

# Homework Assignment 3

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1. Suppose we are given a set of input-output pairs  $D = \{(\mathbf{x}_1, y_1^*), \dots, (\mathbf{x}_N, y_N^*)\}$ , and we want to find the best classifier among the following hypothesis sets:

1.  $H_{\text{perceptron}}$ : Perceptron classifier
2.  $H_{\text{logreg}}$ : Logistic regression
3.  $H_{\text{svm}, C}$ : Support vector machine with a regularization coefficient  $C$

where  $C$  is one of  $\{c_0, \dots, c_M\}$ . The dataset  $D$  is split into 80% training set and 20% test set. Our goal is two folds; (1) choose the best classifier, and (2) report its generalization performance (or its estimate). Describe in words how these two goals are met using the principles of  $K$ -fold cross validation.

2. The distance function of multi-class logistic regression was defined as

$$\begin{aligned} D(y^*, M, \mathbf{x}) &= -\log p_{M^*}(\mathbf{x}) \\ &= -a_{y^*} + \log \sum_{k=1}^K \exp(a_k), \end{aligned}$$

where

$$\mathbf{a} = \mathbf{W}\tilde{\mathbf{x}}.$$

Derive a learning rule step-by-step for each column vector  $\mathbf{w}_c$  of the weight matrix  $\mathbf{W}$ .

SOLUTION: First of all, we know that  $p(C = n|\mathbf{w}) = \frac{\exp(\mathbf{w}_n^\top \tilde{\mathbf{x}})}{\sum_{k=1}^K \exp(a_k)}$  for all  $n \in \{1, \dots, K\}$

For all  $y \in \{1, \dots, K\} \setminus \{y^*\}$

$$\begin{aligned} \frac{\partial D(y^*, M, \mathbf{x})}{\partial \mathbf{w}_y} &= -\frac{\partial}{\partial \mathbf{w}_y} (\mathbf{w}_y^\top \tilde{\mathbf{x}} - \log \sum_{k=1}^K \exp(a_k)) \\ &= -(0 - \frac{\tilde{\mathbf{x}} \exp(\mathbf{w}_y^\top \tilde{\mathbf{x}})}{\sum_{k=1}^K \exp(a_k)}) = -(0 - p(C = y|\mathbf{x}))\tilde{\mathbf{x}}. \end{aligned}$$

For the  $y^*$ -th row vector

$$\begin{aligned} \frac{\partial D(y^*, M, \mathbf{x})}{\partial \mathbf{w}_{y^*}} &= -\frac{\partial}{\partial \mathbf{w}_{y^*}} (\mathbf{w}_{y^*}^\top \tilde{\mathbf{x}} - \log \sum_{k=1}^K \exp(a_k)) \\ &= -(1 - \frac{\tilde{\mathbf{x}} \exp(\mathbf{w}_{y^*}^\top \tilde{\mathbf{x}})}{\sum_{k=1}^K \exp(a_k)}) = -(1 - p(C = y^*|\mathbf{x}))\tilde{\mathbf{x}}. \end{aligned}$$

In order to combine both equations, we need to replace certain notations. Each equation has a constant that is either 0 or 1, which merely corresponds to the desired output for the given input. In our combined equation, we can simply replace this constant with  $\mathbf{y}^*$ , which is a vector representing our desired outputs for all given input. When combining  $p(C = y^*|\mathbf{x})$  and  $p(C = y|\mathbf{x})$  for all  $y \in \{1, \dots, K\}$

### 3. PROGRAMMING ASSIGNMENT