movie

May 24, 2020

1 Project: Investigate Movie Data

1.1 Table of Contents

Introduction In this report, we will be applying data analysis process on TMDb movie data. This data set contains information about 10,000+ movies collected from The Movie Database (TMDb), including user ratings and revenue. Here are the problem we address:

Which genres are most popular from year to year?

What kinds of properties are associated with movies that have high revenues?

Which movie earn the most over time? Which earn the least?

How much has the drama movie revenue improved over time?

What is the proportion of each genre since 1960?

1.1.1 Import All Packages We Need

[119]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import matplotlib.patches as mpatches
import seaborn as sns
import decimal

%matplotlib inline
```

Data Wrangling

1.1.2 Load in the Data

[120]:
```
# Load data and print out a few lines.
movie_df = pd.read_csv('tmdb-movies.csv')
movie_df.head(2)
```

[120]:
```
       id    imdb_id  popularity     budget     revenue      original_title  \
0  135397  tt0369610   32.985763  150000000  1513528810      Jurassic World
1   76341  tt1392190   28.419936  150000000   378436354  Mad Max: Fury Road

                                                cast  \
0  Chris Pratt|Bryce Dallas Howard|Irrfan Khan|Vi…
1  Tom Hardy|Charlize Theron|Hugh Keays-Byrne|Nic…

                        homepage          director             tagline  …  \
0  http://www.jurassicworld.com/  Colin Trevorrow   The park is open.  …
1    http://www.madmaxmovie.com/    George Miller  What a Lovely Day.  …

                                            overview runtime  \
0  Twenty-two years after the events of Jurassic …     124
1  An apocalyptic story set in the furthest reach…     120

                                      genres  \
0  Action|Adventure|Science Fiction|Thriller
1  Action|Adventure|Science Fiction|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

   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 rows x 21 columns]
```

1.1.3 General Properties

Dimensions of the Dataset

[121]:
```
movie_df.shape
```

[121]:
```
(10866, 21)
```

Data types for each feature

[122]:
```
movie_df.dtypes
```

[122]:
```
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
```

Check Nnumber of Missing Value

[123]:
```
movie_df.isnull().sum()
```

[123]:
```
id                         0
imdb_id                   10
popularity                 0
budget                     0
revenue                    0
original_title             0
cast                      76
homepage                7930
director                  44
tagline                 2824
keywords                1493
overview                   4
runtime                    0
genres                    23
production_companies    1030
release_date               0
vote_count                 0
vote_average               0
release_year               0
budget_adj                 0
```

```
revenue_adj              0
dtype: int64
```

Check Number of Dulicate Row

[124]:
```
movie_df.duplicated().sum()
```

[124]:
```
1
```

Problem With Cast and Genres Certain columns, like 'cast' and 'genres', contain multiple values separated by pipe (|)

[125]:
```
movie_df.head(1).cast
```

[125]:
```
0    Chris Pratt|Bryce Dallas Howard|Irrfan Khan|Vi…
Name: cast, dtype: object
```

[126]:
```
movie_df.head(1).genres
```

[126]:
```
0    Action|Adventure|Science Fiction|Thriller
Name: genres, dtype: object
```

1.1.4 Data Cleaning

Drop Unused Columns

[127]:
```
movie_df.drop(['id', 'imdb_id', 'homepage'], axis=1, inplace=True)
```

[128]:
```
# Double-check our columns, ensure we have successfully drop unused columns
movie_df.columns
```

[128]:
```
Index(['popularity', 'budget', 'revenue', 'original_title', 'cast', 'director',
       'tagline', 'keywords', 'overview', 'runtime', 'genres',
       'production_companies', 'release_date', 'vote_count', 'vote_average',
       'release_year', 'budget_adj', 'revenue_adj'],
      dtype='object')
```

Drop Rows with Any Null Aalue

[129]:
```
movie_df.dropna(inplace=True)

# check null values exist or not
movie_df.isnull().sum().any()
```

[129]:
```
False
```

Drop Duplicates

[130]:
```python
movie_df.drop_duplicates(inplace=True)

# print number of duplicates
movie_df.duplicated().sum()
```

[130]: 0

Break Multi Values Cell Since genres contain multi values separated by pipe (|), we need to separate them into multiple rows. Below is the function for separating.

[131]:
```python
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
```

[132]:
```python
movie_df.head(1).genres
```

[132]:
```
0    Action|Adventure|Science Fiction|Thriller
Name: genres, dtype: object
```

[133]:
```python
# Use the function we just created break row to rows
movie_df = splitDataFrameList(movie_df, 'genres', '|')

# double check the yield
movie_df.head(4).genres
```

[133]:
```
0             Action
1          Adventure
2    Science Fiction
3           Thriller
```

```
Name: genres, dtype: object
```

Exploratory Data Analysis

We've trimmed and cleaned our data, we're ready to explore further on our dataset. ### Which genres are most popular from year to year? There are several steps for solving this problem:

Split each year into different group

Split each genre into subgroup in each group

Calculate the sum of popularity of each subgroup

Get the index of the max group

Retrieve the max data points

[134]:
```python
# group by release_year and genres, sum popularity in each genres
sum_pop = movie_df.groupby(['release_year','genres']).agg({'popularity':
 ↪'sum'}).reset_index()

# We then have all the sums for each genres
sum_pop[sum_pop['release_year'] == 1960]
```

[134]:

	release_year	genres	popularity
0	1960	Action	4.007634
1	1960	Adventure	3.504904
2	1960	Comedy	3.112182
3	1960	Crime	0.692959
4	1960	Drama	6.643805
5	1960	Family	0.834191
6	1960	Fantasy	0.856495
7	1960	History	1.610094
8	1960	Horror	4.140147
9	1960	Music	0.423531
10	1960	Romance	2.925109
11	1960	Science Fiction	0.983714
12	1960	Thriller	4.871460
13	1960	Western	3.140119

However, we only need the most popular genre in each year.

[135]:
```python
# get the index of the most popular genres
idx = sum_pop.groupby('release_year').popularity.transform(max) ==
 ↪sum_pop['popularity']

# Retrieve the max data points
df = sum_pop[idx]

# we then have the top genre in each year
```

```
df.reset_index(inplace=True, drop=True)
df.head()
```

[135]:

	release_year	genres	popularity
0	1960	Drama	6.643805
1	1961	Drama	6.915731
2	1962	Drama	7.041713
3	1963	Thriller	7.199292
4	1964	Comedy	7.540430

We already have the data for plotting the diagram. However, I am planning to plot each genre into a different color. Let's check what genres we have:

[136]:
```
# check avaliable genres
gen_arr = df.genres.unique()
gen_arr
```

[136]:
```
array(['Drama', 'Thriller', 'Comedy', 'Adventure', 'Action'], dtype=object)
```

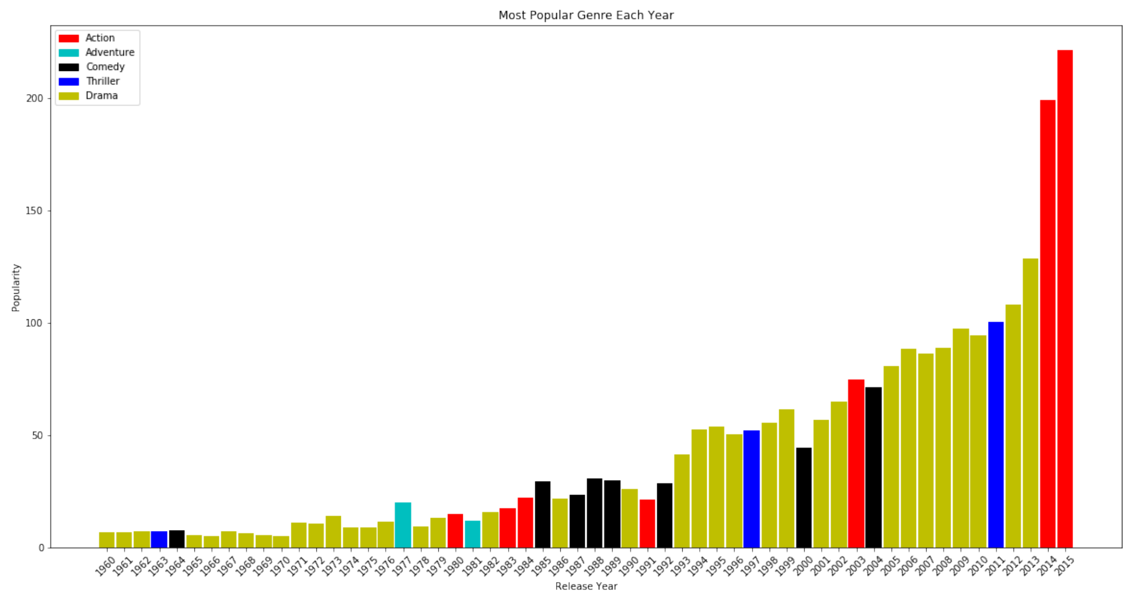
Create x and y for each genre.

[137]:
```
drama_x = df.query('genres == "Drama"').release_year
drama_y = df.query('genres == "Drama"').popularity

thriller_x = df.query('genres == "Thriller"').release_year
thriller_y = df.query('genres == "Thriller"').popularity

comedy_x = df.query('genres == "Comedy"').release_year
comedy_y = df.query('genres == "Comedy"').popularity

adventure_x = df.query('genres == "Adventure"').release_year
adventure_y = df.query('genres == "Adventure"').popularity

action_x = df.query('genres == "Action"').release_year
action_y = df.query('genres == "Action"').popularity
```

plot each x and y.

[138]:
```
plt.figure(figsize=(20,10))

plt.bar(drama_x, drama_y, width = 0.90, align='center', color='y')
plt.bar(thriller_x, thriller_y, width = 0.90, align='center', color='b')
plt.bar(comedy_x, comedy_y, width = 0.90, align='center', color='k')
plt.bar(adventure_x, adventure_y, width = 0.90, align='center', color='c')
plt.bar(action_x, action_y, width = 0.90, align='center', color='r')

plt.xticks(df.release_year, rotation=45)
plt.xlabel('Release Year')
```

```
plt.ylabel('Popularity')
plt.title('Most Popular Genre Each Year')

r_patch = mpatches.Patch(color='red', label='Action')
c_patch = mpatches.Patch(color='c', label='Adventure')
k_patch = mpatches.Patch(color='k', label='Comedy')
b_patch = mpatches.Patch(color='b', label='Thriller')
y_patch = mpatches.Patch(color='y', label='Drama')

plt.legend(handles=[r_patch,c_patch,k_patch,b_patch,y_patch])

plt.show();
```



As we can see, the trend is gradually climbing upwards while there is a drastic increase in 2014; This tells us the population of moviegoers is increasing. Moreover, Drama occupies the top seat for many years since 1960. However, Action movies tend to be favorable recently.

What kinds of properties are associated with movies that have high revenues? There are several steps for solving this problem:

Find the mean of revenues

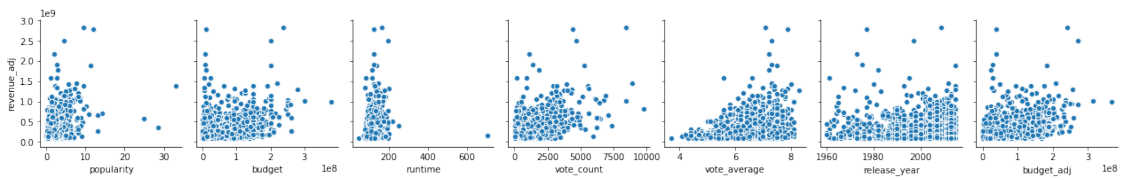
Retrieve those movies that have revenue greater than mean

Find the mean of revenues and retrieve data

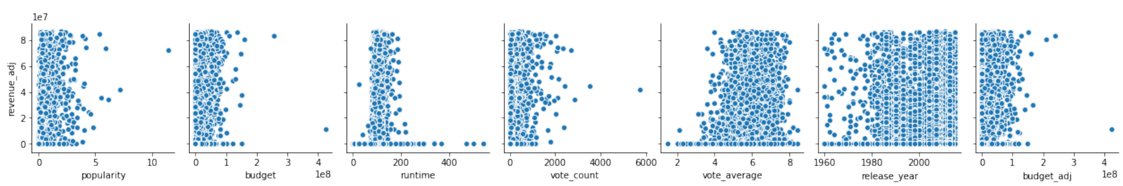
[139]:
```
# Since there is inflation, we use revenue_adj instead of revenue.
# Calculate the mean for this feature.
revenue_mean = movie_df.revenue_adj.mean()
```

```
# retrieve high revenues movies and low revenues movies
high_ren_movie = movie_df.query('revenue_adj >= @revenue_mean')
low_ren_movie = movie_df.query('revenue_adj < @revenue_mean')
```

[140]:
```
sns.pairplot(high_ren_movie,
             x_vars=["popularity", "budget", "runtime", "vote_count",␣
 ↪"vote_average", "release_year", "budget_adj"],
             y_vars=["revenue_adj"],
             kind="scatter", palette="husl")
plt.show()
```



[141]:
```
sns.pairplot(low_ren_movie,
             x_vars=["popularity", "budget", "runtime", "vote_count",␣
 ↪"vote_average", "release_year", "budget_adj"],
             y_vars=["revenue_adj"],
             kind="scatter", palette="husl")
plt.show()
```



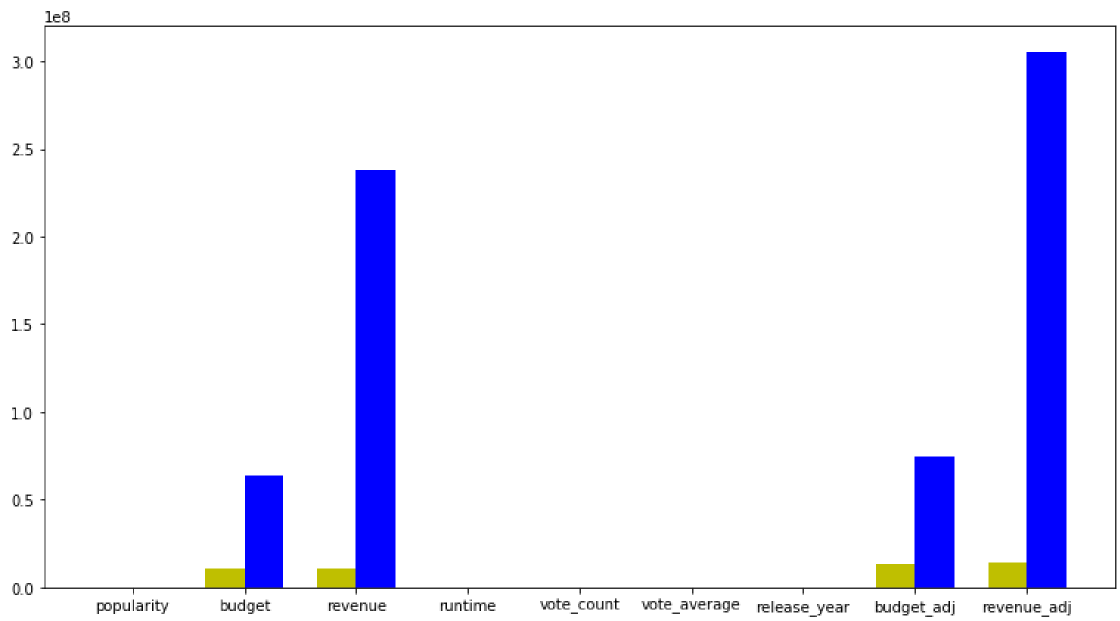
As we can see on the graphs on high revenue movies, revenue_adj has a positive correlation with most of the features except runtime. At the same time, the relationship in low revenue movie is not too noticeable. Let's take a further look.

Find Average and Subtract Find the average of each feature in both low and high revenue data frames:

[144]:
```
# find the properties average of high revenue movie
high = high_ren_movie.mean(axis = 0)
low = low_ren_movie.mean(axis = 0)
```

[145]:
```
# find the properties average of high revenue movie
inc = high - low
```

[146]:
```
ind = np.arange(9)

width = 0.35
plt.figure(figsize=(13, 7))
plt.bar(ind, low, width, color='y', label = "low")
plt.bar(ind + 0.35, high, width, color='b', label = "high")
plt.xticks(ind + width / 2, (low.index))

plt.show()
inc
```



[146]:
```
popularity      1.365998e+00
budget          5.261024e+07
revenue         2.270119e+08
runtime         1.278599e+01
vote_count      8.941145e+02
vote_average    4.785441e-01
release_year    6.586035e-01
budget_adj      6.086291e+07
revenue_adj     2.907299e+08
dtype: float64
```

According to the above data, high revenue movies usually associate with a high budget, high vote_count, and high vote_average. Popularity, runtime, and release_year, on the other hand, have less association. We just made our observation on numeric features. Let's take a look at the text features of the dataset. (cast, director, tagline, keywords, overview, production_companies)

Keywords:

[147]:
```
avg_word_high = high_ren_movie.keywords.apply(lambda x: len(x.split("|"))).
 ↪mean()
avg_word_high
```

[147]: 4.668272388876725

[148]:
```
avg_word_low = low_ren_movie.keywords.apply(lambda x: len(x.split("|"))).mean()
avg_word_low
```

[148]: 4.085902118334551

Overview:

[149]:
```
avg_over_high = high_ren_movie.overview.apply(lambda x: len(x.split("|"))).
 ↪mean()
avg_over_high
```

[149]: 1.0

[150]:
```
avg_over_low = low_ren_movie.overview.apply(lambda x: len(x.split("|"))).mean()
avg_over_low
```

[150]: 1.0001460920379839

Tagline:

[151]:
```
avg_tag_high = high_ren_movie.tagline.apply(lambda x: len(x.split("|"))).mean()
avg_tag_high
```

[151]: 1.0

[152]:
```
avg_tag_low = low_ren_movie.tagline.apply(lambda x: len(x.split("|"))).mean()
avg_tag_low
```

[152]: 1.0

Production_companies:

[153]:
```
avg_production_high = high_ren_movie.production_companies.apply(lambda x: len(x.
 ↪split("|"))).mean()
avg_production_high
```

[153]: 2.8745347054959494

[76]:
```
avg_production_low = low_ren_movie.production_companies.apply(lambda x: len(x.
 ↪split("|"))).mean()
avg_production_low
```

[76]: 2.375018261504748

In conclusion, high revenue movies usually associate with:

a high budget

high vote_count

high vote_average

Slightly more keywords

Slightly more production companies

Which movie earned the most since 1960? Which makes the least? Since inflation is a concern, we use revenue_adj instead of revenue. Profit = revenue - budget.

[87]:
```
movie_df['profit'] = movie_df['revenue_adj'] - movie_df['budget_adj']

most_earn = movie_df[movie_df['profit'] == movie_df['profit'].max()].
 ↪original_title.unique()

least_earn = movie_df[movie_df['profit'] == movie_df['profit'].min()].
 ↪original_title.unique()

print(most_earn[0], "earn the most.")
print(least_earn[0], "earn the least.")
```

```
Star Wars earn the most.
The Warrior's Way earn the least.
```

How much has the drama movie revenue improved over time?

Find all action movies.

Group those action movies by year.

Calculate mean revenue in each group.

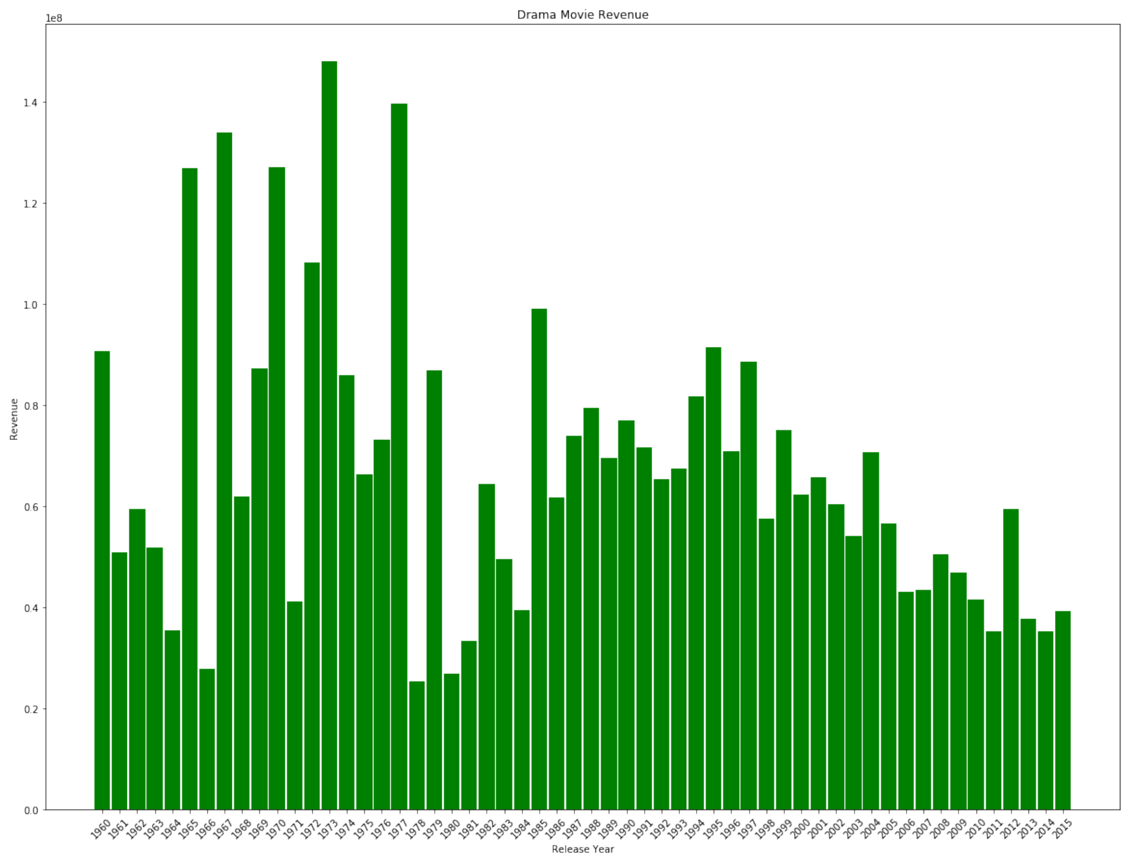
[113]:
```
# find all action movie
drama_df = movie_df.query('genres == "Drama"')

# Group action movie by year, and calculate mean revenue for each group.
drama_ren = drama_df.groupby('release_year').agg({'revenue_adj': 'mean'}).
 ↪reset_index()

drama_ren.head()
```

[113]:

	release_year	revenue_adj
0	1960	9.068750e+07
1	1961	5.085438e+07
2	1962	5.935515e+07

```
3           1963   5.179930e+07
4           1964   3.530610e+07
```

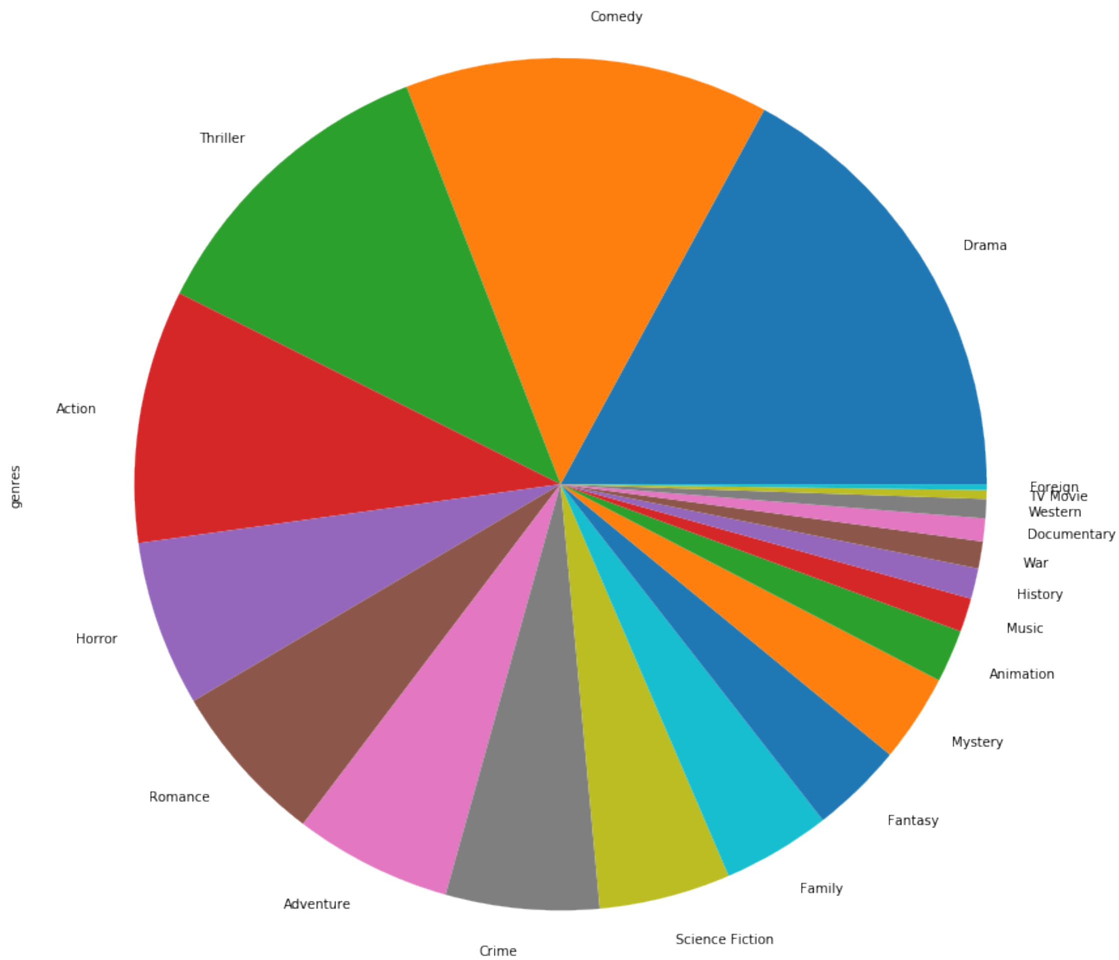
[117]:
```
plt.figure(figsize=(20, 15))

plt.bar(drama_ren.release_year, drama_ren.revenue_adj, width = 0.90,␣
 ↪align='center', color='g')
plt.xticks(drama_ren.release_year, rotation=45)

plt.xlabel('Release Year')
plt.ylabel('Revenue')
plt.title("Drama Movie Revenue")

plt.show();
```



The revenue of the drama movie fluctuates heavily between 1960 and 1985. After 1985, the trend is gradually going downwards.

What is the proportion of each genre since 1960?

[96]:
```
movie_df.genres.value_counts().plot(kind="pie", figsize=(15, 15));
```



As we can see on the above pie chart, the four main genres from highest to lowest are Drama, Comedy, Thriller and Action.

Conclusions

Which genres are most popular from year to year? The trend of popularity is gradually climbing upwards while there is a drastic increase in 2014; This tells us the population of moviegoers is increasing. Moreover, Drama occupies the top seat for many years since 1960. However, Action movies tend to be favorable recently.

What kinds of properties are associated with movies that have high revenues?

High revenue movies usually associate with:

a high budget

high vote_count

high vote_average

Slightly more keywords

Slightly more production companies

Which movie earn the most over time? Which earn the least?

```
        Star Wars earn the most. <br>
        The Warrior's Way earn the least.
    </div>
</li>
<li>
    <a href="#q4">How much has the drama movie revenue improved over time?</a>
    <div>
        The revenue of the drama movie fluctuates heavily between 1960 and 1985. After 1985, th
    </div>
</li>
<li>
    <a href="#q5">What is the proportion of each genre since 1960?</a>
    <div>
        As we can see from the above pie chart, the four main genres from highest to lowest are
    </div>
</li>
```