Statistics and Probability for Data Sciences - Challenges

Project 2

In [1]:
```
import pandas as pd
import numpy as np
import warnings
import matplotlib.pyplot as plt
import seaborn as sns
import statsmodels.stats.proportion as prop
from sklearn.linear_model import LinearRegression
from pandas.core.common import SettingWithCopyWarning
from scipy import stats
```

1.Display the data of white wine and red wine

In [2]:
```
red=pd.read_csv(".\winequality-red.csv",delimiter=';')
red
```

Out[2]:

	fixed acidity	volatile acidity	citric acid	residual sugar	chlorides	free sulfur dioxide	total sulfur dioxide	density	pH	sulphates	alcohol	quality
0	7.4	0.700	0.00	1.9	0.076	11.0	34.0	0.99780	3.51	0.56	9.4	5
1	7.8	0.880	0.00	2.6	0.098	25.0	67.0	0.99680	3.20	0.68	9.8	5
2	7.8	0.760	0.04	2.3	0.092	15.0	54.0	0.99700	3.26	0.65	9.8	5
3	11.2	0.280	0.56	1.9	0.075	17.0	60.0	0.99800	3.16	0.58	9.8	6
4	7.4	0.700	0.00	1.9	0.076	11.0	34.0	0.99780	3.51	0.56	9.4	5
...	...	...	...	...	...	...	...	...	...	...	...	...
1594	6.2	0.600	0.08	2.0	0.090	32.0	44.0	0.99490	3.45	0.58	10.5	5
1595	5.9	0.550	0.10	2.2	0.062	39.0	51.0	0.99512	3.52	0.76	11.2	6
1596	6.3	0.510	0.13	2.3	0.076	29.0	40.0	0.99574	3.42	0.75	11.0	6
1597	5.9	0.645	0.12	2.0	0.075	32.0	44.0	0.99547	3.57	0.71	10.2	5
1598	6.0	0.310	0.47	3.6	0.067	18.0	42.0	0.99549	3.39	0.66	11.0	6

1599 rows × 12 columns

In [3]:
```
white=pd.read_csv(".\winequality-white.csv",delimiter=';')
white
```

Out[3]:

	fixed acidity	volatile acidity	citric acid	residual sugar	chlorides	free sulfur dioxide	total sulfur dioxide	density	pH	sulphates	alcohol	quality
0	7.0	0.27	0.36	20.7	0.045	45.0	170.0	1.00100	3.00	0.45	8.8	6
1	6.3	0.30	0.34	1.6	0.049	14.0	132.0	0.99400	3.30	0.49	9.5	6
2	8.1	0.28	0.40	6.9	0.050	30.0	97.0	0.99510	3.26	0.44	10.1	6
3	7.2	0.23	0.32	8.5	0.058	47.0	186.0	0.99560	3.19	0.40	9.9	6
4	7.2	0.23	0.32	8.5	0.058	47.0	186.0	0.99560	3.19	0.40	9.9	6
...	...	...	...	...	...	...	...	...	...	...	...	...
4893	6.2	0.21	0.29	1.6	0.039	24.0	92.0	0.99114	3.27	0.50	11.2	6
4894	6.6	0.32	0.36	8.0	0.047	57.0	168.0	0.99490	3.15	0.46	9.6	5
4895	6.5	0.24	0.19	1.2	0.041	30.0	111.0	0.99254	2.99	0.46	9.4	6
4896	5.5	0.29	0.30	1.1	0.022	20.0	110.0	0.98869	3.34	0.38	12.8	7
4897	6.0	0.21	0.38	0.8	0.020	22.0	98.0	0.98941	3.26	0.32	11.8	6

4898 rows × 12 columns

2.Get the size of both white wine and red wine.

In [4]:
```
print("\n------------- WHITE WINE -------------\n")
print("Number of rows :", white.shape[0])
print("Number of columns:", white.shape[1])
print("\n-------------- RED WINE --------------\n")
print("Number of rows :", red.shape[0])
print("Number of columns:", red.shape[1])
```

```
------------- WHITE WINE -------------

Number of rows : 4898
Number of columns: 12

-------------- RED WINE --------------

Number of rows : 1599
Number of columns: 12
```

3.Get the number of null in both type of wines

In [5]:
```
print("\n------------- WHITE WINE -------------\n")
print(white.isnull().sum())
print("\n-------------- RED WINE --------------\n")
print(red.isnull().sum())
```

```
------------- WHITE WINE -------------

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

-------------- RED WINE --------------

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
```

4.Check for duplicates and remove them in both type of wine data

In [6]:
```
print("\n------------- WHITE WINE -------------\n")
print("No of rows duplicated:",white.duplicated().sum())
print("Total no of rows:",len(white))
white = white.drop_duplicates()
print("Total no of rows after removing duplicate rows:",len(white))
print("\n-------------- RED WINE --------------\n")
print("No of rows duplicated:",red.duplicated().sum())
print("Total no of rows:",len(red))
red = red.drop_duplicates()
print("Total no of rows after removing duplicate rows:",len(red))
```

```
------------- WHITE WINE -------------

No of rows duplicated: 937
Total no of rows: 4898
Total no of rows after removing duplicate rows: 3961

-------------- RED WINE --------------

No of rows duplicated: 240
Total no of rows: 1599
Total no of rows after removing duplicate rows: 1359
```

5.Get the number of uniques values in all Feature and print them

In [7]:
```
print("\n------------- WHITE WINE -------------\n")
for column in white.columns:
    print("No of Unique values in", column, ":", white[column].nunique())
print("\n-------------- RED WINE --------------\n")
for column in red.columns:
    print("No of Unique values in", column, ":", red[column].nunique())
```

```
------------- WHITE WINE -------------

No of Unique values in fixed acidity : 68
No of Unique values in volatile acidity : 125
No of Unique values in citric acid : 87
No of Unique values in residual sugar : 310
No of Unique values in chlorides : 160
No of Unique values in free sulfur dioxide : 132
No of Unique values in total sulfur dioxide : 251
No of Unique values in density : 890
No of Unique values in pH : 103
No of Unique values in sulphates : 79
No of Unique values in alcohol : 103
No of Unique values in quality : 7

-------------- RED WINE --------------

No of Unique values in fixed acidity : 96
No of Unique values in volatile acidity : 143
No of Unique values in citric acid : 80
No of Unique values in residual sugar : 91
No of Unique values in chlorides : 153
No of Unique values in free sulfur dioxide : 60
No of Unique values in total sulfur dioxide : 144
No of Unique values in density : 436
No of Unique values in pH : 89
No of Unique values in sulphates : 96
No of Unique values in alcohol : 65
No of Unique values in quality : 6
```

6.Print the mean density of both the sets

In [8]:
```
print("Mean density of White wine :",white['density'].mean())
print("Mean density of Red wine :",red['density'].mean())
```

```
Mean density of White wine : 0.9937895304216049
Mean density of Red wine : 0.9967089477557026
```

7.Combine both the datasets with color of the wine in column

In [25]:
```
# Add a new column for color
white['color'] = 0
red['color'] = 1
# This will show warning for adding the new column
warnings.filterwarnings('ignore', category=SettingWithCopyWarning)
# Concatenate both the dataframes
df = pd.concat([white, red], ignore_index=True)
df
```

Out[25]:

	fixed acidity	volatile acidity	citric acid	residual sugar	chlorides	free sulfur dioxide	total sulfur dioxide	density	pH	sulphates	alcohol	quality	color
0	7.0	0.270	0.36	20.7	0.045	45.0	170.0	1.00100	3.00	0.45	8.8	6	0
1	6.3	0.300	0.34	1.6	0.049	14.0	132.0	0.99400	3.30	0.49	9.5	6	0
2	8.1	0.280	0.40	6.9	0.050	30.0	97.0	0.99510	3.26	0.44	10.1	6	0
3	7.2	0.230	0.32	8.5	0.058	47.0	186.0	0.99560	3.19	0.40	9.9	6	0
4	6.2	0.320	0.16	7.0	0.045	30.0	136.0	0.99490	3.18	0.47	9.6	6	0
...	...	...	...	...	...	...	...	...	...	...	...	...	...
5315	6.8	0.620	0.08	1.9	0.068	28.0	38.0	0.99651	3.42	0.82	9.5	6	1
5316	6.2	0.600	0.08	2.0	0.090	32.0	44.0	0.99490	3.45	0.58	10.5	5	1
5317	5.9	0.550	0.10	2.2	0.062	39.0	51.0	0.99512	3.52	0.76	11.2	6	1
5318	5.9	0.645	0.12	2.0	0.075	32.0	44.0	0.99547	3.57	0.71	10.2	5	1
5319	6.0	0.310	0.47	3.6	0.067	18.0	42.0	0.99549	3.39	0.66	11.0	6	1

5320 rows × 13 columns

8.Remove the null values if any

In [10]:
```
print(df.isnull().sum())
```

```
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
color                   0
dtype: int64
```

There is no null value

9.Remove the outliers if any

In [11]:
```
print("Total no of rows:",len(df))
# Calculate z-scores for each column
z_scores = stats.zscore(df)

# Find rows with at least one outlier
outliers = np.where(np.abs(z_scores) > 3)[0]

# Remove the outliers
df = df.drop(outliers)
print("Total no of rows after removing outliers rows:",len(df))
```

```
Total no of rows: 5320
Total no of rows after removing outliers rows: 4869
```

10.Do wines with higher alcohol content receive better ratings?

In [12]:
```
correlation = df['alcohol'].corr(df['quality'])
print('Correlation between alcohol content and quality:', correlation)
```

```
Correlation between alcohol content and quality: 0.4843522307963171
```

The correlation coefficient is positive, it means that as alcohol content increases, the quality rating tends to increase

11.Find correlation between citric acid content and PH.

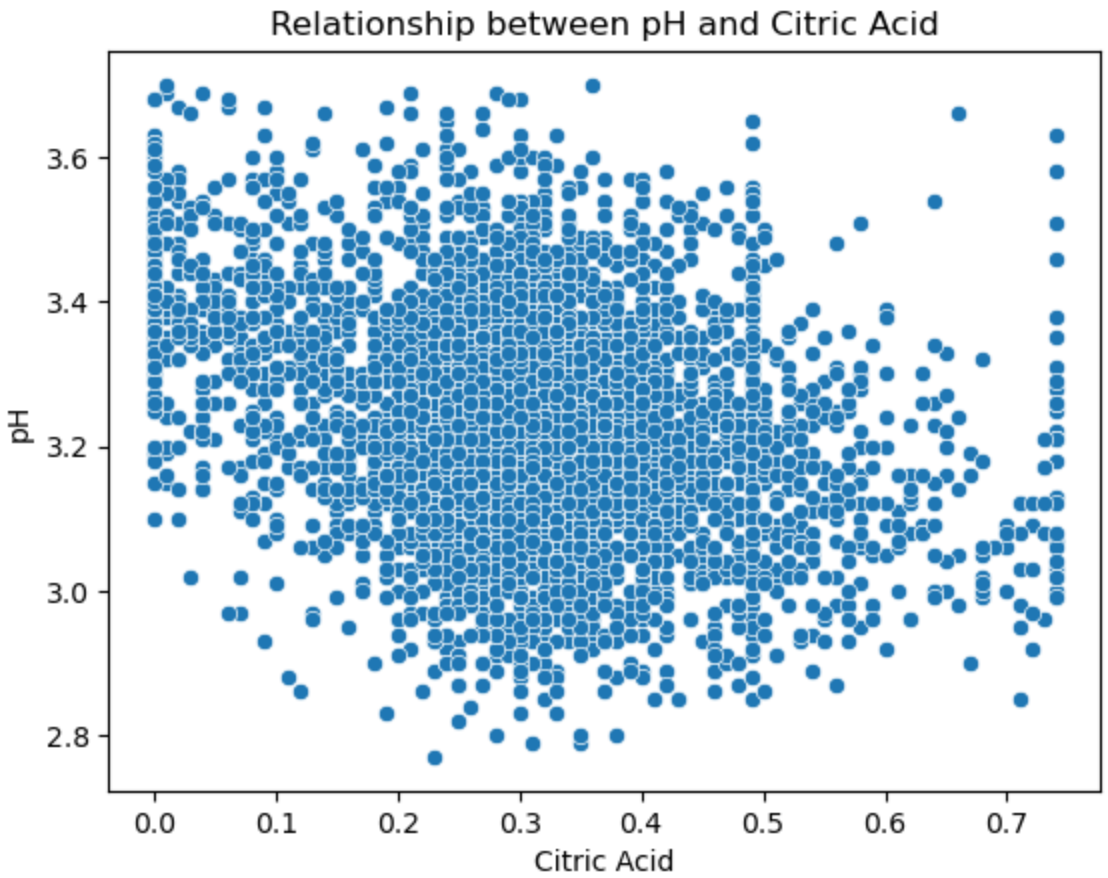
In [13]:
```
correlation = df['citric acid'].corr(df['pH'])
print('Correlation between citric acid and pH:', correlation)
```

```
Correlation between citric acid and pH: -0.30874212158501296
```

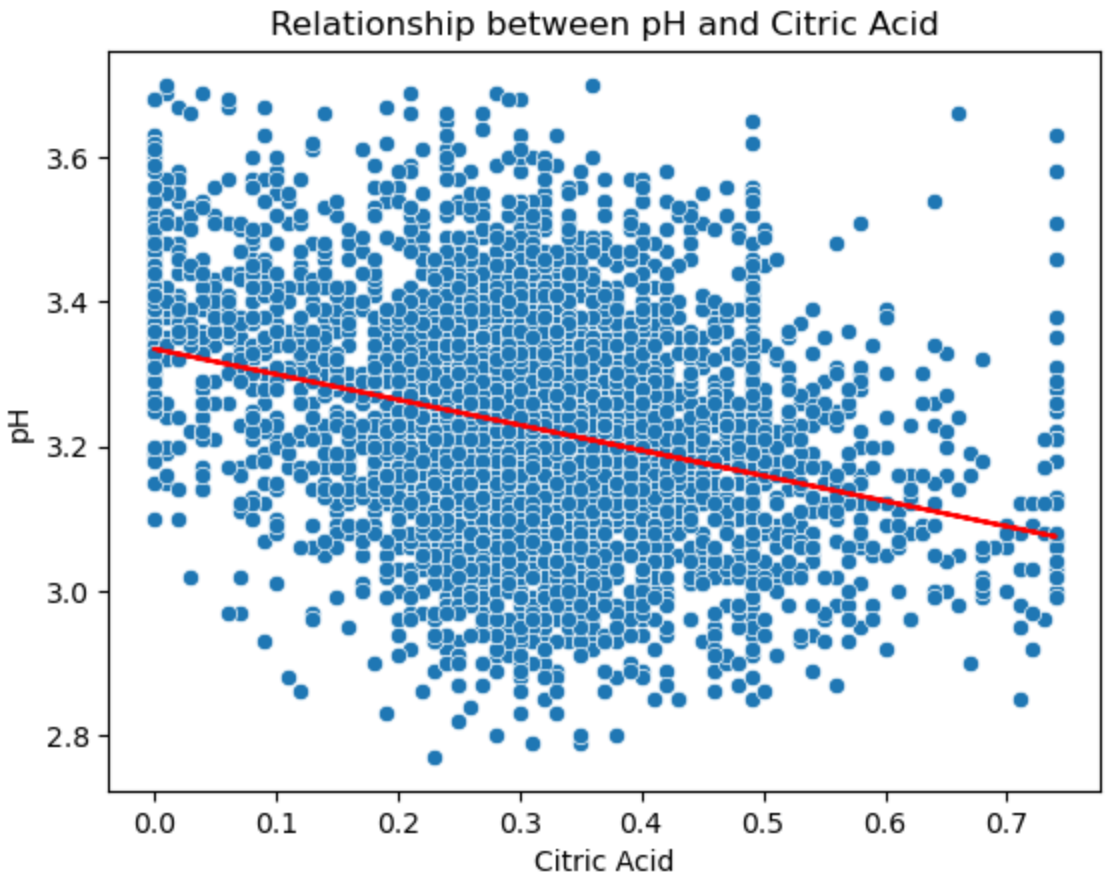
If the correlation coefficient between citric acid content and pH is negative, that indicates a negative correlation between the two variables. In other words, as the citric acid content increases, the pH tends to decrease.

12.Find regression of PH on citric acid

In [14]:
```
sns.scatterplot(x='citric acid', y='pH', data=df)
plt.title('Relationship between pH and Citric Acid')
plt.xlabel('Citric Acid')
plt.ylabel('pH')
plt.show()

X = df[['citric acid']]
y = df['pH']

model = LinearRegression()
model.fit(X, y)

print('Intercept:', model.intercept_)
print('Coefficient:', model.coef_[0])

sns.scatterplot(x='citric acid', y='pH', data=df)
plt.title('Relationship between pH and Citric Acid')
plt.xlabel('Citric Acid')
plt.ylabel('pH')

# Plot the regression line
plt.plot(X, model.predict(X), color='red')

plt.show()
```




```
Intercept: 3.334680804014977
Coefficient: -0.3510934287148778
```



13.Find how many variables are independent

To determine how many variables are independent in this dataset, we can use the correlation matrix and calculate the number of variables that have a correlation coefficient below a certain threshold (e.g., 0.7).

In [15]:
```python
# Calculate the correlation matrix
corr_matrix = df.corr().abs()

# Set the threshold for correlation coefficient
threshold = 0.7

# Find the number of variables that are independent
independent_vars = np.where(np.triu(corr_matrix > threshold, k=1))
num_independent_vars = len(set(independent_vars[0]))

print(f"The number of independent variables is {num_independent_vars}.")
```

```
The number of independent variables is 2.
```

14.Create a new column as the acidity level. Divide the existing data into 5 groups based on the acidity level. The levels are to be named ['High', 'Moderately_High', 'Medium', 'Low']. Acidity may be obtained from the PH.

In [16]:
```
bins = [0, 3.2, 3.4, 3.6, 3.8, 14]

# define the labels for the acidity levels
labels = ['Very low', 'Low', 'Medium', 'Moderately High', 'High']

# create the new column for acidity level
df['acidity level'] = pd.cut(df['pH'], bins=bins, labels=labels)
df
```

Out[16]:

	fixed acidity	volatile acidity	citric acid	residual sugar	chlorides	free sulfur dioxide	total sulfur dioxide	density	pH	sulphates	alcohol	quality	color	acidity level
1	6.3	0.300	0.34	1.6	0.049	14.0	132.0	0.99400	3.30	0.49	9.5	6	0	Low
2	8.1	0.280	0.40	6.9	0.050	30.0	97.0	0.99510	3.26	0.44	10.1	6	0	Low
3	7.2	0.230	0.32	8.5	0.058	47.0	186.0	0.99560	3.19	0.40	9.9	6	0	Very low
4	6.2	0.320	0.16	7.0	0.045	30.0	136.0	0.99490	3.18	0.47	9.6	6	0	Very low
5	8.1	0.220	0.43	1.5	0.044	28.0	129.0	0.99380	3.22	0.45	11.0	6	0	Low
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
5315	6.8	0.620	0.08	1.9	0.068	28.0	38.0	0.99651	3.42	0.82	9.5	6	1	Medium
5316	6.2	0.600	0.08	2.0	0.090	32.0	44.0	0.99490	3.45	0.58	10.5	5	1	Medium
5317	5.9	0.550	0.10	2.2	0.062	39.0	51.0	0.99512	3.52	0.76	11.2	6	1	Medium
5318	5.9	0.645	0.12	2.0	0.075	32.0	44.0	0.99547	3.57	0.71	10.2	5	1	Medium
5319	6.0	0.310	0.47	3.6	0.067	18.0	42.0	0.99549	3.39	0.66	11.0	6	1	Low

4869 rows × 14 columns

15.Find the mean quality of each acidity level with groupby. Use groupby

In [17]:
```
mean_quality = df.groupby("acidity level")["quality"].mean()

print(mean_quality)
```

```
acidity level
Very low           5.773263
Low                5.875632
Medium             5.894454
Moderately High    5.558140
High                    NaN
Name: quality, dtype: float64
```

16.Is a certain type of wine (red or white) associated with higher quality?

In [18]:
```
print("0 = white , 1 =red ")
color_quality = df.groupby("color")["quality"].mean()
print(color_quality)
```

```
0 = white , 1 =red
color
0    5.877875
1    5.649171
Name: quality, dtype: float64
```

From the output, you can see that the mean quality score for color 0 (white) is slightly higher than color 1 (red). However, the difference is very small and may not be statistically significant. Therefore, it's difficult to say that a certain type of color is associated with higher quality based on this data alone.

17.Select samples with alcohol content less than the median

In [19]:
```
median_alcohol = df['alcohol'].median()
low_alcohol = df[df['alcohol'] < median_alcohol]
low_alcohol
```

Out[19]:

	fixed acidity	volatile acidity	citric acid	residual sugar	chlorides	free sulfur dioxide	total sulfur dioxide	density	pH	sulphates	alcohol	quality	color	acidity level
1	6.3	0.300	0.34	1.6	0.049	14.0	132.0	0.99400	3.30	0.49	9.5	6	0	Low
2	8.1	0.280	0.40	6.9	0.050	30.0	97.0	0.99510	3.26	0.44	10.1	6	0	Low
3	7.2	0.230	0.32	8.5	0.058	47.0	186.0	0.99560	3.19	0.40	9.9	6	0	Very low
4	6.2	0.320	0.16	7.0	0.045	30.0	136.0	0.99490	3.18	0.47	9.6	6	0	Very low
7	8.6	0.230	0.40	4.2	0.035	17.0	109.0	0.99470	3.14	0.53	9.7	5	0	Very low
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
5295	7.3	0.690	0.32	2.2	0.069	35.0	104.0	0.99632	3.33	0.51	9.5	5	1	Low
5305	6.2	0.460	0.29	2.1	0.074	32.0	98.0	0.99578	3.33	0.62	9.8	5	1	Low
5311	6.6	0.725	0.20	7.8	0.073	29.0	79.0	0.99770	3.29	0.54	9.2	5	1	Low
5315	6.8	0.620	0.08	1.9	0.068	28.0	38.0	0.99651	3.42	0.82	9.5	6	1	Medium
5318	5.9	0.645	0.12	2.0	0.075	32.0	44.0	0.99547	3.57	0.71	10.2	5	1	Medium

2340 rows × 14 columns

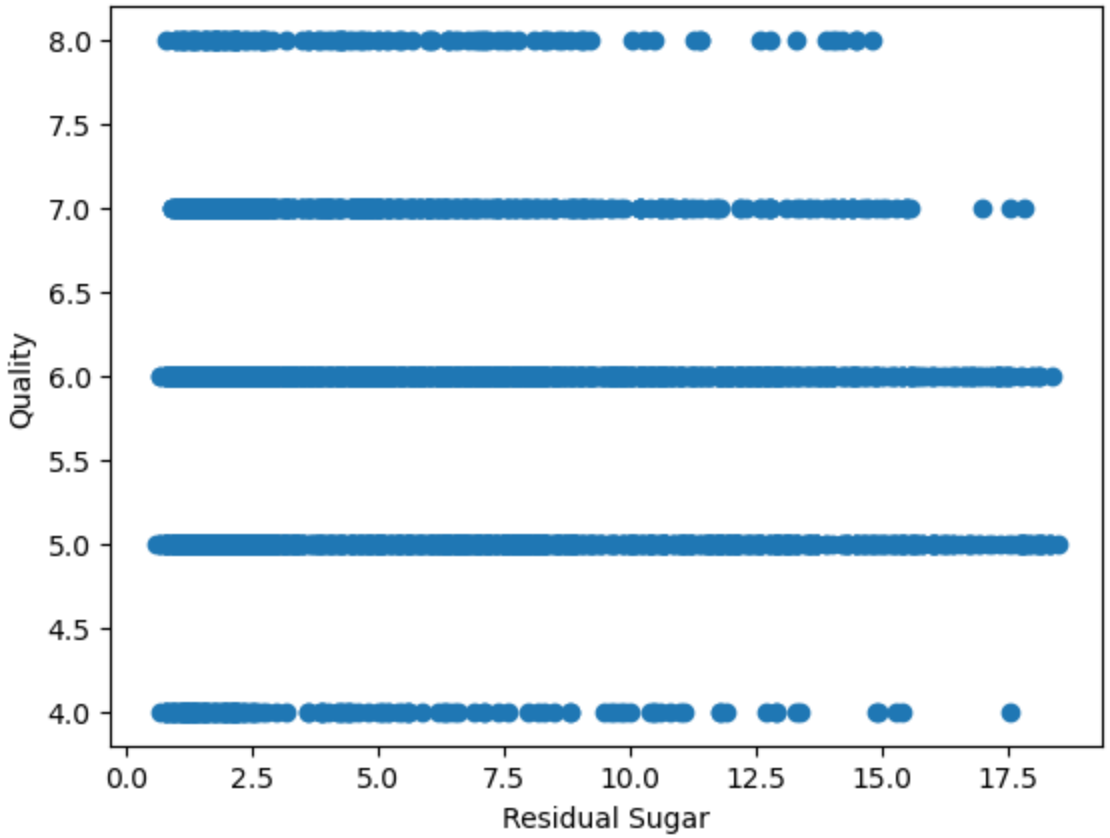
18.Get the quality rating for the low alcohol and high alcohol groups.

In [20]:
```
low_alcohol = df[df['alcohol'] < 10.5]
low_quality = low_alcohol['quality'].mean()
print(f"The average quality rating for the low alcohol group is: {low_quality:.2f}")
high_alcohol = df[df['alcohol'] >= 10.5]
high_quality = high_alcohol['quality'].mean()
print(f"The average quality rating for the high alcohol group is: {high_quality:.2f}")
```

```
The average quality rating for the low alcohol group is: 5.48
The average quality rating for the high alcohol group is: 6.19
```

19.Do sweeter wines get more ratings?

In [21]:
```
plt.scatter(df['residual sugar'], df['quality'])
plt.xlabel('Residual Sugar')
plt.ylabel('Quality')
plt.show()
```



The scatter plot show whether there is a trend between residual sugar and quality. If sweeter wines get more ratings, we would expect to see a positive correlation between residual sugar and quality but here almost the values are same

20.Get the number of counts based on ratings and color of wine.

In [22]:
```
count_ratings_color = df.groupby(['quality', 'color']).size()
print(count_ratings_color)
```

```
quality  color
4        0         144
         1          32
5        0        1111
         1         474
6        0        1720
         1         435
7        0         679
         1         133
8        0         129
         1          12
dtype: int64
```

21.Is the density of red wine and white wine similar?

In [23]:
```
print("0 = white , 1 =red ")
color_quality = df.groupby("color")["density"].mean()
print(color_quality)
```

```
0 = white , 1 =red
color
0    0.993687
1    0.996441
Name: density, dtype: float64
```

yes almost same

22.Is the confidence interval for the differences of the proportion of white wine with rating 3 and the proportion of red wine with rating 3.

Yes, the confidence interval for the difference of proportions of color 0 wine with rating 3 and the proportion of color 1 wine with rating 3 can be calculated

In [26]:
```
rating_3 = df[df['quality'] == 3]

prop_white = rating_3[rating_3['color'] == 0].shape[0] / rating_3.shape[0]
prop_red = rating_3[rating_3['color'] == 1].shape[0] / rating_3.shape[0]

conf_int = prop.confint_proportions_2indep(prop_white * rating_3.shape[0],
                                           rating_3.shape[0],
                                           prop_red * rating_3.shape[0],
                                           rating_3.shape[0],
                                           method='wald')

print('Confidence interval for difference of proportions: ', conf_int)
```

```
Confidence interval for difference of proportions:  (0.09477411417104564, 0.571892552495621)
```

In [ ]: