Assignment -4

| Assignment Date | 06 November 2022 |
|---------------------|------------------|
| Student Name | Mathan R |
| Student Roll Number | 812719104022 |
| Maximum Marks | 4 Marks |

```
import pendas 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 = 38)
    array([[<matplotlib.axes._subplots.AxesSubplotobject at 8x7f3d1b8fb698>,
              <matplotlib.axes._subplots.AxesSubplot object at 0x7f3d1ade4d98>,
<matplotlib.axes._subplots.AxesSubplot object at 0x7f3d1adaa398>,
              \verb|\matplotlib.axes._subplots.AxesSubplot object at Bx7f3d1ad60998>]|,
             [\verb|<matplotl| ib.axes._subplots.AxesSubplot| object at 0x7f3dladl6f98>|,
              <matplotlib.axes._subplots.AxesSubplot object at Bx7f3d1acda5d8>,
              <matplotlib.axes._subplots.AxesSubplot object at Bx7f3dlac8fc58>,
              <matplotlib.axes._subplots.AxesSubplot object at 8x7f3dlac53ld8>]],
            dtype=object)
                       Length
                                                                                                                                                  Whole weight
                                                                                                           Height
                                                350
                                                                                          1400
       350
                                                300
                                                                                          1200
       300
                                                                                                                                     200
                                                                                          3000
       250
                                                                                          800
       200
                                                                                                                                     158
                                                250
       150
                                                                                          600
                                                100
       100
                                                                                          400
       50
                                                 50
                                                                                          200
                                                                    04 05
                                                                                                                                                  10 15 20
                                                           02 03
                                                                                                        04 06
                   Shucked weight
                                                              Viscera weight
                                                                                                         Shell weight
       350
                                                350
                                                                                          350
                                                                                                                                     600
       300
                                                                                          300
       250
                                                250
                                                                                          350
                                                                                                                                     400
       200
                                                200
                                                                                          200
                                                                                                                                     300
       150
                                                                                          150
       100
                                                                                                                                     200
                                                300
                                                                                          100
                                                                                                                                     100
       50
                                                 50
          000 025 050 075 100 125
```

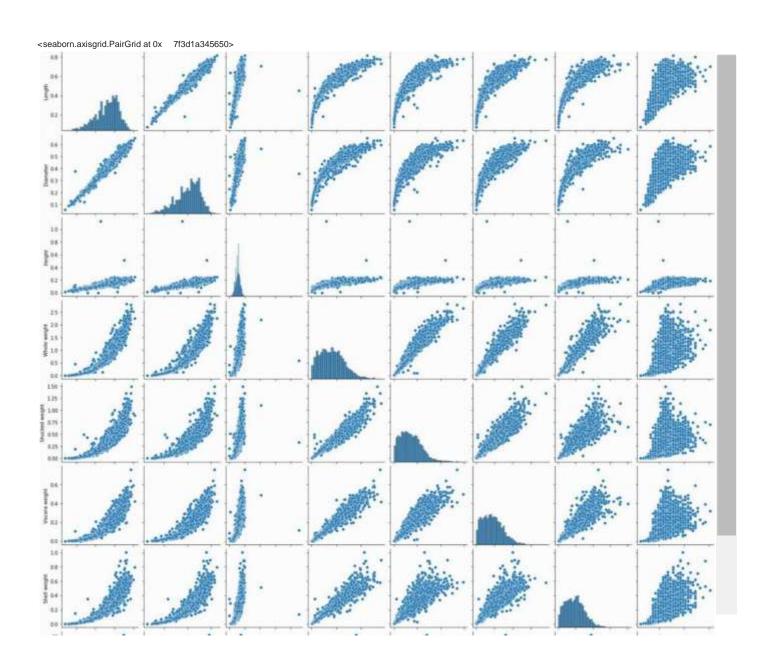
Length Diameter Height whole weight Shucked weight Viscera weight Shell weight age

Sex

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])



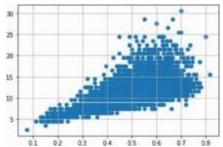
Descriptive statistics

| | df.describe() | | | | | | | | |
|-----|------------------|-------------|-------------|--------------|----------------|----------------|--------------|-------------|----------|
| | Levelle | Diameter | Height | whole weight | Shucked weight | viscera weight | Shell weight | | 1 |
| | Length | | | | | | | age | |
| COL | ınt 417 7.000000 | 4177.000000 | 4177.000000 | 4177.000000 | 4177.000000 | 4177.000000 | 4177.000000 | 4177.000000 | |
| mea | n 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 | |
| mir | 0.075000 | 0.055000 | 0.000000 | 0.002000 | 0.001000 | 0.000500 | 0.001500 | 2.500000 | |
| 25% | 6 0.450000 | 0.350000 | 0.115000 | 0.441500 | 0.186000 | 0.093500 | 0.130000 | 9.500000 | |
| 50% | 6 0.545000 | 0.425000 | 0.140000 | 0.799500 | 0.336000 | 0.171000 | 0.234000 | 10.500000 | |
| 75% | 6 0.615000 | 0.480000 | 0.165000 | 1.153000 | 0.502000 | 0.253000 | 0.329000 | 12.500000 | |
| ma | x 0.815000 | 0.650000 | 1.130000 | 2.825500 | 1.488000 | 0.760000 | 1.005000 | 30.500000 | |
| | | | | | | | | | |

Check for missin g values

```
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)
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
df.drop(df[(df['Shell weight'] > 0.6) & (df['age'] < 25)].index, inplace=True)
\tt df.drop(df[(df['Shell weight']<8.8) 8 (df['age'] \rightarrow 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) df.drop(df[(df['Shucked weight']<1) &
(df['age'] > 28)].iudex, inplace=True)
```

```
var = ' Diameter '
pit . scatter (x = df-[var] , y = df[ ' age ' ] )
 p1t . grid(True)
 df.drop (df-[(df['Diazeten'] <8.1) &
            (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 = ' 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 =</pre>
             True)
 df. drop(df-[ (df[ ' Nhole weight ' ] <2. 5) & ( d-F[ ' age ' ] \rightarrow
 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°[ '
age '] > 25)] . index, 1nplace = 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: https://numpy_org/devdocs/release/1.20.8-notes.html#deprecations

categonica I_featunes

numerical_features

Index([' Length ', ' DI ameter', ' Height ', ' Mhole weight ', ' Shucked weight ', ' Uiscera weight', 'Shell weight', 'age'], dtype='object')

Index(['Sex'], dtype='obj ect')

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 | i |
|---|------|--------|----------|--------|--------------|---|
| 0 | N N4 | 0.455 | 0.265 | 0.005 | 0.5140 | |

| 1 | M | 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 |
| | | | | | |
| | _ | 0.565 | 0.450 | 0.165 | |
| 4172 4173 | F M | 0.590 | 0.440 | 0.135 | 0.8870 0.9660 |

| 4174 | М | 0.600 | 0.475 | 0.205 | 1.1760 |
|------|---|-------|-------|-------|--------|
| 4175 | F | 0.625 | 0.485 | 0.150 | 1.0945 |
| 4176 | M | 0.710 | 0.555 | 0.195 | 1 9485 |

4167 rows • 5 columns Train, Test, Split

y=df.iloc[:,5:]

| | 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 | 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 | we1aht |
|-------------|----------|---------|----------|---------|
| OCK Echigan | Diamoto | ricigin | INITIOIC | wcigiii |



| 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 vls | cera we1ght SI | hell we1ght a | age |
|------|--------------------|----------------|---------------|-----|
| 661 | 0.3055 | 0.1555 | 0.295 | 2.5 |
| 370 | 0.6645 | 0.3455 | 0.415 1 | 7.5 |
| 2272 | 0.6535 | 0.2835 | 0.580 | 6.5 |
| 1003 | 0.5180 | 0.2205 | 0.270 1 | 0.5 |
| 1145 | 0.9450 | 0.4260 | 0.441 | 0.5 |

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