

# Ritesh\_EDA\_Week2

December 14, 2025

```
[100]: import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

## 1 STEP 1 : DATASET LOADING

```
[101]: df = pd.read_csv(r"C:\Users\Lenovo\Downloads\movies dataset.csv")
```

```
[128]: df.head()
```

```
[128]:
```

	NAME	RATING	GENRE	YEAR	\
0	The Shining	R	Drama	1980	
1	The Blue Lagoon	R	Adventure	1980	
2	Star Wars: Episode V - The Empire Strikes Back	PG	Action	1980	
3	Airplane!	PG	Comedy	1980	
4	Caddyshack	R	Comedy	1980	

	RELEASED	SCORE	VOTES	DIRECTOR	\
0	June 13, 1980 (United States)	8.40	927000.00	Stanley Kubrick	
1	July 2, 1980 (United States)	5.80	65000.00	Randal Kleiser	
2	June 20, 1980 (United States)	8.70	1200000.00	Irvin Kershner	
3	July 2, 1980 (United States)	7.70	221000.00	Jim Abrahams	
4	July 25, 1980 (United States)	7.30	108000.00	Harold Ramis	

	WRITER	STAR	COUNTRY	BUDGET	\
0	Stephen King	Jack Nicholson	United Kingdom	19000000.00	
1	Henry De Vere Stacpoole	Brooke Shields	United States	4500000.00	
2	Leigh Brackett	Mark Hamill	United States	18000000.00	
3	Jim Abrahams	Robert Hays	United States	3500000.00	
4	Brian Doyle-Murray	Chevy Chase	United States	6000000.00	

	GROSS	COMPANY	RUNTIME
0	46998772.00	Warner Bros.	146.00
1	58853106.00	Columbia Pictures	104.00
2	538375067.00	Lucasfilm	124.00
3	83453539.00	Paramount Pictures	88.00

```
4 39846344.00      Orion Pictures    98.00
```

```
[129]: df.tail()
```

```
[129]:
```

	NAME	RATING	GENRE	YEAR	\
7659	I Am Fear	Not Rated	Horror	2020	
7660	Aloha Surf Hotel	Unknown	Comedy	2020	
7663	More to Life	Unknown	Drama	2020	
7664	Dream Round	Unknown	Comedy	2020	
7667	Tee em el	Unknown	Horror	2020	

	RELEASED	SCORE	VOTES	DIRECTOR	\
7659	March 3, 2020 (United States)	3.40	447.00	Kevin Shulman	
7660	November 5, 2020 (United States)	7.10	14.00	Stefan C. Schaefer	
7663	October 23, 2020 (United States)	3.10	18.00	Joseph Ebanks	
7664	February 7, 2020 (United States)	4.70	36.00	Dusty Dukatz	
7667	August 19, 2020 (United States)	5.70	7.00	Pereko Mosia	

	WRITER	STAR	COUNTRY	BUDGET	\
7659	Kevin Shulman	Kristina Klebe	United States	21000000.00	
7660	Stefan C. Schaefer	Augie Tulba	United States	21000000.00	
7663	Joseph Ebanks	Shannon Bond	United States	7000.00	
7664	Lisa Huston	Michael Saquella	United States	21000000.00	
7667	Pereko Mosia	Siyabonga Mabaso	South Africa	21000000.00	

	GROSS	COMPANY	RUNTIME
7659	13266.00	Roxwell Films	87.00
7660	20207126.50	Abominable Pictures	90.00
7663	20207126.50	Unknown	90.00
7664	20207126.50	Cactus Blue Entertainment	90.00
7667	20207126.50	PK 65 Films	102.00

```
[104]: df.shape
```

```
[104]: (7668, 15)
```

```
[105]: df.columns
```

```
[105]: Index(['name', 'rating', 'genre', 'year', 'released', 'score', 'votes',
       'director', 'writer', 'star', 'country', 'budget', 'gross', 'company',
       'runtime'],
       dtype='object')
```

```
[106]: df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 7668 entries, 0 to 7667
Data columns (total 15 columns):
```

```
#   Column    Non-Null Count  Dtype  
---  --  
0   name      7668 non-null   object  
1   rating    7591 non-null   object  
2   genre     7668 non-null   object  
3   year      7668 non-null   int64  
4   released   7666 non-null   object  
5   score     7665 non-null   float64 
6   votes     7665 non-null   float64 
7   director   7668 non-null   object  
8   writer    7665 non-null   object  
9   star      7667 non-null   object  
10  country   7665 non-null   object  
11  budget    5497 non-null   float64 
12  gross     7479 non-null   float64 
13  company   7651 non-null   object  
14  runtime   7664 non-null   float64 
dtypes: float64(5), int64(1), object(9)  
memory usage: 898.7+ KB
```

## 2 STEP 2 : DATA CLEANING & PREPROCESSING

```
[127]: df.isnull().sum()
```

```
NAME          0  
RATING        0  
GENRE         0  
YEAR          0  
RELEASED      0  
SCORE          0  
VOTES          0  
DIRECTOR      0  
WRITER        0  
STAR           0  
COUNTRY        0  
BUDGET         0  
GROSS          0  
COMPANY        0  
RUNTIME        0  
dtype: int64
```

```
[108]:
```

```
[109]: df.dropna(subset = ['released', 'score', 'votes', 'writer', 'star', 'country', 'runtime'], inplace = True)
```

```
[110]: df['rating'] = df['rating'].fillna('Unknown')

[111]: df['company'] = df['company'].fillna('Unknown')

[112]: df['gross'] = df['gross'].fillna(df['gross'].median())

[113]: df['budget'] = df['budget'].fillna(df['budget'].median())

[ ]:

[114]: df.duplicated().sum()

[114]: 0

[115]: df.columns = df.columns.str.strip().str.upper()

[ ]:
```

### 3 STEP 3 : EXPLORATORY DATA ANALYSIS (EDA)

```
[116]: df.describe()
```

	YEAR	SCORE	VOTES	BUDGET	GROSS	RUNTIME
count	7656.00	7656.00	7656.00	7656.00	7656.00	7656.00
mean	2000.39	6.39	88177.58	31488981.47	77129113.81	107.27
std	11.14	0.97	163401.76	35726990.28	164020419.91	18.57
min	1980.00	1.90	7.00	3000.00	309.00	63.00
25%	1991.00	5.80	9100.00	14000000.00	4681150.75	95.00
50%	2000.00	6.50	33000.00	21000000.00	20207126.50	104.00
75%	2010.00	7.10	93000.00	32000000.00	72693484.50	116.00
max	2020.00	9.30	2400000.00	356000000.00	2847246203.00	366.00

```
[117]: df.shape
```

```
[117]: (7656, 15)
```

```
[118]: df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 7656 entries, 0 to 7667
Data columns (total 15 columns):
 #   Column    Non-Null Count  Dtype  
 ---  --  
 0   NAME      7656 non-null   object 
 1   RATING    7656 non-null   object 
 2   GENRE     7656 non-null   object 
 3   YEAR      7656 non-null   int64  
 4   RELEASED  7656 non-null   object 
```

```
5   SCORE      7656 non-null    float64
6   VOTES      7656 non-null    float64
7   DIRECTOR   7656 non-null    object
8   WRITER     7656 non-null    object
9   STAR        7656 non-null    object
10  COUNTRY    7656 non-null    object
11  BUDGET     7656 non-null    float64
12  GROSS       7656 non-null    float64
13  COMPANY    7656 non-null    object
14  RUNTIME    7656 non-null    float64
dtypes: float64(5), int64(1), object(9)
memory usage: 957.0+ KB
```

```
[119]: df['GENRE'].value_counts()
```

```
[119]: GENRE
Comedy      2244
Action       1703
Drama        1513
Crime         550
Biography    443
Adventure    427
Animation    337
Horror        321
Fantasy       44
Mystery       20
Thriller      16
Family        11
Sci-Fi        10
Romance       10
Western        3
Musical        2
Music          1
Sport          1
Name: count, dtype: int64
```

```
[120]: df['DIRECTOR'].value_counts()
```

```
[120]: DIRECTOR
Woody Allen      38
Clint Eastwood   31
Steven Spielberg  27
Directors        27
Ron Howard       24
...
Paolo Taviani     1
Lawrence Dane     1
Bobby Roth        1
```

```
Joel Gallen      1  
Pereko Mosia    1  
Name: count, Length: 2943, dtype: int64
```

```
[ ]:
```

```
[133]: avg_budget = df.groupby('GENRE')['BUDGET'].mean()  
avg_budget
```

```
[133]: GENRE  
Action      52075580.19  
Adventure   40037611.24  
Animation   66356290.80  
Biography   24066320.02  
Comedy      22081898.94  
Crime       22004080.15  
Drama       22154515.52  
Family      31954545.45  
Fantasy     17072727.27  
Horror      14334398.75  
Music       21000000.00  
Musical     21000000.00  
Mystery     30245000.05  
Romance     22520000.00  
Sci-Fi      19987000.00  
Sport       21000000.00  
Thriller    15100000.00  
Western     14000000.00  
Name: BUDGET, dtype: float64
```

```
[131]: Total = df.groupby('GENRE')['BUDGET'].sum()  
Total
```

```
[131]: GENRE  
Action      88684713068.00  
Adventure   17096060000.00  
Animation   22362070000.00  
Biography   10661379768.00  
Comedy      49551781215.00  
Crime       12102244080.00  
Drama       33519781987.00  
Family      351500000.00  
Fantasy     751200000.00  
Horror      4601342000.00  
Music       21000000.00  
Musical     42000000.00  
Mystery     604900001.00
```

```
Romance      225200000.00
Sci-Fi       199870000.00
Sport        21000000.00
Thriller     241600000.00
Western      42000000.00
Name: BUDGET, dtype: float64
```

```
[132]: Count = df.groupby('GENRE')['BUDGET'].count()
Count
```

```
GENRE
Action      1703
Adventure   427
Animation   337
Biography   443
Comedy      2244
Crime       550
Drama       1513
Family      11
Fantasy     44
Horror      321
Music       1
Musical     2
Mystery     20
Romance     10
Sci-Fi      10
Sport       1
Thriller    16
Western     3
Name: BUDGET, dtype: int64
```

```
[ ]:
```

```
avg_budget = df.groupby('GENRE')['BUDGET'].mean()

Best_Performing_Genre = avg_budget.sort_values(ascending = False).head()
Best_Performing_Genre
```

```
GENRE
Animation   66356290.80
Action       52075580.19
Adventure   40037611.24
Family       31954545.45
Mystery     30245000.05
Name: BUDGET, dtype: float64
```

```
[135]: Worst_Performing_Genre = avg_budget.sort_values().head()
Worst_Performing_Genre
```

```
[135]: GENRE
Western      14000000.00
Horror       14334398.75
Thriller     15100000.00
Fantasy      17072727.27
Sci-Fi        19987000.00
Name: BUDGET, dtype: float64
```

```
[ ]:
```

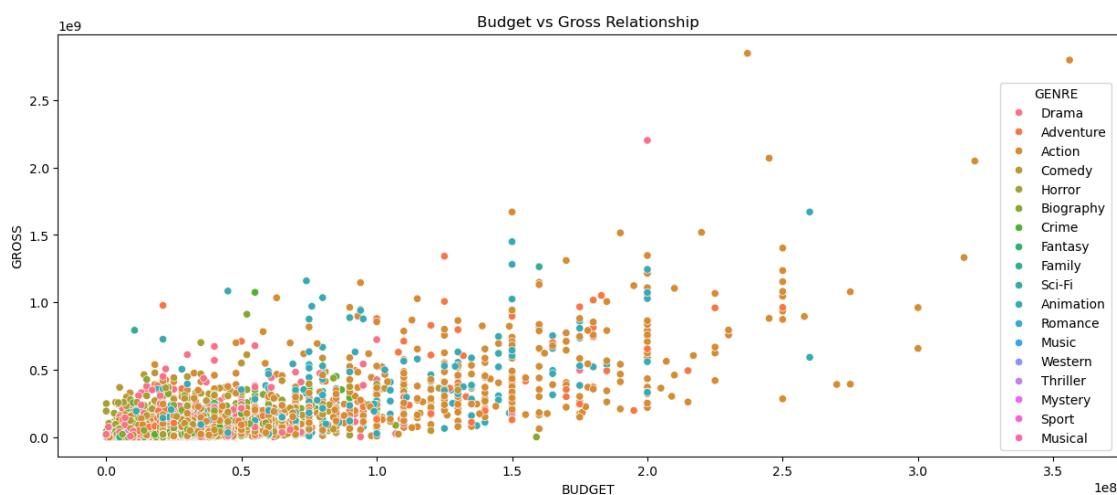
```
[137]: df.corr(numeric_only = True)
```

```
[137]:
```

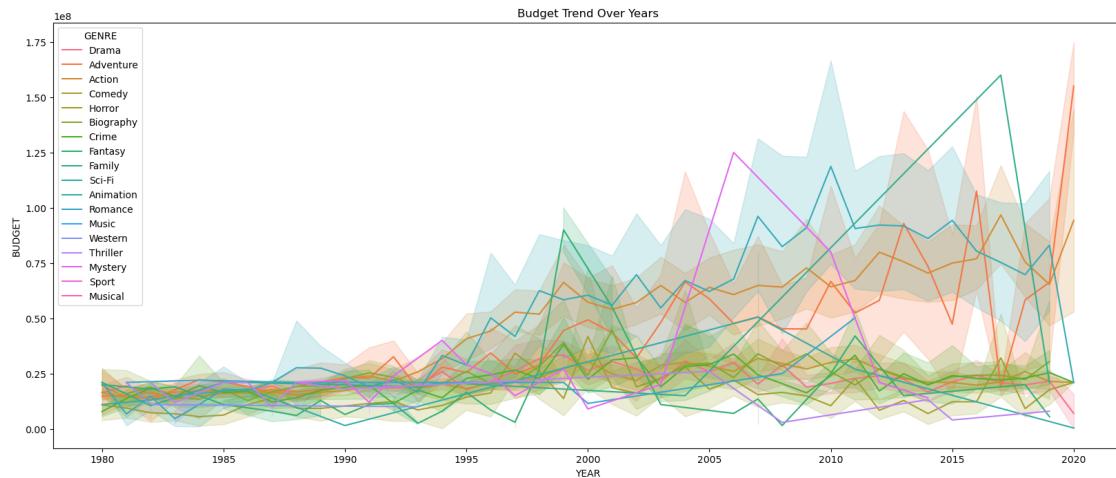
	YEAR	SCORE	VOTES	BUDGET	GROSS	RUNTIME
YEAR	1.00	0.10	0.22	0.29	0.26	0.12
SCORE	0.10	1.00	0.41	0.06	0.19	0.40
VOTES	0.22	0.41	1.00	0.46	0.63	0.31
BUDGET	0.29	0.06	0.46	1.00	0.75	0.27
GROSS	0.26	0.19	0.63	0.75	1.00	0.24
RUNTIME	0.12	0.40	0.31	0.27	0.24	1.00

## 4 STEP 4 : DATA VISUALIZATION

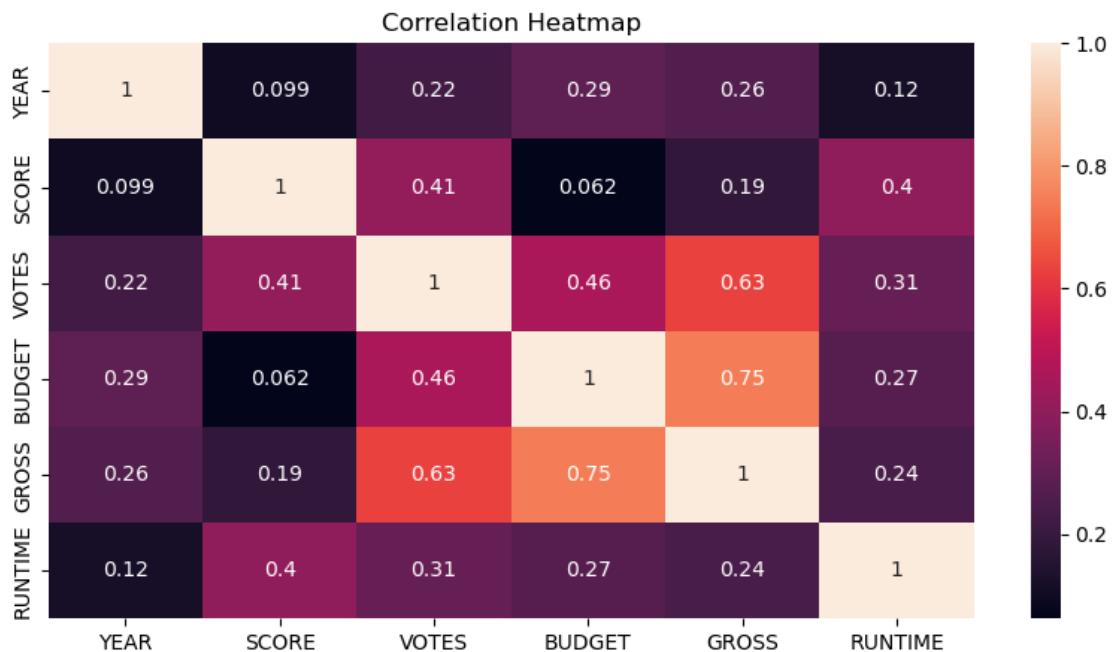
```
[203]: plt.figure(figsize=(15, 6))
sns.scatterplot(x = 'BUDGET', y = 'GROSS', hue = 'GENRE', data = df)
plt.title('Budget vs Gross Relationship')
plt.show()
```



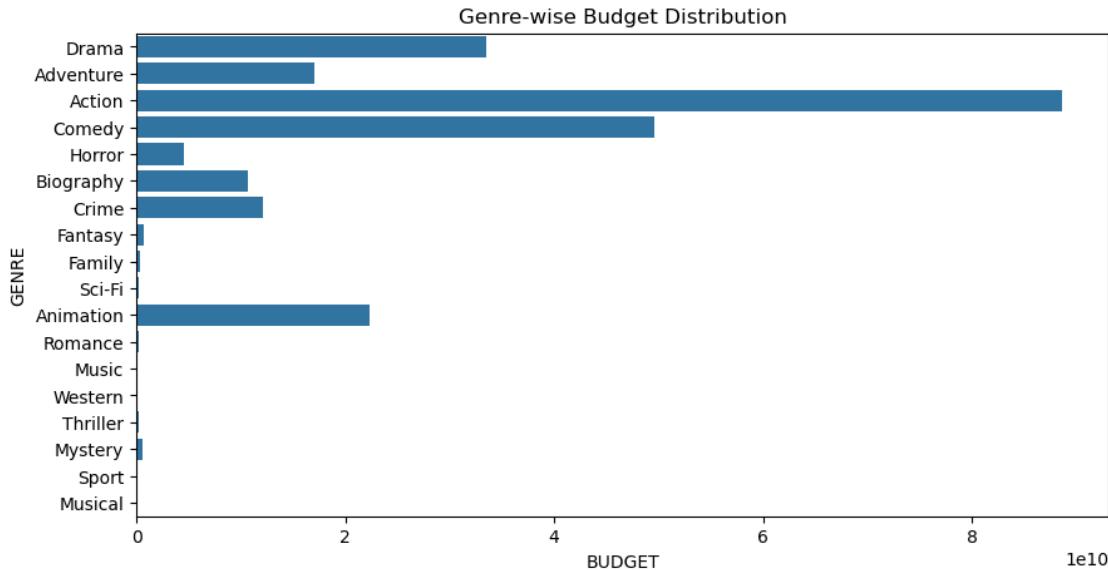
```
[207]: plt.figure(figsize=(20, 8))
sns.lineplot(x = 'YEAR', y = 'BUDGET', hue = 'GENRE', data = df)
plt.title('Budget Trend Over Years')
plt.show()
```



```
[205]: plt.figure(figsize=(10, 5))
sns.heatmap(df.corr(numeric_only=True), annot = True)
plt.title('Correlation Heatmap')
plt.show()
```



```
[206]: plt.figure(figsize=(10, 5))
sns.barplot(y = 'GENRE', x = 'BUDGET', data = df, estimator = sum, u
             ↪errorbar=None)
plt.title('Genre-wise Budget Distribution')
plt.show()
```



## 5 STEP 5 : INSIGHTS AND INTERPRETATION

INSIGHT 1 : Movies with higher budgets generally earns higher gross revenue, showing a strong positive relationship between budget and financial performance.

INSIGHT 2 : Action, Comedy, Drama and Animation genre have the highest average production budgets, while Horror, Biography, Music etc genre typically have much lower budgets.

INSIGHT 3 : Movie production budgets have increased over time, especially after the year 2000, indicating rising production costs in the film industry.

INSIGHT 4 : There is a strong positive correlation between budget and gross revenue, and votes also shows a strong relationship with gross, suggesting that the popular movies tends to earn more.

INSIGHT 5 : Movies with higher number of votes tends to generate higher gross revenue , indicating that audience popularity plays an important role in a movie's financial success.