In [362]:

```
pip install pyforest
```

```
Requirement already satisfied: pyforest in /usr/local/lib/python3.7/dist-packages (1.1.0)
```

In [363]:

```
from pyforest import *
lazy_imports()
import warnings
warnings.filterwarnings("ignore")
from sklearn.tree import DecisionTreeRegressor
```

In [364]:

```
df=pd.read_csv('/content/drive/MyDrive/Project Files/Concrete Compressive Strength.csv')
df.head()
```

Out[364]:

	cement	slag	ash	water	superplastic	coarseagg	fineagg	age	strength
0	540.0	0.0	0.0	162.0	2.5	1040.0	676.0	28	79.986111
1	540.0	0.0	0.0	162.0	2.5	1055.0	676.0	28	61.887366
2	332.5	142.5	0.0	228.0	0.0	932.0	594.0	270	40.269535
3	332.5	142.5	0.0	228.0	0.0	932.0	594.0	365	41.052780
4	198.6	132.4	0.0	192.0	0.0	978.4	825.5	360	44.296075

In [365]:

```
# df=df.rename(columns={'Cement (component 1)(kg in a m^3 mixture)':"cement",
#                        'Blast Furnace Slag (component 2)(kg in a m^3 mixture)':"slag",
#                        'Fly Ash (component 3)(kg in a m^3 mixture)':"ash",
#                        'Water (component 4)(kg in a m^3 mixture)':"Water",
#                        'Superplasticizer (component 5)(kg in a m^3 mixture)':"superplas
tic",
#                        'Coarse Aggregate (component 6)(kg in a m^3 mixture)':"coarseagg
",
#                        'Fine Aggregate (component 7)(kg in a m^3 mixture)':"fineagg",
#                        'Age (day)':"age",
#                        'Concrete compressive strength(MPa, megapascals)':"strength"})
```

In [366]:

```
df.dtypes
```

Out[366]:

```
cement          float64
slag            float64
ash             float64
water           float64
superplastic    float64
coarseagg       float64
fineagg         float64
age               int64
strength        float64
dtype: object
```

In [367]:

```
df.shape
```

Out[367]:

```
(1030, 9)
```

In [368]:

```
#checking NUll values
df.isnull().sum()
```

Out[368]:

```
cement          0
slag            0
ash             0
water           0
superplastic    0
coarseagg       0
fineagg         0
age             0
strength        0
dtype: int64
```

No null values found

In [369]:

```
df.describe().T
```

Out[369]:

	count	mean	std	min	25%	50%	75%	max
cement	1030.0	281.165631	104.507142	102.000000	192.375000	272.900000	350.000000	540.000000
slag	1030.0	73.895485	86.279104	0.000000	0.000000	22.000000	142.950000	359.400000
ash	1030.0	54.187136	63.996469	0.000000	0.000000	0.000000	118.270000	200.100000
water	1030.0	181.566359	21.355567	121.750000	164.900000	185.000000	192.000000	247.000000
superplastic	1030.0	6.203112	5.973492	0.000000	0.000000	6.350000	10.160000	32.200000
coarseagg	1030.0	972.918592	77.753818	801.000000	932.000000	968.000000	1029.400000	1145.000000
fineagg	1030.0	773.578883	80.175427	594.000000	730.950000	779.510000	824.000000	992.600000
age	1030.0	45.662136	63.169912	1.000000	7.000000	28.000000	56.000000	365.000000
strength	1030.0	35.817836	16.705679	2.331808	23.707115	34.442774	46.136287	82.599225

Data Analysis

cement

In [370]:

```
from scipy import stats
Q1=df['cement'].quantile(q=0.25)
Q3=df['cement'].quantile(q=0.75)
print('1st quartile (Q1) is : ',Q1)
print('3rt quartile (Q3) is : ',Q3)
print('Interquartile range (IQR) is ',stats.iqr(df['cement']))
```

```
1st quartile (Q1) is :  192.375
3rt quartile (Q3) is :  350.0
Interquartile range (IQR) is  157.625
```

In [371]:

```
#finding Outliers from Interquartile range

L_outliers = Q1-1.5*(Q3-Q1)
O_outliers = Q3+1.5*(Q3-Q1)
```

```
print('Lower outlier limit in cement: ',L_outliers)
print('Upper outlier limit in cement: ',O_outliers)
```

```
Lower outlier limit in cement:  -44.0625
Upper outlier limit in cement:  586.4375
```

In [372]:

```
# checking presence of outliers with upper and lower limits
print('number of outliers in cement upper: ',df[df['cement']>586.4375]['cement'].count())
print('number of outliers in cement Lower: ',df[df['cement']<-44.0625]['cement'].count()
)
```

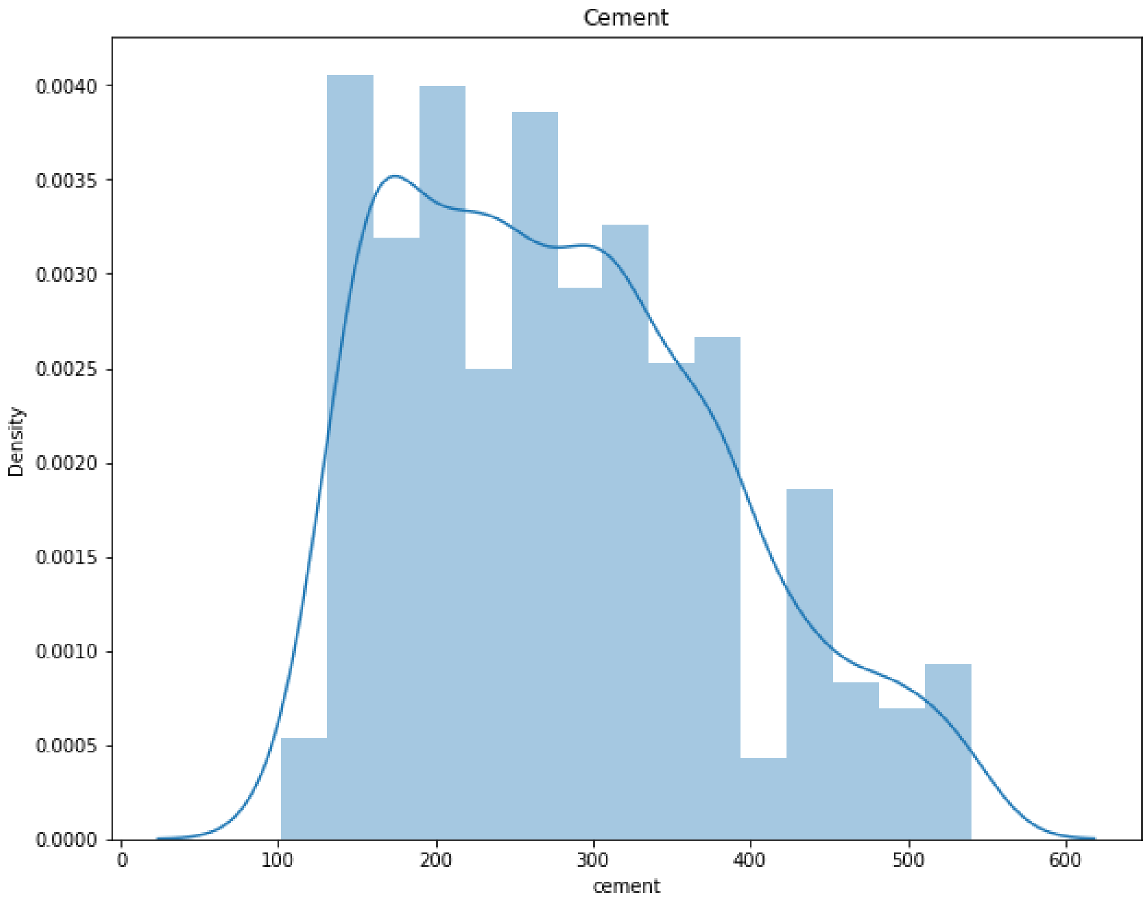
```
number of outliers in cement upper:  0
number of outliers in cement Lower:  0
```

In [373]:

```
plt.figure(figsize=(10,8))
sns.distplot(df['cement']).set_title("Cement")
```

Out[373]:

```
Text(0.5, 1.0, 'Cement')
```

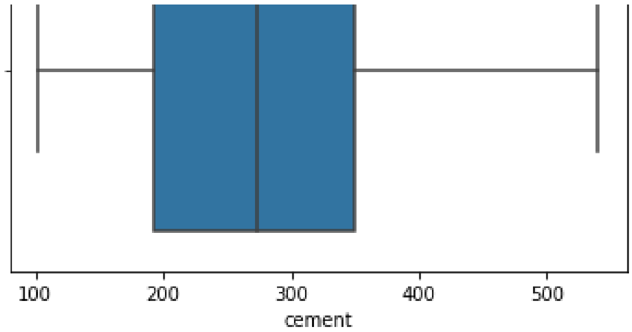


In [374]:

```
#distribution of cement
sns.boxplot(x='cement',data=df,orient='h')

#this shows there are no outliers found visually
```

Out[374]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f26f6a017d0>
```



ASH

In [375]:

```
Q1=df['ash'].quantile(q=0.25)
Q3=df['ash'].quantile(q=0.75)
print('1st quartile (Q1) is : ',Q1)
print('3rt quartile (Q3) is : ',Q3)
print('Interquartile range (IQR) is ',stats.iqr(df['ash']))

#finding Outliers from Interquartile range

L_outliers = Q1-1.5*(Q3-Q1)
O_outliers = Q3+1.5*(Q3-Q1)
print('Lower outlier limit in  Ash: ',L_outliers)
print('Upper outlier limit in Ash: ',O_outliers)
```

```
1st quartile (Q1) is :  0.0
3rt quartile (Q3) is :  118.27
Interquartile range (IQR) is  118.27
Lower outlier limit in  Ash:  -177.405
Upper outlier limit in Ash:  295.675
```

In [376]:

```
# checking presence of outliers with upper and lower limits
print('number of outliers in  Ash upper: ',df[df['ash']>295.675]['ash'].count())
print('number of outliers in  Ash Lower: ',df[df['ash']<-177.405]['ash'].count())
```

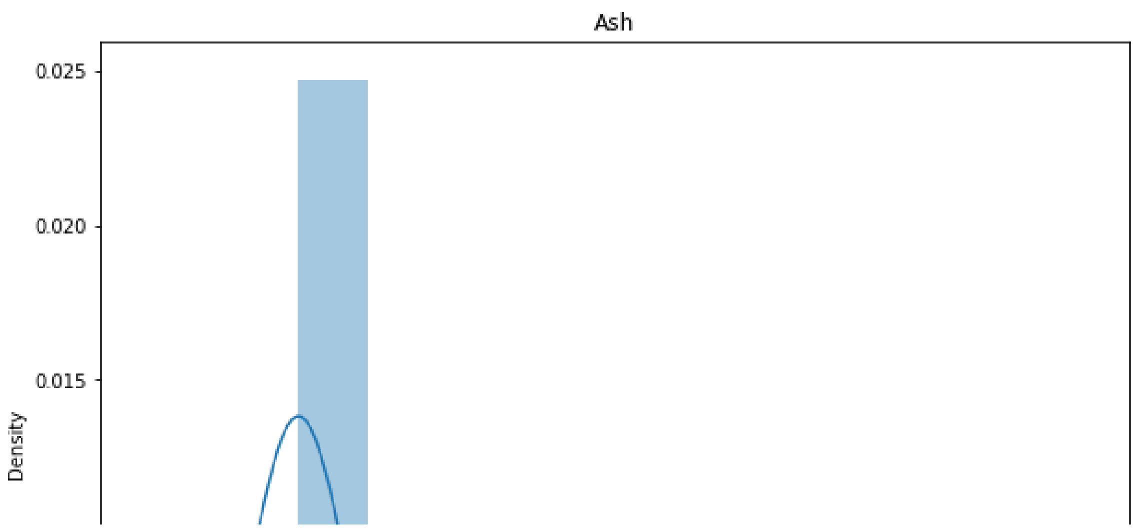
```
number of outliers in  Ash upper:  0
number of outliers in  Ash Lower:  0
```

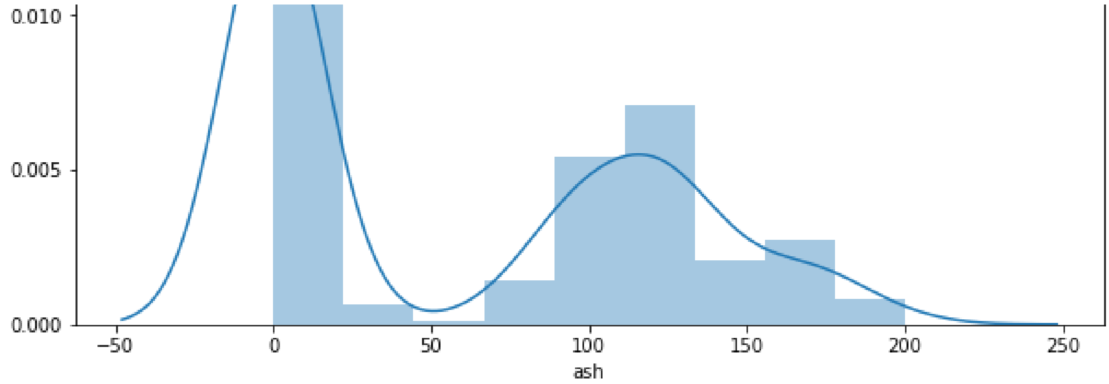
In [377]:

```
plt.figure(figsize=(10,8))
sns.distplot(df['ash']).set_title("Ash")
```

Out[377]:

```
Text(0.5, 1.0, 'Ash')
```



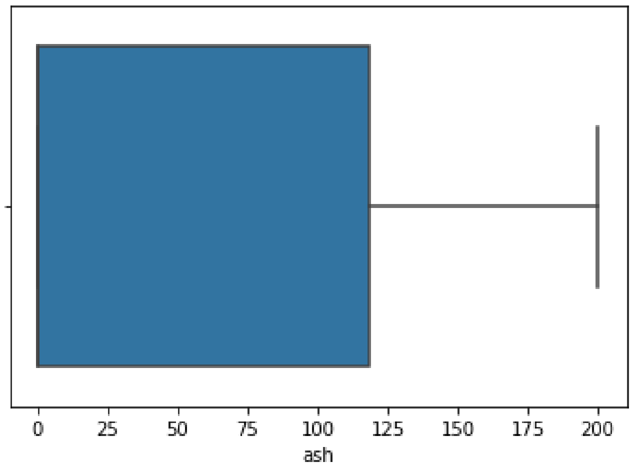


In [378]:

```
#distribution of cement
sns.boxplot(x='ash',data=df,orient='h')

#this shows there are no outliers found visually
```

Out[378]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f26f6865e50>
```



slag

In [379]:

```
Q1=df['slag'].quantile(q=0.25)
Q3=df['slag'].quantile(q=0.75)
print('1st quartile (Q1) is : ',Q1)
print('3rt quartile (Q3) is : ',Q3)
print('Interquartile range (IQR) is ',stats.iqr(df['slag']))

#finding Outliers from Interquartile range

L_outliers = Q1-1.5*(Q3-Q1)
O_outliers = Q3+1.5*(Q3-Q1)
print('Lower outlier limit in  slag: ',L_outliers)
print('Upper outlier limit in slag: ',O_outliers)
```

```
1st quartile (Q1) is :  0.0
3rt quartile (Q3) is :  142.95
Interquartile range (IQR) is  142.95
Lower outlier limit in  slag:  -214.42499999999998
Upper outlier limit in slag:  357.375
```

In [380]:

```
# checking presence of outliers with upper and lower limits
print('number of outliers in  slag upper: ',df[df['slag']>357.375]['slag'].count())
print('number of outliers in  slag Lower: ',df[df['slag']<-214.424999999998]['slag'].cou
nt())
```

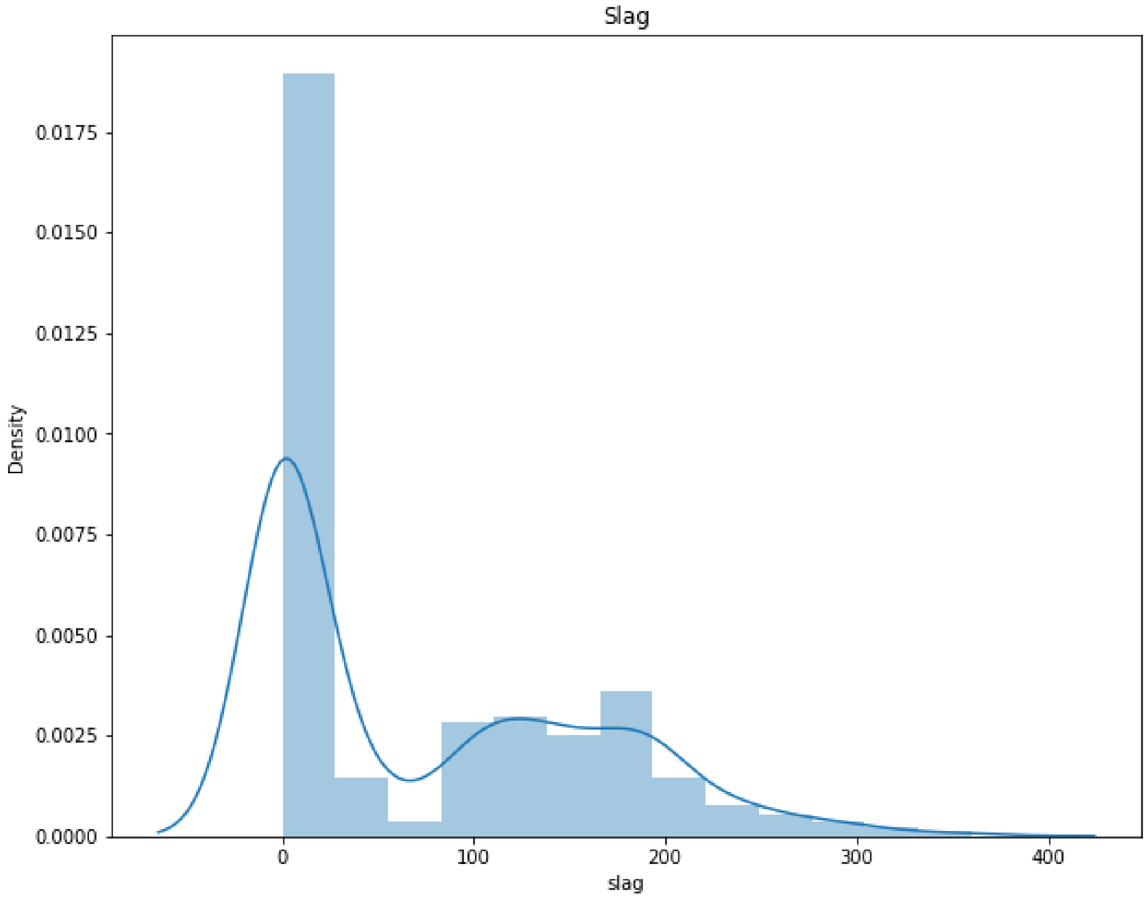
```
number of outliers in  slag upper:  2
number of outliers in  slag Lower:  0
```

In [381]:

```
plt.figure(figsize=(10,8))
sns.distplot(df['slag']).set_title("Slag")
```

Out[381]:

```
Text(0.5, 1.0, 'Slag')
```

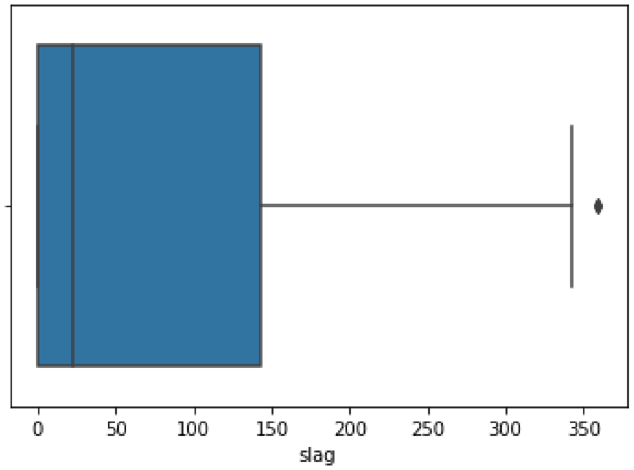


In [382]:

```
#distribution of cement
sns.boxplot(x='slag',data=df,orient='h')

#this shows there are  outliers found visually
```

Out[382]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f26f684d250>
```



In [382]:

```

```

water

In [383]:

```
Q1=df['water'].quantile(q=0.25)
Q3=df['water'].quantile(q=0.75)
print('1st quartile (Q1) is : ',Q1)
print('3rt quartile (Q3) is : ',Q3)
print('Interquartile range (IQR) is ',stats.iqr(df['water']))

#finding Outliers from Interquartile range

L_outliers = Q1-1.5*(Q3-Q1)
O_outliers = Q3+1.5*(Q3-Q1)
print('Lower outlier limit in  water: ',L_outliers)
print('Upper outlier limit in water: ',O_outliers)
```

```
1st quartile (Q1) is :  164.9
3rt quartile (Q3) is :  192.0
Interquartile range (IQR) is  27.099999999999994
Lower outlier limit in  water:  124.25000000000001
Upper outlier limit in water:  232.64999999999998
```

In [384]:

```
# checking presence of outliers with upper and lower limits
print('number of outliers in  water upper: ',df[df['water']>232.64999999999998]['water']
.count())
print('number of outliers in  water Lower: ',df[df['water']<124.25000000000001]['water']
.count())
```

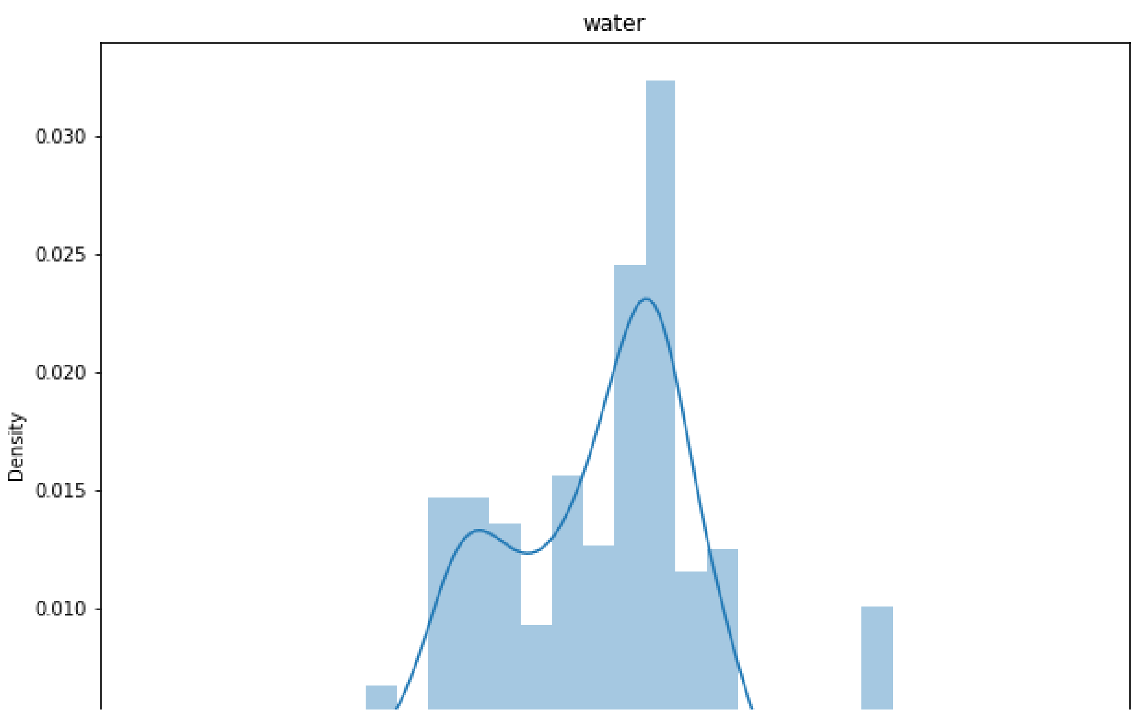
```
number of outliers in  water upper:  4
number of outliers in  water Lower:  5
```

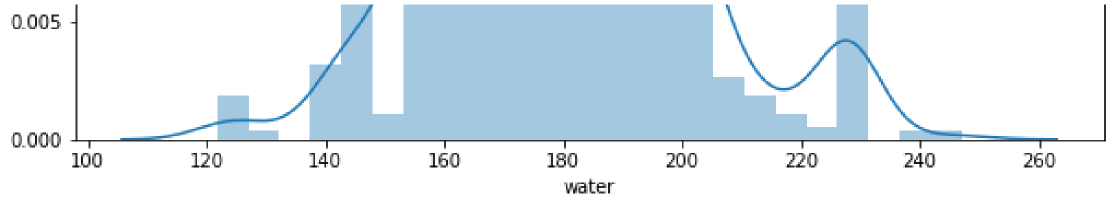
In [385]:

```
plt.figure(figsize=(10,8))
sns.distplot(df['water']).set_title("water")
```

Out[385]:

```
Text(0.5, 1.0, 'water')
```



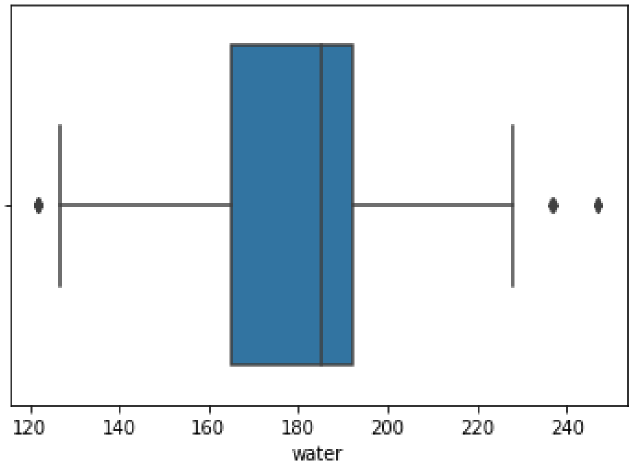


In [386]:

```
#distribution of cement
sns.boxplot(x='water',data=df,orient='h')

#this shows there are  outliers found visually
```

Out[386]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f26f662b750>
```



In [386]:

```
```

superplastic

In [387]:

```
Q1=df['superplastic'].quantile(q=0.25)
Q3=df['superplastic'].quantile(q=0.75)
print('1st quartile (Q1) is : ',Q1)
print('3rt quartile (Q3) is : ',Q3)
print('Interquartile range (IQR) is ',stats.iqr(df['superplastic']))

#finding Outliers from Interquartile range

L_outliers = Q1-1.5*(Q3-Q1)
O_outliers = Q3+1.5*(Q3-Q1)
print('Lower outlier limit in superplastic: ',L_outliers)
print('Upper outlier limit in superplastic: ',O_outliers)
```

```
1st quartile (Q1) is :  0.0
3rt quartile (Q3) is :  10.16
Interquartile range (IQR) is  10.16
Lower outlier limit in superplastic:  -15.24
Upper outlier limit in superplastic:  25.4
```

In [388]:

```
# checking presence of outliers with upper and lower limits
print('number of outliers in  superplastic upper: ',df[df['superplastic']>24.4]['superpla
stic'].count())
print('number of outliers in  superplastic Lower: ',df[df['superplastic']<-15.24]['super
plastic'].count())
```

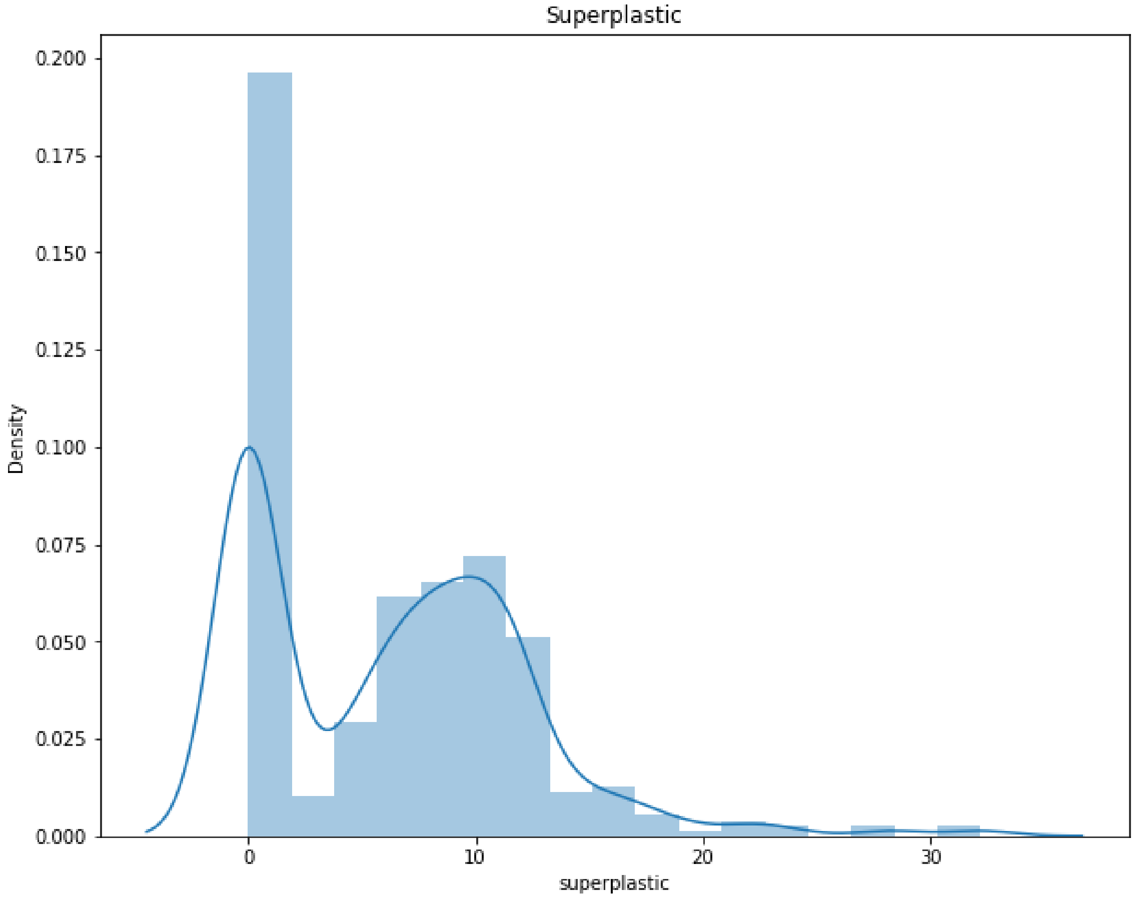
```
number of outliers in  superplastic upper:  10
number of outliers in  superplastic Lower:  0
```

In [389]:

```
plt.figure(figsize=(10,8))
sns.distplot(df['superplastic']).set_title("Superplastic")
```

Out[389]:

```
Text(0.5, 1.0, 'Superplastic')
```

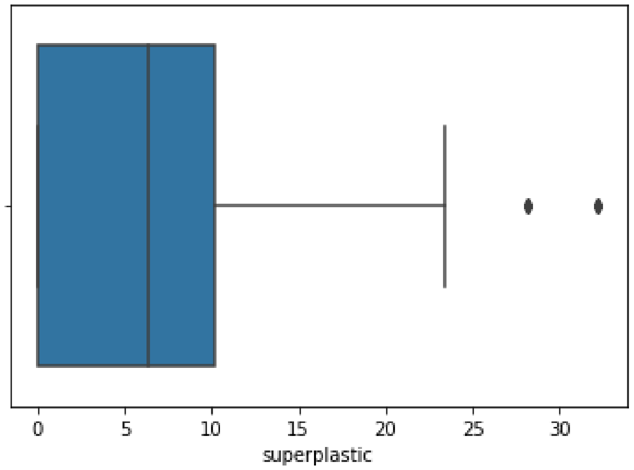


In [390]:

```
#distribution of cement
sns.boxplot(x='superplastic',data=df,orient='h')

#this shows there are  outliers found visually
```

Out[390]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f26f657e910>
```



In [390]:

coarseagg

In [391]:

```
Q1=df['coarseagg'].quantile(q=0.25)
Q3=df['coarseagg'].quantile(q=0.75)
print('1st quartile (Q1) is : ',Q1)
print('3rt quartile (Q3) is : ',Q3)
print('Interquartile range (IQR) is ',stats.iqr(df['coarseagg']))

#finding Outliers from Interquartile range

L_outliers = Q1-1.5*(Q3-Q1)
O_outliers = Q3+1.5*(Q3-Q1)
print('Lower outlier limit in coarseagg: ',L_outliers)
print('Upper outlier limit in coarseagg: ',O_outliers)
```

```
1st quartile (Q1) is :  932.0
3rt quartile (Q3) is :  1029.4
Interquartile range (IQR) is  97.40000000000009
Lower outlier limit in coarseagg:  785.8999999999999
Upper outlier limit in coarseagg:  1175.5000000000002
```

In [392]:

```
# checking presence of outliers with upper and lower limits
print('number of outliers in  water upper: ',df[df['coarseagg']>1175.5000000000002]['coa
rseagg'].count())
print('number of outliers in  water Lower: ',df[df['coarseagg']<785.8999999999999]['coar
seagg'].count())
```

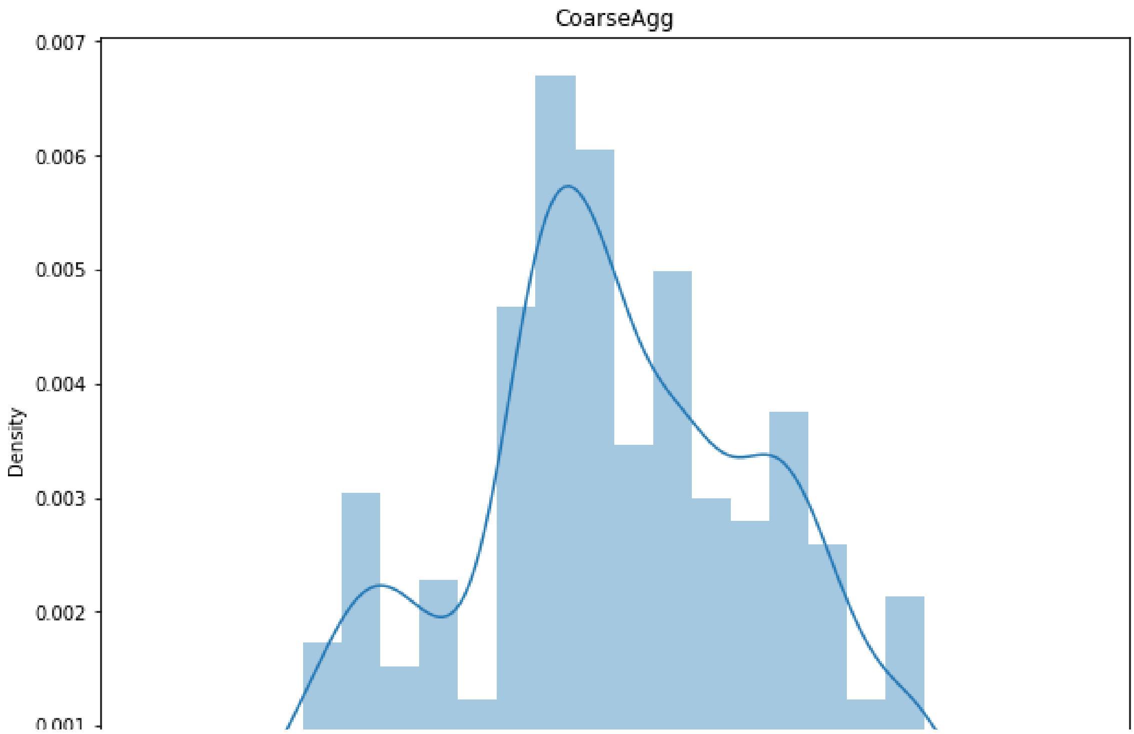
```
number of outliers in  water upper:  0
number of outliers in  water Lower:  0
```

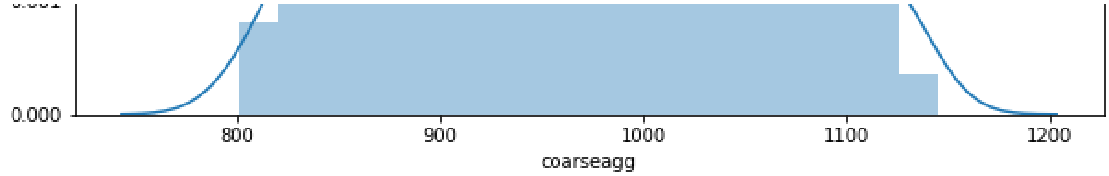
In [393]:

```
plt.figure(figsize=(10,8))
sns.distplot(df['coarseagg']).set_title("CoarseAgg")
```

Out[393]:

```
Text(0.5, 1.0, 'CoarseAgg')
```



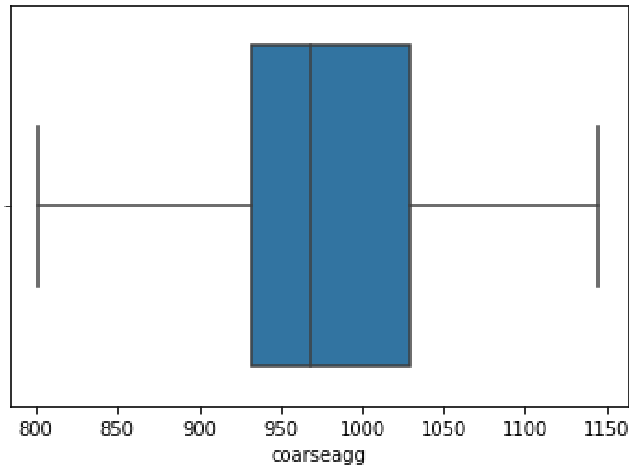


In [394]:

```
#distribution of cement
sns.boxplot(x='coarseagg',data=df,orient='h')

#this shows there are no outliers found visually
```

Out[394]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f26f6753190>
```



In [394]:

```

```

fineagg

In [395]:

```
Q1=df['fineagg'].quantile(q=0.25)
Q3=df['fineagg'].quantile(q=0.75)
print('1st quartile (Q1) is : ',Q1)
print('3rt quartile (Q3) is : ',Q3)
print('Interquartile range (IQR) is ',stats.iqr(df['fineagg']))

#finding Outliers from Interquartile range

L_outliers = Q1-1.5*(Q3-Q1)
O_outliers = Q3+1.5*(Q3-Q1)
print('Lower outlier limit in fineagg: ',L_outliers)
print('Upper outlier limit in fineagg: ',O_outliers)
```

```
1st quartile (Q1) is :  730.9499999999999
3rt quartile (Q3) is :  824.0
Interquartile range (IQR) is  93.05000000000007
Lower outlier limit in fineagg:  591.3749999999998
Upper outlier limit in fineagg:  963.575
```

In [396]:

```
# checking presence of outliers with upper and lower limits
print('number of outliers in  fineagg upper: ',df[df['coarseagg']>963.575]['coarseagg'].
count())
print('number of outliers in  fineagg Lower: ',df[df['coarseagg']<591.3749999999998]['co
arseagg'].count())
```

```
number of outliers in  fineagg upper:  563
```

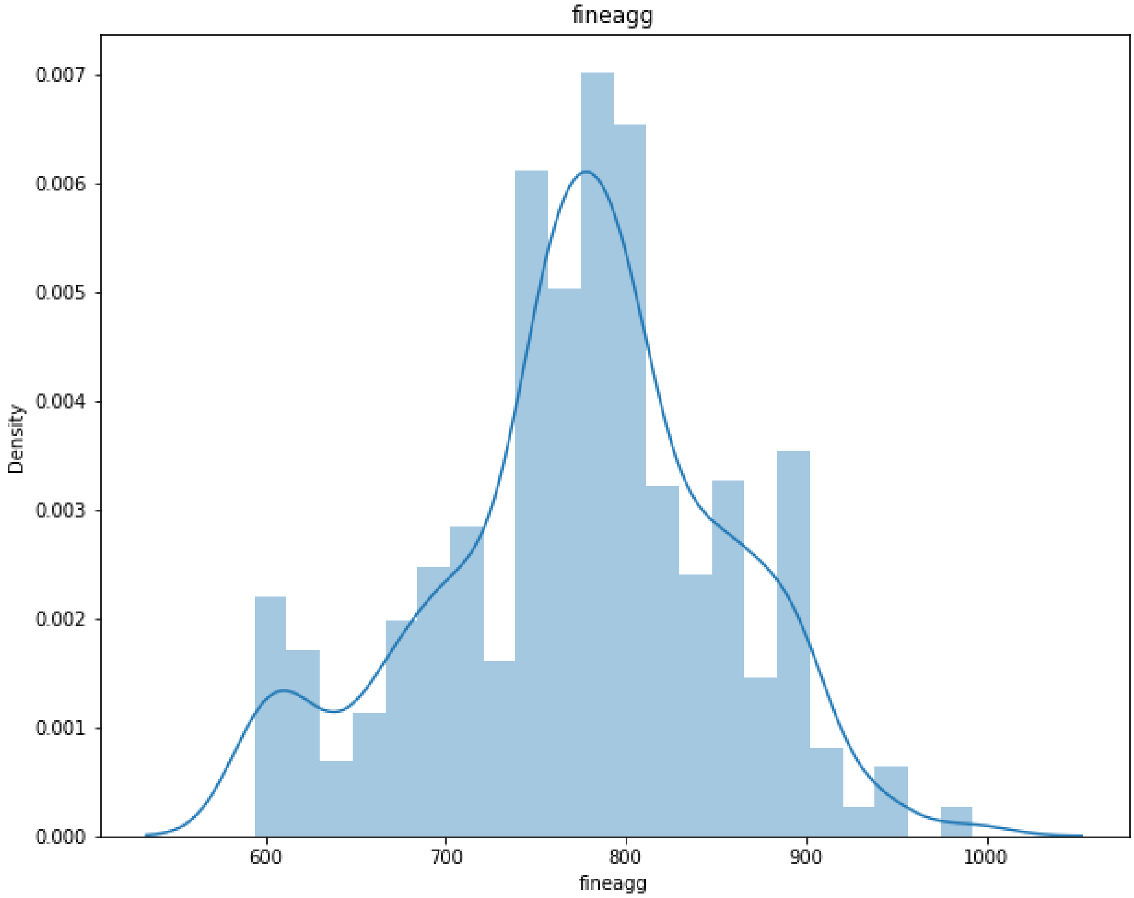
number of outliers in fineagg Lower: 0

In [397]:

```
plt.figure(figsize=(10,8))
sns.distplot(df['fineagg']).set_title("fineagg")
```

Out[397]:

Text(0.5, 1.0, 'fineagg')

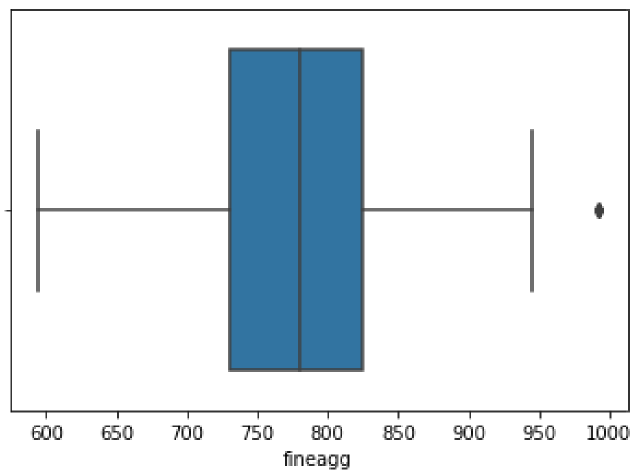


In [398]:

```
#distribution of cement
sns.boxplot(x='fineagg',data=df,orient='h')

#this shows there are  outliers found visually
```

Out[398]:

<matplotlib.axes._subplots.AxesSubplot at 0x7f26f6393910>



In [398]:

age

In [399]:

```
Q1=df['age'].quantile(q=0.25)
Q3=df['age'].quantile(q=0.75)
print('1st quartile (Q1) is : ',Q1)
print('3rt quartile (Q3) is : ',Q3)
print('Interquartile range (IQR) is ',stats.iqr(df['age']))

#finding Outliers from Interquartile range

L_outliers = Q1-1.5*(Q3-Q1)
O_outliers = Q3+1.5*(Q3-Q1)
print('Lower outlier limit in age: ',L_outliers)
print('Upper outlier limit in age: ',O_outliers)
```

```
1st quartile (Q1) is :  7.0
3rt quartile (Q3) is :  56.0
Interquartile range (IQR) is  49.0
Lower outlier limit in age:  -66.5
Upper outlier limit in age:  129.5
```

In [400]:

```
# checking presence of outliers with upper and lower limits
print('number of outliers in age upper: ',df[df['age']>129.5]['age'].count())
print('number of outliers in age Lower: ',df[df['age']<-66.5]['age'].count())
```

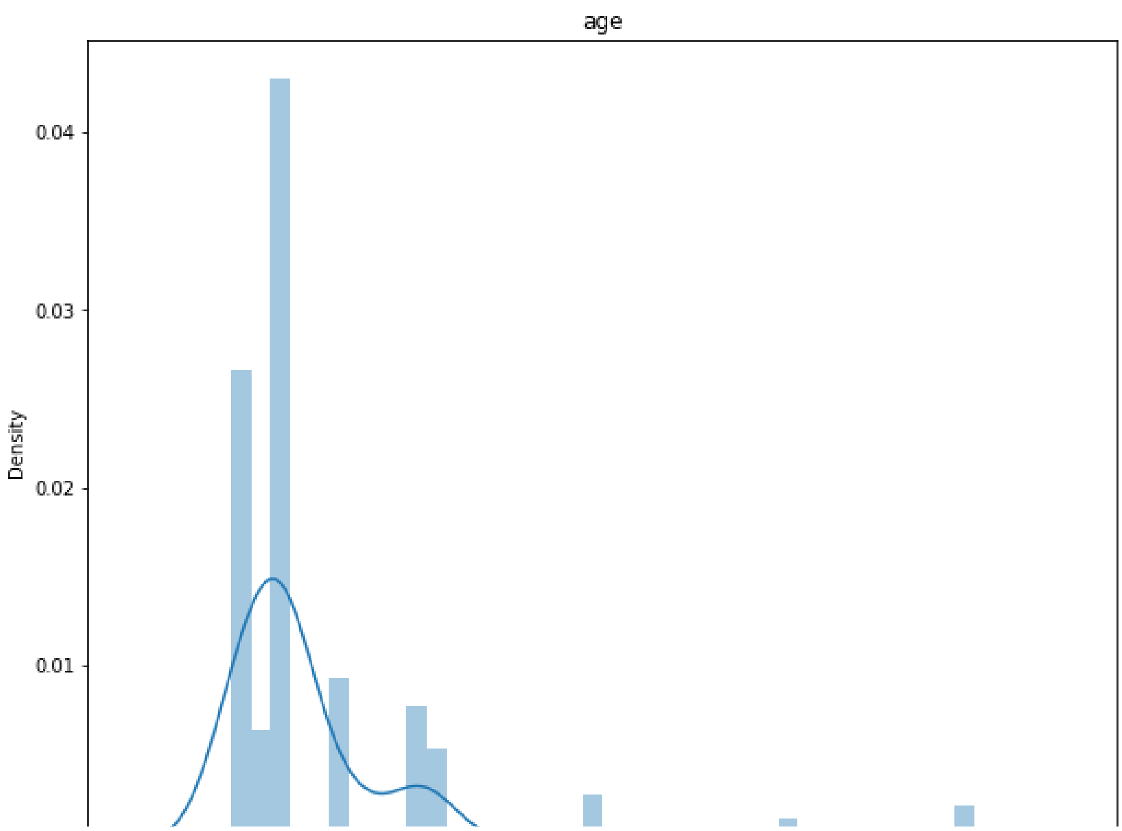
```
number of outliers in age upper:  59
number of outliers in age Lower:  0
```

In [401]:

```
plt.figure(figsize=(10,8))
sns.distplot(df['age']).set_title("age")
```

Out[401]:

```
Text(0.5, 1.0, 'age')
```

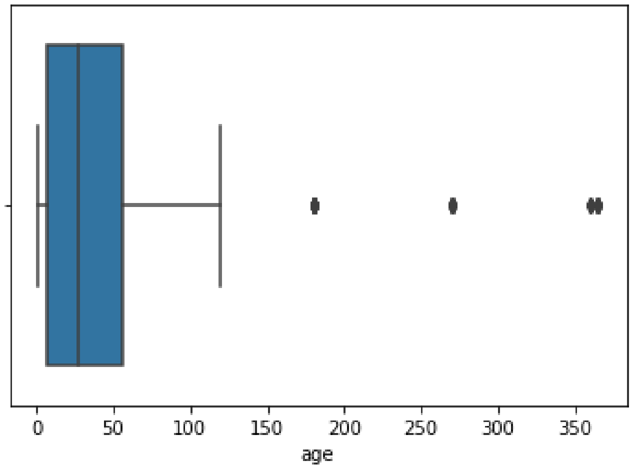


In [402]:

```
#distribution of cement
sns.boxplot(x='age',data=df,orient='h')

#this shows there are outliers found visually
```

Out[402]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f26f6258190>
```



In [402]:

```
```

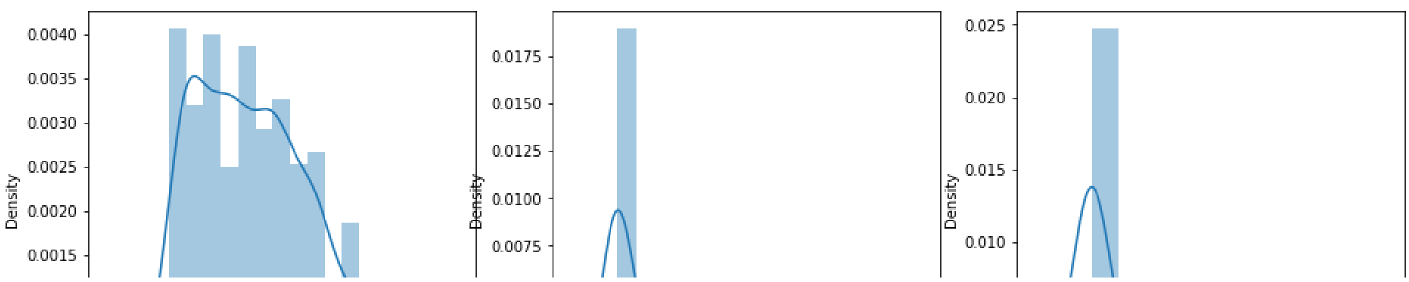
Multivariable Analysis

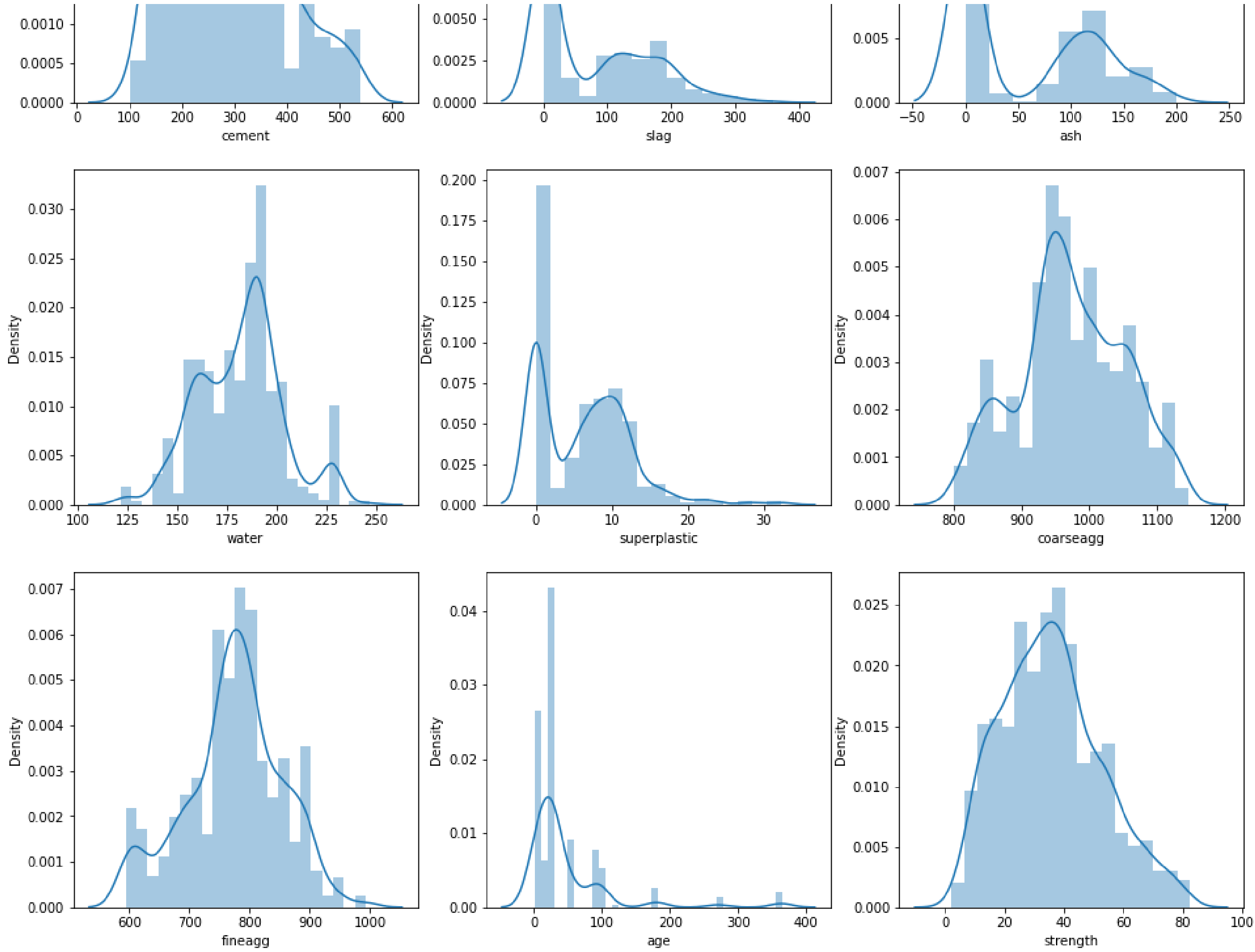
In [403]:

```
#Dist plot
fig, ax2 = plt.subplots(3,3,figsize=(16,16))
sns.distplot(df['cement'],ax=ax2[0][0])
sns.distplot(df['slag'],ax=ax2[0][1])
sns.distplot(df['ash'],ax=ax2[0][2])
sns.distplot(df['water'],ax=ax2[1][0])
sns.distplot(df['superplastic'],ax=ax2[1][1])
sns.distplot(df['coarseagg'],ax=ax2[1][2])
sns.distplot(df['fineagg'],ax=ax2[2][0])
sns.distplot(df['age'],ax=ax2[2][1])
sns.distplot(df['strength'],ax=ax2[2][2])
```

Out[403]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f26f6014290>
```



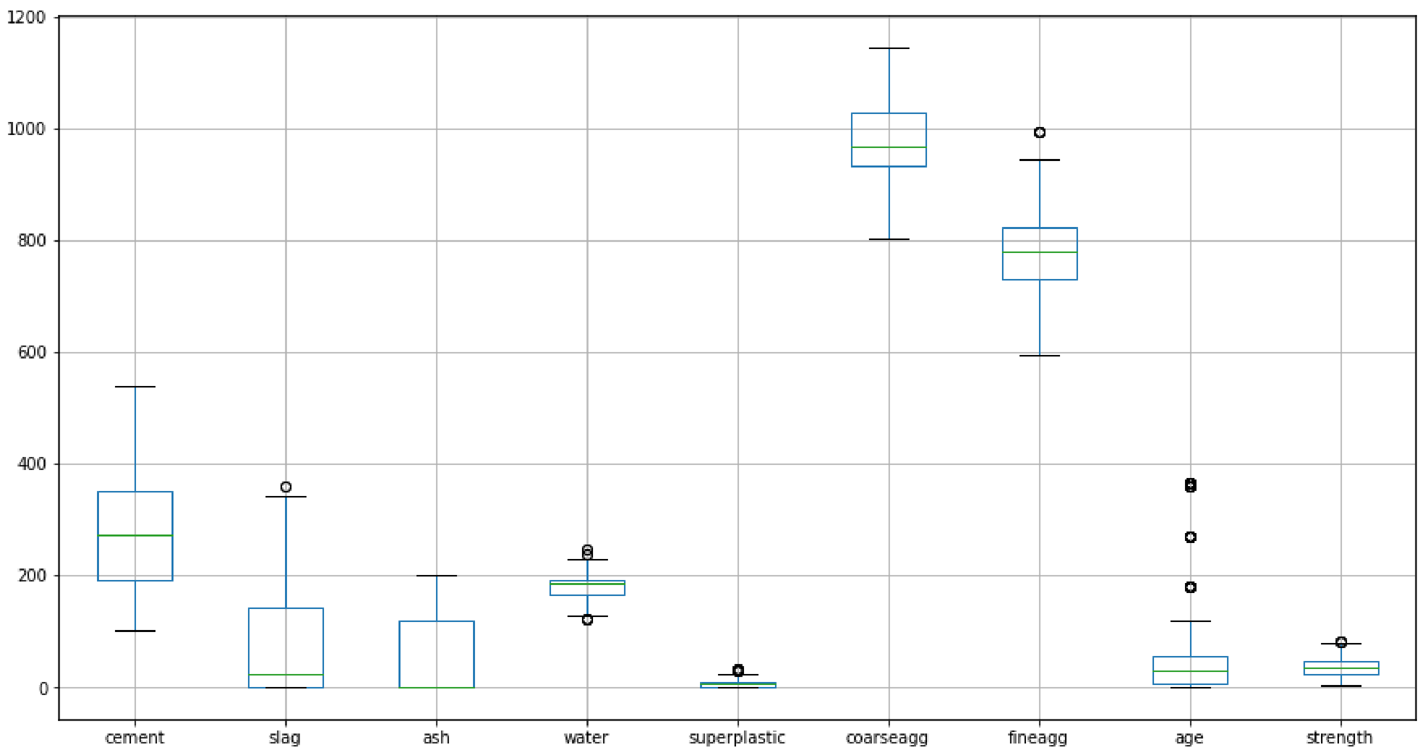


In [404]:

```
df.boxplot(figsize=(15,8))
```

Out[404]:

<matplotlib.axes._subplots.AxesSubplot at 0x7f26f61b9710>



Since we have found outliers present and that may effect the actual outcome , so we are going to remove to minimalize the outlier by considering the median value of there respective column by considering the quantile

In [405]:

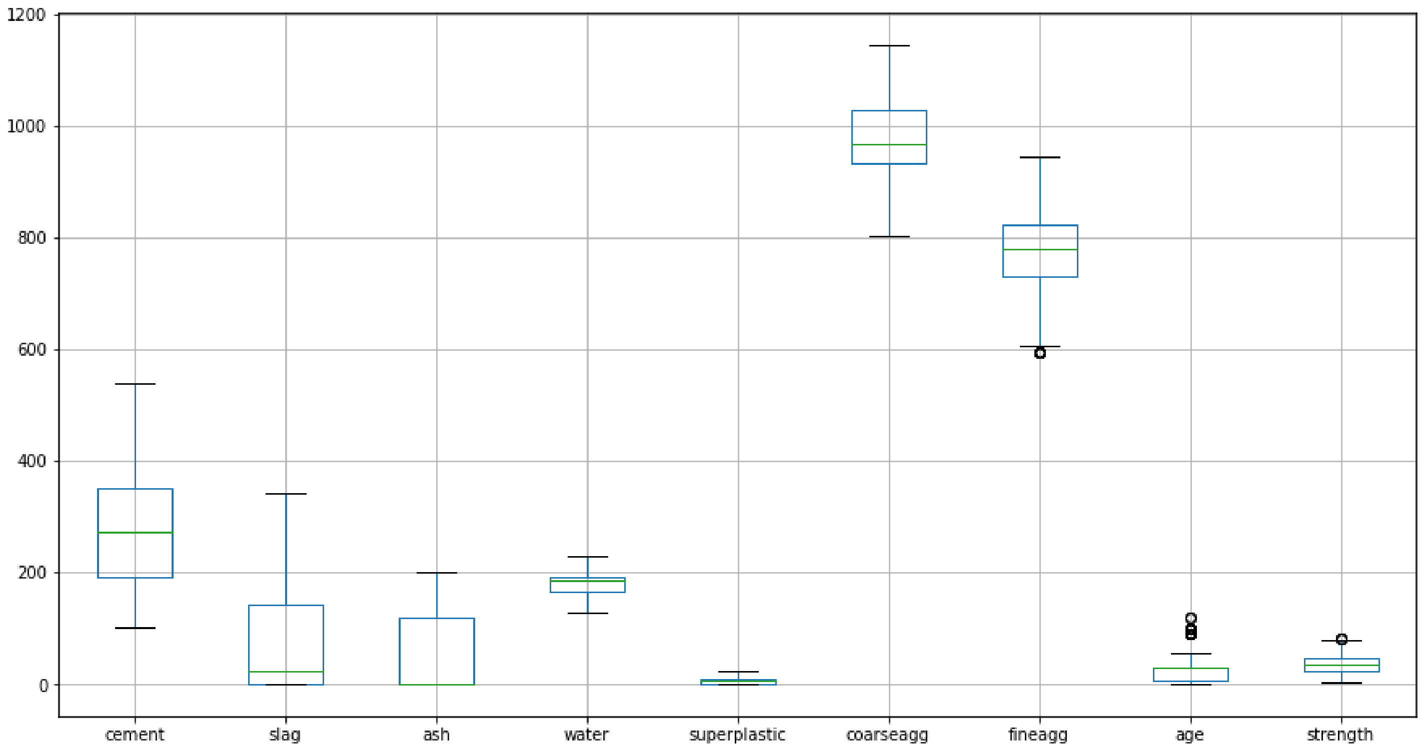
```
for cols in df.columns[:-1]:
  Q1=df[cols].quantile(0.25)
  Q3=df[cols].quantile(0.75)
  iqr= Q3-Q1

  low= Q1-1.5*iqr
  high= Q3+1.5*iqr
  df.loc[(df[cols]<low) | (df[cols]>high),cols] = df[cols].median()
```

In [406]:

```
df.boxplot(figsize=(15,8))
```

Out[406]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f26f6848910>
```



now we can see that the outliers are minimized

In [406]:

```

```

Model Training and finding the best one

In [407]:

```
df.head()
```

Out[407]:

	cement	slag	ash	water	superplastic	coarseagg	fineagg	age	strength
0	540.0	0.0	0.0	162.0	2.5	1040.0	676.0	28	79.986111
1	540.0	0.0	0.0	162.0	2.5	1055.0	676.0	28	61.887366
2	332.5	142.5	0.0	228.0	0.0	932.0	594.0	28	40.269535
3	332.5	142.5	0.0	228.0	0.0	932.0	594.0	28	41.052780
4	198.6	132.4	0.0	192.0	0.0	978.4	825.5	28	44.296075

Now we are splitting the data in Dependent and independent varaibles as x and y

In [408]:

```
x=df.drop('strength',axis=1)
y=df['strength']
```

In [409]:

```
y
```

Out[409]:

```
0       79.986111
1       61.887366
2       40.269535
3       41.052780
4       44.296075
          ...
1025    44.284354
1026    31.178794
1027    23.696601
1028    32.768036
1029    32.401235
Name: strength, Length: 1030, dtype: float64
```

In [410]:

```
x
```

Out[410]:

	cement	slag	ash	water	superplastic	coarseagg	fineagg	age
0	540.0	0.0	0.0	162.0	2.5	1040.0	676.0	28
1	540.0	0.0	0.0	162.0	2.5	1055.0	676.0	28
2	332.5	142.5	0.0	228.0	0.0	932.0	594.0	28
3	332.5	142.5	0.0	228.0	0.0	932.0	594.0	28
4	198.6	132.4	0.0	192.0	0.0	978.4	825.5	28
...	...	...	...	...	...	...	...	...
1025	276.4	116.0	90.3	179.6	8.9	870.1	768.3	28
1026	322.2	0.0	115.6	196.0	10.4	817.9	813.4	28
1027	148.5	139.4	108.6	192.7	6.1	892.4	780.0	28
1028	159.1	186.7	0.0	175.6	11.3	989.6	788.9	28
1029	260.9	100.5	78.3	200.6	8.6	864.5	761.5	28

1030 rows × 8 columns

In [411]:

```
from scipy.stats import zscore
xscaled = x.apply(zscore)
xscaled_df=pd.DataFrame(xscaled,columns=df.columns)
```

In [412]:

```
x_train,x_test,y_train,y_test =train_test_split(xscaled,y,test_size=0.3,random_state=1)
```

Multilinear regression

In [413]:

```
model=LinearRegression()
model.fit(x_train,y_train)
ML_pred= model.predict(x_test)
# ML_train_score=model.score(x_train,y_train)
# ML_test_score=model.score(x_test,y_test)
# print("Multi Linear Regression Training Score = ",ML_train_score)
# print("Multi Linear Regression Test Score = ",ML_test_score)
ML_accuracy=metrics.r2_score(y_test,ML_pred)
print("Multi Linear Regression accuracy = ",accuracy)
MLR_Mean=metrics.mean_squared_error(y_test,ML_pred)
print("Multi Linear regression mean square error =  ",MLR_Mean)
```

```
Multi Linear Regression accuracy =  0.877608456648451

Multi Linear regression mean square error =   88.0394615825152
```

Decision Tree

In [414]:

```
dcr= DecisionTreeRegressor()
dcr.fit(x_train,y_train)
dcr_pred=model.predict(x_test)
dcr_accuracy=metrics.r2_score(y_test,dcr_pred)
print("Decision Tree Regression accuracy = ",dcr_accuracy)
dcr_mean=metrics.mean_squared_error(y_test,dcr_pred)
print("Decsion Tree regressor mean square error = ",dcr_mean)
```

```
Decision Tree Regression accuracy =  0.6641092873372312

Decsion Tree regressor mean square error =  88.0394615825152
```

Random Forest

In [415]:

```
model=RandomForestRegressor()
model.fit(x_train,y_train)
R_pred = model.predict(x_test)
accuracy = metrics.r2_score(y_test,R_pred)
print("Random Forest Accuracy = ",accuracy)
r_Mean=metrics.mean_squared_error(y_test,R_pred)
print("Random Forest mean squrare error = ",r_Mean)
```

```
Random Forest Accuracy =  0.8765582624091046

Random Forest mean squrare error =  32.35500031590237
```

Gradient Boost Regressor

In [416]:

```
GBR_model=GradientBoostingRegressor()
GBR_model.fit(x_train,y_train)
GB_pred=GBR_model.predict(x_test)
GBR_model.score(x_train,y_train)
GBR_model.score(x_test,y_test)
accuracy=metrics.r2_score(y_test,GB_pred)
print("Gradient Boost Regressor Accuracy = ",accuracy)
GB_meansquareerror=metrics.mean_squared_error(y_test,GB_pred)
print("GB Mean square error = ",GB_meansquareerror)
```

```
Gradient Boost Regressor Accuracy =  0.8823816703961012
```

```
GB Mean square error =  30.828641639039436
```

So far as we observed , Gradient Boost have better accuracy and less mean square error

In [416]:

```

```

In [416]:

```

```