UDACITY Data Analysis Nanodegree

Project:- Wine Analysis

Learning about: Appending, Renaming Columns, Visuals, Pandas Groupby, **Pandas Query**

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1. Determine Objectives and Assess the Situation

The task is to answer several questions regarding wine quality, using this data set https://archive.ics.uci.edu/ml/datasets/Wine+Quality (https://archive.ics.uci.edu/ml/datasets/Wine+Quality)

1.1 Outline of Steps

- · We discuss what it is we wish to achieve, and decide which questions we want to ask of the data
- · We will extract the data we need
- · Import the data into Python for analysis
- Perform some rudimentary exploratory data analysis to help understand our data
- · Perform Exploratory Data Analysis
- · Create visualisations to aid exploration
- · Draw our conclusions based on the data

1.2 What are the desired outputs of the project?

- · Accurate project submission
- · Sucesfully answer all queries
- · Learn about Appending, Renaming Columns, Visuals, Pandas Groupby, Pandas Query

1.3 What Questions Are We Trying To Answer?

- · How many samples of red wine are there?
- How many samples of white wine are there?
- · How many columns are in each dataset?
- · Which features have missing values?
- · How many duplicate rows are in the white wine dataset?
- Are duplicate rows in these datasets significant/ need to be dropped?
- How many unique values of quality are in the red wine dataset?
- · How many unique values of quality are in the white wine dataset?
- · What is the mean density in the red wine dataset?
- · Is a certain type of wine (red or white) associated with higher quality?
- What level of acidity (pH value) receives the highest average rating?
- Do wines with higher alcoholic content receive better ratings?
- Do sweeter wines (more residual sugar) receive better ratings
- What level of acidity receives the highest average rating?

1.4 What Resources are Available?

- dataset located at https://archive.ics.uci.edu/ml/datasets/Wine+Quality)
- · Jupyter Python Notebook

2. Data Wrangling and Understanding

The second stage of the process is where we acquire the data listed in the project resources. Describe the methods used to acquire them and any problems encountered. Record problems you encountered and any resolutions achieved. This initial collection includes extraction details and source details, and subsequently loaded into Python and analysed in Jupyter notebook.

2.1 Data Extraction

Simple download from https://archive.ics.uci.edu/ml/datasets/Wine+Quality/

2.2 Describe Data's General Properties

Data description report - Describe the data that has been acquired including its format, its quantity (for example, the number of records and fields in each table), the identities of the fields and any other surface features which have been discovered. Evaluate whether the data acquired satisfies requirements.

```
In [54]:
```

```
import numpy as np
import pandas as pd
%matplotlib inline

import matplotlib.pyplot as plt

import seaborn as sns
sns.set_style('darkgrid')
```

```
In [55]:
```

```
df_r = pd.read_csv('winequality-red.csv', sep=';')
```

In [56]:

```
df_r.head(5)
```

Out[56]:

	fixed acidity	volatile acidity	citric acid	residual sugar	chlorides	free sulfur dioxide	total sulfur dioxide	density	рН	sulphates	alc
0	7.4	0.70	0.00	1.9	0.076	11.0	34.0	0.9978	3.51	0.56	
1	7.8	0.88	0.00	2.6	0.098	25.0	67.0	0.9968	3.20	0.68	
2	7.8	0.76	0.04	2.3	0.092	15.0	54.0	0.9970	3.26	0.65	
3	11.2	0.28	0.56	1.9	0.075	17.0	60.0	0.9980	3.16	0.58	
4	7.4	0.70	0.00	1.9	0.076	11.0	34.0	0.9978	3.51	0.56	
4											•

```
In [57]:
```

```
df_w = pd.read_csv('winequality-white.csv', sep=';')
```

In [58]:

```
df_w.head(5)
```

Out[58]:

	fixed acidity	volatile acidity	citric acid	residual sugar	chlorides	free sulfur dioxide	total sulfur dioxide	density	рН	sulphates	alc
0	7.0	0.27	0.36	20.7	0.045	45.0	170.0	1.0010	3.00	0.45	
1	6.3	0.30	0.34	1.6	0.049	14.0	132.0	0.9940	3.30	0.49	
2	8.1	0.28	0.40	6.9	0.050	30.0	97.0	0.9951	3.26	0.44	
3	7.2	0.23	0.32	8.5	0.058	47.0	186.0	0.9956	3.19	0.40	
4	7.2	0.23	0.32	8.5	0.058	47.0	186.0	0.9956	3.19	0.40	
4											•

In [59]:

```
df_r.shape
```

Out[59]:

(1599, 12)

In [60]:

```
df_r.columns
```

Out[60]:

```
Index(['fixed acidity', 'volatile acidity', 'citric acid', 'residual suga
       'chlorides', 'free sulfur dioxide', 'total sulfur dioxide', 'densit
у',
       'pH', 'sulphates', 'alcohol', 'quality'],
      dtype='object')
```

In [61]:

```
df_w.shape
```

Out[61]:

(4898, 12)

In [62]:

```
df_w.columns
```

Out[62]:

In [63]:

```
df_r.dtypes
```

Out[63]:

fixed acidity float64 volatile acidity float64 float64 citric acid residual sugar float64 chlorides float64 free sulfur dioxide float64 total sulfur dioxide float64 float64 density float64 рΗ float64 sulphates alcohol float64 int64 quality

dtype: object

In [64]:

```
df_w.dtypes
```

Out[64]:

fixed acidity float64 float64 volatile acidity float64 citric acid residual sugar float64 chlorides float64 free sulfur dioxide float64 total sulfur dioxide float64 density float64 float64 рΗ sulphates float64 alcohol float64 quality int64 dtype: object

In [65]:

df r.info()

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1599 entries, 0 to 1598
Data columns (total 12 columns):
fixed acidity
                        1599 non-null float64
volatile acidity
                        1599 non-null float64
citric acid
                        1599 non-null float64
residual sugar
                        1599 non-null float64
                        1599 non-null float64
chlorides
                        1599 non-null float64
free sulfur dioxide
total sulfur dioxide
                        1599 non-null float64
density
                        1599 non-null float64
                        1599 non-null float64
рΗ
sulphates
                        1599 non-null float64
alcohol
                        1599 non-null float64
                        1599 non-null int64
quality
dtypes: float64(11), int64(1)
memory usage: 150.0 KB
```

In [66]:

```
df_w.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 4898 entries, 0 to 4897
Data columns (total 12 columns):
fixed acidity
                        4898 non-null float64
volatile acidity
                        4898 non-null float64
citric acid
                        4898 non-null float64
                        4898 non-null float64
residual sugar
chlorides
                        4898 non-null float64
free sulfur dioxide
                        4898 non-null float64
total sulfur dioxide
                        4898 non-null float64
                        4898 non-null float64
density
                        4898 non-null float64
рΗ
sulphates
                        4898 non-null float64
                        4898 non-null float64
alcohol
                        4898 non-null int64
quality
dtypes: float64(11), int64(1)
memory usage: 459.3 KB
```

In [67]:

df_r.describe()

Out[67]:

	fixed acidity	volatile acidity	citric acid	residual sugar	chlorides	free sulfur dioxide	total
count	1599.000000	1599.000000	1599.000000	1599.000000	1599.000000	1599.000000	1599.0
mean	8.319637	0.527821	0.270976	2.538806	0.087467	15.874922	46.4
std	1.741096	0.179060	0.194801	1.409928	0.047065	10.460157	32.
min	4.600000	0.120000	0.000000	0.900000	0.012000	1.000000	6.0
25%	7.100000	0.390000	0.090000	1.900000	0.070000	7.000000	22.0
50%	7.900000	0.520000	0.260000	2.200000	0.079000	14.000000	38.0
75%	9.200000	0.640000	0.420000	2.600000	0.090000	21.000000	62.0
max	15.900000	1.580000	1.000000	15.500000	0.611000	72.000000	289.0

In [68]:

df_w.describe()

Out[68]:

	fixed acidity	volatile acidity	citric acid	residual sugar	chlorides	free sulfur dioxide	total
count	4898.000000	4898.000000	4898.000000	4898.000000	4898.000000	4898.000000	4898.0
mean	6.854788	0.278241	0.334192	6.391415	0.045772	35.308085	138.
std	0.843868	0.100795	0.121020	5.072058	0.021848	17.007137	42.4
min	3.800000	0.080000	0.000000	0.600000	0.009000	2.000000	9.0
25%	6.300000	0.210000	0.270000	1.700000	0.036000	23.000000	108.0
50%	6.800000	0.260000	0.320000	5.200000	0.043000	34.000000	134.0
75%	7.300000	0.320000	0.390000	9.900000	0.050000	46.000000	167.0
max	14.200000	1.100000	1.660000	65.800000	0.346000	289.000000	440.0
4							•

In [69]:

df_r.nunique()

Out[69]:

fixed acidity 96 volatile acidity 143 citric acid 80 residual sugar 91 chlorides 153 free sulfur dioxide 60 total sulfur dioxide 144 density 436 рΗ 89 sulphates 96 alcohol 65 quality 6 dtype: int64

In [70]:

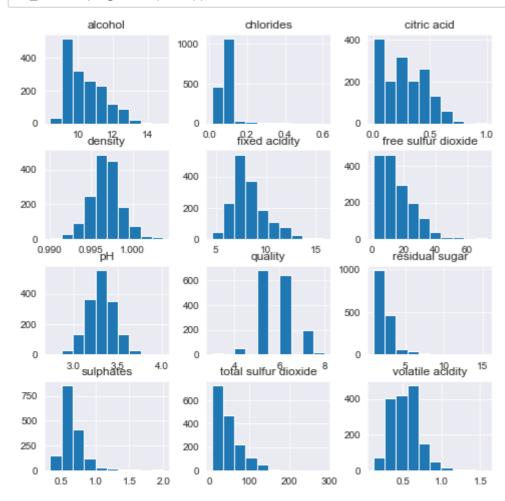
df_w.nunique()

Out[70]:

fixed acidity	68
volatile acidity	125
citric acid	87
residual sugar	310
chlorides	160
free sulfur dioxide	132
total sulfur dioxide	251
density	890
рН	103
sulphates	79
alcohol	103
quality	7
dtype: int64	

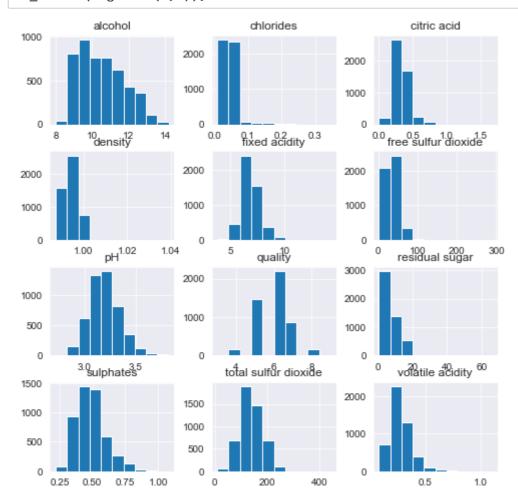
In [114]:

df_r.hist(figsize=(8,8));



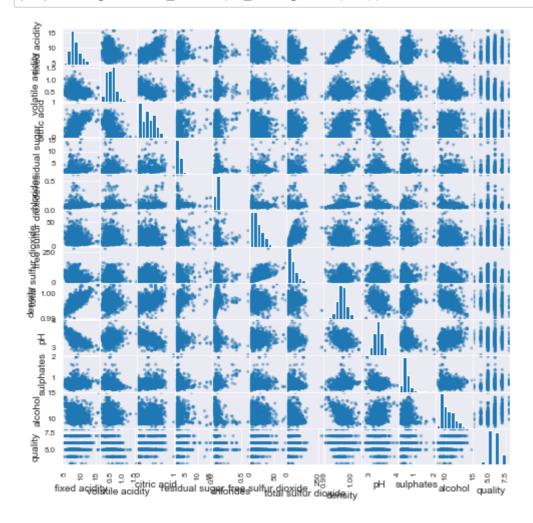
In [71]:

df_w.hist(figsize=(8,8));



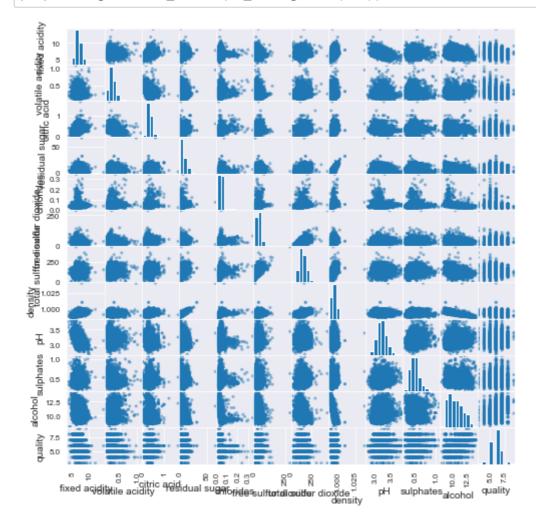
In [116]:

pd.plotting.scatter_matrix(df_r, figsize=(8,8));



In [117]:

pd.plotting.scatter_matrix(df_w, figsize=(8,8));



2.3 Verify Data Quality

Examine the quality of the data, addressing questions such as:

- Is the data complete (does it cover all the cases required)?
- Is it correct, or does it contain errors and, if there are errors, how common are they?
- Are there missing values in the data? If so, how are they represented, where do they occur, and how common are they?

2.3.1. Missing Data

In addition to incorrect datatypes, another common problem when dealing with real-world data is missing values. These can arise for many reasons and have to be either filled in or removed before we train a machine learning model. First, let's get a sense of how many missing values are in each column

While we always want to be careful about removing information, if a column has a high percentage of missing values, then it probably will not be useful to our model. The threshold for removing columns should depend on the problem

In [72]:

```
def missing_values_table(df):
        mis_val = df.isnull().sum()
        mis val percent = 100 * df.isnull().sum() / len(df)
        mis_val_table = pd.concat([mis_val, mis_val_percent], axis=1)
        mis_val_table_ren_columns = mis_val_table.rename(
        columns = {0 : 'Missing Values', 1 : '% of Total Values'})
        mis_val_table_ren_columns = mis_val_table_ren_columns[
            mis_val_table_ren_columns.iloc[:,1] != 0].sort_values(
        '% of Total Values', ascending=False).round(1)
        print ("Your selected dataframe has " + str(df.shape[1]) + " columns.\n"
            "There are " + str(mis_val_table_ren_columns.shape[0]) +
              " columns that have missing values.")
        return mis_val_table_ren_columns
```

In [73]:

```
df_r.isnull().sum()
```

Out[73]:

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

In [74]:

```
missing_values_table(df_r)
```

Your selected dataframe has 12 columns. There are 0 columns that have missing values.

Out[74]:

Missing Values % of Total Values

```
In [75]:
```

```
missing_values_table(df_w)
```

Your selected dataframe has 12 columns. There are 0 columns that have missing values.

Out[75]:

Missing Values % of Total Values

Decision

We may want to remove null rows entirely from the dataset. To do so we would run the following

```
df.dropna()
```

• We may want to drop the columns if they appear to be predominantly NA. To do so we would run the following

```
# Get the columns with > 50% missing
missing_df = missing_values_table(df);
missing_columns = list(missing_df[missing_df['% of Total Values'] > 50].inde
print('We will remove %d columns.' % len(missing_columns))
df = df.drop(list(missing_columns))
```

 We may want to fill the missing values with the mean values from the dataset. To do so we would run the following

```
mean = df['x'].mean()
df['x'].fillna(mean, inplace=True)
```

2.3.2. Outliers

At this point, we may also want to remove outliers. These can be due to typos in data entry, mistakes in units, or they could be legitimate but extreme values. For this project, we will remove anomalies based on the definition of extreme outliers:

```
In [ ]:
```

2.3.3. Duplicates

There may be duplicates in the data. However, these may be legitimate new rows depending on the structure of the data. We need to discover them, then decide what to do with them

```
In [76]:
```

```
sum(df_r.duplicated())
```

Out[76]:

240

In [77]:

```
sum(df_w.duplicated())
```

Out[77]:

937

Decision We may want to remove duplicate rows entirely from the dataset. To do so we would run the following

```
df.drop_duplicates(inplace=True)
```

Data Quality Report

Category	Issue	Decision
Missing Values	N/A	None
Outliers	N/A	None
Duplicates	Duplicates found	None

3. Exploratory Data Analysis

· How many samples of red wine are there?

In [78]:

```
df_r.shape
```

Out[78]:

(1599, 12)

· How many samples of white wine are there?

In [79]:

```
df_w.shape
```

Out[79]:

(4898, 12)

- · How many columns are in each dataset?
- · Which features have missing values?

In [80]:

```
df_r.isnull().sum()
Out[80]:
fixed acidity
                         0
volatile acidity
                         0
citric acid
                         0
residual sugar
                         0
chlorides
free sulfur dioxide
                         0
total sulfur dioxide
                         0
density
                         0
```

quality dtype: int64

sulphates

alcohol

In [81]:

рΗ

```
df_w.isnull().sum()
```

Out[81]:

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

· How many duplicate rows are in the white wine dataset?

0

0

0

0

In [82]:

```
sum(df_r.duplicated())
```

Out[82]:

240

```
In [83]:
```

```
sum(df_w.duplicated())
```

Out[83]:

937

• Are duplicate rows in these datasets significant/ need to be dropped?

```
In [ ]:
```

· How many unique values of quality are in the red wine dataset?

In [84]:

```
df_r.nunique()
```

Out[84]:

```
fixed acidity
                          96
volatile acidity
                         143
citric acid
                          80
residual sugar
                          91
chlorides
                         153
free sulfur dioxide
                          60
total sulfur dioxide
                         144
density
                         436
рΗ
                          89
sulphates
                          96
alcohol
                          65
quality
                           6
dtype: int64
```

· How many unique values of quality are in the white wine dataset?

In [85]:

```
df_w.nunique()
```

Out[85]:

fixed acidity	68
volatile acidity	125
citric acid	87
residual sugar	310
chlorides	160
free sulfur dioxide	132
total sulfur dioxide	251
density	890
рН	103
sulphates	79
alcohol	103
quality	7
dtype: int64	

· What is the mean density in the red wine dataset?

In [86]:

```
df_r.density.mean()
```

Out[86]:

0.9967466791744833

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

First, lets combine datasets

In [87]:

```
#Column name differences between the files, so change to a matching name
df_r=df_r.rename(columns = {'total_sulfur-dioxide':'total_sulfur_dioxide'})
```

In [88]:

```
# create color array for red dataframe
color_red = np.repeat('red', df_r.shape[0])
# create color array for white dataframe
color_white = np.repeat('white', df_w.shape[0])
```

In [89]:

```
df_r['color'] = color_red
df_w['color'] = color_white
```

In [90]:

```
wine_df = df_r.append(df_w)
```

In [91]:

```
wine_df.head()
```

Out[91]:

	fixed acidity	volatile acidity	citric acid	residual sugar	chlorides	free sulfur dioxide	total sulfur dioxide	density	рН	sulphates	alc
0	7.4	0.70	0.00	1.9	0.076	11.0	34.0	0.9978	3.51	0.56	
1	7.8	0.88	0.00	2.6	0.098	25.0	67.0	0.9968	3.20	0.68	
2	7.8	0.76	0.04	2.3	0.092	15.0	54.0	0.9970	3.26	0.65	
3	11.2	0.28	0.56	1.9	0.075	17.0	60.0	0.9980	3.16	0.58	
4	7.4	0.70	0.00	1.9	0.076	11.0	34.0	0.9978	3.51	0.56	
4											•

```
In [92]:
```

28/06/2019

```
wine_df=wine_df.rename(columns = {'residual sugar':'residual_sugar'})
```

In [93]:

```
# Find the mean quality of each wine type (red and white) with groupby
wine_df.groupby('color').mean().quality
```

Out[93]:

```
color
```

red 5.636023 white 5.877909

Name: quality, dtype: float64

· What level of acidity (pH value) receives the highest average rating?

In [94]:

```
wine_df.describe().pH
```

Out[94]:

```
count
         6497.000000
            3.218501
mean
std
            0.160787
            2.720000
min
25%
            3.110000
50%
            3.210000
            3.320000
75%
            4.010000
max
Name: pH, dtype: float64
```

In [95]:

```
# Bin edges that will be used to "cut" the data into groups
bin_edges = [2.72, 3.11, 3.21, 3.32, 4.01]
```

In [96]:

```
# Labels for the four acidity level groups
bin_names = ['high', 'mod_high', 'medium', 'low']
```

Wine Case Study

In [97]:

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```
# Creates acidity levels column
wine_df['acidity_levels'] = pd.cut(wine_df['pH'], bin_edges, labels=bin_names)
# Checks for successful creation of this column
wine df.head()
```

Out[97]:

	fixed acidity	volatile acidity	citric acid	residual_sugar	chlorides	free sulfur dioxide	total sulfur dioxide	density	рН	sulphate
0	7.4	0.70	0.00	1.9	0.076	11.0	34.0	0.9978	3.51	0.4
1	7.8	0.88	0.00	2.6	0.098	25.0	67.0	0.9968	3.20	0.6
2	7.8	0.76	0.04	2.3	0.092	15.0	54.0	0.9970	3.26	0.6
3	11.2	0.28	0.56	1.9	0.075	17.0	60.0	0.9980	3.16	0.4
4	7.4	0.70	0.00	1.9	0.076	11.0	34.0	0.9978	3.51	0.4

In [98]:

```
# Find the mean quality of each acidity level with groupby
wine_df.groupby('acidity_levels').mean().quality
```

Out[98]:

```
acidity_levels
high
            5.783343
mod high
            5.784540
medium
            5.850832
low
            5.859593
```

Name: quality, dtype: float64

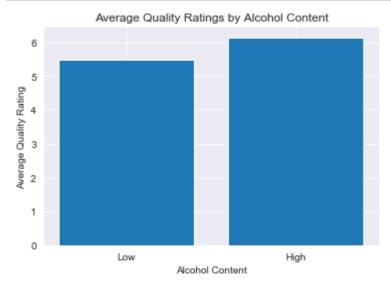
· Do wines with higher alcoholic content receive better ratings?

In [99]:

```
median = wine df['alcohol'].median()
low = wine_df.query('alcohol < {}'.format(median))</pre>
high = wine_df.query('alcohol >= {}'.format(median))
mean_quality_low = low['quality'].mean()
mean quality high = high['quality'].mean()
```

In [100]:

```
locations = [1, 2]
heights = [mean_quality_low, mean_quality_high]
labels = ['Low', 'High']
plt.bar(locations, heights, tick_label=labels)
plt.title('Average Quality Ratings by Alcohol Content')
plt.xlabel('Alcohol Content')
plt.ylabel('Average Quality Rating');
```



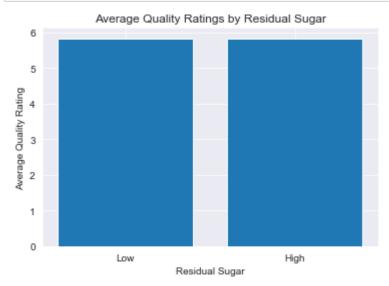
• Do sweeter wines (more residual sugar) receive better ratings

In [101]:

```
# Use query to select each group and get its mean quality
median = wine_df['residual_sugar'].median()
low = wine_df.query('residual_sugar < {}'.format(median))</pre>
high = wine_df.query('residual_sugar >= {}'.format(median))
mean_quality_low = low['quality'].mean()
mean_quality_high = high['quality'].mean()
```

In [102]:

```
# Create a bar chart with proper labels
locations = [1, 2]
heights = [mean_quality_low, mean_quality_high]
labels = ['Low', 'High']
plt.bar(locations, heights, tick_label=labels)
plt.title('Average Quality Ratings by Residual Sugar')
plt.xlabel('Residual Sugar')
plt.ylabel('Average Quality Rating');
```



What level of acidity receives the highest average rating?

In [103]:

```
acidity_level_quality_means = wine_df.groupby('acidity_levels').mean().quality
acidity_level_quality_means
```

Out[103]:

```
acidity_levels
high
            5.783343
mod_high
            5.784540
medium
            5.850832
            5.859593
low
Name: quality, dtype: float64
```

In [104]:

```
locations = [4, 1, 2, 3] # reorder values above to go from low to high
heights = acidity_level_quality_means
# labels = ['Low', 'Medium', 'Moderately High', 'High']
labels = acidity_level_quality_means.index.str.replace('_', ' ').str.title() # alternat
ive to commented out line above
plt.bar(locations, heights, tick_label=labels)
plt.title('Average Quality Ratings by Acidity Level')
plt.xlabel('Acidity Level')
plt.ylabel('Average Quality Rating');
```



In [105]:

```
# get counts for each rating and color
color_counts = wine_df.groupby(['color', 'quality']).count()['pH']
color_counts
```

Out[105]:

color	qua	ality	
red	3		10
	4		53
	5		681
	6		638
	7		199
	8		18
white	3		20
	4		163
	5		1457
	6		2198
	7		880
	8		175
	9		5
Name:	pН,	dtype:	int64

```
In [106]:
```

```
color_totals = wine_df.groupby('color').count()['pH']
color_totals
```

Out[106]:

color

red 1599 white 4898

Name: pH, dtype: int64

In [107]:

```
# get proportions by dividing red rating counts by total # of red samples
red_proportions = color_counts['red'] / color_totals['red']
red_proportions
```

Out[107]:

quality

- 3 0.006254
- 4 0.033146
- 5 0.425891
- 6 0.398999
- 7 0.124453
- 0.011257 8

Name: pH, dtype: float64

In [108]:

```
red_proportions['9'] = 0
red_proportions
```

Out[108]:

quality

- 0.006254
- 4 0.033146
- 5 0.425891
- 6 0.398999
- 7 0.124453
- 8 0.011257
- 0.000000

Name: pH, dtype: float64

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In [109]:

```
white_proportions = color_counts['white'] / color_totals['white']
white_proportions
```

Out[109]:

```
quality
     0.004083
3
4
     0.033279
5
     0.297468
6
     0.448755
7
     0.179665
```

9 0.001021 Name: pH, dtype: float64

0.035729

In [110]:

8

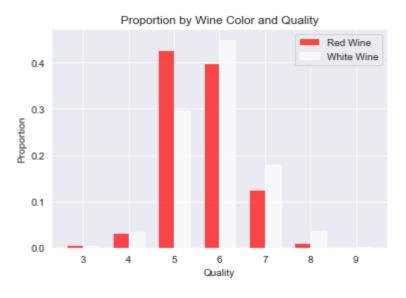
```
ind = np.arange(len(red_proportions)) # the x locations for the groups
width = 0.35
                   # the width of the bars
```

In [111]:

```
# plot bars
red_bars = plt.bar(ind, red_proportions, width, color='r', alpha=.7, label='Red Wine')
white_bars = plt.bar(ind + width, white_proportions, width, color='w', alpha=.7, label=
'White Wine')
# title and labels
plt.ylabel('Proportion')
plt.xlabel('Quality')
plt.title('Proportion by Wine Color and Quality')
locations = ind + width / 2 # xtick locations
labels = ['3', '4', '5', '6', '7', '8', '9'] # xtick Labels
plt.xticks(locations, labels)
# Leaend
plt.legend()
```

Out[111]:

<matplotlib.legend.Legend at 0x2905d7d0a90>



4. Observations and Conclusion

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- How many samples of red wine are there?
 - A 1559
- How many samples of white wine are there?
 - A 4898
- · How many columns are in each dataset?
 - A 12
- · Which features have missing values?
 - A None
- How many duplicate rows are in the white wine dataset?
 - A 937
- · Are duplicate rows in these datasets significant/ need to be dropped?
 - A Not necessarily
- · How many unique values of quality are in the red wine dataset?
 - A 6
- How many unique values of quality are in the white wine dataset?
 - A 7
- · What is the mean density in the red wine dataset?
 - A 0.996747
- Is a certain type of wine (red or white) associated with higher quality?
 - A White
- · What level of acidity (pH value) receives the highest average rating?
 - A Low
- Do wines with higher alcoholic content receive better ratings?
 - A High
- Do sweeter wines (more residual sugar) receive better ratings?
 - A Yes
- · What level of acidity receives the highest average rating?
 - A Low

References

- UCI Wine Quality Data Set: https://archive.ics.uci.edu/ml/datasets/Wine+Quality (https://archive.ics.uci.edu/ml/datasets/Wine+Quality)
- UDACITY Data Analyst Nanodegree: https://eu.udacity.com/course/data-analyst-nanodegree--nd002? v=a (https://eu.udacity.com/course/data-analyst-nanodegree--nd002?v=a)