Assignment -4

Assignment Date	17 November 2022
Student Name	Tummalapalli naga Venkata satya vatsal
Student Roll Number	111619104154
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)
```

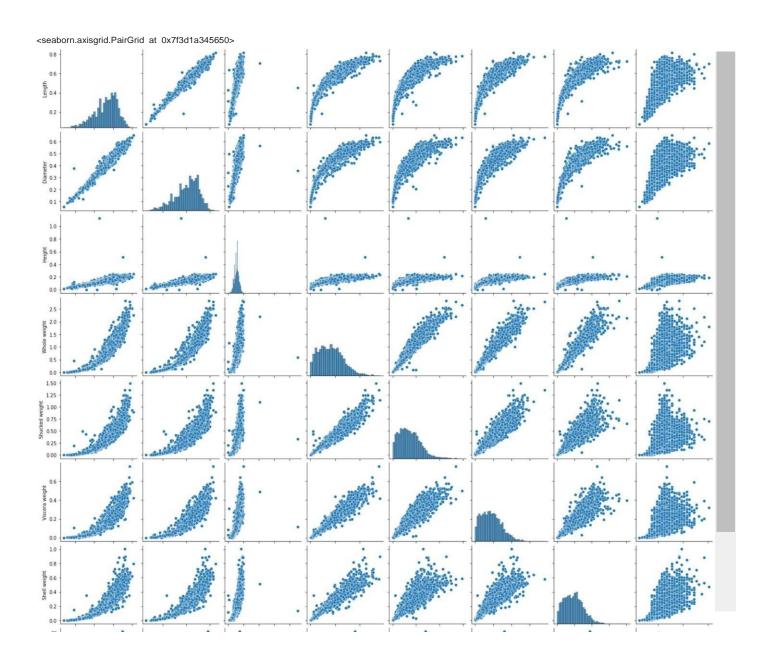
Univariate Analysis

```
df.hist(figsize=(20,10), grid=False, layout=(2, 4), bins = 3B)
      \verb| array([[<matplotlib.axes._subplots.AxesSubplot | object | at | 8x7f3d1b8fb698>, \\
                <matplotlib.axes.subplots.AxesSubplot object at 0x7f3dlade4d98,
<matplotlib.axes.subplots.AxesSubplot object at 0x7f3dladaa398,</pre>
               <matplotlib.axes._subplots.AxesSubplot object at Bx7f3d1ad60998>],
              [(matplotlib.axes._subplots.AxesSubplot object at 0x7f3dlad16f98), (matplotlib.axes._subplots.AxesSubplot object at Bx7f3dlacda5d8>,
               <matp1otlib.axes._subplots.AxesSubplot object at Bx7f3dlac8fc58>,
               <matplotlib.axes._subplots.AxesSubplot object at 8x7f3dlac53ld8>]],
             dtype=object)
                         Length
                                                                      Diameter
                                                                                                                    Height
                                                                                                                                                               Whole weight
                                                                                                 1600
       400
                                                                                                                                                300
                                                     350
                                                                                                 1400
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                                                                                                                       0.6
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                                                                                                                                                               1.0
                                                                                                                                                                    1.5
                                                                      0.3
                                                                                                                  Shell weight
                     Shucked weight
                                                                   Viscera weight
                                                                                                                                                                    age
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           0.00 0.25 0.50 0.75 1.00 1.25 1.50
                                                                                                             0.2
                                                                                                                   0.4
                                                                                                      0.0
```

	Length	Diameter	Height	whole weight	Shucked weight	Viscera weight	Shell weight	age
Sex								
	0.427746	0.326494	0.107996	0.431363	0.191035	0.092010	0.128182	9.390462
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])



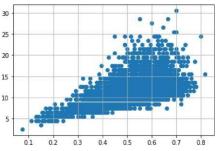
Descriptive statistics

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 4177.000000 4177.000000 4177.000000 4177.000000 4177.000000 4177.000000 4177.000000 4177.000000 4177.000000 4177.000000 4177.000000 4177.000000 4177.000000 4177.000000 4177.000000 4177.000000 4177.000000 4177.000000 4177.000000 4177.000000 4177.000000 4177.000000 4177.000000 4177.000000 4177.000000 4177.000000 4177.000000 4177.000000 4177.000000 4177.000000 4177.000000 4177.000000 4177.000000 4177.000000 0.139203 3.224169 0.139203 3.224169 0.00000 0.001500 0.001500 0.001500 0.001500 0.001500 0.001500 0.001500 0.001500 0.186000 0.005500 0.130000 9.500000 0.001500 0.170000 0.234000 10.50000 <td< th=""><th colspan="9">df.describe()</th></td<>	df.describe()								
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		Length	Diameter	Height	whole weight	Shucked weight	viscera weight	Shell weight	age
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	count	4177.000000	4177.000000	4177.000000	4177.000000	4177.000000	4177.000000	4177.000000	4177.000000
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	mean	0.523992	0.407881	0.139516	0.828742	0.359367	0.180594	0.238831	11.433684
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	std	0.120093	0.099240	0.041827	0.490389	0.221963	0.109614	0.139203	3.224169
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	min	0.075000	0.055000	0.000000	0.002000	0.001000	0.000500	0.001500	2.500000
75% 0.615000 0.480000 0.165000 1.153000 0.502000 0.253000 0.329000 12.500000	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
max 0.815000 0.650000 1.130000 2.825500 1.488000 0.760000 1.005000 30.500000	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 ' ] \gt 0. 5) & (df-[ ' age ' ] \lt 20) ] . Index, inp1ace=True)
\label{eq:dfdf} $$ df.drop(df[(df['Uiscera weight']<0.5) & (df['age'] \rightarrow 25)].index, inplace=True) $$
var - 'Shell weight'
plt.scatter(x = df[var], y = df['age'],)
plt.grid(True)
#Outliers removal
var = 'Shucked weight'
plt.scatter(x = df[var], y = df['age'],)
plt.grid(True)
#Outlier removal
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-[(df['Diazeten'] <8.1) &
\label{eq:df-def} $$ (df['age'] < 5)].index, inplace = True) $$ 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.grid(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^{\circ}['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)</pre>
```



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: https://numpy.org/devdocs/release/1.20.8-notes.html#deprecations

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]

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

y=df.iloc[:,5:]

4167 rows • 5 columns

	Shucked weight	VIscera weight	Shell weight	age	10
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	
4167 ro	ws 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

 $\label{thm:constraint} from sklearn.linear_model import LinearRegression \\ mlr=LinearRegression() \\ mlr.fit(x_train,y_train) \\$

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	М	0.580	0.455	0.195	1.859

y_test[0:5]

	Shucked we1ght	vlscera we1ght	Shell we1ght	age
661	0.3055	0.1555	0.295	12.5
370	0.6645	0.3455	0.415	17.5
2272	0.6535	0.2835	0.580	16.5
1003	0.5180	0.2205	0.270	10.5
1145	0.9450	0.4260	0.441	10.5

Feature Scaling

from sklearn.preprocessing import StandardScaler ss=StandardScaler() x_train=ss.fit_transform(x_train) mlrpred=mlr.predict(x_test[B:9]) mlrpred

Performance measure

I-rom sklearn .metric s Import r2_score r2_s core(m1r . predict (x_test) , y_test)

0.5597133867640833