# Week-5, Practice, Solutions

### **Question-1**

The loss function used for binary classification using logistic regression is the binary cross-entropy loss.

We are talking about logistic regression without feature transform. To understand the decision boundary, we see the following:

$$P(y=1 \mid x) = egin{cases} 1, & \sigma(w^T x) > 0.5 \ 0, & ext{otherwise} \end{cases}$$

When is  $\sigma(w^Tx)>0.5$ ? From the graph of the sigmoid function, we can see that this happens when  $w^Tx>0$ . From this, we see that the decision boundary in the case of a logistic regression model is linear. The other part is that the activation function is the sigmoid function, which is non-linear.

This is something you must be aware of by now.

While using gradient descent in logistic regression, we need to compute the derivatives of the cross-entropy loss with respect to the weights. But this process involves taking the derivative of the sigmoid function by chain rule. Therefore, we need to compute both derivatives.

The formula for precision and recall are:

$$P = \frac{TP}{TP + FP}$$

$$R = \frac{TP}{TP + FN}$$

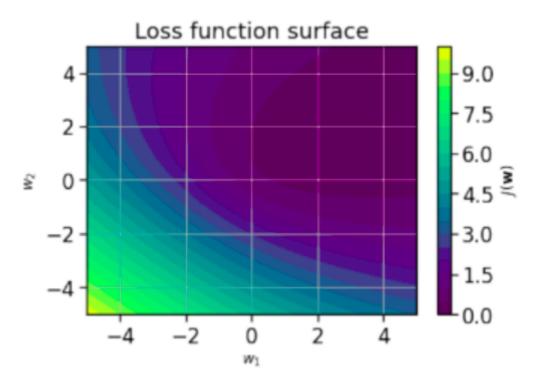
So, the values become:

$$P = \frac{35}{35 + 15} = 0.7$$

$$R = \frac{35}{35 + 15} = 0.7$$

The correct Python expression for the gradient of the loss function with respect to  $\boldsymbol{w}$  is:

```
1   np.transpose(X) @ (y_prob - y) + reg_rate * w
```



From the contours, we see that the deep-blue regions have the lowest loss. So, after performing gradient descent for a sufficient number of epochs, the coordinates are likely to be in the deep-blue region. So, (4,4) is an ideal choice.

The derivative of the sigmoid function is given by:

$$\sigma(z)\cdot(1-\sigma(z))$$

The logistic regression model outputs the following probability:

$$P(y=1 \mid x) = \sigma(w^T x)$$