Importing Libraries & Dataset

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from scipy.stats import skew

df = pd.read_csv('Downloads/abalone.csv')
df.head()

  Sex  Length  Diameter  Height  Whole weight  Shucked weight  Viscera
weight  \
0   M   0.455     0.365   0.095        0.5140          0.2245
0.1010
1   M   0.350     0.265   0.090        0.2255          0.0995
0.0485
2   F   0.530     0.420   0.135        0.6770          0.2565
0.1415
3   M   0.440     0.365   0.125        0.5160          0.2155
0.1140
4   I   0.330     0.255   0.080        0.2050          0.0895
0.0395

   Shell weight  Rings
0         0.150     15
1         0.070      7
2         0.210      9
3         0.155     10
4         0.055      7

df.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 4177 entries, 0 to 4176
Data columns (total 9 columns):
 #   Column          Non-Null Count  Dtype
---  ------          --------------  -----
 0   Sex             4177 non-null   object
 1   Length          4177 non-null   float64
 2   Diameter        4177 non-null   float64
 3   Height          4177 non-null   float64
 4   Whole weight    4177 non-null   float64
 5   Shucked weight  4177 non-null   float64
 6   Viscera weight  4177 non-null   float64
 7   Shell weight    4177 non-null   float64
 8   Rings           4177 non-null   int64
dtypes: float64(7), int64(1), object(1)
memory usage: 293.8+ KB

df.describe()
```

```
            Length     Diameter       Height  Whole weight  Shucked 
weight  \
count  4177.000000  4177.000000  4177.000000   4177.000000   
4177.000000   
mean      0.523992     0.407881     0.139516      0.828742   
0.359367   
std       0.120093     0.099240     0.041827      0.490389   
0.221963   
min       0.075000     0.055000     0.000000      0.002000   
0.001000   
25%       0.450000     0.350000     0.115000      0.441500   
0.186000   
50%       0.545000     0.425000     0.140000      0.799500   
0.336000   
75%       0.615000     0.480000     0.165000      1.153000   
0.502000   
max       0.815000     0.650000     1.130000      2.825500   
1.488000   

       Viscera weight  Shell weight        Rings  
count     4177.000000   4177.000000  4177.000000  
mean         0.180594      0.238831     9.933684  
std          0.109614      0.139203     3.224169  
min          0.000500      0.001500     1.000000  
25%          0.093500      0.130000     8.000000  
50%          0.171000      0.234000     9.000000  
75%          0.253000      0.329000    11.000000  
max          0.760000      1.005000    29.000000  
```

```
df.shape
```

```
(4177, 9)
```

```
df['Age'] = df['Rings']+1.5
df = df.drop('Rings', axis=1)
df.head()
```

```
  Sex  Length  Diameter  Height  Whole weight  Shucked weight  Viscera 
weight  \
0   M   0.455     0.365   0.095        0.5140          0.2245   
0.1010   
1   M   0.350     0.265   0.090        0.2255          0.0995   
0.0485   
2   F   0.530     0.420   0.135        0.6770          0.2565   
0.1415   
3   M   0.440     0.365   0.125        0.5160          0.2155   
0.1140   
4   I   0.330     0.255   0.080        0.2050          0.0895   
0.0395   

   Shell weight   Age  
```

```
0         0.150  16.5
1         0.070   8.5
2         0.210  10.5
3         0.155  11.5
4         0.055   8.5
```

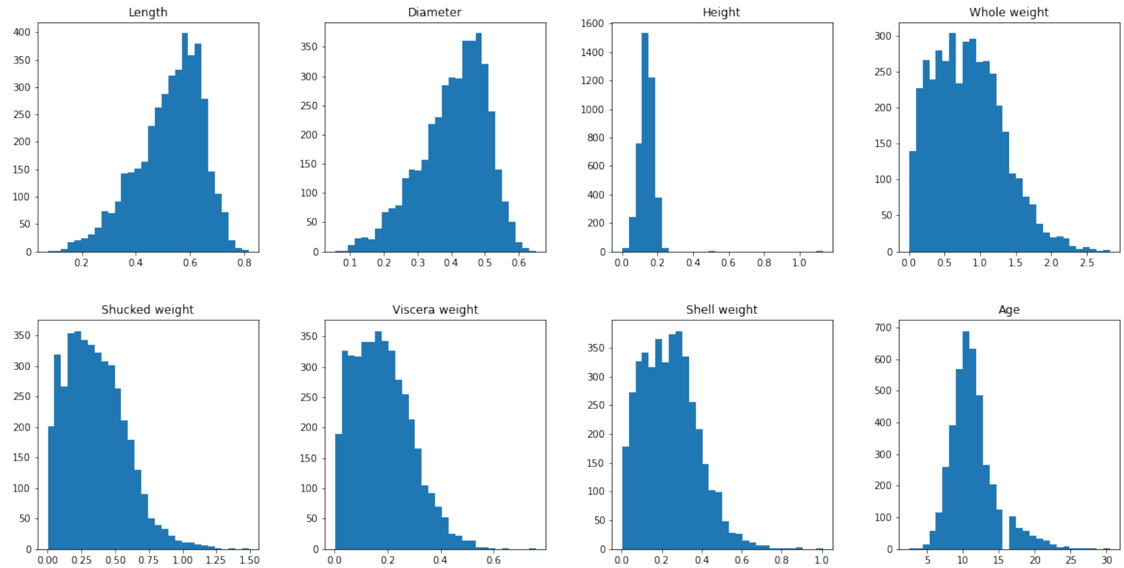
```
df.describe()
```

```
            Length     Diameter       Height  Whole weight  Shucked
weight  \
count  4177.000000  4177.000000  4177.000000   4177.000000
4177.000000
mean      0.523992     0.407881     0.139516      0.828742
0.359367
std       0.120093     0.099240     0.041827      0.490389
0.221963
min       0.075000     0.055000     0.000000      0.002000
0.001000
25%       0.450000     0.350000     0.115000      0.441500
0.186000
50%       0.545000     0.425000     0.140000      0.799500
0.336000
75%       0.615000     0.480000     0.165000      1.153000
0.502000
max       0.815000     0.650000     1.130000      2.825500
1.488000

       Viscera weight  Shell weight          Age
count     4177.000000   4177.000000  4177.000000
mean         0.180594      0.238831    11.433684
std          0.109614      0.139203     3.224169
min          0.000500      0.001500     2.500000
25%          0.093500      0.130000     9.500000
50%          0.171000      0.234000    10.500000
75%          0.253000      0.329000    12.500000
max          0.760000      1.005000    30.500000
```

Data Analysis & Visualization

Univariate Analysis

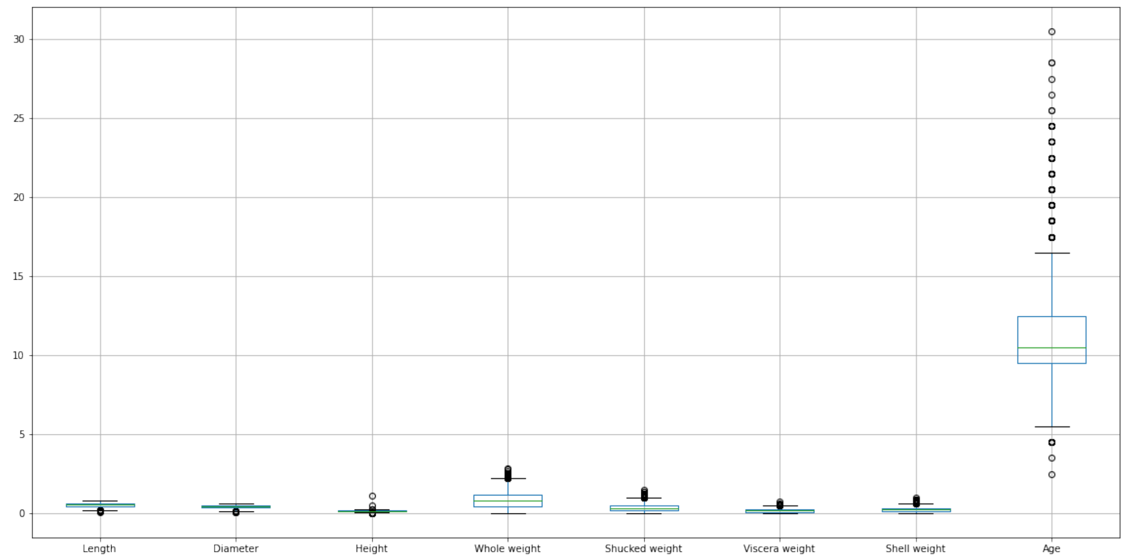
```
df.hist(figsize=(20,10), grid=False, layout=(2,4), bins=30)
plt.show()
```




```
Numerical = df.select_dtypes(include=[np.number]).columns
Categorical = df.select_dtypes(include=[np.object]).columns

skew_values = skew(df[Numerical], nan_policy = 'omit')
dummy = pd.concat([pd.DataFrame(list(Numerical),
columns=['Features']),
           pd.DataFrame(list(skew_values), columns=['Skewness
degree'])], axis = 1)
dummy.sort_values(by = 'Skewness degree' , ascending = False)
```

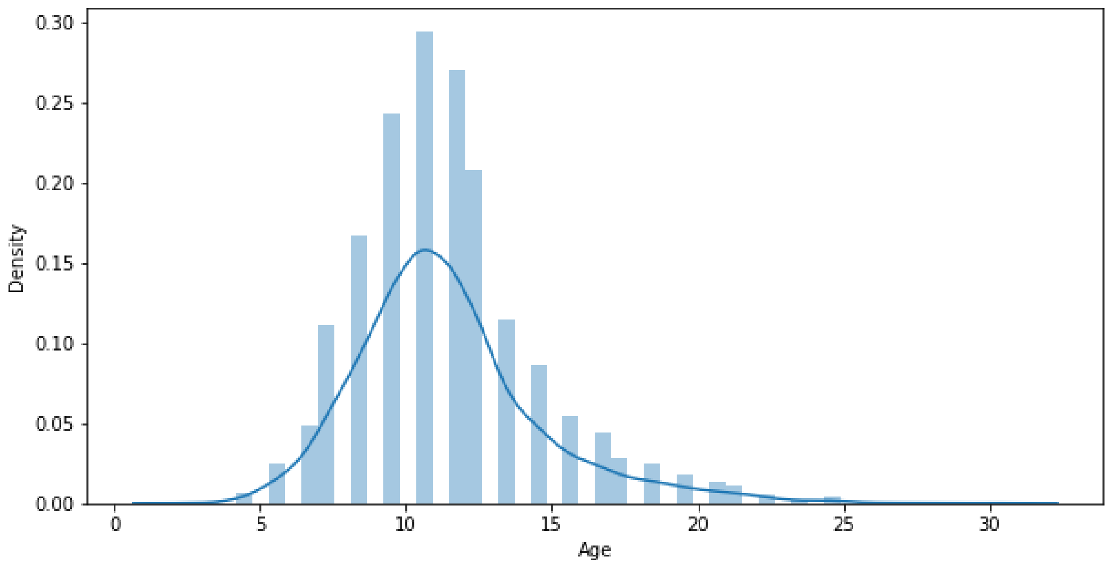
	Features	Skewness degree
2	Height	3.127694
7	Age	1.113702
4	Shucked weight	0.718840
6	Shell weight	0.620704
5	Viscera weight	0.591640
3	Whole weight	0.530768
1	Diameter	-0.608979
0	Length	-0.639643

```
df.boxplot(figsize=(20,10))
plt.show()
```



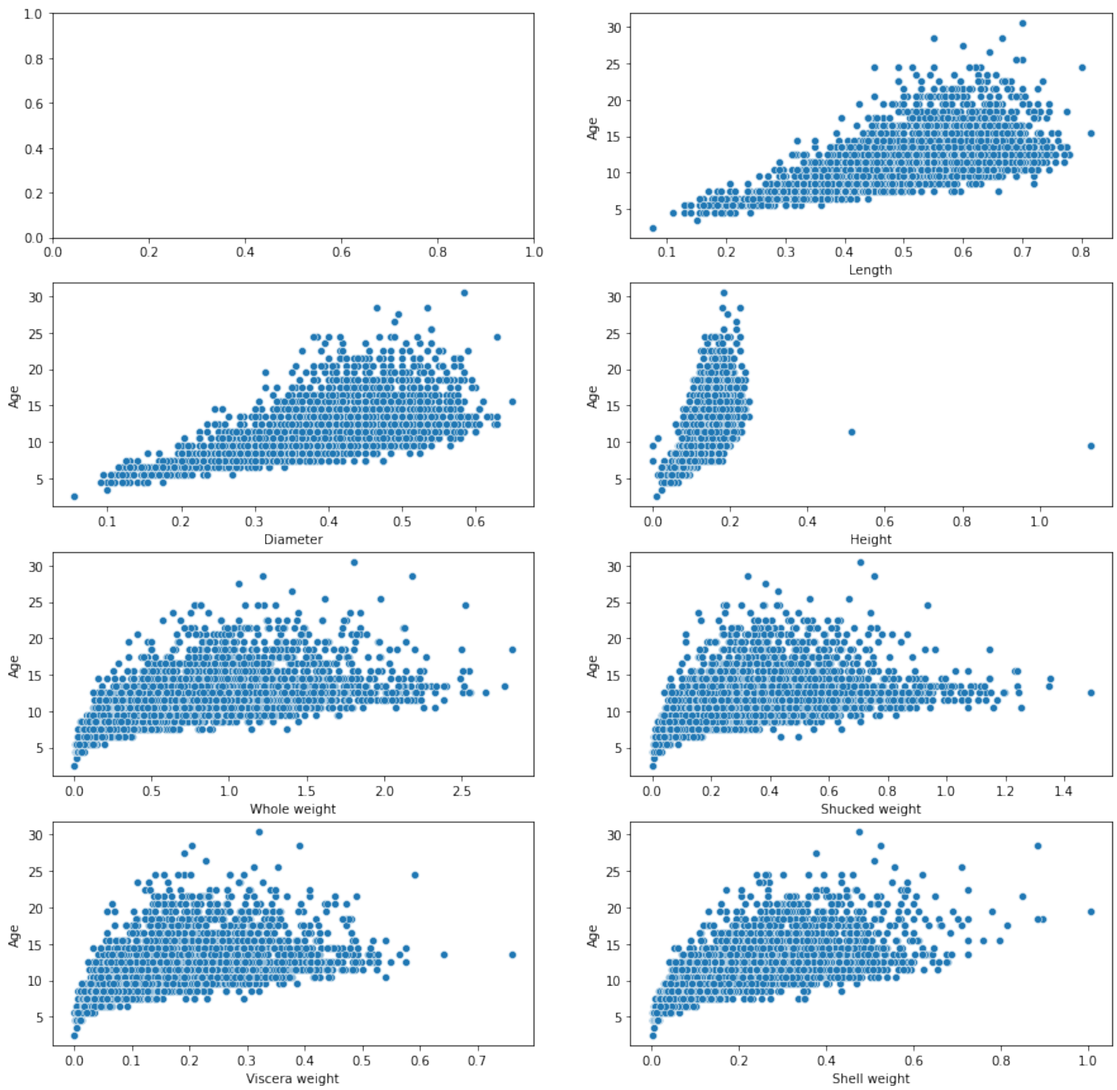

```
plt.figure(figsize=(10,5))
sns.distplot(df['Age'])
plt.show()
```

```
<ipython-input-31-f61500c5e113>:2: UserWarning:

`distplot` is a deprecated function and will be removed in seaborn
v0.14.0.

Please adapt your code to use either `displot` (a figure-level
function with
similar flexibility) or `histplot` (an axes-level function for
histograms).

For a guide to updating your code to use the new functions, please see
https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751

  sns.distplot(df['Age'])
```

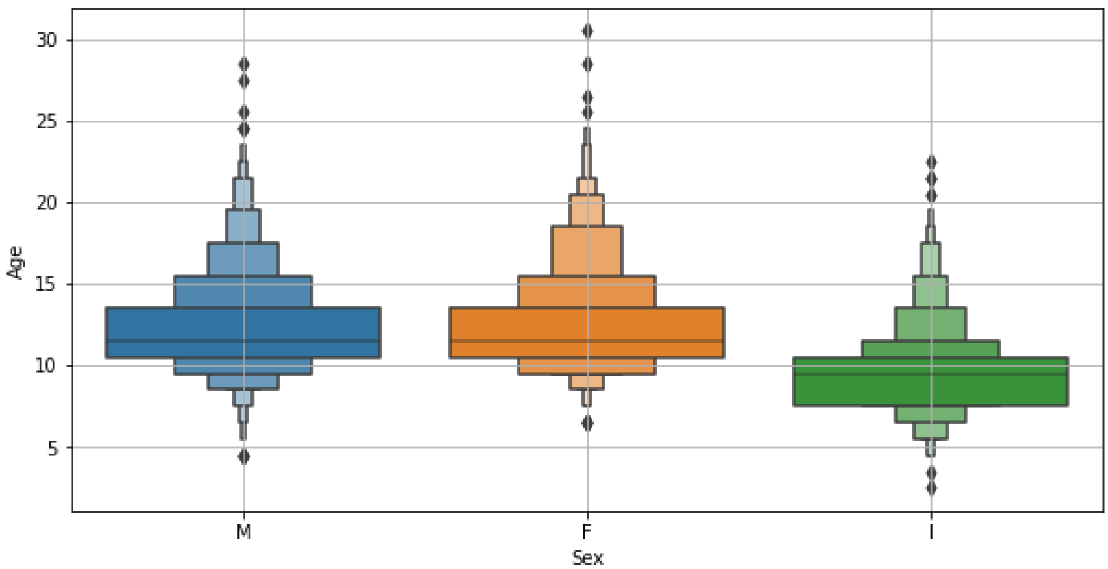


Bivariate Analysis

```
df.head()

  Sex  Length  Diameter  Height  Whole weight  Shucked weight  Viscera
weight  \
0   M   0.455     0.365   0.095        0.5140          0.2245
0.1010
1   M   0.350     0.265   0.090        0.2255          0.0995
0.0485
2   F   0.530     0.420   0.135        0.6770          0.2565
0.1415
3   M   0.440     0.365   0.125        0.5160          0.2155
0.1140
4   I   0.330     0.255   0.080        0.2050          0.0895
0.0395

   Shell weight   Age
0         0.150  16.5
1         0.070   8.5
2         0.210  10.5
3         0.155  11.5
4         0.055   8.5

fig, axes = plt.subplots(4,2, figsize=(15,15))
axes = axes.flatten()
for i in range(1,len(df.columns)-1):
    sns.scatterplot(x=df.iloc[:,i], y=df['Age'], ax=axes[i])
plt.show()
```



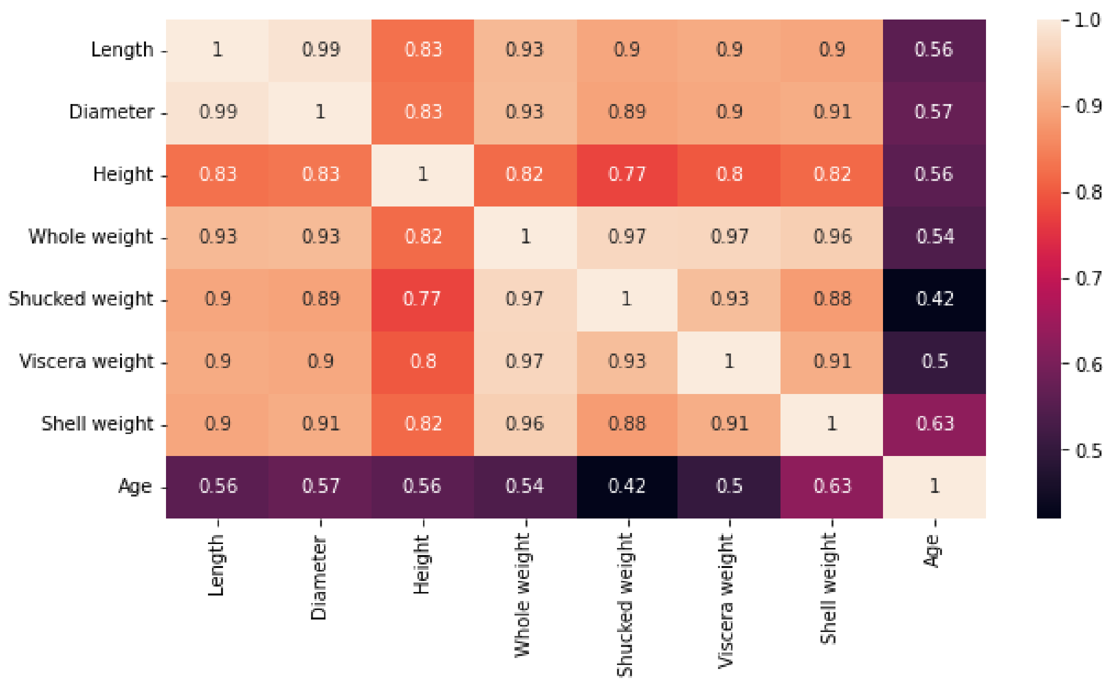

```
plt.figure(figsize=(10,5))
sns.boxenplot(y=df['Age'], x=df['Sex'])
plt.grid()
plt.show()
df.groupby('Sex')['Age'].describe()
```



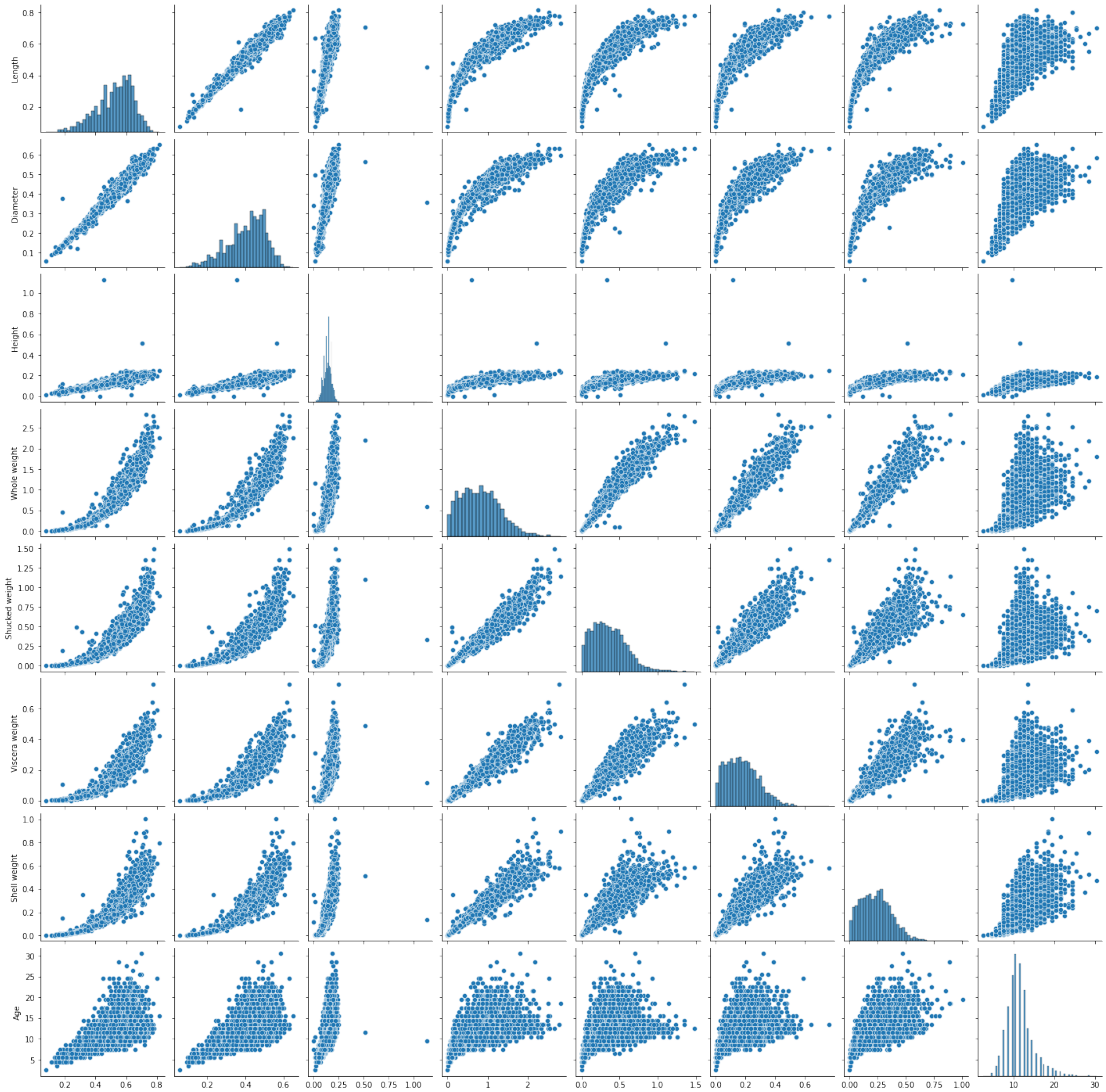
	count	mean	std	min	25%	50%	75%	max
Sex								
F	1307.0	12.629304	3.104256	6.5	10.5	11.5	13.5	30.5
I	1342.0	9.390462	2.511554	2.5	7.5	9.5	10.5	22.5
M	1528.0	12.205497	3.026349	4.5	10.5	11.5	13.5	28.5

Multivariate Analysis

```
plt.figure(figsize=(10,5))
sns.heatmap(df.corr(), annot=True)
plt.show()
```



```
sns.pairplot(df)
plt.show()
```



Preprocessing

Dealing with Categorical Values

```
#encoding
df = pd.get_dummies(df, drop_first=True)
df.head()

   Length  Diameter  Height  Whole weight  Shucked weight  Viscera
weight  \
0   0.455     0.365   0.095        0.5140          0.2245
0.1010
1   0.350     0.265   0.090        0.2255          0.0995
```

```
0.0485
2   0.530     0.420   0.135        0.6770          0.2565
0.1415
3   0.440     0.365   0.125        0.5160          0.2155
0.1140
4   0.330     0.255   0.080        0.2050          0.0895
0.0395

   Shell weight   Age  Sex_I  Sex_M
0         0.150  16.5      0      1
1         0.070   8.5      0      1
2         0.210  10.5      0      0
3         0.155  11.5      0      1
4         0.055   8.5      1      0
```

Statistical Approach

```
X = df.drop(['Age'], axis=1)
y = df['Age']

import statsmodels.api as sm

Xc = sm.add_constant(X)
lr = sm.OLS(y, Xc).fit()
lr.summary()
```

```
<class 'statsmodels.iolib.summary.Summary'>
"""
                            OLS Regression Results

======================================================================
========
Dep. Variable:                    Age   R-squared:
0.538
Model:                            OLS   Adj. R-squared:
0.537
Method:                 Least Squares   F-statistic:
538.9
Date:                Sun, 02 Oct 2022   Prob (F-statistic):
0.00
Time:                        09:23:37   Log-Likelihood:
-9204.1
No. Observations:                4177   AIC:
1.843e+04
Df Residuals:                    4167   BIC:
1.849e+04
Df Model:                           9

Covariance Type:            nonrobust

======================================================================
```

```
============
                  coef    std err          t      P>|t|      [0.025
0.975]
----------------------------------------------------------------------
------------
const           5.3946      0.292     18.502      0.000       4.823
5.966
Length         -0.4583      1.809     -0.253      0.800      -4.005
3.089
Diameter       11.0751      2.227      4.972      0.000       6.708
15.442
Height         10.7615      1.536      7.005      0.000       7.750
13.773
Whole weight    8.9754      0.725     12.373      0.000       7.553
10.398
Shucked weight -19.7869     0.817    -24.209      0.000     -21.389
-18.184
Viscera weight -10.5818     1.294     -8.179      0.000     -13.118
-8.045
Shell weight    8.7418      1.125      7.772      0.000       6.537
10.947
Sex_I          -0.8249      0.102     -8.056      0.000      -1.026
-0.624
Sex_M           0.0577      0.083      0.692      0.489      -0.106
0.221
======================================================================
========
Omnibus:                      947.032   Durbin-Watson:
1.436
Prob(Omnibus):                  0.000   Jarque-Bera (JB):
2710.271
Skew:                           1.181   Prob(JB):
0.00
Kurtosis:                       6.162   Cond. No.
137.
======================================================================
========

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is
correctly specified.
"""
```

Linear Regression

```
from statsmodels.stats.outliers_influence import
variance_inflation_factor as VIF

vif = [VIF(Xc.values, i) for i in range(Xc.shape[1])]
pd.DataFrame(vif, index=Xc.columns, columns=['VIF'])
```

```
                     VIF
const          73.759239
Length         40.945763
Diameter       42.379841
Height          3.581369
Whole weight  109.768710
Shucked weight  28.550546
Viscera weight  17.445012
Shell weight   21.263272
Sex_I           1.983709
Sex_M           1.398273
```

```
X2 = X.drop(['Whole weight'], axis=1)
X2c = sm.add_constant(X2)

vif = [VIF(X2c.values, i) for i in range(X2c.shape[1])]
pd.DataFrame(vif, index=X2c.columns, columns=['VIF'])
```

```
                    VIF
const         73.686878
Length        40.940595
Diameter      42.362677
Height         3.580291
Shucked weight  8.953621
Viscera weight 10.866542
Shell weight   7.824157
Sex_I          1.980900
Sex_M          1.398218
```

```
X2 = X.drop(['Whole weight','Diameter'], axis=1)
X2c = sm.add_constant(X2)

vif = [VIF(X2c.values, i) for i in range(X2c.shape[1])]
pd.DataFrame(vif, index=X2c.columns, columns=['VIF'])
```

```
                    VIF
const         73.574600
Length         8.071189
Height         3.539481
Shucked weight  8.952049
Viscera weight 10.849613
Shell weight   7.479367
Sex_I          1.957221
Sex_M          1.397178
```

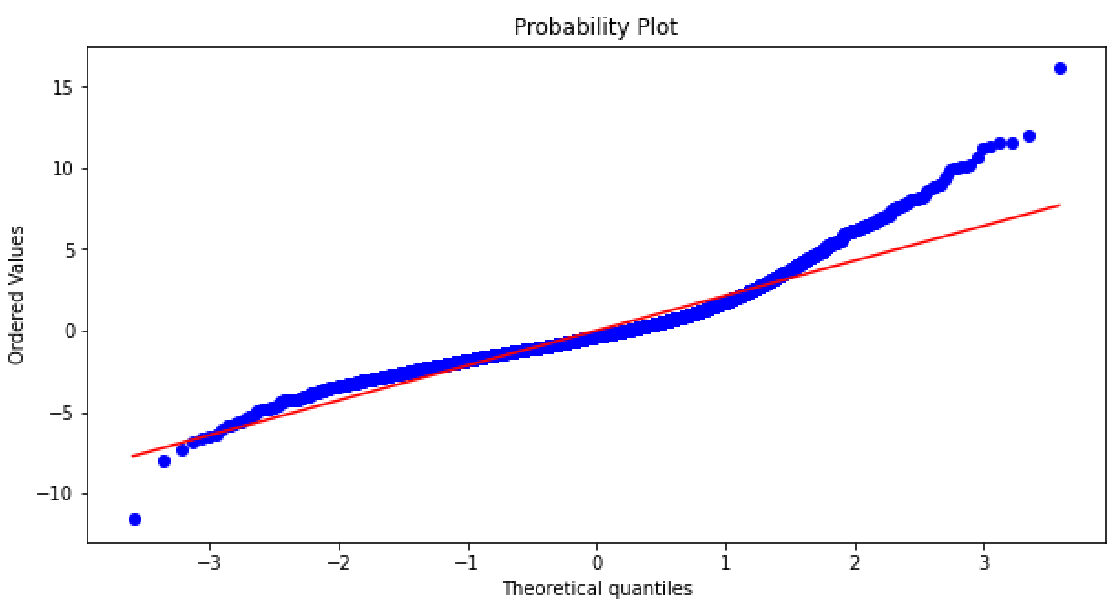
```
X2 = X.drop(['Whole weight','Diameter','Viscera weight'], axis=1)
X2c = sm.add_constant(X2)

vif = [VIF(X2c.values, i) for i in range(X2c.shape[1])]
pd.DataFrame(vif, index=X2c.columns, columns=['VIF'])
```

```
                      VIF
const           72.180555
Length           7.836960
Height           3.524719
Shucked weight   6.154361
Shell weight     6.665183
Sex_I            1.928554
Sex_M            1.392962
```

```
lr = sm.OLS(y, X2c).fit()
lr.summary()
```

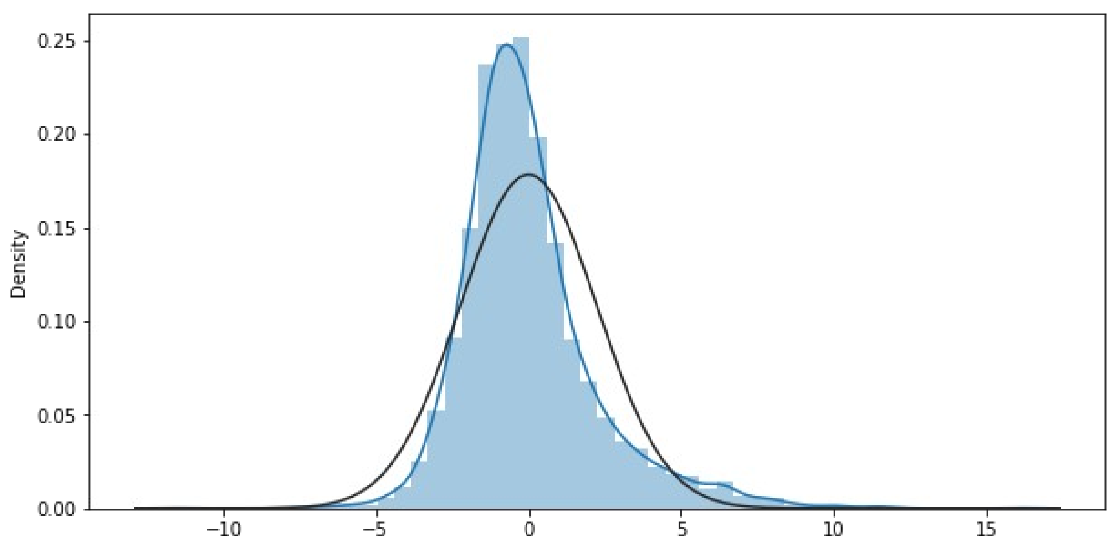
```
<class 'statsmodels.iolib.summary.Summary'>
"""
                            OLS Regression Results

======================================================================
========
Dep. Variable:                    Age   R-squared:
0.518
Model:                            OLS   Adj. R-squared:
0.517
Method:                 Least Squares   F-statistic:
746.3
Date:                Sun, 02 Oct 2022   Prob (F-statistic):
0.00
Time:                        09:31:26   Log-Likelihood:
-9293.0
No. Observations:                4177   AIC:
1.860e+04
Df Residuals:                    4170   BIC:
1.864e+04
Df Model:                           6

Covariance Type:            nonrobust

======================================================================
============
                     coef    std err          t      P>|t|      [0.025
0.975]
----------------------------------------------------------------------
------------
const              5.3789      0.295     18.263      0.000       4.801
5.956
Length             7.6264      0.808      9.436      0.000       6.042
9.211
Height            11.8548      1.556      7.618      0.000       8.804
14.906
Shucked weight   -11.6179      0.388    -29.981      0.000     -12.378
-10.858
```

```
Shell weight       20.3458       0.643     31.641      0.000      19.085
21.606
Sex_I              -0.9194       0.103     -8.918      0.000      -1.121
-0.717
Sex_M               0.0437       0.085      0.514      0.607      -0.123
0.210
======================================================================
========
Omnibus:                     1059.201   Durbin-Watson:
1.416
Prob(Omnibus):                  0.000   Jarque-Bera (JB):
3425.649
Skew:                           1.273   Prob(JB):
0.00
Kurtosis:                       6.634   Cond. No.
60.5
======================================================================
========

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is
correctly specified.
"""

from scipy import stats

resid = lr.resid

plt.figure(figsize=(10,5))
stats.probplot(resid, plot=plt)
plt.show()
```



```
from scipy.stats import norm
norm.fit(resid)

plt.figure(figsize=(10,5))
sns.distplot(resid, fit=norm)
plt.show()
```

```
<ipython-input-70-c7f844f4d1b4>:5: UserWarning:

`distplot` is a deprecated function and will be removed in seaborn
v0.14.0.

Please adapt your code to use either `displot` (a figure-level
function with
similar flexibility) or `histplot` (an axes-level function for
histograms).

For a guide to updating your code to use the new functions, please see
https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751

  sns.distplot(resid, fit=norm)
```




```
stat, pval = stats.jarque_bera(resid)
print(pval)
```

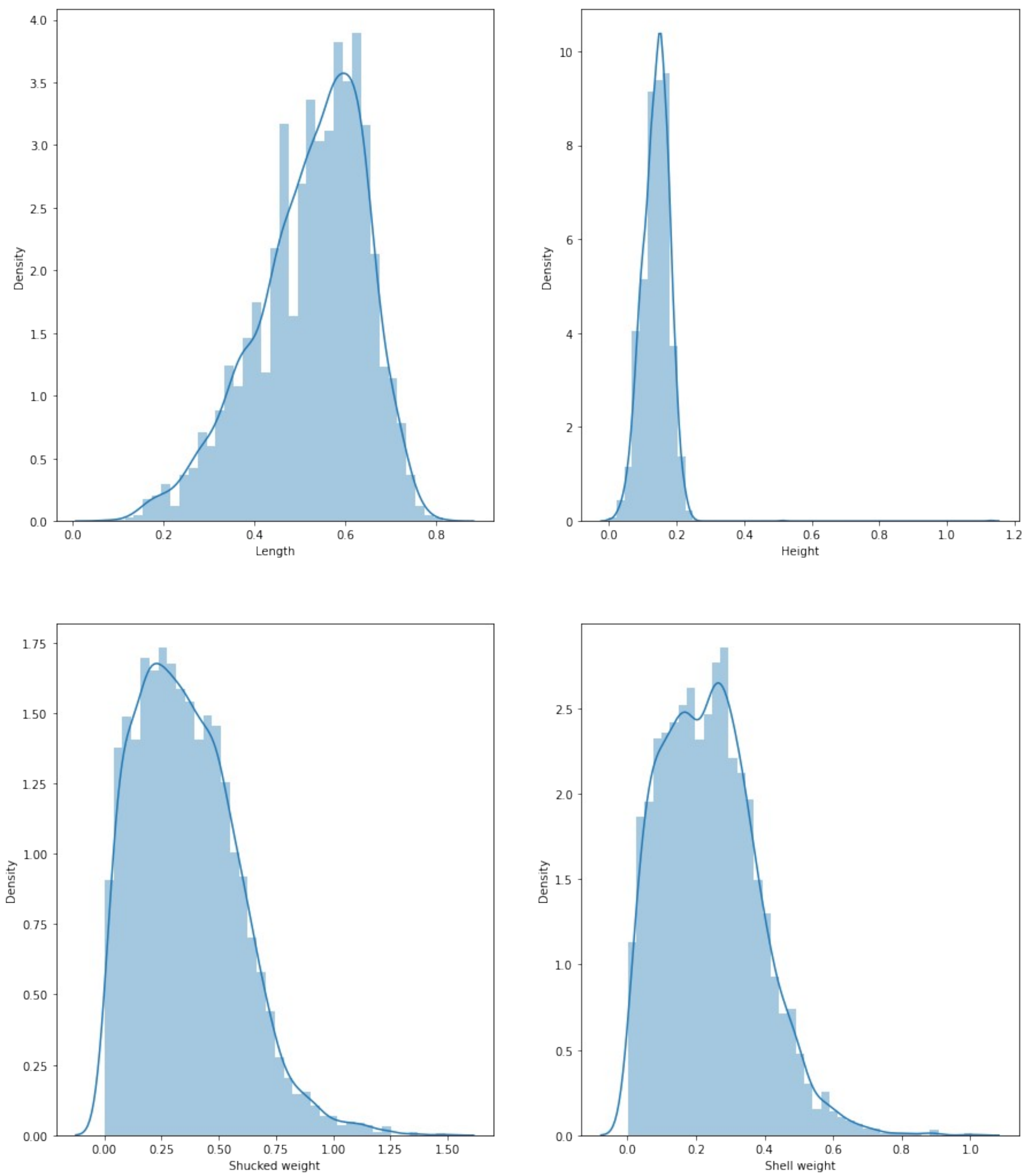
```
0.0
```

```
fig, axes = plt.subplots(2,2, figsize=(15,18))
axes = axes.flatten()

for i in range(len(X2.columns)-2):
    sns.distplot(X2.iloc[:,i], ax=axes[i])
```

```
plt.show()
```

```
<ipython-input-72-318997ca2382>:5: UserWarning:

`distplot` is a deprecated function and will be removed in seaborn
v0.14.0.

Please adapt your code to use either `displot` (a figure-level
function with
similar flexibility) or `histplot` (an axes-level function for
histograms).

For a guide to updating your code to use the new functions, please see
https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751

  sns.distplot(X2.iloc[:,i], ax=axes[i])
<ipython-input-72-318997ca2382>:5: UserWarning:

`distplot` is a deprecated function and will be removed in seaborn
v0.14.0.

Please adapt your code to use either `displot` (a figure-level
function with
similar flexibility) or `histplot` (an axes-level function for
histograms).

For a guide to updating your code to use the new functions, please see
https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751

  sns.distplot(X2.iloc[:,i], ax=axes[i])
<ipython-input-72-318997ca2382>:5: UserWarning:

`distplot` is a deprecated function and will be removed in seaborn
v0.14.0.

Please adapt your code to use either `displot` (a figure-level
function with
similar flexibility) or `histplot` (an axes-level function for
histograms).

For a guide to updating your code to use the new functions, please see
https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751

  sns.distplot(X2.iloc[:,i], ax=axes[i])
<ipython-input-72-318997ca2382>:5: UserWarning:

`distplot` is a deprecated function and will be removed in seaborn
v0.14.0.
```

```
Please adapt your code to use either `displot` (a figure-level
function with
similar flexibility) or `histplot` (an axes-level function for
histograms).

For a guide to updating your code to use the new functions, please see
https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751

  sns.distplot(X2.iloc[:,i], ax=axes[i])
```



```python
while len(X2.columns)>0:
    X_c = sm.add_constant(X2)
    mod = sm.OLS(y,X_c).fit()
    f = mod.pvalues[1:].idxmax()
    if mod.pvalues[1:].max()>0.05:
        X2 = X2.drop(f, axis=1)
    else:
        break

print("The final features are:",X2.columns)
```

```
The final features are: Index(['Length', 'Height', 'Shucked weight',
'Shell weight', 'Sex_I'], dtype='object')
```

```python
mod.summary()
```

```
<class 'statsmodels.iolib.summary.Summary'>
"""
                            OLS Regression Results

==============================================================================
========
Dep. Variable:                    Age   R-squared:
0.518
Model:                            OLS   Adj. R-squared:
0.517
Method:                 Least Squares   F-statistic:
895.6
Date:                Sun, 02 Oct 2022   Prob (F-statistic):
0.00
Time:                        09:44:28   Log-Likelihood:
-9293.2
No. Observations:                4177   AIC:
1.860e+04
Df Residuals:                    4171   BIC:
1.864e+04
Df Model:                           5

Covariance Type:            nonrobust

==============================================================================
============
                     coef    std err          t      P>|t|      [0.025
0.975]
------------------------------------------------------------------------------
------------
const              5.4141      0.286     18.901      0.000       4.852
5.976
Length             7.6066      0.807      9.423      0.000       6.024
9.189
```

```
Height              11.8310      1.555      7.606      0.000       8.782
14.880
Shucked weight     -11.6023      0.386    -30.036      0.000     -12.360
-10.845
Shell weight        20.3337      0.643     31.646      0.000      19.074
21.593
Sex_I               -0.9449      0.090    -10.463      0.000      -1.122
-0.768
======================================================================
========
Omnibus:                     1057.582   Durbin-Watson:
1.417
Prob(Omnibus):                  0.000   Jarque-Bera (JB):
3415.593
Skew:                           1.271   Prob(JB):
0.00
Kurtosis:                       6.628   Cond. No.
57.9
======================================================================
========

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is
correctly specified.
"""
```

Train, Test and Split

```
df.head()

   Length  Diameter  Height  Whole weight  Shucked weight  Viscera
weight  \
0   0.455     0.365   0.095        0.5140          0.2245
0.1010
1   0.350     0.265   0.090        0.2255          0.0995
0.0485
2   0.530     0.420   0.135        0.6770          0.2565
0.1415
3   0.440     0.365   0.125        0.5160          0.2155
0.1140
4   0.330     0.255   0.080        0.2050          0.0895
0.0395

   Shell weight   Age  Sex_I  Sex_M
0         0.150  16.5      0      1
1         0.070   8.5      0      1
2         0.210  10.5      0      0
3         0.155  11.5      0      1
4         0.055   8.5      1      0
```

```
X = df.drop('Age', axis=1)
y = df['Age']

from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y,
test_size=0.33)

from sklearn.preprocessing import StandardScaler
ss = StandardScaler()

X_trains = ss.fit_transform(X_train)
X_tests = ss.transform(X_test)
```

```
#Base model
from sklearn.linear_model import LinearRegression
lr = LinearRegression()

lr.fit(X_trains, y_train)
pred = lr.predict(X_tests)

from sklearn.metrics import r2_score, roc_auc_score,
mean_squared_error
rmse = np.sqrt(mean_squared_error(y_test, pred))
r2 = r2_score(y_test, pred)

print("The root mean Sq error calculated from the base model
is:",rmse)
print("The r2-score is:",r2)
```

```
The root mean Sq error calculated from the base model is:
2.2102250617835075
The r2-score is: 0.5408490346490895
```

```
#selecting best feautre
from sklearn.feature_selection import RFE
lr = LinearRegression()
n = [{'n_features_to_select':list(range(1,10))}]
rfe = RFE(lr)

from sklearn.model_selection import GridSearchCV
gsearch = GridSearchCV(rfe, param_grid=n, cv=3)
gsearch.fit(X, y)

gsearch.best_params_
```

```
{'n_features_to_select': 8}
```

```
lr = LinearRegression()
rfe = RFE(lr, n_features_to_select=8)
rfe.fit(X,y)
```

```
pd.DataFrame(rfe.ranking_, index=X.columns, columns=['Class'])
```

```
                Class
Length              1
Diameter            1
Height              1
Whole weight        1
Shucked weight      1
Viscera weight      1
Shell weight        1
Sex_I               1
Sex_M               2
```

The RFE says that all features are significant except Sex_M

Performance of our Model using multiple Algorithms

```
from sklearn.neighbors import KNeighborsRegressor
from sklearn.ensemble import  RandomForestRegressor
from sklearn.linear_model import LinearRegression
from sklearn.ensemble import  GradientBoostingRegressor
from sklearn.linear_model import  Ridge
from sklearn.svm import SVR
from sklearn import model_selection
from sklearn.model_selection import cross_val_predict

models = [   SVR(),
             RandomForestRegressor(),
             GradientBoostingRegressor(),
             KNeighborsRegressor(n_neighbors = 4)]
results = []
names = ['SVM','Random Forest','Gradient Boost','K-Nearest Neighbors']
for model,name in zip(models,names):
    kfold = model_selection.KFold(n_splits=10)
    cv_results = model_selection.cross_val_score(model, X_train,
y_train, cv=kfold)
    rmse = np.sqrt(mean_squared_error(y, cross_val_predict(model, X ,
y, cv=3)))
    results.append(rmse)
    names.append(name)
    msg = "%s: %f" % (name, rmse)
    print(msg)
```

```
SVM: 2.306551
Random Forest: 2.232707
Gradient Boost: 2.196020
K-Nearest Neighbors: 2.353608
```

The above algorithms gives the similar performance related to our Model