Project: Investigate a Dataset - TMDb Dataset

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Introduction

The entertainment industry has been a major contributor to the growth of many country's Gross Domestic Product (GDP) since the advent of modern technology. More specifically, the movie sector, contributing over 40% to the growth of the industry's GDP, has continued to experience rise in revenue over the years.

This data set contains information about 10,000 movies collected from The Movie Database (TMDb), including user ratings and revenue. The following columns are contained in the data set. columns: id, imdb_id, popularity, budget, revenue, original_title, cast, homepage, director, tagline, overview, runtime, genres, production_companies, release_date, vote_count, vote_average, release_year, budget_adj and revenue_adj.

Identifiying and understanding the major factors contributing to the continuous rise in the sector's revenue is the crux of this analysis. In this Exploratory Data Analysis, some questions relating to the subject matter will be addressed using IMBD dataset. These questions include:

> 1. what is the relationship between revenue and the following - budget, popularity score, runtime, voting average?
>
> 2. what is the impact of budget on revenue?

In [1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import warnings as ws
ws.filterwarnings('ignore')
```

Data Wrangling

General Properties

In [2]:
```
# Here, the data is loaded for preprocessing and cleaning
df=pd.read_csv('C:/Users/LISANDRO/project/tmdb-movies.csv')
df.head()
```

Out[2]:

	id	imdb_id	popularity	budget	revenue	original_title	cast	homepage	director	tagline
0	135397	tt0369610	32.985763	150000000	1513528810	Jurassic World	Chris Pratt|Bryce Dallas Howard|Irrfan Khan|Vi...	http://www.jurassicworld.com/	Colin Trevorrow	The park is open
1	76341	tt1392190	28.419936	150000000	378436354	Mad Max: Fury Road	Tom Hardy|Charlize Theron|Hugh Keays-Byrne|Nic...	http://www.madmaxmovie.com/	George Miller	What a Lovely Day
2	262500	tt2908446	13.112507	110000000	295238201	Insurgent	Shailene Woodley|Theo James|Kate Winslet|Ansel...	http://www.thedivergentseries.movie/#insurgent	Robert Schwentke	One Choice Can Destroy You
3	140607	tt2488496	11.173104	200000000	2068178225	Star Wars: The Force Awakens	Harrison Ford|Mark Hamill|Carrie Fisher|Adam D...	http://www.starwars.com/films/star-wars-episod...	J.J. Abrams	Every generation has a story
4	168259	tt2820852	9.335014	190000000	1506249360	Furious 7	Vin Diesel|Paul Walker|Jason Statham|Michelle ...	http://www.furious7.com/	James Wan	Vengeance Hits Home

5 rows × 21 columns

In [3]:
```
# To examine the number of rows and columns in the data set.
```

```
df.shape
```

Out[3]: (10866, 21)

In [4]:
```
# Here, we seek to know more about the data set we are working with
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10866 entries, 0 to 10865
Data columns (total 21 columns):
 #   Column                Non-Null Count  Dtype
---  ------                --------------  -----
 0   id                    10866 non-null  int64
 1   imdb_id               10856 non-null  object
 2   popularity            10866 non-null  float64
 3   budget                10866 non-null  int64
 4   revenue               10866 non-null  int64
 5   original_title        10866 non-null  object
 6   cast                  10790 non-null  object
 7   homepage              2936 non-null   object
 8   director              10822 non-null  object
 9   tagline               8042 non-null   object
 10  keywords              9373 non-null   object
 11  overview              10862 non-null  object
 12  runtime               10866 non-null  int64
 13  genres                10843 non-null  object
 14  production_companies  9836 non-null   object
 15  release_date          10866 non-null  object
 16  vote_count            10866 non-null  int64
 17  vote_average          10866 non-null  float64
 18  release_year          10866 non-null  int64
 19  budget_adj            10866 non-null  float64
 20  revenue_adj           10866 non-null  float64
dtypes: float64(4), int64(6), object(11)
memory usage: 1.7+ MB
```

From the general information above, it is obvious that there are issues to be addressed in this data set. These issues include:

1. **Correcting the datatype.** For example, changing the datatype for 'release_date' from string to datatime
2. **Filling missing values.** The Non_Null Count for each column is not equal, implying that some values are missing.
3. **Dropping unnecessary Features.** Some features are not useful in the scope of this analysis. Some of these features include cast, homepage, tagline, keywords, etc. ##### To further understand this data set, the next cell explores the basic summary statistics assocciated with each variable.

In [5]:
```
# Here, we explore the descriptive summary of data set.
df.describe(include='all')
```

Out[5]:

	id	imdb_id	popularity	budget	revenue	original_title	cast	homepage	director	tagline	...
count	10866.000000	10856	10866.000000	1.086600e+04	1.086600e+04	10866	10790	2936	10822	8042	...
unique	NaN	10855	NaN	NaN	NaN	10571	10719	2896	5067	7997	...
top	NaN	tt0411951	NaN	NaN	NaN	Hamlet	Louis C.K.	http://www.missionimpossible.com/	Woody Allen	Based on a true story.	...
freq	NaN	2	NaN	NaN	NaN	4	6	4	45	5	...
mean	66064.177434	NaN	0.646441	1.462570e+07	3.982332e+07	NaN	NaN	NaN	NaN	NaN	...
std	92130.136561	NaN	1.000185	3.091321e+07	1.170035e+08	NaN	NaN	NaN	NaN	NaN	...
min	5.000000	NaN	0.000065	0.000000e+00	0.000000e+00	NaN	NaN	NaN	NaN	NaN	...
25%	10596.250000	NaN	0.207583	0.000000e+00	0.000000e+00	NaN	NaN	NaN	NaN	NaN	...
50%	20669.000000	NaN	0.383856	0.000000e+00	0.000000e+00	NaN	NaN	NaN	NaN	NaN	...
75%	75610.000000	NaN	0.713817	1.500000e+07	2.400000e+07	NaN	NaN	NaN	NaN	NaN	...
max	417859.000000	NaN	32.985763	4.250000e+08	2.781506e+09	NaN	NaN	NaN	NaN	NaN	...

11 rows × 21 columns

The descriptive statistics table above provides us with basic descriptive information about thie data set. From the output above, we can extract the following:

1. The minimum amount spent on budget, revenue, budget_adj and revenue_adj is zero (0). This is unacceptable.
2. The maximum runtime for a movie is 900 minutes. This indicates an outlier. ##### These issues are addressed in the next section - data cleaning section.

Data Cleaning

Here, we addresed the various issues noted in the previous section of this report. These issues include:

1. **Correcting the datatype.** For example, changing the datatype for 'release_date' from string to datatime.

> 2. **Filling missing values.** The Non_Null Count for each column is not equal, implying that some values are missing.
>
> 3. **Dropping unnecessary features.** Some of these features include cast, homepage, tagline, keywords, etc.
>
> 4. **Managing data ranges.** It is unrealistic for movies to have a runtime of 900 minutes.

Correcting the datatype

In [6]:
```
#To correct the datatype for release_date from string to date format
from datetime import datetime as dt
df['release_date'] = pd.to_datetime(df['release_date'])
```

Filling Missing Values and Addressing Blanks

In [7]:
```
# Given that "Woody Allen" is the most popular director in this dataset,
# it is acceptable to fill blank spaces with "Woody Allen"
df["director"]=df["director"].fillna("Woody Allen")
```

In [8]:
```
# Here, I decided to drop rows without an imdb_id
df.dropna(subset=["imdb_id"],inplace=True)
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 10856 entries, 0 to 10865
Data columns (total 21 columns):
 #   Column                Non-Null Count  Dtype
---  ------                --------------  -----
 0   id                    10856 non-null  int64
 1   imdb_id               10856 non-null  object
 2   popularity            10856 non-null  float64
 3   budget                10856 non-null  int64
 4   revenue               10856 non-null  int64
 5   original_title        10856 non-null  object
 6   cast                  10780 non-null  object
 7   homepage              2934 non-null   object
 8   director              10856 non-null  object
 9   tagline               8039 non-null   object
 10  keywords              9369 non-null   object
 11  overview              10853 non-null  object
 12  runtime               10856 non-null  int64
 13  genres                10835 non-null  object
 14  production_companies  9831 non-null   object
 15  release_date          10856 non-null  datetime64[ns]
 16  vote_count            10856 non-null  int64
 17  vote_average          10856 non-null  float64
 18  release_year          10856 non-null  int64
 19  budget_adj            10856 non-null  float64
 20  revenue_adj           10856 non-null  float64
dtypes: datetime64[ns](1), float64(4), int64(6), object(10)
memory usage: 1.8+ MB
```

In [9]:
```
# Here, I removed duplicate rows from the data set
df.drop_duplicates(inplace=True)
sum(df.duplicated())
```

Out[9]:
```
0
```

Dropping Features

In [10]:
```
# For this analysis, quantitative variables are more important.
# Thus, the following variables are dropped to promote clarity
columns=["cast","homepage","tagline","keywords","overview","genres","production_companies"]
for i in columns:
    del df[i]
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 10855 entries, 0 to 10865
Data columns (total 14 columns):
 #   Column          Non-Null Count  Dtype
---  ------          --------------  -----
 0   id              10855 non-null  int64
 1   imdb_id         10855 non-null  object
 2   popularity      10855 non-null  float64
 3   budget          10855 non-null  int64
 4   revenue         10855 non-null  int64
 5   original_title  10855 non-null  object
 6   director        10855 non-null  object
 7   runtime         10855 non-null  int64
 8   release_date    10855 non-null  datetime64[ns]
 9   vote_count      10855 non-null  int64
 10  vote_average    10855 non-null  float64
 11  release_year    10855 non-null  int64
 12  budget_adj      10855 non-null  float64
 13  revenue_adj     10855 non-null  float64
dtypes: datetime64[ns](1), float64(4), int64(6), object(3)
memory usage: 1.2+ MB
```

In [11]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 10855 entries, 0 to 10865
Data columns (total 14 columns):
 #   Column          Non-Null Count  Dtype
---  ------          --------------  -----
```

```
 0   id              10855 non-null  int64
 1   imdb_id         10855 non-null  object
 2   popularity      10855 non-null  float64
 3   budget          10855 non-null  int64
 4   revenue         10855 non-null  int64
 5   original_title  10855 non-null  object
 6   director        10855 non-null  object
 7   runtime         10855 non-null  int64
 8   release_date    10855 non-null  datetime64[ns]
 9   vote_count      10855 non-null  int64
 10  vote_average    10855 non-null  float64
 11  release_year    10855 non-null  int64
 12  budget_adj      10855 non-null  float64
 13  revenue_adj     10855 non-null  float64
dtypes: datetime64[ns](1), float64(4), int64(6), object(3)
memory usage: 1.2+ MB
```

Managinng Ranges

In [12]:
```
# Here, budget values less than 100000 have been replaced with the mean bugdet
budget_mean=df["budget"].mean()
df.loc[df["budget"]<100000,"budget"] = budget_mean
df["budget"].min()
```

Out[12]: 100000.0

In [13]:
```
# Here, revenue values less than 100000 have been replaced with the mean revenue
revenue_mean=df["revenue"].mean()
df.loc[df["revenue"]<100000,"revenue"] = revenue_mean
df["revenue"].min()
```

Out[13]: 100000.0

In [14]:
```
# Here, budget_adj values less than 100000 have been replaced with the mean bugdet_adj
bud_adj=df["budget_adj"].mean()
df.loc[df["budget_adj"]<100000,"budget_adj"] = bud_adj
df["budget_adj"].min()
```

Out[14]: 100000.0

In [15]:
```
# Here, revenue_adj values less than 100000 have been replaced with the mean revenue_adj
revenue_adj=df["revenue_adj"].mean()
df.loc[df["revenue_adj"]<100000,"revenue_adj"] = revenue_adj
df["revenue_adj"].min()
```

Out[15]: 100222.075052341

In [16]:
```
# it is quite unrealistic to see standard movies less than 60 minutes.
# For the purpose of this project, I set the minimum runtime at 90 minutes
runtime_mean=df["runtime"].mean()
df.loc[df["runtime"]<90,"runtime"] = runtime_mean
df["runtime"].min()
```

Out[16]: 90.0

In [17]:
```
# it is quite unrealistic to see standard movies greater than 240 minutes.
# For the purpose of this project, I set the maximum runtime at 240 minutes.
df.loc[df["runtime"]>240,"runtime"] = runtime_mean
df["runtime"].max()
```

Out[17]: 240.0

In [18]:
```
df.describe(include='all')
```

Out[18]:

	id	imdb_id	popularity	budget	revenue	original_title	director	runtime	release_date	vote_count	vote_averag
count	10855.000000	10855	10855.000000	1.085500e+04	1.085500e+04	10855	10855	10855.000000	10855	10855.000000	10855.0000
unique	NaN	10855	NaN	NaN	NaN	10561	5064	NaN	5907	NaN	Na
top	NaN	tt2474976	NaN	NaN	NaN	Hamlet	Woody Allen	NaN	2009-01-01 00:00:00	NaN	Na
freq	NaN	1	NaN	NaN	NaN	4	85	NaN	28	NaN	Na
first	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	1972-01-01 00:00:00	NaN	Na
last	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	2071-12-29 00:00:00	NaN	Na
mean	65959.191617	NaN	0.646832	2.246681e+07	6.269791e+07	NaN	NaN	107.064362	NaN	217.584155	5.9738
std	92018.246342	NaN	1.000591	2.793688e+07	1.107714e+08	NaN	NaN	16.671532	NaN	575.877532	0.9346
min	5.000000	NaN	0.000065	1.000000e+05	1.000000e+05	NaN	NaN	90.000000	NaN	10.000000	1.5000
25%	10591.500000	NaN	0.207733	1.463776e+07	3.986359e+07	NaN	NaN	98.000000	NaN	17.000000	5.4000
50%	20618.000000	NaN	0.383998	1.463776e+07	3.986359e+07	NaN	NaN	102.105205	NaN	38.000000	6.0000
75%	75393.500000	NaN	0.714446	1.500000e+07	3.986359e+07	NaN	NaN	111.000000	NaN	146.000000	6.6000
max	417859.000000	NaN	32.985763	4.250000e+08	2.781506e+09	NaN	NaN	240.000000	NaN	9767.000000	9.2000

Exploratory Data Analysis

We explore this cleaned data set at this point to answer key research questions about the data set. This objective will be achieved using statistical computaions and data visualizations. Recall, two research questions were posed. They are:

> 1. what is the relationship between revenue and the following - budget, popularity score, runtime, voting average?
>
> 2. what is the impact of budget on revenue?

What is the relationship between revenue and the following - budget, popularity score, runtime, voting average?

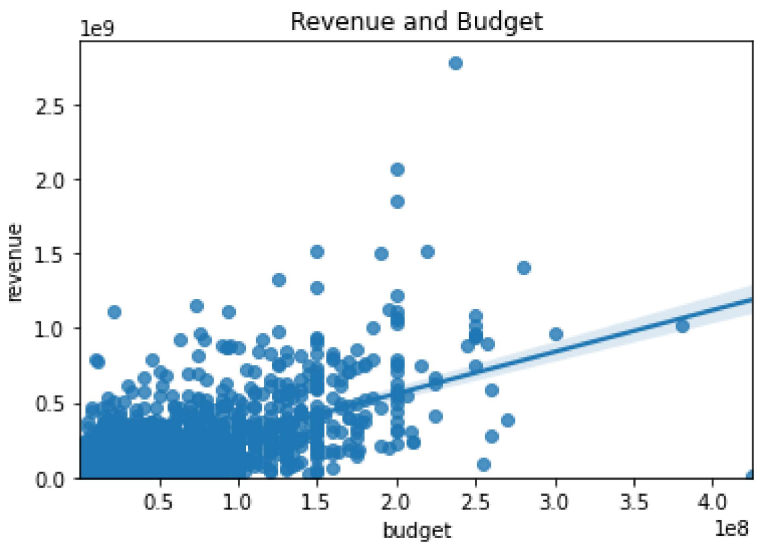
> This question will be addressed by computing correlation coefficients and creating visuals like scatter plots, correlation maps using python libraries.

i. Exploring the relationship between revenue and budget

In [19]:
```
bud=np.array(df["budget"])
rev=np.array(df["revenue"])
print(np.corrcoef(bud,rev))
import seaborn as sns
sns.regplot(x="budget", y="revenue", data=df)
plt.ylim(0,)
plt.title("Revenue and Budget")
```

```
[[1.         0.70555273]
 [0.70555273 1.        ]]
```

Out[19]: Text(0.5, 1.0, 'Revenue and Budget')

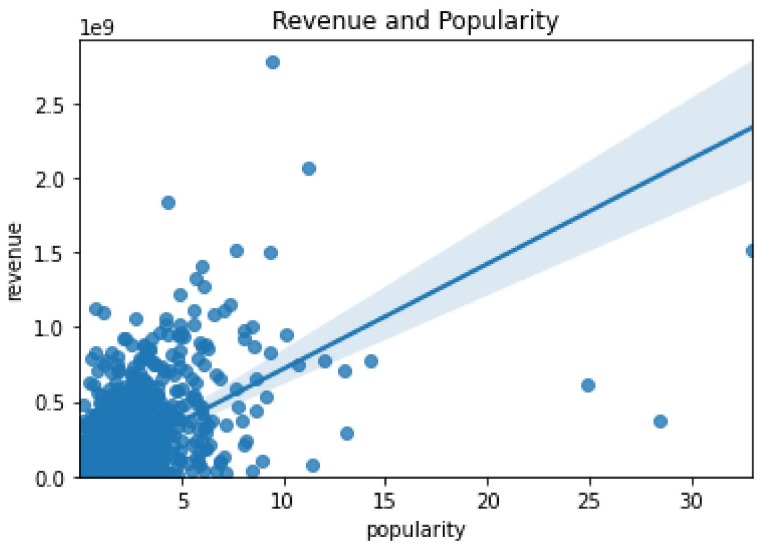


ii. Exploring the relationship between revenue and popularity score

In [20]:
```
pop=np.array(df["popularity"])
rev=np.array(df["revenue"])
print(np.corrcoef(pop,rev))
sns.regplot(x="popularity", y="revenue", data=df)
plt.ylim(0,)
plt.title("Revenue and Popularity")
```

```
[[1.         0.63539249]
 [0.63539249 1.        ]]
```

Out[20]: Text(0.5, 1.0, 'Revenue and Popularity')

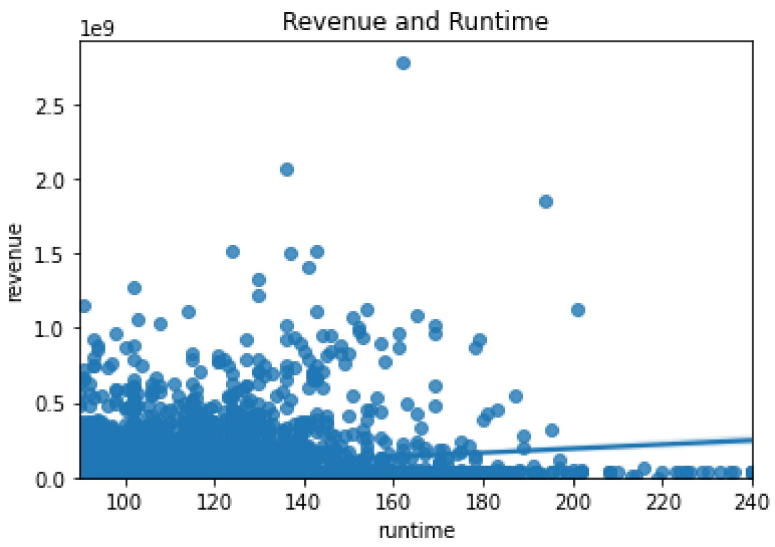


iii. Exploring the relationship between revenue and runtime

In [21]:
```
run=np.array(df["runtime"])
rev=np.array(df["revenue"])
print(np.corrcoef(run,rev))
sns.regplot(x="runtime", y="revenue", data=df)
plt.ylim(0,)
plt.title("Revenue and Runtime")
```

```
[[1.        0.2095643]
 [0.2095643 1.       ]]
```

Out[21]: Text(0.5, 1.0, 'Revenue and Runtime')

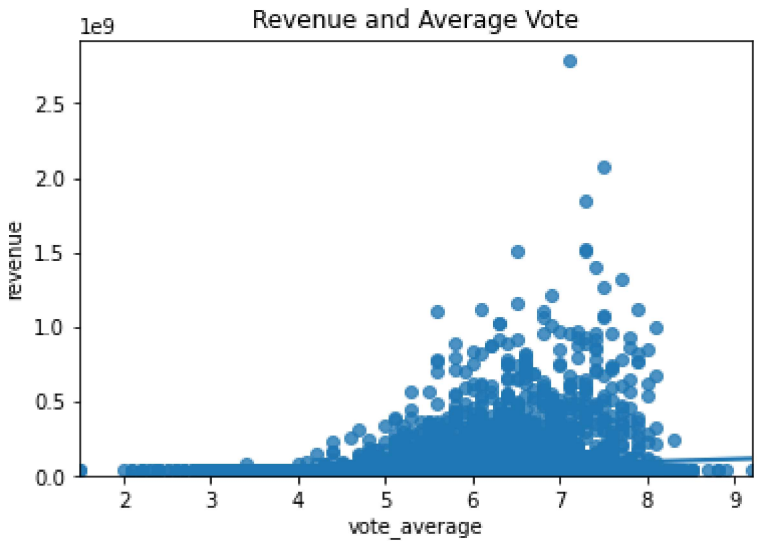


iv. Exploring the relationship between revenue and average votes

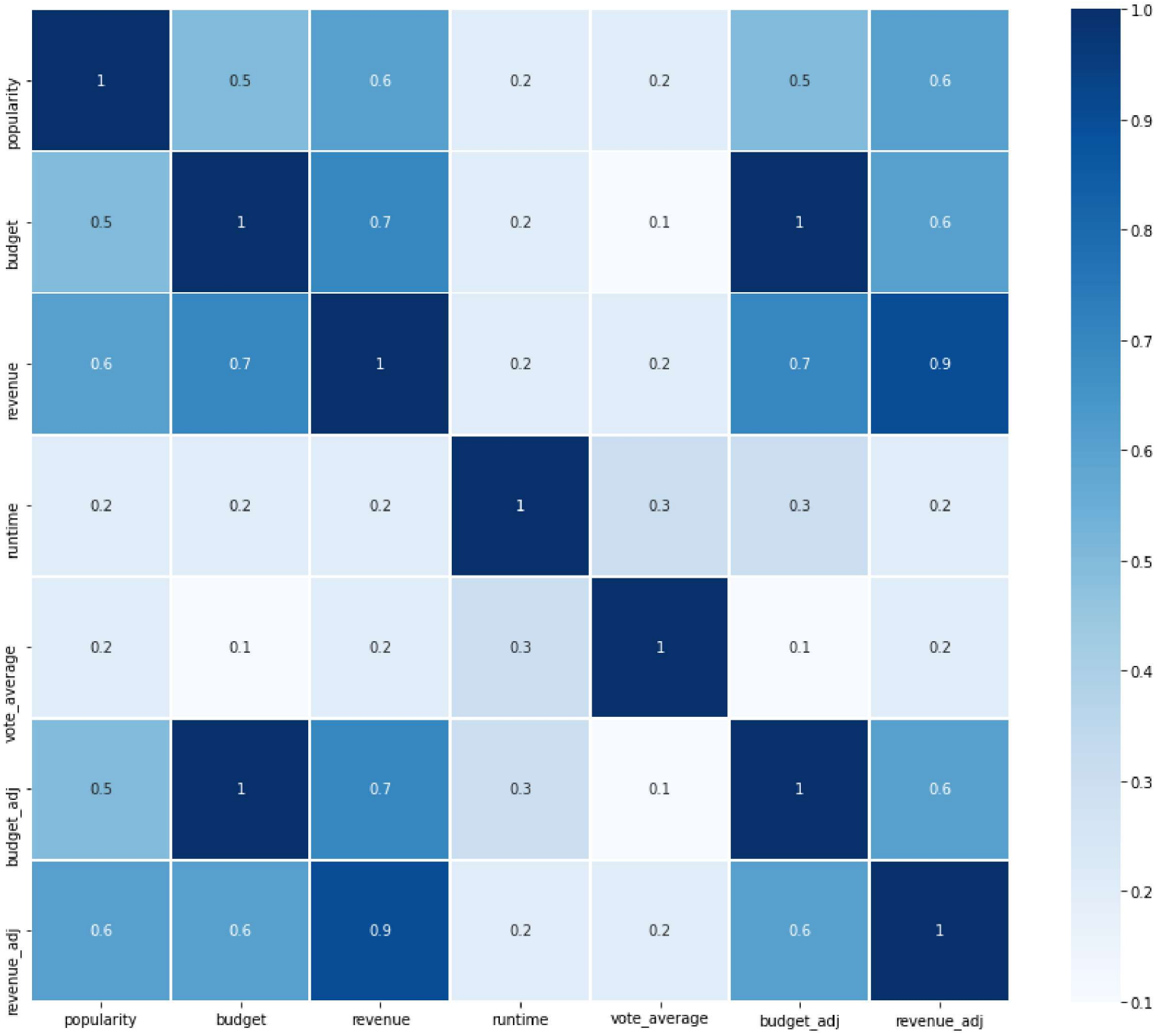
In [22]:
```
v_avg=np.array(df["vote_average"])
rev=np.array(df["revenue"])
print(np.corrcoef(v_avg,rev))
sns.regplot(x="vote_average", y="revenue", data=df)
plt.ylim(0,)
plt.title("Revenue and Average Vote")
```

```
[[1.        0.1509652]
 [0.1509652 1.       ]]
```

Out[22]: Text(0.5, 1.0, 'Revenue and Average Vote')



In [23]:
```
# Here, a heatmap was created to visiualize these relationships as a whole
null_cols=['id',
           'vote_count','release_year'] # excluded features
heat_map = df.drop(columns=null_cols, axis=1)
plt.figure(figsize=(15,12.5))
sns.heatmap(round(heat_map.corr(),1),annot=True,cmap='Blues',linewidth=0.9)
plt.show()
```



Interpretation

From the correlation coefficients and the scatter plots above, it is obvious that there is a positive relationship between revenue and budget,popularity score, vote average and runtime. However, it is important to note that correlation does not necessarily imply causation.

what is the impact of budget on revenue?

> This particular question will be addresed using a mulitiple linear regression model that relates revenue to budget,popularity score, vote average and runtime.

In [24]:
```
df['ln_rev_adj'] = np.log(df['revenue_adj']) #Taking the natural log of adjusted revenue
df['ln_bud_adj'] = np.log(df['budget_adj']) #Taking the natural log of adjusted budget
Z = df[['ln_bud_adj', 'popularity', 'runtime','vote_average']]
Y = df["ln_rev_adj"]
```

In [25]:
```
import statsmodels.api as sm
reg1output=sm.OLS(Y,Z).fit() # Regressing Y on Z
print(reg1output.summary()) # Printing output
```

```
                                 OLS Regression Results
================================================================================
Dep. Variable:             ln_rev_adj   R-squared (uncentered):                   0.995
Model:                            OLS   Adj. R-squared (uncentered):              0.995
Method:                 Least Squares   F-statistic:                          5.286e+05
Date:                Wed, 18 May 2022   Prob (F-statistic):                        0.00
Time:                        12:35:57   Log-Likelihood:                         -17921.
No. Observations:               10855   AIC:                                  3.585e+04
Df Residuals:                   10851   BIC:                                  3.588e+04
Df Model:                           4
Covariance Type:            nonrobust
================================================================================
                   coef    std err          t      P>|t|      [0.025      0.975]
--------------------------------------------------------------------------------
ln_bud_adj       0.9545      0.006    164.162      0.000       0.943       0.966
popularity       0.0708      0.012      5.746      0.000       0.047       0.095
runtime          0.0059      0.001      7.643      0.000       0.004       0.007
vote_average     0.1579      0.013     12.061      0.000       0.132       0.184
==============================================================================
Omnibus:                     2371.688   Durbin-Watson:                   1.875
Prob(Omnibus):                  0.000   Jarque-Bera (JB):            12252.807
Skew:                          -0.958   Prob(JB):                         0.00
Kurtosis:                       7.839   Cond. No.                         124.
==============================================================================

Notes:
[1] R² is computed without centering (uncentered) since the model does not contain a constant.
[2] Standard Errors assume that the covariance matrix of the errors is correctly specified.
```

Result Interpretation

From the regression result above, it is obvious that the variables - ln_bud_adj, popularity, runtime and vote_average are statistically significant influcers of revenue. This is in informed by the individual p-values in the model. This regression model does not have a constant because when no movies are produced, revenue is expected to be zero. The R-Squared value of 0.995 tells us that about 99.5% variation in revenue can be explained by the independent variables. Also, the probability of f-stat (given as 0.00) tells us that the overall model is statistically significant.

Conclusions

In this analysis, I have been able to explore the TMDb data set. As part of the data analysis process, I performed data cleaning such as addressing missing values, managing data ranges, correcting datatype to allow for robust analysis. The dataset was further explored to allow gain insight into the existing relationships in the dataset using correlation values and scatter plots Finally, using regression analysis, I was able to conclude that variables like budget, runtime, etc are significant in explaining the variations in revenue.

In [ ]: