investigate-a-dataset-template

April 30, 2018

1 Project: Investigate a Dataset (Replace this with something more specific!)

1.1 Table of Contents

Introduction

Dataset : TMDb movie data This data set contains information about 10,000 movies collected from The Movie Database (TMDb), including user ratings and revenue.

Certain columns, like 'cast' and 'genres', contain multiple values separated by pipe (|) characters. There are some odd characters in the 'cast' column. Don't worry about cleaning them. You can leave them as is. The final two columns ending with "_adj" show the budget and revenue of the associated movie in terms of 2010 dollars, accounting for inflation over time.

Question : Which genres are most popular from year to year? What kinds of properties are associated with movies that have high revenues?

```
In [18]: import numpy as np
         import pandas as pd
         import seaborn as sn
         import matplotlib.pyplot as plt
         from pprint import pprint
```

Data Wrangling

1.1.1 General Properties

```
In [19]: # Load data
         data = pd.read_csv('data/tmdb-movies.csv')
         #print the first row
         data.iloc[0]
```

```
Out[19]: 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
```

In [20]:
```
#function to clean empty rows
def cleanRow(data, array):
    data[array] = data[array].replace(0, np.NAN)
    # removing NAN
    data.dropna(subset = array, inplace = True)
    return data

def getMean(data, columnName):
    return data[columnName].mean()

def getMaxYieldingRow(data, columnName):
    return data.iloc[data[columnName].argmax()]

def removeEmptyValueInColumn(data, columnName):
    return data[~data[columnName].isnull()]
```

1.1.2 Data Cleaning

Removing duplicate rows if any

In [21]:
```
#  drop  the duplicates present in data
pprint("rows before removing duplicates.."+str(len(data)))
data.drop_duplicates(keep = 'first', inplace = True)
pprint("rows after removing duplicates.."+str(len(data)))
```

```
'rows before removing duplicates..10866'
'rows after removing duplicates..10865'
```

*** Removing rows who genres are empty***

```
In [22]: dataWithGenres = removeEmptyValueInColumn(data,'genres')
         pprint("rows with genres.."+str(len(dataWithGenres)))
```

```
'rows with genres..10842'
```

*** Removing rows whose budget and revenue are zero***

```
In [23]: # remove zero budget and revenue rows
         dataWithGenres = cleanRow(dataWithGenres, ['budget', 'revenue'])
         rows, col = dataWithGenres.shape
         pprint("rows without zero revenue and budget.."+str(len(dataWithGenres)))
```

```
'rows without zero revenue and budget..3854'
```

```
/opt/conda/lib/python3.6/site-packages/pandas/core/frame.py:2352: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: http://pandas.pydata.org/pandas-docs/stable/indexing.html#
  self[k1] = value[k2]
/opt/conda/lib/python3.6/site-packages/ipykernel_launcher.py:5: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: http://pandas.pydata.org/pandas-docs/stable/indexing.html#
  """
```

```
In [24]: # print the datatype of each column
         dataWithGenres.dtypes
```

```
Out[24]: id                         int64
         imdb_id                   object
         popularity               float64
         budget                   float64
         revenue                  float64
         original_title            object
         cast                      object
         homepage                  object
         director                  object
         tagline                   object
         keywords                  object
         overview                  object
         runtime                    int64
```

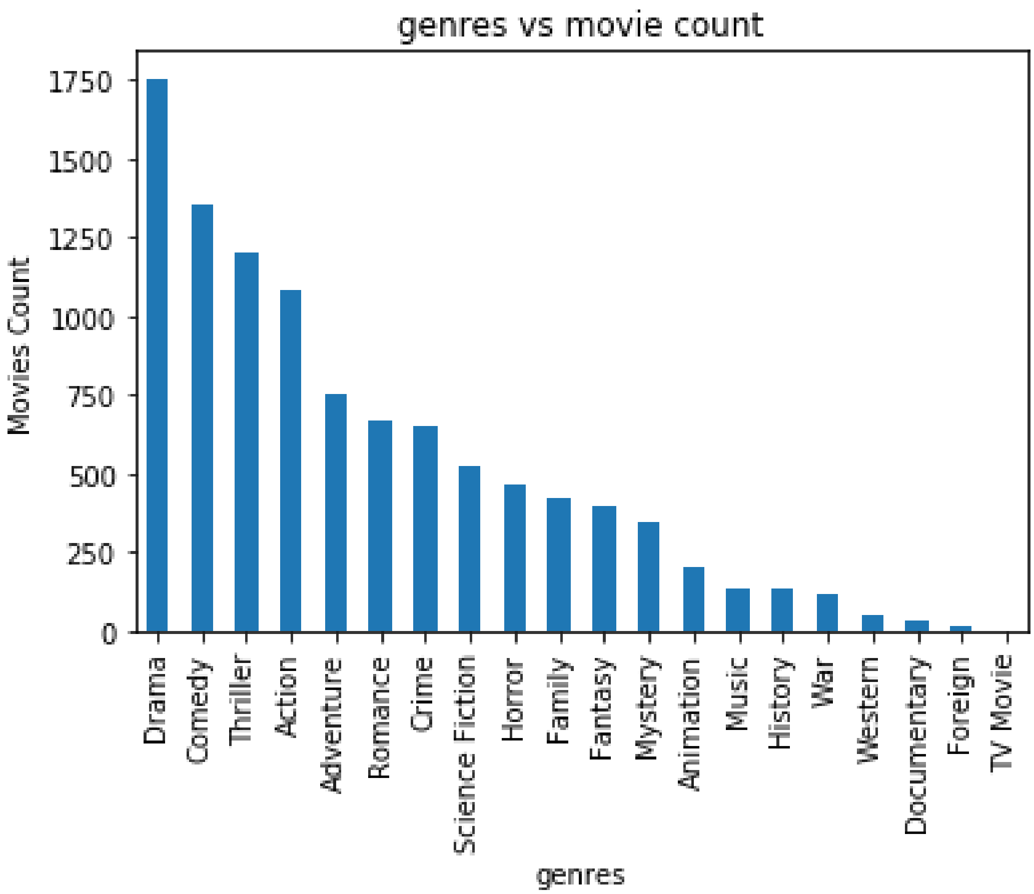
```
genres                    object
production_companies      object
release_date              object
vote_count                 int64
vote_average             float64
release_year               int64
budget_adj               float64
revenue_adj              float64
dtype: object
```

Exploratory Data Analysis
The following need to be identified with the data. 1. Which genres are most popular? 2. What is average budget of movie? 3. Which movie yields high revenue? 4. What is the average runtime of movies? 5. Compare the runtime of movies? 6. Study the revenue yielding year of movies? 7. Study the revenue yield by comparing the runtime of movies? 8. What kinds of properties are associated with movies that have high revenues?

1. Which genres are most popular?

In [25]:
```
genr_arr = []

#split genres by |
genres_data = dataWithGenres['genres'].str.cat(sep = '|')
genres_data_split = pd.Series(genres_data.split('|'))

groupedGenres = genres_data_split.value_counts(ascending = False)
groupedGenres.plot.bar()
plt.xlabel('genres')
#On y-axis
plt.ylabel('Movies Count')
#Name of the graph
plt.title('genres vs movie count')
```

Out[25]:
```
Text(0.5,1,'genres vs movie count')
```



Inference : As per the data calculated, movies with 'drama' genres occupied the market. Drama is followed by comedy and thriller

2. What average budget of movies

```
In [26]: getMean(dataWithGenres, 'budget')
```

```
Out[26]: 37203696.954852104
```

Inference. The everage budget for a movie is 37203696.954852104

3. Which movie yields high revenue?

```
In [27]: maxRevMovie = getMaxYieldingRow(dataWithGenres,'revenue')
         maxRevMovie
```

```
Out[27]: id                                                              9573
         imdb_id                                                    tt0309377
         popularity                                                  0.545907
         budget                                                         5e+07
```

```
revenue                                                     2.61995e+07
original_title                                               Blood Work
cast                        Clint Eastwood|Jeff Daniels|Anjelica Huston|Wa...
homepage                                                            NaN
director                                                 Clint Eastwood
tagline                       He's a heartbeat away from catching the killer
keywords                        houseboat|heart|investigation|police|ex-cop
overview                    Still recovering from a heart transplant, a re...
runtime                                                             110
genres                                    Crime|Drama|Mystery|Thriller
production_companies              Malpaso Productions|Warner Bros. Pictures
release_date                                                     8/4/02
vote_count                                                           89
vote_average                                                        5.7
release_year                                                       2002
budget_adj                                                  6.06131e+07
revenue_adj                                                 3.17607e+07
Name: 4021, dtype: object
```

4. What is the average runtime of movies?

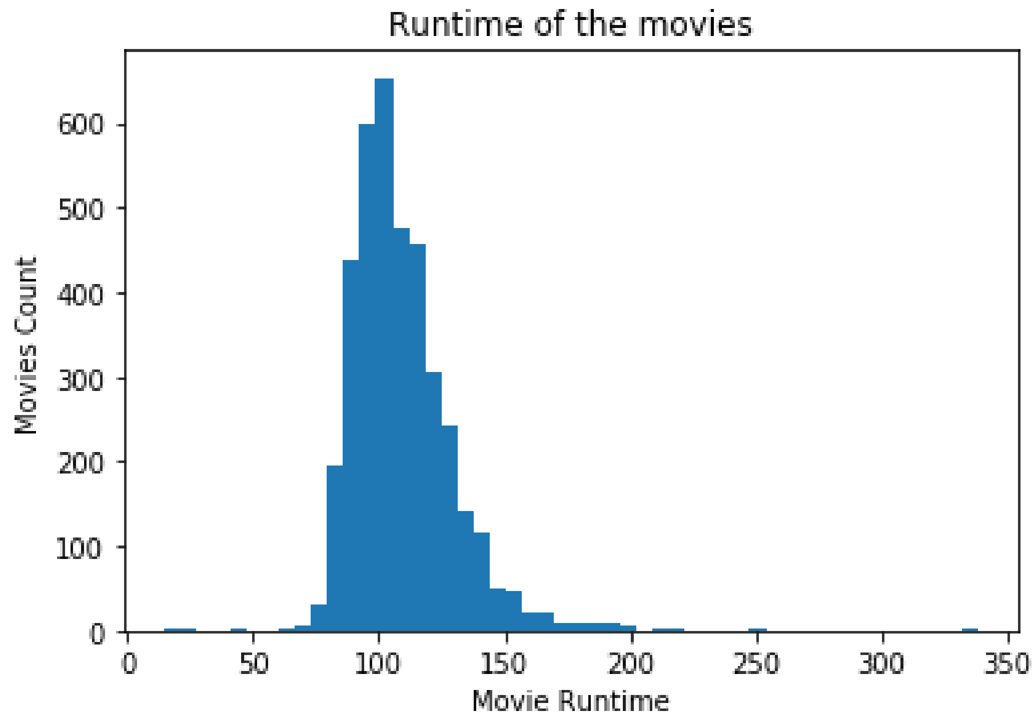
In [28]:
```
getMean(dataWithGenres, 'runtime')
```

Out[28]:
```
109.22029060716139
```

5. Compare the runtime of movies?

In [29]:
```
data_runtime = dataWithGenres['runtime']
plt.hist(data_runtime, bins=50)
plt.xlabel('Movie Runtime')
#On y-axis
plt.ylabel('Movies Count')
#Name of the graph
plt.title('Runtime of the movies')
```

Out[29]:
```
Text(0.5,1,'Runtime of the movies')
```



Inference. The histogram follows positively skewed one where most of the movie runtime falls around 75 to 135.

Will print the statistics based on runtime

```
In [30]: dataWithGenres['runtime'].describe()
```

```
Out[30]: count    3854.000000
         mean      109.220291
         std        19.922820
         min        15.000000
         25%        95.000000
         50%       106.000000
         75%       119.000000
         max       338.000000
         Name: runtime, dtype: float64
```

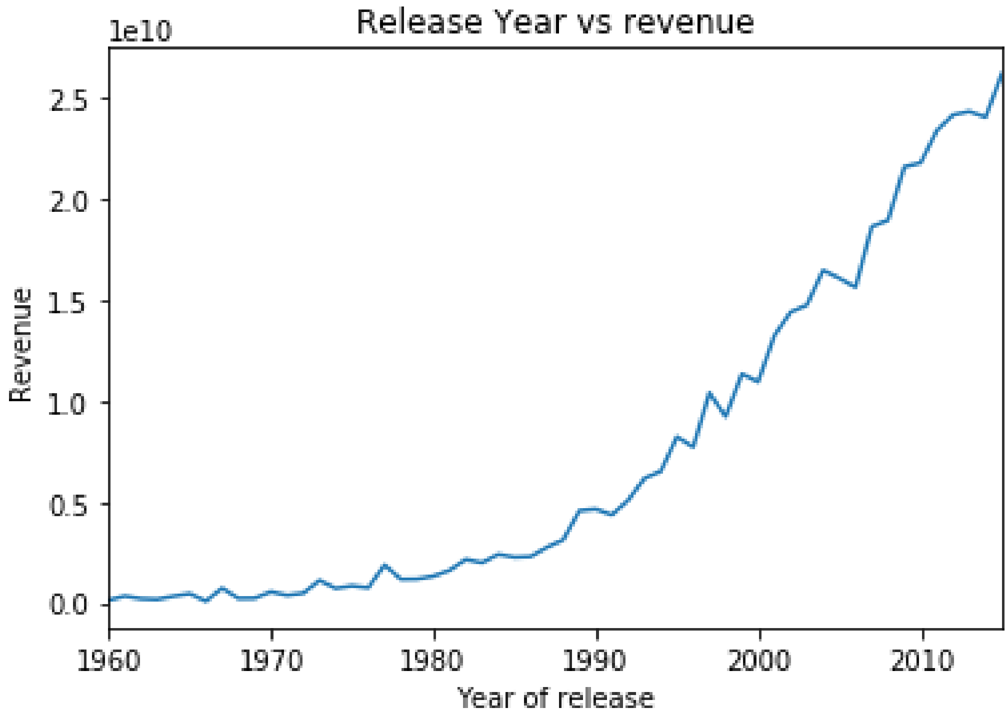
Inference. Based on runtime statistics, average runtime is 109 and it has standard deviation of 19

6. Study the revenue yielding year of movies?

```
In [31]: dataByYar = dataWithGenres.groupby('release_year')['revenue'].sum()
         dataByYar.plot.line()
         plt.xlabel('Year of release')
         #On y-axis
```

```
        plt.ylabel('Revenue')
        #Name of the graph
        plt.title('Release Year vs revenue')
```

Out[31]: Text(0.5,1,'Release Year vs revenue')



Inferenece : The maximum revenue is on 2015

In [32]:
```
dataByYar.describe()
```

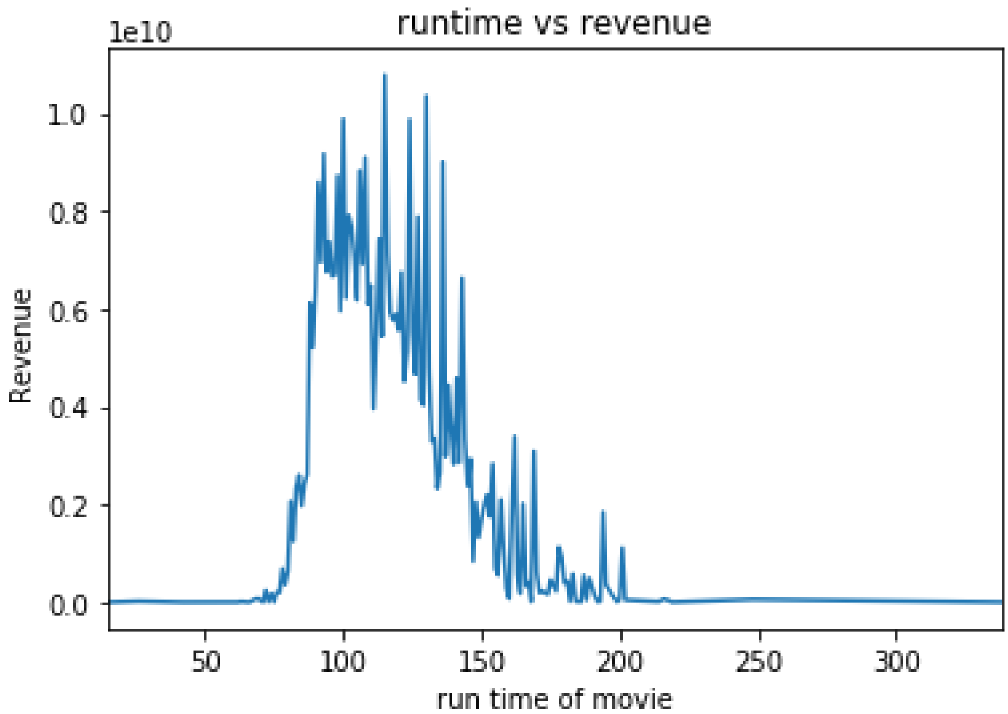
Out[32]:
```
count    5.600000e+01
mean     7.411147e+09
std      8.242757e+09
min      8.473669e+07
25%      7.454036e+08
50%      2.942177e+09
75%      1.353885e+10
max      2.620292e+10
Name: revenue, dtype: float64
```

7. Study the revenue yield by comparing the runtime of movies?

In [33]:
```
datarunRev = dataWithGenres.groupby('runtime')['revenue'].sum()
datarunRev.plot.line()
plt.xlabel('run time of movie')
```

```
#On y-axis
plt.ylabel('Revenue')
#Name of the graph
plt.title('runtime vs revenue')
```

Out[33]: Text(0.5,1,'runtime vs revenue')



Inference : Based on the graph above, the graph is positively skewed where the revenue is contained by the runtime time. After runtime of 130.. the revenue is decreasing.

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

In [34]:
```
#To find the paroperties that are associated with high revenues. We have to find the co
data.corr()
```

Out[34]:

	id	popularity	budget	revenue	runtime	vote_count	\
id	1.000000	-0.014351	-0.141341	-0.099235	-0.088368	-0.035555	
popularity	-0.014351	1.000000	0.545481	0.663360	0.139032	0.800828	
budget	-0.141341	0.545481	1.000000	0.734928	0.191300	0.632719	
revenue	-0.099235	0.663360	0.734928	1.000000	0.162830	0.791174	
runtime	-0.088368	0.139032	0.191300	0.162830	1.000000	0.163273	
vote_count	-0.035555	0.800828	0.632719	0.791174	0.163273	1.000000	
vote_average	-0.058391	0.209517	0.081067	0.172541	0.156813	0.253818	
release_year	0.511393	0.089806	0.115904	0.057070	-0.117187	0.107962	
budget_adj	-0.189008	0.513555	0.968963	0.706446	0.221127	0.587062	

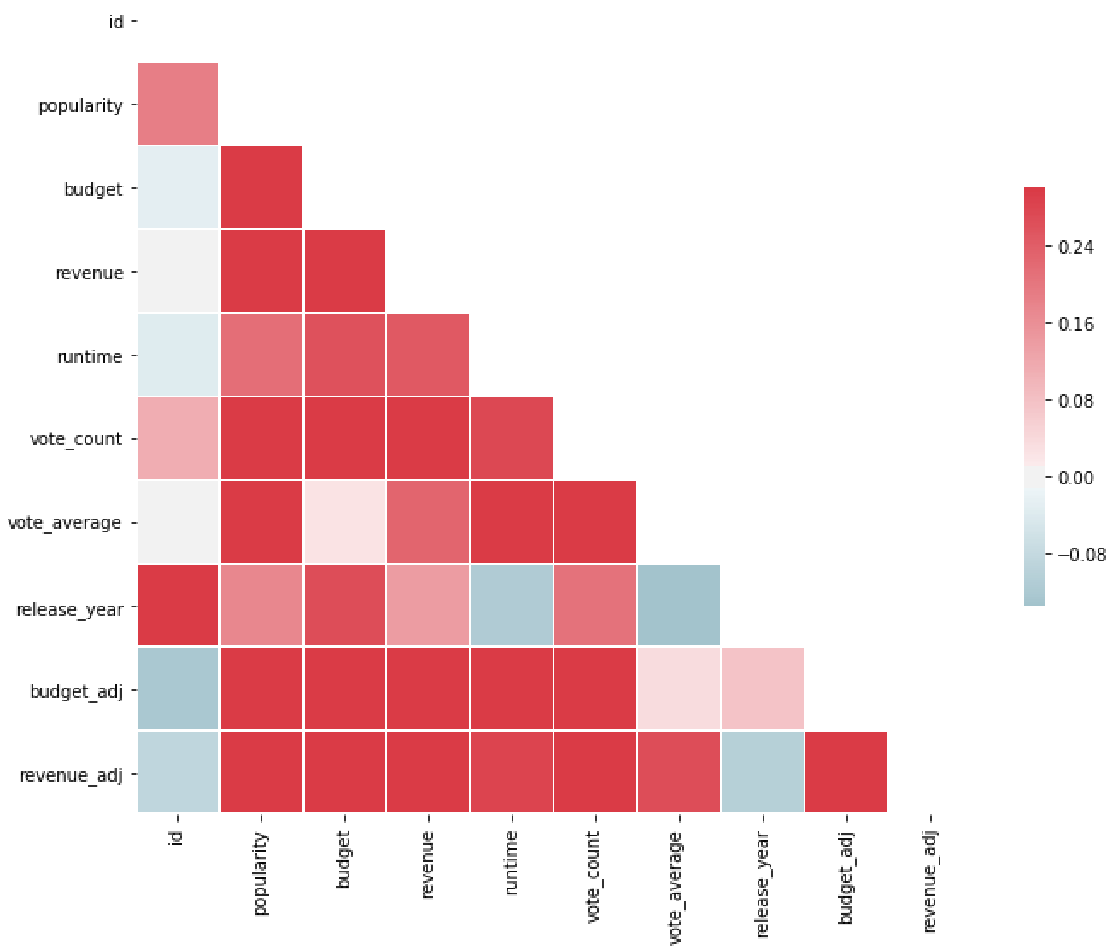
```
revenue_adj   -0.138487    0.609085   0.622531   0.919109   0.175668    0.707941

              vote_average  release_year  budget_adj  revenue_adj
id               -0.058391      0.511393   -0.189008    -0.138487
popularity        0.209517      0.089806    0.513555     0.609085
budget            0.081067      0.115904    0.968963     0.622531
revenue           0.172541      0.057070    0.706446     0.919109
runtime           0.156813     -0.117187    0.221127     0.175668
vote_count        0.253818      0.107962    0.587062     0.707941
vote_average      1.000000     -0.117576    0.093079     0.193062
release_year     -0.117576      1.000000    0.016771    -0.066236
budget_adj        0.093079      0.016771    1.000000     0.646627
revenue_adj       0.193062     -0.066236    0.646627     1.000000
```

As per the table above, revenue is more corrlated with vote_count with the correlation value of 0.79

Inference. Higher the value between columns , higher the correleation is.

In [35]:
```
# Compute the correlation matrix
corr = dataWithGenres.corr()

mask = np.zeros_like(corr, dtype=np.bool)
mask[np.triu_indices_from(mask)] = True

f, ax = plt.subplots(figsize=(11, 9))

cmap = sn.diverging_palette(220, 10, as_cmap=True)

sn.heatmap(corr, mask=mask, cmap=cmap, vmax=.3, center=0,
           square=True, linewidths=.5, cbar_kws={"shrink": .5})
```

Out[35]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7f71392be160>
```



Conclusions

As per the data of movies, High revenue is associated with the following in the order it was associated. 1. Vote_count (having correlation value of 79%). If the vote_count is high then obvious more people come and see the movie which in turns increase the revenue) 2. Budget (having correlation value of 73%. Higher the budget is , higher the revenue of movie as per the dataset) 3. Popularity (having correlation value of 66.3%. Higher the popularity of movie is , higher the revenue of movie as per the dataset)

As per the analysis following are important to be considered 1. To get more revenue, the run time of movies should be aroung 109 2. The mean budget of all movies is 37203696. This is average amount to make a good revenue movie 2. As the years moves on, the revenue of movie increases based on the causation mention just above like vote_count, budget, popularity

Limitations : 1. The runtime measure is not shown whether it is second or minutes 2. The measure of budget/revenue are not shown. 3. Few invalid data/duplicate data's has been excluded from analysis. Not sure whether that affecet our analysis. We need to get that data corrected.