

# Water Quality Index- EDA & Classification

April 20, 2022

```
[5]: import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
import warnings
warnings.filterwarnings('ignore')
```

```
[8]: water_data=pd.read_csv("/Users/jay/Desktop/Codes_Repo/Data Analysis/Water_
↳Quality_EDA/water_quality.csv")
```

```
[11]: water_data.head()
```

```
[11]:
```

	ph	Hardness	Solids	Chloramines	Sulfate	Conductivity \
0	NaN	204.890456	20791.31898	7.300212	368.516441	564.308654
1	3.716080	129.422921	18630.05786	6.635246	NaN	592.885359
2	8.099124	224.236259	19909.54173	9.275884	NaN	418.606213
3	8.316766	214.373394	22018.41744	8.059332	356.886136	363.266516
4	9.092223	181.101509	17978.98634	6.546600	310.135738	398.410813

	Organic_carbon	Trihalomethanes	Turbidity	Potability
0	10.379783	86.990970	2.963135	0
1	15.180013	56.329076	4.500656	0
2	16.868637	66.420093	3.055934	0
3	18.436525	100.341674	4.628771	0
4	11.558279	31.997993	4.075075	0

```
[12]: water_data.tail()
```

```
[12]:
```

	ph	Hardness	Solids	Chloramines	Sulfate \
3271	4.668102	193.681736	47580.99160	7.166639	359.948574
3272	7.808856	193.553212	17329.80216	8.061362	NaN
3273	9.419510	175.762646	33155.57822	7.350233	NaN
3274	5.126763	230.603758	11983.86938	6.303357	NaN
3275	7.874671	195.102299	17404.17706	7.509306	NaN

	Conductivity	Organic_carbon	Trihalomethanes	Turbidity	Potability
3271	526.424171	13.894419	66.687695	4.435821	1
3272	392.449580	19.903225	NaN	2.798243	1

3273	432.044783	11.039070	69.845400	3.298875	1
3274	402.883113	11.168946	77.488213	4.708658	1
3275	327.459761	16.140368	78.698446	2.309149	1

```
[13]: water_data.shape
```

```
[13]: (3276, 10)
```

```
[14]: water_data.columns
```

```
[14]: Index(['ph', 'Hardness', 'Solids', 'Chloramines', 'Sulfate', 'Conductivity',
        'Organic_carbon', 'Trihalomethanes', 'Turbidity', 'Potability'],
        dtype='object')
```

```
[15]: water_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3276 entries, 0 to 3275
Data columns (total 10 columns):
#   Column                Non-Null Count  Dtype
---  -
0   ph                    2785 non-null   float64
1   Hardness              3276 non-null   float64
2   Solids                3276 non-null   float64
3   Chloramines           3276 non-null   float64
4   Sulfate               2495 non-null   float64
5   Conductivity          3276 non-null   float64
6   Organic_carbon        3276 non-null   float64
7   Trihalomethanes       3114 non-null   float64
8   Turbidity             3276 non-null   float64
9   Potability            3276 non-null   int64
dtypes: float64(9), int64(1)
memory usage: 256.1 KB
```

```
[16]: water_data.describe()
```

```
[16]:
```

	ph	Hardness	Solids	Chloramines	Sulfate \
count	2785.000000	3276.000000	3276.000000	3276.000000	2495.000000
mean	7.080795	196.369496	22014.092526	7.122277	333.775777
std	1.594320	32.879761	8768.570828	1.583085	41.416840
min	0.000000	47.432000	320.942611	0.352000	129.000000
25%	6.093092	176.850538	15666.690300	6.127421	307.699498
50%	7.036752	196.967627	20927.833605	7.130299	333.073546
75%	8.062066	216.667456	27332.762125	8.114887	359.950170
max	14.000000	323.124000	61227.196010	13.127000	481.030642

	Conductivity	Organic_carbon	Trihalomethanes	Turbidity	Potability
count	3276.000000	3276.000000	3114.000000	3276.000000	3276.000000

mean	426.205111	14.284970	66.396293	3.966786	0.390110
std	80.824064	3.308162	16.175008	0.780382	0.487849
min	181.483754	2.200000	0.738000	1.450000	0.000000
25%	365.734414	12.065801	55.844536	3.439711	0.000000
50%	421.884968	14.218338	66.622485	3.955028	0.000000
75%	481.792305	16.557652	77.337473	4.500320	1.000000
max	753.342620	28.300000	124.000000	6.739000	1.000000

```
[17]: water_data.isnull().sum()
```

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

```
[18]: water_data['ph'].fillna(water_data['ph'].mode(), inplace=True)
```

```
[20]: water_data['Sulfate'].fillna(water_data['Sulfate'].mode(), inplace=True)
```

```
[22]: water_data['Trihalomethanes'].fillna(water_data['Trihalomethanes'].mode(),
      ↪inplace=True)
```

```
[23]: water_data.isnull().sum()
```

```
[23]: ph                65
      Hardness          0
      Solids            0
      Chloramines        0
      Sulfate           198
      Conductivity       0
      Organic_carbon     0
      Trihalomethanes     7
      Turbidity          0
      Potability         0
      dtype: int64
```

```
[24]: water_data.dropna(inplace=True)
```

```
[25]: water_data.corr()
```

```
[25]:
```

	ph	Hardness	Solids	Chloramines	Sulfate	\
ph	1.000000	0.073546	-0.072102	-0.026261	0.063919	
Hardness	0.073546	1.000000	-0.043753	-0.007834	-0.107853	
Solids	-0.072102	-0.043753	1.000000	-0.075168	-0.133952	
Chloramines	-0.026261	-0.007834	-0.075168	1.000000	0.019461	
Sulfate	0.063919	-0.107853	-0.133952	0.019461	1.000000	
Conductivity	0.011440	-0.010009	0.007726	-0.026439	-0.017806	
Organic_carbon	0.029681	0.004045	0.010430	-0.012763	0.017272	
Trihalomethanes	0.008028	-0.009534	-0.003948	0.020067	-0.012869	
Turbidity	-0.034639	-0.025290	0.017453	0.005258	-0.004721	
Potability	0.021105	-0.013547	0.030630	0.022761	0.001577	

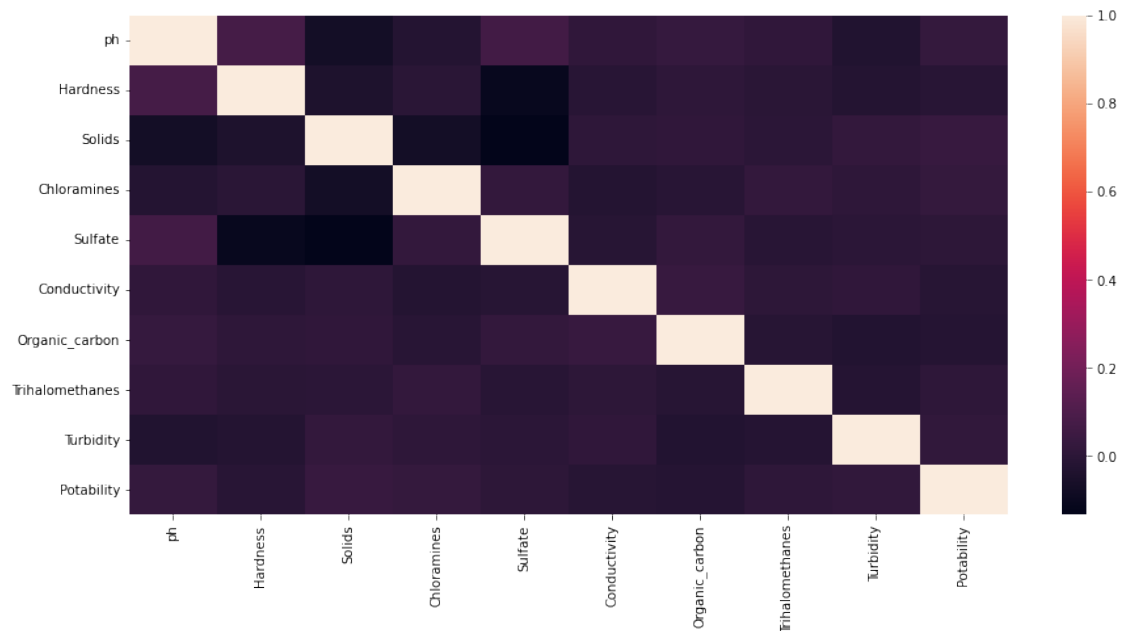
	Conductivity	Organic_carbon	Trihalomethanes	Turbidity	\
ph	0.011440	0.029681	0.008028	-0.034639	
Hardness	-0.010009	0.004045	-0.009534	-0.025290	
Solids	0.007726	0.010430	-0.003948	0.017453	
Chloramines	-0.026439	-0.012763	0.020067	0.005258	
Sulfate	-0.017806	0.017272	-0.012869	-0.004721	
Conductivity	1.000000	0.032167	-0.000832	0.010878	
Organic_carbon	0.032167	1.000000	-0.014785	-0.029307	
Trihalomethanes	-0.000832	-0.014785	1.000000	-0.020466	
Turbidity	0.010878	-0.029307	-0.020466	1.000000	
Potability	-0.016594	-0.019306	0.004839	0.012476	

	Potability
ph	0.021105
Hardness	-0.013547
Solids	0.030630
Chloramines	0.022761
Sulfate	0.001577
Conductivity	-0.016594
Organic_carbon	-0.019306
Trihalomethanes	0.004839
Turbidity	0.012476
Potability	1.000000

```
[26]: plt.figure(figsize=(15,7))
sns.heatmap(water_data.corr())
```

```
[26]: <AxesSubplot:>
```



```
[27]: water_data.Potability.unique()
```

```
[27]: array([0, 1])
```

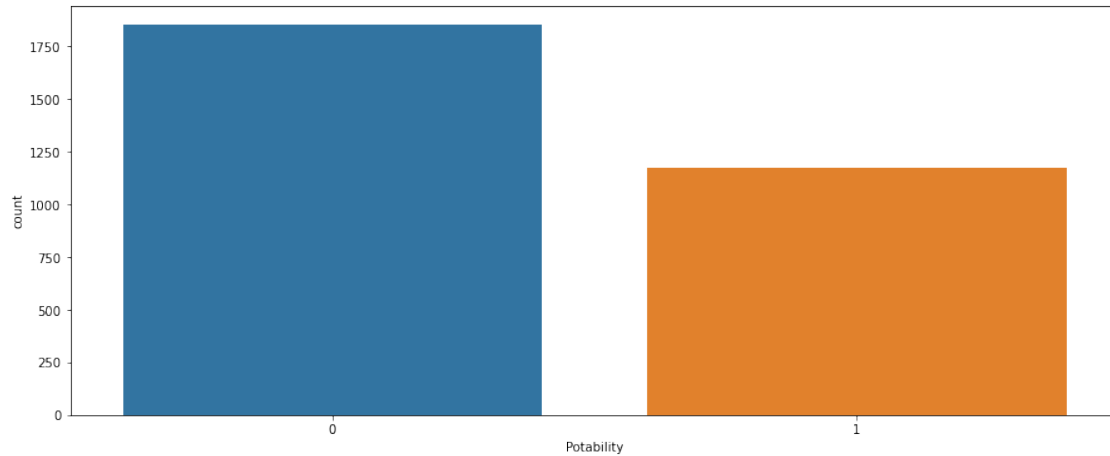
```
[28]: water_data.Potability.value_counts()
```

```
[28]: 0    1853
      1    1173
      Name: Potability, dtype: int64
```

```
[33]: plt.figure(figsize=(15,6))
      sns.countplot('Potability', data=water_data)
      plt.xticks(rotation= 0)
      plt.show()
```

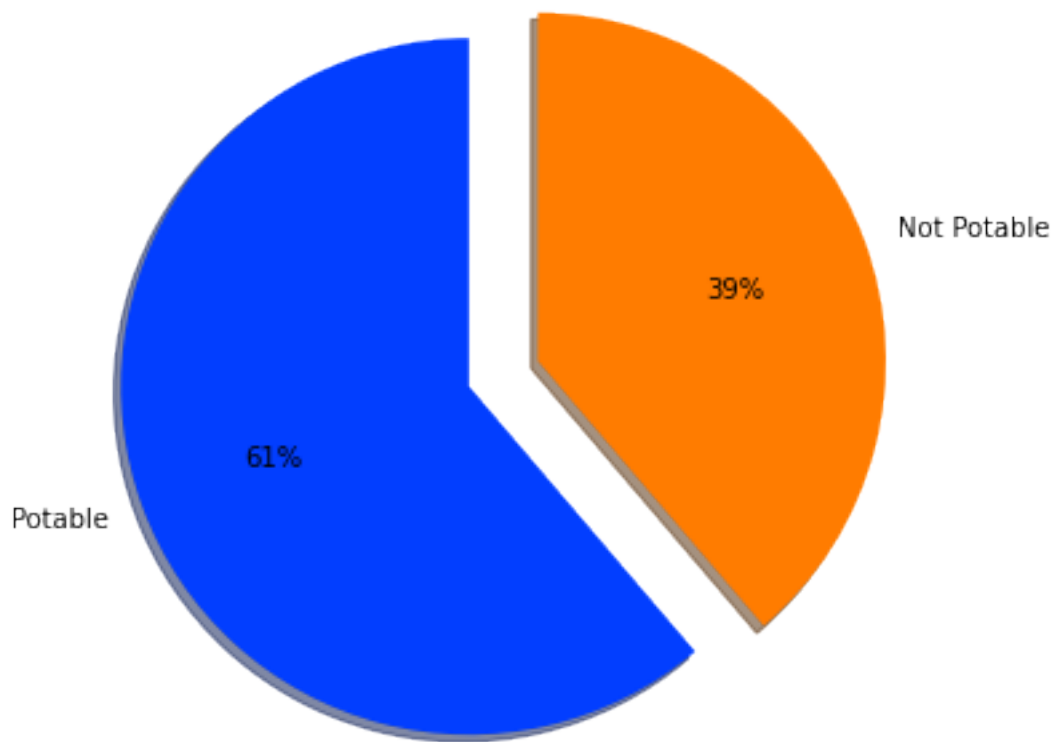
```
-----
AttributeError                                Traceback (most recent call last)
/var/folders/0_/fvfpszcz14j90zh4m8hmf_2yc0000gn/T/ipykernel_1433/211344869.py in
↳ <module>
      1 plt.figure(figsize=(15,6))
      2 sns.countplot('Potability', data=water_data)
----> 3 plt.xticks(rotation= 0)
      4 plt.show()

AttributeError: module 'matplotlib.pyplot' has no attribute 'xticks'
```

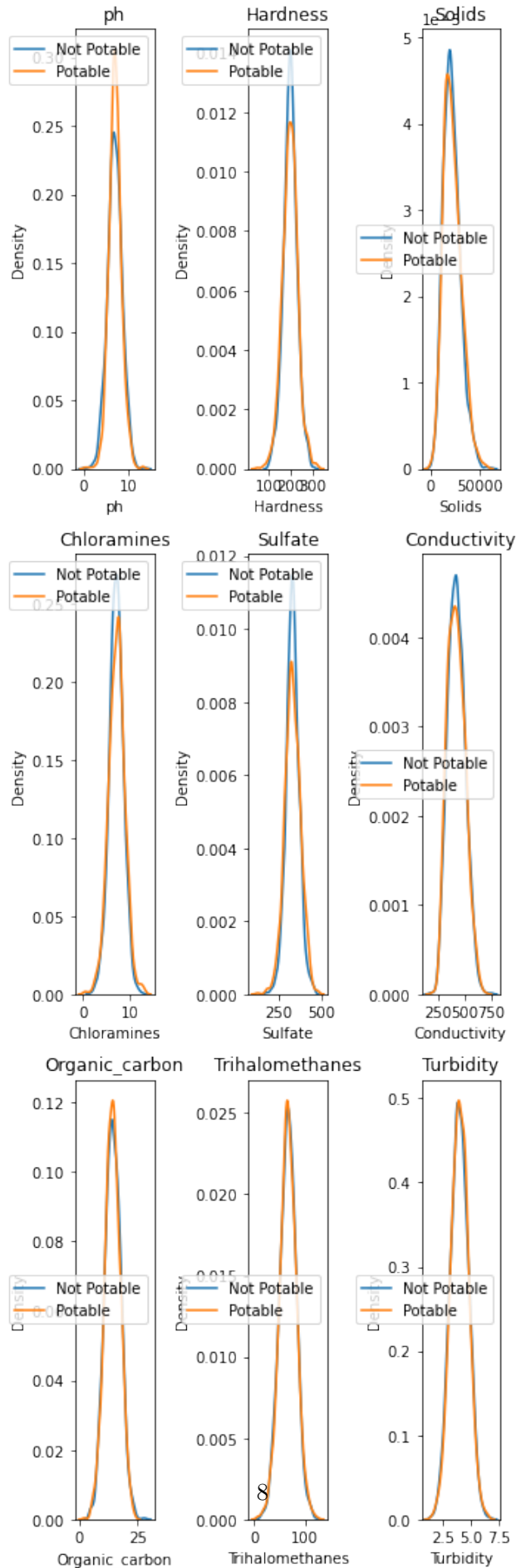


```
[36]: plt.figure(figsize=(15,6))
      explode=[0.2,0.01]
      colors=sns.color_palette('bright')
      plt.pie(water_data['Potability'].value_counts(), labels=['Potable','Not_
      ↳Potable'],
              colors=colors, autopct='%0.0f%%', explode=explode, shadow='True',
              startangle=90)
      plt.show
```

```
[36]: <function matplotlib.pyplot.show(close=None, block=None)>
```



```
[38]: not_potable= water_data.query('Potability==0')
      potable= water_data.query('Potability==1')
      plt.figure(figsize=(5,15))
      for ax, col in enumerate(water_data.columns[:9]):
          plt.subplot(3,3,ax+1)
          plt.title(col)
          sns.kdeplot(x=not_potable[col], label='Not Potable')
          sns.kdeplot(x=potable[col], label='Potable')
          plt.legend()
      plt.tight_layout()
```





```
[39]: x=water_data.drop("Potability", axis=1).values  
      y=water_data["Potability"].values
```

```
[40]: x.shape
```

```
[40]: (3026, 9)
```

```
[41]: y.shape
```

```
[41]: (3026,)
```

```
[42]: from sklearn.model_selection import train_test_split  
      x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.20)
```

```
[44]: from sklearn.tree import DecisionTreeClassifier  
      classifier= DecisionTreeClassifier(criterion='entropy',random_state=0)
```

```
[45]: classifier.fit(x_train,y_train)
```

```
[45]: DecisionTreeClassifier(criterion='entropy', random_state=0)
```

```
[46]: y_pred=classifier.predict(x_test)
```

```
[47]: print("Training Accuracy:", classifier.score(x_train,y_train))  
      print("Testing Accuracy:", classifier.score(x_test,y_test))
```

```
Training Accuracy: 1.0
```

```
Testing Accuracy: 0.599009900990099
```

```
[48]: from sklearn.metrics import confusion_matrix  
      cm=confusion_matrix(y_test,y_pred)
```

```
[49]: cm
```

```
[49]: array([[242, 119],  
          [124, 121]])
```

```
[51]: from sklearn.ensemble import RandomForestClassifier  
      classifier1= RandomForestClassifier(n_estimators= 10, criterion='entropy')
```

```
[52]: classifier1.fit(x_train,y_train)
```

```
[52]: RandomForestClassifier(criterion='entropy', n_estimators=10)
```

```
[53]: y_pred= classifier1.predict(x_test)
```

```
[54]: print("Training Accuracy:", classifier1.score(x_train,y_train))  
      print("Testing Accuracy:", classifier1.score(x_test, y_test))
```

```
Training Accuracy: 0.9855371900826446  
Testing Accuracy: 0.6254125412541254
```

```
[58]: kt=confusion_matrix(y_test,y_pred)
```

```
[59]: kt
```

```
[59]: array([[242, 119],  
            [124, 121]])
```