

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

In [4]:

```
df_scope(bom_mg_df)
df_scope(imdb_tr_df)
df_scope(imdb_tb_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):
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1   studio           3382 non-null   object
2   domestic_gross   3359 non-null   float64
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dtypes: float64(1), int64(1), object(3)
memory usage: 132.4+ KB
None
```

	title	studio	domestic_gross	foreign_gross	year
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unique	3386	257	NaN	1204	NaN
top	Bluebeard	IFC	NaN	1200000	NaN
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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
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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
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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

```
=====
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	tt2055720	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
```

```
count      tconst  averagerating  numvotes
73856      73856      73856.000000  7.385600e+04
unique      73856      NaN      NaN
top      tt2055720      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
```

```
count      tconst  averagerating  numvotes
73856      73856      73856.000000  7.385600e+04
unique      73856      NaN      NaN
top      tt2055720      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
```

```
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
```

```
count      tconst  primary_title  original_title  start_year  \
146144      146144      146144      146123  146144.000000
unique      146144      136071      137773      NaN
top      tt5222638      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	tt5222638	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	primarytitle	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	tt5222638	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	tt5222638	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
```

```
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	tt5222638	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
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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
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      tt5222638      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
```

```
count      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
```

In [5]:

```
# View bom_mg_df
bom_mg_df.head(2)
```

Out[5]:

	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 [6]:

```
imdb_tr_df.head(2)
```

Out[6]:

	tconst	averagerating	numvotes
0	tt10356526	8.3	31
1	tt10384606	8.9	559

In [7]:

```
imdb_tb_df.head(2)
```

Out[7]:

	tconst	primary_title	original_title	start_year	runtime_minutes	genres
0	tt0063540	Sunghursh	Sunghursh	2013	175.0	Action,Crime,Drama
1	tt0066787	One Day Before the Rainy Season	Ashad Ka Ek Din	2019	114.0	Biography,Drama

In [8]:

```
# 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[8]:

(73856, 8)

In [9]:

```
# View data frame
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 Dateframe

In [10]:

```
# View bom_mg_df column names
bom_mg_df.columns
```

Out[10]:

Index(['title', 'studio', 'domestic_gross', 'foreign_gross', 'year'], dtype='object')

In [11]:

```
# Rename both primary title and start year to match with bom_mg_df
imdb_df.rename(columns = {'primary_title':'title'}, inplace = True)
imdb_df.rename(columns = {'start_year':'year'}, inplace = True)
```

In [12]:

```
# Double check column names
imdb_df.tail(2)
```

Out[12]:

	tconst	averagerating	numvotes	title	original_title	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 two common columns, 'title' and 'year'
df = imdb_df.merge(bom_mg_df, on = ['title','year'], how = 'inner')
df.head(2)
```

Out[13]:

	tconst	averagerating	numvotes	title	original_title	year	runtime_minutes	genres	studio	dome
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 [14]:

```
# View combined data frame shape
df.shape
```

Out[14]:

(1847, 11)

In [15]:

In [15]:

```
# View columns in new data frame
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 1847 entries, 0 to 1846
Data columns (total 11 columns):
 #   Column                Non-Null Count  Dtype  
---  -
 0   tconst                 1847 non-null   object  
 1   averagerating          1847 non-null   float64  
 2   numvotes               1847 non-null   int64  
 3   title                  1847 non-null   object  
 4   original_title         1847 non-null   object  
 5   year                   1847 non-null   int64  
 6   runtime_minutes        1843 non-null   float64  
 7   genres                  1845 non-null   object  
 8   studio                 1845 non-null   object  
 9   domestic_gross         1837 non-null   float64  
10   foreign_gross          1269 non-null   object  
dtypes: float64(3), int64(2), object(6)
memory usage: 173.2+ 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]:

```
# View data frame
df.head(2)
```

Out[17]:

	tconst	averagerating	numvotes	title	original_title	year	runtime_minutes	genres	studio	domestic_gross
0	tt1043726	4.2	50352	The Legend of Hercules	The Legend of Hercules	2014	99.0	Action,Adventure,Fantasy	LG/S	10,437,260
1	tt1171222	5.1	8296	Baggage Claim	Baggage Claim	2013	96.0	Comedy	FoxS	11,712,220

In [18]:

```
# View tconst column for duplicates
df['tconst'].duplicated().sum()
```

Out[18]:

0

In [19]:

```
# View original title column for duplicates
df['original_title'].duplicated().sum()
```

Out[19]:

20

In [20]:

```
# Drop duplicates
```

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

```
Out[20]:  
  
(1827, 11)
```

```
In [21]:
```

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

```
Out[21]:  
  
foreign_gross      572  
domestic_gross     10  
studio             2  
genres             1  
runtime_minutes    0  
year              0  
original_title     0  
title              0  
numvotes           0  
averagerating      0  
tconst            0  
dtype: int64
```

```
In [22]:
```

```
# Divide by length of df to view percentage missing  
len(df)  
df.isnull().sum().sort_values(ascending = False)/len(df)
```

```
Out[22]:  
  
foreign_gross      0.313082  
domestic_gross     0.005473  
studio            0.001095  
genres            0.000547  
runtime_minutes    0.000000  
year              0.000000  
original_title     0.000000  
title             0.000000  
numvotes          0.000000  
averagerating      0.000000  
tconst            0.000000  
dtype: float64
```

```
In [23]:
```

```
# Drop foreign gross column (30% missing) and columns I don't need  
# for analysis  
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 [24]:
```

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

```
Out[24]:  
  
(1816, 7)
```

```
In [25]:
```

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

Out[25]:

```
domestic_gross      0
studio              0
genres              0
runtime_minutes     0
title               0
numvotes            0
averagerating       0
dtype: int64
```

In [26]:

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

In [27]:

```
# view df
df.head(2)
```

Out[27]:

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

In [28]:

```
# View descriptive stats for any significant outliers
df.describe()
```

Out[28]:

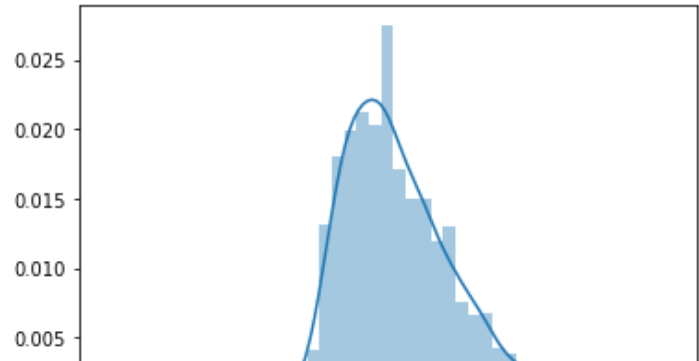
	averagerating	numvotes	runtime_minutes	domestic_gross
count	1816.000000	1.816000e+03	1816.000000	1.816000e+03
mean	6.423073	9.294794e+04	110.953194	4.299649e+07
std	0.998854	1.510763e+05	19.794412	7.751079e+07
min	1.600000	6.000000e+00	25.000000	3.000000e+02
25%	5.800000	8.013750e+03	97.000000	5.835000e+05
50%	6.500000	3.638950e+04	108.000000	1.080000e+07
75%	7.100000	1.071020e+05	123.000000	5.242500e+07
max	8.800000	1.841066e+06	189.000000	7.001000e+08

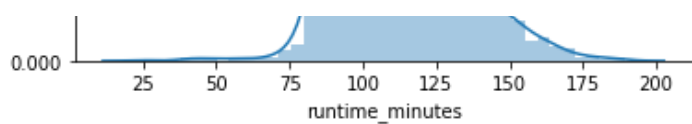
In [29]:

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

Out[29]:

<AxesSubplot:xlabel='runtime_minutes'>





In [30]:

```
# 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 [31]:

```
# View df
df.head(2)
```

Out[31]:

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

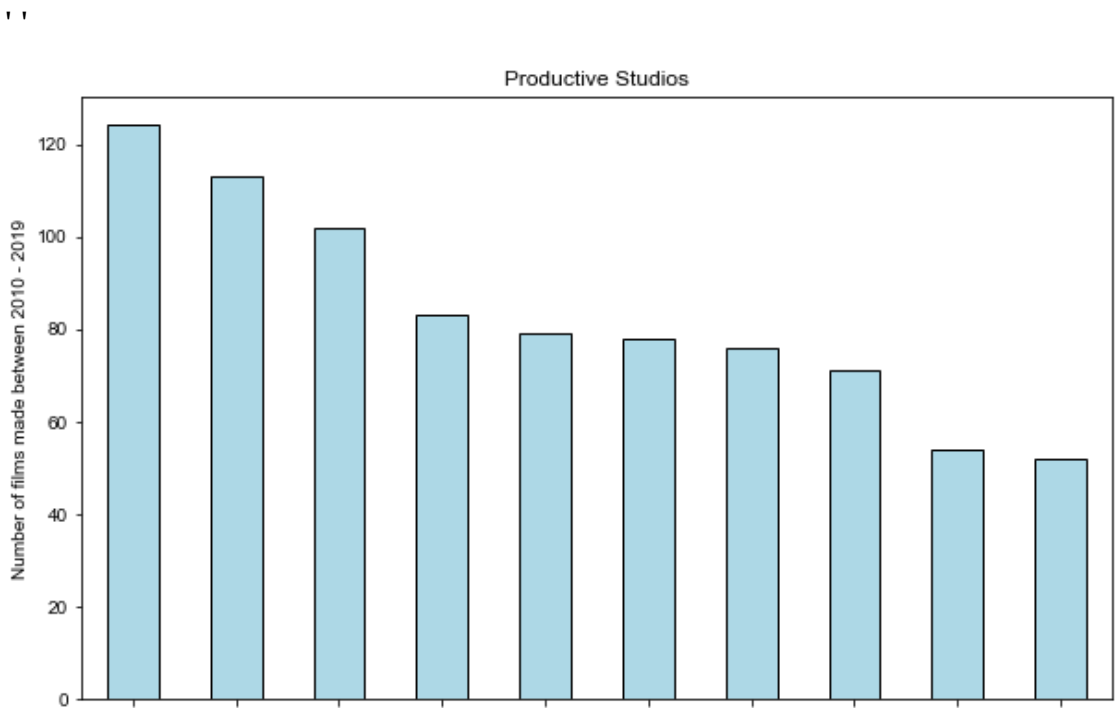
In [32]:

```
# How many films per studio
top_studios = df['studio'].value_counts().head(10)
top_studios.plot(kind = 'bar', figsize = (10,6),
                  color = 'lightblue', edgecolor = 'black'
)

plt.xlabel('Top 10 Studios')
plt.ylabel('Number of films made between 2010 - 2019')
plt.xticks(rotation = 50)
plt.title('Productive Studios')

sns.set()
;
```

Out[32]:



In [33]:

```
# Descriptive stats for top_studios
top_studios.describe()
```

Out[33]:

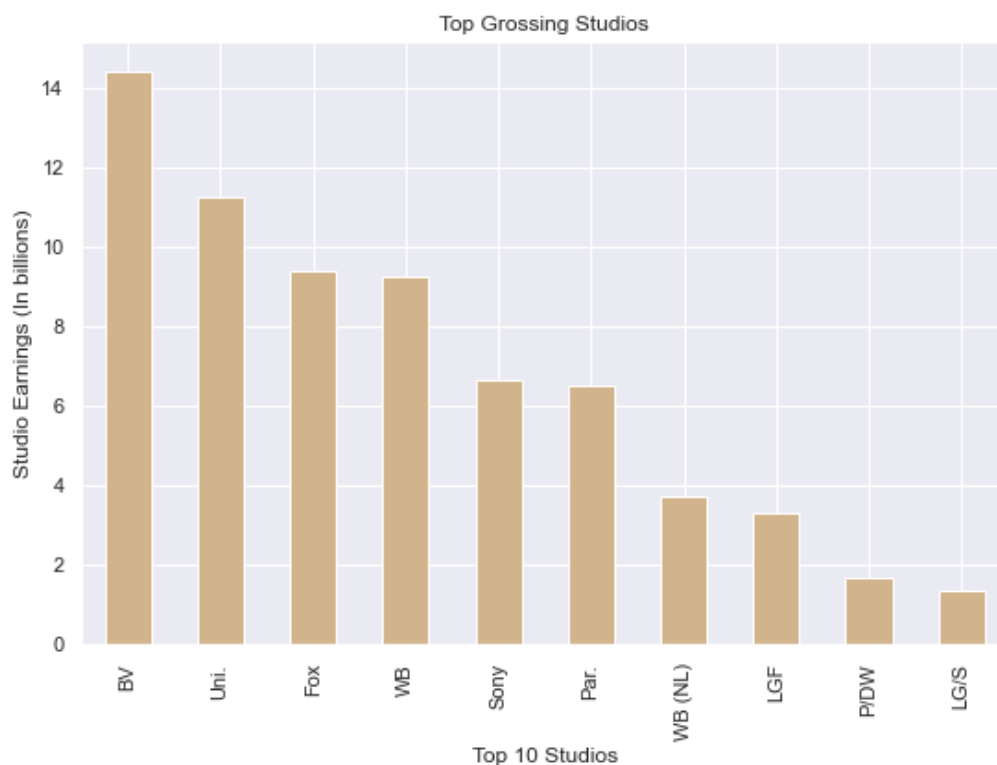
```
count      10.000000
mean       83.200000
std        23.517369
min        52.000000
25%        72.250000
50%        78.500000
75%        97.250000
max        124.000000
Name: studio, dtype: float64
```

In [34]:

```
# Group top studios and their domestic gross sum, divide by a billion
studio_gross = df.groupby('studio').domestic_gross.sum().sort_values(ascending = False).
head(10)
studio_gross = studio_gross/1000000000
```

In [35]:

```
# 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 (In billions)')
plt.title('Top Grossing Studios')
sns.set();
```



The most productive studios from 2010-2019 made over 100 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 [36]:

In [36]:

```
# View domestic gross column stats
df['domestic_gross'].describe()
```

Out[36]:

```
count      1.815000e+03
mean       4.299158e+07
std        7.753186e+07
min        3.000000e+02
25%        5.830000e+05
50%        1.080000e+07
75%        5.245000e+07
max        7.001000e+08
Name: domestic_gross, dtype: float64
```

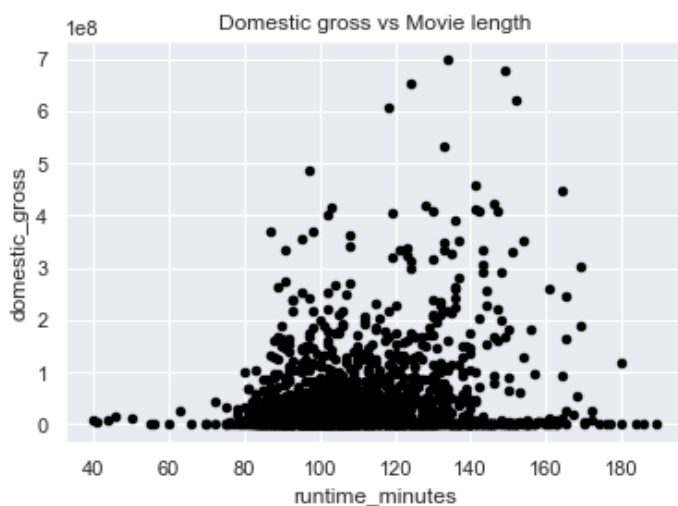
In [37]:

```
# 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 [38]:

```
# View df
df.head(1)
```

Out[38]:

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

In [39]:

```
# Split genres column by column
df['genres'] = df['genres'].str.split(',')
```

In [40]:

```
# Remove df by adding different genres to separate rows
```



```
# Expand df by adding different genres in separate rows
df_explode = df.explode('genres')
```

In [41]:

```
# View df
df_explode.head()
```

Out[41]:

	averagerating	numvotes	title	runtime_minutes	genres	studio	domestic_gross
0	4.2	50352	The Legend of Hercules	99.0	Action	LG/S	18800000.0
0	4.2	50352	The Legend of Hercules	99.0	Adventure	LG/S	18800000.0
0	4.2	50352	The Legend of Hercules	99.0	Fantasy	LG/S	18800000.0
1	5.1	8296	Baggage Claim	96.0	Comedy	FoxS	21600000.0
2	7.6	326657	Moneyball	133.0	Biography	Sony	75600000.0

In [42]:

```
# View new df 'genres' column by value counts
df_explode['genres'].value_counts()
```

Out[42]:

Drama	945
Comedy	651
Action	519
Adventure	361
Romance	298
Thriller	282
Crime	264
Biography	185
Horror	141
Mystery	127
Fantasy	123
Animation	113
Sci-Fi	108
Documentary	95
Family	81
History	71
Music	56
Sport	35
War	22
Musical	12
Western	11
News	1

Name: genres, dtype: int64

In [43]:

```
# Group the data by genres and view sum stats
df_explode.groupby('genres').sum()
```

Out[43]:

	averagerating	numvotes	runtime_minutes	domestic_gross
genres				
Action	3282.6	75396162	60952.0	3.627845e+10
Adventure	2333.4	66684656	40314.0	4.055522e+10
Animation	742.2	12358231	10734.0	1.315974e+10
Biography	1298.3	16012128	21547.0	5.209095e+09
Comedy	4019.2	49300577	69862.0	2.965430e+10
Crime	1703.5	25611913	30020.0	8.177104e+09
Documentary	604.0	888888	8810.0	1.018888e+09

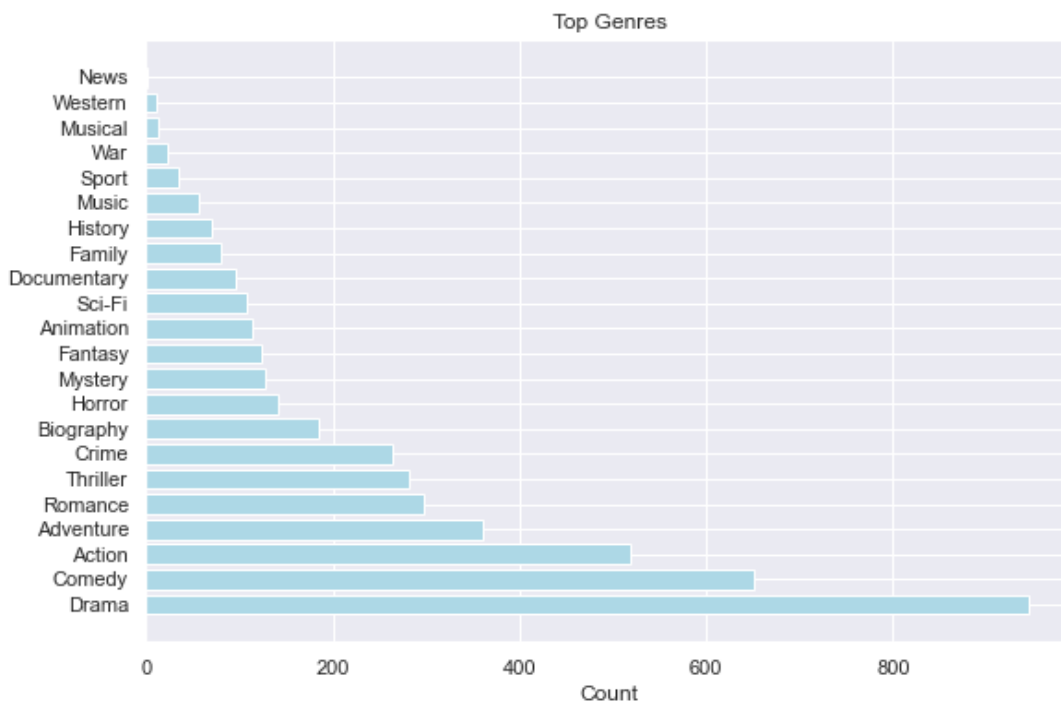
Documentary	average_rating	num_votes	runtime_minutes	domestic_gross
Drama	694.2	900089	9012.0	4.210900e+08
genres	6227.8	71150037	108416.0	2.209239e+10
Family	490.0	5468132	8600.0	4.914445e+09
Fantasy	768.8	16568762	13763.0	8.269386e+09
History	488.0	4898372	8537.0	1.894073e+09
Horror	807.8	10511836	13958.0	4.907666e+09
Music	372.8	3476117	6213.0	1.466830e+09
Musical	72.9	482775	1577.0	3.839827e+08
Mystery	797.6	14373218	13609.0	4.332947e+09
News	6.7	1167	75.0	1.320000e+04
Romance	1864.3	15923321	33351.0	5.875371e+09
Sci-Fi	708.3	32014751	12637.0	1.433445e+10
Sport	246.2	2518741	4236.0	9.992940e+08
Thriller	1767.5	32018330	31040.0	1.140090e+10
War	144.1	630269	2581.0	2.184931e+08
Western	74.5	2026472	1283.0	5.061511e+08

In [44]:

```
# Make a horizontal bar chart with the df_explode['genres'] value counts
fig, ax = plt.subplots(figsize = (9,6))

genre_types = df_explode['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.

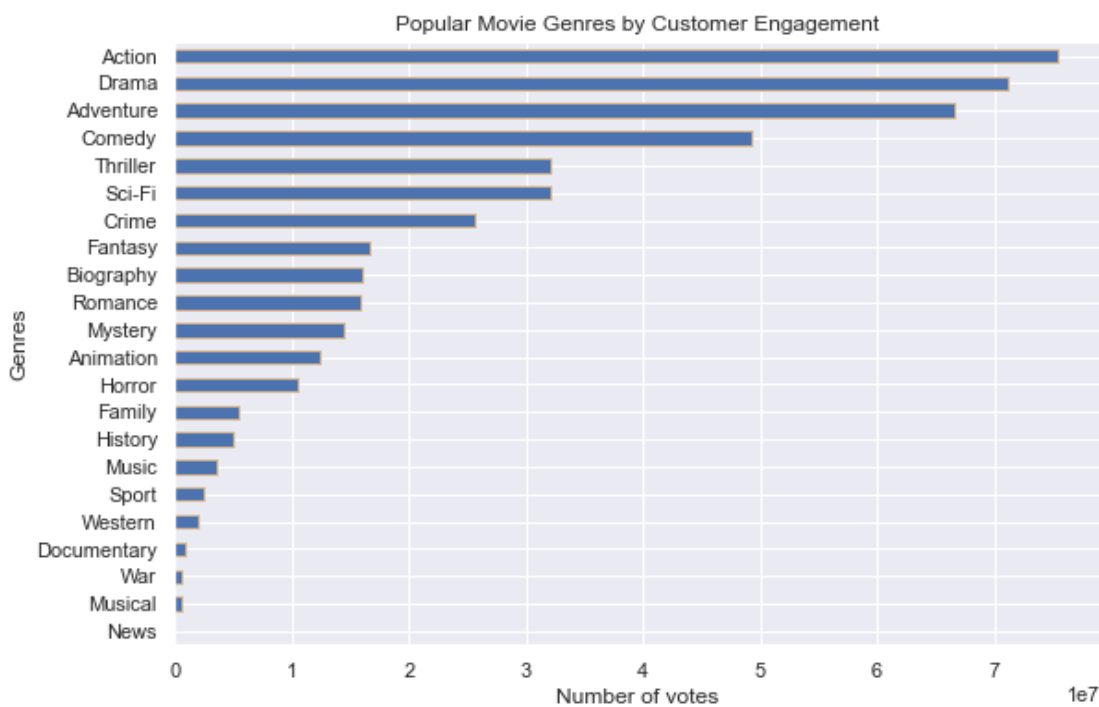
In [45]:

```
# Graph by genre and number of votes - or number of customer interaction
df_explode.groupby(['genres'])['numvotes'].sum().sort_values().plot(kind='barh', figsize=(9,
```

6),

edgecolor = 'tan')

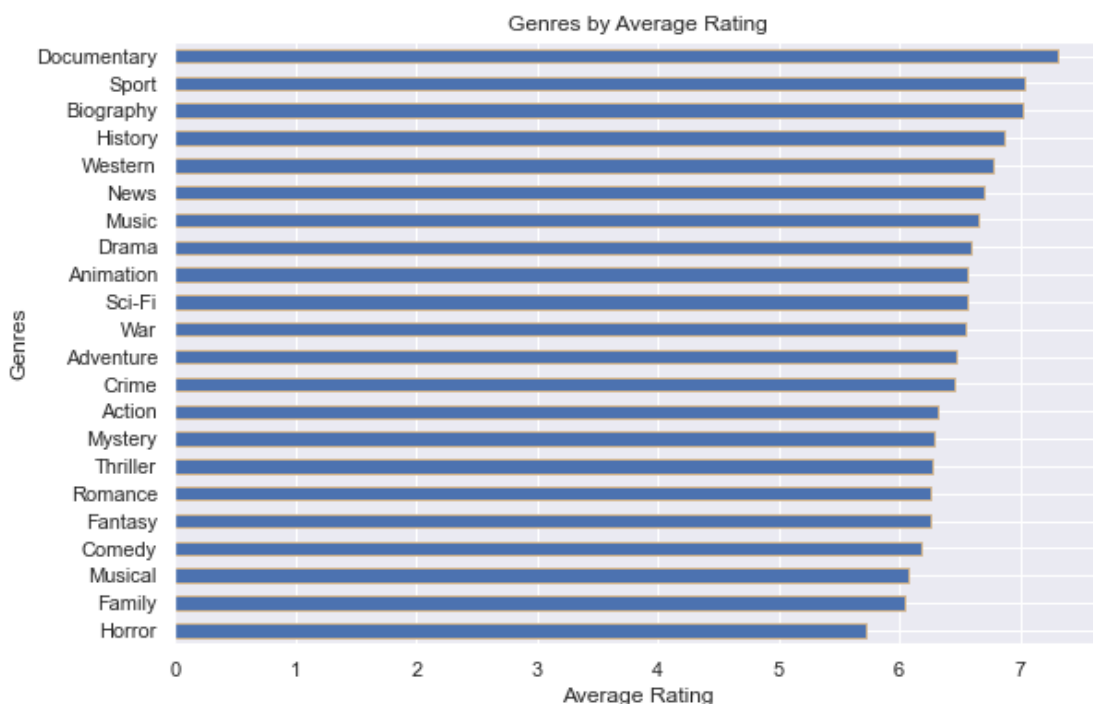
```
plt.title('Popular Movie Genres by Customer Engagement')
plt.xlabel("Number of votes")
plt.ylabel('Genres')
sns.set();
```



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

In [46]:

```
# Use df_explode['genres'] and ['averagerating'] to display average rating
df_explode.groupby(['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 documentary, sport, and biography come out as the top three genres with the highest ratings. However, this would be inaccurate to conclude due 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 action, drama, and comedy are the most frequently made films that also create 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 []: