Date - 24/10/2023

Team ID - 3933

Project Title - Water Quality Analysis

IMPORTING THE PACKAGES

In [30]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn import preprocessing
import scipy
import plotly.express as px
```

READING THE DATASET

In [31]:
```
df=pd.read_csv("D:\\IBM_water_quality\\water_potability.csv")
df_copy=pd.read_csv("D:\\IBM_water_quality\\water_potability.csv")
```

Data Exploration

In [32]:
```
df
```

Out[32]:

	ph	Hardness	Solids	Chloramines	Sulfate	Conductivity	Organic_carbon	Trihalomethanes	Turbidity	Potability
0	NaN	204.890455	20791.318981	7.300212	368.516441	564.308654	10.379783	86.990970	2.963135	0
1	3.716080	129.422921	18630.057858	6.635246	NaN	592.885359	15.180013	56.329076	4.500656	0
2	8.099124	224.236259	19909.541732	9.275884	NaN	418.606213	16.868637	66.420093	3.055934	0
3	8.316766	214.373394	22018.417441	8.059332	356.886136	363.266516	18.436524	100.341674	4.628771	0
4	9.092223	181.101509	17978.986339	6.546600	310.135738	398.410813	11.558279	31.997993	4.075075	0
...	...	...	...	...	...	...	...	...	...	...
3271	4.668102	193.681735	47580.991603	7.166639	359.948574	526.424171	13.894419	66.687695	4.435821	1
3272	7.808856	193.553212	17329.802160	8.061362	NaN	392.449580	19.903225	NaN	2.798243	1
3273	9.419510	175.762646	33155.578218	7.350233	NaN	432.044783	11.039070	69.845400	3.298875	1
3274	5.126763	230.603758	11983.869376	6.303357	NaN	402.883113	11.168946	77.488213	4.708658	1
3275	7.874671	195.102299	17404.177061	7.509306	NaN	327.459760	16.140368	78.698446	2.309149	1

3276 rows × 10 columns

In [33]:
```
df_copy
```

Out[33]:

	ph	Hardness	Solids	Chloramines	Sulfate	Conductivity	Organic_carbon	Trihalomethanes	Turbidity	Potability
0	NaN	204.890455	20791.318981	7.300212	368.516441	564.308654	10.379783	86.990970	2.963135	0
1	3.716080	129.422921	18630.057858	6.635246	NaN	592.885359	15.180013	56.329076	4.500656	0
2	8.099124	224.236259	19909.541732	9.275884	NaN	418.606213	16.868637	66.420093	3.055934	0
3	8.316766	214.373394	22018.417441	8.059332	356.886136	363.266516	18.436524	100.341674	4.628771	0
4	9.092223	181.101509	17978.986339	6.546600	310.135738	398.410813	11.558279	31.997993	4.075075	0
...	...	...	...	...	...	...	...	...	...	...
3271	4.668102	193.681735	47580.991603	7.166639	359.948574	526.424171	13.894419	66.687695	4.435821	1
3272	7.808856	193.553212	17329.802160	8.061362	NaN	392.449580	19.903225	NaN	2.798243	1
3273	9.419510	175.762646	33155.578218	7.350233	NaN	432.044783	11.039070	69.845400	3.298875	1
3274	5.126763	230.603758	11983.869376	6.303357	NaN	402.883113	11.168946	77.488213	4.708658	1
3275	7.874671	195.102299	17404.177061	7.509306	NaN	327.459760	16.140368	78.698446	2.309149	1

3276 rows × 10 columns

ANALYSIS OF THE DATA

In [34]:
```
print(df.columns)
```

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

In [35]:
```
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
```

In [36]:
```
df.shape
```

Out[36]:
```
(3276, 10)
```

In [37]:
```
df[df["Potability"]==0].count()
```

Out[37]:
```
ph                 1684
Hardness           1998
Solids             1998
Chloramines        1998
Sulfate            1510
Conductivity       1998
Organic_carbon     1998
Trihalomethanes    1891
Turbidity          1998
Potability         1998
dtype: int64
```

In [38]:
```
df[df["Potability"]==1].count()
```

Out[38]:
```
ph                 1101
Hardness           1278
Solids             1278
Chloramines        1278
Sulfate             985
Conductivity       1278
Organic_carbon     1278
Trihalomethanes    1223
Turbidity          1278
Potability         1278
dtype: int64
```

In [39]:
```
df.describe()
```

Out[39]:

	ph	Hardness	Solids	Chloramines	Sulfate	Conductivity	Organic_carbon	Trihalomethanes	Turbidity	Potability
count	2785.000000	3276.000000	3276.000000	3276.000000	2495.000000	3276.000000	3276.000000	3114.000000	3276.000000	3276.000000
mean	7.080795	196.369496	22014.092526	7.122277	333.775777	426.205111	14.284970	66.396293	3.966786	0.390110
std	1.594320	32.879761	8768.570828	1.583085	41.416840	80.824064	3.308162	16.175008	0.780382	0.487849
min	0.000000	47.432000	320.942611	0.352000	129.000000	181.483754	2.200000	0.738000	1.450000	0.000000
25%	6.093092	176.850538	15666.690297	6.127421	307.699498	365.734414	12.065801	55.844536	3.439711	0.000000
50%	7.036752	196.967627	20927.833607	7.130299	333.073546	421.884968	14.218338	66.622485	3.955028	0.000000
75%	8.062066	216.667456	27332.762127	8.114887	359.950170	481.792304	16.557652	77.337473	4.500320	1.000000
max	14.000000	323.124000	61227.196008	13.127000	481.030642	753.342620	28.300000	124.000000	6.739000	1.000000

In [40]:
```
df.dtypes
```

Out[40]:
```
ph                float64
Hardness          float64
Solids            float64
Chloramines       float64
Sulfate           float64
Conductivity      float64
Organic_carbon    float64
Trihalomethanes   float64
Turbidity         float64
Potability          int64
dtype: object
```

Data Pre-Processing

In [41]:
```
print(df.isnull().sum())
```

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

Check for Duplicates:

In [42]:
```
duplicates = df.duplicated()
```

In [43]:
```
df = df.drop_duplicates()
```

CLEARING THE NULL VALUES

In [44]:
```
df.dropna(axis=0, how='any', inplace=True)
```

In [45]:
```
df.isnull().sum()
```

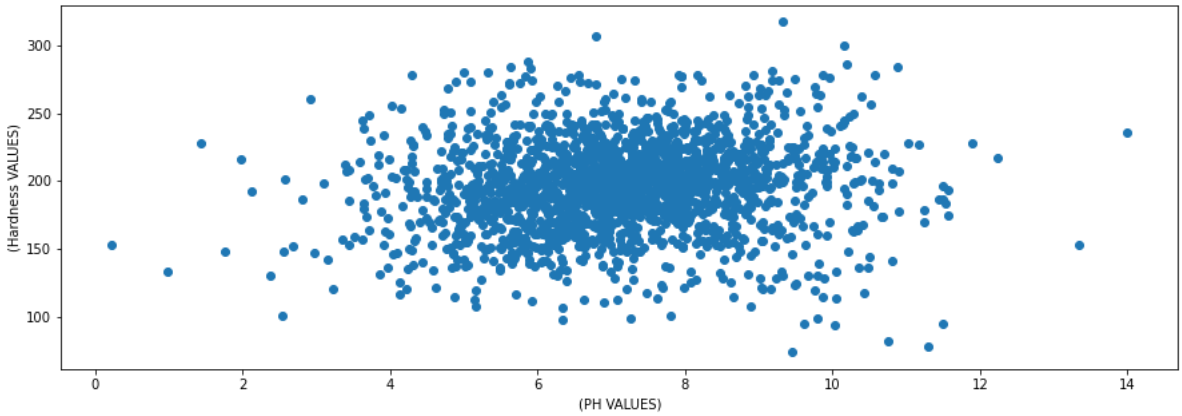
Out[45]:
```
ph                0
Hardness          0
Solids            0
Chloramines       0
Sulfate           0
Conductivity      0
Organic_carbon    0
Trihalomethanes   0
Turbidity         0
Potability        0
dtype: int64
```

In [46]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 2011 entries, 3 to 3271
Data columns (total 10 columns):
 #   Column           Non-Null Count  Dtype  
---  ------           --------------  -----  
 0   ph               2011 non-null   float64
 1   Hardness         2011 non-null   float64
 2   Solids           2011 non-null   float64
 3   Chloramines      2011 non-null   float64
 4   Sulfate          2011 non-null   float64
 5   Conductivity     2011 non-null   float64
 6   Organic_carbon   2011 non-null   float64
 7   Trihalomethanes  2011 non-null   float64
 8   Turbidity        2011 non-null   float64
 9   Potability       2011 non-null   int64  
dtypes: float64(9), int64(1)
memory usage: 172.8 KB
```

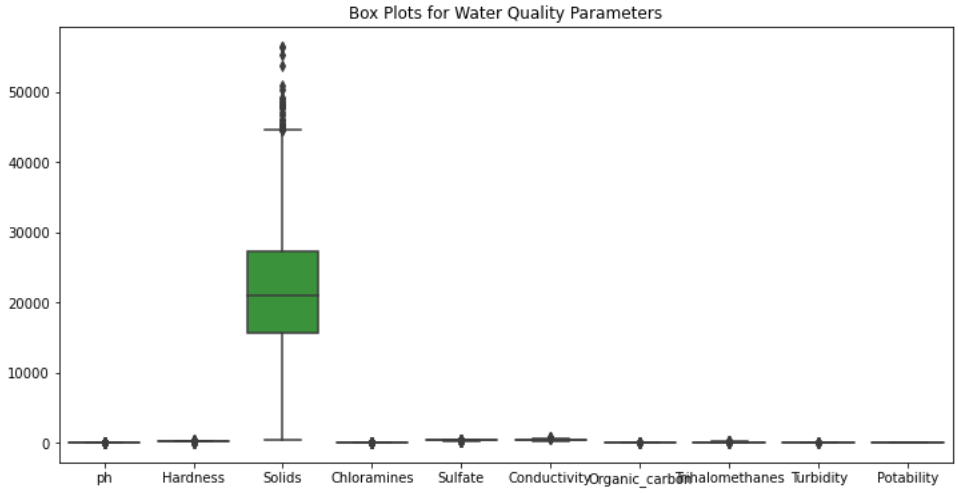
DETECTING OF OUTILERS

In [47]:
```
fig, ax = plt.subplots(figsize = (15,5))
ax.scatter(df['ph'],df['Hardness'])
ax.set_xlabel('(PH VALUES)')
ax.set_ylabel('(Hardness VALUES)')
plt.show()
```



Type *Markdown* and LaTeX: α^2

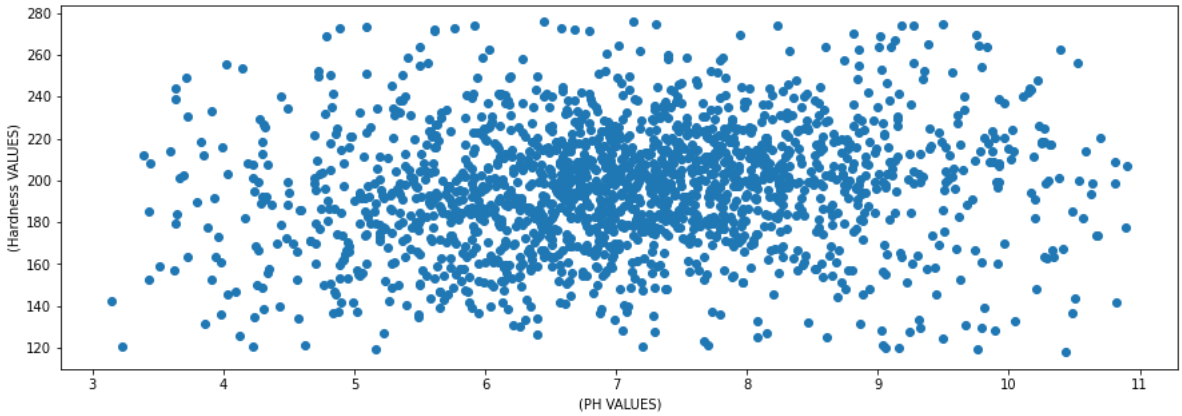
In [48]:
```
plt.figure(figsize=(12, 6))
sns.boxplot(data=df, orient="v")
plt.title("Box Plots for Water Quality Parameters")
plt.show()
```



HANDLING OF OUTILERS

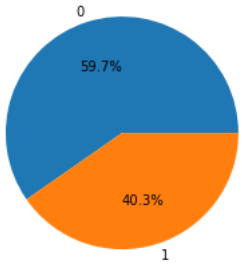
In [49]:
```
def clear_outliers_iqr(df, columns):
    cleaned_data = df.copy()
    for column in columns:
        Q1 = df[column].quantile(0.25)
        Q3 = df[column].quantile(0.75)
        IQR = Q3 - Q1
        lower_bound = Q1 - 1.5 * IQR
        upper_bound = Q3 + 1.5 * IQR
        cleaned_data = cleaned_data[(cleaned_data[column] >= lower_bound) & (cleaned_data[column] <= upper_bound)]
    return cleaned_data


outlier_columns = ['ph', 'Hardness', 'Solids', 'Chloramines', 'Sulfate', 'Conductivity', 'Organic_carbon', 'Trihalomethanes',

cleaned_data = clear_outliers_iqr(df, outlier_columns)
```

In [50]:
```
fig, ax = plt.subplots(figsize = (15,5))
ax.scatter(cleaned_data['ph'],cleaned_data['Hardness'])
ax.set_xlabel('(PH VALUES)')
ax.set_ylabel('(Hardness VALUES)')
plt.show()
```

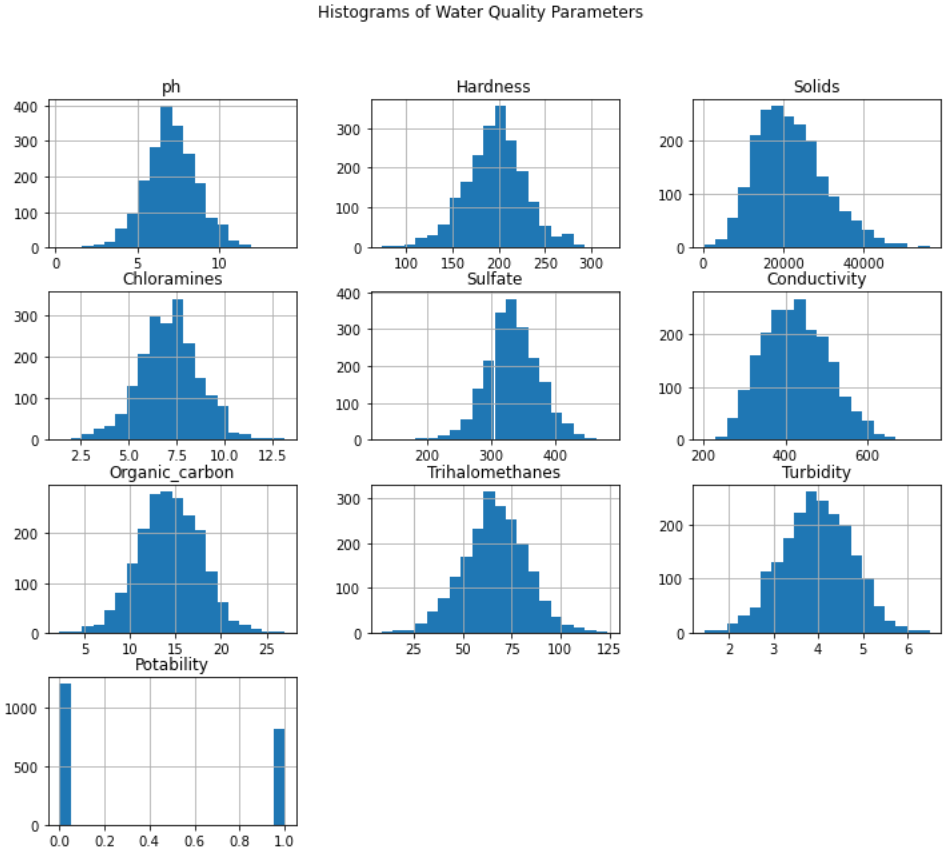


visualization of parameter

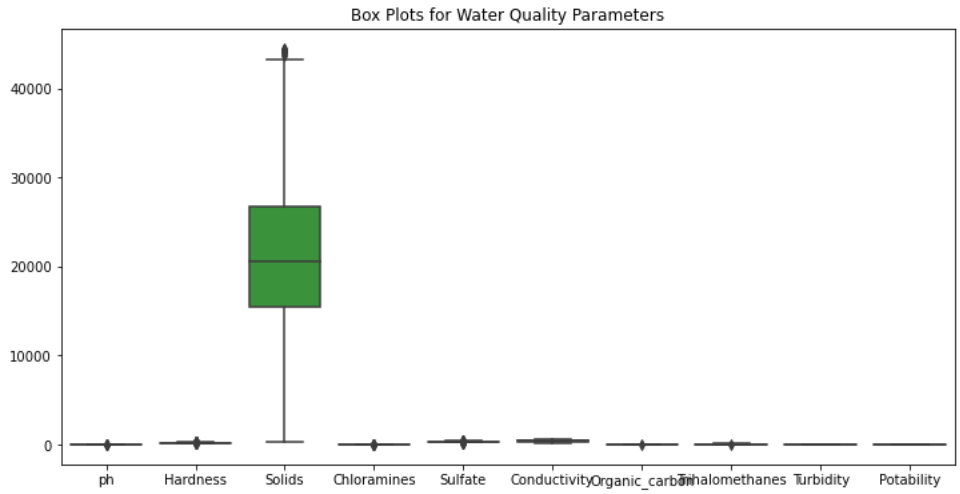
In [51]:
```
plt.pie(df['Potability'].value_counts(),labels = list(df['Potability'].unique()),autopct="%0.1f%%" )
plt.show()
```



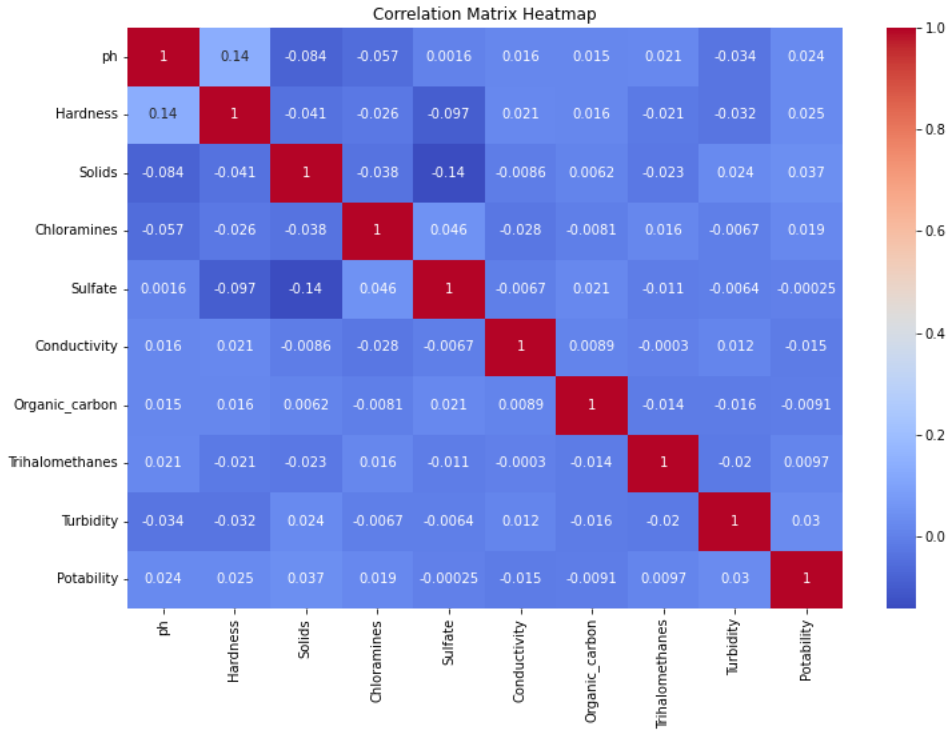
In [52]:
```
df.hist(bins=20, figsize=(12, 10))
plt.suptitle("Histograms of Water Quality Parameters")
plt.show()
```



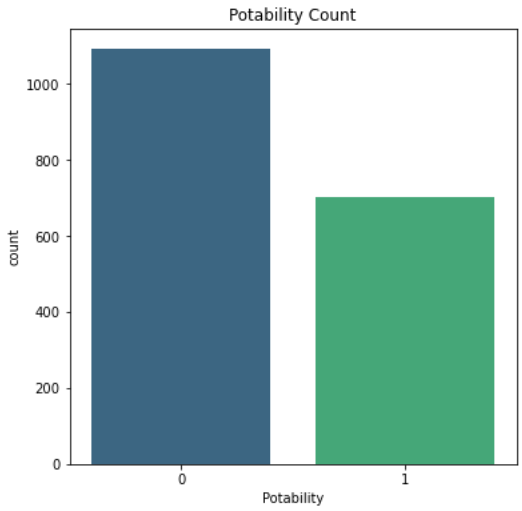
In [53]:
```
plt.figure(figsize=(12, 6))
sns.boxplot(data=cleaned_data, orient="v")
plt.title("Box Plots for Water Quality Parameters")
plt.show()
```



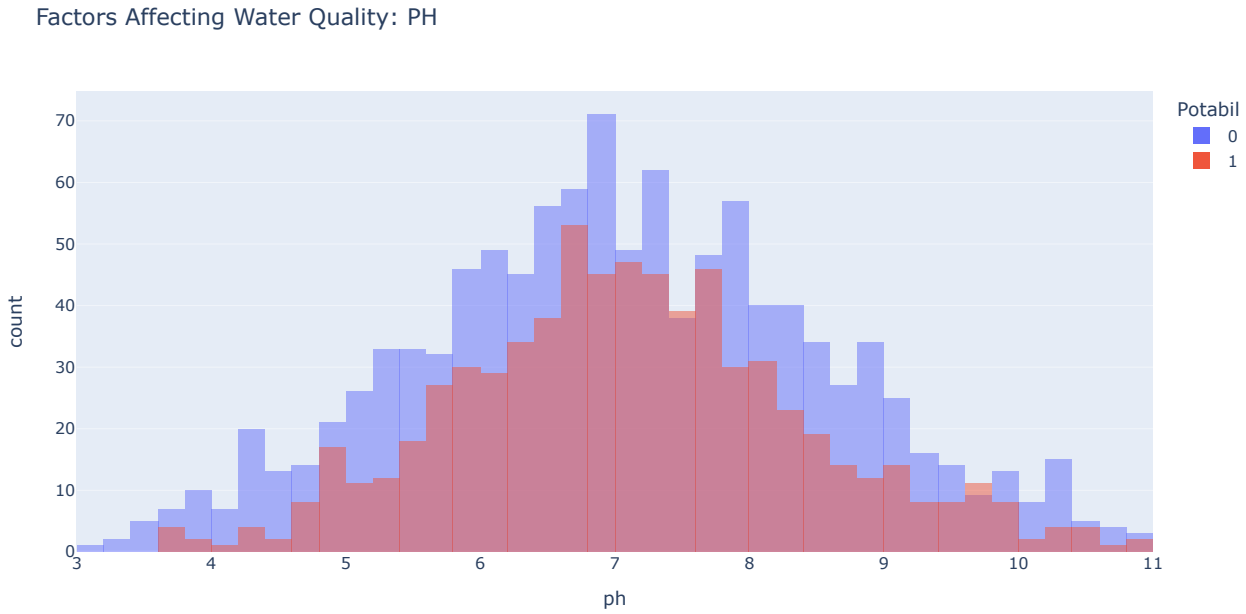
In [54]:
```
correlation_matrix = cleaned_data.corr()
plt.figure(figsize=(12, 8))
sns.heatmap(correlation_matrix, annot=True, cmap="coolwarm")
plt.title("Correlation Matrix Heatmap")
plt.show()
```



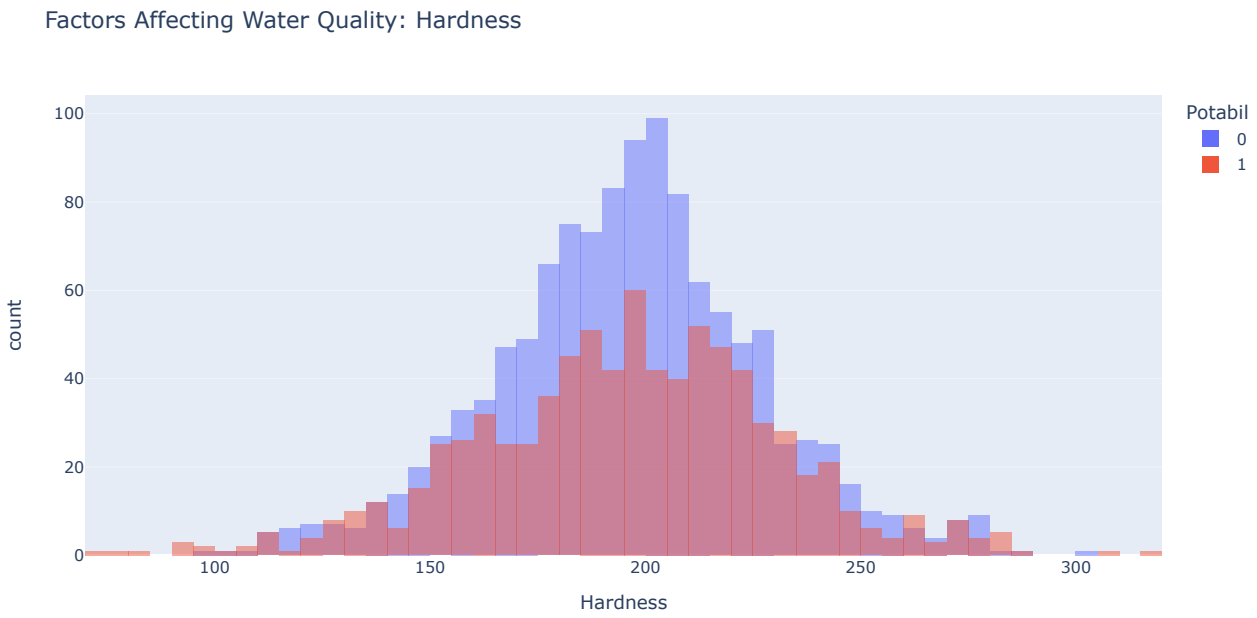
In [55]:
```
plt.figure(figsize=(6, 6))
sns.countplot(data=cleaned_data, x='Potability', palette='viridis')
plt.title("Potability Count")
plt.show()
```



In [56]:
```
px.histogram(cleaned_data, x="ph", color="Potability", barmode="overlay",title= "Factors Affecting Water Quality: PH")
```



In [57]:
```
px.histogram(df, x = "Hardness",color = "Potability", barmode="overlay",title= "Factors Affecting Water Quality: Hardness")
```



In [58]:
```
px.histogram(df, x = "Solids",color = "Potability", barmode="overlay",title= "Factors Affecting Water Quality: Solids")
```

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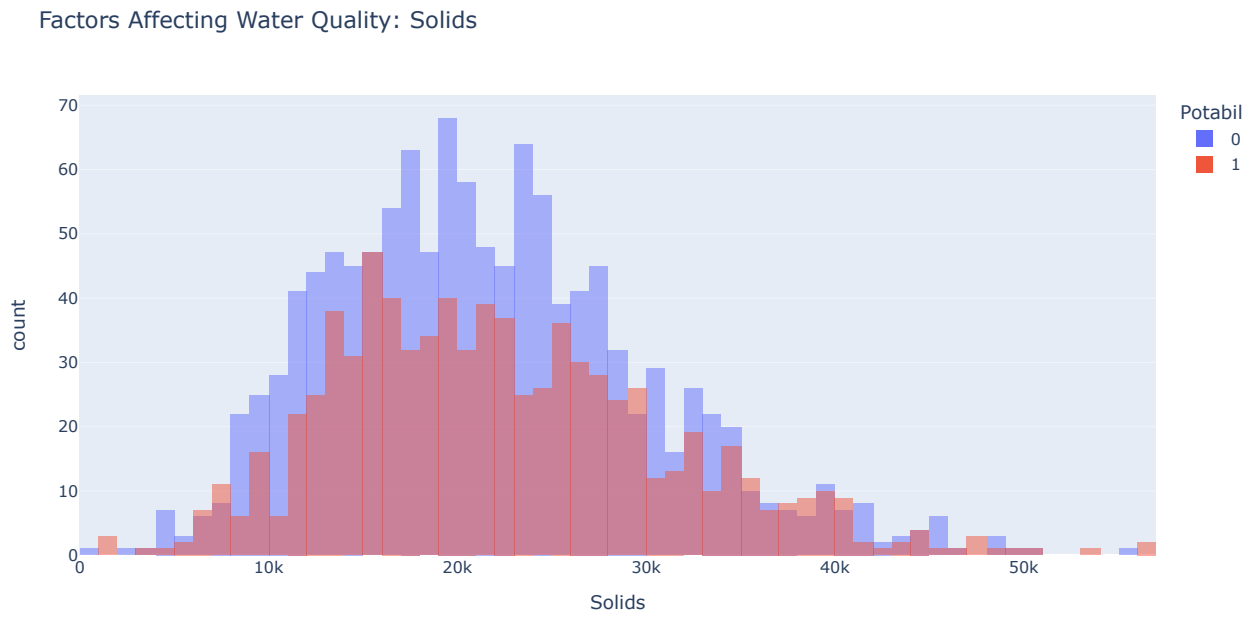
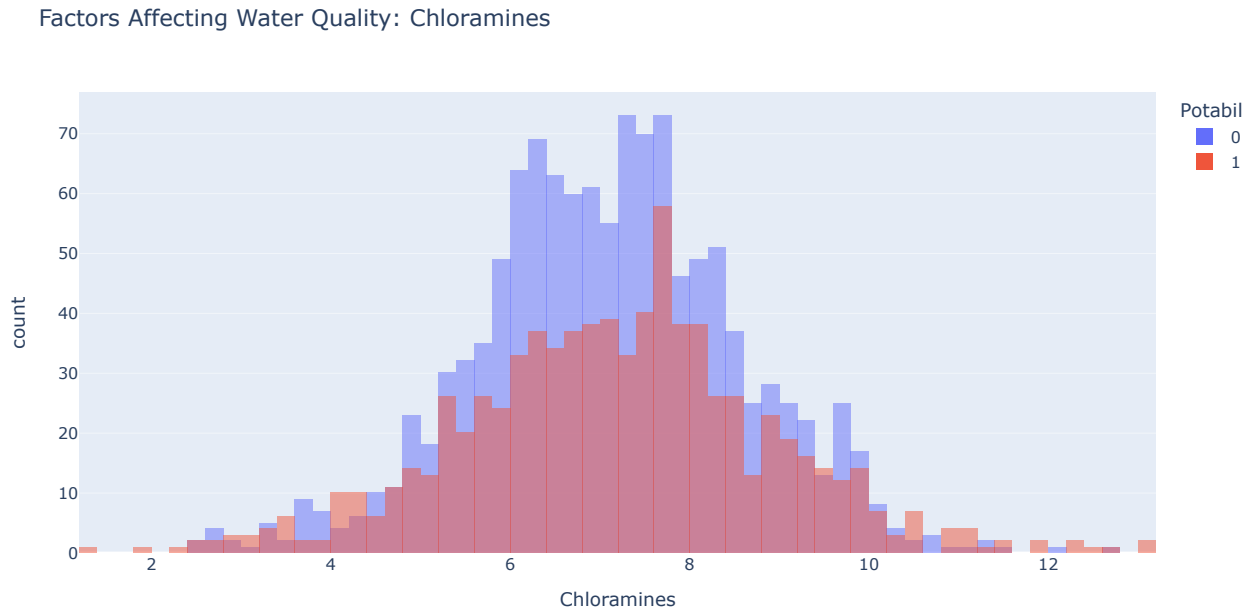
In [59]:
```
px.histogram(df, x = "Solids",color = "Potability", barmode="overlay",title= "Factors Affecting Water Quality: Solids")
```



In [60]:
```
px.histogram(df, x = "Chloramines",color = "Potability", barmode="overlay",title= "Factors Affecting Water Quality: Chloramir
```



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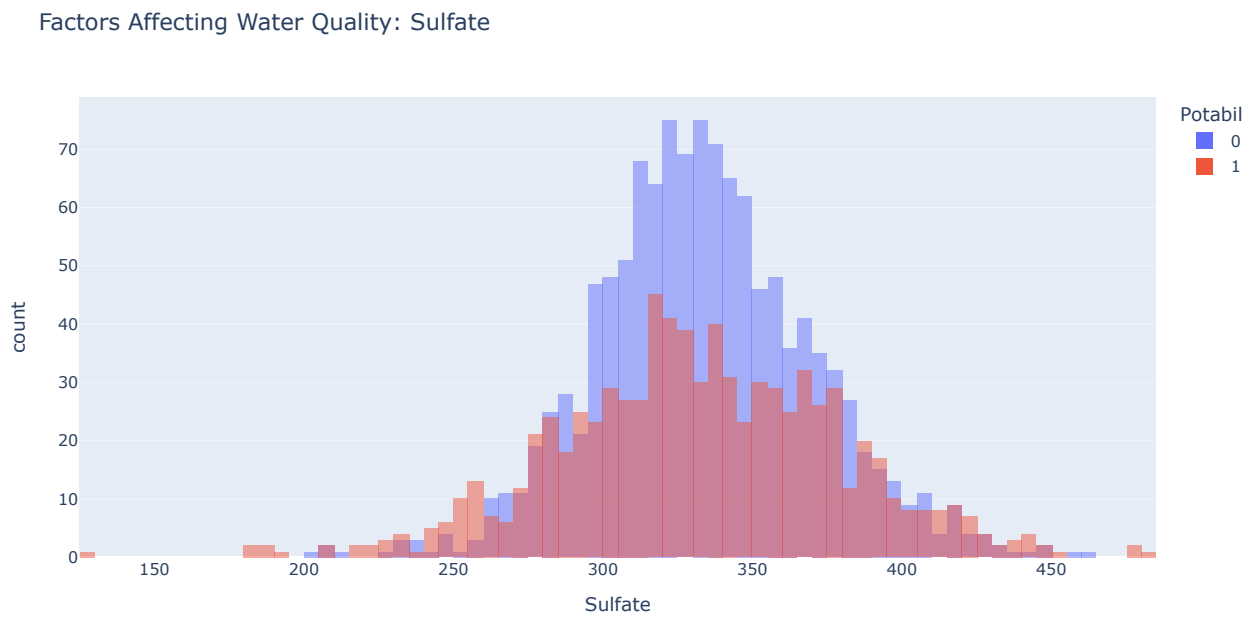
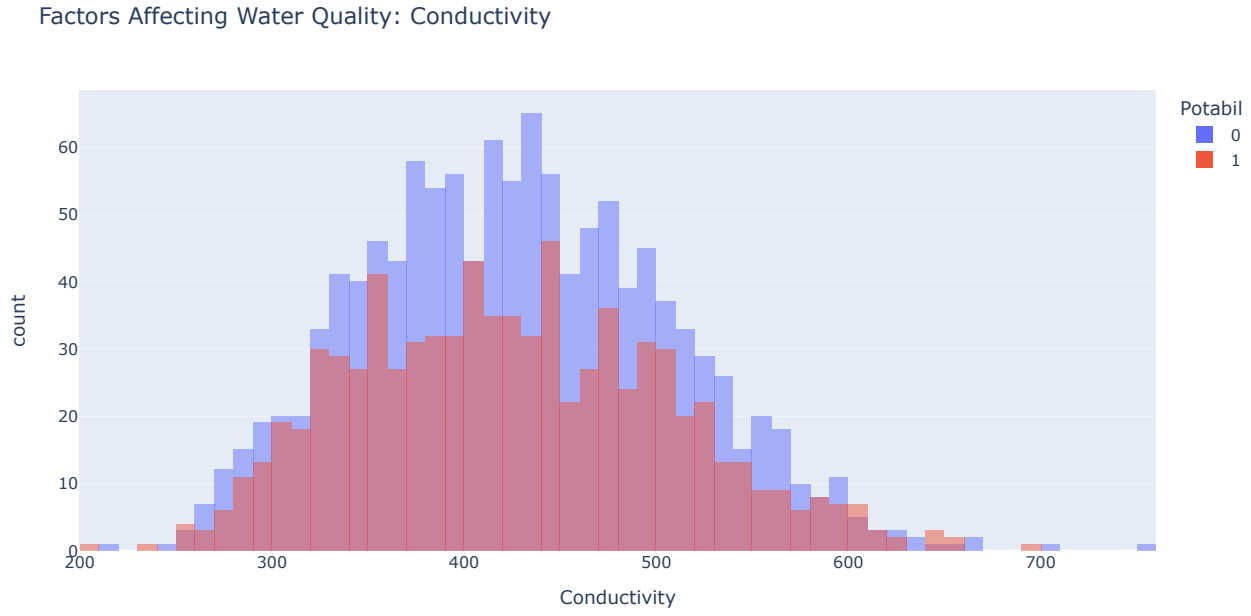
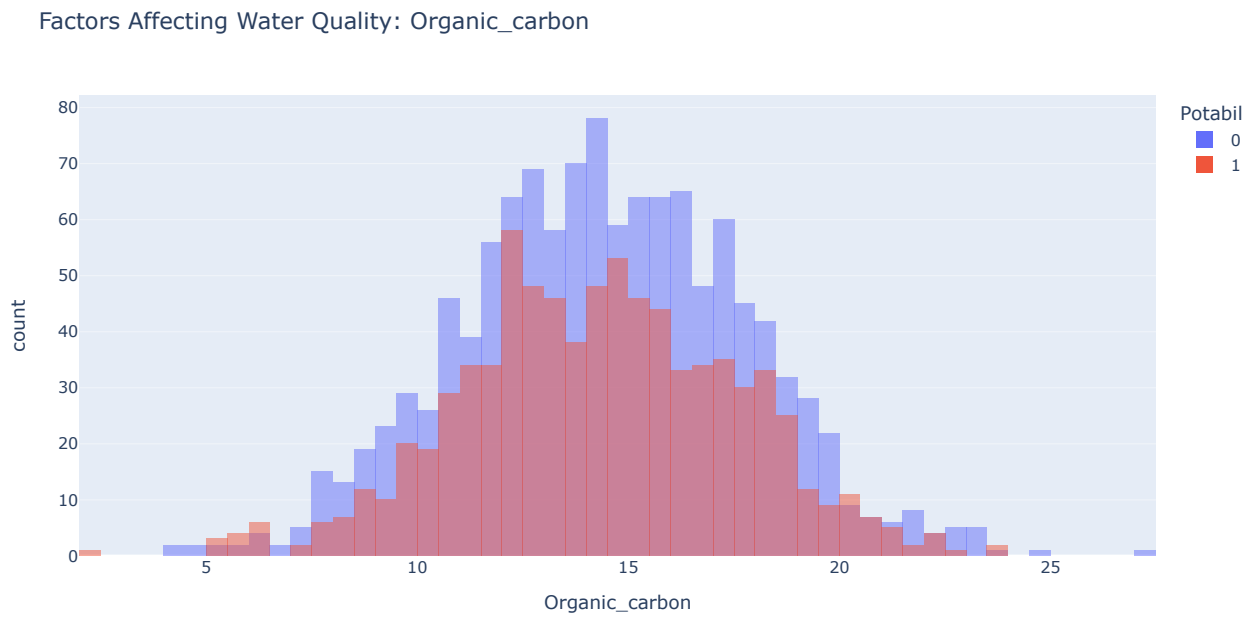
In [61]:
```
px.histogram(df, x = "Sulfate",color = "Potability", barmode="overlay",title= "Factors Affecting Water Quality: Sulfate")
```



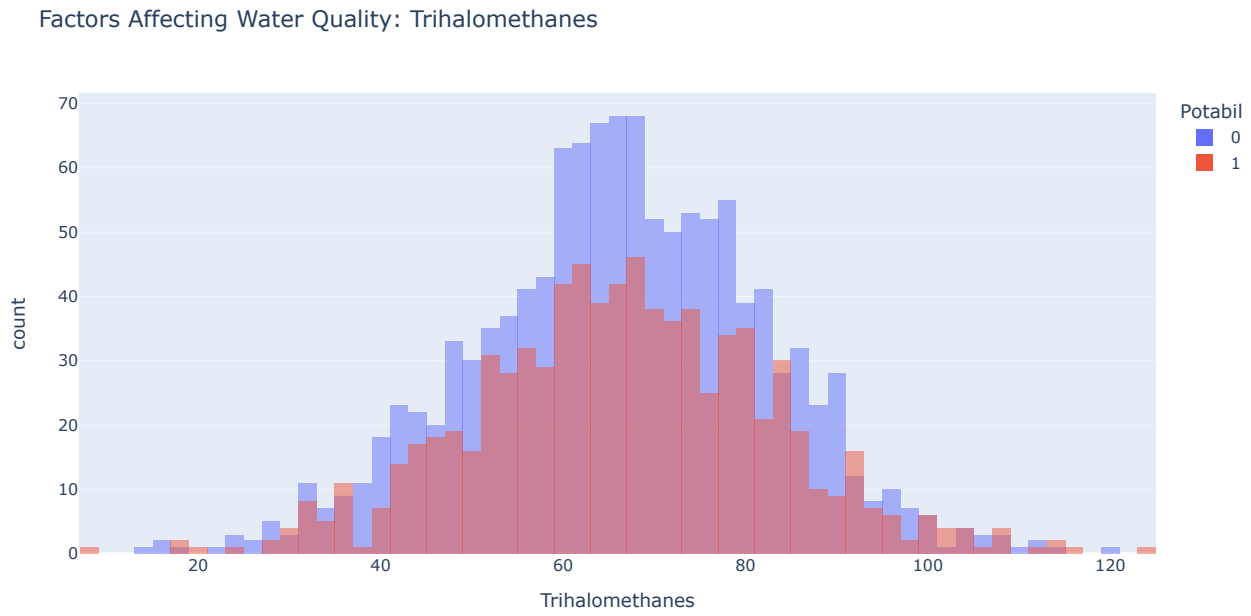
In [62]:
```
px.histogram(df, x = "Conductivity",color = "Potability", barmode="overlay",title= "Factors Affecting Water Quality: Conducti
```



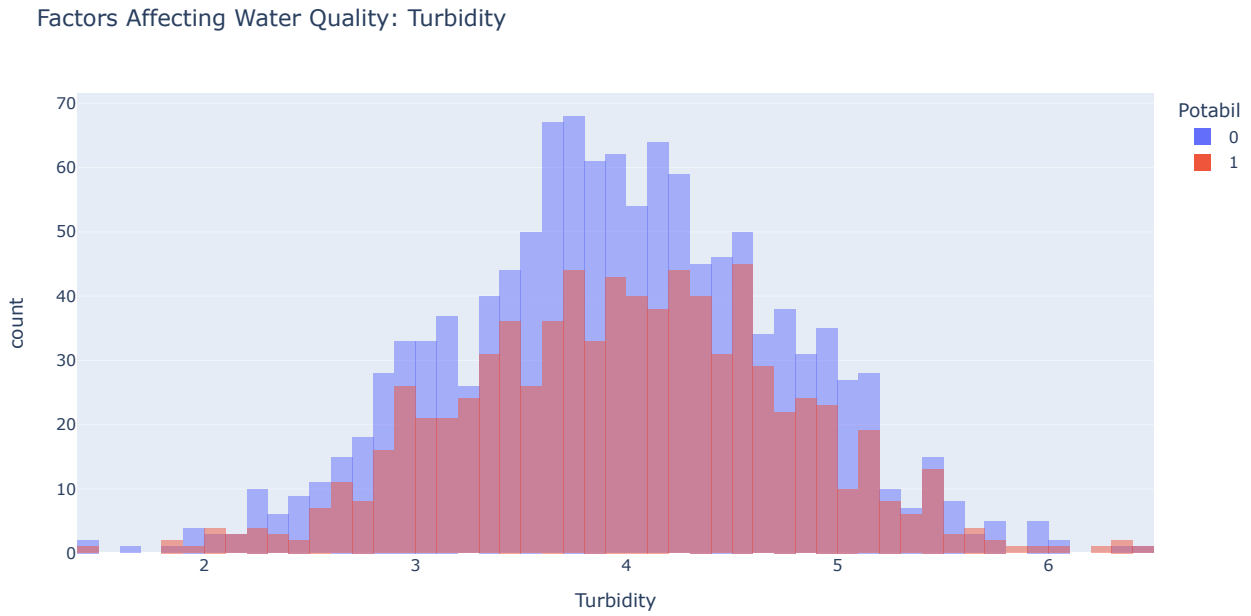
In [63]:
```
px.histogram(df, x = "Organic_carbon",color = "Potability", barmode="overlay",title= "Factors Affecting Water Quality: Organi
```



In [64]:
```
px.histogram(df, x = "Trihalomethanes",color = "Potability", barmode="overlay",title= "Factors Affecting Water Quality: Triha
```



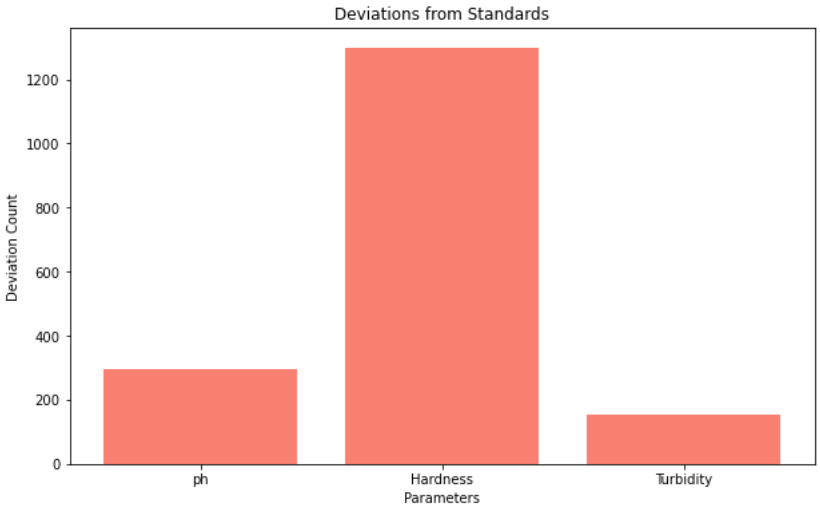
In [65]:
```
px.histogram(df, x = "Turbidity",color = "Potability", barmode="overlay",title= "Factors Affecting Water Quality: Turbidity")
```



potential deviations from standards.

In [66]:
```
standards = {'ph': 8.5, 'Hardness': 180, 'Turbidity': 5.0}
deviations = {param: cleaned_data[cleaned_data[param] > standards[param]].shape[0] for param in standards}

plt.figure(figsize=(10, 6))
plt.bar(deviations.keys(), deviations.values(), color='salmon')
plt.xlabel('Parameters')
plt.ylabel('Deviation Count')
plt.title('Deviations from Standards')
plt.show()
```



splitting data

In [67]:
```
X = cleaned_data.drop('Potability', axis= 1)
y = cleaned_data['Potability']
```

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In [68]:
```
X.shape, y.shape
```

Out[68]: ((1794, 9), (1794,))

In [69]:
```
from sklearn.preprocessing import StandardScaler

scaler = StandardScaler()
```

In [70]:
```
X = scaler.fit_transform(X)
X
```

Out[70]:
```
array([[ 0.86386261,  0.61381129,  0.067647  , ...,  1.24379543,
         2.18882244,  0.86456825],
       [ 1.40325271, -0.51732815, -0.43720308, ..., -0.88414929,
        -2.22263111,  0.13528336],
       [-1.036925  , -0.27214914,  0.90879949, ..., -1.86131842,
        -0.74319752, -1.86064249],
       ...,
       [ 1.33207897,  0.63672394, -0.69435973, ..., -1.39745019,
        -0.73342223,  0.84490664],
       [-0.25895051,  0.37405498, -0.52869705, ...,  0.55722775,
        -2.42398184, -0.69726042],
       [-0.69920233, -0.3283896 ,  0.58261196, ..., -0.7265731 ,
        -0.38805016, -0.39863075]])
```

In [71]:
```
from sklearn.model_selection import train_test_split
```

In [72]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=.25, random_state=42)
```

Selecting a predictive model

In [ ]:
```

```

In [73]:
```
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.svm import SVC
from sklearn.metrics import accuracy_score,confusion_matrix,classification_report
```

In [74]:
```
models = {
    'Decision Tree': DecisionTreeClassifier(random_state=0),
    'Random Forest': RandomForestClassifier(random_state=0),
    'Support Vector Machine': SVC(kernel='rbf', random_state=0)
}
```

In [75]:
```
best_model = None
best_accuracy = 0.0

for model_name, model in models.items():
    model.fit(X_train, y_train)
    y_pred = model.predict(X_test)
    accuracy = accuracy_score(y_test, y_pred)

    print(f'{model_name} Accuracy: {accuracy:.2f}')

    if accuracy > best_accuracy:
        best_accuracy = accuracy
        best_model = model_name

print(f'Best Model: {best_model} with Accuracy: {best_accuracy:.2f}')
```

```
Decision Tree Accuracy: 0.61
Random Forest Accuracy: 0.67
Support Vector Machine Accuracy: 0.70
Best Model: Support Vector Machine with Accuracy: 0.70
```

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Build a predictive model

In [76]:
```
classifier = SVC(kernel='linear', random_state=0)


classifier.fit(X_train, y_train)


y_pred = classifier.predict(X_test)


accuracy = accuracy_score(y_test, y_pred)
conf_matrix = confusion_matrix(y_test, y_pred)
class_report = classification_report(y_test, y_pred)

print('\nAccuracy: {accuracy:.2f}')
print('\nConfusion Matrix:')
print(conf_matrix)
print('\nClassification Report:')
print(class_report)
```

```
Accuracy: {accuracy:.2f}

Confusion Matrix:
[[269   0]
 [180   0]]

Classification Report:
              precision    recall  f1-score   support

           0       0.60      1.00      0.75       269
           1       0.00      0.00      0.00       180

    accuracy                           0.60       449
   macro avg       0.30      0.50      0.37       449
weighted avg       0.36      0.60      0.45       449
```

In [77]:
```
df.to_csv("water_potability1", encoding = 'utf-8')
```

In [78]:
```
```

ANALYSIS AND VISUALIZATION USING IBM COGNOS

Edit

100% Analytics Filters

Tab 1 Tab 2 Tab 3 Tab 4 Tab 5

ph

2.01K

Hardness

2.01K

Solids

2.01K

Chloramines

2.01K

Sulfate

2.01K

Conductivity

2.01K

Organic_carbon

2.01K

Trihalomethanes

2.01K

Turbidity

2.01K

Potability

Select value

Edit | Filter dropdown | 100% | Analytics | Filters

Tab 1 | Tab 2 | Tab 3 | Tab 4 | Tab 5

ph

1.2K

Hardness

1.2K

Solids

1.2K

Chloramines

1.2K

Sulfate

1.2K

Conductivity

1.2K

Organic_carbon

1.2K

Trihalomethanes

1.2K

Turbidity

1.2K

Potability

0

Edit | Filter dropdown | 100% | Analytics | Filters

Tab 1 | Tab 2 | Tab 3 | Tab 4 | Tab 5

ph
811

Hardness
811

Solids
811

Chloramines
811

Sulfate
811

Conductivity
811

Organic_carbon
811

Trihalomethanes
811

Turbidity
811

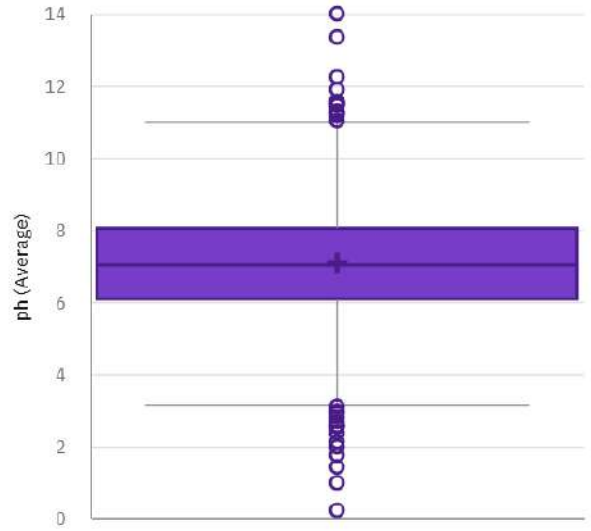
Potability
1

Edit

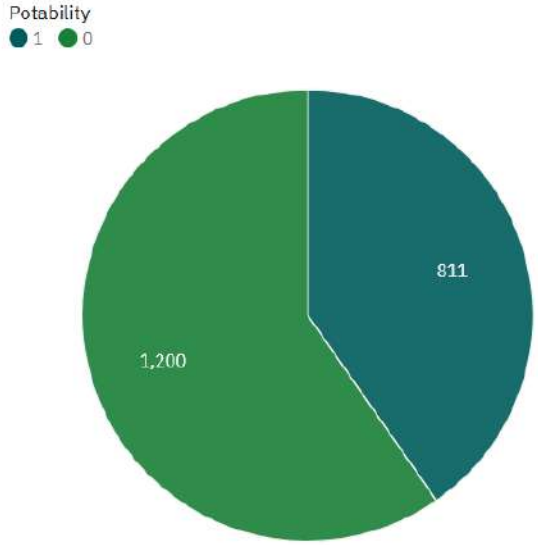
100% Analytics Filters

Tab 1 | Tab 2 | Tab 3 | Tab 4 | Tab 5

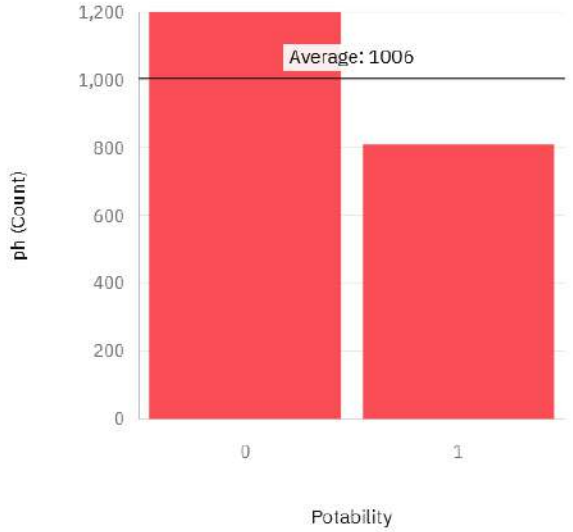
ph by ph



ph by Potability



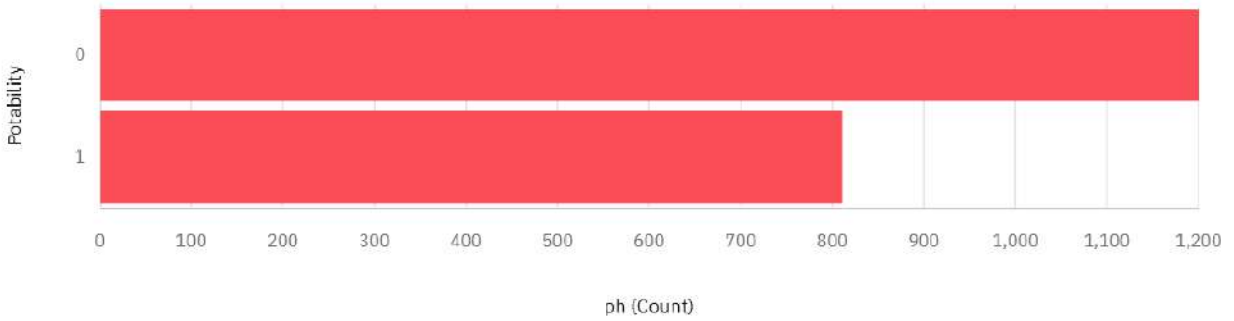
ph by Potability



Potability

0
1

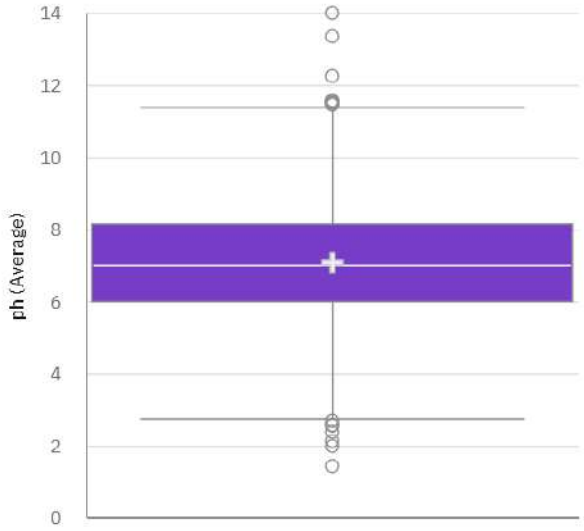
ph by Potability



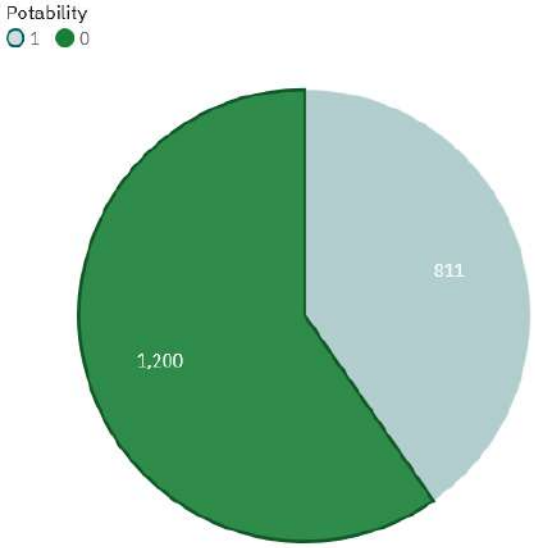
Edit List 100% Analytics Filters

Tab 1 Tab 2 Tab 3 Tab 4 Tab 5

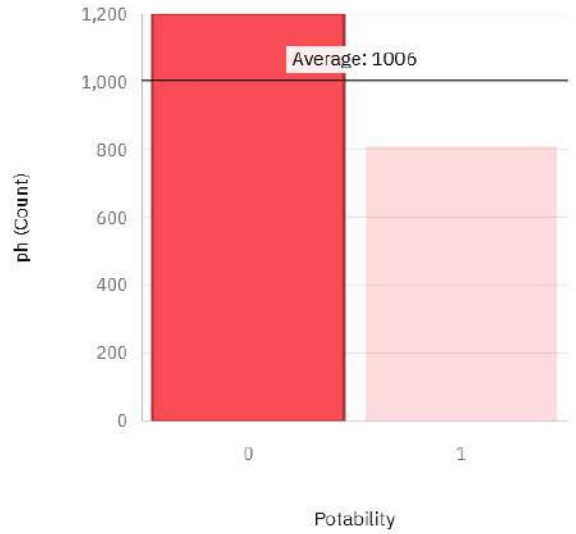
ph by ph



ph by Potability



ph by Potability



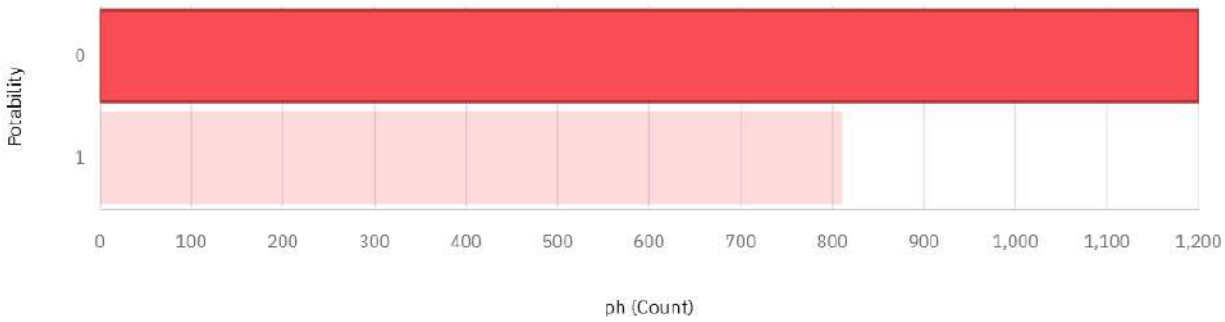
Potability

0

1

ANAL

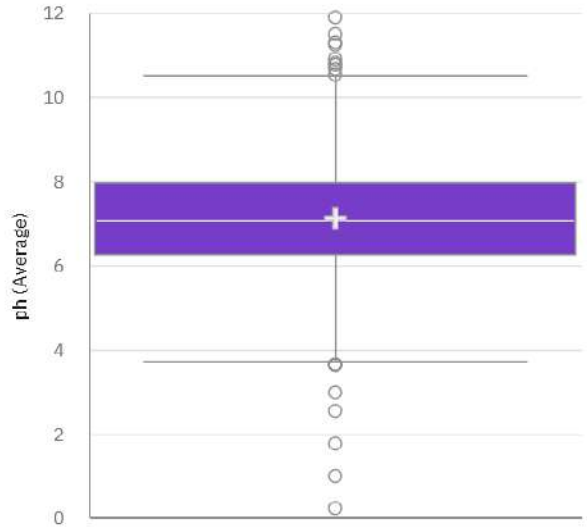
ph by Potability



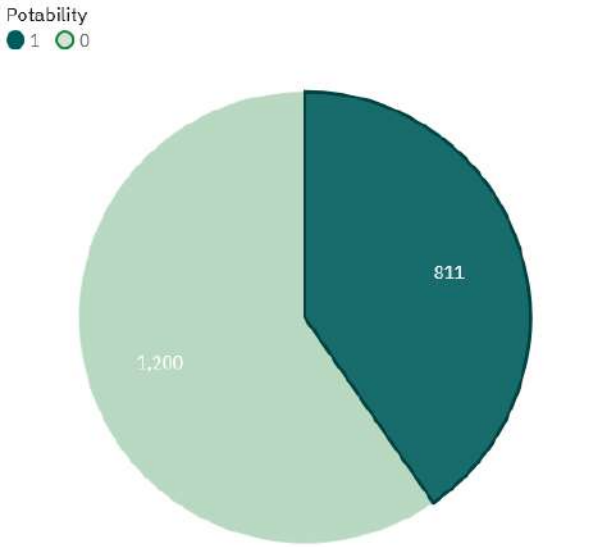
Edit List 100% Analytics Filters

Tab 1 | Tab 2 | Tab 3 | Tab 4 | Tab 5

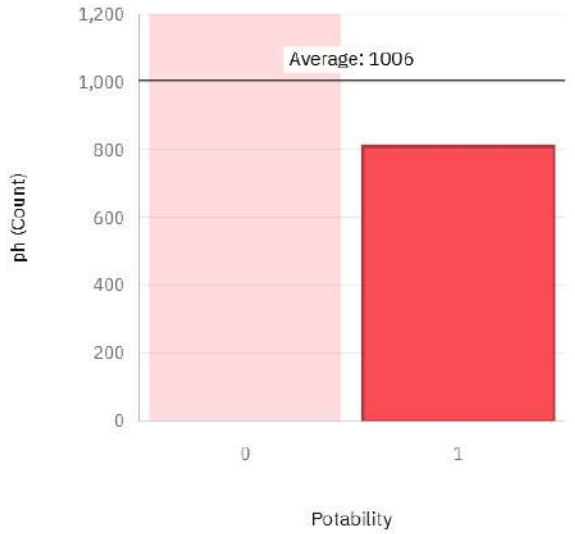
ph by ph



ph by Potability



ph by Potability

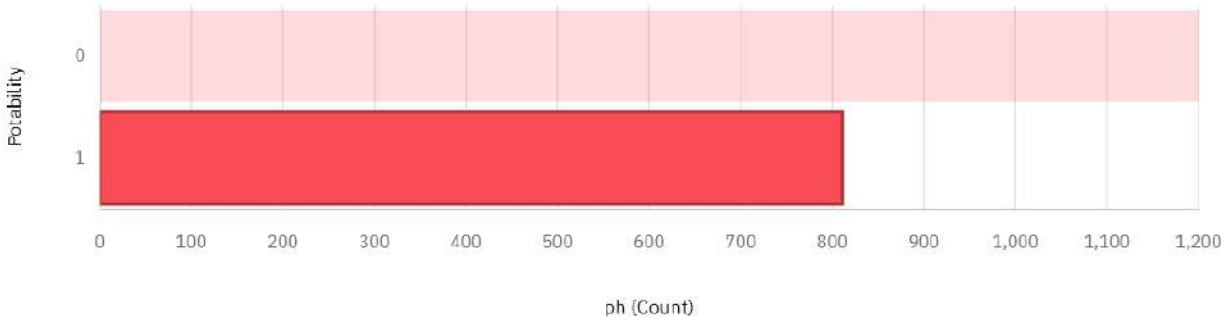


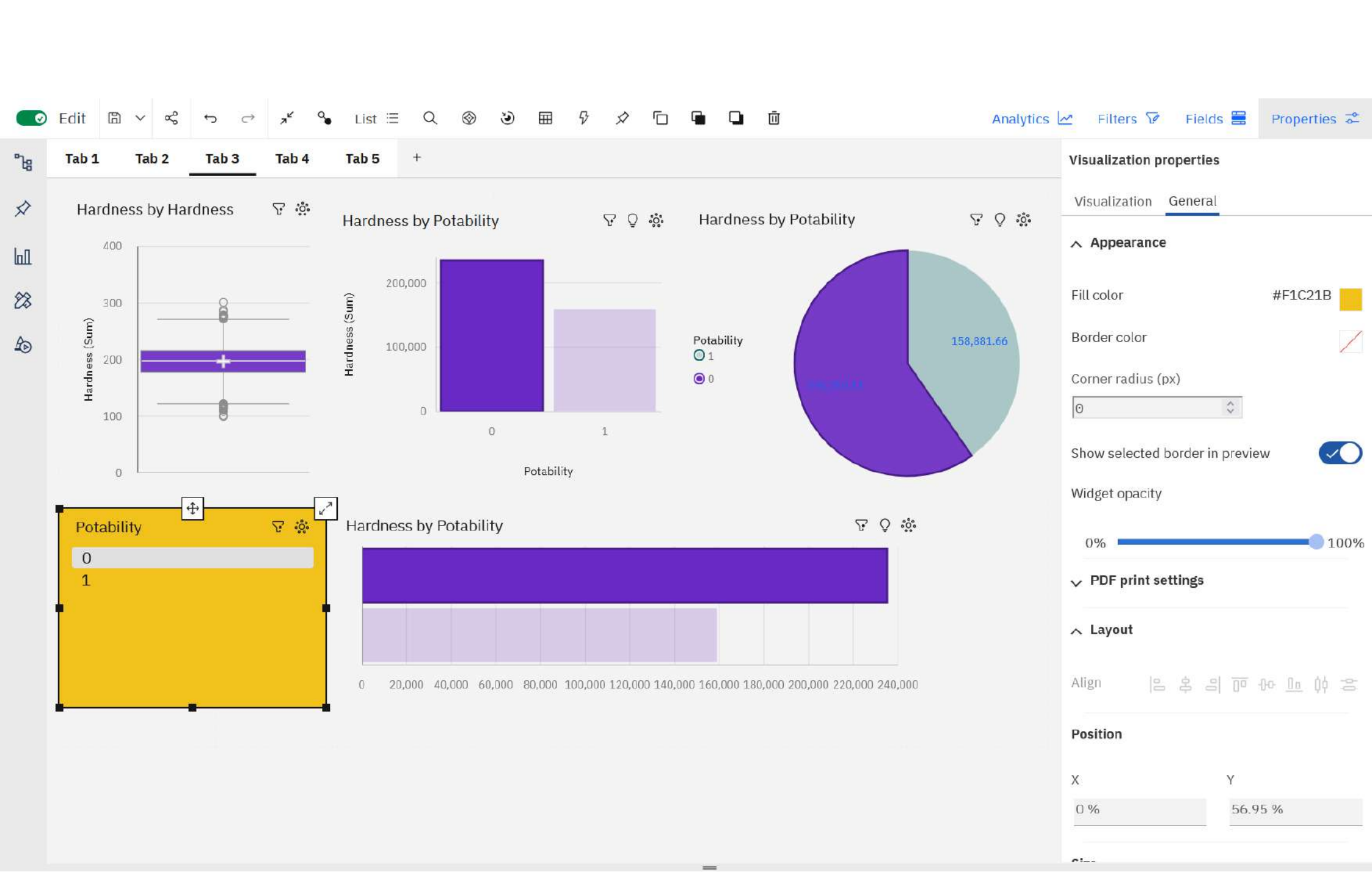
Potability

0

1

ph by Potability




Edit
List
Analytics
Filters
Fields
Properties
Tab 1
Tab 2
Tab 3
Tab 4
Tab 5
Hardness by Hardness
400
300
200
100
0
Hardness (Sum)
Hardness by Potability
200,000
100,000
0
Hardness (Sum)
0
1
Potability
Potability
1
0
Hardness by Potability
158,881.66
Potability
0
1
Hardness by Potability
0
20,000
40,000
60,000
80,000
100,000
120,000
140,000
160,000
180,000
200,000
220,000
240,000
Visualization properties
Visualization
General
Appearance
Fill color
#F1C21B
Border color
Corner radius (px)
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Show selected border in preview
Widget opacity
0%
100%
PDF print settings
Layout
Align
Position
X
Y
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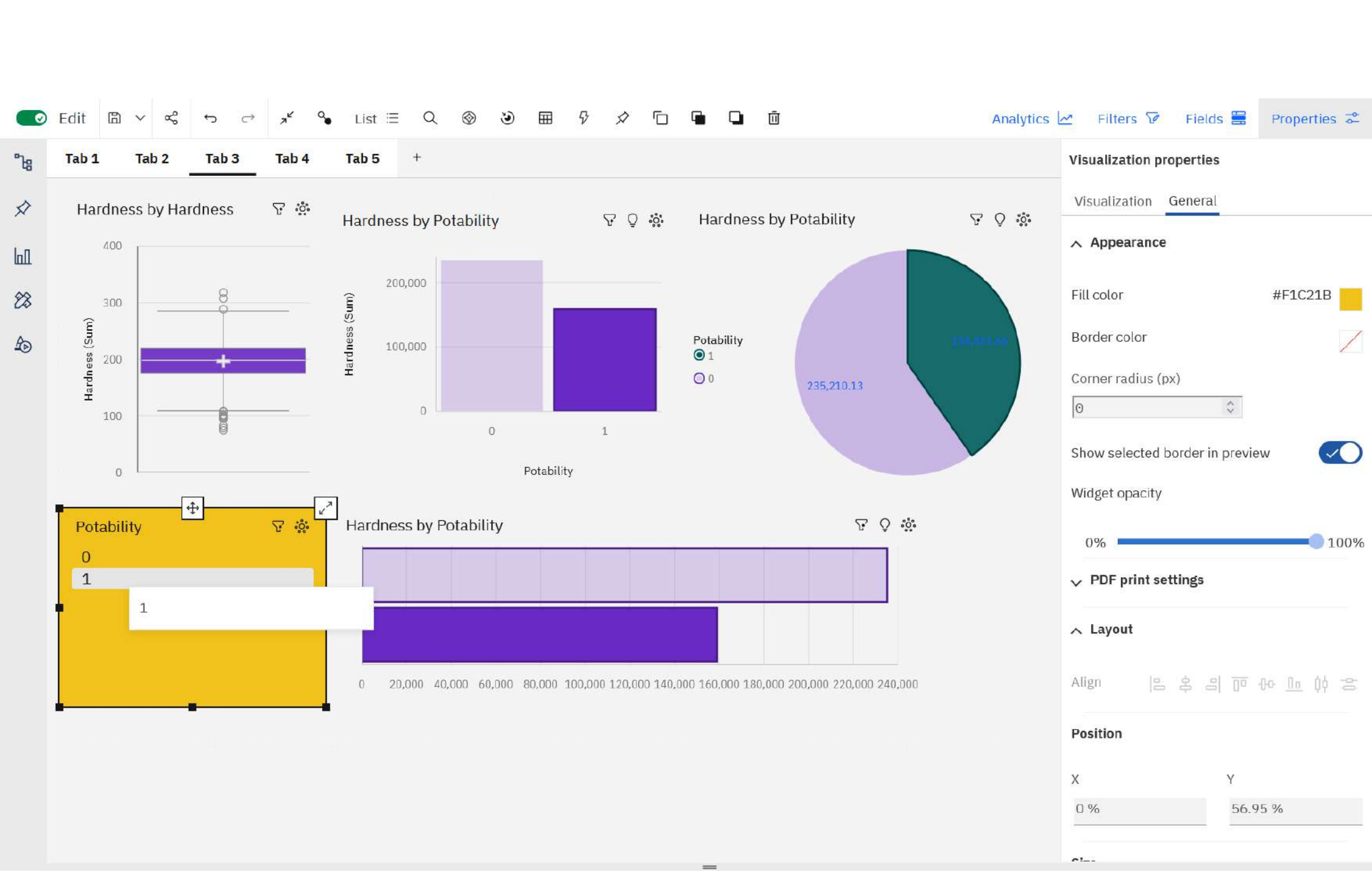
56.95 %


Edit
List
Analytics
Filters
Fields
Properties
Tab 1
Tab 2
Tab 3
Tab 4
Tab 5
Hardness by Hardness
400
300
200
100
0
Hardness (Sum)
Hardness by Potability
200,000
100,000
0
Hardness (Sum)
0
1
Potability
Potability
1
0
Hardness by Potability
235,210.13
Potability
0
1
1
Hardness by Potability
0
20,000
40,000
60,000
80,000
100,000
120,000
140,000
160,000
180,000
200,000
220,000
240,000
Visualization properties
Visualization
General
Appearance
Fill color
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Border color
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PDF print settings
Layout
Align
Position
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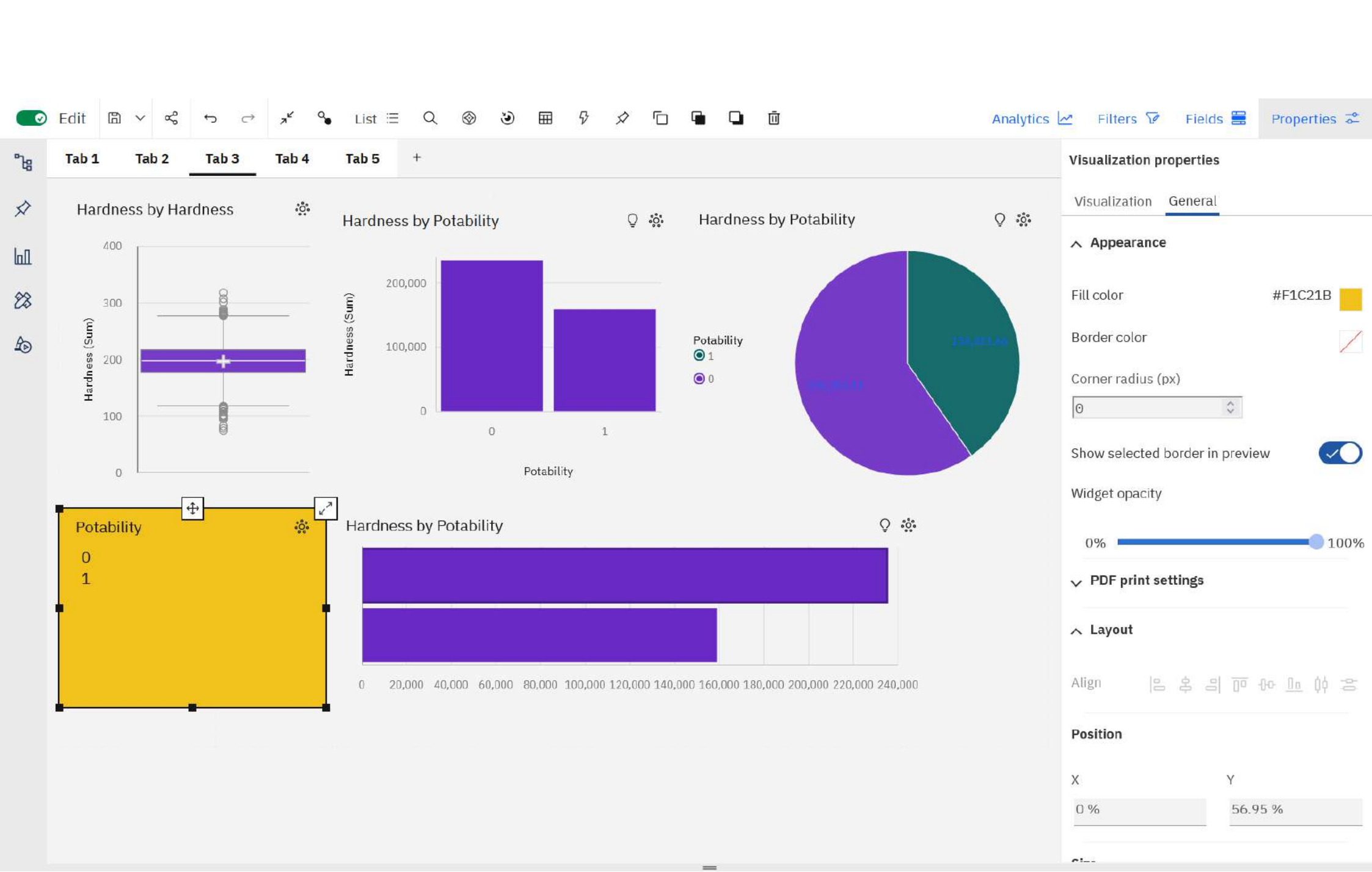
Edit
List
Analytics
Filters
Fields
Properties
Tab 1
Tab 2
Tab 3
Tab 4
Tab 5
Hardness by Hardness
400
300
200
100
0
Hardness (Sum)
Hardness by Potability
200,000
100,000
0
Hardness (Sum)
0
1
Potability
Potability
1
0
Hardness by Potability
Potability
0
1
Hardness by Potability
0
20,000
40,000
60,000
80,000
100,000
120,000
140,000
160,000
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Visualization properties
Visualization
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Appearance
Fill color
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Border color
Corner radius (px)
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Show selected border in preview
Widget opacity
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PDF print settings
Layout
Align
Position
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0 %
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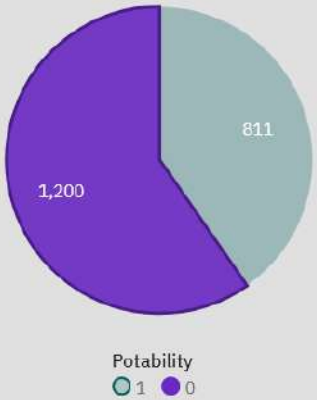
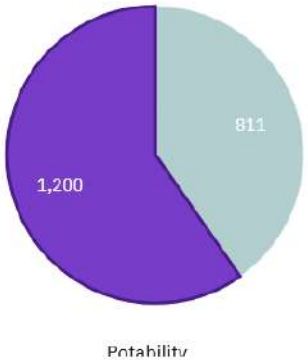
Edit List 100% Analytics Filters

Tab 1 Tab 2 Tab 3 Tab 4 Tab 5

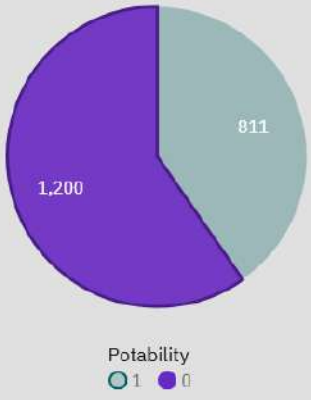
ph by Potability



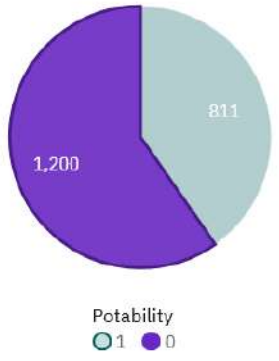
Hardness by Potability



Solids by Potability



Chloramines by Potability

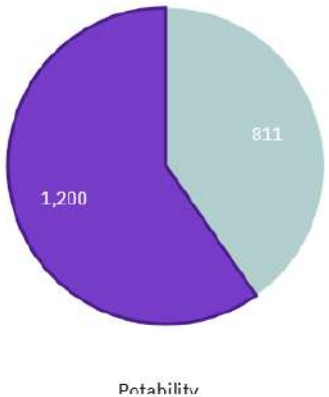


Potability

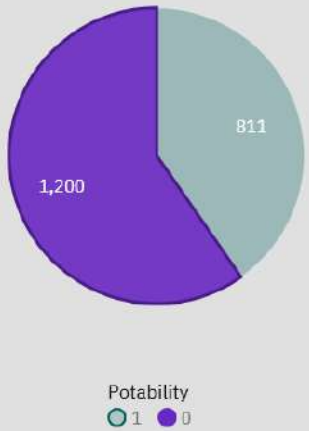
0

1

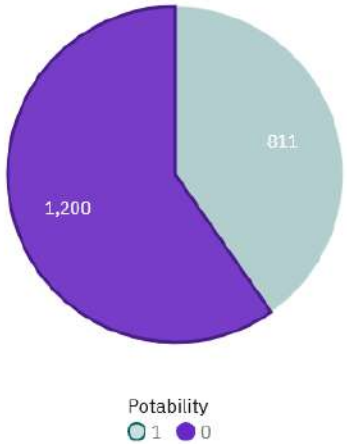
Sulfate by Potability



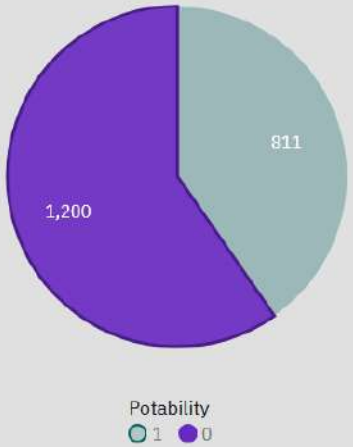
Conductivity by Potability



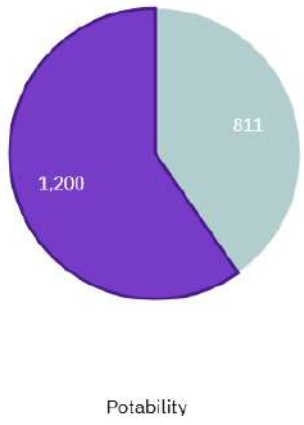
Organic_carbon by Potability



Trihalomethanes by Potability



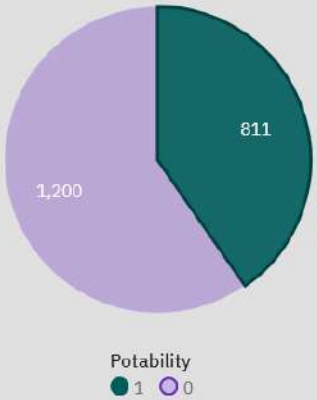
Turbidity by Potability



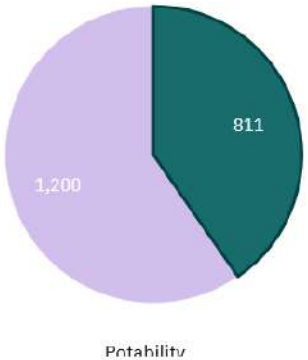
Edit List 100% Analytics Filters

Tab 1 Tab 2 Tab 3 Tab 4 Tab 5

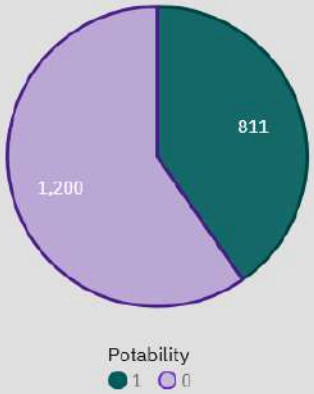
ph by Potability



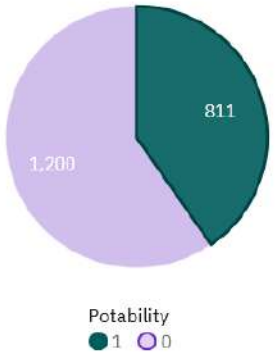
Hardness by Potability



Solids by Potability



Chloramines by Potability

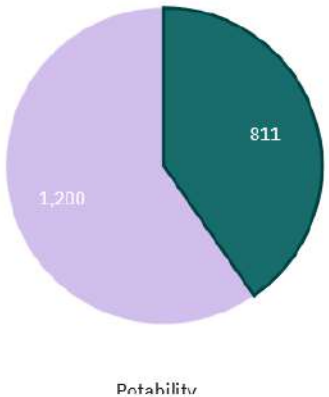


Potability

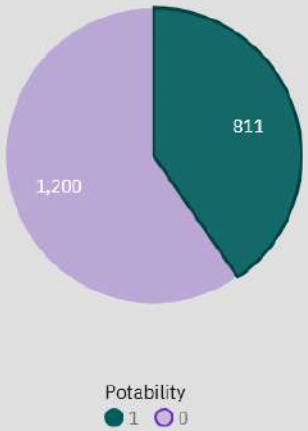
0

1

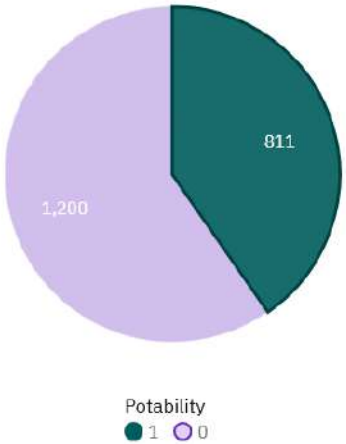
Sulfate by Potability



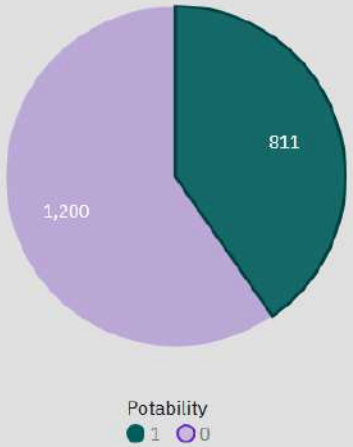
Conductivity by Potability



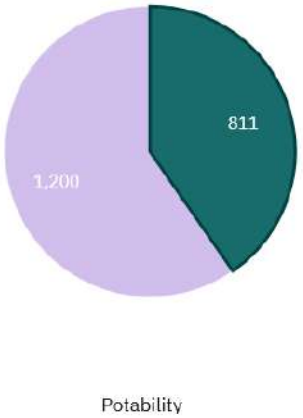
Organic_carbon by Potability



Trihalomethanes by Potability



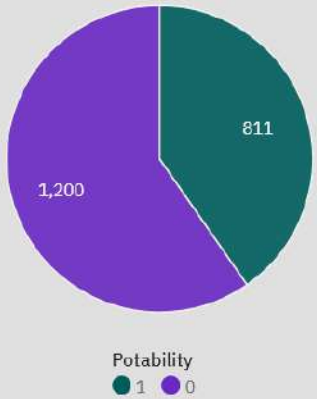
Turbidity by Potability



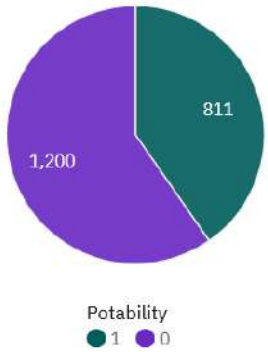
Edit List 100% Analytics Filters

Tab 1 Tab 2 Tab 3 Tab 4 Tab 5

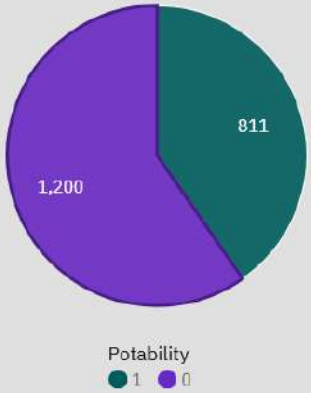
ph by Potability



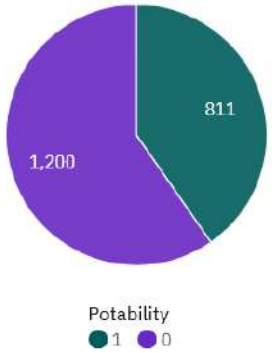
Hardness by Potability



Solids by Potability



Chloramines by Potability

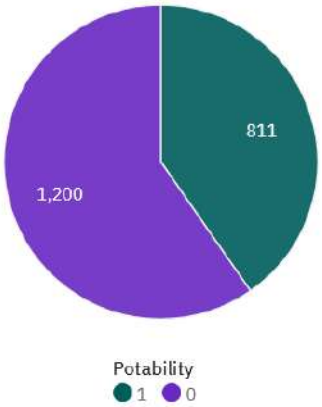


Potability

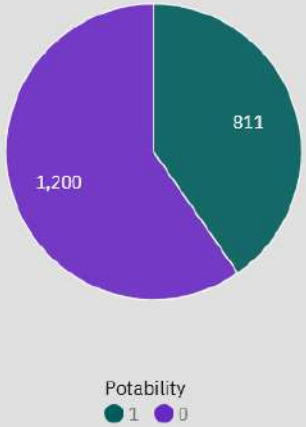
0

1

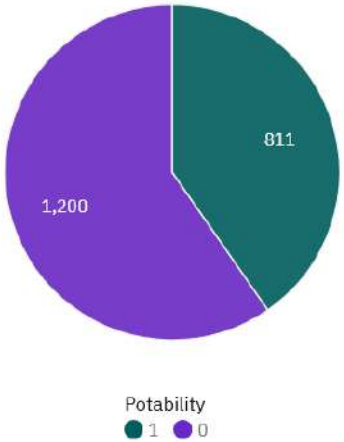
Sulfate by Potability



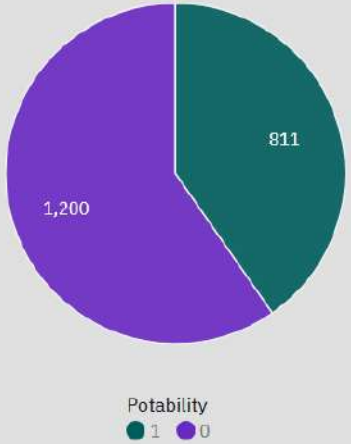
Conductivity by Potability



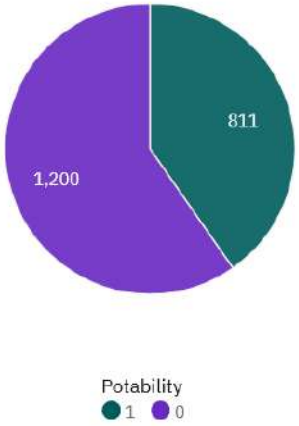
Organic_carbon by Potability



Trihalomethanes by Potability



Turbidity by Potability

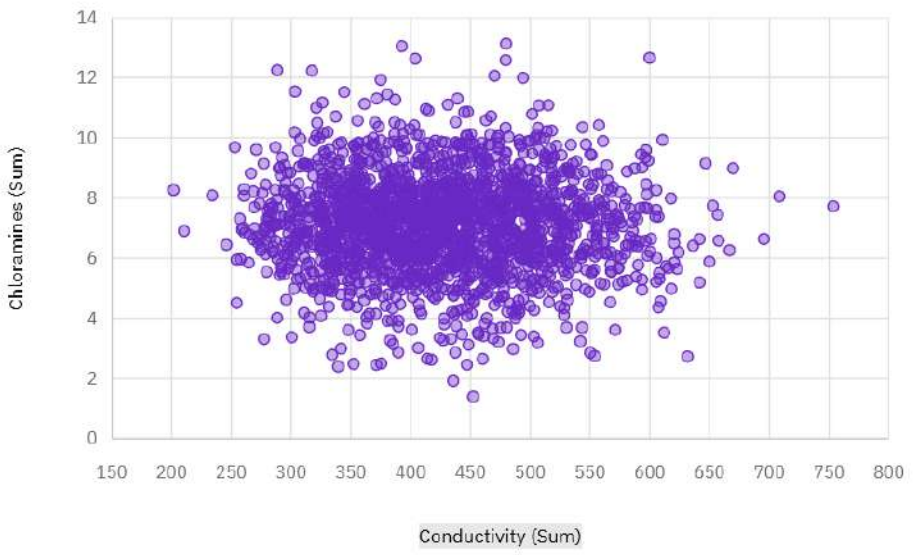


Edit

100% Analytics Filters

Tab 1 | Tab 2 | Tab 3 | Tab 4 | Tab 5

Conductivity by Chloramines with points for Hardness



ph and Hardness

ph	Hardness
2,011	2,011

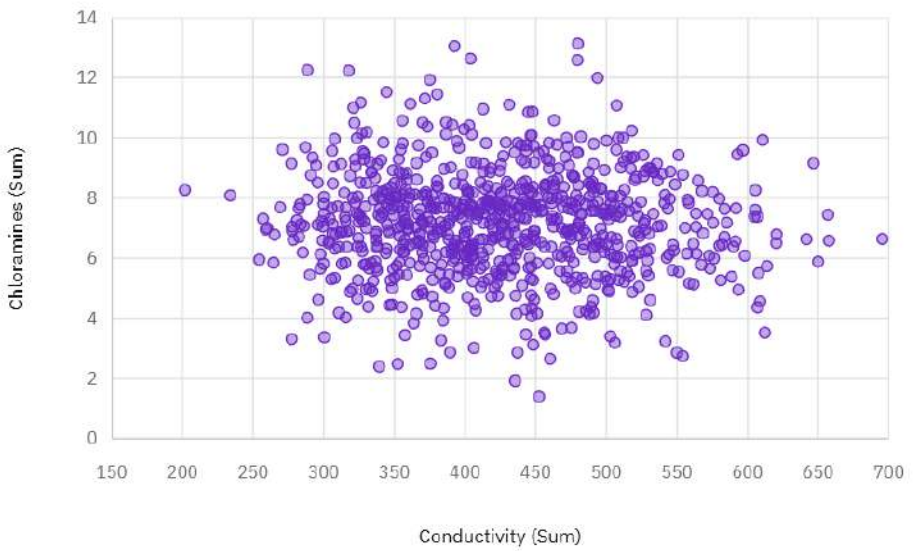
Potability

Select...

Edit | Drop-down list | 100% | Analytics | Filters

Tab 1 | Tab 2 | Tab 3 | Tab 4 | Tab 5

Conductivity by Chloramines with points for Hardness



ph and Hardness

ph	Hardness
811	811

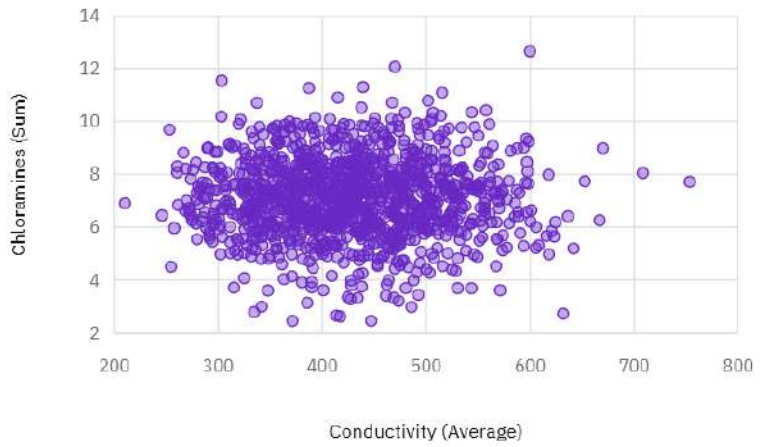
Potability

1

Edit | Drop-down list | Analytics | Filters | Fields | Properties

Tab 1 | Tab 2 | Tab 3 | Tab 4 | Tab 5 | +

Conductivity by Chloramines with points for Hardness



ph and Hardness

ph	Hardness
1,200	1,200

Potability

0

abc Drop-down selections* Required field

Potability

Local filters

Click or drag data here