WaterQuality1

August 22, 2024

1 Water Quality Analysis

[3]:
```
# import libraries

import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import scipy.stats as stats
import statsmodels.api as sm
from scipy.stats import skew
from scipy.stats import ttest_ind


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

We are going to analyze this dataset from Kaggle. We are trying to come up with the key insights and recommendations for the Public Health Department to help them understand and take measures to improve the water quality.

[4]:
```
df = pd.read_csv('water_potability.csv')
```

[5]:
```
df.head()
```

[5]:
```
         ph    Hardness        Solids  Chloramines     Sulfate  Conductivity  \
0       NaN  204.890455  20791.318981     7.300212  368.516441    564.308654
1  3.716080  129.422921  18630.057858     6.635246         NaN    592.885359
2  8.099124  224.236259  19909.541732     9.275884         NaN    418.606213
3  8.316766  214.373394  22018.417441     8.059332  356.886136    363.266516
4  9.092223  181.101509  17978.986339     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       18.436524       100.341674   4.628771           0
```

```
4      11.558279        31.997993   4.075075          0
```

[11]:
```python
df.describe()
```

[11]:

	ph	Hardness	Solids	Chloramines	Sulfate
count	3276.000000	3276.000000	3276.000000	3276.000000	3276.000000
mean	7.074194	196.369496	22014.092526	7.122277	333.608364
std	1.470040	32.879761	8768.570828	1.583085	36.143851
min	0.000000	47.432000	320.942611	0.352000	129.000000
25%	6.277673	176.850538	15666.690297	6.127421	317.094638
50%	7.036752	196.967627	20927.833607	7.130299	333.073546
75%	7.870050	216.667456	27332.762127	8.114887	350.385756
max	14.000000	323.124000	61227.196008	13.127000	481.030642

	Conductivity	Organic_carbon	Trihalomethanes	Turbidity	Potability
count	3276.000000	3276.000000	3276.000000	3276.000000	3276.000000
mean	426.205111	14.284970	66.407478	3.966786	0.390110
std	80.824064	3.308162	15.769958	0.780382	0.487849
min	181.483754	2.200000	0.738000	1.450000	0.000000
25%	365.734414	12.065801	56.647656	3.439711	0.000000
50%	421.884968	14.218338	66.622485	3.955028	0.000000
75%	481.792304	16.557652	76.666609	4.500320	1.000000
max	753.342620	28.300000	124.000000	6.739000	1.000000

[6]:
```python
df.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
```

[5]:
```python
# Data Cleaning
# From df.info(), we can see column 'ph', 'Sulfate', 'Trihalomethanes' have
 ↪null values;
```

```python
# Fill null values based on their skewness.

# list of cols need to clean
clean_list = ['ph', 'Sulfate', 'Trihalomethanes']

# create a function fill_with() to decide fillna with mean or median.
def fill_with(df, col_name):
    col = df[col_name]
    if abs(skew(col)) < 0.5:
        df[col_name] = col.fillna(col.mean())
    else:
        df[col_name] = col.fillna(col.median())
    return df

for col_name in clean_list:
    df = fill_with(df, col_name)

# check whether cleaning is done
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3276 entries, 0 to 3275
Data columns (total 10 columns):
 #   Column           Non-Null Count  Dtype
---  ------           --------------  -----
 0   ph               3276 non-null   float64
 1   Hardness         3276 non-null   float64
 2   Solids           3276 non-null   float64
 3   Chloramines      3276 non-null   float64
 4   Sulfate          3276 non-null   float64
 5   Conductivity     3276 non-null   float64
 6   Organic_carbon   3276 non-null   float64
 7   Trihalomethanes  3276 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
```

1.1 Descriptive Analysis

1.2 What is the distribution of pH values across the dataset?

[5]:
```python
print('Mean pH value:', df['ph'].mean())
print('Median pH value:', df['ph'].median())
print('Standard Deviationof pH value:', df['ph'].std())

# visualization
plt.figure(figsize=(14,8))
```

```
sns.histplot(data=df['ph'], color='#B83A2D')
plt.title('Distribution of pH')
plt.xlabel('pH')
plt.ylabel('Frequency')
plt.show()
```

```
Mean pH value: 7.074193521792814
Median pH value: 7.036752103833548
Standard Deviationof pH value: 1.4700400603035852
```

Most of ph value is around 7, which indicates most of water tested is between the normal range 6.5 to 8.5 recommended by WHO.

1.3 How does the hardness of water vary with its potability?

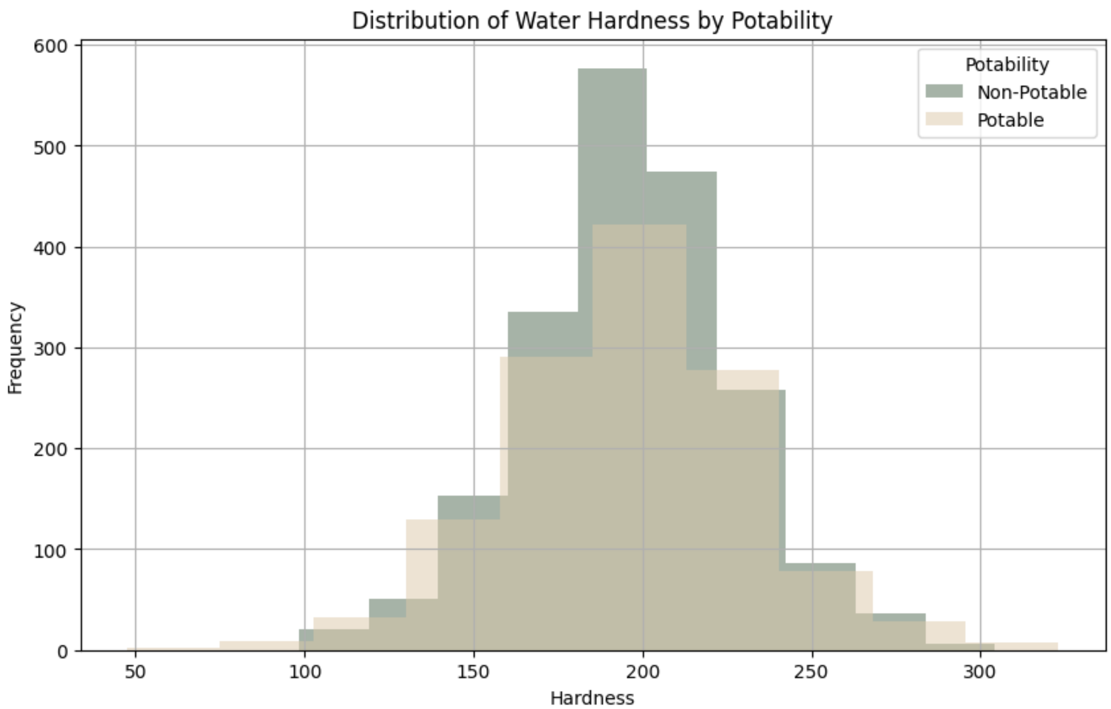
[31]:
```
hardness_stats = df.groupby('Potability')['Hardness'].agg(['mean', 'std',␣
↪'min', 'max'])
hardness_stats
```

[31]:

	mean	std	min	max
Potability				
0	196.733292	31.057540	98.452931	304.235912
1	195.800744	35.547041	47.432000	323.124000

[8]:

```
# Non-visualization
plt.figure(figsize=(10, 6))
colors = {1: '#dcc9a9', 0: '#4e6851'}  # set color
for label, df_group in df.groupby('Potability'):
    potability_label = 'Potable' if label == 1 else 'Non-Potable'
    plt.hist(df_group['Hardness'], bins=10, alpha=0.5, label=potability_label,␣
 ↪color=colors[label])

plt.title('Distribution of Water Hardness by Potability')
plt.xlabel('Hardness')
plt.ylabel('Frequency')
plt.legend(title='Potability')
plt.grid(True)
plt.show()
```



Overall, the results suggest that water hardness does not show a strong or clear distinction between potable and non-potable water.

1.4 What is the correlation between Conductivity and Total Dissolved Solids (TDS)?

[22]:
```
correlation_matrix = df.corr(method='pearson')
correlation = df['Conductivity'].corr(df['Solids'])
print(correlation)
```

```
0.013830898324440384
```

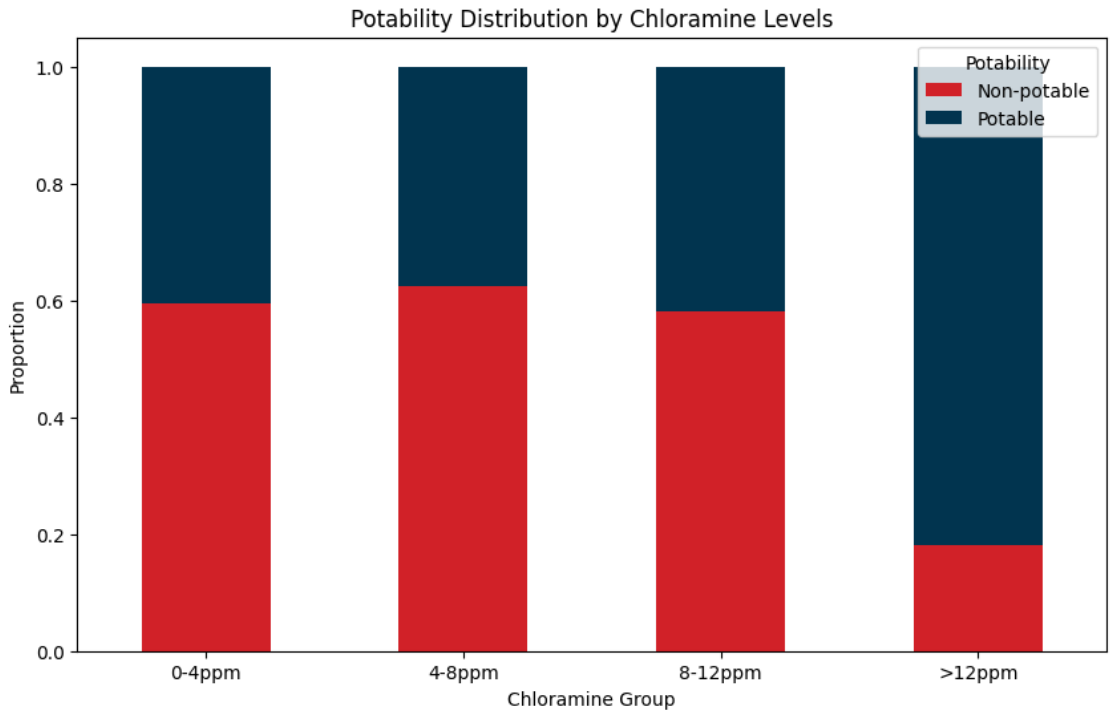
The correlation result shows the correlation between Conductivity and Turbility is weak.

1.5 How does Chloramines affect the Potability?

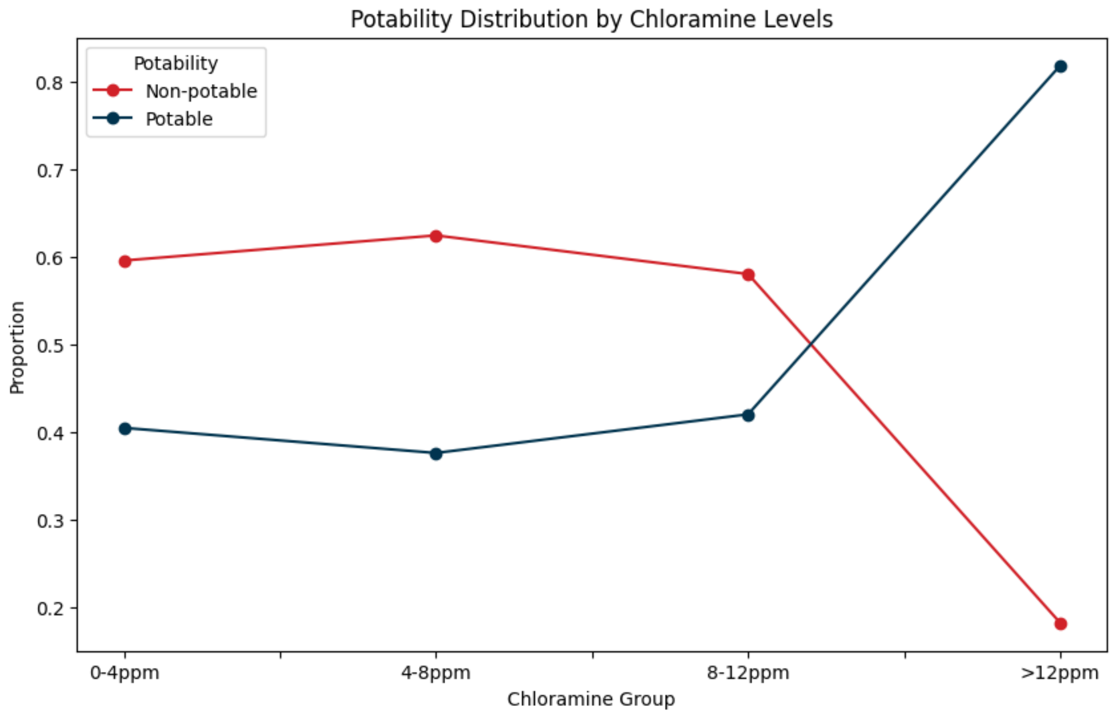
[6]:
```
# Chlorine levels up to 4 parts per million (ppm)) are considered safe in␣
↪drinking water.
# So I wll use 4 as a threshold to cut the chloramines to compare.

# group the data
df['Chloramine_Group'] = pd.cut(df['Chloramines'], bins=[0, 4, 8, 12,␣
↪df['Chloramines'].max()], labels=['0-4ppm', '4-8ppm', '8-12ppm', '>12ppm'])

# calculate each group by their potability
grouped = df.groupby('Chloramine_Group')['Potability'].
↪value_counts(normalize=True).unstack()
print(grouped)
```

```
Potability              0         1
Chloramine_Group
0-4ppm           0.595506  0.404494
4-8ppm           0.624179  0.375821
8-12ppm          0.580067  0.419933
>12ppm           0.181818  0.818182
```

[7]:
```
# visualization
grouped.plot(kind='bar', stacked=True, figsize=(10, 6), color=['#D12128',␣
↪'#01344F'])
plt.title('Potability Distribution by Chloramine Levels')
plt.xlabel('Chloramine Group')
plt.ylabel('Proportion')
plt.xticks(rotation=0)
plt.legend(['Non-potable', 'Potable'], title='Potability')
plt.show()
```



[8]:
```
# visualization2
grouped.plot(kind='line', marker='o', figsize=(10, 6), color=['#D12128',␣
↪'#01344F'])
plt.title('Potability Distribution by Chloramine Levels')
plt.xlabel('Chloramine Group')
plt.ylabel('Proportion')
plt.xticks(rotation=0)
plt.legend(['Non-potable', 'Potable'], title='Potability')
plt.show()
```

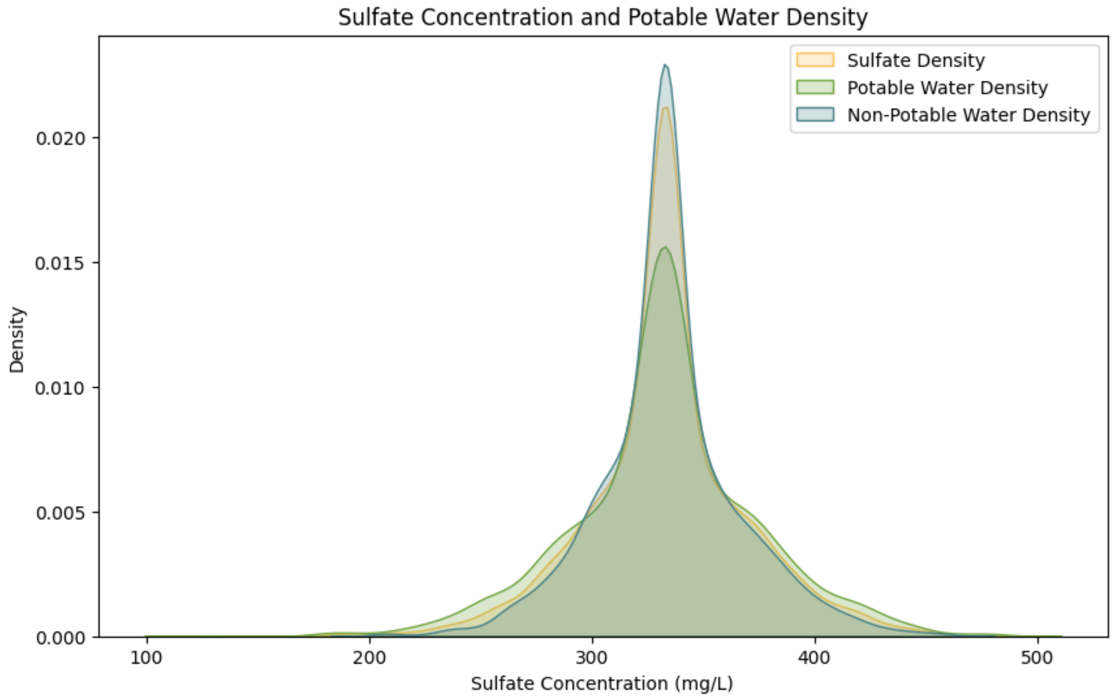


According to the chart, the ratio of probability decreases a bit when chloramine levels exceed 4 ppm, but gradually increases when exceed 8ppm. However, some water samples are still marked as potable despite high chloramine levels, suggesting that we need to consider other factors, such as water treatment and adjustment processes, that may influence chloramine levels.

1.6 How does different levels of sulfate affect water potability?

[13]:
```
# visualization
plt.figure(figsize=(10, 6))

# kdeplot about sulfate density
sns.kdeplot(df['Sulfate'], color='#FBC359', label='Sulfate Density', fill=True)

# kdeplot about potable density
sns.kdeplot(df[df['Potability'] == 1]['Sulfate'], color='#73A642',␣
 ↪label='Potable Water Density', fill=True)
sns.kdeplot(df[df['Potability'] == 0]['Sulfate'], color='#4B848A',␣
 ↪label='Non-Potable Water Density', fill=True)
# add title and label
plt.title('Sulfate Concentration and Potable Water Density')
plt.xlabel('Sulfate Concentration (mg/L)')
plt.ylabel('Density')
plt.legend()
```

```
plt.show()
```



Based on the chart, the three curves (sulfate density, potable water samples, and non-potable water samples) are almost overlapping, particularly around the peak at 330 mg/L. This suggests that, in this dataset, sulfate concentration does not appear to significantly impact the potability of the water.

1.7 What is the relationship between the distribution of Turbidity and potability?

[44]:
```
print('Mean Turbidity value:', df['Turbidity'].mean())
print('Median Turbidity value:', df['Turbidity'].median())
print('Standard Deviationof Turbidity value:', df['Turbidity'].std())

# group potability by Turbidity
turbidity_stats = df.groupby('Potability')['Turbidity']
turbidity_stats.mean()
```

```
Mean Turbidity value: 3.966786169791058
Median Turbidity value: 3.955027562993039
Standard Deviationof Turbidity value: 0.7803824084854124
```

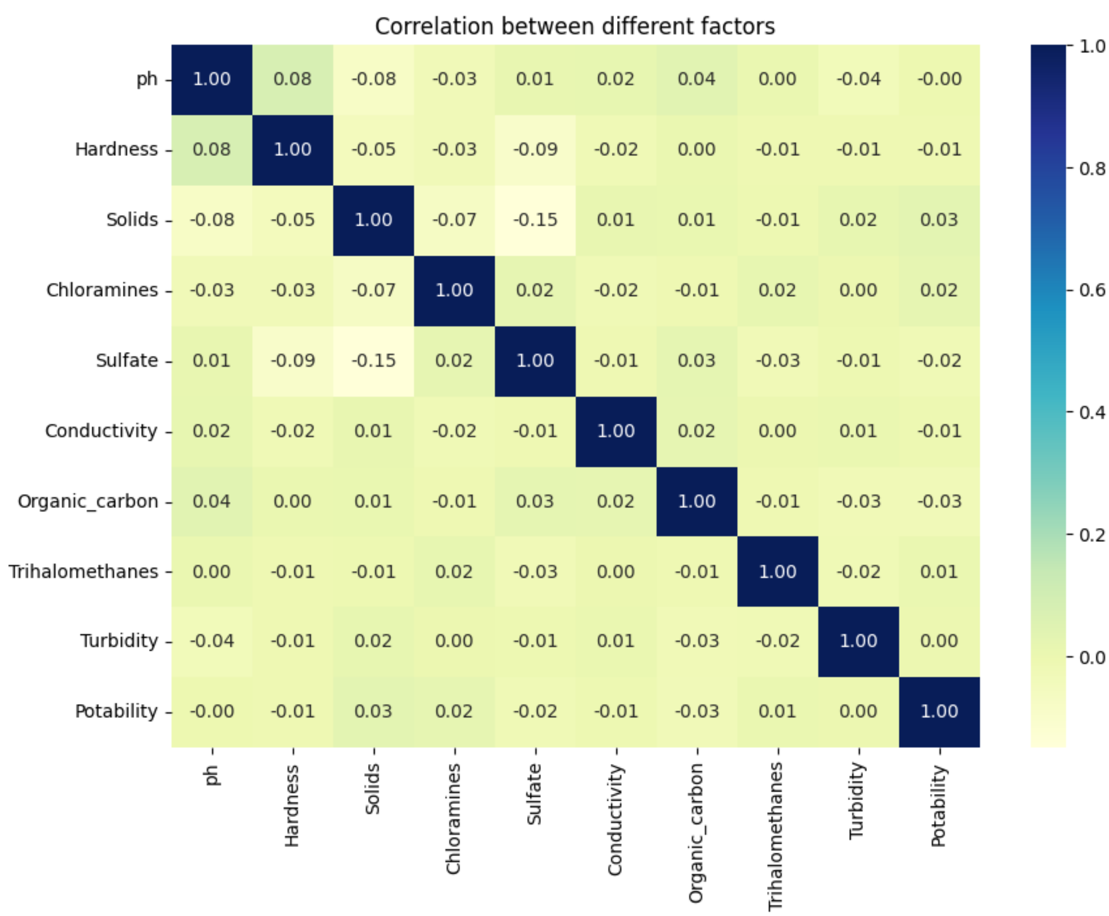
[44]:
```
Potability
0    3.965800
```

```
1    3.968328
Name: Turbidity, dtype: float64
```

The turbidity values in potable and non-potable water samples are very similar, with nearly identical mean and median values. This suggests that the turbidity does not have a significant impact on water potability. The overall distribution of turbidity is also quite concentrated, showing no extreme variation.

1.8 Which variable has a strong correalation with potability?

[56]:
```python
corr = df.drop('Chloramine_Group',axis=1).corr()

# visulization
plt.figure(figsize=(10, 7))
sns.heatmap(corr, annot=True, fmt=".2f", cmap="YlGnBu", cbar=True)
plt.title('Correlation between different factors')
plt.show()
```



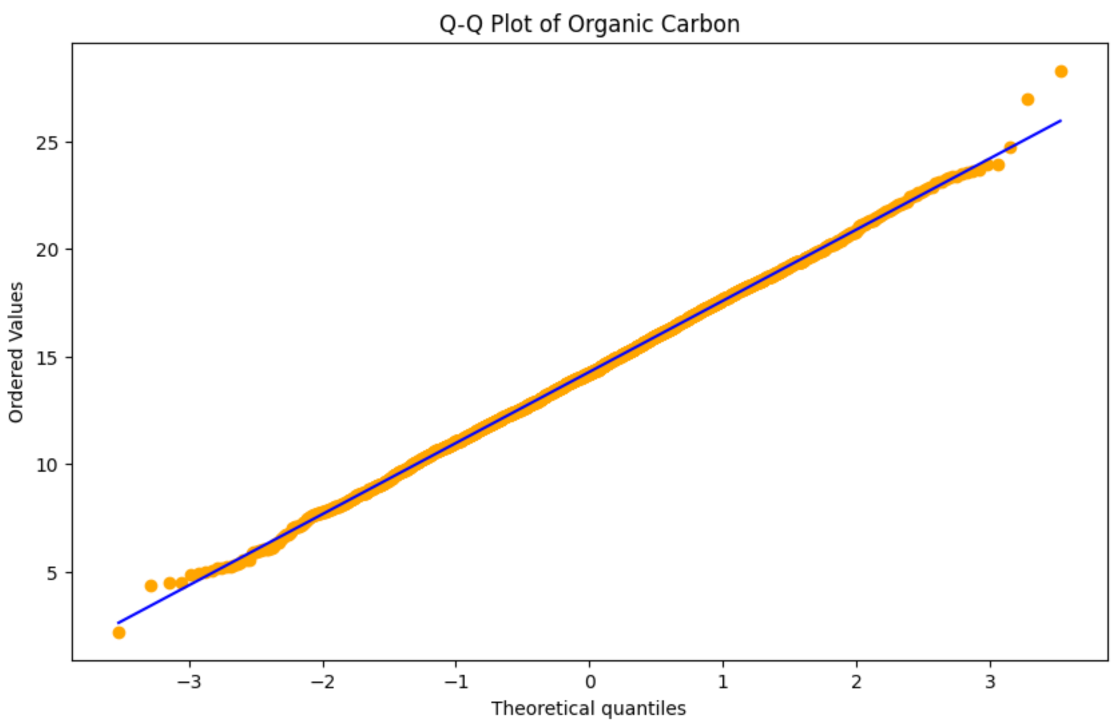
The correlation between each factor is very weak.

1.9 Inferential Analysis

1.10 Does organic carbon siginificantly affect water potability?

[ ]:
```
'''
Null Hypothesis(H0): Organic Carbon doesn't affect water potability␣
↪siginificantly.
Alternative Hypothesis(H1): Organic Carbon affects water potability␣
↪siginificantly.
'''
```

[18]:
```
# plot Q-Qplot to test noamality
plt.figure(figsize=(10, 6))
# set color
line_color = 'blue'
marker_color = 'orange'

# Q-Q plot
qq_plot = stats.probplot(df['Organic_carbon'], dist="norm", plot=plt)
plt.title('Q-Q Plot of Organic Carbon')

# modify color
plt.gca().get_lines()[0].set_color(marker_color)
plt.gca().get_lines()[1].set_color(line_color)

plt.show()
```



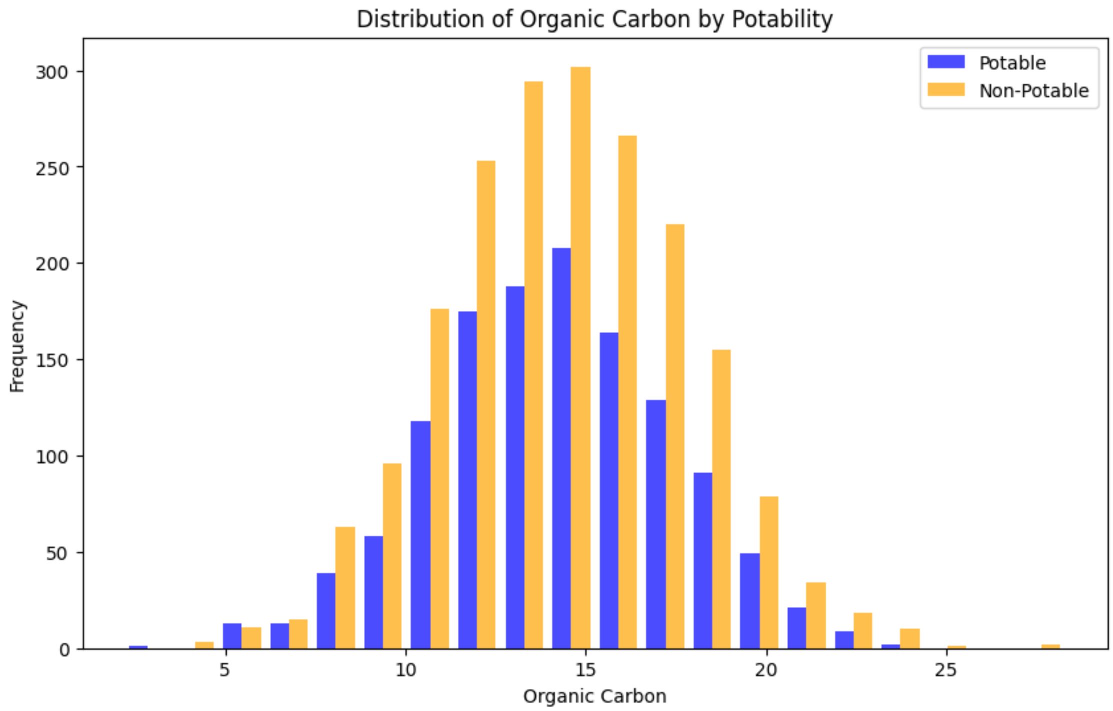
[5]:

```
# Based on the Q-Q plot, the data points closely follow the straight line,␣
↪indicating that the distribution of organic carbon approximates normality.
# Therefore, it is appropriate to use the independent samples t-test.

# groupy the data based on potability
potable = df[df['Potability'] == 1]['Organic_carbon']
non_potable = df[df['Potability'] == 0]['Organic_carbon']

# t-test
t_stat, p_value = ttest_ind(potable, non_potable)

alpha = 0.05
if p_value < 0.05:
    print('Reject null hypothesis. Organic Carbon affect water potability␣
↪siginificantly.')
else:
    print('Fail to reject null hypothesis. Organic Carbon do not affect water␣
↪potability siginificantly.')
```

```
Fail to reject null hypothesis. Organic Carbon do not affect water potability
siginificantly.
```

[6]:

```
plt.figure(figsize=(10, 6))
plt.hist([potable, non_potable], bins=20, color=['blue', 'orange'],␣
↪label=['Potable', 'Non-Potable'], alpha=0.7)
plt.title('Distribution of Organic Carbon by Potability')
plt.xlabel('Organic Carbon')
plt.ylabel('Frequency')
plt.legend()
plt.show()
```



Organic Carbon does not show a strong or clear distinction between potable and non-potable water.

1.11 Is there a siginificant relationship between Trihalomethanes(THMs) and potability?

[ ]:
```
'''
Null Hypothesis(H0): There is no siginificant relationship between␣
↪Trihalomethanes(THMs) and potability.
Alternative Hypothesis(H1): There is a siginificant relationship between␣
↪Trihalomethanes(THMs) and potability.
Logic regression is appropriate for this analysis because it allows us to␣
↪assess the relationship between Trihalomethanes (continuous variable) and␣
↪potability (binary variable).
'''
```

[7]:
```
X = df['Trihalomethanes']
y = df['Potability']

# add constant
X = sm.add_constant(X)

# fit the model
model = sm.Logit(y, X)
```

```
result = model.fit()

result.summary()
```

```
Optimization terminated successfully.
         Current function value: 0.668774
         Iterations 4
```

[7]:

Dep. Variable:	Potability	**No. Observations:**	3276
Model:	Logit	**Df Residuals:**	3274
Method:	MLE	**Df Model:**	1
Date:	Wed, 21 Aug 2024	**Pseudo R-squ.:**	3.546e-05
Time:	10:20:06	**Log-Likelihood:**	-2190.9
converged:	True	**LL-Null:**	-2191.0
Covariance Type:	nonrobust	**LLR p-value:**	0.6934

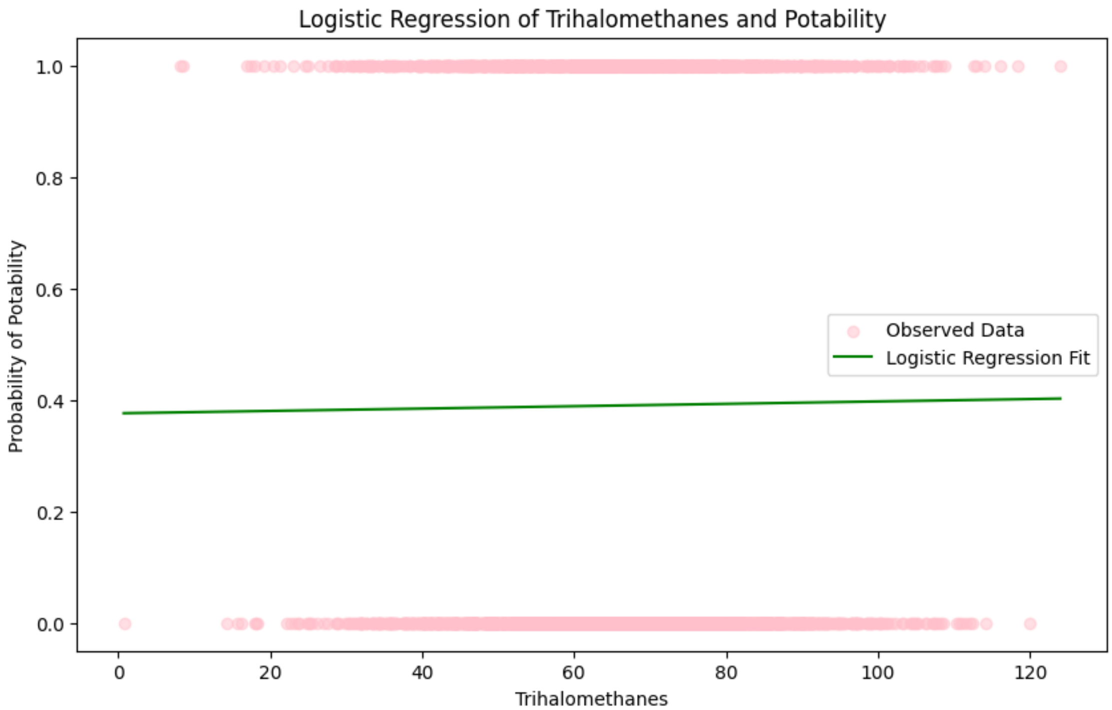
	coef	**std err**	**z**	**P> |z|**	**[0.025**	**0.975]**
const	-0.5063	0.155	-3.263	0.001	-0.811	-0.202
Trihalomethanes	0.0009	0.002	0.394	0.693	-0.004	0.005

[ ]:

```
'''
The p-value for the coefficient is greater than 0.05, which means we fail to␣
↪reject the null hypothesis;
There is no siginificant relationship between Trihalomethanes(THMs) and␣
↪potability.
'''
```

[10]:

```
# visulization
X_plot = np.linspace(X['Trihalomethanes'].min(), X['Trihalomethanes'].max(),␣
↪100)
X_plot = sm.add_constant(X_plot)

# predict y
y_plot = result.predict(X_plot)

plt.figure(figsize=(10, 6))
plt.scatter(df['Trihalomethanes'], df['Potability'], color='pink', alpha=0.5,␣
↪label='Observed Data')
plt.plot(X_plot[:, 1], y_plot, color='green', label='Logistic Regression Fit')
plt.title('Logistic Regression of Trihalomethanes and Potability')
plt.xlabel('Trihalomethanes')
plt.ylabel('Probability of Potability')
plt.legend()
plt.show()
```



From the image, logistic regression isn't the good model to model this data.

1.11.1 Recommendations

1. ****Continuous Monitoring and Optimization of Water Quality Parameters****:

- Since most pH values are around 7, and most water samples fall within the WHO-recommended range of 6.5 to 8.5, it is recommended to maintain regular pH monitoring to ensure water quality remains within this range.

2. ****Focus on the Management and Adjustment of Chloramine Levels****:

- The analysis suggests that the potability of water may decrease when chloramine levels exceed 3 ppm, even though some water samples are still marked as potable at higher chloramine levels. It is recommended to strictly control chloramine levels and assess other factors in the water treatment process (such as water adjustment and treatment processes) to ensure the safety and reliability of water quality.

1.11.2 Summary of Hypothesis Testing

1. ****Is organic carbon significantly affect water potability?****:

- Null Hypothesis(H0): Organic Carbon doesn't affect water potability siginificantly.
- Alternative Hypothesis(H1): Organic Carbon affect water potability siginificantly.
- Result:Fail to reject null hypothesis. Organic Carbon doesn't affect water potability siginificantly.

1. ******Is there a significant relationship between Trihalomethanes(THMs) and potability?****:**

- Null Hypothesis(H0): There is no siginificant relationship between Trihalomethanes(THMs) and potability.
- Alternative Hypothesis(H1): There is a siginificant relationship between Trihalomethanes(THMs) and potability.
- Result:The p-value for the coefficient is greater than 0.05, which means we fail to reject the null hypothesis; There is no siginificant relationship between Trihalomethanes(THMs) and potability.