```
In [1]: # Import the libraries
         import pandas as pd
         import numpy as np
         import matplotlib.pyplot as plt
         import seaborn as sns
         import warnings
         warnings.filterwarnings('ignore')
         /opt/conda/lib/python3.10/site-packages/scipy/ init .py:146: UserWarning: A NumPy v
         ersion >=1.16.5 and <1.23.0 is required for this version of SciPy (detected version
         1.23.5
          warnings.warn(f"A NumPy version >={np_minversion} and <{np_maxversion}"</pre>
In [2]: # Load the data set using the read function
         salary=pd.read_csv('/kaggle/input/salary-dataset-simple-linear-regression/Salary_datas
         salary.head()
Out[2]:
           Unnamed: 0 YearsExperience
                                       Salary
         0
                    0
                                  1.2 39344.0
         1
                    1
                                  1.4 46206.0
         2
                    2
                                  1.6 37732.0
         3
                    3
                                  2.1 43526.0
         4
                    4
                                  2.3 39892.0
In [3]: # Checking the null values
         salary.isna().sum()
        Unnamed: 0
Out[3]:
        YearsExperience
                            0
                            0
         Salary
        dtype: int64
In [4]: # Let's drop the unwanted columns
         salary=salary.drop('Unnamed: 0',axis=1)
         salary.head()
Out[4]:
           YearsExperience
                           Salary
         0
                      1.2 39344.0
         1
                      1.4 46206.0
         2
                      1.6 37732.0
         3
                      2.1 43526.0
         4
                      2.3 39892.0
         salary.columns
In [5]:
        Index(['YearsExperience', 'Salary'], dtype='object')
Out[5]:
```

Linear Regression Model

Absolutely, let's discuss the linear regression model in the context of predicting salary based on years of experience.

In this scenario:

- (y) represents the salary (dependent variable).
- (m) is the slope of the line, which signifies how much the salary changes with a unit change in years of experience.
- (c) is the y-axis intercept of the regression line, indicating the starting salary when years of experience ((x)) is 0.
- (x) corresponds to years of experience (independent variable).

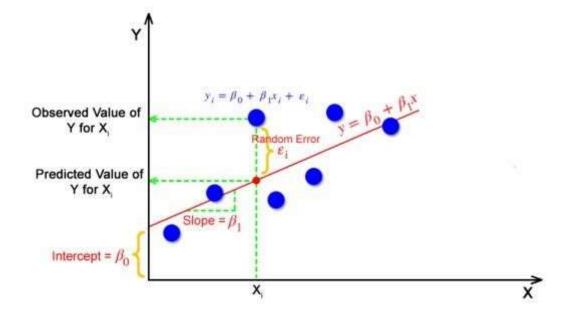
The formula for the linear regression model in this context is: [y = mx + c]

So, if we have a specific value for years of experience (let's say (x = 5.5)), we can plug it into the formula to predict the corresponding salary ((y)).

For example, if (x = 5.5): [$y = m \times 5.5 + c$]

Please note that (m) and (c) would be determined by fitting the linear regression model to the actual data. Once the model is trained, it can be used to make predictions like the one above.

If you have a dataset with actual years of experience and corresponding salaries, you can use libraries like scikit-learn to train a linear regression model and then use the model to make predictions for new values of years of experience.

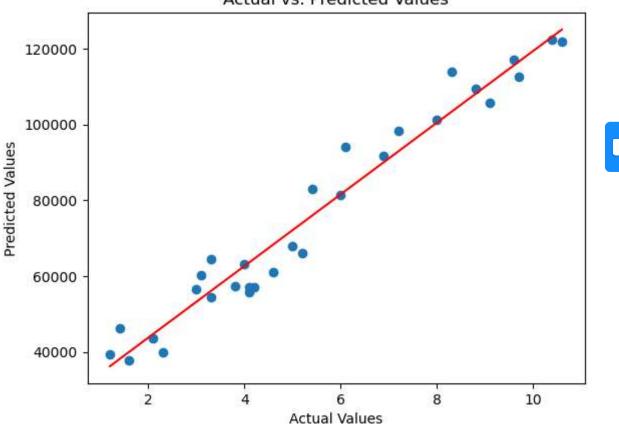




```
# Split the data into dependent and independent variable
 In [6]:
         X=salary['YearsExperience']
         y=salary['Salary']
 In [7]: from sklearn.linear_model import LinearRegression
         from sklearn.metrics import r2_score,mean_squared_error
 In [8]: # Let's install the Linearregression model
         linear model=LinearRegression()
         # fit the model with linear model
         linear_model.fit(X.array.reshape(-1,1),y)
Out[8]: ▼ LinearRegression
         LinearRegression()
 In [9]: # Predict the values with test data
         y pred=linear model.predict(X.array.reshape(-1,1))
         y_pred
         array([ 36188.15875227, 38078.15121656, 39968.14368085, 44693.12484158,
 Out[9]:
                 46583.11730587, 53198.09093089, 54143.08716303, 56033.07962732,
                 56033.07962732, 60758.06078805, 62648.05325234,
                                                                    63593.04948449,
                 63593.04948449, 64538.04571663, 68318.03064522,
                                                                    72098.0155738 ,
                 73988.00803809, 75878.00050238, 81547.97789525, 82492.9741274,
                 90052.94398456, 92887.932681 , 100447.90253816, 103282.8912346 ,
                108007.87239533, 110842.86109176, 115567.84225249, 116512.83848464,
                123127.81210966, 125017.80457395])
         # Checking the coefiencnt
In [10]:
         coeff=linear model.coef [0]
         coeff
         9449.962321455077
Out[10]:
In [11]: # intercept of the model
         intercept=linear model.intercept
         intercept
         24848.203966523193
Out[11]:
In [12]: # Checking the model score
         print('Mean squared error',format(mean squared error(y,y pred)))
         print('R2_score ',format(r2_score(y,y_pred)))
         Mean squared error 31270951.722280953
         R2_score 0.9569566641435086
In [13]: # Let's Create a scatter plot for the actual and preidict values
         plt.scatter(X, y, label='Original Data')
         plt.plot(X, y_pred, color='red', label='Regression Line')
         plt.xlabel('Actual Values')
         plt.ylabel('Predicted Values')
         plt.title('Actual vs. Predicted Values')
         plt.show()
```

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Actual vs. Predicted Values



```
In [14]: # How to calculate the linearregression model
    # formula=y=m*x+c
    #intercept values
    m=9449.962321455077
#year of expreice
    x=5.5
# slop of the values
    c=24848.203
    predicted_values=m*x+c
    predicted_values
```

Out[14]: 76822.99576800293