Linkes to Connect with me:👇 👇 👇 👇 👇 👇 👇

Rajesh Signh - Github-Profile

__[LinkedIn-Profile](https://linkedin.com/in/rajesh-singh/)__

Title:

Movie Correlation Project

Objective:

To analyze the relationships between various features of movies, such as budget, gross earnings, score, votes,
and runtime, and identify key factors that may influence a movie's success.

Hypothesis: A testable statement predicting the relationship between two or more variables.

Hypothesis 1: Higher budgets are positively correlated with higher gross earnings, suggesting that larger financial investments lead to better box office performance.

Hypothesis 2: Movies with higher audience votes tend to have higher scores, indicating a relationship between popularity and perceived quality.

1. Importing Important Libraries

In [2]:

```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib
import matplotlib.pyplot as plt
plt.style.use("ggplot")
%matplotlib inline
from matplotlib.pyplot import figure
matplotlib.rcParams['figure.figsize']  = (8, 4) # cofig. figure sizes
```

In [3]:

```
df = pd.read_csv('/Users/rajeshpanwar/Documents/DATA SCIENCE/Project/Movie c
```

```python
pd.set_option('display.max_rows', None)
```

2. Let's Dive Into Data

In [7]:
```python
# information about data
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
```

As we can see there are some descripencies in data type. So first, we will handle that.

In [10]:
```python
# Checking for missing values
for col in df.columns:
    pct_missing = np.mean(df[col].isnull())
    print("{}-{}%". format(col,pct_missing.round()))
```

```
name-0.0%
rating-0.0%
genre-0.0%
year-0.0%
released-0.0%
score-0.0%
votes-0.0%
director-0.0%
writer-0.0%
star-0.0%
country-0.0%
budget-0.0%
gross-0.0%
company-0.0%
runtime-0.0%
```

In [12]:
```python
# checking for duplicates
df  = df.drop_duplicates()
```

```python
#df
```

In [14]:
```python
# Changing the NaN/inf vlaues into zeros
df['votes']= df["votes"].replace([np.nan, np.inf],0)
df['budget']= df["budget"].replace([np.nan, np.inf],0)
df['gross']= df["gross"].replace([np.nan, np.inf],0)

# Just to make clear name = movie name
df = df.rename(columns = {'name': 'movie'})

# then, amend data types
df['votes']= df["votes"].astype('int64')
df['budget']= df["budget"].astype('int64')
df['gross']= df["gross"].astype('int64')

df.head()
```

Out[14]:

	movie	rating	genre	year	released	score	votes	director	write
0	The Shining	R	Drama	1980	June 13, 1980 (United States)	8.4	927000	Stanley Kubrick	Stephe Kin
1	The Blue Lagoon	R	Adventure	1980	July 2, 1980 (United States)	5.8	65000	Randal Kleiser	Henry D Ver Stacpool
2	Star Wars: Episode V - The Empire Strikes Back	PG	Action	1980	June 20, 1980 (United States)	8.7	1200000	Irvin Kershner	Leig Bracke
3	Airplane!	PG	Comedy	1980	July 2, 1980 (United States)	7.7	221000	Jim Abrahams	Jir Abraham
4	Caddyshack	R	Comedy	1980	July 25, 1980 (United States)	7.3	108000	Harold Ramis	Bria Doyle Murra

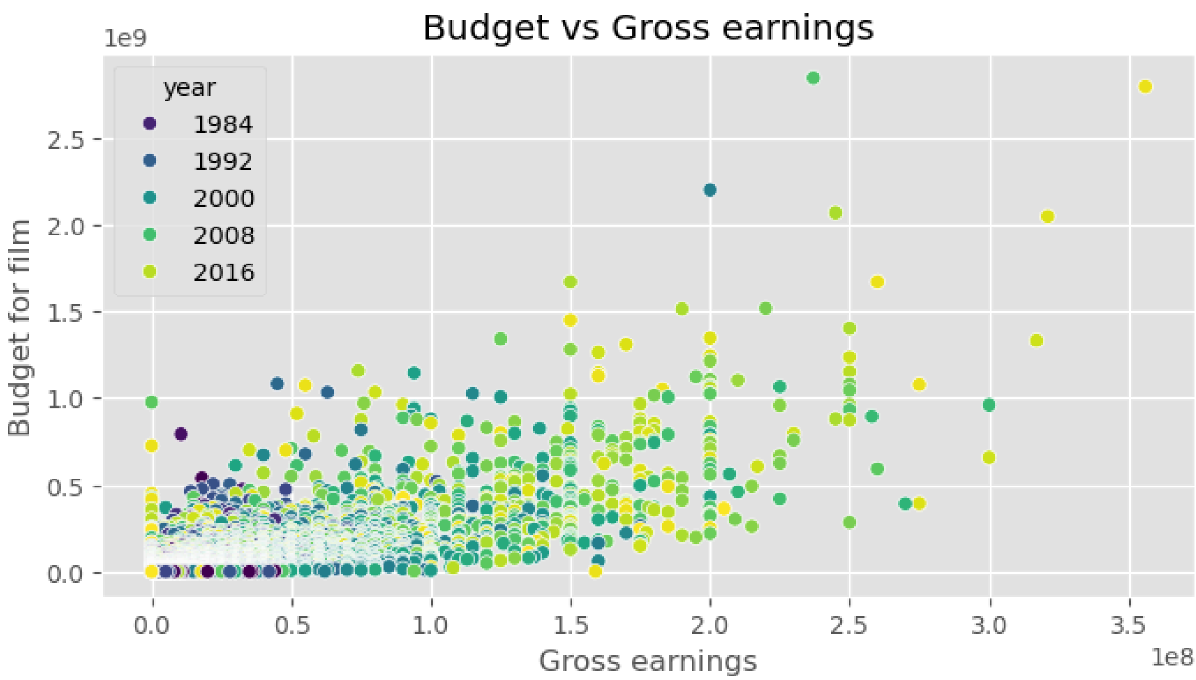
In [16]:
```python
# As there are some discrepancies in year or released feature, let's improve

# Extract year using regex
df['Year_cor'] = df['released'].str.extract(r'(\d{4})')
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 7668 entries, 0 to 7667
Data columns (total 16 columns):
 #   Column    Non-Null Count  Dtype  
---  ------    --------------  -----  
 0   movie     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     7668 non-null   int64  
 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    7668 non-null   int64  
 12  gross     7668 non-null   int64  
 13  company   7651 non-null   object 
 14  runtime   7664 non-null   float64
 15  Year_cor  7666 non-null   object 
dtypes: float64(2), int64(4), object(10)
memory usage: 958.6+ KB
```

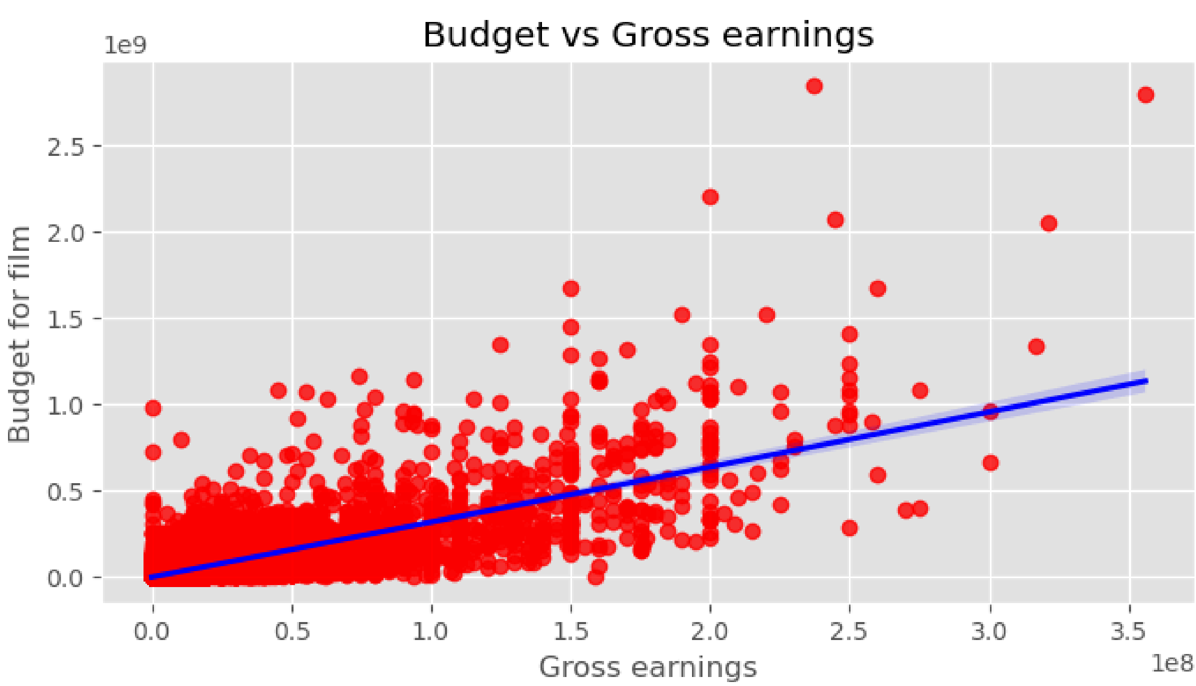
In [18]:
```
df = df.sort_values(by = ['gross'], inplace = False , ascending  = False)
```

3. Plotting Graphs - Scatter plots: Scatter plot is used to see the relationship between two or multiple variable

In [21]:
```
# using seaborn library
sns.scatterplot(data = df, x = 'budget', y = 'gross', hue="year", palette="v
plt.title('Budget vs Gross earnings')
plt.xlabel('Gross earnings')
plt.ylabel('Budget for film')
plt.show()
```



In [22]:
```
# Plot Budget vs Gross by regplot
sns.regplot(data=df, x='budget', y='gross',
            scatter_kws={'color': 'red'},
            line_kws={'color': 'Blue'})
plt.title('Budget vs Gross earnings')
plt.xlabel('Gross earnings')
plt.ylabel('Budget for film')
plt.show()
```



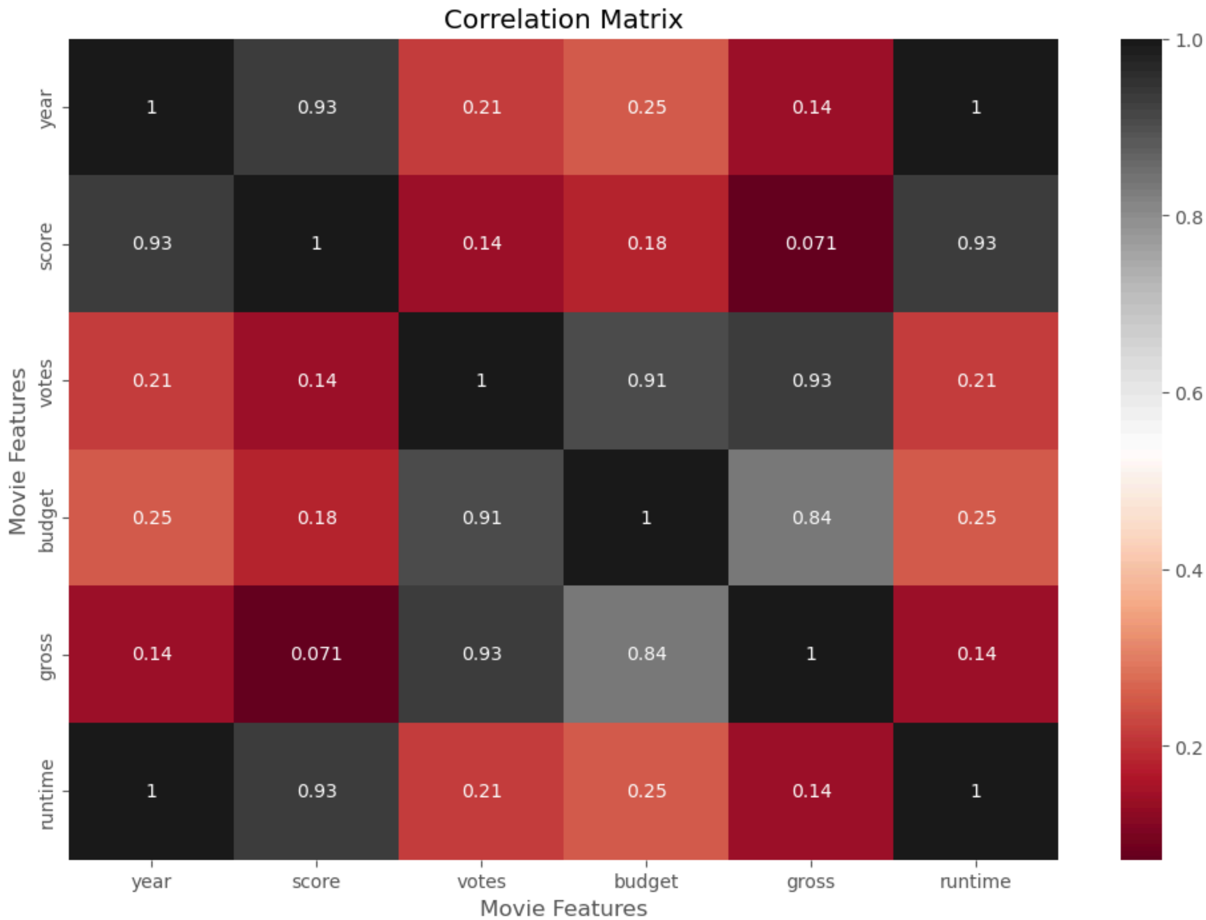
In [23]:
```
# Let's start looking at correlation
# 1. Pearosn, kendall, Spearman
```

In [25]:
```
numeric_col = df.describe() # I was facing ploting Correlation Matrix so,
                                # I have to use describe function to get the
numeric_col.corr(method = 'kendall') # option - 1
#numeric_col.corr(method = 'pearson') # option - 2
#numeric_col.corr(method = 'spearman') # option - 3
```

Out[25]:

	year	score	votes	budget	gross	runtime
year	1.000000	0.928571	0.214286	0.254588	0.142857	1.000000
score	0.928571	1.000000	0.142857	0.181848	0.071429	0.928571
votes	0.214286	0.142857	1.000000	0.909241	0.928571	0.214286
budget	0.254588	0.181848	0.909241	1.000000	0.836502	0.254588
gross	0.142857	0.071429	0.928571	0.836502	1.000000	0.142857
runtime	1.000000	0.928571	0.214286	0.254588	0.142857	1.000000

In [26]:
```
# Calculating the correlation matrix
corr_matrix = numeric_col.corr(method = 'kendall')

# Create a heatmap
plt.figure(figsize = (12, 8))
sns.heatmap(corr_matrix,annot=True, cmap='RdGy',)
plt.title('Correlation Matrix')
plt.xlabel('Movie Features')
plt.ylabel('Movie Features')

plt.show()
```



4. Converting Ojbect to Numeric : It is not possible to plot object data points on a heatmap. To calculate the correlation between all values, the data points need to be converted into numeric format.

These are the objects in the Dataframe:

`name` `rating` `genr` `release` `directo` `write` `sta` `countr` `compan`

In [31]:
```
df.dtypes[df.dtypes == 'object']
```

Out[31]:
```
movie       object
rating      object
genre       object
released    object
director    object
writer      object
star        object
country     object
company     object
Year_cor    object
dtype: object
```

In [34]:
```
df_num = df
for col_name in df_num.columns:
    if (df_num[col_name].dtype == 'object'):
        df_num[col_name] = df_num[col_name].astype('category') # converting
```

```
        df_num[col_name] = df_num[col_name].cat.codes
df_num.head()
```

Out[34]:

	movie	rating	genre	year	released	score	votes	director	writer	star
5445	533	5	0	2009	696	7.8	1100000	1155	1778	2334
7445	535	5	0	2019	183	8.4	903000	162	743	2241
3045	6896	5	6	1997	704	7.8	1100000	1155	1778	1595
6663	5144	5	0	2015	698	7.8	876000	1125	2550	524
7244	536	5	0	2018	192	8.4	897000	162	743	2241

These processes 👇 are just for not being confused :

In [37]:

```
df = df_num # if not done, can caused confusion
df = df.sort_values(by = ['gross'], inplace = False , ascending  = False)  #
df.head()
```

Out[37]:

	movie	rating	genre	year	released	score	votes	director	writer	star
5445	533	5	0	2009	696	7.8	1100000	1155	1778	2334
7445	535	5	0	2019	183	8.4	903000	162	743	2241
3045	6896	5	6	1997	704	7.8	1100000	1155	1778	1595
6663	5144	5	0	2015	698	7.8	876000	1125	2550	524
7244	536	5	0	2018	192	8.4	897000	162	743	2241

5. Correlation of all the features to each other :

In [40]:

```
df_num.corr()
```

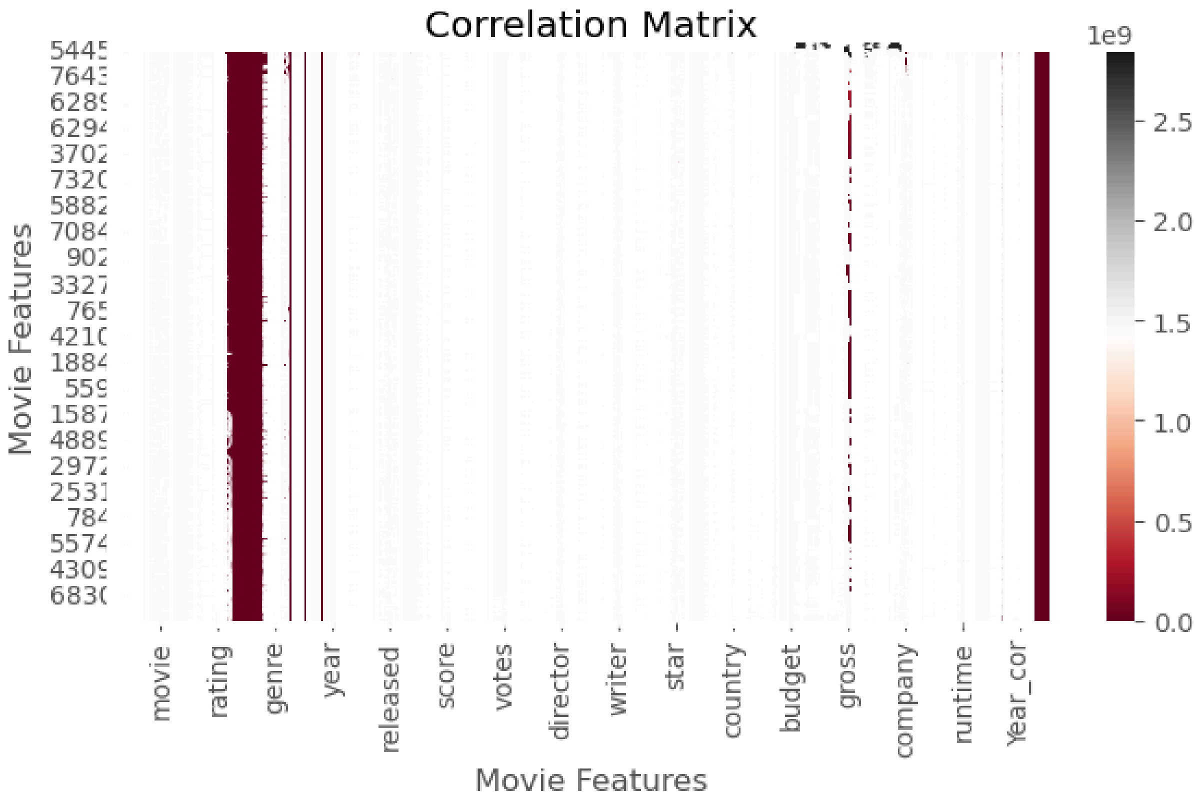
Out[40]:

	movie	rating	genre	year	released	score	vot
movie	1.000000	-0.008069	0.016355	0.011453	-0.011311	0.017097	0.0130
rating	-0.008069	1.000000	0.072423	0.008779	0.016613	-0.001314	0.0337
genre	0.016355	0.072423	1.000000	-0.081261	0.029822	0.027965	-0.1452
year	0.011453	0.008779	-0.081261	1.000000	-0.000695	0.097995	0.2224
released	-0.011311	0.016613	0.029822	-0.000695	1.000000	0.042788	0.0158
score	0.017097	-0.001314	0.027965	0.097995	0.042788	1.000000	0.4091
votes	0.013038	0.033743	-0.145296	0.222427	0.015878	0.409182	1.0000
director	0.009079	0.019483	-0.015258	-0.020795	-0.001478	0.009559	0.0003
writer	0.009081	-0.005921	0.006567	-0.008656	-0.002404	0.019416	0.0011
star	0.006472	0.013405	-0.005477	-0.027242	0.015777	-0.001609	-0.0191
country	-0.010737	0.081244	-0.037615	-0.070938	-0.020427	-0.133348	0.0735
budget	0.020548	-0.081939	-0.334021	0.309212	0.009145	0.055665	0.4869
gross	0.006989	-0.095450	-0.234297	0.261900	0.000519	0.186392	0.6328
company	0.009211	-0.032943	-0.071067	-0.010431	-0.010474	0.001030	0.1334
runtime	0.010392	0.062145	-0.052711	0.120811	0.000868	0.399451	0.3091
Year_cor	0.010225	0.006403	-0.078210	0.996397	-0.003775	0.106295	0.2177

Using heatmap to show all numeric values:

In [43]:

```
# Calculate the correlation matrix

df_num.corr(method = 'pearson')

# Create a heatmap
sns.heatmap(df_num,
            annot=True, cmap='RdGy',)

plt.title('Correlation Matrix')
plt.xlabel('Movie Features')
plt.ylabel('Movie Features')

plt.show()
```

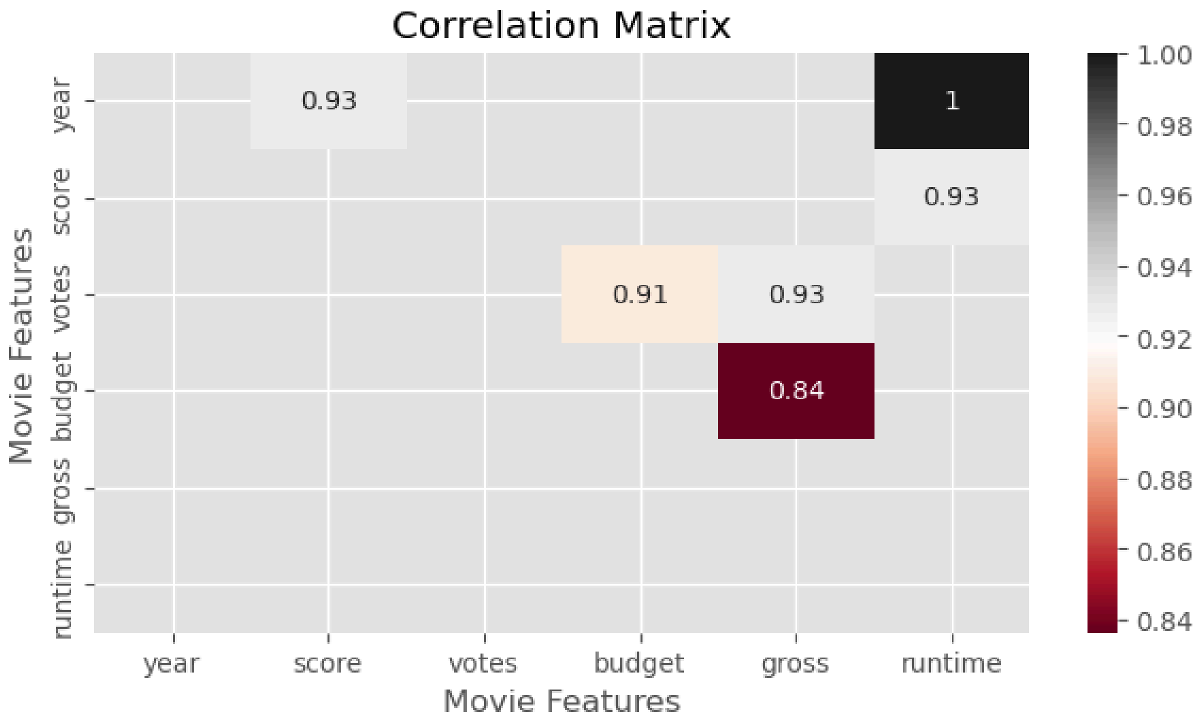


Above is the example of generalised heatmap Plotting with large number of category. Which we can see not working properly

👇 ***Below is the best way to plot this kind of cluttered data***

In [45]:

```
# Create a mask to exclude self-correlations and correlations below 0.5
mask = np.triu(np.ones(corr_matrix.shape)) & (corr_matrix > 0.5) & (corr_mat

# Create the heatmap
plt.figure(figsize=(8, 4))
sns.heatmap(corr_matrix[mask], annot=True, cmap='RdGy')  # Apply mask to cor
plt.title('Correlation Matrix')
plt.xlabel('Movie Features')
plt.ylabel('Movie Features')

plt.show()
```



6. Another way by sorting -

In [47]:
```
corr_matrix = df_num.corr()
corr_matrix
sorted_corr_pairs = corr_matrix.unstack().sort_values() # first we unstacked
sorted_corr_pairs.head(10)
```

Out[47]:
```
budget    genre     -0.334021
genre     budget    -0.334021
          gross     -0.234297
gross     genre     -0.234297
votes     genre     -0.145296
genre     votes     -0.145296
score     country   -0.133348
country   score     -0.133348
rating    gross     -0.095450
gross     rating    -0.095450
dtype: float64
```

In [48]:
```
# Let's filter out useful values i.e higher values
high_corr = sorted_corr_pairs[(sorted_corr_pairs > .4) & (sorted_corr_pairs
high_corr
```

Out[48]:
```
score     votes       0.409182
votes     score       0.409182
          budget      0.486931
budget    votes       0.486931
gross     votes       0.632870
votes     gross       0.632870
gross     budget      0.750157
budget    gross       0.750157
Year_cor  year        0.996397
year      Year_cor    0.996397
dtype: float64
```

Hypothesis 1: Higher budgets are positively correlated with higher gross earnings. Correlation between budget and gross: 0.750157 Conclusion: This is a strong positive correlation (close to 1), indicating that higher budgets tend to result in higher gross earnings. The data supports this hypothesis, suggesting that movies with larger financial investments generally perform better at the box office.

Hypothesis 2: Movies with higher audience votes tend to have higher scores. Correlation between votes and score: 0.409182 Conclusion: This is a moderate positive correlation, suggesting that movies with more audience votes tend to have higher scores. While the relationship is not as strong as budget vs. gross, the data still supports this hypothesis to some extent. It indicates that more popular movies (based on votes) are generally perceived as better in terms of quality.

$In\ summary:$

$Hypothesis 1:$ is strongly supported by the data.
$Hypothesis 2:$ is moderately supported, indicating some positive relationship but with room for other influencing factors.

Current Date and Time: 2024-11-19 05:23:56.629807