investigate-a-dataset-Patrick_Flynn

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1 Project: Investigating the IMDB Movie Dataset

"What it takes to make a great movie"

Analysis by Patrick Flynn

1.1 Table of Contents

Introduction

For this analysis, we will assume we are a data analyst working for screenwriter looking to make the next big blockbuster film! We are armed with an IMDB data set and our goal is to determine what genre(s) of movie we should have our screenwriter write and what features will best determine if the movie will be profitable.

This analysis will attempt to answer three research questions: - What Genre of Movie Gets Produced the Most? - What, If Any, Features Impact the Revenue a Movie Will Make? - Is One Genre More Profitable or Risky Than Another?

We will also look at the typical budget given to a movie as well as how long a movie should be (running time in minutes).

Once these questions have been answered, we should have a good indication as to what genre to suggest to our screenwriter and areas of concern to mention to our screenwriter before he/she begins writing a lengthy film!

Data Source: IMDB Dataset

1.1.1 Libraries/Packages Utilized

[1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.preprocessing import MultiLabelBinarizer
```

Data Wrangling

1.1.2 Data Acquisition

Read in data from CSV and preview first 5 records

[2]:
```
df = pd.read_csv(r'S:\Code\School\WGU_DataAnalyst_NanoDegree\01 - Introduction␣
↪to Data Science\tmdb-movies.csv')
df.head()
```

[2]:
```
       id    imdb_id  popularity     budget     revenue  \
0  135397  tt0369610   32.985763  150000000  1513528810
1   76341  tt1392190   28.419936  150000000   378436354
2  262500  tt2908446   13.112507  110000000   295238201
3  140607  tt2488496   11.173104  200000000  2068178225
4  168259  tt2820852    9.335014  190000000  1506249360

                 original_title  \
0                Jurassic World
1            Mad Max: Fury Road
2                     Insurgent
3  Star Wars: The Force Awakens
4                     Furious 7

                                                cast  \
0  Chris Pratt|Bryce Dallas Howard|Irrfan Khan|Vi...
1  Tom Hardy|Charlize Theron|Hugh Keays-Byrne|Nic...
2  Shailene Woodley|Theo James|Kate Winslet|Ansel...
3  Harrison Ford|Mark Hamill|Carrie Fisher|Adam D...
4  Vin Diesel|Paul Walker|Jason Statham|Michelle ...

                                            homepage          director  \
0                      http://www.jurassicworld.com/   Colin Trevorrow
1                        http://www.madmaxmovie.com/     George Miller
2     http://www.thedivergentseries.movie/#insurgent  Robert Schwentke
3  http://www.starwars.com/films/star-wars-episod...       J.J. Abrams
4                           http://www.furious7.com/         James Wan

                        tagline  ...  \
0              The park is open.  ...
1             What a Lovely Day.  ...
2        One Choice Can Destroy You  ...
3  Every generation has a story.  ...
4             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           6.5          2015  1.379999e+08  1.392446e+09
1           7.1          2015  1.379999e+08  3.481613e+08
2           6.3          2015  1.012000e+08  2.716190e+08
3           7.5          2015  1.839999e+08  1.902723e+09
4           7.3          2015  1.747999e+08  1.385749e+09

[5 rows x 21 columns]
```

Inspect object types/missing data

[3]:
```
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
```

Analysis Note: Several columns are not relavant to the analysis and need to be removed. In addition, there are some important fields (IMDB_ID, Genres) that are missing records and will be removed from the dataset. These values cannot be imputed.

1.2 Data Cleaning

In order to successfully analyze our data and answer our questions, we must first clean the data we have acquired

Rows are dropped from Genres/IMDB_ID that are null. Columns are dropped that are not relavant to analysis (see analyst note)

[4]:
```
df.dropna(subset=['genres', 'imdb_id'], inplace=True)
df.drop(axis=1, columns=['homepage', 'tagline',
                         'keywords', 'production_companies',
                        'cast', 'director', 'overview'], inplace=True)
```

Analysis Note: The fields that are dropped could be of great importance for a future project utilizing natural language processing. However that is beyond the scope of this assignment.

Create function to turn lists nested in genres column to new columns for each genre

[5]:
```
def transform_lists_to_columns(dataframe, column):
    mlb = MultiLabelBinarizer()
    dataframe[column] = dataframe[column].str.split('|')
    dataframe.apply(lambda x: tuple(x[column]), axis=1)
    dataframe = dataframe.join(pd.DataFrame(mlb.
 ↪fit_transform(dataframe[column]),
                                            columns=mlb.classes_,
                                            index=dataframe.index))
    dataframe.drop(axis=1, columns=[column], inplace=True)
    return dataframe
```

Analysis Note: This function will take the "genres" column and create a new column for each value discovered in the column. This will make analysis of individual genres FAR easier. Because this is the primary question involved in our research (to discover what genre to write), this function is incredibly important.

Run function on column and view subset

[6]:
```
df = transform_lists_to_columns(df, 'genres')
genre_cols = list(df.columns[-20:])
df.loc[:, genre_cols].head()
```

[6]:

	Action	Adventure	Animation	Comedy	Crime	Documentary	Drama	Family	\
0	1	1	0	0	0	0	0	0	
1	1	1	0	0	0	0	0	0	
2	0	1	0	0	0	0	0	0	
3	1	1	0	0	0	0	0	0	
4	1	0	0	0	1	0	0	0	

	Fantasy	Foreign	History	Horror	Music	Mystery	Romance	\
0	0	0	0	0	0	0	0	
1	0	0	0	0	0	0	0	
2	0	0	0	0	0	0	0	
3	1	0	0	0	0	0	0	
4	0	0	0	0	0	0	0	

	Science Fiction	TV Movie	Thriller	War	Western
0	1	0	1	0	0
1	1	0	1	0	0
2	1	0	1	0	0
3	1	0	0	0	0
4	0	0	1	0	0

The for each genre, a column inidicating a true(1) or false(0) exists for each movie.

Impute missing revenue and budget data

[7]:
```
print(df[df.revenue_adj == 0].count()['id'], ' Zero Value Revenues')
print(df[df.budget_adj == 0].count()['id'], ' Zero Value Budgets')
```

```
5985  Zero Value Revenues
5667  Zero Value Budgets
```

There are almost 6000 records missing data from the revenue/budget adjusted columns. In order to rectify this, we will impute the revenue based on the mean for all films for the year of our missing film.

[8]:
```
imputed_revenues = df.groupby('release_year').mean()['revenue_adj']
imputed_budgets = df.groupby('release_year').mean()['budget_adj']
```

[9]:
```
for index, row in df.loc[df['revenue_adj'] == 0, :].iterrows():
    df.loc[index, 'revenue_adj'] = imputed_revenues[row['release_year']]

for index, row in df.loc[df['budget_adj'] == 0, :].iterrows():
    df.loc[index, 'budget_adj'] = imputed_budgets[row['release_year']]
```

[10]:
```
print(df[df.revenue_adj == 0].count()['id'], ' Zero Value Revenues')
print(df[df.budget_adj == 0].count()['id'], ' Zero Value Budgets')
```

```
0  Zero Value Revenues
0  Zero Value Budgets
```

Imput missing runtime (length of movie) data There are only a few dozen movies missing runtimes, so in order to impute those values, we will use the overall mean of the dataset.

[11]:
```
df.loc[df['runtime'] == 0, 'runtime'] = df.loc[df['runtime'] != 0, 'runtime'].
 ↪mean()
```

Feature Engineering Create a "profit" variable that will determine if money was made (i.e. did the movie make more than it cost?)

[12]:
```
df['profit'] = df.revenue_adj - df.budget_adj
```

Convert release date to datetime and ensure all columns are of proper data type and all data is present

[13]:
```
#Convert release date to proper DateTime Object
df['release_date'] = pd.to_datetime(df['release_date'])
```

[14]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 10835 entries, 0 to 10865
Data columns (total 34 columns):
id                   10835 non-null int64
imdb_id              10835 non-null object
popularity           10835 non-null float64
budget               10835 non-null int64
revenue              10835 non-null int64
original_title       10835 non-null object
runtime              10835 non-null float64
release_date         10835 non-null datetime64[ns]
vote_count           10835 non-null int64
vote_average         10835 non-null float64
release_year         10835 non-null int64
budget_adj           10835 non-null float64
revenue_adj          10835 non-null float64
Action               10835 non-null int32
Adventure            10835 non-null int32
Animation            10835 non-null int32
Comedy               10835 non-null int32
Crime                10835 non-null int32
Documentary          10835 non-null int32
Drama                10835 non-null int32
Family               10835 non-null int32
Fantasy              10835 non-null int32
Foreign              10835 non-null int32
History              10835 non-null int32
Horror               10835 non-null int32
Music                10835 non-null int32
Mystery              10835 non-null int32
Romance              10835 non-null int32
```

```
Science Fiction     10835 non-null int32
TV Movie            10835 non-null int32
Thriller            10835 non-null int32
War                 10835 non-null int32
Western             10835 non-null int32
profit              10835 non-null float64
dtypes: datetime64[ns](1), float64(6), int32(20), int64(5), object(2)
memory usage: 2.4+ MB
```

Analysis Note: All fields now have the same amount of records and there are no nulls. In our cleaning, we only removed approximately 30 records and all fields are the proper data type.

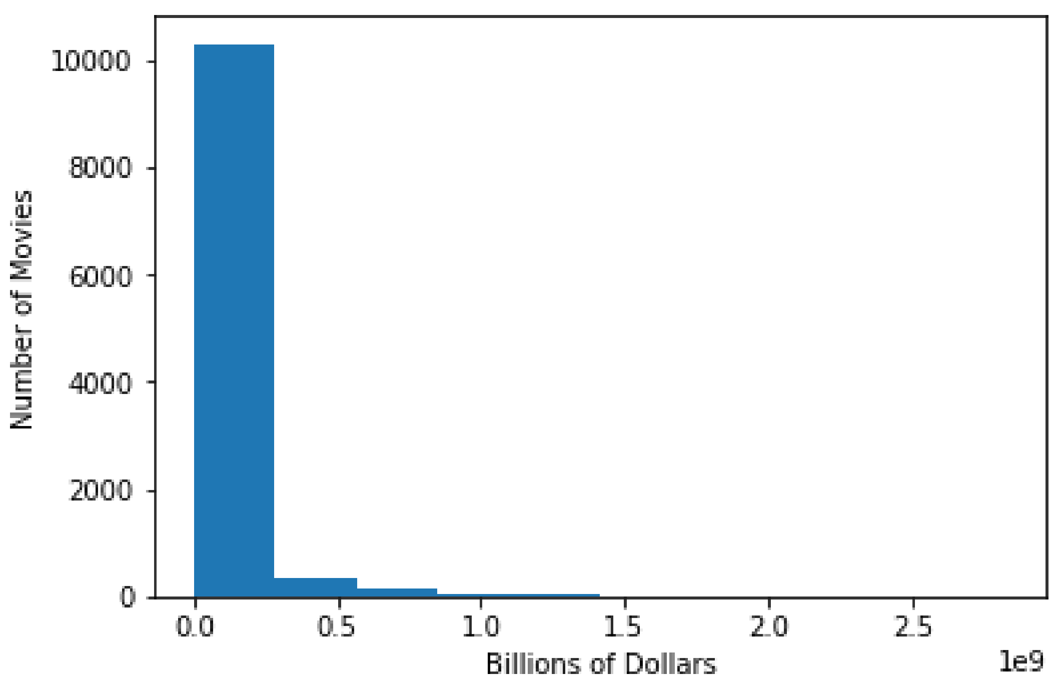
Exploratory Data Analysis
Now that our data has been cleaned and missing/incorrect values have been updated - we are ready to begin exploring our data! Before we begin answering any of our research questions, let's first determine if we can make an inferences about our data based on the patterns a particular variable may display:

1.2.1 Exploration of 1D Variable - Revenue Adjusted

What sort of revenue should we expect from our film? After all, as fun as making a movie might be - we won't get paid if the movie doesnt succeed! Let's take a look at a distribution of revenue for our dataset:

[15]:
```
df.revenue_adj.plot(kind='hist', )
plt.xlabel('Billions of Dollars')
plt.ylabel('Number of Movies')
```

[15]:
```
Text(0,0.5,'Number of Movies')
```



As depicted in the above histogram, the vast majority of movies do not make over even half a billion (500 million) dollars. To further dive into the variable, let's take a look at movies that make over one billion dollars:

What types of movies make BILLIONS of dollars?

[16]:
```
over_billion_movies = df.loc[df['revenue_adj'] >=␣
↪1000000000][['original_title', 'revenue_adj']].sort_values(
    ['revenue_adj'], ascending=False)

print('There are', str(len(over_billion_movies)), 'movies that make over 1␣
↪billion dollars! Those movies are (descending order): \n')
print(', '.join(list(over_billion_movies['original_title'])))
```

```
There are 44 movies that make over 1 billion dollars! Those movies are
(descending order):

Avatar, Star Wars, Titanic, The Exorcist, Jaws, Star Wars: The Force Awakens,
E.T. the Extra-Terrestrial, The Net, One Hundred and One Dalmatians, The
Avengers, The Empire Strikes Back, Jurassic World, Jurassic Park, Furious 7, The
Jungle Book, The Lord of the Rings: The Return of the King, Avengers: Age of
Ultron, Harry Potter and the Deathly Hallows: Part 2, The Godfather, Return of
the Jedi, Star Wars: Episode I - The Phantom Menace, Harry Potter and the
Philosopher's Stone, Frozen, The Lion King, Pirates of the Caribbean: Dead Man's
Chest, Iron Man 3, Independence Day, The Sound of Music, The Lord of the Rings:
The Two Towers, Close Encounters of the Third Kind, Transformers: Dark of the
Moon, The Lord of the Rings: The Fellowship of the Ring, Minions, Toy Story 3,
Harry Potter and the Chamber of Secrets, Shrek 2, Skyfall, The Dark Knight
Rises, Alice in Wonderland, Finding Nemo, The Dark Knight, Pirates of the
Caribbean: At World's End, Superman, Harry Potter and the Goblet of Fire
```

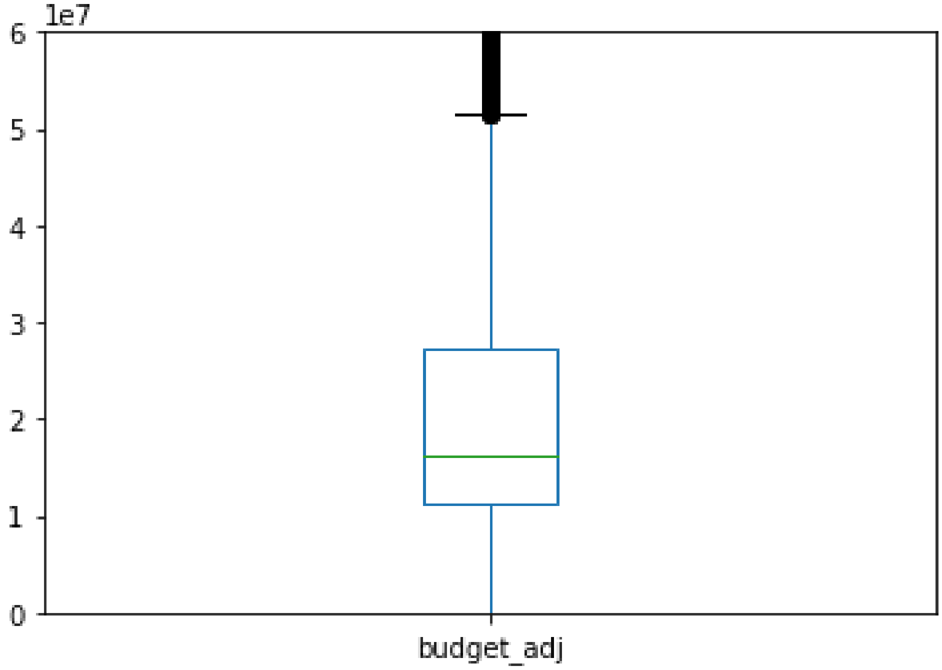
Looking at these films, these are all typical "Blockbusters" and it should be no surprise that these movies have made more than a billion dollars - they are classics!

1.2.2 Exploration of 1D Variable - Budget Adjusted

In order to successfully make our movie, our screenwriter is going to have to request a budget. It will be important for our team to know exactly how much money to ask for and what other films have had in the past!

[17]:
```
df['budget_adj'].plot(kind='box', ylim=(0,60000000))
```

[17]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x26e55ca8518>
```



The average movie seeks a budget of 15,000,000. However, let's see how many movies had a budget over 50,000,000 (our upper quartile) and in turn how much revenue they averaged!

1.2.3 Comparing Budgets to Revenues

[18]:
```
#Create a DF of movies that have an unusually high budget
above_average_budgets = df[df['budget_adj'] >= 50000000]
```

[19]:
```
print('The above average budgeted movies typically had a budget around:',
      str(int(above_average_budgets['budget_adj'].mean())), 'dollars')
```

```
The above average budgeted movies typically had a budget around: 94954673
dollars
```

[20]:
```
print('The above average budgeted movies typically made around:',
      str(int(above_average_budgets['revenue_adj'].mean())), 'dollars')
net_profit = above_average_budgets['revenue_adj'].mean() -␣
 ↪above_average_budgets['budget_adj'].mean()
```

```
The above average budgeted movies typically made around: 253517320 dollars
```

[21]:
```
print('Movies with an above average budget typically made',␣
 ↪str(int(net_profit)), 'dollars in net profit!')
```

```
Movies with an above average budget typically made 158562647 dollars in net
profit!
```

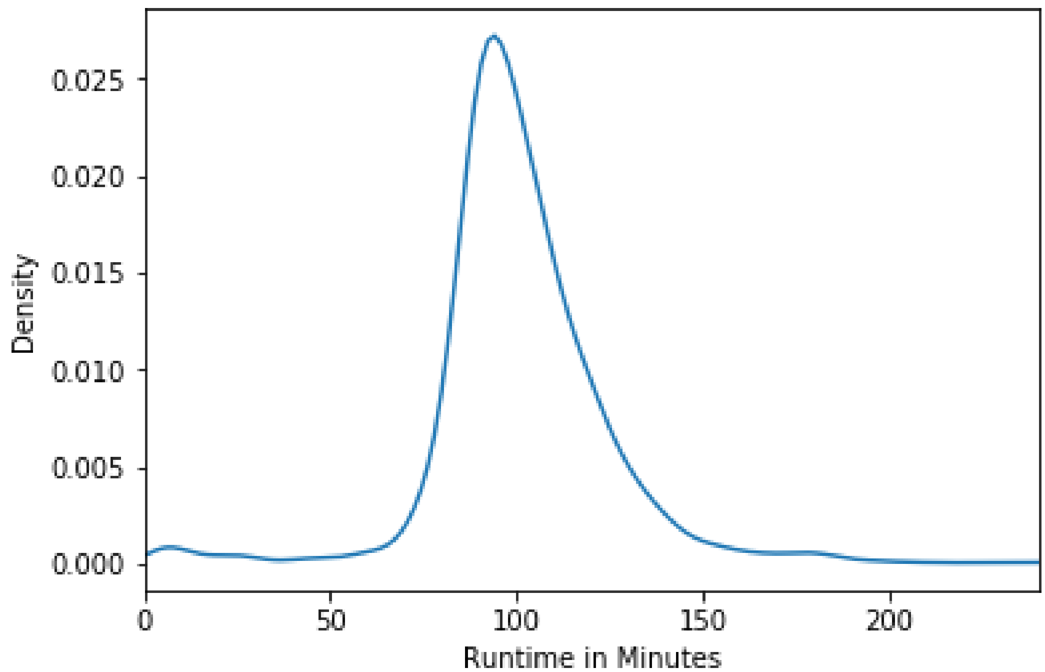
If we can acquire the budget, we stand to make a considerable profit!

1.2.4 Exploration of 1D Variable - Runtime

While not one of our key research questions, it is important to be able to suggest to our screenwriter the length of movie they should write. After all, if our movie is too long or too short, it could impact its performance!

[22]:
```
df['runtime'].plot(kind='kde', xlim=(0,240), x='Data')
plt.xlabel('Runtime in Minutes')
```

[22]:
```
Text(0.5,0,'Runtime in Minutes')
```



The runtime follows a normal distribution with the majority of movies having a runtime around 80-110 minutes. 95 minutes looks to be about the peak of our distribution. We should suggest to our screenwriter they keep their film around 95 minutes. This makes convention sense, most movies seem to be about an hour and a half.

1.2.5 Research Question 1: What Genre of Movie Gets Produced the Most?

Create sub-dataframe that will hold only columns of genres occuring since 1996

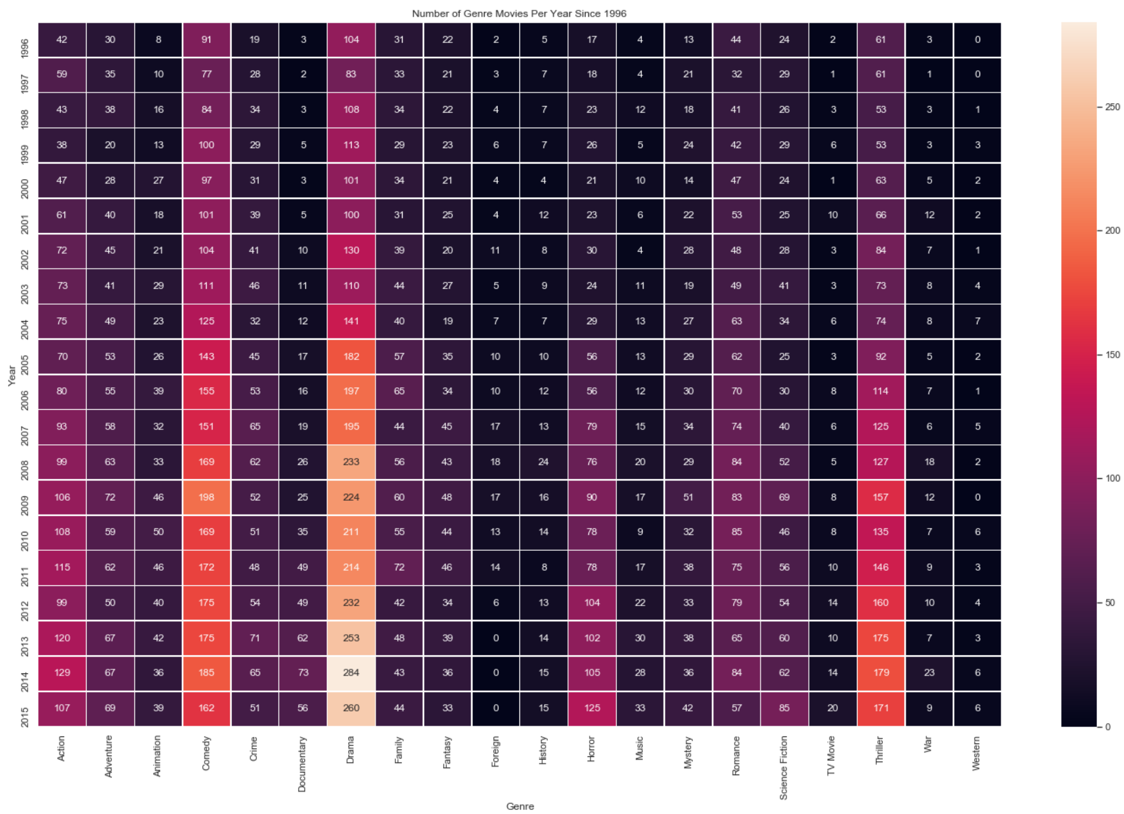
[23]:
```
vis_data = df.groupby('release_year').sum()[genre_cols]
vis_data = vis_data.loc[vis_data.index > 1995, :]
```

Create heatmap based on visualization dataframe created above:

[24]:
```
sns.set()
```

```python
# Draw a heatmap with the numeric values in each cell
f, ax = plt.subplots(figsize=(25, 15))
g = sns.heatmap(vis_data, annot=True, fmt="d", linewidths=.5, ax=ax)
g.set(title = 'Number of Genre Movies Per Year Since 1996')
g.set(xlabel='Genre', ylabel='Year')
```

[24]: [Text(201.5,0.5,'Year'), Text(0.5,111.453,'Genre')]



The above visualization shows three very clear genres that rise against others: Comedy, Drama, Thriller. Movies to stay away from are Foreign/History/War.

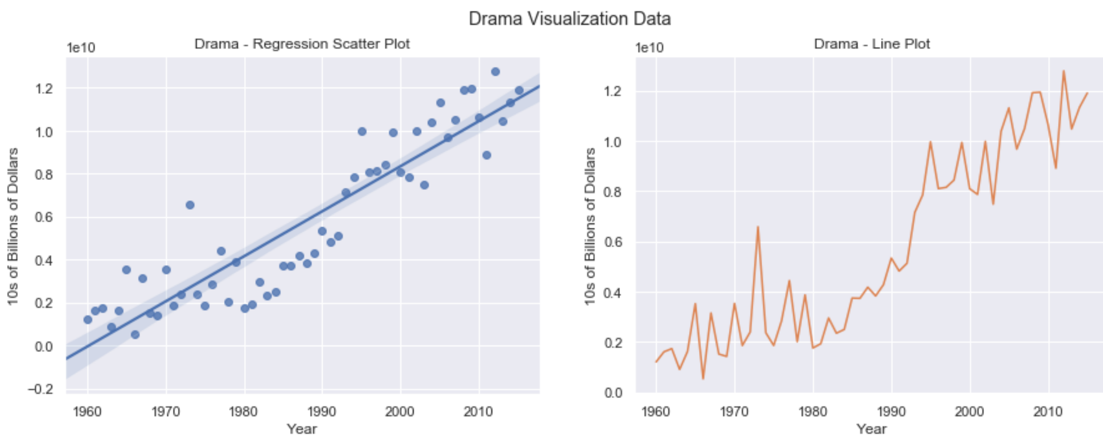
1.2.6 Create Regression/Line Plots

Function to create regression/line subplots and label axis based on column from DF sent to function

[25]:
```python
def create_genre_plots(col, adjusted_y='10s of Billions of Dollars'):
    query_string = col + ' == 1'
    movie_data = df.query(query_string)[['release_year','revenue_adj']].
 ↪groupby('release_year').sum()
    movie_data = movie_data.reset_index()
    fig, axs = plt.subplots(ncols=2, figsize=(15, 5))
    g = sns.regplot(x="release_year", y="revenue_adj",  data=movie_data,␣
 ↪ax=axs[0])
```

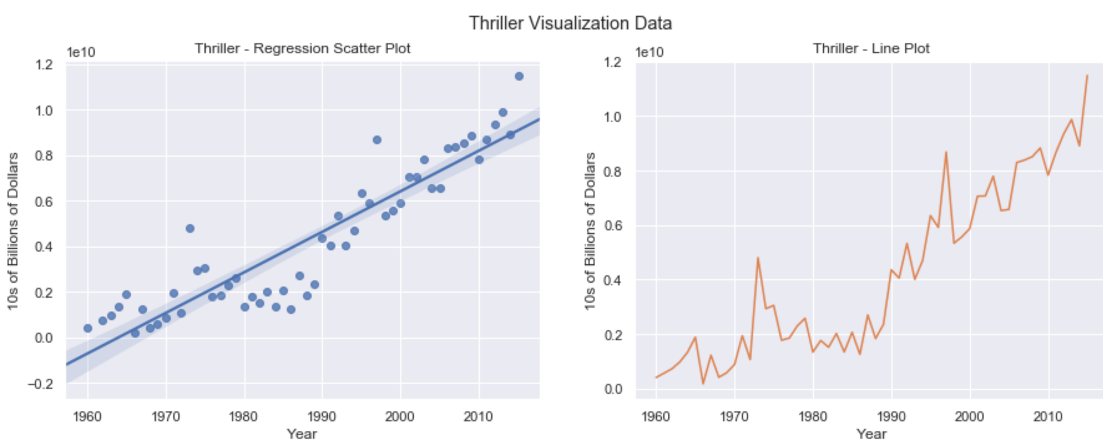
```
    g.set(xlabel='Year', ylabel=adjusted_y)
    g.set(title = col + ' - Regression Scatter Plot')
    gt = sns.lineplot(x="release_year", y="revenue_adj",  data=movie_data,␣
 ↪ax=axs[1])
    gt.set(xlabel='Year', ylabel=adjusted_y)
    gt.set(title = col + ' - Line Plot')
    plt.suptitle(col + ' Visualization Data')
```

[26]:
```
create_genre_plots('Drama')
```



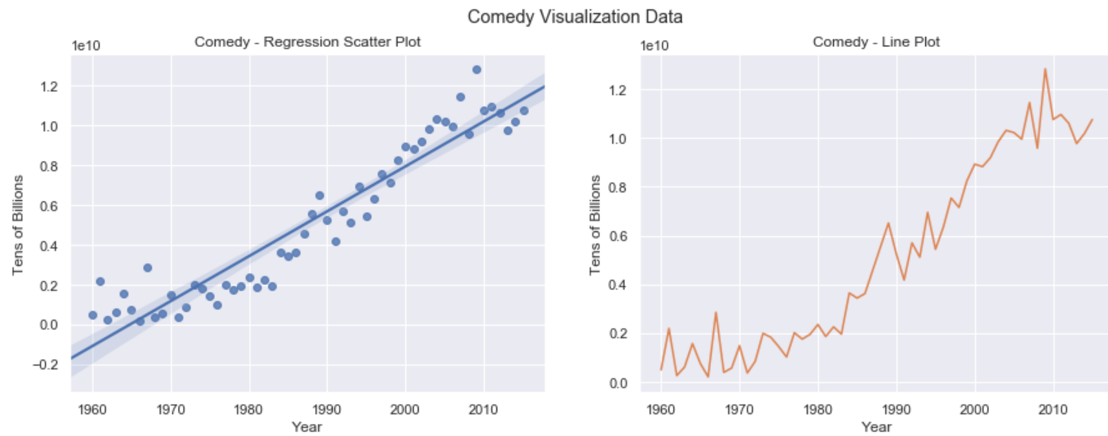
The Drama genre is one of the highest performing genres. While there are a few years in the 2000's that dipped lower than other years, the genre still performs very well and the Regression plot shows an upwards trend.

[27]:
```
create_genre_plots('Thriller')
```



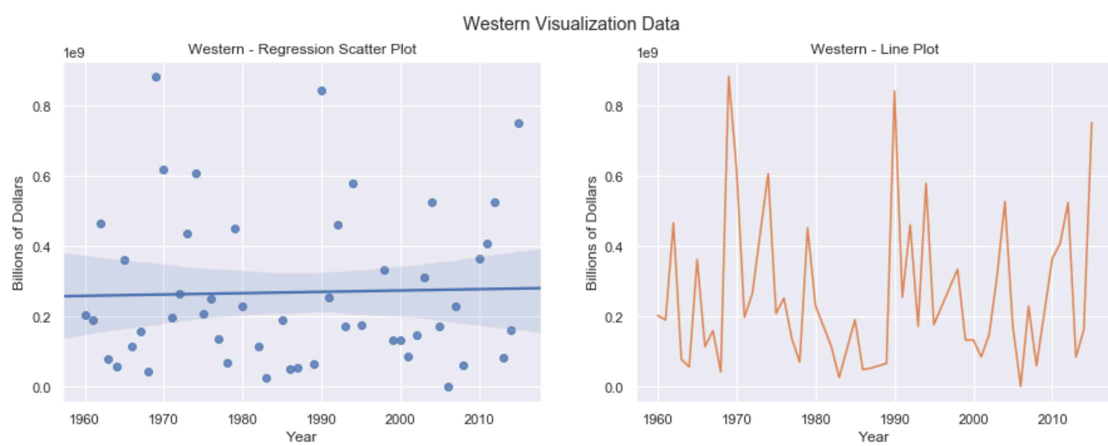
The thriller genre is also a high performing genre, however, since the 2000's the genre doesn't seem "AS" stable as the Drama genre.

[28]:
```
create_genre_plots('Comedy', adjusted_y='Tens of Billions')
```



The comedy genre appears to be the best suited for future growth and has had some of the highest performing years compared to other genres. The mid 90's appear to be a huge boom in comedy.

[29]:
```
create_genre_plots('Western', adjusted_y='Billions of Dollars')
```



This visualization included to shown a potential genre to stay away from. Western films have their periodic blockbusters, but overwhelmingly they do not do well in the box office.

1.2.7 Research Question 2: What, If Any, Features Impact the Revenue a Movie Will Make?

There are no **STRONG** relationships between any of the genres and revenue (revenue_adj). Based on the below correlation matrix, it would appear that a good indicator factor that influences revenue is the budget. As the budget increases, so too does the revenue. The popularity of the movie and the number of votes for the movie also strongly influences the revenue of the movie. This makes sense from a practical standpoint, after all, the more popular a movie is the more people that will see it (earning the film more revenue)

[30]:
```
df.corr()
```

[30]:

```
                     id  popularity    budget   revenue   runtime  \
id             1.000000   -0.012986 -0.140604 -0.098664 -0.075687
popularity    -0.012986    1.000000  0.545205  0.663244  0.136222
budget        -0.140604    0.545205  1.000000  0.734797  0.189601
revenue       -0.098664    0.663244  0.734797  1.000000  0.162047
runtime       -0.075687    0.136222  0.189601  0.162047  1.000000
vote_count    -0.034709    0.800779  0.632544  0.791105  0.162481
vote_average  -0.061468    0.211060  0.082210  0.173758  0.156878
release_year   0.511222    0.090458  0.116616  0.057491 -0.112322
budget_adj    -0.204396    0.480392  0.939378  0.693507  0.207058
revenue_adj   -0.143467    0.576660  0.578070  0.899643  0.162118
Action        -0.076193    0.148205  0.224928  0.149368  0.046001
Adventure     -0.073087    0.200794  0.293414  0.247990  0.049297
Animation      0.006790    0.053847  0.072517  0.079536 -0.291035
Comedy        -0.098170   -0.040330 -0.032392 -0.015040 -0.128889
Crime         -0.074423    0.036646  0.036716  0.007748  0.055692
Documentary    0.148038   -0.104440 -0.102120 -0.072552  0.006907
Drama         -0.044426   -0.049640 -0.079447 -0.080826  0.236672
Family        -0.059625    0.049707  0.100729  0.099447 -0.147200
Fantasy       -0.063512    0.105240  0.176954  0.146804 -0.014632
Foreign       -0.047649   -0.060556 -0.056750 -0.043577  0.022991
History       -0.025694   -0.012796  0.022634 -0.012066  0.195519
Horror         0.044792   -0.076861 -0.115071 -0.083240 -0.103021
Music          0.023911   -0.031456 -0.033233 -0.019049  0.027660
Mystery       -0.031197    0.011992  0.013335  0.000680  0.034483
Romance       -0.072956   -0.024095 -0.029904 -0.015699  0.068432
Science Fiction -0.021903    0.127193  0.120116  0.092752 -0.031281
TV Movie       0.070625   -0.047096 -0.058220 -0.042386 -0.035034
Thriller      -0.024304    0.056708  0.049802  0.009188  0.017088
War           -0.019881    0.012759  0.032154  0.010464  0.130715
Western       -0.030643   -0.007099  0.017306 -0.012068  0.061097
profit        -0.110169    0.530097  0.414280  0.841313  0.130608

               vote_count  vote_average  release_year  budget_adj  \
id              -0.034709     -0.061468      0.511222   -0.204396
popularity       0.800779      0.211060      0.090458    0.480392
budget           0.632544      0.082210      0.116616    0.939378
revenue          0.791105      0.173758      0.057491    0.693507
runtime          0.162481      0.156878     -0.112322    0.207058
vote_count       1.000000      0.255265      0.108466    0.564474
vote_average     0.255265      1.000000     -0.120723    0.085171
release_year     0.108466     -0.120723      1.000000    0.031924
budget_adj       0.564474      0.085171      0.031924    1.000000
revenue_adj      0.683392      0.180073     -0.105536    0.600129
Action           0.161743     -0.106951     -0.052472    0.228323
```

Adventure	0.203301	-0.014475	-0.059661	0.310037
Animation	0.039036	0.120565	0.054679	0.091439
Comedy	-0.052815	-0.053459	-0.028383	-0.021414
Crime	0.039832	0.061131	-0.053401	0.020282
Documentary	-0.071149	0.224410	0.122373	-0.086871
Drama	-0.054300	0.181798	-0.026274	-0.077352
Family	0.033886	0.008981	-0.015076	0.132834
Fantasy	0.107426	-0.036688	-0.024633	0.187055
Foreign	-0.046422	0.001183	0.000933	-0.032482
History	-0.010580	0.083540	-0.053051	0.044528
Horror	-0.071665	-0.287162	-0.006311	-0.140217
Music	-0.031996	0.106231	-0.017528	-0.024733
Mystery	0.009390	-0.007999	-0.032349	0.003468
Romance	-0.039004	0.032383	-0.029421	-0.025224
Science Fiction	0.136639	-0.119950	-0.038039	0.118951
TV Movie	-0.039858	-0.024794	0.032470	-0.038554
Thriller	0.039383	-0.144420	0.018308	0.027899
War	0.014638	0.055589	-0.065027	0.046042
Western	-0.002637	0.014644	-0.139676	0.020181
profit	0.629448	0.182120	-0.127671	0.423752

	revenue_adj	...	Horror	Music	Mystery	Romance	\
id	-0.143467	...	0.044792	0.023911	-0.031197	-0.072956	
popularity	0.576660	...	-0.076861	-0.031456	0.011992	-0.024095	
budget	0.578070	...	-0.115071	-0.033233	0.013335	-0.029904	
revenue	0.899643	...	-0.083240	-0.019049	0.000680	-0.015699	
runtime	0.162118	...	-0.103021	0.027660	0.034483	0.068432	
vote_count	0.683392	...	-0.071665	-0.031996	0.009390	-0.039004	
vote_average	0.180073	...	-0.287162	0.106231	-0.007999	0.032383	
release_year	-0.105536	...	-0.006311	-0.017528	-0.032349	-0.029421	
budget_adj	0.600129	...	-0.140217	-0.024733	0.003468	-0.025224	
revenue_adj	1.000000	...	-0.069850	-0.007494	-0.005682	-0.018079	
Action	0.142426	...	-0.090619	-0.084885	-0.053335	-0.158938	
Adventure	0.245262	...	-0.121155	-0.061226	-0.058244	-0.097647	
Animation	0.074651	...	-0.099061	0.007555	-0.058797	-0.090895	
Comedy	-0.020289	...	-0.178796	0.010746	-0.144561	0.194082	
Crime	-0.000146	...	-0.098725	-0.049744	0.134418	-0.100284	
Documentary	-0.068779	...	-0.082557	0.128433	-0.058827	-0.094796	
Drama	-0.077218	...	-0.225887	0.018813	0.029152	0.193767	
Family	0.103210	...	-0.145280	0.024171	-0.080701	-0.064886	
Fantasy	0.128470	...	-0.006439	-0.012748	-0.033167	-0.021188	
Foreign	-0.033155	...	-0.014612	-0.022535	-0.016271	0.023825	
History	-0.003307	...	-0.069274	-0.012767	-0.038513	-0.018700	
Horror	-0.069850	...	1.000000	-0.069790	0.131913	-0.157316	
Music	-0.007494	...	-0.069790	1.000000	-0.048774	0.047498	
Mystery	-0.005682	...	0.131913	-0.048774	1.000000	-0.071182	
Romance	-0.018079	...	-0.157316	0.047498	-0.071182	1.000000	

```
Science Fiction     0.091072  ...  0.100850 -0.058272 -0.006182 -0.094735
TV Movie           -0.027563  ... -0.025587  0.018626 -0.009926  0.001259
Thriller            0.005749  ...  0.249290 -0.108703  0.276866 -0.177294
War                 0.019810  ... -0.059175 -0.025354 -0.031933 -0.010814
Western             0.002089  ... -0.037730 -0.012676 -0.023885 -0.016677
profit              0.978841  ... -0.043226 -0.002159 -0.007322 -0.014020

                 Science Fiction  TV Movie  Thriller       War   Western  \
id                     -0.021903  0.070625 -0.024304 -0.019881 -0.030643
popularity              0.127193 -0.047096  0.056708  0.012759 -0.007099
budget                  0.120116 -0.058220  0.049802  0.032154  0.017306
revenue                 0.092752 -0.042386  0.009188  0.010464 -0.012068
runtime                -0.031281 -0.035034  0.017088  0.130715  0.061097
vote_count              0.136639 -0.039858  0.039383  0.014638 -0.002637
vote_average           -0.119950 -0.024794 -0.144420  0.055589  0.014644
release_year           -0.038039  0.032470  0.018308 -0.065027 -0.139676
budget_adj              0.118951 -0.038554  0.027899  0.046042  0.020181
revenue_adj             0.091072 -0.027563  0.005749  0.019810  0.002089
Action                  0.185790 -0.035618  0.225998  0.066775  0.077832
Adventure               0.155726  0.013915 -0.037273  0.014517  0.047617
Animation               0.029934  0.009947 -0.144380 -0.037090 -0.020318
Comedy                 -0.103711  0.000870 -0.330888 -0.093715 -0.028041
Crime                  -0.103261 -0.033713  0.284814 -0.049699 -0.021951
Documentary            -0.077352 -0.010522 -0.130977 -0.008132 -0.027893
Drama                  -0.174447  0.004000 -0.006826  0.100702  0.002320
Family                 -0.007408  0.104015 -0.206895 -0.055341 -0.034997
Fantasy                 0.129868  0.024079 -0.096753 -0.042099 -0.026870
Foreign                -0.025122 -0.016626 -0.010300 -0.003105 -0.016524
History                -0.061988  0.012362 -0.065844  0.300337  0.017065
Horror                  0.100850 -0.025587  0.249290 -0.059175 -0.037730
Music                  -0.058272  0.018626 -0.108703 -0.025354 -0.012676
Mystery                -0.006182 -0.009926  0.276866 -0.031933 -0.023885
Romance                -0.094735  0.001259 -0.177294 -0.010814 -0.016677
Science Fiction         1.000000  0.000282  0.073155 -0.047727 -0.037258
TV Movie                0.000282  1.000000 -0.053801 -0.010389 -0.009441
Thriller                0.073155 -0.053801  1.000000 -0.035362 -0.046405
War                    -0.047727 -0.010389 -0.035362  1.000000 -0.000540
Western                -0.037258 -0.009441 -0.046405 -0.000540  1.000000
profit                  0.072697 -0.021349 -0.000627  0.010654 -0.002797

                   profit
id              -0.110169
popularity       0.530097
budget           0.414280
revenue          0.841313
runtime          0.130608
vote_count       0.629448
```

```
vote_average      0.182120
release_year     -0.127671
budget_adj        0.423752
revenue_adj       0.978841
Action            0.102870
Adventure         0.198414
Animation         0.061140
Comedy           -0.017497
Crime            -0.005354
Documentary      -0.055660
Drama            -0.067651
Family            0.082890
Fantasy           0.097624
Foreign          -0.029235
History          -0.015135
Horror           -0.043226
Music            -0.002159
Mystery          -0.007322
Romance          -0.014020
Science Fiction   0.072697
TV Movie         -0.021349
Thriller         -0.000627
War               0.010654
Western          -0.002797
profit            1.000000

[31 rows x 31 columns]
```

1.2.8 Research Question 3: Is One Genre More Profitable or Risky Than Another?

Two dataframes are created that contain movies that have lost more than 0 dollars (losses DF) and movies that have profitted more than 1,000,000 dollars. It is important to look at both losses and profits, especially if one of our target genres has far more losses or profits versus the other genres.

[31]:
```
profits = df[df.index > 1995].query("profit >= 1000000")[genre_cols]
losses = df[df.index > 1995].query("profit < 0")[genre_cols]
profits = pd.DataFrame(profits.sum()).reset_index().rename(columns={'index':
 ↪'genre', 0:'Num_Movies'})
losses = pd.DataFrame(losses.sum()).reset_index().rename(columns={'index':
 ↪'genre', 0:'Num_Movies'})
```

> **Analysis Note:** Each dataframe is created, aggregated by genre, and given new column names

Visualization to Compare Profits/Losses

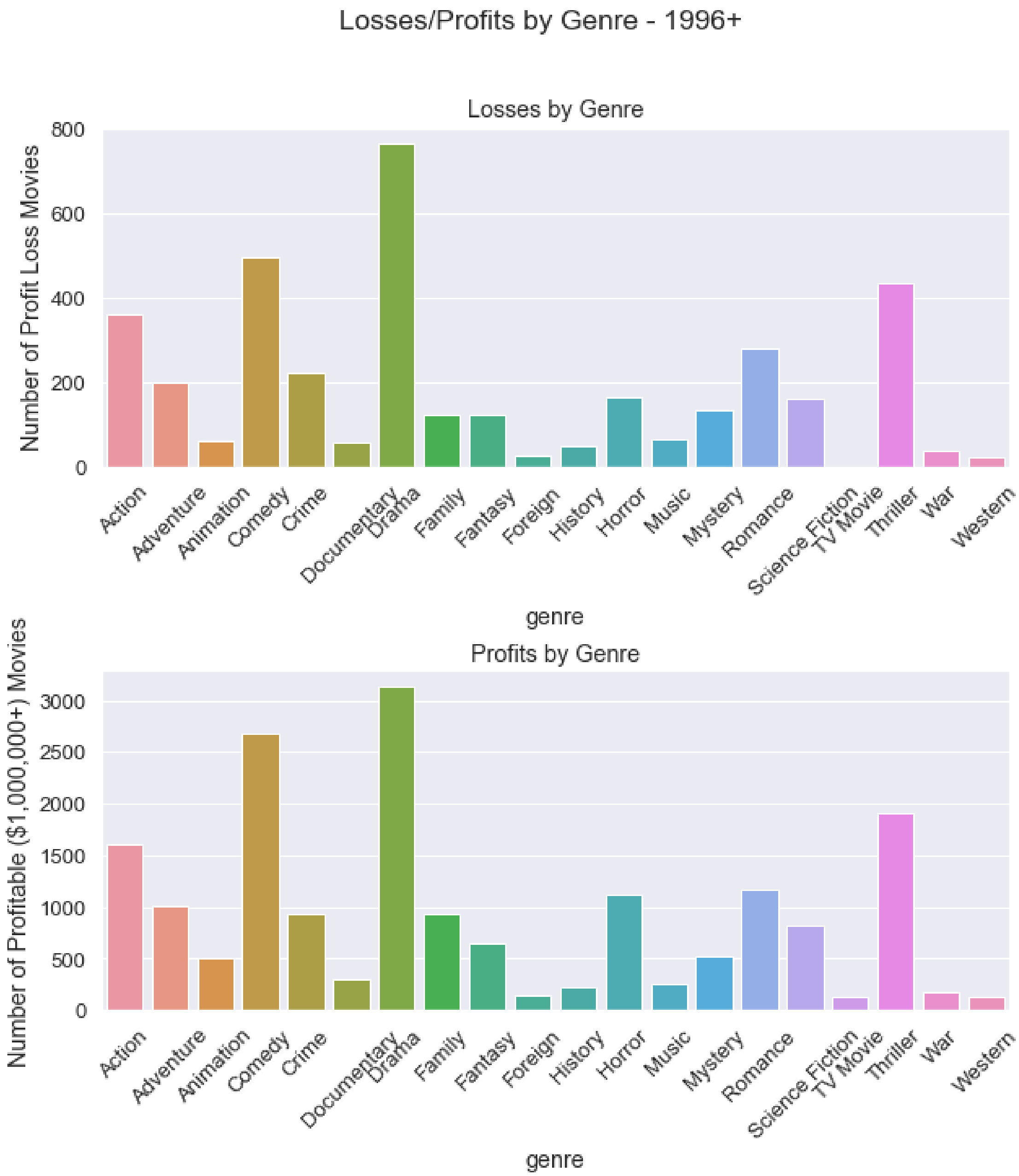
[32]:
```
#Ensure font size is viewable
sns.set(font_scale = 1.2)
```

```python
#Create two rows of one column each
fig, axs = plt.subplots(nrows=2, figsize=(10, 10))

#Losses graph
g = sns.barplot(x='genre', y='Num_Movies', data=losses, ax=axs[0])
g.set(ylabel='Number of Profit Loss Movies')
g.set(title = 'Losses by Genre')

#profits graph
gr = sns.barplot(x='genre', y='Num_Movies', data=profits, ax=axs[1])
gr.set(ylabel='Number of Profitable ($1,000,000+) Movies')
gr.set(title = 'Profits by Genre')

#Tilt axis ticks for each figure
for ax in fig.axes:
    plt.sca(ax)
    plt.xticks(rotation=45)
plt.suptitle('Losses/Profits by Genre - 1996+')
#Add space between two plots
plt.subplots_adjust(hspace = 0.6)
```



It can be seen that large profits and losses tend to occur in the same categories (Comedy, Drama, and Thriller). These also are the same genres of movies that have the highest amount of movies made. It is likely that people like these movie genres the most and because of this, these genres are written the most. This data indicates that a comedy movie still has better profitability than dramas/thrillers.

Conclusions

Based on the analysis above, one winner emerges from the highest performing/earning genres: Comedy. The comedy genre has seen a steady increase since the mid 1980s. While the genre is clearly a popular one and one of the highest revenue earning, more important is making a movie that is popular and has a high budget as these features are often correlated with higher revenue.

In our data exploration we determined that our movie should be about 80-110 minutes long. If we are able to acquire a higher budget, we may be able to make a nice net profit based on historical data. We should also provide the list of movies that made more than a billion dollars of revenue as an ispiration to our screenwriter (perhaps in their craft they can glean a pattern/trend from the movies that the data cannot).

While the Comedy genre looks promising, the main takeaway from this analysis is that while Comedies/Dramas/Thrillers are the most produced movies; they are also the movies with the largest losses. Having a marketing/PR team would prove to be almost as important as choosing the right genre!

Limitations:

- Incompleteness of data
  - Because the revenue/budget data was paramount to our analysis, over half of the data was imputed on the mean of the remaining data by year. This may result in an incomplete picture of what revenues were actually like. Fortunately because this is to model movie revenues, it should be suitable for our purposes.
- Dataset ends in 2015
  - Just recently, Avengers: Endgame toppled the charts and is racing to beat Avatar for the highest grossing film of all time. Because our dataset ends in 2015, other films such as Avengers: Endgame are not in our dataset and may not capture trends from the last 5 years.
- Markets change
  - Although the data we have is somewhat dated, even if we had up to date data - the market trends could suddenly shift. For example, if we decide to make our comedy movie and all of a sudden the market favors against comedies, we could see results that do not match the patterns in our analysis.
- The craft is an art
  - Because the content of our analysis is largely subjective and artistic, all the data/analysis in the world could provide to be unfruitful. Our movie may be entered into the market right after a blockbuster movie and the limelight is taken from ours. This is where we will lean on our screenwriter for domain knowledge.

Future Analysis:

- Do certain words in the title impact the profits/revenue of a movie?
- Do certain production studios have consistently higher revenues/losses? (i.e. should a screenwriter seek to work for these?)
- Do blended genres (i.e. Romantic Comedies) have higher revenues than just solo genres?

References

Proper Utilization of Multilabel Binarizer
Pandas API
Seaborn Visualization API