Predictive Modelling

Linear Regression

Anime Ratings Case Study

Problem Statement

Objective

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.

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. mediaType: 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

```
Start coding or generate with AI.
```

Installing and Importing Necessary Libraries

```
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
```

Loading the dataset

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

Displaying the first few rows of the dataset

```
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
3	Nausicaa of the Valley of the Wind	Movie	1	67.0	1984	1984	One thousand years after the Giant Warriors ca...	No	4649	184	4.444	3100.0	Othe
4	Miru Tights Special	DVD Special	1	4.0	2019	2019	Yua is asked to model an illustrator's designs...	No	346	8	2.494	234.0	Othe

- The dataset contains information about different anime
- Many anime seem to have a single episode only, which are movies
- Description seems to be missing for some anime

Checking the shape of the dataset

```
data.shape
```

```
(6523, 15)
```

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

Checking the data types of the columns for the dataset

```
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
```

- 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

Statistical summary of the dataset

```
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
genre	6523	9	Other	5468	NaN	NaN	NaN	NaN	NaN	NaN	NaN

- 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

Checking for duplicate values

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

```
0
```

- There are no duplicate values in the data

Checking for missing values

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

```
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.

```
# creating a copy of the data so that original data remains unchanged
df = data.copy()
```

Exploratory Data Analysis (EDA)

```
Start coding or generate with AI.
```

Data Preprocessing

Missing Value Treatment

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

```
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

```
# 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")
)
```

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

```
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`

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

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

```
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.

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

```
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
3	Nausicaa of the Valley of the Wind	Movie	1	67.0	One thousand years after the Giant Warriors ca...	No	4649	184	4.444	3100.0	Others	No
4	Miru Tights Special	DVD Special	1	4.0	Yua is asked to model an illustrator's designs...	No	346	8	2.494	234.0	Others	No

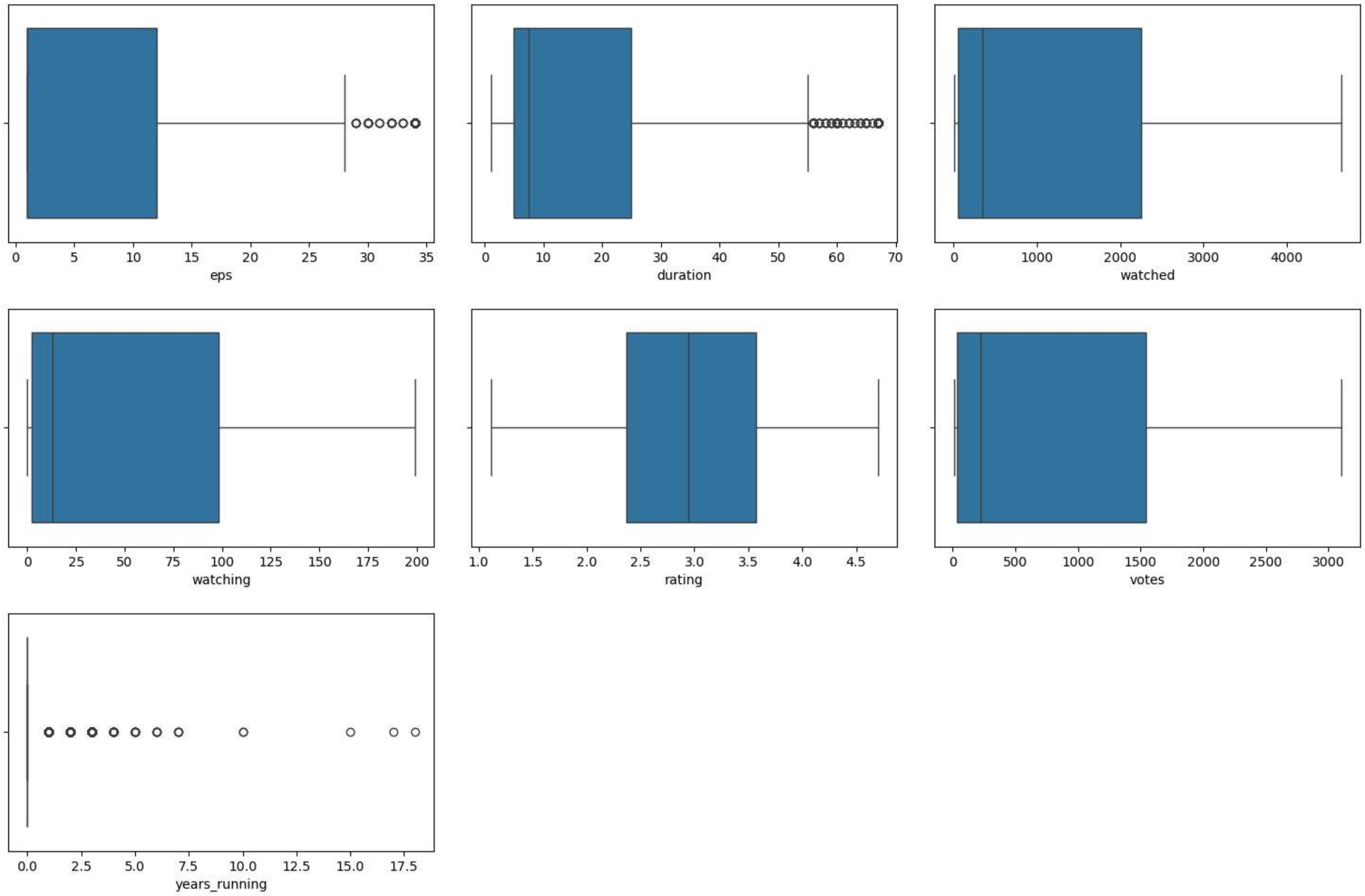
Outlier Detection

```
# 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

```
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

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

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

```
# 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)


# creating dummy variables
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	...	studio_primary_T Animat
0	1.0	1	67.0	4649	86	3100.0	0	True	False	False	...	T
1	1.0	1	5.0	10	0	10.0	0	True	False	False	...	Fa
2	1.0	1	46.0	1630	16	1103.0	0	False	False	False	...	Fa
3	1.0	1	67.0	4649	184	3100.0	0	True	False	False	...	Fa
4	1.0	1	4.0	346	8	234.0	0	False	False	False	...	Fa

5 rows × 34 columns

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

	const	eps	duration	watched	watching	votes	years_running	mediaType_Movie	mediaType_Music Video	mediaType_OVA	...	studio_primary_T Animat
0	1.0	1.0	67.0	4649.0	86.0	3100.0	0.0	1.0	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	...	
2	1.0	1.0	46.0	1630.0	16.0	1103.0	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	...	
4	1.0	1.0	4.0	346.0	8.0	234.0	0.0	0.0	0.0	0.0	...	

5 rows × 34 columns

```
# 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
```

Model Building - Linear Regression

```
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:                Wed, 04 Sep 2024   Prob (F-statistic):               0.00
Time:                        12:13:23   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
```

Interpreting the Regression Results

PART-1:

Start coding or generate with AI.

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**.

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 R^2.
- We will define a function to calculate MAPE and adjusted R^2.
    - 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.

```
# 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)  # to compute R-squared
    rmse = np.sqrt(mean_squared_error(target, pred))  # to compute RMSE
    mae = mean_absolute_error(target, pred)  # to compute MAE
    # creating a dataframe of metrics
    df_perf = pd.DataFrame(
        {
            "RMSE": rmse,
            "MAE": mae,
            "R-squared": r2,},index=[0])

    return df_perf
```

Start coding or generate with AI.

```
# 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

Observations

- The training R^2 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

Start coding or generate with AI.

2- Checking Linear Regression Assumptions

We will be checking the following Linear Regression assumptions:

1. **No Multicollinearity**
2. **Linearity of variables**

3. **Independence of error terms**
4. **Normality of error terms**
5. **No Heteroscedasticity**

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 β_k 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 β_k 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.

Let's define a function to check VIF.

```
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

- 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)

Removing 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.

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

        # 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
```

```
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

```
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)]

# Check VIF now
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

- We have dealt with multicollinearity in the data
- Let's rebuild the model using the updated set of predictors variables

```
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:                Wed, 04 Sep 2024   Prob (F-statistic):               0.00
Time:                        12:18:15   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.
```

Interpreting the Regression Results:

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.
   - For each independent feature, there is a null hypothesis and an alternate hypothesis. Here β_i is the coefficient of the ith independent variable.
     - H_o : Independent feature is not significant ($\beta_i = 0$)
     - H_a : Independent feature is that it is significant ($\beta_i \neq 0$)
   - (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

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.

```
# 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', '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:                Wed, 04 Sep 2024   Prob (F-statistic):               0.00
Time:                        12:18:32   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

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**

TEST FOR LINEARITY AND INDEPENDENCE

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.

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.

How to fix if this assumption is not followed?

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

```
# let us create a dataframe with actual, fitted and residual values
df_pred = pd.DataFrame()

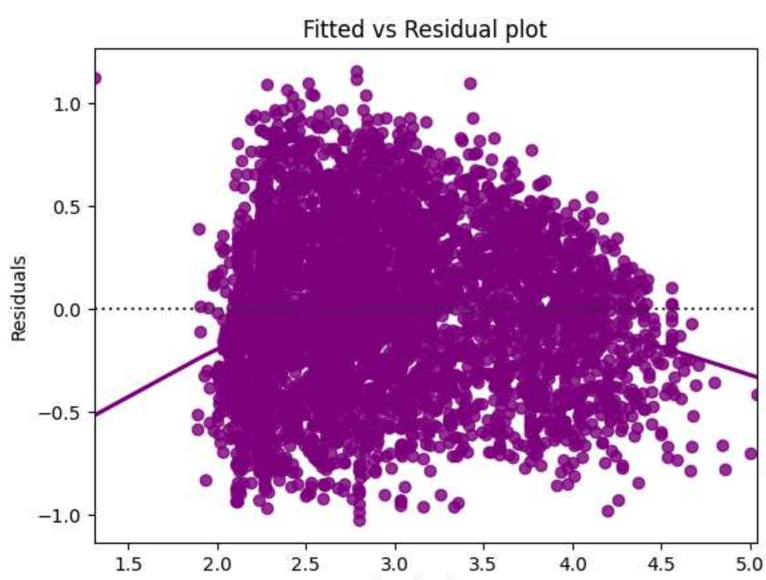
df_pred["Actual Values"] = y_train  # actual values
df_pred["Fitted Values"] = olsmod2.fittedvalues  # predicted values
df_pred["Residuals"] = olsmod2.resid  # residuals

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

```
# 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.**

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.

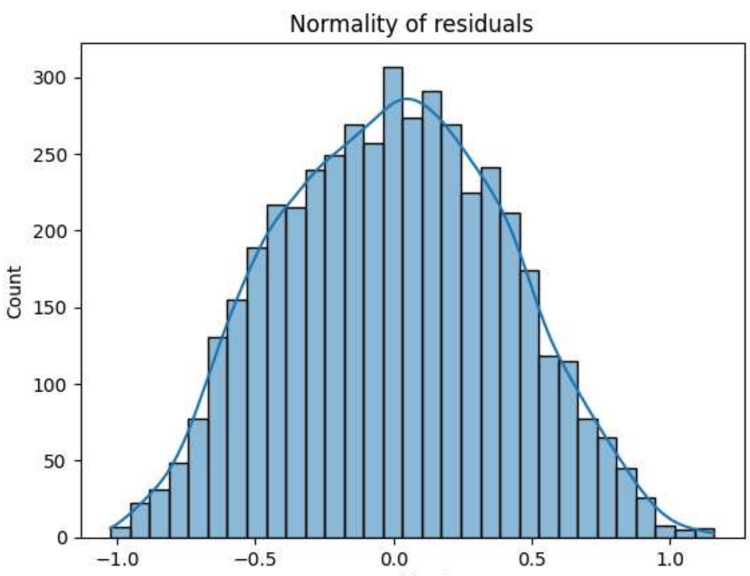
How to check normality?

- 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.

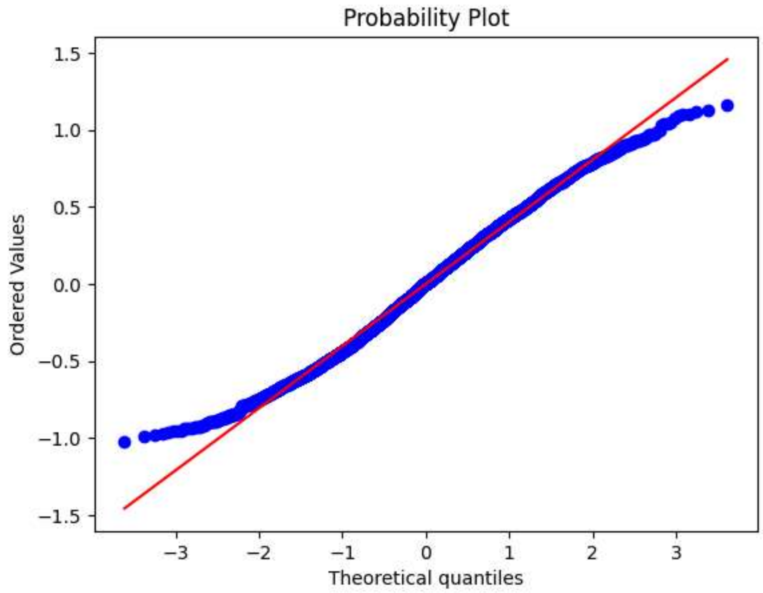
```
sns.histplot(data=df_pred, x="Residuals", kde=True)
plt.title("Normality of residuals")
plt.show()
```



- The histogram of residuals does have a bell shape.
- Let's check the Q-Q plot.

```
import pylab
import scipy.stats as stats

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



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

```
stats.shapiro(df_pred["Residuals"])
```

```
ShapiroResult(statistic=0.9934884905815125, pvalue=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.**

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.

```
import statsmodels.stats.api as sms
from statsmodels.compat import lzip

name = ["F statistic", "p-value"]
test = sms.het_goldfeldquandt(df_pred["Residuals"], x_train3)
lzip(name, test)
```

```
[('F statistic', 1.048458241344956), ('p-value', 0.130479678454497)]
```

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

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.

```
# predictions on the test set
pred = olsmod2.predict(x_test3)

df_pred_test = pd.DataFrame({"Actual": y_test, "Predicted": pred})
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

- We can observe here that our model has returned pretty good prediction results, and the actual and predicted values are comparable

Final Model

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

```
x_train_final = x_train3.copy()
x_test_final = x_test3.copy()
```

```
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:                Wed, 04 Sep 2024   Prob (F-statistic):               0.00
Time:                        12:19:07   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
```

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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
```