Investigate_a_Dataset

August 9, 2022

1 Project: Investigate a Dataset - The Movie Database Review and Revenue

1.1 Table of Contents

1.2 1. Introduction

The Movie Database (TMDb) is a collaborative database about movies . The project was founded by Travis Bell in 2008 to collect movie posters. The initial database was a donation from the free Open Media Database(omdb) project. TMDb is a competitor project to the commercial Internet Movie Database. The objective of the project is to analysis the data to get more insight and get answer the research questions.

1.2.1 a). Dataset Description

The dataset to use for this project can be found here.
Below is the dataset glossary:

- id - The identification number of the Movie in the dataset
- imdb_id - The identification number of the Movie in the imdb
- popularity - The score of a movie being liked
- budget - The total cost for the production of a movie
- revenue - The total income from a movie
- original_title - The name of the movie
- cast - The actors in the movies
- homepage - The website link to the movies
- director - The director of the movie
- tagline - A catch phrase of the movie
- keywords - Unique words associated with the movie
- overview - A small explanation of the movie
- runtime - The time period for the movie
- genres - The classification type of the movie

- production_companies - The companies that were involved in the production of the movie
- release_date - The date a movie was released
- vote_count - The vote number a movie received
- vote_average - The average votes received
- release_year - The year of release
- budget_adj - The budget of the associated movie in terms of 2010 dollars, accounting for inflation over time
- revenue_adj - The revenue of the associated movie in terms of 2010 dollars, accounting for inflation over time

1.2.2 b). Research Questions for Analysis

i). Which genres are most popular from year to year?

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

iii). Does vote average affect revenues?

iv). Which Production Company have the highest number of Movie titles and revenue?

1.3 2. Data Wrangling

1.3.1 a). Importing the Python Libraries

```
In [1]: import pandas as pd
        import numpy as np
        import matplotlib.pyplot as plt
        import seaborn as sns
        pd.set_option("display.max_columns", None)
        %matplotlib inline
```

1.3.2 b). Loading the Data

```
In [2]: movies_df = pd.read_csv("https://d17h27t6h515a5.cloudfront.net/topher/2017/October/59dd1
```

1.3.3 c). Accessing the Data

```
In [3]: # Checking the top 3 rows of the dataframe

        movies_df.head(3)
```

```
Out[3]:        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
        2  262500  tt2908446   13.112507  110000000   295238201           Insurgent

                                                        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...

                                         homepage          director  \
0                   http://www.jurassicworld.com/   Colin Trevorrow
1                     http://www.madmaxmovie.com/     George Miller
2  http://www.thedivergentseries.movie/#insurgent  Robert Schwentke

                     tagline  \
0           The park is open.
1          What a Lovely Day.
2  One Choice Can Destroy You

                                              keywords  \
0  monster|dna|tyrannosaurus rex|velociraptor|island
1   future|chase|post-apocalyptic|dystopia|australia
2  based on novel|revolution|dystopia|sequel|dyst...

                                              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

                                      genres  \
0  Action|Adventure|Science Fiction|Thriller
1  Action|Adventure|Science Fiction|Thriller
2         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
2  Summit Entertainment|Mandeville Films|Red Wago...      3/18/15        2480

   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
```

In [4]:
```python
# Checking the bottom 3 rows of the dataframe

movies_df.tail(3)
```

Out[4]:
```
          id    imdb_id  popularity  budget  revenue  \
10863  39768  tt0060161    0.065141       0        0
10864  21449  tt0061177    0.064317       0        0
10865  22293  tt0060666    0.035919   19000        0

                 original_title  \
```

```
10863       Beregis Avtomobilya
10864    What's Up, Tiger Lily?
10865  Manos: The Hands of Fate

                                                    cast homepage  \
10863  Innokentiy Smoktunovskiy|Oleg Efremov|Georgi Z...      NaN
10864  Tatsuya Mihashi|Akiko Wakabayashi|Mie Hama|Joh...      NaN
10865  Harold P. Warren|Tom Neyman|John Reynolds|Dian...      NaN

               director                                       tagline  \
10863    Eldar Ryazanov                                           NaN
10864       Woody Allen                      WOODY ALLEN STRIKES BACK!
10865  Harold P. Warren  It's Shocking! It's Beyond Your Imagination!

                                   keywords  \
10863              car|trolley|stealing car
10864                                 spoof
10865  fire|gun|drive|sacrifice|flashlight

                                                overview  runtime  \
10863  An insurance agent who moonlights as a carthie...       94
10864  In comic Woody Allen's film debut, he took the...       80
10865  A family gets lost on the road and stumbles up...       74

               genres     production_companies release_date  vote_count  \
10863  Mystery|Comedy                  Mosfilm       1/1/66          11
10864   Action|Comedy  Benedict Pictures Corp.      11/2/66          22
10865          Horror                Norm-Iris     11/15/66          15

       vote_average  release_year     budget_adj  revenue_adj
10863           6.5          1966       0.000000          0.0
10864           5.4          1966       0.000000          0.0
10865           1.5          1966  127642.279154          0.0
```

In [5]:
```
# Checking the shape of the dataframe

print(f'The dataframe has {movies_df.shape[0]} rows and {movies_df.shape[1]} columns')
```

```
The dataframe has 10866 rows and 21 columns
```

In [6]:
```
# Checking the columns of the dataframe

print(movies_df.columns)
```

```
Index(['id', 'imdb_id', 'popularity', 'budget', 'revenue', 'original_title',
       'cast', 'homepage', 'director', 'tagline', 'keywords', 'overview',
       'runtime', 'genres', 'production_companies', 'release_date',
       'vote_count', 'vote_average', 'release_year', 'budget_adj',
```

```
 'revenue_adj'],
dtype='object')
```

In [7]:
```
# Checking more information about the dataframe

print(movies_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
None
```

1.3.4 c). Tidying the Dataset

1.3.5 i). Checking for Null Values

This process involves checking for the missing values in the dataset and dealing with them.

In [8]:
```
total = movies_df.isnull().sum().sort_values(ascending=False)
percentage = (movies_df.isnull().sum()/movies_df.isnull().count()*100).sort_values(ascen
missing_value = pd.concat([total,percentage],axis=1,keys=['Total','Percentage'])
missing_value.head(10)
```

Out[8]:
```
                      Total  Percentage
homepage               7930   72.979937
```

```
tagline                 2824   25.989324
keywords                1493   13.740107
production_companies    1030    9.479109
cast                      76    0.699429
director                  44    0.404933
genres                    23    0.211669
imdb_id                   10    0.092030
overview                   4    0.036812
popularity                 0    0.000000
```

Dealing with the missing values

- From the above we can see we have close to 73% of missing values in the homepage column and we shall proceed to drop the entire columns since the remaining observations will affect our analysis due to low numbers.
- We shall also drop the tagline,keywords column, imdb, overview and id in as much as it does not have missing values since they are not relevant to our analysis.
- The other columns, we shall drop only the missing values

```
In [9]: # Dropping the unnecessary columns

        movies_df.drop(['homepage','keywords','imdb_id','overview','tagline'],axis=1,inplace=Tru
```

```
In [10]: # Dropping the rows with null values

         movies_df.dropna(axis=0,inplace=True)
```

```
In [11]: # Checking that the dataframe has no null values

         movies_df.isnull().sum().sum()
```

```
Out[11]: 0
```

ii). Checking for Duplicates

```
In [12]: movies_df.duplicated().sum()
```

```
Out[12]: 1
```

We only have one duplicate record and we shall drop.

```
In [13]: # Dropping the duplicated rows

         movies_df.drop_duplicates(inplace=True)
```

```
In [14]: # Confirming

         movies_df.duplicated().sum()
```

```
Out[14]: 0
```

iii). Checking the Datatypes

In [15]:
```
movies_df.dtypes
```

Out[15]:
```
id                        int64
popularity              float64
budget                    int64
revenue                   int64
original_title           object
cast                     object
director                 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
```

Correcting the Datatypes

- The release_date column should be in datetime format

In [16]:
```
# Converting the release date column to the appropriate data type

movies_df['release_date'] = pd.to_datetime(movies_df['release_date'])
```

In [17]:
```
# Checking to confirm that the data type of the release date column is now a datetime o

movies_df.dtypes
```

Out[17]:
```
id                               int64
popularity                     float64
budget                           int64
revenue                          int64
original_title                  object
cast                            object
director                        object
runtime                          int64
genres                          object
production_companies            object
release_date            datetime64[ns]
vote_count                       int64
vote_average                   float64
release_year                     int64
budget_adj                     float64
revenue_adj                    float64
dtype: object
```

1.4 iv). Data Consistency

In [18]:
```
# We shall categorize the genres properly

genres_unique =  pd.DataFrame(movies_df.genres.str.split('|').tolist()).stack().unique(

genres_unique = pd.DataFrame(genres_unique, columns=['genre'])

# We shall then merge the genres with the movies dataframe

movies_df = movies_df.join(movies_df.genres.str.get_dummies().astype(bool))

# We shall then drop the genres column

movies_df.drop(['genres'],axis=1,inplace=True)
```

In [19]:
```
# Checking the dataframe

movies_df.head(3)
```

Out[19]:
```
       id  popularity     budget     revenue      original_title  \
0  135397   32.985763  150000000  1513528810      Jurassic World
1   76341   28.419936  150000000   378436354  Mad Max: Fury Road
2  262500   13.112507  110000000   295238201           Insurgent

                                                cast          director  \
0  Chris Pratt|Bryce Dallas Howard|Irrfan Khan|Vi...   Colin Trevorrow
1  Tom Hardy|Charlize Theron|Hugh Keays-Byrne|Nic...     George Miller
2  Shailene Woodley|Theo James|Kate Winslet|Ansel...  Robert Schwentke

   runtime                               production_companies release_date  \
0      124  Universal Studios|Amblin Entertainment|Legenda...   2015-06-09
1      120  Village Roadshow Pictures|Kennedy Miller Produ...   2015-05-13
2      119  Summit Entertainment|Mandeville Films|Red Wago...   2015-03-18

   vote_count  vote_average  release_year    budget_adj   revenue_adj  Action  \
0        5562           6.5          2015  1.379999e+08  1.392446e+09    True
1        6185           7.1          2015  1.379999e+08  3.481613e+08    True
2        2480           6.3          2015  1.012000e+08  2.716190e+08   False

   Adventure  Animation  Comedy  Crime  Documentary  Drama  Family  Fantasy  \
0       True      False   False  False        False  False   False    False
1       True      False   False  False        False  False   False    False
2       True      False   False  False        False  False   False    False

   Foreign  History  Horror  Music  Mystery  Romance  Science Fiction  \
0    False    False   False  False    False    False             True
1    False    False   False  False    False    False             True
2    False    False   False  False    False    False             True
```

```
   TV Movie  Thriller    War  Western
0     False      True  False    False
1     False      True  False    False
2     False      True  False    False
```

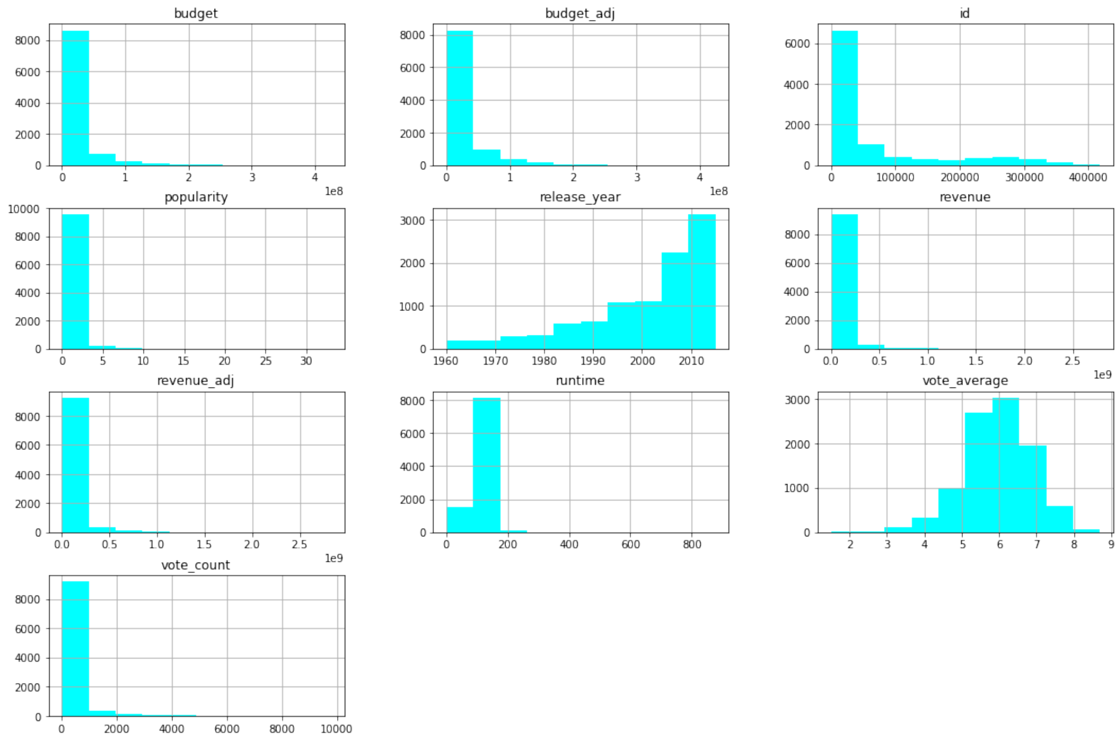
In [20]:
```
# We shall rename the columns appropriately

movies_df.rename(columns = lambda x: x.replace(' ','_').lower(),inplace = True)

# Confirming to check the change

movies_df.columns
```

Out[20]:
```
Index(['id', 'popularity', 'budget', 'revenue', 'original_title', 'cast',
       'director', 'runtime', 'production_companies', 'release_date',
       'vote_count', 'vote_average', 'release_year', 'budget_adj',
       'revenue_adj', 'action', 'adventure', 'animation', 'comedy', 'crime',
       'documentary', 'drama', 'family', 'fantasy', 'foreign', 'history',
       'horror', 'music', 'mystery', 'romance', 'science_fiction', 'tv_movie',
       'thriller', 'war', 'western'],
      dtype='object')
```

1.5 3). Exploratory Data Analysis(EDA)

We shall first do the Univariate analysis. This is the simplest form of analyzing data. "Uni" means "one", so in other words the analysis involves only one variable. It doesn't deal with causes or relationships and it's major purpose is to describe. It takes data, summarizes that data and finds patterns in the data.

In [25]:
```
# Plotting Histogram for the Numeric columns

num_cols = movies_df[movies_df.select_dtypes(include=['float64','int64']).columns]


num_cols.hist(bins=10, figsize=[18,12], color = 'cyan')
plt.show()
```

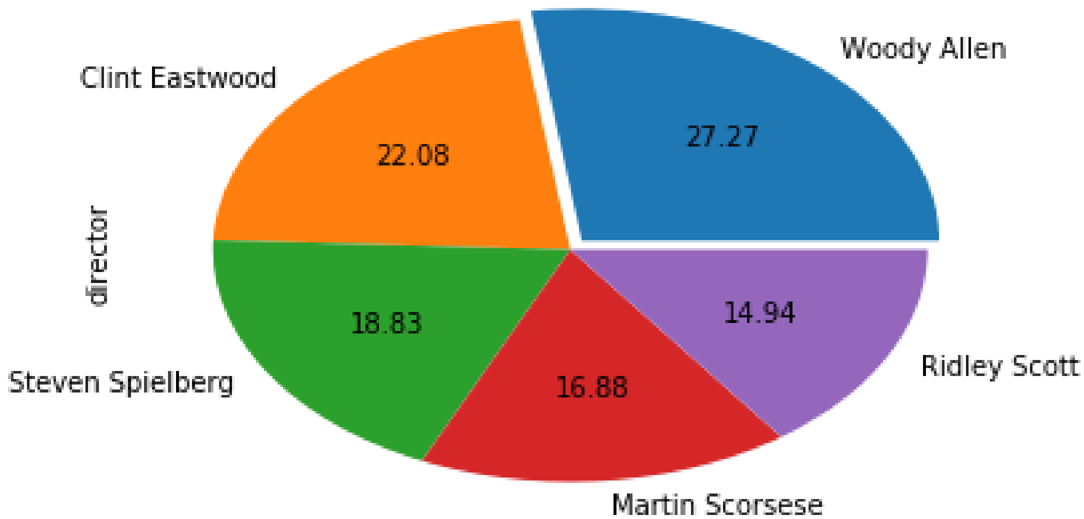


- We can clear see that Movie production has been increasing over the years.
- We can also see that the average vote is around 6 for most movies.

In [26]:
```
# Using barplot to plot the categorical columns

# Selecting categorical columns

cat_cols = movies_df.select_dtypes(include=['object']).columns

cat_cols
```

Out[26]:
```
Index(['original_title', 'cast', 'director', 'production_companies'], dtype='object')
```

In [40]:
```
# Plotting pie chart for directors
explode=(0.05, 0,0,0,0)

movies_df.director.value_counts().head(5).plot(kind='pie',autopct='%.2f',explode=explod
```

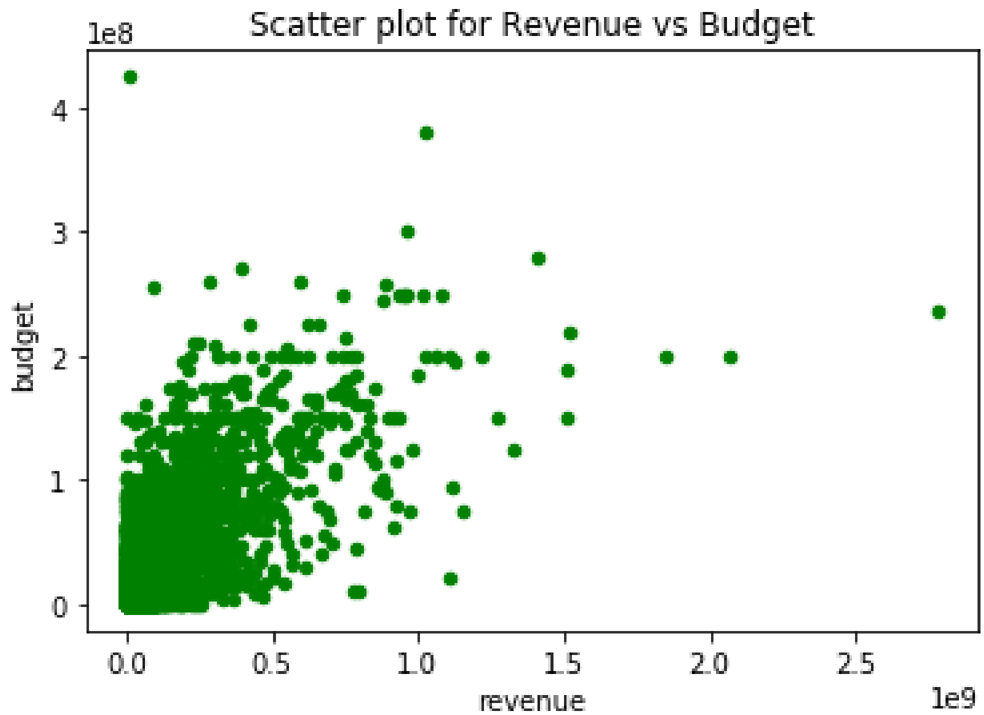


We can clearly see that of the top 5 directors, Woody Allen is the one with the most movies

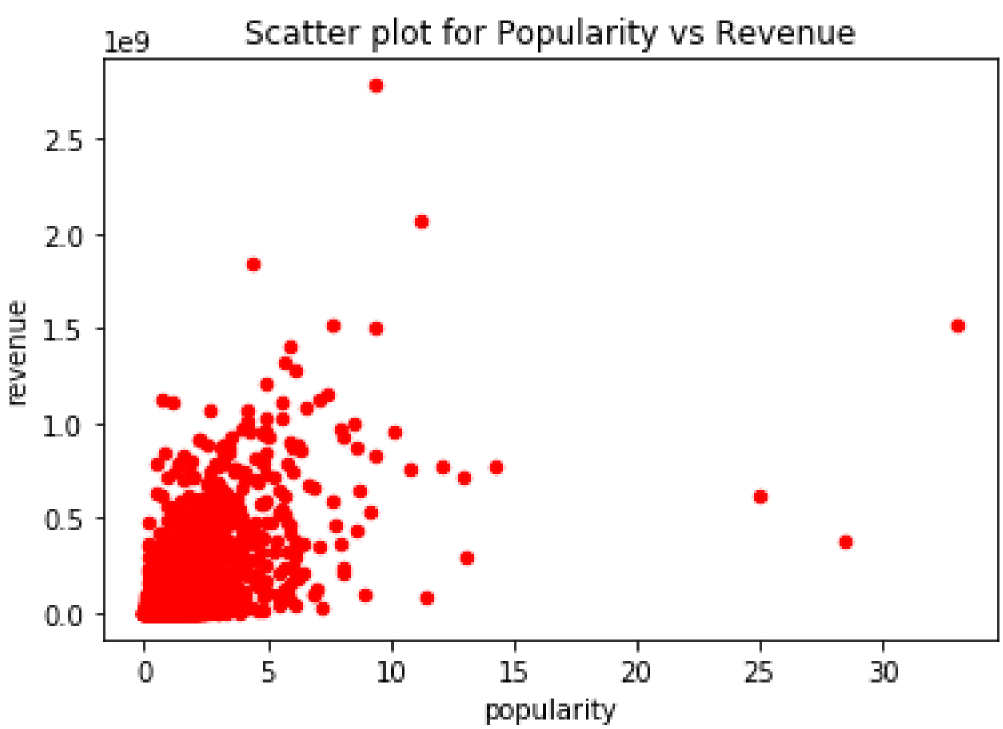
We can also do Bivariate statistical analyses. This type uses two variables (e.g. self-efficacy and academic performance). Bivariate analyses can be descriptive (e.g. a scatterplot), but the goal is typically to compare or examine the relationship between two variables. For instance, researchers may examine whether student self-efficacy in mathematics is a significant predictor of mathematics standardized test scores.

```
In [36]: # Creating a function to plot the various scatterplot

         def scatter_plot(x,y,color,title):
             movies_df.plot(x,y,kind='scatter',color=color,title=title)
```

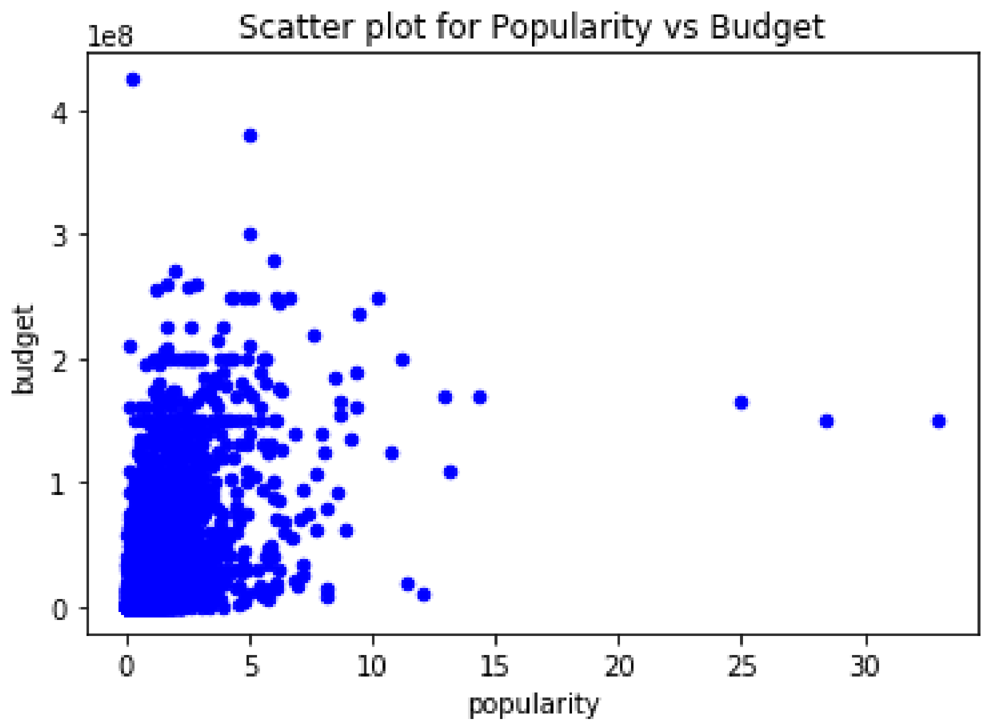
```
In [37]: # Scatter plot for Revenue vs Budget

         scatter_plot('revenue','budget','green','Scatter plot for Revenue vs Budget')
```




```
In [38]: # Scatterplot to compare the popularity and revenue

         scatter_plot('popularity','revenue','red','Scatter plot for Popularity vs Revenue')
```



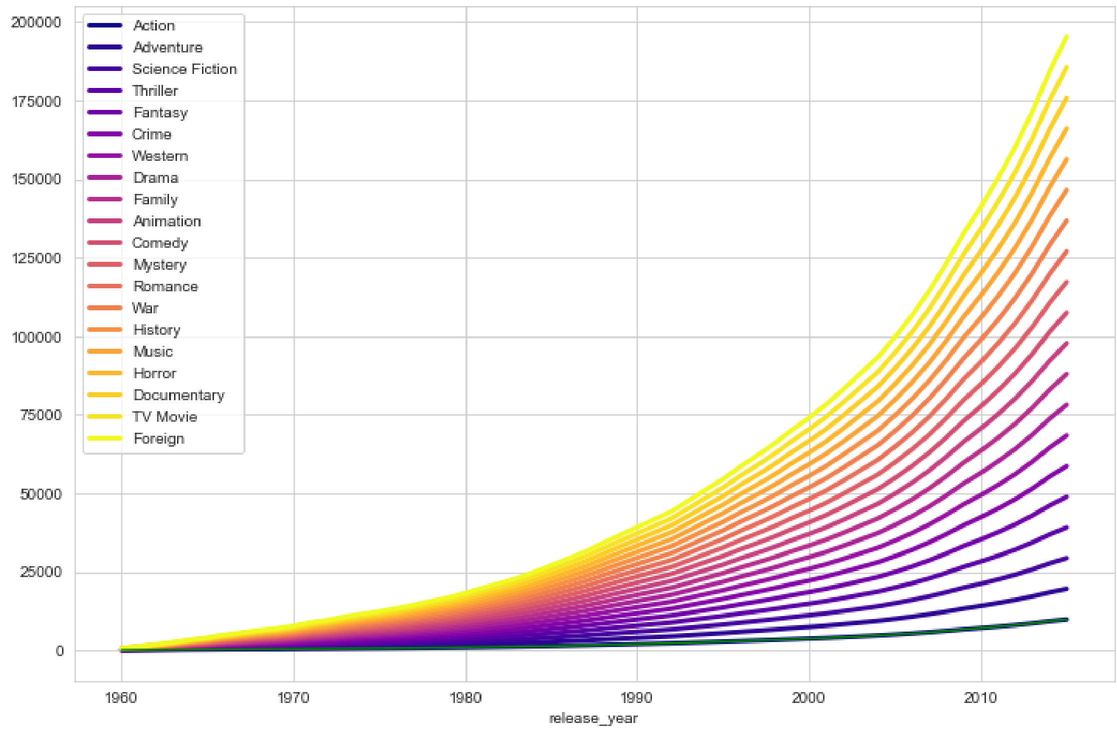
In [40]:
```
# Scatterplot to compare the popularity and budget

scatter_plot('popularity','budget','blue','Scatter plot for Popularity vs Budget')
```



1.6 4. Answering the Research questions for Analysis

i). Which genres are most popular from year to year?

In [292]:
```
df_movi = movies_df[['id','release_year']].groupby('release_year')

df = pd.DataFrame({'Movies' : df_movi.id.nunique().cumsum()})

for genre in genres_unique.genre:
    df_movie = movies_df[movies_df[genre]][['id','release_year']].groupby('release_yea
    df[genre] = df_movi.id.nunique().cumsum()


df.loc[:,df.columns != 'Movies'].plot(stacked=True, figsize=(12,8),linewidth=3, cmap='
plt.plot(df['Movies'], color='green');
```



We can see from the above that Foreign Movies have been having the highest increase popularity rate over the years while Action movies have been having the lowest rate.

ii). What kinds of properties are associated with movies that have high revenues? We shall select movies above median to be of high revenue

In [321]:
```
# We shall create bins to categorize revenue

movies_df['revenue_category'] = movies_df.revenue.apply(lambda x: 'High' if x > movies
```

In [320]:
```
# Movies with high and low revenue categories

movies_df.groupby('revenue_category').mean().astype(int)
```

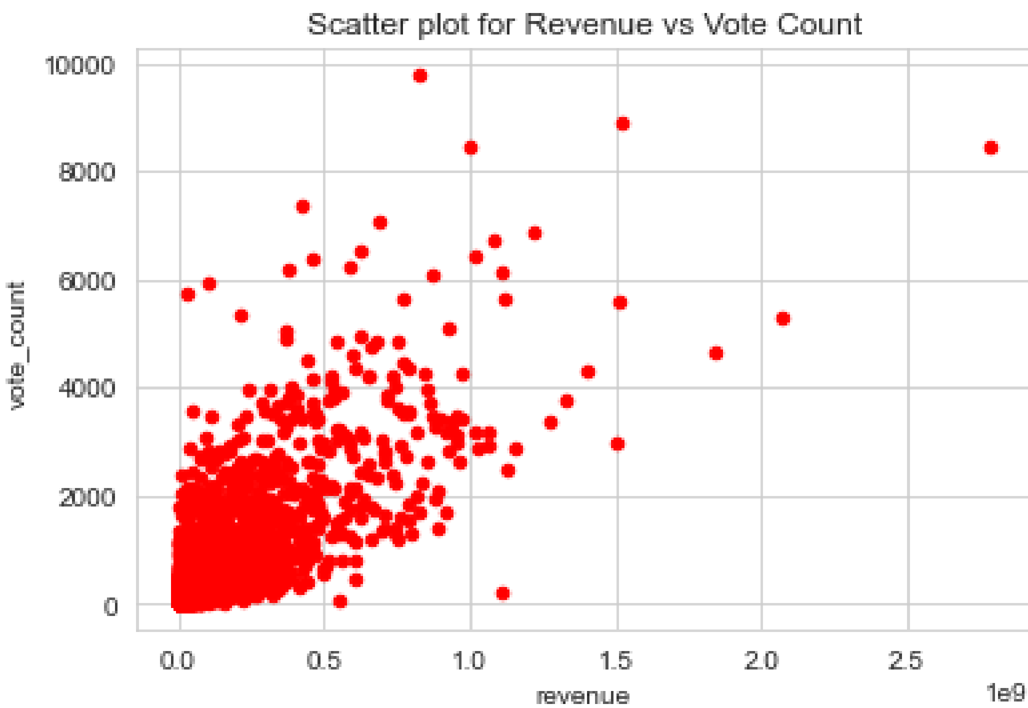
Out[320]:
```
                     id  popularity    budget   revenue  runtime  vote_count  vote_ave
revenue_category
High              44390           1  30125984  90995236      108         444
Low               80970           0   2988707         0       97          44

                  Adventure  Animation  Comedy  Crime  Documentary  Drama  Family  Fan
revenue_category
High                      0          0       0      0            0      0       0
Low                       0          0       0      0            0      0       0

                  Science Fiction  TV Movie  Thriller  War  Western
```

```
revenue_category
High                                     0         0         0    0         0
Low                                      0         0         0    0         0
```

We can clearly see that most of the movies with high revenue are usually associated with High popularity, runtime, vote_count,vote_average and adjusted revenue

iii). Does vote average affect revenues?

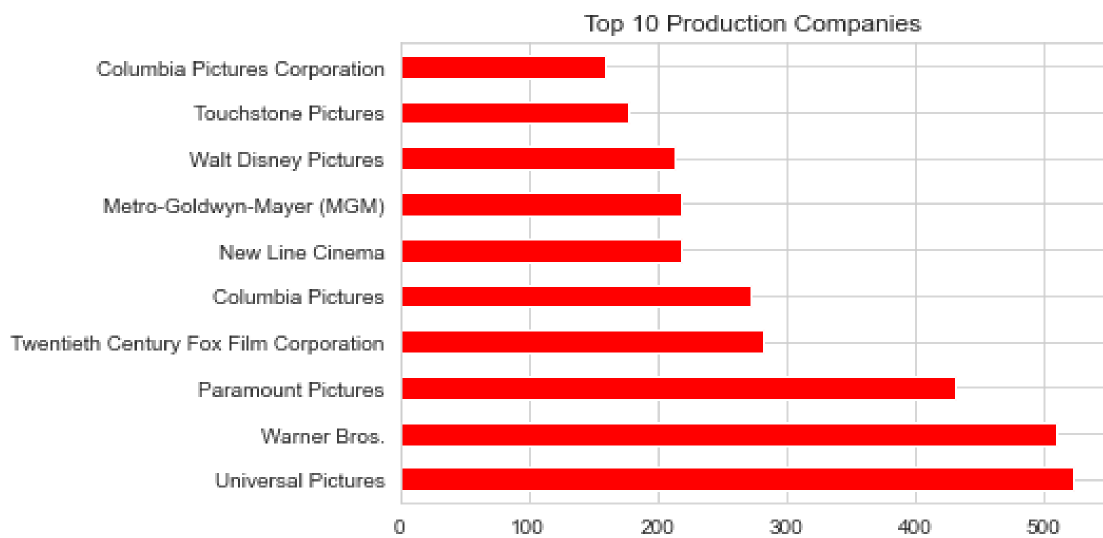
```
In [331]: # We shall plot a scatter plot to compare the revenue and Vote Count

          movies_df.plot(x='revenue', y='vote_count', kind='scatter', color='red', title='Scatte
```



From the above we can easily tell the higher the vote count, the higher the revenue from the movie title

iv). Which Production Company have the highest number of Movie titles and revenue?

```
In [342]: # We shall split the individual companies in the production_companies column

          df_movies = movies_df.production_companies.str.split('|').apply(pd.Series, 1).stack().
          df_movies.name = 'production_companies'

          df_movies.value_counts().head(10).plot(kind='barh', color='red', title='Top 10 Product
```



We can clear see that Universal Pictures is the most popular production company

1.7 5. Conclusion

From the analysis, we can note that Foreign movies, Tv Movie and Documentaries have being getting more common with time and since most movies have an average vote rating of 6, that means slightly more people are preferring the content.

The more budget is invested in a movie production, the higher the chances of the revenue being high and this can be clearly shown by the revenue behavior of the top companies like Universal Pictures, Warner Bros and Paramount pictures.

We can also note that most High voted movies are associated which a much longer runtime.

Limitation

The 'keyword' and 'tagline' columns could have been important features in the text analysis but it was severely affected by many null values.