Simple Linear Regression

Import libraries and load dataset

In [1]:
```
import pandas as pd
import numpy as np

import matplotlib.pyplot as plt
import seaborn as sns
```

In [2]:
```
df = pd.read_csv('Salary_Data.csv')

df.head()
```

Out[2]:

	YearsExperience	Salary
0	1.1	39343.0
1	1.3	46205.0
2	1.5	37731.0
3	2.0	43525.0
4	2.2	39891.0

In [3]:
```
df.isnull().sum()
```

Out[3]:
```
YearsExperience    0
Salary             0
dtype: int64
```

observations :

```
* There are no missing values.
```

Separating independent and dependent data

In [4]:
```
# independent features
x = df.drop(columns = ['Salary'], axis = 1)

# dependent features
y = df['Salary']
```

Train Test Split

In [5]:
```
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 = 42)
```

Model Training

In [6]:
```
from sklearn.linear_model import LinearRegression

regressor = LinearRegression()
regressor.fit(x_train, y_train)
```

Out[6]:
```
LinearRegression()
```

Prediction

In [7]:
```
y_pred = regressor.predict(x_test)

y_pred
```

Out[7]:
```
array([115573.62288352,  71679.93878159, 102498.90847018,  75415.57147111,
        55803.4998511 ,  60473.04071301, 122110.98009019, 107168.44933209,
        63274.76523015])
```

Evaluation

In [8]:
```
from sklearn.metrics import r2_score

score = r2_score(y_test, y_pred)
print(score)
```

```
0.9414466227178214
```

1. Visualising training result

In [9]:
```
plt.scatter(x_train, y_train)
plt.plot(x_train, regressor.predict(x_train), color = 'orange')

plt.title('Salary vs Experience (Training set)')
plt.xlabel('Years of Experience')
plt.ylabel('Salary')
plt.show()
```

Assumption 1:

In [10]:
```
plt.scatter(x_test, y_test)
plt.plot(x_test, regressor.predict(x_test), color = 'orange')

plt.title('Salary vs Experience (Test set)')
plt.xlabel('Years of Experience')
plt.ylabel('Salary')
plt.show()
```

Simple Linear Regression

Import library and load dataset

In [1]:
```python
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
```

In [2]:
```python
df = pd.read_csv('height-weight.csv')

df.head()
```

Out[2]:

	Weight	Height
0	45	120
1	58	135
2	48	123
3	60	145
4	70	160

In [3]:
```python
df.shape
```

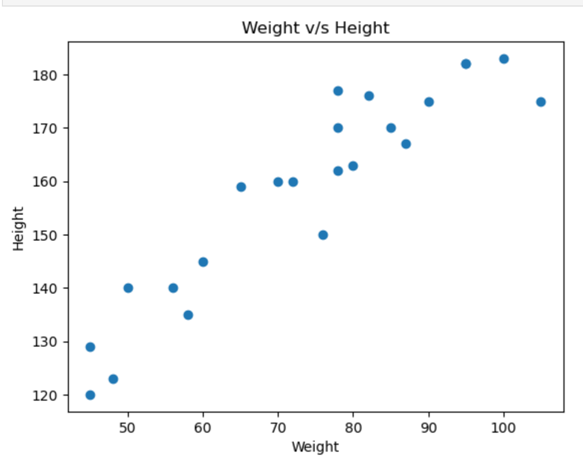
Out[3]:
```
(23, 2)
```

In [4]:
```python
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 23 entries, 0 to 22
Data columns (total 2 columns):
 #   Column  Non-Null Count  Dtype
---  ------  --------------  -----
 0   Weight  23 non-null     int64
 1   Height  23 non-null     int64
dtypes: int64(2)
memory usage: 496.0 bytes
```

Visual represetation of data

In [5]:
```python
plt.scatter(x = df['Weight'],y = df['Height'])
plt.title('Weight v/s Height')
plt.xlabel('Weight')
plt.ylabel('Height')

plt.show()
```



Aim :

- To Create a best fit line which has least error.

In machine learning before training model we need to perform some steps :

1. Divide the features based on independent and dependent features.
2. Train, Test split of dataset.
3. Standardize the data.
4. Train the model using LinearRegression
5. Test model.
6. Performance metrics.
7. Assumptions.

---

1. Divide the features based on independent and dependent features.

In [6]:
```python
# x is independent feature
x = df[['Weight']]

# y is dependent feature
y = df['Height']
```

In [7]:
```python
print(x)
print()
print(y)
```

```
    Weight
0       45
1       58
2       48
3       60
4       70
5       78
6       80
7       90
8       95
9       78
10      82
11      95
12     105
13     100
14      85
15      78
16      50
17      65
18      76
19      87
20      45
21      56
22      72

0     120
1     135
2     123
3     145
4     160
5     162
6     163
7     175
8     182
9     170
10    176
11    182
12    175
13    183
14    170
15    177
16    140
17    159
18    150
19    167
20    129
21    140
22    160
Name: Height, dtype: int64
```

---

2. Train Test split

In [8]:
```python
from sklearn.model_selection import train_test_split
```

In [9]:
```python
x_train , x_test , y_train , y_test = train_test_split(x,y,test_size=0.2,random_state=42)
```

In [10]:
```python
print('Length of Dataset :',len(df['Weight']))

print('Length of train data :',len(x_train))
# test data size is 20% of actual data size.
print('Length of test data :',len(x_test))
```

```
Length of Dataset : 23
Length of train data : 18
Length of test data : 5
```

---

3. Standardize the train independent data.

Because weight vary in different scale i.e 50-100. Therefore, we need to scale down the data so that our gradient descent optimization will happen quickly.

In [11]:
```python
from sklearn.preprocessing import StandardScaler
```

In [12]:
```python
scaler = StandardScaler()
```

We need to optimize our training data also based on the observation got in the test data.

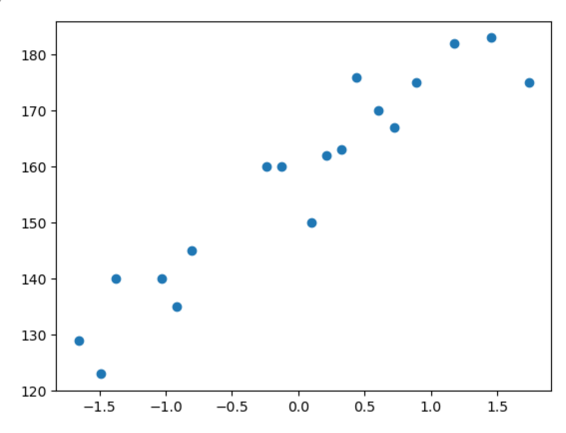
In [13]:
```python
# it will apply the z-score for every point in the dataset
# we need mean and std to apply z-score that will be calculated by fit
# transform applies the z-score

x_train = scaler.fit_transform(x_train)

# no need to calculate the mean and std as it is already calculated above so fit is not required
# here, in x_test it will take the mean and std of train dataset and apply the z-score for test data
x_test = scaler.transform(x_test)
```

We do only transform on test dataset because of data leakage

We do this because our model should not know anything about our test data but it should have only information about the train data such as mean and std

In [14]:
```python
plt.scatter(x_train,y_train)
```

Out[14]:
```
<matplotlib.collections.PathCollection at 0x1a805531e50>
```



Observation :

- Here, our weight feature is scale down between -1.5 to +1.5

---

4. Train the simple linear regression model.

In [15]:
```python
from sklearn.linear_model import LinearRegression
```

In [16]:
```python
regressor = LinearRegression()
```

fit will find intercept and slope value

In [17]:
```python
regressor.fit(x_train,y_train)
```

Out[17]:
```
LinearRegression()
```

In [18]:
```python
print('The slope or coefficient of weight is',regressor.coef_)
# it will give the slope of the features
# Here, we have one feature so only 1 slope
```

```
The slope or coefficient of weight is [17.03440872]
```

In [19]:
```python
print('The intercept of weight is',regressor.intercept_)
```

```
The intercept of weight is 157.5
```

Observation :

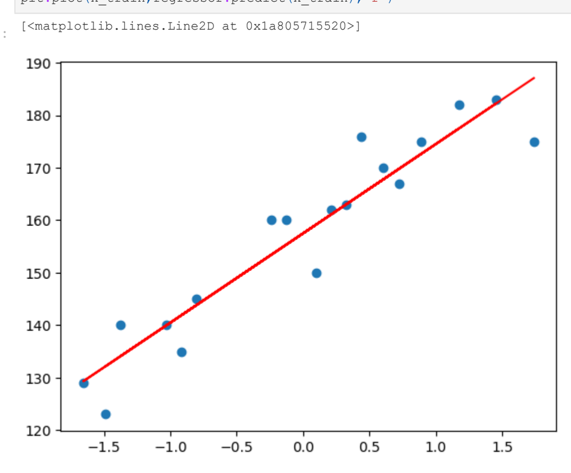
- θ_0 = 157.5 (Intercept)
- θ_1 = 17.03440872 (Coefficient or slope)

Line equation : $h_\theta(x) = \theta_0 + \theta_1 x$

Now, we will create the best fit line

In [20]:
```python
plt.scatter(x_train,y_train)
plt.plot(x_train,regressor.predict(x_train),'r')
```

Out[20]:
```
[<matplotlib.lines.Line2D at 0x1a805715520>]
```



---

prediction of train data

1. predicted height output = intercept + coef_(Weights)
2. y_pred_train = 157.5 + 17.03(X_train)

prediction of test data

1. predicted height output = intercept + coef_(Weights)
2. y_pred_test = 157.5 + 17.03(X_test)

---

5. Test model with test data.

In [21]:
```python
y_pred = regressor.predict(x_test)
```

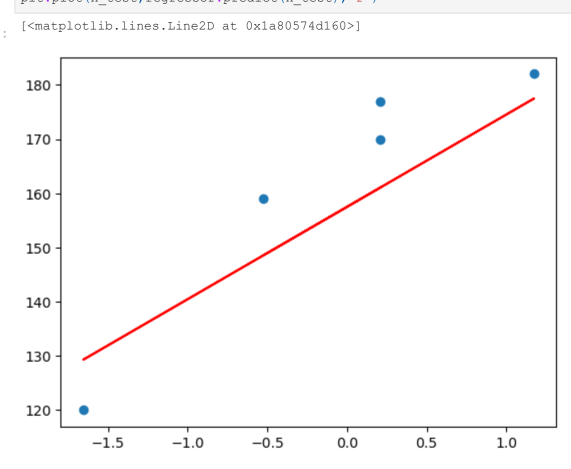
In [22]:
```python
y_pred , y_test
```

Out[22]:
```
(array([161.08467086, 161.08467086, 129.3041561 , 177.45645118,
        148.56507414]),
 15    177
 9     170
 0     120
 8     182
 17    159
 Name: Height, dtype: int64)
```

We can compare and calculate the accuracy

In [23]:
```python
# for actual point
plt.scatter(x_test,y_test)

# best fit line is calculated
plt.plot(x_test,regressor.predict(x_test),'r')
```

Out[23]:
```
[<matplotlib.lines.Line2D at 0x1a80574d160>]
```



---

6. Performance metrics.

- MSE, MAE and RMSE.
- R^2 and Adjusted R^2

In [24]:
```python
from sklearn.metrics import mean_squared_error,mean_absolute_error
```

In [25]:
```python
mse = mean_squared_error(y_test,y_pred)
mae = mean_absolute_error(y_test,y_pred)
rmse = np.sqrt(mse)
```

Less the error then better the will be model.

In [26]:
```python
print(mse)
print(mae)
print(rmse)
```

```
109.77592599051654
9.822657814519227
10.477400726827076
```

How good our model is ?..

$$R_{squared} = 1 - \frac{\sum(y_i - \hat{y_i})^2}{\sum(y_i - \bar{y_i})^2}$$

$$Adjusted_{R_{squared}} = 1 - \frac{(1 - R^2) \times (N - 1)}{N - p - 1}$$

In [27]:
```python
from sklearn.metrics import r2_score
```

In [28]:
```python
r_square = r2_score(y_test,y_pred)
```

In [29]:
```python
print('Our model is',round((r_square*100),2),'% accurate calculated using r square.')
```

```
Our model is 77.7 % accurate calculated using r square.
```

In [30]:
```python
n = len(y_test)
p = x_test.shape[1]

adjusted_r_square = 1 - ((1-r_square)*(n-1)/(n-p-1))
```

In [31]:
```python
print('Our model is',round((adjusted_r_square*100),2),'% accurate calculated using adjusted r square.')
```

```
Our model is 70.26 % accurate calculated using adjusted r square.
```

Always : $R_{squared} > Adjusted_{R_{squared}}$

For any new weight

1. Scale the weight.
2. predict the height.
3. Render the resuls.

In [32]:
```python
weight = 80
scaled_weight = scaler.transform([[weight]])
scaled_weight
```

```
D:\Anconda\lib\site-packages\sklearn\base.py:450: UserWarning: X does not have valid feature names, but StandardScaler was fitted with feature names
  warnings.warn(
```

Out[32]:
```
array([[0.32350772]])
```

In [33]:
```python
height_pred = regressor.predict(scaled_weight)
height_pred
```

Out[33]:
```
array([163.01076266])
```

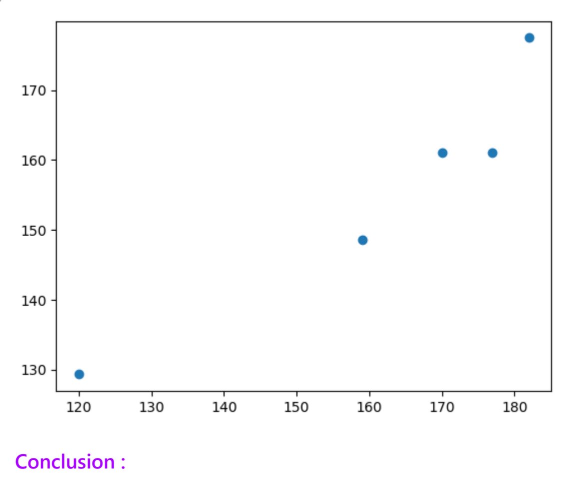
In [34]:
```python
print(f'Height predicted for weight {weight} kg is {round(height_pred[0],2)} cm')
```

```
Height predicted for weight 80 kg is 163.01 cm
```

Assumptions

In [35]:
```python
# Assumption 1
# plot scatter plot for the actual value and predicted value
plt.scatter(y_test,y_pred)
```

Out[35]:
```
<matplotlib.collections.PathCollection at 0x1a8057c6dc0>
```



Conclusion :

- If plot looks linear then our prediction is done well.

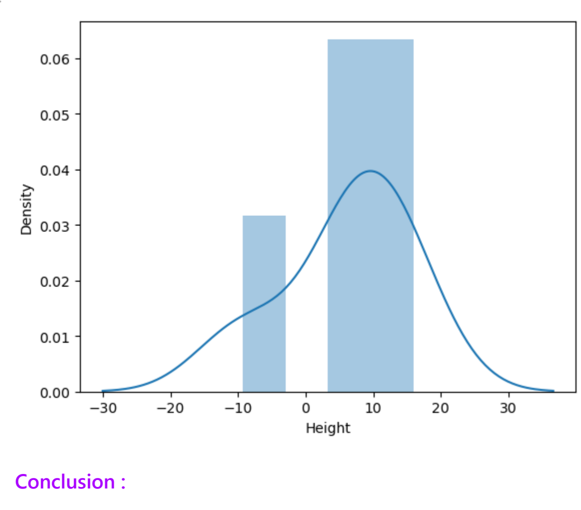
In [36]:
```python
# Assumption 2
# Residuals

residuals = y_test - y_pred
residuals
```

Out[36]:
```
15    15.915329
9      8.915329
0     -9.304156
8      4.543549
17    10.434926
Name: Height, dtype: float64
```

In [37]:
```python
# plot the residuals

import seaborn as sns
sns.distplot(residuals , kde = True)
```

```
D:\Anconda\lib\site-packages\seaborn\distributions.py:2619: FutureWarning: `distplot` is a deprecated function and will be removed in a future version. Please adapt your code to use either `displot` (a figure-level function with similar flexibility) or `histplot` (an axes-level function for histograms).
  warnings.warn(msg, FutureWarning)
```

Out[37]:
```
<AxesSubplot:xlabel='Height', ylabel='Density'>
```

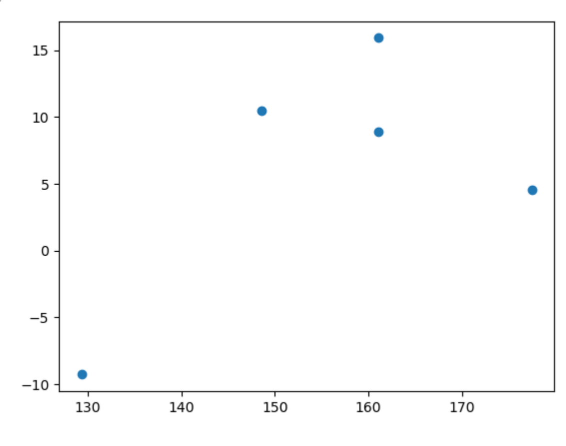


Conclusion :

- If normal distribution then better model is created.

In [38]:
```python
# scatter plot with respect to prediction and residuals

plt.scatter(y_pred,residuals)
```

Out[38]:
```
<matplotlib.collections.PathCollection at 0x1a805f7bc70>
```



Conclusion :

- If uniform distribution then better model is created.

Pickling the model - model is converted into file and used to predict output for any new data.
