# **Assignment -4**

Assignment Date	06 November 2022
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Student Roll Number	812719104045
Maximum Marks	4 Marks

```
import pandas as pd
import numpy as np
from matplotlib import pyplot as plt
import seaborn as sns
from sklearn.linear_model import LinearRegression

df=pd.read_csv("/content/drive/NyDrive/Colab Notebooks/abalone.csv")

d-F['age'] = d-F['Rings']+1.5
df = df.drop('Rings', axis = 1)
```

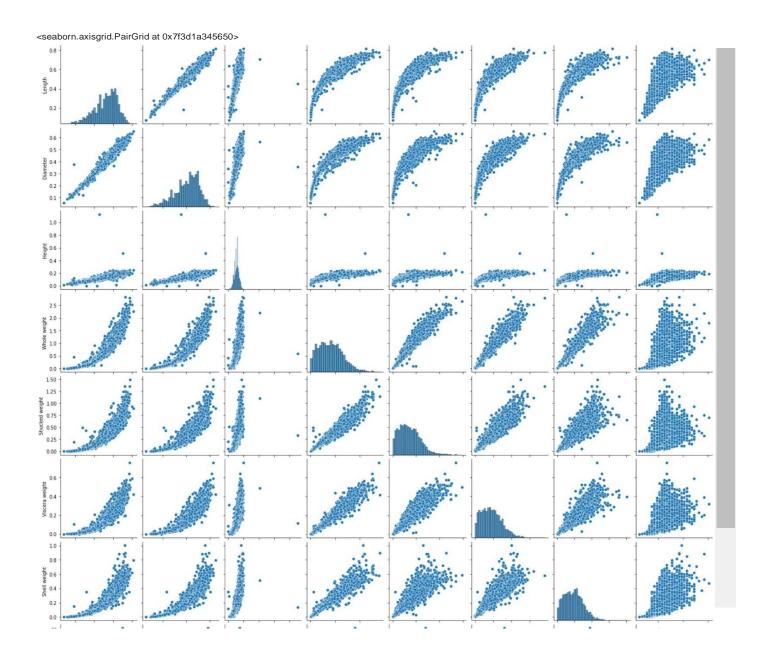
### Univariate Analysis

```
df.hist(figsize=(20,10), grid=False, layout=(2, 4), bins = 3B)
     array([[<matplotlib.axes._subplots.AxesSubplot object at 8x7f3d1b8fb698>, <matplotlib.axes._subplots.AxesSubplot object at 0x7f3d1ade4d98>,
               <matplotlib.axes._subplots.AxesSubplot object at 0x7f3dladaa398>,
              (matplotlib.axes._subplots.AxesSubplot object at Bx7f3dlad60998>],
(matplotlib.axes._subplots.AxesSubplot object at 0x7f3dlad16f98>,
               <matplotlib.axes._subplots.AxesSubplot object at 8x7f3dlac53ld8>]],
             dtype=object)
                                                                                                                                                                   Whole weight
                         Length
                                                                       Diameter
                                                                                                                       Height
                                                                                                    1600
       400
                                                                                                                                                    300
                                                      350
                                                                                                    1400
       350
                                                                                                                                                    250
                                                      300
                                                                                                    1200
       300
                                                      250
                                                                                                                                                   200
                                                                                                    1000
       250
                                                      200
                                                                                                    800
                                                                                                                                                    150
                                                      150
                                                                                                    600
                                                                                                                                                    100
                                                      100
       100
                                                                                                    400
                                                       50
                                                                                                    200
        50
                                                                             0.4
                                                                                                                          0.6
                                                                                                                                0.8
                                                                                                                                                             0.5
                                                                                                                                                                   1.0
                                                                                                                                                                         1.5
                                                                       0.3
                                                                                                                    0.4
                                                                                                                     Shell weight
                     Shucked weight
                                                                     Viscera weight
       350
                                                      350
                                                                                                    350
                                                                                                                                                   600
       300
                                                      300
                                                                                                    300
                                                                                                                                                    500
       250
                                                      250
                                                                                                    250
                                                                                                                                                   400
       200
                                                      200
                                                                                                    200
                                                                                                                                                    300
       150
                                                      150
                                                                                                    150
       100
                                                      100
                                                                                                                                                    200
                                                                                                    100
                                                       50
                                                                                                                                                    100
        50
                                                                                                      50
           0.00 0.25 0.50 0.75 1.00 1.25 1.50
                                                                   0.2
                                                                           0.4
                                                                                    0.6
                                                                                                               0.2
                                                                                                                      0.4
                                                                                                                            0.6
                                                                                                                                   0.8
```

Sex									
		0.427746	0.326494	0.107996	0.431363	0.191035	0.092010	0.128182	9.390462
ı	M	0.561391	0.439287	0.151381	0.991459	0.432946	0.215545	0.281969	12.205497
	F	0.579093	0.454732	0.158011	1.046532	0.446188	0.230689	0.302010	12.629304

# Bivariate Analysis

numerical\_features = df.select\_dtypes(include = [np.number]).columns
sns.pairplot(df[numerical\_features])



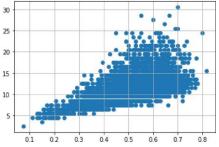
# Descriptive statistics

df.describe()											
	Length	Diameter	Height	whole weight	Shucked weight	viscera weight	Shell weight	age			
count	4177.000000	4177.000000	4177.000000	4177.000000	4177.000000	4177.000000	4177.000000	4177.000000			
mean	0.523992	0.407881	0.139516	0.828742	0.359367	0.180594	0.238831	11.433684			
std	0.120093	0.099240	0.041827	0.490389	0.221963	0.109614	0.139203	3.224169			
min	0.075000	0.055000	0.000000	0.002000	0.001000	0.000500	0.001500	2.500000			
25%	0.450000	0.350000	0.115000	0.441500	0.186000	0.093500	0.130000	9.500000			
50%	0.545000	0.425000	0.140000	0.799500	0.336000	0.171000	0.234000	10.500000			
75%	0.615000	0.480000	0.165000	1.153000	0.502000	0.253000	0.329000	12.500000			
max	0.815000	0.650000	1.130000	2.825500	1.488000	0.760000	1.005000	30.500000			

Check for missing values

df.isnull().sum()

```
df - pd.get dummies(df)
dummy_da ta = df . copy()
var = 'Viscera weight'
plt.scatter(x = df[var], y = df['age'],)
plt.grid(True)
# outliers removal
d-F. drop(df[ (d-F[ ' VI scera weight ' ] > 0. 5) & (df-[ ' age ' ] < 20) ] . Index, inp1ace=True)
\tt df.drop\,(df[(df['Uiscera\ weight']<0.5)\ \&\ (df['age']\ >\ 25)].index,\ inplace=True)
var - 'Shell weight'
plt.scatter(x = df[var], y = df['age'],)
plt.grid(True)
#Outliers removal
\label{eq:dfdf} $$ df.drop(df[(df['Shell weight'] > 0.6) & (df['age'] < 25)].index, inplace=True) $$
df.drop(df[(df['Shell weight']<8.8) 8 (df['age'] > 25)].index, inplace=True)
var = 'Shucked weight'
plt.scatter(x = df[var], y = df['age'],)
plt.grid(True)
#Outlier removal
df.drop(df[(df['Shucked weight'] >= 1) & (df['age'] < 28)].index, inplace=True)</pre>
df.drop(df[(df['Shuckedweight']<1) & (df['age'] > 28)].iudex, inplace=True)
var = ' Nhole weight '
pit . scatter (x = df-[var] , y = df[ ' age ' ] )
p1t . grid(True)
df.drop(df[(df['Whole weight'] >= 2.5) &
           (df['age'] < 25)].index, inplace = True)</pre>
df. drop(df-[(df['Nhole weight']<2.5) & (
d-F['age'] \rightarrow 25)]. Index, 1nplace = True)
var = ' Diameter '
pit . scatter (x = df-[var] , y = df[ ' age ' ] )
p1t . grid(True)
df.drop~(df\hbox{-}[(df\hbox{['Diazeten']}~<8.~1)~\&
           (df['age'] < 5)].index, inplace = True)</pre>
df. drop(df-[ (df[ ' Diameter ' ] <0. 6) & (
d-F['age'] > 25)]. Index, 1nplace = True)
d-F- . drop(df-[ (d1°[ ' Diameter ' ] >=0. 6) & (
df-[ ' age ' ] < 25) ] . Index, 1nplace = True)
var = 'Height'
p1t . scatter (x - df[var], y - df['age'])
p1t.arid(True)
d-F. drop(d-I- [ (df-[ ' Height '] > 6 . 4) &
           (df[ ' age ' ] < 15) ] . Index, Inplace = True)
d-F. drop(df-[ (d-F[ ' Height ' ] <0. 4) & (
d-I°['age'] > 25)]. index, 1nplace = True)
var = 'Length'
plt.scatter(x = df[var], y = df['age'])
plt.grid(True)
df.drop(df[(df['Leugth'] <8.1) &
          (df['age'] < 5)].index, inplace = True)</pre>
dfdropd[df['Leugth]<0.8) & (
df['age'] > 25)].index, inplace = True)
df.dropd[df['Length]>=8.8) & (
df['age'] < 25)].iudex, inplace = True)
```



### Categorical columns

numerical\_features = df.select\_dtypes(include = [np.number]).columns categorica1\_features = df.select\_dtypes(include = [np.object]).columns

/usr/local/lib/python3.7/dist-packages/ipykernel\_launcher.py:2: Deprecationwarning: 'up.object' is a deprecated alias for the builtin 'object' To siler Deprecated in NumPy 1.20; for more details and guidance: <a href="https://numpy.org/devdocs/release/1.20.8-notes.html#deprecations">https://numpy.org/devdocs/release/1.20.8-notes.html#deprecations</a>

#### numerical\_features

### categonica I\_featunes

Index(['Sex'], dtype='object')

#### **ENCODING**

from sklearn.preprocessing import LabelEncoder le=LabelEncoder() print(df.Sex.value\_counts())

M 1525 1 1341 F 1301

Name: Sex, dtype: int64

### x=df.iloc[:, :5]

	Sex	Length	Diameter	Helght	Nhole we1ght	1			
0	М	0.455	0.365	0.095	0.5140				
1	М	0.350	0.265	0.090	0.2255				
2	F	0.530	0.420	0.135	0.6770				
3	М	0.440	0.365	0.125	0.5160				
4		0.330	0.255	0.080	0.2050				
4172	F	0.565	0.450	0.165	0.8870				
4173	М	0.590	0.440	0.135	0.9660				
4174	М	0.600	0.475	0.205	1.1760				
4175	F	0.625	0.485	0.150	1.0945				
4176	М	0.710	0.555	0.195	1.9485				
4167 rows • 5 columns									

y=df.iloc[:,5:]

	Shucked weight	VIscera weight	Shell weight	age	2
0	0.2245	0.1010	0.1500	16.5	
1	0.0995	0.0485	0.0700	8.5	
2	0.2565	0.1415	0.2100	10.5	
3	0.2155	0.1140	0.1550	11.5	
4	0.0895	0.0395	0.0550	8.5	
4172	0.3700	0.2390	0.2490	12.5	
4173	0.4390	0.2145	0.2605	11.5	
4174	0.5255	0.2875	0.3080	10.5	
4175	0.5310	0.2610	0.2960	11.5	
4176	0.9455	0.3765	0.4950	13.5	
440=					

4167 rows 4 columns

 $from \ sk1earn.model\_selection \ import \ train\_test\_split \\ x\_train,x\_test,y\_train,y\_test=train\_test\_split(x,y,test\_size=0.2)$ 

Model Building

from sklearn.linear\_model import LinearRegression mlr=LinearRegression() mlr.fit(x\_train,y\_train)

Train and Test model

## x\_test [6:5]

	Sex	Length	Diameter	Height	Nhole we1ght
661		0.535	0.450	0.170	0.781
370	F	0.650	0.545	0.165	1.566
2272	М	0.635	0.510	0.210	1.598
1003	М	0.595	0.455	0.150	1.044
1145	M	0.580	0.455	0.195	1.859

#### y\_test[0:5]

е	Shell v	t Shel	ght S	we	vlscera	e1ght	Shucked w		
(		5	555	0		0.3055		661	
(		5	455	0		0.6645		370	
(		5	335	0		0.6535		2272	2
(		5	205	0		0.5180		1003	•
(		)	260	0		0.9450		1145	

### Feature Scaling

Performance measure

I-rom sklearn .metric s Import r2\_score r2\_s core(m1r . predict (x\_test) , y\_test )

0.5597133867640833