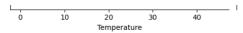
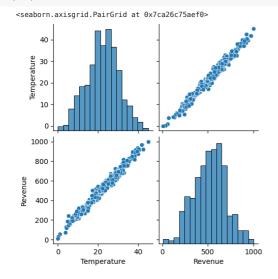
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
IceCream = pd.read_csv(r'/IceCream.csv')
IceCream.head(100)
          Temperature Revenue
              24.566884 534.799028
      1
             26.005191 625.190122
      2
             27.790554 660.632289
       3
             20.595335 487.706960
              11.503498 316.240194
              9.018860 212.591740
      95
      96
              20.265012 474.749392
      97
              19.363153 460.402500
              14.685944 343.362905
      98
              9.954357 283.834327
      99
     100 rows × 2 columns
IceCream.tail()
           Temperature Revenue
                                        22.274899 524.746364
      495
      496
               32.893092 755.818399
      497
               12.588157 306.090719
               22.362402 566.217304
      499
              28.957736 655.660388
IceCream.describe()
             Temperature
                               Revenue
               500.000000 500.000000
      count
      mean
                22.232225 521.570777
       std
                 8.096388 175.404751
       min
                 0.000000 10.000000
       25%
                 17.122258 405.558681
       50%
                22.392791 529.368565
       75%
                27.740674 642.257922
                45.000000 1000.000000
       max
IceCream.info()
     <class 'pandas.core.frame.DataFrame'>
RangeIndex: 500 entries, 0 to 499
Data columns (total 2 columns):
# Column Non-Null Count Dtype
     0 Temperature 500 non-null float64 1 Revenue 500 non-null float64 dtypes: float64(2)
     memory usage: 7.9 KB
sns.jointplot(x='Temperature', y='Revenue', data = IceCream)
     <seaborn.axisgrid.JointGrid at 0x7ca27728bf40>
          1000
          800
          600
          400
          200
```



```
sns.pairplot(IceCream)
```



sns.lmplot(x='Temperature', y='Revenue', data=IceCream)

Temperature

y = IceCream['Revenue']

X = IceCream[['Temperature']]

X

Т	==			
0	24.566884	ıl.		
1	26.005191			
2	27.790554			
3	20.595335			
4	11.503498			
495	22.274899			
496	32.893092			
497	12.588157			
498	22.362402			
499	28.957736			
500 rows × 1 columns				

from sklearn.model_selection import train_test_split

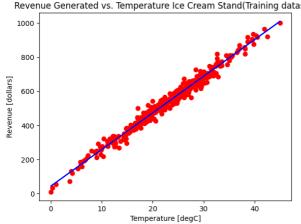
 $X_train, \ X_test, \ y_train, \ y_test = train_test_split(X, \ y, \ test_size=0.25)$

X_train.shape

(375, 1)

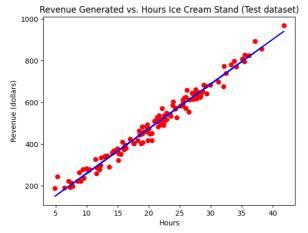
 $from \ sklearn.linear_model \ import \ LinearRegression$

```
08/02/2024, 10:28
                                                                                     28C_AbhaySharma_ADS_exp-5.ipynb - Colaboratory
     regressor = LinearRegression(fit_intercept =True)
     regressor.fit(X_train,y_train)
            ▼ LinearRegression
           LinearRegression()
    print('Linear Model Coefficient (m): ', regressor.coef_)
print('Linear Model Coefficient (b): ', regressor.intercept_)
          Linear Model Coefficient (m): [21.4676156]
Linear Model Coefficient (b): 44.104951851985504
     y_pred = regressor.predict(X_test)
     y test
           20
                   612.153949
           276
                   535.708920
                   450.708589
264.123914
           425
           385
                   278.418265
                   463.480508
           322
           72
                   643.648601
                   682.808566
526.547065
           477
           459
           405
                   242.509855
           Name: Revenue, Length: 125, dtype: float64
     plt.scatter(X_train, y_train, color = 'red')
    plt.plot(X_train, regressor.predict(X_train), color = 'blue')
plt.ylabel('Revenue [dollars]')
plt.xlabel('Temperature [degC]')
     plt.title('Revenue Generated vs. Temperature Ice Cream Stand(Training dataset)')
           {\sf Text}(0.5,\ 1.0,\ {\sf 'Revenue\ Generated\ vs.\ Temperature\ Ice\ Cream\ Stand}({\sf Training\ dataset})\,{\sf '})
              Revenue Generated vs. Temperature Ice Cream Stand(Training dataset)
```



```
#VISUALIZE TEST SET RESULTS
plt.scatter(X_test, y_test, color='red')
plt.plot(X_test, regressor.predict (X_test), color = 'blue')
plt.ylabel('Revenue (dollars)')
plt.xlabel('Hours')
plt.title('Revenue Generated vs. Hours Ice Cream Stand (Test dataset)')
```

Text(0.5, 1.0, 'Revenue Generated vs. Hours Ice Cream Stand (Test dataset)')



```
from sklearn import metrics
 from sklearn.metrics import r2_score
print('R2 score', r2_score(y_test,y_pred))
print('Mean Absolute Error',metrics.mean_absolute_error(y_test,y_pred))
print('Mean Squared Error', metrics.mean_squared_error(y_test,y_pred))
print('Root Mean Squared Error',np.sqrt(metrics.mean_squared_error(y_test,y_pred)))
```

R2 score 0.9778277188752224 Mean Absolute Error 19.909938925872133 Mean Squared Error 641.3951329487671 Root Mean Squared Error 25.325780006719775

Conclusion:

there is a linear relation between temperature and revenue and R2 Score is 97.7%

```
#importing libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
#importing dataset and declaring independent and dependent variable #the dependent variable is in last column, hence y is assigned with [: lumn)
ds = pd.read_csv('/50_Startups.csv')
x = ds.iloc[:,:-1].values
y = ds.iloc[:,-1].values
ds.head()
               R&D Spend Administration Marketing Spend State
                                                                                                                     Profit
                165349.20
                                               136897.80
                                                                                471784.10 New York 192261.83
                 162597.70
                                               151377.59
                                                                                443898.53 California 191792.06
          2 153441.51
                                              101145.55
                                                                               407934.54
                                                                                                    Florida 191050.39
                                             118671.85
                                                                               383199.62 New York 182901.99
          3 144372.41
          4 142107 34
                                               91391.77
                                                                               366168.42 Florida 166187.94
ds.isnull().anv()
         R&D Spend
                                              False
         Administration
Marketing Spend
         State
                                              False
         Profit
         dtype: bool
#categorical data found in column [3]
 #encoding categorical data using OneHotEncoding
 from sklearn.preprocessing import OneHotEncoder
from \ sklearn.compose \ import \ ColumnTransformer
ct = ColumnTransformer(transformers = [('encoding', OneHotEncoder(), [3])], remainder = 'passthrough')
x= np.array(ct.fit_transform(x))
print(x)
         [[0.0 0.0 1.0 165349.2 136897.8 471784.1]

[1.0 0.0 0.0 162597.7 151377.59 443898.53]

[0.0 1.0 0.0 153441.51 101145.55 407934.54]

[0.0 0.0 1.0 144372.41 118671.85 383199.62]

[0.0 1.0 0.0 142107.34 91391.77 366168.42]

[0.0 0.0 1.0 131876.9 99814.71 362861.36]
           [1.0 0.0 0.0 134615.46 147198.87 127716.82]
[0.0 1.0 0.0 130298.13 145530.06 323876.68]
[0.0 0.0 1.0 120542.52 148718.95 311613.29]
            [1.0 0.0 0.0 123334.88 108679.17 304981.62]
[0.0 1.0 0.0 101913.08 110594.11 229160.95]
[1.0 0.0 0.0 100671.96 91790.61 249744.55]
           [0.0 1.0 0.0 93863.75 127320.38 249839.44]
[1.0 0.0 0.0 91992.39 135495.07 252664.93]
[0.0 1.0 0.0 119943.24 156547.42 256512.92]
           [0.0 0.0 1.0 1.0 114943.24 150547.42 250512.92]
[1.0 0.0 0.0 1.0 114523.61 122616.84 261776.23]
[1.0 0.0 0.0 78013.11 121597.55 264346.06]
[0.0 0.0 1.0 94657.16 145977.58 282574.31]
[0.0 1.0 0.0 91749.16 114175.79 294919.57]
[0.0 0.0 1.0 86419.7 153514.11 0.0]
           [1.0 0.0 0.0 76253.86 113867.3 298664.47]
[0.0 0.0 1.0 78389.47 153773.43 299737.29]
[0.0 1.0 0.0 73994.56 122782.75 303319.26]
           [0.0 1.0 0.0 67532.53 105751.03 304768.73]
[0.0 0.0 1.0 77044.01 99281.34 140574.81]
[1.0 0.0 0.0 64664.71 139553.16 137962.62]
           [0.0 1.0 0.0 075328.87 144135.98 134050.07]
[0.0 0.0 1.0 72107.6 127864.55 353183.81]
[0.0 1.0 0.0 66051.52 182645.56 118148.2]
[0.0 0.0 1.0 65605.48 153032.06 107138.38]
[0.0 1.0 0.0 61994.48 115641.28 91131.24]
           [0.0 0.0 1.0 61136.38 152701.92 88218.23]

[1.0 0.0 0.0 63408.86 129219.61 46085.25]

[0.0 1.0 0.0 55493.95 103657.49 214634.81]

[1.0 0.0 0.0 46426.07 157693.92 210797.67]

[0.0 0.0 1.0 46014.02 85047.44 205517.64]

[0.0 1.0 0.0 28663.76 127056.21 201126.82]
            [1.0 0.0 0.0 44069.95 51283.14 197029.42]
[0.0 0.0 1.0 20229.59 65947.93 185265.1]
[1.0 0.0 0.0 38558.51 82982.09 174999.3]
           [1.0 0.0 0.0 0.0 38558.51 52982.09 174999.3]

[1.0 0.0 0.0 28754.3 3118546.05 172795.67]

[0.0 1.0 0.0 27892.92 84710.77 164470.71]

[1.0 0.0 0.1 0.0 15505.73 127382.3 35534.17]

[1.0 0.0 0.1 0.1 01505.73 127382.3 35534.17]

[1.0 0.0 0.0 1.0 1500.23 124153.04 1903.93]

[0.0 1.0 0.0 1315.46 115816.21 297114.46]

[1.0 0.0 0.0 0.0 135426.92 0.0]
            [0.0 0.0 1.0 542.05 51743.15 0.0]
            [1.0 0.0 0.0 0.0 116983.8 45173.06]]
#splitting dataset in training and testing set
from sklearn.model_selection import train_test_split
x_train, x_test, y_train, y_test = train_test_split(x,y, test_size =0.2, random_state=0)
#training the model
from sklearn.linear_model import LinearRegression
lr = LinearRegression()
lr.fit(x_train, y_train)
```

```
v LinearRegression
LinearRegression()
```

```
from sklearn.metrics import r2_score
r2_score(y_test, lr.predict(x_test))
```

0.9347068473282546

Conclusion:

there are multiple independent variable and one dependent variable we have applied multiple linear regression to find the realationship between the independent and dependent variable the R2_score is 93.4% Higher the R2_score better the fit of the model.

```
import numpy as np
import matplotLib.pyplot as plt
import pandas as pd
import seaborn as sns
from sklearn.linear_model import LinearRegression
```

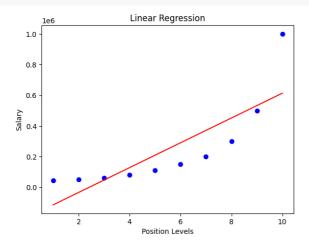
dataset = pd.read_csv(r'/PositionSalaries_Data.csv')
dataset

	Position	Level	Salary	
0	Business Analyst	1	45000	ıl.
1	Junior Consultant	2	50000	
2	Senior Consultant	3	60000	
3	Manager	4	80000	
4	Country Manager	5	110000	
5	Region Manager	6	150000	
6	Partner	7	200000	
7	Senior Partner	8	300000	
8	C-level	9	500000	
9	CEO	10	1000000	

```
X = dataset.iloc[:, 1:-1].values
y = dataset.iloc[:, -1].values
regressor = LinearRegression()
regressor.fit(X, y)
```

v LinearRegression LinearRegression()

```
#Visulaizing the result for Linear Regression model
plt.scatter (X, y, color="blue")
plt.plot(X, regressor.predict (X), color="red")
plt.title("Linear Regression")
plt.xlabel("Position Levels")
plt.ylabel("Salary")
plt.show()
```

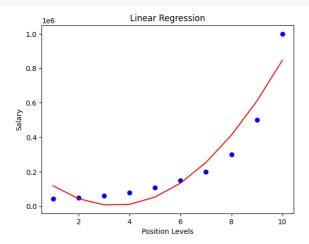


```
from sklearn.preprocessing import PolynomialFeatures
from sklearn.linear_model import LinearRegression
poly_reg = PolynomialFeatures(degree = 2)
X_poly = poly_reg.fit_transform(X)
lin_reg = LinearRegression()
lin_reg.fit(X_poly, y)
```

v LinearRegression LinearRegression()

```
# Visulaizing the result for Linear Regression model
plt.scatter (X, y, color="blue")
plt.plot(X, lin_reg.predict(pply_reg.fit_transform(X)),color="red")
plt.title("Linear Regression")
plt.xlabel("Position Levels")
```

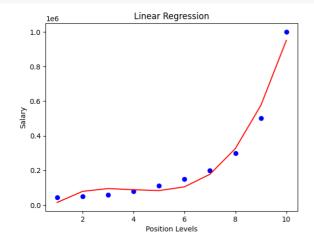
```
plt.ylabel("Salary")
plt.show()
```



```
from sklearn.preprocessing import PolynomialFeatures
from sklearn.linear_model import LinearRegression
poly_regs = PolynomialFeatures (degree = 3)
X_polyn = poly_regs.fit_transform(X)
lin_reg = LinearRegression()
lin_reg.fit (X_polyn, y)
```

v LinearRegression LinearRegression()

```
#Visulaizing the result for Linear Regression model
plt.scatter (X,y,color="blue")
plt.plot(X, lin_reg.predict(poly_regs.fit_transform(X)),color="red")
plt.title("Linear Regression")
plt.xlabel("Position Levels")
plt.ylabel("Salary")
plt.show()
```



```
poly_pred = lin_reg.predict(poly_regs.fit_transform([[6.5]]))
print(poly_pred)
```

[133259.46969697]

Conclusion:

As the degree increases the model train well with the data and fit more accurately