# 01 - About the Dataset

October 23, 2022

## 1 Predicting Cement Compressive Strength

In this study, we will be predicting cement compressive strength based on its material composition. We will be using the readily available Concrete Compressive Strength data set from UCI Machine learning repository.

### 1.1 About the Dataset

> Given are the variable name, variable type, the measurement unit and a brief description. The concrete compressive strength is the regression problem. The order of this listing corresponds to the order of numerals along the rows of the database.

#### 1.1.1 Input Features:

1. **Cement** expressed in $(\frac{Kg}{m^3})$
2. **Blast Furnace Slag** expressed in $(\frac{Kg}{m^3})$
3. **Fly Ash** expressed in $(\frac{Kg}{m^3})$
4. **Water** expressed in $(\frac{Kg}{m^3})$
5. **Superplasticizer** expressed in $(\frac{Kg}{m^3})$
6. **Coarse Aggregate** expressed in $(\frac{Kg}{m^3})$
7. **Fine Aggregate** expressed in $(\frac{Kg}{m^3})$
8. **Age** expressed in days (from 1 to 365)

#### 1.1.2 Output:

1. *Concrete compressive strength* expressed in Mega-Pascals.

### 1.2 Previewing the Dataset

The following code snippets below downloads the dataset into the memory, then tabulates the first 5 observations. The next table shows the basic summary statistics.

[ ]:
```
import numpy as np
import matplotlib.pyplot as plt

import seaborn as sns
import pandas as pd

# Statistical Calculations
```

```
from statsmodels.api import qqplot
from scipy.stats import normaltest, zscore

plt.style.use(["science", "notebook"])
```

[ ]:
```
DATASET_URI = "https://archive.ics.uci.edu/ml/machine-learning-databases/
 ↪concrete/compressive/Concrete_Data.xls"

dataset = pd.read_excel(DATASET_URI)

# Replace the Headers for Readability
attributes = ["Cement", "Blast Furnace Slag", "Fly Ash", "Water",␣
 ↪"Superplasticizer", "Coarse Aggregate", "Fine Aggregate", "Age", "Concrete␣
 ↪Compressive Strength"]
dataset.columns = attributes
```

[ ]:
```
dataset.describe()
```

[ ]:
```
            Cement  Blast Furnace Slag      Fly Ash        Water  \
count  1030.000000         1030.000000  1030.000000  1030.000000
mean    281.165631           73.895485    54.187136   181.566359
std     104.507142           86.279104    63.996469    21.355567
min     102.000000            0.000000     0.000000   121.750000
25%     192.375000            0.000000     0.000000   164.900000
50%     272.900000           22.000000     0.000000   185.000000
75%     350.000000          142.950000   118.270000   192.000000
max     540.000000          359.400000   200.100000   247.000000

       Superplasticizer  Coarse Aggregate  Fine Aggregate          Age  \
count       1030.000000       1030.000000     1030.000000  1030.000000
mean           6.203112        972.918592      773.578883    45.662136
std            5.973492         77.753818       80.175427    63.169912
min            0.000000        801.000000      594.000000     1.000000
25%            0.000000        932.000000      730.950000     7.000000
50%            6.350000        968.000000      779.510000    28.000000
75%           10.160000       1029.400000      824.000000    56.000000
max           32.200000       1145.000000      992.600000   365.000000

       Concrete Compressive Strength
count                    1030.000000
mean                       35.817836
std                        16.705679
min                         2.331808
25%                        23.707115
50%                        34.442774
75%                        46.136287
max                        82.599225
```

### 1.2.1 Findings on the Dataset

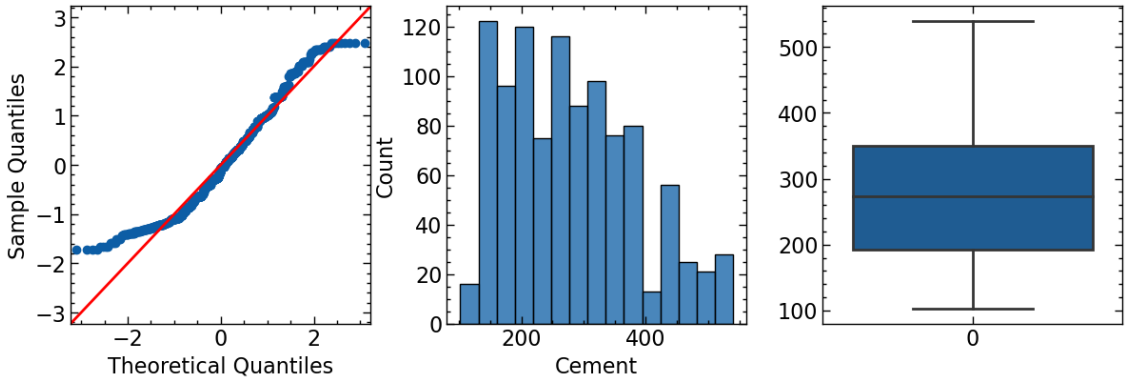
1. All 9 attributes have no missing data with a total of 1030 observations each.
2. The min and max values of all attributes were highly skewed.
3. Outliers exists on some of the attributes.

## 1.3 Visualizing the Dataset

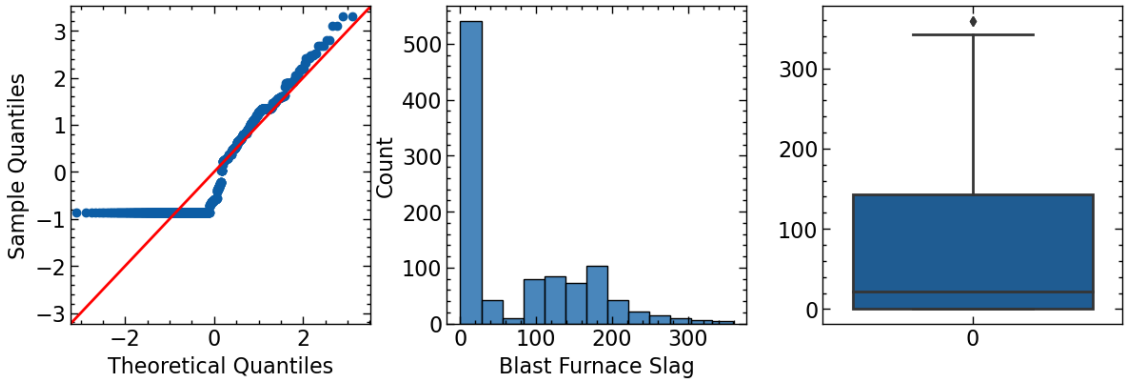
The following function below will display the QQ-plot, histogram, and box plot of a selected feature.

[ ]:
```
def visualize_attribute(attr_index):
  # Current Attribute to be visualized
  cur_attribute = dataset.iloc[:, attr_index]

  # Instanciate Matplotlib Figure
  figure, axes = plt.subplots(1,3)
  figure.set_size_inches(12,4)
  figure.tight_layout()

  # Statistical Calculations (Z-score conversion and normality tests)
  std_cur_attribute = zscore(cur_attribute)

  # Plot the attribute
  qqplot(std_cur_attribute, line='45', ax=axes[0])
  sns.histplot(cur_attribute,ax=axes[1])
  sns.boxplot(cur_attribute,ax=axes[2])
```

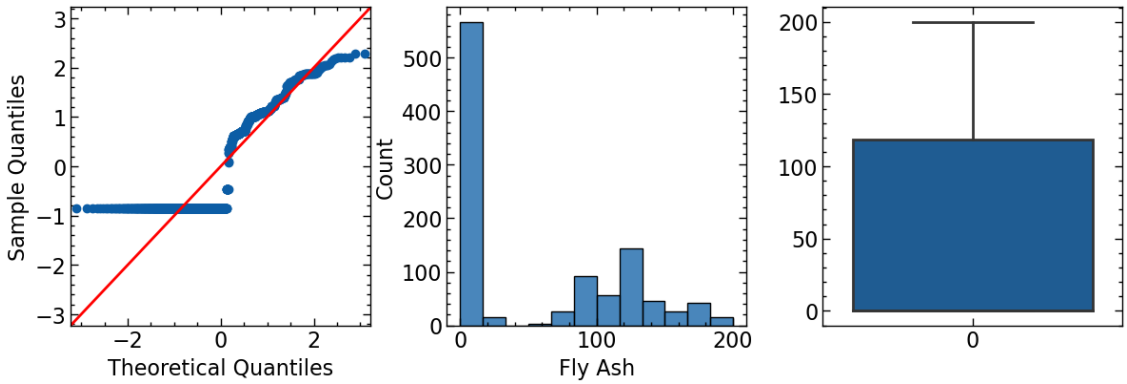
[ ]:
```
visualize_attribute(attr_index=0)
```



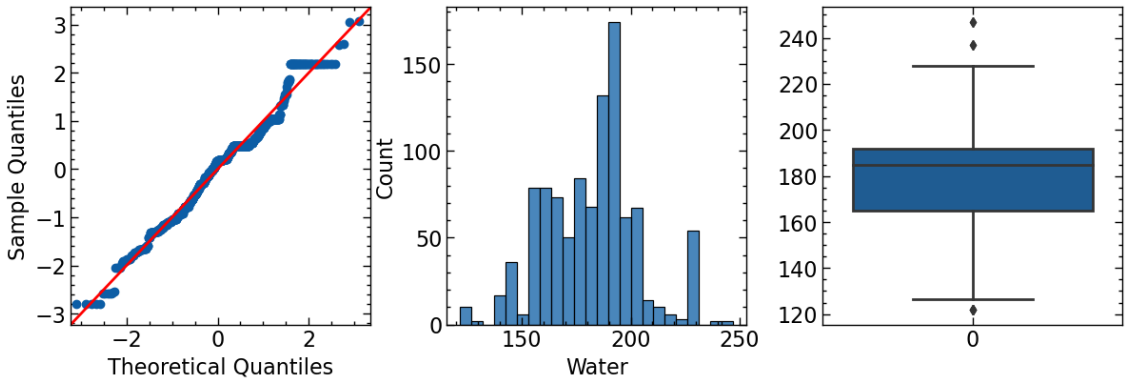

[ ]:
```
visualize_attribute(attr_index=1)
```



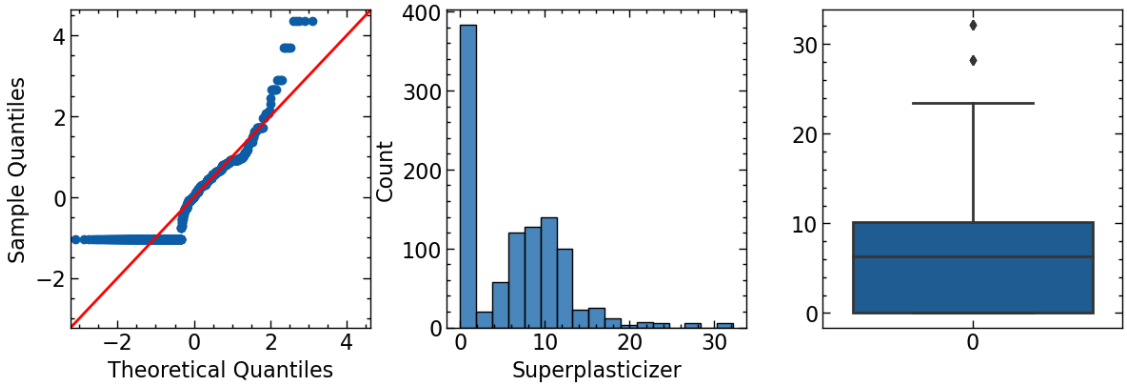

[ ]:
```
visualize_attribute(attr_index=2)
```



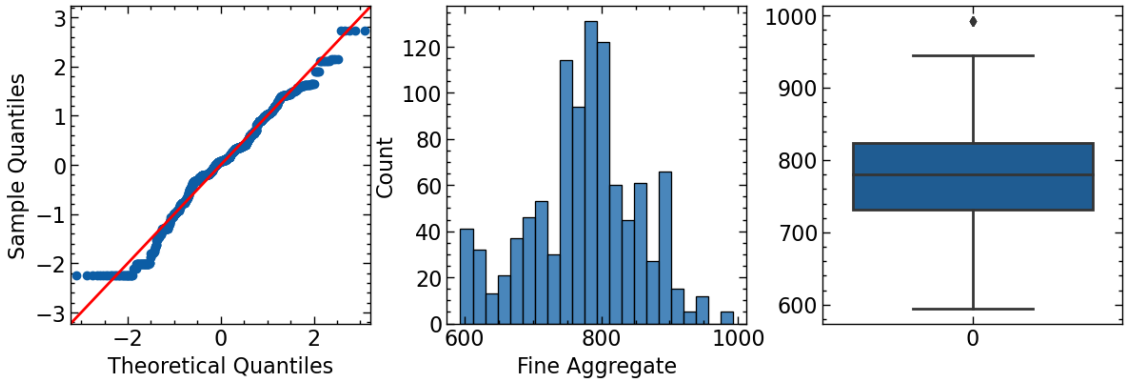

[ ]:
```
visualize_attribute(attr_index=3)
```



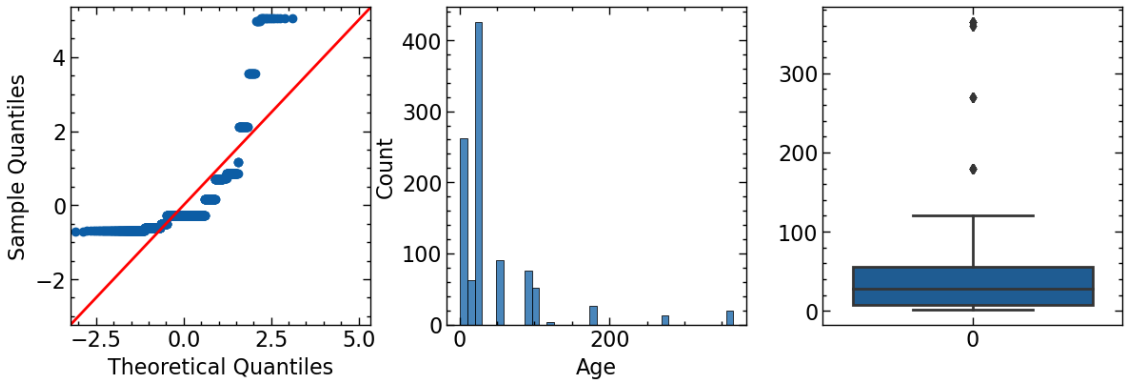

[ ]:
```
visualize_attribute(attr_index=4)
```



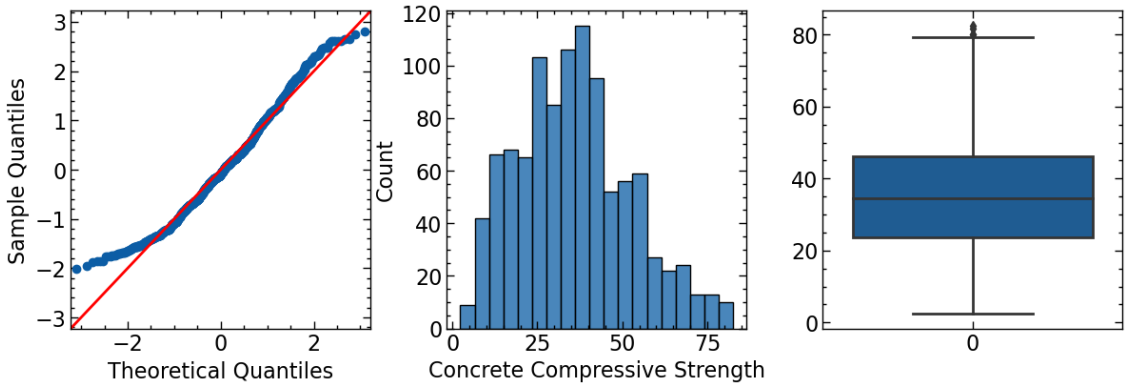

[ ]:
```
visualize_attribute(attr_index=6)
```




[ ]:
```
visualize_attribute(attr_index=7)
```




[ ]:
```
visualize_attribute(attr_index=8)
```




### 1.4 Normality Test

The following code snippets below will conduct a normality check based on D'Agostino and Pearson's tests. - **Null Hypothesis**: the dataset x comes from a normal distribution. - **Alternate Hypothesis**: the dataset does not come from a normal distribution.

[ ]:
```
def conduct_normaltest(attr_index):
  cur_attribute = dataset.iloc[:, attr_index]
  return normaltest(cur_attribute)

attrs = dataset.columns
stats = []
ps = []

for index in range(0, dataset.shape[1]):
  stats.append(conduct_normaltest(index)[0])
  ps.append(conduct_normaltest(index)[1])

pd.DataFrame({
  "Attributes": attrs,
  "Statistic": stats,
  "P-Value": ps
})
```

[ ]:

| | Attributes | Statistic | P-Value |
|---|---|---|---|
| 0 | Cement | 61.766063 | 3.869634e-14 |
| 1 | Blast Furnace Slag | 107.600073 | 4.314605e-24 |
| 2 | Fly Ash | 3991.162348 | 0.000000e+00 |
| 3 | Water | 1.663222 | 4.353474e-01 |
| 4 | Superplasticizer | 140.502118 | 3.092806e-31 |
| 5 | Coarse Aggregate | 32.569233 | 8.466052e-08 |
| 6 | Fine Aggregate | 11.188767 | 3.718691e-03 |
| 7 | Age | 727.478896 | 1.071433e-158 |

```
8  Concrete Compressive Strength    33.646242   4.940959e-08
```

### 1.4.1 Findings on the Normality Test

Based on the result of D'Agostino and Pearson's tests, only the water attribute is normally distributed. The rest of the attributes comes from a different distributions.

## 1.5 Outlier Counts

The following snippets below counts all outliers on both ends of the distribution of each attributes.

> Based on the result of normality test, only the water component is normally distributed. The rest of the attributes comes from a non-normal distribution.

[ ]:
```
Q1 = dataset.quantile(0.25)
Q3 = dataset.quantile(0.75)
IQR = Q3 - Q1
```

[ ]:
```
# Outliers less than 25th percentile
((dataset < (Q1 - 1.5 * IQR))).sum()
```

[ ]:
```
Cement                          0
Blast Furnace Slag              0
Fly Ash                         0
Water                           5
Superplasticizer                0
Coarse Aggregate                0
Fine Aggregate                  0
Age                             0
Concrete Compressive Strength   0
dtype: int64
```

[ ]:
```
# Outliers greater than 25th percentile
(dataset > (Q3 + 1.5 * IQR)).sum()
```

[ ]:
```
Cement                          0
Blast Furnace Slag              2
Fly Ash                         0
Water                           4
Superplasticizer               10
Coarse Aggregate                0
Fine Aggregate                  5
Age                            59
Concrete Compressive Strength   4
dtype: int64
```

### 1.5.1 Findings on Outlier Checks:

1. Only the water attribute have outliers below 25th percentile.

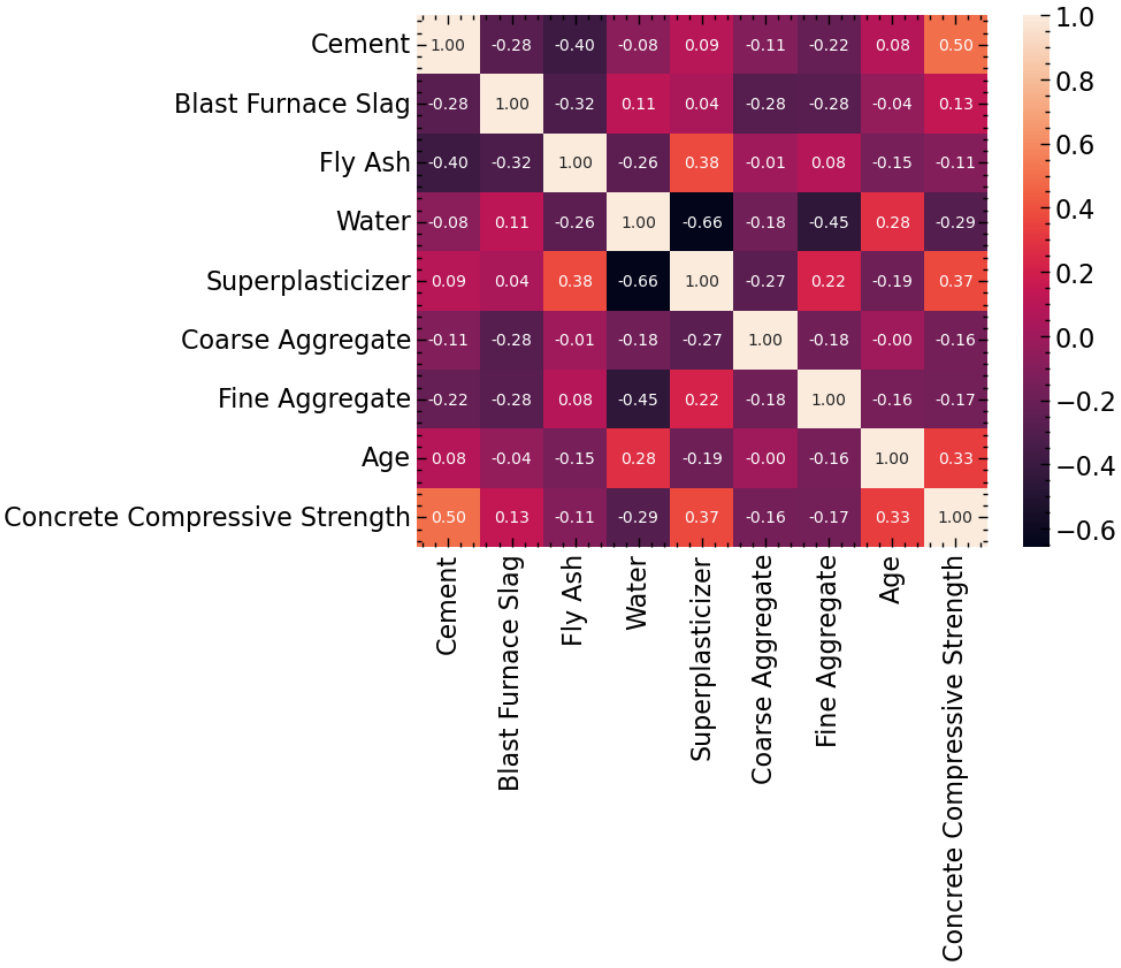
2. Age, Superplasticizer, Fine Aggregate, Water, Concrete Compressive Strength, and Blast furnace have outliers outside 75th percentile.

### 1.6 Correlation Matrix

Finally, the following code snippets below shows the correlation matrix of each attributes.

```
[ ]: sns.heatmap(dataset.apply(zscore).corr(), annot=True, fmt=".2f")
```

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




#### 1.6.1 Findings on Correlation Matrix

Not considering interaction effects among the attributes, Cement, Superplasticizer, and Age were the most highly correlated with concrete compressive strength.

## 1.7 Ending Note

Now that the dataset was explored and familiarized, machine learning preprocessing and modelling can be conducted.