```
In [24]: import pandas as pd
          import matplotlib.pyplot as plt
          import numpy as np
 In [2]: df = pd.read_csv('income.data.csv')
 In [3]: df.head()
 Out[3]:
             Unnamed: 0
                           income
                                    happiness
          0
                          3.862647
                                     2.314489
                       2 4.979381
                                     3.433490
          2
                       3 4.923957
                                     4.599373
          3
                         3.214372
                                     2.791114
          4
                       5 7.196409
                                     5.596398
 In [4]: df.drop(columns='Unnamed: 0', inplace=True)
 In [5]: df.head()
Out[5]:
              income
                       happiness
            3.862647
                        2.314489
                        3.433490
          1 4.979381
          2 4.923957
                        4.599373
                        2.791114
            3.214372
            7.196409
                        5.596398
```

Implementing Statistical Simple Linear Regression from scratch

$$\widehat{y} = \widehat{B_0} + \widehat{B_1} x$$

$$\widehat{B_0} = \overline{y} - \widehat{B_1} \overline{x}$$

$$SXY = \sum xy - n \overline{x} \overline{y}$$

$$SXX = \sum x^2 - n \overline{x}^2$$

$$SSE = \sum (y - \widehat{y})^2$$

$$MSE = \frac{SEE}{n - 2}$$

```
In [6]: y = df['happiness']
         x = df['income']
 In [7]: y_bar = y_mean()
          x_bar = x.mean()
          n = len(y)
 In [8]: SXX = sum(x^{**2}) - n * x_bar^{**2}
          SXY = sum(x * y) - n * x_bar * y_bar
 In [9]: B_1 = SXY / SXX
In [10]: B_0 = y_bar - B_1 * x_bar
In [17]: print(f'y = \{B_0:.3f\} + \{B_1:.3f\} x')
        y = 0.204 + 0.714 \times
In [12]: y_hat = B_0 + B_1 * x
In [13]: e = y - y_hat
In [14]: SSE = sum(e^{**2})
In [15]: MSE = SSE / (n-2)
In [27]: print(f'MSE = {MSE:.3f}')
        MSE = 0.516
```

In [18]:

Implementing Statistical Simple Linear Regression from scratch

$$\hat{y} = \widehat{B_0} + \widehat{B_1} x$$

$$\widehat{B_1} = \frac{SXY}{SXX}$$

$$SXY = \sum xy - n \, \overline{x} \, \overline{y}$$

$$SXX = \sum x^2 - n \, \overline{x}^2$$

$$\widehat{B_0} = \overline{y} - \widehat{B_1} \, \overline{x}$$

$$SSE = \sum (y - \hat{y})^2$$

$$MSE = \frac{SEE}{n-2}$$

```
class SimpleLinearRegression:

def __init__(self):
    """
    Initializes the SimpleLinearRegression model.

Attributes:
    -----
B_0 : float
```

```
The intercept of the regression line.
    B_1 : float
        The slope of the regression line.
    MSE : float
       Mean squared error.
    self.B_0 = None
    self.B_1 = None
    self.MSE = None
def fit(self, X, y):
    Fits the simple linear regression model to the training data.
    Calculates and sets the intercept (B_0) and slope (B_1) of the
    regression line and then calculates the evaluation metrics for
    the model which is the MSE.
    Parameters:
    _____
    X : array-like
       The input feature array.
    y : array-like
        The target variable array.
    # 1. Ensure X and y are numpy arrays
    X = np.array(X)
    y = np.array(y)
    # 2. Calculate the mean of X and y
    x_bar = X.mean()
    y_bar = y.mean()
    # 3. Calculate SXX and SXY
    SXX = sum(X**2) - len(X) * x_bar**2
    SXY = sum(X * y) - len(X) * x_bar * y_bar
    # 4. Calculate coefficients
    self.B 1 = SXY / SXX
    self.B_0 = y_bar - self.B_1 * x_bar
    # 5. Calculate estimated error
    y_hat = self.predict(X)
    e = y - y_hat
    SSE = sum(e**2)
    self.MSE = SSE / (len(X) - 2)
def predict(self, X):
    Predicts the target variable for new input values using the fitted model.
    Parameters:
    _____
    X : array-like
        The input feature array for which to predict the target variable.
    Returns:
```

```
array-like
        Predicted values of the target variable.
    Raises:
    ValueError
        If the model has not been fitted yet.
    # 1. Raise a ValueError if the model has not been fitted yet
    if self.B_0 is None or self.B_1 is None:
        raise ValueError("The model has not been fitted yet.")
    # 2. Ensure that X is a numpy array
    X = np.array(X)
    # 3. Return the estimated y
    return self.B_0 + self.B_1 * X
def plot(self, X, y):
    Plots the scatter plot of the data points and the regression line.
    Parameters:
    X : array-like
        The input feature array.
    y : array-like
        The target variable array.
    if self.B_0 is None or self.B_1 is None:
        raise ValueError("The model has not been fitted yet.")
    # Ensure X and y are numpy arrays
    X = np.array(X)
    y = np.array(y)
    # Predicted values
    y_pred = self.predict(X)
    # PLot
    plt.scatter(X, y, color='blue', label='Data points')
    plt.plot(X, y_pred, color='red', label='Regression line')
    plt.xlabel('X')
    plt.ylabel('y')
    plt.title(f'Simple Linear Regression with line of best fit: y = {round(self
    plt.legend()
    plt.show()
```

Taking an object and fitting our data to it

```
In [19]: model = SimpleLinearRegression()
model.fit(x, y)
```

```
In [26]: print("Evaluation of the model")
         print(" -----")
         print(f'Line of best fit is: y = {model.B_0:.3f} + {model.B_1:.3f} x')
         print(f'Mean squared error is: {model.MSE:.3f}')
        Evaluation of the model
        Line of best fit is: y = 0.204 + 0.714 \times
        Mean squared error is: 0.516
In [22]: predictions = model.predict([6, 7])
         print(predictions)
        [4.48722347 5.20104898]
         model.plot(x, y)
In [23
            Simple Linear Regression with line of best fit: y = 0.2 + 0.71 x
                    Data points
                    Regression line
           6
           5
           3
           2
           1
```

5

Χ

6

3

7