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Project 3: Investigate a Dataset - TMDB Movie Data

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Introduction

The chosen dataset for this project is TMDb movie data.

This data set contains information about about 10866 movies.

There are 21 columns with different information about each movie such as id, [imdb_id](https://www.imdb.com/ IMDB), original title, budget, revenue, release year, etc.

Possible questions

1. What's the relationship between *popularity and vote_count, vote_average and revenue?
2. What genre produces more revenue in average?
3. Which genres are most popular from year to year?
4. Which year produced more revenue?
5. What's the average revenue per genre per year?
6. Budget statistics.

> *Popularity is cumulative decided by number of star ratings. source

Imports

In [1]:

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
% matplotlib inline
import seaborn as sns
sns.set_style('darkgrid')
import matplotlib.patches as mpatches #https://matplotlib.org/users/legend_guide.html
```

Data Wrangling

General Properties

In [2]:

```
#Loading csv into DataFrame
df = pd.read_csv('tmdb-movies.csv')
df.head(2)
```

Out[2]:

	id	imdb_id	popularity	budget	revenue	original_title	cast	homepage	direc
0	135397	tt0369610	32.985763	150000000	1513528810	Jurassic World	Chris Pratt|Bryce Dallas Howard|Irrfan Khan|Vi...	http://www.jurassicworld.com/	Colin Trevorr
1	76341	tt1392190	28.419936	150000000	378436354	Mad Max: Fury Road	Tom Hardy|Charlize Theron|Hugh Keays-Byrne|Nic...	http://www.madmaxmovie.com/	George Miller

2 rows × 21 columns

In [3]:

```
print("df rows: {}.\ndf columns: {}.".format(df.shape[0], df.shape[1]))
```

```
df rows: 10866.
df columns: 21.
```

In [4]:

```
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
```

Data Cleaning

Checking for null values

In [5]:

```
df.isnull().sum()
```

Out[5]:

```
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
```

As shown in the previous cell, `imdb_id`, `cast`, `homepage`, `director`, `tagline`, `keywords`, `overview`, `genres` and `production_companies` have null values. However, the only fields that affect any of the proposed questions are `director` , `genres` and `cast`. Hence I'll just drop rows with null values for those columns and won't use `df.dropna()` method.

As `homepage` field has 7930 NaN values, using `drop_na()` will cause a major loss of significant data.

In [6]:

```
def drop_rows(df_temp, df):
    """
    Removes specific rows from a dataframe and returns it.

    Args:
        (DataFrame) df_temp - DataFrame with data that needs to be removed
        (DataFrame) df - DataFrame to be transformed
    Returns:
        Dataframe with removed rows.
    """
    index_array = np.array(df_temp.index) #array of indexes for rows with NaN/duplicated values
    for row in index_array:
```

```
        df = df.drop(row)
    return df
```

- **Droping Director**

In [7]:

```
# DataFrame with movies with NaN director
df_null_director = df[df['director'].isnull()]

print("Rows in df before droping ones with NaN value for director: {}.".format(df.shape[0]))
df = drop_rows(df_null_director, df)
print("Rows in df after droping ones with NaN value for director: {}.".format(df.shape[0]))
print("Is there still any NaN director? - {}.".format(df['director'].isnull().any()))
```

```
Rows in df before droping ones with NaN value for director: 10866.
Rows in df after droping ones with NaN value for director: 10822.
Is there still any NaN director? - False.
```

I created a dataframe containing rows where director is null. Inside `drop_rows` method, I iterate over those rows and drop them from original df.

The same methods are used to drop NaN values in cast and genre.

- **Droping Cast**

In [8]:

```
# DataFrame with movies with NaN cast
df_null_cast = df[df['cast'].isnull()]
print("Rows in df before droping ones with NaN value for cast: {}.".format(df.shape[0]))
df = drop_rows(df_null_cast, df)
print("Rows in df after droping ones with NaN value for cast: {}.".format(df.shape[0]))
print("Is there still any NaN cast? - {}.".format(df['cast'].isnull().any()))
```

```
Rows in df before droping ones with NaN value for cast: 10822.
Rows in df after droping ones with NaN value for cast: 10752.
Is there still any NaN cast? - False.
```

- **Droping Genre**

In [9]:

```
# DataFrame with movies with NaN genres
df_null_genres = df[df['genres'].isnull()]
print("Rows in df before droping ones with NaN value for genres: {}.".format(df.shape[0]))
df = drop_rows(df_null_genres, df)
print("Rows in df after droping ones with NaN value for genres: {}.".format(df.shape[0]))
print("Is there still any NaN genres? - {}.".format(df['genres'].isnull().any()))
```

```
Rows in df before droping ones with NaN value for genres: 10752.
Rows in df after droping ones with NaN value for genres: 10732.
Is there still any NaN genres? - False.
```

Checking for duplicates

In [10]:

```
df['id'].duplicated().sum()
```

Out[10]:

```
1
```

In [11]:

```
print("Rows in df before droping duplicates: {}.".format(df.shape[0]))
df.drop_duplicates(inplace=True)
print("Rows in df after droping duplicates: {}.".format(df.shape[0]))
```

```
Rows in df before droping duplicates: 10732.
Rows in df after droping duplicates: 10731.
```

As there is one duplicated id I droped it.

Checking DataTypes

- **Pipe separated string values to list**

In [12]:

```
df.iloc[0]
```

Out[12]:

```
id                                                                 135397
imdb_id                                                         tt0369610
popularity                                                        32.9858
budget                                                          150000000
revenue                                                        1513528810
original_title                                             Jurassic World
cast                    Chris Pratt|Bryce Dallas Howard|Irrfan Khan|Vi...
homepage                                  http://www.jurassicworld.com/
director                                                  Colin Trevorrow
tagline                                                 The park is open.
keywords                monster|dna|tyrannosaurus rex|velociraptor|island
overview                Twenty-two years after the events of Jurassic ...
runtime                                                               124
genres                          Action|Adventure|Science Fiction|Thriller
production_companies    Universal Studios|Amblin Entertainment|Legenda...
release_date                                                       6/9/15
vote_count                                                           5562
vote_average                                                          6.5
release_year                                                         2015
budget_adj                                                       1.38e+08
revenue_adj                                                   1.39245e+09
Name: 0, dtype: object
```

By checking the information above it can be seen that some columns, such as:

- cast,
- keywords,
- genres,
- production_companies and
- director

contain more than one value separated by a pipe (|).

Such information is saved as string ("Chris Pratt|Bryce Dallas Howard|Irrfan Khan|Vincent D'Onofrio|Nick Robinson") making it difficult to analyse the separate values contained in that field. That's why I consider best to save that values in a list of strings so the different values can be accessed easily.

For example `df.iloc[0]['cast'][0]` for 'Chris Pratt'.

The function below helps solving this.

In [13]:

In [13]:

```
def split_pipes(part):
    """
    Takes string input and splits it by the pipe | symbol.

    Args:
        (str) part - string value from series
    Returns:
        Python list of string values from input field.
    """
    part = str(part)
    return part.split('|')
```

In [14]:

```
df['cast'] = df['cast'].apply(split_pipes)
df['keywords'] = df['keywords'].apply(split_pipes)
df['genres'] = df['genres'].apply(split_pipes)
df['production_companies'] = df['production_companies'].apply(split_pipes)
df['director'] = df['director'].apply(split_pipes)
```

In [15]:

```
df[['cast','keywords','genres','production_companies', 'director']].head()
```

Out[15]:

	cast	keywords	genres	production_companies	director
0	[Chris Pratt, Bryce Dallas Howard, Irrfan Khan...	[monster, dna, tyrannosaurus rex, velociraptor...	[Action, Adventure, Science Fiction, Thriller]	[Universal Studios, Amblin Entertainment, Lege...	[Colin Trevorrow]
1	[Tom Hardy, Charlize Theron, Hugh Keays-Byrne,...	[future, chase, post-apocalyptic, dystopia, au...	[Action, Adventure, Science Fiction, Thriller]	[Village Roadshow Pictures, Kennedy Miller Pro...	[George Miller]
2	[Shailene Woodley, Theo James, Kate Winslet, A...	[based on novel, revolution, dystopia, sequel,...	[Adventure, Science Fiction, Thriller]	[Summit Entertainment, Mandeville Films, Red W...	[Robert Schwentke]
3	[Harrison Ford, Mark Hamill, Carrie Fisher, Ad...	[android, spaceship, jedi, space opera, 3d]	[Action, Adventure, Science Fiction, Fantasy]	[Lucasfilm, Truenorth Productions, Bad Robot]	[J.J. Abrams]
4	[Vin Diesel, Paul Walker, Jason Statham, Miche...	[car race, speed, revenge, suspense, car]	[Action, Crime, Thriller]	[Universal Pictures, Original Film, Media Righ...	[James Wan]

It can be seen that all strings separated by | are now lists of strings.

- **Release_date to datetime type**

In [16]:

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

In [17]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 10731 entries, 0 to 10865
Data columns (total 21 columns):
id                      10731 non-null int64
imdb_id                 10726 non-null object
popularity              10731 non-null float64
budget                  10731 non-null int64
revenue                 10731 non-null int64
original_title          10731 non-null object
cast                    10731 non-null object
```

```
cast                     10731 non-null object
homepage                 2893 non-null object
director                 10731 non-null object
tagline                  8001 non-null object
keywords                 10731 non-null object
overview                 10729 non-null object
runtime                  10731 non-null int64
genres                   10731 non-null object
production_companies     10731 non-null object
release_date             10731 non-null datetime64[ns]
vote_count               10731 non-null int64
vote_average             10731 non-null float64
release_year             10731 non-null int64
budget_adj               10731 non-null float64
revenue_adj              10731 non-null float64
dtypes: datetime64[ns](1), float64(4), int64(6), object(10)
memory usage: 1.8+ MB
```

`released_date` was saved as string. I converted it to datetime in case it's needed later to manipulate field as date.

Exploratory Data Analysis

Research Question 1- What's the relationship between `popularity` and `vote_count`?

- **`Popularity` vs. `vote_count`**

In [18]:

```python
df['popularity'].describe()
```

Out[18]:

```
count    10731.000000
mean         0.652615
std          1.004804
min          0.000188
25%          0.210765
50%          0.387081
75%          0.720889
max         32.985763
Name: popularity, dtype: float64
```

In [19]:

```python
df['vote_count'].describe()
```

Out[19]:

```
count    10731.000000
mean       219.812972
std        578.815324
min         10.000000
25%         17.000000
50%         39.000000
75%        148.000000
max       9767.000000
Name: vote_count, dtype: float64
```

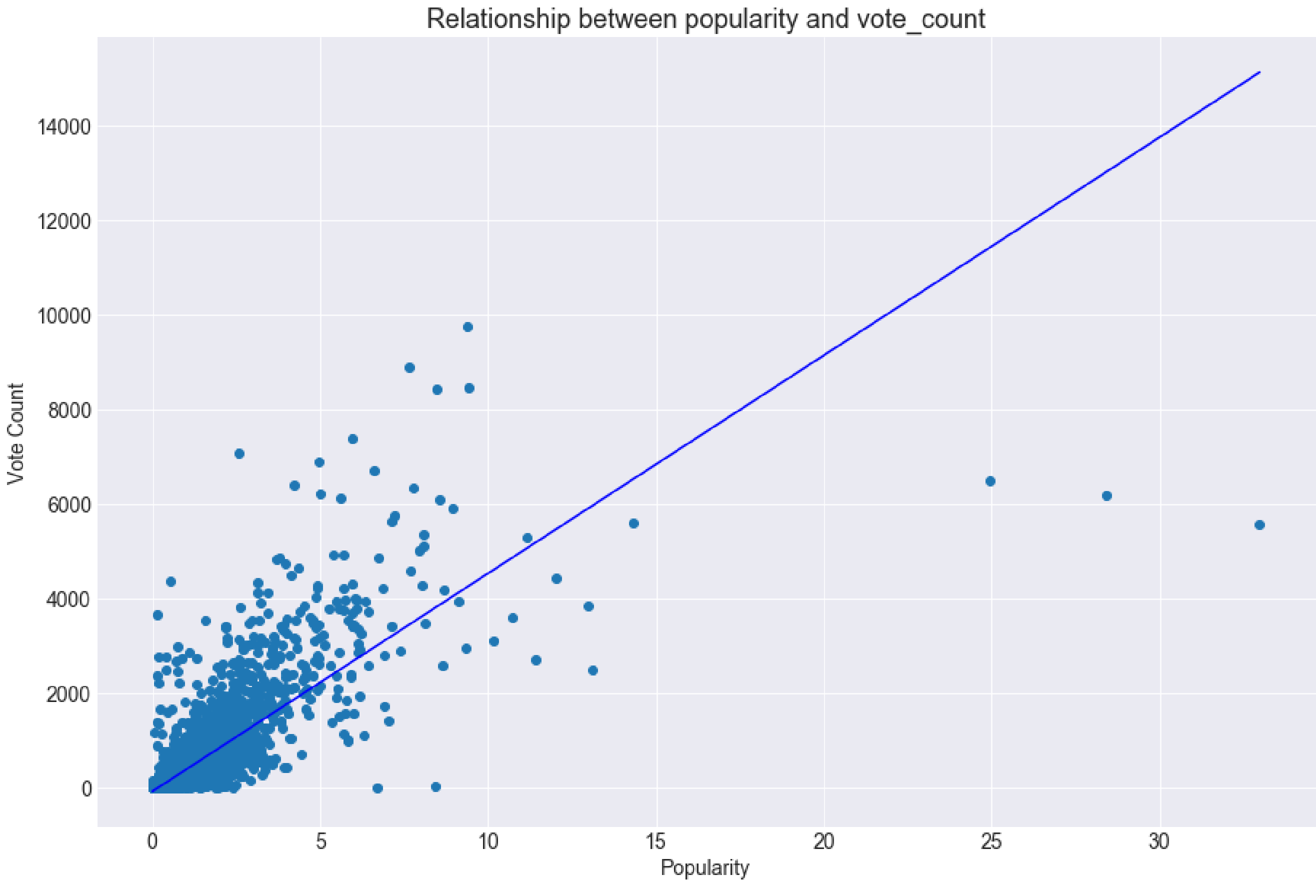
In [20]:

```python
#https://stackoverflow.com/questions/41635448/how-can-i-draw-scatter-trend-line-on-matplot-python-pandas?noredirect=1&lq=1
def draw_scatter_with_trend_line(x, y, title, xLabel, yLabel):
    """
    Draws a scatter plot with trend lines

    Args:
```

```
        (DataFrame column) x - DataFrame column for x axis
        (DataFrame columns) y - DataFrame column for y axis
        (str) - Plot title
        (str) - Label for x axis
        (str) - Label for y axis
    """
    plt.figure(figsize=(15,10))
    plt.scatter(x, y)
    z = np.polyfit(x, y, 1)
    p = np.poly1d(z)
    plt.title(title, fontsize=18)
    plt.xlabel(xLabel, fontsize=14)
    plt.ylabel(yLabel, fontsize=14)
    plt.xticks(fontsize=14)
    plt.yticks(fontsize=14)
    plt.plot(x,p(x),"b-");
```

In [21]:

```
draw_scatter_with_trend_line(df['popularity'], df['vote_count'], 'Relationship between popularity and vote_count', 'Popularity', 'Vote Count')
```



The above graph shows that there is a **strong positive** relationship between popularity of a movie and the number of users who vote.

In [22]:

```
#https://pandas.pydata.org/pandas-docs/stable/generated/pandas.DataFrame.corr.html
df[['popularity', 'vote_count']].corr(method='pearson')['popularity'].vote_count
```

Out[22]:

```
0.8006187445347125
```

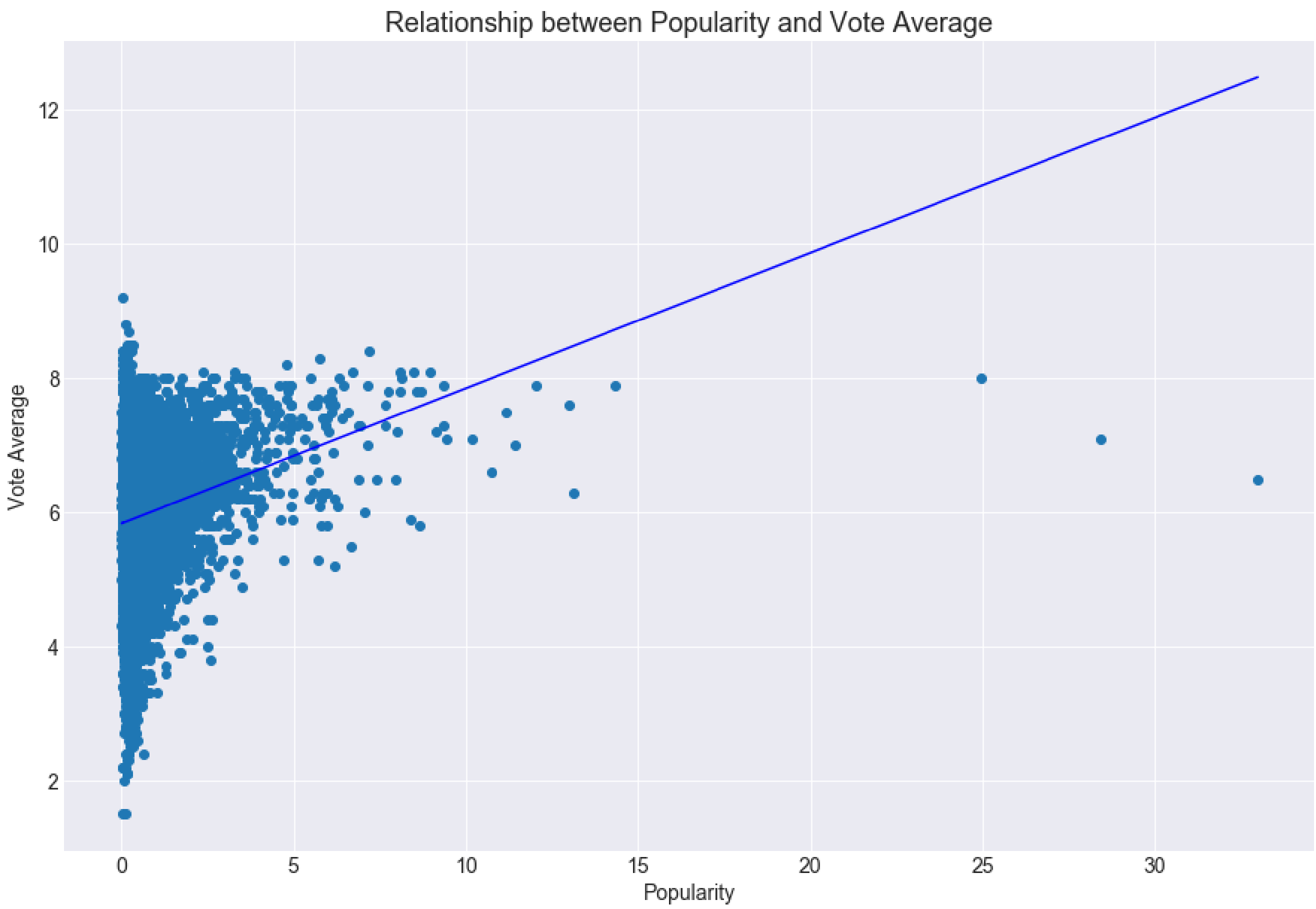
Taking into account Pearson's r it can be seen that the correlation coefficient is 0.8006187445347125, prety near to 1, confirming a strong and positive relationship between this two variables.

It can be the case that as the popularity increases, more people see the movie and want to rate it.

- **Popularity vs. vote_average**

In [23]:

```
draw_scatter_with_trend_line(df['popularity'], df['vote_average'],"Relationship between Popularity and Vote Average", "Popularity", 'Vote Average')
```



In [24]:

```
df[['popularity', 'vote_average']].corr(method='pearson')['popularity'].vote_average
```

Out[24]:

```
0.2179063121675616
```

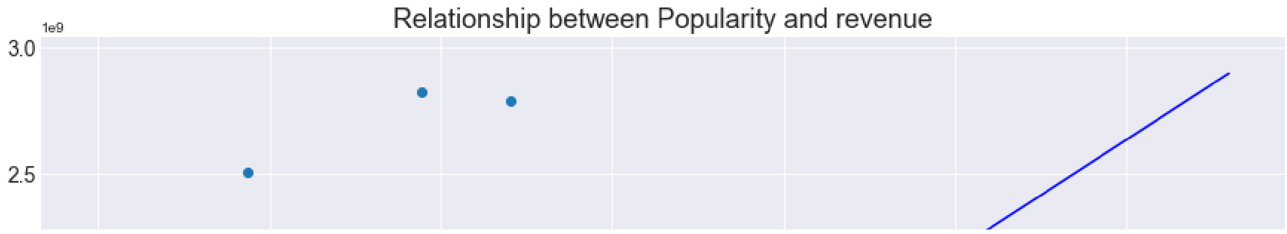
In this case, the relationship has a correlaction coefficient of 0.2179063121675616 showing that, although there is a positive correlation between popularity and vote average, the **relationship is weak**.

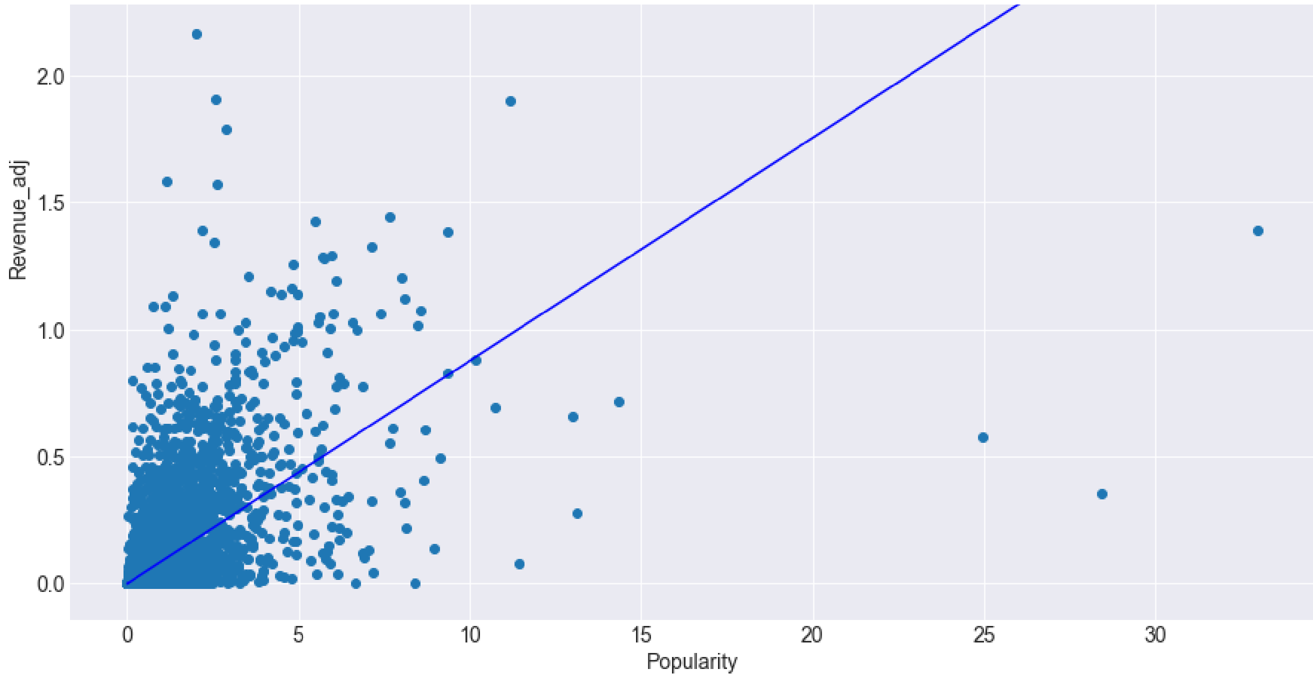
This could be caused by the fact that a movie may be popular due to a lot of advertising but may not be so good.

- **Popularity vs. revenue_adj**

In [25]:

```
draw_scatter_with_trend_line(df['popularity'], df['revenue_adj'],"Relationship between Popularity and revenue", "Popularity", 'Revenue_adj')
```





In [26]:

```
df[['popularity', 'revenue_adj']].corr(method='pearson')['popularity'].revenue_adj
```

Out[26]:

```
0.6083836708004083
```

Both from the plot and from the correlation coefficient of 0.6083836708004083 it can be seen that there is a **positive and moderate** relationship between these two variables.

It appears that as more popular is a movie, more revenue has.

I chose to use `revenue_adj` field instead of `revenue` one so I don't have to account for inflation while comparing revenue to popularity.

- **Conclusion**

In conclusion, from the three variables compared to popularity, it can be seen that a movie that's watched by many people increases the number of people that vote, hence a higher `vote_count` value, and though the movie may or may not be good, if many peplo vote, `popularity`, which is the sum of raitings, raises.

However, if the movie it's not so good, `vote_average` won't always be high besides movie being popular. This means that a movie being popular doesn't mean the movie will be good, hence the relationship between this two variables is weak.

Finally, if popularity is high, it usually means that many people watched the movie so this means that `revenue_adj` is greater.

Research Question 2- What genre produces more renevue in average?

To be able to answer this question I need to group by genre. As genres column consists of list values, this needs to be corrected.

For this question I will split genres into multiple rows for each movie. This is going to be done just for this question and not modifing `df` since the duplicated values on other columns may affect other questions' results.

I tried doing my own function but it took considerable time and I actually never saw it finished so I searched for a function already written and modified it to fit my df.

In [27]:

```
#https://gist.github.com/jlln/338b4b0b55bd6984f883
def splitDataFrameList(df,target_column):
    """
```

```
    Draws a scatter plot with trend lines

    Args:
        (DataFrame) - DataFrame to split
        (DataFrame columns) - the column containing the list values to split
    Returns:
        (DataFrame) - a dataframe with each entry for the target column separated, with each eleme
nt moved into a new row.
                    The values in the other columns are duplicated across the newly divided rows.
    """
    def splitListToRows(row,row_accumulator,target_column):
        split_row = row[target_column]
        for s in split_row:
            new_row = row.to_dict()
            new_row[target_column] = s
            row_accumulator.append(new_row)
    new_rows = []
    df.apply(splitListToRows,axis=1,args = (new_rows,target_column))
    new_df = pd.DataFrame(new_rows)
    return new_df
```

In [28]:

```
df_genres = splitDataFrameList(df,'genres')
df_genres.head(2)
```

Out[28]:

	budget	budget_adj	cast	director	genres	homepage	id	imdb_id	keywords	c
0	150000000	1.379999e+08	[Chris Pratt, Bryce Dallas Howard, Irrfan Khan...	[Colin Trevorrow]	Action	http://www.jurassicworld.com/	135397	tt0369610	[monster, dna, tyrannosaurus rex, velociraptor...	J V
1	150000000	1.379999e+08	[Chris Pratt, Bryce Dallas Howard, Irrfan Khan...	[Colin Trevorrow]	Adventure	http://www.jurassicworld.com/	135397	tt0369610	[monster, dna, tyrannosaurus rex, velociraptor...	J V

2 rows × 21 columns

Just from the two rows above it can be seen that data has been duplicated and genres have been divided into different rows.

In [29]:

```
mean_rev_per_genre = df_genres.groupby('genres')['revenue_adj'].mean()
mean_rev_per_genre
```

Out[29]:

```
genres
Action             9.206722e+07
Adventure          1.422555e+08
Animation          8.975005e+07
Comedy             4.812243e+07
Crime              5.667827e+07
Documentary        2.425647e+06
Drama              4.053378e+07
Family             8.896531e+07
Fantasy            1.122142e+08
Foreign            1.762528e+06
History            4.852978e+07
Horror             2.409743e+07
Music              4.770555e+07
```

```
Mystery            5.101526e+07
Romance            4.830658e+07
Science Fiction    8.754830e+07
TV Movie           3.604266e+05
Thriller           5.538135e+07
War                7.050840e+07
Western            4.638237e+07
Name: revenue_adj, dtype: float64
```

In [30]:

```
max_revenue = mean_rev_per_genre.max()
max_revenue
```

Out[30]:

```
142255467.8765137
```

In [31]:

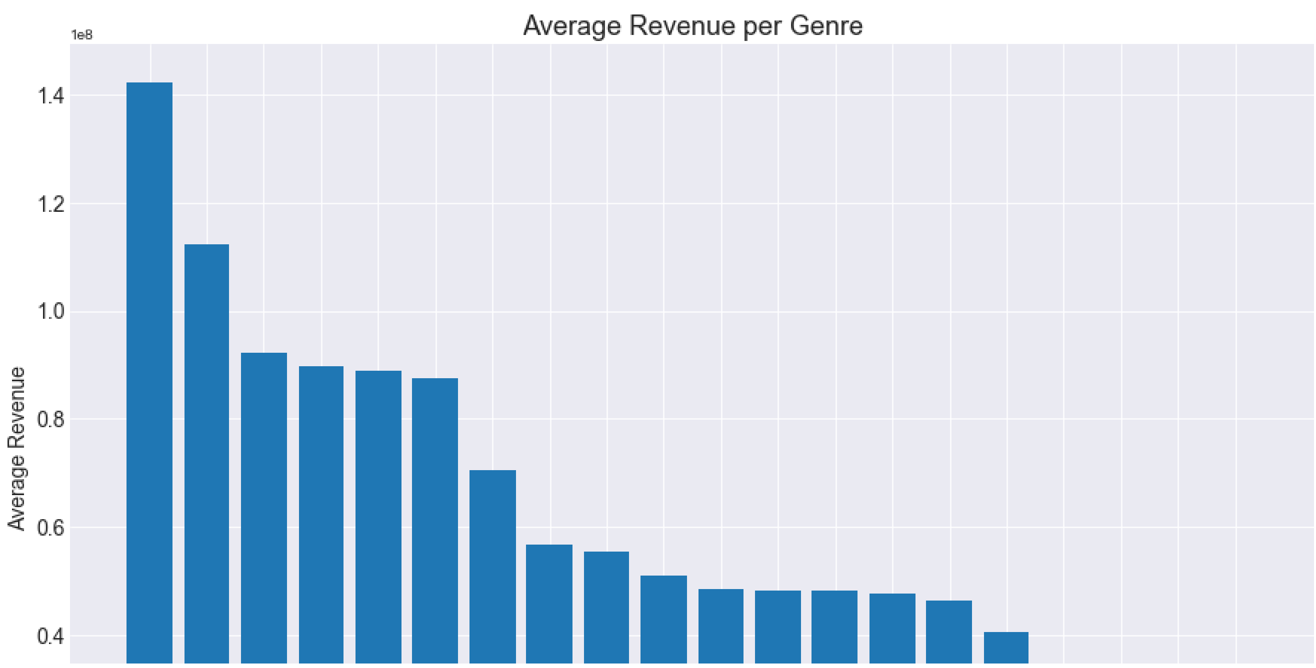
```
#https://preinventedwheel.com/easy-matplotlib-bar-chart/
mean_rev_per_genre_sorted = mean_rev_per_genre.sort_values(ascending=False)
```

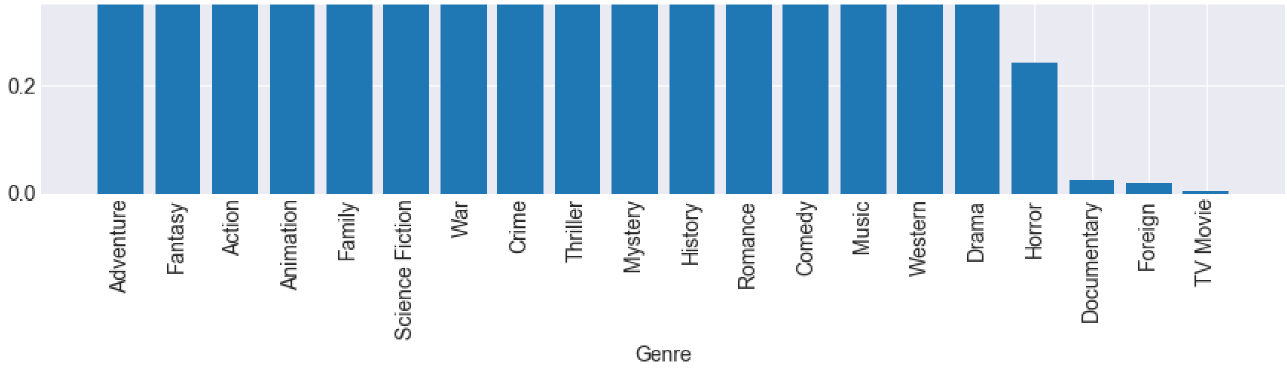
In [32]:

```
def draw_bar_plot(data, title, xLabel, yLabel, fig=(15,10)):
    """
    Draws a bar plot

    Args:
        (Series) - Series with data
        (str) - Plot title
        (str) - Label for x axis
        (str) - Label for y axis
    """
    locations = range(len(data.index))
    plt.figure(figsize=fig)
    plt.xticks(rotation=90, fontsize=14)
    plt.yticks(fontsize=14)
    plt.title(title, fontsize='18')
    plt.xlabel(xLabel, fontsize=14)
    plt.ylabel(yLabel, fontsize=14)
    plt.bar(locations,data, tick_label=data.index);
```

In [33]:

```
draw_bar_plot(mean_rev_per_genre_sorted, 'Average Revenue per Genre', 'Genre', 'Average Revenue')
```





It can easily be seen from the plot that Adventure genre is the one with max average revenue - with 142255467.8765137 USD (2010).

Research Question 3- Which genres are most popular from year to year?

In [34]:

```
#calculate mean popularity for genre per year
genre_popularity_by_year = pd.DataFrame(df_genres.groupby(['release_year', 'genres'],
as_index=False)['popularity'].mean())
genre_popularity_by_year.rename(columns={'popularity':'mean_popularity'}, inplace=True)
#genre_popularity_by_year.head(14)
```

In [35]:

```
#get the max popularity for each year
max_mean_pop_per_year = genre_popularity_by_year.groupby(['release_year'], as_index=False)
['mean_popularity'].max()
max_mean_pop_per_year.rename(columns={'mean_popularity':'mean_popularity_max'}, inplace=True)
#max_mean_pop_per_year.head()
```

In [36]:

```
#merge genre_popularity_by_year with max_mean_pop_per_year to get the genre for each max
most_popular_genre_per_year = max_mean_pop_per_year.merge(genre_popularity_by_year,
how='left',left_on=max_mean_pop_per_year['mean_popularity_max'], right_on=genre_popularity_by_year
['mean_popularity'])
most_popular_genre_per_year.drop(['key_0','release_year_y',  'mean_popularity'], axis=1, inplace=T
rue)
most_popular_genre_per_year.rename(columns={'release_year_x':'release_year'}, inplace=True)
most_popular_genre_per_year
```

Out[36]:

	release_year	mean_popularity_max	genres
0	1960	0.811910	Thriller
1	1961	2.631987	Animation
2	1962	0.942513	Adventure
3	1963	2.180410	Animation
4	1964	0.930959	War
5	1965	0.968850	Music
6	1966	0.585717	Animation
7	1967	2.550704	Animation
8	1968	1.519456	Mystery
9	1969	0.948020	Crime
10	1970	1.127718	Animation
11	1971	1.530722	Family
12	1971	1.530722	Fantasy

	release_year	mean_popularity_max	genres
13	1972	1.072768	Crime
14	1973	0.956526	Animation
15	1974	0.702035	Mystery
16	1975	0.880297	Adventure
17	1976	0.707249	Crime
18	1977	1.419319	Action
19	1978	0.679805	Music
20	1979	1.410014	Action
21	1980	0.897143	Science Fiction
22	1981	0.875815	Adventure
23	1982	1.143183	War
24	1983	0.900596	Adventure
25	1984	0.823924	Family
26	1985	0.924311	Family
27	1986	0.798935	Adventure
28	1987	0.815643	History
29	1988	0.749364	Animation
30	1989	1.354143	Animation
31	1990	0.801768	Adventure
32	1991	1.665002	Animation
33	1992	1.286893	Animation
34	1993	0.918601	Fantasy
35	1994	1.297888	Crime
36	1995	1.467780	Animation
37	1996	0.976838	Crime
38	1997	1.140241	Science Fiction
39	1998	1.246619	War
40	1999	1.012306	Adventure
41	2000	0.854593	Adventure
42	2001	1.565260	Fantasy
43	2002	1.430465	Fantasy
44	2003	1.747524	Fantasy
45	2004	1.320568	Fantasy
46	2005	1.146827	Fantasy
47	2006	1.023134	Fantasy
48	2007	0.957349	Fantasy
49	2008	1.008385	Adventure
50	2009	1.153656	Adventure
51	2010	1.378913	Adventure
52	2011	1.175800	Western
53	2012	1.732778	Western
54	2013	1.294491	Adventure
55	2014	2.430526	Adventure
56	2015	3.283786	Adventure

The above information shows the most popular genre per year and it's popularity value.

For achieving this result it was necessary to:

1. Calculate the mean popularity for each genre per year
2. Calculate the max popularity for each year
3. Merge both information to get no only the max popularity for each year but to which genre it belonged.

Let's check the information on a bar chart.

In [37]:

```
#https://jaxenter.com/implement-switch-case-statement-python-138315.html
def switch_color(genre):
    """
    Returns a hex color code for a genre

    Args:
        (str) - genre to switch from
    Returns:
        A string with hex value for the passed genre
    """
    switcher = {
        'Thriller': "#2e8b57",
        'Animation': "#adf7c2",
        'Adventure': "#ff1a72",
        'War': "#3933c9",
        'Music': "#fa959f",
        'Mystery': "#5a80b4",
        'Crime': "#40e0d0",
        'Family': "#088da5",
        'Fantasy': "#718da5",
        'Action': "#f6546a",
        'Science Fiction': "#2c4b25",
        'History': "#ffe638",
        'Western': "#ffd5f9",
        'Comedy': "#899982",
        'Drama': "#00ffff",
        'Foreign': "#bf00ff",
        'Horror': "#ff0000",
        'Romance': "#ff00ff",
        'TV Movie': "#ff8000",
        'Documentary': "#cc6666"
    }
    return switcher.get(genre)
```

In [38]:

```
def get_colors(ls_genres):
    """
    Returns list of hex color codes

    Args:
        (np.array) - array of genres
    Returns:
        A list of hex color values.
    """
    colors = []
    for i in range(len(ls_genres)):
        color = switch_color(ls_genres[i])
        colors.append(color)

    return colors
```

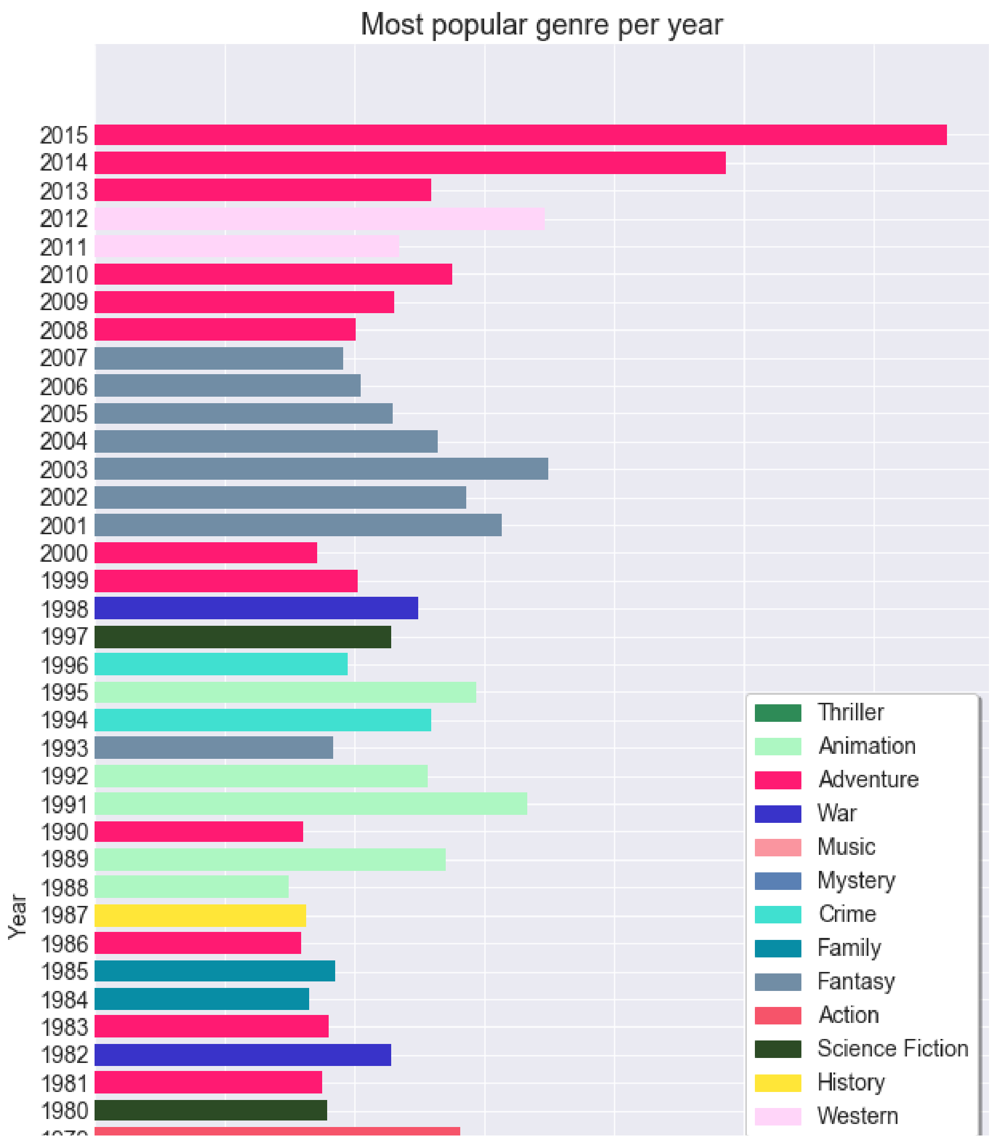
In [39]:

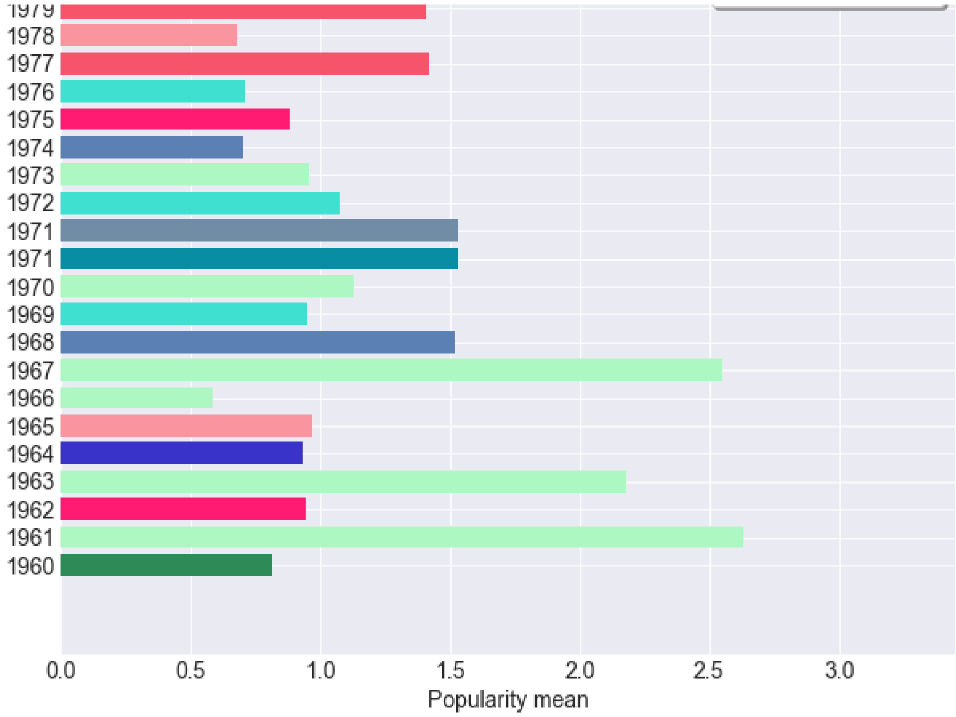
```
def create_patches(ls_genres):
    """
    Returns list of patches

    Args:
        (np.array) - array of genres
    Returns:
```

```
        A list of patches.
    """
    #https://matplotlib.org/users/legend_guide.html
    patches = []
    for genre in ls_genres:
        patch = mpatches.Patch(color=switch_color(genre), label=genre)
        patches.append(patch)

    return patches
```

In [40]:

```
locations = np.array(range(len(most_popular_genre_per_year['release_year'])))
heights = np.array(most_popular_genre_per_year['mean_popularity_max'])
labels = np.array(most_popular_genre_per_year['release_year'])
genres = np.array(most_popular_genre_per_year['genres'])
colors = get_colors(genres)

plt.figure(figsize=(10,20))

plt.xticks(fontsize=14)
plt.yticks(fontsize=14)
plt.title('Most popular genre per year', fontsize='18')
plt.xlabel('Popularity mean', fontsize=14)
plt.ylabel('Year', fontsize=14)

#https://matplotlib.org/users/legend_guide.html
legend = plt.legend(handles= create_patches(np.array(most_popular_genre_per_year['genres'].unique()
)), fontsize=14, shadow=True, facecolor='w', framealpha=1, frameon=True)
#https://stackoverflow.com/questions/30729473/seaborn-legend-with-background-color
#frame_on=True for the frame to be seen using sns

plt.barh(locations, heights, tick_label=labels, color=colors);
```





The above plot shows in a more graphic way the information from `most_popular_genre_per_year` dataframe.

Research Question 4- Which year produced more revenue?

In [41]:

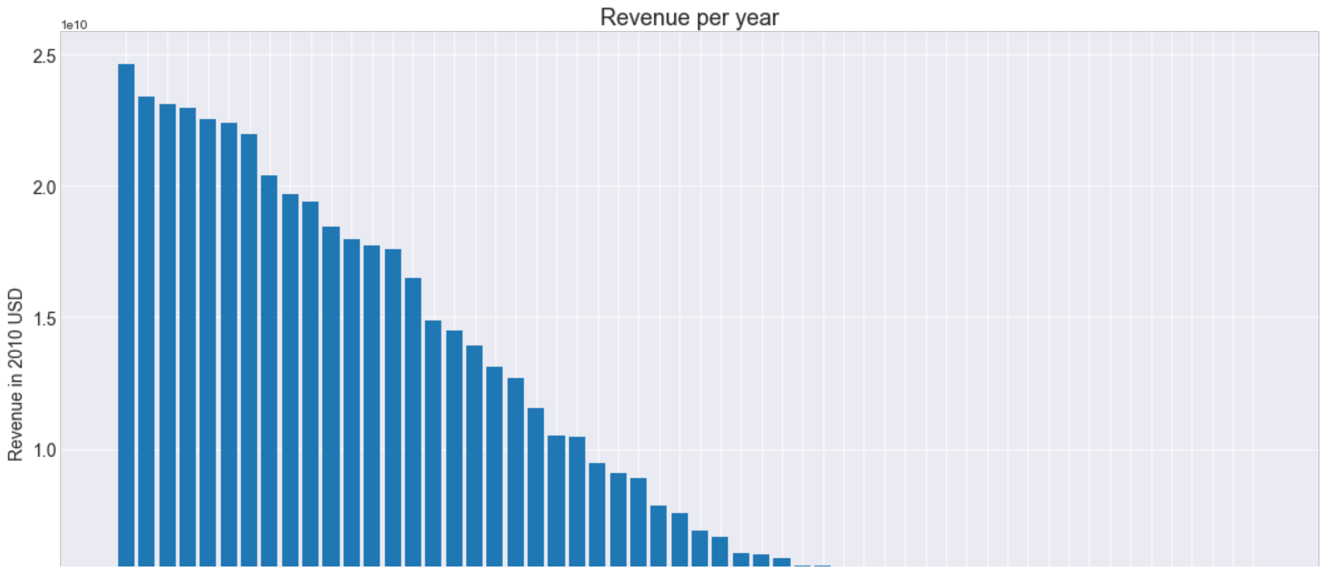
```
sorted_rev_per_year = df.groupby('release_year')['revenue_adj'].sum()
sorted_rev_per_year.sort_values(ascending=False, inplace=True)
sorted_rev_per_year.head()
```

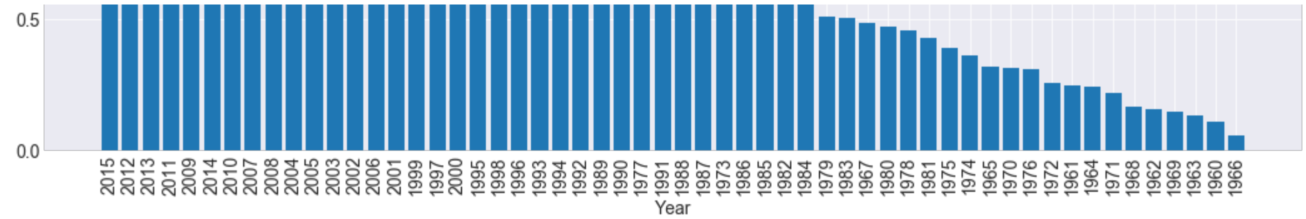
Out[41]:

```
release_year
2015    2.462144e+10
2012    2.339698e+10
2013    2.312342e+10
2011    2.297046e+10
2009    2.254393e+10
Name: revenue_adj, dtype: float64
```

In [42]:

```
draw_bar_plot(sorted_rev_per_year, 'Revenue per year', 'Year', 'Revenue in 2010 USD', (18,10))
```





In [43]:

```
sorted_rev_per_year.max()
```

Out[43]:

```
24621443643.124752
```

It can be seen both from `sorted_rev_per_year` and from the plot that 2015 was the year that produces more revenue, with 24621443643.124752 USD(2010).

Research Question 5- What's the average revenue per genre per year?

In [44]:

```
#calculate mean revenue for genre per year
mean_rev_per_year_genre = pd.DataFrame(df_genres.groupby(['release_year', 'genres'],
as_index=False)['revenue_adj'].mean())
mean_rev_per_year_genre.rename(columns={'revenue_adj':'mean_revenue_adj'}, inplace=True)
mean_rev_per_year_genre.head(20)
```

Out[44]:

	release_year	genres	mean_revenue_adj
0	1960	Action	5.981781e+07
1	1960	Adventure	7.232881e+06
2	1960	Comedy	4.432997e+07
3	1960	Crime	0.000000e+00
4	1960	Drama	6.975962e+07
5	1960	Family	2.457656e+07
6	1960	Fantasy	0.000000e+00
7	1960	Foreign	0.000000e+00
8	1960	History	8.847561e+07
9	1960	Horror	3.370499e+07
10	1960	Music	0.000000e+00
11	1960	Romance	4.681834e+07
12	1960	Science Fiction	0.000000e+00
13	1960	Thriller	3.932249e+07
14	1960	War	0.000000e+00
15	1960	Western	6.027401e+06
16	1961	Action	3.459848e+07
17	1961	Adventure	2.976060e+08
18	1961	Animation	1.574815e+09
19	1961	Comedy	1.709770e+08

The DataFrame above shows average revenue per genre per year.

Research Question 6- Budget statistics

In [45]:

```
df['budget'].describe()
```

Out[45]:

```
count    1.073100e+04
mean     1.480365e+07
std      3.106456e+07
min      0.000000e+00
25%      0.000000e+00
50%      0.000000e+00
75%      1.600000e+07
max      4.250000e+08
Name: budget, dtype: float64
```

It seems there are several movies with budget 0. As this cannnot be a real data, I'm droping those results and having only movies with budget bigger than 0 on new DataFrame df_budget_clean. Is over this new dataframe that the describe method will be applied.

In [46]:

```
df_budget_clean = pd.DataFrame(df.query('budget > 0'))
stats = pd.DataFrame(df_budget_clean['budget'].describe())
stats
```

Out[46]:

	budget
count	5.153000e+03
mean	3.082824e+07
std	3.893199e+07
min	1.000000e+00
25%	6.000000e+06
50%	1.750000e+07
75%	4.000000e+07
max	4.250000e+08

In [47]:

```
data = np.array(df_budget_clean['budget'])
data
```

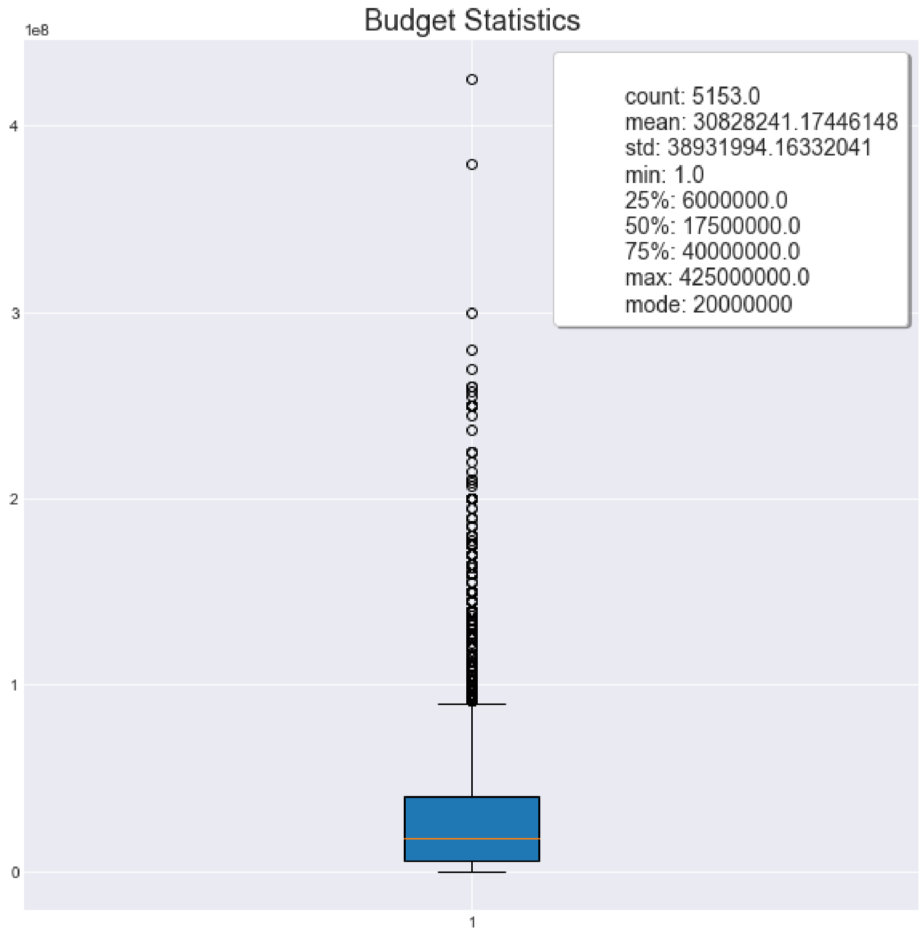
Out[47]:

```
array([150000000, 150000000, 110000000, ...,   5115000,    700000,
           19000], dtype=int64)
```

In [48]:

```
plt.figure(figsize = (10,10))

plt.title('Budget Statistics', fontsize='18');
legend_str = ""
for x,y in stats.iterrows():
    temp = "{}: {}".format(x,y[0])
    legend_str = legend_str + '\n' + temp

legend_str = legend_str + '\nmode: {}'.format(df_budget_clean['budget'].mode()[0])

patches= []
```

```
patch = mpatches.Patch(label=legend_str, color='white')
patches.append(patch)
legend = plt.legend(handles=patches, fontsize=14, shadow=True, facecolor='w', framealpha=1, frameon
=True)


plt.boxplot(data, patch_artist=True); #patch_artist=True for colors
```



Conclusions

From the proposed questions it can be seen there is a positive correlation between popularity and vote_count, vote_average and revenue.

However, the correlation is not the same since the correlation between popularity and vote_count is strong, the correlation between popularity and vote_average is weak and the correlation between popularity and revenue_adj is moderate.

Though no causation could be inferred, it's plausible to think that when a movie has high popularity is watched by many people, this may help to increase the revenue and to have more people voting. However, if the movie is not good, the vote average may not be either.

I learned that the genre that produces more revenue are adventure, fantasy, action, animation, family.

The fact that in the top 17 most popular genres are 8 Adventure and 7 Fantasy (also 2 music though music is the only two times that appears on the plot as most popular), supports the idea that popularity is correlated with revenue.

Summary statistics from budget can be found on last question and information about average revenue per genre per year on `mean_rev_per_year_genre`.