

## Assignment-2

1) Given binary label as  $y_i \in \{-1, +1\}$ . To prove that the empirical loss function on a data sample takes the form of:-

$$l(w; x_i, y_i) = \log(1 + \exp(-y_i w^T x_i))$$

→ Representing logistic regression probability model:-

Logistic regression models the probability of having input  $x_i$  and belonging to class  $y_i \in \{-1, +1\}$  as:-

$$P(y_i | x_i) = \frac{1}{1 + \exp(-y_i w^T x_i)}, \text{ here } w \text{ is the weight vector.}$$

→ Using log-likelihood function:-

The likelihood of observing the entire dataset  $\{(x_i, y_i)\}$  where  $i=1$  to  $n$  under the given model is:-  $L(w) = \prod_{i=1}^n P(y_i | x_i)$

Logarithm of log-likelihood is given as:-  $\log(L(w))$

$$\Rightarrow \log(L(w)) = \sum_{i=1}^n \log(P(y_i | x_i))$$

Substituting  $P(y_i | x_i)$ :

$$\begin{aligned} \log(L(w)) &= \sum_{i=1}^n \log\left(\frac{1}{1 + \exp(-y_i w^T x_i)}\right) \\ &= \sum_{i=1}^n -\log(1 + \exp(-y_i w^T x_i)) \end{aligned}$$

→ Negative log-likelihood as loss function:-

From the above step if we define empirical loss function; we minimize the negative log-likelihood by the below statement:-

$$l(w; x_i, y_i) = \log(1 + \exp(-y_i w^T x_i))$$

Thus, we have shown that the empirical loss function for logistic regression would be in the form as:-

$$l(w; x_i, y_i) = \log(1 + \exp(-y_i w^T x_i))$$

2) The objective function of Logistic regression with L2-regularization is also called as Ridge regression.

Given sensitive dataset  $\{x_i\}_{i \in [1, n]}$ , where binary label is represented as  $y_i \in \{-1, +1\}$ , here empirical loss for single data point is given by:-

$$\ell(w; x_i, y_i) = \log(1 + \exp(-y_i w^T x_i))$$

→ Consider Average Empirical loss:-

The total empirical loss over  $n$  samples is deduced as:-

$$L(w) = \frac{1}{n} \sum_{i=1}^n \log(1 + \exp(-y_i w^T x_i))$$

→ Introducing Regularization term:-

To avoid overfitting, we introduce an L2-norm regularization term, which is given by :-  $\frac{\lambda}{2} \|w\|^2 = \frac{\lambda}{2} \sum_{j=1}^d w_j^2$ ; here  $\lambda > 0$  which is a regularization parameter, this controls the overfitting of data and maintains model complexity low.

After introducing regularization term, the objective function is given by

$$\begin{aligned} J(w) &= \frac{1}{n} \sum_{i=1}^n \log(1 + \exp(-y_i w^T x_i)) + \frac{\lambda}{2} \sum_{j=1}^d w_j^2 \\ &= \frac{1}{n} \sum_{i=1}^n \log(1 + \exp(-y_i w^T x_i)) + \frac{\lambda}{2} \|w\|^2 \end{aligned}$$

Therefore, the objective function of Logistic regression, considering average loss of data samples and to use L2-norm to avoid overfitting is given

by:-

$$J(w) = \frac{1}{n} \sum_{i=1}^n \log(1 + \exp(-y_i w^T x_i)) + \frac{\lambda}{2} \|w\|^2$$