

```
In [1]: 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'] = (12,8) # adjust the configuration of
```

```
In [2]: # Read in the data
df = pd.read_csv(r"C:\Users\tamil\Desktop\Tamil\DATA ANALYST\Python\Movies\m
```

```
In [3]: df.head()
```

```
Out[3]:
```

	name	rating	genre	year	released	score	votes	director	
0	The Shining	R	Drama	1980	1980-06-13	8.4	927000	Stanley Kubrick	S
1	The Blue Lagoon	R	Adventure	1980	1980-07-02	5.8	65000	Randal Kleiser	H St
2	Star Wars: Episode V - The Empire Strikes Back	PG	Action	1980	1980-06-20	8.7	1200000	Irvin Kershner	E
3	Airplane!	PG	Comedy	1980	1980-07-02	7.7	221000	Jim Abrahams	Ab
4	Caddyshack	R	Comedy	1980	1980-07-25	7.3	108000	Harold Ramis	

```
In [9]: # Find missing data's
for col in df.columns:
    pct_missing = np.mean(df[col].isnull())
    print('{} - {}'.format(col,pct_missing))
```

```
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 [5]: # data types for our columns
df.dtypes
```

```
Out[5]: name          object
        rating        object
        genre         object
        year          int64
        released      object
        score         float64
        votes         int64
        director      object
        writer        object
        star          object
        country       object
        budget        int64
        gross         int64
        company       object
        runtime       int64
dtype: object
```

```
In [8]: # Replace null values
#df['budget'] = pd.to_numeric(df['budget'], errors='coerce') # Converts non-numeric to NaN
df['rating'] = df['rating'].fillna(0).astype(object)

#df['gross'] = pd.to_numeric(df['gross'], errors='coerce') # Converts non-numeric to NaN
df['company'] = df['company'].fillna(0).astype(object)
```

```
In [7]: df
```

Out[7]:

	name	rating	genre	year	released	score	votes	director
<b>0</b>	The Shining	R	Drama	1980	1980-06-13	8.4	927000	Stanley Kubrick
<b>1</b>	The Blue Lagoon	R	Adventure	1980	1980-07-02	5.8	65000	Randal Kleiser
<b>2</b>	Star Wars: Episode V - The Empire Strikes Back	PG	Action	1980	1980-06-20	8.7	1200000	Irvin Kershner
<b>3</b>	Airplane!	PG	Comedy	1980	1980-07-02	7.7	221000	Jim Abrahams
<b>4</b>	Caddyshack	R	Comedy	1980	1980-07-25	7.3	108000	Harold Ramis
...	...	...	...	...	...	...	...	...
<b>1103</b>	True Colors	R	Drama	1991	1991-03-15	6.3	5000	Herbert Ross
<b>1104</b>	A Kiss Before Dying	R	Crime	1991	1991-04-26	5.7	5100	James Dearden
<b>1105</b>	Bingo	PG	Adventure	1991	1991-08-09	4.9	2700	Matthew Robbins
<b>1106</b>	Body Parts	R	Horror	1991	1991-08-02	5.6	4100	Eric Red
<b>1107</b>	One Good Cop	R	Action	1991	1991-05-03	5.9	3900	Heywood Gould

1108 rows × 15 columns

In [10]: `df.sort_values(by=['gross'], inplace = False, ascending = False)`

Out[10]:

	name	rating	genre	year	released	score	votes	director	
<b>107</b>	E.T. the Extra-Terrestrial	PG	Family	1982	1982-06-11	7.8	381000	Steven Spielberg	M
<b>2</b>	Star Wars: Episode V - The Empire Strikes Back	PG	Action	1980	1980-06-20	8.7	1200000	Irvin Kershner	E
<b>1002</b>	Terminator 2: Judgment Day	R	Action	1991	1991-07-03	8.5	1000000	James Cameron	C
<b>896</b>	Ghost	PG-13	Drama	1990	1990-07-13	7.1	203000	Jerry Zucker	
<b>895</b>	Home Alone	PG	Comedy	1990	1990-11-16	7.6	501000	Chris Columbus	
...	...	...	...	...	...	...	...	...	
<b>1049</b>	The Lovers on the Bridge	R	Drama	1991	1999-07-02	7.6	13000	Leos Carax	
<b>256</b>	My Brother's Wedding	Not Rated	Drama	1983	March 1985	7.2	826	Charles Burnett	
<b>403</b>	Smooth Talk	PG-13	Drama	1985	1985-11-15	6.5	2200	Joyce Chopra	
<b>423</b>	Crimewave	PG-13	Comedy	1985	1986-04-25	5.7	5300	Sam Raimi	
<b>154</b>	Parasite	R	Horror	1982	1982-03-12	3.9	2300	Charles Band	

1108 rows × 15 columns

```
In [11]: pd.set_option('display.max_rows', None)
```

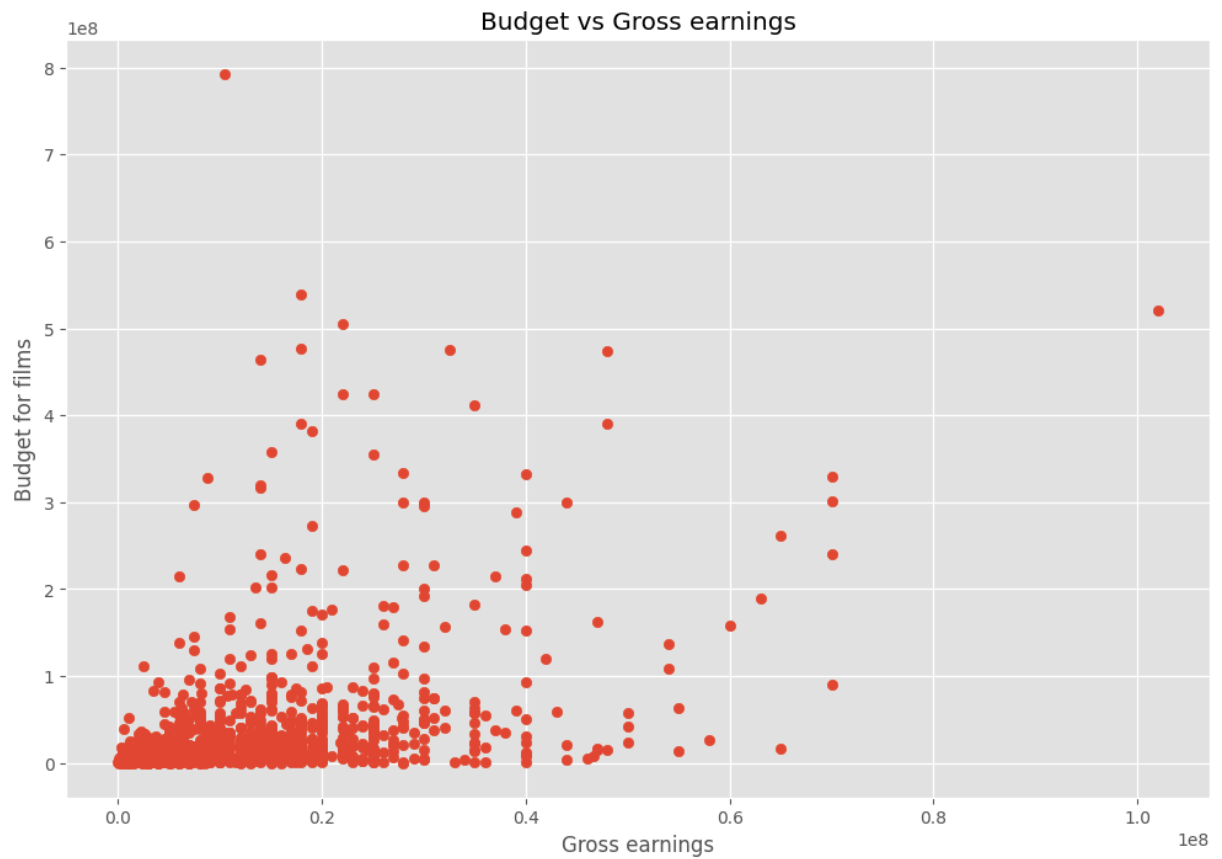
```
In [12]: # drop duplicates
df.drop_duplicates()
```

Out[12]:

	name	rating	genre	year	released	score	votes	
<b>0</b>	The Shining	R	Drama	1980	1980-06-13	8.4	927000	
<b>1</b>	The Blue Lagoon	R	Adventure	1980	1980-07-02	5.8	65000	Ran
<b>2</b>	Star Wars: Episode V - The Empire Strikes Back	PG	Action	1980	1980-06-20	8.7	1200000	Irvin
<b>3</b>	Airplane!	PG	Comedy	1980	1980-07-02	7.7	221000	Jim
<b>4</b>	Caddyshack	R	Comedy	1980	1980-07-25	7.3	108000	Hal
<b>5</b>	Friday the 13th	R	Horror	1980	1980-05-09	6.4	123000	Cu
<b>6</b>	The Blues Brothers	R	Action	1980	1980-06-20	7.9	188000	Jc
<b>7</b>	Raging Bull	R	Biography	1980	1980-12-19	8.2	330000	
<b>8</b>	Superman II	PG	Action	1980	1981-06-19	6.8	101000	Rich
<b>9</b>	The Long Riders	R	Biography	1980	1980-05-16	7.0	10000	
<b>10</b>	Any Which Way You Can	PG	Action	1980	1980-12-17	6.1	18000	I
<b>11</b>	The Gods Must Be Crazy	PG	Adventure	1980	1984-10-26	7.3	54000	
<b>12</b>	Popeye	PG	Adventure	1980	1980-12-12	5.3	30000	Robt
<b>13</b>	Ordinary People	R	Drama	1980	1980-09-19	7.7	49000	
<b>14</b>	Dressed to Kill	R	Crime	1980	1980-07-25	7.1	37000	
<b>15</b>	Somewhere in Time	PG	Drama	1980	1980-10-03	7.2	27000	
<b>16</b>	9 to 5	PG	Comedy	1980	1980-12-19	6.9	29000	Co
<b>17</b>	The Fog	R	Horror	1980	1980-02-08	6.8	66000	
<b>18</b>	Cruising	R	Crime	1980	1980-02-15	6.5	20000	
<b>19</b>	Heaven's Gate	R	Adventure	1980	1981-04-24	6.8	14000	

	name	rating	genre	year	released	score	votes	
<b>1095</b>	Mortal Thoughts	R	Mystery	1991	1991-04-19	5.7	8400	Ala
<b>1096</b>	Another You	R	Comedy	1991	1991-07-26	5.4	3700	
<b>1097</b>	For the Boys	R	Comedy	1991	1991-11-27	6.4	5300	M
<b>1098</b>	Beastmaster 2: Through the Portal of Time	PG-13	Action	1991	1991-08-30	4.1	3000	Sy
<b>1099</b>	Eve of Destruction	R	Action	1991	1991-01-18	4.9	2100	
<b>1100</b>	A Rage in Harlem	R	Comedy	1991	1991-05-03	5.9	2000	
<b>1101</b>	The Super	R	Comedy	1991	1991-10-04	5.6	5400	I
<b>1102</b>	At Play in the Fields of the Lord	R	Drama	1991	1991-12-06	6.8	3100	
<b>1103</b>	True Colors	R	Drama	1991	1991-03-15	6.3	5000	He
<b>1104</b>	A Kiss Before Dying	R	Crime	1991	1991-04-26	5.7	5100	
<b>1105</b>	Bingo	PG	Adventure	1991	1991-08-09	4.9	2700	
<b>1106</b>	Body Parts	R	Horror	1991	1991-08-02	5.6	4100	
<b>1107</b>	One Good Cop	R	Action	1991	1991-05-03	5.9	3900	

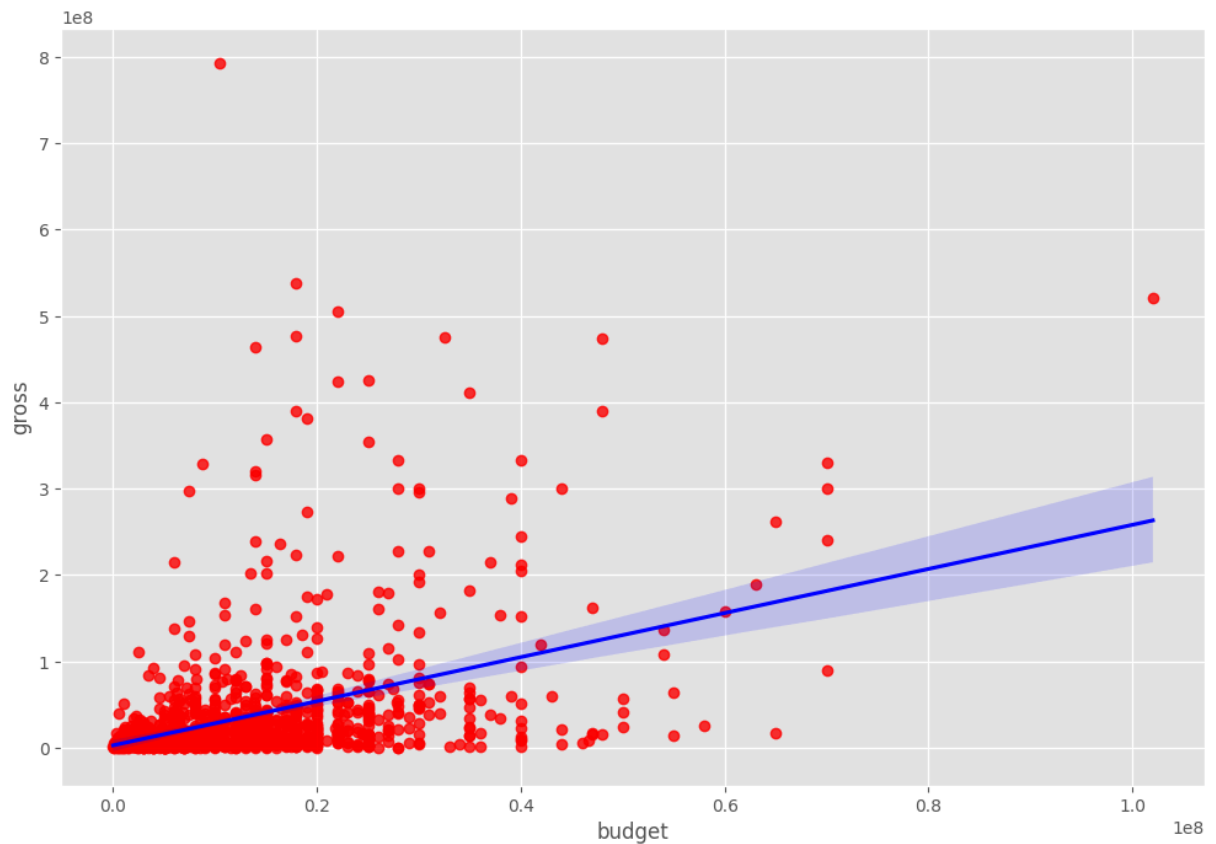
```
In [13]: # Scattre plot with budget vs gross
plt.scatter(x=df['budget'], y=df['gross'])
plt.title('Budget vs Gross earnings')
plt.xlabel('Gross earnings')
plt.ylabel('Budget for films')
plt.show()
```



```
In [14]: # Plot budget vs gross using seaborn
```

```
sns.regplot(x='budget', y='gross', data=df, scatter_kws={"color":"red"}, lin
```

```
Out[14]: <Axes: xlabel='budget', ylabel='gross'>
```



```
In [16]: # Looking at correlation
df.select_dtypes(include='number').corr(method='pearson')
```

```
Out[16]:
```

	year	score	votes	budget	gross	runtime
year	1.000000	-0.006319	0.003583	0.220788	0.083008	-0.038301
score	-0.006319	1.000000	0.480645	0.117596	0.323590	0.369157
votes	0.003583	0.480645	1.000000	0.279210	0.622154	0.228393
budget	0.220788	0.117596	0.279210	1.000000	0.395682	0.386728
gross	0.083008	0.323590	0.622154	0.395682	1.000000	0.192768
runtime	-0.038301	0.369157	0.228393	0.386728	0.192768	1.000000

```
In [19]: # High correlation between gross and votes
```

```
In [19]: correlation_matrix = df.select_dtypes(include='number').corr(method='pearson')
sns.heatmap(correlation_matrix, annot=True)

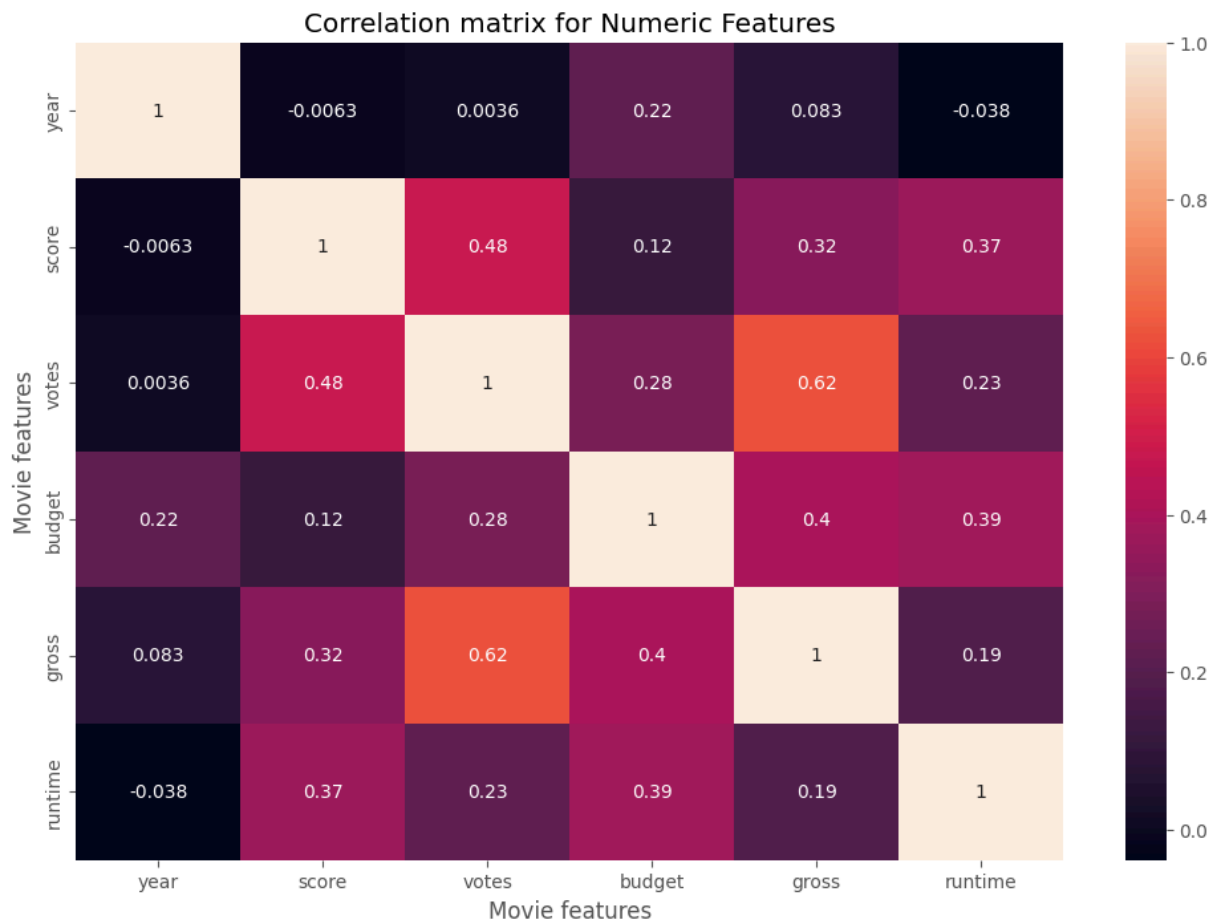
plt.title('Correlation matrix for Numeric Features')

plt.xlabel('Movie features')

plt.ylabel('Movie features')

plt.show()
```





```
In [20]: df_numerized = df

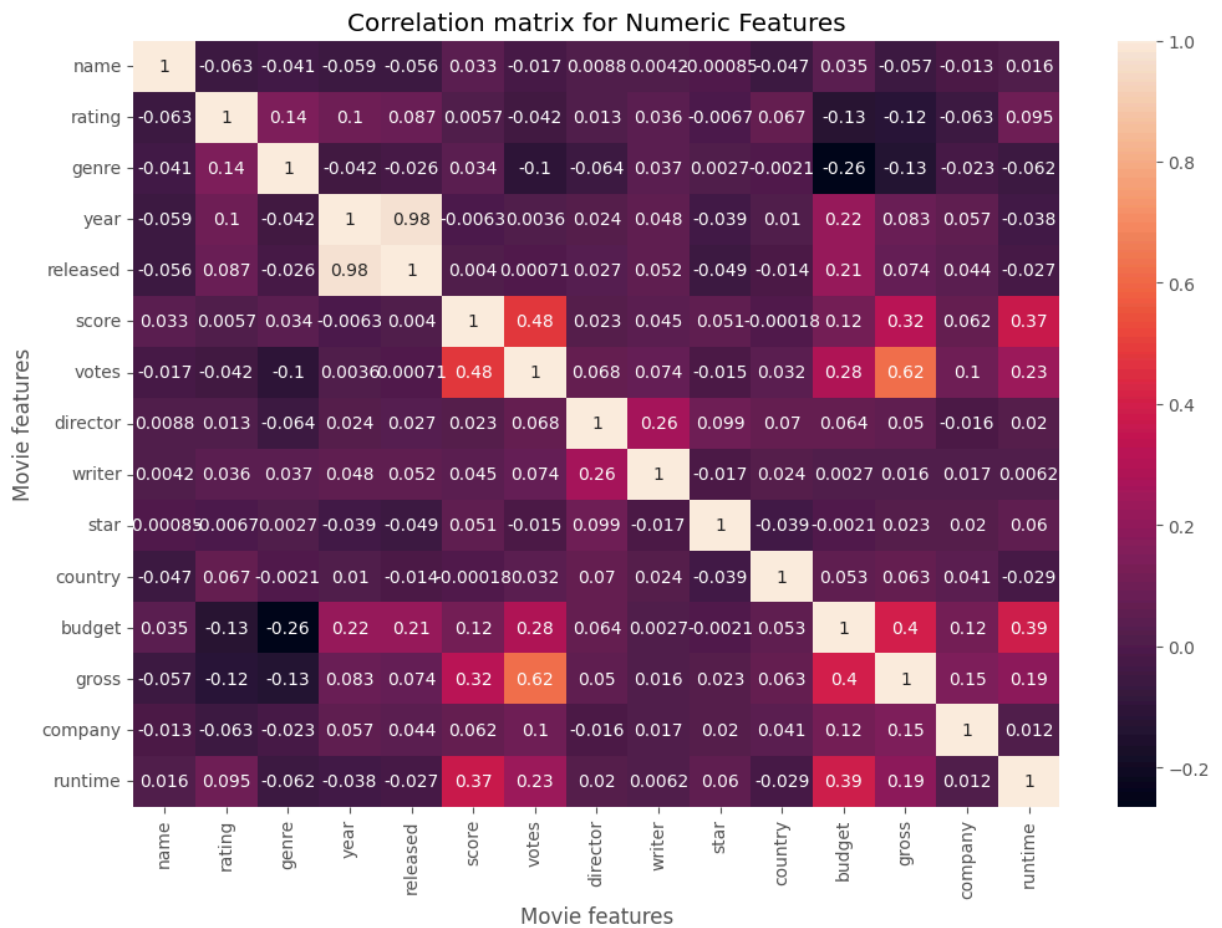
for col_name in df_numerized.columns:
    if (df_numerized[col_name].dtype == 'object'):
        df_numerized[col_name] = df_numerized[col_name].astype('category')
        df_numerized[col_name] = df_numerized[col_name].cat.codes
df_numerized
```

Out[20]:

	name	rating	genre	year	released	score	votes	director	writer	
<b>0</b>	985	7	6	1980	8	8.4	927000	492	719	
<b>1</b>	848	7	1	1980	12	5.8	65000	421	305	
<b>2</b>	782	5	0	1980	9	8.7	1200000	186	470	
<b>3</b>	37	5	4	1980	12	7.7	221000	229	369	
<b>4</b>	148	7	4	1980	14	7.3	108000	168	81	
<b>5</b>	322	7	9	1980	4	6.4	123000	480	781	
<b>6</b>	849	7	0	1980	9	7.9	188000	266	141	
<b>7</b>	661	7	3	1980	26	8.2	330000	332	327	
<b>8</b>	804	5	0	1980	39	6.8	101000	432	367	
<b>9</b>	929	7	3	1980	5	7.0	10000	543	63	
<b>10</b>	62	5	0	1980	25	6.1	18000	53	711	
<b>11</b>	889	5	1	1980	182	7.3	54000	212	345	
<b>12</b>	629	5	1	1980	24	5.3	30000	444	434	
<b>13</b>	590	7	6	1980	19	7.7	49000	452	432	
<b>14</b>	255	7	5	1980	14	7.1	37000	45	80	
<b>15</b>	762	5	6	1980	21	7.2	27000	218	638	
<b>16</b>	6	5	4	1980	26	6.9	29000	72	577	
<b>17</b>	883	7	9	1980	1	6.8	66000	251	392	
<b>18</b>	205	7	5	1980	2	6.5	20000	552	802	
<b>19</b>	381	7	1	1980	33	6.8	14000	344	519	
<b>20</b>	878	5	0	1980	15	6.7	22000	107	759	
<b>21</b>	1097	5	8	1980	16	5.3	12000	448	632	
<b>22</b>	142	7	5	1980	9	7.2	17000	510	784	
<b>23</b>	49	7	5	1980	0	6.2	22000	391	590	
<b>24</b>	158	5	6	1980	33	6.1	604	306	164	
<b>25</b>	643	7	4	1980	22	6.2	24000	181	549	
<b>26</b>	898	7	4	1980	6	6.3	4300	125	250	
<b>27</b>	534	7	4	1980	23	6.0	11000	302	659	
<b>28</b>	990	7	0	1980	11	7.1	9000	437	465	
<b>29</b>	908	7	0	1980	8	5.3	3900	356	598	
<b>30</b>	950	5	0	1980	4	5.1	3100	70	511	
<b>31</b>	785	5	4	1980	20	7.3	22000	559	819	
<b>32</b>	507	7	4	1980	19	6.8	4500	279	70	

	name	rating	genre	year	released	score	votes	director	writer
<b>1089</b>	957	7	0	1991	524	6.0	3800	321	159
<b>1090</b>	1058	7	5	1991	573	6.5	3800	485	709
<b>1091</b>	964	2	2	1991	582	6.8	2600	290	671
<b>1092</b>	664	7	6	1991	554	6.6	4700	327	90
<b>1093</b>	654	5	4	1991	548	5.8	6700	368	251
<b>1094</b>	286	6	0	1991	531	5.9	9000	431	667
<b>1095</b>	531	7	10	1991	528	5.7	8400	10	812
<b>1096</b>	61	7	4	1991	545	5.4	3700	337	821
<b>1097</b>	315	7	4	1991	564	6.4	5300	325	554
<b>1098</b>	90	6	0	1991	552	4.1	3000	514	25
<b>1099</b>	275	7	0	1991	517	4.9	2100	114	216
<b>1100</b>	21	7	4	1991	530	5.9	2000	33	114
<b>1101</b>	991	7	4	1991	556	5.6	5400	459	700
<b>1102</b>	71	7	6	1991	565	6.8	3100	171	602
<b>1103</b>	1043	7	6	1991	524	6.3	5000	174	453
<b>1104</b>	13	7	5	1991	529	5.7	5100	199	314
<b>1105</b>	107	5	1	1991	548	4.9	2700	336	376
<b>1106</b>	125	7	9	1991	547	5.6	4100	121	615
<b>1107</b>	588	7	0	1991	530	5.9	3900	175	306

```
In [21]: correlation_matrix = df_numerized.corr(method='pearson')
sns.heatmap(correlation_matrix, annot=True)
plt.title('Correlation matrix for Numeric Features')
plt.xlabel('Movie features')
plt.ylabel('Movie features')
plt.show()
```



```
In [22]: correlation_mat = df_numerized.corr()
          corr_pairs = correlation_mat.unstack()
          corr_pairs
```

```

Out[22]: name      name      1.000000
          rating    -0.062527
          genre     -0.040568
          year      -0.059270
          released  -0.056298
          score     0.032979
          votes     -0.017372
          director  0.008806
          writer    0.004160
          star      -0.000852
          country   -0.047315
          budget    0.035302
          gross     -0.056939
          company   -0.013220
          runtime   0.016358
rating    name      -0.062527
          rating    1.000000
          genre     0.141235
          year      0.102554
          released  0.087159
          score     0.005737
          votes     -0.042434
          director  0.013426
          writer    0.035815
          star      -0.006734
          country   0.067382
          budget    -0.125042
          gross     -0.116418
          company   -0.063346
          runtime   0.095424
genre     name      -0.040568
          rating    0.141235
          genre     1.000000
          year      -0.042129
          released  -0.026211
          score     0.034008
          votes     -0.101856
          director  -0.064215
          writer    0.037447
          star      0.002719
          country   -0.002066
          budget    -0.264239
          gross     -0.131967
          company   -0.022781
          runtime   -0.061529
year      name      -0.059270
          rating    0.102554
          genre     -0.042129
          year      1.000000
          released  0.978338
          score     -0.006319
          votes     0.003583
          director  0.024055
          writer    0.047829
          star      -0.038926
          country   0.010144

```

	budget	0.220788
	gross	0.083008
	company	0.056962
	runtime	-0.038301
released	name	-0.056298
	rating	0.087159
	genre	-0.026211
	year	0.978338
	released	1.000000
	score	0.004043
	votes	0.000708
	director	0.027373
	writer	0.052320
	star	-0.048765
	country	-0.013692
	budget	0.210905
	gross	0.074048
	company	0.043520
	runtime	-0.026950
score	name	0.032979
	rating	0.005737
	genre	0.034008
	year	-0.006319
	released	0.004043
	score	1.000000
	votes	0.480645
	director	0.023295
	writer	0.044893
	star	0.051408
	country	-0.000182
	budget	0.117596
	gross	0.323590
	company	0.061902
	runtime	0.369157
votes	name	-0.017372
	rating	-0.042434
	genre	-0.101856
	year	0.003583
	released	0.000708
	score	0.480645
	votes	1.000000
	director	0.067950
	writer	0.074264
	star	-0.015312
	country	0.032470
	budget	0.279210
	gross	0.622154
	company	0.103676
	runtime	0.228393
director	name	0.008806
	rating	0.013426
	genre	-0.064215
	year	0.024055
	released	0.027373
	score	0.023295
	votes	0.067950

	director	1.000000
	writer	0.260299
	star	0.099348
	country	0.069799
	budget	0.063775
	gross	0.049715
	company	-0.016137
	runtime	0.020369
writer	name	0.004160
	rating	0.035815
	genre	0.037447
	year	0.047829
	released	0.052320
	score	0.044893
	votes	0.074264
	director	0.260299
	writer	1.000000
	star	-0.016638
	country	0.024477
	budget	0.002747
	gross	0.015603
	company	0.016878
	runtime	0.006188
star	name	-0.000852
	rating	-0.006734
	genre	0.002719
	year	-0.038926
	released	-0.048765
	score	0.051408
	votes	-0.015312
	director	0.099348
	writer	-0.016638
	star	1.000000
	country	-0.038505
	budget	-0.002095
	gross	0.023099
	company	0.020439
	runtime	0.059706
country	name	-0.047315
	rating	0.067382
	genre	-0.002066
	year	0.010144
	released	-0.013692
	score	-0.000182
	votes	0.032470
	director	0.069799
	writer	0.024477
	star	-0.038505
	country	1.000000
	budget	0.052961
	gross	0.063399
	company	0.040723
	runtime	-0.029232
budget	name	0.035302
	rating	-0.125042
	genre	-0.264239

	year	0.220788
	released	0.210905
	score	0.117596
	votes	0.279210
	director	0.063775
	writer	0.002747
	star	-0.002095
	country	0.052961
	budget	1.000000
	gross	0.395682
	company	0.117075
	runtime	0.386728
gross	name	-0.056939
	rating	-0.116418
	genre	-0.131967
	year	0.083008
	released	0.074048
	score	0.323590
	votes	0.622154
	director	0.049715
	writer	0.015603
	star	0.023099
	country	0.063399
	budget	0.395682
	gross	1.000000
	company	0.147032
	runtime	0.192768
company	name	-0.013220
	rating	-0.063346
	genre	-0.022781
	year	0.056962
	released	0.043520
	score	0.061902
	votes	0.103676
	director	-0.016137
	writer	0.016878
	star	0.020439
	country	0.040723
	budget	0.117075
	gross	0.147032
	company	1.000000
	runtime	0.011635
runtime	name	0.016358
	rating	0.095424
	genre	-0.061529
	year	-0.038301
	released	-0.026950
	score	0.369157
	votes	0.228393
	director	0.020369
	writer	0.006188
	star	0.059706
	country	-0.029232
	budget	0.386728
	gross	0.192768
	company	0.011635



```
runtime      1.000000  
dtype: float64
```

```
In [23]: sorted_pairs = corr_pairs.sort_values()  
sorted_pairs
```

```

Out[23]: genre      budget      -0.264239
         budget     genre      -0.264239
         gross      genre      -0.131967
         genre      gross      -0.131967
         rating     budget     -0.125042
         budget     rating     -0.125042
         gross      rating     -0.116418
         rating     gross      -0.116418
         genre      votes      -0.101856
         votes      genre      -0.101856
         director   genre      -0.064215
         genre      director   -0.064215
         rating     company    -0.063346
         company    rating     -0.063346
         rating     name       -0.062527
         name       rating     -0.062527
         runtime    genre      -0.061529
         genre      runtime    -0.061529
         year       name       -0.059270
         name       year       -0.059270
         name       gross      -0.056939
         gross      name       -0.056939
         name       released   -0.056298
         released   name       -0.056298
         star       released   -0.048765
         released   star       -0.048765
         name       country    -0.047315
         country    name       -0.047315
         votes      rating     -0.042434
         rating     votes      -0.042434
         year       genre      -0.042129
         genre      year       -0.042129
         name       name       -0.040568
         name       genre      -0.040568
         star       year       -0.038926
         year       star       -0.038926
         star       country    -0.038505
         country    star       -0.038505
         year       runtime    -0.038301
         runtime    year       -0.038301
         country    country    -0.029232
         country    runtime    -0.029232
         runtime    released   -0.026950
         released   runtime    -0.026950
         genre      genre      -0.026211
         genre      released   -0.026211
         company    company    -0.022781
         company    genre      -0.022781
         votes      name       -0.017372
         name       votes      -0.017372
         writer     star       -0.016638
         star       writer     -0.016638
         company    director   -0.016137
         director   company    -0.016137
         votes      star       -0.015312
         star       votes      -0.015312

```

country	released	-0.013692
released	country	-0.013692
name	company	-0.013220
company	name	-0.013220
star	rating	-0.006734
rating	star	-0.006734
score	year	-0.006319
year	score	-0.006319
budget	star	-0.002095
star	budget	-0.002095
genre	country	-0.002066
country	genre	-0.002066
star	name	-0.000852
name	star	-0.000852
score	country	-0.000182
country	score	-0.000182
votes	released	0.000708
released	votes	0.000708
star	genre	0.002719
genre	star	0.002719
writer	budget	0.002747
budget	writer	0.002747
votes	year	0.003583
year	votes	0.003583
score	released	0.004043
released	score	0.004043
name	writer	0.004160
writer	name	0.004160
score	rating	0.005737
rating	score	0.005737
runtime	writer	0.006188
writer	runtime	0.006188
name	director	0.008806
director	name	0.008806
year	country	0.010144
country	year	0.010144
runtime	company	0.011635
company	runtime	0.011635
rating	director	0.013426
director	rating	0.013426
writer	gross	0.015603
gross	writer	0.015603
runtime	name	0.016358
name	runtime	0.016358
company	writer	0.016878
writer	company	0.016878
director	runtime	0.020369
runtime	director	0.020369
company	star	0.020439
star	company	0.020439
gross	star	0.023099
star	gross	0.023099
score	director	0.023295
director	score	0.023295
	year	0.024055
year	director	0.024055

writer	country	0.024477
country	writer	0.024477
released	director	0.027373
director	released	0.027373
country	votes	0.032470
votes	country	0.032470
name	score	0.032979
score	name	0.032979
	genre	0.034008
genre	score	0.034008
name	budget	0.035302
budget	name	0.035302
rating	writer	0.035815
writer	rating	0.035815
	genre	0.037447
genre	writer	0.037447
country	company	0.040723
company	country	0.040723
released	company	0.043520
company	released	0.043520
writer	score	0.044893
score	writer	0.044893
year	writer	0.047829
writer	year	0.047829
gross	director	0.049715
director	gross	0.049715
score	star	0.051408
star	score	0.051408
writer	released	0.052320
released	writer	0.052320
budget	country	0.052961
country	budget	0.052961
company	year	0.056962
year	company	0.056962
runtime	star	0.059706
star	runtime	0.059706
score	company	0.061902
company	score	0.061902
gross	country	0.063399
country	gross	0.063399
budget	director	0.063775
director	budget	0.063775
rating	country	0.067382
country	rating	0.067382
votes	director	0.067950
director	votes	0.067950
country	director	0.069799
director	country	0.069799
released	gross	0.074048
gross	released	0.074048
votes	writer	0.074264
writer	votes	0.074264
gross	year	0.083008
year	gross	0.083008
rating	released	0.087159
released	rating	0.087159

rating	runtime	0.095424
runtime	rating	0.095424
star	director	0.099348
director	star	0.099348
rating	year	0.102554
year	rating	0.102554
votes	company	0.103676
company	votes	0.103676
	budget	0.117075
budget	company	0.117075
	score	0.117596
score	budget	0.117596
genre	rating	0.141235
rating	genre	0.141235
company	gross	0.147032
gross	company	0.147032
runtime	gross	0.192768
gross	runtime	0.192768
released	budget	0.210905
budget	released	0.210905
	year	0.220788
year	budget	0.220788
votes	runtime	0.228393
runtime	votes	0.228393
director	writer	0.260299
writer	director	0.260299
budget	votes	0.279210
votes	budget	0.279210
score	gross	0.323590
gross	score	0.323590
runtime	score	0.369157
score	runtime	0.369157
budget	runtime	0.386728
runtime	budget	0.386728
budget	gross	0.395682
gross	budget	0.395682
votes	score	0.480645
score	votes	0.480645
votes	gross	0.622154
gross	votes	0.622154
released	year	0.978338
year	released	0.978338
released	released	1.000000
score	score	1.000000
rating	rating	1.000000
name	name	1.000000
genre	genre	1.000000
year	year	1.000000
director	director	1.000000
votes	votes	1.000000
writer	writer	1.000000
star	star	1.000000
budget	budget	1.000000
country	country	1.000000
gross	gross	1.000000
company	company	1.000000

```
runtime    runtime    1.000000  
dtype: float64
```

```
In [24]: high_corr = sorted_pairs[(sorted_pairs)>0.5]  
high_corr
```

```
Out[24]: votes      gross      0.622154  
gross      votes      0.622154  
released   year       0.978338  
year       released   0.978338  
released   released   1.000000  
score      score      1.000000  
rating     rating     1.000000  
name       name       1.000000  
genre      genre      1.000000  
year       year       1.000000  
director   director   1.000000  
votes      votes      1.000000  
writer     writer     1.000000  
star       star       1.000000  
budget     budget     1.000000  
country    country    1.000000  
gross      gross      1.000000  
company    company    1.000000  
runtime    runtime    1.000000  
dtype: float64
```

```
In [ ]:
```