predicting_profitability_movies

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Predicting profitability from movies dataset

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###

Introduction

The main objective of this project is to accuratly predict the profitability of a movie based on numerous parameters shown below. I will start with EDA to get familiar with the data and start to think about crafting a possible solution to this problem. I will then proceed to wrangling and cleaning the data for our model to work properly. Finally, I will configure several machine learning models and decide which one gives us the best results.

Note: If you have any questions about this project please feel free to shoot over an email: a19garcia95@gmail.com.

###

Dataset

The data comes from www.IMBd.com which is a website used to review movies. Here is a preview of what the data looks like.

```
In [3]: import pandas as pd
        df = pd.read_csv("box_office_predictions.csv")
        df.head()
```

```
Out[3]:        budget country           director   genre        gross  \
        0  237000000.0      UK      James Cameron  Action  760507625.0
        1  200000000.0     USA      James Cameron   Drama  658672302.0
        2  150000000.0     USA    Colin Trevorrow  Action  652270625.0
        3  220000000.0     USA        Joss Whedon  Action  623357910.0
```

```
4  185000000.0     USA  Christopher Nolan  Action  534858444.0

                     name rating  runtime  score               star  \
0           Avatar (2009)  PG-13      162    7.8    Sam Worthington
1          Titanic (1997)  PG-13      194    7.8  Leonardo DiCaprio
2   Jurassic World (2015)  PG-13      124    7.0        Chris Pratt
3     The Avengers (2012)  PG-13      143    8.1  Robert Downey Jr.
4  The Dark Knight (2008)  PG-13      152    9.0     Christian Bale

                               studio    votes
0  Twentieth Century Fox Film Corporation   958400
1  Twentieth Century Fox Film Corporation   865551
2                    Universal Pictures   470625
3                        Marvel Studios  1069292
4                          Warner Bros.  1845853
```

###
Exploratory Data Analysis

In [4]:
```
df.describe()
```

Out[4]:

	budget	gross	runtime	score	votes
count	6.000000e+03	6.000000e+03	6000.000000	6000.000000	6.000000e+03
mean	2.469918e+07	3.341635e+07	106.587000	6.386383	7.188537e+04
std	3.721710e+07	5.735205e+07	18.026885	0.994921	1.308033e+05
min	0.000000e+00	4.410000e+02	50.000000	1.500000	2.700000e+01
25%	0.000000e+00	1.527796e+06	95.000000	5.800000	7.791750e+03
50%	1.100000e+07	1.229897e+07	102.000000	6.500000	2.660150e+04
75%	3.262500e+07	4.007256e+07	115.000000	7.100000	7.677475e+04
max	3.000000e+08	7.605076e+08	366.000000	9.300000	1.868308e+06

Interesting enough, when we run the describe() function through the dataset, we are able to observe that the upper quartile is where most of the data is concentrated. An example of this is the cell below that shows that the top 6 countries account for most of the countries where movies are made.

In [5]:
```
df['country'].value_counts()
```

Out[5]:
```
USA                                 4281
UK                                   615
France                               249
Canada                               126
Germany                              119
Australia                             71
Japan                                 59
Spain                                 50
Italy                                 47
Ireland                               40
Hong Kong                             38
```

```
India                                36
Denmark                              31
China                                23
South Korea                          18
New Zealand                          17
Sweden                               17
Belgium                              15
Mexico                               13
Netherlands                          12
Russia                               10
Iran                                 10
Argentina                            10
Czech Republic                        8
Norway                                8
Taiwan                                7
Hungary                               7
Switzerland                           6
South Africa                          6
Brazil                                5
West Germany                          4
Greece                                4
Israel                                4
Austria                               4
Romania                               3
Chile                                 3
Finland                               3
Peru                                  2
Colombia                              2
Portugal                              2
Indonesia                             2
Poland                                2
Thailand                              2
Iceland                               1
Bahamas                               1
Republic of Macedonia                 1
Malta                                 1
Palestine                             1
Federal Republic of Yugoslavia        1
Jamaica                               1
Saudi Arabia                          1
Soviet Union                          1
Name: country, dtype: int64
```

In [6]:
```
df[['score', 'votes', 'budget', 'gross', 'runtime']].corr()
```

Out[6]:

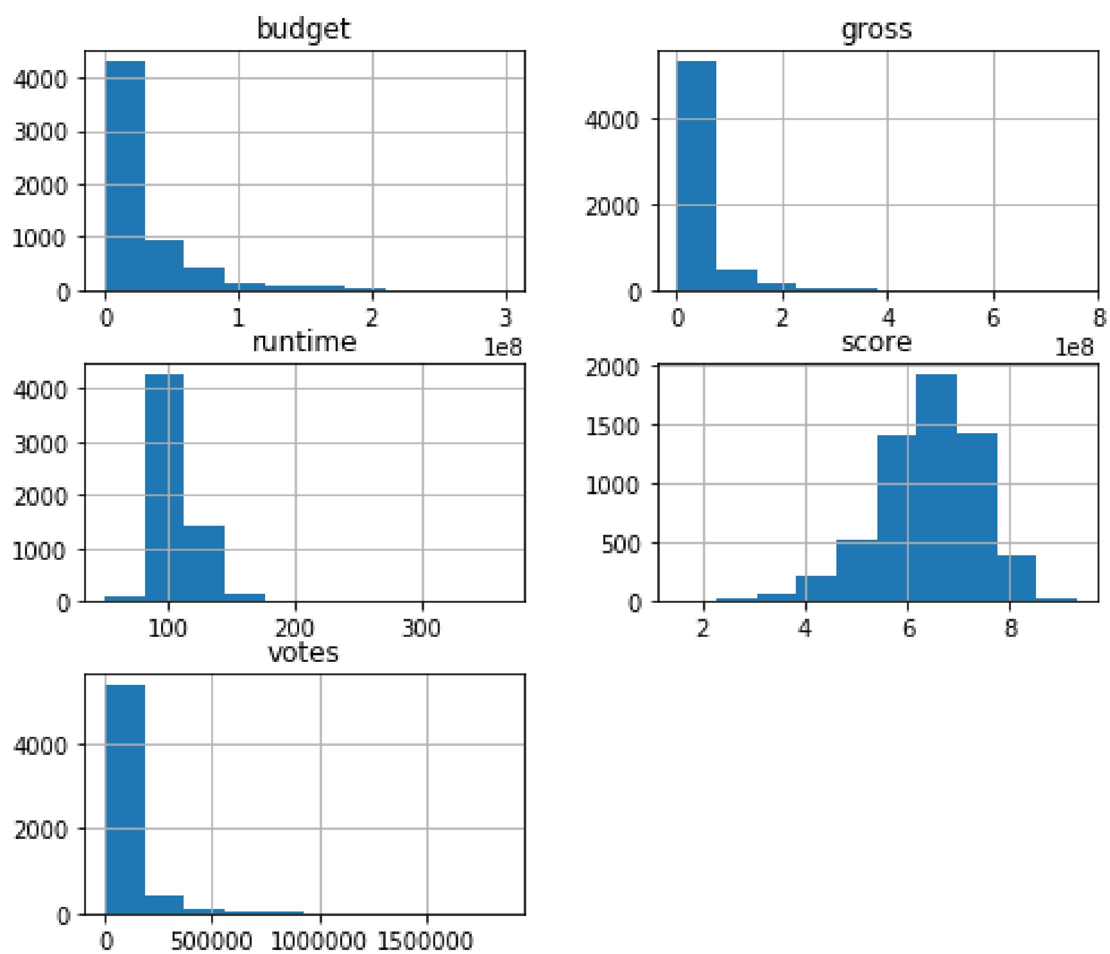
	score	votes	budget	gross	runtime
score	1.000000	0.393703	0.039169	0.161371	0.393470
votes	0.393703	1.000000	0.504808	0.664010	0.308524

```
budget    0.039169  0.504808  1.000000  0.716826  0.264963
gross     0.161371  0.664010  0.716826  1.000000  0.224996
runtime   0.393470  0.308524  0.264963  0.224996  1.000000
```

We can state that if the correlation between 2 variables is over 50%, it is highly correleated and therefore important for our machine learning model later on. In this case, budget-votes, gross-votes, budget-gross, are highly correlated. Later on I will run the same function on our cleaned dataset and observe wether the correleations remain the same.

Another graph that I find very helpful when trying to understand the data given to use, is the histrogram. In this case we can observe how our numerical variables behave. (Histogram shown below)

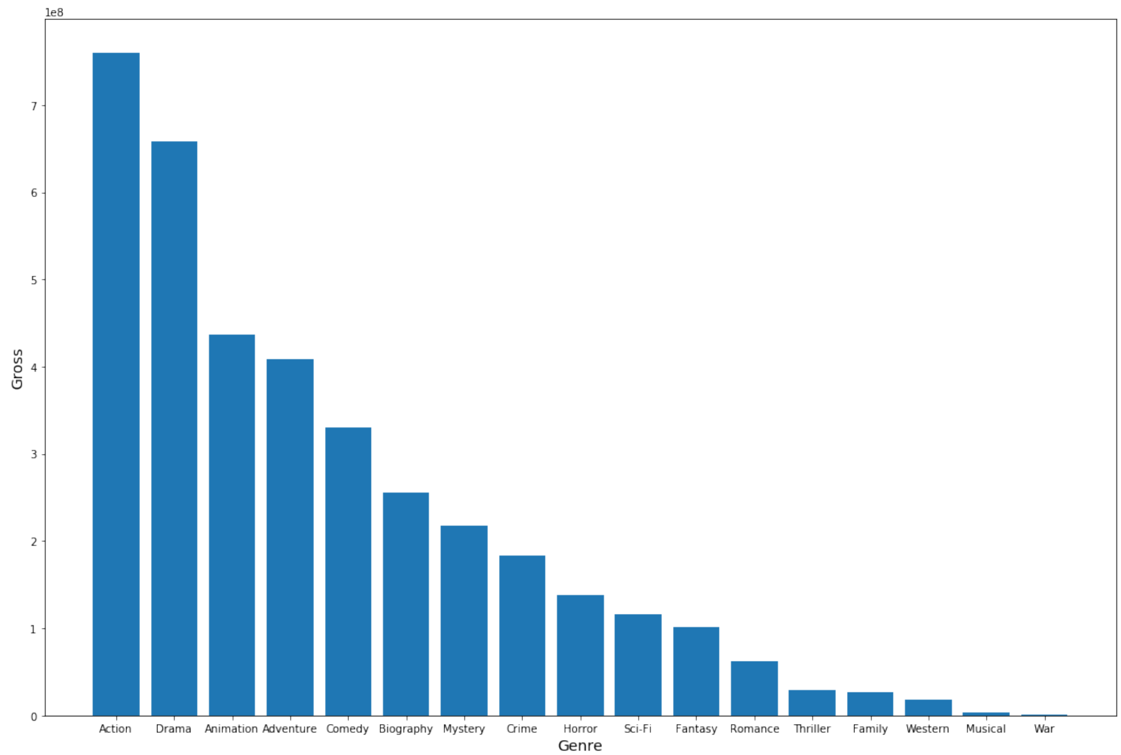
```
In [7]: import matplotlib.pyplot as plt
        %matplotlib inline
        df.hist(figsize=(8,7))
        plt.show()
```



0.1.7 NOTE: The next couple of bar graphs show how diferent categorical variables relate to our most important variable so far, which is 'Gross'. This is the revenue generated. I state that 'Gross' is our most important variable because the more revenue generated, the better the movie. This is generally how it goes. Of course, this is not always the case.

```
In [8]: x_axis = df['genre']
        y_axis = df['gross']
        width = 18
        height = 12
        plt.figure(figsize=(width, height))
        plt.bar(x_axis, y_axis)
        plt.xlabel('Genre', fontsize=14)
        plt.ylabel('Gross', fontsize=14)
```

```
Out[8]: Text(0,0.5,'Gross')
```




```
In [9]: print(df['genre'].head(10))
```

```
0        Action
1         Drama
2        Action
3        Action
4        Action
5        Action
```

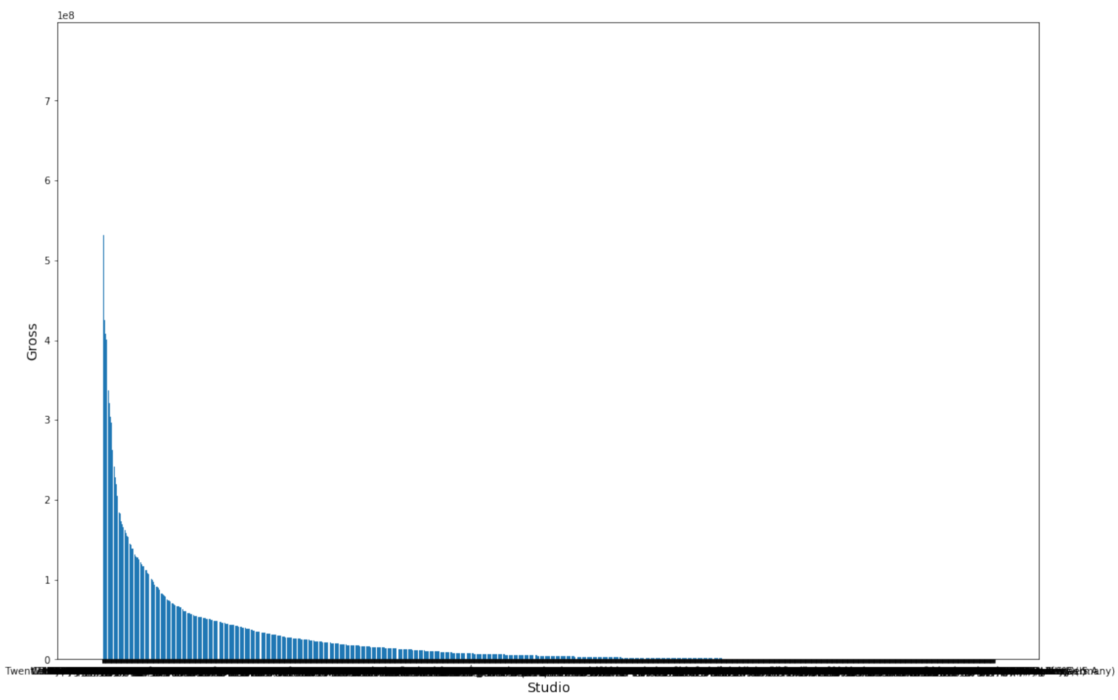
```
6        Action
7        Action
8        Action
9     Animation
Name: genre, dtype: object
```

```
In [10]: xx = df['studio'].where(df['gross'] > 200000000)
         type(xx)
```

```
Out[10]: pandas.core.series.Series
```

```
In [11]: x_axis = df['studio']
         y_axis = df['gross']
         width = 18
         height = 12
         plt.figure(figsize=(width, height))
         plt.bar(x_axis, y_axis)
         plt.xlabel('Studio', fontsize=14)
         plt.ylabel('Gross', fontsize=14)
```

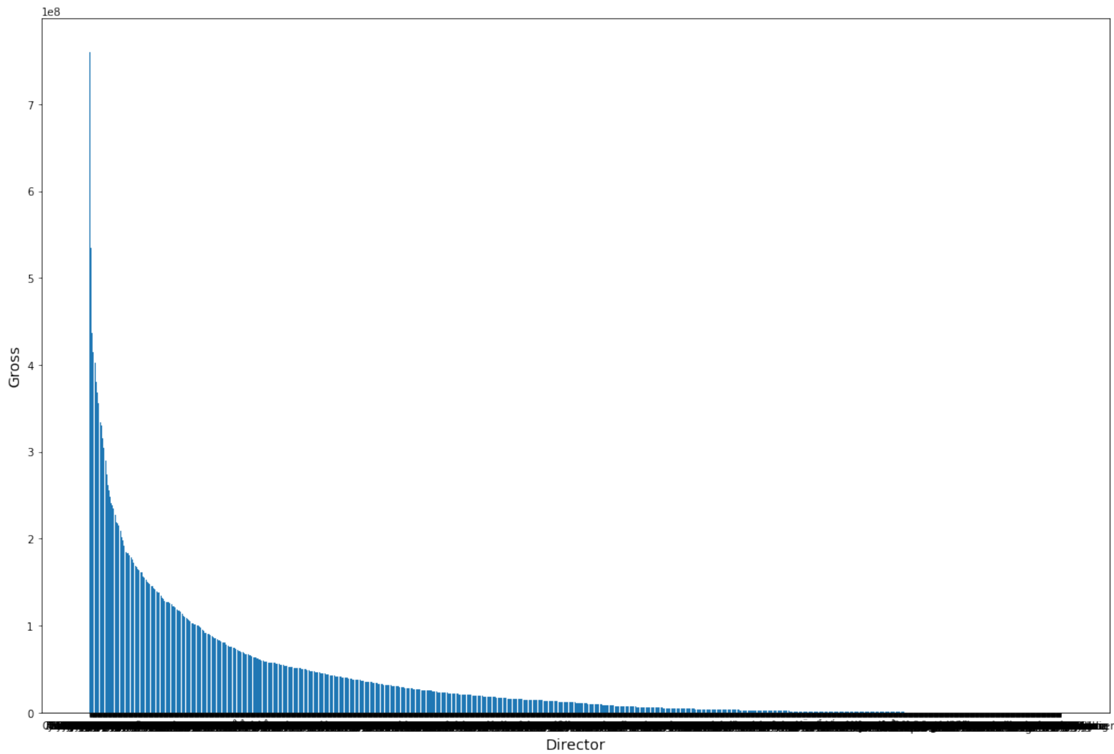
```
Out[11]: Text(0,0.5,'Gross')
```




```
In [12]: x_axis = df['director']
         y_axis = df['gross']
```

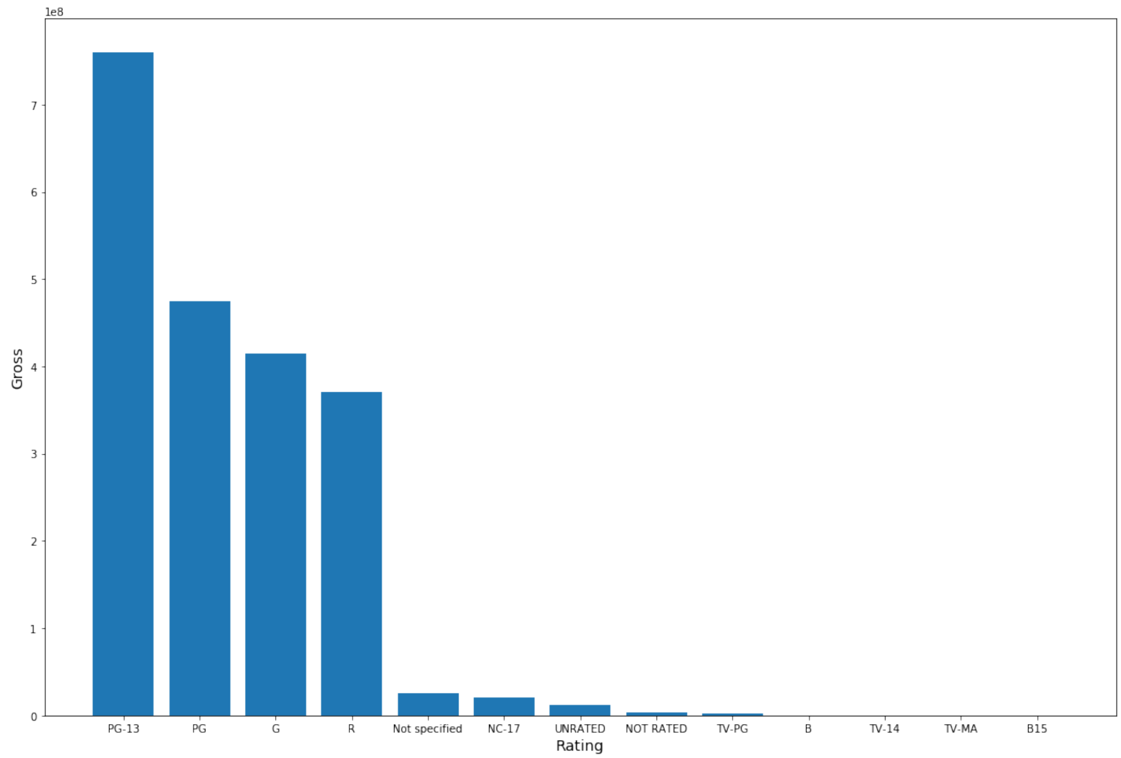
```
width = 18
height = 12
plt.figure(figsize=(width, height))
plt.bar(x_axis, y_axis)
plt.xlabel('Director', fontsize=14)
plt.ylabel('Gross', fontsize=14)
```

Out[12]: Text(0,0.5,'Gross')



In [13]:
```
x_axis = df['rating']
y_axis = df['gross']
width = 18
height = 12
plt.figure(figsize=(width, height))
plt.bar(x_axis, y_axis)
plt.xlabel('Rating', fontsize=14)
plt.ylabel('Gross', fontsize=14)
```

Out[13]: Text(0,0.5,'Gross')



###
Data Wrangling

In [15]:
```
df[df.budget == 0].head()
```

Out[15]:
```
     budget country          director      genre        gross  \
56      0.0      UK       David Yates  Adventure  295983305.0
207     0.0     USA       Walt Becker     Action  168273550.0
431     0.0     USA  John G. Avildsen     Action  115103979.0
553     0.0     USA       Nora Ephron     Comedy   95318203.0
592     0.0     USA       Tyler Perry     Comedy   90485233.0

                                                  name rating  runtime  score  \
56   Harry Potter and the Deathly Hallows: Part 1 (...  PG-13      146    7.7
207                                  Wild Hogs (2007)  PG-13      100    5.9
431                        The Karate Kid Part II (1986)     PG      113    5.9
553                                    Michael (1996)     PG      105    5.7
592                         Madea Goes to Jail (2009)  PG-13      103    4.3

                  star                           studio   votes
56   Daniel Radcliffe                     Warner Bros.  370003
207          Tim Allen              Touchstone Pictures  104657
431         Pat Morita  Columbia Pictures Corporation   58596
553      John Travolta              Turner Pictures (I)   36553
592        Tyler Perry         Tyler Perry Company, The   10095
```

In [ ]:
```
df = df.loc[df.budget > 0,:] #removing missing values
```

In [16]:
```
#Profit would be a useful variable since not profitability is what determines success
df['profit'] = df.gross - df.budget
```

In [17]:
```
df.describe(include=['object'])
```

Out[17]:
```
       country     director   genre                    name rating  \
count     6000         6000    6000                    6000   6000
unique      52         2549      17                    6000     13
top        USA  Woody Allen  Comedy  Gnomeo & Juliet (2011)      R
freq      4281           29    1818                       1   3009

                star              studio
count           6000                6000
unique          2317                1996
top     Nicolas Cage  Universal Pictures
freq              38                 269
```

In [18]:
```
#lets condense the dataset, this will give us a sense of what matters the most
```

In [19]:
```
studio_counts = df.studio.value_counts()

one_timers = studio_counts[studio_counts <= 1].index
three_timers = studio_counts[(studio_counts > 1) & (studio_counts <= 3)].index
five_timers = studio_counts[(studio_counts > 3) & (studio_counts <= 5)].index
ten_timers = studio_counts[(studio_counts > 5) & (studio_counts <= 10)].index

df['studio'].replace(one_timers, 'One Timer', inplace=True)
df['studio'].replace(three_timers, 'Three Timer', inplace=True)
df['studio'].replace(five_timers, 'Five Timer', inplace=True)
df['studio'].replace(ten_timers, 'Ten Timer', inplace=True)
```

In [20]:
```
star_counts = df.star.value_counts()

one_timers = star_counts[star_counts <= 1].index
three_timers = star_counts[(star_counts > 1) & (star_counts <= 3)].index
five_timers = star_counts[(star_counts > 3) & (star_counts <= 5)].index
ten_timers = star_counts[(star_counts > 5) & (star_counts <= 10)].index

df['star'].replace(one_timers, 'One Timer', inplace=True)
df['star'].replace(three_timers, 'Three Timer', inplace=True)
df['star'].replace(five_timers, 'Five Timer', inplace=True)
df['star'].replace(ten_timers, 'Ten Timer', inplace=True)
```

In [21]:
```
director_counts = df.director.value_counts()

one_timers = director_counts[director_counts <= 1].index
three_timers = director_counts[(director_counts > 1) & (director_counts <= 3)].index
```

```
five_timers = director_counts[(director_counts > 3) & (director_counts <= 5)].index
ten_timers = director_counts[(director_counts > 5) & (director_counts <= 10)].index

df['director'].replace(one_timers, 'One Timer', inplace=True)
df['director'].replace(three_timers, 'Three Timer', inplace=True)
df['director'].replace(five_timers, 'Five Timer', inplace=True)
df['director'].replace(ten_timers, 'Ten Timer', inplace=True)
```

In [22]:
```
country_counts = df.country.value_counts()

other_countries = country_counts[country_counts < 50].index
df['country'].replace(other_countries, 'Other', inplace=True)

df.country.value_counts()
```

Out[22]:
```
USA          4281
UK            615
Other         430
France        249
Canada        126
Germany       119
Australia      71
Japan          59
Spain          50
Name: country, dtype: int64
```

In [23]:
```
genre_counts = df.genre.value_counts()

other_genres = genre_counts[genre_counts < 50].index
df['genre'].replace(other_genres, 'Other', inplace=True)

df.genre.value_counts()
```

Out[23]:
```
Comedy       1818
Drama        1280
Action       1175
Crime         463
Adventure     340
Biography     309
Animation     246
Horror        243
Other         126
Name: genre, dtype: int64
```

In [24]:
```
df['rating'].replace(['NOT RATED', 'UNRATED', 'Not specified'], 'NR', inplace=True)
```

In [57]:
```
#Function will return how long the movie has been out

def extract_age(s, today=2014):
```

```
        return today - int( s[-5:-1] )

    extract_age('Titanic (1997)')
```

Out[57]: 17

```
In [58]: df['age'] = df.name.apply(extract_age)
```

###
Machine Learning

```
In [59]: #A good place to start diving into the ML section is by computing correlations

         df[['score', 'votes', 'profit', 'budget']].corr()
```

Out[59]:

	score	votes	profit	budget
score	1.000000	0.393703	0.194065	0.039169
votes	0.393703	1.000000	0.480234	0.504808
profit	0.194065	0.480234	1.000000	0.096927
budget	0.039169	0.504808	0.096927	1.000000

```
In [60]: #We define as 'correlated' if its greater than 50%

In [61]: from sklearn.ensemble import RandomForestRegressor
         from sklearn.metrics import r2_score

In [62]: abt = pd.get_dummies ( df.drop(['name', 'gross', 'votes', 'score'], axis=1) ) #recall

In [63]: train = abt[abt.age >= 0]
         test = abt[abt.age <= 0]

         y_train = train.profit
         X_train = train.drop(['profit'], axis=1)

         y_test = test.profit
         X_test = test.drop(['profit'], axis=1)

In [64]: # Useful article for why choosing a random forest regressor: https://towardsdatascien
```

0.2 From the article above:

0.2.1 Random Forest is also considered as a very handy and easy to use algorithm, because it's default hyperparameters often produce a good prediction result. The number of hyperparameters is also not that high and they are straightforward to understand. One of the big problems in machine learning is overfitting, but most of the time this won't happen that easy to a random forest classifier. That's because if there are enough trees in the forest, the classifier won't overfit the model.

```
In [65]: # Train a basic random forest model
         rf = RandomForestRegressor(random_state=1234)
         rf.fit(X_train, y_train)
```

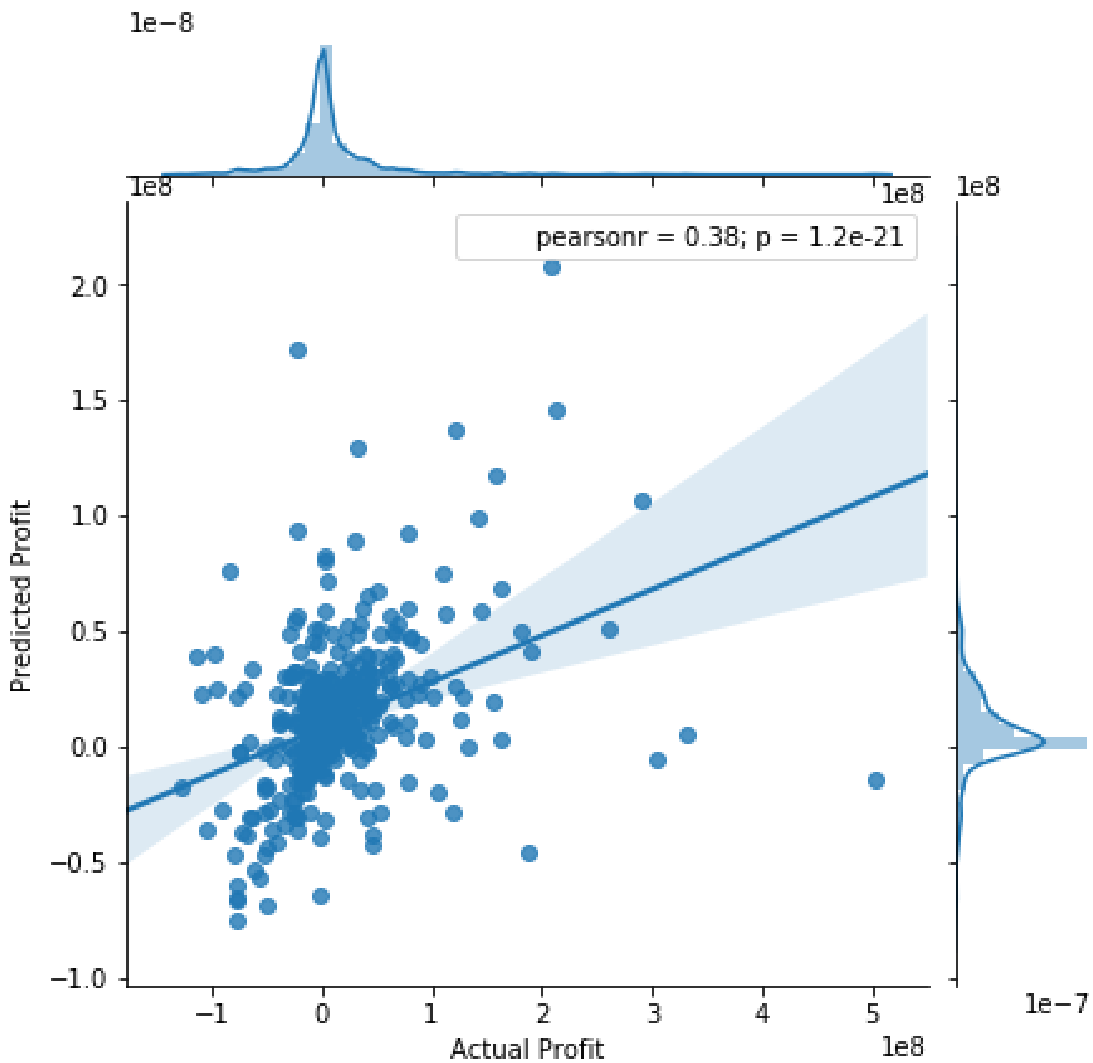
```
Out[65]: RandomForestRegressor(bootstrap=True, criterion='mse', max_depth=None,
                    max_features='auto', max_leaf_nodes=None,
                    min_impurity_decrease=0.0, min_impurity_split=None,
                    min_samples_leaf=1, min_samples_split=2,
                    min_weight_fraction_leaf=0.0, n_estimators=10, n_jobs=1,
                    oob_score=False, random_state=1234, verbose=0, warm_start=False)
```

```
In [66]: # Make prediction on test set
         pred = rf.predict(X_test)
```

```
In [68]: import seaborn as sns
```

```
In [69]: sns.jointplot(y_test, pred, kind='reg')
         plt.xlabel('Actual Profit')
         plt.ylabel('Predicted Profit')
         plt.show()
```

```
/Users/alejandrogarcia/anaconda3/lib/python3.6/site-packages/matplotlib/axes/_axes.py:6462: Use
  warnings.warn("The 'normed' kwarg is deprecated, and has been "
/Users/alejandrogarcia/anaconda3/lib/python3.6/site-packages/matplotlib/axes/_axes.py:6462: Use
  warnings.warn("The 'normed' kwarg is deprecated, and has been "
```



R^2 (coefficient of determination) regression score function.

Best possible score is 1.0 and it can be negative (because the model can be arbitrarily worse). A constant model that always predicts the expected value of y, disregarding the input features, would get a R^2 score of 0.0.

```
In [70]: r2_score(y_test, pred)
```

```
Out[70]: 0.12471120486001908
```

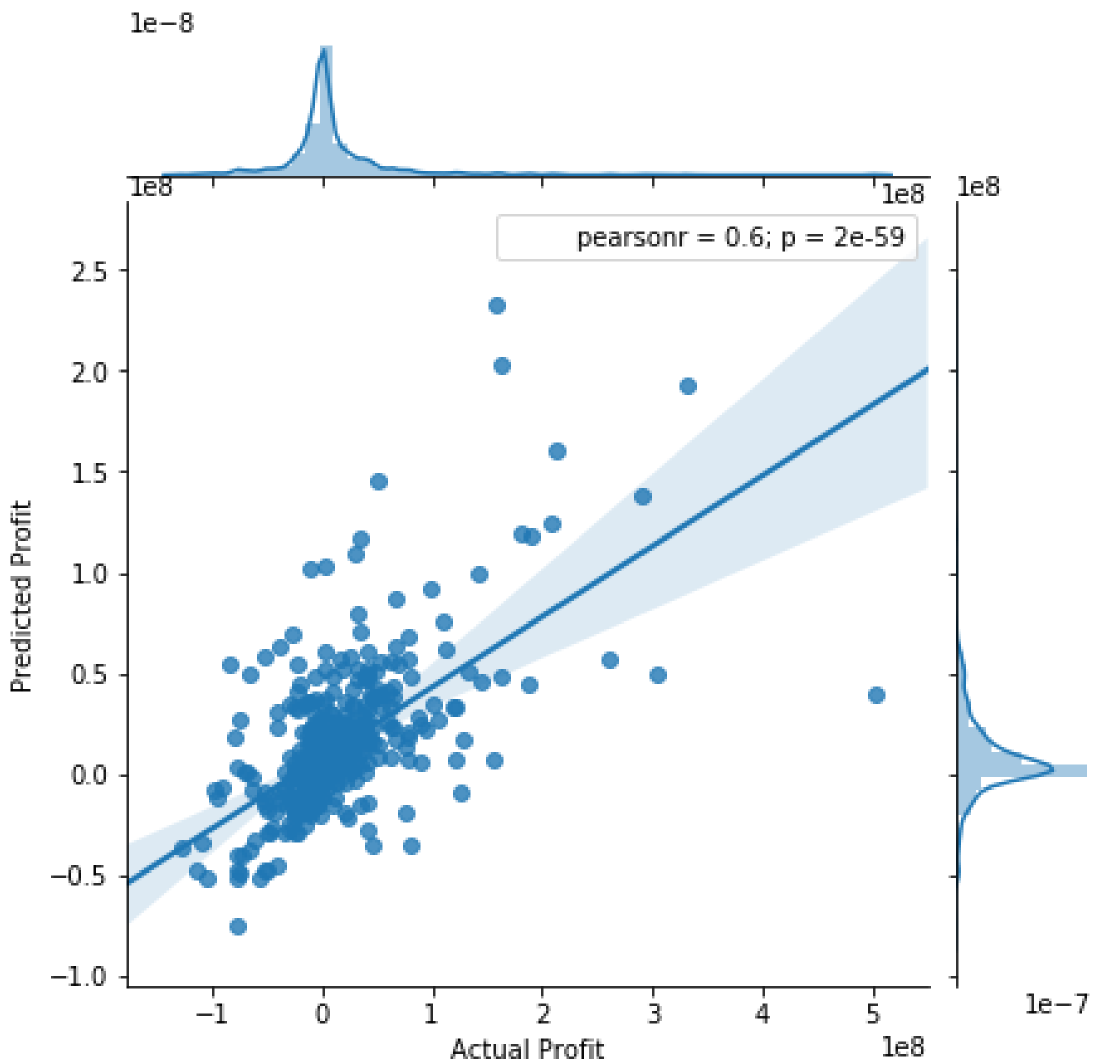
```
In [71]: # NOT A GREAT R2 SCORE
```

```
In [72]: abt_ps = pd.get_dummies ( df.drop(['name', 'gross', 'votes'], axis=1) ) #we kept the
```

```
train = abt_ps[abt_ps.age >= 0]
test = abt_ps[abt_ps.age <= 0]

y_train = train.profit
X_train = train.drop(['profit'], axis=1)

y_test = test.profit
X_test = test.drop(['profit'], axis=1)

rf = RandomForestRegressor(random_state=1234)
rf.fit(X_train, y_train)

pred = rf.predict(X_test)
```

In [73]:
```
sns.jointplot(y_test, pred, kind='reg')
plt.xlabel('Actual Profit')
plt.ylabel('Predicted Profit')
plt.show()
```

```
/Users/alejandrogarcia/anaconda3/lib/python3.6/site-packages/matplotlib/axes/_axes.py:6462: Use
  warnings.warn("The 'normed' kwarg is deprecated, and has been "
/Users/alejandrogarcia/anaconda3/lib/python3.6/site-packages/matplotlib/axes/_axes.py:6462: Use
  warnings.warn("The 'normed' kwarg is deprecated, and has been "
```



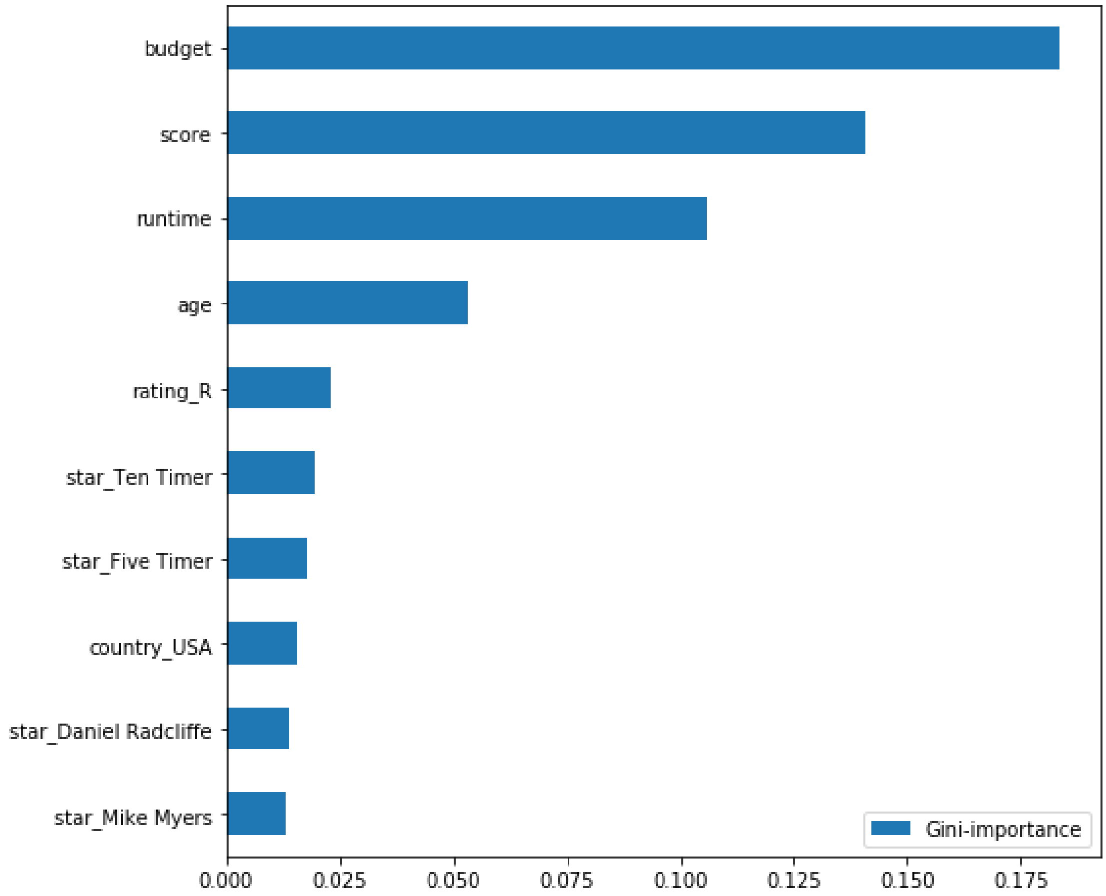

```
In [74]: r2_score(y_test, pred)
```

```
Out[74]: 0.36381519145681196
```

```
In [75]: #Much better R2 score
```

```
In [78]: def plot_feature_importances(columns, feature_importances, show_top_n=10):
             feats = dict( zip(columns, feature_importances) )
             imp = pd.DataFrame.from_dict(feats, orient='index').rename(columns={0: 'Gini-impo
             imp.sort_values(by='Gini-importance').tail(show_top_n).plot(kind='barh', figsize=
             plt.show()
```

```
In [79]: import matplotlib.pyplot as plt
         %matplotlib inline

         plot_feature_importances(X_train.columns, rf.feature_importances_)
```




```
In [80]: #As some Data Scientists might say, more data does not mean more results. Clearly onl
```