case-study-predictive-analysis

November 26, 2024

1 Predictive Modelling

1.1 Linear Regression

1.2 objective

1.2.1 A straming company is focusing on the anime available in their portal and wants to identify the most important factors involved in rating an anime. As a data scientist, you are tasked with analyzing the portal's anime data and identifying the important factors by building a predictive model to predict the rating of an anime.

1.3 Data Dictionary

Each record in the database provides a description of an anime. A detailed data dictionary can be found below.

1. **title: title of the anime**

2. **media Type: format of publication**

3. **eps: number of episodes (movies are considered 1 episode)**

4. **duration: duration of an episode in minutes**

5. **startYr: the year that airing started**

6. **finishYr: the year that airing finished**

7. **description: the synopsis of the plot**

8. **contentWarn: content warning**

9. **watched: number of users that completed it**

10. **watching: number of users that are watching it**

11. **rating: average user rating**

12. votes: number of votes that contribute to the rating

13. studio_primary: studios responsible for creation

14. studios_colab: whether there was a collaboration between studios for anime production

15. genre: genre to which the anime belongs

2 Importing Libaries

[2]:
```
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
```

3 Loading Dataset

[4]:
```
df = pd.read_csv('/Users/vishal/Desktop/CSV files/anime_rating_dataset.csv')
```

3.0.1 Displaying the first few rows of data set

[6]:
```
df.head()
```

[6]:
```
                                title    mediaType  eps  duration  \
0  Dragon Ball Z Movie 15: Resurrection 'F'        Movie    1      67.0
1                     Kuripuri*Kuripura        Movie    1       5.0
2                                GJ-bu@  TV Special    1      46.0
3         Nausicaa of the Valley of the Wind        Movie    1      67.0
4                    Miru Tights Special  DVD Special    1       4.0

   startYr  finishYr                                        description  \
0     2015      2015  Even the complete obliteration of his physical…
1     2008      2008                                               NaN
2     2014      2014  The story is set during the spring vacation im…
3     1984      1984  One thousand years after the Giant Warriors ca…
4     2019      2019  Yua is asked to model an illustrator's designs…

  contentWarn  watched  watching  rating   votes  studio_primary  \
0          No     4649        86   3.979  3100.0  Toei Animation
1          No       10         0   2.120    10.0          Others
2          No     1630        16   3.758  1103.0          Others
```

```
3          No      4649        184    4.444  3100.0           Others
4          No       346          8    2.494   234.0           Others

  studios_colab  genre
0            No  Other
1            No  Other
2            No  Other
3            No  Drama
4            No  Other
```

3.0.2 Checking the shape of the dataset

[8]:
```
df.shape
```

[8]:
```
(6523, 15)
```

- **The dataset contains information (15 attributes) about 6523 anime**

3.0.3 Checking the data types of the columns for the dataset

[11]:
```
df.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
```

- **There are 8 numeric (float and int type) and 7 string (object type) columns in the data**

- **The target variable is the rating of an anime, which is of float type**

4 Statistical summary of the dataset

[14]:
```
df.describe()
```

[14]:
```
               eps     duration      startYr     finishYr      watched  \
count  6523.000000  6248.000000  6523.000000  6523.000000  6523.000000
mean      8.716235    18.396287  2005.241147  2005.575349  1347.948643
std      11.002479    20.949350    12.911035    12.568169  1737.138112
min       1.000000     1.000000  1967.000000  1970.000000     5.000000
25%       1.000000     5.000000  2000.000000  2000.000000    56.000000
50%       1.000000     7.000000  2010.000000  2010.000000   349.000000
75%      12.000000    25.000000  2015.000000  2015.000000  2252.500000
max      34.000000    67.000000  2020.000000  2020.000000  4649.000000

          watching       rating        votes
count  6523.000000  6523.000000  6496.000000
mean     57.445654     2.962553   906.253233
std      76.527405     0.760486  1171.677648
min       0.000000     1.111000    10.000000
25%       2.000000     2.371000    34.000000
50%      13.000000     2.944000   227.500000
75%      98.000000     3.568000  1567.750000
max     199.000000     4.702000  3100.000000
```

- **We can see that the anime ratings vary between 1.1 and 4.7, which suggests that the anime were rated on a scale of 0-5**

- **The general rating of anime is 2.96**

- **TV is the most occurring type of media.**

- **The number of views for the anime in the data varies from 5 to ~5000**

- **The number of votes received by an anime in the data varies from 10 to 3100**

5 Checking for duplicate values

[17]:
```
df.duplicated().sum()
```

[17]: 0

- **There are no duplicate values in the data**

6 Checking for missing values

[20]:
```
df.isnull().sum()
```

[20]:
```
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
dtype: int64
```

- **There are missing values in many columns.**

7 Data Preprocessing

[23]:
```
df.isnull().sum()
```

[23]:
```
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
dtype: int64
```

Let's fix the missing values in the data.

- **For the variable mediaType, we will impute the missing values with 'Other' as the exact values for that category are not known**

- **For the variables duration and votes, we will impute the missing values in each column with the median grouped by genre and mediaType as both the columns have skewed distributions**

[25]:
```
# we first create a copy of the data to avoid changes to it
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")
)
```

[26]:
```
df1.isnull().sum()
```

[26]:
```
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
dtype: int64
```

- **We will impute the remaining missing values in the duration column with the median grouped by genre**

[28]:
```
df1["duration"] = df1["duration"].fillna(
value=df1.groupby(["genre"]) ["duration"]. transform("median")
)
```

[29]:
```
df1.isnull().sum()
```

[29]:
```
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
dtype: int64
```

- **All the missing values have been treated.**

8 Feature Engineering

- **Let's create a new feature years_running by taking the difference between finishYr and startyr columns**

- **We will drop the original columns once the new feature is created as the year values themselves are not numerical in nature**

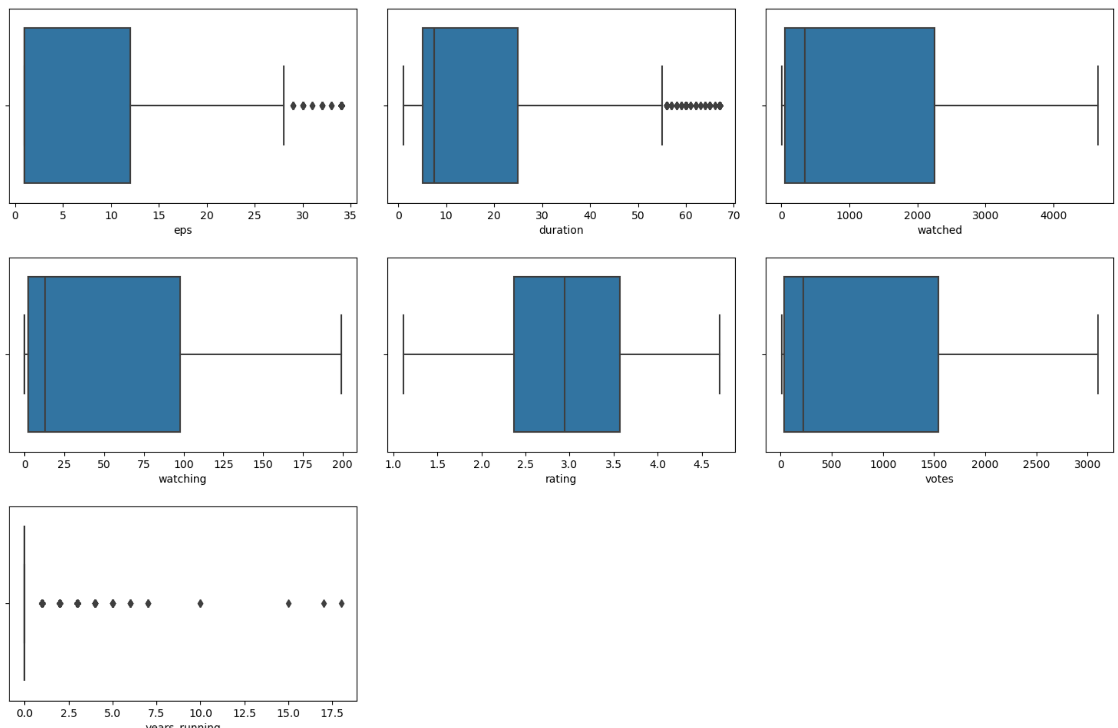
[33]:
```
df1["years_running"] = df1["finishYr"] - df1["startYr"]
df1.drop(["startYr"
, "finishYr"], axis=1, inplace=True)
df1. head()
```

[33]:
```
                                      title    mediaType  eps  duration  \
0  Dragon Ball Z Movie 15: Resurrection 'F'        Movie    1      67.0
1                         Kuripuri*Kuripura        Movie    1       5.0
2                                     GJ-bu@  TV Special    1      46.0
3        Nausicaa of the Valley of the Wind        Movie    1      67.0
4                       Miru Tights Special  DVD Special    1       4.0

                                         description contentWarn  watched  \
0  Even the complete obliteration of his physical…          No     4649
1                                                NaN          No       10
2  The story is set during the spring vacation im…          No     1630
3  One thousand years after the Giant Warriors ca…          No     4649
4  Yua is asked to model an illustrator's designs…          No      346

   watching  rating   votes  studio_primary studios_colab  genre  \
0        86   3.979  3100.0  Toei Animation            No  Other
1         0   2.120    10.0          Others            No  Other
```

```
2        16   3.758  1103.0          Others              No   Other
3       184   4.444  3100.0          Others              No   Drama
4         8   2.494   234.0          Others              No   Other

   years_running
0              0
1              0
2              0
3              0
4              0
```

9 Outlier detection

[35]:
```python
# outlier detection using boxplot
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()
```



- **There are quite a few outliers in the data**

- **However, we will not treat them as they are proper values**

- **We will drop the columns title and description as they contain a lot of text and too many unique values, and can be excluded from modeling**

[37]:
```
df1.drop(["title", "description"], axis=1, inplace=True)
```

[38]:
```
df1.head()
```

[38]:
```
     mediaType  eps  duration contentWarn  watched  watching  rating   votes  \
0        Movie    1      67.0          No     4649        86   3.979  3100.0
1        Movie    1       5.0          No       10         0   2.120    10.0
2   TV Special    1      46.0          No     1630        16   3.758  1103.0
3        Movie    1      67.0          No     4649       184   4.444  3100.0
4  DVD Special    1       4.0          No      346         8   2.494   234.0

    studio_primary studios_colab  genre  years_running
0  Toei Animation            No  Other              0
1          Others            No  Other              0
2          Others            No  Other              0
3          Others            No  Drama              0
4          Others            No  Other              0
```

10 Data Preparation for modeling

- **We want to predict the rating of an anime**

- **Before we proceed to build a model, we'll have to encode categorical features**

- **We'll split the data into train and test to be able to evaluate the model that we build on the train data**

- **We will build a Linear Regression model using the train data and then check it's performance**

[41]:
```
df2=df1.copy()
```

[42]:
```
# defining X and y variables
X = df2.drop(["rating"], axis=1)
y = df2["rating"]

# let's add the intercept to data
X = sm.add_constant(X)  # Corrected this line

# creating dummy variables
X = pd.get_dummies(
```

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

[42]:

```
   const  eps  duration  watched  watching   votes  years_running  \
0    1.0    1      67.0     4649        86  3100.0              0
1    1.0    1       5.0       10         0    10.0              0
2    1.0    1      46.0     1630        16  1103.0              0
3    1.0    1      67.0     4649       184  3100.0              0
4    1.0    1       4.0      346         8   234.0              0

   mediaType_Movie  mediaType_Music Video  mediaType_OVA  …  \
0             True                  False          False  …
1             True                  False          False  …
2            False                  False          False  …
3             True                  False          False  …
4            False                  False          False  …

   studio_primary_Toei Animation  studios_colab_Yes  genre_Adventure  \
0                           True              False            False
1                          False              False            False
2                          False              False            False
3                          False              False            False
4                          False              False            False

   genre_Based on a Manga  genre_Comedy  genre_Drama  genre_Fantasy  \
0                   False         False        False          False
1                   False         False        False          False
2                   False         False        False          False
3                   False         False         True          False
4                   False         False        False          False

   genre_Other  genre_Romance  genre_Sci Fi
0         True          False         False
1         True          False         False
2         True          False         False
3        False          False         False
4         True          False         False

[5 rows x 34 columns]
```

[43]:

```
# converting the input attributes into float type for modeling
x = X.astype(float)
X. head ()
```

[43]:

```
   const  eps  duration  watched  watching   votes  years_running  \
0    1.0    1      67.0     4649        86  3100.0              0
1    1.0    1       5.0       10         0    10.0              0
2    1.0    1      46.0     1630        16  1103.0              0
3    1.0    1      67.0     4649       184  3100.0              0
4    1.0    1       4.0      346         8   234.0              0

   mediaType_Movie  mediaType_Music Video  mediaType_OVA  …  \
0             True                  False          False  …
1             True                  False          False  …
2            False                  False          False  …
3             True                  False          False  …
4            False                  False          False  …

   studio_primary_Toei Animation  studios_colab_Yes  genre_Adventure  \
0                           True              False            False
1                          False              False            False
2                          False              False            False
3                          False              False            False
4                          False              False            False

   genre_Based on a Manga  genre_Comedy  genre_Drama  genre_Fantasy  \
0                   False         False        False          False
1                   False         False        False          False
2                   False         False        False          False
3                   False         False         True          False
4                   False         False        False          False

   genre_Other  genre_Romance  genre_Sci Fi
0         True          False         False
1         True          False         False
2         True          False         False
3        False          False         False
4         True          False         False

[5 rows x 34 columns]
```

[44]:

```
# splitting the data in 70:30 ratio for train to test data
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
```

11 Model Building - Linear Regression

[57]:
```
print(X_train.dtypes)
print(X_test.dtypes)
```

```
const                              float64
eps                                  int64
duration                           float64
watched                              int64
watching                             int64
votes                              float64
years_running                        int64
mediaType_Movie                       bool
mediaType_Music Video                 bool
mediaType_OVA                         bool
mediaType_Other                       bool
mediaType_TV                          bool
mediaType_TV Special                  bool
mediaType_Web                         bool
contentWarn_Yes                       bool
studio_primary_J.C. Staff             bool
studio_primary_MADHOUSE               bool
studio_primary_OLM                    bool
studio_primary_Others                 bool
studio_primary_Production I.G         bool
studio_primary_Studio Deen            bool
studio_primary_Studio Pierrot         bool
studio_primary_Sunrise                bool
studio_primary_TMS Entertainment      bool
studio_primary_Toei Animation         bool
studios_colab_Yes                     bool
genre_Adventure                       bool
genre_Based on a Manga                bool
genre_Comedy                          bool
genre_Drama                           bool
genre_Fantasy                         bool
genre_Other                           bool
genre_Romance                         bool
genre_Sci Fi                          bool
dtype: object
const                              float64
eps                                  int64
duration                           float64
watched                              int64
watching                             int64
votes                              float64
years_running                        int64
```

```
mediaType_Movie                        bool
mediaType_Music Video                  bool
mediaType_OVA                          bool
mediaType_Other                        bool
mediaType_TV                           bool
mediaType_TV Special                   bool
mediaType_Web                          bool
contentWarn_Yes                        bool
studio_primary_J.C. Staff              bool
studio_primary_MADHOUSE                bool
studio_primary_OLM                     bool
studio_primary_Others                  bool
studio_primary_Production I.G          bool
studio_primary_Studio Deen             bool
studio_primary_Studio Pierrot          bool
studio_primary_Sunrise                 bool
studio_primary_TMS Entertainment       bool
studio_primary_Toei Animation          bool
studios_colab_Yes                      bool
genre_Adventure                        bool
genre_Based on a Manga                 bool
genre_Comedy                           bool
genre_Drama                            bool
genre_Fantasy                          bool
genre_Other                            bool
genre_Romance                          bool
genre_Sci Fi                           bool
dtype: object
```

[59]:
```python
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

# Convert all boolean columns to integers
X_train = X_train.astype({col: 'int' for col in X_train.
 ↪select_dtypes(include=['bool']).columns})
X_test = X_test.astype({col: 'int' for col in X_test.
 ↪select_dtypes(include=['bool']).columns})

# Ensure all columns are numeric
print(X_train.dtypes)
print(X_test.dtypes)
```

```python
# Fit the model again
olsmodel = sm.OLS(y_train, X_train).fit()
print(olsmodel.summary())
```

```
const                             float64
eps                                 int64
duration                          float64
watched                             int64
watching                            int64
votes                             float64
years_running                       int64
mediaType_Movie                     int64
mediaType_Music Video               int64
mediaType_OVA                       int64
mediaType_Other                     int64
mediaType_TV                        int64
mediaType_TV Special                int64
mediaType_Web                       int64
contentWarn_Yes                     int64
studio_primary_J.C. Staff           int64
studio_primary_MADHOUSE             int64
studio_primary_OLM                  int64
studio_primary_Others               int64
studio_primary_Production I.G       int64
studio_primary_Studio Deen          int64
studio_primary_Studio Pierrot       int64
studio_primary_Sunrise              int64
studio_primary_TMS Entertainment    int64
studio_primary_Toei Animation       int64
studios_colab_Yes                   int64
genre_Adventure                     int64
genre_Based on a Manga              int64
genre_Comedy                        int64
genre_Drama                         int64
genre_Fantasy                       int64
genre_Other                         int64
genre_Romance                       int64
genre_Sci Fi                        int64
dtype: object
const                             float64
eps                                 int64
duration                          float64
watched                             int64
watching                            int64
votes                             float64
years_running                       int64
mediaType_Movie                     int64
```

```
mediaType_Music Video                  int64
mediaType_OVA                          int64
mediaType_Other                        int64
mediaType_TV                           int64
mediaType_TV Special                   int64
mediaType_Web                          int64
contentWarn_Yes                        int64
studio_primary_J.C. Staff              int64
studio_primary_MADHOUSE                int64
studio_primary_OLM                     int64
studio_primary_Others                  int64
studio_primary_Production I.G          int64
studio_primary_Studio Deen             int64
studio_primary_Studio Pierrot          int64
studio_primary_Sunrise                 int64
studio_primary_TMS Entertainment       int64
studio_primary_Toei Animation          int64
studios_colab_Yes                      int64
genre_Adventure                        int64
genre_Based on a Manga                 int64
genre_Comedy                           int64
genre_Drama                            int64
genre_Fantasy                          int64
genre_Other                            int64
genre_Romance                          int64
genre_Sci Fi                           int64
dtype: object
                            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:                        22:39:51   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
strong multicollinearity or other numerical problems.
```

12 Interpreting the Regression Results

13 PART - 1

1. Adjusted. R-squared: It reflects the fit of the model.

• Adjusted R-squared values generally range from 0 to 1, where a higher value generally indicates a better fit, assuming certain conditions are met.

• In our case, the value for adj. R-squared is 0.722, which is good.

2. const coefficient: It is the Y-intercept.

• It means that if all the predictor variable coefficients are zero, then the expected output (i.e., Y) would be equal to the const coefficient.

• In our case, the value for const coefficient is 2.7707

3. Coefficient of a predictor variable: It represents the change in the output Y due to a change in the predictor variable (everything else held constant).

- **In our case, the coefficient of duration is 0.0123.**

14 Model Performance Check

Let's check the performance of the model using different metrics.

- **We will be using metric functions defined in sklearn for RMSE, MAE, and R2**

- **We will define a function to calculate MAPE and adjusted R2**

- **The mean absolute percentage error (MAPE) measures the accuracy of predictions as a percentage, and can be calculated as the average absolute percent error for each predicted value minus actual values divided by actual values. It works best if there are no extreme values in the data and none of the actual values are 0.**

- **We will create a function which will print out all the above metrics in one go.**

[67]:
```python
# 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)  # Compute R-squared
    rmse = np.sqrt(mean_squared_error(target, pred))  # Compute RMSE
    mae = mean_absolute_error(target, pred)  # Compute MAE

    # Creating a dataframe of metrics
    df_perf = pd.DataFrame({
        "RMSE": [rmse],
        "MAE": [mae],
        "R-squared": [r2]
    })
    return df_perf
```

[69]:
```python
# Checking model performance on train set (seen 70% data)
print("Training Performance\n")
olsmodel_train_perf = model_performance_regression(olsmodel, X_train, y_train)
print(olsmodel_train_perf)
```

```
Training Performance

      RMSE       MAE  R-squared
0  0.40112  0.330417   0.722387
```

```
[71]: # Checking model performance on test set (seen 30% data)
print("Test Performance\n")
olsmodel_test_perf = model_performance_regression(olsmodel, X_test, y_test)
print(olsmodel_test_perf)
```

```
Test Performance

       RMSE       MAE  R-squared
0  0.413096  0.340426   0.703053
```

Observations

- **The training R? is 0.72, so the model is not underfitting**

- **The train and test RMSE and MAE are comparable, so the model is not overfitting either**

- **MAE suggests that the model can predict anime ratings within a mean error of 0.34 on the test data**

15 2- Checking Linear Regression Assumptions

We will be checking the following Linear Regression assumptions:

. No Multicollinearity

2. Linearity of variables

3. Independence of error terms

4. Normality of error terms

5. No Heteroscedasticity

16 TEST FOR MULTICOLLINEARITY

- **Multicollinearity occurs when predictor variables in a regression model are correlated. This correlation is a problem because predictor variables should be independent. If the correlation between variables is high, it can cause problems when we fit the model and interpret the results. When we have multicollinearity in the linear model, the coefficients that the model suggests are unreliable.**

- **There are different ways of detecting (or testing) multicollinearity. One such way is by using the Variance Inflation Factor, or VIF.**

- **Variance Inflation Factor (VIF): Variance inflation factors measure the inflation in the variances of the regression parameter estimates due to collinearities that exist among the predictors. It is a measure of how much the variance of the estimated regression coefficient Bk is "inflated" by the existence of correlation among the predictor variables in the model.**

- **If VIF is 1, then there is no correlation among the kth predictor and the remaining predictor variables, and hence, the variance of Bk is not inflated at all.**

- **General Rule of thumb:**

- **If VIF is between 1 and 5, then there is low multicollinearity.**

- **If VIF is between 5 and 10, we say there is moderate multicollinearity.**

- **If VIF is exceeding 10, it shows signs of high multicollinearity.**

[80]:
```
from statsmodels.stats.outliers_influence import variance_inflation_factor
import pandas as pd

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
vif_df = checking_vif(X_train).sort_values('VIF', ascending=False)
print(vif_df)
```

```
                          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
```

- **There are multiple columns with very high VIF values, indicating presence of strong multicollinearity**
- **We will systematically drop numerical columns with VIF > 5**
- **We will ignore the VIF values for dummy variables and the constant (intercept)**

17 Remove Multicollinearity

To remove multicollinearity

1. **Drop every column one by one that has a VIF score greater than 5.**
2. **Look at the adjusted R-squared and RMSE of all these models.**
3. **Drop the variable that makes the least change in adjusted R-squared.**
4. **Check the VIF scores again.**
5. **Continue till you get all VIF scores under 5.**

Let's define a function that will help us do this.

[89]:
```python
def treating_multicollinearity(predictors, target, high_vif_columns):
    """
```

```
    Checking the effect of dropping the columns showing high multicollinearity␣
↪on model performance (adj. R-squared and RMSE)
    predictors: independent variables
    target: dependent variable
    high_vif_columns: columns having high VIF
    """

    # 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 col in high_vif_columns:
        # Defining the new train set
        train = predictors.loc[:, ~predictors.columns.str.startswith(col)]

        # Create the model
        olsmodel = sm.OLS(target, train).fit()

        # Adding adj. R-squared and RMSE to the lists
        adj_r2.append(olsmodel.rsquared_adj)
        rmse.append(np.sqrt(olsmodel.mse_resid))

    # Creating a dataframe for the results
    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

# Example usage
col_list = ["watched", "votes"]
res = treating_multicollinearity(X_train, y_train, col_list)
print(res)
```

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

[91]:
```
col_to_drop = "votes"

# Creating new train and test sets by dropping the specified column
```

```python
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)]

# Check VIF now
vif = checking_vif(X_train2)
print("VIF after dropping", col_to_drop)
print(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
```

- **We have dealt with multicollinearity in the data**

- **Let's rebuild the model using the updated set of predictors variables**

[96]:

```python
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:                        22:56:23   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.
```

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.

18 Interpreting the Regression Results:

19 Part 2

4. std err: It reflects the level of accuracy of the coefficients.

• The lower it is, the higher is the level of accuracy.

5. P>t|: It is p-value.

independent variable.

• For each independent feature, there is a null hypothesis and an alternate hypothesis. Here S _i$ is the coefficient of the SiSth #### • SH_O: $Independent feature is not significant (S\beta_i = O)$ **#### • SH_a:** $Independent feature is that it is significant (S\beta_i \neq 0)$ **#### • (P>|t|) gives the p-value for each independent feature to check that null hypothesis. We are considering 0.05 (5%) as significance level. #### • A p-value of less than 0.05 is considered to be statistically significant. #### 6. Confidence Interval: It represents the range in which our coefficients are likely to fall (with a likelihood of 95%). #### Observations #### • We can see that adj. R-squared has dropped from 0.720 to 0.717, which shows that the dropped columns did not have much effect on the model #### • As there is no multicollinearity, we can look at the p-values of predictor variables to check their significance**

20 Dealing with high p-value variables

• Some of the dummy variables in the data have p-value > 0.05. So, they are not significant and we'll drop them

• But sometimes p-values change after dropping a variable. So, we'll not drop all variables at once

• Instead, we will do the following:

- **Build a model, check the p-values of the variables, and drop the column with the highest p-value**

- **Create a new model without the dropped feature, check the p-values of the variables, and drop the column with the highest p-value**

- **Repeat the above two steps till there are no columns with p-value > 0.05**

Note: The above process can also be done manually by picking one variable at a time that has a high p-value, dropping it, and building a model again. But that might be a little tedious and using a loop will be more efficient.

[106]:
```python
# Initial list of columns
predictors = X_train2.copy()
cols = predictors.columns.tolist()

# Setting an initial max p-value
max_P_value = 1

while len(cols) > 0:
    # Defining the train set
    X_train_aux = predictors[cols]

    # Fitting the model
    model = sm.OLS(y_train, X_train_aux).fit()

    # Getting the p-values and the maximum p-value
    p_values = model.pvalues
    max_P_value = max(p_values)

    # Name of the variable with maximum p-value
    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', 'mediaType_Other',
'mediaType_TV', 'mediaType_TV Special', 'mediaType_Web', 'contentWarn_Yes',
'studio_primary_J.C. Staff', 'studio_primary_MADHOUSE', 'studio_primary_OLM',
'studio_primary_Others', 'studio_primary_Studio Deen', 'studio_primary_Studio
Pierrot', 'studio_primary_Sunrise', 'studio_primary_Toei Animation',
'genre_Adventure', 'genre_Comedy', 'genre_Drama']
```

[108]:
```python
# Using selected features to create new train and test sets
X_train3 = X_train2[selected_features]
X_test3 = X_test2[selected_features]

# Fitting the OLS model with the new training set
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:                        23:04:49   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.
```

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.

[111]:
```
# Checking model performance on train set (seen 70% data)
print("Training Performance\n")
olsmod2_train_perf = model_performance_regression(olsmod2, X_train3, y_train)
print(olsmod2_train_perf)
```

```
Training Performance

      RMSE      MAE  R-squared
0  0.40399  0.33291     0.7184
```

[113]:
```
# Checking model performance on test set (seen 30% data)
print("Test Performance\n")
olsmod2_test_perf = model_performance_regression(olsmod2, X_test3, y_test)
print(olsmod2_test_perf)
```

```
Test Performance

       RMSE       MAE  R-squared
0  0.414583  0.341345   0.700912
```

Observations

- **Now no feature has p-value greater than 0.05, so we'll consider the features in x_train3 as the final set of predictor variables and olsmod2 as the final model to move forward with**

- **Now adjusted R-squared is 0.717, i.e., our model is able to explain ~72% of the variance**

- **The adjusted R-squared in olsmod1 (where we considered the variables without multicollinearity) was 0.717**

- **This shows that the variables we dropped were not affecting the model**

- **RMSE and MAE values are comparable for train and test sets, indicating that the model is not overfitting**

Now we'll check the rest of the assumptions on olsmod2.

2. Linearity of variables

3. Independence of error terms

4. Normality of error terms

5. No Heteroscedasticity

21 TEST FOR LINEARITY AND INDEPENDENCE

21.0.1 Why the test?

- **Linearity describes a straight-line relationship between two variables, predictor variables must have a linear relation with the dependent variable.**

- **The independence of the error terms (or residuals) is important. If the residuals are not independent, then the confidence intervals of the coefficient estimates will be narrower and make us incorrectly conclude a parameter to be statistically significant.**

21.0.2 How to check linearity and independence?

- **Make a plot of fitted values vs residuals.**

- **If they don't follow any pattern, then we say the model is linear and residuals are independent.**

- **Otherwise, the model is showing signs of non-linearity and residuals are not independent.**

21.0.3 How to fix if this assumption is not followed?

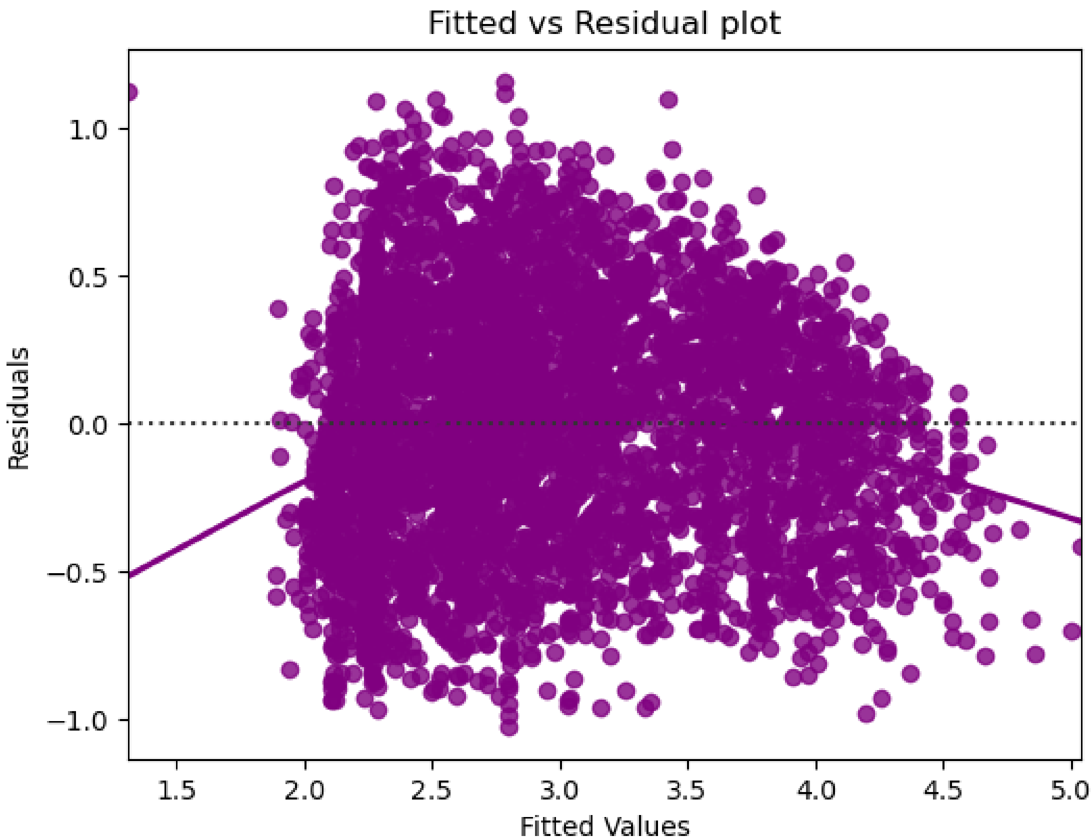
- **We can try to transform the variables and make the relationships linear.**

[119]:
```
# Create a dataframe with actual, fitted, and residual values
df_pred = pd.DataFrame()
df_pred["Actual Values"] = y_train  # actual values
df_pred["Fitted Values"] = olsmod2.fittedvalues  # predicted values
df_pred["Residuals"] = olsmod2.resid  # residuals
print(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
```

[121]:
```
import seaborn as sns
import matplotlib.pyplot as plt

# Let's plot the fitted values vs residuals
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()
```



- **The scatter plot shows the distribution of residuals (errors) vs fitted values (predicted values).**

- **If there exist any pattern in this plot, we consider it as signs of non-linearity in the data and a pattern means that the model doesn't capture non-linear effects.**

- **We see no pattern in the plot above. Hence, the assumptions of linearity and independence are satisfied.**

22 Test For Normality

Why the test?

- **Error terms, or residuals, should be normally distributed. If the error terms are not normally distributed, confidence intervals of the coefficient estimates may become too wide or narrow. Once confidence interval becomes unstable, it leads to difficulty in**

estimating coefficients based on minimization of least squares. Non-normality suggests that there are a few unusual data points that must be studied closely to make a better model.

How to check normality?

- **The shape of the histogram of residuals can give an initial idea about the normality.**

- **It can also be checked via a Q-Q plot of residuals. If the residuals follow a normal distribution, they will make a straight line plot, otherwise not.**

- **Other tests to check for normality includes the Shapiro-Wilk test.**

- **Null hypothesis: Residuals are normally distributed**

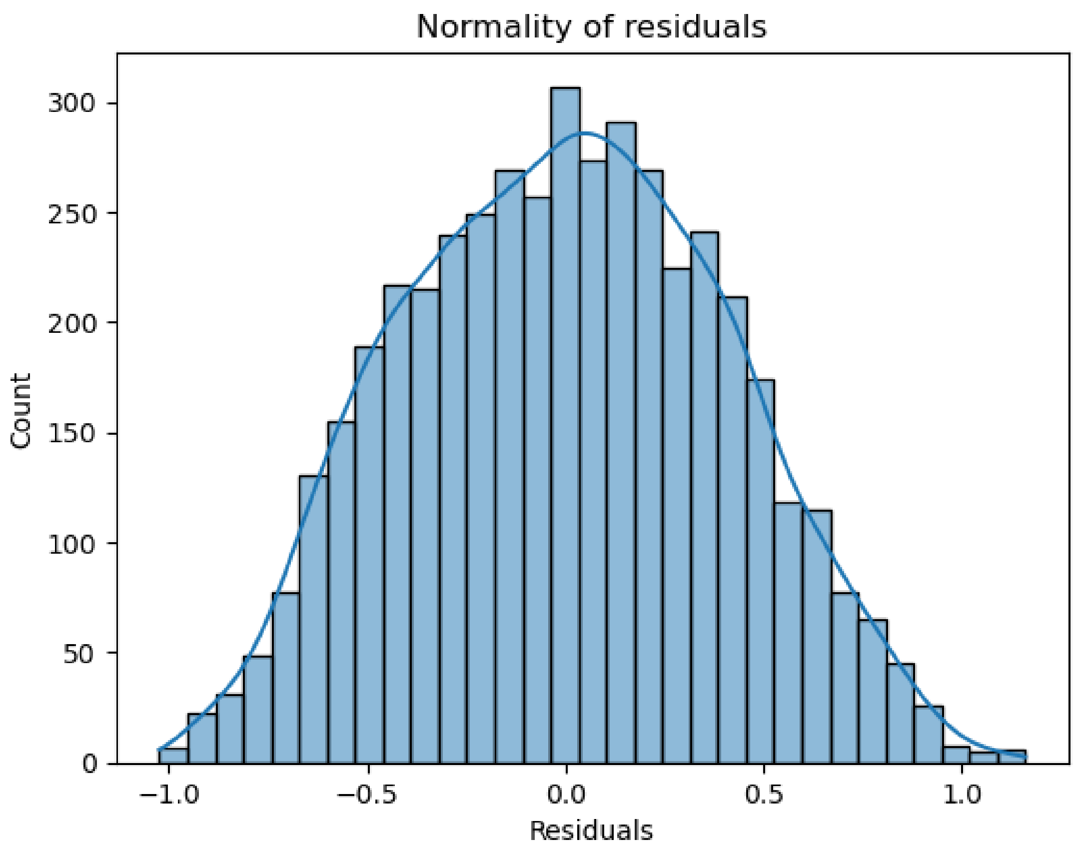
- **Alternate hypothesis: Residuals are not normally distributed**

How to fix if this assumption is not followed?

- **We can apply transformations like log, exponential, arcsinh, etc. as per our data.**

[126]:
```
import seaborn as sns
import matplotlib.pyplot as plt

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

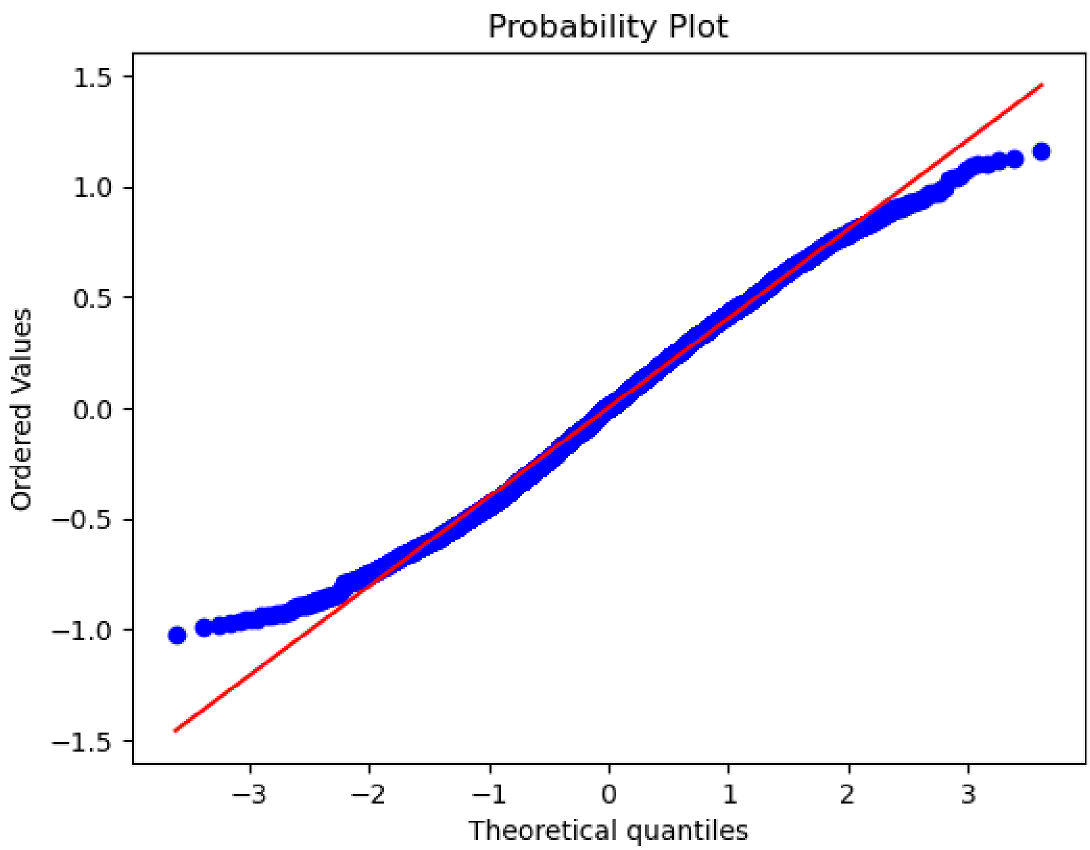
```
/opt/anaconda3/lib/python3.11/site-packages/seaborn/_oldcore.py:1119:
FutureWarning: use_inf_as_na option is deprecated and will be removed in a
future version. Convert inf values to NaN before operating instead.
  with pd.option_context('mode.use_inf_as_na', True):
```



- **The histogram of residuals does have a bell shape.**

- **Let's check the Q-Q plot.**

[129]:
```
import pylab
import scipy.stats as stats

# Q-Q plot to check the normality of residuals
stats.probplot(df_pred["Residuals"], dist="norm", plot=pylab)
pylab.show()
```



- **The residuals more or less follow a straight line except for the tails.**
- **Let's check the results of the Shapiro-Wilk test.**

[132]:
```
from scipy.stats import shapiro

# Perform the Shapiro-Wilk test on the residuals
shapiro_test = shapiro(df_pred["Residuals"])
print("Shapiro-Wilk Test:")
print("Test Statistic:", shapiro_test.statistic)
print("p-value:", shapiro_test.pvalue)
```

```
Shapiro-Wilk Test:
Test Statistic: 0.9934884905815125
p-value: 1.4591795924768364e-13
```

- **Since p-value < 0.05, the residuals are not normal as per the Shapiro-Wilk test.**
- **Strictly speaking, the residuals are not normal.**

- **However, as an approximation, we can accept this distribution as close to being normal.**

- **So, the assumption is satisfied.**

23 TEST FOR HOMOSCEDASTICITY

- **Homoscedascity: If the variance of the residuals is symmetrically distributed across the regression line, then the data is said to be homoscedastic.**

- **Heteroscedascity: If the variance is unequal for the residuals across the regression line, then the data is said to be heteroscedastic.**

Why the test?

- **The presence of non-constant variance in the error terms results in heteroscedasticity. Generally, non-constant variance arises in presence of outliers.**

How to check for homoscedasticity?

- **The residual vs fitted values plot can be looked at to check for homoscedasticity. In the case of heteroscedasticity, the residuals can form an arrow shape or any other non-symmetrical shape.**

- **The goldfeldquandt test can also be used. If we get a p-value $>$ 0.05 we can say that the residuals are homoscedastic. Otherwise, they are heteroscedastic.**

- **Null hypothesis: Residuals are homoscedastic**

- **Alternate hypothesis: Residuals have heteroscedasticity**

How to fix if this assumption is not followed?

- **Heteroscedasticity can be fixed by adding other important features or making transformations.**

[139]:
```
import statsmodels.stats.api as sms
from statsmodels.compat import lzip

# Define the names for the test statistics
names = ["F statistic", "p-value"]

# Perform the Goldfeld-Quandt test
test = sms.het_goldfeldquandt(y_train, X_train3)

# Print the results
results = dict(lzip(names, test))
```

```python
print(results)
```

```
{'F statistic': 1.0484582413449557, 'p-value': 0.1304796784544968}
```

Since p-value > 0.05, we can say that the residuals are homoscedastic. So, this assumption is satisfied.

24 Predictions on test data

Now that we have checked all the assumptions of linear regression and they are satisfied, let's go ahead with prediction.

[144]:
```python
# Predictions on the test set
pred = olsmod2.predict(X_test3)

# Creating a DataFrame with actual and predicted values
df_pred_test = pd.DataFrame({"Actual": y_test, "Predicted": pred})

# Sampling 10 random rows from the DataFrame
print(df_pred_test.sample(10, random_state=1))
```

```
      Actual  Predicted
2023   2.039   2.262980
4543   3.236   3.784680
1914   2.314   2.323405
4856   2.457   2.176779
4405   2.322   2.331494
5755   4.344   3.928340
2341   2.858   2.279015
1637   3.976   3.879616
5730   3.728   3.588967
1385   2.692   2.420355
```

25 Final Model

Let's recreate the final model and print it's summary to gain insights.

[147]:
```python
# Final training and testing sets
X_train_final = X_train3.copy()
X_test_final = X_test3.copy()

# Fit the final OLS model
olsmodel_final = sm.OLS(y_train, X_train_final).fit()
print(olsmodel_final.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:                        23:21:21   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.
```