2_Investigate_A_Dataset

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1 Project: Investigate A Dataset – Movies

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1.1 Introduction

I selected TMDb movie data (cleaned from original data on Kaggle). This data set contains information about 10,000 movies collected from The Movie Database (TMDb), including user ratings and revenue.

- Certain columns, like `cast` and `genres`, contain multiple values separated by pipe (`|`) characters.
- There are some odd characters in the `cast` column. Don't worry about cleaning them. You can leave them as is.
- The final two columns ending with `_adj` show the budget and revenue of the associated movie in terms of 2010 dollars, accounting for inflation over time.

1.1.1 Questions

Here are the questions I set out to answer:

- Which movies were most and least profitable?
- What was the most profitable movie each year?
- Have movie budgets increased over time?
- Are blockbuster movies longer than non-blockbusters?
- What is the most profitable genre?

1.2 Imports and settings

In [1]:
```
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
from scipy import stats

%matplotlib inline
%config InlineBackend.figure_format = 'retina'
```

In [2]:
```
# PyPlot style sheets
plt.style.use('fivethirtyeight')
plt.style.use('seaborn-poster')

# Format floats to show commas and two decimals
pd.options.display.float_format = "{0:,.2f}".format
```

1.3 Data wrangling

1.3.1 General properties

In [3]:
```
# Load your data and print out a few lines.
df = pd.read_csv('data/tmdb-movies.csv')
df.head()
```

Out[3]:

	id	imdb_id	popularity	budget	revenue	original_title	cast	homepage	director	tagline	...
0	135397	tt0369610	32.99	150000000	1513528810	Jurassic World	Chris Pratt|Bryce Dallas Howard|Irrfan Khan|Vi...	http://www.jurassicworld.com/	Colin Trevorrow	The park is open.	...
1	76341	tt1392190	28.42	150000000	378436354	Mad Max: Fury Road	Tom Hardy|Charlize Theron|Hugh Keays-Byrne|Nic...	http://www.madmaxmovie.com/	George Miller	What a Lovely Day.	...
2	262500	tt2908446	13.11	110000000	295238201	Insurgent	Shailene Woodley|Theo James|Kate Winslet|Ansel...	http://www.thedivergentseries.movie/#insurgent	Robert Schwentke	One Choice Can Destroy You	...
3	140607	tt2488496	11.17	200000000	2068178225	Star Wars: The Force Awakens	Harrison Ford|Mark Hamill|Carrie Fisher|Adam D...	http://www.starwars.com/films/star-wars-episod...	J.J. Abrams	Every generation has a story.	...
4	168259	tt2820852	9.34	190000000	1506249360	Furious 7	Vin Diesel|Paul Walker|Jason Statham|Michelle ...	http://www.furious7.com/	James Wan	Vengeance Hits Home	...

```
                                                overview runtime  \
0  Twenty-two years after the events of Jurassic ...     124
1  An apocalyptic story set in the furthest reach...     120
2  Beatrice Prior must confront her inner demons ...     119
3  Thirty years after defeating the Galactic Empi...     136
4  Deckard Shaw seeks revenge against Dominic Tor...     137

                                       genres  \
0  Action|Adventure|Science Fiction|Thriller
1  Action|Adventure|Science Fiction|Thriller
2         Adventure|Science Fiction|Thriller
3   Action|Adventure|Science Fiction|Fantasy
4                     Action|Crime|Thriller

                                production_companies release_date vote_count  \
0  Universal Studios|Amblin Entertainment|Legenda...       6/9/15       5562
1  Village Roadshow Pictures|Kennedy Miller Produ...      5/13/15       6185
2  Summit Entertainment|Mandeville Films|Red Wago...      3/18/15       2480
3          Lucasfilm|Truenorth Productions|Bad Robot     12/15/15       5292
4  Universal Pictures|Original Film|Media Rights ...       4/1/15       2947

   vote_average  release_year     budget_adj      revenue_adj
0          6.50          2015 137,999,939.28 1,392,445,892.52
1          7.10          2015 137,999,939.28   348,161,292.49
2          6.30          2015 101,199,955.47   271,619,025.41
3          7.50          2015 183,999,919.04 1,902,723,129.80
4          7.30          2015 174,799,923.09 1,385,748,801.47

[5 rows x 21 columns]
```

Perform operations to inspect data types and look for instances of missing or possibly errant data.

```
In [4]: df.dtypes
```

```
Out[4]: id                      int64
        imdb_id                object
        popularity            float64
        budget                  int64
        revenue                 int64
        original_title         object
        cast                   object
        homepage               object
        director               object
        tagline                object
        keywords               object
        overview               object
```

```
runtime                   int64
genres                   object
production_companies     object
release_date             object
vote_count                int64
vote_average            float64
release_year              int64
budget_adj              float64
revenue_adj             float64
dtype: object
```

```
In [5]: df.shape
```

```
Out[5]: (10866, 21)
```

```
In [6]: df.describe()
```

Out[6]:

	id	popularity	budget	revenue	runtime	\
count	10,866.00	10,866.00	10,866.00	10,866.00	10,866.00	
mean	66,064.18	0.65	14,625,701.09	39,823,319.79	102.07	
std	92,130.14	1.00	30,913,213.83	117,003,486.58	31.38	
min	5.00	0.00	0.00	0.00	0.00	
25%	10,596.25	0.21	0.00	0.00	90.00	
50%	20,669.00	0.38	0.00	0.00	99.00	
75%	75,610.00	0.71	15,000,000.00	24,000,000.00	111.00	
max	417,859.00	32.99	425,000,000.00	2,781,505,847.00	900.00	

	vote_count	vote_average	release_year	budget_adj	revenue_adj
count	10,866.00	10,866.00	10,866.00	10,866.00	10,866.00
mean	217.39	5.97	2,001.32	17,551,039.82	51,364,363.25
std	575.62	0.94	12.81	34,306,155.72	144,632,485.04
min	10.00	1.50	1,960.00	0.00	0.00
25%	17.00	5.40	1,995.00	0.00	0.00
50%	38.00	6.00	2,006.00	0.00	0.00
75%	145.75	6.60	2,011.00	20,853,251.08	33,697,095.72
max	9,767.00	9.20	2,015.00	425,000,000.00	2,827,123,750.41

```
In [7]: df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10866 entries, 0 to 10865
Data columns (total 21 columns):
id                      10866 non-null int64
imdb_id                 10856 non-null object
popularity              10866 non-null float64
budget                  10866 non-null int64
revenue                 10866 non-null int64
original_title          10866 non-null object
cast                    10790 non-null object
```

```
homepage                2936 non-null object
director                10822 non-null object
tagline                 8042 non-null object
keywords                9373 non-null object
overview                10862 non-null object
runtime                 10866 non-null int64
genres                  10843 non-null object
production_companies    9836 non-null object
release_date            10866 non-null object
vote_count              10866 non-null int64
vote_average            10866 non-null float64
release_year            10866 non-null int64
budget_adj              10866 non-null float64
revenue_adj             10866 non-null float64
dtypes: float64(4), int64(6), object(11)
memory usage: 1.7+ MB
```

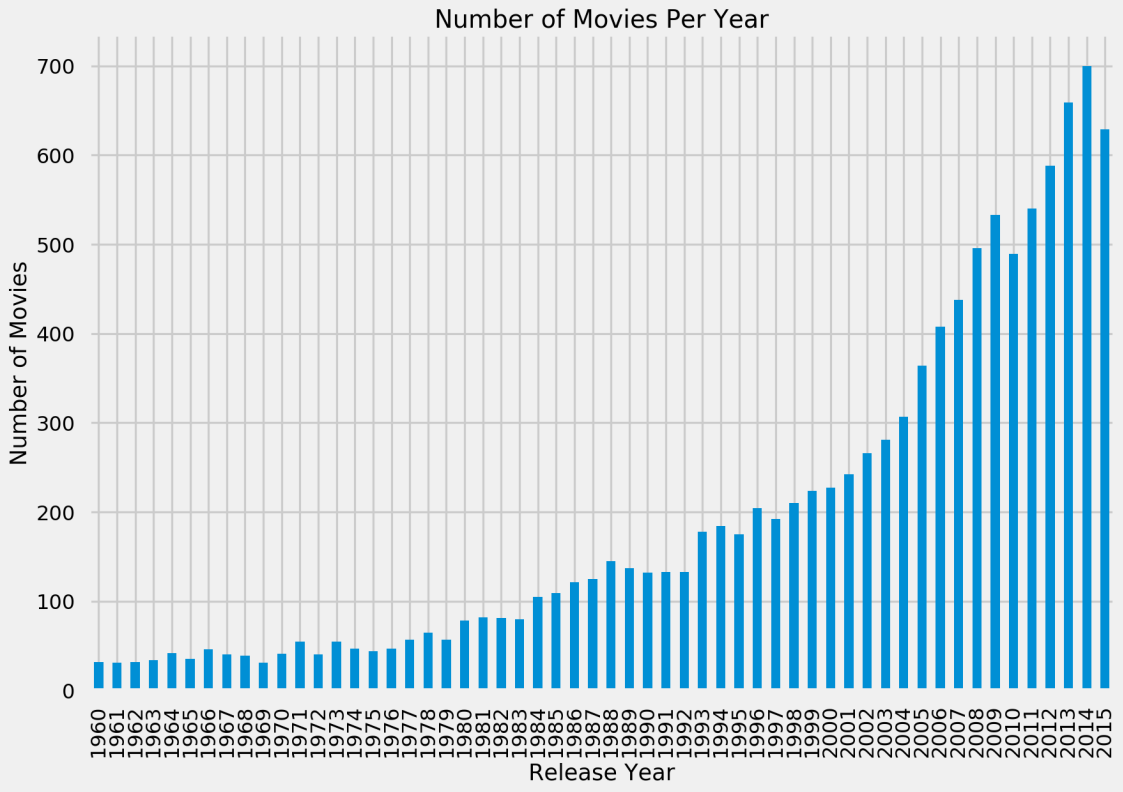
```
In [8]: df.nunique()
```

```
Out[8]: id                      10865
        imdb_id                 10855
        popularity              10814
        budget                    557
        revenue                  4702
        original_title          10571
        cast                    10719
        homepage                 2896
        director                 5067
        tagline                  7997
        keywords                 8804
        overview                10847
        runtime                   247
        genres                   2039
        production_companies     7445
        release_date             5909
        vote_count               1289
        vote_average               72
        release_year               56
        budget_adj               2614
        revenue_adj              4840
        dtype: int64
```

How are the movies distributed by release year?

```
In [63]: df.groupby('release_year')['id'].count().plot.bar()
         plt.xlabel('Release Year')
         plt.ylabel('Number of Movies')
```

```
plt.title('Number of Movies Per Year')
plt.show()
```



1.4 Data cleaning

1.4.1 Eliminate duplicates

I noticed that there is at least one duplicate row (there are 10866 entries but only 10865 unique ids).

```
In [11]: # Get rid of any duplicate rows
         df.drop_duplicates(inplace=True)
```

1.4.2 Fix datatypes

The `release_date` column is an object, but it should be a datetime.

```
In [12]: df.release_date.head()
```

```
Out[12]: 0      6/9/15
         1     5/13/15
         2     3/18/15
         3    12/15/15
         4      4/1/15
         Name: release_date, dtype: object
```

```
In [13]: # Convert to a datetime
         df['release_date'] = pd.to_datetime(df['release_date'])

In [14]: df.release_date.head()

Out[14]: 0   2015-06-09
         1   2015-05-13
         2   2015-03-18
         3   2015-12-15
         4   2015-04-01
         Name: release_date, dtype: datetime64[ns]
```

1.4.3 Add derived columns

I intend to look at profitability, so I'm going to add a `net_income` column.

```
In [15]: df['revenue_adj'].describe()

Out[15]: count          10,865.00
         mean       51,369,001.76
         std       144,638,333.13
         min                 0.00
         25%                 0.00
         50%                 0.00
         75%        33,701,729.01
         max     2,827,123,750.41
         Name: revenue_adj, dtype: float64

In [16]: df['budget_adj'].describe()

Out[16]: count        10,865.00
         mean     17,549,894.04
         std      34,307,526.66
         min               0.00
         25%               0.00
         50%               0.00
         75%      20,853,251.08
         max     425,000,000.00
         Name: budget_adj, dtype: float64
```

There are a lot of zeros and I don't want to include them in any income calculations. Here's a quick function to calculate net income *only* if both budget and revenue are greater than zero. I'll return `NaN` if not so I can easily drop those rows later.

Since I'm going to be comparing profits over time, I want to make sure to use the inflation-adjusted revenue and budget numbers. I'll be using the `_adj` columns.

```
In [17]: # Calculate net income only if both budget_adj and revenue_adj are > 0
         def income(row):
             if row['budget_adj'] > 0 and row['revenue_adj'] > 0:
```

```
            val = row['revenue_adj'] - row['budget_adj']
        else:
            val = float('NaN')
        return val
```

```
In [18]: # Now run the function on every row to create a new column called net_income
         df['net_income'] = df.apply(income, axis=1)
```

```
In [19]: df.net_income.describe()
```

```
Out[19]: count           3,854.00
         mean       92,824,697.22
         std       194,071,459.74
         min      -413,912,431.00
         25%        -1,504,994.63
         50%        27,370,641.16
         75%       107,454,751.41
         max     2,750,136,650.92
         Name: net_income, dtype: float64
```

1.4.4 Normalize overloaded columns

The `cast` and `genres` columns are pipe-delimited strings. I'm going to extract them into new dataframes and create lookup dataframes to handle the relationships.

```
In [20]: # I found this function for flattening columns that contain
         # multiple delimited values. It does exactly what I need.
         # Found here: https://gist.github.com/jlln/338b4b0b55bd6984f883
         def splitDataFrameList(df, target_column, separator):
             ''' df = dataframe to split,
             target_column = the column containing the values to split
             separator = the symbol used to perform the split
             returns: a dataframe with each entry for the target column
             separated, with each element moved into a new row.
             The values in the other columns are duplicated across
             the newly divided rows.
             '''
             row_accumulator = []

             def splitListToRows(row, separator):
                 split_row = row[target_column].split(separator)
                 for s in split_row:
                     new_row = row.to_dict()
                     new_row[target_column] = s
                     row_accumulator.append(new_row)

             df.apply(splitListToRows, axis=1, args=(separator, ))
             new_df = pd.DataFrame(row_accumulator)
             return new_df
```

```
In [21]: # Split and flatten the cast and genres categories
         df_flat = splitDataFrameList(df.dropna(), 'cast', '|')
         df_flat = splitDataFrameList(df_flat.dropna(), 'genres', '|')
         df_flat = splitDataFrameList(df_flat.dropna(), 'keywords', '|')

In [22]: df_flat.describe()
```

Out[22]:

	budget	budget_adj	id	net_income	popularity
count	79,400.00	79,400.00	79,400.00	79,400.00	79,400.00
mean	60,724,919.60	63,757,724.78	49,444.64	172,223,733.42	2.03
std	59,801,738.44	59,404,434.38	70,693.56	295,085,244.58	2.46
min	1.00	0.97	11.00	-413,912,431.00	0.01
25%	17,000,000.00	19,387,960.85	4,464.00	5,387,689.10	0.76
50%	40,000,000.00	43,622,911.92	17,979.00	60,073,390.00	1.32
75%	85,000,000.00	91,941,878.45	60,308.00	210,161,353.21	2.49
max	425,000,000.00	425,000,000.00	333,348.00	2,750,136,650.92	32.99

	release_year	revenue	revenue_adj	runtime	vote_average
count	79,400.00	79,400.00	79,400.00	79,400.00	79,400.00
mean	2,006.67	208,570,350.20	235,981,458.19	111.02	6.30
std	8.49	281,825,273.88	326,061,177.81	19.43	0.80
min	1,961.00	43.00	43.00	63.00	2.20
25%	2,005.00	31,670,620.00	34,084,779.31	97.00	5.80
50%	2,009.00	101,371,017.00	110,662,825.91	108.00	6.30
75%	2,011.00	284,600,000.00	320,834,306.77	122.00	6.90
max	2,015.00	2,781,505,847.00	2,827,123,750.41	201.00	8.30

	vote_count
count	79,400.00
mean	1,110.75
std	1,377.22
min	10.00
25%	228.00
50%	560.00
75%	1,527.00
max	9,767.00

To keep things clean, I'm going to make separate dataframes:

- `df_film` will contain only columns I won't be summing or averaging (such as genre and cast)
- `df_vals` will contain the remaining columns

```
In [23]: df_film = df_flat.drop(columns=[
             'budget', 'budget_adj', 'net_income', 'revenue', 'revenue_adj',
             'vote_average', 'vote_count'
         ])
         df_film.head()
```

Out[23]:

	cast	director	genres	homepage	id	imdb_id	keywords	original_title	overview	popularity	production_companies	release_date	release_year	runtime	tagline
0	Chris Pratt	Colin Trevorrow	Action	http://www.jurassicworld.com/	135397	tt0369610	monster	Jurassic World	Twenty-two years after the events of Jurassic ...	32.99	Universal Studios|Amblin Entertainment|Legenda...	2015-06-09	2015	124	The park is open.
1	Chris Pratt	Colin Trevorrow	Action	http://www.jurassicworld.com/	135397	tt0369610	dna	Jurassic World	Twenty-two years after the events of Jurassic ...	32.99	Universal Studios|Amblin Entertainment|Legenda...	2015-06-09	2015	124	The park is open.
2	Chris Pratt	Colin Trevorrow	Action	http://www.jurassicworld.com/	135397	tt0369610	tyrannosaurus rex	Jurassic World	Twenty-two years after the events of Jurassic ...	32.99	Universal Studios|Amblin Entertainment|Legenda...	2015-06-09	2015	124	The park is open.
3	Chris Pratt	Colin Trevorrow	Action	http://www.jurassicworld.com/	135397	tt0369610	velociraptor	Jurassic World	Twenty-two years after the events of Jurassic ...	32.99	Universal Studios|Amblin Entertainment|Legenda...	2015-06-09	2015	124	The park is open.
4	Chris Pratt	Colin Trevorrow	Action	http://www.jurassicworld.com/	135397	tt0369610	island	Jurassic World	Twenty-two years after the events of Jurassic ...	32.99	Universal Studios|Amblin Entertainment|Legenda...	2015-06-09	2015	124	The park is open.

In [24]:
```
df_vals = df_flat.drop(columns=['genres', 'cast', 'keywords'])
df_vals.drop_duplicates(inplace=True)
df_vals.head()
```

Out[24]:

	budget	budget_adj	director	homepage	id	imdb_id	original_title	overview	popularity	production_companies	release_date	release_year	runtime	tagline
0	150000000	137,999,939.28	Colin Trevorrow	http://www.jurassicworld.com/	135397	tt0369610	Jurassic World	Twenty-two years after the events of Jurassic ...	32.99	Universal Studios|Amblin Entertainment|Legenda...	2015-06-09	2015	124	The park is open.
100	150000000	137,999,939.28	George Miller											
200	110000000	101,199,955.47	Robert Schwentke											
275	200000000	183,999,919.04	J.J. Abrams											
375	190000000	174,799,923.09	James Wan											

```
100                         http://www.madmaxmovie.com/   76341  tt1392190
200     http://www.thedivergentseries.movie/#insurgent  262500  tt2908446
275  http://www.starwars.com/films/star-wars-episod...  140607  tt2488496
375                           http://www.furious7.com/  168259  tt2820852

          net_income                original_title  \
0   1,254,445,953.24                Jurassic World
100   210,161,353.21            Mad Max: Fury Road
200   170,419,069.94                      Insurgent
275 1,718,723,210.76  Star Wars: The Force Awakens
375 1,210,948,878.38                      Furious 7

                                              overview  popularity  \
0    Twenty-two years after the events of Jurassic ...       32.99
100  An apocalyptic story set in the furthest reach...       28.42
200  Beatrice Prior must confront her inner demons ...       13.11
275  Thirty years after defeating the Galactic Empi...       11.17
375  Deckard Shaw seeks revenge against Dominic Tor...        9.34

                                  production_companies release_date  \
0    Universal Studios|Amblin Entertainment|Legenda...   2015-06-09
100  Village Roadshow Pictures|Kennedy Miller Produ...   2015-05-13
200  Summit Entertainment|Mandeville Films|Red Wago...   2015-03-18
275          Lucasfilm|Truenorth Productions|Bad Robot   2015-12-15
375  Universal Pictures|Original Film|Media Rights ...   2015-04-01

     release_year     revenue      revenue_adj  runtime  \
0            2015  1513528810 1,392,445,892.52      124
100          2015   378436354   348,161,292.49      120
200          2015   295238201   271,619,025.41      119
275          2015  2068178225 1,902,723,129.80      136
375          2015  1506249360 1,385,748,801.47      137

                           tagline  vote_average  vote_count
0                The park is open.          6.50        5562
100              What a Lovely Day.          7.10        6185
200     One Choice Can Destroy You          6.30        2480
275  Every generation has a story.          7.50        5292
375             Vengeance Hits Home          7.30        2947
```

1.5 Exploratory data analysis

1.5.1 Research Question: Which movies were most and least profitable?

What are the most profitable movies?

```
In [25]: df_vals.sort_values(['net_income'], ascending=False)[[
             'id', 'original_title', 'budget_adj', 'revenue_adj', 'net_income'
         ]].head()
```

Out[25]:

	id	original_title	budget_adj	revenue_adj	net_income
9910	11	Star Wars	39,575,591.36	2,789,712,242.28	2,750,136,650.92
10060	19995	Avatar	240,886,902.89	2,827,123,750.41	2,586,236,847.52
49789	597	Titanic	271,692,064.21	2,506,405,735.42	2,234,713,671.21
79025	9552	The Exorcist	39,289,276.63	2,167,324,901.20	2,128,035,624.57
77245	578	Jaws	28,362,748.20	1,907,005,841.92	1,878,643,093.71

What are the *least* profitable movies?

In [26]:
```
df_vals.sort_values(['net_income'], ascending=True)[[
    'id', 'original_title', 'budget_adj', 'revenue_adj', 'net_income'
]].head()
```

Out[26]:

	id	original_title	budget_adj	revenue_adj	net_income
23771	46528	The Warrior's Way	425,000,000.00	11,087,569.00	-413,912,431.00
52909	57201	The Lone Ranger	238,688,504.95	83,578,333.82	-155,110,171.13
37094	50321	Mars Needs Moms	145,409,706.39	37,799,503.28	-107,610,203.11
59184	11619	Flushed Away	161,168,704.59	69,723,654.08	-91,445,050.50
76025	10153	Sphere	100,327,160.18	17,523,810.64	-82,803,349.54

According to this, *The Warrior's Way* (2010) was the least profitable movie of all time, with a \$425M budget and only \$11M in revenue. Hold on, though, that seems suspiciously bad. According to the film's Wikipedia page, the movie had a budget of **\$42M**, not \$425M! The data is off by an order of magnitude. Still a turkey, but not a nine-figure turkey.

Finding inaccuracies in the dataset makes me question its quality. I'll proceed with caution when it comes to budget and revenue. Since this one is such an outlier, I'll manually correct it by just dropping the row and moving on.

In [27]:
```
# Drop The Warrior's Way (id=46528)
df_vals = df_vals[df_vals.id != 46528]
```

In [28]:
```
df_vals.sort_values(['net_income'], ascending=True)[[
    'id', 'original_title', 'budget_adj', 'revenue_adj', 'net_income'
]].head()
```

Out[28]:

	id	original_title	budget_adj	revenue_adj	net_income
52909	57201	The Lone Ranger	238,688,504.95	83,578,333.82	-155,110,171.13
37094	50321	Mars Needs Moms	145,409,706.39	37,799,503.28	-107,610,203.11
59184	11619	Flushed Away	161,168,704.59	69,723,654.08	-91,445,050.50
76025	10153	Sphere	100,327,160.18	17,523,810.64	-82,803,349.54
56894	10077	A Sound of Thunder	89,325,063.17	6,687,812.14	-82,637,251.03

1.5.2 Research Question: What was the most profitable movie each year?

To see what the most profitable movie was for each year in the dataset, I want to use groupby and then select the max, adding the index of each row to `idx`.

In [29]:
```
idx = df.groupby(['release_year'
                  ])['net_income'].transform(max) == df['net_income']
df[idx].sort_values(['release_year'], ascending=True)[[
    'id', 'original_title', 'release_year', 'budget_adj', 'net_income'
]]
```

Out[29]:

	id	original_title	release_year	\
10143	967	Spartacus	1960	
10110	12230	One Hundred and One Dalmatians	1961	
9849	646	Dr. No	1962	
10438	657	From Russia With Love	1963	
9881	658	Goldfinger	1964	
10690	15121	The Sound of Music	1965	
10822	396	Who's Afraid of Virginia Woolf?	1966	
10398	9325	The Jungle Book	1967	
9719	62	2001: A Space Odyssey	1968	
10725	642	Butch Cassidy and the Sundance Kid	1969	
10654	9062	Love Story	1970	
9925	681	Diamonds Are Forever	1971	
7269	238	The Godfather	1972	
10594	9552	The Exorcist	1973	
9767	11072	Blazing Saddles	1974	
9806	578	Jaws	1975	
10208	19610	A Star Is Born	1976	
1329	11	Star Wars	1977	
10758	1924	Superman	1978	
7833	1367	Rocky II	1979	
7309	1891	The Empire Strikes Back	1980	
8375	85	Raiders of the Lost Ark	1981	
8889	601	E.T. the Extra-Terrestrial	1982	
7987	1892	Return of the Jedi	1983	
7883	87	Indiana Jones and the Temple of Doom	1984	
6081	105	Back to the Future	1985	
10475	744	Top Gun	1986	
9613	10998	Fatal Attraction	1987	
9454	380	Rain Man	1988	
9180	89	Indiana Jones and the Last Crusade	1989	
9986	251	Ghost	1990	
9317	280	Terminator 2: Judgment Day	1991	
8243	812	Aladdin	1992	
10223	329	Jurassic Park	1993	
4180	8587	The Lion King	1994	
8094	1642	The Net	1995	
8457	602	Independence Day	1996	
5231	597	Titanic	1997	
8970	95	Armageddon	1998	
2412	1893	Star Wars: Episode I - The Phantom Menace	1999	
8666	955	Mission: Impossible II	2000	
2634	671	Harry Potter and the Philosopher's Stone	2001	
3911	121	The Lord of the Rings: The Two Towers	2002	
4949	122	The Lord of the Rings: The Return of the King	2003	
6977	809	Shrek 2	2004	
6190	674	Harry Potter and the Goblet of Fire	2005	
6555	58	Pirates of the Caribbean: Dead Man's Chest	2006	

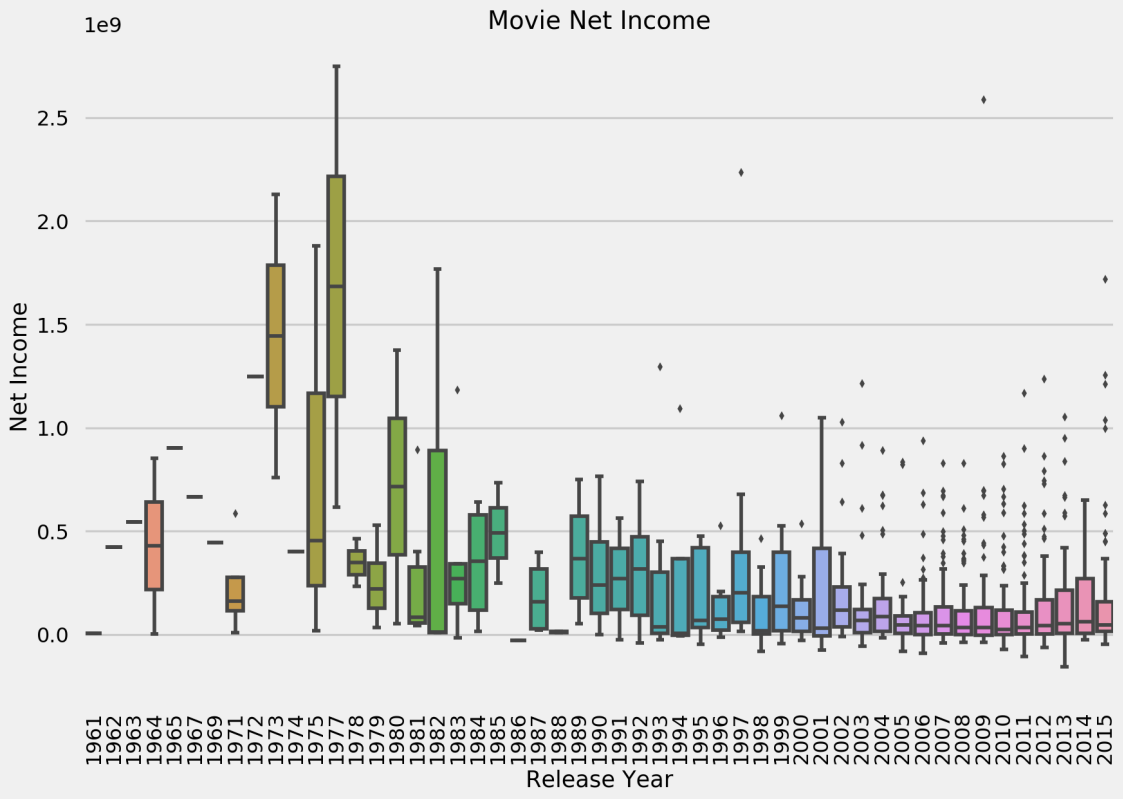
7388	675	Harry Potter and the Order of the Phoenix	2007
2875	155	The Dark Knight	2008
1386	19995	Avatar	2009
1930	10193	Toy Story 3	2010
3374	12445	Harry Potter and the Deathly Hallows: Part 2	2011
4361	24428	The Avengers	2012
5422	109445	Frozen	2013
634	122917	The Hobbit: The Battle of the Five Armies	2014
3	140607	Star Wars: The Force Awakens	2015

	budget_adj	net_income
10143	88,475,609.49	353,902,437.95
10110	29,179,444.83	1,545,635,294.87
9849	7,929,293.77	421,694,259.41
10438	17,800,448.43	543,972,910.57
9881	24,605,935.94	853,474,463.61
10690	56,748,622.29	1,072,786,239.70
10822	50,385,110.19	176,258,462.18
10398	26,147,054.96	1,319,404,004.03
9719	75,227,563.38	280,319,033.83
10725	35,665,585.21	572,485,481.13
10654	12,356,010.36	753,716,631.75
9925	38,773,403.38	585,909,206.69
7269	31,287,365.59	1,246,626,366.80
10594	39,289,276.63	2,128,035,624.57
9767	11,497,938.11	516,964,986.57
9806	28,362,748.20	1,878,643,093.71
10208	22,990,188.17	593,913,194.41
1329	39,575,591.36	2,750,136,650.92
10758	183,848,538.22	819,690,439.17
7833	21,031,878.02	580,426,232.04
7309	47,628,661.55	1,376,997,526.22
8375	43,167,434.49	891,949,443.74
8889	23,726,245.23	1,767,968,064.02
7987	70,824,243.13	1,182,994,737.99
7883	58,773,177.10	640,207,821.95
6081	38,516,154.99	734,056,616.72
10475	29,841,096.16	680,039,989.06
9613	26,867,126.13	587,518,210.63
9454	46,097,275.58	608,162,158.78
9180	84,431,277.07	749,629,788.20
9986	36,715,767.89	806,077,994.97
9317	160,109,284.19	672,458,993.61
8243	43,512,679.13	739,793,586.73
10223	95,096,607.59	1,293,766,704.17
4180	66,200,020.27	1,093,391,569.74
8094	31,481,271.08	1,551,568,265.28
8457	104,266,255.42	1,031,498,096.17

```
5231  271,692,064.21 2,234,713,671.21
8970  187,277,365.67   553,537,804.54
2412  150,541,077.36 1,059,439,453.10
8666  158,286,514.29   533,600,434.44
2634  153,936,014.59 1,048,582,021.48
3911   95,768,650.10 1,027,133,804.32
4949  111,423,148.61 1,214,854,861.87
6977  173,166,809.97   888,736,812.77
6190  167,484,493.45   832,868,045.78
6555  216,333,831.66   936,357,520.21
7388  157,750,287.39   828,938,572.98
2875  187,365,527.25   827,367,505.23
1386  240,886,902.89 2,586,236,847.52
1930  200,000,000.00   863,171,911.00
3374  121,174,755.32 1,166,009,242.24
4361  208,943,741.90 1,234,247,693.31
5422  140,405,002.91 1,052,306,488.21
634   230,272,762.69   649,479,526.45
3     183,999,919.04 1,718,723,210.76
```

What's the distribution of net income by year?

```
In [62]: ax = sns.boxplot(x='release_year',
                          y='net_income',
                          data=df_vals)
         ax.set_xticklabels(ax.get_xticklabels(), rotation=90)
         plt.xlabel('Release Year')
         plt.ylabel('Net Income')
         plt.title('Movie Net Income')
         plt.show()
```

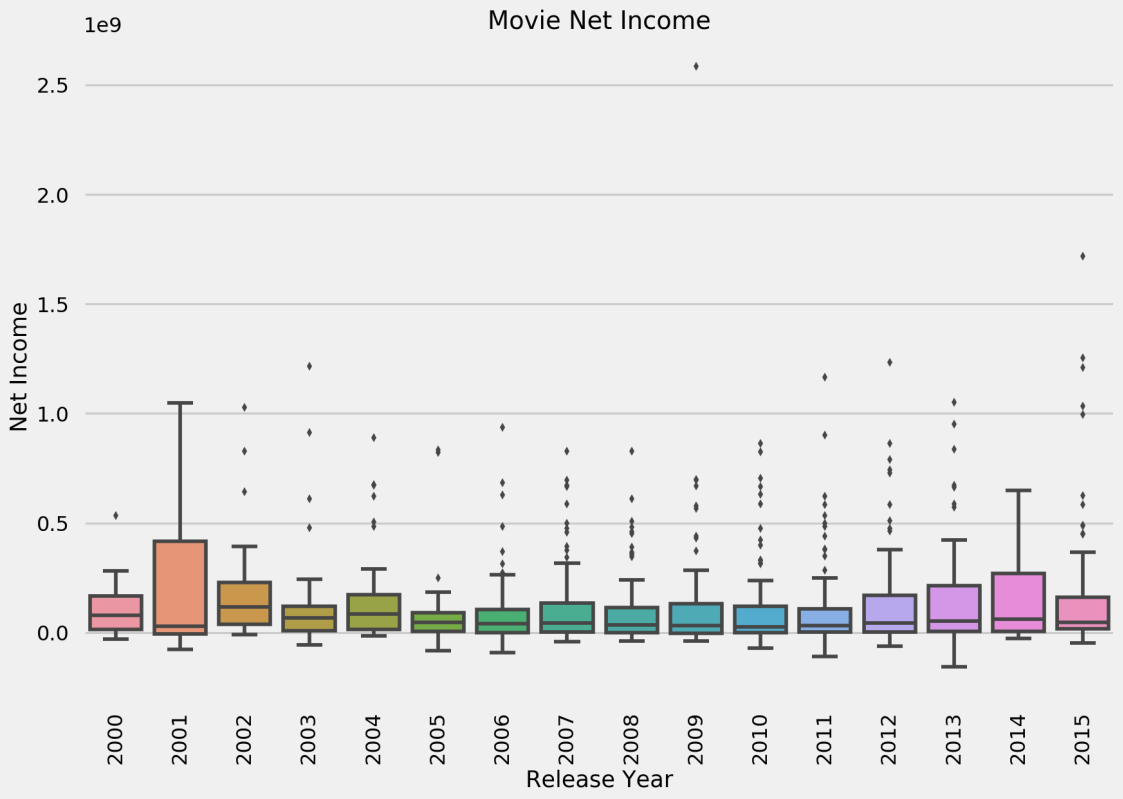


What's going on in the 1960s and 1970s? Well, for one thing there aren't many datapoints. In my bar chart above we can see there are fewer than 50 movies in the set for many of those years. And there are some big, profitable outliers, such as Jaws, The Exorcist, and Star Wars – 3 of the 5 most profitable movies in history!

This illustrates a limitation of boxplots: if your sample size is small, boxplots aren't as useful and can inflate underlying distributions.

So let's switch our boxplot to only show more recent years where we have plenty of data.

```
In [61]: ax = sns.boxplot(x='release_year',
                          y='net_income',
                          data=df_vals[df_vals['release_year'] >= 2000])
         ax.set_xticklabels(ax.get_xticklabels(), rotation=90)
         plt.xlabel('Release Year')
         plt.ylabel('Net Income')
         plt.title('Movie Net Income')
         plt.show()
```



Which films in history have netted a billion dollars or more (in 2010 dollars)?

```
In [32]: df_vals[df_vals['net_income'] >= 1e9][[
             'id', 'original_title', 'release_year', 'net_income'
         ]]
```

Out[32]:

	id	original_title	release_year	\
0	135397	Jurassic World	2015	
275	140607	Star Wars: The Force Awakens	2015	
375	168259	Furious 7	2015	
1200	99861	Avengers: Age of Ultron	2015	
9910	11	Star Wars	1977	
10060	19995	Avatar	2009	
24361	1893	Star Wars: Episode I - The Phantom Menace	1999	
25571	671	Harry Potter and the Philosopher's Stone	2001	
31424	12445	Harry Potter and the Deathly Hallows: Part 2	2011	
40734	121	The Lord of the Rings: The Two Towers	2002	
42334	8587	The Lion King	1994	
42599	24428	The Avengers	2012	
48084	122	The Lord of the Rings: The Return of the King	2003	
49789	597	Titanic	1997	
50324	109445	Frozen	2013	
65054	238	The Godfather	1972	

```
65104    1891                      The Empire Strikes Back          1980
71875    1892                           Return of the Jedi          1983
75525     601                E.T. the Extra-Terrestrial          1982
77245     578                                      Jaws          1975
78470     329                            Jurassic Park          1993
79025    9552                             The Exorcist          1973
```

```
            net_income
0     1,254,445,953.24
275   1,718,723,210.76
375   1,210,948,878.38
1200  1,035,032,450.23
9910  2,750,136,650.92
10060 2,586,236,847.52
24361 1,059,439,453.10
25571 1,048,582,021.48
31424 1,166,009,242.24
40734 1,027,133,804.32
42334 1,093,391,569.74
42599 1,234,247,693.31
48084 1,214,854,861.87
49789 2,234,713,671.21
50324 1,052,306,488.21
65054 1,246,626,366.80
65104 1,376,997,526.22
71875 1,182,994,737.99
75525 1,767,968,064.02
77245 1,878,643,093.71
78470 1,293,766,704.17
79025 2,128,035,624.57
```

```
In [33]: # Is there any correlation between movie runtime and net income?
         df_vals['runtime'].corr(df_vals['net_income'])
```

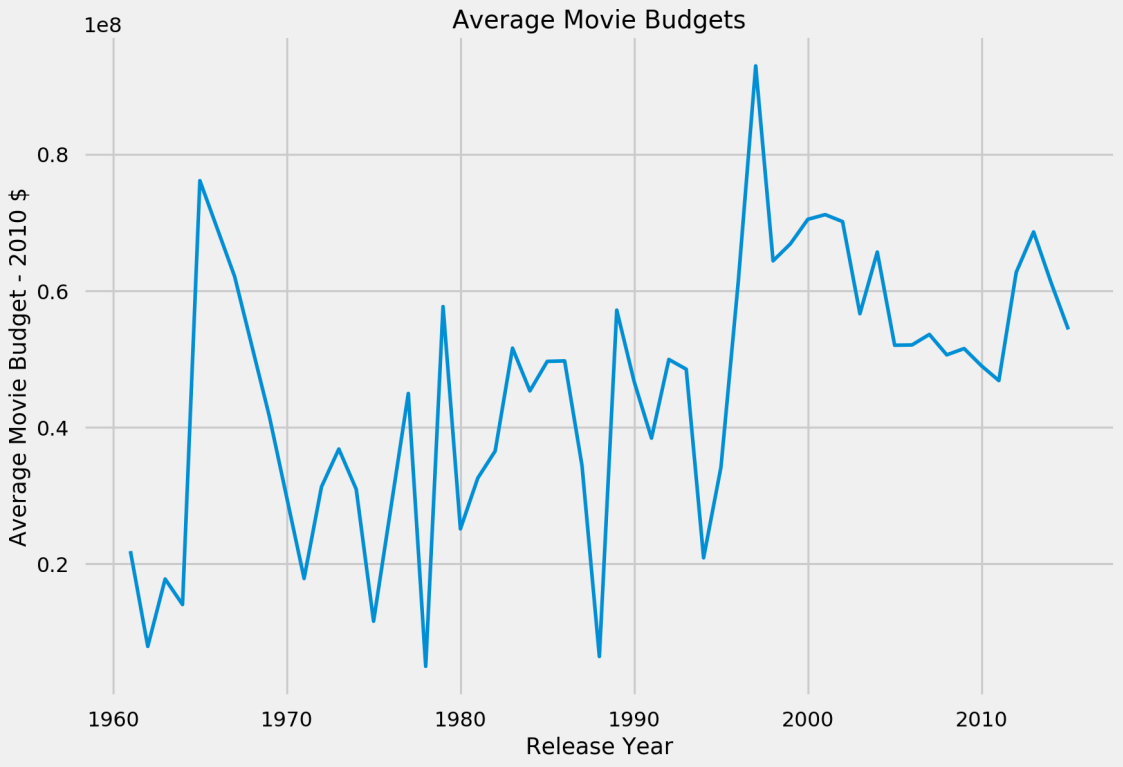
```
Out[33]: 0.33892777804141205
```

Conclusion: there is a weak positive correlation.

1.5.3 Research Question: Have movie budgets increased over time?

What is the *average* budget (in 2010 dollars) of the movies released each year?

```
In [60]: # Drop movies with 0 budget
         plt.plot(df_vals[df_vals['budget_adj'] > 0].groupby(
             'release_year').budget_adj.mean())
         plt.xlabel('Release Year')
         plt.ylabel('Average Movie Budget - 2010 $')
         plt.title('Average Movie Budgets')
         plt.show()
```



What were the biggest movie budgets of all time (in 2010 dollars)?

```
In [36]: df_vals.sort_values(['budget_adj'], ascending=False)[[
             'id', 'original_title', 'release_year', 'budget_adj', 'net_income'
         ]].head(10)
```

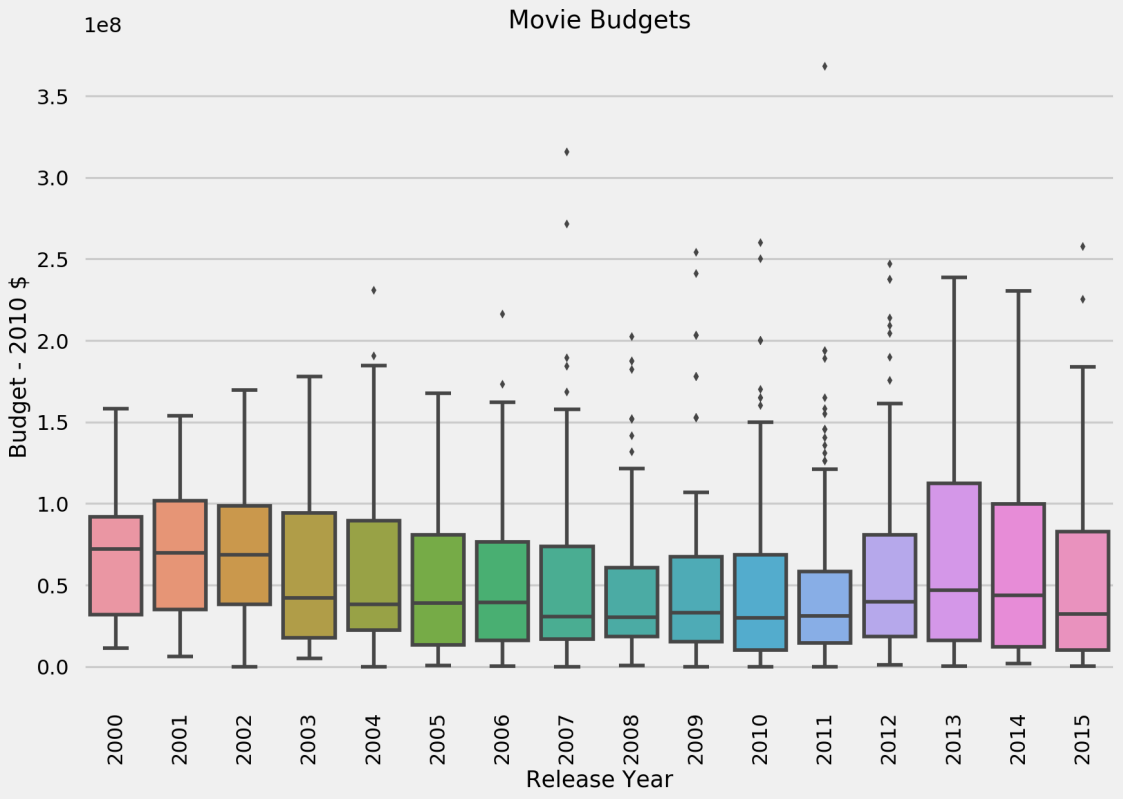
Out[36]:

	id	original_title	release_year	budget_adj	net_income
31499	1865	Pirates of the Caribbean: On Stranger Tides	2011	368,371,256.18	622,046,244.16
65204	285	Pirates of the Caribbean: At World's End	2007	315,500,574.79	695,152,933.12
49789	597	Titanic	1997	271,692,064.21	2,234,713,671.21
65804	559	Spider-Man 3	2007	271,330,494.32	665,571,205.90
17590	38757	Tangled	2010	260,000,000.00	331,794,936.00
1200	99861	Avengers: Age of Ultron	2015		
10260	767	Harry Potter and the Half-Blood Prince	2009		
17140	12444	Harry Potter and the Deathly Hallows: Part 1	2010		
45094	49529	John Carter	2012		
10060	19995	Avatar	2009		

```
1200   257,599,886.66 1,035,032,450.23
10260  254,100,108.53   695,176,424.75
17140  250,000,000.00   704,305,868.00
45094  246,933,513.15    22,925,972.18
10060  240,886,902.89 2,586,236,847.52
```

Let's look at boxplots so we can understand the distribution of budgets.

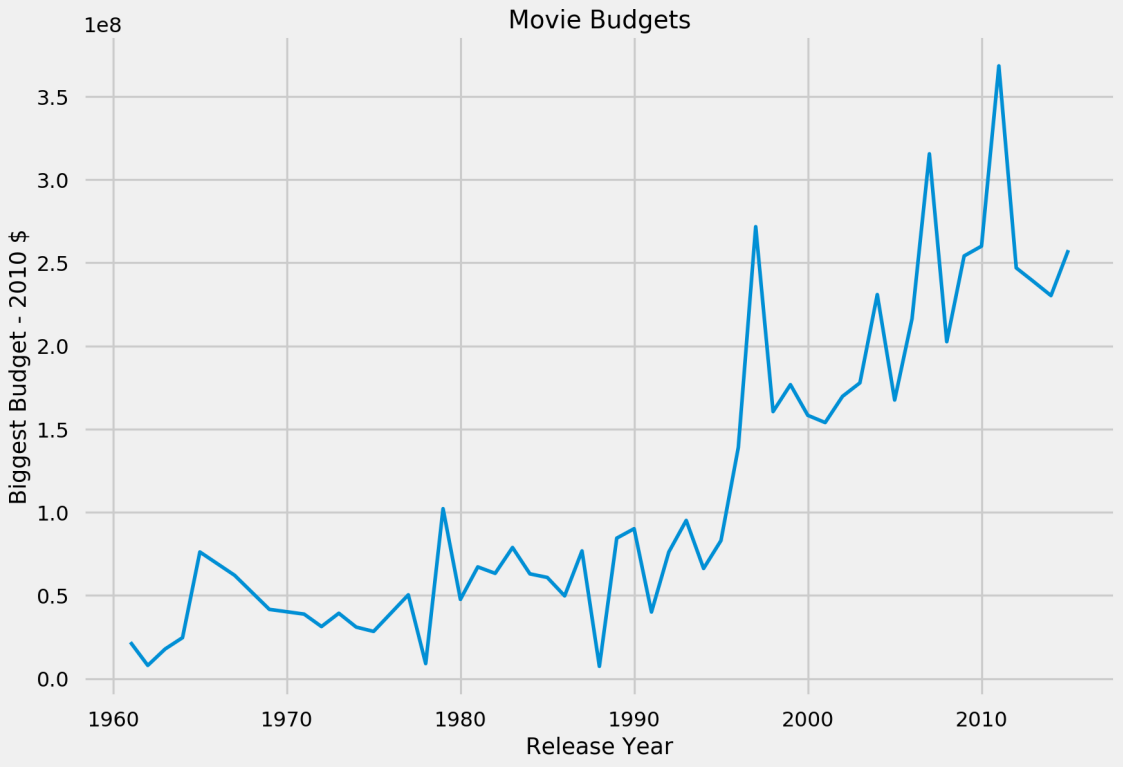
```
In [59]: # Drop movies with >0 budget, only year 2000+
         df_vals2000 = df_vals.query('budget_adj > 0 & release_year >= 2000')
         ax = sns.boxplot(x='release_year',
                          y='budget_adj',
                          data=df_vals2000)
         ax.set_xticklabels(ax.get_xticklabels(), rotation=90)
         plt.xlabel('Release Year')
         plt.ylabel('Budget - 2010 $')
         plt.title('Movie Budgets')
         plt.show()
```



Conclusion: the median movie budget has declined since 2000 with more outliers. There's an increasing inequality between the biggest budget movie and the average movie. Unless it's a blockbuster, your movie's budget has probably declined. So I would say movie budgets on average have not increased over time, but the budgets of the big blockbusters have increased.

What was the most expensive movie released each year?

```
In [58]: # Drop movies with 0 budget
         plt.plot(df_vals[df_vals['budget_adj'] > 0].groupby(
             'release_year').budget_adj.max())
         plt.xlabel('Release Year')
         plt.ylabel('Biggest Budget - 2010 $')
         plt.title('Movie Budgets')
         plt.show()
```

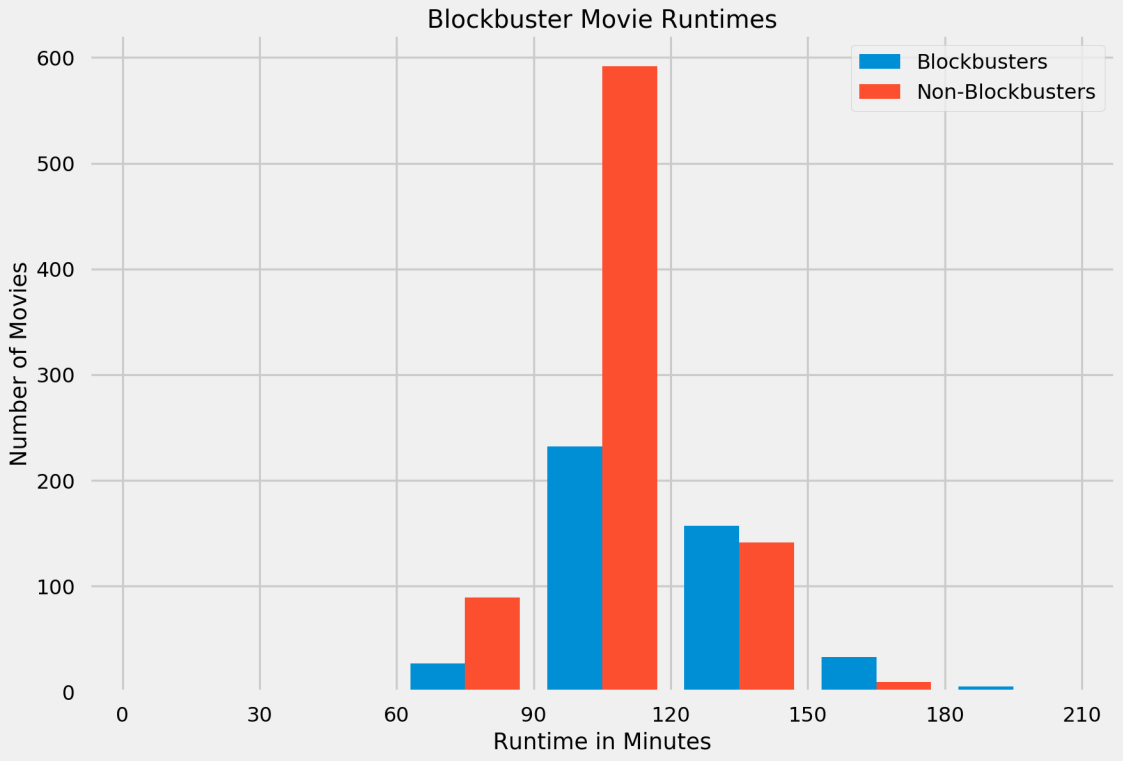


1.5.4 Research Question: Are blockbuster movies longer than non-blockbusters?

I define a blockbuster as a movie that has a net income of at least one hundred million dollars. Here I plot a histogram of blockbusters compared to non-blockbusters by runtime, grouped into 30 minute bins. We can see that movies that are 2+ hours long are more likely to be blockbusters than not.

```
In [56]: blockbusters = df_vals.query('net_income >= 1e8')
         alltherest = df_vals.query('net_income < 1e8')

         fig, ax = plt.subplots()
         bins = [0, 30, 60, 90, 120, 150, 180, 210]
         ax.set_xticks(bins)
         ax.hist([blockbusters['runtime'], alltherest['runtime']],
                 bins=bins,
```

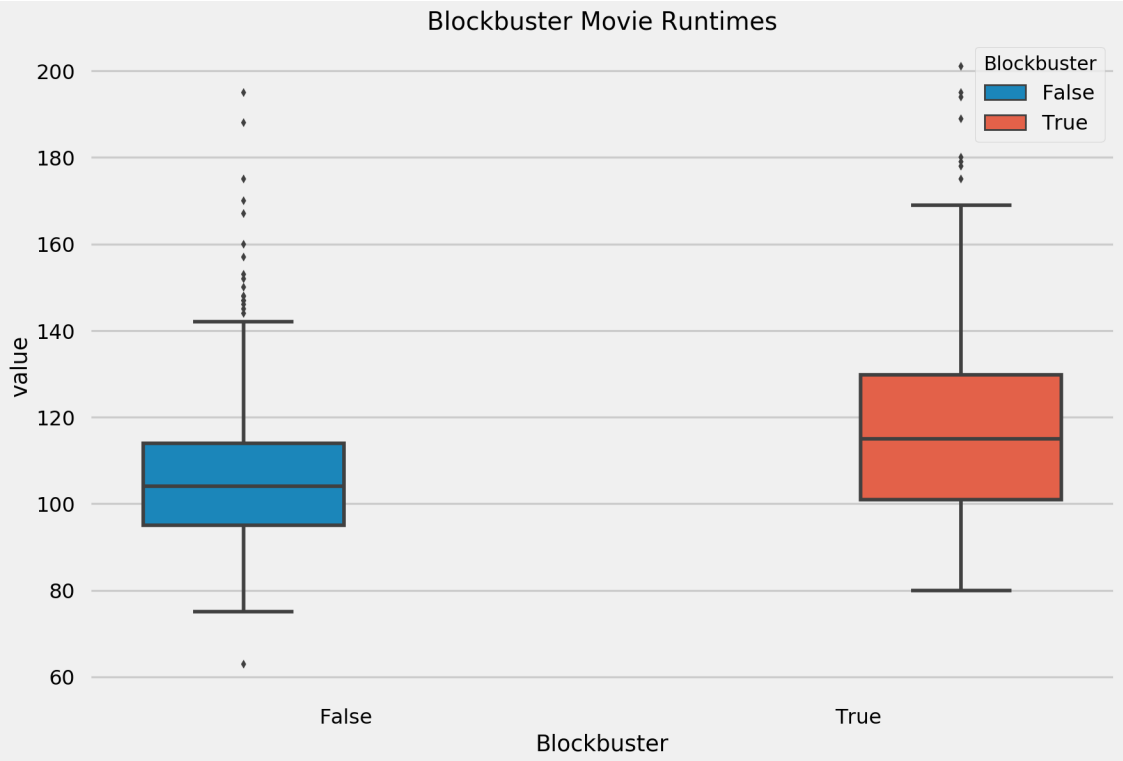
```
            label=['Blockbusters', 'Non-Blockbusters'])
plt.xlabel('Runtime in Minutes')
plt.ylabel('Number of Movies')
plt.title('Blockbuster Movie Runtimes')
ax.legend(loc='upper right')
plt.show()
```




```
In [41]: print("Blockbusters:", blockbusters.runtime.describe())
         print("Non-Blockbusters:", alltherest.runtime.describe())

Blockbusters: count   454.00
mean    117.39
std      21.53
min      80.00
25%     101.00
50%     115.00
75%     129.75
max     201.00
Name: runtime, dtype: float64
Non-Blockbusters: count   832.00
mean    106.40
std      15.88
min      63.00
```

```
25%      95.00
50%     104.00
75%     115.00
max     188.00
Name: runtime, dtype: float64
```

```
In [55]: data1 = pd.DataFrame(blockbusters,
                              columns=['runtime']).assign(Blockbuster=True)
         data2 = pd.DataFrame(alltherest, columns=['runtime']).assign(Blockbuster=False)

         cdf = pd.concat([data1, data2])
         mdf = pd.melt(cdf, id_vars=['Blockbuster'])
         plt.ylabel('Number of Movies')
         plt.title('Blockbuster Movie Runtimes')
         ax = sns.boxplot(x="Blockbuster", y="value", hue="Blockbuster", data=mdf)
         plt.show()
```

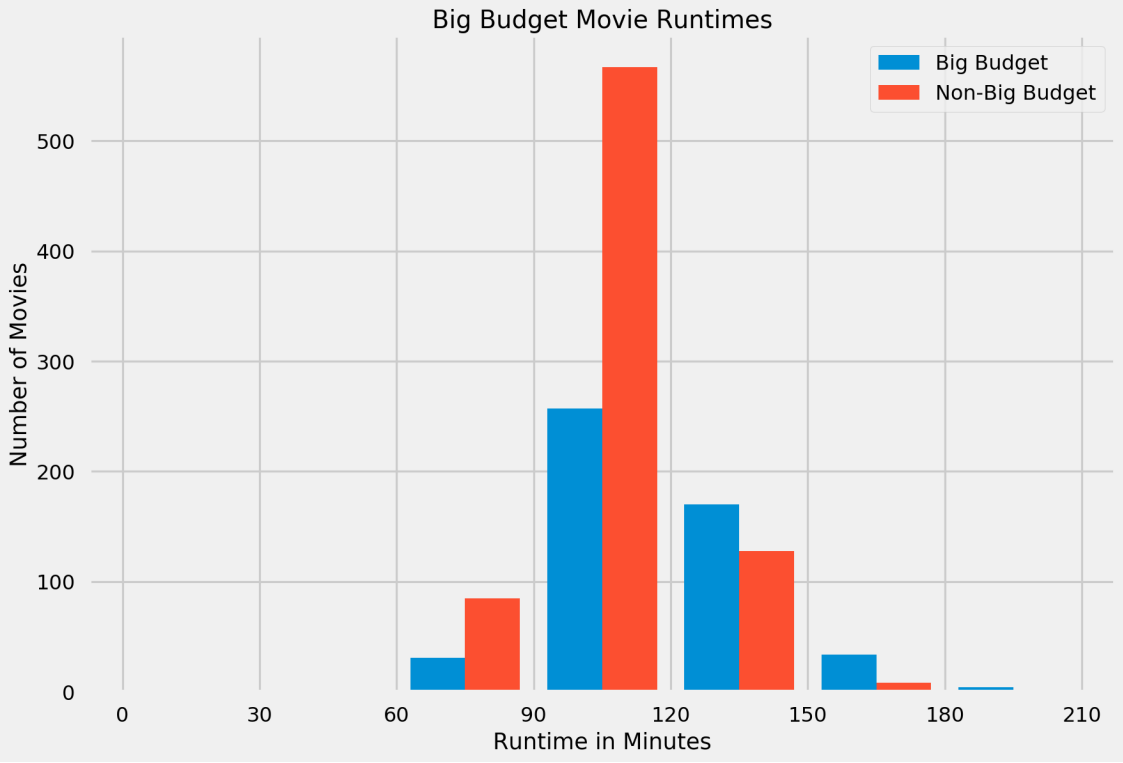



```
In [40]: stats.ttest_ind(blockbusters['runtime'], alltherest['runtime'])

Out[40]: Ttest_indResult(statistic=10.42111754706735, pvalue=1.8194114863425537e-24)
```

We can see from the t-test that although the median blockbuster is longer than the median non-blockbuster, there is no statistical significance to the difference.

When we look at budgets, we see a similar effect. If you're making a movie of over 2 hours, it's more likely you'll have a budget of more than fifty million dollars. We don't know cause-and-effect here though: if you have a bigger budget do you make a longer movie, or is the case that if you make a longer movie you require a bigger budget?

```
In [57]: bigbudget = df_vals.query('budget_adj >= 50000000')
         alltherest = df_vals.query('budget_adj < 50000000')

         fig, ax = plt.subplots()
         bins = [0, 30, 60, 90, 120, 150, 180, 210]
         ax.set_xticks(bins)
         ax.hist([bigbudget['runtime'], alltherest['runtime']],
                 bins=bins,
                 label=['Big Budget', 'Non-Big Budget'])
         ax.legend(loc='upper right')
         plt.xlabel('Runtime in Minutes')
         plt.ylabel('Number of Movies')
         plt.title('Big Budget Movie Runtimes')
         plt.show()
```



1.5.5 Research Question: What is the most profitable genre?

To look at net income by genre, we're going to need to create a new dataframe that joins `df_film` (to get genres) and `df_vals` (to get net income).

In [44]:
```
# Join the two dfs on the id key
result = pd.merge(df_film, df_vals, on='id', how='inner')
```

In [45]:
```
# We only care about a few columns, easier to just grab them then
# to drop the ones we don't want later
result = result[[
    'id', 'original_title_x', 'genres', 'revenue_adj', 'budget_adj',
    'net_income'
]]

# We ended up with original_title columns from both dfs, let's rename
# it back to original_title
result.rename(columns={'original_title_x': 'original_title'}, inplace=True)

# We have a bunch of duplicates from the expanded set, remove them
result.drop_duplicates(inplace=True)
result.head()
```

Out[45]:

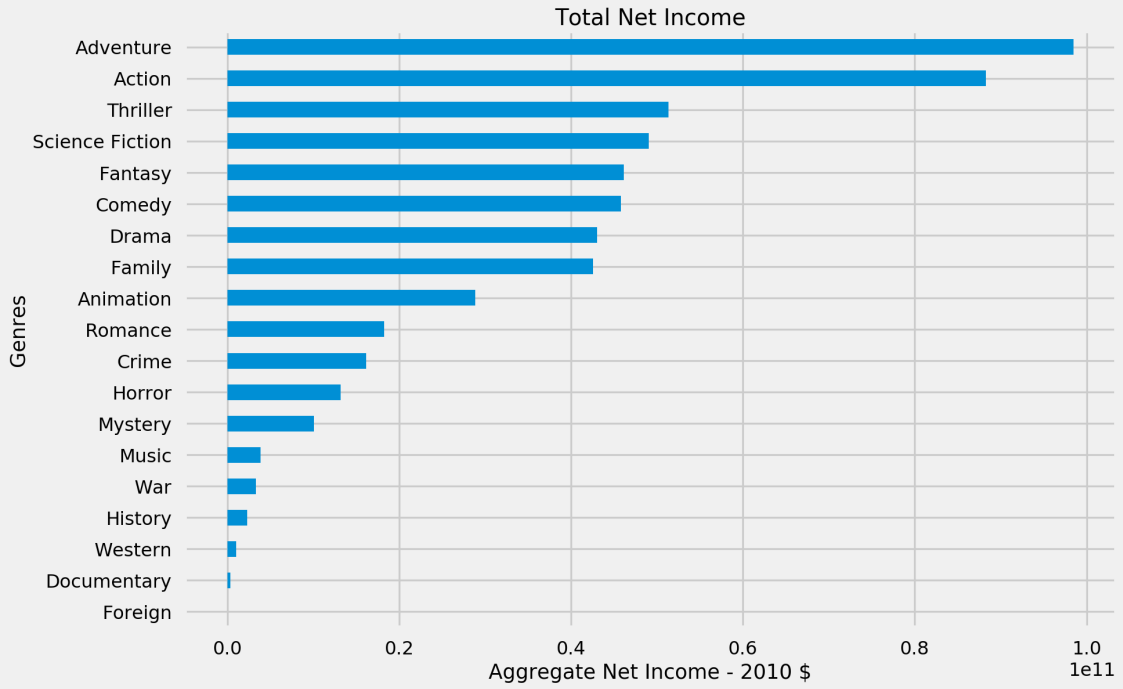
	id	original_title	genres	revenue_adj	budget_adj	net_income
0	135397	Jurassic World	Action	1,392,445,892.52	137,999,939.28	1,254,445,953.24
5	135397	Jurassic World	Adventure	1,392,445,892.52	137,999,939.28	1,254,445,953.24
10	135397	Jurassic World	Science Fiction	1,392,445,892.52	137,999,939.28	1,254,445,953.24
15	135397	Jurassic World	Thriller	1,392,445,892.52	137,999,939.28	1,254,445,953.24
100	76341	Mad Max: Fury Road	Action	348,161,292.49	137,999,939.28	210,161,353.21

In [46]:
```
result.groupby('genres').net_income.sum().sort_values(ascending=False)
```

Out[46]:
```
genres
Adventure         98,456,298,773.66
Action            88,288,139,536.53
Thriller          51,317,872,536.73
Science Fiction   49,058,392,574.84
Fantasy           46,129,163,396.99
Comedy            45,795,267,298.12
Drama             43,013,208,139.53
Family            42,587,558,778.80
Animation         28,823,610,050.17
Romance           18,211,014,055.05
Crime             16,132,383,057.04
Horror            13,179,400,828.52
Mystery           10,054,564,194.13
Music              3,881,078,931.43
```

```
War                3,342,155,586.45
History            2,288,072,621.76
Western              987,440,385.54
Documentary          309,092,494.58
Foreign               -1,312,284.00
Name: net_income, dtype: float64
```

```
In [50]: result.groupby('genres')['net_income'].sum().sort_values(
             ascending=True).plot.barh(title="Total Net Income")
         plt.xlabel('Aggregate Net Income - 2010 $')
         plt.ylabel('Genres')
         plt.show()
```



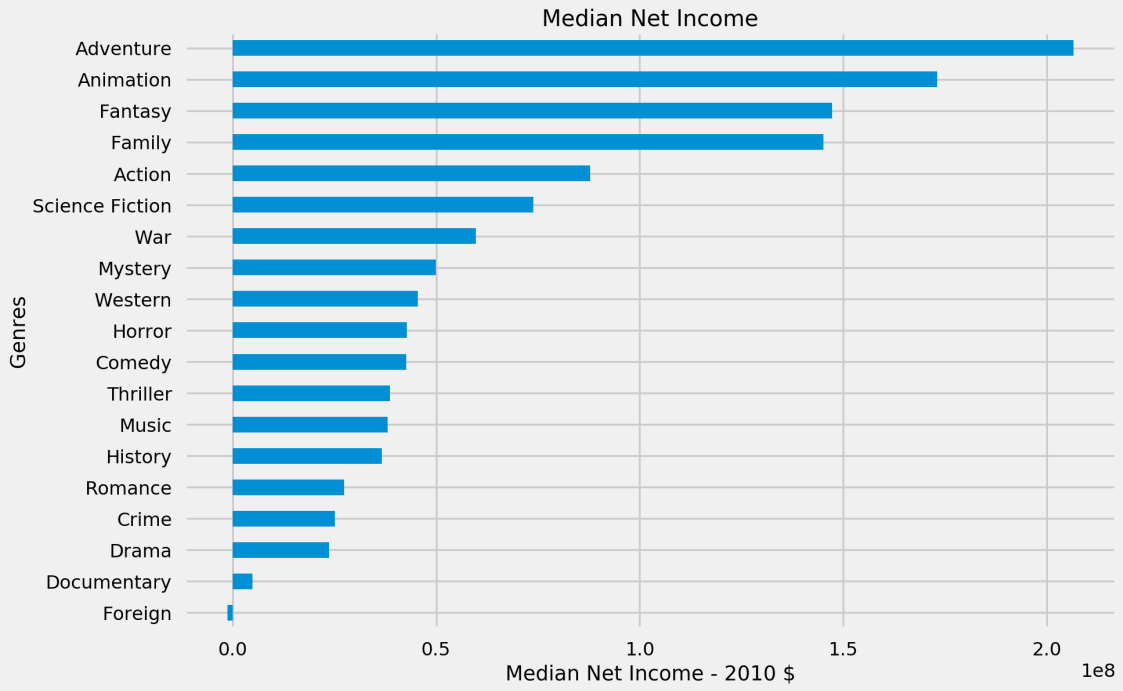
We can see that the "Adventure" and "Action" genres are the most profitable in terms of total earnings. But let's lok at median earnings too because some categories have many more movies than others.

```
In [46]: result.groupby('genres').net_income.median().sort_values(ascending=False)
```

```
Out[46]: genres
         Adventure          206,548,546.11
         Animation          173,046,127.20
         Fantasy            147,255,456.74
         Family             145,160,115.59
         Action              87,844,176.72
         Science Fiction     73,775,255.80
```

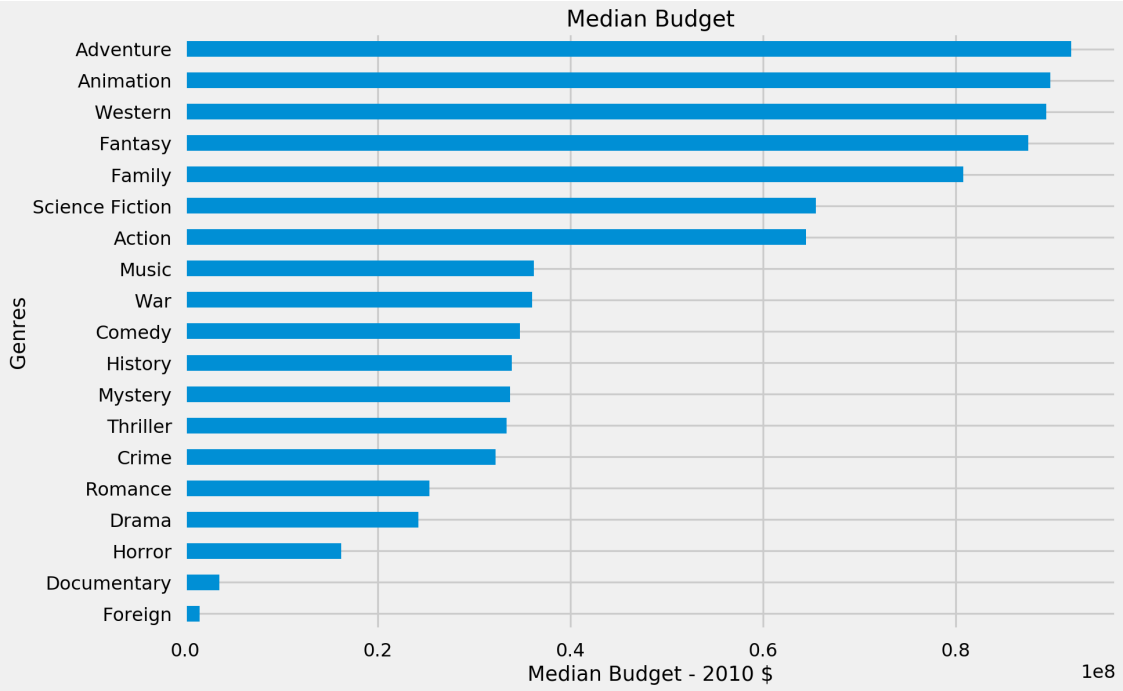
```
War                59,760,706.04
Mystery            49,842,431.91
Western            45,524,262.55
Horror             42,824,791.60
Comedy             42,682,397.09
Thriller           38,595,818.80
Music              38,125,266.45
History            36,597,934.24
Romance            27,402,303.09
Crime              25,051,586.39
Drama              23,666,130.70
Documentary         4,789,857.13
Foreign            -1,312,284.00
Name: net_income, dtype: float64
```

```
In [51]: result.groupby('genres')['net_income'].median().sort_values(
             ascending=True).plot.barh(title="Median Net Income")
         plt.xlabel('Median Net Income - 2010 $')
         plt.ylabel('Genres')
         plt.show()
```



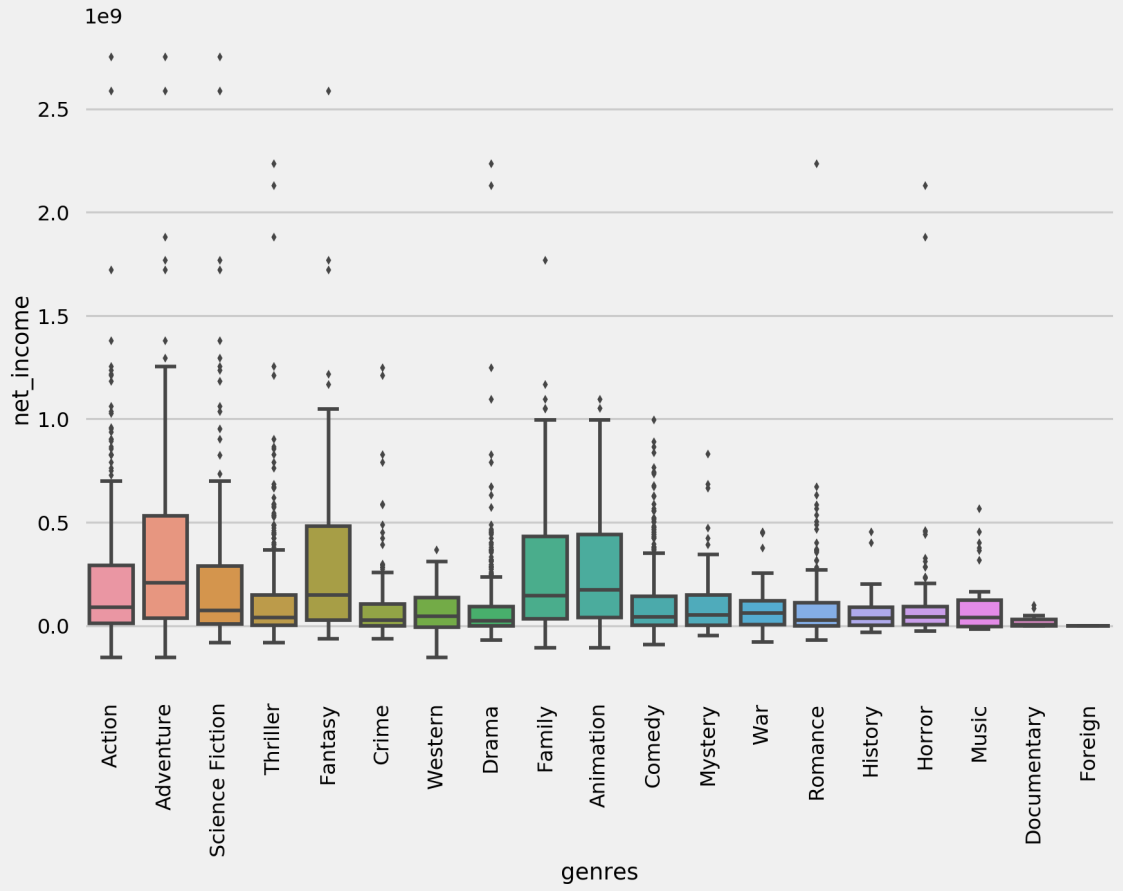
Here we can see that in median net income, Adventure is still number one. But Animation has jumped up to the second spot! The median net income on an animated film is \$173M. Wow. We missed that when we looked at total earnings, presumably because there are far fewer animated movies in our data set than action.

```
In [52]: result.groupby('genres')['budget_adj'].median().sort_values(
             ascending=True).plot.barh(title="Median Budget")
         plt.xlabel('Median Budget - 2010 $')
         plt.ylabel('Genres')
         plt.show()
```



Animation movies are profitable, but they also have huge budgets. The median Animation budget is almost as big as the median Adventure budget. So it's good that they're also profitable!

```
In [53]: ax = sns.boxplot(x='genres', y='net_income', data=result)
         ax.set_xticklabels(ax.get_xticklabels(), rotation=90)
         plt.show()
```



1.6 Conclusions

1.6.1 Which movies were most and least profitable?

The five most profitable movies in history (using inflation-adjusted 2010 dollars) are: (1) *Star Wars* (2) *Avatar* (3) *Titanic* (4) *The Exorcist* (5) *Jaws*. The least profitable movies are (1) *The Lone Ranger* (2) *Mars Needs Moms* (3) *Flushed Away* (4) *Sphere* (5) *A Sound of Thunder*.

Limitations: Several movies had 0 for budget and/or revenue. There might be more or less profitable movies where the data was missing. Also, my original analysis uncovered an error where the budget for *The Warrior's Way* was off by an order of magnitude. There may be other similar errors in the data.

1.6.2 What was the most profitable movie each year?

Above I list the most profitable movies for every year from 1960 to 2015, in inflation-adjusted 2010 dollars. They ranged from *Spartacus* (1960) to *Star Wars: The Force Awakens* (2015). It was interesting to note that three of the most five most profitable movies of all time were released in the 1970s. Only 22 movies in history have made over one billion dollars and four of them were released in the 1970s (the three just listed as well as *The Godfather*).

Limitations: Several movies had 0 for budget and/or revenue. There might be more or less profitable movies where the data was missing. Also, my original analysis uncovered an error where the budget for *The Warrior's Way* was off by an order of magnitude. There may be other similar errors in the data.

1.6.3 Have movie budgets increased over time?

There's an interesting answer to this question: sort of. The median movie budget has actually declined since 2000. But the budgets for the biggest budget movies have increased significantly, increasing by 60% since 2000. This exhibits an increasing inequality between the average movie and the few blockbusters produced.

Limitations: Several movies had 0 for budget and/or revenue. There might be more or less profitable movies where the data was missing. Also, my original analysis uncovered an error where the budget for *The Warrior's Way* was off by an order of magnitude. There may be other similar errors in the data.

1.6.4 Are blockbuster movies longer than non-blockbusters?

A longer movie (2+ hours) is more likely to be a blockbuster, and a shorter movie (<1.5hrs) is more likely to not be a blockbuster, but there is no statistically significant difference in runtimes for blockbusters and non-blockbusters.

Limitations: The sample of blockbuster movies is small. Also, runtimes tend to have a normal distribution. Some differences might be statistically significant if we were to compare categories of runtime as opposed to total length in minutes. (For example, we might see a difference if we compared movies of 2+ hrs to movies of <2 hrs.) With some more sophisticated statistics skills I might be able to identify these relationships.

1.6.5 What is the most profitable genre?

The most profitable genres – measured by total profits across the entire category – are Adventure, Action, and Thrillers. Looking at median profitability, the categories are Adventure, Animation, and Fantasy. These two lists are different because median controls for the number of movies released. Although Animation and Fantasy are profitable categories, fewer of those movies are produced. I saw similar effects when I looked at budgets.

Limitations: Several movies had 0 for budget and/or revenue. There might be more or less profitable movies where the data was missing. Also, my original analysis uncovered an error where the budget for *The Warrior's Way* was off by an order of magnitude. There may be other similar errors in the data.

In [ ]: