In [53]:

```
# data handeling libraries
import pandas as pd
import numpy as np
from collections import OrderedDict

# data visualisation libraries

import matplotlib.pyplot as plt
import seaborn as sns

## library to filter warnings

import warnings
warnings.filterwarnings ("ignore")

##preprocessing library

from sklearn.preprocessing import StandardScaler
from sklearn.decomposition import PCA

## model bulding libraries

from sklearn.model_selection import train_test_split,cross_val_score,GridSearchCV,le

## model evaluation libraries

from sklearn.metrics import r2_score, mean_squared_error

## machien learning model libraries

from sklearn.linear_model import LinearRegression,Lasso,Ridge
from sklearn.tree import DecisionTreeRegressor
from sklearn.ensemble import RandomForestRegressor,AdaBoostRegressor,GradientBoostin
from sklearn.neighbors import KNeighborsRegressor
from sklearn.svm import SVR

import xgboost
from xgboost import XGBRegressor

## importing clustering
from sklearn.cluster import KMeans
```

In [2]:

```
df = pd.read_excel("Capstone Project.xlsx")
df.head()
```

Out[2]:

| | cement | slag | ash | water | superplastic | coarseagg | fineagg | age | strength |
|---|---|---|---|---|---|---|---|---|---|
| **0** | 141.3 | 212.0 | 0.0 | 203.5 | 0.0 | 971.8 | 748.5 | 28 | 29.89 |
| **1** | 168.9 | 42.2 | 124.3 | 158.3 | 10.8 | 1080.8 | 796.2 | 14 | 23.51 |
| **2** | 250.0 | 0.0 | 95.7 | 187.4 | 5.5 | 956.9 | 861.2 | 28 | 29.22 |
| **3** | 266.0 | 114.0 | 0.0 | 228.0 | 0.0 | 932.0 | 670.0 | 28 | 45.85 |
| **4** | 154.8 | 183.4 | 0.0 | 193.3 | 9.1 | 1047.4 | 696.7 | 28 | 18.29 |

In [3]:

```
df.shape
```

```
(1030, 9)
```

Out[3]:

In [4]:

```
def custom_summary(df):

    result = []

    for col in df.columns:

        if df[col].dtype != 'O':

            stats = OrderedDict ({
                'Feature_Name' : col,
                'Count':df[col].count(),
                'Minimum':df[col].min(),
                'Quarter 1':df[col].quantile(0.25),
                "Mean":df[col].mean(),
                'Median':df[col].median(),
                'Quarter 3':df[col].quantile(0.75),
                'Maximum':df[col].max(),
                "Variance":df[col].var(),
                'Standard Deviation':df[col].std(),
                "Kurtosis":df[col].kurt(),
                'Skewness':df[col].skew() ,
                'IQR':df[col].quantile(0.75) - df[col].quantile(0.25)
            })

            result.append(stats)


    result = pd.DataFrame(result)
    ##skewness type

    skewtype =[]

    for i in result['Skewness']:
        if i<=-1:
            skewtype.append('Highly Negatively Skewed')
        elif i<= -0.5:
            skewtype.append('Moderately Negatively Skewed')
        elif -0.5 < i < 0 :
            skewtype.append('Approx Normal Distribution (-ve)')
        elif 0 <= i < 0.5:
            skewtype.append('Approx Normal Distribution (+ve)')
        elif 0.5<= i < 1:
            skewtype.append('Moderately Positively Skewed')
        elif i >= 1:
            skewtype.append('Highly Positively Skewed')

    result['Skew_Type'] = skewtype
   ## Kurtosis Type
    k_type = []

    for i in result['Kurtosis']:
        if i <=  -1:
            k_type.append('Highly Platykurtic Curve')
        elif -1 < i <= -0.5:
            k_type.append('Moderately Platykurtic Curve')
        elif -0.5 < i <= 0.5:
            k_type.append('Mesokurtic Curve')
        elif 0.5<= i < 1:
            k_type.append('Moderately Leptokurtic Curve')
        elif i >= 1:
            k_type.append('Highly Leptokurtic Curve')
```

```
    result['Kurtosis_Type'] = k_type

    #Outlier detection


    Upper_limit = stats['Quarter 3'] + 1.5*stats['IQR']

    lower_limit = stats['Quarter 1'] -1.5*stats['IQR']

    if len([x for x in df[col] if (x < lower_limit) or (x > Upper_limit)]) > 0:

        outlier_comment = 'has outliers'
        outlier_percentage = len([x for x in df[col] if (x < lower_limit) or (x > Up
    else:
        oulier_comment = 'no outliers'

        outlier_percentage = 0

    result['outlier_comment'] = outlier_comment

    result['outlier_percentage'] = outlier_percentage

    return result
```

In [5]:

```
custom_summary(df)
```

Out[5]:

| | Feature_Name | Count | Minimum | Quarter 1 | Mean | Median | Quarter 3 | Maximum | Varianc |
|---|---|---|---|---|---|---|---|---|---|
| **0** | cement | 1030 | 102.00 | 192.375 | 281.167864 | 272.900 | 350.000 | 540.0 | 10921.58022 |
| **1** | slag | 1030 | 0.00 | 0.000 | 73.895825 | 22.000 | 142.950 | 359.4 | 7444.12481 |
| **2** | ash | 1030 | 0.00 | 0.000 | 54.188350 | 0.000 | 118.300 | 200.1 | 4095.61654 |
| **3** | water | 1030 | 121.80 | 164.900 | 181.567282 | 185.000 | 192.000 | 247.0 | 456.00265 |
| **4** | superplastic | 1030 | 0.00 | 0.000 | 6.204660 | 6.400 | 10.200 | 32.2 | 35.68678 |
| **5** | coarseagg | 1030 | 801.00 | 932.000 | 972.918932 | 968.000 | 1029.400 | 1145.0 | 6045.67735 |
| **6** | fineagg | 1030 | 594.00 | 730.950 | 773.580485 | 779.500 | 824.000 | 992.6 | 6428.18779 |

| | Feature_Name | Count | Minimum | Quarter 1 | Mean | Median | Quarter 3 | Maximum | Varianc |
|---|---|---|---|---|---|---|---|---|---|
| 7 | age | 1030 | 1.00 | 7.000 | 45.662136 | 28.000 | 56.000 | 365.0 | 3990.43772 |
| 8 | strength | 1030 | 2.33 | 23.710 | 35.817961 | 34.445 | 46.135 | 82.6 | 279.08181 |

# conclusions from the custom summary

In [6]:
```
# 1 from the above custom summary we can say that there are no any null values.
# 2 from the above data we can say that age is highly positively skewed
# 3 cement,slag,ash,superplastic this features are moderately positively skewed
# 4 age and superplastic is highly leptokurtic.
# 5 ash is highly platykurtic.
# 6 almost all columns in the dataset has outliers and in same %
# so there are high chances that some particular records are noisy.
# 7 from maximum age we can say that data is for yearly data.
```

In [7]:
```
def outlier_treatment(df,col,method="quartile",strategy = "median"):
    col_data = df[col]

    # using quartile method to find outliers

    if method == "quartile":
        q2 = df[col].median()
        q1 = df[col].quantile(0.25)
        q3 = df[col].quantile(0.75)
        iqr = q3-q1
        lowerlimit = q1 - 1.5*iqr
        upperlimit = q3 + 1.5*iqr

     # using std dav method to find outliers

    elif method == "standerd_daviation":
        col_mean = df[col].mean()
        col_std = df[col].std()
        lowerlimit = col_mean - 2*col_std
        upperlimit = col_mean + 2*col_std

    else:
        print("Pass a correct method")

    # printing outliers

    outliers = df.loc[( col_data < lowerlimit ) | (col_data > upperlimit) ,col]
    outlier_density = round(len(outliers)/len(df),2)

    if len(outliers) == 0 :
        print(f"the column {col} has no outliers")
    else:
        print(f"the column {col} has outliers")
        print("the outlier percentage is", outlier_density)
        print("outliers of column are : ")
        display(df[( col_data < lowerlimit ) | (col_data > upperlimit)])
```

```
    ## replacing outliers
    if strategy == "median":
        df.loc[( col_data < lowerlimit ) | (col_data > upperlimit) ,col] = df[col].m

    elif strategy == "mean":
        df.loc[( col_data < lowerlimit ) | (col_data > upperlimit) ,col] = df[col].m

    else:
        print("Pass a correct strategy")

    return (df)
```

# ODT plots : Outlier detection plot

- in this we plot three graphs
- 1 Boxplot for descriptive statistics
- 2 histogram with outliers
- 3 histogram without outliers

In [8]:

```
def odt_plot(df,col):
    f,(ax1,ax2,ax3) = plt.subplots(1,3,figsize=(20,20))

    # plotting boxplot

    sns.boxplot(df[col],ax=ax1)
    ax1.set_title(col + " Boxplot")
    ax1.set_xlabel("Boxplot")
    ax1.set_ylabel("Values")

    # plotting Histogram with outliers

    sns.distplot(df[col],ax=ax2)
    ax2.set_title(col + " Histogram with outliers")
    ax2.set_xlabel("Density")
    ax2.set_ylabel("Values")


    # plotting Histogram without outliers

    y = outlier_treatment(df,col)

    sns.distplot(y[col],ax=ax3)
    ax3.set_title(col + " Histogram without outliers")
    ax3.set_xlabel("Density")
    ax3.set_ylabel("Values")
```

In [9]:

```
for col in df.columns:
    odt_plot(df,col)
```

```
the column cement has no outliers
the column slag has outliers
the outlier percentage is 0.0
outliers of column are :
```

| | cement | slag | ash | water | superplastic | coarseagg | fineagg | age | strength |
|---|---|---|---|---|---|---|---|---|---|
| **918** | 239.6 | 359.4 | 0.0 | 185.7 | 0.0 | 941.6 | 664.3 | 28 | 39.44 |

| | cement | slag | ash | water | superplastic | coarseagg | fineagg | age | strength |
|---|---|---|---|---|---|---|---|---|---|
| **990** | 239.6 | 359.4 | 0.0 | 185.7 | 0.0 | 941.6 | 664.3 | 7 | 25.42 |

```
the column ash has no outliers
the column water has outliers
the outlier percentage is 0.01
outliers of column are :
```

| | cement | slag | ash | water | superplastic | coarseagg | fineagg | age | strength |
|---|---|---|---|---|---|---|---|---|---|
| **66** | 237.0 | 92.0 | 71.0 | 247.0 | 6.0 | 853.0 | 695.0 | 28 | 28.63 |
| **263** | 236.9 | 91.7 | 71.5 | 246.9 | 6.0 | 852.9 | 695.4 | 28 | 28.63 |
| **432** | 168.0 | 42.1 | 163.8 | 121.8 | 5.7 | 1058.7 | 780.1 | 28 | 24.24 |
| **462** | 168.0 | 42.1 | 163.8 | 121.8 | 5.7 | 1058.7 | 780.1 | 100 | 39.23 |
| **587** | 168.0 | 42.1 | 163.8 | 121.8 | 5.7 | 1058.7 | 780.1 | 3 | 7.75 |
| **740** | 140.0 | 164.0 | 128.0 | 237.0 | 6.0 | 869.0 | 656.0 | 28 | 35.23 |
| **789** | 168.0 | 42.1 | 163.8 | 121.8 | 5.7 | 1058.7 | 780.1 | 56 | 32.85 |
| **826** | 139.7 | 163.9 | 127.7 | 236.7 | 5.8 | 868.6 | 655.6 | 28 | 35.23 |
| **914** | 168.0 | 42.1 | 163.8 | 121.8 | 5.7 | 1058.7 | 780.1 | 14 | 17.82 |

```
the column superplastic has outliers
the outlier percentage is 0.01
outliers of column are :
```

| | cement | slag | ash | water | superplastic | coarseagg | fineagg | age | strength |
|---|---|---|---|---|---|---|---|---|---|
| **44** | 531.3 | 0.0 | 0.0 | 141.8 | 28.2 | 852.1 | 893.7 | 91 | 59.2 |
| **156** | 531.3 | 0.0 | 0.0 | 141.8 | 28.2 | 852.1 | 893.7 | 28 | 56.4 |
| **232** | 469.0 | 117.2 | 0.0 | 137.8 | 32.2 | 852.1 | 840.5 | 56 | 69.3 |
| **292** | 469.0 | 117.2 | 0.0 | 137.8 | 32.2 | 852.1 | 840.5 | 91 | 70.7 |
| **538** | 531.3 | 0.0 | 0.0 | 141.8 | 28.2 | 852.1 | 893.7 | 7 | 46.9 |
| **744** | 469.0 | 117.2 | 0.0 | 137.8 | 32.2 | 852.1 | 840.5 | 7 | 54.9 |
| **816** | 469.0 | 117.2 | 0.0 | 137.8 | 32.2 | 852.1 | 840.5 | 28 | 66.9 |
| **838** | 531.3 | 0.0 | 0.0 | 141.8 | 28.2 | 852.1 | 893.7 | 56 | 58.8 |
| **955** | 469.0 | 117.2 | 0.0 | 137.8 | 32.2 | 852.1 | 840.5 | 3 | 40.2 |
| **1026** | 531.3 | 0.0 | 0.0 | 141.8 | 28.2 | 852.1 | 893.7 | 3 | 41.3 |

```
the column coarseagg has no outliers
the column fineagg has outliers
the outlier percentage is 0.0
outliers of column are :
```

| | cement | slag | ash | water | superplastic | coarseagg | fineagg | age | strength |
|---|---|---|---|---|---|---|---|---|---|
| **129** | 375.0 | 93.8 | 0.0 | 126.6 | 23.4 | 852.1 | 992.6 | 91 | 62.5 |
| **447** | 375.0 | 93.8 | 0.0 | 126.6 | 23.4 | 852.1 | 992.6 | 7 | 45.7 |
| **504** | 375.0 | 93.8 | 0.0 | 126.6 | 23.4 | 852.1 | 992.6 | 3 | 29.0 |
| **584** | 375.0 | 93.8 | 0.0 | 126.6 | 23.4 | 852.1 | 992.6 | 56 | 60.2 |
| **857** | 375.0 | 93.8 | 0.0 | 126.6 | 23.4 | 852.1 | 992.6 | 28 | 56.7 |

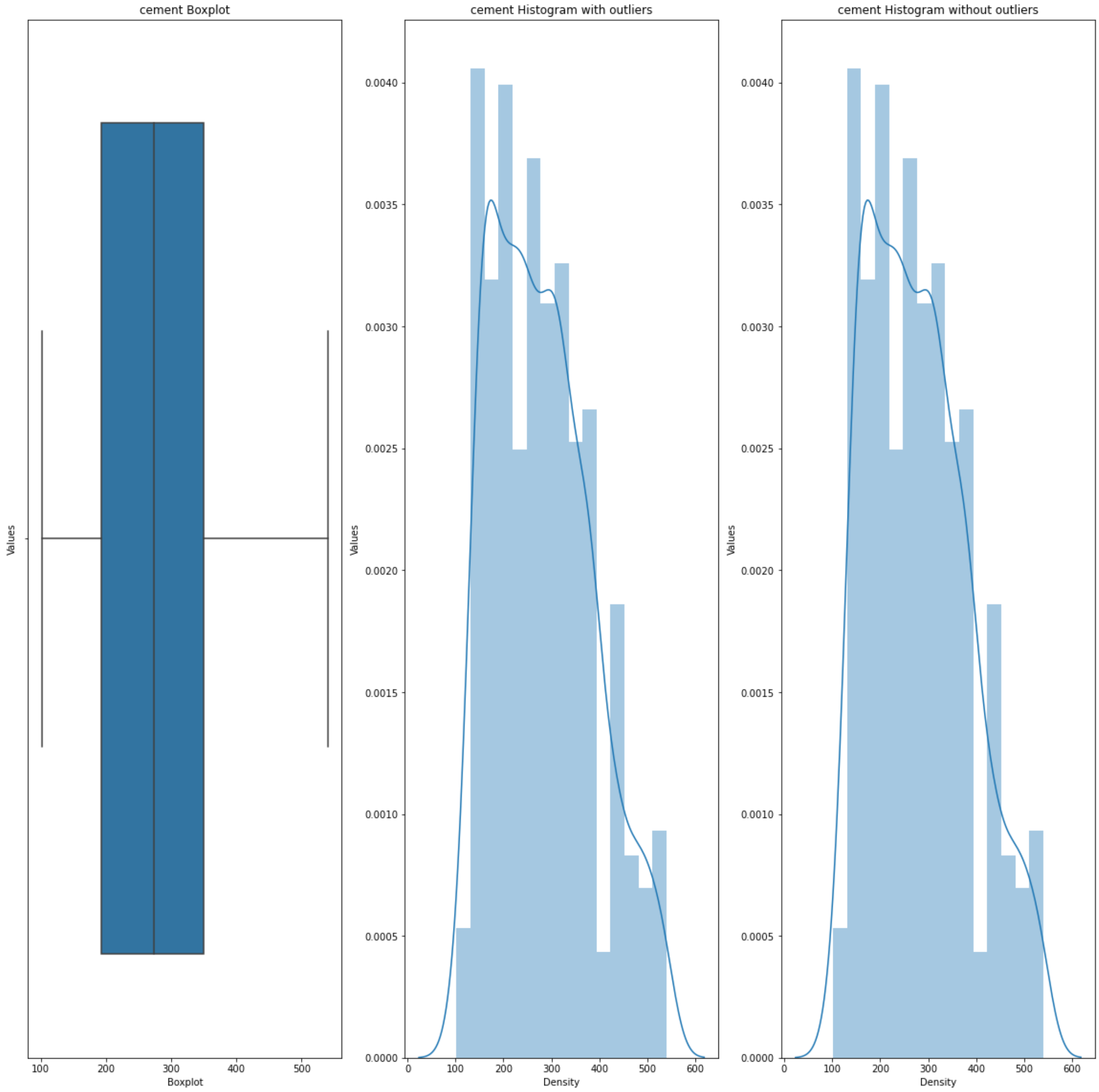
```
the column age has outliers
the outlier percentage is 0.06
outliers of column are :
```

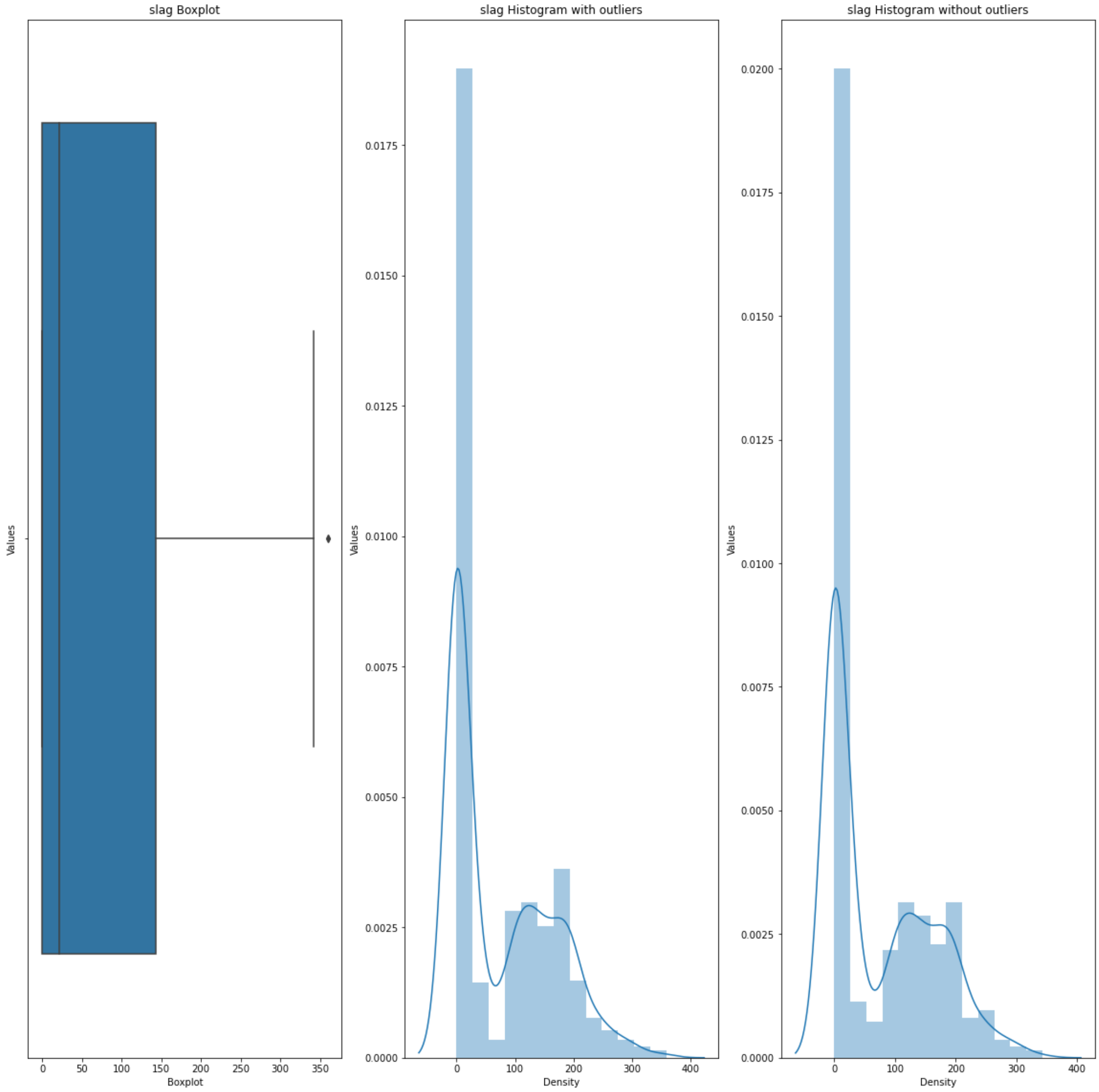
| | cement | slag | ash | water | superplastic | coarseagg | fineagg | age | strength |
|---|---|---|---|---|---|---|---|---|---|
| **51** | 331.0 | 0.0 | 0.0 | 192.0 | 0.0 | 978.0 | 825.0 | 180 | 39.00 |
| **64** | 332.5 | 142.5 | 0.0 | 228.0 | 0.0 | 932.0 | 594.0 | 365 | 41.05 |
| **93** | 427.5 | 47.5 | 0.0 | 228.0 | 0.0 | 932.0 | 594.0 | 180 | 41.84 |
| **99** | 237.5 | 237.5 | 0.0 | 228.0 | 0.0 | 932.0 | 594.0 | 180 | 36.25 |
| **103** | 380.0 | 0.0 | 0.0 | 228.0 | 0.0 | 932.0 | 670.0 | 180 | 53.10 |
| **133** | 236.0 | 0.0 | 0.0 | 193.0 | 0.0 | 968.0 | 885.0 | 365 | 25.08 |
| **144** | 302.0 | 0.0 | 0.0 | 203.0 | 0.0 | 974.0 | 817.0 | 180 | 26.74 |
| **149** | 380.0 | 95.0 | 0.0 | 228.0 | 0.0 | 932.0 | 594.0 | 270 | 41.15 |
| **152** | 322.0 | 0.0 | 0.0 | 203.0 | 0.0 | 974.0 | 800.0 | 180 | 29.59 |
| **157** | 198.6 | 132.4 | 0.0 | 192.0 | 0.0 | 978.4 | 825.5 | 360 | 44.30 |
| **159** | 304.0 | 76.0 | 0.0 | 228.0 | 0.0 | 932.0 | 670.0 | 365 | 55.26 |
| **198** | 266.0 | 114.0 | 0.0 | 228.0 | 0.0 | 932.0 | 670.0 | 365 | 52.91 |
| **199** | 277.0 | 0.0 | 0.0 | 191.0 | 0.0 | 968.0 | 856.0 | 180 | 32.33 |
| **207** | 190.0 | 190.0 | 0.0 | 228.0 | 0.0 | 932.0 | 670.0 | 180 | 46.93 |
| **256** | 525.0 | 0.0 | 0.0 | 189.0 | 0.0 | 1125.0 | 613.0 | 270 | 67.11 |
| **262** | 266.0 | 114.0 | 0.0 | 228.0 | 0.0 | 932.0 | 670.0 | 270 | 51.73 |
| **270** | 500.0 | 0.0 | 0.0 | 200.0 | 0.0 | 1125.0 | 613.0 | 270 | 55.16 |
| **297** | 475.0 | 0.0 | 0.0 | 228.0 | 0.0 | 932.0 | 594.0 | 270 | 42.13 |
| **302** | 342.0 | 38.0 | 0.0 | 228.0 | 0.0 | 932.0 | 670.0 | 180 | 52.12 |
| **312** | 236.0 | 0.0 | 0.0 | 193.0 | 0.0 | 968.0 | 885.0 | 180 | 24.10 |
| **313** | 540.0 | 0.0 | 0.0 | 173.0 | 0.0 | 1125.0 | 613.0 | 270 | 74.17 |
| **323** | 139.6 | 209.4 | 0.0 | 192.0 | 0.0 | 1047.0 | 806.9 | 360 | 44.70 |
| **359** | 475.0 | 0.0 | 0.0 | 228.0 | 0.0 | 932.0 | 594.0 | 180 | 42.62 |
| **361** | 277.0 | 0.0 | 0.0 | 191.0 | 0.0 | 968.0 | 856.0 | 360 | 33.70 |
| **370** | 266.0 | 114.0 | 0.0 | 228.0 | 0.0 | 932.0 | 670.0 | 180 | 48.70 |
| **393** | 342.0 | 38.0 | 0.0 | 228.0 | 0.0 | 932.0 | 670.0 | 365 | 56.14 |
| **448** | 331.0 | 0.0 | 0.0 | 192.0 | 0.0 | 978.0 | 825.0 | 360 | 41.24 |
| **465** | 427.5 | 47.5 | 0.0 | 228.0 | 0.0 | 932.0 | 594.0 | 365 | 43.70 |
| **484** | 237.5 | 237.5 | 0.0 | 228.0 | 0.0 | 932.0 | 594.0 | 365 | 39.00 |
| **539** | 304.0 | 76.0 | 0.0 | 228.0 | 0.0 | 932.0 | 670.0 | 180 | 50.95 |
| **570** | 190.0 | 190.0 | 0.0 | 228.0 | 0.0 | 932.0 | 670.0 | 270 | 50.66 |
| **581** | 525.0 | 0.0 | 0.0 | 189.0 | 0.0 | 1125.0 | 613.0 | 180 | 61.92 |
| **594** | 339.0 | 0.0 | 0.0 | 197.0 | 0.0 | 968.0 | 781.0 | 180 | 36.45 |
| **601** | 339.0 | 0.0 | 0.0 | 197.0 | 0.0 | 968.0 | 781.0 | 365 | 38.89 |

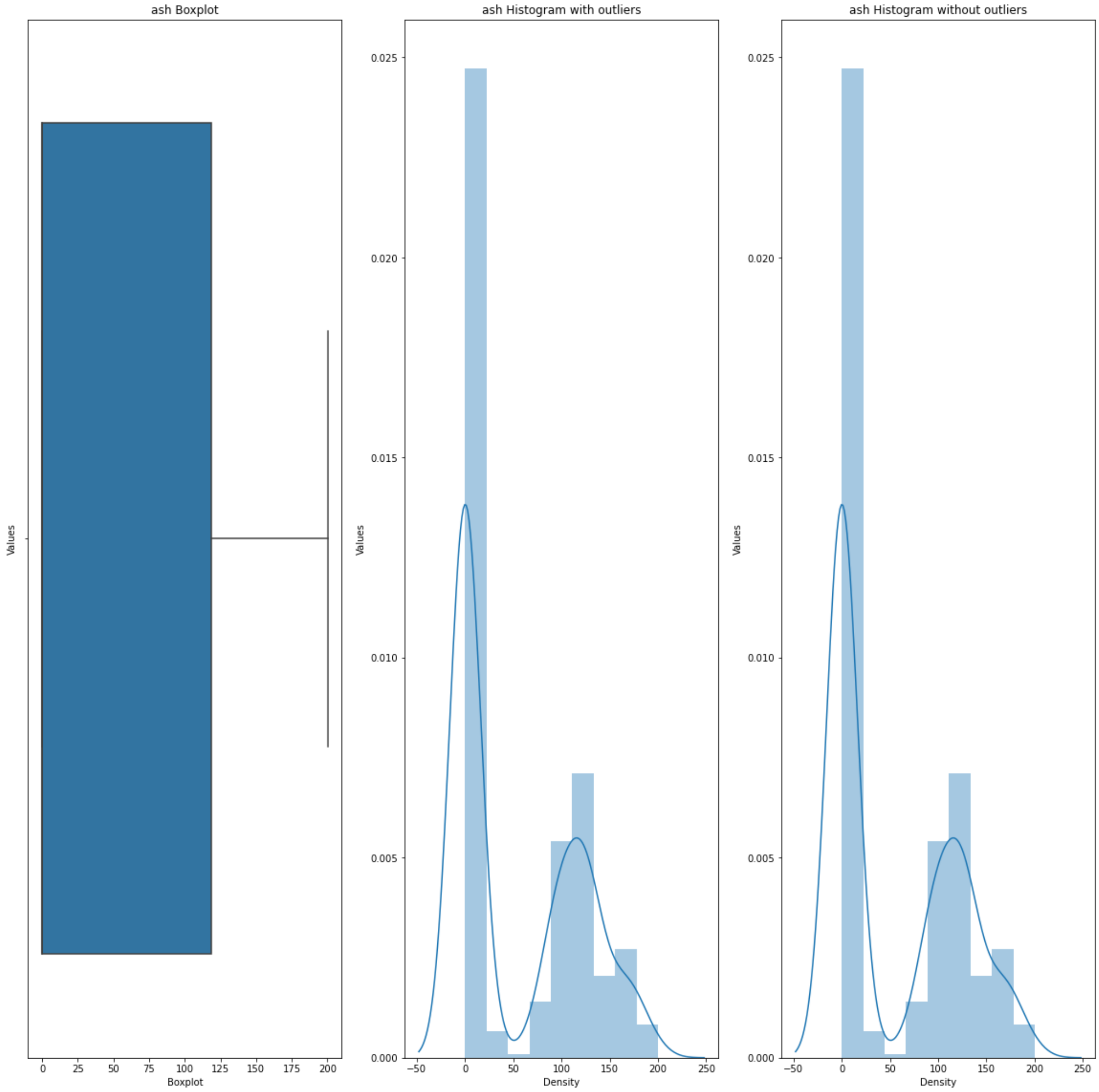
| | cement | slag | ash | water | superplastic | coarseagg | fineagg | age | strength |
|---|---|---|---|---|---|---|---|---|---|
| **620** | 332.5 | 142.5 | 0.0 | 228.0 | 0.0 | 932.0 | 594.0 | 180 | 39.78 |
| **622** | 380.0 | 95.0 | 0.0 | 228.0 | 0.0 | 932.0 | 594.0 | 180 | 40.76 |
| **623** | 380.0 | 0.0 | 0.0 | 228.0 | 0.0 | 932.0 | 670.0 | 270 | 53.30 |
| **632** | 304.0 | 76.0 | 0.0 | 228.0 | 0.0 | 932.0 | 670.0 | 270 | 54.38 |
| **642** | 198.6 | 132.4 | 0.0 | 192.0 | 0.0 | 978.4 | 825.5 | 180 | 41.72 |
| **696** | 307.0 | 0.0 | 0.0 | 193.0 | 0.0 | 968.0 | 812.0 | 180 | 34.49 |
| **713** | 190.0 | 190.0 | 0.0 | 228.0 | 0.0 | 932.0 | 670.0 | 365 | 53.69 |
| **720** | 380.0 | 95.0 | 0.0 | 228.0 | 0.0 | 932.0 | 594.0 | 365 | 43.70 |
| **721** | 500.0 | 0.0 | 0.0 | 200.0 | 0.0 | 1125.0 | 613.0 | 180 | 51.04 |
| **754** | 254.0 | 0.0 | 0.0 | 198.0 | 0.0 | 968.0 | 863.0 | 365 | 29.79 |
| **755** | 349.0 | 0.0 | 0.0 | 192.0 | 0.0 | 1047.0 | 806.0 | 360 | 42.13 |
| **776** | 540.0 | 0.0 | 0.0 | 173.0 | 0.0 | 1125.0 | 613.0 | 180 | 71.62 |
| **850** | 427.5 | 47.5 | 0.0 | 228.0 | 0.0 | 932.0 | 594.0 | 270 | 43.01 |
| **861** | 310.0 | 0.0 | 0.0 | 192.0 | 0.0 | 970.0 | 850.0 | 180 | 37.33 |
| **878** | 237.5 | 237.5 | 0.0 | 228.0 | 0.0 | 932.0 | 594.0 | 270 | 38.41 |
| **900** | 254.0 | 0.0 | 0.0 | 198.0 | 0.0 | 968.0 | 863.0 | 180 | 27.63 |
| **901** | 475.0 | 0.0 | 0.0 | 228.0 | 0.0 | 932.0 | 594.0 | 365 | 41.93 |
| **919** | 310.0 | 0.0 | 0.0 | 192.0 | 0.0 | 970.0 | 850.0 | 360 | 38.11 |
| **951** | 332.5 | 142.5 | 0.0 | 228.0 | 0.0 | 932.0 | 594.0 | 270 | 40.27 |
| **957** | 307.0 | 0.0 | 0.0 | 193.0 | 0.0 | 968.0 | 812.0 | 365 | 36.15 |
| **971** | 349.0 | 0.0 | 0.0 | 192.0 | 0.0 | 1047.0 | 806.0 | 180 | 41.05 |
| **985** | 350.0 | 0.0 | 0.0 | 203.0 | 0.0 | 974.0 | 775.0 | 180 | 32.72 |
| **995** | 380.0 | 0.0 | 0.0 | 228.0 | 0.0 | 932.0 | 670.0 | 365 | 52.52 |
| **1017** | 139.6 | 209.4 | 0.0 | 192.0 | 0.0 | 1047.0 | 806.9 | 180 | 44.21 |
| **1028** | 342.0 | 38.0 | 0.0 | 228.0 | 0.0 | 932.0 | 670.0 | 270 | 55.06 |

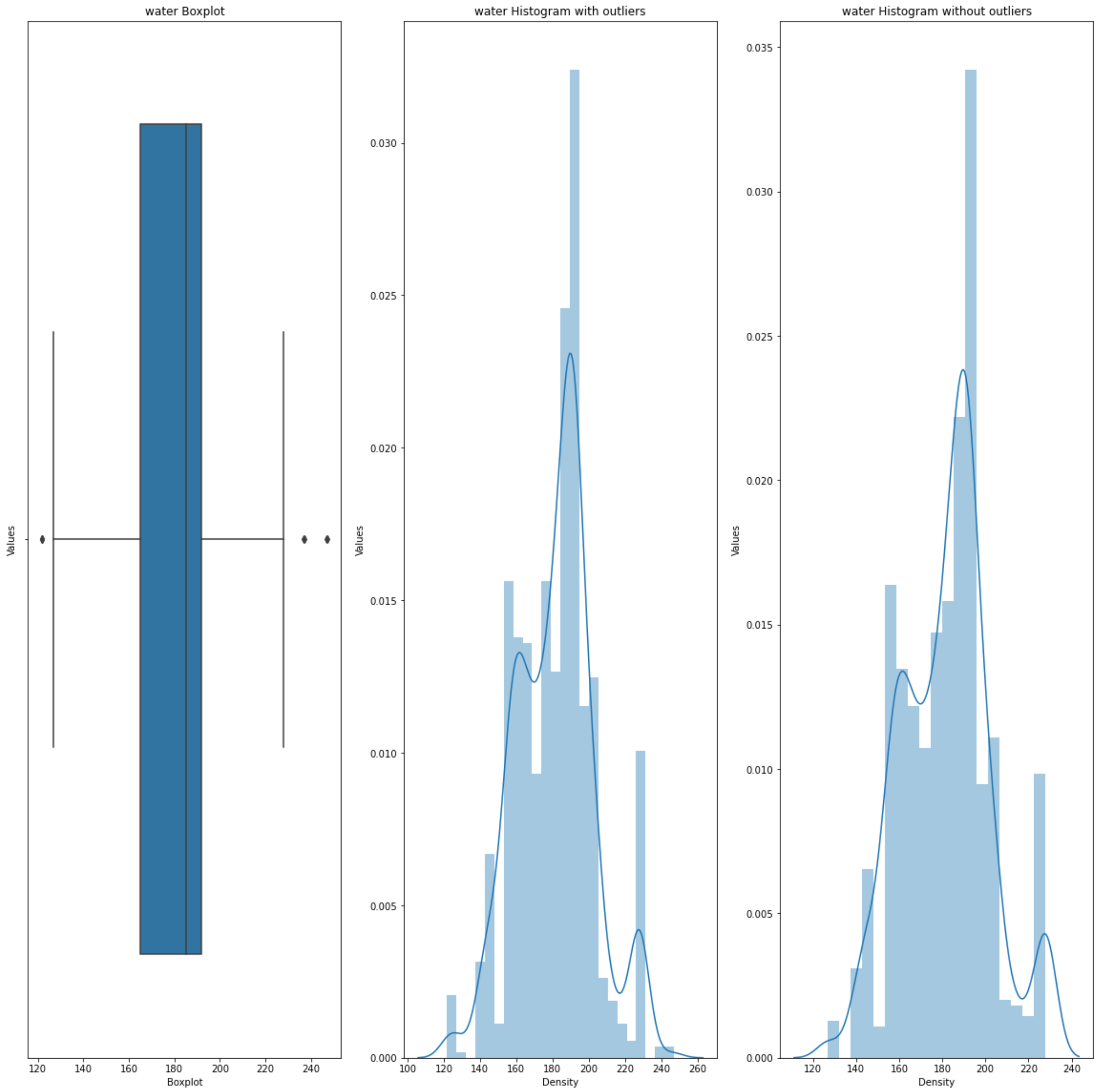
```
the column strength has outliers
the outlier percentage is 0.0
outliers of column are :
```

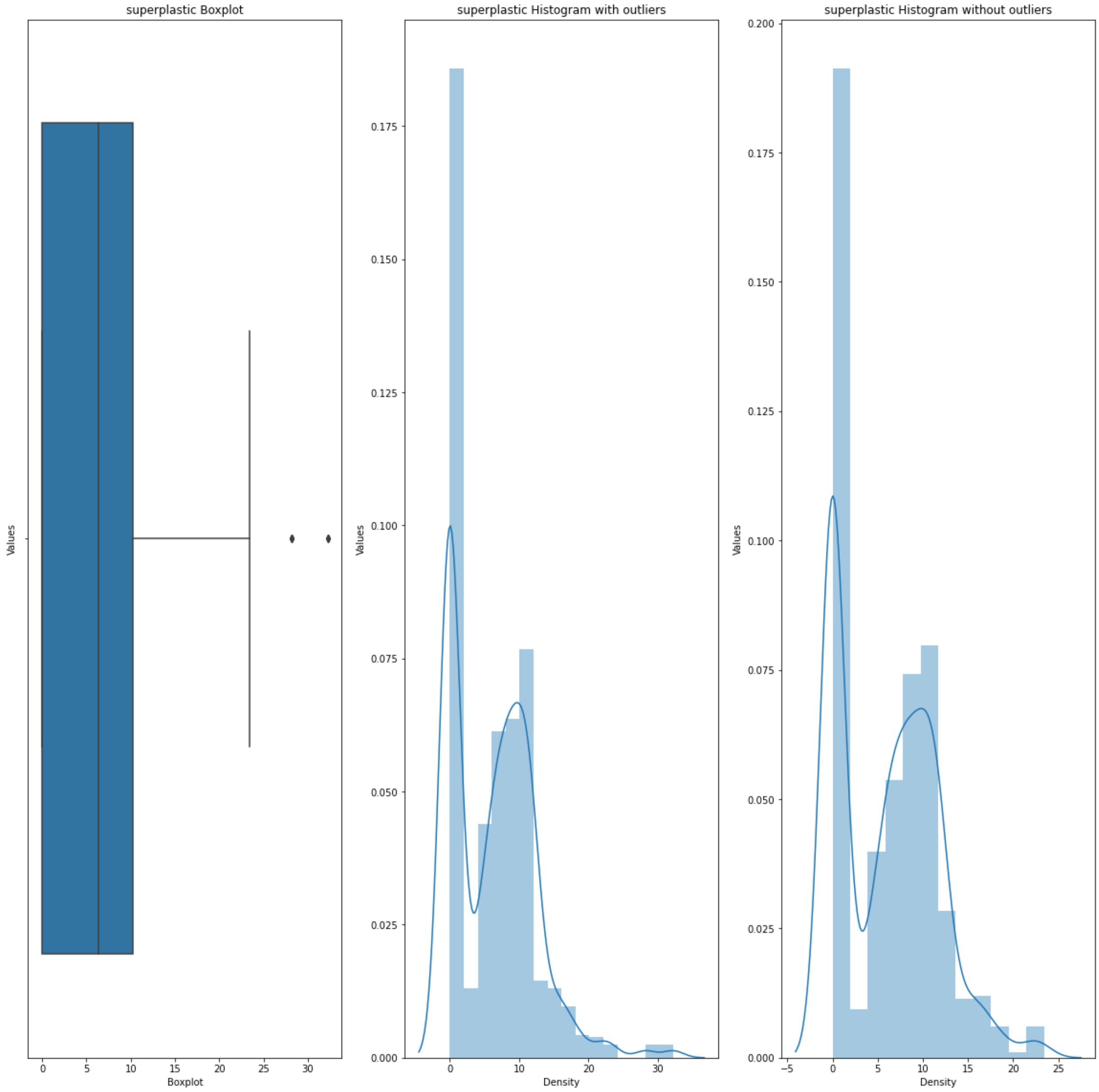
| | cement | slag | ash | water | superplastic | coarseagg | fineagg | age | strength |
|---|---|---|---|---|---|---|---|---|---|
| **192** | 315.0 | 137.0 | 0.0 | 145.0 | 5.9 | 1130.0 | 745.0 | 28 | 81.75 |
| **732** | 540.0 | 0.0 | 0.0 | 162.0 | 2.5 | 1040.0 | 676.0 | 28 | 79.99 |
| **950** | 389.9 | 189.0 | 0.0 | 145.9 | 22.0 | 944.7 | 755.8 | 91 | 82.60 |
| **1003** | 323.7 | 282.8 | 0.0 | 183.8 | 10.3 | 942.7 | 659.9 | 56 | 80.20 |

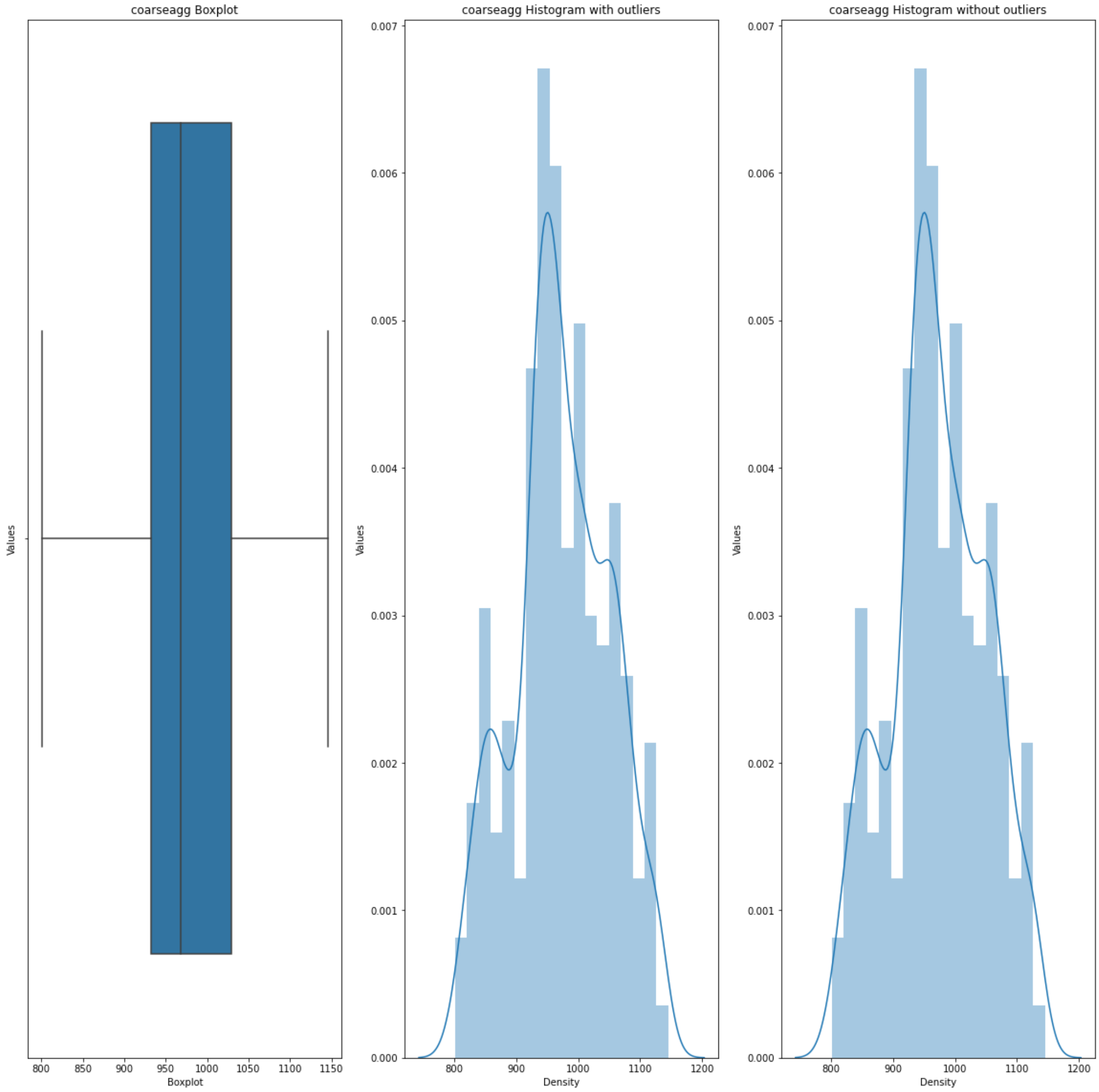

cement Boxplot
Values
Boxplot
100
200
300
400
500
cement Histogram with outliers
Values
Density
0.0000
0.0005
0.0010
0.0015
0.0020
0.0025
0.0030
0.0035
0.0040
0
100
200
300
400
500
600
cement Histogram without outliers
Values
Density
0.0000
0.0005
0.0010
0.0015
0.0020
0.0025
0.0030
0.0035
0.0040
0
100
200
300
400
500
600

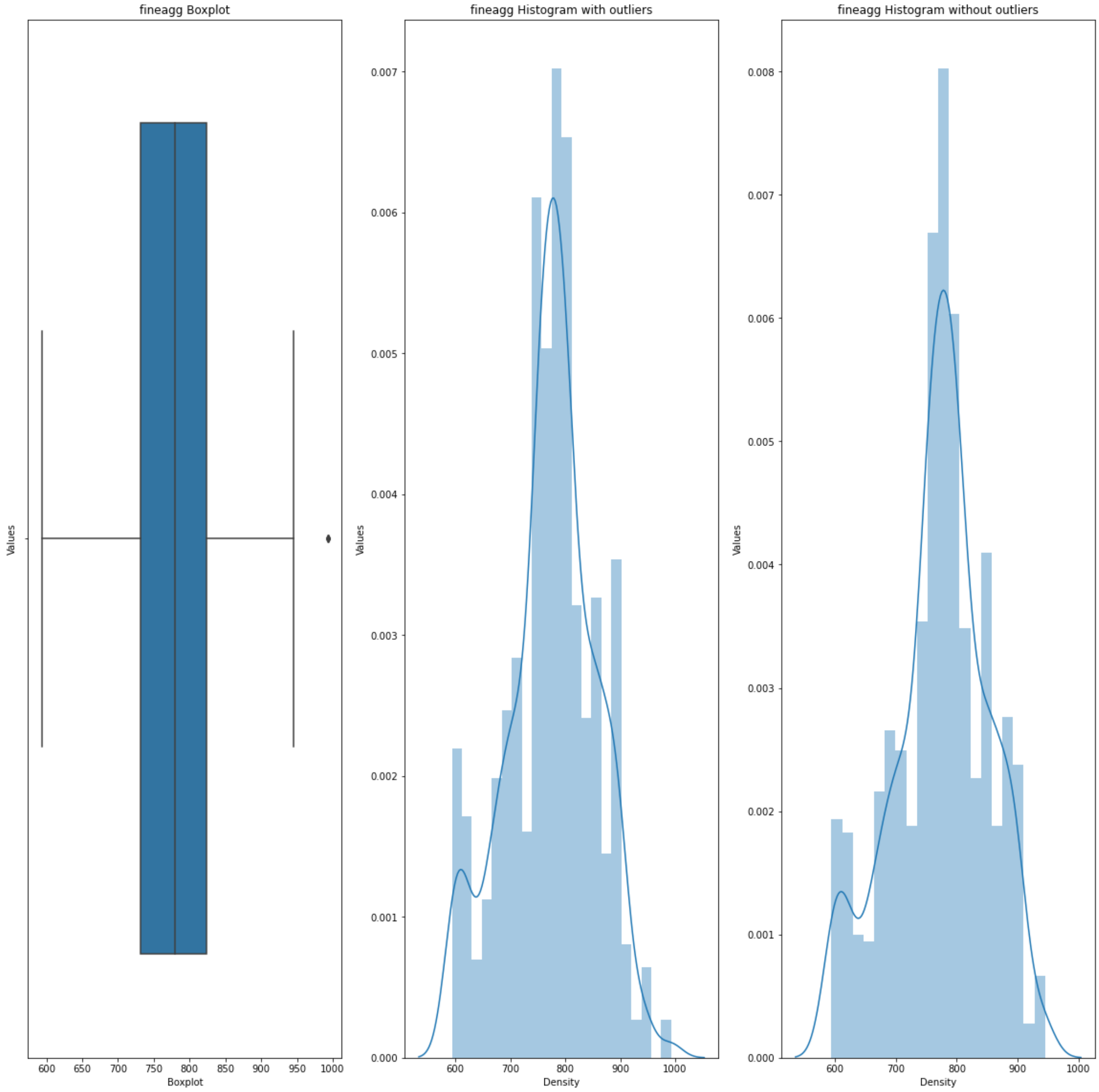

slag Boxplot
Values
Boxplot
0
50
100
150
200
250
300
350
slag Histogram with outliers
Values
Density
0.0000
0.0025
0.0050
0.0075
0.0100
0.0125
0.0150
0.0175
0
100
200
300
400
slag Histogram without outliers
Values
Density
0.0000
0.0025
0.0050
0.0075
0.0100
0.0125
0.0150
0.0175
0.0200
0
100
200
300
400

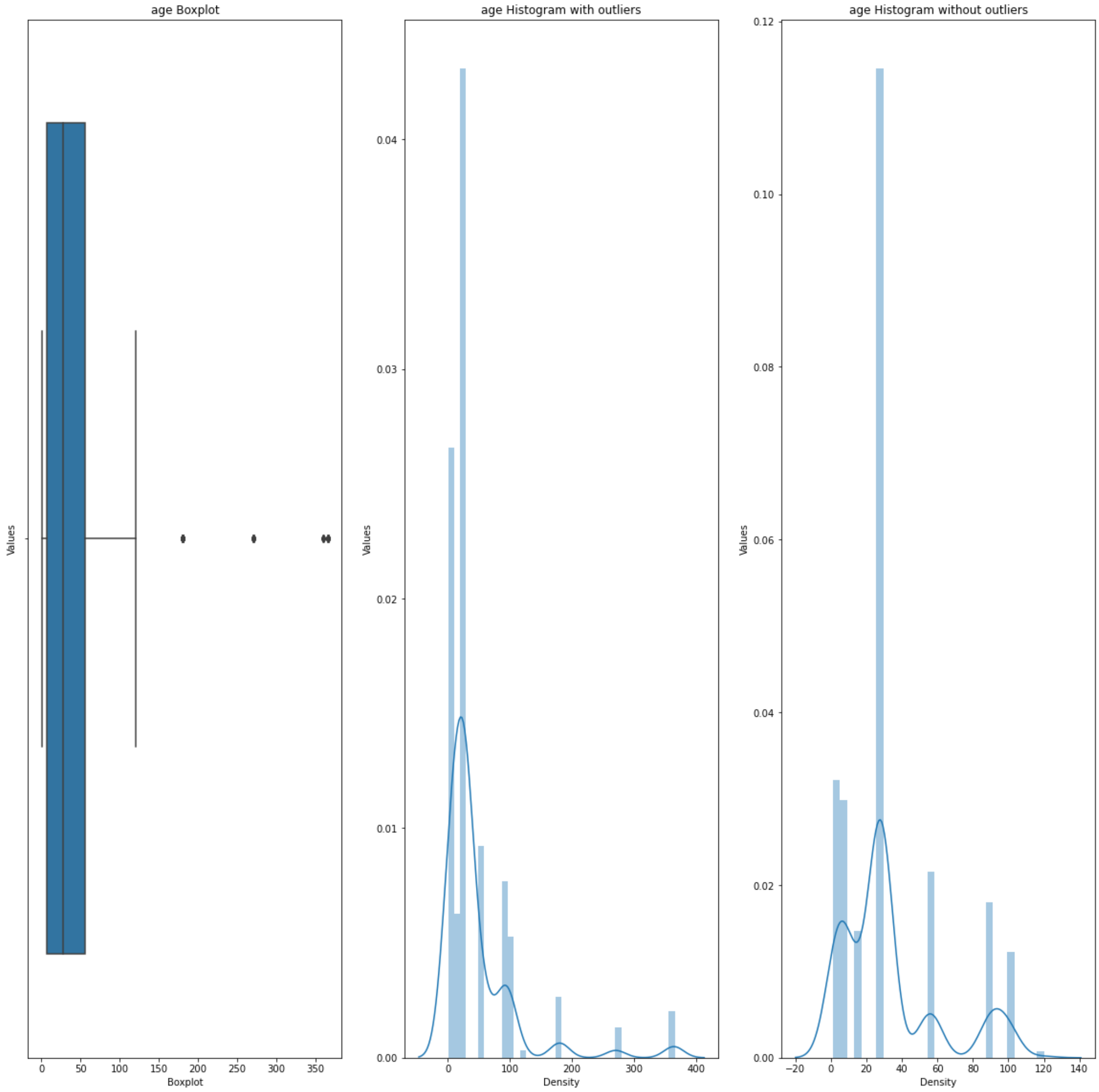

ash Boxplot
Values
Boxplot
0
25
50
75
100
125
150
175
200
ash Histogram with outliers
Values
Density
0.000
0.005
0.010
0.015
0.020
0.025
−50
0
50
100
150
200
250
ash Histogram without outliers
Values
Density
0.000
0.005
0.010
0.015
0.020
0.025
−50
0
50
100
150
200
250

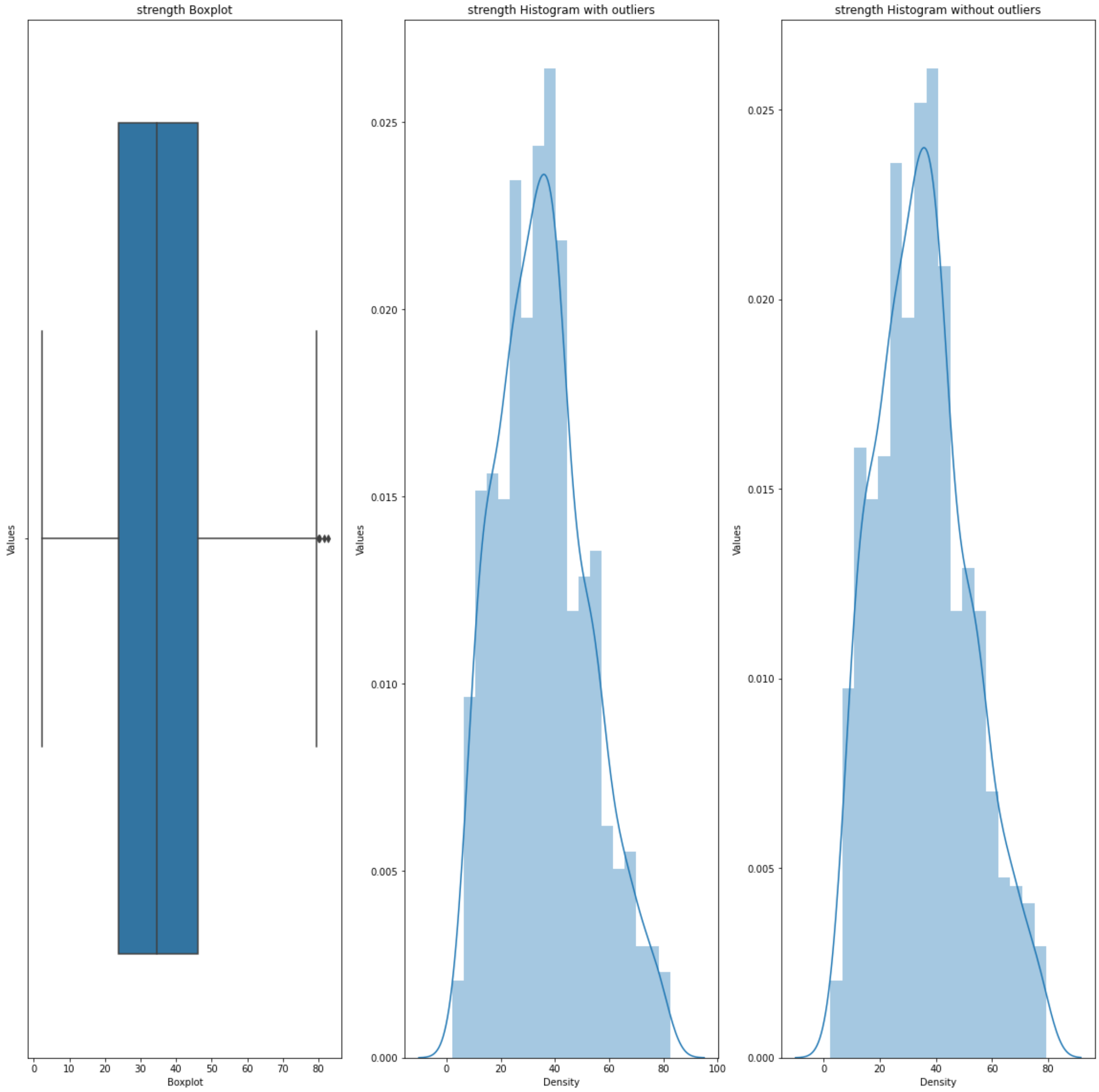

water Boxplot
Values
Boxplot
water Histogram with outliers
Values
Density
water Histogram without outliers
Values
Density


superplastic Boxplot
Values
Boxplot
0
5
10
15
20
25
30
superplastic Histogram with outliers
Values
Density
0.000
0.025
0.050
0.075
0.100
0.125
0.150
0.175
0
10
20
30
superplastic Histogram without outliers
Values
Density
0.000
0.025
0.050
0.075
0.100
0.125
0.150
0.175
0.200
−5
0
5
10
15
20
25


coarseagg Boxplot
Values
800
850
900
950
1000
1050
1100
1150
Boxplot
coarseagg Histogram with outliers
0.000
0.001
0.002
0.003
0.004
0.005
0.006
0.007
Values
800
900
1000
1100
1200
Density
coarseagg Histogram without outliers
0.000
0.001
0.002
0.003
0.004
0.005
0.006
0.007
Values
800
900
1000
1100
1200
Density

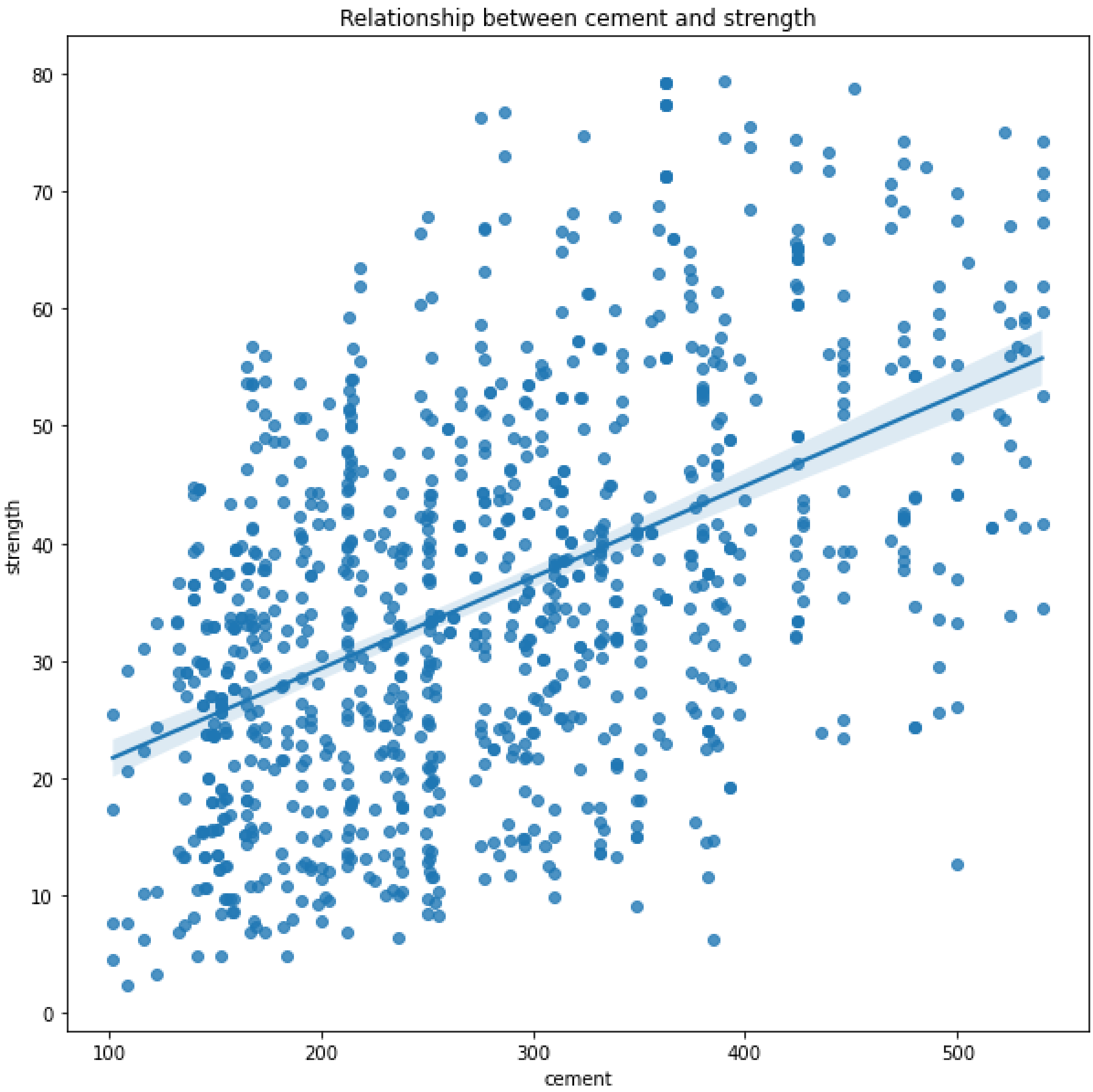

fineagg Boxplot
Values
600
650
700
750
800
850
900
950
1000
Boxplot
fineagg Histogram with outliers
Values
0.000
0.001
0.002
0.003
0.004
0.005
0.006
0.007
600
700
800
900
1000
Density
fineagg Histogram without outliers
Values
0.000
0.001
0.002
0.003
0.004
0.005
0.006
0.007
0.008
600
700
800
900
1000
Density

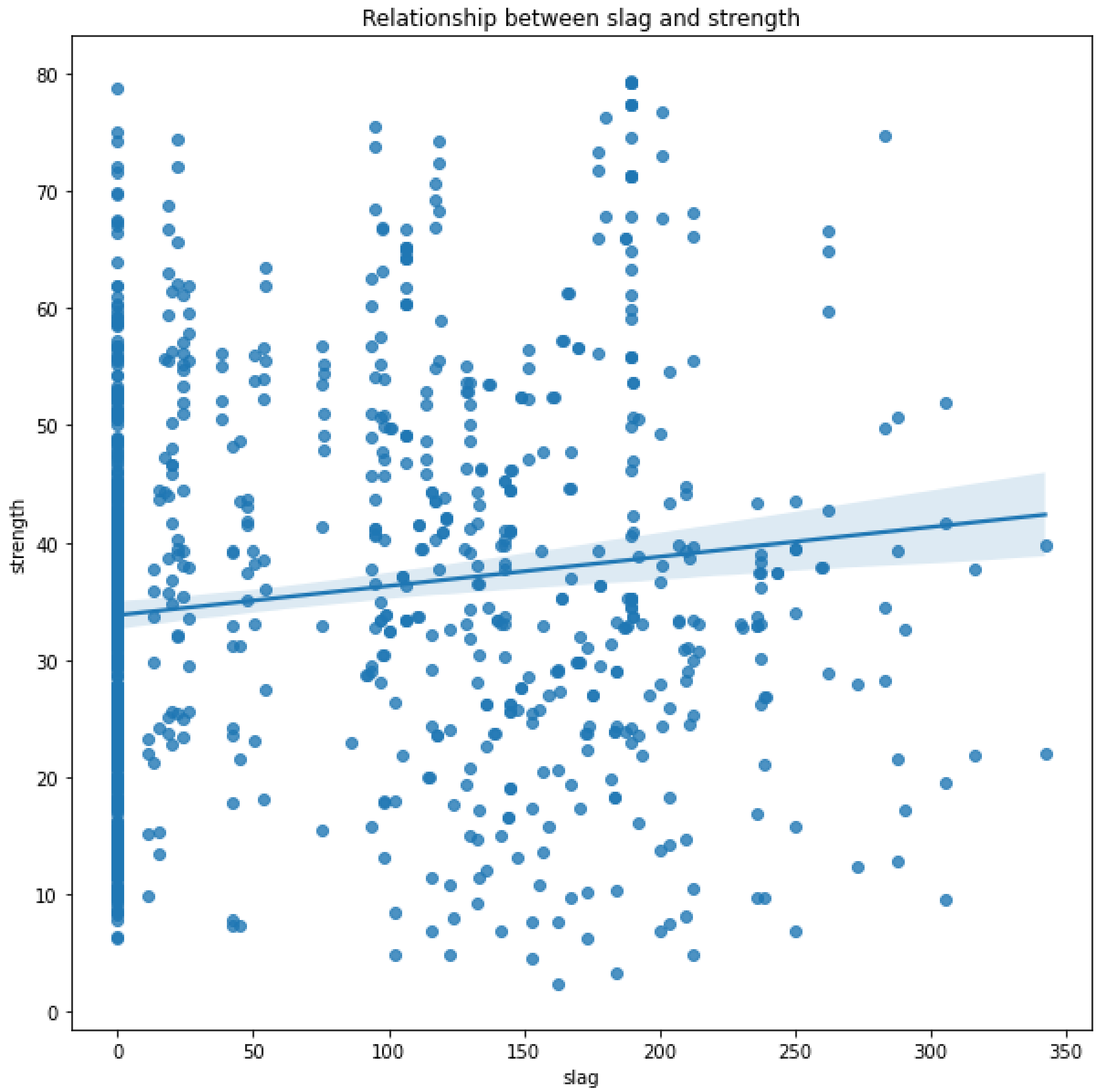

age Boxplot
Values
Boxplot
0
50
100
150
200
250
300
350
age Histogram with outliers
Values
Density
0.00
0.01
0.02
0.03
0.04
0
100
200
300
400
age Histogram without outliers
Values
Density
0.00
0.02
0.04
0.06
0.08
0.10
0.12
−20
0
20
40
60
80
100
120
140

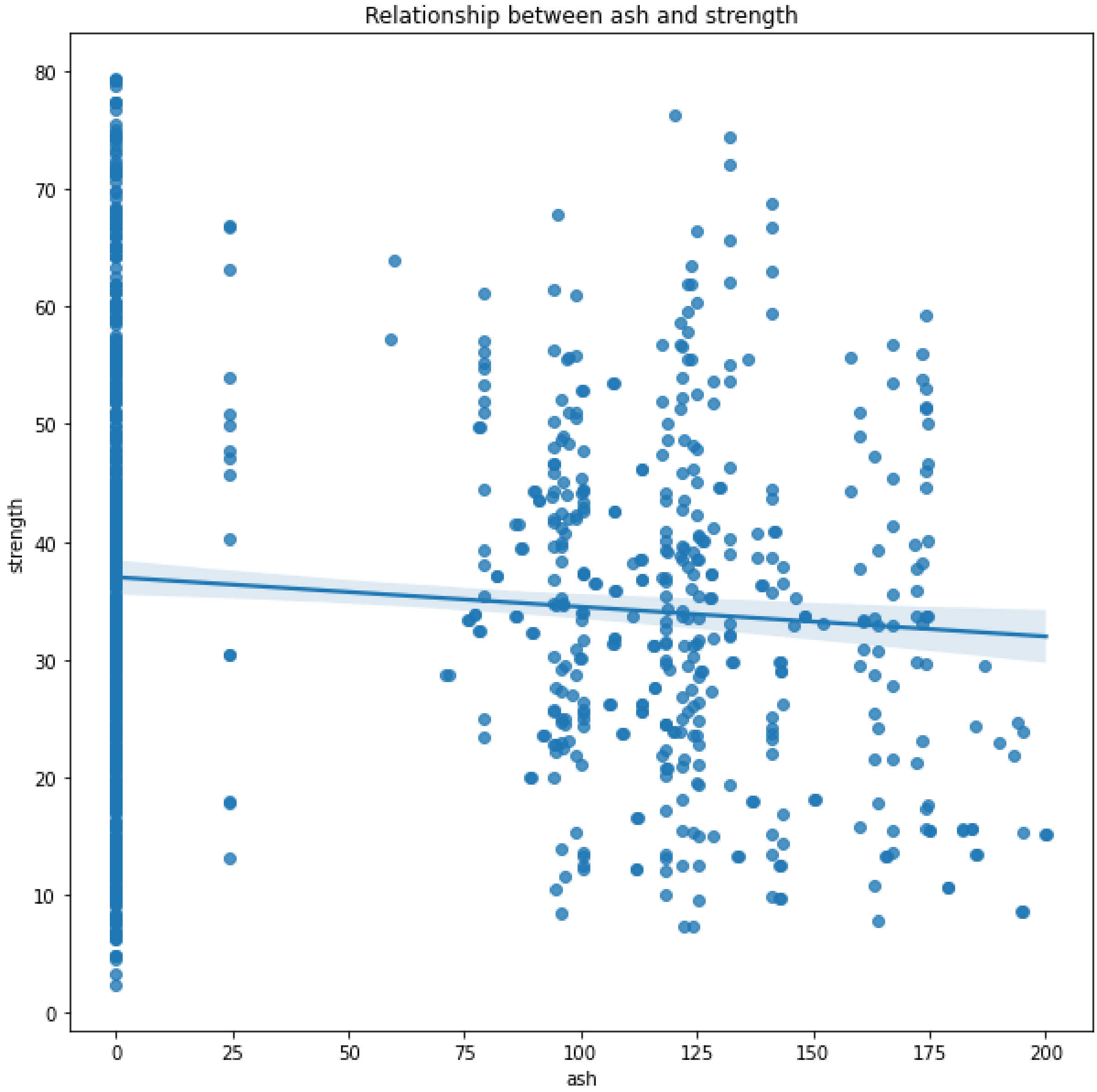


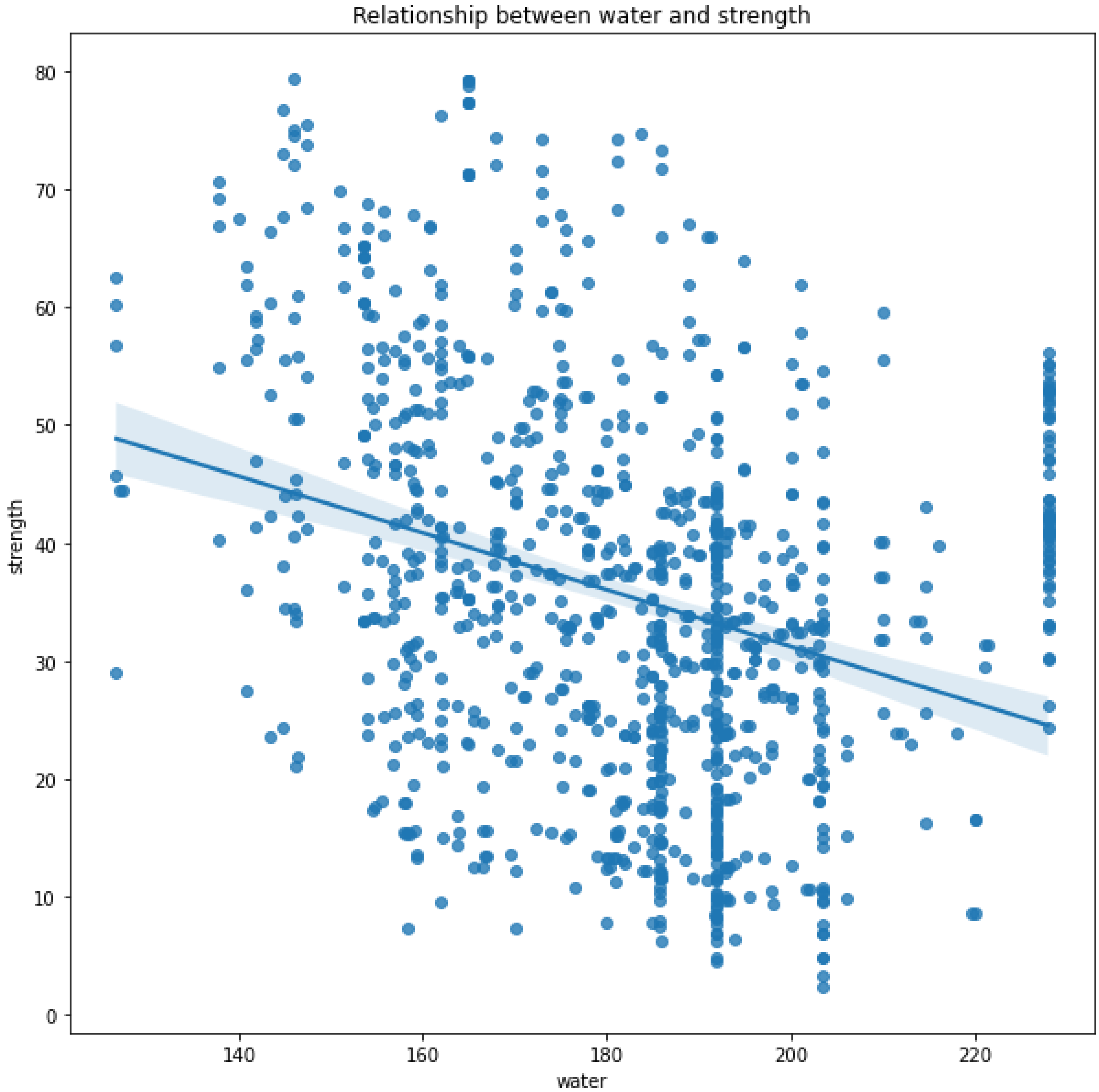

# multivariate analysis

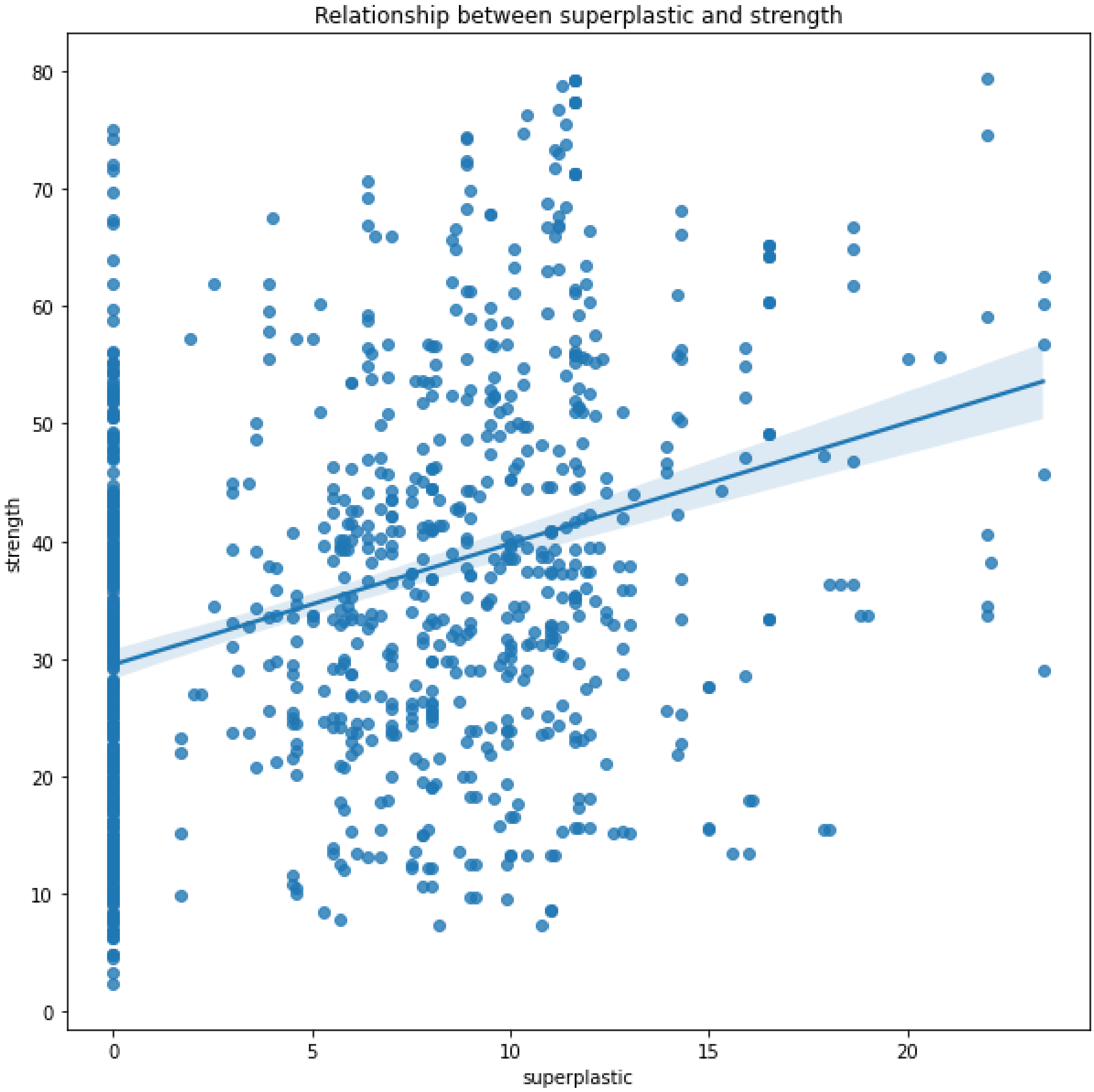
In [10]:
```
for col in df.columns:
    if col != "strength":
        f,ax = plt.subplots(figsize = (10,10))
        sns.regplot(x=df[col],y=df["strength"],ax=ax).set_title(f"Relationship betwe
```

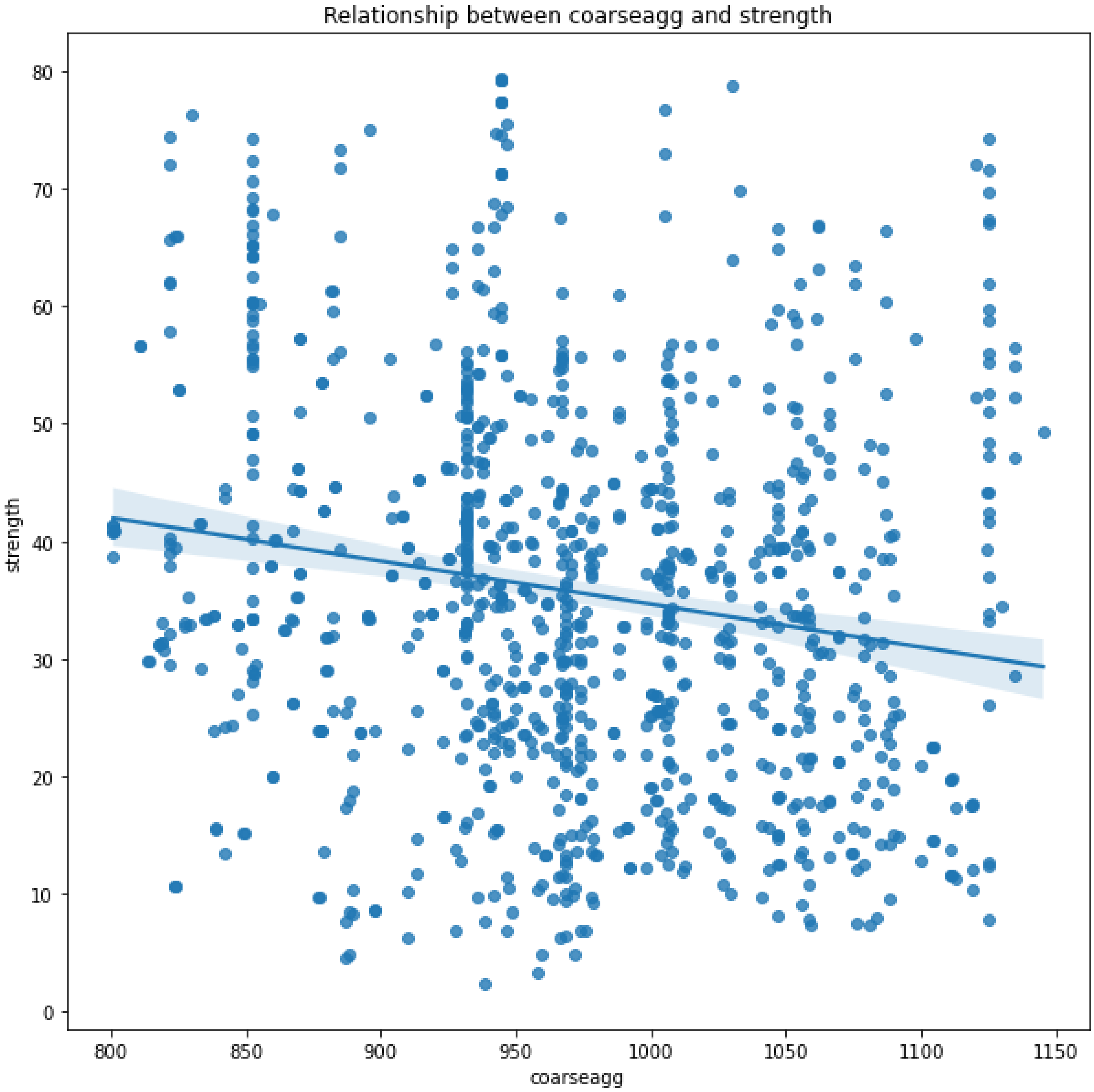

Relationship between cement and strength
strength
cement
0
10
20
30
40
50
60
70
80
100
200
300
400
500

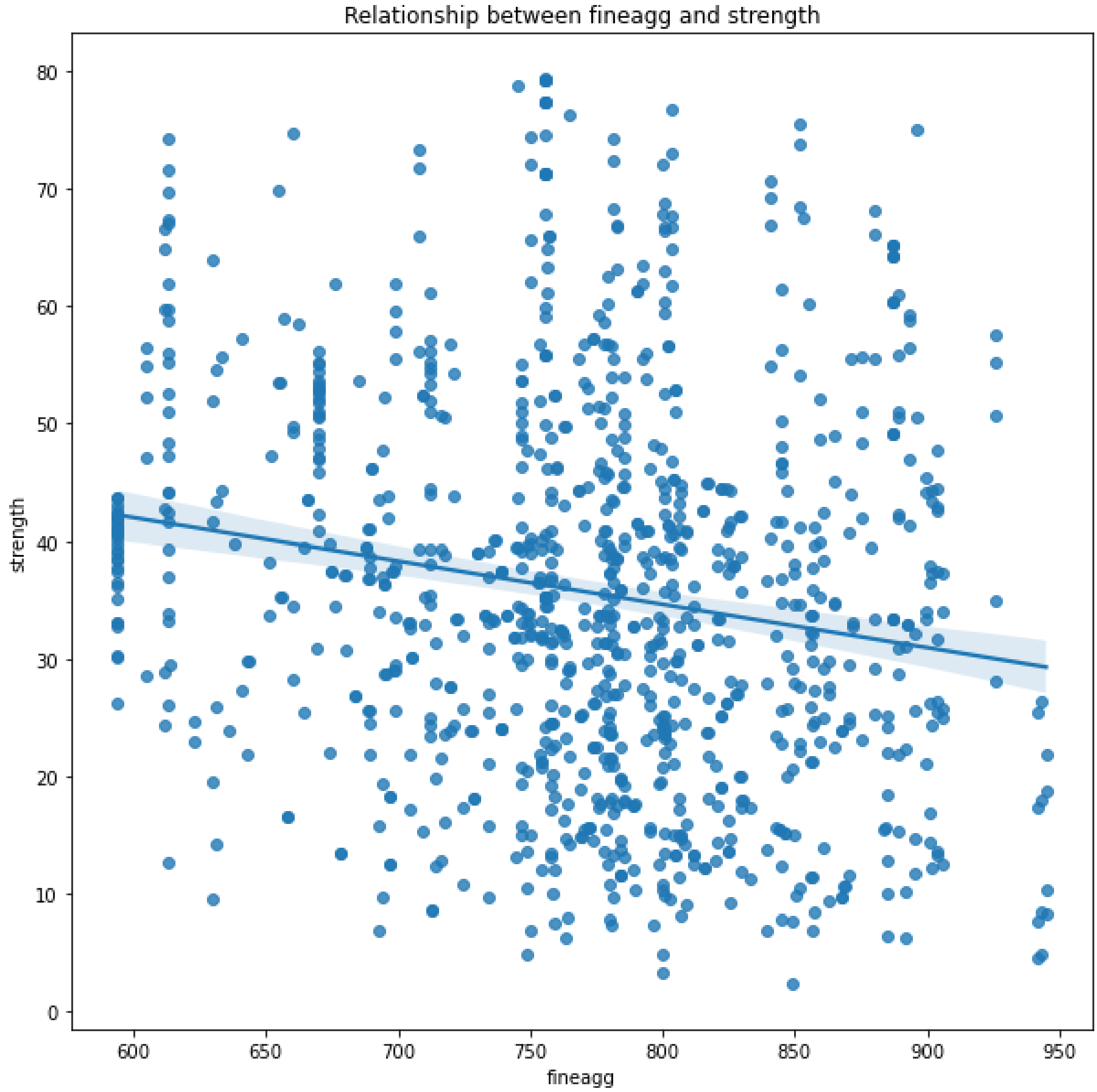

Relationship between slag and strength
strength
slag
0
10
20
30
40
50
60
70
80
0
50
100
150
200
250
300
350

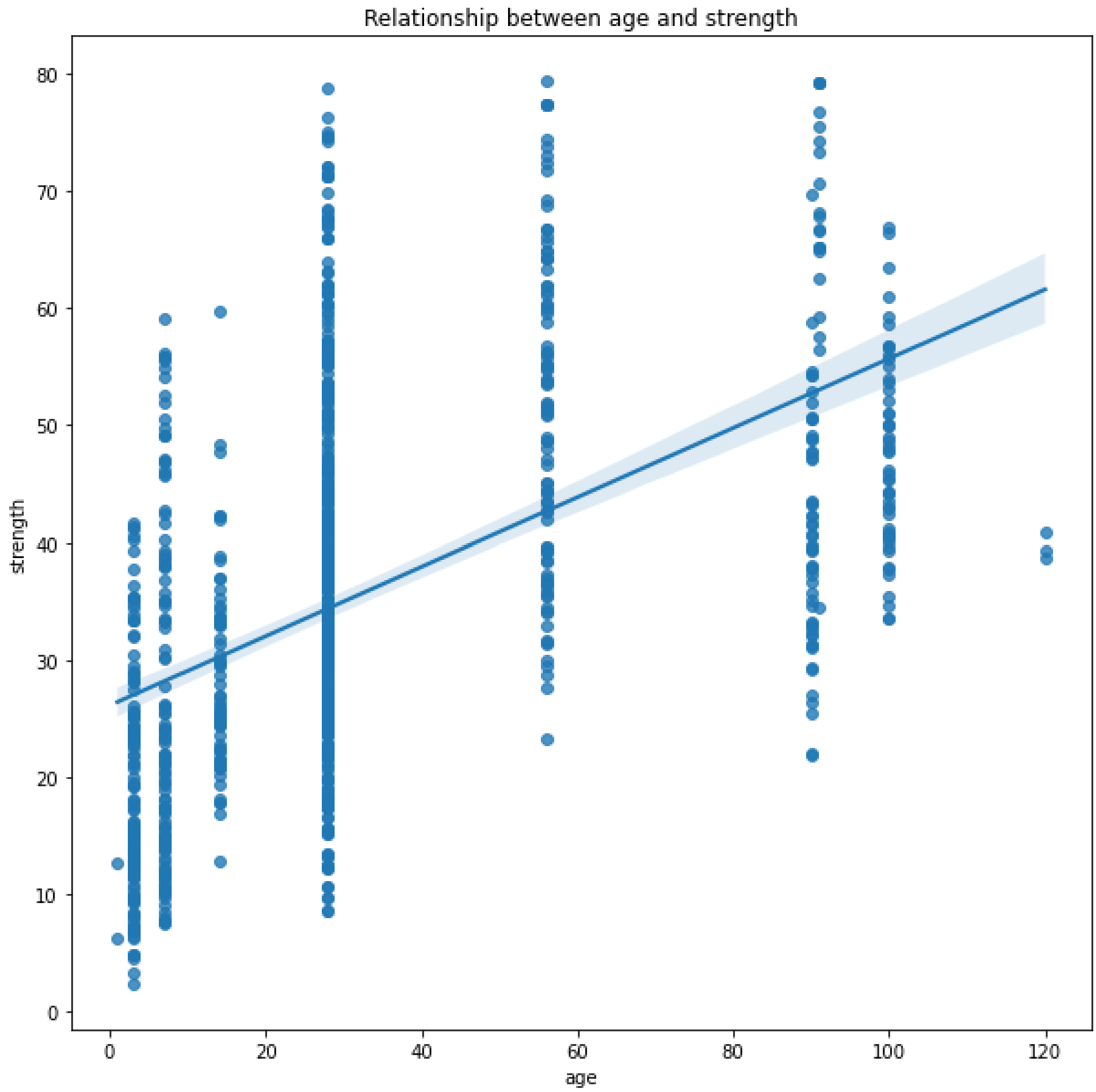

Relationship between ash and strength
strength
ash
0
10
20
30
40
50
60
70
80
0
25
50
75
100
125
150
175
200


Relationship between water and strength
strength
water
0
10
20
30
40
50
60
70
80
140
160
180
200
220


Relationship between superplastic and strength
strength
superplastic
0
10
20
30
40
50
60
70
80
0
5
10
15
20


Relationship between coarseagg and strength
strength
0
10
20
30
40
50
60
70
80
coarseagg
800
850
900
950
1000
1050
1100
1150


Relationship between fineagg and strength
strength
fineagg
0
10
20
30
40
50
60
70
80
600
650
700
750
800
850
900
950




## conclusions of multi-covariate analysis

- 1.strength and cement has positive correlation 49%
- 2.strength and slag has slight positive correlation 12%
- 3.strength and ash has slightly negative correlation 9%
- 4.strength and water has negative correlation 30%
- 5.strength and superplastic has positive correlation 34%
- 6.strength and coarsagg has negative correlation 17%
- 7.strength and fineagg has negative correlation 17%
- 8.strength and age has positive correlation 50%

## finding out correlation percentage

In [11]:

```
def correlation_target(df,t_col):
    ind_var = df.drop(t_col,axis=1).columns
    corr_result = []
    for col in ind_var:
        corr_result.append(df[t_col].corr(df[col]))

    result_df = pd.DataFrame([ind_var,corr_result],index=["variable","correaltion"])
    return result_df.sort_values("correaltion",ascending=False)
```

In [12]:

```
correlation_target(df,"strength")
```

Out[12]:

| | variable | correaltion |
|---|---|---|
| **7** | age | 0.499711 |
| **0** | cement | 0.493518 |
| **4** | superplastic | 0.342633 |
| **1** | slag | 0.129561 |
| **2** | ash | -0.097973 |
| **5** | coarseagg | -0.173234 |
| **6** | fineagg | -0.176113 |
| **3** | water | -0.300043 |

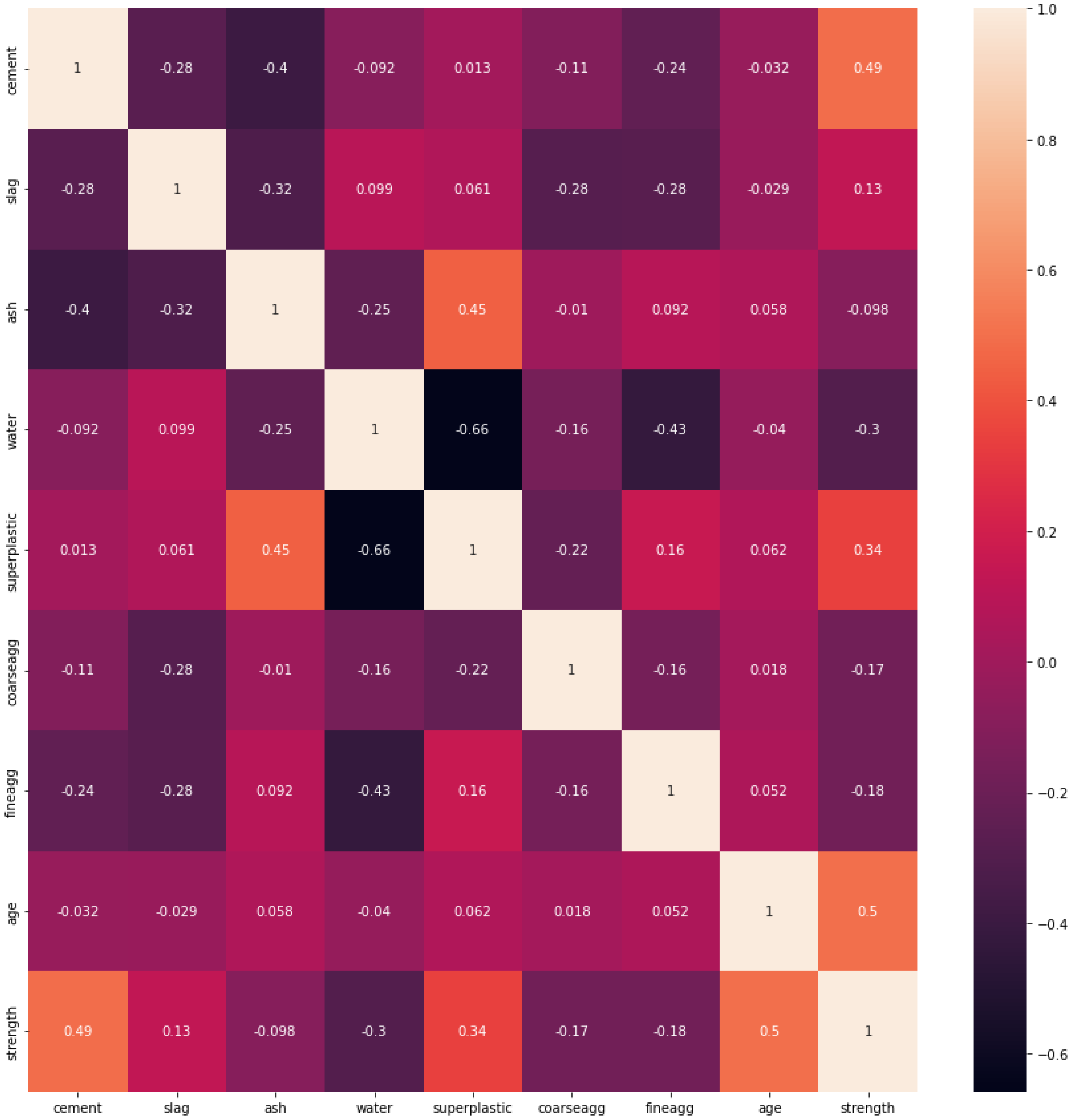
In [13]:

```
## checking for multi-collinearity

cor = df.corr()
f,ax = plt.subplots(figsize=(15,15))
sns.heatmap(cor,annot=True)
```

Out[13]:

```
<AxesSubplot:>
```




In [14]:

```
# conclusions of multicollinearity check
# 1.superplatic and ash 45%
# 2.superplatic and water 66%
# 3.slag and ash 32%
# 4.slash and fineagg 31%
# 5.water and fineagg 33%
# 6.cement and ash 40%
```

# Mulicollenearity check 2 (VIF Method)

- VIF stands for varaiance inflation factor
- In VIF we regress every independant variable with each other and find the r-square
- after finding r-square we use below VIF formula to find VIF index
- VIF index = 1/1-r.square
- if VIF is more than 5 then we say that multi-collinearity exists

In [15]:

```
def vif(ind_var):
    from statsmodels.stats.outliers_influence import variance_inflation_factor
    result_df = pd.DataFrame()
```

```
    result_df["Feature"] = ind_var.columns
    result_df["vif"] = [variance_inflation_factor(ind_var.values,i)for i in range(in
    return result_df
```

In [16]:
```
vif(df.drop("strength",axis=1)) ## as the VIF value is very high he data is multi-co
```

Out[16]:

| | Feature | vif |
|---|---|---|
| **0** | cement | 14.291158 |
| **1** | slag | 3.342314 |
| **2** | ash | 4.415840 |
| **3** | water | 81.963087 |
| **4** | superplastic | 5.724145 |
| **5** | coarseagg | 86.938582 |
| **6** | fineagg | 68.664404 |
| **7** | age | 2.368372 |

# as the data has the lot of multicollinerity applying PCA

In [17]:
```
def apply_pca(x):

    col = []
    n_comp = len(x.columns)

    # step1: applying standerd scaler

    x = StandardScaler().fit_transform(x)

    # step2: applying PCA

    for i in range(1,n_comp):
        pca = PCA(n_components = i)
        p_components = pca.fit_transform(x)

        evr = np.cumsum(pca.explained_variance_ratio_)

        if evr[i-1] > 0.9:
            n_components = i
            break

    ## creating the DataFrame

    for j in range(1,n_components+1):
        col.append("PC_"+str(j))

    result_df = pd.DataFrame(p_components,columns=col)

    return result_df
```

In [18]:
```
x = df.drop("strength",axis=1)
x.head()
```

Out[18]:

| | cement | slag | ash | water | superplastic | coarseagg | fineagg | age |
|---|---|---|---|---|---|---|---|---|
| **0** | 141.3 | 212.0 | 0.0 | 203.5 | 0.0 | 971.8 | 748.5 | 28 |
| **1** | 168.9 | 42.2 | 124.3 | 158.3 | 10.8 | 1080.8 | 796.2 | 14 |
| **2** | 250.0 | 0.0 | 95.7 | 187.4 | 5.5 | 956.9 | 861.2 | 28 |
| **3** | 266.0 | 114.0 | 0.0 | 228.0 | 0.0 | 932.0 | 670.0 | 28 |
| **4** | 154.8 | 183.4 | 0.0 | 193.3 | 9.1 | 1047.4 | 696.7 | 28 |

In [19]:

```
y = df[["strength"]]
y.head()
```

Out[19]:

| | strength |
|---|---|
| **0** | 29.89 |
| **1** | 23.51 |
| **2** | 29.22 |
| **3** | 45.85 |
| **4** | 18.29 |

In [20]:

```
x_pca = apply_pca(x)
```

In [21]:

```
x_pca.head()
```

Out[21]:

| | PC_1 | PC_2 | PC_3 | PC_4 | PC_5 | PC_6 |
|---|---|---|---|---|---|---|
| **0** | 1.810919 | 1.331664 | -1.284484 | -0.306148 | -0.067652 | -0.886110 |
| **1** | -1.823833 | -0.573436 | -1.058973 | 0.893130 | -0.913984 | -0.751061 |
| **2** | -0.739819 | -0.463200 | -0.541643 | -1.033210 | -0.308068 | 0.611045 |
| **3** | 2.766368 | 0.602978 | -0.512532 | 0.008806 | 0.086415 | 0.850548 |
| **4** | 0.892523 | 0.966627 | -0.863624 | 1.148561 | -0.064439 | -1.221228 |

# model_building

In [23]:

```
#1 normal model building
#2 cross validation
#3 hyper parameter tunning
```

In [24]:

```
def train_and_test_split(x,y,test_size=0.3):
    return train_test_split(x,y,test_size=test_size,random_state=40)
```

In [25]:

```
def build_model(model_name,estimator,x,y):
    x_train,x_test,y_train,y_test = train_and_test_split(x,y)
    estimator.fit(x_train,y_train)
    y_pred = estimator.predict(x_test)
    r2score = r2_score(y_test,y_pred)
```

```
    rmse = np.sqrt(mean_squared_error(y_test,y_pred))
    temp = [model_name,r2score,rmse]

    return temp
```

In [26]:

```
build_model("Linear_Regression",LinearRegression(),x_pca,y)
```

Out[26]:

```
['Linear_Regression', 0.6719558938761188, 9.32019549758269]
```

In [27]:

```
def build_multiple_model(x,y):
    result_df = pd.DataFrame(columns=["Model_Name","R2_Score","RMSE"])

    result_df.loc[len(result_df)] = build_model("Linear_Regression",LinearRegression
    result_df.loc[len(result_df)] = build_model("Lasso_Reression",Lasso(),x,y)
    result_df.loc[len(result_df)] = build_model("Ridge_Regression",Ridge(),x,y)
    result_df.loc[len(result_df)] = build_model("KNN_Regression",KNeighborsRegressor
    result_df.loc[len(result_df)] = build_model("Decision_Tree_Regression",DecisionT
    result_df.loc[len(result_df)] = build_model("Random_Forest_Regression",RandomFor
    result_df.loc[len(result_df)] = build_model("Adaboost_Regression",AdaBoostRegres
    result_df.loc[len(result_df)] = build_model("GBoost_Regression",GradientBoosting
    result_df.loc[len(result_df)] = build_model("XGB_Regression",XGBRegressor(),x,y)
    result_df.loc[len(result_df)] = build_model("Support_Vector_Regression",SVR(),x,

    return result_df.sort_values("R2_Score",ascending=False)
```

In [28]:

```
build_multiple_model(x_pca,y)
```

Out[28]:

| | Model_Name | R2_Score | RMSE |
|---|---|---|---|
| 5 | Random_Forest_Regression | 0.851051 | 6.280261 |
| 8 | XGB_Regression | 0.843865 | 6.429975 |
| 7 | GBoost_Regression | 0.827281 | 6.762842 |
| 3 | KNN_Regression | 0.751607 | 8.110144 |
| 6 | Adaboost_Regression | 0.740296 | 8.292745 |
| 4 | Decision_Tree_Regression | 0.734247 | 8.388763 |
| 0 | Linear_Regression | 0.671956 | 9.320195 |
| 2 | Ridge_Regression | 0.671954 | 9.320220 |
| 1 | Lasso_Reression | 0.655825 | 9.546597 |
| 9 | Support_Vector_Regression | 0.653021 | 9.585403 |

In [29]:

```
def k_fold_cv(x,y,fold=10):

    score_lr = cross_val_score(LinearRegression(),x,y,cv=fold)
    score_la = cross_val_score(Lasso(),x,y,cv=fold)
    score_rd = cross_val_score(Ridge(),x,y,cv=fold)
    score_dtr = cross_val_score(DecisionTreeRegressor(),x,y,cv=fold)
    score_knn = cross_val_score(KNeighborsRegressor(),x,y,cv=fold)
    score_rf = cross_val_score(RandomForestRegressor(),x,y,cv=fold)
    score_ad = cross_val_score(AdaBoostRegressor(),x,y,cv=fold)
    score_g = cross_val_score(GradientBoostingRegressor(),x,y,cv=fold)
    score_xgb = cross_val_score(XGBRegressor(),x,y,cv=fold)
```

```
    score_svr = cross_val_score(SVR(),x,y,cv=fold)

    score = [score_lr,score_la,score_rd,score_dtr,score_knn,score_rf,score_ad,score_
    models = ["Linear Regression","Lasso Regression","Ridge Regression","Decision Tr

    result = []

    for i in range(0,len(models)):
        score_mean = np.mean(score[i])
        score_std = np.std(score[i])
        model_name = models[i]
        temp = [model_name,score_mean,score_std]
        result.append(temp)

    result_df = pd.DataFrame(result,columns=["model_name","score_mean","score_std"])

    return result_df.sort_values("score_mean",ascending=False)
```

In [30]:

```
k_fold_cv(x_pca,y)
```

Out[30]:

| | model_name | score_mean | score_std |
|---|---|---|---|
| **8** | XGBoost Regression | 0.873262 | 0.036061 |
| **5** | Random forest Regression | 0.866264 | 0.033087 |
| **7** | GBoost Regression | 0.829250 | 0.050252 |
| **4** | KNN Regression | 0.767825 | 0.055738 |
| **3** | Decision Tree Regression | 0.762318 | 0.058614 |
| **6** | Adaboost Regression | 0.723020 | 0.043631 |
| **9** | Support vector machines Regression | 0.703117 | 0.042765 |
| **2** | Ridge Regression | 0.663935 | 0.059437 |
| **0** | Linear Regression | 0.663928 | 0.059476 |
| **1** | Lasso Regression | 0.649837 | 0.049887 |

In [31]:

```
def hyperparameter_tunning(x,y,fold=10):
    param_ls = {"alpha": [1e-15, 1e-13,1e-11,1e-9,1e-7,1e-5, 1e-3,0.001,0.01,0.1,1,2
    param_rd = {"alpha": [1e-15, 1e-13,1e-11,1e-9,1e-7,1e-5, 1e-3,0.001,0.01,0.1,1,2
    param_knn = {"n_neighbors":[1,2,3,4,5,6,7,8,9,10,11,12,13,14,15]}
    param_adb = {"n_estimators" : [1,2,3,4,5,6,7,8,9,10,20,30,40,50,60,70,80,90,100,
         "learning_rate" : [0.00001,0.0001,0.001,0.01,0.1,0.2,0.3,0.4,0.5,0.6,0.7,0.
    param_gb = {"alpha": [0,0.1,0.2,0.3,0.4,0.5,0.6,0.7,0.8,0.9,1.0],"learning_rate"
    param_xgb = {'learning_rate' : [0.001,0.01,0.1,0.2,0.3,0.4,0.5,0.6,0.7,0.8,0.9,1
         'reg_lambda' : [1,2,3,4,5,6,7,8,9,10],
         'max_depth': [1,2,3,4,5,6,7,8,9,10]}
    param_rf = {"n_estimators":[10,20,30,40,50,60,70,80,90,110,130,150,170,190],'min
          "bootstrap":[True,False]}


    tunned_lasso=GridSearchCV(Lasso(),param_ls,cv=fold)
    tunned_ridge=GridSearchCV(Ridge(),param_rd,cv=fold)
    tunned_knn=GridSearchCV(KNeighborsRegressor(),param_knn,cv=fold)
    tunned_adb=GridSearchCV(AdaBoostRegressor(),param_adb,cv=fold)
    tunned_gb=GridSearchCV(GradientBoostingRegressor(),param_gb,cv=fold)
    tunned_xgb=GridSearchCV(XGBRegressor(),param_xgb,cv=fold)
    tunned_rf=GridSearchCV(RandomForestRegressor(),param_rf,cv=fold)
```

```
    tunned_lasso.fit(x,y)
    tunned_ridge.fit(x,y)
    tunned_knn.fit(x,y)
    tunned_adb.fit(x,y)
    tunned_gb.fit(x,y)
    tunned_xgb.fit(x,y)
    tunned_rf.fit(x,y)


    tunned = [tunned_lasso,tunned_ridge,tunned_knn,tunned_adb,tunned_gb,tunned_xgb,t
    models = ["Lasso","Ridge","KNeighborRegressor","AdaBoostRegressor","GradientBoos

    for i in range (0,len(tunned)):
        print("model",models[i])
        print("best_parameters",tunned[i].best_params_)
```

In [32]:

```
hyperparameter_tunning(x_pca,y,fold=10)
```

```
model Lasso
best_parameters {'alpha': 0.1}
model Ridge
best_parameters {'alpha': 6}
model KNeighborRegressor
best_parameters {'n_neighbors': 4}
model AdaBoostRegressor
best_parameters {'learning_rate': 1.0, 'n_estimators': 60}
model GradientBoostingRegressor
best_parameters {'alpha': 0.6, 'learning_rate': 0.3}
model XGBRegressor
best_parameters {'learning_rate': 0.1, 'max_depth': 10, 'reg_lambda': 7}
model RandomForestRegressor
best_parameters {'bootstrap': True, 'min_impurity_decrease': 0.0, 'n_estimators': 15
0}
```

In [37]:

```
def k_fold_cv_tunned(x,y,fold=10):

    score_lr = cross_val_score(LinearRegression(),x,y,cv=fold)
    score_la = cross_val_score(Lasso(alpha = 0.1),x,y,cv=fold)
    score_rd = cross_val_score(Ridge(alpha= 6),x,y,cv=fold)
    score_dtr = cross_val_score(DecisionTreeRegressor(),x,y,cv=fold)
    score_knn = cross_val_score(KNeighborsRegressor(n_neighbors= 4),x,y,cv=fold)
    score_rf = cross_val_score(RandomForestRegressor(bootstrap= True, min_impurity_d
    score_ad = cross_val_score(AdaBoostRegressor(learning_rate= 1.0, n_estimators= 6
    score_g = cross_val_score(GradientBoostingRegressor(alpha= 0.6, learning_rate= 0
    score_xgb = cross_val_score(XGBRegressor(learning_rate= 0.1, max_depth= 10, reg_
    score_svr = cross_val_score(SVR(),x,y,cv=fold)

    score = [score_lr,score_la,score_rd,score_dtr,score_knn,score_rf,score_ad,score_
    models = ["Linear Regression","Lasso Regression","Ridge Regression","Decision Tr

    result = []

    for i in range(0,len(models)):
        score_mean = np.mean(score[i])
        score_std = np.std(score[i])
        model_name = models[i]
        temp = [model_name,score_mean,score_std]
        result.append(temp)
```

```
    result_df = pd.DataFrame(result,columns=["model_name","score_mean","score_std"])

    return result_df.sort_values("score_mean",ascending=False)
```

In [50]:
```
k_fold_cv_tunned(x_pca,y,fold=10)
```

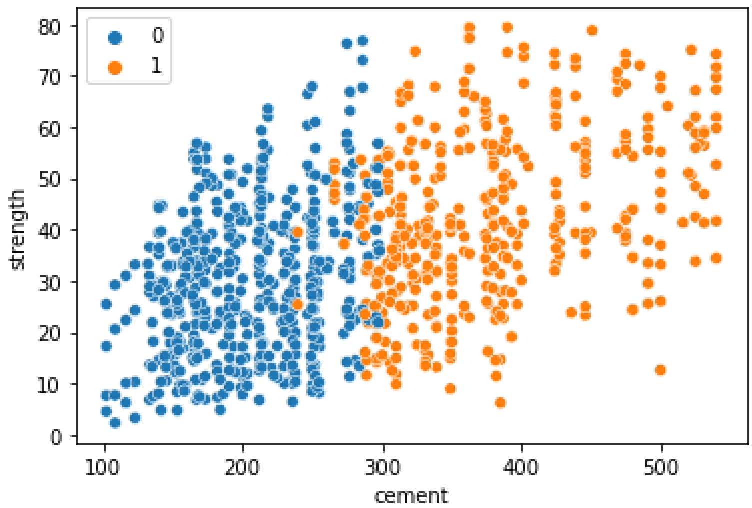
Out[50]:

| | model_name | score_mean | score_std |
|---|---|---|---|
| 8 | XGBoost Regression | 0.887288 | 0.035679 |
| 5 | Random forest Regression | 0.866422 | 0.031719 |
| 7 | GBoost Regression | 0.859156 | 0.050244 |
| 4 | KNN Regression | 0.771068 | 0.054454 |
| 3 | Decision Tree Regression | 0.767302 | 0.063291 |
| 6 | Adaboost Regression | 0.732104 | 0.036805 |
| 9 | Support vector machines Regression | 0.703117 | 0.042765 |
| 1 | Lasso Regression | 0.664143 | 0.058426 |
| 2 | Ridge Regression | 0.663951 | 0.059242 |
| 0 | Linear Regression | 0.663928 | 0.059476 |

# clustering

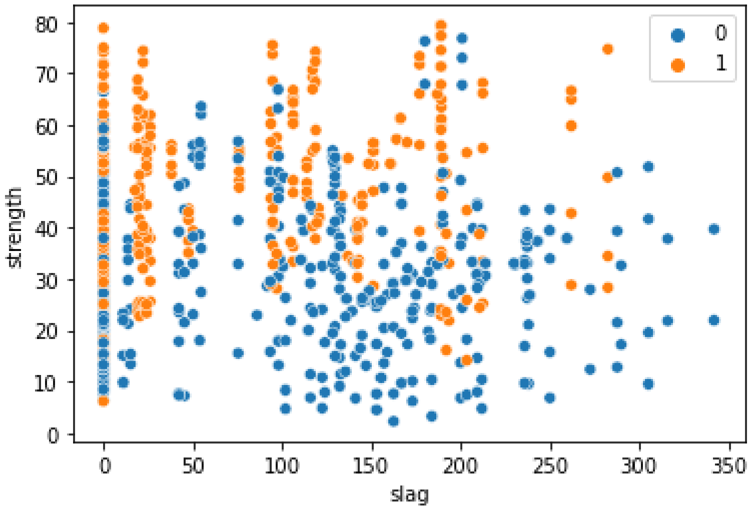
In [41]:
```
labels = KMeans(n_clusters=2,random_state=42).fit_predict(x)
sns.scatterplot(x=x.cement,y=y.strength,hue= labels)
```

Out[41]: <AxesSubplot:xlabel='cement', ylabel='strength'>




In [42]:
```
sns.scatterplot(x=x.slag,y=y.strength,hue= labels)
```

Out[42]: <AxesSubplot:xlabel='slag', ylabel='strength'>




In [43]:
```
## Only cement has clusters with strength
```

In [44]:
```
df_labels = pd.DataFrame(labels,columns=["labels"])
df_labels.head()
```

Out[44]:

| | labels |
|---|---|
| **0** | 0 |
| **1** | 0 |
| **2** | 0 |
| **3** | 1 |
| **4** | 0 |

In [45]:
```
df_new = df.join(df_labels,how="inner")
```

In [46]:
```
df_new.head()
```

Out[46]:

| | cement | slag | ash | water | superplastic | coarseagg | fineagg | age | strength | labels |
|---|---|---|---|---|---|---|---|---|---|---|
| **0** | 141.3 | 212.0 | 0.0 | 203.5 | 0.0 | 971.8 | 748.5 | 28 | 29.89 | 0 |
| **1** | 168.9 | 42.2 | 124.3 | 158.3 | 10.8 | 1080.8 | 796.2 | 14 | 23.51 | 0 |
| **2** | 250.0 | 0.0 | 95.7 | 187.4 | 5.5 | 956.9 | 861.2 | 28 | 29.22 | 0 |
| **3** | 266.0 | 114.0 | 0.0 | 228.0 | 0.0 | 932.0 | 670.0 | 28 | 45.85 | 1 |
| **4** | 154.8 | 183.4 | 0.0 | 193.3 | 9.1 | 1047.4 | 696.7 | 28 | 18.29 | 0 |

In [47]:
```
x_new = df_new.drop("strength",axis=1)
```

In [48]:
```
y_new = df[["strength"]]
```

In [49]:
```
build_multiple_model(x_new,y_new)
```

Out[49]:

| | Model_Name | R2_Score | RMSE |
|---|---|---|---|
| 8 | XGB_Regression | 0.885537 | 5.505430 |
| 5 | Random_Forest_Regression | 0.873724 | 5.782552 |
| 7 | GBoost_Regression | 0.873334 | 5.791462 |
| 4 | Decision_Tree_Regression | 0.783363 | 7.574004 |
| 6 | Adaboost_Regression | 0.767005 | 7.854742 |
| 2 | Ridge_Regression | 0.697942 | 8.943423 |
| 0 | Linear_Regression | 0.697934 | 8.943552 |
| 1 | Lasso_Reression | 0.697402 | 8.951418 |
| 3 | KNN_Regression | 0.628237 | 9.921833 |
| 9 | Support_Vector_Regression | 0.188101 | 14.662563 |

# after applying clustering accuracy has increased almost 5 %

In [52]:

```
k_fold_cv_tunned(x_new,y_new,fold=10)
```

Out[52]:

| | model_name | score_mean | score_std |
|---|---|---|---|
| 8 | XGBoost Regression | 0.904985 | 0.042959 |
| 5 | Random forest Regression | 0.888420 | 0.036132 |
| 7 | GBoost Regression | 0.887132 | 0.059068 |
| 3 | Decision Tree Regression | 0.830604 | 0.051726 |
| 6 | Adaboost Regression | 0.740663 | 0.041387 |
| 1 | Lasso Regression | 0.686926 | 0.062433 |
| 2 | Ridge Regression | 0.686677 | 0.062324 |
| 0 | Linear Regression | 0.686640 | 0.062314 |
| 4 | KNN Regression | 0.684321 | 0.078541 |
| 9 | Support vector machines Regression | 0.223931 | 0.038833 |

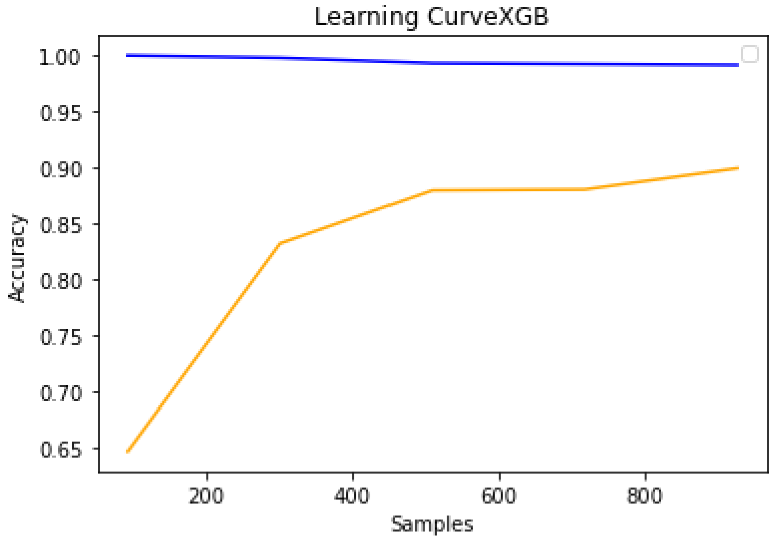
# learning curve

In [60]:

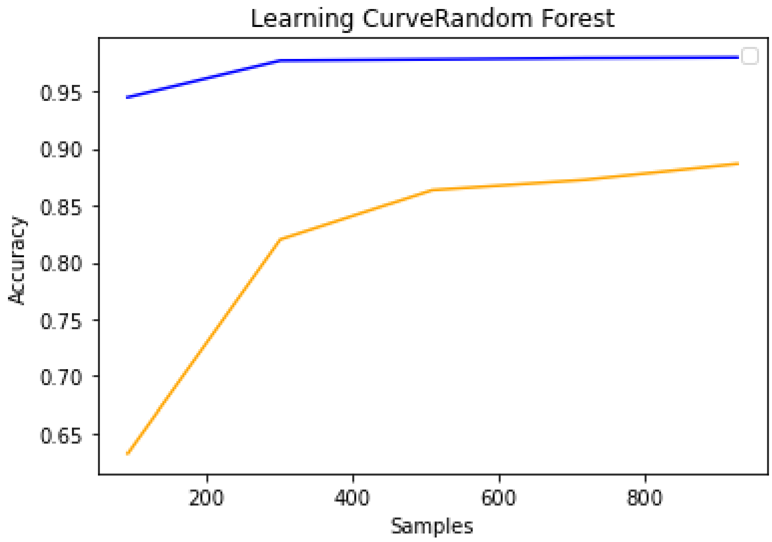
```
def genrate_learning_curve(model_name,estimator,x,Y,fold=10):
    train_size,train_score,test_score = learning_curve(estimator=estimator,X=x,y=Y,c
    train_score_mean = np.mean(train_score,axis=1)
    test_score_mean = np.mean(test_score,axis=1)
    plt.plot(train_size,train_score_mean,color="blue")
    plt.plot(train_size,test_score_mean,color="orange")

    plt.xlabel("Samples")
    plt.ylabel("Accuracy")
    plt.title("Learning Curve" + model_name)
    plt.legend("Training accurcy","Testing accurcy")
```

In [61]:
```
genrate_learning_curve("XGB",XGBRegressor(),x_new,y_new,fold=10)
```




In [62]:
```
genrate_learning_curve("Random Forest",RandomForestRegressor(),x_new,y_new,fold=10)
```




# Feature Importance by using XGBoost Package

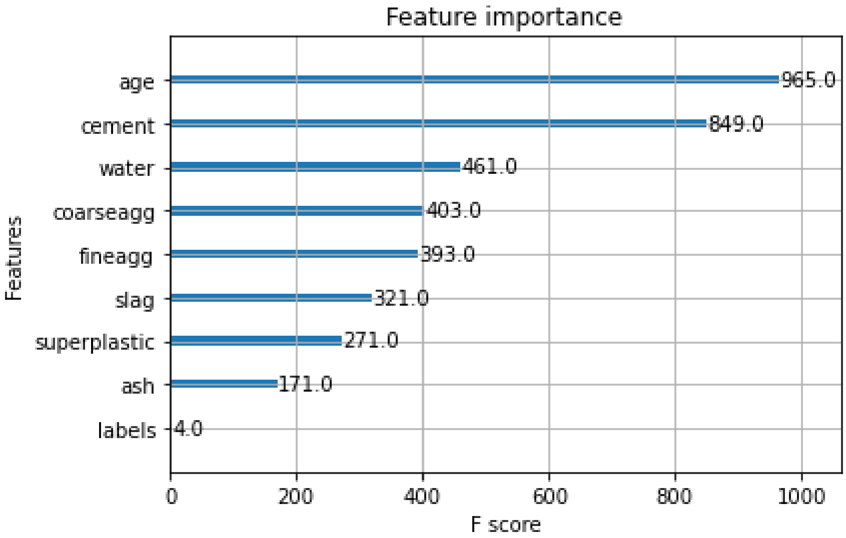
In [66]:
```
x_train,x_test,y_train,y_test = train_test_split(x_new,y_new,test_size=0.2,random_st

xgb = XGBRegressor()
xgb.fit(x_train,y_train)
```

Out[66]:
```
XGBRegressor(base_score=0.5, booster='gbtree', callbacks=None,
             colsample_bylevel=1, colsample_bynode=1, colsample_bytree=1,
             early_stopping_rounds=None, enable_categorical=False,
             eval_metric=None, gamma=0, gpu_id=-1, grow_policy='depthwise',
             importance_type=None, interaction_constraints='',
             learning_rate=0.300000012, max_bin=256, max_cat_to_onehot=4,
             max_delta_step=0, max_depth=6, max_leaves=0, min_child_weight=1,
             missing=nan, monotone_constraints='()', n_estimators=100, n_jobs=0,
             num_parallel_tree=1, predictor='auto', random_state=0, reg_alpha=0,
             reg_lambda=1, ...)
```

In [67]:
```
xgboost.plot_importance(xgb)
```

Out[67]: <AxesSubplot:title={'center':'Feature importance'}, xlabel='F score', ylabel='Features'>




In [68]:

```
x_neww = df[["age","cement","water","coarseagg","fineagg","slag"]]
y_neww = df[["strength"]]
```

In [69]:

```
k_fold_cv(x_neww,y_neww)
```

Out[69]:

| | model_name | score_mean | score_std |
|---|---|---|---|
| **8** | XGBoost Regression | 0.896645 | 0.046915 |
| **5** | Random forest Regression | 0.886192 | 0.033316 |
| **7** | GBoost Regression | 0.875495 | 0.046392 |
| **3** | Decision Tree Regression | 0.832355 | 0.052452 |
| **6** | Adaboost Regression | 0.734975 | 0.038066 |
| **1** | Lasso Regression | 0.679548 | 0.061547 |
| **2** | Ridge Regression | 0.679539 | 0.061858 |
| **0** | Linear Regression | 0.679539 | 0.061858 |
| **4** | KNN Regression | 0.656448 | 0.088739 |
| **9** | Support vector machines Regression | 0.261459 | 0.037619 |

In [70]:

```
k_fold_cv_tunned(x_neww,y_neww,fold=10)
```

Out[70]:

| | model_name | score_mean | score_std |
|---|---|---|---|
| **8** | XGBoost Regression | 0.905265 | 0.042435 |
| **7** | GBoost Regression | 0.890261 | 0.048877 |
| **5** | Random forest Regression | 0.885325 | 0.034559 |
| **3** | Decision Tree Regression | 0.825229 | 0.050821 |
| **6** | Adaboost Regression | 0.739431 | 0.032794 |
| **1** | Lasso Regression | 0.679542 | 0.061827 |

| | model_name | score_mean | score_std |
|---|---|---|---|
| **2** | Ridge Regression | 0.679539 | 0.061857 |
| **0** | Linear Regression | 0.679539 | 0.061858 |
| **4** | KNN Regression | 0.668799 | 0.085377 |
| **9** | Support vector machines Regression | 0.261459 | 0.037619 |