DCS 630 Predictive Analytics (DSC630-T302 2231-1)

Bellevue University

Term Project: Prediction of Water Quality

Milestone 4: Finalizing the Results

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For Milestone 4 Predictive Model code, see the Predictive Modeling and Evaluation section.

Dataset Source

The objective of this project is to construct a model to predict whether water is potable based on water quality measurements. The dataset used for this analysis can be found through the link below:
Prediction of Water Quality Dataset

Import Necessary Libraries

In [1]:
```
'''
Import the necessary libraries for the analysis.
'''
import numpy as np
import pandas as pd
import seaborn as sns
import scipy.stats
import sklearn
import operator
import matplotlib
import matplotlib.pyplot as plt
from scipy import stats
from collections import OrderedDict
from scipy.stats import shapiro
from scipy.stats import pointbiserialr
from sklearn.model_selection import train_test_split
from sklearn.decomposition import PCA
from sklearn.linear_model import LogisticRegression
from sklearn.neighbors import KNeighborsClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.tree import plot_tree
from sklearn.ensemble import RandomForestClassifier, GradientBoostingClassifier, BaggingCl
from sklearn.svm import SVC
from sklearn.preprocessing import StandardScaler
from sklearn.preprocessing import MinMaxScaler
from sklearn.metrics import roc_auc_score
from sklearn.model_selection import cross_val_score
from sklearn.metrics import precision_score, recall_score, f1_score
from sklearn.metrics import confusion_matrix, accuracy_score, classification_report
```

In [2]:
```
'''
```

```
'''
Check the versions of the packages.
'''
print('numpy version:', np.__version__)
print('pandas version:', pd.__version__)
print('seaborn version:', sns.__version__)
print('matplotlib version:', matplotlib.__version__)
print('sklearn:', sklearn.__version__)
```

```
numpy version: 1.20.3
pandas version: 1.3.4
seaborn version: 0.11.2
matplotlib version: 3.4.3
sklearn: 0.24.2
```

Overview of Dataset

In [3]:
```
'''
Import the dataset.
Note: A copy of the CSV file was placed into the same directory as this notebook.
Utilize pd.read_csv() to read the file as a pandas data frame.
'''
df = pd.read_csv('water_potability.csv')
```

In [4]:
```
'''
Use head() function to display the first 10 rows of data of df.
'''
df.head(10)
```

Out[4]:

	ph	Hardness	Solids	Chloramines	Sulfate	Conductivity	Organic_carbon	Trihalomethanes	Tur
0	NaN	204.890456	20791.31898	7.300212	368.516441	564.308654	10.379783	86.990970	2.9
1	3.716080	129.422921	18630.05786	6.635246	NaN	592.885359	15.180013	56.329076	4.5
2	8.099124	224.236259	19909.54173	9.275884	NaN	418.606213	16.868637	66.420093	3.0
3	8.316766	214.373394	22018.41744	8.059332	356.886136	363.266516	18.436525	100.341674	4.6
4	9.092223	181.101509	17978.98634	6.546600	310.135738	398.410813	11.558279	31.997993	4.0
5	5.584087	188.313324	28748.68774	7.544869	326.678363	280.467916	8.399735	54.917862	2.5
6	10.223862	248.071735	28749.71654	7.513408	393.663395	283.651634	13.789695	84.603556	2.6
7	8.635849	203.361523	13672.09176	4.563009	303.309771	474.607645	12.363817	62.798309	4.4
8	NaN	118.988579	14285.58385	7.804174	268.646941	389.375566	12.706049	53.928846	3.5
9	11.180284	227.231469	25484.50849	9.077200	404.041635	563.885481	17.927806	71.976601	4.3

In [5]:
```
'''
Understand the shape of the dataset.
'''
print('There are {} rows and {} columns in this dataset.'.format(df.shape[0], df.shape[1]))
```

```
There are 3276 rows and 10 columns in this dataset.
```

In [6]:
```
'''
Display the total size of this dataset.
'''
print('This dataset contains {} records.'.format(df.size))
```

```
This dataset contains 32760 records.
```

In [7]:
```
'''
Find the type of data within each column initially.
'''
df.dtypes
```

Out[7]:
```
ph                 float64
Hardness           float64
Solids             float64
Chloramines        float64
Sulfate            float64
Conductivity       float64
Organic_carbon     float64
Trihalomethanes    float64
Turbidity          float64
Potability           int64
dtype: object
```

In [8]:
```
'''
Understand if there are any missing values in the dataset.
'''
df.isna().sum().sort_values(ascending = False)
```

Out[8]:
```
Sulfate            781
ph                 491
Trihalomethanes    162
Hardness             0
Solids               0
Chloramines          0
Conductivity         0
Organic_carbon       0
Turbidity            0
Potability           0
dtype: int64
```

In [9]:
```
'''
Understand how many missing values are in the dataset initially.
'''
missing_values = df.isna().sum().sum()
print('This dataset contains {} total missing values.'.format(missing_values))
```

```
This dataset contains 1434 total missing values.
```

The missing values are located within Sulfate, ph, and Trihalomethane features. There are 781, 491, and 162 missing values in each respective feature. This will need to be addressed during the Data Preparation step.

Highlights for Dataset Overview:

- There are 3276 records and 10 features in the dataset.
- There are 1434 missing values within Sulfate, ph, and Trihalomethanes features.

Data Understanding - Preliminary Preparation

In [10]:
```
'''
Revise the column headers for the dataset.
Intended to make specific feature calls easier by converting to lowercase.
'''
column_names = ['ph', 'hardness', 'solids', 'chloramines', 'sulfate', 'conductivity',
                'organic_carbon', 'trihalomethanes', 'turbidity', 'potability']
df.columns = column_names
```

In [11]:
```
'''
Understand the descriptive statistics with describe() for the numeric features.
'''
df.describe()
```

Out[11]:

	ph	hardness	solids	chloramines	sulfate	conductivity	organic_carbon	trihalometha
count	2785.000000	3276.000000	3276.000000	3276.000000	2495.000000	3276.000000	3276.000000	3114.000
mean	7.080795	196.369496	22014.092526	7.122277	333.775777	426.205111	14.284970	66.396
std	1.594320	32.879761	8768.570828	1.583085	41.416840	80.824064	3.308162	16.175
min	0.000000	47.432000	320.942611	0.352000	129.000000	181.483754	2.200000	0.738
25%	6.093092	176.850538	15666.690300	6.127421	307.699498	365.734414	12.065801	55.844
50%	7.036752	196.967627	20927.833605	7.130299	333.073546	421.884968	14.218338	66.622
75%	8.062066	216.667456	27332.762125	8.114887	359.950170	481.792305	16.557652	77.337
max	14.000000	323.124000	61227.196010	13.127000	481.030642	753.342620	28.300000	124.000

In [12]:
```
'''
Review the percentage of missing features for sulfate, ph, and trihalomethanes.
'''
perc_missing = round(df.isnull().sum() * 100 / len(df),2)
df_missing = pd.DataFrame({'feature': df.columns, 'percent_missing': perc_missing})
df_missing.sort_values(by= 'percent_missing', ascending = False)
```

Out[12]:

	feature	percent_missing
sulfate	sulfate	23.84
ph	ph	14.99
trihalomethanes	trihalomethanes	4.95
hardness	hardness	0.00
solids	solids	0.00
chloramines	chloramines	0.00
conductivity	conductivity	0.00
organic_carbon	organic_carbon	0.00
turbidity	turbidity	0.00
potability	potability	0.00

Identify a plan on how to handle the missing values in sulfate, ph, and trihalomethane columns. Evaluate whether to replace the missing values (with mean or median) or remove the values from the data set.

In [13]:
```
'''
Evaluate the median for the missing values in the sulfate column for potable and non-potab
'''
df.groupby('potability')['sulfate'].median()
```

Out[13]:
```
potability
0    333.389426
```

```
1    331.838167
Name: sulfate, dtype: float64
```

In [14]:
```
'''
Evaluate the mean for the missing values in the sulfate column for potable and non-potable
'''
df.groupby('potability')['sulfate'].mean()
```

Out[14]:
```
potability
0    334.56429
1    332.56699
Name: sulfate, dtype: float64
```

In [15]:
```
'''
Evaluate the median for the missing values in the ph column for potable and non-potable wa
'''
df.groupby('potability')['ph'].median()
```

Out[15]:
```
potability
0    7.035456
1    7.036752
Name: ph, dtype: float64
```

In [16]:
```
'''
Evaluate the mean for the missing values in the sulfate column for potable and non-potable
'''
df.groupby('potability')['ph'].mean()
```

Out[16]:
```
potability
0    7.085378
1    7.073783
Name: ph, dtype: float64
```

In [17]:
```
'''
Evaluate the median for the missing values in the trihalomethanes column for potable and r
'''
df.groupby('potability')['trihalomethanes'].median()
```

Out[17]:
```
potability
0    66.542198
1    66.678214
Name: trihalomethanes, dtype: float64
```

In [18]:
```
'''
Evaluate the mean for the missing values in the trihalomethanes column for potable and nor
'''
df.groupby('potability')['trihalomethanes'].mean()
```

Out[18]:
```
potability
0    66.303555
1    66.539684
Name: trihalomethanes, dtype: float64
```

Based on the descriptive statistics above, the mean or median may be a suitable choice to replace the features for each respective variables. As a result, I'll replace the sulfate, ph, and trihalomethane values with the median of each respective feature.

In [19]:
```
'''
Handle the missing values as described above.
Replace the NaN values for sulfate, trihalomethanes, and ph with the median values of each
Drop the remaining missing values from the sulfate column.
```

```
'''
df['sulfate'].fillna(value=df['sulfate'].median(), inplace = True)
df['trihalomethanes'].fillna(value=df['trihalomethanes'].median(), inplace = True)
df['ph'].fillna(value=df['ph'].median(), inplace = True)
```

In [20]:
```
'''
Show that all missing values have been replaced using same methodology as above.
'''
perc_missing_rev = round(df.isnull().sum() * 100 / len(df),2)
df_missing_rev = pd.DataFrame({'feature': df.columns, 'percent_missing': perc_missing_rev})
df_missing_rev.sort_values(by= 'percent_missing', ascending = False)
```

Out[20]:

	feature	percent_missing
ph	ph	0.0
hardness	hardness	0.0
solids	solids	0.0
chloramines	chloramines	0.0
sulfate	sulfate	0.0
conductivity	conductivity	0.0
organic_carbon	organic_carbon	0.0
trihalomethanes	trihalomethanes	0.0
turbidity	turbidity	0.0
potability	potability	0.0

In [21]:
```
'''
Show the revised dataframe after preliminary prepearation steps.
'''
df.head()
```

Out[21]:

	ph	hardness	solids	chloramines	sulfate	conductivity	organic_carbon	trihalomethanes	turbic
0	7.036752	204.890456	20791.31898	7.300212	368.516441	564.308654	10.379783	86.990970	2.963
1	3.716080	129.422921	18630.05786	6.635246	333.073546	592.885359	15.180013	56.329076	4.500
2	8.099124	224.236259	19909.54173	9.275884	333.073546	418.606213	16.868637	66.420093	3.055
3	8.316766	214.373394	22018.41744	8.059332	356.886136	363.266516	18.436525	100.341674	4.628
4	9.092223	181.101509	17978.98634	6.546600	310.135738	398.410813	11.558279	31.997993	4.075

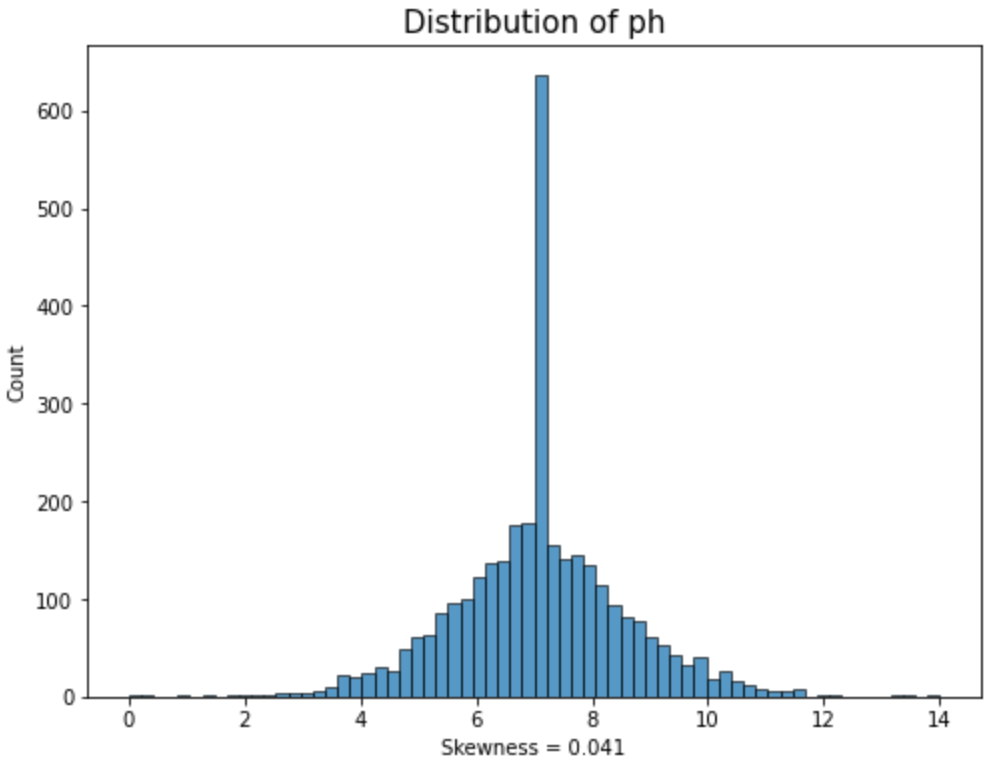
Highlights for Preliminary Data Preparation:

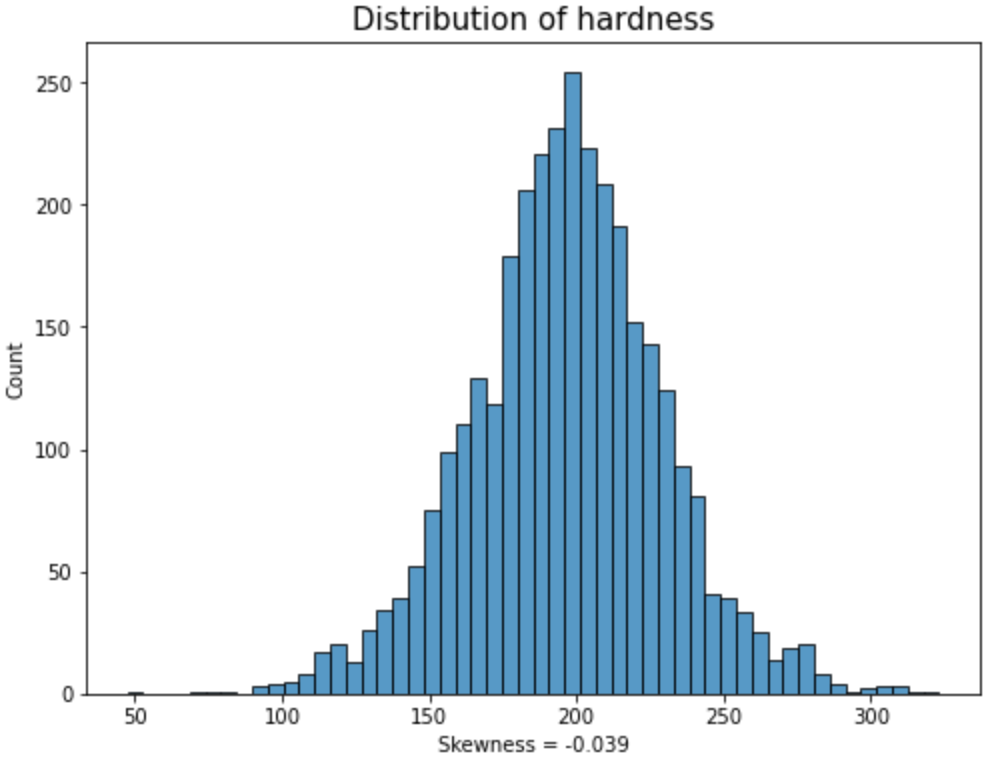
- Columns were renamed for convenience of analysis.
- Descriptive statistics of each numeric variable were displayed.
- Missing values for sulfate,ph, and trihalomethanes were replaced with the median values for each respective feature.

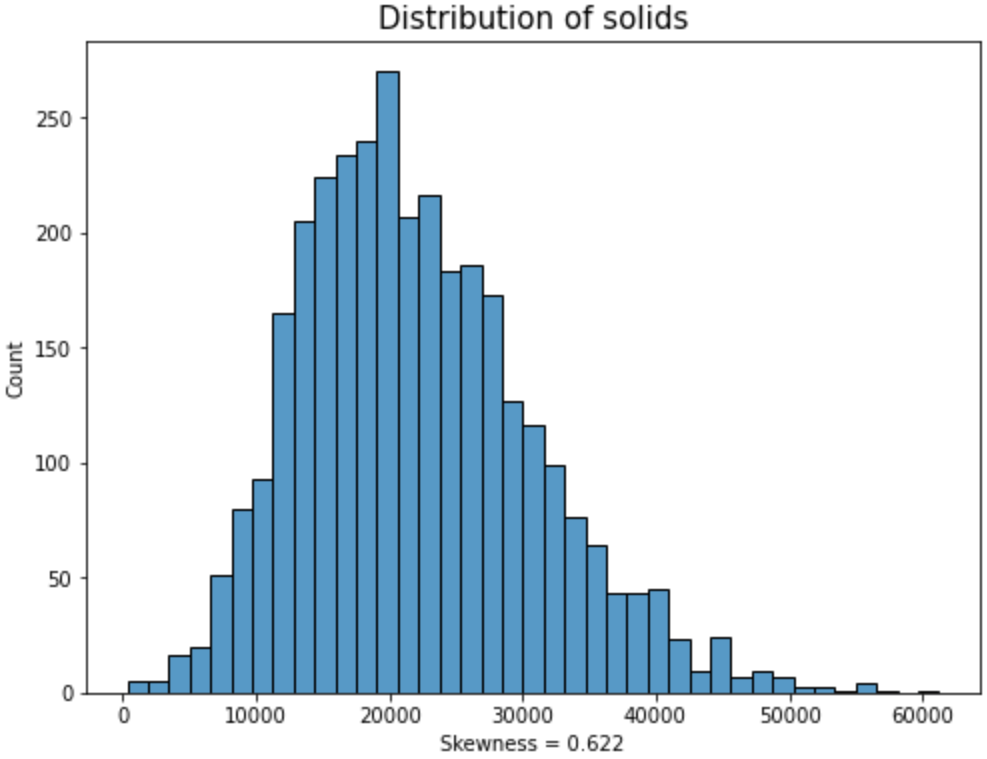
Data Understanding - Univariate Analysis

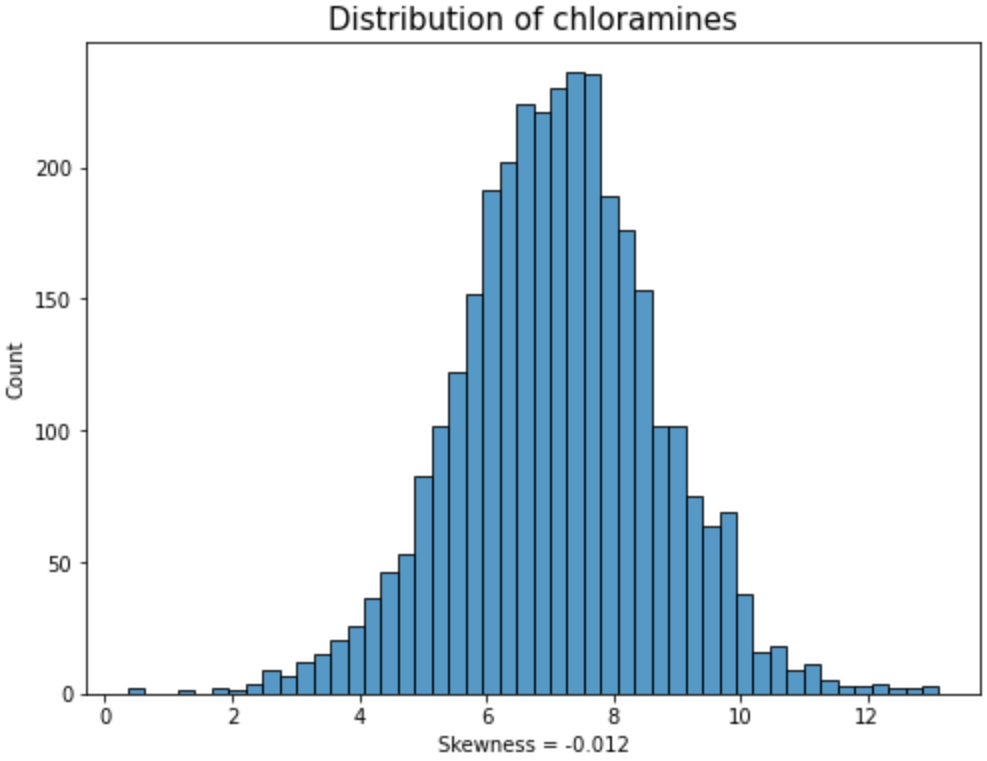
In [22]:

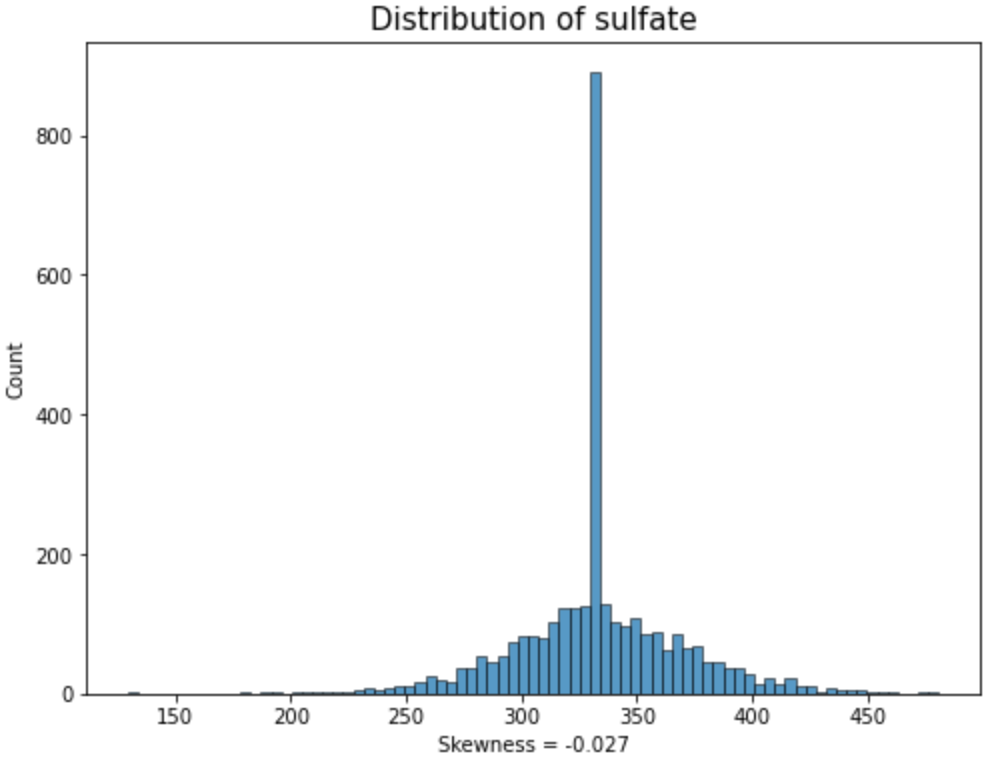
```
'''
Understand the distribution for the features within the dataset.
The code below will loop through each feature and illustrate how the feature is distribute
The skewness value will also be included below the chart.
'''
revised_columns = df[['ph', 'hardness', 'solids', 'chloramines', 'sulfate', 'conductivity'
                'organic_carbon', 'trihalomethanes', 'turbidity']]

for col in revised_columns:
    plt.figure(figsize=(8,6))
    sns.histplot(x =df[col])
    plt.title("Distribution of {}".format(col), fontsize=15)
    plt.xlabel(f"Skewness = {round(df[col].skew(),3)}", fontsize=10)
    plt.xticks(fontsize=10)
    plt.yticks(fontsize=10)
    plt.show()
```

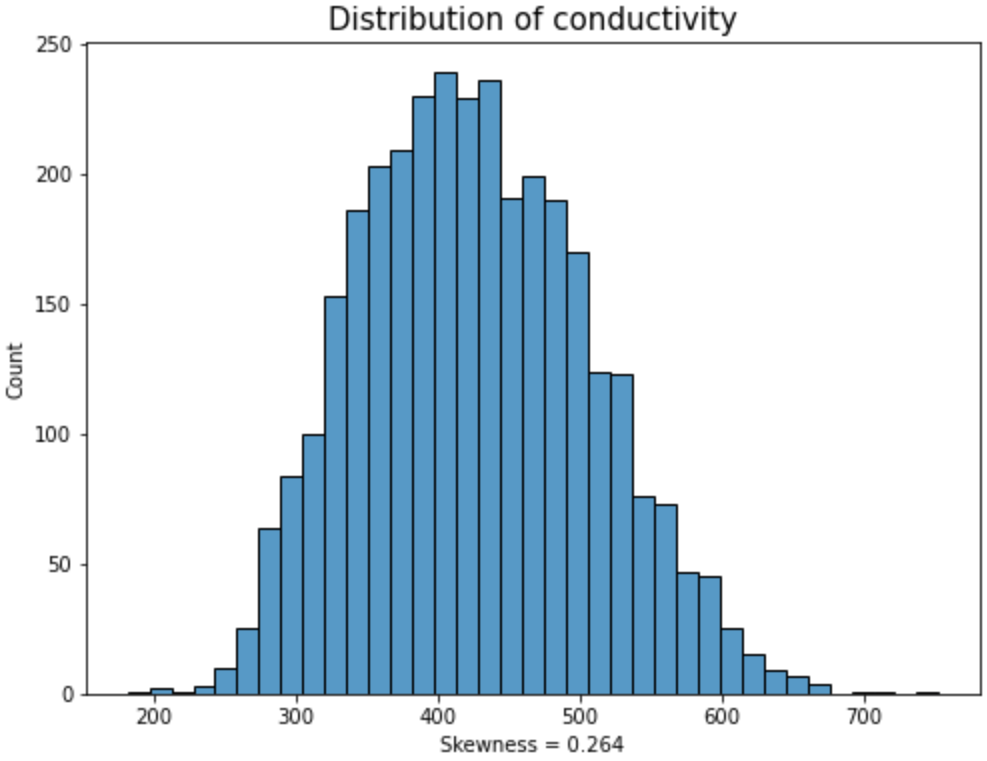


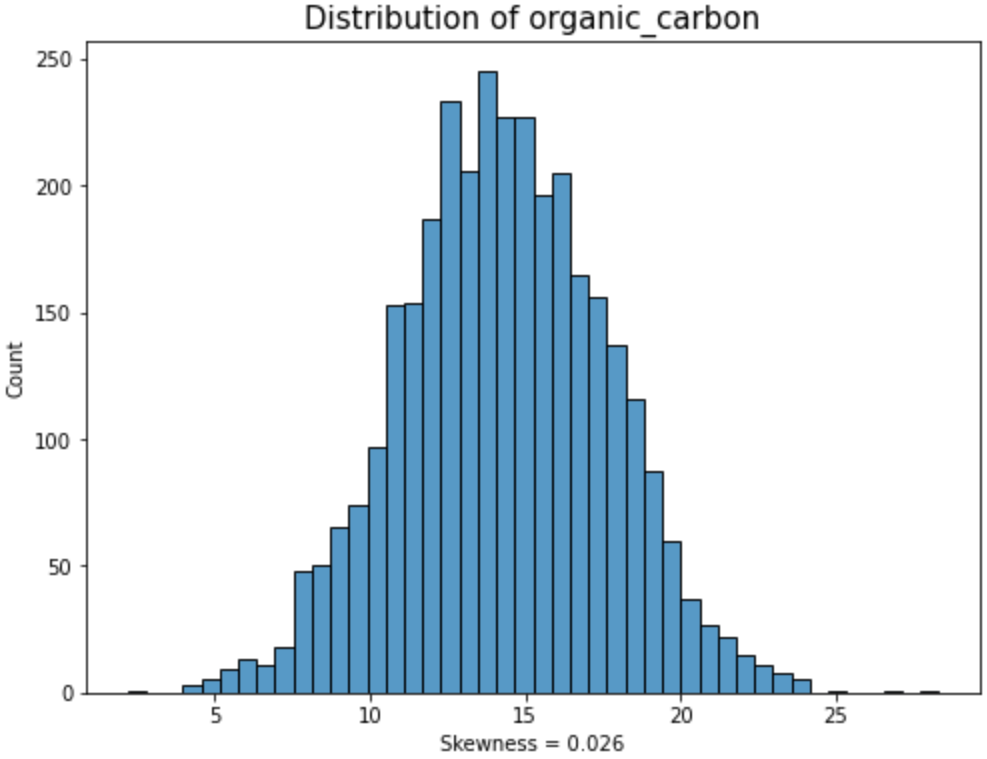

Distribution of hardness
Count
Skewness = -0.039

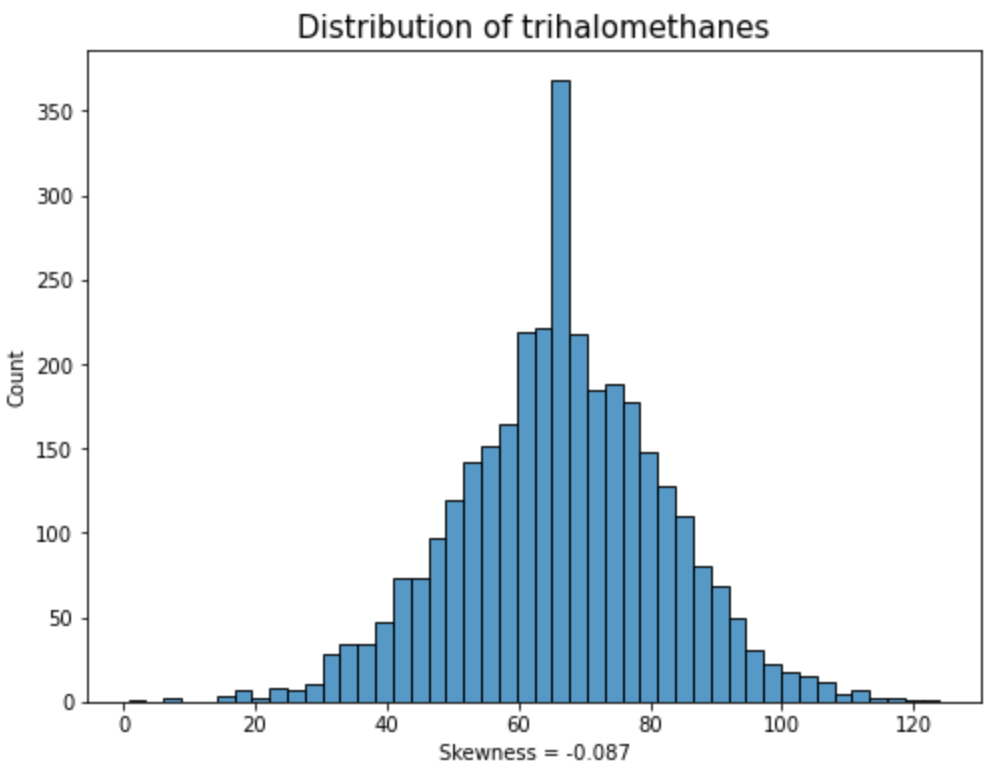

Distribution of solids
Count
Skewness = 0.622

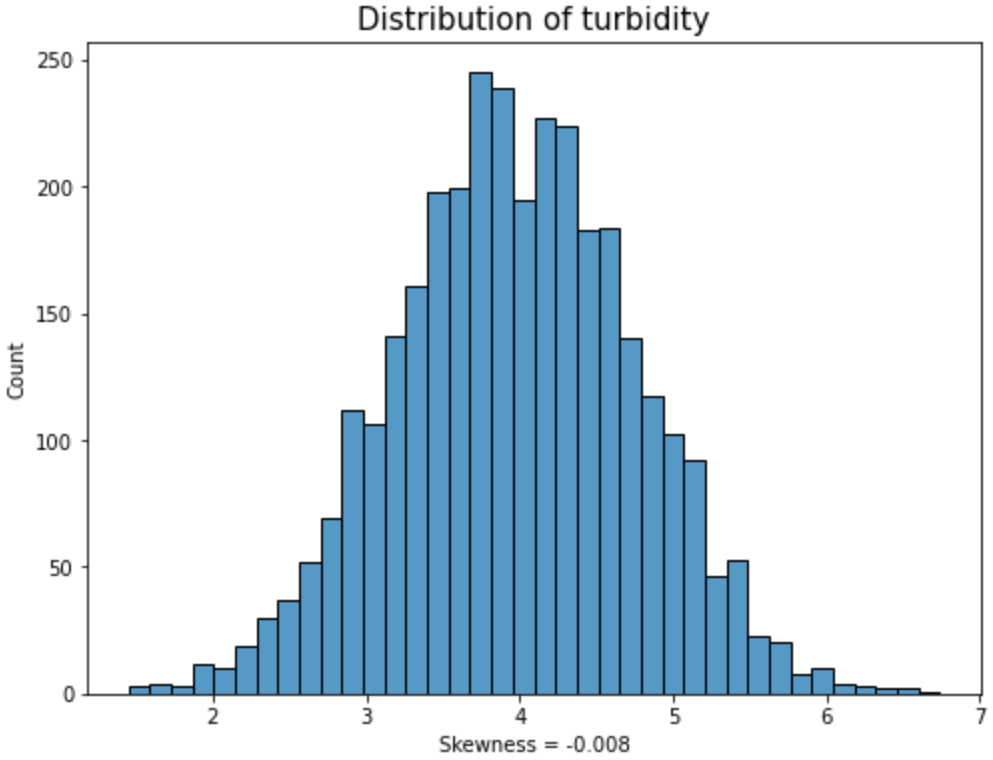

Distribution of chloramines
Count
0
50
100
150
200
0
2
4
6
8
10
12
Skewness = -0.012


Distribution of sulfate
Count
0
200
400
600
800
150
200
250
300
350
400
450
Skewness = -0.027


Distribution of conductivity
Count
Skewness = 0.264


Distribution of organic_carbon
Count
Skewness = 0.026



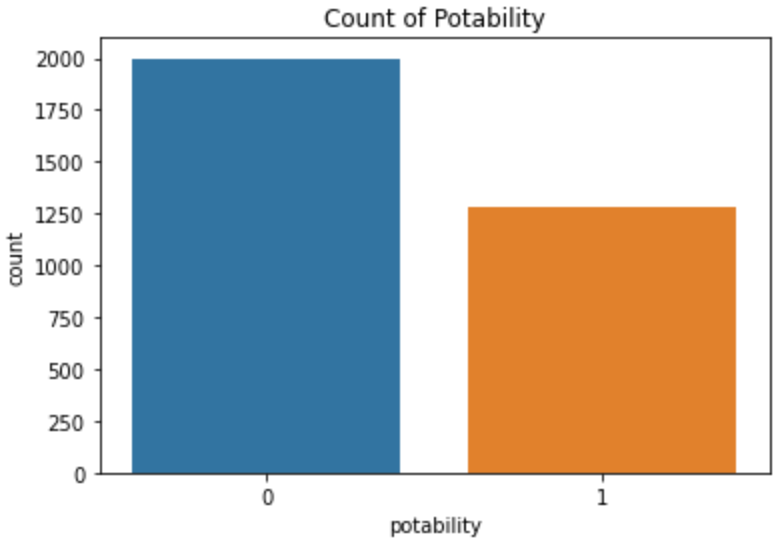


In [23]:
```
'''
Use describe() to understand the target variable descriptive statistics.
'''
df['potability'].value_counts()
```

Out[23]:
```
0    1998
1    1278
Name: potability, dtype: int64
```

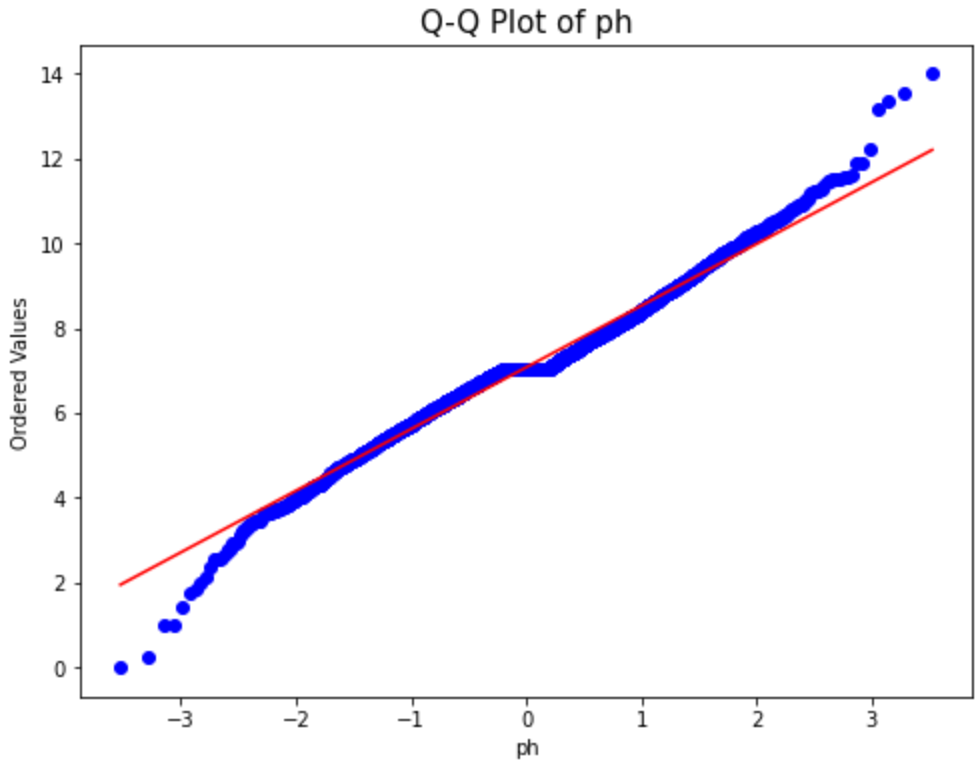
In [24]:
```
'''
Understand the balance of the 'potability' variable with a countplot.
The count will illustrate potable (1) and non-potable (0) records from the dataset.
'''
```

```
sns.countplot(x='potability', data = df).set(title = 'Count of Potability')
plt.show()
```

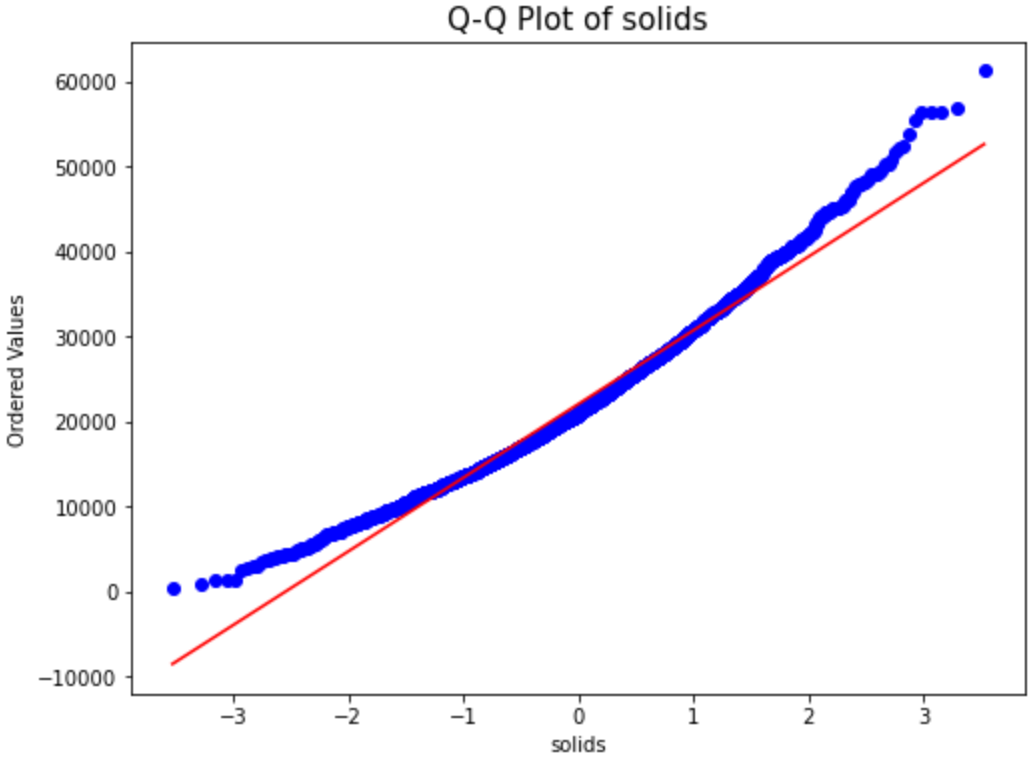


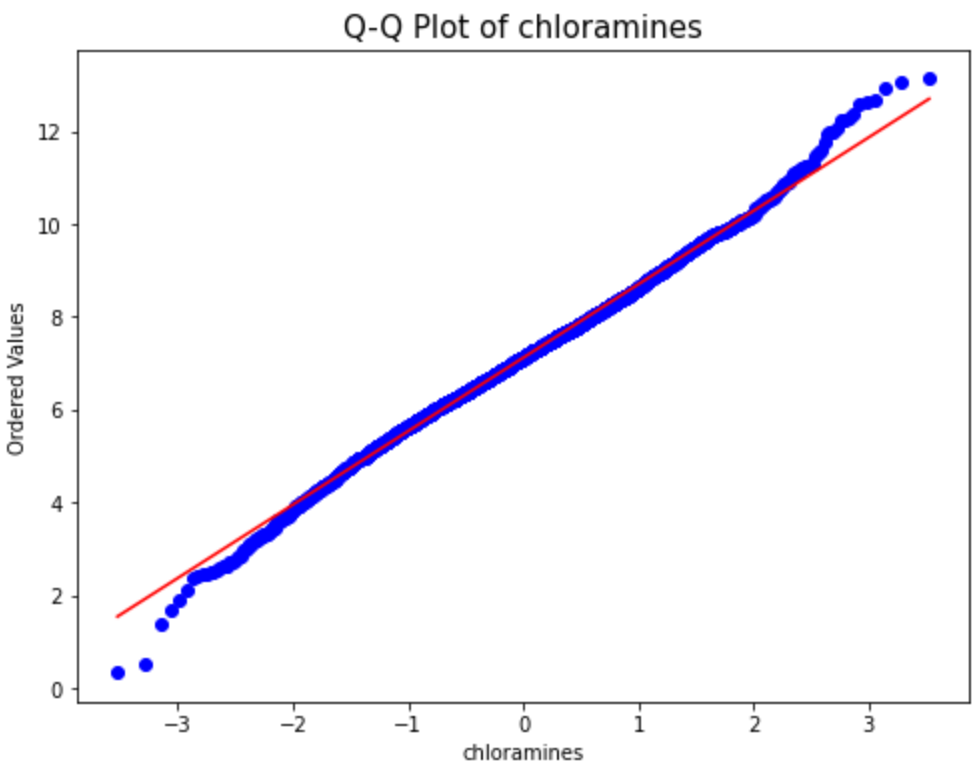
In [25]:

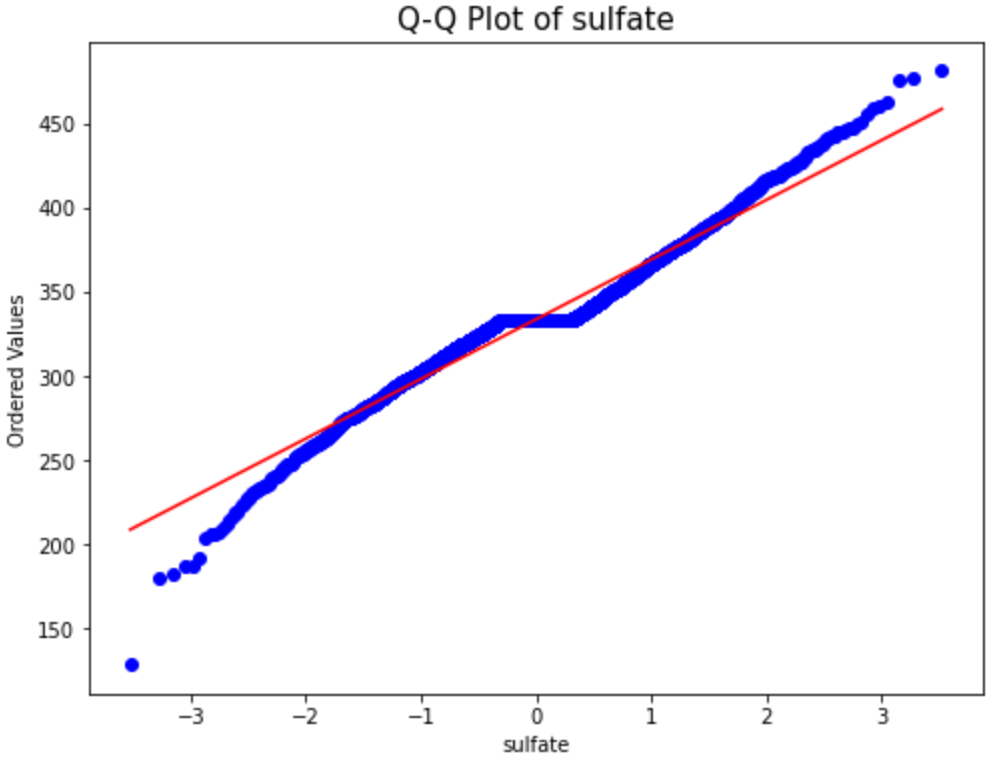
```
'''
Understand whether the features within the dataset are normally distributed with a Q-Q Plo
The code below will loop through each feature and illustrate how the feature is distribute
'''
revised_columns = df[['ph', 'hardness', 'solids', 'chloramines', 'sulfate', 'conductivity'
                      'organic_carbon', 'trihalomethanes', 'turbidity']]

for col in revised_columns:
    plt.figure(figsize=(8,6))
    fig = stats.probplot(df[col], plot = sns.mpl.pyplot)
    plt.title("Q-Q Plot of {}".format(col), fontsize=15)
    plt.xlabel("{}".format(col), fontsize=10)
    plt.xticks(fontsize=10)
    plt.yticks(fontsize=10)
    plt.show()
```

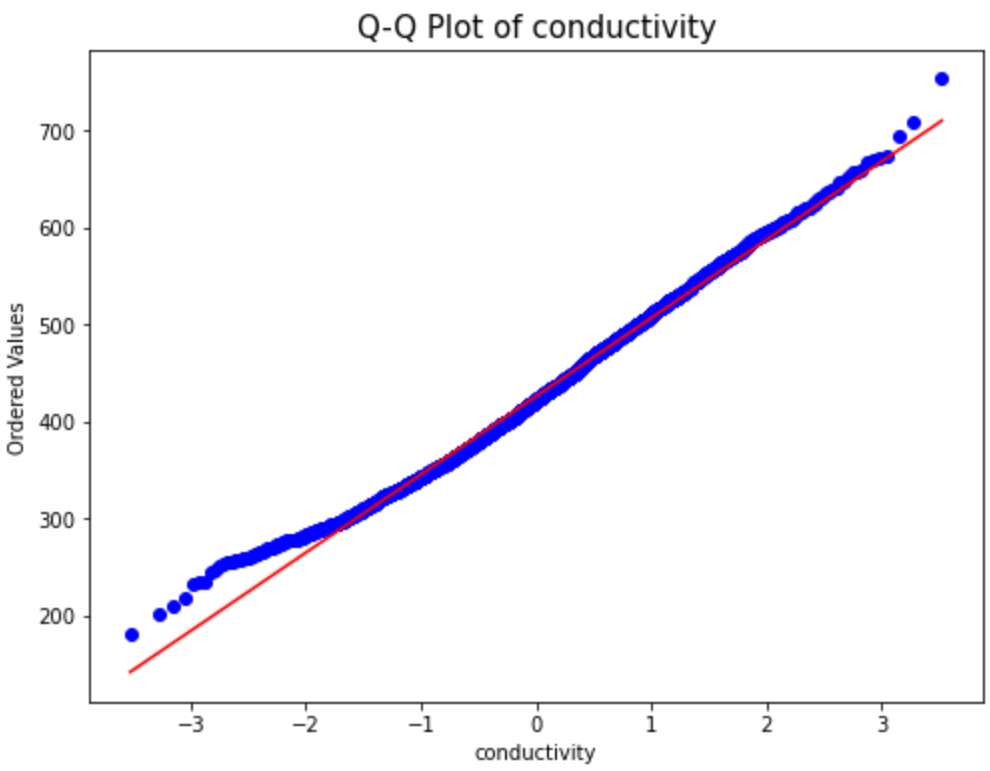


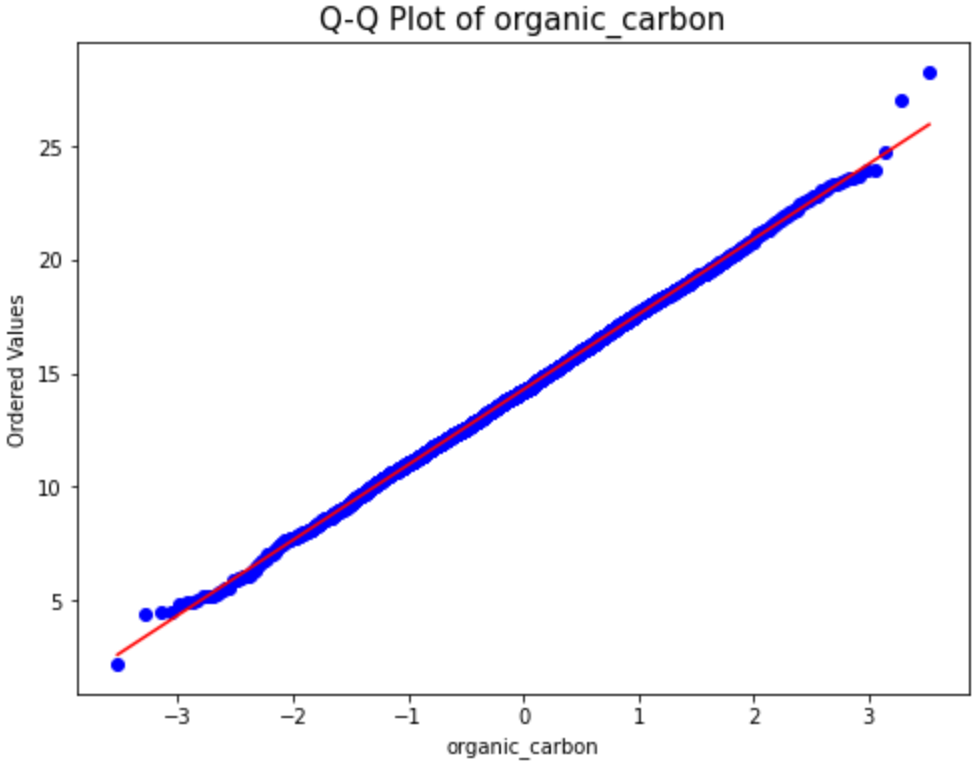

Q-Q Plot of hardness
Ordered Values
hardness
300
250
200
150
100
50
−3
−2
−1
0
1
2
3

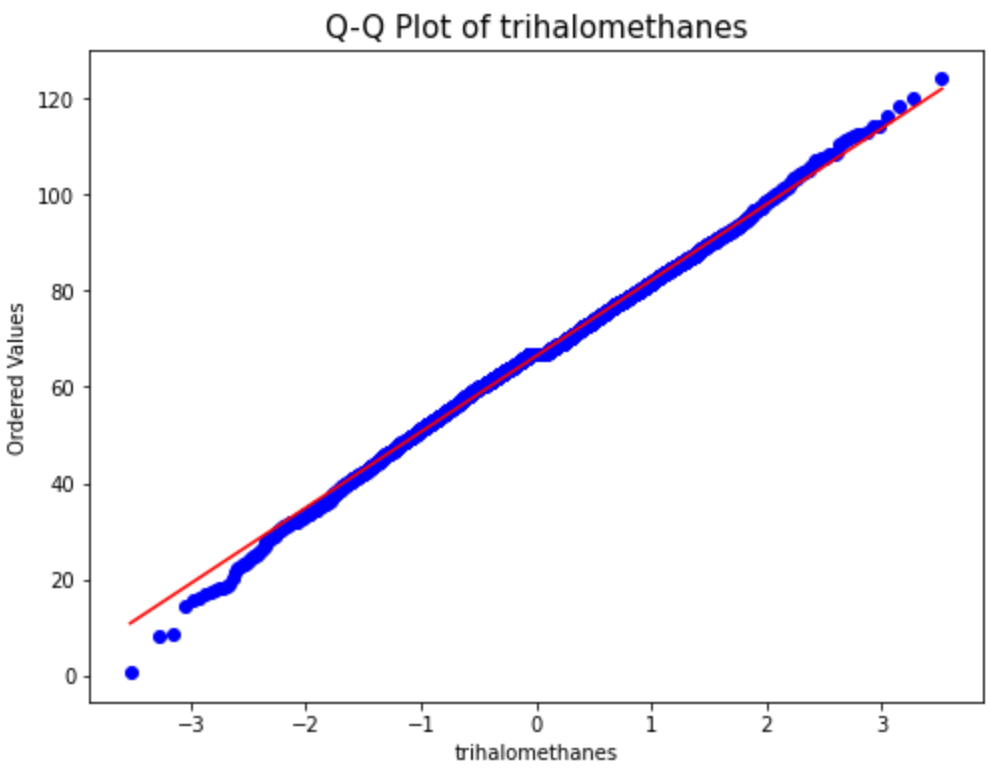

Q-Q Plot of solids
Ordered Values
solids
60000
50000
40000
30000
20000
10000
0
−10000
−3
−2
−1
0
1
2
3

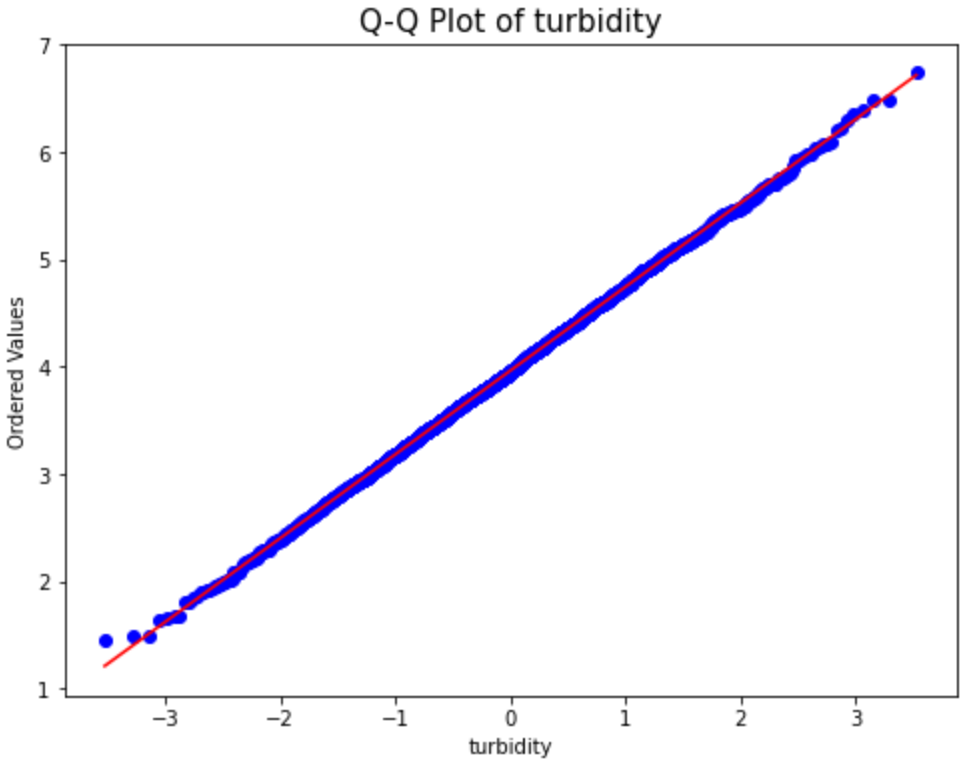

Q-Q Plot of chloramines
Ordered Values
chloramines
0
2
4
6
8
10
12
−3
−2
−1
0
1
2
3


Q-Q Plot of sulfate
Ordered Values
sulfate
150
200
250
300
350
400
450
−3
−2
−1
0
1
2
3


Q-Q Plot of conductivity
Ordered Values
conductivity
700
600
500
400
300
200
−3
−2
−1
0
1
2
3


Q-Q Plot of organic_carbon
Ordered Values
organic_carbon
25
20
15
10
5
−3
−2
−1
0
1
2
3





In [26]:

```
'''
Run Shapiro-Wilk test for normality on the features.
'''
shapiro_test_ph = shapiro(df['ph'])
shapiro_test_hardness = shapiro(df['hardness'])
shapiro_test_solids = shapiro(df['solids'])
shapiro_test_chloramines = shapiro(df['chloramines'])
shapiro_test_sulfate = shapiro(df['sulfate'])
shapiro_test_conductivity = shapiro(df['conductivity'])
shapiro_test_oc = shapiro(df['organic_carbon'])
shapiro_test_trih = shapiro(df['trihalomethanes'])
shapiro_test_turbidity = shapiro(df['turbidity'])

normality_tests = {'ph_test':shapiro_test_ph, 'hardness_test':shapiro_test_hardness, 'soli
                   'chloramines_test':shapiro_test_chloramines, 'sulfate_test':shapiro_tes
```

```
                    'conductivity_test':shapiro_test_conductivity, 'oc_test':shapiro_test_c
                    'trih_test':shapiro_test_trih, 'turbidity_test':shapiro_test_turbidity}
normality_tests
```

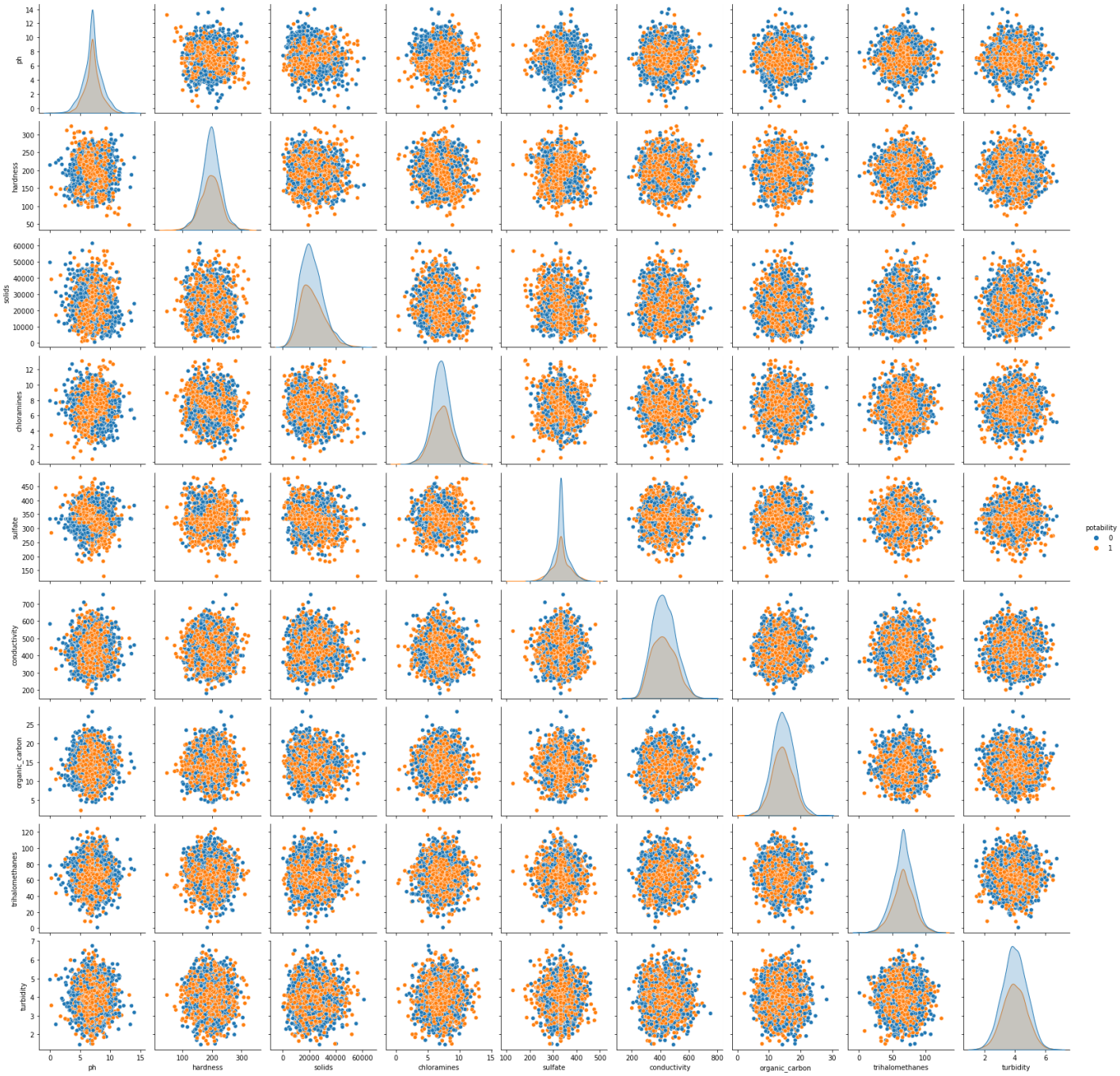
Out[26]:

```
{'ph_test': ShapiroResult(statistic=0.9797217845916748, pvalue=3.0514745303663042e-21),
 'hardness_test': ShapiroResult(statistic=0.9959700703620911, pvalue=9.639764897428904e-0
8),
 'solids_test': ShapiroResult(statistic=0.9777269959449768, pvalue=2.955943348526295e-22),
 'chloramines_test': ShapiroResult(statistic=0.996772289276123, pvalue=1.8142625322070671e
-06),
 'sulfate_test': ShapiroResult(statistic=0.9589979648590088, pvalue=1.8103824232042315e-2
9),
 'conductivity_test': ShapiroResult(statistic=0.9929702281951904, pvalue=1.503264700219997
3e-11),
 'oc_test': ShapiroResult(statistic=0.9995213747024536, pvalue=0.6210277080535889),
 'trih_test': ShapiroResult(statistic=0.99696284532547, pvalue=3.835944426100468e-06),
 'turbidity_test': ShapiroResult(statistic=0.9996957778930664, pvalue=0.9306948781013489)}
```

Data Understanding - Multivariate Analysis

In [27]:

```
'''
Construct a pairplot() to illustrate bivariate relationships present in the dataset by pot
'''
sns.pairplot(df, hue = 'potability')
plt.show()
```

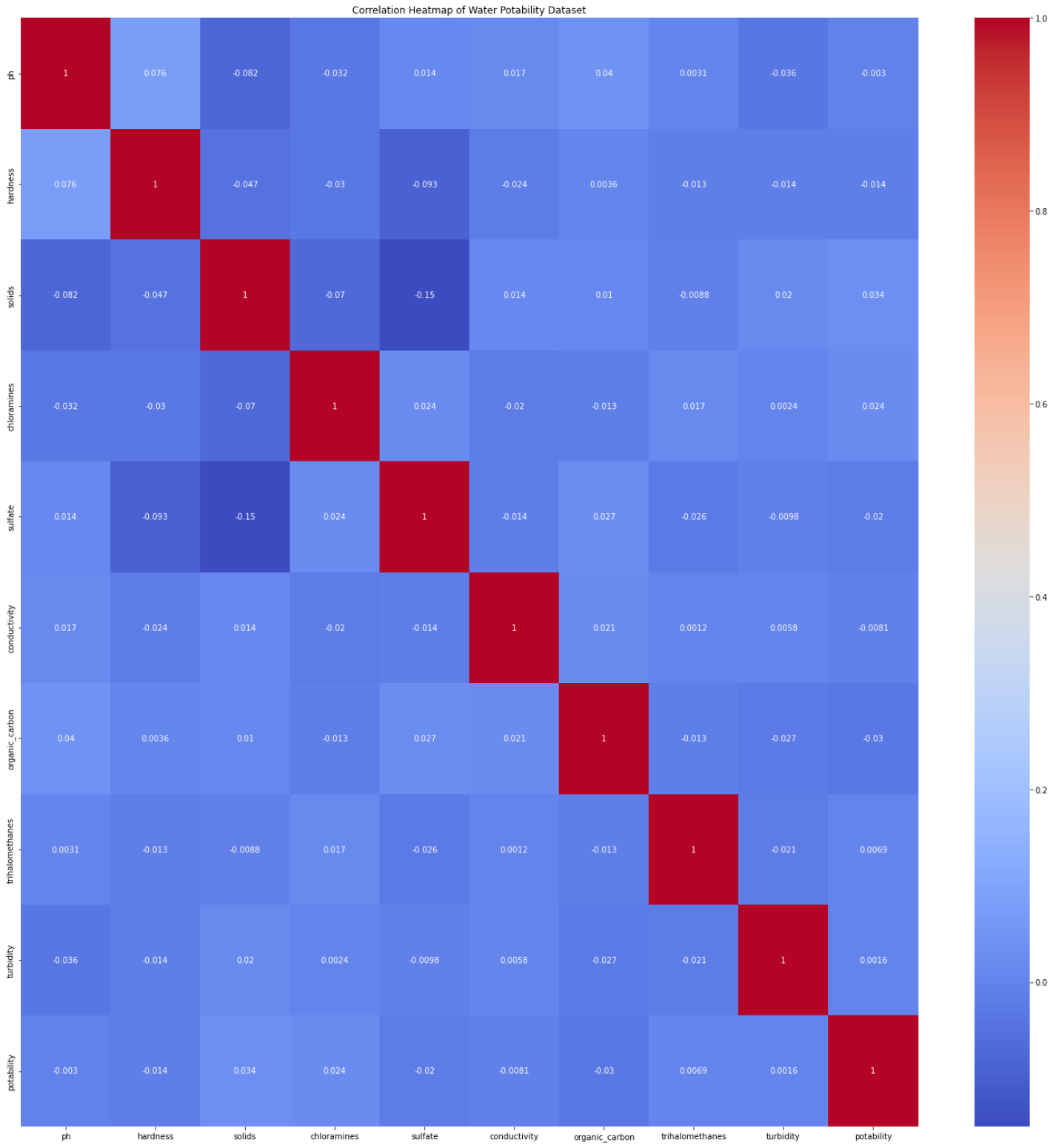


In [28]:

```
'''
Display a correlation heatmap. Utilize sns.heatmap() to generate the figure.
'''
# Calculate the correlation coefficient with corr().
correlation_number = df.corr()

# Create the heatmap for the correlation coefficients calculated above.
fig, ax = plt.subplots(1, 1, figsize=(20,20), tight_layout = True)
sns.heatmap(correlation_number, annot = True, cmap = 'coolwarm')
plt.title('Correlation Heatmap of Water Potability Dataset')
```

Out[28]:

```
Text(0.5, 1.0, 'Correlation Heatmap of Water Potability Dataset')
```



In [29]:

```
'''
Check pointbiserial correlations for potability to see if there are any significant differ
'''
# Calculate the correlation coefficient for features with potability.
correlation_number_pb1 = pointbiserialr(df['potability'],df['ph'])
correlation_number_pb2 = pointbiserialr(df['potability'],df['hardness'])
correlation_number_pb3 = pointbiserialr(df['potability'],df['solids'])
correlation_number_pb4 = pointbiserialr(df['potability'],df['chloramines'])
correlation_number_pb5 = pointbiserialr(df['potability'],df['sulfate'])
correlation_number_pb6 = pointbiserialr(df['potability'],df['conductivity'])
correlation_number_pb7 = pointbiserialr(df['potability'],df['organic_carbon'])
correlation_number_pb8 = pointbiserialr(df['potability'],df['trihalomethanes'])
correlation_number_pb9 = pointbiserialr(df['potability'],df['turbidity'])

# Create a dictionary of the pointbiserial correlation values.
```

```
pb_corr_dict = {'ph_corr':correlation_number_pb1, 'hardness_corr':correlation_number_pb2,
           'solids_corr':correlation_number_pb3, 'chloramines_corr':correlation_number_pb4
           'sulfate_corr':correlation_number_pb5, 'conductivity':correlation_number_pb6,
           'organic_carbon_corr':correlation_number_pb7, 'trihalomethanes_corr':correlatic
           'turbidity_corr':correlation_number_pb9}
pb_corr_dict
```

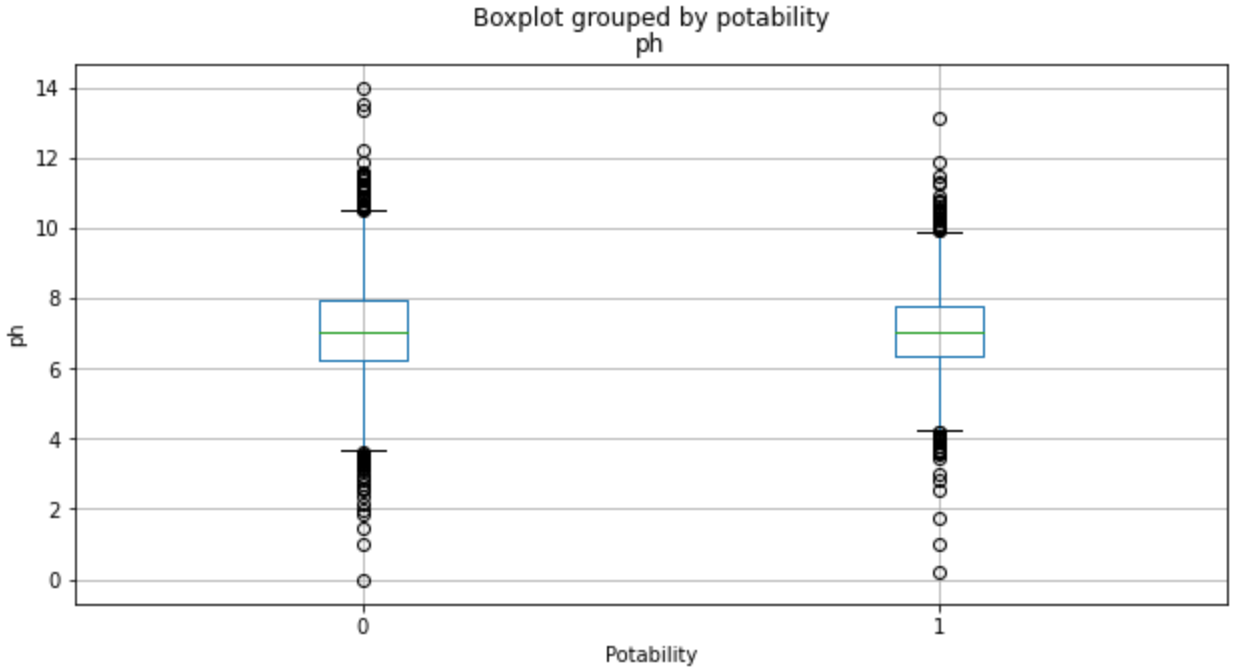
Out[29]:
```
{'ph_corr': PointbiserialrResult(correlation=-0.0030139288906728037, pvalue=0.8630909569723499),
 'hardness_corr': PointbiserialrResult(correlation=-0.013836558096163432, pvalue=0.42854158703761713),
 'solids_corr': PointbiserialrResult(correlation=0.033743313390906485, pvalue=0.05346363820366133),
 'chloramines_corr': PointbiserialrResult(correlation=0.0237789720027849, pvalue=0.1736102245030519),
 'sulfate_corr': PointbiserialrResult(correlation=-0.020476394607078924, pvalue=0.2413296939297576),
 'conductivity': PointbiserialrResult(correlation=-0.00812831972472755, pvalue=0.6418845484637925),
 'organic_carbon_corr': PointbiserialrResult(correlation=-0.030001366622918028, pvalue=0.08599746151306269),
 'trihalomethanes_corr': PointbiserialrResult(correlation=0.006886582826791652, pvalue=0.6935683946431569),
 'turbidity_corr': PointbiserialrResult(correlation=0.0015806819408441912, pvalue=0.9279391626737951)}
```

In [30]:
```
'''
Sort the dictionary by correlation value.
'''
sorted_dict = sorted(pb_corr_dict.items(), key = operator.itemgetter(1))
sorted_dict
```

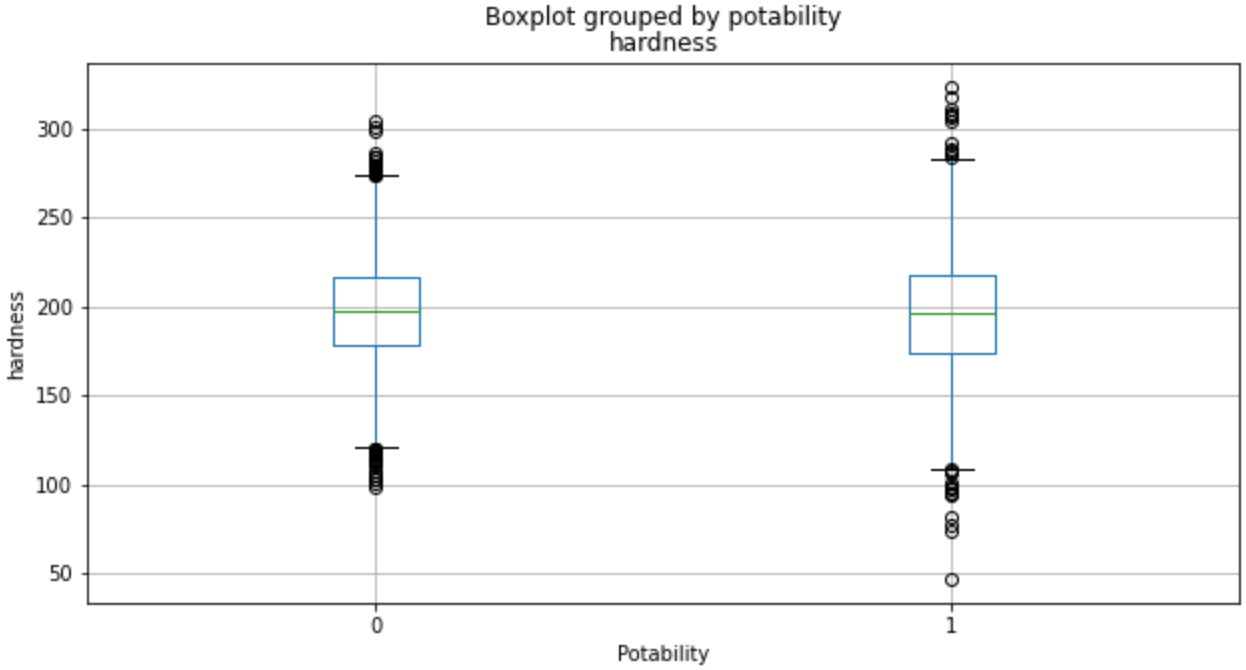
Out[30]:
```
[('organic_carbon_corr',
  PointbiserialrResult(correlation=-0.030001366622918028, pvalue=0.08599746151306269)),
 ('sulfate_corr',
  PointbiserialrResult(correlation=-0.020476394607078924, pvalue=0.2413296939297576)),
 ('hardness_corr',
  PointbiserialrResult(correlation=-0.013836558096163432, pvalue=0.42854158703761713)),
 ('conductivity',
  PointbiserialrResult(correlation=-0.00812831972472755, pvalue=0.6418845484637925)),
 ('ph_corr',
  PointbiserialrResult(correlation=-0.0030139288906728037, pvalue=0.8630909569723499)),
 ('turbidity_corr',
  PointbiserialrResult(correlation=0.0015806819408441912, pvalue=0.9279391626737951)),
 ('trihalomethanes_corr',
  PointbiserialrResult(correlation=0.006886582826791652, pvalue=0.6935683946431569)),
 ('chloramines_corr',
  PointbiserialrResult(correlation=0.0237789720027849, pvalue=0.1736102245030519)),
 ('solids_corr',
  PointbiserialrResult(correlation=0.033743313390906485, pvalue=0.05346363820366133))]
```

In [31]:
```
'''
Construct box plots to understand each feature distribution based on potability.
'''
for col in df.columns[0:9]:
    plt.figure(figsize=(8,4))
    df.boxplot(column=col, by='potability',figsize=(10,5))
    plt.xlabel("Potability".format(col), fontsize=10)
    plt.ylabel("{}".format(col), fontsize=10)
    plt.show()
```

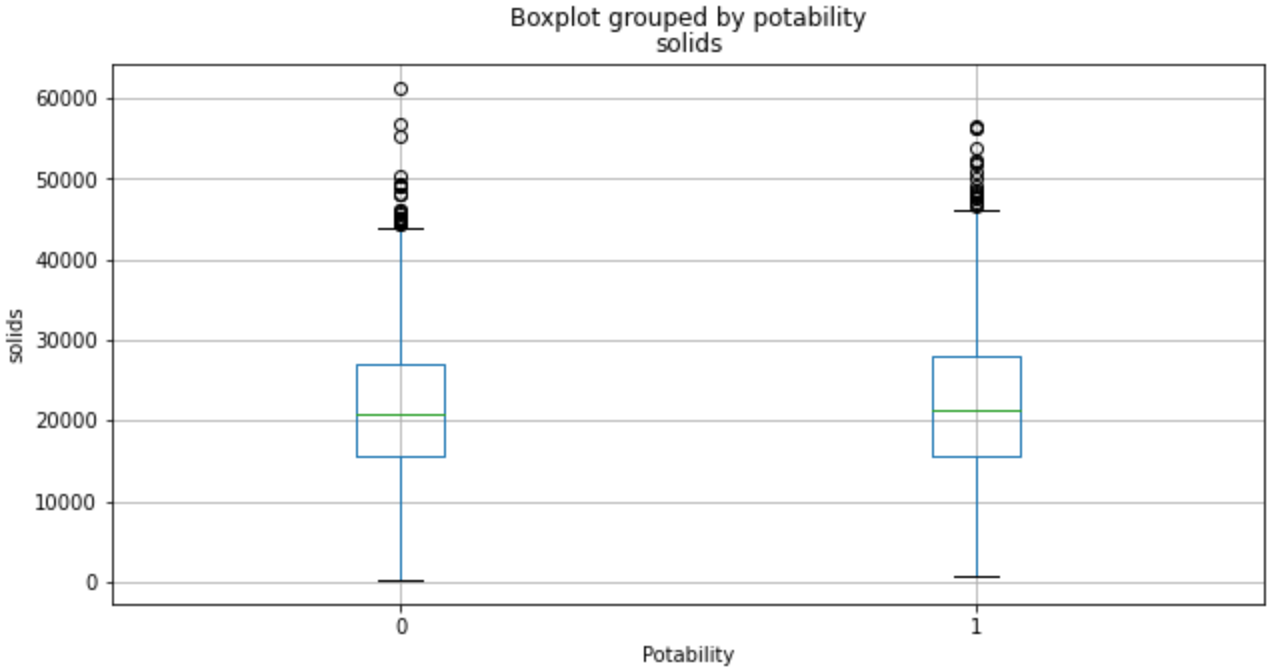
```
<Figure size 576x288 with 0 Axes>
```



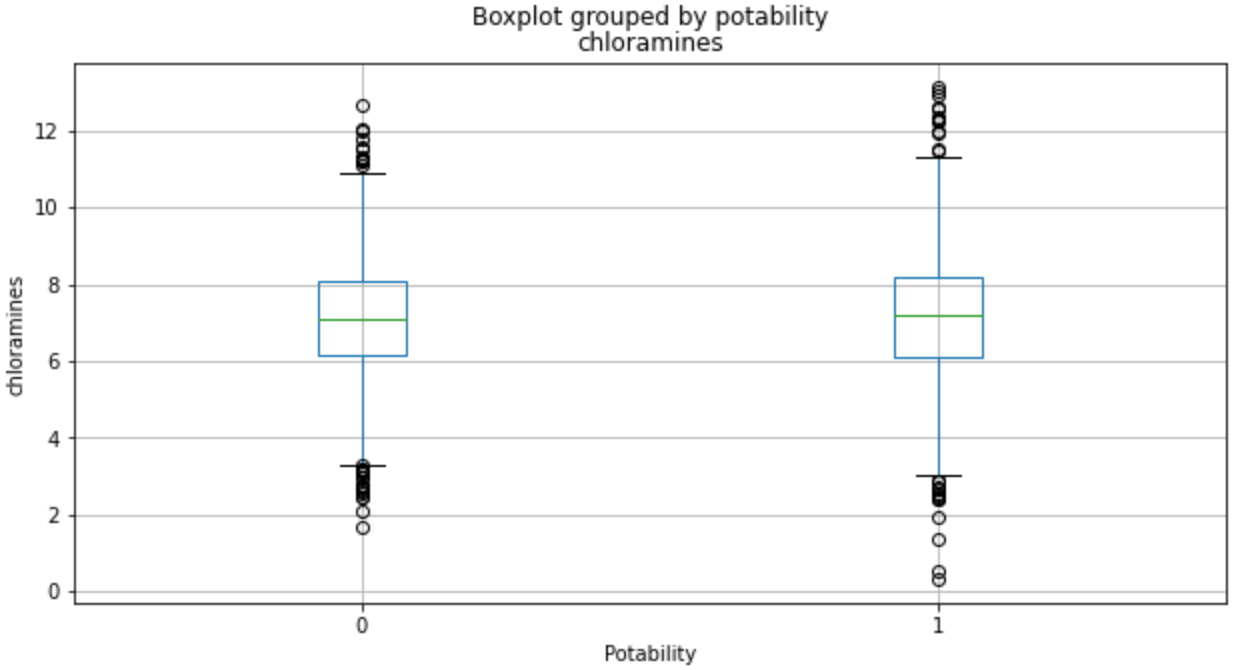
<Figure size 576x288 with 0 Axes>



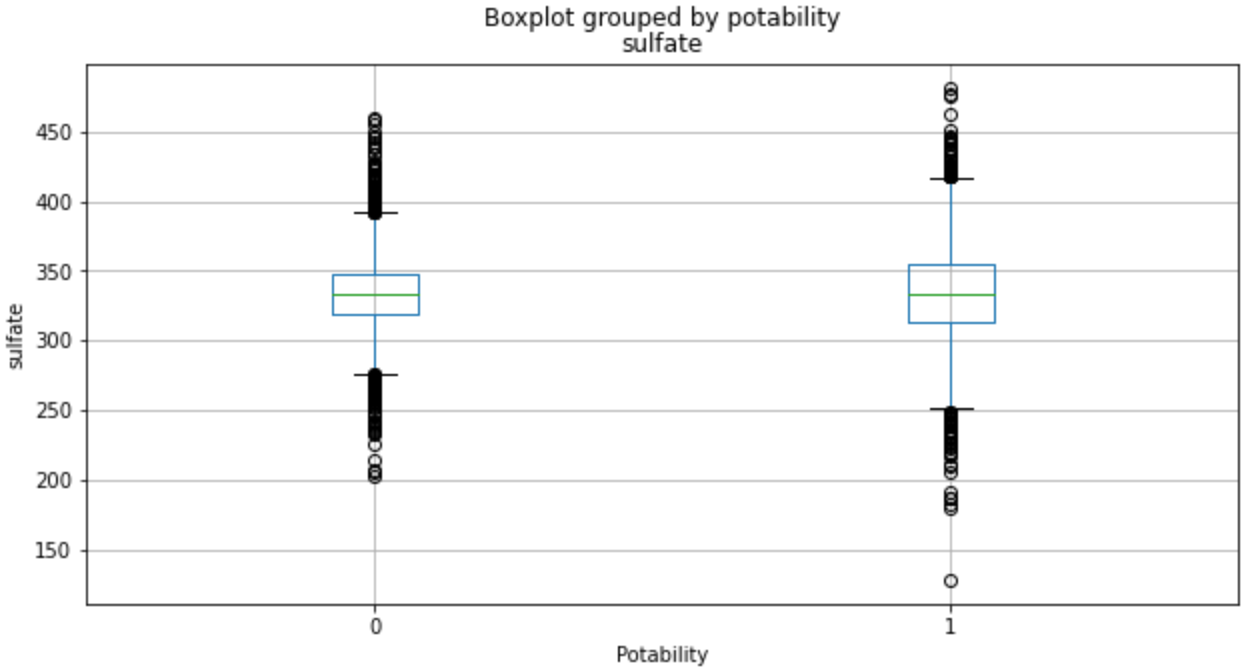
<Figure size 576x288 with 0 Axes>



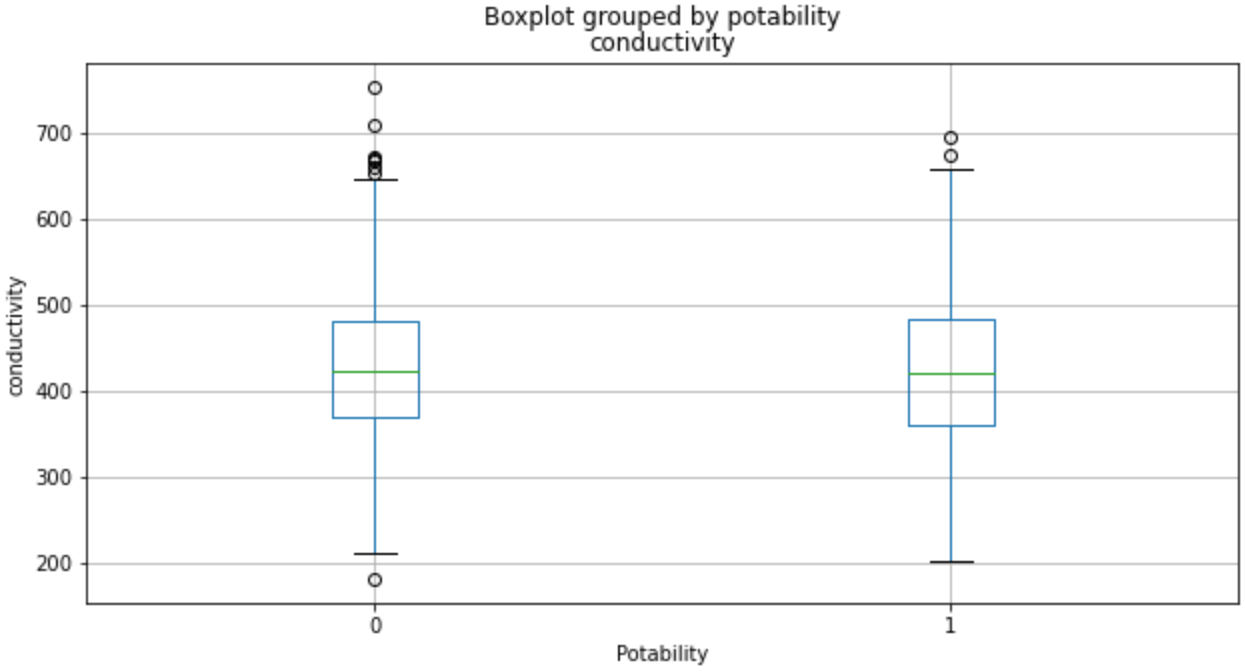
<Figure size 576x288 with 0 Axes>



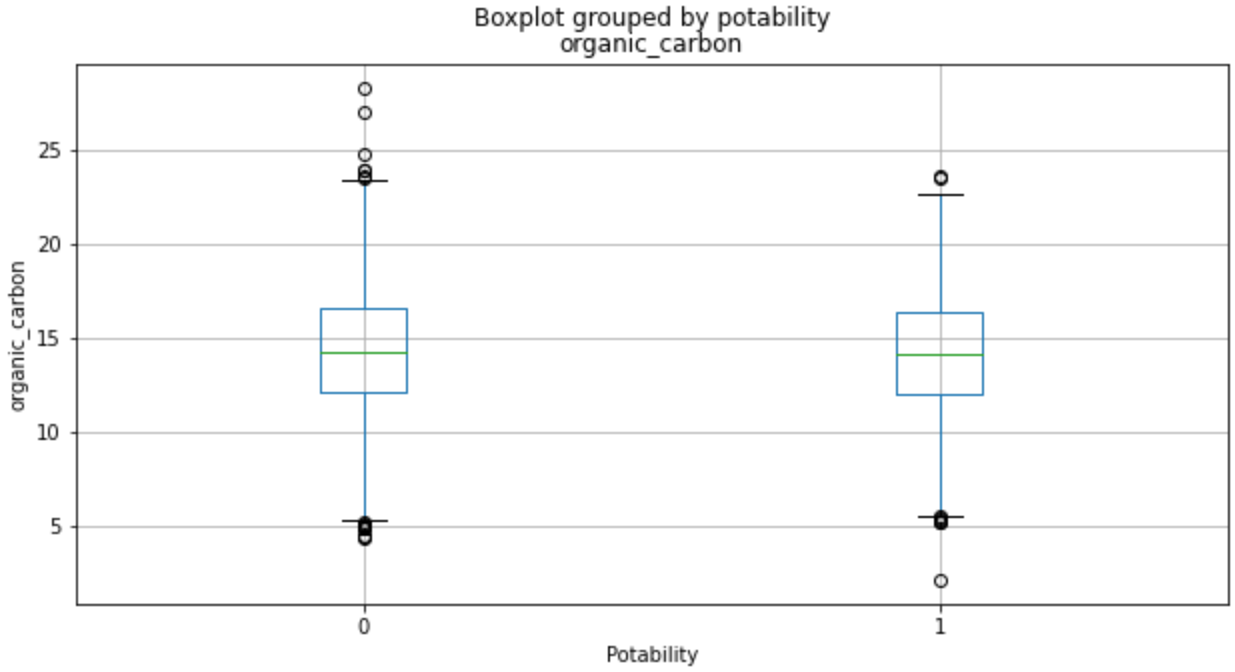
<Figure size 576x288 with 0 Axes>



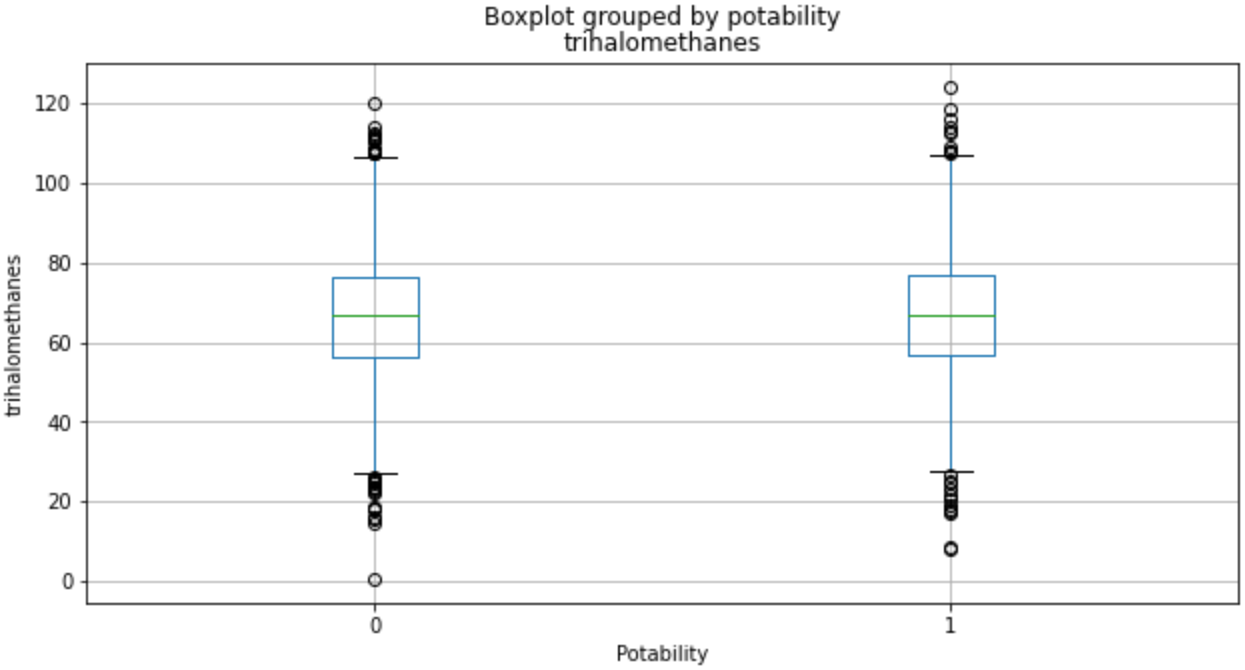
<Figure size 576x288 with 0 Axes>



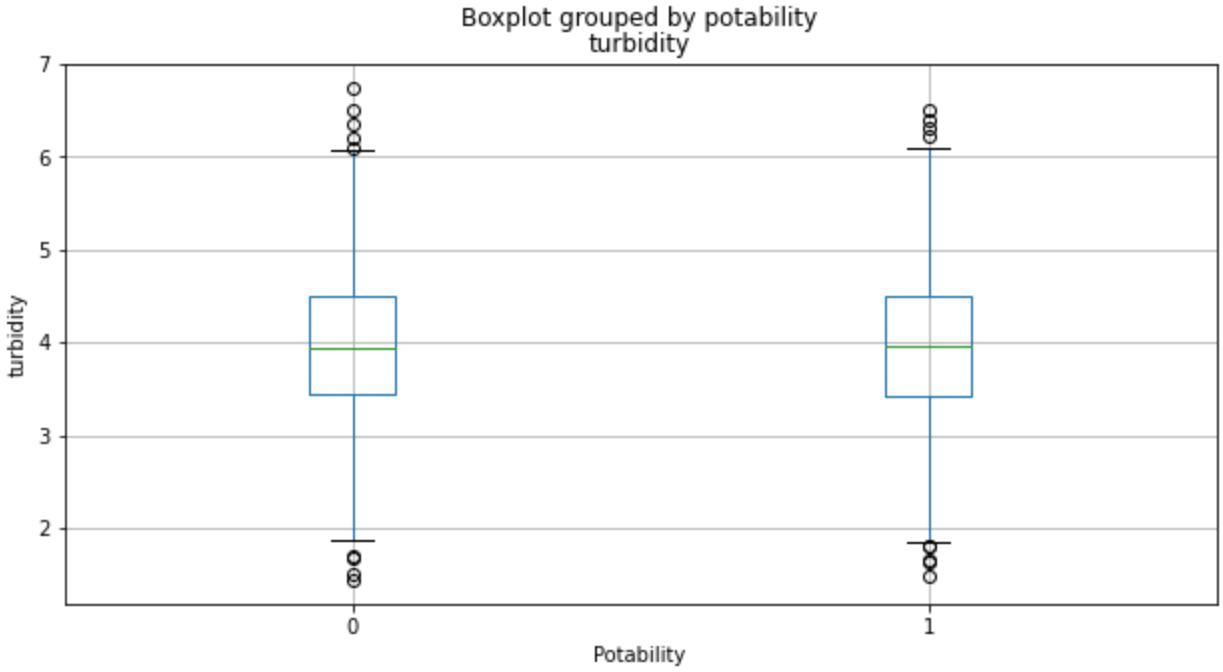
<Figure size 576x288 with 0 Axes>



<Figure size 576x288 with 0 Axes>



<Figure size 576x288 with 0 Axes>



Data Preparation

In [32]:
```
'''
Split the data into training and test set, where 'potability' is the target.
'''
X = df.drop('potability', axis = 1)
y = df['potability']
```

In [33]:
```
'''
Split the data with train_test_split from sklearn.
Use test_size = 0.2 to split the data into 80% training and 20% testing data.
'''
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.2, random_state =
```

In [34]:
```
'''
Print out the shape of the resulting datasets for training and testing.
'''
print("The original data set shape was {} rows and {} columns.".format(df.shape[0],df.shap
print("The X_train shape is {} rows and {} columns.".format(X_train.shape[0],X_train.shape
print("The y_train shape is {} rows.".format(y_train.shape[0]))
print("The X_test shape is {} rows and {} columns.".format(X_test.shape[0],X_test.shape[1]
print("The y_test shape is {} rows.".format(y_test.shape[0]))
```

```
The original data set shape was 3276 rows and 10 columns.
The X_train shape is 2620 rows and 9 columns.
The y_train shape is 2620 rows.
The X_test shape is 656 rows and 9 columns.
The y_test shape is 656 rows.
```

Predictive Modeling and Evaluation

Logistic Regression Model

In [35]:
```
'''
Setup the Logistic Regression Classifier.
Setting the class_weight to balanced.
'''
lr = LogisticRegression(class_weight = 'balanced')
```

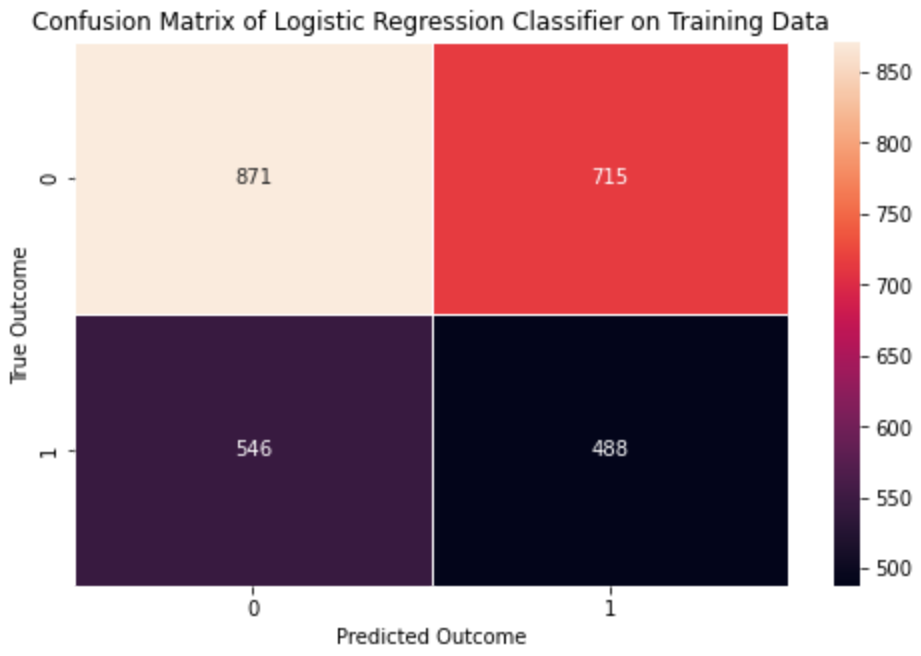
In [36]:
```
'''
Fit the Logistic Regression Classifier on the training dataset.
'''
lr_classifier = lr.fit(X_train, y_train)
lr_classifier
```

Out[36]:
```
LogisticRegression(class_weight='balanced')
```

In [37]:
```
'''
Obtain the y_prediction probabilities for each record in the training dataset.
'''
y_predictions_lr_train = lr.predict(X_train)
```

In [38]:
```
'''
Generate a Confusion Matrix for the Logistic Regression Classifier based on the training d
'''
cm_lr_train = confusion_matrix(y_train, y_predictions_lr_train)
```

In [39]:
```
'''
Plot the confusion matrix so it is clearly labelled and illustrated.
'''
f, ax = plt.subplots(figsize = (8,5))
sns.heatmap(cm_lr_train, annot = True, linewidths = 0.5, fmt = ".0f", ax = ax)
plt.xlabel('Predicted Outcome')
plt.ylabel('True Outcome')
plt.title('Confusion Matrix of Logistic Regression Classifier on Training Data')
plt.show()
```



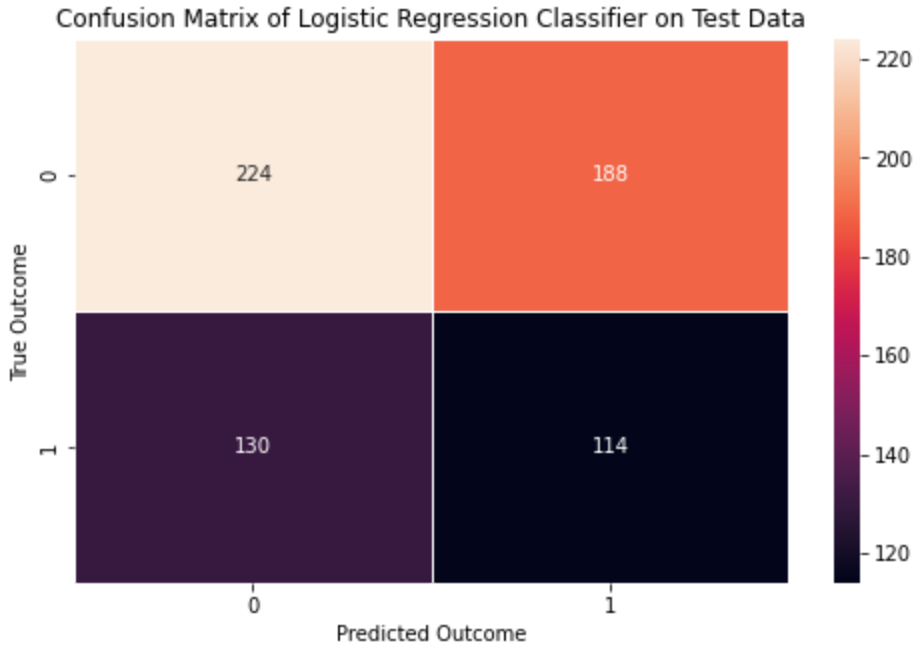
In [40]:
```
'''
Obtain the y_prediction probabilities for each record in the test dataset.
'''
y_predictions_lr_test = lr.predict(X_test)
```

In [41]:
```
'''
Generate a Confusion Matrix for the Logistic Regression Classifier based on the test datas
```

```
'''
cm_lr_test = confusion_matrix(y_test, y_predictions_lr_test)
```

In [42]:

```
'''
Plot the confusion matrix so it is clearly labelled and illustrated.
'''
f, ax = plt.subplots(figsize = (8,5))
sns.heatmap(cm_lr_test, annot = True, linewidths = 0.5, fmt = ".0f", ax = ax)
plt.xlabel('Predicted Outcome')
plt.ylabel('True Outcome')
plt.title('Confusion Matrix of Logistic Regression Classifier on Test Data')
plt.show()
```



In [43]:

```
'''
Show the classification report for the test data.
'''
print(classification_report(y_test, y_predictions_lr_test))
```

```
              precision    recall  f1-score   support

           0       0.63      0.54      0.58       412
           1       0.38      0.47      0.42       244

    accuracy                           0.52       656
   macro avg       0.51      0.51      0.50       656
weighted avg       0.54      0.52      0.52       656
```

In [44]:

```
'''
Calculate the accuracy for the model based on training and test data. Also, report the
Precision, Recall, and F1 score for the model predications against the test data.
'''
accuracy_lr_train = accuracy_score(y_train, y_predictions_lr_train)
accuracy_lr_test = accuracy_score(y_test, y_predictions_lr_test)
precision_lr = precision_score(y_test, y_predictions_lr_test)
recall_lr = recall_score(y_test, y_predictions_lr_test)
f1_lr = f1_score(y_test, y_predictions_lr_test)
print("Accuracy of Logistic Regression Model on training data is:{}".format(accuracy_lr_tr
print("Accuracy of Logistic Regression Model on testing data is:{}".format(accuracy_lr_tes
print("Precision of Logistic Regression Model on testing data is:{}".format(precision_lr))
```

```
print("Recall of Logistic Regression Model on testing data is:{}".format(recall_lr))
print("F1 Score of Logistic Regression Model on testing data is:{}".format(f1_lr))
```

```
Accuracy of Logistic Regression Model on training data is:0.5187022900763358
Accuracy of Logistic Regression Model on testing data is:0.5152439024390244
Precision of Logistic Regression Model on testing data is:0.37748344370860926
Recall of Logistic Regression Model on testing data is:0.4672131147540984
F1 Score of Logistic Regression Model on testing data is:0.4175824175824176
```

K-NN (K-Neareast Neighbor) Model

In [45]:
```
'''
Standardize the X_train and X_test datasets for the remainder of the models being evaluate
'''
sc = StandardScaler()
X_train = sc.fit_transform(X_train)
X_test = sc.transform(X_test)
```

In [46]:
```
'''
Create the KNN Classifier.
K = 38 based on Error Rate evaluation shown in this section.
'''
knn = KNeighborsClassifier(n_neighbors = 38)
```

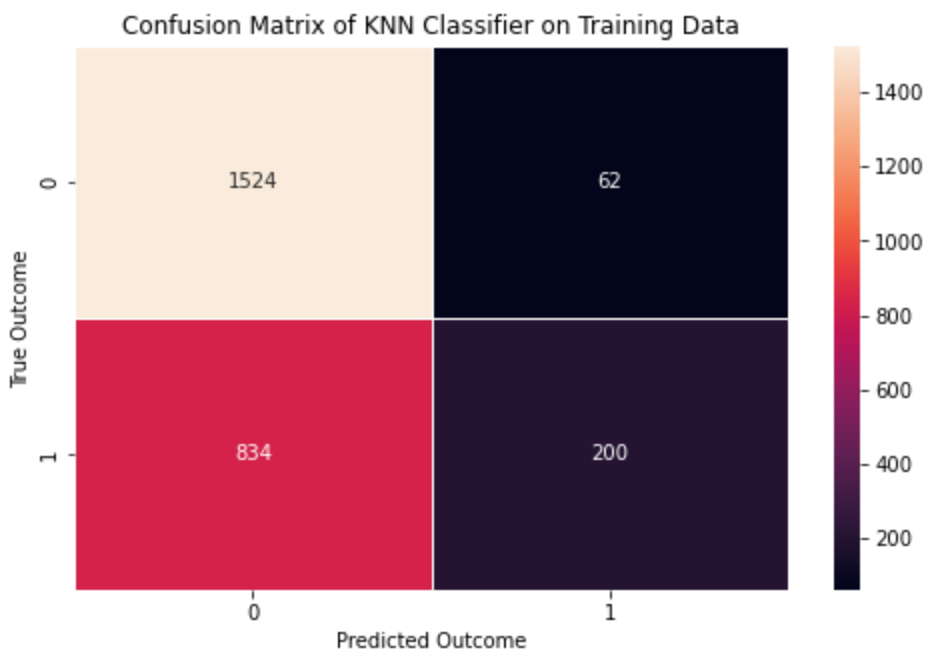
In [47]:
```
'''
Fit the KNN Classifier on the training dataset.
'''
knn_classifier = knn.fit(X_train, y_train )
knn_classifier
```

Out[47]:
```
KNeighborsClassifier(n_neighbors=38)
```

In [48]:
```
'''
Obtain the y_prediction probabilities for each record in the training dataset.
'''
y_predictions_knn_train = knn.predict(X_train)
```

In [49]:
```
'''
Generate a Confusion Matrix for the Logistic Regression Classifier based on the training d
'''
cm_knn_train = confusion_matrix(y_train, y_predictions_knn_train)
```

In [50]:
```
'''
Plot the confusion matrix so it is clearly labelled and illustrated.
'''
f, ax = plt.subplots(figsize = (8,5))
sns.heatmap(cm_knn_train, annot = True, linewidths = 0.5, fmt = ".0f", ax = ax)
plt.xlabel('Predicted Outcome')
plt.ylabel('True Outcome')
plt.title('Confusion Matrix of KNN Classifier on Training Data')
plt.show()
```

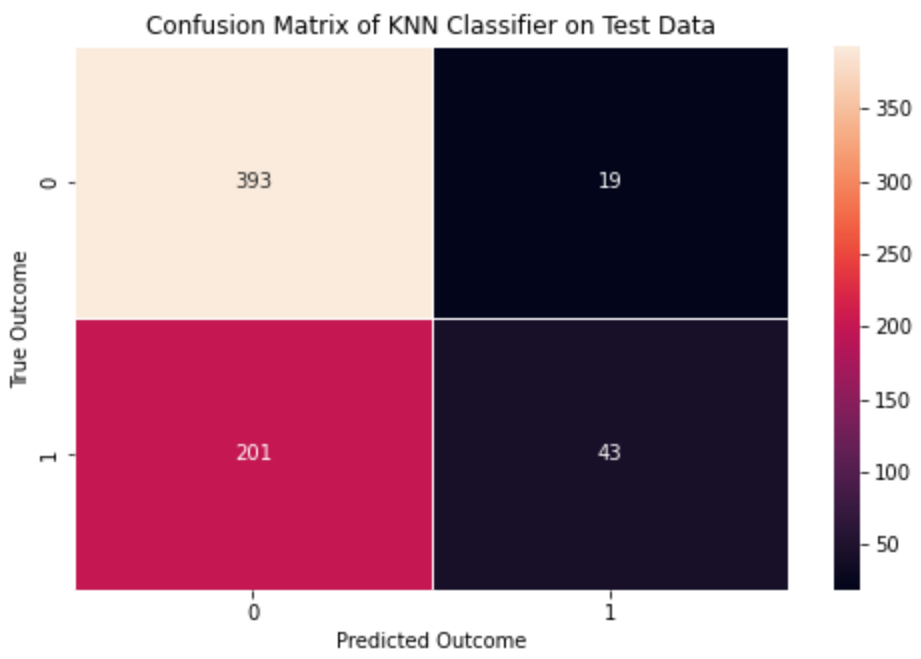


In [51]:
```
'''
Obtain the y_predictions for the KNN Classifier.
'''
y_predictions_knn_test = knn.predict(X_test)
```

In [52]:
```
'''
Generate a confusion matrix based on the test data set.
'''
cm_knn = confusion_matrix(y_test, y_predictions_knn_test)
cm_knn
```

Out[52]:
```
array([[393,  19],
       [201,  43]], dtype=int64)
```

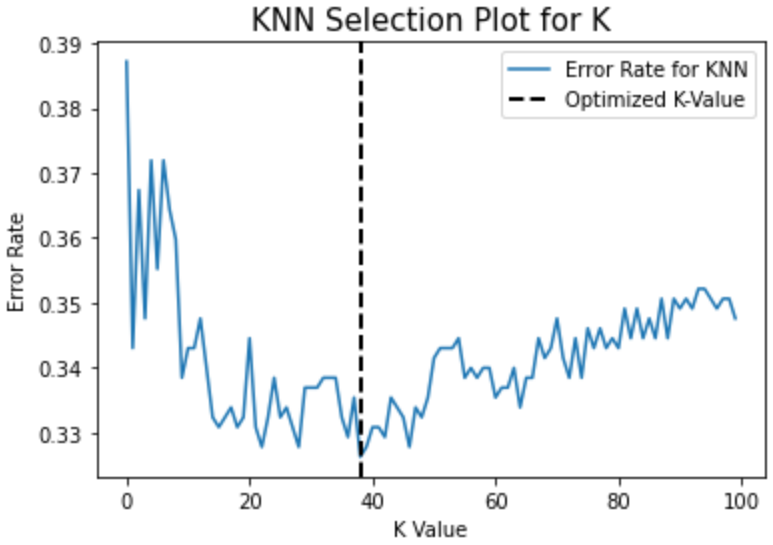
In [53]:
```
'''
Plot the confusion matrix so it is clearly labelled and illustrated.
'''
f, ax = plt.subplots(figsize = (8,5))
sns.heatmap(cm_knn, annot = True, linewidths = 0.5, fmt = ".0f", ax = ax)
plt.xlabel('Predicted Outcome')
plt.ylabel('True Outcome')
plt.title('Confusion Matrix of KNN Classifier on Test Data')
plt.show()
```



In [54]:
```
'''
Show the classification report for the test data.
'''
print(classification_report(y_test, y_predictions_knn_test))
```

```
              precision    recall  f1-score   support

           0       0.66      0.95      0.78       412
           1       0.69      0.18      0.28       244

    accuracy                           0.66       656
   macro avg       0.68      0.57      0.53       656
weighted avg       0.67      0.66      0.60       656
```

In [55]:
```
'''
Choose an optimal K value for KNN by plotting the error rate for the model against the dat
'''
# Create an empty list for error rate.
error_rate = []

# Create a for loop to get error rates appended to the error_rate list.
for i in np.arange(1, 101):

    new_model = KNeighborsClassifier(n_neighbors = i)

    new_model.fit(X_train, y_train)

    new_predictions = new_model.predict(X_test)

    error_rate.append(np.mean(new_predictions != y_test))

# Create the plot to assist with selecting a K value for the KNN classifier.
plt.plot(error_rate, label = 'Error Rate for KNN')
plt.title("KNN Selection Plot for K", fontsize=15)
plt.xlabel("K Value", fontsize=10)
plt.ylabel("Error Rate", fontsize=10)
plt.xticks(fontsize=10)
plt.yticks(fontsize=10)
plt.axvline(x=pd.Series(error_rate).idxmin(), linewidth = 2, color = 'k', linestyle = '--'
plt.legend(loc = 'upper right')
plt.show()
```



In [56]:
```
'''
Show the optimum number of K based on the plot above.
'''
print('Optimum K-Value for KNN:{}'.format(pd.Series(error_rate).idxmin()))
```

```
Optimum K-Value for KNN:38
```

In [57]:
```
'''
Calculate the accuracy for the model based on training and test data. Also, report the
Precision, Recall, and F1 score for the model predications against the test data.
'''
accuracy_knn_train = accuracy_score(y_train, y_predictions_knn_train)
accuracy_knn_test = accuracy_score(y_test, y_predictions_knn_test)
precision_knn = precision_score(y_test, y_predictions_knn_test)
recall_knn = recall_score(y_test, y_predictions_knn_test)
f1_knn = f1_score(y_test, y_predictions_knn_test)
print("Accuracy of KNN Model on training data is:{}".format(accuracy_knn_train))
print("Accuracy of KNN Model on testing data is:{}".format(accuracy_knn_test))
print("Precision of KNN Model on testing data is:{}".format(precision_knn))
print("Recall of KNN Model on testing data is:{}".format(recall_knn))
print("F1 Score of KNN Model on testing data is:{}".format(f1_knn))
```

```
Accuracy of KNN Model on training data is:0.6580152671755726
Accuracy of KNN Model on testing data is:0.6646341463414634
Precision of KNN Model on testing data is:0.6935483870967742
Recall of KNN Model on testing data is:0.1762295081967213
F1 Score of KNN Model on testing data is:0.28104575163398693
```

Decision Tree Model

In [58]:
```
'''
Create the Decision Tree Classifier.
'''
dt = DecisionTreeClassifier()
```

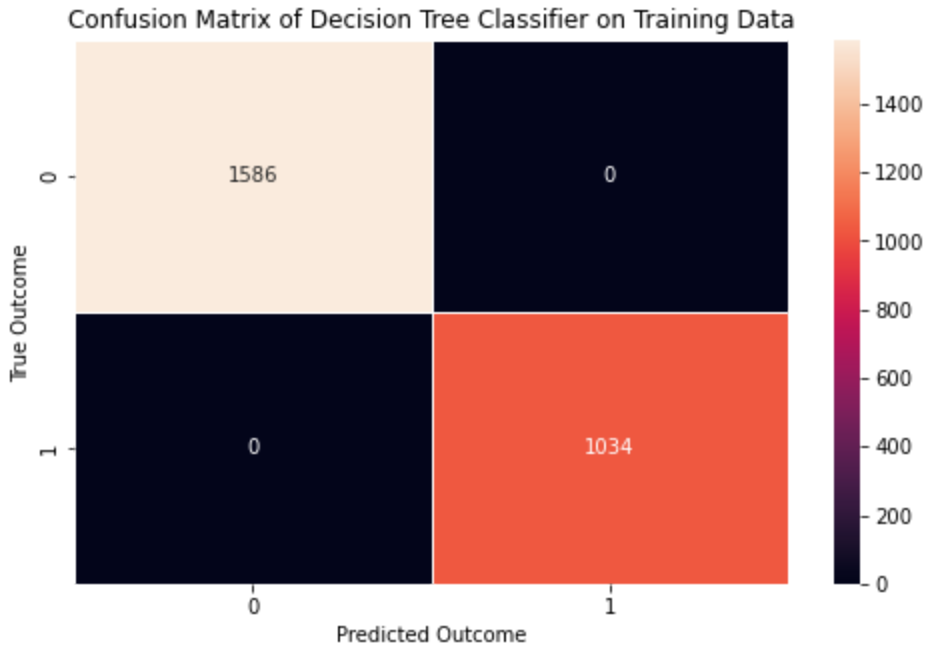
In [59]:
```
'''
Fit the Decision Tree Classifier on the training dataset.
'''
decision_tree_classifier = dt.fit(X_train, y_train )
decision_tree_classifier
```

Out[59]:
```
DecisionTreeClassifier()
```

In [60]:
```
'''
Obtain the y_prediction probabilities for each record in the training dataset.
'''
y_predictions_dt_train = dt.predict(X_train)
```

In [61]:
```
'''
Generate a Confusion Matrix for the Decision Tree Classifier based on the training dataset
'''
cm_dt_train = confusion_matrix(y_train, y_predictions_dt_train)
```

In [62]:
```
'''
Plot the confusion matrix so it is clearly labelled and illustrated.
'''
f, ax = plt.subplots(figsize = (8,5))
sns.heatmap(cm_dt_train, annot = True, linewidths = 0.5, fmt = ".0f", ax = ax)
plt.xlabel('Predicted Outcome')
plt.ylabel('True Outcome')
plt.title('Confusion Matrix of Decision Tree Classifier on Training Data')
plt.show()
```



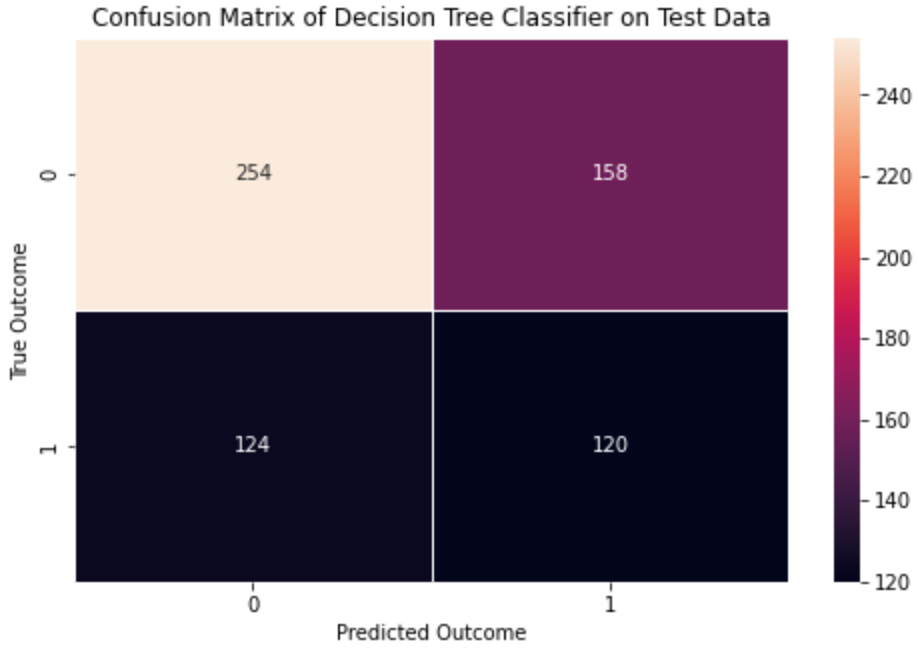
In [63]:
```
'''
Obtain the y_predictions for the decision tree classifier.
'''
y_predictions_dt_test = dt.predict(X_test)
```

In [64]:
```
'''
Generate a confusion matrix based on the test data set.
'''
cm_dt = confusion_matrix(y_test, y_predictions_dt_test)
cm_dt
```

Out[64]:
```
array([[254, 158],
       [124, 120]], dtype=int64)
```

In [65]:
```
'''
Plot the confusion matrix so it is clearly labelled and illustrated.
'''
```

```
f, ax = plt.subplots(figsize = (8,5))
sns.heatmap(cm_dt, annot = True, linewidths = 0.5, fmt = ".0f", ax = ax)
plt.xlabel('Predicted Outcome')
plt.ylabel('True Outcome')
plt.title('Confusion Matrix of Decision Tree Classifier on Test Data')
plt.show()
```



In [66]:

```
'''
Show the classification report for the test data.
'''
print(classification_report(y_test ,y_predictions_dt_test))
```

```
              precision    recall  f1-score   support

           0       0.67      0.62      0.64       412
           1       0.43      0.49      0.46       244

    accuracy                           0.57       656
   macro avg       0.55      0.55      0.55       656
weighted avg       0.58      0.57      0.57       656
```

In [67]:

```
'''
Calculate the accuracy for the model based on training and test data. Also, report the
Precision, Recall, and F1 score for the model predications against the test data.
'''
accuracy_dt_train = accuracy_score(y_train, y_predictions_dt_train)
accuracy_dt_test = accuracy_score(y_test, y_predictions_dt_test)
precision_dt = precision_score(y_test, y_predictions_dt_test)
recall_dt = recall_score(y_test, y_predictions_dt_test)
f1_dt = f1_score(y_test, y_predictions_dt_test)
print("Accuracy of Decision Tree Model on training data is:{}".format(accuracy_dt_train))
print("Accuracy of Decision Tree Model on testing data is:{}".format(accuracy_dt_test))
print("Precision of Decision Tree Model on testing data is:{}".format(precision_dt))
print("Recall of Decision Tree Model on testing data is:{}".format(recall_dt))
print("F1 Score of Decision Tree Model on testing data is:{}".format(f1_dt))
```

```
Accuracy of Decision Tree Model on training data is:1.0
Accuracy of Decision Tree Model on testing data is:0.5701219512195121
Precision of Decision Tree Model on testing data is:0.4316546762589928
Recall of Decision Tree Model on testing data is:0.4918032786885246
F1 Score of Decision Tree Model on testing data is:0.45977011494252873
```

Random Forest Model

In [68]:
```
'''
Create the Random Forest Classifier.
Select number of estimators at 31 based on error reduction plot for this model.
'''
rf = RandomForestClassifier(n_estimators = 31)
```

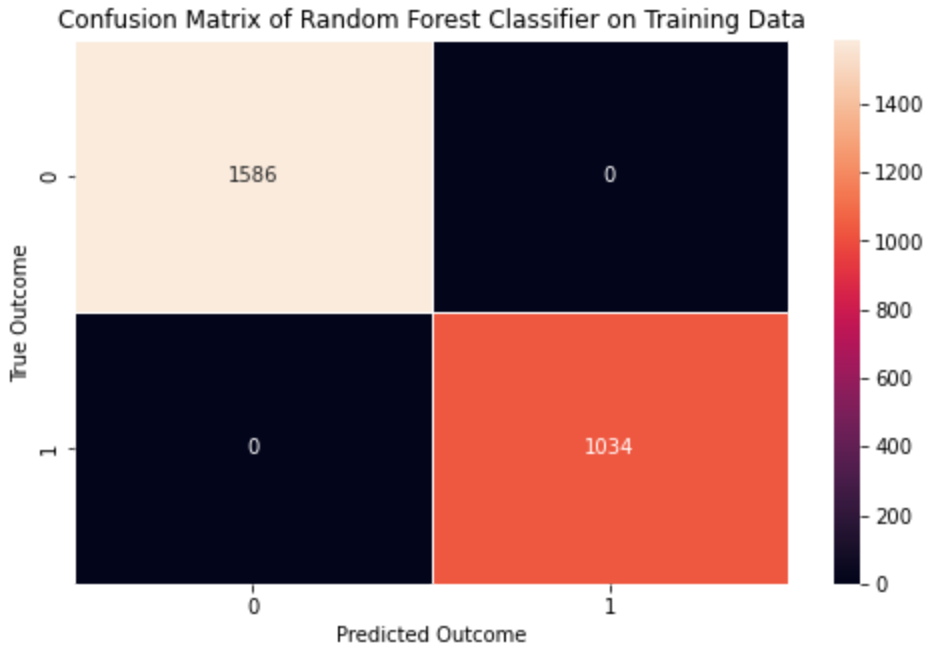
In [69]:
```
'''
Fit the Random Forest Classifier on the training dataset.
'''
random_forest_classifier = rf.fit(X_train, y_train )
random_forest_classifier
```

Out[69]:
```
RandomForestClassifier(n_estimators=31)
```

In [70]:
```
'''
Obtain the y_prediction probabilities for each record in the training dataset.
'''
y_predictions_rf_train = rf.predict(X_train)
```

In [71]:
```
'''
Generate a Confusion Matrix for the Random Forest Classifier based on the training dataset
'''
cm_rf_train = confusion_matrix(y_train, y_predictions_rf_train)
```

In [72]:
```
'''
Plot the confusion matrix so it is clearly labelled and illustrated.
'''
f, ax = plt.subplots(figsize = (8,5))
sns.heatmap(cm_rf_train, annot = True, linewidths = 0.5, fmt = ".0f", ax = ax)
plt.xlabel('Predicted Outcome')
plt.ylabel('True Outcome')
plt.title('Confusion Matrix of Random Forest Classifier on Training Data')
plt.show()
```



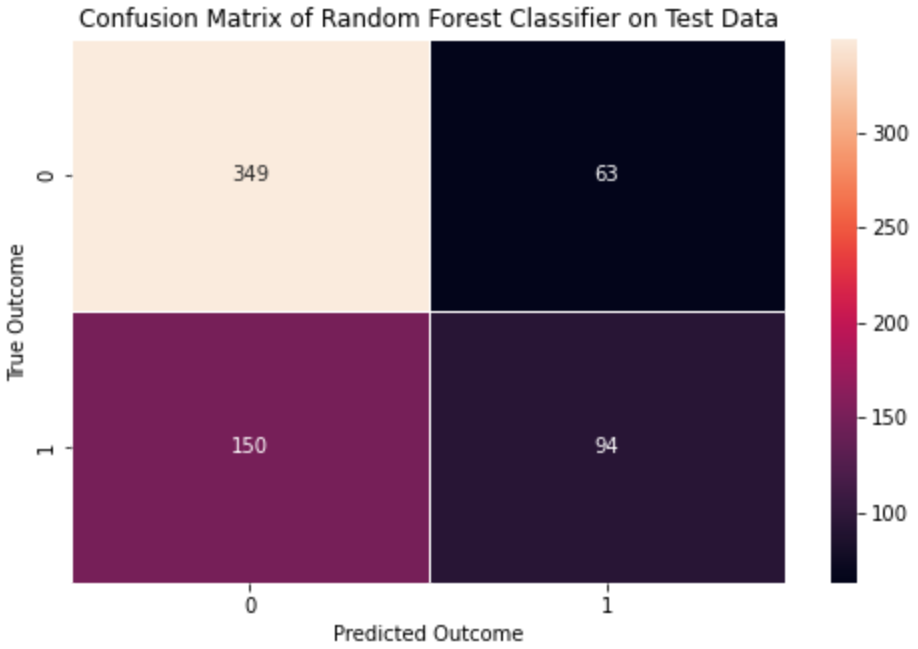
In [73]:
```
'''
```

```
Obtain the y_predictions for the Random Forest classifier.
'''
y_predictions_rf_test = rf.predict(X_test)
```

In [74]:
```
'''
Generate a confusion matrix based on the test data set.
'''
cm_rf = confusion_matrix(y_test, y_predictions_rf_test)
cm_rf
```

Out[74]:
```
array([[349,  63],
       [150,  94]], dtype=int64)
```

In [75]:
```
'''
Plot the confusion matrix so it is clearly labelled and illustrated.
'''
f, ax = plt.subplots(figsize = (8,5))
sns.heatmap(cm_rf, annot = True, linewidths = 0.5, fmt = ".0f", ax = ax)
plt.xlabel('Predicted Outcome')
plt.ylabel('True Outcome')
plt.title('Confusion Matrix of Random Forest Classifier on Test Data')
plt.show()
```

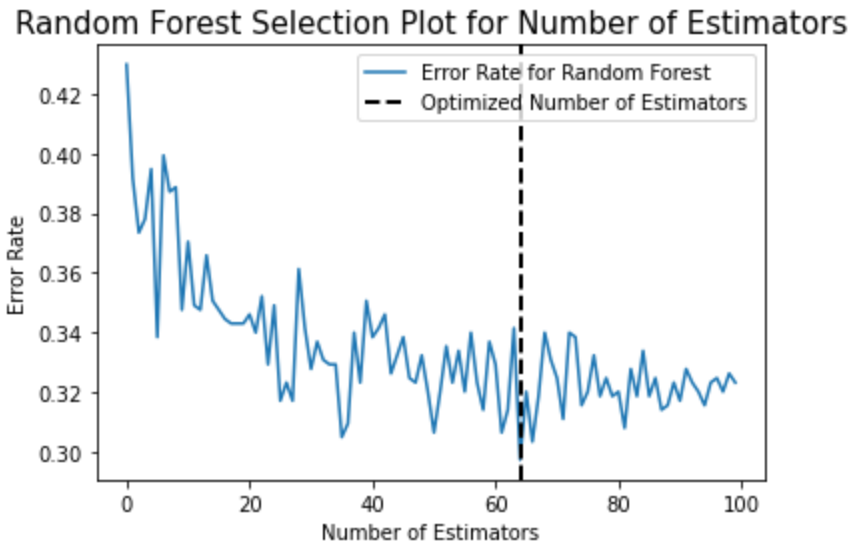


In [76]:
```
'''
Show the classification report for the test data.
'''
print(classification_report(y_test ,y_predictions_rf_test))
```

```
              precision    recall  f1-score   support

           0       0.70      0.85      0.77       412
           1       0.60      0.39      0.47       244

    accuracy                           0.68       656
   macro avg       0.65      0.62      0.62       656
weighted avg       0.66      0.68      0.66       656
```

In [77]:
```
'''
Choose an optimal number of estimators for Random Forest by plotting the error rate for th
```

```
'''
# Create an empty list for error rate.
error_rate_rf = []

# Create a for loop to get error rates appended to the error_rate list.
for i in np.arange(1, 101):

    new_model = RandomForestClassifier(n_estimators = i)

    new_model.fit(X_train, y_train)

    new_predictions = new_model.predict(X_test)

    error_rate_rf.append(np.mean(new_predictions != y_test))

# Create the plot to assist with selecting a K value for the KNN classifier.
plt.plot(error_rate_rf, label = 'Error Rate for Random Forest')
plt.title("Random Forest Selection Plot for Number of Estimators", fontsize=15)
plt.xlabel("Number of Estimators", fontsize=10)
plt.ylabel("Error Rate", fontsize=10)
plt.xticks(fontsize=10)
plt.yticks(fontsize=10)
plt.axvline(x=pd.Series(error_rate_rf).idxmin(), linewidth = 2, color = 'k', linestyle = '
            label = 'Optimized Number of Estimators')
plt.legend(loc = 'upper right')
plt.show()
```



In [78]:

```
'''
Show the optimum number of estimators on the plot above.
'''
print('Optimum number of estimators for Random Forest:{}'.format(pd.Series(error_rate_rf).
```

```
Optimum number of estimators for Random Forest:64
```

In [79]:

```
'''
Calculate the accuracy for the model based on training and test data. Also, report the
Precision, Recall, and F1 score for the model predications against the test data.
'''
accuracy_rf_train = accuracy_score(y_train, y_predictions_rf_train)
accuracy_rf_test = accuracy_score(y_test, y_predictions_rf_test)
precision_rf = precision_score(y_test, y_predictions_rf_test)
recall_rf = recall_score(y_test, y_predictions_rf_test)
f1_rf = f1_score(y_test, y_predictions_rf_test)
print("Accuracy of Random Forest Model on training data is:{}".format(accuracy_rf_train))
print("Accuracy of Random Forest Model on testing data is:{}".format(accuracy_rf_test))
```

```
print("Precision of Random Forest Model on testing data is:{}".format(precision_rf))
print("Recall of Random Forest Model on testing data is:{}".format(recall_rf))
print("F1 Score of Random Forest Model on testing data is:{}".format(f1_rf))
```

```
Accuracy of Random Forest Model on training data is:1.0
Accuracy of Random Forest Model on testing data is:0.6753048780487805
Precision of Random Forest Model on testing data is:0.5987261146496815
Recall of Random Forest Model on testing data is:0.38524590163934425
F1 Score of Random Forest Model on testing data is:0.4688279301745636
```

Support Vector Machine (SVM) Model

In [80]:
```
'''
Create the SVM Classifier.
'''
svm = SVC()
```

In [81]:
```
'''
Fit the SVM Classifier on the training dataset.
'''
svm_classifier = svm.fit(X_train, y_train )
svm_classifier
```

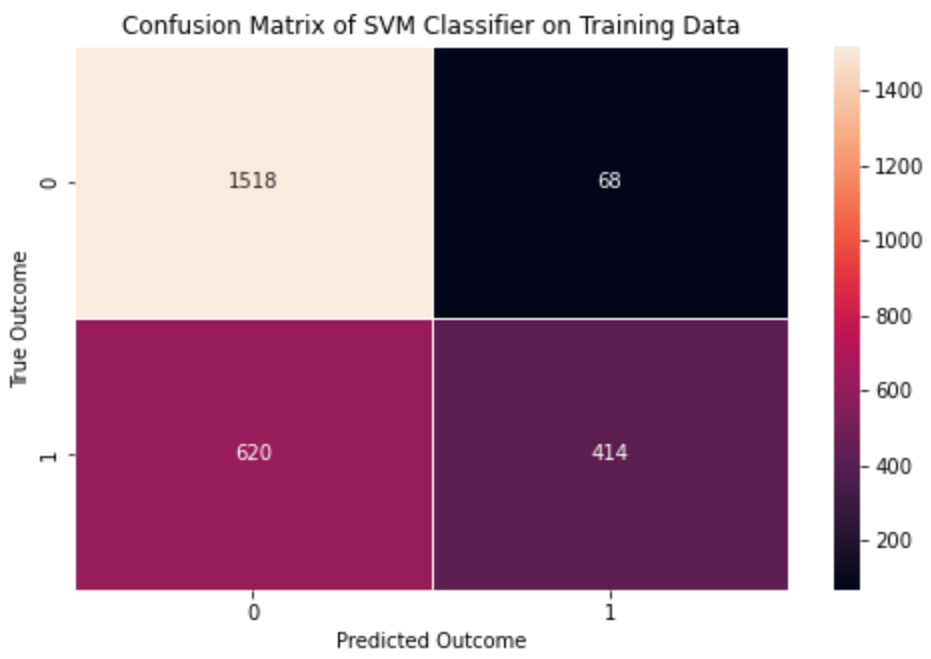
Out[81]:
```
SVC()
```

In [82]:
```
'''
Obtain the y_predictions for the SVM Classifier.
'''
y_predictions_svm = svm.predict(X_test)
```

In [83]:
```
'''
Obtain the y_prediction probabilities for each record in the training dataset.
'''
y_predictions_svm_train = svm.predict(X_train)
```

In [84]:
```
'''
Generate a Confusion Matrix for the Support Vector Machine Model based on the training dat
'''
cm_svm_train = confusion_matrix(y_train, y_predictions_svm_train)
```

In [85]:
```
'''
Plot the confusion matrix so it is clearly labelled and illustrated.
'''
f, ax = plt.subplots(figsize = (8,5))
sns.heatmap(cm_svm_train, annot = True, linewidths = 0.5, fmt = ".0f", ax = ax)
plt.xlabel('Predicted Outcome')
plt.ylabel('True Outcome')
plt.title('Confusion Matrix of SVM Classifier on Training Data')
plt.show()
```

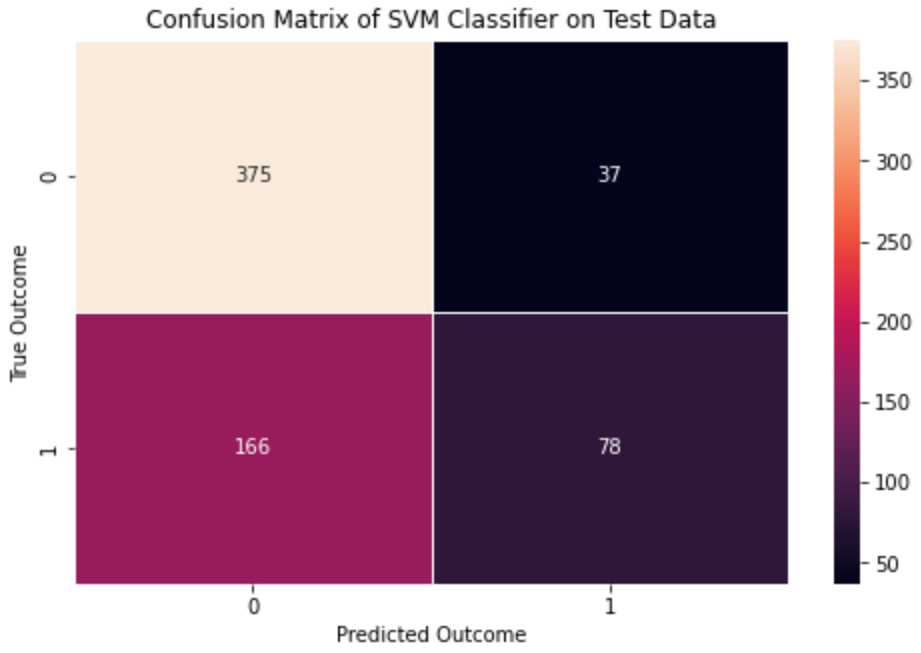


In [86]:
```
'''
Obtain the y_predictions for the SVM classifier.
'''
y_predictions_svm_test = svm.predict(X_test)
```

In [87]:
```
'''
Generate a confusion matrix based on the test data set.
'''
cm_svm = confusion_matrix(y_test, y_predictions_svm_test)
cm_svm
```

Out[87]:
```
array([[375,  37],
       [166,  78]], dtype=int64)
```

In [88]:
```
'''
Plot the confusion matrix so it is clearly labelled and illustrated.
'''
f, ax = plt.subplots(figsize = (8,5))
sns.heatmap(cm_svm, annot = True, linewidths = 0.5, fmt = ".0f", ax = ax)
plt.xlabel('Predicted Outcome')
plt.ylabel('True Outcome')
plt.title('Confusion Matrix of SVM Classifier on Test Data')
plt.show()
```



In [89]:
```
'''
Show the classification report for the test data.
'''
print(classification_report(y_test ,y_predictions_svm_test))
```

```
              precision    recall  f1-score   support

           0       0.69      0.91      0.79       412
           1       0.68      0.32      0.43       244

    accuracy                           0.69       656
   macro avg       0.69      0.61      0.61       656
weighted avg       0.69      0.69      0.66       656
```

In [90]:
```
'''
Calculate the accuracy for the model based on training and test data. Also, report the
Precision, Recall, and F1 score for the model predications against the test data.
'''
accuracy_svm_train = accuracy_score(y_train, y_predictions_svm_train)
accuracy_svm_test = accuracy_score(y_test, y_predictions_svm_test)
precision_svm = precision_score(y_test, y_predictions_svm_test)
recall_svm = recall_score(y_test, y_predictions_svm_test)
f1_svm = f1_score(y_test, y_predictions_svm_test)
print("Accuracy of SVM Model on training data is:{}".format(accuracy_svm_train))
print("Accuracy of SVM Model on testing data is:{}".format(accuracy_svm_test))
print("Precision of SVM Model on testing data is:{}".format(precision_svm))
print("Recall of SVM Model on testing data is:{}".format(recall_svm))
print("F1 Score of SVM Model on testing data is:{}".format(f1_svm))
```

```
Accuracy of SVM Model on training data is:0.7374045801526717
Accuracy of SVM Model on testing data is:0.6905487804878049
Precision of SVM Model on testing data is:0.6782608695652174
Recall of SVM Model on testing data is:0.319672131147541
F1 Score of SVM Model on testing data is:0.43454038997214484
```

Adaboost Model

In [91]:
```
'''
Create the Adaboost Classifier.
Choose n_estimators = 20 based on error reduction plot shown in this section.
```

```
'''
adaboost = AdaBoostClassifier(n_estimators=20)
```

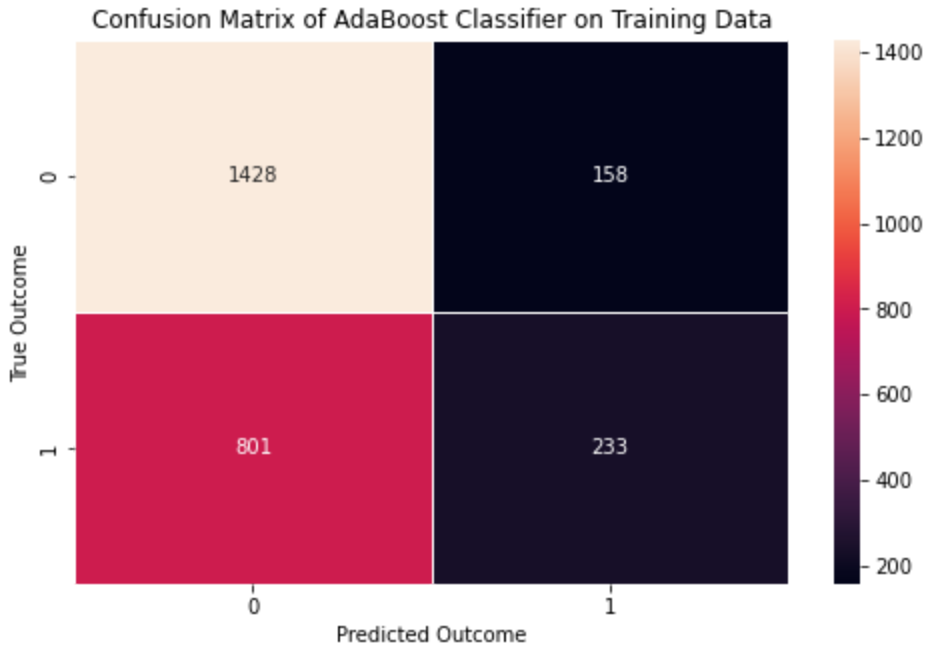
In [92]:
```
'''
Fit the Adaboost Classifier on the training dataset.
'''
adaboost_classifier = adaboost.fit(X_train, y_train )
adaboost_classifier
```

Out[92]:
```
AdaBoostClassifier(n_estimators=20)
```

In [93]:
```
'''
Obtain the y_prediction probabilities for each record in the training dataset.
'''
y_predictions_adaboost_train = adaboost.predict(X_train)
```

In [94]:
```
'''
Generate a Confusion Matrix for the AdaBoost Model based on the training dataset.
'''
cm_adaboost_train = confusion_matrix(y_train, y_predictions_adaboost_train)
```

In [95]:
```
'''
Plot the confusion matrix so it is clearly labelled and illustrated.
'''
f, ax = plt.subplots(figsize = (8,5))
sns.heatmap(cm_adaboost_train, annot = True, linewidths = 0.5, fmt = ".0f", ax = ax)
plt.xlabel('Predicted Outcome')
plt.ylabel('True Outcome')
plt.title('Confusion Matrix of AdaBoost Classifier on Training Data')
plt.show()
```

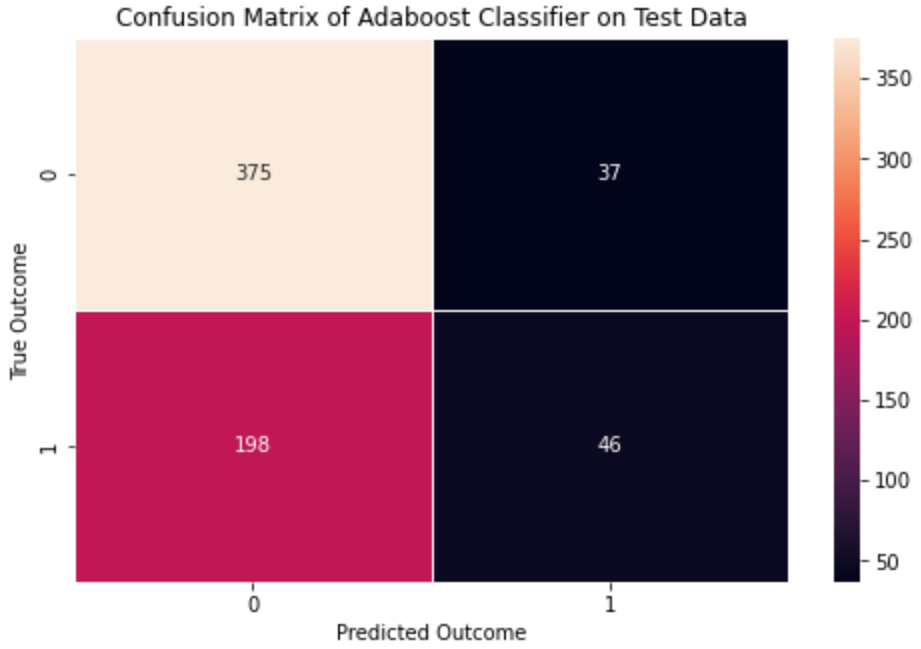


In [96]:
```
'''
Obtain the y_predictions for the SVM classifier.
'''
y_predictions_adaboost_test = adaboost.predict(X_test)
```

In [97]:
```
'''
Generate a confusion matrix based on the test data set.
'''
cm_adaboost = confusion_matrix(y_test, y_predictions_adaboost_test)
cm_adaboost
```

Out[97]:
```
array([[375,  37],
       [198,  46]], dtype=int64)
```

In [98]:
```
'''
Plot the confusion matrix so it is clearly labelled and illustrated.
'''
f, ax = plt.subplots(figsize = (8,5))
sns.heatmap(cm_adaboost, annot = True, linewidths = 0.5, fmt = ".0f", ax = ax)
plt.xlabel('Predicted Outcome')
plt.ylabel('True Outcome')
plt.title('Confusion Matrix of Adaboost Classifier on Test Data')
plt.show()
```

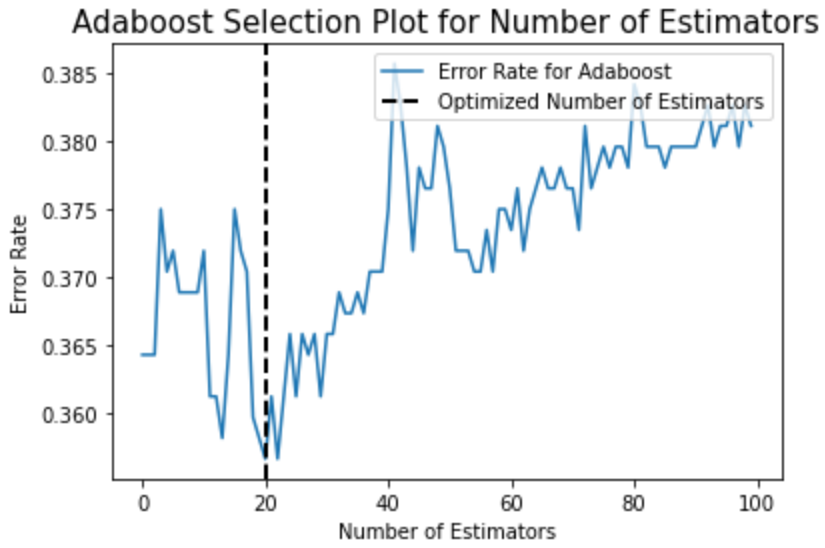


In [99]:
```
'''
Show the classification report for the test data.
'''
print(classification_report(y_test ,y_predictions_adaboost_test))
```

```
              precision    recall  f1-score   support

           0       0.65      0.91      0.76       412
           1       0.55      0.19      0.28       244

    accuracy                           0.64       656
   macro avg       0.60      0.55      0.52       656
weighted avg       0.62      0.64      0.58       656
```

In [100…
```
'''
Choose an optimal number of Estimatorsfor Adaboost by plotting the error rate for the mode
'''
# Create an empty list for error rate.
error_rate_adaboost = []

# Create a for loop to get error rates appended to the error_rate list.
```

```
for i in np.arange(1, 101):

    new_model = AdaBoostClassifier(n_estimators = i)

    new_model.fit(X_train, y_train)

    new_predictions = new_model.predict(X_test)

    error_rate_adaboost.append(np.mean(new_predictions != y_test))

# Create the plot to assist with selecting a K value for the KNN classifier.
plt.plot(error_rate_adaboost, label = 'Error Rate for Adaboost')
plt.title("Adaboost Selection Plot for Number of Estimators", fontsize=15)
plt.xlabel("Number of Estimators", fontsize=10)
plt.ylabel("Error Rate", fontsize=10)
plt.xticks(fontsize=10)
plt.yticks(fontsize=10)
plt.axvline(x=pd.Series(error_rate_adaboost).idxmin(), linewidth = 2, color = 'k', linesty
            label = 'Optimized Number of Estimators')
plt.legend(loc = 'upper right')
plt.show()
```



In [101…

```
'''
Show the optimum number of estimators on the plot above.
'''
print('Optimum Number of Estimators for AdaBoost Classifier:{}'.format(pd.Series(error_rat
```

```
Optimum Number of Estimators for AdaBoost Classifier:20
```

In [102…

```
'''
Calculate the accuracy for the model based on training and test data. Also, report the
Precision, Recall, and F1 score for the model predications against the test data.
'''
accuracy_adaboost_train = accuracy_score(y_train, y_predictions_adaboost_train)
accuracy_adaboost_test = accuracy_score(y_test, y_predictions_adaboost_test)
precision_adaboost = precision_score(y_test, y_predictions_adaboost_test)
recall_adaboost = recall_score(y_test, y_predictions_adaboost_test)
f1_adaboost = f1_score(y_test, y_predictions_adaboost_test)
print("Accuracy of AdaBoost Model on training data is:{}".format(accuracy_adaboost_train))
print("Accuracy of AdaBoost Model on testing data is:{}".format(accuracy_adaboost_test))
print("Precision of SAdaBoostM Model on testing data is:{}".format(precision_adaboost))
print("Recall of AdaBoost Model on testing data is:{}".format(recall_adaboost))
print("F1 Score of AdaBoost Model on testing data is:{}".format(f1_adaboost))
```

```
Accuracy of AdaBoost Model on training data is:0.6339694656488549
```

```
Accuracy of AdaBoost Model on testing data is:0.6417682926829268
Precision of SAdaBoostM Model on testing data is:0.5542168674698795
Recall of AdaBoost Model on testing data is:0.1885245901639344
F1 Score of AdaBoost Model on testing data is:0.28134556574923547
```

Summary of Findings from Analysis and Model Deployment Recommendation

In [104…

```
'''
Create a dictionary summarizing the evaluation criteria for the six models.
'''
summary_data = OrderedDict([('Model', ['Logistic_Regression', 'KNN', 'Decision_Tree','Rand
                            ('Model_Accuracy_Test',[accuracy_lr_test, accuracy_knn_test, ac
                                                    accuracy_rf_test, accuracy_svm_test,accu
                             ('Model_Accuracy_Training',[accuracy_lr_train, accuracy_knn_tr
                                                         accuracy_rf_train, accuracy_svm_trai
                            ('Model_Precision_Score',[precision_lr,precision_knn,precision_
                                                      precision_rf,precision_svm,precision_a
                            ('Model_Recall_Score',[recall_lr,recall_knn,recall_dt,
                                                   recall_rf,recall_svm,recall_adaboost]),
                            ('Model_F1_Score', [f1_lr,f1_knn,f1_dt,
                                                f1_rf,f1_svm,f1_adaboost]),])
```

In [105…

```
'''
Display the summary evaluation metrics for the four models in a pandas dataframe.
Sort the Models based on accuracy for each model from the test dataset.
'''
summary_df = pd.DataFrame(summary_data, index = summary_data['Model'])
display(summary_df.sort_values(by = 'Model_Accuracy_Test', ascending = False))
```

	Model	Model_Accuracy_Test	Model_Accuracy_Training	Model_Precision_Score	Model_
SVM	SVM	0.690549	0.737405	0.678261	
Random_Forest	Random_Forest	0.675305	1.000000	0.598726	
KNN	KNN	0.664634	0.658015	0.693548	
Adaboost	Adaboost	0.641768	0.633969	0.554217	
Decision_Tree	Decision_Tree	0.570122	1.000000	0.431655	
Logistic_Regression	Logistic_Regression	0.515244	0.518702	0.377483	

Thus far, the SVM Model provides the highest accuracy on the test dataset. To improve the accuracy, try hyperparameter tuning for these models to see if a significant difference can be acheived. At this stage in the analysis, even the best model (SVM) is not ready to be deployed and only has an accuracy of 69% on unseen data. I'd like to also look into cross-validation for these models to see which model(s) are the most repeatable.