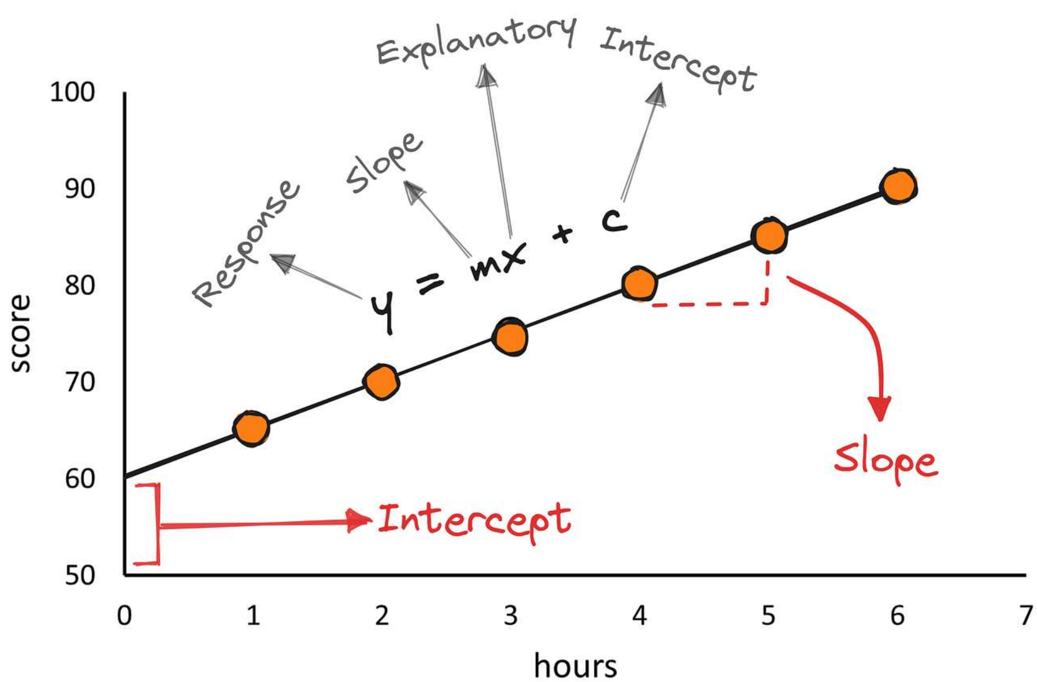
Linear Regression

It is a statistical model which estimates the **linear relationship** between a **target** (scalar response) and one or more **input variables**.

Types of Linear Regression:

1. **Simple Linear Regression** involves one independent variable.
2. While **Multiple Linear Regression** involves more than one.
3. **Polynomial Regression** extends linear regression by considering polynomial relationships between variables by capturing non-linear patterns in the data.

Simple Linear Regression:



In Simple Linear Regression, we have two variables:

-- **Independent Variable/ Predictor / Input Variable (X)**:

This variable is used to predict the value of the dependent variable.

-- **Dependent Variable/ Response / Output variable (Y)**:

This is the variable we want to predict.

The relationship between X and Y is modeled as a straight line:

```
Y=mX+b
```

where:

- Y is the dependent variable (what we want to predict),
- X is the independent variable,
- m is the slope of the line (how much
- Y changes with each unit change in (X),
- b is the y-intercept (the value of Y when X is 0).

Creating Dataset

Creating a Dataset with One Input and One Target Column using sklearn's `make_regression` class for applying **Simple Linear Regression** Class.

In [36]:
```
from sklearn.datasets import make_regression
```

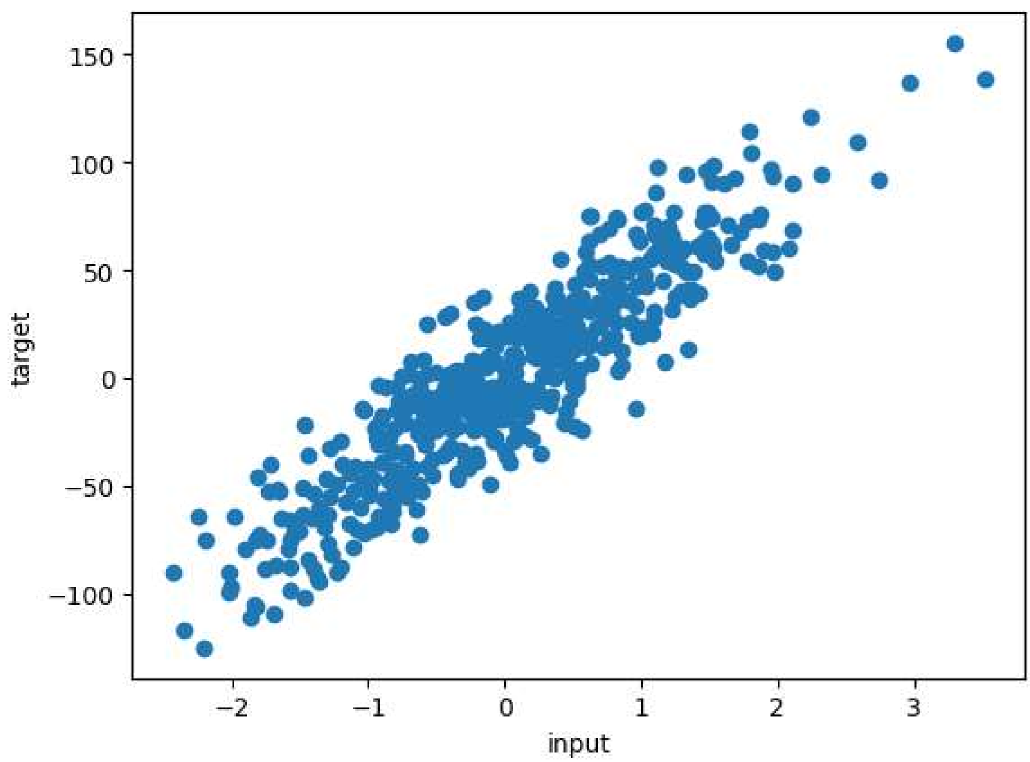
In [62]:
```
input_,target_ = make_regression(n_samples=500, n_features=1, n_informative=3, n_targets=
```

Plotting the dataset

In [28]:
```
import matplotlib.pyplot as plt
```

In [63]:
```
plt.scatter(input_,target_)
plt.xlabel('input')
plt.ylabel('target')
```

Out[63]: `Text(0, 0.5, 'target')`



Splitting data into train and test datasets

In [11]:
```
from sklearn.model_selection import train_test_split
```

In [64]:
```
train_input, test_input, train_target, test_target = train_test_split(input_, target_, te
```

In [65]:
```
train_input.shape
```

Out[65]: (400, 1)

In [66]:
```
test_input.shape
```

Out[66]: (100, 1)

In [67]:
```
train_target.shape
```

Out[67]: (400,)

Building our own **Simple Linear Regression** Class.

In [91]:
```
class SimpleLinearRegression:

    # Creating an initializor
    def __init__(self):
        self.m = None
        self.b = None


    # Creating 'fit' Function
    def fit(self, train_input, test_input):

        # Calculating slope of the line (m):
        numerator = 0
        denominator = 0

        for i in range(train_input.shape[0]):

            numerator = numerator + ((train_input[i] - train_input.mean()) * (train_targe
            denominator = denominator + ((train_input[i] - train_input.mean()) * (train_i

        self.m = numerator/denominator

        # Calculating coefficent of the line(b):
        self.b = train_target.mean() - (self.m * train_input.mean())

    @property
    def coefficients(self):
        if self.m is not None:
            return self.m
        else:
            print("Model not fitted yet.")
            return None

    @property
    def intercept(self):
        if self.b is not None:
            return self.b
        else:
            print("Model not fitted yet.")
            return None
```

```python
    # Creating 'predict' Function
    def predict(self, test_input):
        return self.m * test_input + self.b
```

In [70]:
```python
train_input.shape[0]
```

Out[70]: 400

In [92]:
```python
slr = SimpleLinearRegression()
```

In [93]:
```python
slr.fit(train_input, train_target)
```

In [112…
```python
slr_pred = slr.predict(test_input)
```

In [95]:
```python
slr.coefficients
```

Out[95]: array([43.44732032])

In [96]:
```python
slr.intercept
```

Out[96]: array([0.56700561])

Validation Results: Using sklearn's **LinearRegression** class

In [97]:
```python
from sklearn.linear_model import LinearRegression
```

In [98]:
```python
lr = LinearRegression()
```

In [99]:
```python
lr.fit(train_input, train_target)
```

Out[99]: LinearRegression()

In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.
On GitHub, the HTML representation is unable to render, please try loading this page with nbviewer.org.

In [103…
```python
lr.coef_
```

Out[103… array([43.44732032])

In [104…
```python
lr.intercept_
```

Out[104… 0.5670056086028308

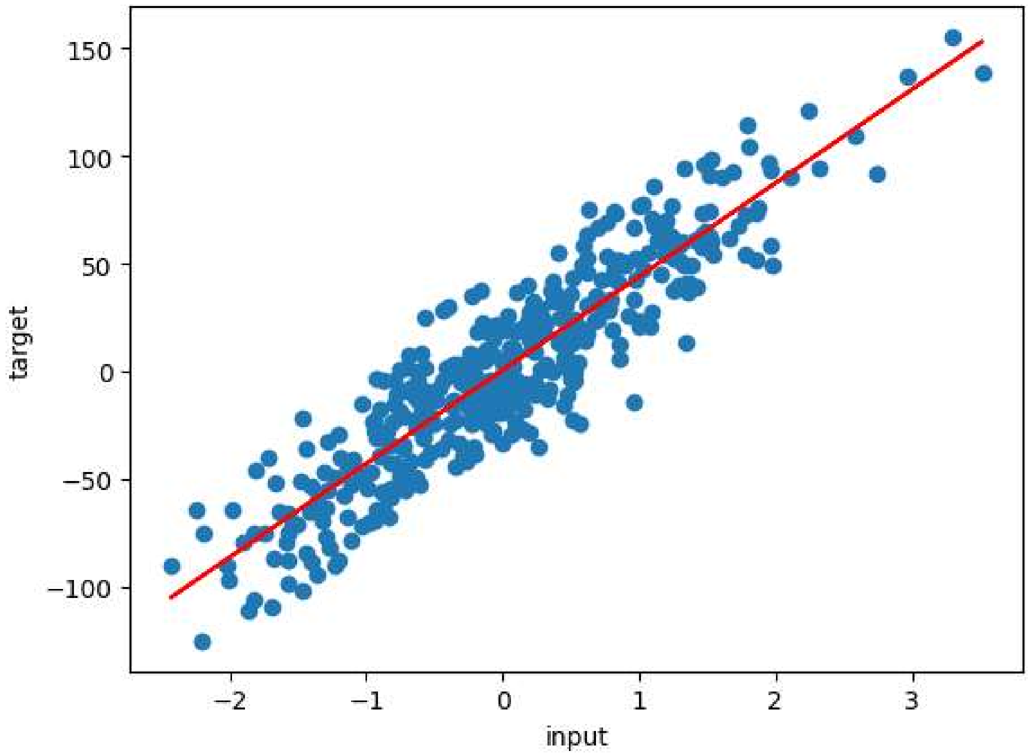
sklearn LinearRegression is giving exactly same as our made **SimpleLinearRegression** Class

sklearn LinearRegression is giving exactly same as our made **SimpleLinearRregression** Class.

Plotting the Regression Line

In [109…

```
plt.scatter(train_input, train_target)
plt.plot(train_input,lr.predict(train_input),color='red')
plt.xlabel('input')
plt.ylabel('target')
plt.show()
```



In [114…

```
lr_pred = lr.predict(test_input)
```

Checking Regression Metrics

Regression metrics are used to evaluate the performance of regression models, which predict continuous numerical values. Scikit-analyze provides several metrics, each with its own strengths and boundaries, to assess how well a model suits the statistics.

Note: We will compare our model result with sklearn's metrics.

Types of Regression Metrics

Some common regression metrics in scikit-learn with examples

- Mean Absolute Error (MAE)
- Mean Squared Error (MSE)
- Root Mean Squared Error (RMSE)
- R-squared (R^2) Score
- Adjusted R-squared (R^2) Score

In [110…

```
from sklearn.metrics import mean_absolute_error, mean_squared_error,r2_score
```

Mean Absolute Error (MAE):

It is the average of the absolute differences between the predicted and actual values.

Formula: $MAE = \frac{1}{n}\sum_{i=1}^{n}|x_i - y_i|$

Where:

- xi represents the actual or observed values for the i-th data point.
- yi represents the predicted value for the i-th data point.

In [115…

```
print("LR MAE",mean_absolute_error(test_target,lr_pred))
print("SLR MAE",mean_absolute_error(test_target,slr_pred))
```

```
LR MAE 16.544520539567298
SLR MAE 16.544520539567298
```

Mean Squared Error (MSE):

It is the average of the squared differences between the predicted and actual values.

Formula: $MSE = \frac{1}{n}\sum_{i=1}^{n}(x_i - y_i)^2$

Where:

- xi represents the actual or observed value for the i-th data point.
- yi represents the predicted value for the i-th data point.

In [116…

```
print("LR MSE",mean_squared_error(test_target,lr_pred))
print("SLR MSE",mean_squared_error(test_target,slr_pred))
```

```
LR MSE 416.40820543796923
SLR MSE 416.4082054379692
```

Root Mean Squared Error (RMSE):

It is the square root of the MSE and provides the error in the same units as the target variable.

Formula: $RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(x_i - y_i)^2}$

Where:

- xi represents the actual or observed value for the i-th data point.
- yi represents the predicted value for the i-th data point.

In [117…

```
import numpy as np
```

In [118…

```
print("LR RMSE",np.sqrt(mean_squared_error(test_target,lr_pred)))
print("SLR RMSE",np.sqrt(mean_squared_error(test_target,slr_pred)))
```

```
LR RMSE 20.406082559814593
SLR RMSE 20.40608255981459
```

R-squared (R2):

It measures the proportion of the variance in the dependent variable that is predictable from the independent variables.

Formula: $R^2 = 1 - \frac{SSR}{SST}$

Where:

- R2 is the R-Squared.
- SSR represents the sum of squared residuals between the predicted values and actual values.
- SST represents the total sum of squares, which measures the total variance in the dependent variable.

Ranges from 0 to 1, where 1 indicates a perfect fit.

In [121…

```
print("LR R2",r2_score(test_target,lr_pred))

print("SLR R2",r2_score(test_target,slr_pred))
```

```
LR R2 0.8085900589912272
SLR R2 0.8085900589912273
```

In [120…

```
lr_r2 = r2_score(test_target,lr_pred)
slr_r2 = r2_score(test_target,slr_pred)
```

Adjusted R2 score

Similar to R-squared but penalizes for adding irrelevant features to the model.

Adjusts the R-squared value based on the number of predictors.

-- Useful in multiple linear regression.

In [124…

```
print("LR Adjusted R2 score", 1 - ((1-lr_r2)*(100-1)/(100-1-1)))
print("SLR Adjusted R2 score", 1 - ((1-slr_r2)*(100-1)/(100-1-1)))
```

```
LR Adjusted R2 score 0.8066368963278723
SLR Adjusted R2 score 0.8066368963278725
```

Yay, we got same results.

These metrics help in assessing how well a regression model performs in terms of accuracy and precision in predicting continuous outcomes.

Remember: The choice of metric depends on the specific characteristics and requirements of the problem at hand.

Stay tuned for *Multiple Linear Regression* and Don't forget to ***Star*** this Github Repository for more such contents.