

## Problem 1

Given a data set  $D = \{(x_i, y_i)\}_{i=1}^m$ , where  $x_i \in \mathbb{R}^d$  and  $y_i \in \mathbb{R}$ . We want to use an unregularized least squares regression model to best fit this data set. This can be formulated as the following optimization problem:

$$\min_{w \in \mathbb{R}^d, b \in \mathbb{R}} \ell(w, b) := \frac{1}{2} \sum_{i=1}^m (w^T x_i + b - y_i)^2. \quad (1-1)$$

Try to answer the following questions:

- (1) Is the optimal parameter  $(w^*, b^*)$  unique? If not, please give the condition for guaranteeing the uniqueness of  $(w^*, b^*)$ .
- (2) The data set  $D$  is shown in the Table 1, where each sample has 3 dimensions ( $d_1, d_2, d_3$ ). Please calculate the optimal parameter  $(w^*, b^*)$ .

Table 1 Training set for linear regression

$d_1$	2	9	8	8	2	8	4	1	3	5
$d_2$	9	3	3	8	1	4	3	8	3	3
$d_3$	5	4	2	1	6	7	8	2	6	7
$y$	8	10	6	7	3	4	12	7	5	4

## Problem 2

In a binary classification problem, each instance  $x_i \in \mathbb{R}^d$  in a data set  $D = \{(x_i, y_i)\}_{i=1}^m$  has a label  $y_i \in \{0, 1\}$ . We have already known the logistic regression model Eq.(2-1) is a powerful tool to handle this kind of problem.

$$y = \frac{1}{1 + e^{-(w^T x + b)}} \quad (2-1)$$

To simplify this problem, we assume that  $\beta = (w; b)$ ,  $\hat{x} = (x; 1)$ . Since its negative log-likelihood function Eq.(2-2) is convex, we can optimize it efficiently with Gradient Descent method, Newton Method, and so on.

$$\ell(\beta) = \sum_{i=1}^m \left( -y_i \beta^T \hat{x}_i + \ln(1 + e^{\beta^T \hat{x}_i}) \right) \quad (2-2)$$

- (1) Prove the Eq.(2-2) is convex.
- (2) Suppose we are facing a  $K$ -class classification problem instead of a binary classification problem, where  $y_i \in \{1, 2, \dots, K\}$ . Please expand the logistic regression model Eq.(2-1) to a multi-class version and give the log-likelihood function of this multi-class logistic regression model.

### Problem 3

In a binary classification problem, given the true label  $y$  of the sample and the predicted values  $y_{C_1}$ ,  $y_{C_2}$  of the two classifiers  $C_1$ ,  $C_2$ , calculate the relevant performance measures.

Table 2 True label and predicted values of two classifiers

$y$	1	0	1	1	1	0	0	1
$y_{C_1}$	0.62	0.39	0.18	0.72	0.45	0.01	0.32	0.93
$y_{C_2}$	0.36	0.12	0.82	0.89	0.17	0.75	0.36	0.97

- (1) AUC
- (2) Confusion Matrix (threshold=0.4 and 0.9 for  $C_1$  and  $C_2$  respectively)
- (3)  $F1$ -Score (threshold=0.4 and 0.9 for  $C_1$  and  $C_2$  respectively)

### Problem 4

Suppose you have a regression problem where the training data has 1000 samples and each sample has 20 features. Now you fit the training data with a polynomial regression model of degree  $d$  and use mean squared error (MSE) as the loss function. Try to answer the following questions:

- (1) If  $d = 1$ , is the model prone to overfitting? Why?
- (2) If  $d = 20$ , is the model prone to overfitting? Why?
- (3) How to choose an appropriate  $d$  value to balance the bias and variance of the model?