Assignment 3

Assignment Date	03 October 2022
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Project Name	AI Based Discourse For Banking Industry
Maximum Marks	2 Marks

Problem Statement: Abalone Age Prediction

- Download the dataset: Dataset
- Load the dataset into the tool.

```
import numpy as
np import pandas
as pd

ds=pd.read_csv("abalone.csv")

# Rings / integer / -- / +1.5 gives the age in years
ds['Age']=ds["Rings"]+1

.5ds.head(5)
```

	Sex	Length	Diameter	Height	Whole	weight	Shucked	weight	Viscera		
we	ight	\				_					
•	M	0.455	0.365	0.095		0.5140		0.2245			
0.	1010										
•	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										
	Shel	ll weight	Rings	Age							
0		0.150	15	16.5							
1	0.070 7		8.5								
2	0.210 9		10.5								
3		0.155	10	11.5							
4		0.055	7	8.5							

• Perform Below Visualizations.

plt.title('Density Curve')

- Univariate Analysis
- Bi-Variate Analysis

```
    Multi-Variate Analysis

# univarient analysis
#frequency table for
age
ft = ds1['Age'].value counts()
print("Frequency table for Age is given below")
print("{}\n\n".format(ft))
# mean
print("Mean, Median, std \n")
ma=ds1['Age'].mean() #mean of
age
mh = ds1['Height'].mean() #mean of height
mel = ds1['Length'].median() #median value of length
stw = ds1['Whole weight'].std() #standard devation of whole weight
#chart
import matplotlib.pyplot as plt # library for plot or graph
import seaborn as sns
plt.subplot(1,2,1)
ch = ds1.boxplot(column='Diameter',grid=True,color ='red')
plt.title('Box plot')
plt.subplot(1,2,2)
sns.kdeplot(ds1['Diameter'])
```

```
print("1-mean of age = ",ma)
print("2-mean of height =
",mh)
print("3-median value of length = ",mel) #
print("4-standard devation of whole weight = ",stw)
print("5-frequency table for rings = \n {}"
    .format(fre))print("\nChart\n\n6-boxplot of
Diameter",flush=True)
```

Frequency table for Age is given below

11.5	32
10.5	28
8.5	20
9.5	18
13.5	17
12.5	16
14.5	13
15.5	11
16.5	10
17.5	7
6.5	6

7.5	5		
21.5	4		
5.5	4		
20.5	3		
19.5	3		
22.5	2		
18.5	1		
Name:	Age,	dtype:	int64

Mean, Median, std

```
1-mean of age = 12.235
2-mean of height =
0.134825000000000033-median value of
length = 0.53
4-standard devation of whole weight =
0.482925552690013145-frequency table for rings =
```

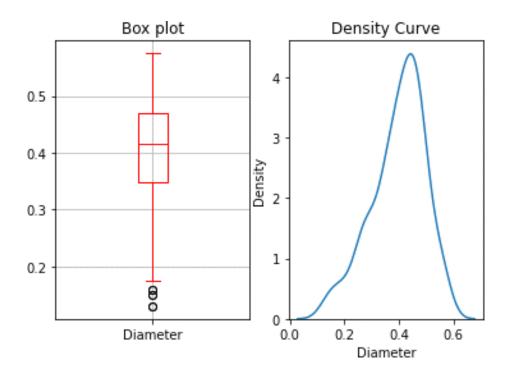
10	32
9	28
7	20
8	18
12	17
11	16
13	13
14	11

15	10
16	7
5	6
6	5
20	4
	4
19	3
18	3
21	2
17	1

Name: Rings, dtype:

int64Chart

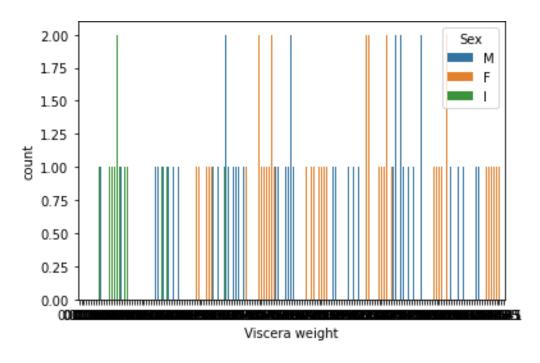
6-boxplot of Diameter



#multi-varient analysis

```
import matplotlib.pyplot as
pltimport seaborn as sns

ds1=ds.head(200)
df=sns.countplot(x="Viscera weight", hue='Sex', data=ds1)
print(df)
AxesSubplot(0.125, 0.125; 0.775x0.75
5)
```



• Perform descriptive statistics on the dataset.

ds.describe()

		Length	Diameter	Height	Whole	weight S	hucked
weight	\						
count	41	77.000000 41	77.000000 41	77.000000	4177.	000000	
4177.00	000	00					
mean		0.523992	0.407881	0.139516	0.	828742	
0.35936	67						
std		0.120093	0.099240	0.041827	0.	490389	
0.22196	63						
min		0.075000	0.055000	0.000000	0.	002000	
0.00100	00						
25%		0.450000	0.350000	0.115000	0.	441500	
0.18600	00						
50%		0.545000	0.425000	0.140000	0.	799500	
0.33600	00						
75%		0.615000	0.480000	0.165000	1.	153000	
0.50200	0.0						
max		0.815000	0.650000	1.130000	2.	825500	
1.48800	00						
	Vi	scera weight	Shell weight	Rin	ngs	Age	
count	ant 4177.00000		4177.000000	4177.0000	000 41	77.00000	
mean	n 0.180594		0.238831	9.933	684	11.433684	
std		0.109614	0.139203	3.2241	169	3.224169	
min		0.000500	0.001500	1.0000	1.000000 2.5000		
25%		0.093500	0.130000	8.0000	000	9.500000	

50%	0.171000	0.234000	9.000000	10.500000
75%	0.253000	0.329000	11.000000	12.500000
max	0.760000	1.005000	29.000000	30.500000
	1	-		•

• Check for Missing values and deal with them.

ds.info()

```
<class
```

'pandas.core.frame.DataFrame'>
RangeIndex: 4177 entries, 0 to 4176
Data columns (total 10 columns):

		/ -	
#	Column	Non-Null Count	Dtype
•	Sex	4177 non-null	object
•	Length	4177 non-null	float64
•	Diameter	4177 non-null	float64
•	Height	4177 non-null	float64
•	Whole weight	4177 non-null	float64
•	Shucked weight	4177 non-null	float64
•	Viscera weight	4177 non-null	float64
•	Shell weight	4177 non-null	float64
•	Rings	4177 non-null	int64
•	Age	4177 non-null	

float64dtypes: float64(8), int64(1),

object(1) memory usage: 326.5+ KB

ds.isnull().sum()

Sex 0 Length 0 Diameter Height 0 Whole weight Shucked weight 0 Viscera weight 0 Shell weight 0 Rings Age 0

1190							
	S	L	D	Н	M	S	\
	е	е	i	е	h	h	
	X	n	a	i	0	u	
		g	m	g	1	С	
		t	е	h	е	k	
		h	t	t	W	е	
			е		е	d	
			r		i	W	
					g	е	
					h	i	
					t	g	
						h	

						t	
0	Т	Т	Т	Т	Т	Т	
	r	r	r	r	r	r	
	u	u	u	u	u	u	
	е	е	е	е	е	е	
1	Т	Т	Т	Т	Т	Т	
	r	r	r	r	r	r	
	u	u	u	u	u	u	
	е	е	е	е	е	е	
2	Т	Т	Т	Т	Т	Т	
	r	r	r	r	r	r	
	u	u	u	u	u	u	
	е	е	е	е	е	е	
3	Т	Т	Т	Т	Т	Т	
	r	r	r	r	r	r	
	u	u	u	u	u	u	
	е	е	е	е	е	е	
4	Т	Т	Т	Т	Т	Т	
	r	r	r	r	r	r	
	u	u	u	u	u	u	
	е	е	е	е	е	е	
		•	•	•	•	•	
4	Т	Т	Т	Т	Т	Т	
1	r	r	r	r	r	r	
7	u	u	u	u	u	u	
2	е	е	е	е	е	е	
4	Т	Т	Т	Т	Т	Т	
1	r	r	r	r	r	r	
7	u	u	u	u	u	u	
3	е	е	е	е	е	Ф	
4	Т	Т	Т	Т	Т	Т	
1	r	r	r	r	r	r	
7	u	u	u	u	u	u	
4	е	е	е	е	Ф	Φ	
4	Т	Т	Т	Т	Т	Т	
1	r	r	r	r	r	r	
7	u	u	u	u	u	u	
5	е	е	е	е	Ф	е	

dtype:

int64

ds.notnull

()

	4176	True	True	True	True	True	True
--	------	------	------	------	------	------	------

	Viscera	weight	Shell	weight	Rings	Age
0		True		True	True	True
1		True		True	True	True
2		True		True	True	True
3		True		True	True	True
4		True		True	True	True
4172		True		True	True	True
4173		True		True	True	True
4174		True		True	True	True
4175		True		True	True	True
4176		True		True	True	True

[4177 rows x 10 columns]

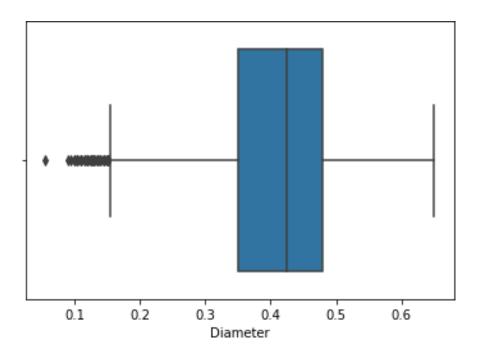
• Find the outliers and replace them outliers

#occurence of outliers
#a data point in a data set that is distant from all other
observations

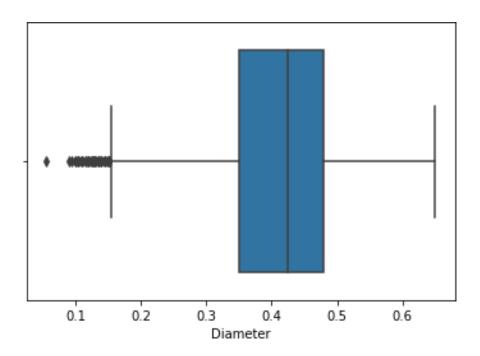
sns.boxplot(ds.Diameter)

/home/lokesh/anaconda3/lib/python3.9/site-packages/seaborn/ _decorators.py:36: FutureWarning: Pass the following variable as a keyword arg: x. From version 0.12, the only valid positional argumentwill be `data`, and passing other arguments without an explicit keyword will result in an error or misinterpretation. warnings.warn(

<AxesSubplot:xlabel='Diameter'>



```
0.1 =
ds.Diameter.quantile(0.25)
Q3=ds.Diameter.quantile(0.75
)
          #spread the middle values are
IQR=Q3-Q1
upper limit =Q3 +
1.5*IQRlower limit =Q1
- 1.5*IQR
ds['Diameter'] =
np.where(ds['Diameter']>upper_limit,30,ds['Diameter'])
sns.boxplot(ds.Diameter)
/home/lokesh/anaconda3/lib/python3.9/site-packages/seaborn/
decorators.py:36: FutureWarning: Pass the following variable as a
keyword arg: x. From version 0.12, the only valid positional
argumentwill be `data`, and passing other arguments without an
explicit keyword will result in an error or misinterpretation.
  warnings.warn(
<AxesSubplot:xlabel='Diameter'>
```



• Check for Categorical columns and perform encoding.

from sklearn.preprocessing import LabelEncoder
le = LabelEncoder()

ds1['Sex'] = le.fit_transform(ds1['Sex'])
ds1

0 = female, 1 = infant, 2 = male

	Sex	Length	Di	ameter	Height	Whole	weight	Shucked	weight	\
0	2	0.455	0.365		0.095		0.5140		0.2245	
1	2	0.350		0.265	0.090		0.2255		0.0995	
2	0	0.530		0.420	0.135		0.6770		0.2565	
3	2	0.440		0.365	0.125		0.5160		0.2155	
4	1	0.330		0.255	0.080		0.2050		0.0895	
195	2	0.500		0.405	0.155		0.7720		0.3460	
196	0	0.505		0.410	0.150		0.6440		0.2850	
197	2	0.640		0.500	0.185		1.3035		0.4445	
198	2	0.560		0.450	0.160		0.9220		0.4320	
199	2	0.585		0.460	0.185		0.9220		0.3635	
	Visc	era weig	ht	Shell	weight	Rings	Age			
0		0.10	10		0.150	15	16.5			
1		0.04	85		0.070	7	8.5			
2		0.14	15		0.210	9	10.5			
3		0.11	40		0.155	10	11.5			
4		0.03	95		0.055	7	8.5			

	• • •	• • •		
195	0.1535	0.245	12	13.5
196	0.1450	0.210	11	12.5
197	0.2635	0.465	16	17.5
198	0.1780	0.260	15	16.5
199	0.2130	0.285	10	11.5

[200 rows x 10 columns]

• Split the data into dependent and independent variables.

#Splitting the Dataset into the Independent Feature Matrix

$$x = ds1.iloc[:, 0:9]x$$

	0	т	4- 1-	D.:		TT = 21- +-	T-71 1 -		Q111		\
	Sex		ngth	DI	ameter	Height	Whole		Shucked	_	\
0	2		. 455		0.365	0.095		0.5140		0.2245	
1	2		.350		0.265	0.090		0.2255		0.0995	
2	0	0	.530		0.420	0.135		0.6770		0.2565	
3	2	0	.440		0.365	0.125		0.5160		0.2155	
4	1	0	.330		0.255	0.080		0.2050		0.0895	
195	2	0	.500		0.405	0.155		0.7720		0.3460	
196	0	0	.505		0.410	0.150		0.6440		0.2850	
197	2	0	.640		0.500	0.185		1.3035		0.4445	
198	2	0	.560		0.450	0.160		0.9220		0.4320	
199	2	0	.585		0.460	0.185		0.9220		0.3635	
	Visc	era	weig	ht	Shell	weight	Rings				
0			0.10			0.150	15				
1			0.04			0.070	7				
2			0.14	15		0.210	9				
3			0.11	40		0.155	10				
4			0.03	95		0.055	7				
195			0.15	35		0.245	12				
196			0.14			0.210	11				
197			0.26			0.465	16				
198			0.17			0.260	15				
199			0.21			0.285	10				
199			0.21	50		0.200	10				

[200 rows x 9 columns]

#Extracting the Dataset to Get the Dependent Vector

```
y =
ds1.iloc[:,9:10]
print(y)
```

```
Age 0 16.5
```

1	8.5			
2	10.5			
3	11.5			
4	8.5			
195	13.5			
196	12.5			
197	17.5			
198	16.5			
199	11.5			
[200	rows	Х	1	columns]

• Scale the independent variables

#scaling the independent variables using scale and MinMaxScaler

```
from sklearn.preprocessing import scale
from sklearn.preprocessing import MinMaxScaler
mm = MinMaxScaler()
x scaled =
mm.fit_transform(x)y_scaled
= mm.fit_transform(y)
x scaled
              , 0.51351351, 0.52808989, ..., 0.17680075,
array([[1.
0.14070352,
        0.64705882],
                  , 0.32432432, 0.30337079, ..., 0.07857811,
       [1.
0.06030151,
        0.17647059],
                 , 0.64864865, 0.65168539, ..., 0.2525725 ,
0.20100503,
        0.29411765],
       [1.
                  , 0.84684685, 0.83146067, ..., 0.4808232 ,
0.45728643,
        0.70588235],
                  , 0.7027027 , 0.71910112, ..., 0.32086062,
       [1.
0.25125628,
        0.64705882],
       [1.
                 , 0.74774775, 0.74157303, ..., 0.38634238,
0.27638191,
        0.35294118]])
```

```
y scaled
array([[0.64705882
],
       [0.17647059],
       [0.29411765],
       [0.35294118],
       [0.17647059],
       [0.23529412],
       [0.94117647],
       [0.70588235],
       [0.29411765],
       [0.88235294],
       [0.58823529],
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       [0.41176471],
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       [0.47058824],
       [0.64705882],
       [0.41176471],
       [0.35294118],
       [0.64705882],
       [0.82352941],
       [0.88235294],
       [0.52941176],
       [0.23529412],
       [0.70588235],
       [0.23529412],
       [0.41176471],
       [0.29411765],
       [0.29411765],
       [0.58823529],
       [0.05882353],
       [0.05882353],
```

```
[0.
[0.17647059],
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```

```
[0.35294118],
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```

```
[0.70588235],
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[0.23529412],
[0.
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[0.58823529],
[1.
           ],
[0.35294118],
[0.35294118],
[0.47058824],
[0.52941176],
[0.47058824],
[0.35294118],
[0.41176471],
[0.29411765],
[0.52941176],
```

```
[0.47058824],
[0.58823529],
[0.23529412],
[0.35294118],
[0.47058824],
[0.41176471],
[0.70588235],
[0.64705882],
[0.35294118]])
```

Split the data into training and testing

```
from sklearn.model_selection import train_test_split # library for
split the data into training and testing
```

```
x train,x test,y train,y test =
train_test_split(x_scaled, y_scaled, train size=0.80, test size =
0.20, random state=0)
x train
                 , 0.17117117, 0.15730337, ..., 0.0261927,
array([[0.5
0.01809045,
        0.17647059],
                  , 0.71171171, 0.69662921, ..., 0.34985968,
0.31155779,
        0.47058824],
                  , 0.73873874, 0.71910112, ..., 0.49672591,
       .01
0.27638191,
        0.41176471],
       . . . ,
                   , 0.48648649, 0.47191011, ..., 0.16651076,
       [1.
0.15577889,
        0.35294118],
                  , 0.52252252, 0.5505618 , ..., 0.19363891,
       [0.
0.14070352,
        0.17647059],
       [1.
                   , 0.63963964, 0.68539326, ..., 0.42376052,
0.27638191,
        0.23529412]])
y train
array([[0.17647059
],
       [0.47058824],
       [0.41176471],
       [0.29411765],
       [0.58823529],
```

```
[0.17647059],
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[0.64705882],
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[0.41176471],
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[0.11764706],
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[0.
           ],
[0.35294118],
[0.35294118],
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[1. ,	0.75675676,	0.7752809 ,	0.55263158, 0.40595238,
0.40660377,	0.47801684,	0.31658291,	0.64705882],
[1. ,	0.53153153,	0.51685393,	0.34210526, 0.15912698,
0.15235849,	0.18802619,	0.16582915,	0.29411765],
[0.	0.71171171,	0.69662921,	0.60526316, 0.3609127 ,
0.39339623,	0.38821328,	0.26130653,	0.47058824],
[0.	0.74774775,	0.74157303,	0.68421053, 0.35813492,
0.33443396,	0.494855 ,	0.28140704,	0.29411765],
[1. ,	0.97297297,	0.92134831,	0.65789474, 0.76547619,
0.71320755,	0.47614593,	0.77386935,	0.82352941],
[0.5 ,	0.28828829,	0.28089888,	0.21052632, 0.06944444,
0.0745283 ,	0.06173994,	0.04522613,	0.17647059],

```
[1. , 0.76576577, 0.7752809 , 0.63157895, 0.5109127 , 0.375 , 0.42563143, 0.57286432, 1. ], [0. , 0.67567568, 0.6741573 , 0.65789474, 0.30634921,
```

0.26698113, 0.33021515, 0.27135678, 0.41176471]])

```
y_test
```

```
array([[0.17647059]
      [0.58823529],
      [0.35294118],
      [0.17647059],
      [0.23529412],
      [0.35294118],
      [0.23529412],
      [0.35294118],
      [0.41176471],
      [0.35294118],
      [0.29411765],
      [0.05882353],
      [0.58823529],
      [0.47058824],
      [0.29411765],
      [0.70588235],
      [0.88235294],
      [0.76470588],
      [0.23529412],
      [0.52941176],
      [0.35294118],
      [0.35294118],
      [0.17647059],
        [0.52941176],
        [0.17647059],
        [0.11764706],
        [0.41176471],
        [0.52941176],
        [0.58823529],
        [0.
        [0.17647059],
        [0.23529412],
        [0.64705882],
        [0.29411765],
        [0.47058824],
        [0.29411765],
        [0.82352941],
        [0.17647059],
        [1.
                    ],
        [0.41176471]])
```

```
print(x_scaled.shap
e)
print(y_scaled.shap
e)
print(x_train.shape)
print(y_train.shape)
print(x_test.shape)
print(y_test.shape)

(200, 9)
(200, 1)
(160, 9)
(160, 1)
(40, 9)
(40, 1)
```

Build the Model

from sklearn.linear_model import LinearRegression
mlr = LinearRegression()
mlr.fit(x_train,y_trai
n)LinearRegression()

• Train the Model

• Test the Model

```
prediction
mlr.predict(x_test)prediction
array([[1.76470588e-
       01],
       [5.88235294e-
       01],
       [3.52941176e-
       01],
       [1.76470588e-
       01],
       [2.35294118e-
       01],
       [3.52941176e-
       01],
       [2.35294118e-
       01],
       [3.52941176e-
```

```
01],
[4.11764706e-
01],
[3.52941176e-
01],
[2.94117647e-
01],
[5.88235294e-
02],
[5.88235294e-
01],
[4.70588235e-
01],
[2.94117647e-
01],
[7.05882353e-
01],
[8.82352941e-
01],
[7.64705882e-
01],
[2.35294118e-
01],
[5.29411765e-
01],
[3.52941176e-
01],
[3.52941176e-
01],
[1.76470588e-
01],
[5.29411765e-
01],
[1.76470588e-
01],
[1.17647059e-
01],
[4.11764706e-
01],
[5.29411765e-
01],
[5.88235294e-
01],
[2.20691474e-
16],
[1.76470588e-
01],
[2.35294118e-
01],
[6.47058824e-
```

```
[2.94117647e-
        01],
        [4.70588235e-
        01],
        [2.94117647e-
        01],
        [8.23529412e-
        01],
        [1.76470588e-
        01],
        [1.0000000e+00]
        , [4.11764706e-
        01]])
prediction.astype(int)
array([[0]
      [0],
      [0],
      [0],
      [0],
      [0],
      [0],
      [0],
      [0],
      [0],
      [0],
        [0],
        [0],
        [0],
        [0],
        [0],
        [0],
        [0],
        [0],
        [0],
        [0],
        [0],
        [0],
        [0],
        [0],
        [0],
        [0],
        [0],
        [0],
        [0],
        [0],
```

01],

```
[0],
[0],
        [0],
         [0],
         [0],
         [0],
         [0],
        [1],
        [0]])
y_test.astype(in
t)array([[0],
        [0],
         [0],
         [0],
        [0],
         [0],
        [0],
[0],
[0],
        [0],
        [0],
        [0],
        [0],
        [0],
         [0],
        [0],
        [0],
         [0],
        [0],
         [0],
         [0],
         [0],
        [0],
[0],
         [0],
         [0],
        [0],
        [0],
         [0],
         [0],
         [0],
        [0],
         [0],
        [0],
         [0],
         [0],
```

```
[0],
[1],
[0]])
```

Measure the performance using Metrics.

```
from sklearn.metrics import
r2 score
r2 score(prediction, y test)
1.0
from sklearn.preprocessing import PolynomialFeatures
plr = PolynomialFeatures (degree=2)
x poly =
plr.fit transform(x)x poly
array([[1.00000e+00, 2.00000e+00, 4.55000e-01, ..., 2.25000e-02,
        2.25000e+00, 2.25000e+02],
       [1.00000e+00, 2.00000e+00, 3.50000e-01, ..., 4.90000e-
        03,4.90000e-01, 4.90000e+01],
       [1.00000e+00, 0.00000e+00, 5.30000e-01, ..., 4.41000e-02,
        1.89000e+00, 8.10000e+01],
       [1.00000e+00, 2.00000e+00, 6.40000e-01, ..., 2.16225e-01,
        7.44000e+00, 2.56000e+02],
       [1.00000e+00, 2.00000e+00, 5.60000e-01, ..., 6.76000e-02,
        3.90000e+00, 2.25000e+021,
       [1.00000e+00, 2.00000e+00, 5.85000e-01, ..., 8.12250e-02,
        2.85000e+00, 1.00000e+02]])
```

Abalone Age Prediction

LinearRegression

```
from sklearn.linear_model import LinearRegression
lr = LinearRegression()
lr.fit(x_poly,y)

LinearRegression
()
lr.predict(plr.transform([[1,0.350,0.410,0.185,1.3035,0.3635,0.1010,0.285,16]]))
/home/lokesh/anaconda3/lib/python3.9/site-packages/sklearn/base.py:450: UserWarning: X does not have valid feature names, but PolynomialFeatures was fitted with feature names warnings.war
n(
```

```
array([[17.5]]

    Ridge

from sklearn.linear model import
Ridger = Ridge()
r.fit(x,
у)
Ridge()
r.predict([[1,0.350,0.410,0.185,1.3035,0.3635,0.1010,0.285,16]])
/home/lokesh/anaconda3/lib/python3.9/site-packages/sklearn/
base.py:450: UserWarning: X does not have valid feature names, but
Ridge was fitted with feature names
 warnings.warn(
array([[17.49624459]
1)
Lasso
from sklearn.linear model import
Lassol = Lasso()
l.fit(x,
у)
Lasso()
l.predict([[1,0.350,0.410,0.185,1.3035,0.3635,0.1010,0.285,16]])
/home/lokesh/anaconda3/lib/python3.9/site-packages/sklearn/
base.py:450: UserWarning: X does not have valid feature names, but
Lasso was fitted with feature names
 warnings.warn(
array([17.08721342
1)
```