TMDB Movie Database - Analysis

Project Hypothesis : Budget spent on movies And Revenue generated have increased considerably over time are in positive correlation with one another.

Project Outlines and Steps Followed :

```
* Gathering data from provided CSV.
* Data Cleaning and Engineering using Python on Google Colab.
* Dropping Un-neccesary Columns and Dividing columns with
heterogeneous data into new individual columns.
* Following our hypothesis. I have further plotted graphs and have
mentioned key take aways from each one of them as we move along this
project.
* Python Scripts with Concludding graphs can be easily found below.
```

Importing Required Library and provided DB : TMDB database (CSV file)

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from matplotlib.pyplot import figure
figure(figsize=(8, 6), dpi=80)
%matplotlib inline
df=pd.read_csv('/content/drive/MyDrive/tmdb-movies.csv')
df.head(1)
```

	id	imdb_id	popularity	...	release_year	budget_adj	revenue_adj
0	135397	tt0369610	32.985763	...	2015	1.379999e+08	1.392446e+09

[1 rows x 21 columns]

Movies DB Gathered till 2015

df.tail(1)

```
id   imdb_id  popularity  ...  release_year   budget_adj   revenue_adj

10865   22293   tt0060666    0.035919   ...          1966   127642.279154
0.0

[1 rows x 21 columns]
```

Movies DB Gathered from 1966

Initial DB analysis for factors such as MAX, MIN and MEAN of values per given column

```
df.describe()
```

```
                 id    popularity  ...    budget_adj   revenue_adj
count   10866.000000  10866.000000  ...  1.086600e+04  1.086600e+04
mean    66064.177434      0.646441  ...  1.755104e+07  5.136436e+07
std     92130.136561      1.000185  ...  3.430616e+07  1.446325e+08
min         5.000000      0.000065  ...  0.000000e+00  0.000000e+00
25%     10596.250000      0.207583  ...  0.000000e+00  0.000000e+00
50%     20669.000000      0.383856  ...  0.000000e+00  0.000000e+00
75%     75610.000000      0.713817  ...  2.085325e+07  3.369710e+07
max    417859.000000     32.985763  ...  4.250000e+08  2.827124e+09

[8 rows x 10 columns]
```

Acquiring info about Null/Non-Null attributes per column

```
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
```

Dropping non-required columns from the Database

```
df.drop(['imdb_id','keywords','budget_adj','revenue_adj','overview','t
agline','homepage','cast', 'director','original_title'], axis = 1 ,
inplace= True)
```

Checking for new Engineered Database with only suitable columns

```
df.head(1)

       id  popularity     budget  ...  vote_count  vote_average
release_year
0  135397   32.985763  150000000  ...        5562           6.5
2015

[1 rows x 11 columns]
```

Splitting 'Genres' (heterogeneous) columns in new individual columns for better Data Analysis and Trend study

```
df[['genre1','genre2','genre3','genre4','genre5']] =
df.genres.str.split('|', expand=True)
```

Splitting 'Production Companies' (heterogeneous) columns in new individual columns for better Data Analysis and Trend study

```
df[['prod1','prod2','prod3','prod4','prod5']] =
df.production_companies.str.split('|', expand=True)
```

Now, Checking for desired columns in our database after splitting above columns.

```
df.head(1)

       id  popularity  ...                      prod4   prod5
0  135397   32.985763  ...  Fuji Television Network  Dentsu

[1 rows x 21 columns]
```

Further dropping two of columns 'genres' and 'production_companies',

After splitting data into new individual columns and storing in our database.

```
df.drop(['genres','production_companies'], axis = 1 , inplace= True)

df.head(1)

       id  popularity  ...                      prod4   prod5
0  135397   32.985763  ...  Fuji Television Network  Dentsu

[1 rows x 19 columns]
```

Analysing Null / Non-Null values in Engineered Data base.

```
df.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10866 entries, 0 to 10865
Data columns (total 19 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   id             10866 non-null  int64
 1   popularity     10866 non-null  float64
 2   budget         10866 non-null  int64
 3   revenue        10866 non-null  int64
```

```
 4   runtime        10866 non-null  int64
 5   release_date   10866 non-null  object
 6   vote_count     10866 non-null  int64
 7   vote_average   10866 non-null  float64
 8   release_year   10866 non-null  int64
 9   genre1         10843 non-null  object
 10  genre2         8515 non-null   object
 11  genre3         5079 non-null   object
 12  genre4         1981 non-null   object
 13  genre5         542 non-null    object
 14  prod1          9836 non-null   object
 15  prod2          6396 non-null   object
 16  prod3          3816 non-null   object
 17  prod4          2053 non-null   object
 18  prod5          1126 non-null   object
dtypes: float64(2), int64(6), object(11)
memory usage: 1.6+ MB
```

Plotting Graphs against Time Period for Trend Analysis.

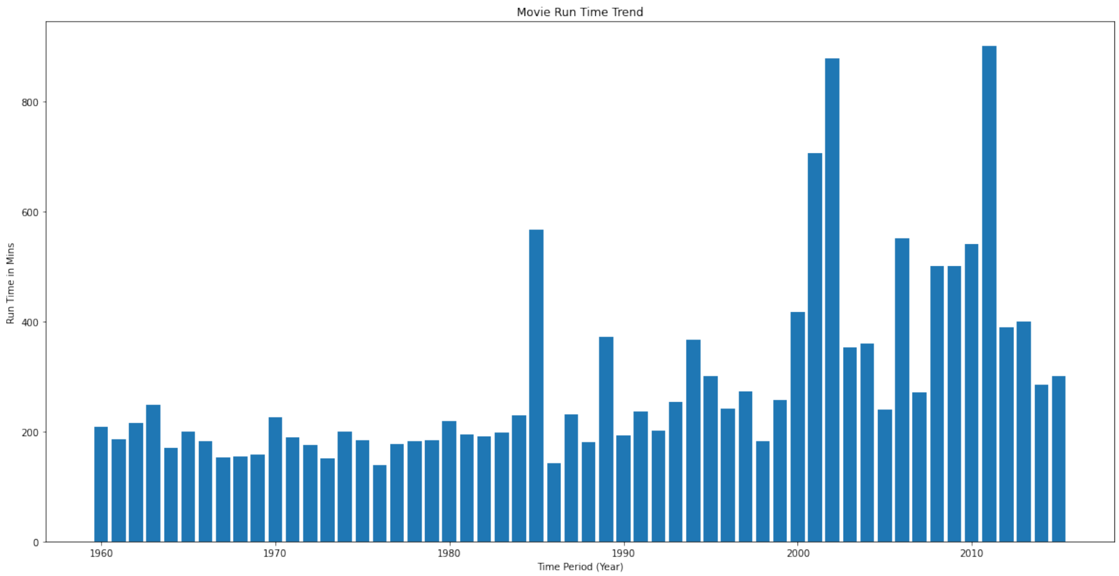
Runtime VS Time Period Graph Analysis .

As inffered from Graph below, here are my Analysed points :

- Mean Run Time has remained constant for large part of our provided data.
- There have been some outlier values which are evident in the years 1985,2001,2002,2005 and 2011.
- The Mean Run Time per movie can be seen to be around 150 Mins per year.

```
plt.figure(figsize = (20,10))
plt. bar(df['release_year'],df['runtime'])
plt.xlabel('Time Period (Year)')
plt.ylabel('Run Time in Mins')
plt.title('Movie Run Time Trend')
```

```
Text(0.5, 1.0, 'Movie Run Time Trend')
```



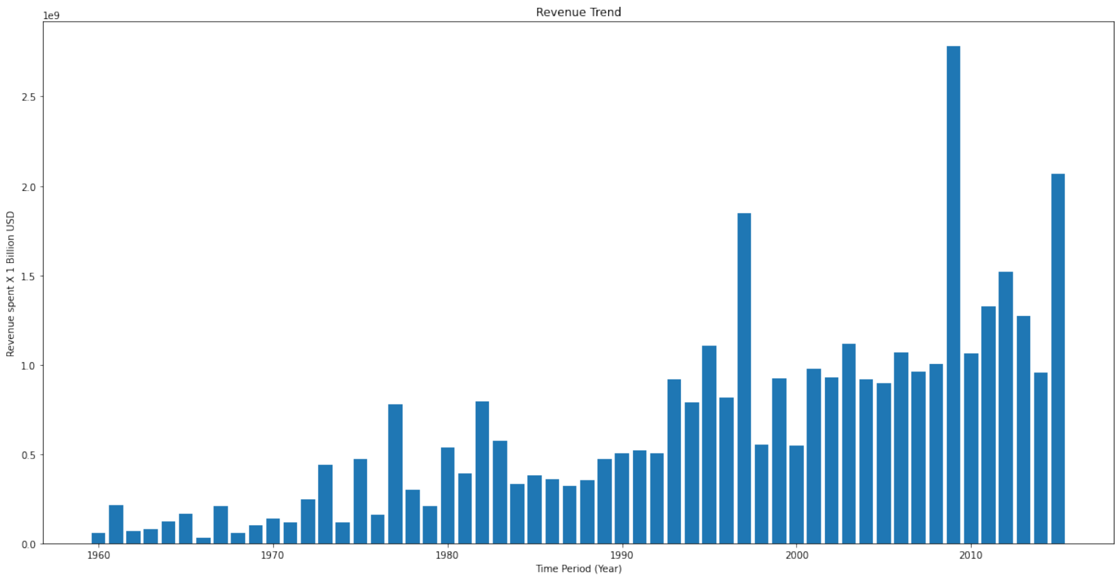
Revenue VS Time Period Graph Analysis .

As inffered from Graph below, here are my Analysed points :

- An Increase in Revenue tendency can be inferred from the graph below.
- The Gross mark of 1 Bn. USD is seen to be crossed only after the year 1995, and significant growth is seen overall.
- Revenue peek is seen in the year : 2010

```
plt.figure(figsize = (20,10))
plt. bar(df['release_year'],df['revenue'])
plt.xlabel('Time Period (Year)')
plt.ylabel('Revenue spent X 1 Billion USD')
plt.title('Revenue Trend')
```

```
Text(0.5, 1.0, 'Revenue Trend')
```



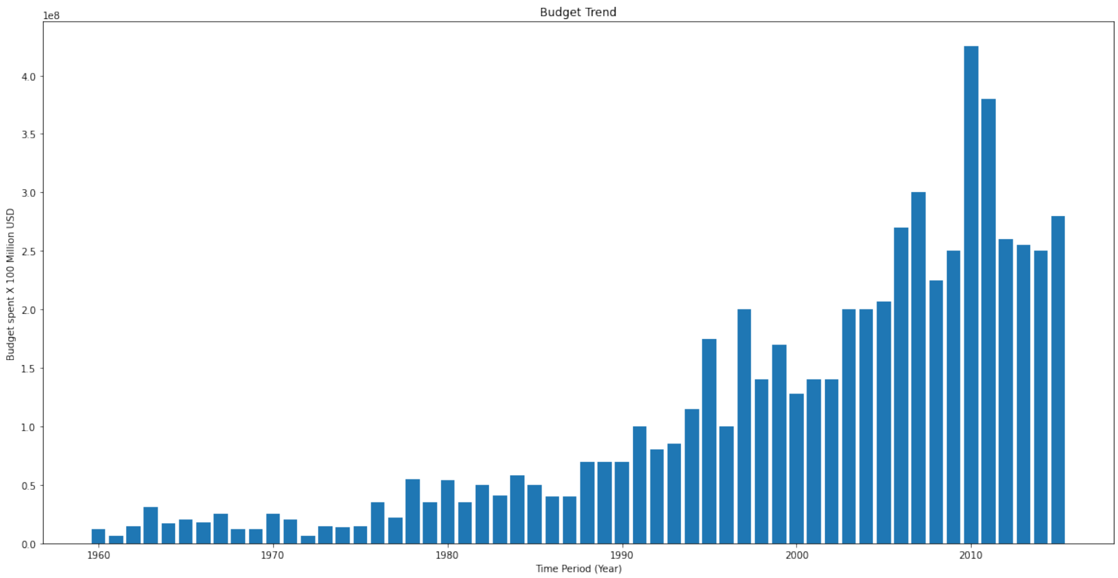
Budget VS Time Period Graph Analysis .

As inffered from Graph below, here are my Analysed points :

- An Increase in budget tendency can be inferred from the graph below.
- The Gross mark of 1 Bn. USD is seen to be crossed only after the year 1995, and significant growth is seen overall.
- Revenue peek is seen in the year : 2010

```
plt.figure(figsize = (20,10))
plt. bar(df['release_year'],df['budget'])
plt.xlabel('Time Period (Year)')
plt.ylabel('Budget spent X 100 Million USD')
plt.title('Budget Trend')
```

```
Text(0.5, 1.0, 'Budget Trend')
```



Conclusion from above Graphs and Analysis :

- Both Budget and Revenue Indices have increased over time and share the same increasing tendency.
- Both Graphs show a spike in the year 2009.
- Above, two graphs prove our hypothesis about Budget,Revenue Correlation and its nature of being directly proportional on one another.

(Above given conclusions concern certain exceptions, but share above stated results over all.)

```
df.head(1)
```

```
       id  popularity  ...                    prod4   prod5
0  135397   32.985763  ...  Fuji Television Network  Dentsu

[1 rows x 19 columns]
```

#Now, we will be adressing scenarios based on Genres in the given time period in Database.

A pie chart inferring, the frequency of genre/genres(overall) with their percentage count in the pie diagram.

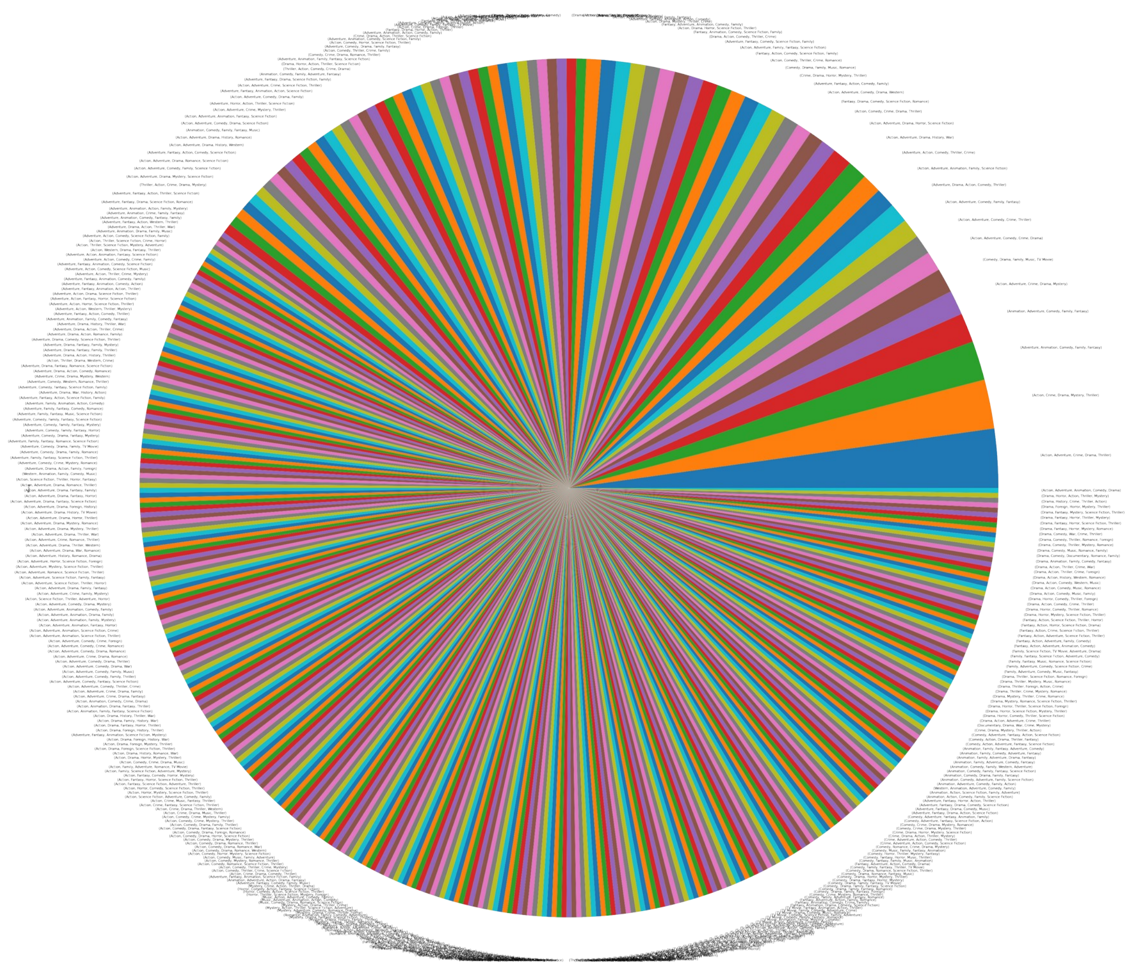
Given below we can find these conclusions :

- 'Action, Adventure, Crime, Drama, Thriller' have been the most frequent made genre combination for a movie in the given period (1960 - 2015).
- Above genre combination is followed by these 4 genre combination movies :
  - 'Action, Crime, Drama, Mystery, Thriller'
  - 'Adventure, Animation, Comedy, Family, Fantasy'

- 'Animation, Adventure, Comedy, Family, Fantasy'
- 'Action, Adventure, Crime, Drama, Mystery'

```
plt.figure(figsize = (60, 60))
df[['genre1','genre2','genre3','genre4','genre5']].value_counts().plot
.pie()
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f439ac7b310>
```

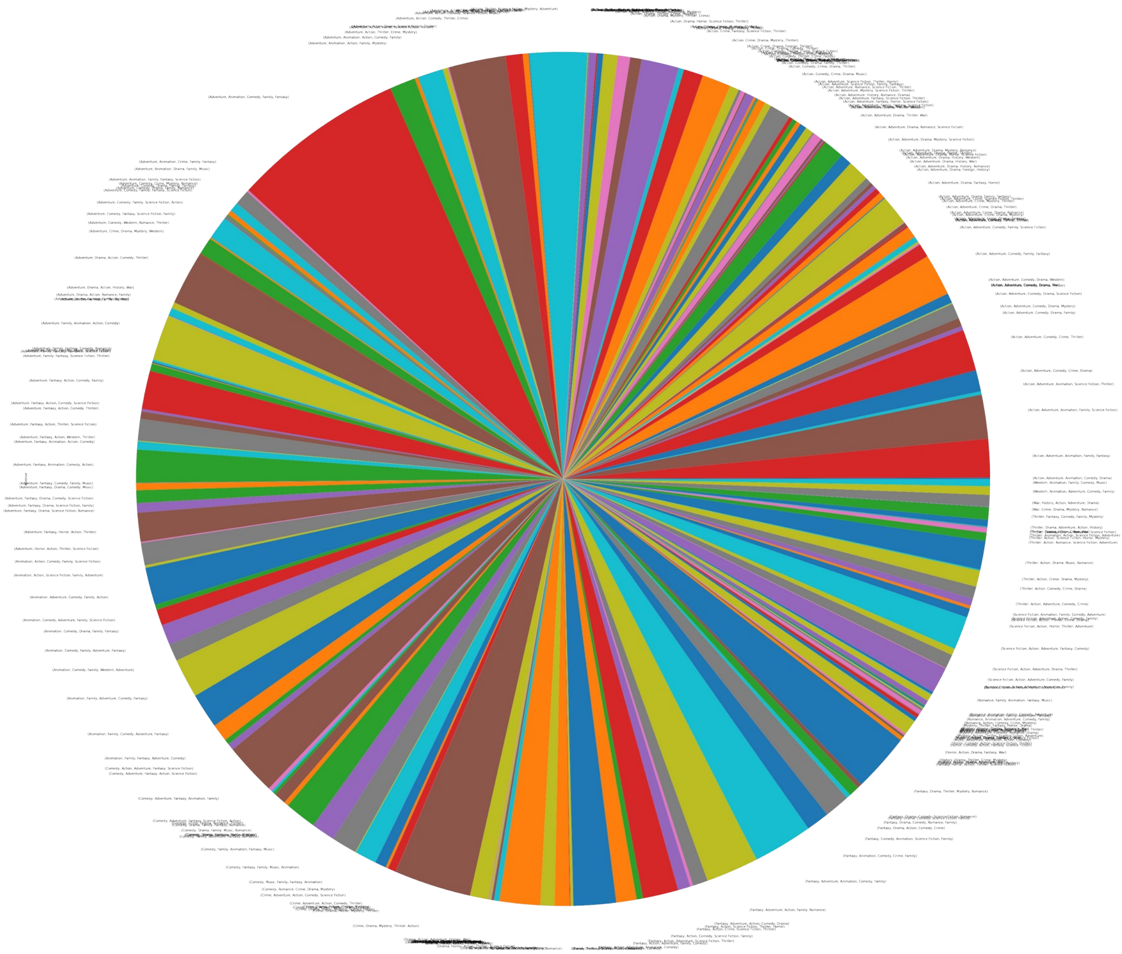


Given Pie charts infer to genres with gross revenue amounts associated.

- Based on below pie chart indices we can clearly see given 'Adventure, Animation, Comedy, Family, Fantasy' genres grossed highest revenue sum through out the periiod.

```
plt.figure(figsize = (60, 60))
df.groupby(['genre1', 'genre2', 'genre3', 'genre4',
'genre5']).revenue.sum().plot.pie()
```

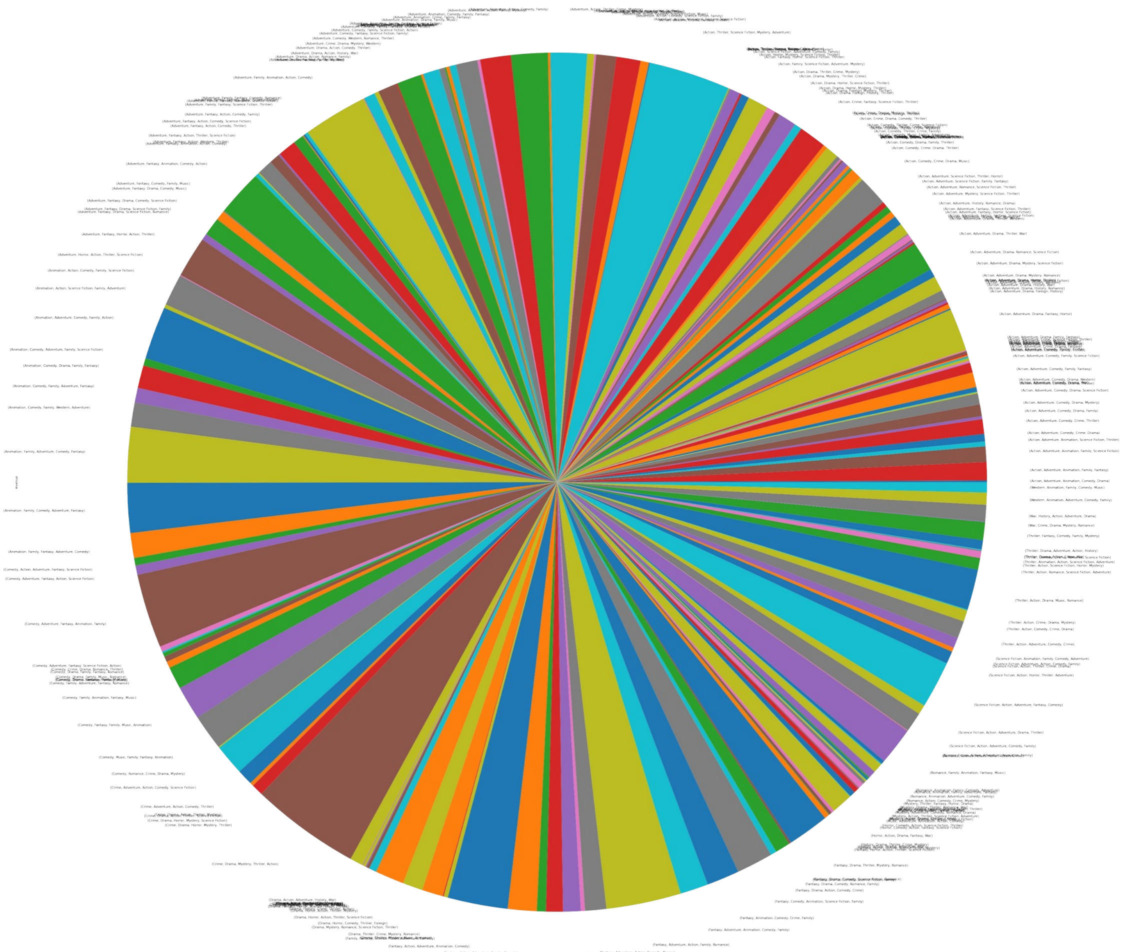
```
<matplotlib.axes._subplots.AxesSubplot at 0x7f438e2c1710>
```



- Based on below pie chart indices we can clearly see given 'Crime, Drama, Mystery, Thriller, Action' genres grossed highest revenue mean through out the periiod.

```
plt.figure(figsize = (60, 60))
df.groupby(['genre1', 'genre2', 'genre3', 'genre4',
'genre5']).revenue.mean().plot.pie()
```

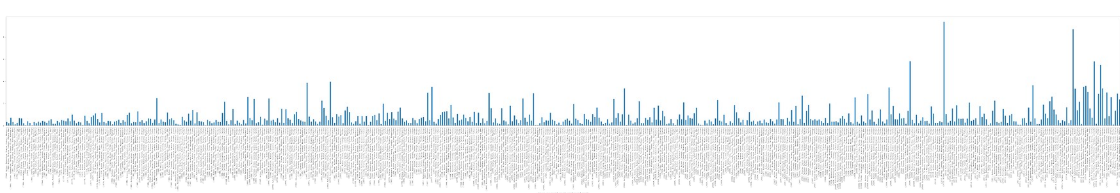
```
<matplotlib.axes._subplots.AxesSubplot at 0x7f438e8db450>
```



- Moving ahead, we can see the movie genres per year along with their popularity mean indexed on Y-axis of the below graph. And we can infer to the most popular movies per year from 1960 to 2015

```
plt.figure(figsize = (60, 10))
df.groupby(['release_year','genre1', 'genre2', 'genre3', 'genre4', 'genre5']).popularity.mean().plot.bar()
```

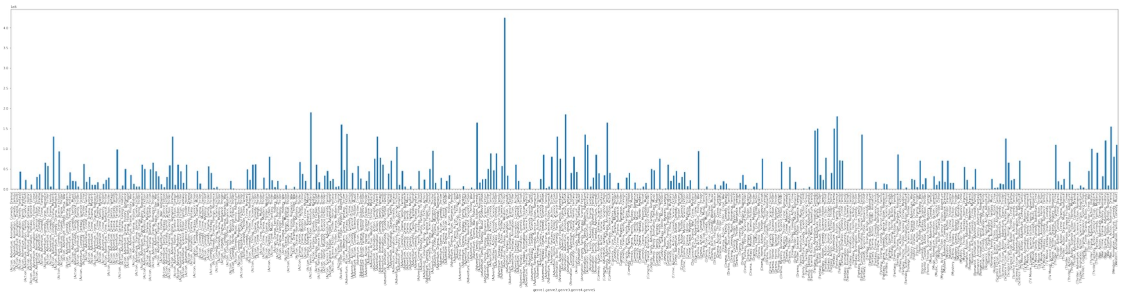
```
<matplotlib.axes._subplots.AxesSubplot at 0x7fb830d7e250>
```



- Next, we can find the movies along with their budget means for the movie genres in our database. Further, we can also find maximum mean of the budgets spent per movie genre per year.

```
plt.figure(figsize = (60, 10))
df.groupby(['genre1', 'genre2', 'genre3', 'genre4',
'genre5']).budget.mean().plot.bar()
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fb84b891d50>
```



Conclusion to our Hypothesis.

Budget and Revenue are positively Correlated and have direct proportional relation between them.

This can finally be verrified using Dataframe.corr() method and checking for correlation between the above two. Now Since here the value is '0.734901' (which is positive), giving a satisfying conclusion to our hypothesis.

```
df.corr()
```

	id	popularity	...	vote_average	release_year
id	1.000000	-0.014350	...	-0.058363	0.511364
popularity	-0.014350	1.000000	...	0.209511	0.089801
budget	-0.141351	0.545472	...	0.081014	0.115931
revenue	-0.099227	0.663358	...	0.172564	0.057048
runtime	-0.088360	0.139033	...	0.156835	-0.117204
vote_count	-0.035551	0.800828	...	0.253823	0.107948
vote_average	-0.058363	0.209511	...	1.000000	-0.117632
release_year	0.511364	0.089801	...	-0.117632	1.000000

[8 rows x 8 columns]

Sources Reffered :

- Stackoverflow.com
- numpy.org
- geekforgeeks.org
- w3schools.com
- pandas.pydata.com