In [1]:
```
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
from sklearn import metrics
from sklearn.neighbors import KNeighborsClassifier
```

In [2]:
```
df = pd.read_csv('D:\\24 - Machine_Learning\\download files\\winequality-red.csv', sep=";")
df
```

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]:
```
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 [4]:
```
df.describe()
```

Out[4]:

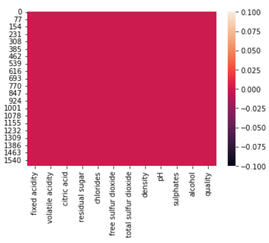
	fixed acidity	volatile acidity	citric acid	residual sugar	chlorides	free sulfur dioxide	total sulfur dioxide	density	pH	sulphates	alcohol	quality
count	1599.000000	1599.000000	1599.000000	1599.000000	1599.000000	1599.000000	1599.000000	1599.000000	1599.000000	1599.000000	1599.000000	1599.000000
mean	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 [5]:
```
df.isnull
```

Out[5]:
```
<bound method DataFrame.isnull of       fixed acidity  volatile acidity  citric acid  residual sugar  chlorides  \
0               7.4             0.700         0.00             1.9      0.076   
1               7.8             0.880         0.00             2.6      0.098   
2               7.8             0.760         0.04             2.3      0.092   
3              11.2             0.280         0.56             1.9      0.075   
4               7.4             0.700         0.00             1.9      0.076   
...             ...               ...          ...             ...        ...   
1594            6.2             0.600         0.08             2.0      0.090   
1595            5.9             0.550         0.10             2.2      0.062   
1596            6.3             0.510         0.13             2.3      0.076   
1597            5.9             0.645         0.12             2.0      0.075   
1598            6.0             0.310         0.47             3.6      0.067   

      free sulfur dioxide  total sulfur dioxide  density    pH  sulphates  \
0                    11.0                  34.0  0.99780  3.51       0.56   
1                    25.0                  67.0  0.99680  3.20       0.68   
2                    15.0                  54.0  0.99700  3.26       0.65   
3                    17.0                  60.0  0.99800  3.16       0.58   
4                    11.0                  34.0  0.99780  3.51       0.56   
...                   ...                   ...      ...   ...        ...   
1594                 32.0                  44.0  0.99490  3.45       0.58   
1595                 39.0                  51.0  0.99512  3.52       0.76   
1596                 29.0                  40.0  0.99574  3.42       0.75   
1597                 32.0                  44.0  0.99547  3.57       0.71   
1598                 18.0                  42.0  0.99549  3.39       0.66   

      alcohol  quality  
0         9.4        5  
1         9.8        5  
2         9.8        5  
3         9.8        6  
4         9.4        5  
...       ...      ...  
1594     10.5        5  
1595     11.2        6  
1596     11.0        6  
1597     10.2        5  
1598     11.0        6  

[1599 rows x 12 columns]>
```

In [6]:
```
sns.heatmap(df.isnull())
```

Out[6]:
```
<AxesSubplot:>
```



In [7]:
```
df.shape
```

Out[7]:
```
(1599, 12)
```

In [8]:
```
features = df.drop('quality', axis=1).values
features
```

Out[8]:
```
array([[ 7.4  ,  0.7  ,  0.   , ...,  3.51 ,  0.56 ,  9.4  ],
       [ 7.8  ,  0.88 ,  0.   , ...,  3.2  ,  0.68 ,  9.8  ],
       [ 7.8  ,  0.76 ,  0.04 , ...,  3.26 ,  0.65 ,  9.8  ],
       ...,
       [ 6.3  ,  0.51 ,  0.13 , ...,  3.42 ,  0.75 , 11.   ],
       [ 5.9  ,  0.645,  0.12 , ...,  3.57 ,  0.71 , 10.2  ],
       [ 6.   ,  0.31 ,  0.47 , ...,  3.39 ,  0.66 , 11.   ]])
```

In [9]:
```
classes = df['quality'].values
classes
```

Out[9]:
```
array([5, 5, 5, ..., 6, 5, 6], dtype=int64)
```

In [10]:
```
(train_feat, test_feat, train_classes, test_classes) = train_test_split(features, classes, train_size = 0.8, random_state=40)
```

In [11]:
```
knn = KNeighborsClassifier(n_neighbors=2)
```

In [12]:
```
knn.fit(train_feat, train_classes)
```

Out[12]:
```
KNeighborsClassifier(n_neighbors=2)
```

In [13]:
```
pred = knn.predict(test_feat)
```

In [14]:
```
print("Accuracy: ", metrics.accuracy_score(test_classes, pred))
```

```
Accuracy:  0.496875
```

In [15]:
```
neighbors = np.arange(1,9)
```

In [16]:
```
train_accuracy = np.empty(len(neighbors))
```

In [17]:
```
test_accuracy = np.empty(len(neighbors))
```

In [18]:
```
for i,k in enumerate(neighbors):
    #Setup a knn classifier with k neighbors
    knn = KNeighborsClassifier(n_neighbors=k)
    #Fit the model
    knn.fit(train_feat, train_classes)
    #compute accuracy on training set
    train_accuracy[i] = knn.score(train_feat, train_classes)
    #compute accuracy on test set
    test_accuracy[i] = knn.score(test_feat, test_classes)
```

In [21]:
```
plt.title('k-NN varying number of neighbors')
plt.plot(neighbors, test_accuracy, label='Testing Accuracy')
plt.plot(neighbors, train_accuracy, label='Training Accuracy')
plt.legend()
plt.xlabel('Number of neighbors')
plt.ylabel('Accuracy')
plt.show()
```