

CSE 404: Introduction to Machine Learning (Fall 2020)

Homework #6

Due 11/9/2020 by 11.59pm

Note: (1) LFD refers to the textbook “Learning from Data”. (2) Please upload a soft copy of your homework on D2L.

1. (50 points) **Exercise 3.6 (page 92) in LFD.** Cross-entropy error measure.

- (a) (25 points) More generally, if we are learning from ± 1 data to predict a noisy target $P(y|\mathbf{x})$ with candidate hypothesis h , show that the maximum likelihood method reduces to the task of finding h that minimizes

$$E_{in}(\mathbf{w}) = \sum_{n=1}^N \mathbb{I}[y_n = +1] \ln \frac{1}{h(\mathbf{x}_n)} + \mathbb{I}[y_n = -1] \ln \frac{1}{1 - h(\mathbf{x}_n)}$$

Hint: Use the likelihood $p(y|x) = \begin{cases} h(x) & \text{for } y = +1 \\ 1 - h(x) & \text{for } y = -1 \end{cases}$ and derive the maximum likelihood formulation.

- (b) (25 points) For the case $h(\mathbf{x}) = \theta(\mathbf{w}^T \mathbf{x})$, argue that minimizing the in-sample error in part (a) is equivalent to minimizing the one given below

$$E_{in}(\mathbf{w}) = \frac{1}{N} \sum_{n=1}^N \ln(1 + e^{-y_n \mathbf{w}^T \mathbf{x}_n})$$

Note from Book: For two probability distributions $\{p, 1 - p\}$ and $\{q, 1 - q\}$ with binary outcomes, the cross-entropy (from information theory) is

$$p \log \frac{1}{q} + (1 - p) \log \frac{1}{1 - q}.$$

The in-sample error in part (a) corresponds to a cross-entropy error measure on the data point (\mathbf{x}_n, y_n) , with $p = \mathbb{I}[y_n = +1]$ and $q = h(\mathbf{x}_n)$.

2. (50 points) **Exercise 3.7 (page 92) in LFD.** For logistic regression, show that

$$\begin{aligned} \nabla E_{in}(\mathbf{w}) &= -\frac{1}{N} \sum_{n=1}^N \frac{y_n \mathbf{x}_n}{1 + e^{y_n \mathbf{w}^T \mathbf{x}_n}} \\ &= \frac{1}{N} \sum_{n=1}^N -y_n \mathbf{x}_n \theta(-y_n \mathbf{w}^T \mathbf{x}_n) \end{aligned}$$

Argue that a ‘misclassified’ example contributes more to the gradient than a correctly classified one.

Hint: Remember the logistic regression objective function $E_{in}(\mathbf{w}) = \frac{1}{N} \sum_{n=1}^N \ln(1 + \exp(-y_n \mathbf{w}^T \mathbf{x}_n))$ and take its derivative with respect to \mathbf{w} .