Import Dependencies

In [1]:
```
import numpy as np
import pandas as pd
from matplotlib import pyplot as plt
%matplotlib inline
import seaborn as sns

from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score
from sklearn.metrics import confusion_matrix, classification_report, roc_curve, auc
from sklearn.model_selection import RandomizedSearchCV

import warnings
warnings.filterwarnings("ignore")
```

Load Dataset

In [4]:
```
df = pd.read_csv("C:/Users/akula/Downloads/winequality-red.csv")
df.head()
```

Out[4]:

	fixed acidity	volatile acidity	citric acid	residual sugar	chlorides	free sulfur dioxide	total sulfur dioxide	density	pH	sulphates	alcohol	quality
0	7.4	0.70	0.00	1.9	0.076	11.0	34.0	0.9978	3.51	0.56	9.4	5
1	7.8	0.88	0.00	2.6	0.098	25.0	67.0	0.9968	3.20	0.68	9.8	5
2	7.8	0.76	0.04	2.3	0.092	15.0	54.0	0.9970	3.26	0.65	9.8	5
3	11.2	0.28	0.56	1.9	0.075	17.0	60.0	0.9980	3.16	0.58	9.8	6
4	7.4	0.70	0.00	1.9	0.076	11.0	34.0	0.9978	3.51	0.56	9.4	5

In [5]:
```
# check shape
df.shape
```

Out[5]:
```
(1599, 12)
```

In [6]:
```
# check some information about data
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1599 entries, 0 to 1598
Data columns (total 12 columns):
 #   Column                Non-Null Count  Dtype
---  ------                --------------  -----
 0   fixed acidity         1599 non-null   float64
 1   volatile acidity      1599 non-null   float64
 2   citric acid           1599 non-null   float64
 3   residual sugar        1599 non-null   float64
 4   chlorides             1599 non-null   float64
 5   free sulfur dioxide   1599 non-null   float64
 6   total sulfur dioxide  1599 non-null   float64
 7   density               1599 non-null   float64
 8   pH                    1599 non-null   float64
 9   sulphates             1599 non-null   float64
 10  alcohol               1599 non-null   float64
 11  quality               1599 non-null   int64
dtypes: float64(11), int64(1)
memory usage: 150.0 KB
```

In [7]:
```
# check description
df.describe()
```

Out[7]:

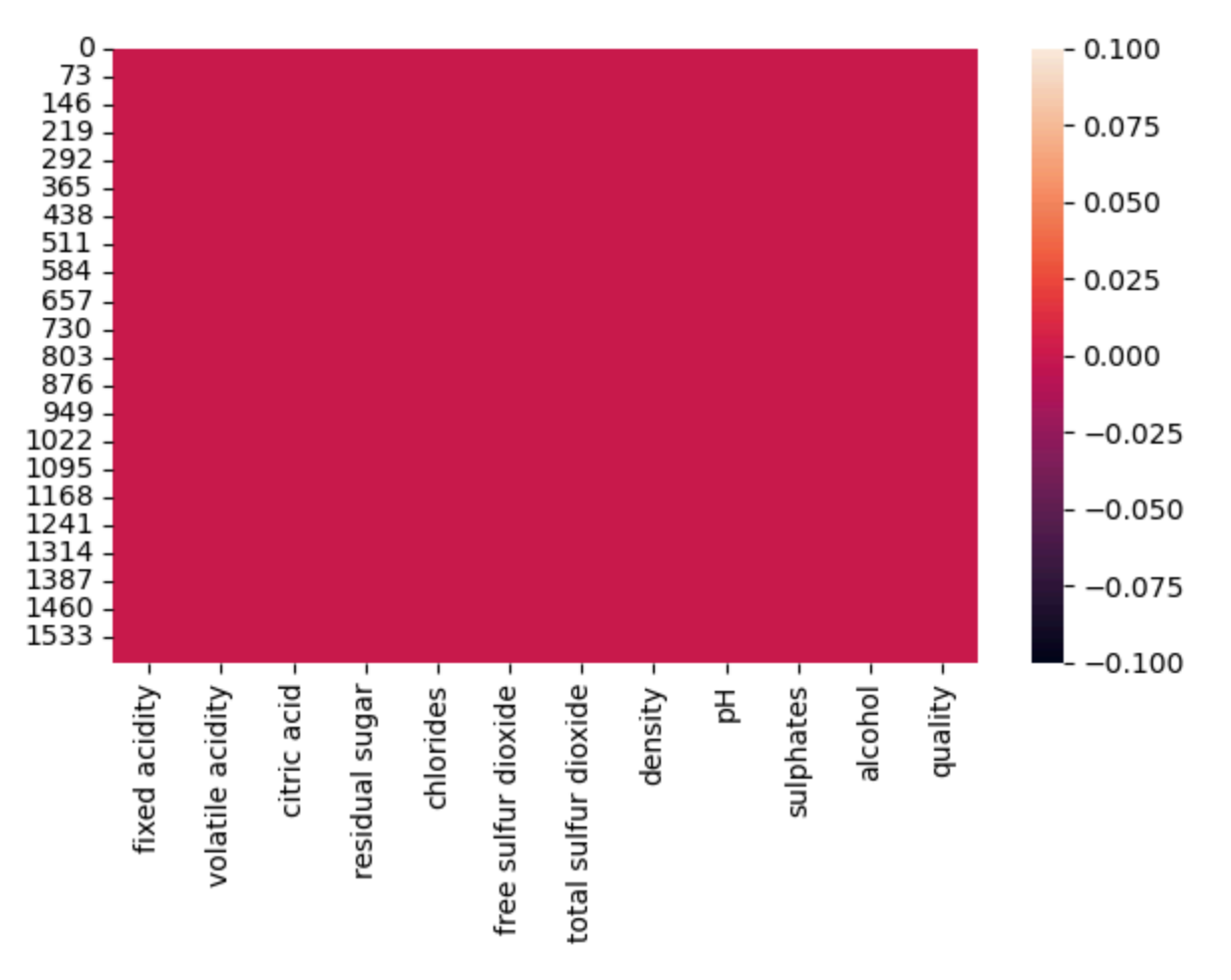
	fixed acidity	volatile acidity	citric acid	residual sugar	chlorides	free sulfur dioxide	total sulfur dioxide	density	pH	sulphates	alcohol	quality
count	1599.000000	1599.000000	1599.000000	1599.000000	1599.000000	1599.000000	1599.000000	1599.000000	1599.000000	1599.000000	1599.000000	1599.000000
mean	8.319637	0.527821	0.270976	2.538806	0.087467	15.874922	46.467792	0.996747	3.311113	0.658149	10.422983	5.636023
std	1.741096	0.179060	0.194801	1.409928	0.047065	10.460157	32.895324	0.001887	0.154386	0.169507	1.065668	0.807569
min	4.600000	0.120000	0.000000	0.900000	0.012000	1.000000	6.000000	0.990070	2.740000	0.330000	8.400000	3.000000
25%	7.100000	0.390000	0.090000	1.900000	0.070000	7.000000	22.000000	0.995600	3.210000	0.550000	9.500000	5.000000
50%	7.900000	0.520000	0.260000	2.200000	0.079000	14.000000	38.000000	0.996750	3.310000	0.620000	10.200000	6.000000
75%	9.200000	0.640000	0.420000	2.600000	0.090000	21.000000	62.000000	0.997835	3.400000	0.730000	11.100000	6.000000
max	15.900000	1.580000	1.000000	15.500000	0.611000	72.000000	289.000000	1.003690	4.010000	2.000000	14.900000	8.000000

In [8]:
```
# check null values
df.isna().sum()
```

Out[8]:
```
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
```

In [9]:
```
plt.figure(figsize=(7,4))
sns.heatmap(df.isnull())
```

Out[9]:
```
<Axes: >
```



In [10]:
```
df.nunique()
```

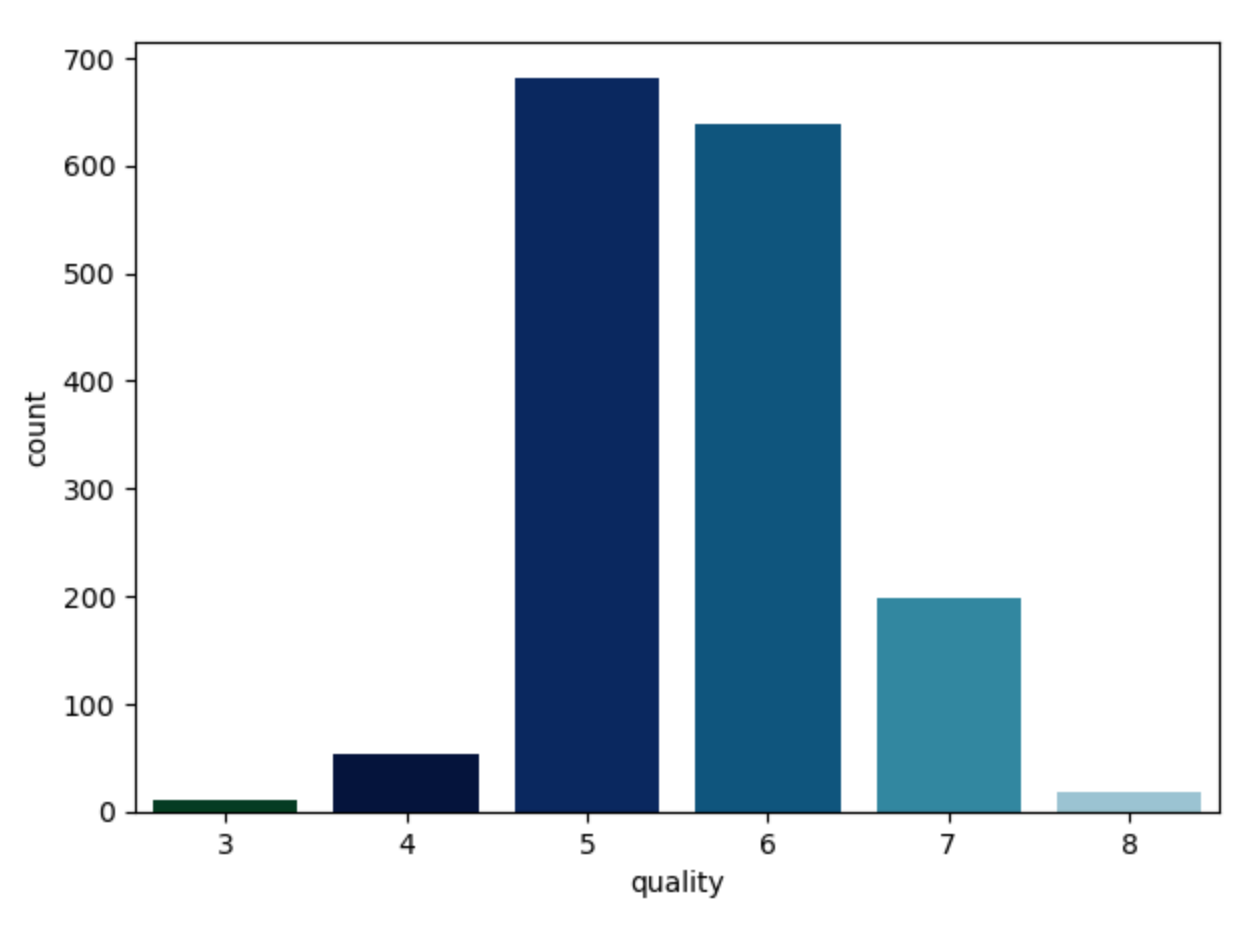
Out[10]:
```
fixed acidity            96
volatile acidity        143
citric acid              80
residual sugar           91
chlorides               153
free sulfur dioxide      60
total sulfur dioxide    144
density                 436
pH                       89
sulphates                96
alcohol                  65
quality                   6
dtype: int64
```

In [11]:
```
df.quality.value_counts()
```

Out[11]:
```
quality
5    681
6    638
7    199
4     53
8     18
3     10
Name: count, dtype: int64
```

In [12]:
```
# Number of wines in each quality category
plt.figure(figsize=(7,5))
sns.countplot(x='quality', data=df, palette='ocean')
```

Out[12]:
```
<Axes: xlabel='quality', ylabel='count'>
```



Visualize Data and gain some insights

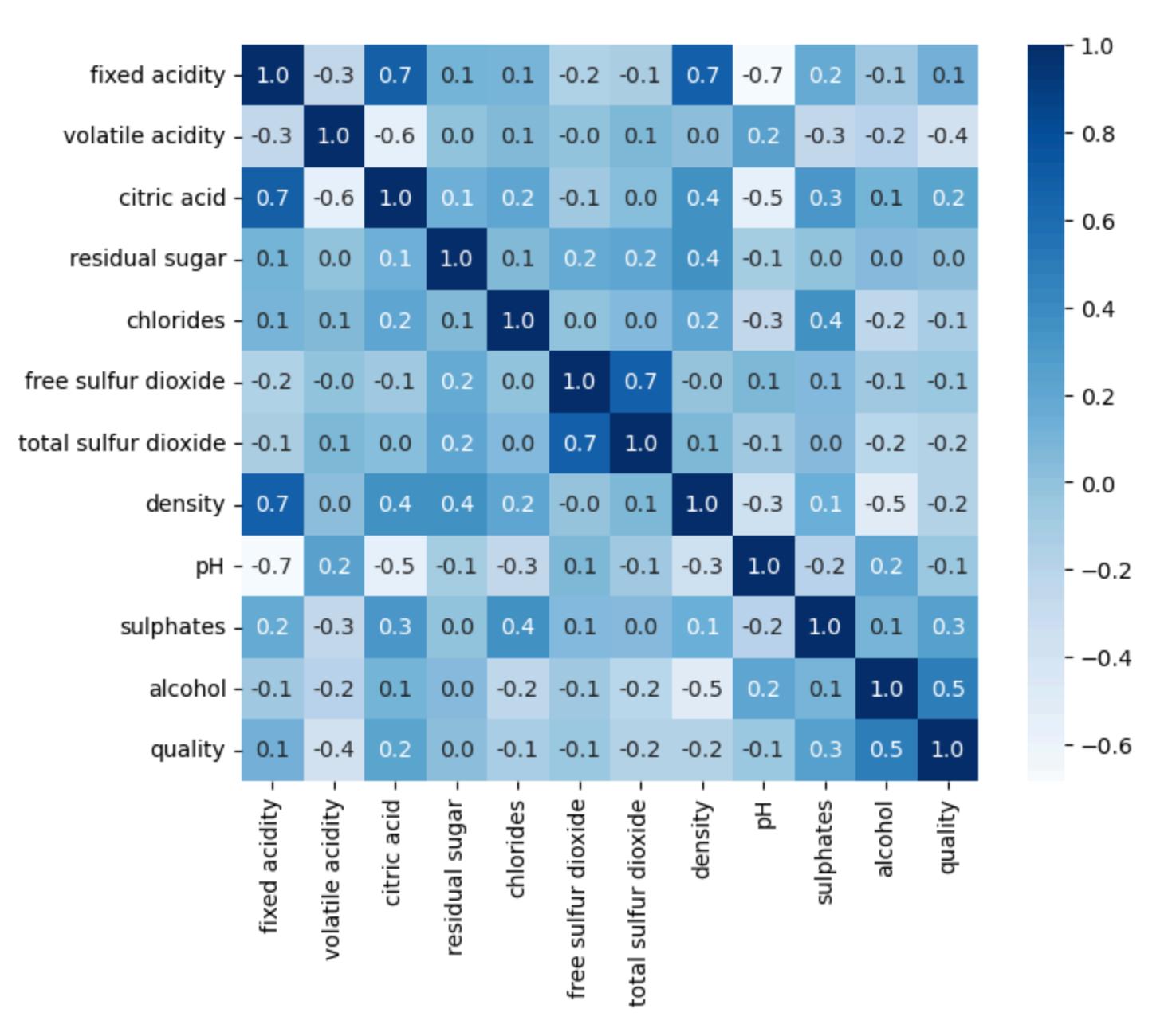
In [13]:
```
# look for correlations
df.corr()
```

Out[13]:

	fixed acidity	volatile acidity	citric acid	residual sugar	chlorides	free sulfur dioxide	total sulfur dioxide	density	pH	sulphates	alcohol	quality
fixed acidity	1.000000	-0.256131	0.671703	0.114777	0.093705	-0.153794	-0.113181	0.668047	-0.682978	0.183006	-0.061668	0.124052
volatile acidity	-0.256131	1.000000	-0.552496	0.001918	0.061298	-0.010504	0.076470	0.022026	0.234937	-0.260987	-0.202288	-0.390558
citric acid	0.671703	-0.552496	1.000000	0.143577	0.203823	-0.060978	0.035533	0.364947	-0.541904	0.312770	0.109903	0.226373
residual sugar	0.114777	0.001918	0.143577	1.000000	0.055610	0.187049	0.203028	0.355283	-0.085652	0.005527	0.042075	0.013732
chlorides	0.093705	0.061298	0.203823	0.055610	1.000000	0.005562	0.047400	0.200632	-0.265026	0.371260	-0.221141	-0.128907
free sulfur dioxide	-0.153794	-0.010504	-0.060978	0.187049	0.005562	1.000000	0.667666	-0.021946	0.070377	0.051658	-0.069408	-0.050656
total sulfur dioxide	-0.113181	0.076470	0.035533	0.203028	0.047400	0.667666	1.000000	0.071269	-0.066495	0.042947	-0.205654	-0.185100
density	0.668047	0.022026	0.364947	0.355283	0.200632	-0.021946	0.071269	1.000000	-0.341699	0.148506	-0.496180	-0.174919
pH	-0.682978	0.234937	-0.541904	-0.085652	-0.265026	0.070377	-0.066495	-0.341699	1.000000	-0.196648	0.205633	-0.057731
sulphates	0.183006	-0.260987	0.312770	0.005527	0.371260	0.051658	0.042947	0.148506	-0.196648	1.000000	0.093595	0.251397
alcohol	-0.061668	-0.202288	0.109903	0.042075	-0.221141	-0.069408	-0.205654	-0.496180	0.205633	0.093595	1.000000	0.476166
quality	0.124052	-0.390558	0.226373	0.013732	-0.128907	-0.050656	-0.185100	-0.174919	-0.057731	0.251397	0.476166	1.000000

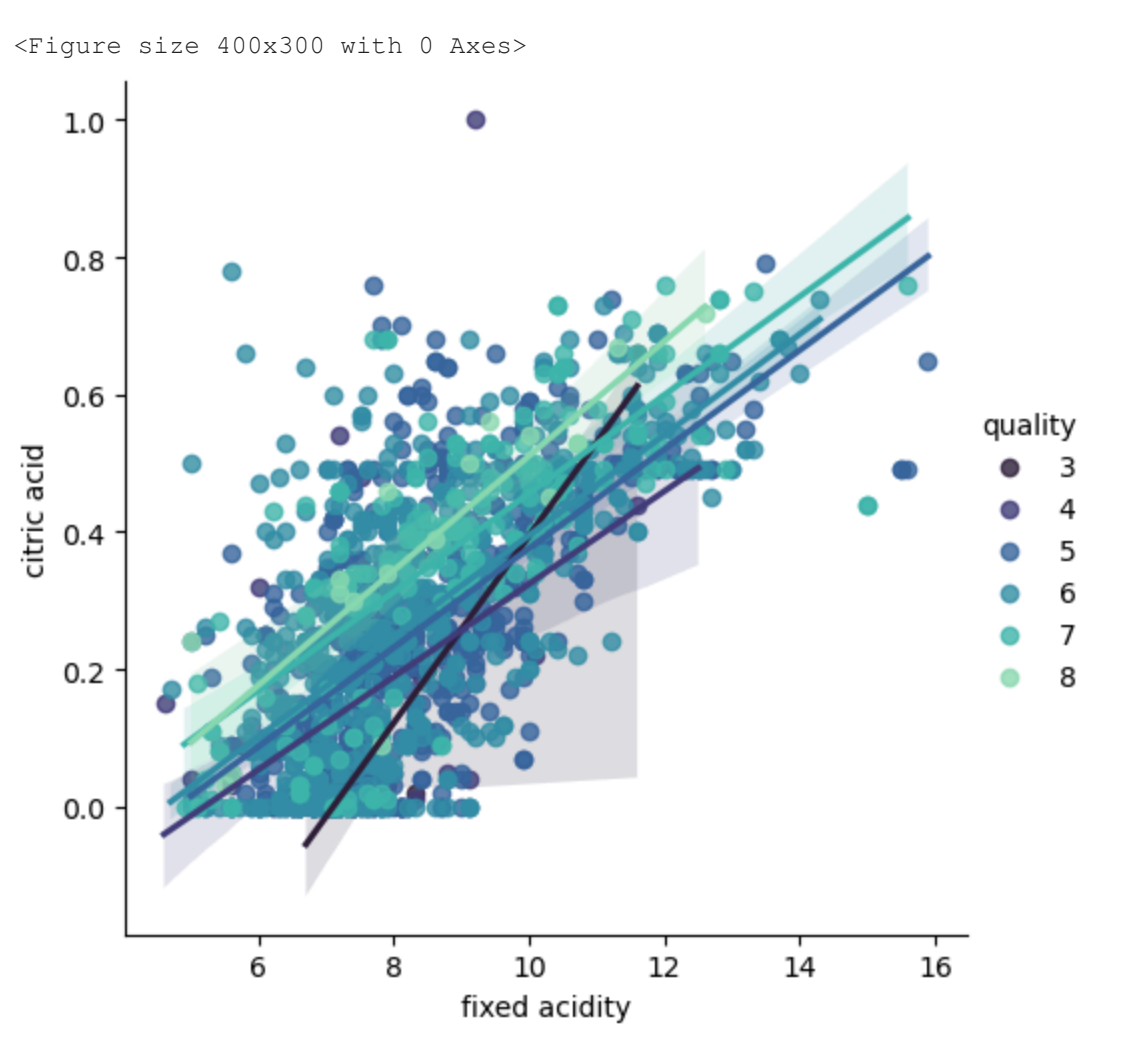
In [14]:
```
# visualize correlations
plt.figure(figsize=(8,6))
sns.heatmap(df.corr(), cbar=True, square=True, fmt = '.1f', annot = True, annot_kws={'size':10}, cmap = 'Blues')
```

Out[14]:
```
<Axes: >
```



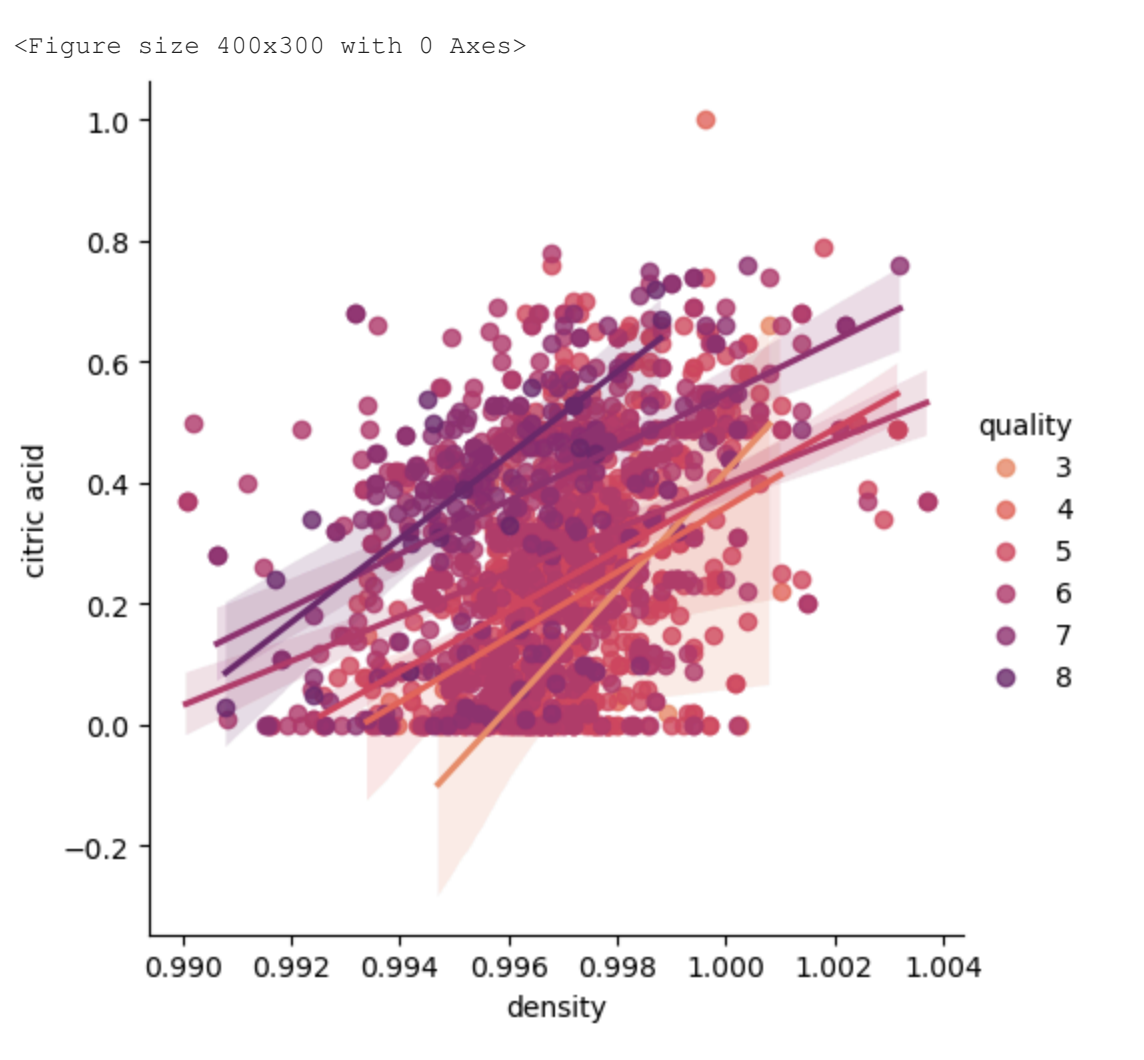
In [15]:
```
# Plot the correlated features
plt.figure(figsize=(4,3))
sns.lmplot(y='citric acid', x='fixed acidity', hue='quality', data=df, palette='mako')
```

Out[15]:
```
<seaborn.axisgrid.FacetGrid at 0x2724d96d650>
<Figure size 400x300 with 0 Axes>
```



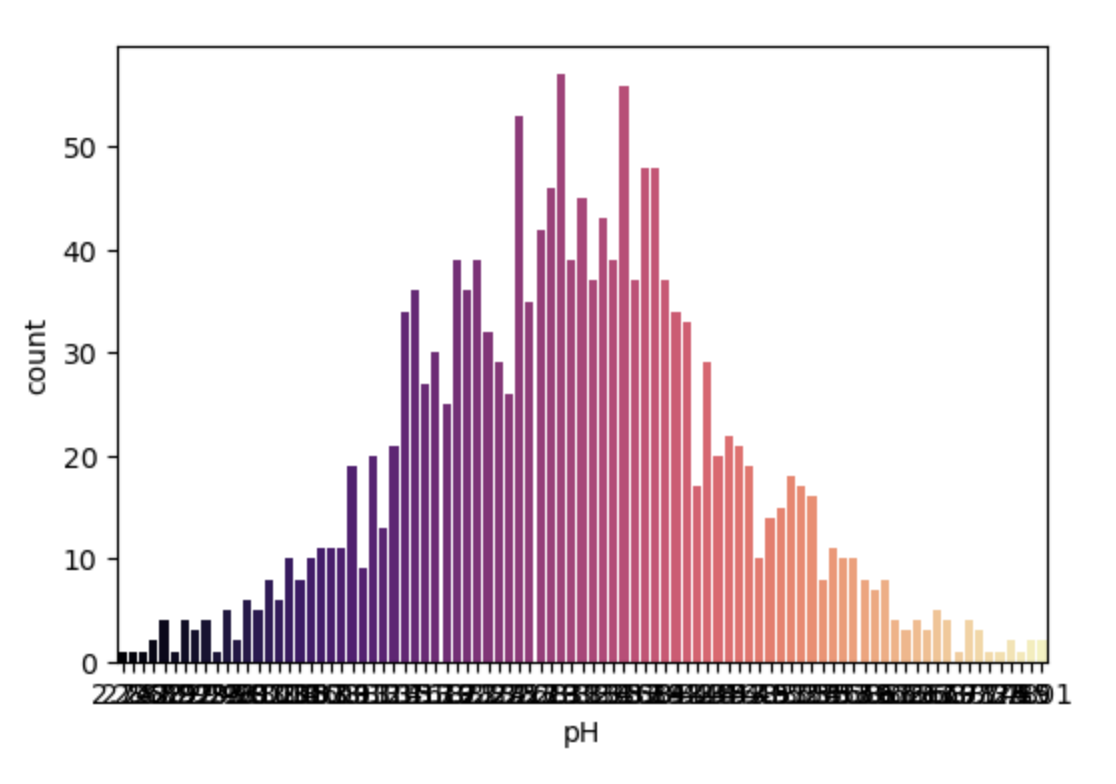
In [16]:
```
plt.figure(figsize=(4,3))
sns.lmplot(y='citric acid', x='density', hue='quality', data=df, palette='flare')
```

Out[16]:
```
<seaborn.axisgrid.FacetGrid at 0x2724da09210>
<Figure size 400x300 with 0 Axes>
```



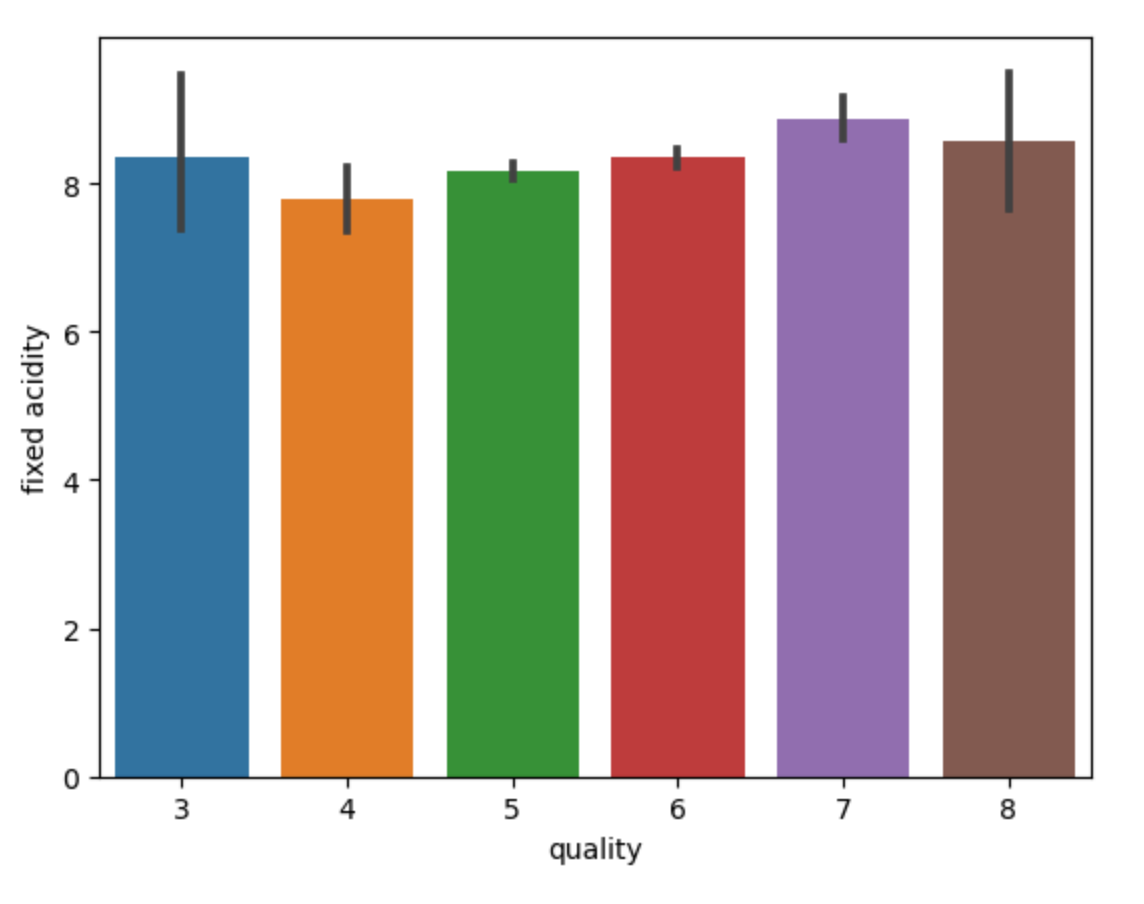
In [17]:
```
plt.figure(figsize=(6,4))
sns.countplot(data=df ,x="pH", palette='magma')
```

Out[17]:
```
<Axes: xlabel='pH', ylabel='count'>
```



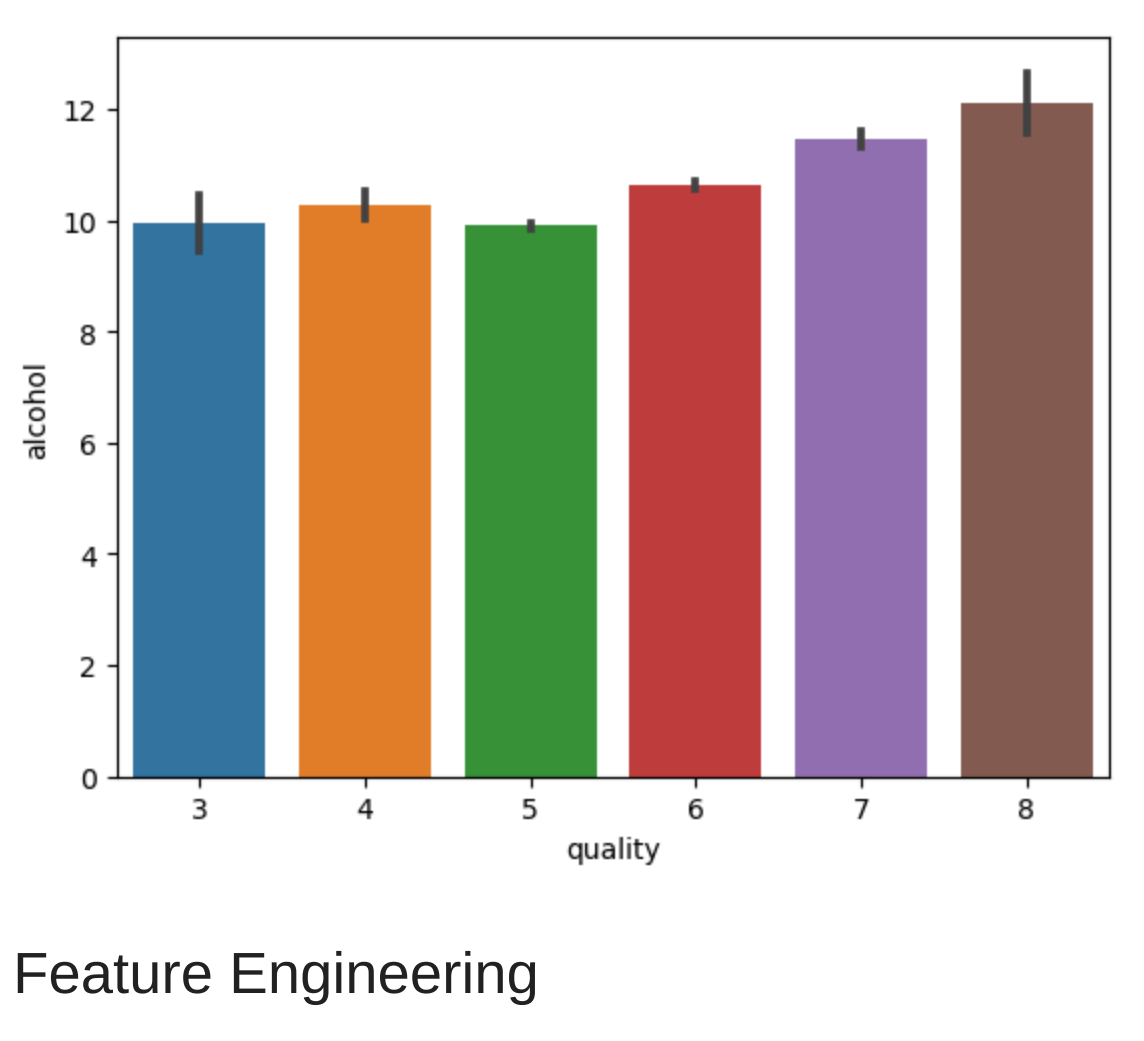
In [18]:
```
# plotting a barplot for quality vs fixed acidity
sns.barplot(x='quality', y='fixed acidity', data=df)
```

Out[18]:
```
<Axes: xlabel='quality', ylabel='fixed acidity'>
```



In [19]:
```
# plotting a barplot for quality vs alcohol
sns.barplot(x='quality', y='alcohol', data=df)
```

Out[19]:
```
<Axes: xlabel='quality', ylabel='alcohol'>
```



Feature Engineering

In [20]:
```
X = df.drop('quality', axis= 1)
y = df['quality'].apply(lambda y_value: 1 if y_value >= 7 else 0)
```

Scalling data

In [21]:
```
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)
X_scaled
```

Out[21]:
```
array([[-0.52835961,  0.96187667, -1.39147228, ...,  1.28864292,
        -0.57920652, -0.96024611],
       [-0.29854743,  1.96744245, -1.39147228, ..., -0.7199333 ,
         0.1289504 , -0.58477711],
       [-0.29854743,  1.29706527, -1.18607043, ..., -0.33117661,
        -0.04808883, -0.58477711],
       ...,
       [-1.1603431 , -0.09955388, -0.72391627, ...,  0.70550789,
         0.54204194,  0.54162988],
       [-1.39015528,  0.65462046, -0.77526673, ...,  1.6773996 ,
         0.30598963, -0.20930812],
       [-1.33270223, -1.21684919,  1.02199944, ...,  0.51112954,
         0.01092425,  0.54162988]])
```

In [22]:
```
y.value_counts()
```

Out[22]:
```
quality
0    1382
1     217
Name: count, dtype: int64
```

Spliting data into training and testing

In [23]:
```
X_train, X_test, y_train, y_test = train_test_split(X_scaled, y, test_size=0.25, random_state=0)
```

Modeling using RandomForest Classifier

In [24]:
```
model = RandomForestClassifier(min_samples_split=2, max_depth=20, n_estimators=100, random_state=42)
model.fit(X_train, y_train)
```

Out[24]:
```
RandomForestClassifier
RandomForestClassifier(max_depth=20, random_state=42)
```

In [25]:
```
#accuracy on test data
y_pred = model.predict(X_test)
test_accuracy = accuracy_score(y_test, y_pred)
print("Test accuracy is :", test_accuracy * 100, "%")
```

```
Test accuracy is : 92.5 %
```

In [26]:
```
# classification report
print(classification_report(y_test,y_pred))
```

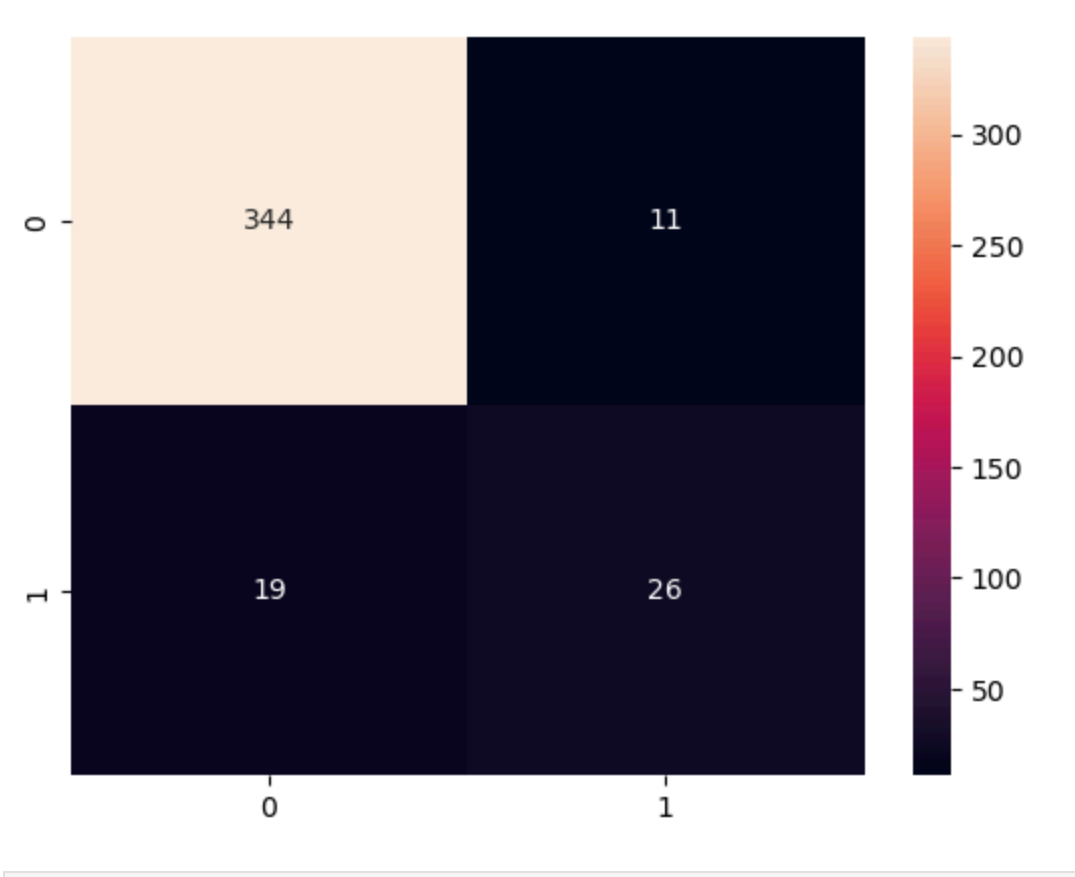
```
              precision    recall  f1-score   support

           0       0.95      0.97      0.96       355
           1       0.70      0.58      0.63        45

    accuracy                           0.93       400
   macro avg       0.83      0.77      0.80       400
weighted avg       0.92      0.93      0.92       400
```

In [27]:
```
cm = confusion_matrix(y_test, y_pred)
sns.heatmap(cm, annot=True, fmt='d')
```

Out[27]:
```
<Axes: >
```



In [ ]: