carnegie_luca_a3

March 25, 2025

1 Assignment 3

INF412: Data Analytics - Informed Decisions with Data Luca Carnegie

[1]:
```
# import necessary libraries
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import sklearn.metrics as metrics
import statsmodels.api as stats
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from statsmodels.stats.outliers_influence import variance_inflation_factor
from scipy.stats import shapiro
```

1. Multiple Linear Regression (6 points) The Winequality dataset ('winequality.csv') contains physicochemical properties of white wine samples and their corresponding quality ratings. The columns and their descriptions are at below.

Feature Name	Description
fixed acidity	The amount of non-volatile acids in wine (e.g., tartaric acid). Affects wine's taste and stability.
volatile acidity	The amount of acetic acid in wine. High values may lead to an unpleasant vinegar taste.
citric acid	A natural preservative found in wine, adding freshness and reducing oxidation.
residual sugar	The sugar left after fermentation. Affects sweetness; wines with high values are sweeter.
chlorides	The amount of salt in wine. Higher values may contribute to a salty taste.
free sulfur dioxide	The SO available in wine to prevent microbial growth and oxidation.
total sulfur dioxide	The total SO present (bound + free). Excessive levels can cause undesirable aromas.
density	The wine's mass per unit volume, influenced by sugar, alcohol, and other dissolved substances.

Feature Name	Description
pH	The measure of acidity or alkalinity. Lower values indicate higher acidity.
sulphates	A compound that contributes to wine preservation and enhances bitterness.
alcohol	The ethanol content in wine (%). Affects body, aroma, and overall sensory experience.
quality	Wine quality score (integer from 3 to 9) based on sensory analysis by wine tasters.

Load and Explore the Dataset

[2]:
```python
# Load the dataset into a Pandas DataFrame.
wine = pd.read_csv('winequality.csv')

# Display the first five rows, column names, and data types
print("\n===== FIRST 5 ROWS OF THE DATASET =====")
print(wine.head(5))

print("\n===== COLUMN NAMES =====")
for i, col in enumerate(wine.columns):
    print(f"{i+1}. {col}")

print("\n===== DATA TYPES =====")
dtypes_df = pd.DataFrame(wine.dtypes, columns=['Data Type'])
dtypes_df.index.name = 'Column'
print(dtypes_df)

# Display basic dataset dimensions
print(f"\n===== DATASET DIMENSIONS =====")
print(f"Number of samples: {wine.shape[0]}")
print(f"Number of features: {wine.shape[1]}")
```

```
===== FIRST 5 ROWS OF THE DATASET =====
   fixed acidity  volatile acidity  citric acid  residual sugar  chlorides  \
0            7.0              0.27         0.36            20.7      0.045
1            6.3              0.30         0.34             1.6      0.049
2            8.1              0.28         0.40             6.9      0.050
3            7.2              0.23         0.32             8.5      0.058
4            7.2              0.23         0.32             8.5      0.058

   free sulfur dioxide  total sulfur dioxide  density    pH  sulphates  \
0                 45.0                 170.0   1.0010  3.00       0.45
1                 14.0                 132.0   0.9940  3.30       0.49
2                 30.0                  97.0   0.9951  3.26       0.44
3                 47.0                 186.0   0.9956  3.19       0.40
4                 47.0                 186.0   0.9956  3.19       0.40
```

```
   alcohol  quality
0      8.8        6
1      9.5        6
2     10.1        6
3      9.9        6
4      9.9        6

===== COLUMN NAMES =====
1. fixed acidity
2. volatile acidity
3. citric acid
4. residual sugar
5. chlorides
6. free sulfur dioxide
7. total sulfur dioxide
8. density
9. pH
10. sulphates
11. alcohol
12. quality

===== DATA TYPES =====
                     Data Type
Column
fixed acidity          float64
volatile acidity       float64
citric acid            float64
residual sugar         float64
chlorides              float64
free sulfur dioxide    float64
total sulfur dioxide   float64
density                float64
pH                     float64
sulphates              float64
alcohol                float64
quality                  int64

===== DATASET DIMENSIONS =====
Number of samples: 4898
Number of features: 12
```

[3]:
```python
# Print summary statistics
print("\n===== COVARIATE SUMMARY STATISTICS =====")
print(wine.describe().transpose().round(2))
```

```
===== COVARIATE SUMMARY STATISTICS =====
```

```
                      count    mean    std   min     25%     50%     75%  \
Column
fixed acidity        4898.0    6.85   0.84  3.80    6.30    6.80    7.30
volatile acidity     4898.0    0.28   0.10  0.08    0.21    0.26    0.32
citric acid          4898.0    0.33   0.12  0.00    0.27    0.32    0.39
residual sugar       4898.0    6.39   5.07  0.60    1.70    5.20    9.90
chlorides            4898.0    0.05   0.02  0.01    0.04    0.04    0.05
free sulfur dioxide  4898.0   35.31  17.01  2.00   23.00   34.00   46.00
total sulfur dioxide 4898.0  138.36  42.50  9.00  108.00  134.00  167.00
density              4898.0    0.99   0.00  0.99    0.99    0.99    1.00
pH                   4898.0    3.19   0.15  2.72    3.09    3.18    3.28
sulphates            4898.0    0.49   0.11  0.22    0.41    0.47    0.55
alcohol              4898.0   10.51   1.23  8.00    9.50   10.40   11.40
quality              4898.0    5.88   0.89  3.00    5.00    6.00    6.00

                        max
Column
fixed acidity         14.20
volatile acidity       1.10
citric acid            1.66
residual sugar        65.80
chlorides              0.35
free sulfur dioxide  289.00
total sulfur dioxide 440.00
density                1.04
pH                     3.82
sulphates              1.08
alcohol               14.20
quality                9.00
```

[4]:
```python
# Identify and handle missing values (if any)
print(wine.isnull().sum())
```

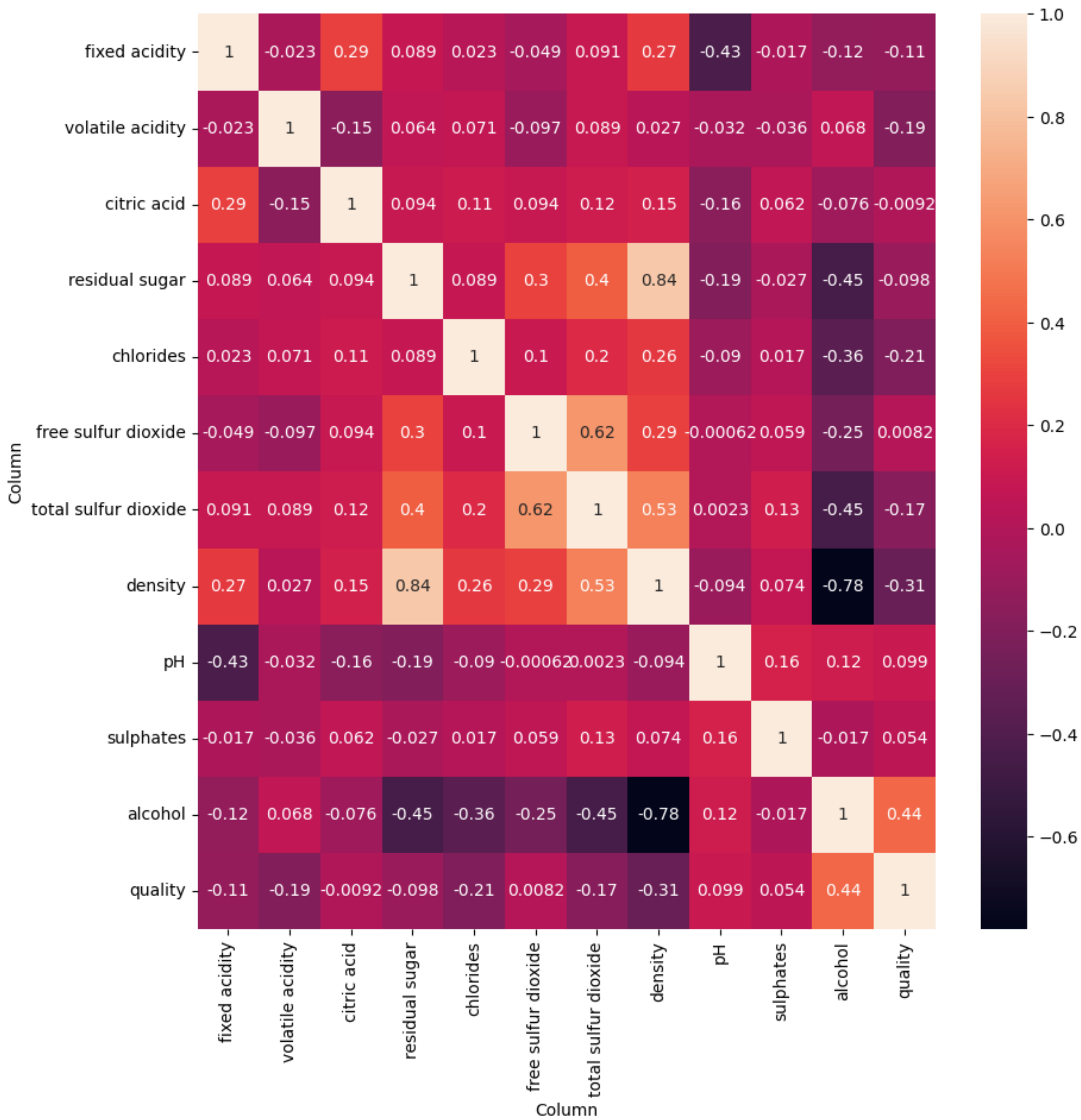
```
Column
fixed acidity           0
volatile acidity        0
citric acid             0
residual sugar          0
chlorides               0
free sulfur dioxide     0
total sulfur dioxide    0
density                 0
pH                      0
sulphates               0
alcohol                 0
quality                 0
dtype: int64
```

It appears that there are no missing values, which makes our life easy.

[5]:

```python
# Compute the correlation matrix between variables and create visualization with seaborn.
corr_matrix = wine.corr()
plt.figure(figsize=(10, 10))
sns.heatmap(corr_matrix, annot=True)
```

[5]: `<Axes: xlabel='Column', ylabel='Column'>`



Looking at the variable descriptions and the correlation matrix, we can see a few preliminary relationships between certain variables, from positive to negative. We'll say that for a correlation between variables to be 'significant', it should be above 0.5 (i.e. at least 50% of the variance in one variable is explained by the other)

Positive: 1. There is a large positive relationship between **density** and **residual sugar** (+0.84), which makes sense since sugar left in the wine would increase it's g/mL. 2. There is a decent positive relationship between **free sulfur dioxide** and **total sulfer dioxide** (+0.62) 3. There is a decent positive relationship between **total sulfur dioxide** and **density** (+0.53)

Negative: 1. There is a large negative relationship (-0.78) between **alcohol** and **density**

Performing Multiple Linear Regression (MLR) Identify independent (X) and dependent (y) variables: - **Our goal:** find what factors affect the variable 'quality' - **Dependent variable:** quality - **Independent variables:** fixed acidity, volatile acidity, citric acid, residual sugar, chlorides, free sulfur dioxide, total sulfur dioxide, density, pH, sulphates, alcohol

Assumption Checks

[6]:
```
# Split the dataset into training (80%) and testing (20%) subsets.

# Shuffle rows (to remove problems, if any, due to ordering)
wine = wine.sample(frac=1).reset_index(drop=True)

# Split the dataset into features and target variable
Y = wine['quality']
X = wine.drop('quality', axis=1)

# Split the dataset into training (80%) and testing (20%) subsets
X_train, X_test, Y_train, Y_test = train_test_split(X, Y, test_size=0.2,␣
↪random_state=42)
```

[7]:
```
# train a linear regression model with sci-kit-learn
model = LinearRegression()
lin_reg = model.fit(X_train, Y_train)

# Model summary
## Coefficients
coefficients = model.coef_
intercept = model.intercept_
summary = pd.DataFrame(coefficients, index=X.columns, columns=['Coefficient'])
summary.loc['Intercept'] = intercept

# Evaluation Metrics (on train and test data)
r2_train = metrics.r2_score(Y_train, model.predict(X_train))
r2_test = metrics.r2_score(Y_test, model.predict(X_test))

mse_train = metrics.mean_squared_error(Y_train, model.predict(X_train))
mse_test = metrics.mean_squared_error(Y_test, model.predict(X_test))

rmse_train = np.sqrt(mse_train)
rmse_test = np.sqrt(mse_test)
```

```
metrics_df = pd.DataFrame({'R^2': [r2_train, r2_test], 'MSE': [mse_train,␣
↪mse_test], 'RMSE': [rmse_train, rmse_test]}, index=['Train', 'Test'])

print("\n===== MODEL SUMMARY =====")
print(summary.round(3))
print("\n===== EVALUATION METRICS =====")
print(metrics_df.round(3))
```

```
===== MODEL SUMMARY =====
                     Coefficient
Column
fixed acidity              0.054
volatile acidity          -1.866
citric acid                0.063
residual sugar             0.078
chlorides                 -0.330
free sulfur dioxide        0.003
total sulfur dioxide      -0.000
density                 -140.956
pH                         0.656
sulphates                  0.645
alcohol                    0.200
Intercept                141.054

===== EVALUATION METRICS =====
         R^2    MSE   RMSE
Train  0.279  0.562  0.750
Test   0.292  0.568  0.754
```

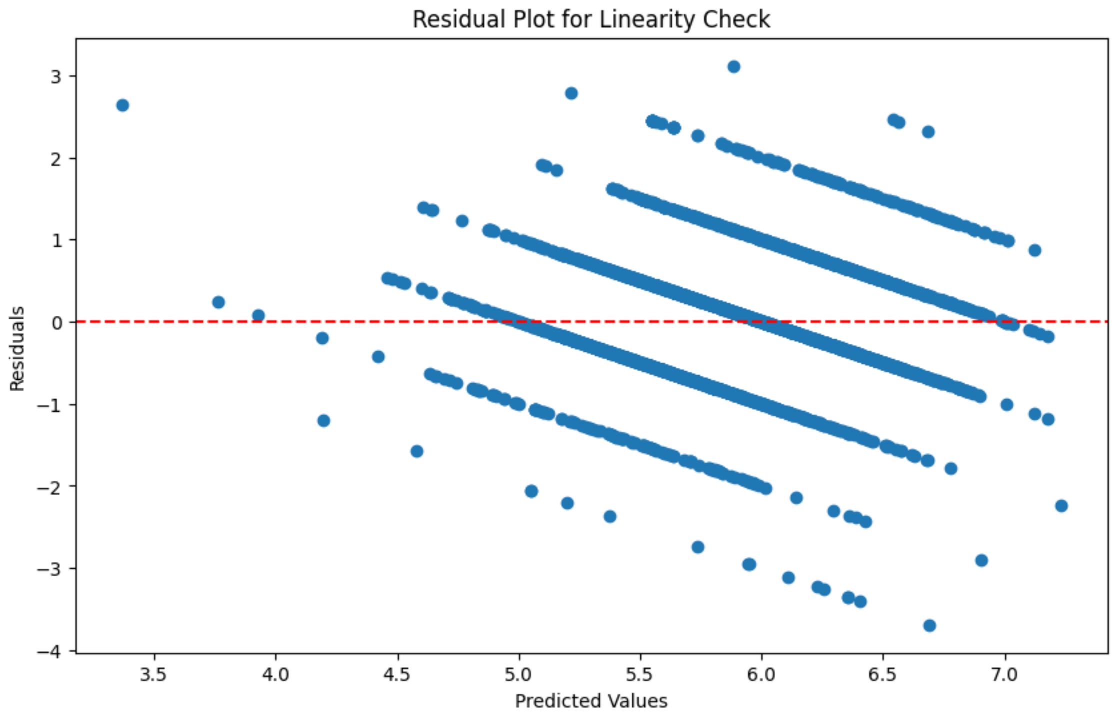
Interpreting the values of the model's adjusted R^2, on the training and test data, we can conclude that the current model covariates don't fit the data particularly well. We see this in the adjusted R-squared of 0.282 (train), which means that about 28% of the variance in the data is explained by the model itself. That said, when testing the model on new data (test), we get an R-squared of a similar magnitude, 0.280, meaning the model does generalize fairly well to new data it was not fitted on. That still does not negate the model's unsatisfactory explanatory power.

This conclusion is also corroborated in the squared errors. Given the root mean squared error of 0.747 (test), it means that on average, the predictions of quality score (ranging from 3 to 9) for new data, based on the predictors, is off by an average of 0.747 score units or 12.5%. One explanation for this poor predictive power is that "wine quality" is very subjective, particularly since the scores in the dataset were judged by human tasters - one taster's score of "4" could means another taster's "5", or similar. Therefore, a high amount of scatter in wine quality is to be expected.

Assumption Checks

[8]:
```
# Compute residuals
Y_pred_train = model.predict(X_train)
residuals = Y_train - Y_pred_train
```

```python
# 1. Linearity Check - Residual Plot
plt.figure(figsize=(10, 6))
plt.scatter(Y_pred_train, residuals)
plt.axhline(y=0, color='r', linestyle='--')
plt.xlabel('Predicted Values')
plt.ylabel('Residuals')
plt.title('Residual Plot for Linearity Check')
plt.show()
```



This unusual plot of the residuals show how the wine quality training data is discrete (from 3 to 9, with no values in between), but are being treated as continuous when an OLS regression is run. This is commonly observed when modeling ordinal data (like the wine quality ratings) with linear regression instead of using more appropriate methods like classification.

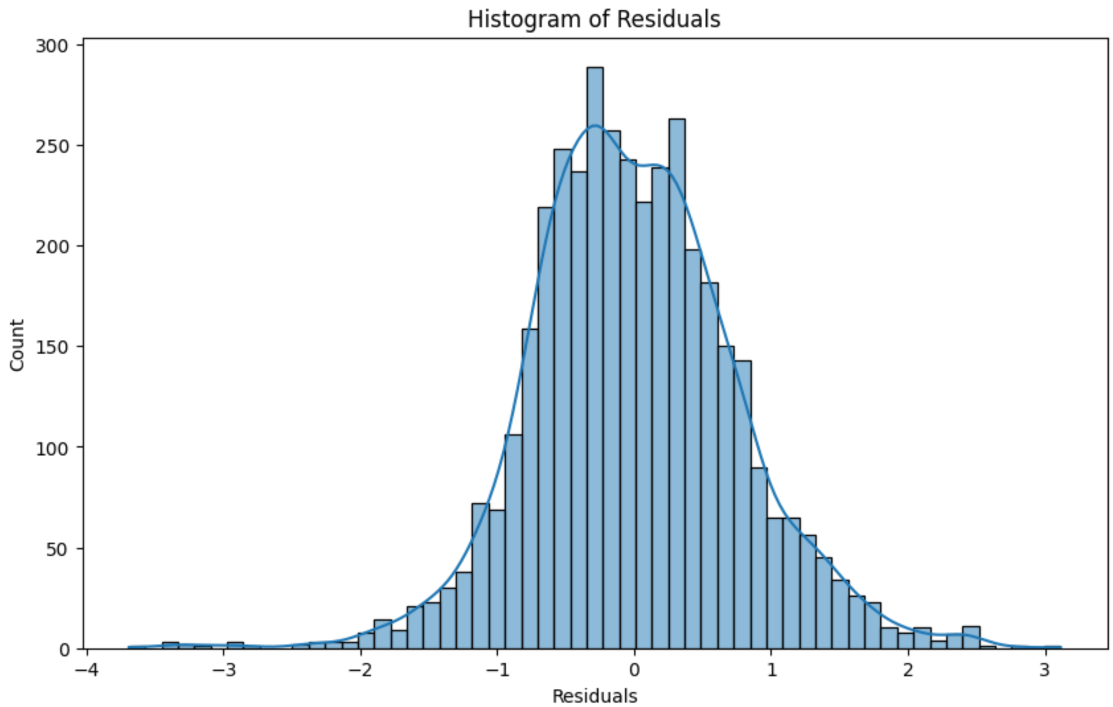
[9]:
```python
# 2. Multicollinearity Check - VIF

# Calculate VIF for each feature
vif_data = pd.DataFrame()
vif_data["Predictor"] = X_train.columns
vif_data["VIF"] = [variance_inflation_factor(X_train.values, i) for i in␣
 ↪range(X_train.shape[1])]

print("Variance Inflation Factors:")
```

```
print(vif_data.sort_values("VIF", ascending=False).round(2))
```

```
Variance Inflation Factors:
               Predictor      VIF
7                density  1046.04
8                     pH   605.58
10               alcohol   116.93
0          fixed acidity    91.93
6   total sulfur dioxide    24.83
9              sulphates    20.91
2            citric acid    10.16
1       volatile acidity     9.92
5    free sulfur dioxide     9.12
4              chlorides     6.46
3         residual sugar     3.79
```

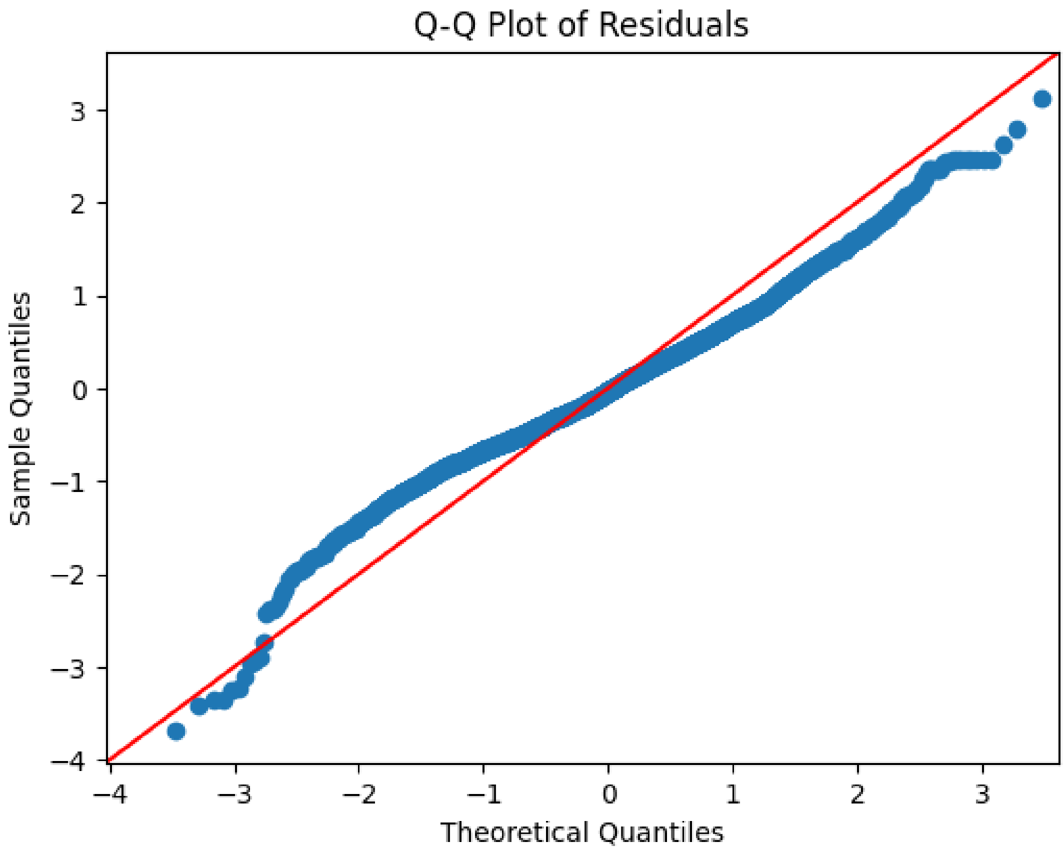
Based on the output, density, pH, alcohol, fixed acidity, total sulfur dioxide, and sulphates exhibit significant multicollinearity with VIF values above the commonly accepted threshold of 5. Density has an extremely high VIF of 1048.93, followed by pH at 610.31 and alcohol at 118.79, indicating these three features are highly correlated with other variables in the dataset. The substantial multicollinearity among these chemical properties suggests they likely measure related aspects of the wine composition, which could lead to unstable coefficient estimates and reduced reliability in subsequent statistical modeling.

[10]:
```
# 3. Normality of Residuals
# Histogram
plt.figure(figsize=(10, 6))
sns.histplot(residuals, kde=True)
plt.title('Histogram of Residuals')
plt.xlabel('Residuals')
plt.show()
```



Residuals look about normally distributed when put in a histogram format.

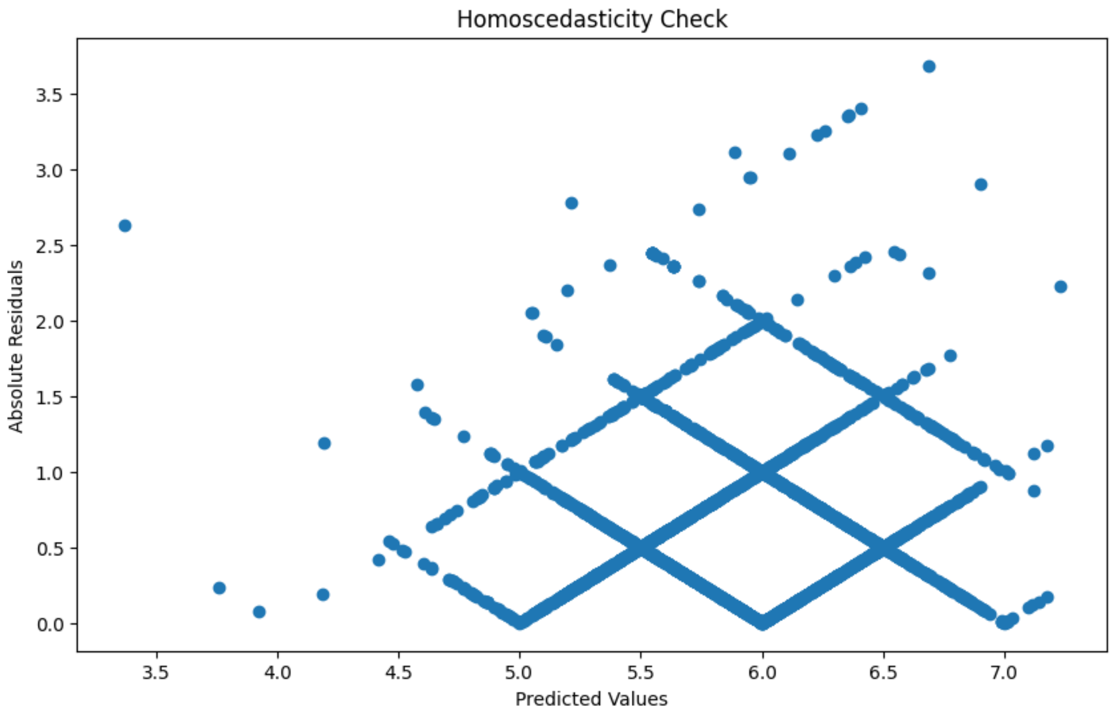
[11]:
```
# Q-Q Plot
stats.qqplot(residuals, line="45")
plt.title("Q-Q Plot of Residuals")
plt.show()

# Shapiro-Wilk Test
shapiro_test = shapiro(residuals)
print("\n===== SHAPIRO-WILK TEST =====")
print(f"Test Statistic: {shapiro_test[0].round(3)}")
print(f"P-value: {shapiro_test[1].round(5)}")
```




```
===== SHAPIRO-WILK TEST =====
Test Statistic: 0.989
P-value: 0.0
```

Given the large deviation of most of the collected data quantiles from "normal" quantiles, we can quite easily say that residuals of this data are not very normally distributed. This is further corroborated with doing a Shapiro-Wilk test, which, given the data, comes to the same conclusion - this data is not normally distributed.

[12]:
```
# 4. Homoscedasticity Check
plt.figure(figsize=(10, 6))
plt.scatter(Y_pred_train, np.abs(residuals))
plt.xlabel('Predicted Values')
plt.ylabel('Absolute Residuals')
plt.title('Homoscedasticity Check')
plt.show()
```



Similar to the linearity check plot, this unusual residual plot with distinct diamond-shaped patterns suggests the data comes from a discrete or categorical dependent variable that's being treated as continuous in a regression model. The diamond patterns form because the absolute residuals can only take certain specific values - when you predict a continuous value for something that can only be integers or fixed categories (like ratings on a 1-7 scale), the residuals follow these geometric patterns. This is typically observed when modeling ordinal data (like the wine quality ratings) with linear regression instead of using more appropriate methods like classification.

The horizontal lines at specific residual values indicate the quantization effect where predictions can only be wrong by certain amounts because the actual values are restricted to specific levels. This plot suggests our modelling strategy should be majorly reconsidered with this dataset.

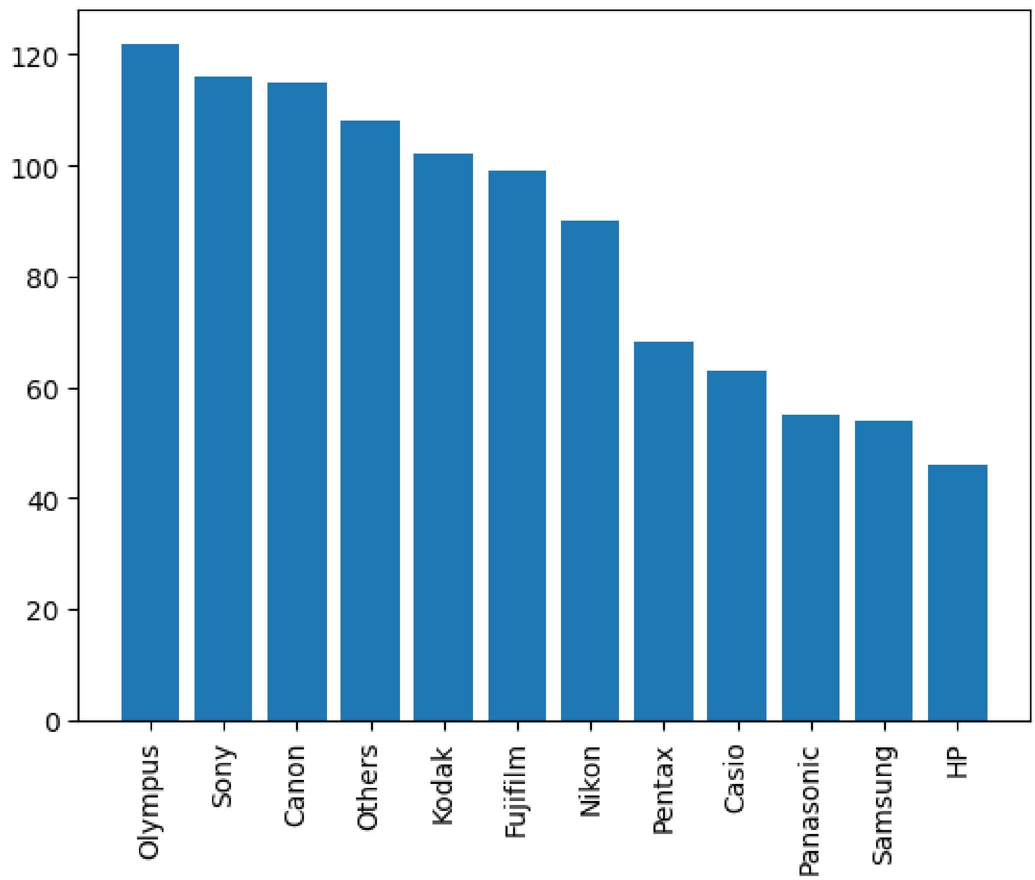
2. Data Wrangling (4 points) Use the data set 'camera dataset.csv'. This dataset features 1038 cameras with 9 properties respectively. Please proceed with the data preparation.

[13]:
```
camera = pd.read_csv('camera.csv')
```

Task 1

[14]:
```
# Name all brands that are lower than 3% in number of models as one category␣
↪"others"

# 1. extract the brand names from model column
camera["brand"] = camera["Model"].str.split().str[0]
```

```
# 2. count the number of models for each brand
brand_counts = camera["brand"].value_counts(normalize=True)

# 3. create a list of brands that make up lower than 3% of all models
other_brands = brand_counts[brand_counts < 0.03].index

# 4. replace the brand names with "others" for the brands in the list
camera["brand"] = camera["brand"].replace(other_brands, "Others")

# Use this revised dataset to develop a bar chart to show the counts of models␣
↪by brand.
plt.bar(camera["brand"].value_counts().index, camera["brand"].value_counts().
↪values)
plt.xticks(rotation=90)
plt.show()
```



[15]:
```
'''
Calculate and report the mean and standard deviation values for the 'Max.
↪resolution',
```

```
'Low.resolution', 'Zoom wide (W)' , and 'Zoom Tele (T)' columns within each year
('Release.date'). You can only use "groupby" and "agg" function, and the␣
 ↪calculation
should be written a single line of code.'
'''

camera.groupby('Release date').agg(
    {
        'Max resolution': ['mean', 'std'],
        'Low resolution': ['mean', 'std'],
        'Zoom wide (W)': ['mean', 'std'],
        'Zoom tele (T)': ['mean', 'std']
    }
).round(decimals=2)
```

[15]:

```
             Max resolution         Low resolution         Zoom wide (W)  \
                       mean     std           mean     std          mean
Release date
1994                1524.00     NaN           0.00     NaN          0.00
1995                3060.00     NaN           0.00     NaN          0.00
1996                 784.00  183.83         448.00  156.77         42.25
1997                 849.45  282.02         378.18  279.64         41.64
1998                1282.50  387.47         546.00  222.29         31.88
1999                1470.34  353.03         716.08  307.08         33.51
2000                1796.59  428.05        1049.90  450.12         34.05
2001                1866.65  469.17        1116.61  503.31         34.65
2002                2095.60  591.02        1390.76  558.35         33.98
2003                2263.73  447.53        1484.65  635.36         33.64
2004                2535.04  601.48        1836.51  655.73         32.89
2005                2754.68  395.64        2180.77  531.15         32.62
2006                3017.46  398.94        2409.73  400.51         30.93
2007                3289.84  402.98        2501.84  692.97         32.61

                    Zoom tele (T)
                std          mean     std
Release date
1994            NaN          0.00     NaN
1995            NaN          0.00     NaN
1996           7.32         57.00   33.33
1997           5.71         70.73   40.65
1998          10.86         86.50  106.35
1999          10.15         89.21   73.79
2000           9.56        111.79   89.77
2001           9.34        104.95   84.30
2002           9.41        105.85   73.65
2003           8.82        118.19   84.04
2004          10.02        123.51   89.17
```

```
2005           9.96        130.20   96.21
2006          12.44        134.65  102.70
2007          10.14        146.68  103.83
```

Task 2

[16]:
```python
# For every column that is numerical type, keep only the rows where the␣
↪condition
# value > 30 is satisfied.

# Get numerical columns
numerical_columns = camera.select_dtypes(include=['int', 'float']).columns

# Keep rows where numerical columns only have values > 30
camera = camera[camera[numerical_columns].gt(30).all(axis=1)]

# Filter rows with values > 30 only in columns starting with letter 'z' or end␣
↪with letter 'e'
e_z_cols = camera.filter(regex="(?i)(^z|e$)", axis=1).columns

camera = camera[camera[e_z_cols].gt(30).all(axis=1)]

# Select only rows 'Olympus', 'Sony', 'Canon', 'Kodak', and 'Fujifilm.' with␣
↪price > 350
camera = camera[(camera["brand"].isin(['Olympus', 'Sony', 'Canon', 'Kodak',␣
↪'Fujifilm'])) & (camera["Price"] > 350)]

camera
```

[16]:
```
                        Model  Release date  Max resolution  Low resolution  \
42     Canon PowerShot A720 IS          2007            3264            2592
65          Canon PowerShot G1          2000            2048            1024
66          Canon PowerShot G2          2001            2272            1600
67          Canon PowerShot G3          2002            2272            1600
69          Canon PowerShot G6          2004            3072            2592
…                         …             …               …               …
991                Sony DSC-V3          2004            3072            2592
992                Sony DSC-W1          2004            2592            2048
994              Sony DSC-W200          2007            4000            3264
997                Sony DSC-W5          2005            2592            2048
1003              Sony DSC-W90          2007            3254            2592

      Zoom wide (W)  Zoom tele (T)  Normal focus range  \
42               35            210                  55
65               34            102                  70
66               34            102                  70
67               35            140                  50
69               35            140                  50
```

```
…             …            …                  …
991              34            136                   40
992              38            114                   50
994              35            105                   34
997              38            114                   50
1003             35            105                   50

      Weight (inc. batteries)  Dimensions  Price  brand
42                      250.0        97.0    399  Canon
65                      490.0       120.0    499  Canon
66                      510.0       121.0    499  Canon
67                      490.0       121.0    499  Canon
69                      467.0       105.0    499  Canon
…                       …         …    …    …
991                     390.0       120.0    429   Sony
992                     250.0        91.0    429   Sony
994                     195.0        91.0    399   Sony
997                     250.0        91.0    429   Sony
1003                    175.0        91.0    429   Sony

[113 rows x 11 columns]
```