Movie Correlations

February 18, 2025

1 Movie Correlations

1.0.1 import libraries

[19]:
```
import pandas as pd
import seaborn as sns
import numpy as np
import matplotlib
import matplotlib.pyplot as plt
plt.style.use('ggplot')
from matplotlib.pyplot import figure

%matplotlib inline
matplotlib.rcParams['figure.figsize'] = (8, 6) # resizing the plot
pd.options.display.float_format = '{:.2f}'.format # limit outputs to 2 decimal␣
↪places
```

[20]:
```
df = pd.read_csv(r"D:\Analyst materials\projects\files\movies.csv")
df.head()
```

[20]:
```
                                              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
```

[21]:
```
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
```

1.1 First we do some Data Cleaning

1.1.1 Check for null values in each column

[22]:
```
df.isnull().sum()
```

[22]:
```
name         0
rating      77
genre        0
year         0
released     2
score        3
votes        3
```

```
director       0
writer         3
star           1
country        3
budget      2171
gross        189
company       17
runtime        4
dtype: int64
```

1.1.2 Drop rows where budget or gross is null because much of the analysis will be reliant on those values

[23]:
```
df =  df.dropna(subset=['budget', 'gross'])
```

1.1.3 Changing data type of budget and gross from float to int

[24]:
```
df['budget'] = df['budget'].astype(int)
df['gross'] = df['gross'].astype(int)
```

1.1.4 Sort movies by highest grossing

[25]:
```
df.sort_values(by=['gross'], inplace=True, ascending=False)
```

1.1.5 Check and drop any duplicates

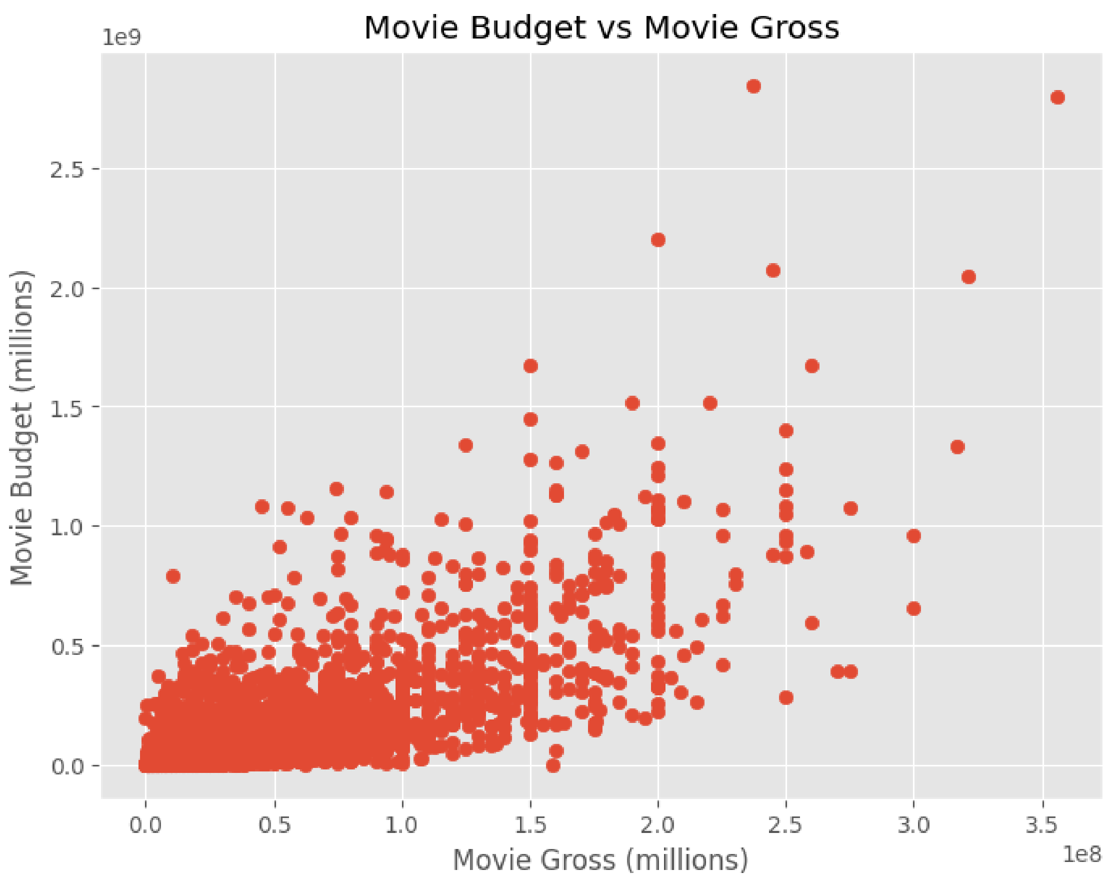
[35]:
```
df[df.duplicated()]
# no duplicates!
```

[35]:
```
Empty DataFrame
Columns: [name, rating, genre, year, released, score, votes, director, writer,
star, country, budget, gross, company, runtime]
Index: []
```

1.2 Now we create some visualizations

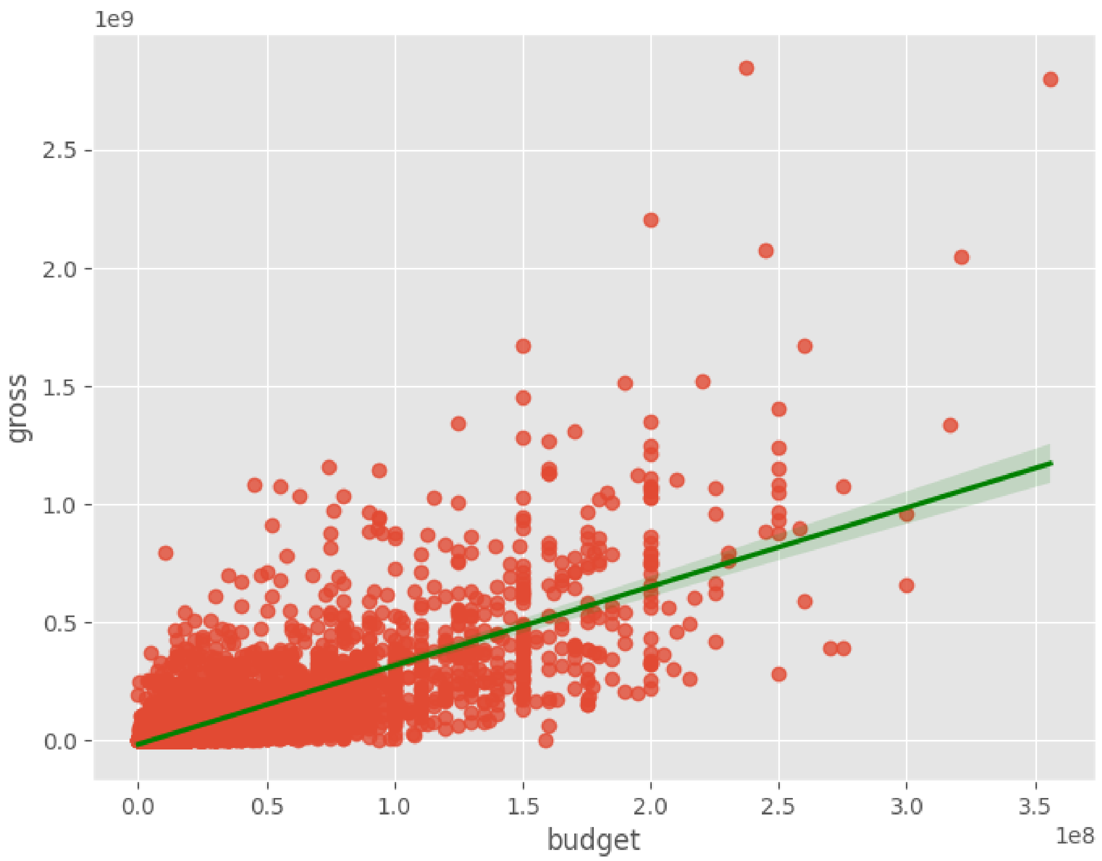
1.2.1 Scatterplot with budget vs gross

[28]:
```
plt.scatter(x=df['budget'], y=df['gross'])
plt.title('Movie Budget vs Movie Gross')
plt.xlabel('Movie Gross (millions)')
plt.ylabel('Movie Budget (millions)')
plt.show()
```



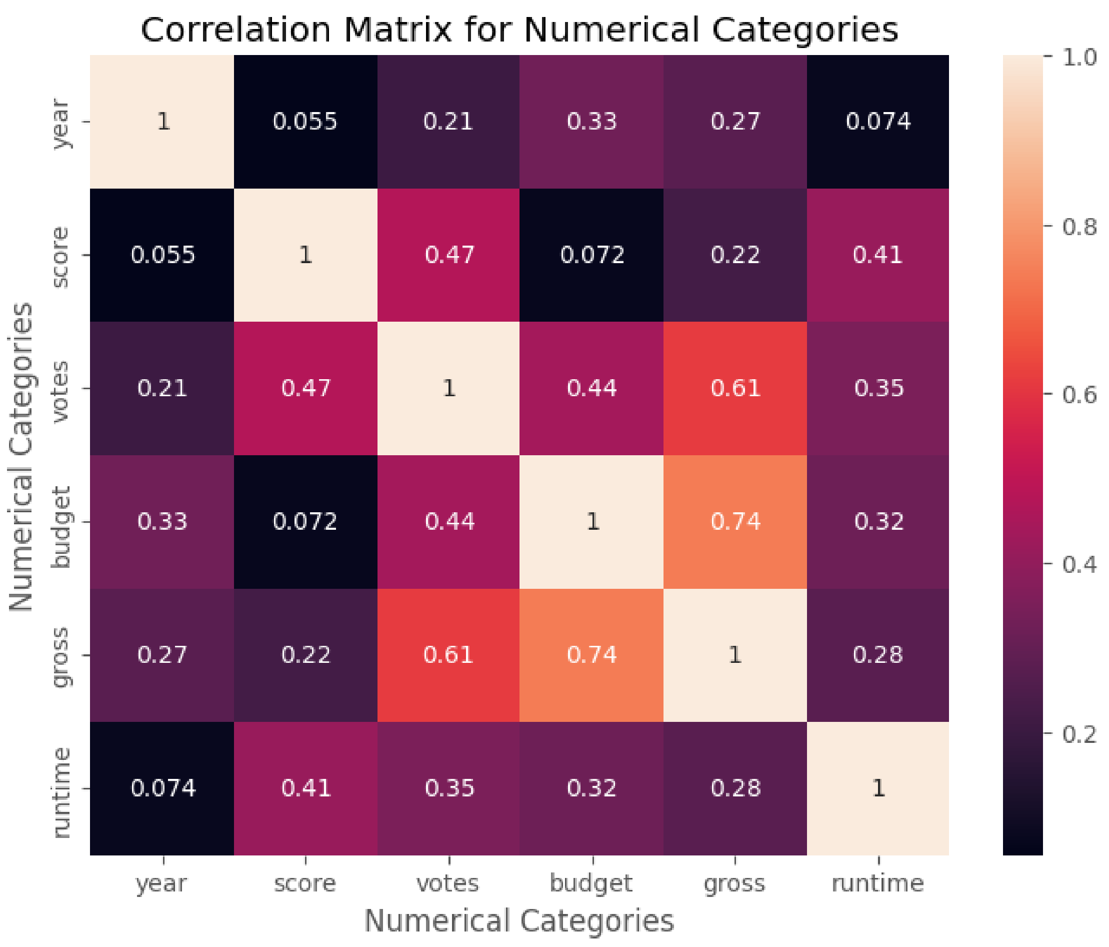
```
[29]: sns.regplot(x='budget', y='gross', data=df, line_kws={"color": "green"})
```

```
[29]: <Axes: xlabel='budget', ylabel='gross'>
```



1.2.2 Check Correlations

[30]:
```
corr_matrix = df.corr(numeric_only=True)
sns.heatmap(corr_matrix, annot=True)
plt.title('Correlation Matrix for Numerical Categories')
plt.xlabel('Numerical Categories')
plt.ylabel('Numerical Categories')
plt.show()
```



1.2.3 *We can see a high correlation between* budget *and* gross*, and a moderately-high correlation between* votes *and* gross

1.2.4 Want to incorporate non-numeric values into the correlation analysis

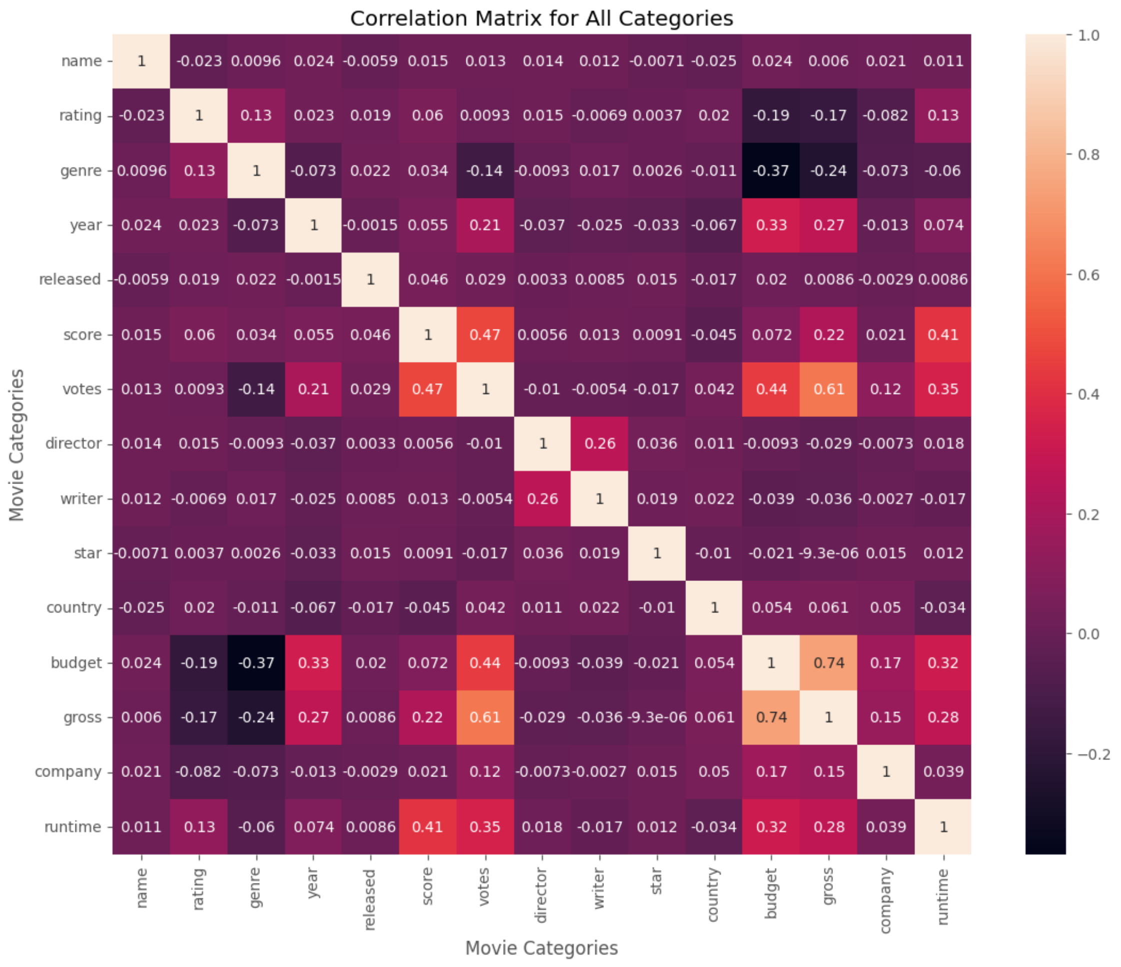
[31]:
```
# assign numerical values to non-numeric fields using category codes
df_num = df
for col in df_num.columns:
    if(df_num[col].dtype == 'object'):
        df_num[col] = df_num[col].astype('category')
        df_num[col] = df_num[col].cat.codes
df_num.head()
```

[31]:
```
      name  rating  genre  year  released  score      votes  director  writer  \
5445   387       5      0  2009       528   7.80 1100000.00       787    1265
7445   389       5      0  2019       138   8.40  903000.00       106     515
3045  4923       5      6  1997       535   7.80 1100000.00       787    1265
6663  3656       5      0  2015       530   7.80  876000.00       770    1810
```

```
7244   390        5       0  2018        146    8.40  897000.00        106      515

      star  country     budget       gross  company  runtime
5445  1538       47  237000000  2847246203     1388   162.00
7445  1474       47  356000000  2797501328      987   181.00
3045  1076       47  200000000  2201647264     1388   194.00
6663   357       47  245000000  2069521700      949   138.00
7244  1474       47  321000000  2048359754      987   149.00
```

[32]:
```python
corr_matrix = df_num.corr(numeric_only=True)
plt.figure(figsize=(13, 10))
sns.heatmap(corr_matrix, annot=True)
plt.title('Correlation Matrix for All Categories')
plt.xlabel('Movie Categories')
plt.ylabel('Movie Categories')
plt.show()
```



[33]:
```
unstacked_corr = df_num.corr().unstack()
unstacked_corr
```

[33]:
```
name     name        1.00
         rating     -0.02
         genre       0.01
         year        0.02
         released   -0.01
                     …
runtime  country    -0.03
         budget      0.32
         gross       0.28
         company     0.04
         runtime     1.00
Length: 225, dtype: float64
```

[34]:
```
# check for all highly correlated variables
high_corr = unstacked_corr[unstacked_corr > 0.5]
high_corr
```

[34]:
```
name      name        1.00
rating    rating      1.00
genre     genre       1.00
year      year        1.00
released  released    1.00
score     score       1.00
votes     votes       1.00
          gross       0.61
director  director    1.00
writer    writer      1.00
star      star        1.00
country   country     1.00
budget    budget      1.00
          gross       0.74
gross     votes       0.61
          budget      0.74
          gross       1.00
company   company     1.00
runtime   runtime     1.00
dtype: float64
```

1.2.5 *Seems like the only highly correlated variables are what we learned from our insight earlier, which is that only* `budget` *and* `gross` *and* `votes` *and* `gross` *are highly correlated!*