import numpy as np import pandas as pd import seaborn as sns import matplotlib.pyplot as plt import statsmodels.formula.api as smf

#Importing the dataset

df = pd.DataFrame (data= {'YearsExperience':[1.1,1.3,1.5,2,2.2,2.9,3,3.2,3.2,3.7,3.9,4,4,4.1,4.5,4.9,5.1,5.3,5.9,6,6.8,7.1,7.9,8.2,8.7,9,9.5,9.6,10.3,10.5],

'Salary':[39343,46205,37731,43525,39891,56642,60150,54445,64445,57189,63218,55794, 56957,57081,61111,67938,66029,83088,81363,93940,91738,98273,101302,113812, 109431,105582,116969,112635,122391,121872]})

df.head()

	YearsExperien	се	Salary
0	1	1.1	39343
1	1	1.3	46205
2	1	1.5	37731
3	2	2.0	43525
4	2	2.2	39891

df.describe()

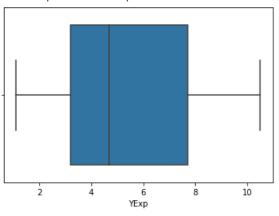
	YearsExperience	Salary
count	30.000000	30.000000
mean	5.313333	76003.000000
std	2.837888	27414.429785
min	1.100000	37731.000000
25%	3.200000	56720.750000
50%	4.700000	65237.000000
75%	7.700000	100544.750000
max	10.500000	122391.000000

#Renaming the columns for ease of usage df1=df.rename({'YearsExperience':'YExp', 'Salary':'Sal'},axis=1)

## **CHECKING FOR OUTLIERS**

sns.boxplot(x='YExp', data=df1)

<AxesSubplot:xlabel='YExp'>



sns.boxplot(x='Sal', data=df1)

In [2]:

In [1]:

In [3]:

Out[3]:

In [4]:

Out[4]:

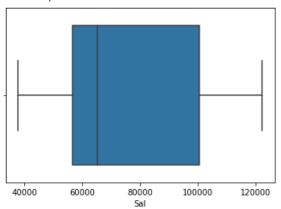
In [5]:

In [6]:

Out[6]:

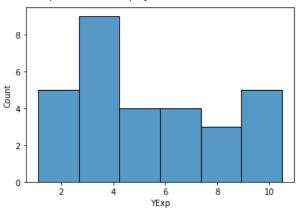
In [7]:

<AxesSubplot:xlabel='Sal'>



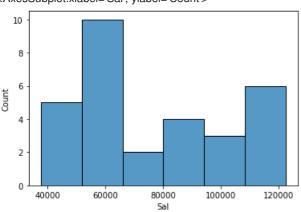
sns.histplot(df1.YExp)

<AxesSubplot:xlabel='YExp', ylabel='Count'>



sns.histplot(df1.Sal)

<AxesSubplot:xlabel='Sal', ylabel='Count'>



## **Checking for duplicated rows**

df1[df1.duplicated()].shape

(0, 2)

**Building the model** 

model = smf.ols('Sal~YExp', data=df1).fit()

sns.regplot(x='YExp', y='Sal', data=df1)

In [8]:

Out[7]:

Out[8]:

In [9]:

Out[9]:

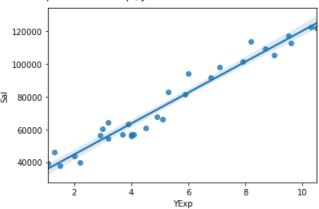
In [10]:

Out[10]:

In [11]:

In [12]:

<AxesSubplot:xlabel='YExp', ylabel='Sal'>



model.params

Intercept 25792.200199 YExp 9449.962321

dtype: float64

print('pvalue:', model.pvalues, '\n','\n','Rsquared value is:', model.rsquared, '\n','\n', 'Adjusted Rsquared value is:', model.rsquared\_adj)

pvalue: Intercept 5.511950e-12

YExp 1.143068e-20

dtype: float64

Rsquared value is: 0.9569566641435086

Adjusted Rsquared value is: 0.9554194021486339

#The R-Squared value is >0.95, hence we can say it's an excellent model and there's no need for any interation.

## Predicting the existing data

pred = pd.DataFrame (model.predict(df1), columns=['Predicted Salary'])

pred

In [13]:

Out[12]:

Out[13]:

In [14]:

In [15]:

In [16]:

In [17]:

38077.151217 39967.143681 44692.124842 46582.117306 53197.090931 54142.087163 56032.079627 60757.060788 62647.053252 63592.049484 63592.049484 64537.045717 68317.030645 72097.015574 73987.000502 81546.977895 82491.974127 90051.943985 92886.932681 100446.902538 103281.891235 108006.872395 110841.861092 115566.842252 116511.838485 123126.812110 125016.804574		
38077.151217 39967.143681 44692.124842 46582.117306 53197.090931 54142.087163 56032.079627 60757.060788 62647.053252 63592.049484 63592.049484 64537.045717 68317.030645 72097.015574 73987.000502 81546.977895 82491.974127 90051.943985 92886.932681 100446.902538 103281.891235 108006.872395 110841.861092 115566.842252 116511.838485 123126.812110 125016.804574		
39967.143681 44692.124842 46582.117306 53197.090931 54142.087163 56032.079627 56032.079627 60757.060788 62647.053252 63592.049484 63592.049484 64537.045717 68317.030645 72097.015574 73987.000502 81546.977895 82491.974127 90051.943985 92886.932681 100446.902538 103281.891235 108006.872395 110841.861092 115566.842252 116511.838485 123126.812110 125016.804574	0	
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46582.117306 53197.090931 54142.087163 56032.079627 56032.079627 60757.060788 62647.053252 63592.049484 63592.049484 64537.045717 68317.030645 72097.015574 73987.008038 75877.000502 81546.977895 82491.974127 90051.943985 92886.932681 100446.902538 103281.891235 108006.872395 110841.861092 115566.842252 116511.838485 123126.812110 125016.804574	2	39967.143681
53197.090931 54142.087163 56032.079627 56032.079627 60757.060788 62647.053252 63592.049484 63592.049484 64537.045717 68317.030645 72097.015574 73987.000502 81546.977895 82491.974127 90051.943985 92886.932681 100446.902538 103281.891235 108006.872395 110841.861092 115566.842252 116511.838485 123126.812110 125016.804574	3	44692.124842
54142.087163 56032.079627 56032.079627 60757.060788 62647.053252 63592.049484 63592.049484 64537.045717 68317.030645 72097.015574 73987.000502 81546.977895 82491.974127 90051.943985 92886.932681 100446.902538 103281.891235 108006.872395 110841.861092 115566.842252 116511.838485 123126.812110 125016.804574	4	
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56032.079627 60757.060788 62647.053252 63592.049484 63592.049484 64537.045717 68317.030645 72097.015574 73987.000502 81546.977895 82491.974127 90051.943985 92886.932681 100446.902538 103281.891235 108006.872395 110841.861092 115566.842252 116511.838485 123126.812110 125016.804574	6	54142.087163
60757.060788 62647.053252 63592.049484 63592.049484 64537.045717 68317.030645 72097.015574 73987.000502 81546.977895 82491.974127 90051.943985 92886.932681 100446.902538 103281.891235 108006.872395 110841.861092 115566.842252 116511.838485 123126.812110 125016.804574	7	56032.079627
62647.053252 63592.049484 63592.049484 64537.045717 68317.030645 72097.015574 73987.008038 75877.000502 81546.977895 82491.974127 90051.943985 92886.932681 100446.902538 103281.891235 108006.872395 110841.861092 115566.842252 116511.838485 123126.812110 125016.804574	8	56032.079627
63592.049484 63592.049484 64537.045717 68317.030645 72097.015574 73987.000502 81546.977895 82491.974127 90051.943985 92886.932681 100446.902538 103281.891235 108006.872395 110841.861092 115566.842252 116511.838485 123126.812110 125016.804574	9	60757.060788
63592.049484 64537.045717 68317.030645 72097.015574 73987.008038 75877.000502 81546.977895 82491.974127 90051.943985 92886.932681 100446.902538 103281.891235 108006.872395 110841.861092 115566.842252 116511.838485 123126.812110 125016.804574	10	62647.053252
64537.045717 68317.030645 72097.015574 73987.008038 75877.000502 81546.977895 82491.974127 90051.943985 92886.932681 100446.902538 103281.891235 108006.872395 110841.861092 115566.842252 116511.838485 123126.812110 125016.804574	11	63592.049484
68317.030645 72097.015574 73987.008038 75877.000502 81546.977895 82491.974127 90051.943985 92886.932681 100446.902538 103281.891235 108006.872395 110841.861092 115566.842252 116511.838485 123126.812110 125016.804574	12	63592.049484
72097.015574 73987.008038 75877.000502 81546.977895 82491.974127 90051.943985 92886.932681 100446.902538 103281.891235 108006.872395 110841.861092 115566.842252 116511.838485 123126.812110	13	64537.045717
73987.008038 75877.000502 81546.977895 82491.974127 90051.943985 92886.932681 100446.902538 103281.891235 108006.872395 110841.861092 115566.842252 116511.838485 123126.812110 125016.804574	14	68317.030645
75877.000502 81546.977895 82491.974127 90051.943985 92886.932681 100446.902538 103281.891235 108006.872395 110841.861092 115566.842252 116511.838485 123126.812110 125016.804574	15	72097.015574
81546.977895 82491.974127 90051.943985 92886.932681 100446.902538 103281.891235 108006.872395 110841.861092 115566.842252 116511.838485 123126.812110 125016.804574	16	73987.008038
82491.974127 90051.943985 92886.932681 100446.902538 103281.891235 108006.872395 110841.861092 115566.842252 116511.838485 123126.812110 125016.804574	17	75877.000502
90051.943985 92886.932681 100446.902538 103281.891235 108006.872395 110841.861092 115566.842252 116511.838485 123126.812110 125016.804574	18	81546.977895
92886.932681 100446.902538 103281.891235 108006.872395 110841.861092 115566.842252 116511.838485 123126.812110 125016.804574	19	82491.974127
100446.902538 103281.891235 108006.872395 110841.861092 115566.842252 116511.838485 123126.812110 125016.804574	20	90051.943985
100446.902538 103281.891235 108006.872395 110841.861092 115566.842252 116511.838485 123126.812110 125016.804574	21	
108006.872395 110841.861092 115566.842252 116511.838485 123126.812110 125016.804574	22	
108006.872395 110841.861092 115566.842252 116511.838485 123126.812110 125016.804574	23	103281.891235
110841.861092 115566.842252 116511.838485 123126.812110 125016.804574	24	
115566.842252 116511.838485 123126.812110 125016.804574	25	
116511.838485 123126.812110 125016.804574	26	
123126.812110 125016.804574	27	
125016.804574	28	
	29	
	-	
$\Delta dI = nd concet/L$	nrod	11 = pd.concat([c

pred1

In [20]:

	YExp	Sal	Predicted Salary
0	1.1	39343	36187.158752
1	1.3	46205	38077.151217
2	1.5	37731	39967.143681
3	2.0	43525	44692.124842
4	2.2	39891	46582.117306
5	2.9	56642	53197.090931
6	3.0	60150	54142.087163
7	3.2	54445	56032.079627
8	3.2	64445	56032.079627
9	3.7	57189	60757.060788
10	3.9	63218	62647.053252
11	4.0	55794	63592.049484
12	4.0	56957	63592.049484
13	4.1	57081	64537.045717
14	4.5	61111	68317.030645
15	4.9	67938	72097.015574
16	5.1	66029	73987.008038
17	5.3	83088	75877.000502
18	5.9	81363	81546.977895
19	6.0	93940	82491.974127
20	6.8	91738	90051.943985
21	7.1	98273	92886.932681
22	7.9	101302	100446.902538
23	8.2	113812	103281.891235
24	8.7	109431	108006.872395
25	9.0	105582	110841.861092
26	9.5	116969	115566.842252
27	9.6	112635	116511.838485
28	10.3	122391	123126.812110
29	10.5	121872	125016.804574

Error = pd.DataFrame ((pred1['Sal']- pred1['Predicted Salary']), columns=['Error'])

final = pd.concat ([pred1, Error], axis=1)

final

In [21]:

Out[20]:

In [22]:

In [23]:

	YExp	Sal	Predicted Salary	Error
0	1.1	39343	36187.158752	3155.841248
1	1.3	46205	38077.151217	8127.848783
2	1.5	37731	39967.143681	-2236.143681
3	2.0	43525	44692.124842	-1167.124842
4	2.2	39891	46582.117306	-6691.117306
5	2.9	56642	53197.090931	3444.909069
6	3.0	60150	54142.087163	6007.912837
7	3.2	54445	56032.079627	-1587.079627
8	3.2	64445	56032.079627	8412.920373
9	3.7	57189	60757.060788	-3568.060788
10	3.9	63218	62647.053252	570.946748
11	4.0	55794	63592.049484	-7798.049484
12	4.0	56957	63592.049484	-6635.049484
13	4.1	57081	64537.045717	-7456.045717
14	4.5	61111	68317.030645	-7206.030645
15	4.9	67938	72097.015574	-4159.015574
16	5.1	66029	73987.008038	-7958.008038
17	5.3	83088	75877.000502	7210.999498
18	5.9	81363	81546.977895	-183.977895
19	6.0	93940	82491.974127	11448.025873
20	6.8	91738	90051.943985	1686.056015
21	7.1	98273	92886.932681	5386.067319
22	7.9	101302	100446.902538	855.097462
23	8.2	113812	103281.891235	10530.108765
24	8.7	109431	108006.872395	1424.127605
25	9.0	105582	110841.861092	-5259.861092
26	9.5	116969	115566.842252	1402.157748
27	9.6	112635	116511.838485	-3876.838485
28	10.3	122391	123126.812110	-735.812110

## Predicting the new data

new\_data= pd.Series([5,7,11,15,20])

pred\_new = pd.DataFrame(new\_data, columns=['YExp'])

125016.804574 -3144.804574

model.predict(pred\_new)

10.5 121872

0 73042.011806

1 91941.936449

2 129741.7857353 167541.635020

4 214791.446628

dtype: float64

In [24]:

Out[23]:

In [25]:

In [26]:

Out[26]:

In [ ]: