Libraries

In [63]:
```
# Basic Libraries
import numpy as np
import pandas as pd
from warnings import filterwarnings
from collections import Counter

# Visualizations Libraries
import matplotlib.pyplot as plt
import seaborn as sns
import plotly
import plotly.offline as pyo
import plotly.express as px
import plotly.graph_objs as go
pyo.init_notebook_mode()
import plotly.figure_factory as ff
#import missingno as msno

# Data Pre-processing Libraries
from sklearn import preprocessing
from sklearn.preprocessing import StandardScaler,MinMaxScaler
from sklearn.model_selection import train_test_split
from sklearn.impute import SimpleImputer

# Modelling Libraries

from sklearn.linear_model import LogisticRegression,RidgeClassifier,SGDClassifier,Passiv
from sklearn.linear_model import Perceptron
from sklearn.svm import SVC,LinearSVC,NuSVC
from sklearn.neighbors import KNeighborsClassifier,NearestCentroid
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier,AdaBoostClassifier,GradientBoostingC
from sklearn.naive_bayes import GaussianNB,BernoulliNB
from sklearn.ensemble import VotingClassifier

# Evaluation & CV Libraries
from sklearn.metrics import precision_score,accuracy_score
from sklearn.model_selection import RandomizedSearchCV,GridSearchCV,RepeatedStratifiedKF

from sklearn import model_selection, svm
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import confusion_matrix,classification_report,accuracy_score,roc_au
from sklearn.preprocessing import RobustScaler,MinMaxScaler,StandardScaler
```

In [64]:
```
df = pd.read_csv("water_potability.csv")
```

In [65]:
```
df
```

Out[65]:

	ph	Hardness	Solids	Chloramines	Sulfate	Conductivity	Organic_carbon	Trihalomethane
0	NaN	204.890455	20791.318981	7.300212	368.516441	564.308654	10.379783	86.99097
1	3.716080	129.422921	18630.057858	6.635246	NaN	592.885359	15.180013	56.32907
2	8.099124	224.236259	19909.541732	9.275884	NaN	418.606213	16.868637	66.42009
3	8.316766	214.373394	22018.417441	8.059332	356.886136	363.266516	18.436524	100.34167
4	9.092223	181.101509	17978.986339	6.546600	310.135738	398.410813	11.558279	31.99799

...	...	...	...	...	...	...	...	...
3271	4.668102	193.681735	47580.991603	7.166639	359.948574	526.424171	13.894419	66.68769
3272	7.808856	193.553212	17329.802160	8.061362	NaN	392.449580	19.903225	NaN
3273	9.419510	175.762646	33155.578218	7.350233	NaN	432.044783	11.039070	69.84540
3274	5.126763	230.603758	11983.869376	6.303357	NaN	402.883113	11.168946	77.48821
3275	7.874671	195.102299	17404.177061	7.509306	NaN	327.459760	16.140368	78.69844

3276 rows × 10 columns

In [66]:
```
df.describe().transpose()
```

Out[66]:

	count	mean	std	min	25%	50%	75%	
ph	2785.0	7.080795	1.594320	0.000000	6.093092	7.036752	8.062066	14.(
Hardness	3276.0	196.369496	32.879761	47.432000	176.850538	196.967627	216.667456	323.1
Solids	3276.0	22014.092526	8768.570828	320.942611	15666.690297	20927.833607	27332.762127	61227.1
Chloramines	3276.0	7.122277	1.583085	0.352000	6.127421	7.130299	8.114887	13.1
Sulfate	2495.0	333.775777	41.416840	129.000000	307.699498	333.073546	359.950170	481.(
Conductivity	3276.0	426.205111	80.824064	181.483754	365.734414	421.884968	481.792304	753.3
Organic_carbon	3276.0	14.284970	3.308162	2.200000	12.065801	14.218338	16.557652	28.3
Trihalomethanes	3114.0	66.396293	16.175008	0.738000	55.844536	66.622485	77.337473	124.(
Turbidity	3276.0	3.966786	0.780382	1.450000	3.439711	3.955028	4.500320	6.7
Potability	3276.0	0.390110	0.487849	0.000000	0.000000	0.000000	1.000000	1.(

In [67]:
```
df.info()
```

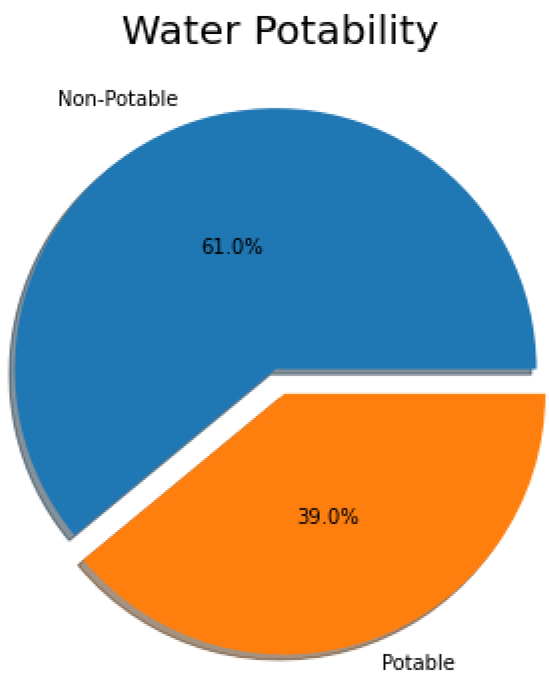
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3276 entries, 0 to 3275
Data columns (total 10 columns):
 #   Column           Non-Null Count  Dtype  
---  ------           --------------  -----  
 0   ph               2785 non-null   float64
 1   Hardness         3276 non-null   float64
 2   Solids           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 [68]:
```
df['Potability'].value_counts()
```

Out[68]:
```
0    1998
1    1278
Name: Potability, dtype: int64
```

In [69]:
```
labels = ['Non-Potable', 'Potable']
data = [df['Potability'].value_counts()[0],
        df['Potability'].value_counts()[1]
```

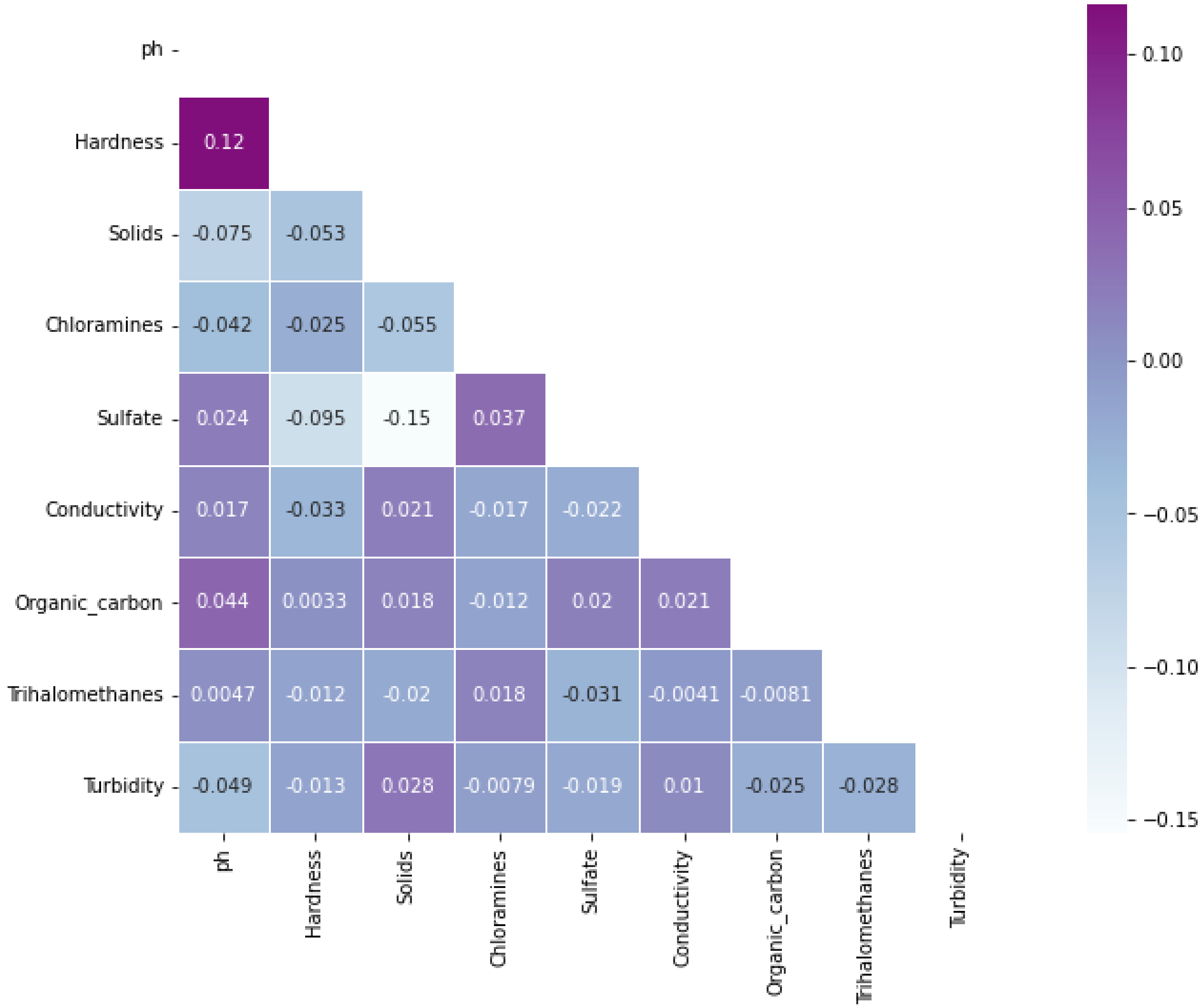
```
        ]
fig1, ax1 = plt.subplots(figsize=[15,6])
ax1.pie(data, labels=labels,explode=[0.05]*2, autopct='%1.1f%%',pctdistance=0.5, shadow=
plt.title("Water Potability", fontsize=20);
plt.show()
```



Correlation Matrix

In [18]:
```
df = df.drop(columns=["Potability"])

#correlation matrix

corr = df.corr(method='spearman')

# Generate a mask for the upper triangle
mask = np.zeros_like(corr, dtype=bool)
mask[np.triu_indices_from(mask)] = True

# Set up the matplotlib figure
f, ax = plt.subplots(figsize=(15, 8))

# Draw the heatmap with the mask and correct aspect ratio
sns.heatmap(corr, annot = True, mask=mask, cmap="BuPu", center=0,
            square=True, linewidths=.5)
```

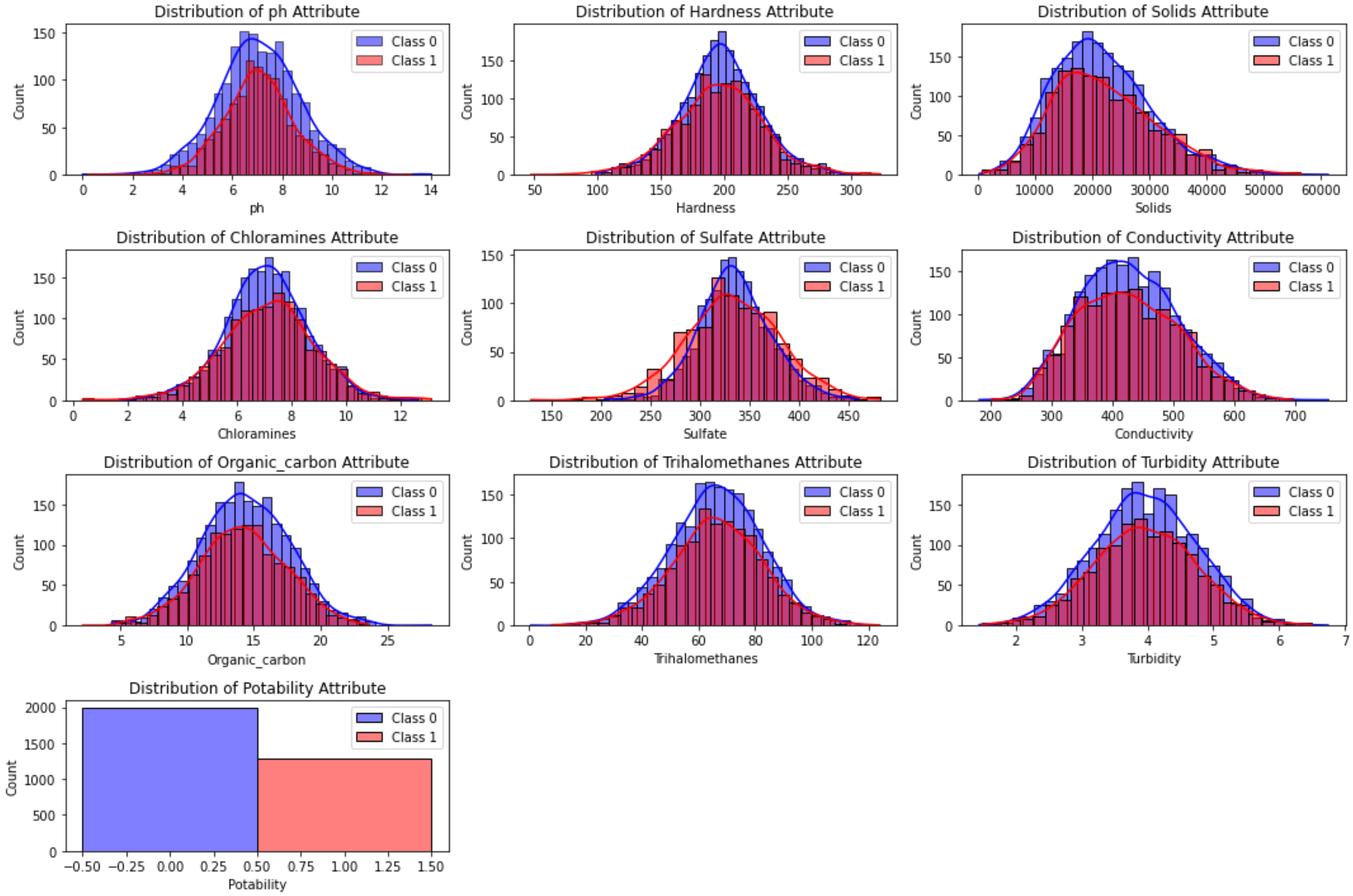
Out[18]: <AxesSubplot:>



Distributions of Different Atrributes

In [21]:
```
df = pd.read_csv("water_potability.csv")
```

In [22]:
```
plt.figure(figsize=(15,10))
for i,col in enumerate(df.columns,1):
    plt.subplot(4,3,i)
    plt.title(f"Distribution of {col} Attribute")
    sns.histplot(df[df['Potability']==0][col],kde=True, color='blue', label='Class 0')
    sns.histplot(df[df['Potability']==1][col],kde=True, color='red', label='Class 1')
    plt.legend()
    plt.tight_layout()
    plt.plot()
```

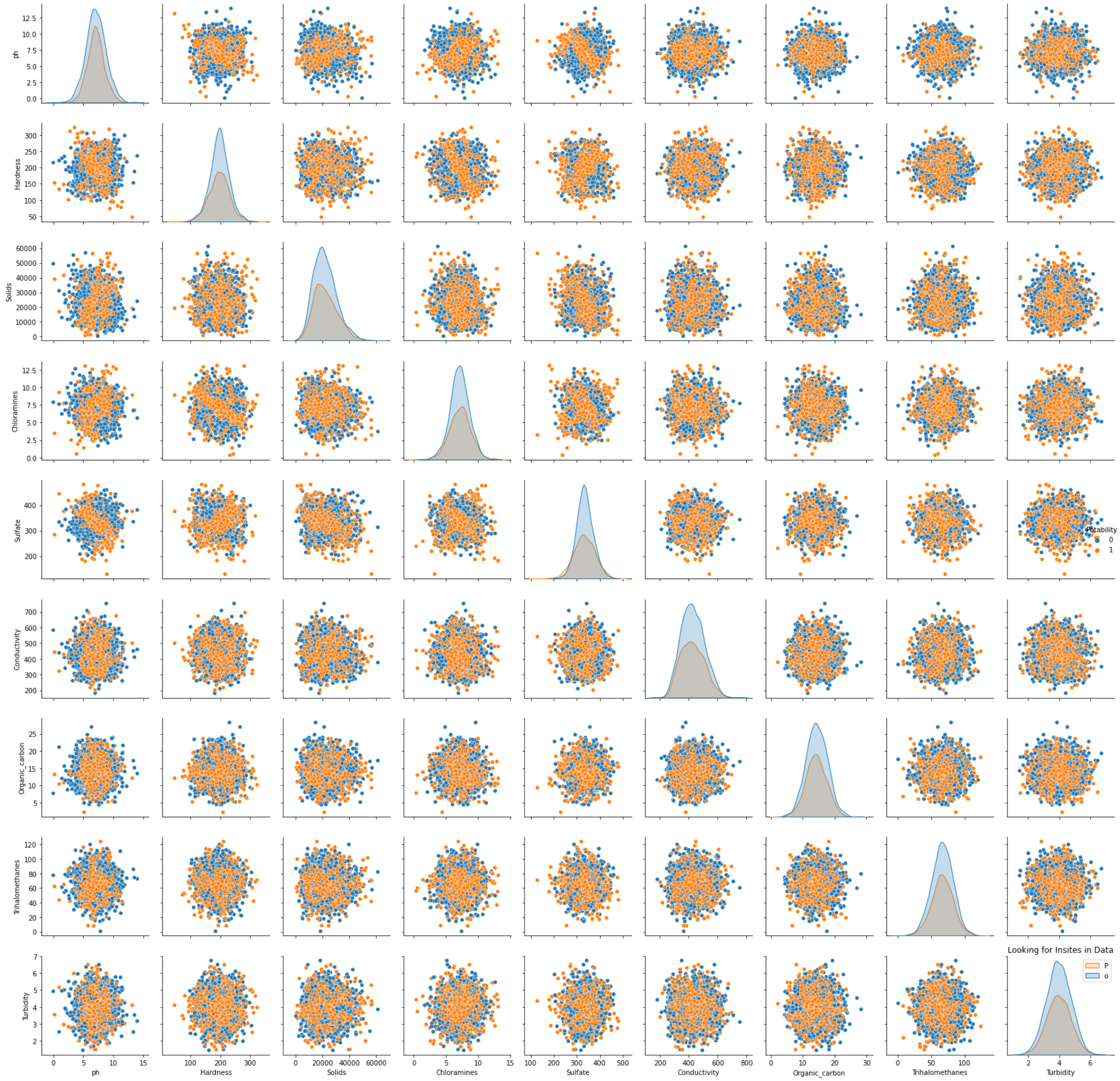


Multiple Pairwise Bivariate Distributions

In [24]:
```
plt.figure(figsize=(15,10))
sns.pairplot(df,hue="Potability")
plt.title("Looking for Insites in Data")
plt.legend("Potability")
plt.tight_layout()
plt.plot()
```

Out[24]:
```
[]
```

```
<Figure size 1080x720 with 0 Axes>
```



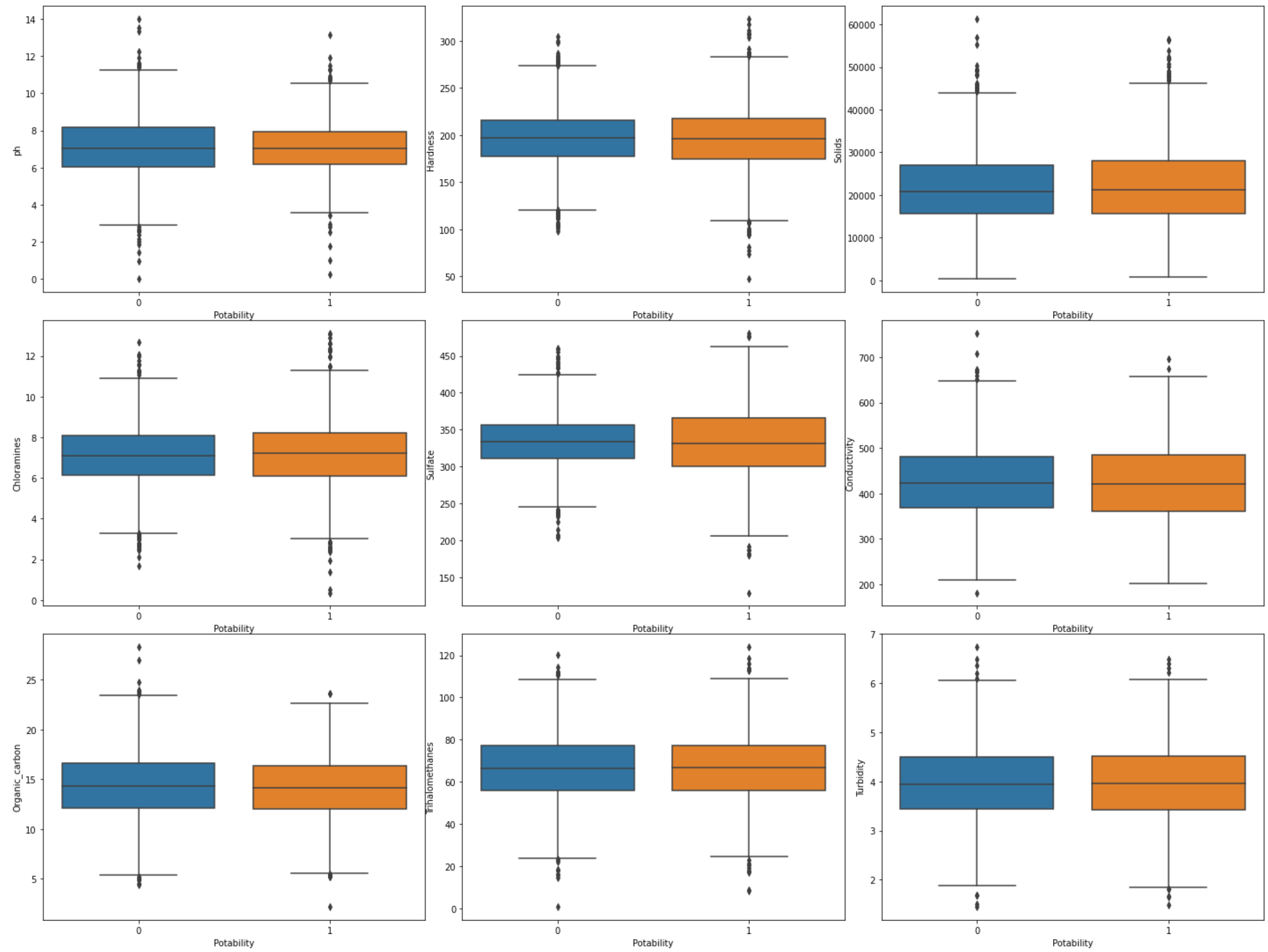
Data Pre-processing

Outliers

In [17]:
```
fig, ax = plt.subplots(3,3, figsize = (20,15))
fig.tight_layout()
k = 0
for i in range(3):
    for j in range(3):
        sns.boxplot(x="Potability", y=df.columns[k], data=df,ax=ax[i,j])
```

```
        k = k+1
plt.show
```

Out[17]: <function matplotlib.pyplot.show(close=None, block=None)>



Handling Null Values :

In [25]:

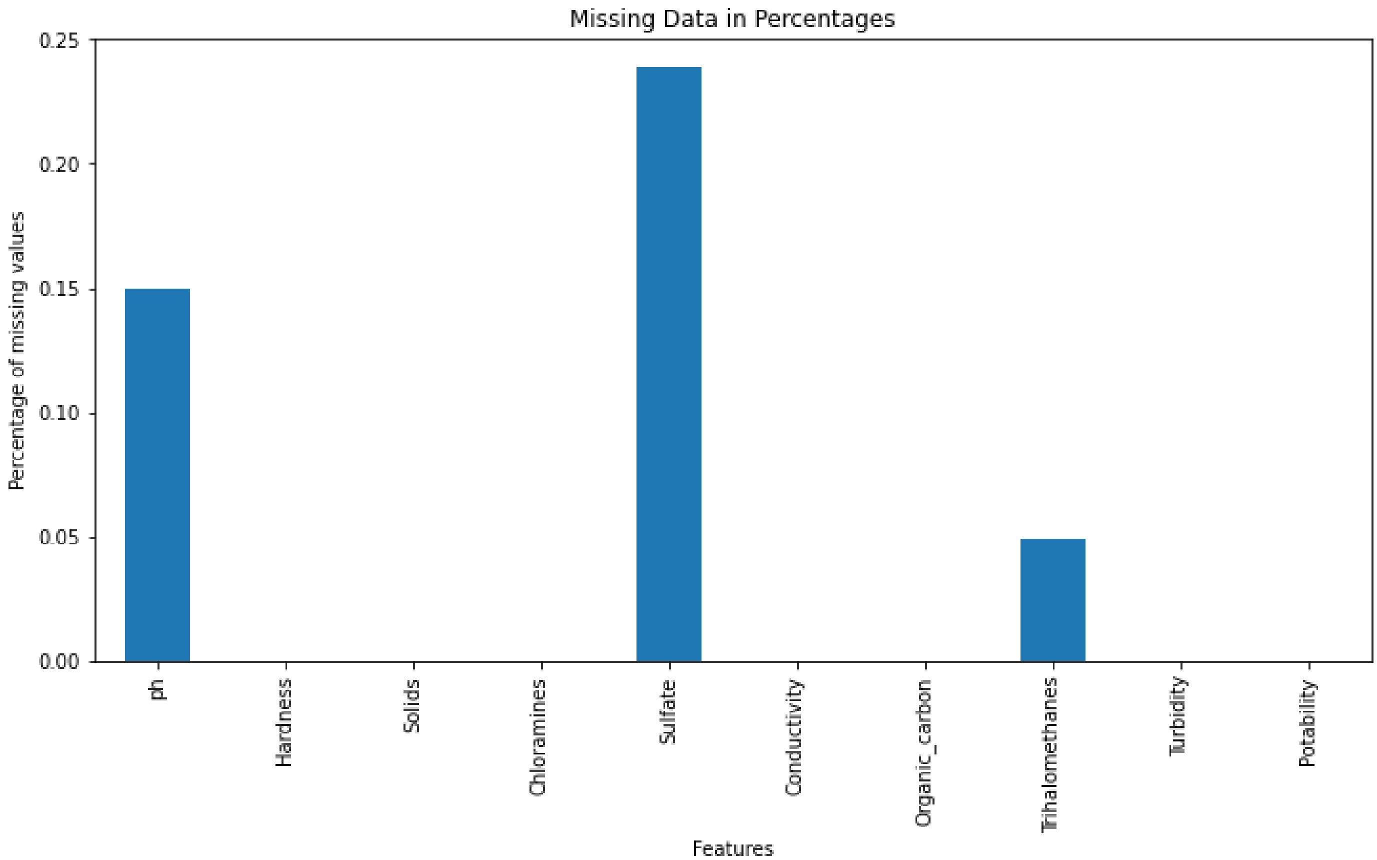
```
# Checking for NULLs in the data
df.isnull().sum()
```

Out[25]:

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

In [26]:

```
df.isnull().mean().plot.bar(figsize=(12,6))
plt.ylabel('Percentage of missing values')
plt.xlabel('Features')
plt.title('Missing Data in Percentages');
```



Pre-processing pipeline

In [48]:
```
df = pd.read_csv('water_potability.csv')

X = df.drop('Potability',axis = 'columns')
y = df['Potability']

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.20,stratify=y, ran
```

procesing test and train separately

In [49]:
```


#filling missing valueswith median
imputer = SimpleImputer(strategy='median') # median imputation ('mean' for mean and 'mos
imputer.fit(X_train) # SimpleImputer() learns the median values from the train data
X_train = imputer.transform(X_train) # replace missing values with medians
X_test = imputer.transform(X_test) # replace missing values with medians
X_test=pd.DataFrame(X_test)
X_train= pd.DataFrame(X_train)


# standardazing
# Import the StandardScaler class
from sklearn.preprocessing import StandardScaler
# Create a StandardScaler instance
scaler = StandardScaler()
# Fit the StandardScaler to the training data
scaler.fit(X_train)
# Transform the training and test data using the trained StandardScaler
X_train = scaler.transform(X_train)
X_test = scaler.transform(X_test)
X_test=pd.DataFrame(X_test)
```

```
X_train= pd.DataFrame(X_train)


#balancing
# Create a SMOTE instance
from imblearn.over_sampling import SMOTE
smote = SMOTE(sampling_strategy='minority')
# Use SMOTE to balance the training data
X_train, y_train = smote.fit_resample(X_train, y_train)
X_train= pd.DataFrame(X_train)


# Concatenate the input and target data

X_train.reset_index(drop=True, inplace=True)
y_train.reset_index(drop=True, inplace=True)

X_test.reset_index(drop=True, inplace=True)
y_test.reset_index(drop=True, inplace=True)

Train = pd.concat([X_train, y_train], axis=1)
Test = pd.concat([X_test, y_test],axis=1)
```

In [70]:
```
Train
```

Out[70]:

	0	1	2	3	4	5	6	7	8	Potability
0	-1.088364	0.674203	-0.844800	-0.961589	-0.014877	0.571636	-1.131057	0.430003	1.259188	1
1	-0.029623	-0.311281	1.044320	0.318969	-0.184158	-0.339766	1.548195	0.913298	-0.726151	1
2	0.298865	-0.111338	-0.566485	1.079502	0.357708	-1.967767	0.482451	1.076931	0.452490	0
3	-2.006272	-2.507406	2.115127	-0.406610	-0.014877	-0.420901	0.441209	0.155565	-0.583976	0
4	-2.072732	0.217984	2.320486	0.909951	-1.504019	0.952174	-0.172799	-1.272073	0.272115	0
...	...	...	...	...	...	...	...	...	...	...
3191	0.313128	0.389233	-1.584811	1.291870	2.591026	-1.106425	-0.863377	1.194495	-0.263795	1
3192	0.302798	-1.040034	-0.300742	0.893572	-1.194109	0.202403	-0.267737	0.955277	-0.403189	1
3193	0.716068	-0.337339	1.509527	0.420437	-1.268638	0.362636	-2.193536	0.220455	-0.750824	1
3194	-1.021976	-1.476991	-0.118880	0.650817	1.455481	0.129922	0.439317	0.237674	-0.034308	1
3195	-0.167317	-0.941181	1.134763	-0.992641	-1.263371	-0.447529	-1.395001	0.011099	1.444503	1

3196 rows × 10 columns

In [44]:
```
Train.to_csv('./Train2.csv', index=False)
```

In [29]:
```
Test.to_csv('./Test2.csv', index=False)
```

In [ ]: