Day 39 – Simple Linear Regression (SLR)

Today we are learning our **first machine learning algorithm – Simple Linear Regression (SLR)**.

This is a type of **supervised learning algorithm**, and it belongs to the **regression category** of ML tasks.

In machine learning, there are mainly three types of problems:

1. **Regression** – when we predict continuous values (like salary, house price)
2. **Classification** – when we predict categories (like spam or not spam)
3. **Clustering** – when we group data based on similarity without labeled output

Since **SLR predicts continuous values**, it is a **regression algorithm**.

Note -

- We will use **Spyder** to build and run our machine learning model, as it provides a powerful IDE for writing and testing Python scripts efficiently.
- For **documentation, explanations, and visual presentation**, we use **Jupyter Notebook** to keep everything well-organized and easy to understand.

In this notebook, we will:

- Understand the theory behind Simple Linear Regression
- Learn the formula `Y = mX + c` and how each part works
- Train a regression model using `scikit-learn` in Python
- Visualize the model and make predictions for new data points

Introduction to Regression

Regression is a statistical method used to model the relationship between a dependent (target) variable and one or more independent (input) variables.

Purpose:

- Predict future outcomes based on past data.
- Understand how changes in the input affect the output.

What is Simple Linear Regression?

Simple Linear Regression is a regression technique with:

- One independent variable (X)
- One dependent variable (Y)
- A linear (straight-line) relationship between them

Formula:

$$Y = mX + c$$

Where:

- Y: Predicted value (e.g., Salary)
- X: Input variable (e.g., Years of Experience)
- m: Slope (change in Y for each unit of X)
- c: Intercept (value of Y when X = 0)

Understanding the Variables:

- **X**: Independent variable (e.g., years of experience). This is the input feature.
- **Y**: Dependent variable (e.g., salary). This is the output we are trying to predict.
- $\hat{Y}$ **(Y hat)**: Predicted value of Y using our regression equation.

How to Calculate Slope (m) and Intercept (c)

To calculate the regression line manually:

Step 1: Find the mean of X ($\bar{X}$) and mean of Y ($\bar{Y}$)

Step 2: Use the formulas:

- **Slope (m):**

$$m = \frac{\sum (X - \bar{X})(Y - \bar{Y})}{\sum (X - \bar{X})^2}$$

- **Intercept (c):**

$$c = \bar{Y} - m \cdot \bar{X}$$

Simple Example:

Let's say:

- X =

$$1, 2, 3, 4, 5$$

- Y =

$$2, 4, 5, 4, 5$$

Then:

- $\bar{X} = 3, \bar{Y} = 4$
- Numerator = (X - $\bar{X}$) * (Y - $\bar{Y}$) =

$$4, 0, 0, 0, 2$$

  → Sum = 6
- Denominator = (X - $\bar{X}$)^2 =

$$4, 1, 0, 1, 4$$

  → Sum = 10

So:

- m = 6 / 10 = 0.6
- c = 4 - (0.6 * 3) = 2.2

The final equation becomes:

$$Y = 0.6X + 2.2$$

This line can now be used to predict future Y values based on X.

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

1. Load dataset

In [2]:
```
# Load dataset
df = pd.read_csv(r'C:\Users\Lenovo\Downloads\Salary_Data.csv')

# Check columns
print(df.columns)
```

```
Index(['YearsExperience', 'Salary'], dtype='object')
```

In [4]:
```
df.head()
```

Out[4]:

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

2. Separate features and target

In [5]:
```
# Separate features and target
x = df.iloc[:, :-1]  # Input variable (Years of Experience)
y = df.iloc[:, -1]   # Target variable (Salary)
```

In [8]:
```
# Check for missing values
print(df.isnull().sum())
```

```
YearsExperience    0
Salary             0
dtype: int64
```

3. Split into training and testing sets

In [9]:
```
from sklearn.model_selection import train_test_split
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=0.20, random_st
```

In [13]:
```
df.shape
```

Out[13]: (30, 2)

In [10]:
```
# Number of rows (samples) in training set
print("Number of training samples (x_train):", len(x_train))
print("Number of training labels (y_train):", len(y_train))
```

```
Number of training samples (x_train): 24
Number of training labels (y_train): 24
```

In [11]:
```
# Number of rows (samples) in testing set
print("Number of test samples (x_test):", len(x_test))
print("Number of test labels (y_test):", len(y_test))
```

```
Number of test samples (x_test): 6
Number of test labels (y_test): 6
```

4. Import and train the model

In [14]:
```
from sklearn.linear_model import LinearRegression
# We create the linear regression model
regressor = LinearRegression()
# We fit the model using the training data
regressor.fit(x_train, y_train)
```

Out[14]:
```
▾ LinearRegression
LinearRegression()
```

5. Predict test set

In [17]:
```
# Using the trained model to make predictions on test data
y_pred = regressor.predict(x_test)
print(y_pred)
```

```
[ 40748.96184072 122699.62295594  64961.65717022  63099.14214487
 115249.56285456 107799.50275317]
```

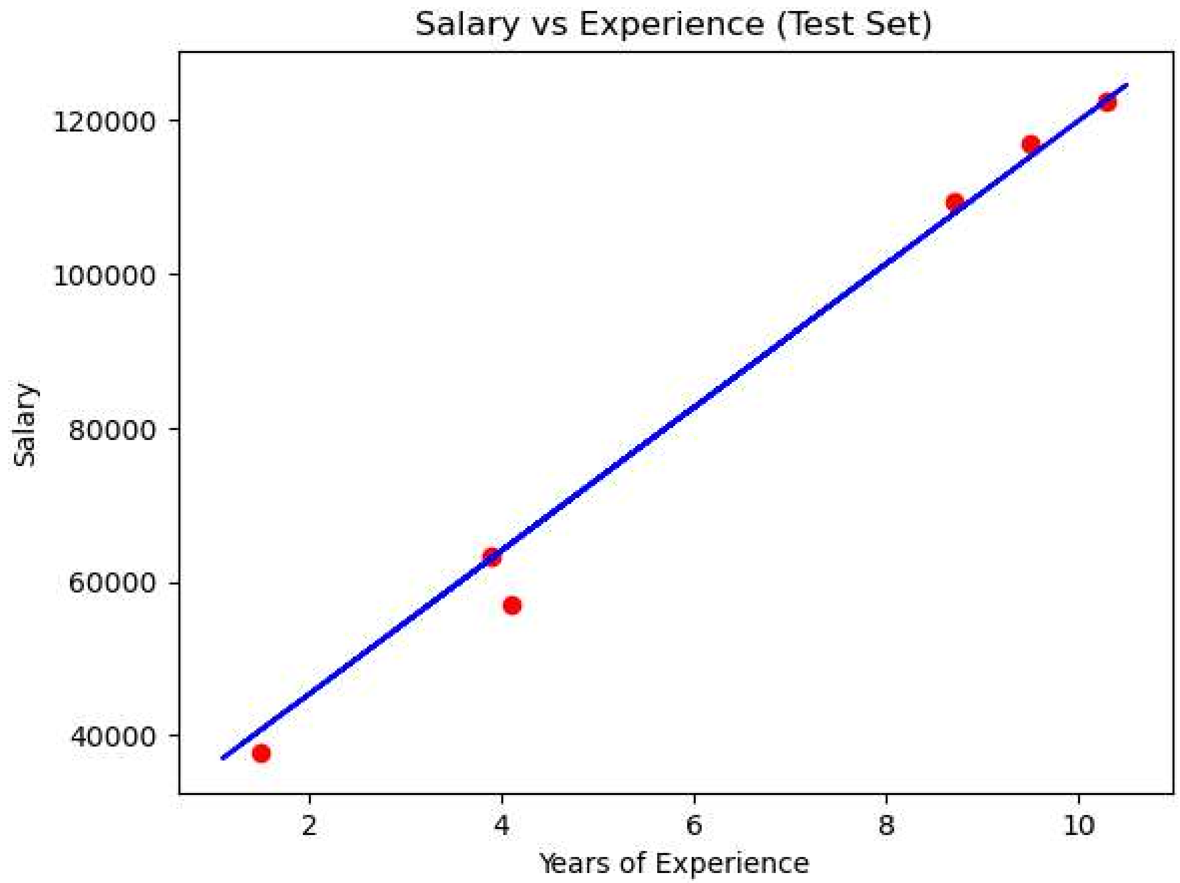
6. Compare actual vs predicted

In [18]:
```
# Creating a DataFrame to compare actual and predicted salaries
comparison = pd.DataFrame({'Actual': y_test, 'Predict': y_pred})
print(comparison)
```

```
    Actual        Predict
2    37731   40748.961841
28  122391  122699.622956
13   57081   64961.657170
10   63218   63099.142145
26  116969  115249.562855
24  109431  107799.502753
```

7. Visualize the results

In [19]:
```
# Red points are actual test data, blue line is the regression prediction
plt.scatter(x_test, y_test, color='red')
plt.plot(x_train, regressor.predict(x_train), color='blue')
plt.title("Salary vs Experience (Test Set)")
plt.xlabel("Years of Experience")
plt.ylabel("Salary")
plt.show()
```



8. Calculate Slope (m) and Intercept (c)

In [20]:
```
# Get the slope (m) of the regression line
m_slope = regressor.coef_
print("Slope:", m_slope)
```

```
Slope: [9312.57512673]
```

In [21]:
```
# Get the intercept (c) of the regression line
c_intercept = regressor.intercept_
print("Intercept:", c_intercept)
```

```
Intercept: 26780.099150628186
```

9. Predict salary on unseen data

Let's Predict for 12 and 20 years of experience

In [23]:
```
# Using the formula: Y = mX + c
y_12 = (m_slope * 12) + c_intercept
print("Predicted Salary for 12 Years of Experience:", y_12)
```

```
Predicted Salary for 12 Years of Experience: [138531.00067138]
```

In [24]:
```
# Predict for 20 years
y_20 = (m_slope * 20) + c_intercept
print("Predicted Salary for 20 Years of Experience:", y_20)
```

```
Predicted Salary for 20 Years of Experience: [213031.60168521]
```

10. Summary – What We Did Today

- We learned what regression is and where Simple Linear Regression fits in the ML world.
- We studied the formula `Y = mX + c` and understood the roles of slope (m), intercept (c), input (X), and prediction (Y).
- We explored how to calculate slope and intercept manually with a simple example.
- Then we used Python and `scikit-learn` to:
  - Load a dataset
  - Train a linear regression model
  - Make predictions on test data
  - Visualize actual vs predicted values
  - Predict salaries for 12 and 20 years of experience

This was our first hands-on ML project using real data. With this foundation, we are now ready to explore more complex models and datasets.

Note -

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