.958075
std	NaN	NaN	6.698250e+07	NaN	2.478141
min	NaN	NaN	1.000000e+02	NaN	2010.000000
25%	NaN	NaN	1.200000e+05	NaN	2012.000000
50%	NaN	NaN	1.400000e+06	NaN	2014.000000
75%	NaN	NaN	2.790000e+07	NaN	2016.000000
max	NaN	NaN	9.367000e+08	NaN	2018.000000

=====

=====

studio  
(3387, 5)

<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  
None

	title	studio	domestic_gross	foreign_gross	year
count	3387	3382	3.359000e+03	2037	3387.000000
unique	3386	257	NaN	1204	NaN
top	Bluebeard	IFC	NaN	1200000	NaN
freq	2	166	NaN	23	NaN
mean	NaN	NaN	2.874585e+07	NaN	2013.958075
std	NaN	NaN	6.698250e+07	NaN	2.478141
min	NaN	NaN	1.000000e+02	NaN	2010.000000
25%	NaN	NaN	1.200000e+05	NaN	2012.000000
50%	NaN	NaN	1.400000e+06	NaN	2014.000000
75%	NaN	NaN	2.790000e+07	NaN	2016.000000
max	NaN	NaN	9.367000e+08	NaN	2018.000000

```
=====
domestic_gross
(3387, 5)
```

```
<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
None
```

	title	studio	domestic_gross	foreign_gross	year
count	3387	3382	3.359000e+03	2037	3387.000000
unique	3386	257	NaN	1204	NaN
top	Bluebeard	IFC	NaN	1200000	NaN
freq	2	166	NaN	23	NaN
mean	NaN	NaN	2.874585e+07	NaN	2013.958075
std	NaN	NaN	6.698250e+07	NaN	2.478141
min	NaN	NaN	1.000000e+02	NaN	2010.000000
25%	NaN	NaN	1.200000e+05	NaN	2012.000000
50%	NaN	NaN	1.400000e+06	NaN	2014.000000
75%	NaN	NaN	2.790000e+07	NaN	2016.000000
max	NaN	NaN	9.367000e+08	NaN	2018.000000

```
=====
foreign_gross
(3387, 5)
```

```
<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
None
```

	title	studio	domestic_gross	foreign_gross	year
count	3387	3382	3.359000e+03	2037	3387.000000
unique	3386	257	NaN	1204	NaN
top	Bluebeard	IFC	NaN	1200000	NaN
freq	2	166	NaN	23	NaN
mean	NaN	NaN	2.874585e+07	NaN	2013.958075
std	NaN	NaN	6.698250e+07	NaN	2.478141
min	NaN	NaN	1.000000e+02	NaN	2010.000000
25%	NaN	NaN	1.200000e+05	NaN	2012.000000
50%	NaN	NaN	1.400000e+06	NaN	2014.000000
75%	NaN	NaN	2.790000e+07	NaN	2016.000000
max	NaN	NaN	9.367000e+08	NaN	2018.000000

```
=====
year
(3387, 5)
```

```
<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
None
```

	title	studio	domestic_gross	foreign_gross	year
count	3387	3382	3.359000e+03	2037	3387.000000
unique	3386	257	NaN	1204	NaN
top	Bluebeard	IFC	NaN	1200000	NaN
freq	2	166	NaN	23	NaN
mean	NaN	NaN	2.874585e+07	NaN	2013.958075
std	NaN	NaN	6.698250e+07	NaN	2.478141
min	NaN	NaN	1.000000e+02	NaN	2010.000000
25%	NaN	NaN	1.200000e+05	NaN	2012.000000
50%	NaN	NaN	1.400000e+06	NaN	2014.000000
75%	NaN	NaN	2.790000e+07	NaN	2016.000000
max	NaN	NaN	9.367000e+08	NaN	2018.000000

In [4]:

```
bom_mg_df.head(2)
```

Out[4]:

	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

IMDB Title Basics Data

In [5]:

```
# Repeat function
def df_scope(imdb_tb_df):
    #print name, .shape, .info, .describe
    for name, df in imdb_tb_df.items():
        print('=' * 100)
        print(name)
        print(imdb_tb_df.shape, '\n')
        print(imdb_tb_df.info(), '\n')
        print(imdb_tb_df.describe(include='all'))
df_scope(imdb_tb_df)
```

=====

```
tconst
(146144, 6)
```

```
<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
None
```

	tconst	primary_title	original_title	start_year	\
count	146144	146144	146123	146144.000000	
unique	146144	126071	127772	NaN	

```
unique      146144      136071      137773      NaN
top      tt5348172      Home      Broken      NaN
freq      1      24      19      NaN
mean      NaN      NaN      NaN      2014.621798
std      NaN      NaN      NaN      2.733583
min      NaN      NaN      NaN      2010.000000
25%      NaN      NaN      NaN      2012.000000
50%      NaN      NaN      NaN      2015.000000
75%      NaN      NaN      NaN      2017.000000
max      NaN      NaN      NaN      2115.000000
```

```
      runtime_minutes      genres
count      114405.000000      140736
unique      NaN      1085
top      NaN      Documentary
freq      NaN      32185
mean      86.187247      NaN
std      166.360590      NaN
min      1.000000      NaN
25%      70.000000      NaN
50%      87.000000      NaN
75%      99.000000      NaN
max      51420.000000      NaN
```

```
=====
primary_title
(146144, 6)
```

```
<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
None
```

```
      tconst primary_title original_title      start_year \
count      146144      146144      146123      146144.000000
unique      146144      136071      137773      NaN
top      tt5348172      Home      Broken      NaN
freq      1      24      19      NaN
mean      NaN      NaN      NaN      2014.621798
std      NaN      NaN      NaN      2.733583
min      NaN      NaN      NaN      2010.000000
25%      NaN      NaN      NaN      2012.000000
50%      NaN      NaN      NaN      2015.000000
75%      NaN      NaN      NaN      2017.000000
max      NaN      NaN      NaN      2115.000000
```

```
      runtime_minutes      genres
count      114405.000000      140736
unique      NaN      1085
top      NaN      Documentary
freq      NaN      32185
mean      86.187247      NaN
std      166.360590      NaN
min      1.000000      NaN
25%      70.000000      NaN
50%      87.000000      NaN
75%      99.000000      NaN
max      51420.000000      NaN
```

```
=====
original_title
(146144, 6)
```

```
<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
None
```

	tconst	primary_title	original_title	start_year	\
count	146144	146144	146123	146144.000000	
unique	146144	136071	137773	NaN	
top	tt5348172	Home	Broken	NaN	
freq	1	24	19	NaN	
mean	NaN	NaN	NaN	2014.621798	
std	NaN	NaN	NaN	2.733583	
min	NaN	NaN	NaN	2010.000000	
25%	NaN	NaN	NaN	2012.000000	
50%	NaN	NaN	NaN	2015.000000	
75%	NaN	NaN	NaN	2017.000000	
max	NaN	NaN	NaN	2115.000000	

	runtime_minutes	genres
count	114405.000000	140736
unique	NaN	1085
top	NaN	Documentary
freq	NaN	32185
mean	86.187247	NaN
std	166.360590	NaN
min	1.000000	NaN
25%	70.000000	NaN
50%	87.000000	NaN
75%	99.000000	NaN
max	51420.000000	NaN

```
=====
=====
start_year
(146144, 6)
```

```
<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
None
```

	tconst	primary_title	original_title	start_year	\
count	146144	146144	146123	146144.000000	
unique	146144	136071	137773	NaN	
top	tt5348172	Home	Broken	NaN	
freq	1	24	19	NaN	
mean	NaN	NaN	NaN	2014.621798	
std	NaN	NaN	NaN	2.733583	
min	NaN	NaN	NaN	2010.000000	
25%	NaN	NaN	NaN	2012.000000	
50%	NaN	NaN	NaN	2015.000000	
75%	NaN	NaN	NaN	2017.000000	
max	NaN	NaN	NaN	2115.000000	

```
max      NaN      NaN      NaN      2115.000000
```

```
runtime_minutes  genres
count      114405.000000      140736
unique              NaN      1085
top              NaN  Documentary
freq              NaN      32185
mean          86.187247      NaN
std          166.360590      NaN
min           1.000000      NaN
25%          70.000000      NaN
50%          87.000000      NaN
75%          99.000000      NaN
max          51420.000000      NaN
```

```
runtime_minutes
(146144, 6)
```

```
<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
None
```

```
      tconst primary_title original_title  start_year \
count      146144      146144      146123  146144.000000
unique      146144      136071      137773         NaN
top      tt5348172      Home      Broken         NaN
freq           1          24          19         NaN
mean         NaN         NaN         NaN    2014.621798
std         NaN         NaN         NaN       2.733583
min         NaN         NaN         NaN    2010.000000
25%         NaN         NaN         NaN    2012.000000
50%         NaN         NaN         NaN    2015.000000
75%         NaN         NaN         NaN    2017.000000
max         NaN         NaN         NaN    2115.000000
```

```
runtime_minutes  genres
count      114405.000000      140736
unique              NaN      1085
top              NaN  Documentary
freq              NaN      32185
mean          86.187247      NaN
std          166.360590      NaN
min           1.000000      NaN
25%          70.000000      NaN
50%          87.000000      NaN
75%          99.000000      NaN
max          51420.000000      NaN
```

```
genres
(146144, 6)
```

```
<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
```

```
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
None
```

	tconst	primary_title	original_title	start_year	\
count	146144	146144	146123	146144.000000	
unique	146144	136071	137773	NaN	
top	tt5348172	Home	Broken	NaN	
freq	1	24	19	NaN	
mean	NaN	NaN	NaN	2014.621798	
std	NaN	NaN	NaN	2.733583	
min	NaN	NaN	NaN	2010.000000	
25%	NaN	NaN	NaN	2012.000000	
50%	NaN	NaN	NaN	2015.000000	
75%	NaN	NaN	NaN	2017.000000	
max	NaN	NaN	NaN	2115.000000	

	runtime_minutes	genres
count	114405.000000	140736
unique	NaN	1085
top	NaN	Documentary
freq	NaN	32185
mean	86.187247	NaN
std	166.360590	NaN
min	1.000000	NaN
25%	70.000000	NaN
50%	87.000000	NaN
75%	99.000000	NaN
max	51420.000000	NaN

IMDB Title Ratings Data

In [6]:

```
# Repeat function
def df_scope(imdb_tr_df):
    #print name, .shape, .info, .describe
    for name, df in imdb_tr_df.items():
        print('=' * 100)
        print(name)
        print(imdb_tr_df.shape, '\n')
        print(imdb_tr_df.info(), '\n')
        print(imdb_tr_df.describe(include='all'))
df_scope(imdb_tr_df)
```

```
=====
=====
tconst
(73856, 3)

<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
None
```

	tconst	averagerating	numvotes
count	73856	73856.000000	7.385600e+04
unique	73856	NaN	NaN
top	tt7938092	NaN	NaN
freq	1	NaN	NaN
mean	NaN	6.332729	3.523662e+03
std	NaN	1.474978	3.029402e+04



```

min      NaN      1.000000  5.000000e+00
25%      NaN      5.500000  1.400000e+01
50%      NaN      6.500000  4.900000e+01
75%      NaN      7.400000  2.820000e+02
max      NaN      10.000000  1.841066e+06

```

```

=====
averagerating
(73856, 3)

```

```

<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
None

```

```

          tconst  averagerating  numvotes
count      73856  73856.000000  7.385600e+04
unique      73856             NaN         NaN
top      tt7938092             NaN         NaN
freq         1             NaN         NaN
mean        NaN      6.332729  3.523662e+03
std          NaN      1.474978  3.029402e+04
min          NaN      1.000000  5.000000e+00
25%          NaN      5.500000  1.400000e+01
50%          NaN      6.500000  4.900000e+01
75%          NaN      7.400000  2.820000e+02
max          NaN      10.000000  1.841066e+06

```

```

=====
numvotes
(73856, 3)

```

```

<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
None

```

```

          tconst  averagerating  numvotes
count      73856  73856.000000  7.385600e+04
unique      73856             NaN         NaN
top      tt7938092             NaN         NaN
freq         1             NaN         NaN
mean        NaN      6.332729  3.523662e+03
std          NaN      1.474978  3.029402e+04
min          NaN      1.000000  5.000000e+00
25%          NaN      5.500000  1.400000e+01
50%          NaN      6.500000  4.900000e+01
75%          NaN      7.400000  2.820000e+02
max          NaN      10.000000  1.841066e+06

```

```
In [7]:
```

```

# Combine both IMDB data frames on common column
imdb_df = pd.merge(imdb_tr_df, imdb_tb_df, on='tconst', how='inner')
imdb_df.shape

```

```
Out[7]:
```

(73856, 8)

In [8]:

```
imdb_df.head(2)
```

Out[8]:

	tconst	averagerating	numvotes	primary_title	original_title	start_year	runtime_minutes	genres
0	tt10356526	8.3	31	Laiye Je Yaarian	Laiye Je Yaarian	2019	117.0	Romance
1	tt10384606	8.9	559	Borderless	Borderless	2019	87.0	Documentary

In [9]:

```
imdb_df.head(2)
```

Out[9]:

	tconst	averagerating	numvotes	primary_title	original_title	start_year	runtime_minutes	genres
0	tt10356526	8.3	31	Laiye Je Yaarian	Laiye Je Yaarian	2019	117.0	Romance
1	tt10384606	8.9	559	Borderless	Borderless	2019	87.0	Documentary

Combined Dataframe

In [10]:

```
imdb_df.rename(columns = {'primary_title':'title'}, inplace = True)
```

In [11]:

```
bom_mg_df.head(2)
```

Out[11]:

	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

In [12]:

```
imdb_df.tail(2)
```

Out[12]:

	tconst	averagerating	numvotes	title	original_title	start_year	runtime_minutes	genres
73854	tt9886934	7.0	5	The Projectionist	The Projectionist	2019	81.0	Documentary
73855	tt9894098	6.3	128	Sathru	Sathru	2019	129.0	Thriller

In [13]:

```
# Merge both data frames on common column, 'title'
df = imdb_df.merge(bom_mg_df, on = ['title'], how = 'inner')
df.head(2)
```

Out[13]:

	tconst	averagerating	numvotes	title	original_title	start_year	runtime_minutes	genres	studio
0	tt1043726	4.2	50352	The Legend of Hercules	The Legend of Hercules	2014	99.0	Action,Adventure,Fantasy	LG/S

In [14]:

```
df.shape
```

Out[14]:

```
(3027, 12)
```

In [15]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 3027 entries, 0 to 3026
Data columns (total 12 columns):
 #   Column                Non-Null Count  Dtype
---  -
 0   tconst                 3027 non-null   object
 1   averagerating         3027 non-null   float64
 2   numvotes              3027 non-null   int64
 3   title                 3027 non-null   object
 4   original_title        3027 non-null   object
 5   start_year            3027 non-null   int64
 6   runtime_minutes       2980 non-null   float64
 7   genres                3020 non-null   object
 8   studio               3024 non-null   object
 9   domestic_gross        3005 non-null   float64
10   foreign_gross         1832 non-null   object
11   year                  3027 non-null   int64
dtypes: float64(3), int64(3), object(6)
memory usage: 307.4+ KB
```

## Data Preparation

To begin the data cleaning process I chose to examine and drop any duplicates in the two columns, 'tconst' and 'original\_title'. Then find all missing values, check the percentages and drop those, as well.

In [16]:

```
# Check for duplicates and missing values for combined df
```

In [17]:

```
df.head(2)
```

Out[17]:

	tconst	averagerating	numvotes	title	original_title	start_year	runtime_minutes	genres	studio
0	tt1043726	4.2	50352	The Legend of Hercules	The Legend of Hercules	2014	99.0	Action,Adventure,Fantasy	LG/S
1	tt1171222	5.1	8296	Baggage Claim	Baggage Claim	2013	96.0	Comedy	FoxS

In [18]:

```
df['tconst'].duplicated().sum()
```

Out[18]:

```
2
```

In [19]:

```
In [19]:
```

```
df.drop_duplicates(subset=['tconst'], inplace = True)
df.shape
```

```
Out[19]:
```

```
(3025, 12)
```

```
In [20]:
```

```
df['original_title'].duplicated().sum()
```

```
Out[20]:
```

```
298
```

```
In [21]:
```

```
df.drop_duplicates(subset = ['original_title'], inplace = True)
df.shape
```

```
Out[21]:
```

```
(2727, 12)
```

```
In [22]:
```

```
# Find missing values
df.isnull().sum().sort_values(ascending=False)
```

```
Out[22]:
```

```
foreign_gross      1091
runtime_minutes     22
domestic_gross     17
genres              5
studio              3
year                0
start_year         0
original_title      0
title               0
numvotes            0
averagerating       0
tconst              0
dtype: int64
```

```
In [23]:
```

```
len(df)
df.isnull().sum().sort_values(ascending = False)/len(df)
```

```
Out[23]:
```

```
foreign_gross      0.400073
runtime_minutes    0.008067
domestic_gross     0.006234
genres              0.001834
studio              0.001100
year                0.000000
start_year         0.000000
original_title      0.000000
title               0.000000
numvotes            0.000000
averagerating       0.000000
tconst              0.000000
dtype: float64
```

```
In [24]:
```

```
# Drop unnecessary columns
df.drop('foreign_gross', axis = 1, inplace = True)
df.drop('tconst', axis = 1, inplace = True)
df.drop('year', axis = 1, inplace = True)
```

```
df.drop('original_title', axis = 1, inplace = True)
```

In [25]:

```
# Drop missing values from the other columns
df.dropna(subset=['genres', 'runtime_minutes', 'domestic_gross', 'studio'], inplace=True)
df.shape
```

Out[25]:

(2683, 8)

In [26]:

```
# Double check for missing values
df.isnull().sum().sort_values(ascending=False)
```

Out[26]:

domestic\_gross 0  
studio 0  
genres 0  
runtime\_minutes 0  
start\_year 0  
title 0  
numvotes 0  
averagerating 0  
dtype: int64

In [27]:

```
# rename column
df.rename(columns = {'start_year':'release_date'}, inplace = True)
```

In [28]:

```
df.head(2)
```

Out[28]:

	averagerating	numvotes	title	release_date	runtime_minutes	genres	studio	domestic_gross
0	4.2	50352	The Legend of Hercules	2014	99.0	Action,Adventure,Fantasy	LG/S	18800000.0
1	5.1	8296	Baggage Claim	2013	96.0	Comedy	FoxS	21600000.0

In [29]:

```
df.describe()
```

Out[29]:

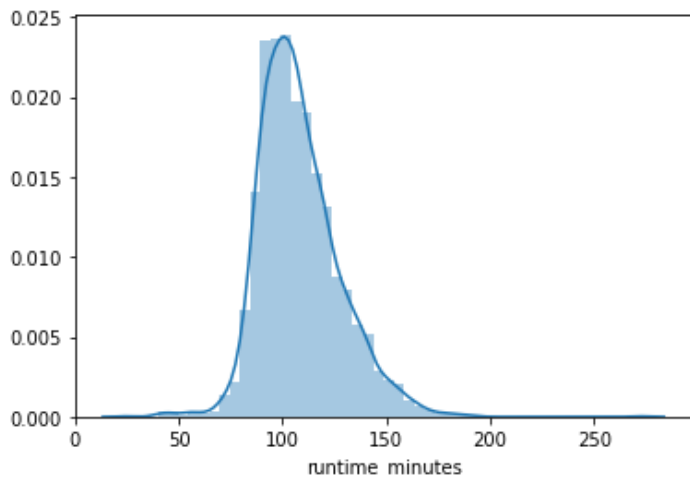
	averagerating	numvotes	release_date	runtime_minutes	domestic_gross
count	2683.000000	2.683000e+03	2683.000000	2683.000000	2.683000e+03
mean	6.486545	6.653972e+04	2013.751025	108.044726	3.027196e+07
std	0.962640	1.302484e+05	2.441232	19.484201	6.709432e+07
min	1.600000	5.000000e+00	2010.000000	25.000000	1.000000e+02
25%	6.000000	3.345500e+03	2012.000000	95.000000	1.260000e+05
50%	6.600000	1.561200e+04	2014.000000	105.000000	1.800000e+06
75%	7.200000	7.119100e+04	2016.000000	119.000000	3.120000e+07
max	8.900000	1.841066e+06	2019.000000	272.000000	7.001000e+08

In [30]:

```
# Check for outliers
sns.distplot(df['runtime_minutes'])
```

Out[30]:

<AxesSubplot:xlabel='runtime\_minutes'>



In [31]:

```
# Remove outliers
df = df[df.runtime_minutes != 272]
df = df[df.runtime_minutes != 25]
```

## Data Modeling

**Question 1: How many films have the top studios made from 2010-2019, and which studio brings in the most earnings? In other words, what are the studios that will be Microsoft's biggest competition?**

In [32]:

```
df.head(2)
```

Out[32]:

	averagerating	numvotes	title	release_date	runtime_minutes	genres	studio	domestic_gross
0	4.2	50352	The Legend of Hercules	2014	99.0	Action,Adventure,Fantasy	LG/S	18800000.0
1	5.1	8296	Baggage Claim	2013	96.0	Comedy	FoxS	21600000.0

In [33]:

```
# How many films per studio
top_studios = df['studio'].value_counts().head(10)
top_studios
```

Out[33]:

```
IFC          133
Uni.         131
Fox          121
Magn.        108
WB           107
SPC           99
BV            86
Sony          82
Par.          80
LGF           80
Name: studio, dtype: int64
```

In [34]:

```
top_studios.describe()
```

Out[34]:

```
count      10.000000
mean       102.700000
std        20.688429
min        80.000000
25%        83.000000
50%       103.000000
75%       117.750000
max       133.000000
Name: studio, dtype: float64
```

In [35]:

```
# Bar graph of top 10 studios and number of movies made
studio = ['IFC', 'Universal', 'Fox', 'Magnolia', 'WB', 'SPC', 'BV', 'Sony', 'LGF', 'Para
mount']
num_film = [133, 131, 121, 108, 107, 99, 86, 82, 80, 80]

plt.figure(figsize=(9,6))

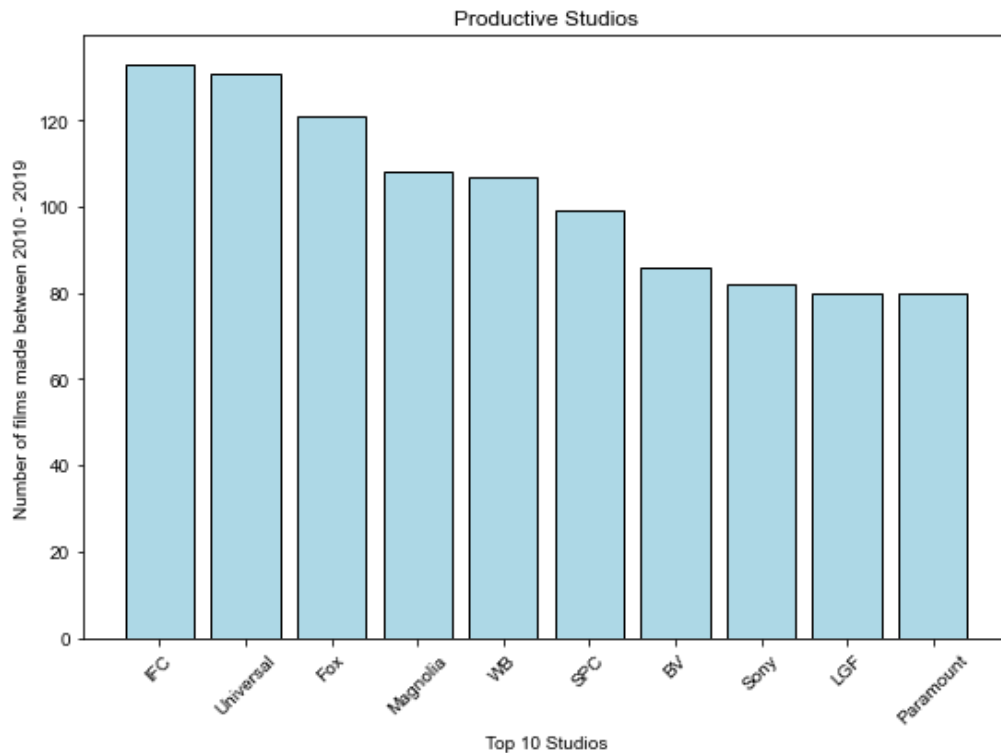
plt.bar(x= studio,

        height= num_film,

        color = 'lightblue', edgecolor = 'black')

plt.xlabel('Top 10 Studios')
plt.ylabel('Number of films made between 2010 - 2019')
plt.xticks(rotation=45)
plt.title('Productive Studios')

sns.set();
```



In [36]:

```
# Group top studios and their domestic gross sum
studio_gross = df.groupby('studio').domestic_gross.sum().sort_values(ascending = False).
head(10)
studio_gross
```

Out[36]:

```
studio
RV      1.474870e+10
```

```

DV.          1.171070e+10
Uni.         1.152670e+10
Fox          9.853700e+09
WB           9.415000e+09
Sony         6.809846e+09
Par.         6.517213e+09
WB (NL)      3.962400e+09
LGF          3.440950e+09
P/DW         1.682900e+09
Wein.        1.485199e+09
Name: domestic_gross, dtype: float64

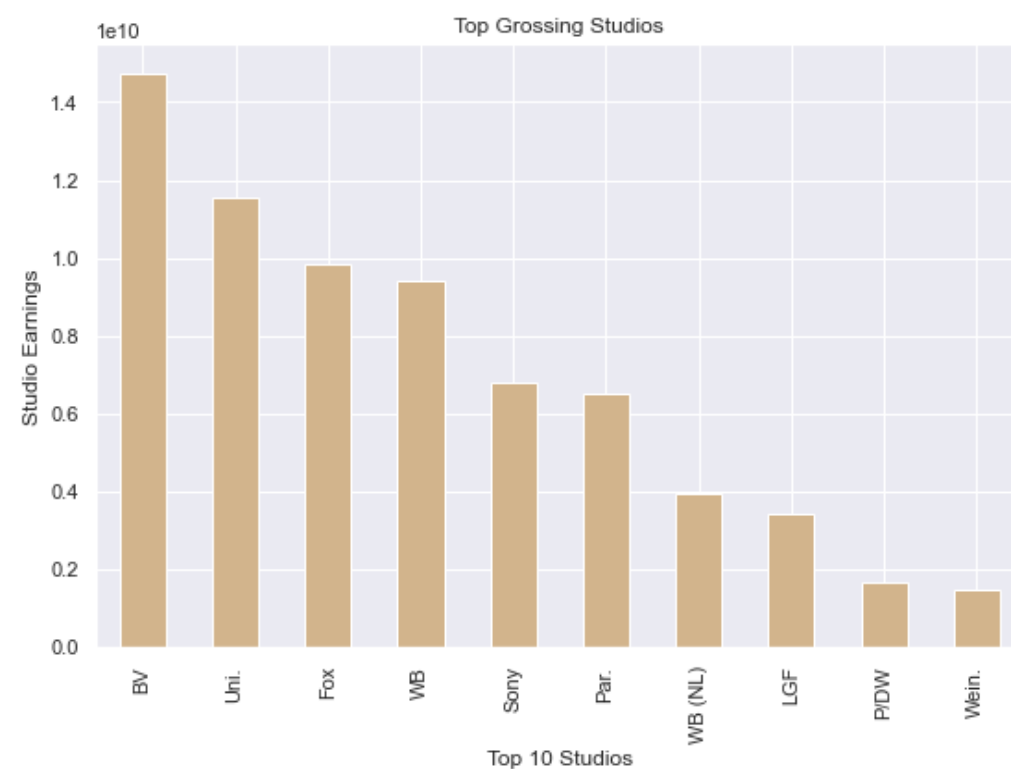
```

In [37]:

```

# Bar graph of studios and domestic gross sum
studio_gross.plot.bar(figsize=(9,6), color = 'tan',
                      edgecolor = 'white'
                      )
plt.xlabel('Top 10 Studios')
plt.ylabel('Studio Earnings')
plt.title('Top Grossing Studios')
sns.set();

```



The most productive studios from 2010-2019 made over 80 films in that time with Buena Vista studios bringing in the highest earnings.

**Question 2: Is there a correlation between film length and domestic gross?**

In [38]:

```
df['domestic_gross'].describe()
```

Out[38]:

```

count      2.681000e+03
mean       3.027515e+07
std        6.711552e+07
min        1.000000e+02
25%        1.260000e+05
50%        1.800000e+06
75%        3.120000e+07
max        7.001000e+08
Name: domestic_gross, dtype: float64

```

In [39]:

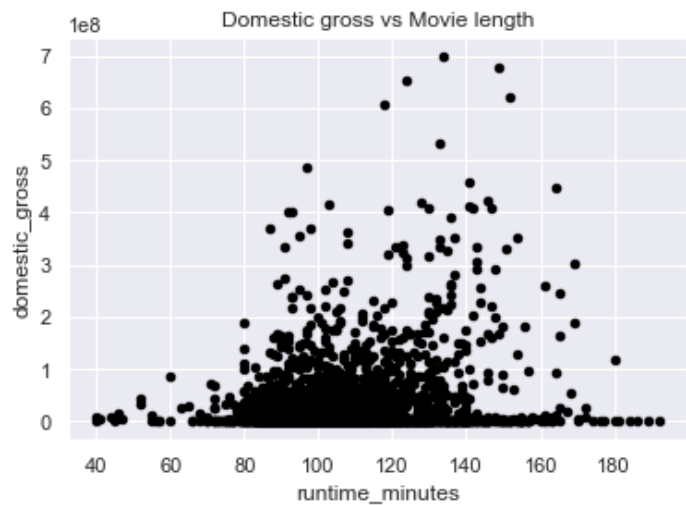


```
# Scatter plot of domestic gross vs movie length
plt.figure(figsize = (9, 6))
df.plot.scatter(x = 'runtime_minutes', y = 'domestic_gross', color = 'black')
plt.title("Domestic gross vs Movie length")

plt.show()

sns.set();
```

<Figure size 648x432 with 0 Axes>



It looks there is a slight positive correlation between the two with the higher grossing films being in the 2 - 2.5 hour range. Perhaps making a film that length would be a good move.

Question 3: What are the most popular movie genres?

In [40]:

```
df.head(1)
```

Out[40]:

	averagerating	numvotes	title	release_date	runtime_minutes	genres	studio	domestic_gross
0	4.2	50352	The Legend of Hercules	2014	99.0	Action,Adventure,Fantasy	LG/S	18800000.0

In [41]:

```
# Organize genres by first genre in string - for simplification
df['new_genres'] = df['genres'].str.split(pat=",").str[0]
df['new_genres'].value_counts()
```

Out[41]:

Drama	677
Action	592
Comedy	569
Biography	227
Adventure	203
Documentary	128
Crime	116
Horror	84
Animation	35
Thriller	18
Fantasy	11
Mystery	8
Romance	8
Family	2
Sci-Fi	1
Sport	1
Music	1

Name: new\_genres, dtype: int64

In [42]:

```
# Group the data by genres
df.groupby('new_genres').sum()
```

Out[42]:

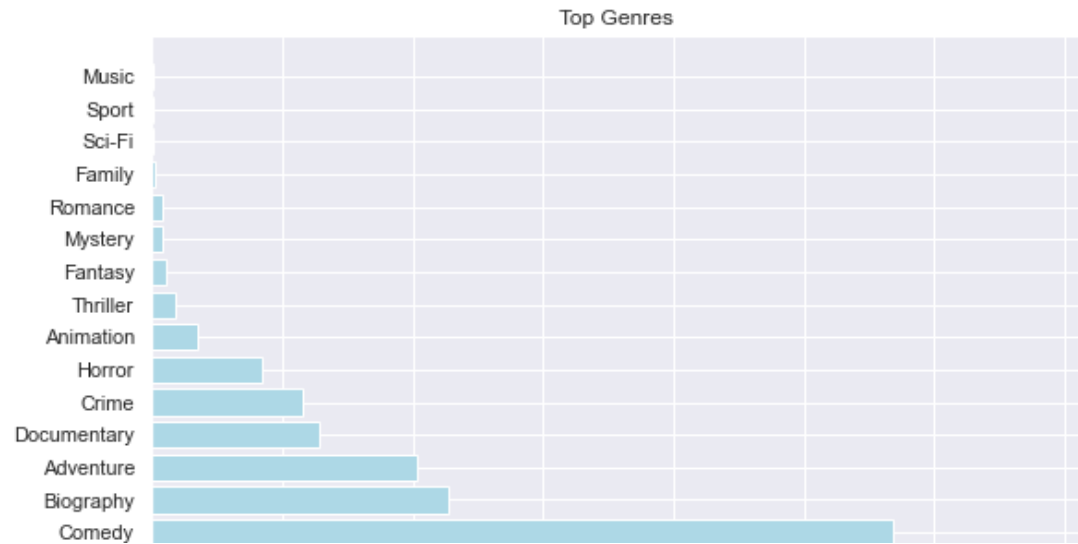
	averagerating	numvotes	release_date	runtime_minutes	domestic_gross
new_genres					
Action	3751.5	76494734	1192261	68654.0	3.653866e+10
Adventure	1319.1	20258369	408849	21020.0	1.475267e+10
Animation	238.7	1524793	70493	3339.0	9.411647e+08
Biography	1589.0	14129553	457249	25461.0	4.291921e+09
Comedy	3547.9	25024900	1145600	59980.0	1.132005e+10
Crime	776.9	7325512	233595	13067.0	1.469601e+09
Documentary	929.0	646155	257718	11595.0	1.092938e+09
Drama	4470.5	25172473	1363243	73239.0	7.027175e+09
Family	12.7	145	4033	182.0	1.398400e+07
Fantasy	70.4	200047	22151	1215.0	4.656020e+08
Horror	453.0	5400191	169172	7960.0	2.562128e+09
Music	7.2	15592	2013	93.0	3.400000e+06
Mystery	56.2	2011759	16108	902.0	3.426180e+08
Romance	46.9	263754	16113	885.0	6.489330e+07
Sci-Fi	5.9	3501	2018	89.0	7.800000e+04
Sport	7.9	77	2014	114.0	5.300000e+06
Thriller	105.2	51572	36241	1792.0	2.754883e+08

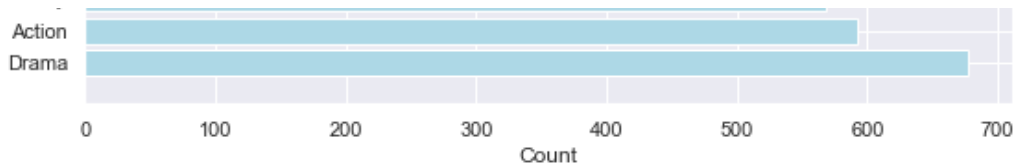
In [43]:

```
# Horizontal Bar chart
fig, ax = plt.subplots(figsize = (9,6))

genre_types = df['new_genres'].value_counts()

ax.barh(y=genre_types.index,
        width=genre_types.values, color = 'lightblue', edgecolor = 'white'
)
ax.set_xlabel('Count')
ax.set_title('Top Genres')
sns.set();
```

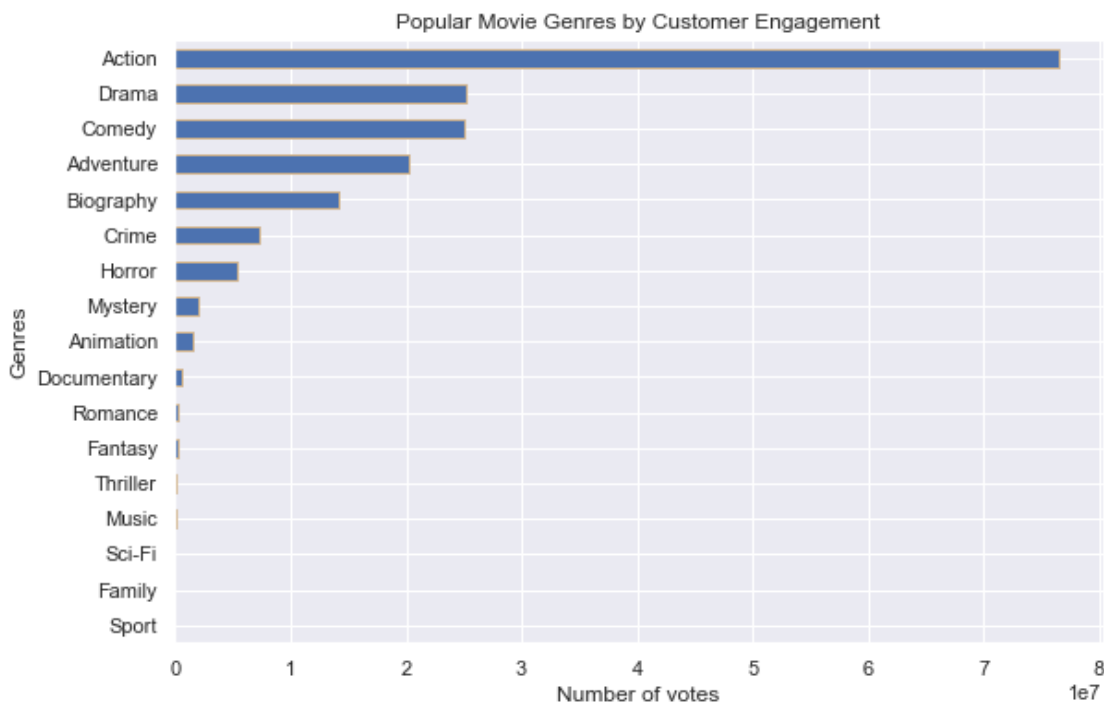




Results show drama, action, and comedy are the most frequently made movies.

In [44]:

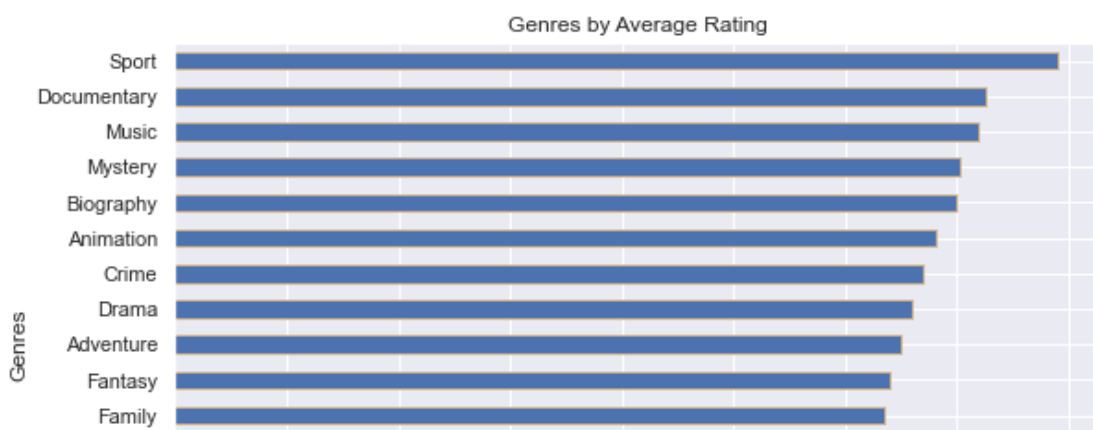
```
# Graph by genre and number of votes - or number of customer interaction
df.groupby(['new_genres'])['numvotes'].sum().sort_values().plot(kind='barh', figsize=(9, 6), edgecolor = 'tan')
plt.title('Popular Movie Genres by Customer Engagement')
plt.xlabel("Number of votes")
plt.ylabel('Genres')
sns.set();
```

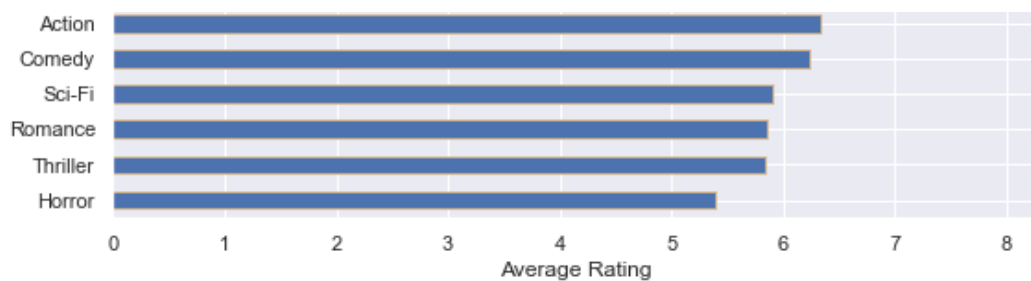


Results show that action films result in a lot more online engagement compared the other genres.

In [45]:

```
# Bar graph
df.groupby(['new_genres'])['averagerating'].mean().sort_values().plot(kind='barh', figsize=(9, 6), edgecolor = 'tan')
plt.title("Genres by Average Rating")
plt.xlabel('Average Rating')
plt.ylabel('Genres')
sns.set();
```





Results seem to show that sport, documentary, and music come out as the top three genres with the highest ratings. However, this would be inaccurate to conclude due to the low number of votes for those particular genres.

Looking at the previous three graphs, it appears action, drama, and comedy are the most successful genres with audiences.

## Evaluation

The visualizations show that the top movie studios today have made an average of 102.7 films between 2010-2019 with that being about 11.4 films a year. The other visualization shows that movies that make a higher domestic gross are between 2 - 2.5 hours long. With the final visualizations, it looks like drama, action, and comedy are the most frequently made films with the action genre creating the most 'buzz'/customer engagement.

## Conclusions

With all this in mind, I would recommend Microsoft to make a movie that is between 2 to 2.5 hours long and also to consider a film in the action, drama, or comedy genre. Additionally, I would recommend making about 11.4 films a year in order to compete with the top studios. This analysis has gaps due to the small data set and with only including domestic gross as a measure of earnings. To improve this project, I would like to work with foreign gross and cost of production data to understand the bigger picture of potential earnings per film.

In [ ]: