Linear Regression

It is method that defines relationship between dependent variable (y) and independent variable (x).

GOAL: The goal is to draw a best fit line between x and y that estimates the relationship between x and y.

The equation that it follows is:

Y = mX + b, where

Y = output(dependent variable)

X = features (independent variable)

m = scale factor or coefficient

b = bias coefficient -> gives an extra degree of freedom to this model

the total error of the linear model is the sum of the error of each point. I.e. , $\sum_{i=1}^n r_i^2$

ri = Distance between the line and ith point.

n =Total number of points.

#importing libraries

import numpy as np import pandas as pd

import matplotlib.pyplot as plt

dataset = pd.read csv('dataset.csv')

#printing dataset size on the basis of row and column

print(dataset.shape)

printing some top dataset values

print(dataset.head(10))

Importing dataset and checking the dataset size using shape function and printing the top 10 value using the head(10) function.

Output will be

Now we have to find the relationship between head size and brain weight so we are taking this two features into two variables X & Y.

```
X = dataset['Head Size(cm^3)'].values
Y = dataset['Brain Weight(grams)'].values
#finding mean of input and output
x mean = np.mean(X)
y mean = np.mean(Y)
n = len(X)
numerator = 0
denominator = 0
for i in range(n):
  numerator += (X[i] - x mean) * (Y[i] - y mean)
 denominator += (X[i] - x mean) ** 2
b1 = numerator / denominator
b0 = y mean - (b1 * x mean)
```

Print coefficients print(b1, b0)

Above we have solved two equations. They are:

$$\beta_1 = \frac{\sum_{i=1}^{m} (x_i - \bar{x})(y_i - \bar{y})}{\sum_{i=1}^{m} (x_i - \bar{x})^2}$$
$$\beta_0 = \bar{y} - \beta_1 \bar{x}$$

These are coefficients and the output will be:

B1 = 0.26342933948939945

B0 = 325.57342104944223

Then we have to find the straight line of the following equation:

$$Y = \beta_0 + \beta_1 X$$

It means our expected functions will be:

BrainWeight = 325.573421049 + 0.263429339489 * HeadSize

Plotting Values and Regression Line

```
\max_{x} x = \text{np.max}(X) + 100
\min_{x} x = \text{np.min}(X) - 100
```

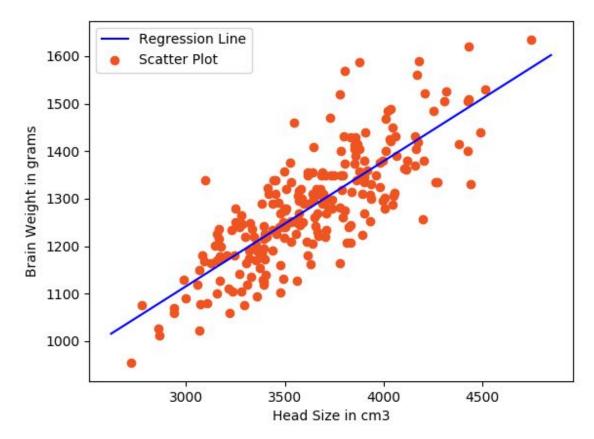
```
# Calculating line values x and y
x = np.linspace(min_x, max_x, 1000)
y = b0 + b1 * x
```

Now plotting on graph.

plt.show()

```
# Ploting Line
plt.plot(x, y, color='blue', label='Regression Line')
# Ploting Scatter Points
plt.scatter(X, Y, c='#ef5423', label='Scatter Plot')

plt.xlabel('Head Size in cm3')
plt.ylabel('Brain Weight in grams')
plt.legend()
```



To know about linespace visit https://www.numpy.org/devdocs/reference/generated/numpy.linspace.html

Now we will find the accuracy. At first we will use RMSE(root mean squared error). The equation is:

$$RMSE = \sqrt{\sum_{i=1}^{m} \frac{1}{m}(\hat{y_i} - y_i)^2}$$

Here we have to predict y_pred value for each ith value of X. then we have to find the difference of $(y[i] - y_pred)^2$

```
# Calculating Root Mean Squares Error
rmse = 0
for i in range(n):
    y pred = b0 + b1 * X[i]
    rmse += (Y[i] - y pred) ** 2
```

```
rmse = np.sqrt(rmse/n)
print(rmse)
```

Another way to find accuracy is R^2 score. The equation is:

$$SS_t = \sum_{i=1}^m (y_i - ar{y})^2$$
 $SS_r = \sum_{i=1}^m (y_i - \hat{y_i})^2$ $R^2 \equiv 1 - rac{SS_r}{SS_t}$

```
# Calculating R^2 Error
ss t = 0
ss r = 0
for i in range(n):
    y pred = b0 + b1 * X[i]
    ss t += (Y[i] - y mean) ** 2
    ss r += (Y[i] - y pred) ** 2
r2 = (1 - (ss r/ss t))*100
print(r2)
```

Reference Sites:

- 1. https://towardsdatascience.com/linear-regression-from-scratch-cd0dee067f72
- 2. https://mubaris.com/posts/linear-regression/