step for regression model with statsmodel

```
import pandas as pd
```

```
import numpy as np
```

```
import matplotlib.pyplot as plt
```

```
import seaborn as sns
```

import dataframe

```
df=pd.read_csv('https://github.com/YBI-Foundation/Dataset/raw/main/Fish.csv')
```

```
df.head()
```

	Category	Species	Weight	Height	Width	Length1	Length2	Length3
0	1	Bream	242.0	11.5200	4.0200	23.2	25.4	30.0
1	1	Bream	290.0	12.4800	4.3056	24.0	26.3	31.2
2	1	Bream	340.0	12.3778	4.6961	23.9	26.5	31.1
3	1	Bream	363.0	12.7300	4.4555	26.3	29.0	33.5
4	1	Bream	430.0	12.4440	5.1340	26.5	29.0	34.0

✓ 2s completed at 5:12 PM

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 159 entries, 0 to 158
Data columns (total 8 columns):
 #   Column    Non-Null Count  Dtype  
---  ------    --------------  -----  
 0   Category  159 non-null    int64  
 1   Species   159 non-null    object 
 2   Weight    159 non-null    float64
 3   Height    159 non-null    float64
 4   Width     159 non-null    float64
 5   Length1   159 non-null    float64
 6   Length2   159 non-null    float64
 7   Length3   159 non-null    float64
dtypes: float64(6), int64(1), object(1)
memory usage: 10.1+ KB
```

get a summary statics

```
df.describe()
```

	Category	Weight	Height	Width	Length1	Length2	Length3
count	159.000000	159.000000	159.000000	159.000000	159.000000	159.000000	159.000000
mean	3.264151	398.326415	8.970994	4.417486	26.247170	28.415723	31.227044
std	1.704249	357.978317	4.286208	1.685804	9.996441	10.716328	11.610246
min	1.000000	0.000000	1.728400	1.047600	7.500000	8.400000	8.800000
25%	2.000000	120.000000	5.944800	3.385650	19.050000	21.000000	23.150000
50%	3.000000	273.000000	7.786000	4.248500	25.200000	27.300000	29.400000

75%	4.500000	650.000000	12.365900	5.584500	32.700000	35.500000	39.650000
max	7.000000	1650.000000	18.957000	8.142000	59.000000	63.400000	68.000000

get the shape

```
df.shape
```

```
(159, 8)
```

```
df.columns
```

```
Index(['Category', 'Species', 'Weight', 'Height', 'Width', 'Length1',
       'Length2', 'Length3'],
      dtype='object')
```

define y(depedent, lable or target variable) x(indepedent of feturs of independent variable)

```
y=df['Weight']
```

```
y.shape
```

```
(159,)
```

```
y
```

```
0      242.0
1      290.0
```

```
1      290.0
2      340.0
3      363.0
4      430.0
       ...
154     12.2
155     13.4
156     12.2
157     19.7
158     19.9
Name: Weight, Length: 159, dtype: float64
```

```
x=df[['Height', 'Width', 'Length1', 'Length2', 'Length3']]
```

use drop function to define x

```
x=df.drop(['Category', 'Species', 'Weight'],axis=1)
```

```
x.shape
```

```
(159, 5)
```

```
x
```

	Height	Width	Length1	Length2	Length3
0	11.5200	4.0200	23.2	25.4	30.0
1	12.4800	4.3056	24.0	26.3	31.2
2	12.3778	4.6961	23.9	26.5	31.1
3	12.7300	4.4555	26.3	29.0	33.5
4	12.4440	5.1340	26.5	29.0	34.0

...	...	...	...	...	...
154	2.0904	1.3936	11.5	12.2	13.4
155	2.4300	1.2690	11.7	12.4	13.5
156	2.2770	1.2558	12.1	13.0	13.8
157	2.8728	2.0672	13.2	14.3	15.2
158	2.9322	1.8792	13.8	15.0	16.2

159 rows × 5 columns

add constant to feature (X) intercept estimation

```
import·statsmodels.api·as·sm
```

```
    /usr/local/lib/python3.7/dist-packages/statsmodels/tools/_testing.py:19: FutureWarning: pandas.util.testing is depre
      import pandas.util.testing as tm
```

```
x=sm.add_constant(x)
```

```
    /usr/local/lib/python3.7/dist-packages/statsmodels/tsa/tsatools.py:117: FutureWarning: In a future version of pandas
      x = pd.concat(x[::order], 1)
```

```
x.head()
```

	const	Height	Width	Length1	Length2	Length3
0	1.0	11.5200	4.0200	23.2	25.4	30.0
1	1.0	12.4800	4.3056	24.0	26.3	31.2
2	1.0	12.3778	4.6961	23.9	26.5	31.1
3	1.0	12.7300	4.4555	26.3	29.0	33.5

```
4    1.0  12.4440  5.1340    26.5    29.0    34.0
```

get train test split

```
from sklearn.model_selection import train_test_split
```

```
x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.3,random_state=2529)
```

```
x_train.shape,x_test.shape,y_train.shape,y_test.shape
```

```
((111, 6), (48, 6), (111,), (48,))
```

get model train

```
import statsmodels.api as sm
```

```
model=sm.OLS(y_train,x_train).fit()
```

get model prediction

```
y_pred=model.predict(x_test)
```

```
y_pred
```

```
6      485.768263
```

```
54     502.247209
80      94.723820
138    876.571171
91     184.078918
48     219.301305
52     322.325322
103    376.223260
57     372.357305
149   -182.675371
153   -160.604868
108    454.335862
90     159.597558
118    843.485252
131    587.216806
100    299.535214
15     597.729508
46     197.146054
132    639.890467
79      91.200679
64     150.954248
35    -103.083206
133    627.197128
116    795.691769
31     814.687330
146   -204.149651
53     329.987469
28     715.892880
1      359.756344
117    792.324392
9      532.703671
12     552.008323
129    433.484727
111    687.617503
147   -204.763625
125    932.536683
120    810.742342
158    -80.062172
51     284.362879
34     907.080360
23     642.582834
127    959.338482
21     675.287923
```

```
21     679.287929
113    718.863055
109    623.898492
101    376.483470
10     530.838281
157    -86.235707
dtype: float64
```

```
y_pred.shape
```

```
(48,)
```

get model evaluation

```
from sklearn.metrics import mean_squared_error,mean_absolute_error,mean_absolute_percentage_error,r2_score
```

```
mean_squared_error(y_test,y_pred)
```

```
16397.34452441141
```

```
mean_absolute_error(y_test,y_pred)
```

```
103.02952922678567
```

```
mean_absolute_percentage_error(y_test,y_pred)
```

```
2.508285347160016
```

```
r2_score(y_test,y_pred)
```

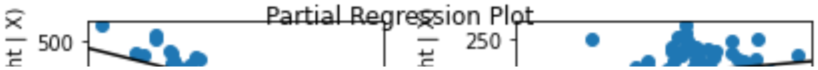
```
0.8349141424416875
```

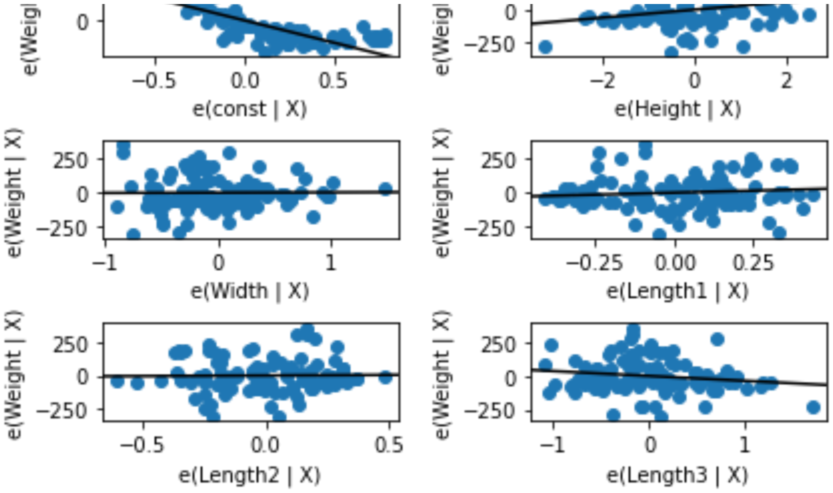
get model summary

```
print(model.summary())
```

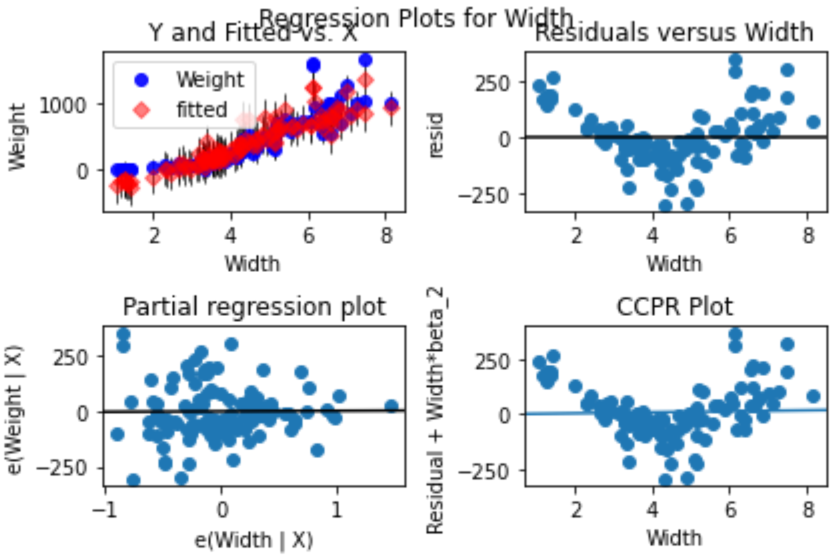
```
                            OLS Regression Results                            
==============================================================================
Dep. Variable:                 Weight   R-squared:                       0.896
Model:                            OLS   Adj. R-squared:                  0.891
Method:                 Least Squares   F-statistic:                     181.2
Date:                Sun, 24 Apr 2022   Prob (F-statistic):           5.84e-50
Time:                        11:35:27   Log-Likelihood:                -689.20
No. Observations:                 111   AIC:                             1390.
Df Residuals:                     105   BIC:                             1407.
Df Model:                           5                                         
Covariance Type:            nonrobust                                         
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const       -519.2834     34.659    -14.983      0.000    -588.005    -450.562
Height        29.8643     10.826      2.759      0.007       8.398      51.330
Width          2.2594     26.105      0.087      0.931     -49.502      54.020
Length1       58.3379     52.151      1.119      0.266     -45.068     161.743
Length2        8.5339     51.806      0.165      0.869     -94.189     111.256
Length3      -36.1521     21.444     -1.686      0.095     -78.671       6.367
==============================================================================
Omnibus:                        5.384   Durbin-Watson:                   2.008
Prob(Omnibus):                  0.068   Jarque-Bera (JB):                4.993
Skew:                           0.391   Prob(JB):                       0.0824
Kurtosis:                       3.684   Cond. No.                         331.
==============================================================================

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
```

```
fig=sm.graphics.plot_partregress_grid(model)
```





```
fig=sm.graphics.plot_regress_exog( model,"Width")
```


Regression Plots for Width
Y and Fitted vs. X
Weight
fitted
Weight
1000
0
Width
Residuals versus Width
resid
250
0
−250
2
4
6
8
Width
Partial regression plot
e(Weight | X)
e(Width | X)
−1
0
1
CCPR Plot
Residual + Width*beta_2
Width