

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
import statsmodels.api as sm
from sklearn.metrics import mean_absolute_error, mean_squared_error, r2_score
```

```
data=pd.read_csv("anime_ratings_data.csv")
data.head()
```

	title	mediaType	eps	duration	startYr	finishYr	description	contentWarn	watched	watching	rating	votes	studio_primar
0	Dragon Ball Z Movie 15: Resurrection 'F'	Movie	1	67.0	2015	2015	Even the complete obliteration of his physical...	No	4649	86	3.979	3100.0	Toei Animatic
1	Kuripuri*Kuripura	Movie	1	5.0	2008	2008	NaN	No	10	0	2.120	10.0	Othe
2	GJ-bu@	TV Special	1	46.0	2014	2014	The story is set during the spring vacation im...	No	1630	16	3.758	1103.0	Othe
	Nausicaa of the Valley of the Wind	Movie	1	86.0	1984	1984	One thousand years ago...	No	1000	10	3.500	100.0	Othe

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data.shape

(6523, 15)

data.info()

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 6523 entries, 0 to 6522
Data columns (total 15 columns):
#   Column                Non-Null Count  Dtype
---  -
0   title                  6523 non-null   object
1   mediaType              6496 non-null   object
2   eps                    6523 non-null   int64
3   duration                6248 non-null   float64
4   startYr                6523 non-null   int64
5   finishYr               6523 non-null   int64
6   description             4114 non-null   object
7   contentWarn            6523 non-null   object
8   watched                6523 non-null   int64
9   watching               6523 non-null   int64
10  rating                 6523 non-null   float64
11  votes                  6496 non-null   float64
12  studio_primary         6523 non-null   object
13  studios_colab          6523 non-null   object
14  genre                  6523 non-null   object
dtypes: float64(3), int64(5), object(7)
memory usage: 764.5+ KB
```

data.describe(include="all").T




	count	unique		top	freq	mean	std	min	25%	50%	75%	max
title	6523	6523	Dragon Ball Z Movie 15: Resurrection 'F'		1	NaN	NaN	NaN	NaN	NaN	NaN	NaN
mediaType	6496	8		TV	2145	NaN	NaN	NaN	NaN	NaN	NaN	NaN
eps	6523.0	NaN		NaN	NaN	8.716235	11.002479	1.0	1.0	1.0	12.0	34.0
duration	6248.0	NaN		NaN	NaN	18.396287	20.94935	1.0	5.0	7.0	25.0	67.0
startYr	6523.0	NaN		NaN	NaN	2005.241147	12.911035	1967.0	2000.0	2010.0	2015.0	2020.0
finishYr	6523.0	NaN		NaN	NaN	2005.575349	12.568169	1970.0	2000.0	2010.0	2015.0	2020.0
description	4114	4081	In 19th century Belgium, in the Flanders count...		3	NaN	NaN	NaN	NaN	NaN	NaN	NaN
contentWarn	6523	2		No	5825	NaN	NaN	NaN	NaN	NaN	NaN	NaN
watched	6523.0	NaN		NaN	NaN	1347.948643	1737.138112	5.0	56.0	349.0	2252.5	4649.0
watching	6523.0	NaN		NaN	NaN	57.445654	76.527405	0.0	2.0	13.0	98.0	199.0
rating	6523.0	NaN		NaN	NaN	2.962553	0.760486	1.111	2.371	2.944	3.568	4.702
votes	6496.0	NaN		NaN	NaN	906.253233	1171.677648	10.0	34.0	227.5	1567.75	3100.0
studio_primary	6523	11		Others	4684	NaN	NaN	NaN	NaN	NaN	NaN	NaN
studios_colab	6523	2		No	6210	NaN	NaN	NaN	NaN	NaN	NaN	NaN

```
data.duplicated().sum()
```



0


```
data.isnull().sum()
```



	0
title	0
mediaType	27
eps	0
duration	275
startYr	0
finishYr	0
description	2409
contentWarn	0
watched	0
watching	0
rating	0
votes	27
studio_primary	0
studios_colab	0
genre	0

```
df=data.copy()
```

```
df.isnull().sum()
```



	0
title	0
mediaType	27
eps	0
duration	275
startYr	0
finishYr	0
description	2409
contentWarn	0
watched	0
watching	0
rating	0
votes	27
studio_primary	0
studios_colab	0
genre	0


```
df1=df.copy()
```

```
df1.mediaType.fillna("Other",inplace=True)
```

```
df1["duration"] = df1["duration"].fillna( value=df1.groupby (["genre", "mediaType"]) ["duration"].transform("median") )
```

```
df1["votes"] = df1["votes"].fillna( value=df1.groupby (["genre", "mediaType"]) ["votes"].transform("median") )
```


```
df1.isnull().sum()
```



	0
title	0
mediaType	0
eps	0
duration	8
startYr	0
finishYr	0
description	2409
contentWarn	0
watched	0
watching	0
rating	0
votes	0
studio_primary	0
studios_colab	0
genre	0


```
df1["duration"] = df1 ["duration"].fillna( value=df1.groupby (["genre"]) ["duration"].transform("median") )
```

```
df1.isnull().sum()
```



	0
title	0
mediaType	0
eps	0
duration	0
startYr	0
finishYr	0
description	2409
contentWarn	0
watched	0
watching	0
rating	0
votes	0
studio_primary	0
studios_colab	0
genre	0

```
df1["years_running"] = df1["finishYr"]- df1["startYr"]
df1.drop(["startYr", "finishYr"], axis=1, inplace=True)
df1.head()
```

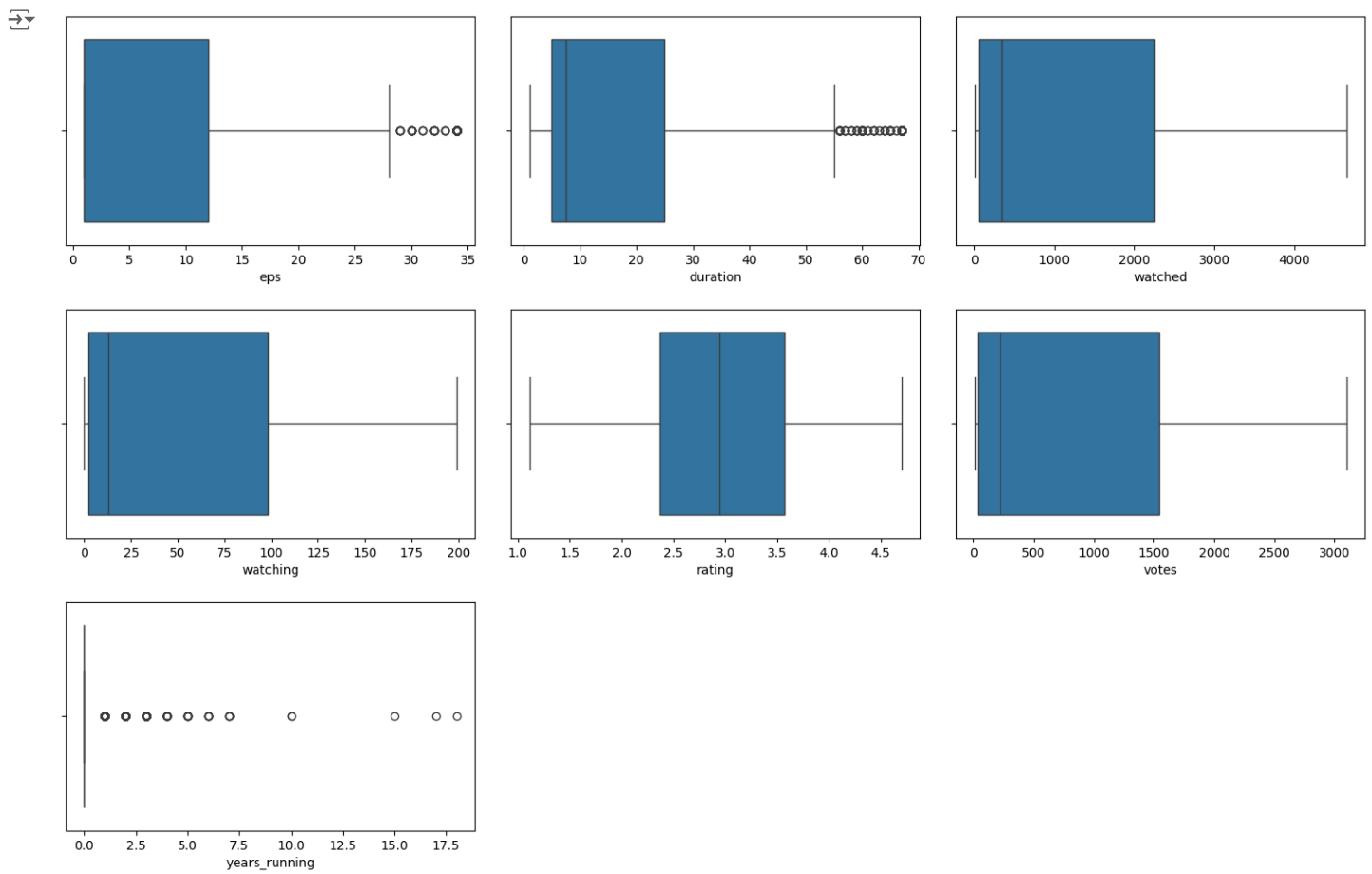


	title	mediaType	eps	duration	description	contentWarn	watched	watching	rating	votes	studio_primary	studios_colab
0	Dragon Ball Z Movie 15: Resurrection 'F'	Movie	1	67.0	Even the complete obliteration of his physical...	No	4649	86	3.979	3100.0	Toei Animation	No
1	Kuripuri*Kuripura	Movie	1	5.0	NaN	No	10	0	2.120	10.0	Others	No
2	GJ-bu@	TV Special	1	46.0	The story is set during the spring vacation im...	No	1630	16	3.758	1103.0	Others	No

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```
num_cols= df1.select_dtypes(include=np.number).columns.tolist()
plt.figure(figsize=(15,10))
for i, variable in enumerate(num_cols):
    plt.subplot(3, 3, i + 1)
    sns.boxplot(data=df1, x=variable)
plt.tight_layout(pad=2)
plt.show()
```



```
df1.drop(["title", "description"], axis=1, inplace=True)
df1.head()
```

	mediaType	eps	duration	contentWarn	watched	watching	rating	votes	studio_primary	studios_colab	genre	years_running
0	Movie	1	67.0	No	4649	86	3.979	3100.0	Toei Animation	No	Other	0
1	Movie	1	5.0	No	10	0	2.120	10.0	Others	No	Other	0
2	TV Special	1	46.0	No	1630	16	3.758	1103.0	Others	No	Other	0
3	Movie	1	67.0	No	4649	184	4.444	3100.0	Others	No	Drama	0
4	DVD Special	1	4.0	No	346	8	2.494	234.0	Others	No	Other	0

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```
df2=df1.copy()
```

```
x = df2.drop(["rating"], axis=1)
y = df2["rating"]
```

```
x = sm.add_constant(x)
```

```
x = pd.get_dummies( x, columns =x.select_dtypes (include=["object", "category"]).columns.tolist(), drop_first=True )
x.head()
```

	const	eps	duration	watched	watching	votes	years_running	mediaType_Movie	mediaType_Music Video	mediaType_OVA	mediaType_Other	medi.
0	1.0	1	67.0	4649	86	3100.0	0	True	False	False	False	
1	1.0	1	5.0	10	0	10.0	0	True	False	False	False	
2	1.0	1	46.0	1630	16	1103.0	0	False	False	False	False	
3	1.0	1	67.0	4649	184	3100.0	0	True	False	False	False	
4	1.0	1	4.0	346	8	234.0	0	False	False	False	False	

```
x=x.astype(float)
x.head()
```

	const	eps	duration	watched	watching	votes	years_running	mediaType_Movie	mediaType_Music Video	mediaType_OVA	mediaType_Other	medi.
0	1.0	1.0	67.0	4649.0	86.0	3100.0	0.0	1.0	0.0	0.0	0.0	
1	1.0	1.0	5.0	10.0	0.0	10.0	0.0	1.0	0.0	0.0	0.0	
2	1.0	1.0	46.0	1630.0	16.0	1103.0	0.0	0.0	0.0	0.0	0.0	
3	1.0	1.0	67.0	4649.0	184.0	3100.0	0.0	1.0	0.0	0.0	0.0	
4	1.0	1.0	4.0	346.0	8.0	234.0	0.0	0.0	0.0	0.0	0.0	

```
x_train, x_test, y_train, y_test= train_test_split(x,y,test_size=0.3, random_state=1)
print("Number of rows in train data", x_train.shape[0])
print("Number of rows in test data=" , x_test.shape[0])
```

```
Number of rows in train data 4566
Number of rows in test data= 1957
```

```
olsmodel = sm.OLS(y_train, x_train).fit()
print(olsmodel.summary())
```

OLS Regression Results						
Dep. Variable:	rating	R-squared:	0.722			
Model:	OLS	Adj. R-squared:	0.720			
Method:	Least Squares	F-statistic:	357.4			
Date:	Tue, 26 Nov 2024	Prob (F-statistic):	0.00			
Time:	15:18:21	Log-Likelihood:	-2307.9			
No. Observations:	4566	AIC:	4684.			
Df Residuals:	4532	BIC:	4902.			
Df Model:	33					
Covariance Type:	nonrobust					
	coef	std err	t	P> t	[0.025	0.975]
const	2.7707	0.074	37.657	0.000	2.626	2.915
eps	0.0193	0.001	17.871	0.000	0.017	0.021
duration	0.0123	0.000	25.656	0.000	0.011	0.013
watched	0.0004	2.82e-05	14.213	0.000	0.000	0.000
watching	0.0037	0.000	21.258	0.000	0.003	0.004
votes	-0.0003	4.52e-05	-7.460	0.000	-0.000	-0.000
years_running	-0.0767	0.008	-9.039	0.000	-0.093	-0.060
mediaType_Movie	-0.2975	0.032	-9.168	0.000	-0.361	-0.234
mediaType_Music Video	-0.2911	0.030	-9.717	0.000	-0.350	-0.232
mediaType_OVA	-0.3017	0.030	-10.094	0.000	-0.360	-0.243
mediaType_Other	-0.2731	0.035	-7.885	0.000	-0.341	-0.205
mediaType_TV	-0.5301	0.034	-15.800	0.000	-0.596	-0.464
mediaType_TV Special	-0.1854	0.039	-4.757	0.000	-0.262	-0.109
mediaType_Web	-0.4087	0.031	-13.263	0.000	-0.469	-0.348
contentWarn_Yes	-0.1776	0.020	-8.735	0.000	-0.218	-0.138
studio_primary_J.C. Staff	-0.1578	0.055	-2.850	0.004	-0.266	-0.049
studio_primary_MADHOUSE	-0.2071	0.057	-3.635	0.000	-0.319	-0.095
studio_primary_OLM	-0.3696	0.064	-5.785	0.000	-0.495	-0.244
studio_primary_Others	-0.2482	0.044	-5.603	0.000	-0.335	-0.161
studio_primary_Production I.G	0.0828	0.058	1.430	0.153	-0.031	0.196
studio_primary_Studio Deen	-0.1264	0.061	-2.083	0.037	-0.245	-0.007
studio_primary_Studio Pierrot	-0.2311	0.062	-3.747	0.000	-0.352	-0.110
studio_primary_Sunrise	-0.0689	0.054	-1.282	0.200	-0.174	0.036

```

studio_primary_TMS Entertainment      0.0361      0.057      0.639      0.523      -0.075      0.147
studio_primary_Toei Animation         -0.1817     0.051     -3.580      0.000      -0.281     -0.082
studios_colab_Yes                     0.0021      0.028      0.072      0.942      -0.054      0.058
genre_Adventure                      -0.1219     0.062     -1.964      0.050      -0.244     -0.000
genre_Based on a Manga                -0.0056     0.086     -0.065      0.948      -0.175      0.164
genre_Comedy                         -0.2693     0.075     -3.602      0.000      -0.416     -0.123
genre_Drama                          0.2504     0.067      3.740      0.000      0.119      0.382
genre_Fantasy                        0.0621     0.075      0.823      0.411      -0.086      0.210
genre_Other                          -0.0436     0.055     -0.791      0.429      -0.152      0.064
genre_Romance                        0.0026     0.065      0.040      0.968      -0.125      0.130
genre_Sci Fi                         -0.0596     0.068     -0.874      0.382      -0.193      0.074
=====

```

```

Omnibus:          147.177   Durbin-Watson:          1.944
Prob(Omnibus):    0.000   Jarque-Bera (JB):       70.085
Skew:             0.052   Prob(JB):               6.04e-16
Kurtosis:         2.402   Cond. No.               7.64e+04
=====

```

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.  
 [2] The condition number is large, 7.64e+04. This might indicate that there are

```

# function to compute different metrics to check performance of a regression model
def model_performance_regression (model, predictors, target):
    pred = model.predict(predictors)
    r2 = r2_score (target, pred)
    rmse = np.sqrt(mean_squared_error(target, pred))
    mae = mean_absolute_error(target, pred)
    df_perf = pd.DataFrame( { "RMSE": rmse, "MAE": mae, "R-squared": r2,}, index=[0])
    return df_perf

```

```

# checking model performance on train set (seen 70% data)
print("Training Performance\n")
olsmodel_train_perf = model_performance_regression (olsmodel, x_train, y_train)
olsmodel_train_perf

```

↗ Training Performance

	RMSE	MAE	R-squared	
0	0.40112	0.330417	0.722387	

```

# checking model performance on test set (seen 30% data)
print("Test Performance\n")
olsmodel_test_perf = model_performance_regression (olsmodel, x_test, y_test)
olsmodel_test_perf

```

↗ Test Performance



	RMSE	MAE	R-squared	
0	0.413096	0.340426	0.703053	

```

from statsmodels.stats.outliers_influence import variance_inflation_factor
def checking_vif(predictors):
    vif = pd.DataFrame()
    vif["feature"] = predictors.columns
    # calculating VIF for each feature
    vif["VIF"] = [variance_inflation_factor(predictors.values, i) for i in range(len(predictors.columns))]
    return vif
checking_vif(x_train).sort_values('VIF', ascending=False)

```




	feature	VIF		
0	const	152.488126		
5	votes	79.580182		
3	watched	68.407244		
31	genre_Other	11.591914		
18	studio_primary_Others	11.131121		
11	mediaType_TV	6.998184		
4	watching	4.997799		
26	genre_Adventure	4.197895		
7	mediaType_Movie	4.062291		
24	studio_primary_Toei Animation	3.983035		
1	eps	3.907746		
32	genre_Romance	3.349247		
9	mediaType_OVA	3.049100		
29	genre_Drama	2.915488		
22	studio_primary_Sunrise	2.881062		
2	duration	2.752909		
33	genre_Sci Fi	2.698722		
23	studio_primary_TMS Entertainment	2.530580		
15	studio_primary_J.C. Staff	2.512300		
8	mediaType_Music Video	2.409153		
16	studio_primary_MADHOUSE	2.359150		
19	studio_primary_Production I.G	2.240209		
13	mediaType_Web	2.228931		
28	genre_Comedy	2.175454		
30	genre_Fantasy	2.080246		
20	studio_primary_Studio Deen	2.004036		
21	studio_primary_Studio Pierrot	2.002522		
17	studio_primary_OLM	1.882586		
12	mediaType_TV Special	1.756936		
10	mediaType_Other	1.735561		
27	genre_Based on a Manga	1.687548		
6	years_running	1.272615		
14	contentWarn_Yes	1.125939		
25	studios_colab_Yes	1.043084		

```
def treating_multicollinearity (predictors, target, high_vif_columns):
    # empty lists to store adj. R-squared and RMSE values
    adj_r2 = []
    rmse = []
    # build ols models by dropping one of the high VIF columns at a time
    # store the adjusted R-squared and RMSE in the lists defined previously
    for cols in high_vif_columns:
        train = predictors.loc[:, ~predictors.columns.str.startswith(cols)]
        olsmodel = sm.OLS (target, train).fit()
        adj_r2.append(olsmodel.rsquared_adj)
        rmse.append(np.sqrt(olsmodel.mse_resid))
    temp = pd.DataFrame( {
        "col": high_vif_columns,
        "Adj. R-squared after_dropping col": adj_r2,
        "RMSE after dropping col": rmse, } ).sort_values (by="Adj. R-squared after_dropping col", ascending=False)
    temp.reset_index(drop=True, inplace=True)
```





```
return temp
```

```
col_list = ["watched", "votes"]  
res = treating_multicollinearity (x_train, y_train, col_list)  
res
```




	col	Adj. R-squared after dropping col	RMSE after dropping col
0	votes	0.716994	0.405042
1	watched	0.707967	0.411451






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```
col_to_drop = "votes"  
x_train2 = x_train.loc[:, ~x_train.columns.str.startswith(col_to_drop)]  
x_test2 = x_test.loc[:, ~x_test.columns.str.startswith(col_to_drop)]  
vif = checking_vif(x_train2)  
print("VIF after dropping", col_to_drop)  
vif
```

 VIF after dropping votes

	feature	VIF	
0	const	152.249342	
1	eps	3.873093	
2	duration	2.752030	
3	watched	3.235392	
4	watching	4.154724	
5	years_running	1.272523	
6	mediaType_Movie	4.060078	
7	mediaType_Music Video	2.408173	
8	mediaType_OVA	3.049085	
9	mediaType_Other	1.729382	
10	mediaType_TV	6.924966	
11	mediaType_TV Special	1.756017	
12	mediaType_Web	2.227588	
13	contentWarn_Yes	1.125939	
14	studio_primary_J.C. Staff	2.512299	
15	studio_primary_MADHOUSE	2.359013	
16	studio_primary_OLM	1.882550	
17	studio_primary_Others	11.126123	
18	studio_primary_Production I.G	2.240164	
19	studio_primary_Studio Deen	2.003836	
20	studio_primary_Studio Pierrot	2.002485	
21	studio_primary_Sunrise	2.879639	
22	studio_primary_TMS Entertainment	2.530283	
23	studio_primary_Toei Animation	3.982565	
24	studios_colab_Yes	1.042889	
25	genre_Adventure	4.197219	
26	genre_Based on a Manga	1.687052	
27	genre_Comedy	2.175119	
28	genre_Drama	2.913752	
29	genre_Fantasy	2.079839	
30	genre_Other	11.583777	
31	genre_Romance	3.348489	
32	genre_Sci Fi	2.697440	

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```
olsmod1 = sm.OLS(y_train, x_train2).fit()
print(olsmod1.summary())
```



## OLS Regression Results

```
=====
Dep. Variable:          rating    R-squared:                0.719
Model:                  OLS      Adj. R-squared:           0.717
Method:                 Least Squares    F-statistic:            362.4
Date:                  Tue, 26 Nov 2024    Prob (F-statistic):      0.00
Time:                  15:34:46    Log-Likelihood:         -2335.7
No. Observations:      4566    AIC:                    4737.
Df Residuals:          4533    BIC:                    4950.
Df Model:              32
Covariance Type:       nonrobust
=====
                    coef    std err          t      P>|t|      [0.025    0.975]
=====
```

const	2.7925	0.074	37.755	0.000	2.647	2.937
eps	0.0200	0.001	18.545	0.000	0.018	0.022
duration	0.0122	0.000	25.374	0.000	0.011	0.013
watched	0.0002	6.17e-06	31.678	0.000	0.000	0.000
watching	0.0031	0.000	19.836	0.000	0.003	0.003
years_running	-0.0761	0.009	-8.922	0.000	-0.093	-0.059
mediaType_Movie	-0.3031	0.033	-9.289	0.000	-0.367	-0.239
mediaType_Music Video	-0.2957	0.030	-9.811	0.000	-0.355	-0.237
mediaType_OVA	-0.3012	0.030	-10.017	0.000	-0.360	-0.242
mediaType_Other	-0.2577	0.035	-7.409	0.000	-0.326	-0.189
mediaType_TV	-0.5557	0.034	-16.551	0.000	-0.621	-0.490
mediaType_TV Special	-0.1787	0.039	-4.560	0.000	-0.256	-0.102
mediaType_Web	-0.4143	0.031	-13.370	0.000	-0.475	-0.354
contentWarn_Yes	-0.1776	0.020	-8.680	0.000	-0.218	-0.137
studio_primary_J.C. Staff	-0.1579	0.056	-2.835	0.005	-0.267	-0.049
studio_primary_MADHOUSE	-0.2104	0.057	-3.670	0.000	-0.323	-0.098
studio_primary_OLM	-0.3675	0.064	-5.717	0.000	-0.494	-0.242
studio_primary_Others	-0.2552	0.045	-5.728	0.000	-0.343	-0.168
studio_primary_Production I.G	0.0808	0.058	1.388	0.165	-0.033	0.195
studio_primary_Studio Deen	-0.1219	0.061	-1.997	0.046	-0.242	-0.002
studio_primary_Studio Pierrot	-0.2331	0.062	-3.757	0.000	-0.355	-0.111
studio_primary_Sunrise	-0.0600	0.054	-1.110	0.267	-0.166	0.046
studio_primary_TMS Entertainment	0.0407	0.057	0.715	0.474	-0.071	0.152
studio_primary_Toei Animation	-0.1859	0.051	-3.639	0.000	-0.286	-0.086
studios_colab_Yes	0.0050	0.029	0.173	0.863	-0.051	0.061
genre_Adventure	-0.1278	0.062	-2.047	0.041	-0.250	-0.005
genre_Based on a Manga	-0.0166	0.087	-0.191	0.848	-0.187	0.154
genre_Comedy	-0.2762	0.075	-3.673	0.000	-0.424	-0.129
genre_Drama	0.2382	0.067	3.538	0.000	0.106	0.370
genre_Fantasy	0.0542	0.076	0.714	0.475	-0.095	0.203
genre_Other	-0.0545	0.055	-0.983	0.326	-0.163	0.054
genre_Romance	-0.0047	0.065	-0.072	0.942	-0.133	0.124
genre_Sci Fi	-0.0707	0.069	-1.031	0.303	-0.205	0.064

```
=====
Omnibus:          146.326   Durbin-Watson:          1.946
Prob(Omnibus):    0.000   Jarque-Bera (JB):          69.874
Skew:             0.053   Prob(JB):          6.71e-16
Kurtosis:         2.403   Cond. No.          6.35e+04
=====
```

## Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.  
 [2] The condition number is large, 6.35e+04. This might indicate that there are strong multicollinearity or other numerical problems.

```
predictors = x_train2.copy()
cols = predictors.columns.tolist()
max_p_value = 1
while len(cols) > 0:
    x_train_aux = predictors[cols]
    model = sm.OLS(y_train, x_train_aux).fit()
    p_values = model.pvalues
    max_p_value = max(p_values)
    feature_with_p_max= p_values.idxmax()
    if max_p_value > 0.05:
        cols.remove(feature_with_p_max)
    else:
        break
selected_features = cols
print(selected_features)
```

```
['const', 'eps', 'duration', 'watched', 'watching', 'years_running', 'mediaType_Movie', 'mediaType_Music Video', 'mediaType_OVA', 'media
```

```
x_train3= x_train2[selected_features]
x_test3 = x_test2[selected_features]
```

```
olsmod2= sm.OLS(y_train, x_train3).fit()
print(olsmod2.summary())
```

```
OLS Regression Results
=====
Dep. Variable:          rating   R-squared:          0.718
Model:                  OLS     Adj. R-squared:       0.717
Method:                 Least Squares   F-statistic:       482.7
Date:                  Tue, 26 Nov 2024   Prob (F-statistic): 0.00
Time:                  15:38:48   Log-Likelihood:    -2340.4
No. Observations:      4566   AIC:               4731.
Df Residuals:          4541   BIC:               4891.
Df Model:              24
```

Covariance Type: nonrobust

	coef	std err	t	P> t	[0.025	0.975]
const	2.7875	0.033	84.367	0.000	2.723	2.852
eps	0.0201	0.001	18.671	0.000	0.018	0.022
duration	0.0123	0.000	26.100	0.000	0.011	0.013
watched	0.0002	6.16e-06	31.750	0.000	0.000	0.000
watching	0.0031	0.000	19.918	0.000	0.003	0.003
years_running	-0.0762	0.009	-8.944	0.000	-0.093	-0.059
mediaType_Movie	-0.3078	0.032	-9.550	0.000	-0.371	-0.245
mediaType_Music Video	-0.2987	0.030	-9.971	0.000	-0.357	-0.240
mediaType_OVA	-0.3016	0.030	-10.092	0.000	-0.360	-0.243
mediaType_Other	-0.2607	0.035	-7.548	0.000	-0.328	-0.193
mediaType_TV	-0.5598	0.033	-16.781	0.000	-0.625	-0.494
mediaType_TV Special	-0.1816	0.039	-4.657	0.000	-0.258	-0.105
mediaType_Web	-0.4164	0.031	-13.523	0.000	-0.477	-0.356
contentWarn_Yes	-0.1786	0.020	-8.745	0.000	-0.219	-0.139
studio_primary_J.C. Staff	-0.2017	0.041	-4.865	0.000	-0.283	-0.120
studio_primary_MADHOUSE	-0.2532	0.043	-5.844	0.000	-0.338	-0.168
studio_primary_OLM	-0.4121	0.052	-7.941	0.000	-0.514	-0.310
studio_primary_Others	-0.2993	0.024	-12.445	0.000	-0.346	-0.252
studio_primary_Studio Deen	-0.1657	0.048	-3.432	0.001	-0.260	-0.071
studio_primary_Studio Pierrot	-0.2740	0.049	-5.591	0.000	-0.370	-0.178
studio_primary_Sunrise	-0.1088	0.039	-2.815	0.005	-0.185	-0.033
studio_primary_Toei Animation	-0.2325	0.034	-6.853	0.000	-0.299	-0.166
genre_Adventure	-0.0783	0.032	-2.467	0.014	-0.140	-0.016
genre_Comedy	-0.2271	0.052	-4.374	0.000	-0.329	-0.125
genre_Drama	0.2881	0.040	7.192	0.000	0.210	0.367

```

=====
Omnibus:            143.175   Durbin-Watson:           1.946
Prob(Omnibus):      0.000   Jarque-Bera (JB):         68.833
Skew:               0.052   Prob(JB):                 1.13e-15
Kurtosis:           2.407   Cond. No.                  2.81e+04
=====

```


Notes:


[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.  
 [2] The condition number is large, 2.81e+04. This might indicate that there are strong multicollinearity or other numerical problems.

```

# checking model performance on train set (seen 70% data)
print("Training Performance\n")
olsmod2_train_perf = model_performance_regression(olsmod2, x_train3, y_train)
olsmod2_train_perf

```

 Training Performance

	RMSE	MAE	R-squared	
0	0.40399	0.33291	0.7184	

```

# checking model performance on test set (seen 30% data)
print("Test Performance\n")
olsmod2_test_perf = model_performance_regression(olsmod2, x_test3, y_test)
olsmod2_test_perf

```

 Test Performance

	RMSE	MAE	R-squared	
0	0.414583	0.341345	0.700912	

```

df_pred= pd.DataFrame()
df_pred["Actual Values"] = y_train
df_pred["Fitted Values"] = olsmod2.fittedvalues
df_pred["Residuals"] = olsmod2.resid
df_pred.head()

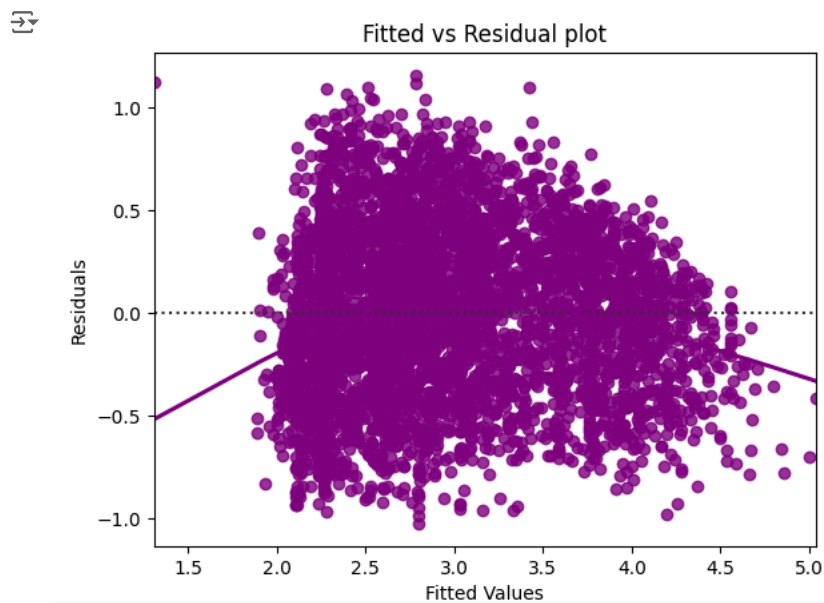
```

	Actual Values	Fitted Values	Residuals
5432	2.872	2.795321	0.076679
5326	2.766	2.275887	0.490113
1021	4.049	4.446845	-0.397845
836	3.153	3.176604	-0.023604
1396	2.167	2.265921	-0.098921

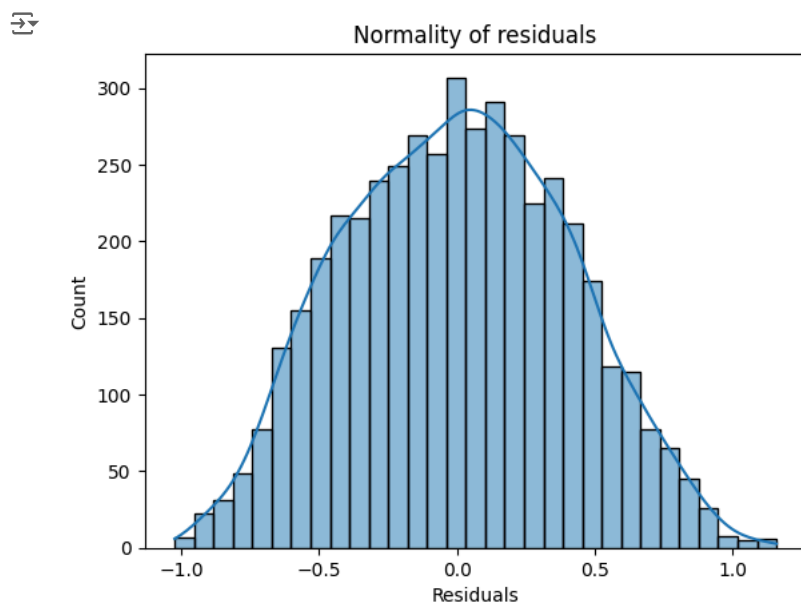
Next steps:

[View recommended plots](#)[New interactive sheet](#)

```
sns.residplot( data=df_pred, x="Fitted Values", y="Residuals", color="purple", lowess = True )
plt.xlabel("Fitted Values")
plt.ylabel("Residuals")
plt.title("Fitted vs Residual plot")
plt.show()
```



```
sns.histplot(data=df_pred, x="Residuals", kde=True)
plt.title("Normality of residuals")
plt.show()
```



```
import pylab
import scipy.stats as stats
stats.probplot(df_pred ["Residuals"], dist="norm", plot=pylab)
plt.show()
```

