** Difference Between Simple And Multiple Linear Regression

- Simple linear regression has only one x and one y variable.
- Multiple linear regression has one y and two or more x variables.
- For instance, when we predict rent based on square feet alone that is simple linear regression.
- When we predict rent based on square feet and age of the building that is an example of multiple linear regression.

An extension of simple linear regression

In simple linear regression there is a one-to-one relationship between the input variable and the output variable. But in multiple linear regression, as the name implies there is a many-to-one relationship, instead of just using one input variable, you use several.

Multiple Linear Regression

Till now, we have created the model based on only one feature. Now, we'll include multiple features and create a model to see the relationship between those features and the label column. This is called **Multiple Linear Regression**.

y = b0 + b1x1+ b2x2... + bnxn

What do terms represent?

- y is the response or the target variable
- x1,x2,x3...xn are the feature as it is multiple
- b1,b2...bn are the coefficient of x1,x2,..xn respectively
- b0 is the intercept

Each x represents a different feature, and each feature has its own coefficient

Implementation

Step1: Import data

In [1]:

```
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
import seaborn as sns
```

In [2]:

```
dataset = pd.read_csv('data/50_Startups.csv')
```

In [3]:

```
dataset.head()
```

Out[3]:

	R&D Spend	Administration	Marketing Spend	State	Profit
0	165349.20	136897.80	471784.10	New York	192261.83
1	162597.70	151377.59	443898.53	California	191792.06
2	153441.51	101145.55	407934.54	Florida	191050.39
3	144372.41	118671.85	383199.62	New York	182901.99
4	142107.34	91391.77	366168.42	Florida	166187.94

- See here more than one feature so it is multiplt linear regression
- Here Profit is our Target Feature

In [4]:

```
dataset.shape
```

Out[4]:

```
(50, 5)
```

Step2: Visuallize The Data

In [5]:

```
#sns.pairplot(dataset)
```

In [6]:

```
dataset = dataset.drop('State',axis=True)
```

- Here i simply drop the State feature.
- in next some days i will show how to deal with categorical feature.

In [7]:

```
dataset.head()
```

Out[7]:

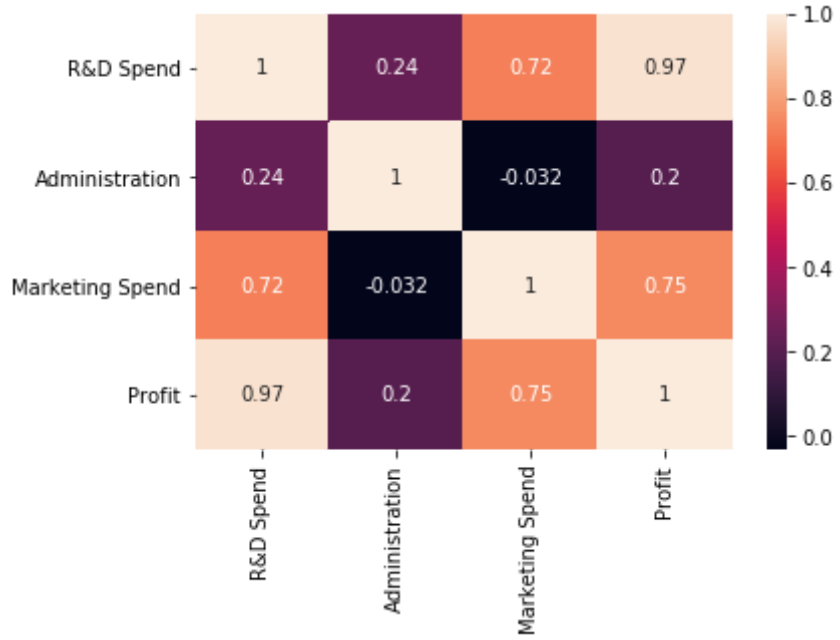
	R&D Spend	Administration	Marketing Spend	Profit
0	165349.20	136897.80	471784.10	192261.83
1	162597.70	151377.59	443898.53	191792.06
2	153441.51	101145.55	407934.54	191050.39
3	144372.41	118671.85	383199.62	182901.99
4	142107.34	91391.77	366168.42	166187.94

In [8]:

```
corr = dataset.corr()
sns.heatmap(corr,annot=True)
```

Out[8]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x2e6d767ad08>
```



Evaluate The Model

Scalling The Data

In [9]:

```
X = dataset.drop('Profit',axis=True)
y = dataset['Profit']
```

In [10]:

```
X.head() #before standardized data
```

Out[10]:

	R&D Spend	Administration	Marketing Spend
0	165349.20	136897.80	471784.10
1	162597.70	151377.59	443898.53
2	153441.51	101145.55	407934.54
3	144372.41	118671.85	383199.62
4	142107.34	91391.77	366168.42

In [11]:

```
from sklearn.preprocessing import StandardScaler
sc = StandardScaler()
X = sc.fit_transform(X)
```

- As here all data are in very big range so we need to take all the data in same range.
- So here i use StandardScaler which take all data in same range
- here it use z score to standardized data
- Z- score formula

$$Z = x-\mu /\sigma$$

- Z = standard score
- x = observed value
- μ = mean of the sample
- σ = standard deviation of the sample
- Some Of the Algorithm Like Tree Base Algorithm not require scalling

In [12]:

```
X #after standardized/scalling data
```

Out[12]:

```
array([[ 2.01641149e+00,  5.60752915e-01,  2.15394309e+00],
       [ 1.95586034e+00,  1.08280658e+00,  1.92360040e+00],
       [ 1.75436374e+00, -7.28257028e-01,  1.62652767e+00],
       [ 1.55478369e+00, -9.63646307e-02,  1.42221024e+00],
       [ 1.50493720e+00, -1.07991935e+00,  1.28152771e+00],
       [ 1.27980001e+00, -7.76239071e-01,  1.25421046e+00],
       [ 1.34006641e+00,  9.32147208e-01, -6.88149930e-01],
       [ 1.24505666e+00,  8.71980011e-01,  9.32185978e-01],
       [ 1.03036886e+00,  9.86952101e-01,  8.30886909e-01],
       [ 1.09181921e+00, -4.56640246e-01,  7.76107440e-01],
       [ 6.20398248e-01, -3.87599089e-01,  1.49807267e-01],
       [ 5.93085418e-01, -1.06553960e+00,  3.19833623e-01],
       [ 4.43259872e-01,  2.15449064e-01,  3.20617441e-01],
       [ 4.02077603e-01,  5.10178953e-01,  3.43956788e-01],
       [ 1.01718075e+00,  1.26919939e+00,  3.75742273e-01],
       [ 8.97913123e-01,  4.58678535e-02,  4.19218702e-01],
       [ 9.44411957e-02,  9.11841968e-03,  4.40446224e-01],
       [ 4.60720127e-01,  8.55666318e-01,  5.91016724e-01],
       [ 3.96724938e-01, -2.58465367e-01,  6.92992062e-01],
       [ 2.79441650e-01,  1.15983657e+00, -1.74312698e+00],
       [ 5.57260867e-02, -2.69587651e-01,  7.23925995e-01],
       [ 1.02723599e-01,  1.16918609e+00,  7.32787791e-01],
       [ 6.00657792e-03,  5.18495648e-02,  7.62375876e-01],
       [-1.36200724e-01, -5.62211268e-01,  7.74348908e-01],
       [ 7.31146008e-02, -7.95469167e-01, -5.81939297e-01],
       [-1.99311688e-01,  6.56489139e-01, -6.03516725e-01],
       [ 3.53702028e-02,  8.21717916e-01, -6.35835495e-01],
       [-3.55189938e-02,  2.35068543e-01,  1.17427116e+00],
       [-1.68792717e-01,  2.21014050e+00, -7.67189437e-01],
       [-1.78608540e-01,  1.14245677e+00, -8.58133663e-01],
       [-2.58074369e-01, -2.05628659e-01, -9.90357166e-01],
       [-2.76958231e-01,  1.13055391e+00, -1.01441945e+00],
       [-2.26948675e-01,  2.83923813e-01, -1.36244978e+00],
       [-4.01128925e-01, -6.59324033e-01,  2.98172434e-02],
       [-6.00682122e-01,  1.31053525e+00, -1.87861793e-03],
       [-6.09749941e-01, -1.30865753e+00, -4.54931587e-02],
       [-9.91570153e-01,  2.05924691e-01, -8.17625734e-02],
       [-6.52532310e-01, -2.52599402e+00, -1.15608256e-01],
       [-1.17717755e+00, -1.99727037e+00, -2.12784866e-01],
       [-7.73820359e-01, -1.38312156e+00, -2.97583276e-01],
       [-9.89577015e-01, -1.00900218e-01, -3.15785883e-01],
       [-1.00853372e+00, -1.32079581e+00, -3.84552407e-01],
       [-1.10210556e+00, -9.06937535e-01, -5.20595959e-01],
       [-1.28113364e+00,  2.17681524e-01, -1.44960468e+00],
       [-1.13430539e+00,  1.20641936e+00, -1.50907418e+00],
       [-1.60035036e+00,  1.01253936e-01, -1.72739998e+00],
       [-1.59341322e+00, -1.99321741e-01,  7.11122474e-01],
       [-1.62236202e+00,  5.07721876e-01, -1.74312698e+00],
       [-1.61043334e+00, -2.50940884e+00, -1.74312698e+00],
       [-1.62236202e+00, -1.57225506e-01, -1.36998473e+00]])
```

In [13]:

```
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)
```

In [14]:

```
X_train.shape,X_test.shape,y_train.shape,y_test.shape
```

Out[14]:

```
((40, 3), (10, 3), (40,), (10,))
```

Build Model

In [15]:

```
from sklearn.linear_model import LinearRegression
regressor = LinearRegression()
regressor.fit(X_train, y_train)
```

Out[15]:

```
LinearRegression()
```

In [16]:

```
y_pred = regressor.predict(X_test).round(1)
```

In [17]:

```
calculation = pd.DataFrame(np.c_[y_test,y_pred], columns = ["Original Salary","Predict
 Salary"])
calculation.head(5)
```

Out[17]:

	Original Salary	Predict Salary
0	103282.38	103901.9
1	144259.40	132763.1
2	146121.95	133567.9
3	77798.83	72911.8
4	191050.39	179627.9

In [18]:

```
print("Training Accuracy :", regressor.score(X_train, y_train))
print("Testing Accuracy :", regressor.score(X_test, y_test))
```

```
Training Accuracy : 0.9499572530324031
Testing Accuracy : 0.9393955917820571
```

In [19]:

```
regressor.intercept_
```

Out[19]:

```
111297.71256204927
```

In [20]:

```
regressor.coef_
```

Out[20]:

```
array([35391.2501208 ,   815.21987542,  4202.06618916])
```

Test The Model

In [21]:

```
feature = [165349.20,136897.80,471784.10]
scale_feature = sc.transform([feature])
scale_feature
```

Out[21]:

```
array([[2.01641149, 0.56075291, 2.15394309]])
```

In [22]:

```
y_pred_test = regressor.predict(scale_feature)
y_pred_test  #By Using Sklearn Library
```

Out[22]:

```
array([192169.18440985])
```

In [23]:

```
# Here I use b1x1+b2x2+b3x3+b0 BY MANUAL
35391.2501208*2.01641149+815.21987542*0.56075291+4202.06618916*2.15394309+ 111297.71256
204927
```

Out[23]:

```
192169.1843003897
```

- Now above you see manual and automatic prediction on the same data in this way linear regression predict the data