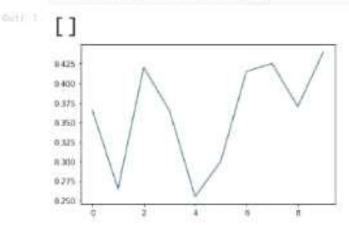
Assignment date	07 November 2022
Student Name	Ms.A.Anusuya
Student Roll Number	821719106006
Maximum Marks	2 Marks

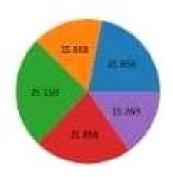
```
(array([ 13., 66., 180., 344., 812., 1017., 934., 275., 23.]), array([0.055, 0.1145, 0.174, 0.23393, 0.3525, 0.412, 0.4715, 0.531, 0.5905, 0.65]),
```

plt.plot(data['Diameter'].bead(10))

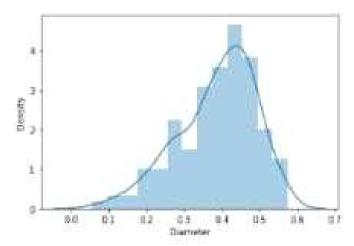


plt.pie(data['D(ameter'].head(),autopct='%.2f')

(L, [Text(0.8507215626110557, 0.6973 76, ''), Text(-0.32611344931648134, 1.05 1026, ''), Text(-1.0998053664078908, -0.02 47144, ''), Text(-0.08269436219656089, -1.0 0709, ''), Text(0.9758446362287218, -0.507 241, '')1, [Text(0.46402994324239394, 0.380 369, '21.856'), Text(-0.17788006326353525, 0.57 2377, '15.868'), Text(-0.5998938362224858, -0.01 984419, '25.150'), Text(-0.045106015743578656, -0. 712958, '21.856'), Text(0.5322788924883937, -0.276 768, '15.269')])

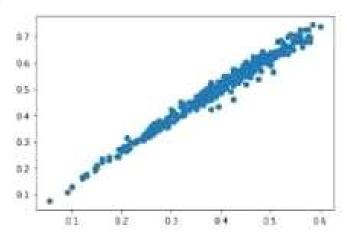






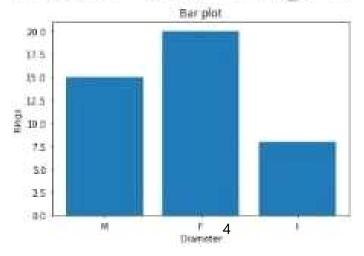
plt.scatter(data['Olimeter'].head(486).data['Length'].head(400))

### forth d.



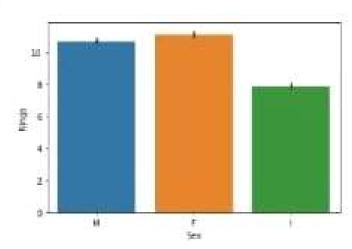
plt.bar(data['Ses'].bead(20).data['Wings'].bead(20))
plt.title('Bar plot')
plt.xlabel('Diameter')
plt.ylabel('Wingt')

# Text(0, 0.5, 'Rings')



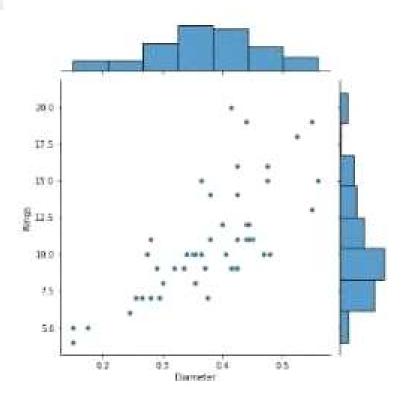
```
in | | sms.barplot(data['Swm'], data['Range'])
```





sns.jointplot(data('Diameter').head(50).data('Rings').head(10R))

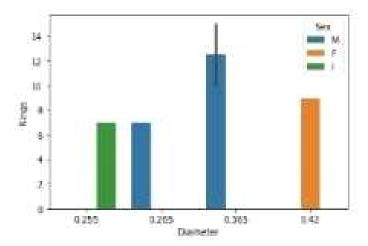
30.00



sns.barplot("Diameter", "Rings", hue="See", data=data.head())

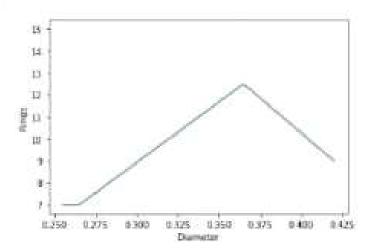
(60H) to

.....



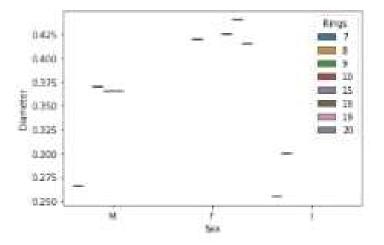
sns.lineplot(data['Diameter'].bead().data['Wings'].head())

941 I



sna.boxplot(data['Sex']\_head(10)\_data['Dimmeter']\_head(10)\_data['Rin

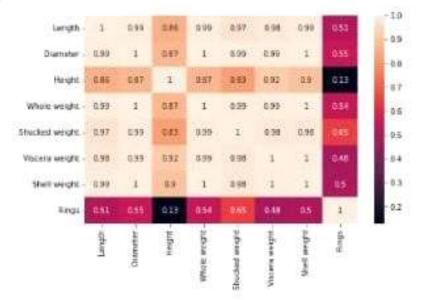
THE REAL PROPERTY.



fig=plt.figura(figsize=(#,56 sns.beatnap(data.bead().corr(),annot=True)

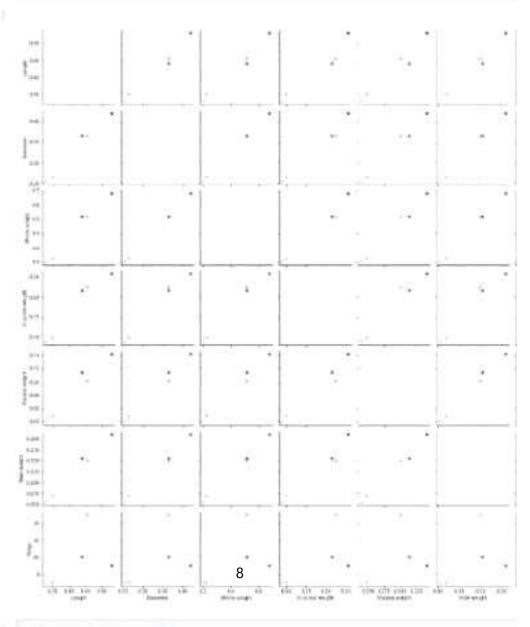






sos.pairplot(data.head(),hus='Height')

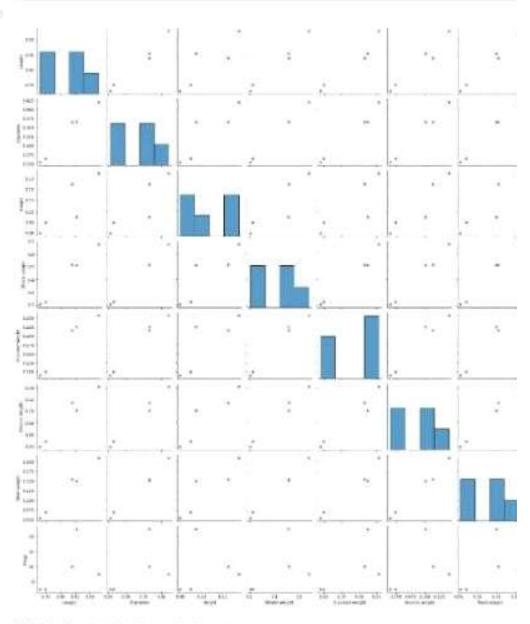
#### Shirt



sns.pairplot(data.head())

. . . . .





3 Perform Descriptive Statistics on the dataset

MODEL IN	does been	40.4

	Sex.	Length	Diameter	Height	Whole weight	Shucked weight	Viscera weight	Shell weight	Rings
ō	¥	0.455	0.365	0.095	0.5140	0.2245	0.1010	0.150	15
1	M	0.350	0.265	0.090	0.2255	0.0995	0.6465	0.070	1
2	F	0.530	0.420	0.135	0.6770	0.2565	0.1415	0.210	- 9
3	M	0.440	0.365	0.125	9.5160	0.2155	0.1140	0.155	10
4	1	0.330	0.255	0.000	0.2050	0.0005	0.0396	0.055	. 7

	Sec. 4	1500	100	

		Ses	Length	Diameter	Height	Whole weight	Shucked weight	Viscors weight	Shell weight	Hings
41	72	ŧ	0.505	0.450	0.385	9.8870	9.3700	0.2390	0.2490	33
41	73	М	0.590	0.440	0.135	0.9660	0.4390	0.2165	0.2605	10
41	74	14	0.600	0.475	0.205	1.776	0 0 5255	9.2875	0.3080	. 9
41	75	F	0.625	0.485	0.150	1.0945	0.5310	0.2610	0.2950	- 10
41	76	M	0.710	0.555	0.195	1.9485	0.9455	0.5765	0.4950	17
1157	283		1100	1133		A STATE	2 (27)	STEELS IN		- Lineson

In L 1	data,info()		
	STORY CONTRACTOR STORY		

RangeIndex: 4177 entries, 0 to 4176 Data columns (total 9 columns): Non-Null Count Column -----4177 non-null 0 Sex Length 1 4177 non-null 4 4177 non-null 2 Diameter 4 Height 3 4177 non-null 4 Whole weight 4177 non-null 4 4 Shucked weight 4177 non-null 5 4 Viscera weight 4177 non-null 6 4 Shell weight 4177 non-null 7 4

dtypes: float64(7), int64(1), objec

4177 non-null

Rings

memory usage: 293.8+ KB

8

	5,00	tigth.	Diameter	Height	Whole weight	Shucked neight	Visceru w
count	4177 000	0000	A177-000006	#177.000mm	A177.000000	4177.000000	4177 00
Heesen.	0.523	992	0.407881	0.139316	0.828742	0.359367	0.18
stef	0.120	1093	0.099240	0.041827	0.190389	0.221963	0.10
min	0.975	0000	0.055000	0.000000	0,002000	0.001000	0.00
25%	0.450	node	0.350000	0.115000	9.441500	0.166000	0.09
50%	0.541	000	0,425000	0.148000	0.799500	5.336000	0.17
75%	0.673	7000	0.490000	0.165000	1.153000	0.502000	35.25
HIME	0.015	2000	0.650000	1.130000	2.825500	1,428000	0.76
data	,made( )	Ţ					
			0 1				
	Sea		M Nak				
	Length	0.	55 0 n25				
	Diameter	0.	45 Nahi				
	Height	0.	15 NuN				
Who	lic weight	0.22	75 NoS				
Shucks	ed weight.	1.0.1	75 NaN				
Visce	ra weight	0.17	15 NaN				
5he	ell weight	0.7	3 - 1111				
	Hings	- 83	0 NaN				
dete	.shape						
(4	177	,	9)				
data	,kurt()						
Le	ngt	h			0	. 06462	1
Di	ame	te	r		-0	.04547	6
			Ů.			.02550	
	igh		20.50				
Wh	ole	W	eigh	t	-0	.02364	.4
Sh	uck	ed	wei	ght	٥	. 59512	4
Very letter				New York Control of the Control of t	47.0		
			wei	Terrant .		.08401	
greet All Con-	PI	- W	eigh	t.	0	. 53192	6
5n	·	2.0	0"	12	0.77(1)		0.000
	ngs		0''	12	2	. 33068	

WYS:	data.skee()	
	Length Diameter Height Whole weight Shucked weight Viscera weight Shell weight Rings dtype: float64	-0.639873 -0.609198 3.128817 0.530959 0.719098 0.591852 0.620927 1.114102
-13	data.var()	
an I t	Length Diameter Height Whole weight Shucked weight Viscera weight Shell weight Rings dtype: float64	0.014422 0.009849 0.001750 0.240481 0.049268 0.012015 0.019377 10.395266
In I I	data.nunique()	
Ouvil T	Sex Length Diameter Height Whole weight Shucked weight Viscera weight Shell weight Rings dtype: int64	3 134 111 51 2429 1515 880 926 28

4 Check for missing values and deal with them

		Sec	Length	Diameter	Height	Whole weight	Shucked weight	Viscera weight	Shell weight	Rings
	p	Fulme	Følse	Falor	False	False	False	Folse	Febre	Faine
	1	False	False	False	False	Fahe	Faise	Folze	False	False
	2	False	False	False	False	False	Folse	False	False	False
	1	False	False	False	False	Felse	False	False	False	False
	4	False	False	Felse	False	Felse	False	False	False	False
	14				J.	100	12			( 3
4	172	False	Faire	Faian	False	False	False	False	Falce	False
4	173	False	False	Falan	False	False	False	False	False	False
.4	174	False	Faine	Farse	Faine	False	Falsa	False	False	Fatue
4	175	False	False	Faise	False	False	Falsa	False	False	False
4	176	False	False	Fatou	False	Felse	Fallaki	False	False	False

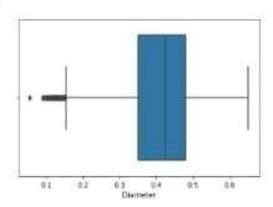
## 4177 rows × 9 columns

gr. ii	deta.isna().any()	
MT :	Sex	False
	Length	False
	Diameter	False
	Height	False
	Whole weight	False
	Shucked weight	False
	Viscera weight	False
	Shell weight	False
	Rings	False
	dtype: bool	
11.1	data.isma().sum()	
int. 2	Sex	0
	Length	0
	Diameter	0
	Height	0
	Whole weight	0
	Shucked weight	0
	Viscera weight	0
	Shell weight	0
	Rings	0 16
	dtype: int64	10
	data.isna().any().som()	

11.

```
in ( | sna.boxplot(data[ Dimmeter'])
```

DHETCH



quant=data.quantile(q=[0.25,0.75]) quant

 Corril I
 Length Diameter
 Height Whole weight Shucked weight Viscera weight Shell weight Rings

 0.25
 0.450
 0.35
 0.116
 0.4415
 0.186
 0.0935
 0.130
 8.0

 0.75
 0.615
 0.40
 0.165
 1.1530
 0.502
 0.2030
 0.329
 11.0

igr=quant.loc[0.75]-quant.loc[0.25]

Length 0.1650 Diameter 0.1300 Height 0.0500 Whole weight 0.7115 Shucked weight 0.3160 Viscera weight 0.1595 Shell weight 0.1990 Rings 3.0000

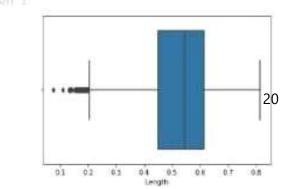
dtype: float64

low=quant.loc(0.25]-(1.5\*iqr)

0.20250 Length 0.15500 Diameter 0.04000 Height -0.62575 Whole weight Shucked weight -0.28800 Viscera weight 180.14575 Shell weight -0.16850 Rings 3.50000 dtype: float64

	Length	0.20250
	Diameter	0.15500
	Height	0.04000
	Whole weight	-0.62575
	Shucked weight	-0.28800
	Viscera weight	-0.14575
	Shell weight	-0.16850
	Rings	3.50000
	dtype: float64	
20 7 37	up*quant.loc[0.75]*(1.5*iqr) up	
0011-30	Length	0.86250
	Diameter	0.67500
	Height	0.24000
	Whole weight	2.22025
	Shucked weight	0.97600
	Viscera weight	0.49225
	Shell weight	0.62750
	Rings	15.50000
	dtype: float64	
201 1	<pre>data['Diameter']=np.where(data['Ds. sns.boxplot(data['Diameter'])</pre>	sector"]<0.155,0.4078,data['Siameter'])
nati I		
	/*	·
	62 03 04 05	96
	Diameter	
THE 10	CU LO SUCCESSION OF THE SUCCES	

## ses.boxplot(data['Leigth'])



```
data['Longth']mp.where(data['Longth']+0.23,0.52, data['Longth'])
sns.boxplot(data['Longth'])
                                        0.5
Length
            sns.bosplot(dats["Height"])
                                        06
Height
              0.0
                        0.2
                                                     0.8
                                                               10
data['Height']=np.where(data['Height']>0.6d,0.139. data['Height'])
data['Height']=np.where(data['Height']>0.23,0.139. data['Height'])
sns.boxplot(data['Height'])
                8050 0075 0100 0125 0150 0176 0200 0225
            sns.boxplot(dats['Whole weight'])
                                                                         22
                                 10 15
Wrote weight
              ôε
                        55
```

data['Whole weight']=np.where(data['Whole meight']>0.0.0.0.02, data['Whole meight'])
sns.boxplot(data['Whole meight'])

```
data['Shucked meight']=np.where(data['Shucked weight']>0.93,0.35, data['Shucked weight'])
                                £4 (
Shicked engit
                                                        6.8
            46
                       0.1
                                             0.6
          ins.boxplot(data[ Vincera weight ])
                                9.1 9.4
Vicera weight
                          0.2
                                                    0.6
                                                           0.7
           data['Viscora weight']=np.where(data['Viscora weight']=0.46,0.19, data['Viscora weight']=0.46,0.19, data['Viscora weight'])
                                 0.2 0.3
Viscora weight
           sns.boxplot(dats["Shell weight"])
                                       24
```

04 06 Shell weight

0.0

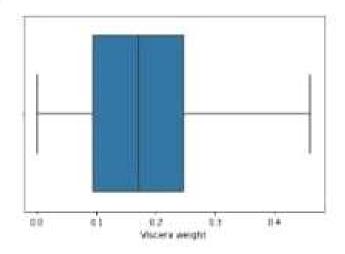
0.2

1.0

ü II

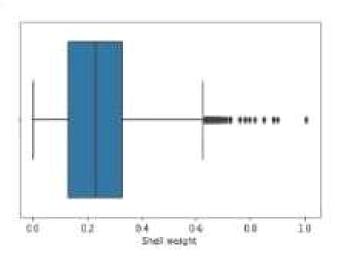
data['Viscora meight']=op.where(data['Viscora weight']>0.46.0.18, data[boxplot(data['Viscora weight'])





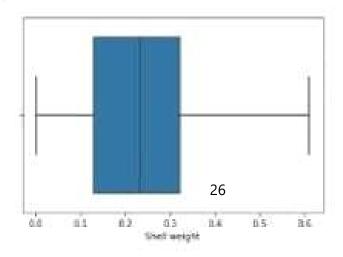
sns.boxplot(data[ Shell weight ])

#### Black III



data['Shell weight'] onp.where(data['Shell weight']>0.61,0.238E, data ins.boxplot(data['Shell weight'])

Chitilitie



6. Check for Categorical columns and perform encoding.

	See	Lieigth	Diameter	Height	Whole weight	Shucked weight	Viscera weight	She
0	- 1	0.455	0.365	12 0 0 5	0.51411	0.2245	0.1010	
- 1	- 1	0.350	0.265	0.000	0.2265	0.0005	0.0485	
2	n	0.530	0.420	0.535	0.6776	0.2565	0.1415	
3	1.3	0.440	0.365	0.125	0.5160	0.2152	0.1140	
*	3.7	0.300	0.255	0.080	0.2050	0.0695	0.0393	
J.Hi								
4172	0	0.565	0.450	II 155	0.8870	9.3700	0.2390	
4173		0.590	0.660	0.135	0.8200	0.4390	0.2345	
4174	7	0.600	0.475	0.205	5.8200	0.5255	0.2875	
4175	0	0.625	0.465	0.150	0.6200	0.5310	0.2610	
4176	4	0.710	0.555	0.145	0.8200	9.3500	0.3765	

# 4177 rows × 9 columns

7 Split the data into dependent and independent variables.

9 1 1	y*da	tal:	trop(co		Kingt	1)			
het h		Sex	Length	Diameter	Height	Whole weight	Shucked weight	Viacera weight	Sho
	0	- 1	0.455	0.365	13-005	0.5740	5.2245	0.1010	
	- 1	1	0.350	0.265	0.000	0.2255	5,0995	8,0485	
	2	0	0.530	0.420	0.155	0.6770	0.2565	8.1415	
	3	- 1	0.440	0.565	0.125	0.5168	0.2155	0.1140	
	4	- 2	0.330	0.255	0.050	0.2050	0.6895	0.0395	
	340			-					
	4172	:0	0.565	9,450	0.565	0.6870	0.2700	0.2390	
	4173	.1	0.590	0.440	0.135	0.8200	0,4390	0.2745	
	4174	1	0.606	0.435	0.205	5.B200	B 5255	0.2675	
	4175	0	0.625	0.485	0.150	0.0200	Ø 5010	0.2610	
	4176	1	0.710	0.555	11.115	0 R200	9.3508	0.9765	

### 4177 rows x 8 columns

```
0
                15
                7
     1
     2
                 9
     3
                10
                7
     4172
               11
     4173
               10
    4174
               9
     4175
               10
               12
     4176
     Name: Rings, Length: 4177, dtype: int64
     B Scale the independent variables
from aklearm.preprocessing import scale
array([[-0.0105225 , -0.67088921, -0.501796
     94, ..., -0.61037964,
               -0.7328165 , -0.64358742],
              [-0.0105225 , -1.61376082, -1.573044
     87, ..., -1.22513334,
               -1.24343929, -1.25742181],
              [-1.26630752, 0.00259051, 0.087389
     42, ..., -0.45300269,
               -0.33890749, -0.18321163],
              [-0.0105225 , 0.63117159 , 0.676575
     77, ..., 0.86994729,
                 1.08111018, 0.56873549],
              [-1.26630752, 0.85566483, 0.783700
     57, ..., 0.89699645,
                 0.82336724, 0.47666033],
              [-0.0105225 , 1.61894185 , 1.533574
     12, ..., 0.00683308,
                 1.94673739, 2.00357336]])
     9. Split the data into training and testing
from skiearn.model_selection import train_test_split
a_train. a_test, y_train, y_test = train_test_split(x,y, test_size = 0.2)
print(x_train.shape, x_test.shape)
     (3341, 8) (836, 8)
     10 Build the Model
from sklears.linear_model import LinearRegression
     MLR=LinearHegrossion()
                                    30
     11 Train the model
MER.fit(w_train,y_train)
LinearRegression()
```

y\_pred=MLR.predict(x\_test)

```
array([ 6.27730521, 5.11464173, 11.2906194
   7, 8.84719371, 11.31342551,
          14.27587505, 11.89677849, 12.3964822
   5, 8.55248601, 8.08961834,
          12.09449868, 10.56528709, 9.7895849
   9.
      8.59686646, 7.76585939,
           8.47357248, 11.36977123, 9.5280555
   6, 12.36997291, 6.51973298,
           6.71785594, 11.05744841, 11.6901007
   4, 10.75739263, 6.5544077,
           6.82824096, 9.5306839 , 7.5119168
   9,
       5.82377217, 10.47024617,
          13.13730038, 10.34700988, 11.4119617
   7, 10.59789269, 13.25077032,
          14.82997416, 12.28691696, 10.9214164
    , 12.87901037, 11.59049406,
           8.5462146 , 8.52536272, 9.9537730
       7.94745203, 6.85150487,
   9,
           9.45338836, 8.86394805, 11.5806935
       6.06270743, 4.07194007,
   8,
          10.72813151, 8.62455986, 10.9224726
   4,
       8.31707157, 3.31458267,
          10.83423943, 9.36311705, 9.9259695
   7,
       7.17213853, 11.12938437,
          13.91273686, 7.42159167, 9.9633253
   4, 13.92006698, 11.33472246,
           9.06493075, 10.20822237, 9.2684450
   5, 10.24458569, 8.00893436,
           6.65277356, 9.9852585 , 8.5866735
   2, 11.43900078, 9.16014079,
           9.50575436, 10.974906 , 9.3115556
   1, 10.85487744, 10.47876918,
          10.89867355, 9.57567238, 7.3775531
   6, 10.26968745, 8.68813991,
           9.66582988, 3.98888101, 6.6801349
   2.
       9.98844442, 8.20535208,
          14.65659649, 11.55465815, 10.8217179
   7, 6.76120381, 8.9003516,
          13.21613708, 10.1018605 , 8.2471845
       7.45995921, 10.21992407,
   3,
          11.59425676, 10.66513659, 13.3792795
   6, 10.94076906, 10.60418916,
```

11 27500775 0 12004022 12 0246627

```
4, 10./33304/0, 11.43130144,
        6.20410519, 8.62148935, 12.5795445
, 6.69882956, 12.00242043,
        9.3306056 , 9.98680774, 8.9656372
5, 10.93545618, 6.79192911,
        9.70880805, 10.70932137, 8.9335340
2, 9.50496905, 8.07991477,
        8.95737614, 10.93209418, 7.7644968
, 8.13978903, 10.95470452,
       10.31933582, 13.16703248, 10.1301335
8, 9.83546825, 9.90633339,
       7.01510185, 7.90500802, 11.0718584
9, 9.29098045, 11.97645598,
       10.72209476, 8.01227134, 12.5263092
, 12.14710337, 7.46207783,
       6.40507134, 11.11733617, 7.3223731
3, 11.74140484, 10.62073403,
       6.7070387 , 8.26673972, 8.0359016
5, 11.01898624, 6.86794371,
       10.81252025, 10.428314 , 8.7164497
8, 11.55298684, 10.54060743,
        7.8005991 , 7.77758003, 12.8386618
, 8.93468911, 11.39965158,
      14.96420885, 3.44108358, 12.1693500
9, 5.50036395, 11.35043959,
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1. 7.84382717. 11.44647106.

```
in 1 1 Finitializing model
   rg=Ridge(alpha=0.01.normalize=True)
    ##15 the model
    rg.fit(s_train.y_train)
Ridgo(aipha=0.01, normalize=True)
    #prediction
rg_pred=rg.predict(s_test)
    rg ored
array([ 6.30300957, 5.24101358, 11.239
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pred-NLR,predict(x_troin)
array([13.90916896, 7.94417688, 10.9917352
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            6.26813443, 9.885908221)
from sklearn metrics import r2_score
    accuracy=r2 score(y test,y pred)
    0.4482390430138421
NER.product([[1,0.455,0.165,0.095,0.5140,0,2345,0.1010,0.150]])
array([9.8732734])
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rg.coef_
array([-0.34874321, -0.70989254,
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          -1.45851724, -0.14684477,
   41)
metrics.r2_score(y_test_rg_pred)
0.4493030433197964
np.sqrt(mean_squared_error(y_test,rg_pred))
2.401672354777648
```

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C 0 00437074 40 33304043

```
2.403991367956563
from sklears.linear_model import Lasso. Ridge
sintialising model
     Ino=Lasso(alpha=0.01.normaliz==True)
     lso.fit(*_train,y_train)
Lasso(alpha=0.01. normalize=True)
*prediction on test data
     1so_pred=1so.predict(x_test)
     coef=lso.coef
    array([-0.01293987, 0.
                                                   0.
     , 0.50666281, 0.15925177,
                                                   0.7739190
                             , 0.
     3])
from sklearn import metrics
from sklearn setrics import mean squared error
     metrics.r2_score(y_test.Iso_pred)
0.36871210321772163
np.sqrt(mean_squared_error(y_test,iso_pred))
2.571408956644621
     RIDGE
| | | #initialising model
     rg=Ridgs(alpha=0.01,normalize=True)
     rg.fit(x_train,y_train)
Ridge(alpha=0.01, normalize=True)
     #prediction
rg_pred=rg.predict(x_test)
    array([ 6.30300957, 5.24101358, 11.2391992
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