Microsoft Movie Studio Analysis

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Introduction

Microsoft wants to create original video content. However, they do not know much about creating movies, or which types of movies are most successful at the box office. The purpose of this analysis is to evaluate box office data and to provide Microsoft with recommendations on which types of content would make them most successful in their endeavor.

Suggestions for types of content:

Create movies that have the highest ROI to maximize initial investment & early profitability. Focus on movies that are appealing to a broader audience and international box offices. Develop franchise movies to optimize box office performance and additional opportunities for monetization.

In [1]:

```
# import cleaning, analysis, and charting packages

import pandas as pd
import numpy as np
import sqlite3
import requests as rq
from sklearn.preprocessing import OneHotEncoder
from zipfile import ZipFile
from matplotlib import pyplot as plt
import matplotlib.ticker as mtick
import seaborn as sns


%matplotlib inline
plt.style.use('seaborn-talk')
```

Datasets explore

Viewing and connecting to initial datasets that were provided. Including dataset that I found as well through Opus.

bom.movie_gross dataset

In [2]:
```
df = pd.read_csv('data/bom.movie_gross.csv')
df.head()
## need tmdb.movies file for genres
```

Out[2]:

	title	studio	domestic_gross	foreign_gross	year
0	Toy Story 3	BV	415000000.0	652000000	2010
1	Alice in Wonderland (2010)	BV	334200000.0	691300000	2010
2	Harry Potter and the Deathly Hallows Part 1	WB	296000000.0	664300000	2010
3	Inception	WB	292600000.0	535700000	2010
4	Shrek Forever After	P/DW	238700000.0	513900000	2010

In [3]:
```
print('The "bom.movie_gross.csv" dataset starts in year', df['year'].min(),'and ends in', df['year'].max(),'.')
print('There are', df['title'].count(),'movie title records in the dataset.')
```

```
The "bom.movie_gross.csv" dataset starts in year 2010 and ends in 2018 .
There are 3387 movie title records in the dataset.
```

In [4]:
```
#cleaning gnarliness in the foreign gross column and changing to int
df['foreign_gross'] = pd.to_numeric(df['foreign_gross'], errors='coerce')
df = df.dropna(subset=['foreign_gross'])
df['foreign_gross'] = df['foreign_gross'].astype(int)
```

Dataset is pretty simple. Looking for more data around performance to understand success. Would be a good dataframe to join if needed split between domestic and foreign gross box office performance or studio information.

tmdb.movies dataset

In [5]:
```
data = pd.read_csv('data/tmdb.movies.csv')
data.head()
```

Out[5]:

	Unnamed: 0	genre_ids	id	original_language	original_title	popularity	release_date	title	vote_average	vote_count
0	0	[12, 14, 10751]	12444	en	Harry Potter and the Deathly Hallows: Part 1	33.533	2010-11-19	Harry Potter and the Deathly Hallows: Part 1	7.7	10788
1	1	[14, 12, 16, 10751]	10191	en	How to Train Your Dragon	28.734	2010-03-26	How to Train Your Dragon	7.7	7610
2	2	[12, 28, 878]	10138	en	Iron Man 2	28.515	2010-05-07	Iron Man 2	6.8	12368
3	3	[16, 35, 10751]	862	en	Toy Story	28.005	1995-11-22	Toy Story	7.9	10174
4	4	[28, 878, 12]	27205	en	Inception	27.920	2010-07-16	Inception	8.3	22186

In [6]:
```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 26517 entries, 0 to 26516
Data columns (total 10 columns):
 #   Column             Non-Null Count  Dtype  
---  ------             --------------  -----  
 0   Unnamed: 0         26517 non-null  int64  
 1   genre_ids          26517 non-null  object 
 2   id                 26517 non-null  int64  
 3   original_language  26517 non-null  object 
 4   original_title     26517 non-null  object 
 5   popularity         26517 non-null  float64
 6   release_date       26517 non-null  object 
 7   title              26517 non-null  object 
 8   vote_average       26517 non-null  float64
 9   vote_count         26517 non-null  int64  
dtypes: float64(2), int64(3), object(5)
memory usage: 2.0+ MB
```

Dataset has good information around popularity and consumer sentiment around interest. Good information, however, I think revenue will be more import. Interesting information around genre, and language. Also has specific release date vs release year.

budgets dataset

In [7]:
```
budgets = pd.read_csv('data/tn.movie_budgets.csv')
budgets.head()
```

Out[7]:

	id	release_date	movie	production_budget	domestic_gross	worldwide_gross
0	1	Dec 18, 2009	Avatar	$425,000,000	$760,507,625	$2,776,345,279
1	2	May 20, 2011	Pirates of the Caribbean: On Stranger Tides	$410,600,000	$241,063,875	$1,045,663,875
2	3	Jun 7, 2019	Dark Phoenix	$350,000,000	$42,762,350	$149,762,350
3	4	May 1, 2015	Avengers: Age of Ultron	$330,600,000	$459,005,868	$1,403,013,963
4	5	Dec 15, 2017	Star Wars Ep. VIII: The Last Jedi	$317,000,000	$620,181,382	$1,316,721,747

In [8]:
```
budgets.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5782 entries, 0 to 5781
Data columns (total 6 columns):
 #   Column             Non-Null Count  Dtype 
---  ------             --------------  ----- 
 0   id                 5782 non-null   int64 
 1   release_date       5782 non-null   object
 2   movie              5782 non-null   object
 3   production_budget  5782 non-null   object
 4   domestic_gross     5782 non-null   object
 5   worldwide_gross    5782 non-null   object
dtypes: int64(1), object(5)
memory usage: 271.2+ KB
```

Another simple dataset, however includes budget! Will continue to review all the datasets to understand best suited for my analysis.

Mov_Info dataset

In [9]:
```
mov_info = pd.read_csv('data/rt.movie_info.tsv', sep='\t')
mov_info.head()
#keep id, synopsis, rating, genre, theatre date, dvd date, runtime, studio
```

Out[9]:

	id	synopsis	rating	genre	director	writer	theater_date	dvd_date	currency	box_office	runtim
0	1	This gritty, fast-paced, and innovative police...	R	Action and Adventure|Classics|Drama	William Friedkin	Ernest Tidyman	Oct 9, 1971	Sep 25, 2001	NaN	NaN	10 minute

	id	synopsis	rating	genre	director	writer	theater_date	dvd_date	currency	box_office	runtim
1	3	New York City, not-too-distant-future: Eric Pa...	R	Drama|Science Fiction and Fantasy	David Cronenberg	David Cronenberg|Don DeLillo	Aug 17, 2012	Jan 1, 2013	$	600,000	10 minute
2	5	Illeana Douglas delivers a superb performance ...	R	Drama|Musical and Performing Arts	Allison Anders	Allison Anders	Sep 13, 1996	Apr 18, 2000	NaN	NaN	11 minute
3	6	Michael Douglas runs afoul of a treacherous su...	R	Drama|Mystery and Suspense	Barry Levinson	Paul Attanasio|Michael Crichton	Dec 9, 1994	Aug 27, 1997	NaN	NaN	12 minute
4	7	NaN	NR	Drama|Romance	Rodney Bennett	Giles Cooper	NaN	NaN	NaN	NaN	20 minute

In [10]:

```
mov_info.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1560 entries, 0 to 1559
Data columns (total 12 columns):
 #   Column        Non-Null Count  Dtype 
---  ------        --------------  ----- 
 0   id            1560 non-null   int64 
 1   synopsis      1498 non-null   object
 2   rating        1557 non-null   object
 3   genre         1552 non-null   object
 4   director      1361 non-null   object
 5   writer        1111 non-null   object
 6   theater_date  1201 non-null   object
 7   dvd_date      1201 non-null   object
 8   currency      340 non-null    object
 9   box_office    340 non-null    object
 10  runtime       1530 non-null   object
 11  studio        494 non-null    object
dtypes: int64(1), object(11)
memory usage: 146.4+ KB
```

Interesting information around synopsis, rating, writer, director, however not a lot of records in this dataset. Concern would be getting into small sample sizes with 1 to 2 filters.

rt.reviews dataset

In [11]:
```
reviews = pd.read_csv('data/rt.reviews.tsv', sep='\t', encoding= 'unicode_escape')
reviews.head()
```

Out[11]:

	id	review	rating	fresh	critic	top_critic	publisher	date
0	3	A distinctly gallows take on contemporary fina...	3/5	fresh	PJ Nabarro	0	Patrick Nabarro	November 10, 2018
1	3	It's an allegory in search of a meaning that n...	NaN	rotten	Annalee Newitz	0	io9.com	May 23, 2018
2	3	... life lived in a bubble in financial dealin...	NaN	fresh	Sean Axmaker	0	Stream on Demand	January 4, 2018
3	3	Continuing along a line introduced in last yea...	NaN	fresh	Daniel Kasman	0	MUBI	November 16, 2017
4	3	... a perverse twist on neorealism...	NaN	fresh	NaN	0	Cinema Scope	October 12, 2017

In [12]:
```
reviews.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 54432 entries, 0 to 54431
Data columns (total 8 columns):
 #   Column      Non-Null Count  Dtype 
---  ------      --------------  ----- 
 0   id          54432 non-null  int64 
 1   review      48869 non-null  object
 2   rating      40915 non-null  object
 3   fresh       54432 non-null  object
 4   critic      51710 non-null  object
 5   top_critic  54432 non-null  int64 
 6   publisher   54123 non-null  object
 7   date        54432 non-null  object
dtypes: int64(2), object(6)
memory usage: 3.3+ MB
```

Once again interesting information around reviews and consumer sentiment, but not sure if that always translates to box office success. Going to continue to move on until find a dataset with good information around return.

Movies SQL database

In [13]:
```
# movie_basics and movie_ratings tables are most relevant
conn = sqlite3.connect('data/im.db')
```

```
lang = pd.read_sql("""SELECT * FROM movie_basics mb
            LEFT JOIN movie_akas ma ON mb.movie_id = ma.movie_id
            ;""", conn)
```

In [14]:

```
lang.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 355545 entries, 0 to 355544
Data columns (total 14 columns):
 #   Column             Non-Null Count   Dtype  
---  ------             --------------   -----  
 0   movie_id           355545 non-null  object 
 1   primary_title      355545 non-null  object 
 2   original_title     355513 non-null  object 
 3   start_year         355545 non-null  int64  
 4   runtime_minutes    314219 non-null  float64
 5   genres             348882 non-null  object 
 6   movie_id           331703 non-null  object 
 7   ordering           331703 non-null  float64
 8   title              331703 non-null  object 
 9   region             278410 non-null  object 
 10  language           41715 non-null   object 
 11  types              168447 non-null  object 
 12  attributes         14925 non-null   object 
 13  is_original_title  331678 non-null  float64
dtypes: float64(3), int64(1), object(10)
memory usage: 38.0+ MB
```

In [15]:

```
conn.close()
```

A lot of information in this database, however still not includes all fields that I am interested in understanding. Moving on to external datasets to understand if there is something I can review and or join back to this information that was curated.

Opus Movie Data

In [16]:

```
mdo = pd.read_csv('data/MovieData.csv')
mdo.head()
```

Out[16]:

	movie_name	production_year	movie_odid	production_budget	domestic_box_office	international_box_office	rating	creative_type
0	Madea's Family Reunion	2006	8220100	10000000	63257940	62581	PG-13	Contemporary Fiction
1	Krrish	2006	58540100	10000000	1430721	31000000	Not Rated	Science Fiction

	movie_name	production_year	movie_odid	production_budget	domestic_box_office	international_box_office	rating	creative_type
2	End of the Spear	2006	34620100	10000000	11748661	175380	PG-13	Historical Fiction
3	A Prairie Home Companion	2006	24910100	10000000	20342852	6373339	PG-13	Contemporary Fiction
4	Saw III	2006	5840100	10000000	80238724	83638091	R	Contemporary Fiction

In [17]:

```
mdo.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1936 entries, 0 to 1935
Data columns (total 13 columns):
 #   Column                    Non-Null Count  Dtype  
---  ------                    --------------  -----  
 0   movie_name                1936 non-null   object 
 1   production_year           1936 non-null   int64  
 2   movie_odid                1936 non-null   int64  
 3   production_budget         1936 non-null   int64  
 4   domestic_box_office       1936 non-null   int64  
 5   international_box_office  1936 non-null   int64  
 6   rating                    1913 non-null   object 
 7   creative_type             1923 non-null   object 
 8   source                    1915 non-null   object 
 9   production_method         1925 non-null   object 
 10  genre                     1926 non-null   object 
 11  sequel                    1934 non-null   float64
 12  running_time              1822 non-null   float64
dtypes: float64(2), int64(5), object(6)
memory usage: 196.8+ KB
```

This dataset has the most interesting categories to me and what I am trying to understand about movie success. Even though the films have a budget of >= $10M, I think that we can deliberately call that out as a part of the parameters reviewed. I don't think Microsoft will be moving into the industry without expecting an investment. With that being said, my focus is to understand how can we give Microsoft the best recommendations to maximize their ROI.

Opus Movie Data Selection

OpusData *Cleaning*

In [18]:

```python
# read in dataframe from OpusData CSV.
df = pd.read_csv('data/MovieData.csv')
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1936 entries, 0 to 1935
Data columns (total 13 columns):
 #   Column                  Non-Null Count  Dtype  
---  ------                  --------------  -----  
 0   movie_name              1936 non-null   object 
 1   production_year         1936 non-null   int64  
 2   movie_odid              1936 non-null   int64  
 3   production_budget       1936 non-null   int64  
 4   domestic_box_office     1936 non-null   int64  
 5   international_box_office  1936 non-null   int64  
 6   rating                  1913 non-null   object 
 7   creative_type           1923 non-null   object 
 8   source                  1915 non-null   object 
 9   production_method       1925 non-null   object 
 10  genre                   1926 non-null   object 
 11  sequel                  1934 non-null   float64
 12  running_time            1822 non-null   float64
dtypes: float64(2), int64(5), object(6)
memory usage: 196.8+ KB
```

In [19]:

```python
# removed na data from the dataset.  1,795 values remain.
mdo = df.dropna(axis=0)
mdo.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 1795 entries, 3 to 1935
Data columns (total 13 columns):
 #   Column                  Non-Null Count  Dtype  
---  ------                  --------------  -----  
 0   movie_name              1795 non-null   object 
 1   production_year         1795 non-null   int64  
 2   movie_odid              1795 non-null   int64  
 3   production_budget       1795 non-null   int64  
 4   domestic_box_office     1795 non-null   int64  
 5   international_box_office  1795 non-null   int64  
 6   rating                  1795 non-null   object 
 7   creative_type           1795 non-null   object 
 8   source                  1795 non-null   object 
 9   production_method       1795 non-null   object 
 10  genre                   1795 non-null   object 
 11  sequel                  1795 non-null   float64
 12  running_time            1795 non-null   float64
dtypes: float64(2), int64(5), object(6)
memory usage: 196.3+ KB
```

Cleaned dataframe and created a new variable called 'mdo_clean'. This variable which now includes 1,795 records will be the dataset in which I perform my analysis. After viewing the the fields available, I have decided to create a few additional measures and categorical variables or dimensions. I used a pretty heavy hand when cleaning, I didn't lose a ton of records in this process..moving forward with analysis.

In [20]:

```
# Adding total box office metric, which is the sum of the domestic and international box offices.
mdo_clean = mdo.copy()
mdo_clean.loc[:,'total_box_office'] = (
    mdo['domestic_box_office'] + mdo['international_box_office']
    )

mdo_clean.head()
```

Out[20]:

	movie_name	production_year	movie_odid	production_budget	domestic_box_office	international_box_office	rating	creative_type
3	A Prairie Home Companion	2006	24910100	10000000	20342852	6373339	PG-13	Contemporary Fictior
5	Employee of the Month	2006	19540100	10000000	28444855	9920000	PG-13	Contemporary Fictior
13	Crank	2006	19850100	12000000	27838408	16086515	R	Contemporary Fictior
14	Fateless	2006	75540100	12000000	196857	0	R	Historica Fictior
16	Step Up	2006	7780100	12000000	65328121	45661036	PG-13	Contemporary Fictior

In [21]:

```
# Adding ROI cacluation (total box office/ production budget - 1)
mdo_clean.loc[:,'return'] = (
    mdo_clean['total_box_office']/ mdo_clean['production_budget'] - 1
    )

mdo_clean.head()
```

Out[21]:

	movie_name	production_year	movie_odid	production_budget	domestic_box_office	international_box_office	rating	creative_type
3	A Prairie Home Companion	2006	24910100	10000000	20342852	6373339	PG-13	Contemporary Fictior

	movie_name	production_year	movie_odid	production_budget	domestic_box_office	international_box_office	rating	creative_type
5	Employee of the Month	2006	19540100	10000000	28444855	9920000	PG-13	Contemporary Fiction
13	Crank	2006	19850100	12000000	27838408	16086515	R	Contemporary Fiction
14	Fateless	2006	75540100	12000000	196857	0	R	Historical Fiction
16	Step Up	2006	7780100	12000000	65328121	45661036	PG-13	Contemporary Fiction

In [22]:

```
# Adding percent of international to total box office
mdo_clean.loc[:,'percent_of_int'] = (
    mdo_clean['international_box_office'] / mdo_clean['total_box_office']
    )

mdo_clean.head()
```

Out[22]:

	movie_name	production_year	movie_odid	production_budget	domestic_box_office	international_box_office	rating	creative_type
3	A Prairie Home Companion	2006	24910100	10000000	20342852	6373339	PG-13	Contemporary Fiction
5	Employee of the Month	2006	19540100	10000000	28444855	9920000	PG-13	Contemporary Fiction
13	Crank	2006	19850100	12000000	27838408	16086515	R	Contemporary Fiction
14	Fateless	2006	75540100	12000000	196857	0	R	Historical Fiction
16	Step Up	2006	7780100	12000000	65328121	45661036	PG-13	Contemporary Fiction

In [23]:

```
# adding flag for profitability.
conditions = [mdo_clean.loc[:,'return'] >= 0,
              mdo_clean.loc[:,'return'] < 0]
```

```python
values = [1,0]

mdo_clean.loc[:,'is_profitable'] = np.select(conditions, values, default=0)
mdo_clean.groupby('rating')['is_profitable'].mean()
```

Out[23]:

```
rating
G            0.911765
NC-17        1.000000
Not Rated    0.606061
PG           0.848993
PG-13        0.823370
R            0.682540
Name: is_profitable, dtype: float64
```

In [24]:

```python
# adding friendly label for sequel categorical
conditions = [mdo_clean.loc[:,'sequel'] > 0,
              mdo_clean.loc[:,'sequel'] == 0]

values = ['Has Sequel','No Sequel']

mdo_clean.loc[:,'is_sequel'] = np.select(conditions, values, default=0)
```

Since my primary focus for "success" is ROI, I have added a total box office category, along with a ROI measure, and a profitablitiy flag. In addition to adding these columns, I added a charting friendly categorical variable for the sequel column.

OpusData *Analysis*

In [25]:

```python
# Summary stats for numeric columns; initial understanding of data distribution and which
# measure of central tendency will be best applied for my analyses.

mdo_clean.describe()
```

Out[25]:

	production_year	movie_odid	production_budget	domestic_box_office	international_box_office	sequel	running_time
count	1795.000000	1.795000e+03	1.795000e+03	1.795000e+03	1.795000e+03	1795.000000	1795.000000
mean	2011.533705	1.382248e+08	5.558087e+07	6.829396e+07	1.011146e+08	0.154318	109.650139
std	3.367719	8.241984e+07	5.484957e+07	8.968159e+07	1.641493e+08	0.361354	18.807721
min	2006.000000	2.010000e+04	1.000000e+07	0.000000e+00	0.000000e+00	0.000000	0.000000
25%	2009.000000	5.822510e+07	2.000000e+07	1.431418e+07	1.059444e+07	0.000000	97.000000
50%	2011.000000	1.451401e+08	3.500000e+07	3.853638e+07	3.884555e+07	0.000000	108.000000

	production_year	movie_odid	production_budget	domestic_box_office	international_box_office	sequel	running_time
75%	2015.000000	2.008451e+08	7.000000e+07	8.446791e+07	1.112000e+08	0.000000	120.000000
max	2018.000000	3.348301e+08	4.250000e+08	9.366622e+08	2.015838e+09	1.000000	201.000000

In [26]:

```
# Organizing counts and total box office sum for summary chart

counts = (
    mdo_clean
    .groupby('production_year')['movie_odid']
    .count()
    .reset_index()
    )

totalboxyear = (
    mdo_clean
    .groupby('production_year')['total_box_office']
    .sum()
    .reset_index()
    )


result = pd.merge(counts, totalboxyear, how="inner", on=['production_year', 'production_year'])
result
```

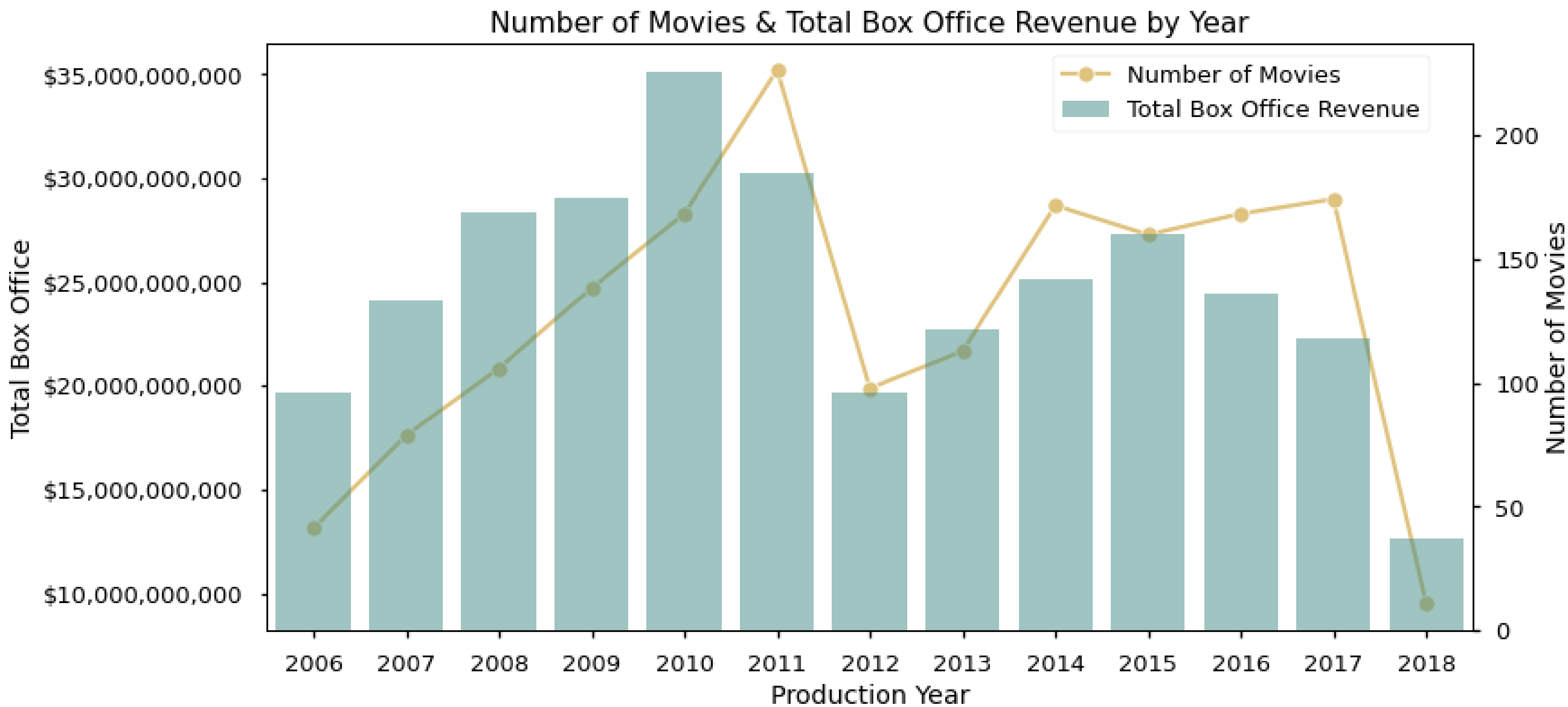
Out[26]:

	production_year	movie_odid	total_box_office
0	2006	96	13139666540
1	2007	133	17609479712
2	2008	169	20841914089
3	2009	175	24708029118
4	2010	226	28282185867
5	2011	185	35216319041
6	2012	96	19885339850
7	2013	122	21668174194
8	2014	142	28684658909
9	2015	160	27279573182

	production_year	movie_odid	total_box_office
10	2016	136	28285207426
11	2017	118	28989517783
12	2018	37	9498367645

In [27]:

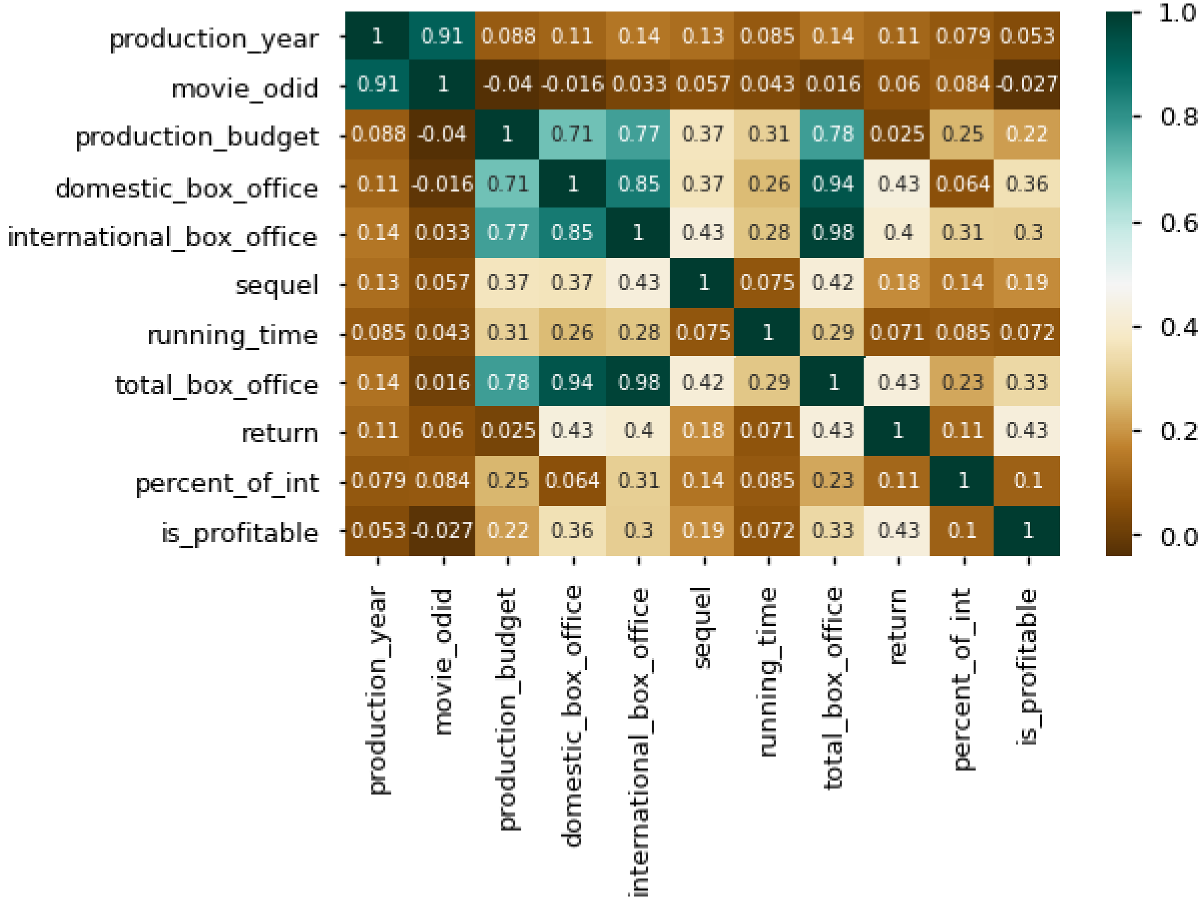
```
# Summary chart for number of movies and total box office by year

fig, ax1 = plt.subplots(figsize=(12,6))

lp = sns.lineplot(data = result['total_box_office'],
                  marker='o',
                  sort = False,
                  ax=ax1,
                  label='Number of Movies',
                  color='#dfc27d')

ax2 = ax1.twinx()

bp = sns.barplot(data = result,
                 x='production_year',
                 y='movie_odid',
                 alpha=0.5,
                 ax=ax2,
                 color='#35978f',
                 label='Total Box Office Revenue')

ax1.set_title('Number of Movies & Total Box Office Revenue by Year')
ax1.set_xlabel('Production Year')
ax1.set_ylabel('Total Box Office')
ax2.set_ylabel('Number of Movies')
fig.legend(loc='upper right', bbox_to_anchor=(.88,.88))
ax1.get_legend().remove()
fmt = '${x:,.0f}'
tick = mtick.StrMethodFormatter(fmt)
ax1.yaxis.set_major_formatter(tick);
```



Initial chart to understand values and trends over time. Focusing on the macro trends, the number of records and total box office spend for each time period represented. Based on this visualization, I have a better understanding of which years I should not weight disproportionally (i.e. 2012, 2018). It would be interesting to understand at a macro level what happened in 2012, because it seems as if movies that are included in this dataset both dropped off from a release count perspective and a total box office. Since I only have year in this dataset, and not date, I have decided not to focus too much on date.

In [28]:

```
# Correlation matrix of numerical values in opus dataset.

plt.figure(figsize = (8,5))
corrM = mdo_clean.corr()

sns.heatmap(corrM, annot=True, cmap='BrBG')
plt.show()
```

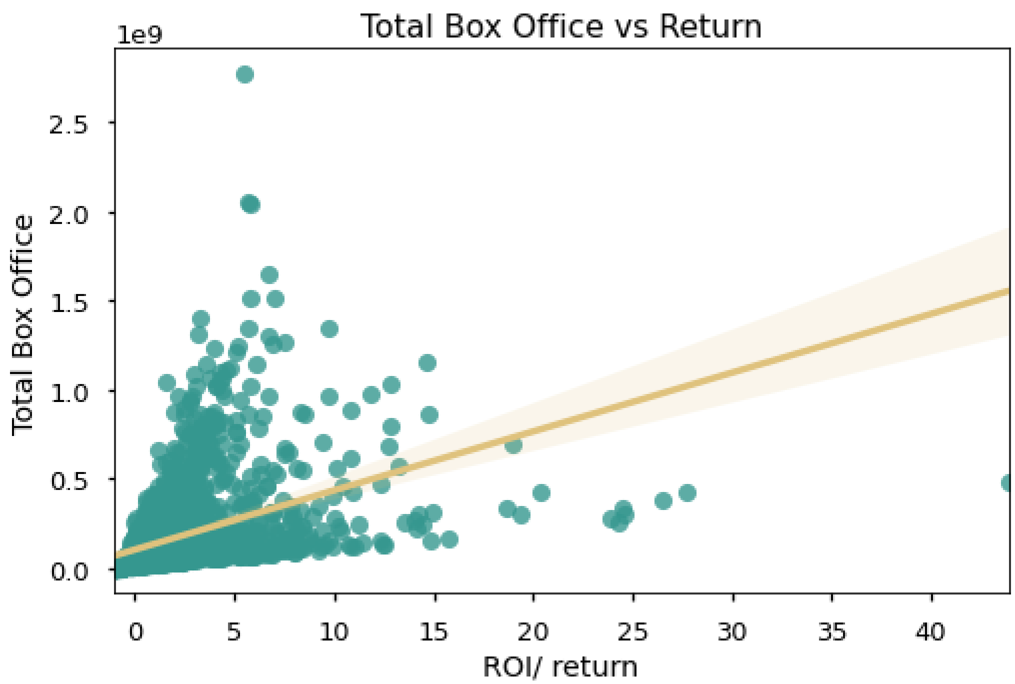


Stronger positive correlations exist between box office results and production budget. This gives me confidence in my data set since I selected a data set that was limited to larger budgets. Would like to further evaluate international box office as a potential solution.

In [29]:

```
#sns.scatterplot(data=mdo_clean, x='return', y='total_box_office')

plt.figure(figsize = (8,5))

rp = sns.regplot(x='return',
            y='total_box_office',
            data=mdo_clean,
            scatter_kws={"color": '#35978f'},
            line_kws={"color": '#dfc27d'})

rp.set_ylabel('Total Box Office')
```

```
rp.set_xlabel('ROI/ return')
rp.set_title('Total Box Office vs Return');
```



Visualized total box office and return in a different way vs the correlation matrix above, displaying the strong positive relationship.

Argument for "Family Movies"

Create movies that have the highest ROI to maximize initial investment & early profitability.

Rating seems to be a interesting category to understand. I charted a quick count of records to make sure the categories I was comparing had enough experience.

In [30]:

```
# Summary of totals by rating category

(mdo_clean
 .groupby(['rating'])
 .sum()
 .reset_index()
 .sort_values(by='total_box_office',
              ascending=False)
)
```

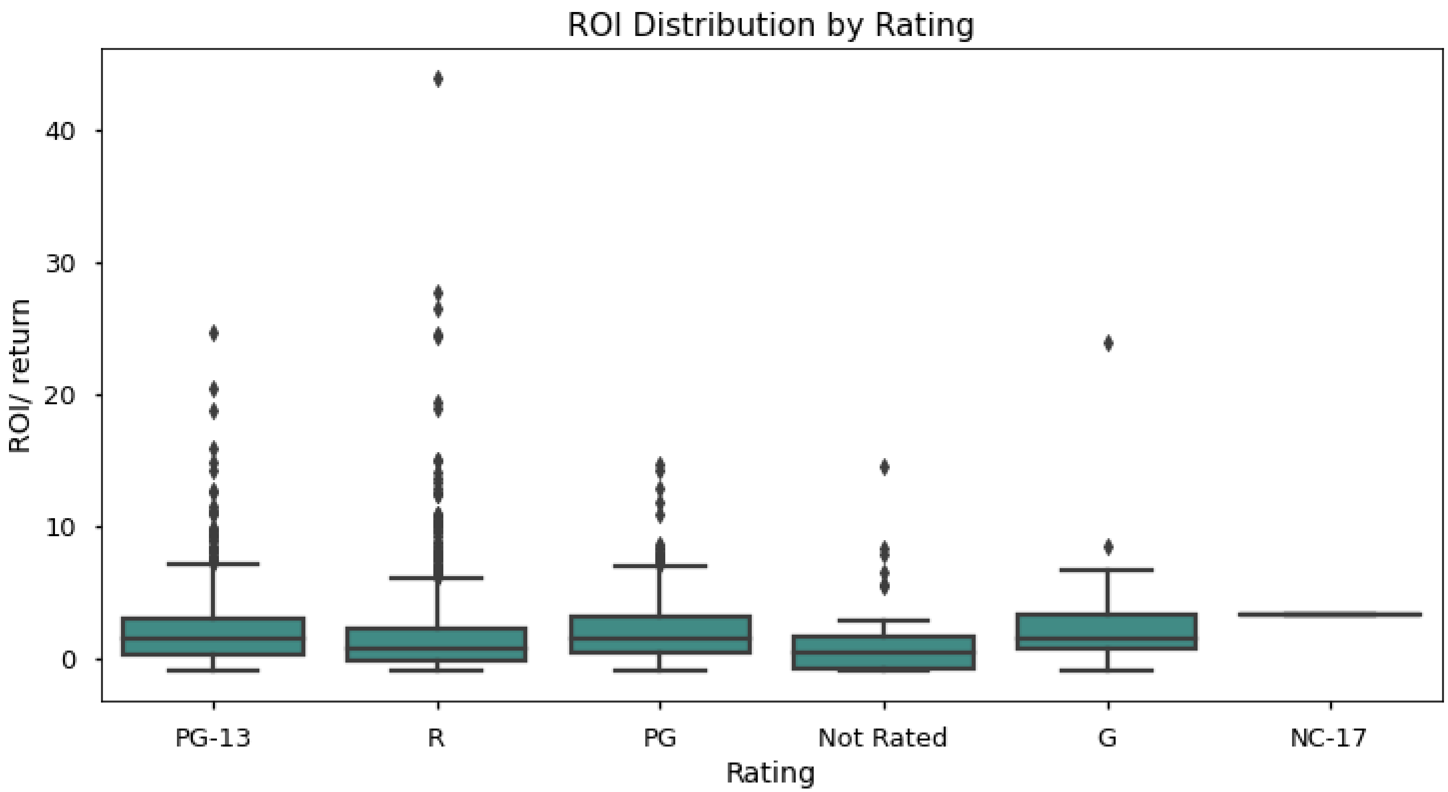
Out[30]:

	rating	production_year	movie_odid	production_budget	domestic_box_office	international_box_office	sequel	running_time	to
4	PG-13	1480530	99547583600	51482400000	64071363498	98938185069	136.0	83164.0	
3	PG	599407	38854699800	21963600000	27868757027	42455279143	55.0	29786.0	
5	R	1394012	100226299300	23256270000	27687192501	33370015189	75.0	76899.0	
0	G	68321	2853693400	2357500000	2894929346	4866246539	9.0	3181.0	
2	Not Rated	66426	6583723300	692900000	60805933	1810491681	2.0	3634.0	
1	NC-17	2007	47450100	15000000	4604982	60562448	0.0	158.0	

In [31]:

```
# Creating boxplots of return by rating to understand the distribution of ROI between rating categories.

fig, ax = plt.subplots(figsize=(12,6))

ax.set_title('ROI Distribution by Rating')


bp = sns.boxplot(data=mdo_clean,
            y='return',
            x='rating',
            color='#35978f')

bp.set_ylabel('ROI/ return')
bp.set_xlabel('Rating')
;
```

Out[31]: ''



PG-13 total box office driven by outliers. G rated movies have the highest median (total) box office performance, however not a lot of experience. PG rated movies have both a high median and a decent amount of experience at the box office. I am going to group these variables together into a 'family' flag next to see how the experience weights the results.

In [32]:
```
# adding flag for 'family movies' vs 'non-family movies'.  'family movies' defined as IN (G, PG, PG-13).

conditions = (
    [mdo_clean.loc[:,'rating']
     .isin(['G', 'PG', 'PG-13']),

     mdo_clean.loc[:,'rating']
     .isin(['Not Rated', 'NC-17', 'R'])]
    )

values = ['Family','Non-Family']

mdo_clean.loc[:,'Family'] = np.select(conditions, values, default=0)
mdo_clean['Family'].value_counts()
```

Out[32]:
```
Family        1068
Non-Family     727
Name: Family, dtype: int64
```

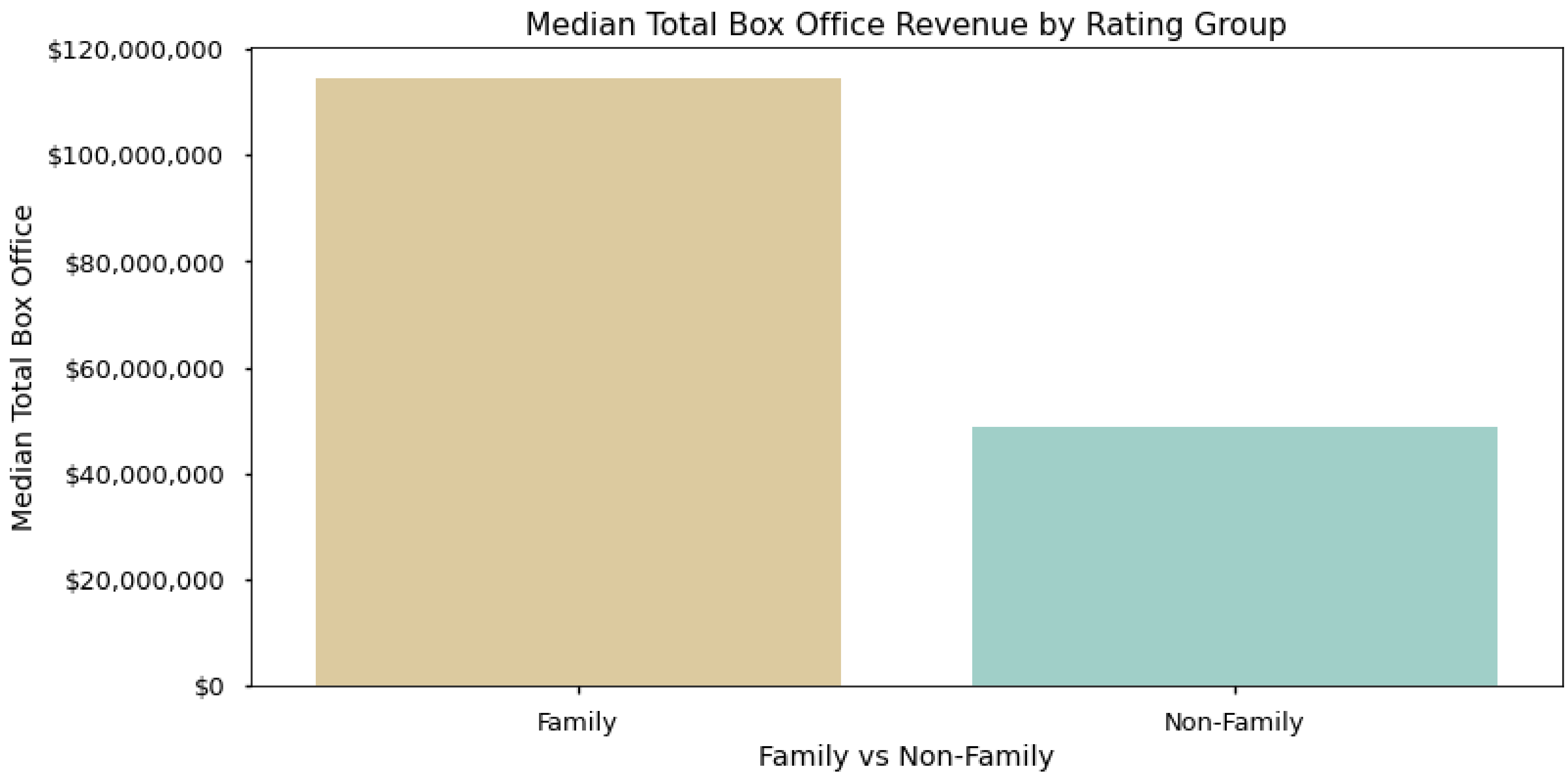
In [33]:
```
# Median values for family vs non family numerical data.

fam_group = (
    mdo_clean.groupby('Family')
    .median()
    .reset_index()
    )

fam_group
```

Out[33]:

	Family	production_year	movie_odid	production_budget	domestic_box_office	international_box_office	sequel	running_time	tota
0	Family	2011.0	143645100.0	45000000.0	53303923.5	58189214.0	0.0	107.0	
1	Non-Family	2011.0	149540100.0	25000000.0	23591043.0	23334984.0	0.0	110.0	

In [34]:
```
# Chart to show delta between family and non family median international box office.

fig, ax = plt.subplots(figsize=(12,6))

bp = sns.barplot(data=fam_group,
            y='total_box_office',
            x='Family',
            palette = 'BrBG')

bp.set_ylabel('Median Total Box Office')
bp.set_xlabel('Family vs Non-Family')
bp.set_title('Median Total Box Office Revenue by Rating Group')

fmt = '${x:,.0f}'
tick = mtick.StrMethodFormatter(fmt)
ax.yaxis.set_major_formatter(tick)
;
```

Out[34]: ''



Family movies clearly have a higher median box office vs non-family movies. This is primarily being driven by a higher percentage of international movie box office percentages - shown below.

In [35]:
```
mdo_clean.groupby('rating')['percent_of_int'].median()

#plt.figure(figsize = (8,4))
#sns.barplot(y='percent_of_int', x='rating', data = fam_mov, palette='BrBG', order = fam_mov.sort_values('perce

#Not rated, and NC-17 rated movies have a higher international box office impact on the total box office.  G/PG
```

Out[35]:
```
rating
G            0.613246
NC-17        0.929336
Not Rated    0.986614
PG           0.555254
PG-13        0.535883
R            0.508475
Name: percent_of_int, dtype: float64
```

In [36]:
```
# create variable/ pivot table to undersand return within family and non family movies
```

```
medfams = pd.pivot_table(mdo_clean,
                         values='return',
                         columns='Family',
                         index='production_year',
                         aggfunc=np.median,
                         fill_value=0)

medfams
```

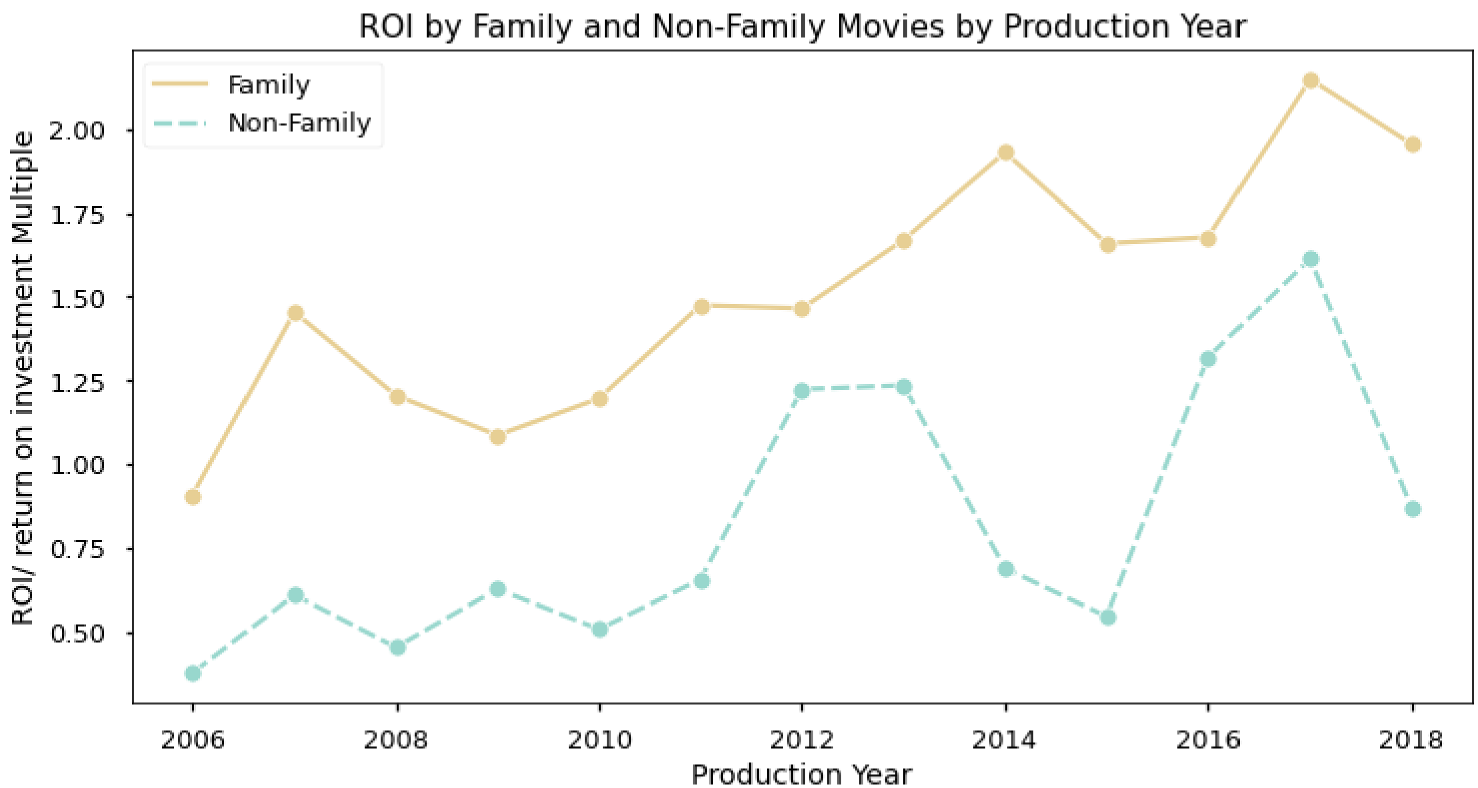
Out[36]:

Family	Family	Non-Family
production_year		
2006	0.908239	0.379025
2007	1.454847	0.611666
2008	1.206220	0.456290
2009	1.087926	0.629676
2010	1.197185	0.509634
2011	1.475338	0.658262
2012	1.466032	1.224738
2013	1.669760	1.236402
2014	1.929897	0.691226
2015	1.659514	0.547951
2016	1.678453	1.320263
2017	2.148097	1.613940
2018	1.954738	0.870399

In [37]:

```
# create chart showing roi for fam vs non fam movies by year

plt.subplots(figsize=(12,6))

lp = sns.lineplot(data = medfams, marker='o', sort = False, palette='BrBG')

lp.set_title('ROI by Family and Non-Family Movies by Production Year')
lp.set_xlabel('Production Year')
```

```
lp.set_ylabel('ROI/ return on investment Multiple')
lp.legend(title = False);
```



Family movies have consistently performed better over the experience in this period. Even though there are a few ups and downs in the line chart, the relative ratio to non-family movies is pretty clear. Going to create a family movie specific dataset now and continue my analysis within family rated movies only.

In [38]:

```
# create new dataframe with G, PG, and PG-13 titles only.

fam_mov = (
    mdo_clean[mdo_clean['rating']
              .isin(['G', 'PG', 'PG-13'])]
    )

fam_mov.head()
```

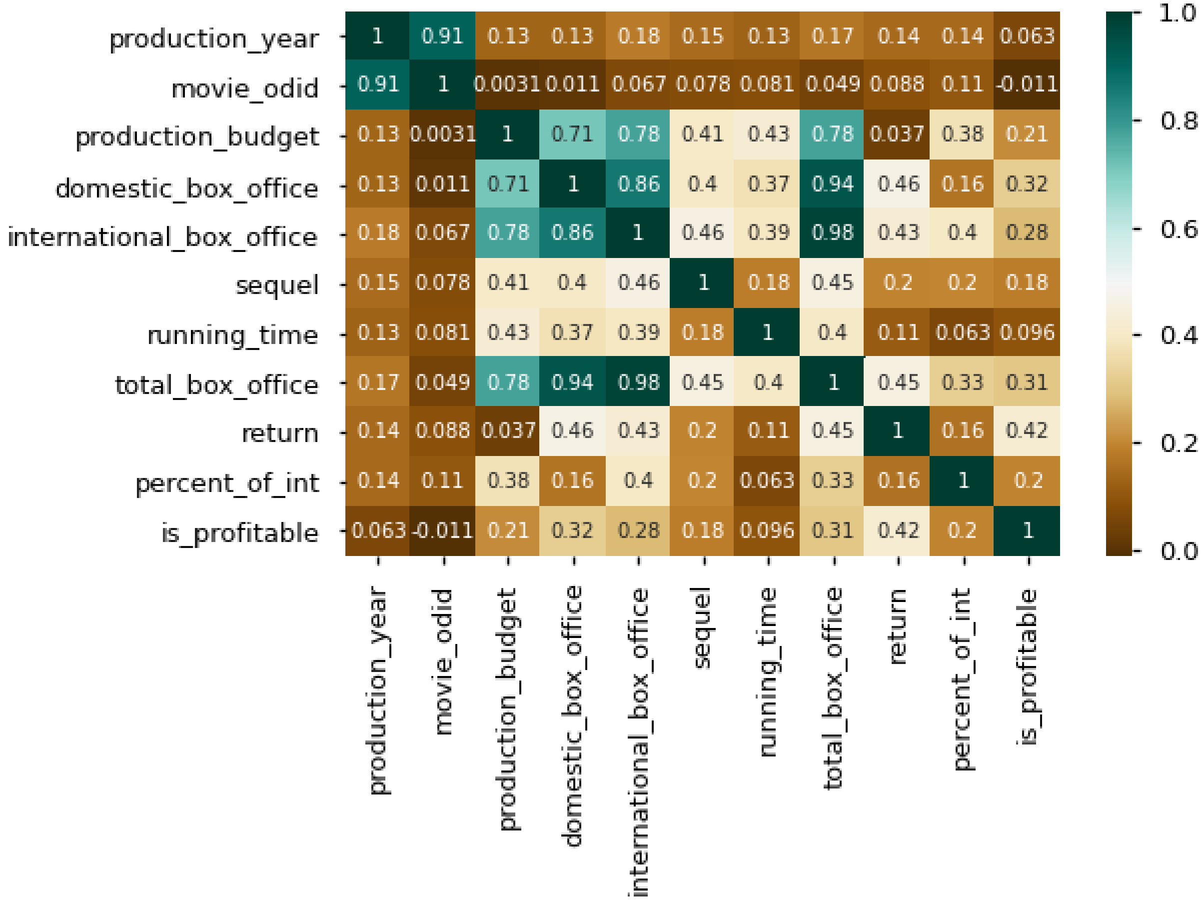
Out[38]:

movie_name	production_year	movie_odid	production_budget	domestic_box_office	international_box_office	rating	creative_type

	movie_name	production_year	movie_odid	production_budget	domestic_box_office	international_box_office	rating	creative_type
3	A Prairie Home Companion	2006	24910100	10000000	20342852	6373339	PG-13	Contemporary Fiction
5	Employee of the Month	2006	19540100	10000000	28444855	9920000	PG-13	Contemporary Fiction
16	Step Up	2006	7780100	12000000	65328121	45661036	PG-13	Contemporary Fiction
23	An American Haunting	2006	130560100	14000000	16298046	14145231	PG-13	Historical Fiction
28	Flicka	2006	24440100	15000000	21000147	896220	PG	Contemporary Fiction

In [39]:

```
# Correlation matrix of family movie data to understand any relationships between variables.

plt.figure(figsize = (8,5))
corrFamMov = fam_mov.corr()

sns.heatmap(corrFamMov, annot=True, cmap='BrBG')
plt.show()
```



Displayed a correlation matrix to determine any relationships between our numerical values. Family movies are still showing strong relationships between box office performance, and production budget.

Argument for Animated Movies

Focus on movies that have a production method of animation vs live action.

In [40]:

```
# Create a field that groups our production methods together into a group.  This will make understanding easier
# as most of the categories will be listed under animation.

# Create a list of our conditions
conditions = (
    [mdo_clean.loc[:,'production_method']
     .isin(['Live Action']),
```

```
    mdo_clean.loc[:,'production_method']
    .isin(['Animation/Live Action',
       'Digital Animation',
       'Stop-Motion Animation',
       'Hand Animation',
       'Multiple Production Methods',
       'Rotoscoping'])]
   )

# Create a list of the values we want to assign for each condition
values = ['Live Action','Animation']


# Create a new column and use np.select to assign values to it using our lists as arguments
mdo_clean.loc[:,'prod_method_group'] = np.select(conditions, values, default=0)
mdo_clean['prod_method_group'].value_counts()
```

Out[40]:

```
Live Action    1560
Animation       235
Name: prod_method_group, dtype: int64
```

In [41]:

```
mdo_clean.groupby('prod_method_group')['return'].median()
```

Out[41]:

```
prod_method_group
Animation      1.800777
Live Action    1.101905
Name: return, dtype: float64
```

Animated movies have a 60% higher median return vs live action films.

In [42]:

```
# Creating a pivot table to show the rating records between animated and non-animated movies.
# Just making sure there is representation in each category (i.e. not all rated R movies are live action)
pd.pivot_table(mdo_clean,
                        values='return',
                        columns='prod_method_group',
                        index='rating',
                        aggfunc='count',
                        fill_value=0)
```

Out[42]:

prod_method_group	Animation	Live Action
rating		
G	23	11
NC-17	0	1

prod_method_group	Animation	Live Action
rating		
Not Rated	3	30
PG	160	138
PG-13	39	697
R	10	683

In [43]:

```
# Dataframe to plot median total box office by year, and production year.

intarg = (
    mdo_clean
    .groupby(['prod_method_group', 'production_year'])['total_box_office']
    .median()
    .reset_index()
    )

intarg
```

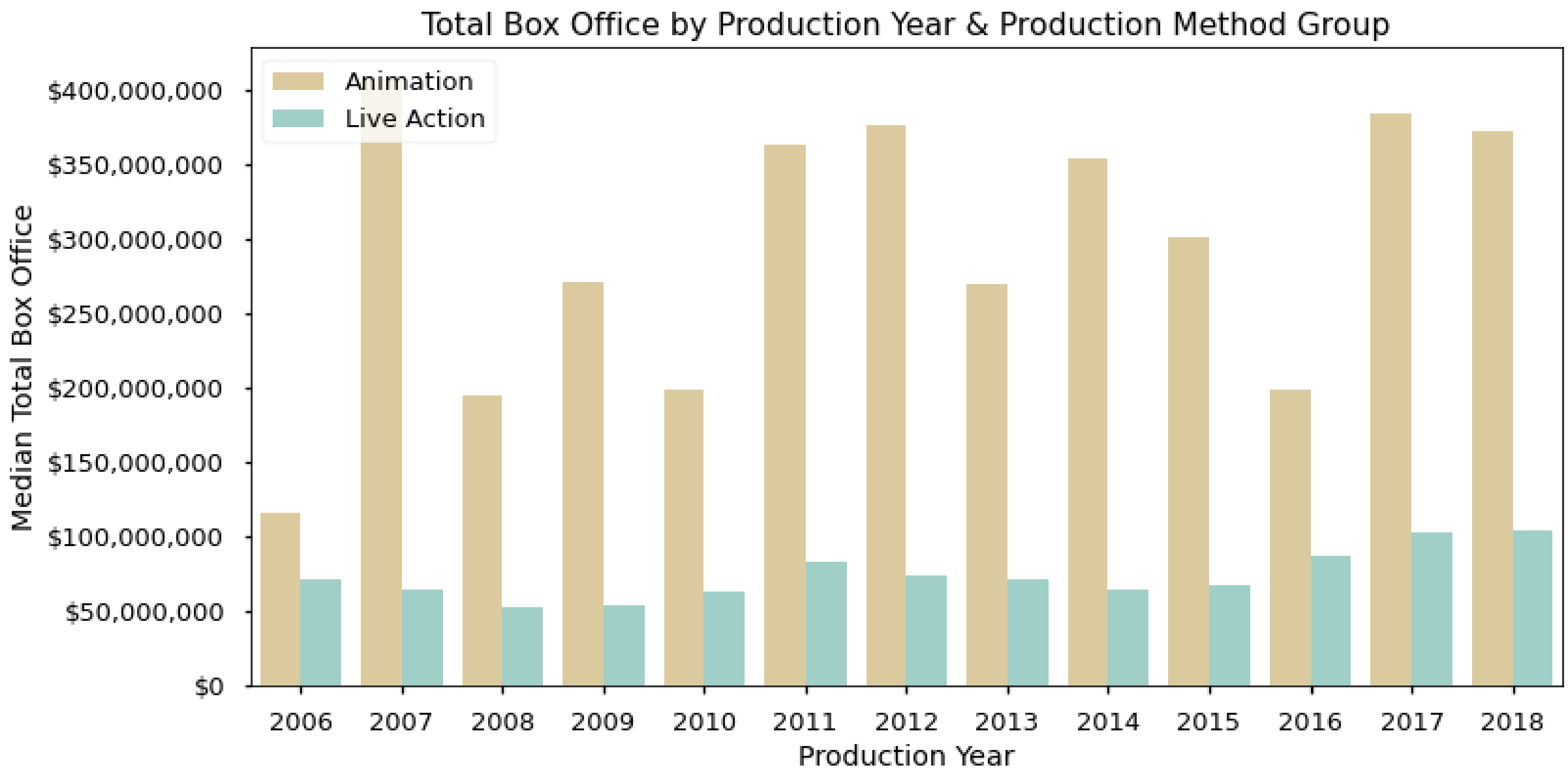
Out[43]:

	prod_method_group	production_year	total_box_office
0	Animation	2006	115954793.5
1	Animation	2007	408383484.0
2	Animation	2008	194980101.5
3	Animation	2009	270997378.0
4	Animation	2010	199256333.5
5	Animation	2011	362485352.0
6	Animation	2012	375740705.0
7	Animation	2013	269806430.0
8	Animation	2014	353756621.0
9	Animation	2015	301209748.5
10	Animation	2016	198612633.0
11	Animation	2017	383549151.0

	prod_method_group	production_year	total_box_office
12	Animation	2018	372570147.5
13	Live Action	2006	71315090.0
14	Live Action	2007	64232714.0
15	Live Action	2008	52649951.0
16	Live Action	2009	53679692.5
17	Live Action	2010	63355123.5
18	Live Action	2011	82925064.0
19	Live Action	2012	74326015.0
20	Live Action	2013	70949793.0
21	Live Action	2014	65282732.0
22	Live Action	2015	67591298.0
23	Live Action	2016	87120291.0
24	Live Action	2017	102445196.0
25	Live Action	2018	104233865.0

In [44]:

```
# Chart to show grouping above of median total box office by production method group and year.

fig, ax1 = plt.subplots(figsize=(12,6))

sns.barplot(data = intarg,
            x='production_year',
            y='total_box_office',
            hue='prod_method_group',
            palette='BrBG')

ax1.set_title('Total Box Office by Production Year & Production Method Group')
ax1.set_xlabel('Production Year')
ax1.set_ylabel('Median Total Box Office')
ax1.legend(title = False, loc='upper left')

fmt = '${x:,.0f}'
tick = mtick.StrMethodFormatter(fmt)
ax1.yaxis.set_major_formatter(tick);
```



Animated movies have a higher median total box office performance year over year. We know this value is higher, but this chart shows that animated movies have performed this way consistently over time. There is a little variance between years when looking at animated movies alone, however that is most likely due to the smaller sample size.

Argument for Sequels

Develop franchise movies to optimize box office performance and additional opportunities for monetization.

In [45]:

```
# Group by sequel flag to understand impact within family movies.

fam_mov.groupby('sequel').median()
```

Out[45]:

	production_year	movie_odid	production_budget	domestic_box_office	international_box_office	running_time	total_box_offic
sequel							
0.0	2011.0	141835100.0	39000000.0	43684162.5	45732940.0	106.0	90140118.(

	production_year	movie_odid	production_budget	domestic_box_office	international_box_office	running_time	total_box_offic
sequel							
1.0	2013.0	160385100.0	125000000.0	139990127.5	243964033.5	113.0	385504519.(

In [46]:

```
# create variable for grouping percent of international box office sequel, and year.

fambox = pd.pivot_table(fam_mov,
                        values='return',
                        columns='sequel',
                        index='production_year',
                        aggfunc=np.median,
                        fill_value=0)

fambox
```

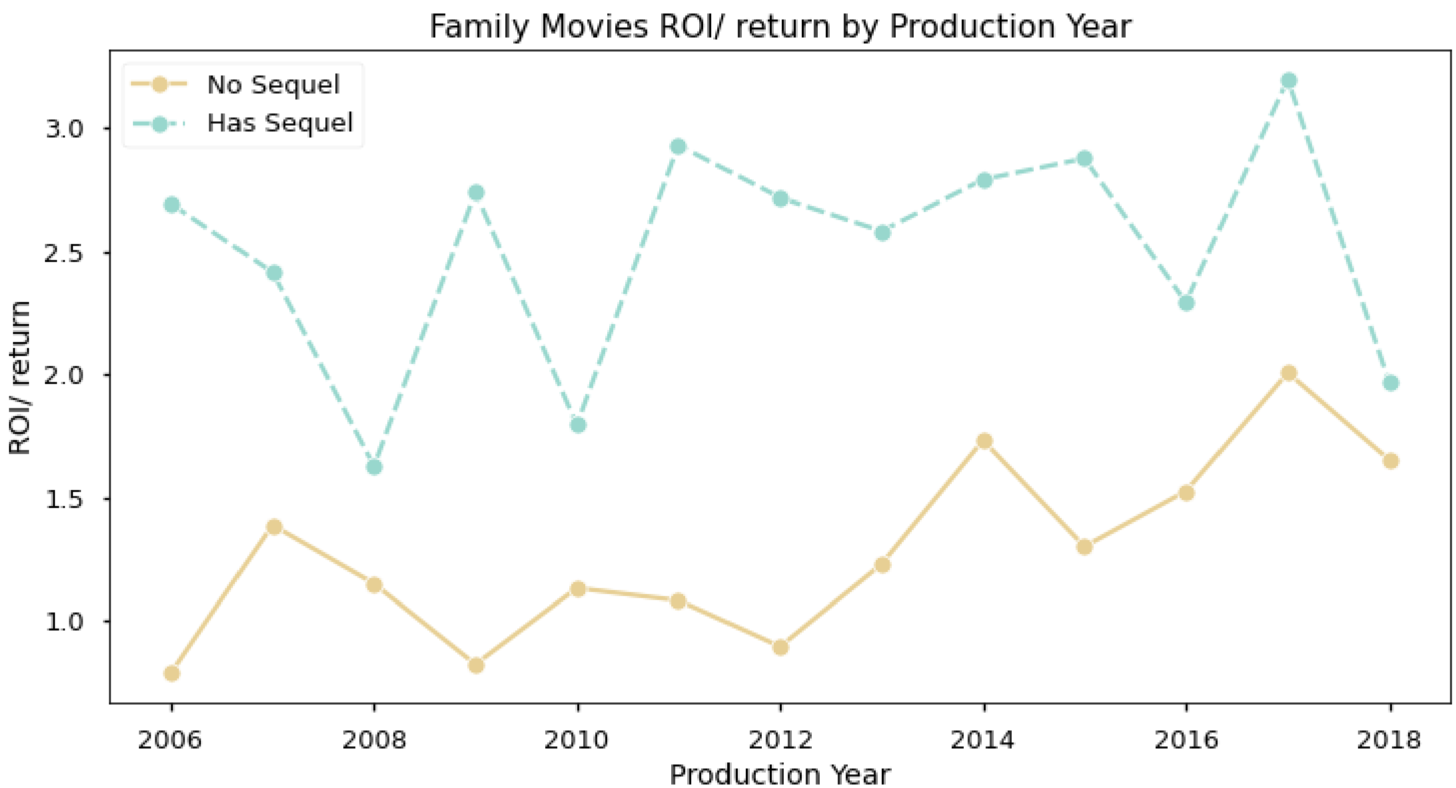
Out[46]:

sequel	0.0	1.0
production_year		
2006	0.785761	2.694373
2007	1.386720	2.415718
2008	1.149311	1.626732
2009	0.822305	2.740855
2010	1.131426	1.794282
2011	1.081241	2.930699
2012	0.894264	2.717942
2013	1.228403	2.583173
2014	1.731787	2.791125
2015	1.299485	2.876652
2016	1.524627	2.292976
2017	2.006765	3.199105
2018	1.652283	1.968023

In [47]:

```
# Chart showing data above
```

```
fig, ax1 = plt.subplots(figsize=(12,6))

sns.lineplot(data = fambox,
             marker='o',
             palette='BrBG')

ax1.set_title('Family Movies ROI/ return by Production Year')
ax1.set_xlabel('Production Year')
ax1.set_ylabel('ROI/ return')
ax1.legend(title = False, labels=['No Sequel', 'Has Sequel']);
```



Movies that have a sequel have performed better on the international stage. Having a higher percentage of international box office has a higher return median. Thus with these variables, having a sequel or franchise based movies, will further ensure success for return on investment.

In [48]:
```
# high level view of genre movie counts, just understanding records between the categories.

fam_mov['production_method'].value_counts()
```

Out[48]:
```
Live Action               846
Digital Animation         135
Animation/Live Action      73
Stop-Motion Animation       9
Hand Animation              5
Name: production_method, dtype: int64
```

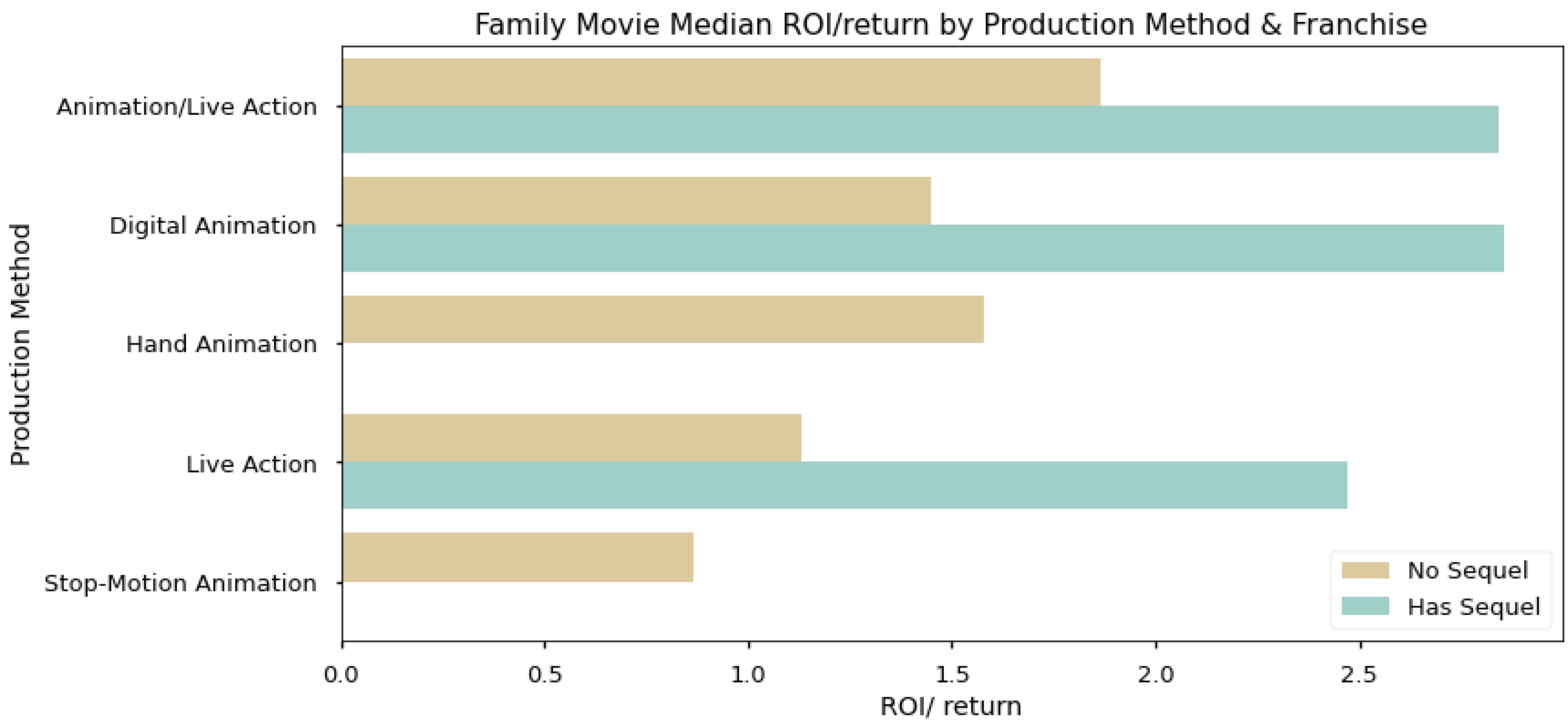
In [49]:
```
# creating a pivot table for charting below.

tabledf = (
    fam_mov
    .groupby(['sequel', 'production_method'])['return']
    .median()
    .reset_index()
    )

tabledf
```

Out[49]:

	sequel	production_method	return
0	0.0	Animation/Live Action	1.867156
1	0.0	Digital Animation	1.447918
2	0.0	Hand Animation	1.580927
3	0.0	Live Action	1.131426
4	0.0	Stop-Motion Animation	0.865771
5	1.0	Animation/Live Action	2.841467
6	1.0	Digital Animation	2.856657
7	1.0	Live Action	2.468451

In [50]:
```
labels = ['No Sequel', 'Has Sequel']

fig, ax = plt.subplots(figsize=(12,6))

sns.barplot(data = tabledf,
            x='return',
            y='production_method',
            hue='sequel',
            orient='h',
            palette='BrBG'
            )
```

```
ax.set_title('Family Movie Median ROI/return by Production Method & Franchise')
ax.set_xlabel('ROI/ return')
ax.set_ylabel('Production Method')


h, l = ax.get_legend_handles_labels()
ax.legend(h, labels, loc='lower right');
```



We know that movies with a sequel have a higher return. In addition, family rated movies that have a sequel perform the best as animated films.

Conclusion

Most movies that were released in this data set (between 2006 and 2018, and have a budget of over $10M) are profitable. However, when you start to look at the type of content (rating) of the movies, you can begin to dicern a higher probability of profitability. Something that is really important for a company that is just beginning their content journey.

For Microsoft, creating profitable movies from the start of the studio will help their chances of being successful, and funding additional films with revenue generated from previous movies. In summary, focusing on these 3 movie attributes and distribution will make them most successful:

1. **Create G, PG, PG-13 (“Family”) rated movies to optimize ROI.**
2. **Animated movies perform the best at the box office.**
3. **Develop franchise movies to optimize box office performance & ROI.**

Next Steps

Further analyses could yield additional insights to further improve success at Microsoft:

1. **Look at production studio data to determine inital success of movies types within the suggested rating categories.**
2. **Understand review data and how it impacts success for both studio, and franchises.**
3. **Look at sequel success in relation to cast consistency; are people going to see the movie because of the story, or the cast.**