

Q) Linear Regression

① Solving following linear Regression problem using matrix approach.

$x_i$ (week)	1	2	3	4
$y_i$ (Sales in thousand)	2	4	5	9

Implementation

```
import numpy as np
```

```
X = np.array([ [1, 1],
                [1, 2],
                [1, 3],
                [1, 4] ])
```

```
Y = np.array([2, 4, 5, 9])
```

```
XT = X.T
```

```
XTX = np.dot(XT, X)
```

```
XTX-1inv = np.linalg.inv(XTX)
```

```
XTY = np.dot(XT, Y)
```

```
beta = np.dot(XTX-1inv, XTY)
```

```
beta_0, beta_1 = beta
```

```
print(f"Intercept (B0): {beta_0: .2f}")
```

```
print(f"Shape (B1): {beta_1: .2f}")
```

```
Y_pred = np.dot(X, beta)
```

```
print("Predicted Sales:", Y_pred)
```

Output :

Intercept ( $\beta_0$ ) : -0.50

Slope ( $\beta_1$ ) : 2.20

predicted sales : [1.7, 3.9, 6.1, 8.3]

### ⑤ Multiple Linear Regression

To predict glucose level of diabetes - `diabetes.csv` using MLR.

`diabetes.csv` :

Age	BMI	BP	Insulin	D.PedigreeFunc	glucose.
50	25.3	80	150	0.5	140
'	'	'	'	'	'
'	'	'	'	'	'
33	29.1	81	145	0.67	160

### Implementation

```
import numpy as np
```

```
import pandas as pd
```

```
df = pd.read_csv("diabetes.csv")
```

```
x = df[['Age', 'BMI', 'BP', 'Insulin', 'D.PedigreeFunc']].values
```

```
y = df['glucose'].values
```

```
x = np.c_[np.ones(x.shape[0]), x]
```

train\_size = int(0.8 \* len(X))

X\_train, X\_test = X[:train\_size], X[train\_size:]

Y\_train, Y\_test = Y[:train\_size], Y[train\_size:]

theta = np.linalg.pinv(X\_train.T @ X\_train) @ X\_train.T @ Y\_train

Y\_pred = X\_test @ theta

mse = np.mean((Y\_test - Y\_pred)\*\*2)

R2 = 1 - (np.sum((Y\_test - Y\_pred)\*\*2) / np.sum((Y\_test - np.mean(Y\_test))\*\*2))

print("Multiple Linear Regressor model (Age, BMI, I, DP => B12)

print(f"Mean Squared Error : {mse}")

print(f"R^2 score : {R2}")

Output :-

MLR :-

Mean Squared Error : 41.23512336576399

R^2 score : 0.9312747943903934



## ⑧ Logistic Regression

```
X = df[['Age', 'BMI', 'BP', 'Insulin', 'DPF']].values
```

```
y = df['Diabetes'].values
```

```
X = np.c_[np.ones(X.shape[0]), X]
```

```
theta = np.zeros(X.shape[1])
```

```
def sigmoid(z):
```

```
    return 1 / (1 + np.exp(-z))
```

```
def compute_cost(X, y, theta):
```

```
    m = len(y)
```

```
    h = sigmoid(X @ theta)
```

```
    return (-1/m) * np.sum(y * np.log(h) + (1-y) * np.log(1-h))
```

```
def gradient_descent(X, y, theta, alpha, iterations):
```

```
    m = len(y)
```

```
    h = sigmoid(X @ theta)
```

```
    gradient = (1/m) * (X.T @ (h - y))
```

```
    theta -= alpha * gradient
```

```
    cost_history.append(compute_cost(X, y, theta))
```

```
    return theta, cost_history
```

```
alpha = 0.01
```

```
iterations = 1000
```

```
theta, cost_history = gradient_descent(X, y, theta, alpha, iterations)
```

```
print(" Final theta:", theta)
```

```
def predict(x, theta):
```

```
    return (sigmoid(x @ theta) > 0.5).astype(int)
```

```
predictions = predict(x, theta)
```

```
accuracy = np.mean(predictions == y) * 100
```

```
print(f" L R A : {accuracy}, {f} %")
```

Output :-

final theta values

[0.0046, 3.8204, -0.0034, 1.0843, -1.8403, -0.010]

Accuracy = 100.00 %