Project TMDb movie Analysis

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Introducation

In this project we will be analysing data assocaiated with the TMDb movie data (cleaned from original data on Kaggle) This data set contains information about 10,000 movies collected from The Movie Database (TMDb), including user ratings and show the budget and revenue of the associated movie in terms of 2010 dollars, accounting for inflation over time.In particular, we will be intrested in finding:

- The original title for the movie have the highest runtime in 1990.
- Which genre (romance / horror) has the highest popularity (with the release bettwen years (1960 - 1990))
- Is there a relationship between budget and revenue
- Number of movie releases per year

```
# Import Python necessary  package essential for our analysis
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns
from IPython.display import display
```

Date Wrangling

General properties

```
# Load your data and print out a few lines. Perform operations to inspect data
df = pd.read_csv('tmdb-movies.csv')
df.head(100000)
```

	id	imdb_id	popularity	budget	revenue	original_title	cast	
0	135397	tt0369610	32.985763	150000000	1513528810	Jurassic World	Chris Pratt|Bryce Dallas Howard|Irrfan Khan|Vi...	
1	76341	tt1392190	28.419936	150000000	378436354	Mad Max: Fury Road	Tom Hardy|Charlize Theron|Hugh Keays-Byrne|Nic...	
2	262500	tt2908446	13.112507	110000000	295238201	Insurgent	Shailene Woodley|Theo James|Kate Winslet|Ansel...	http:/
3	140607	tt2488496	11.173104	200000000	2068178225	Star Wars: The Force Awakens	Harrison Ford|Mark Hamill|Carrie Fisher|Adam D...	
4	168259	tt2820852	9.335014	190000000	1506249360	Furious 7	Vin Diesel|Paul Walker|Jason Statham|Michelle ...	
...	...	...	...	...	...	...	...	
10861	21	tt0060371	0.080598	0	0	The Endless Summer	Michael Hynson|Robert August|Lord 'Tally Ho' B...	
							James Garner|Eva	

```
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')
```

```
# Shape of our dataset.
df.shape
```

```
(10866, 21)
```

```
# describe the dataset
df.describe()
```

	id	popularity	budget	revenue	runtime	vote_count	vote_aver
count	10866.000000	10866.000000	1.086600e+04	1.086600e+04	10866.000000	10866.000000	10866.000
mean	66064.177434	0.646441	1.462570e+07	3.982332e+07	102.070863	217.389748	5.974
std	92130.136561	1.000185	3.091321e+07	1.170035e+08	31.381405	575.619058	0.935
min	5.000000	0.000065	0.000000e+00	0.000000e+00	0.000000	10.000000	1.500
25%	10596.250000	0.207583	0.000000e+00	0.000000e+00	90.000000	17.000000	5.400
50%	20669.000000	0.383856	0.000000e+00	0.000000e+00	99.000000	38.000000	6.000
75%	75610.000000	0.713817	1.500000e+07	2.400000e+07	111.000000	145.750000	6.600
max	417859.000000	32.985763	4.250000e+08	2.781506e+09	900.000000	9767.000000	9.200

```
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
```

```
# to defind how much null value in each culome
df.isnull().sum()
```

```
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
```

We know the culome (popularity ,budget ,revenue ,original_title ,runtime,release_date,revenue,vote_count ,vote_average ,release_year,budget_adj,revenue_adj) not have null value.

```
# Check for duplicated rows:
df.duplicated().sum()
```

```
1
```

```
#drop these duplicated rows
df.drop_duplicates(inplace=True)
# To confirme is drop Duplicate
df.duplicated().sum()
```

```
0
```

```
# Drop the coulme we will not used in data anlaysis
df.drop(
    ['homepage','tagline','production_companies','keywords','overview'
     ,'cast','director','release_date','vote_count','vote_average'], inplace = True, axis = 1)
```

Exploratory Data Analysis

Research Question 1 (The original title for the movie have the highest runtime in 1990 ?)

```
#Step 1
#show all row when release_year = 1990
#df.query('release_year == 1990')
#get runtime
release_copy=df.query('release_year == 1990').get(["original_title","runtime"])
#release_copy=df.query('release_year == 1990')
release_copy.head(10866)
#get the original title for the movie have the highest runtime in 1990
print(release_copy['runtime'].max())
print("Movie have highest runtime in 1990")
print(release_copy.query('runtime==192').get(["original_title"]))
```

```
192
Movie have highest runtime in 1990
         original_title
9995  Stephen King's It
```

Observations : The original_title of Movie have highest runtime in 1990 is Stephen King's It

Research Question 2 (Which genre (romance / horror) has the highest popularity (with the release bettwen years (1960 - 1990)

```
# Step 1
from pandas.core.window.expanding import Axis
from os import access
# to split the genres
genres = df.genres.str.get_dummies()
# concat the dummies with the data set
genres1=pd.concat([df,genres],axis=1)
# To make sure of the merge print the name of columns
genres1.columns
```

```
Index(['id', 'imdb_id', 'popularity', 'budget', 'revenue', 'original_title',
       'runtime', 'genres', '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')
```

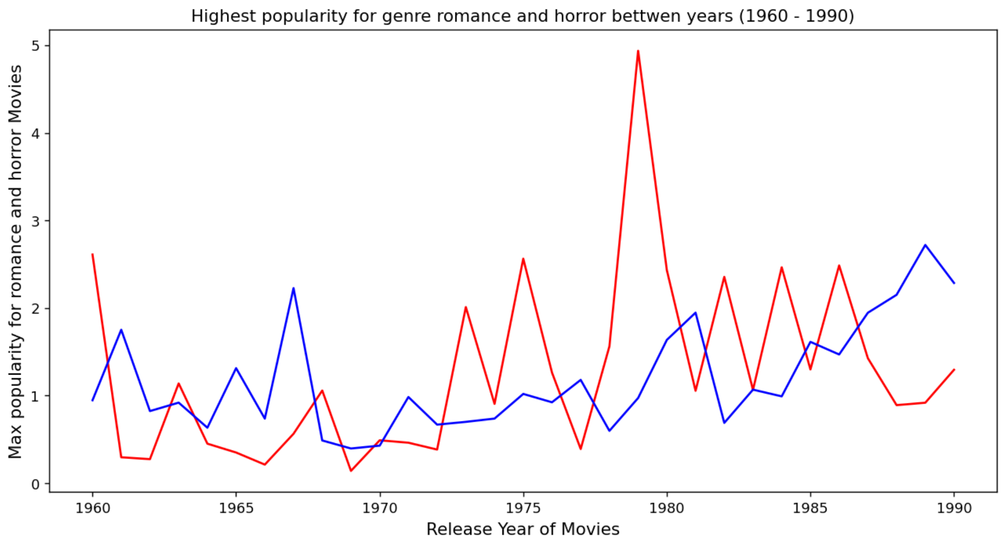
```
from matplotlib import colors
from numpy.lib.shape_base import tile
#step 2
# query about release_year with the release bettwen years (1960 - 1990) have 1 in Romance or Horror
Quetion2=genres1.query('release_year >= 1960 & release_year <= 1990').get(["release_year","popularity","Romance","Horror"])

# find the MAX popularity in Romance
romance=Quetion2.query('Romance == 1').get(["release_year","popularity"]).groupby('release_year')[['popularity']].max()

# find the MAX popularity in Horror
Horror=Quetion2.query('Horror == 1').get(["release_year","popularity"]).groupby('release_year')[['popularity']].max()

#Step 3
#and storing all this in variable
Horror_polt= Horror.groupby('release_year')[['popularity']].sum()
romance_polt=romance.groupby('release_year')[['popularity']].sum()
#giving the figure size(width, height)
plt.figure(figsize=(12,6), dpi = 130)
#labeling x-axis
plt.xlabel('Release Year of Movies', fontsize = 12)
#labeling y-axis
plt.ylabel('Max popularity for romance and horror Movies', fontsize = 12)
#title of a the plot
plt.title('Highest popularity for genre romance and horror bettwen years (1960 - 1990)')
#plotting what needs to be plotted
plt.plot(Horror_polt, color='red')
plt.plot(romance_polt, color= 'blue')
#showing the plot
```

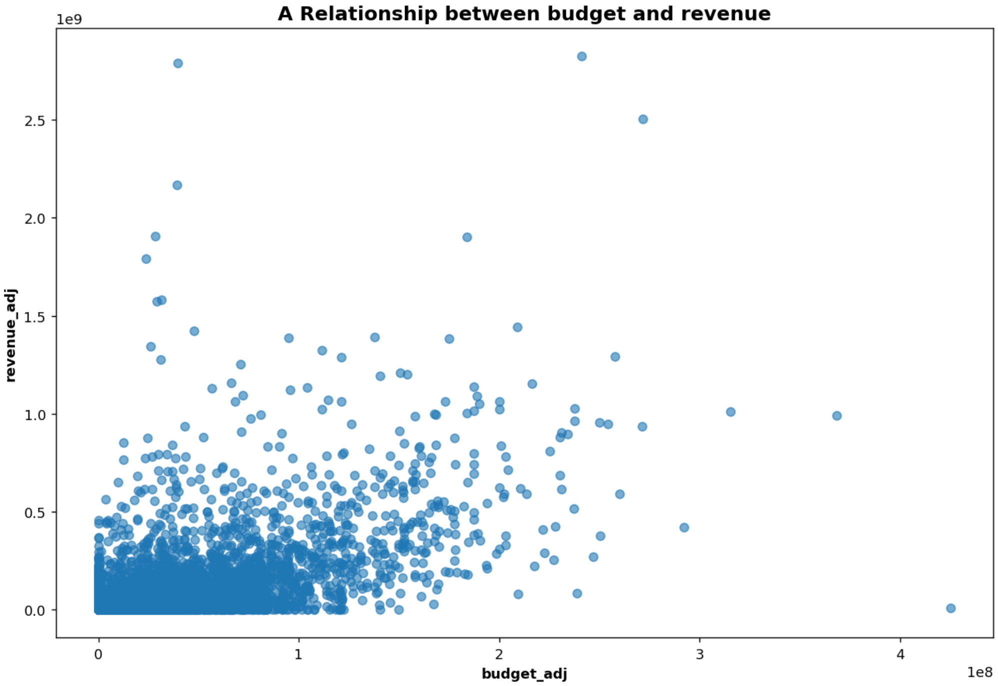
```
plt.show()
```



Observations: The popularity of Romance Movies began from 1982 to 1990 and achieved the highest prevalence in 1990, while horror Movies began to decline in popularity after 1986, and the highest value of spread was in 1979.

Research Question 3 (Is there a relationship between budget and revenue?)

```
from matplotlib import colors
from numpy.lib.shape_base import tile
#Research Question 2 (Is there a relationship between budget and revenue?)
#Step 1
#giving the figure size(width, height)
plt.figure(figsize=(12,8), dpi = 130)
# Plotting the relation between revenue & vote counts
Quetion3= plt.scatter(df['budget_adj'],
            df['revenue_adj'],
            alpha = 0.6) #transparency level of points on the plot. Used to avoid overplotting
# add and format additional elements, such as titles and axis labels
#title of a the plot
plt.title('A Relationship between budget and revenue',fontsize = 14,
          weight = "bold")
#labeling x-axis
plt.xlabel("budget_adj", weight = "bold")
#labeling y-axis
plt.ylabel("revenue_adj", weight = "bold")
#showing the plot
plt.show()
```



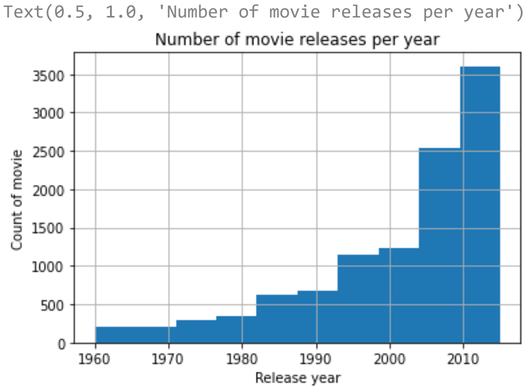
Observations:

1. The graph shows that the most Movies that had a budget between 0 to 1 million dollars (in dollar value in 2010) got a Revenue equal to the budget or less than 0.5 of the budget .
2. The highest Revenue value was 2.9 million dollars(in dollar value in 2010) for a movie with a budget of 2.4
3. The value of the budget spent on the movies is not the main factor in increasing the Revenue

Research Question 4 (Number of movie releases per year ?)

```
#Research Question 4 (Number of movie releases per year ?)
Release_Movie=df.query('release_year >=1960').get(["release_year"])
Release_Movie.release_year.hist()
# title and labels
plt.xlabel('Release year')
plt.ylabel('Count of movie')
plt.title('Number of movie releases per year')
```

```
Text(0.5, 1.0, 'Number of movie releases per year')
```



Observations:

1. From 1960 to 1984, the number of Movies produced each year did not exceed 100 Movies.
2. The graph shows The Movie production sector began to grow in 1979's.
3. 700 Movie were produced in 2015, which is the highest value so far.

Conclusions

Data Limitations:

Although our dataset contains more than 10,000 rows it's pretty insufficient to draw precise conclusions :

1. Most of the data columns are irrelevant for the analysis
2. many NAN values are missing from our dataset for an uncertain reason (We should try a better web scrapping for a better data quality or prepare data from a different source).
3. The formula for writing budget, Revenue, etc. is inaccurate

Conclusions :

- The original_title of Movie have highest runtime in 1990 is Stephen King's It
- The popularity of Romance Movies began from 1982 to 1990 and achieved the highest prevalence in 1990, while horror Movies began to decline in popularity after 1986, and the highest value of spread was in 1979.
- The graph shows that the most Movies that had a budget between 0 to 1 million dollars (in dollar value in 2010) got a Revenue equal to the budget or less than 0.5 of the budget .
- The highest Revenue value was 2.9 million dollars(in dollar value in 2010) for a movie with a budget of 2.4
- The value of the budget spent on the movies is not the main factor in increasing the Revenue .
- From 1960 to 1984, the number of Movies produced each year did not exceed 100 Movies.
- The graph shows The Movie production sector began to grow in 1979's.
- 700 Movie were produced in 2015, which is the highest value so far.