

Management Sciences Topics: Convex Optimization

Final Project

1 Problem setup

We need to solve the optimization problem of a one-hidden-layer neural network

$$\min_{x_k \in \mathbb{R}^d, y_k \in \mathbb{R}, z \in \mathbb{R}^K, w \in \mathbb{R}} \frac{1}{n} \sum_{i=1}^n \mathcal{L} \left(b_i w + b_i \sum_{k=1}^K \sigma(a_i^\top x_k + y_k) z_k \right), \quad (1.1)$$

where K is the number of neurons, $a_i \in \mathbb{R}^d$ is a data point, $b_i \in \{-1, 1\}$ is the class label of a_i , $\sigma(z) = \max(z, 0)$ or $\frac{\exp(z)}{1+\exp(z)}$, $\mathcal{L}(z) = \max(1 - z, 0)$ or $\log(1 + \exp(-z))$.

2 Stochastic subgradient method

We first consider the subgradient with respect to each variables.

First, define the variables

$$X = [x_1, x_2, \dots, x_K] \in \mathbb{R}^{d \times K}, \quad Y = [y_1, y_2, \dots, y_K]^\top \in \mathbb{R}^{K \times 1}, \quad Z = [z_1, z_2, \dots, z_K]^\top \in \mathbb{R}^{K \times 1}. \quad (2.1)$$

Then a forward pass through the network can be written as

$$\begin{aligned} A_1 &= AX \oplus Y^\top, \\ A_2 &= \sigma(A_1)Z \oplus w \\ f &= \frac{1}{n} 1^\top L(b \odot A_2). \end{aligned} \quad (2.2)$$

By chain rule, the subgradients of f with respect to each variable are

$$\begin{aligned} \frac{\partial f}{\partial A_2} &= \frac{1}{n} L'(b \odot A_2) \odot b \\ \frac{\partial f}{\partial w} &= \frac{\partial f}{\partial A_2} \frac{\partial A_2}{\partial w} = \text{rowsum} \left(\frac{\partial f}{\partial A_2} \odot 1 \right) = \left(\frac{\partial f}{\partial A_2} \right)^\top 1, \\ \frac{\partial f}{\partial Z} &= \frac{\partial f}{\partial A_2} \frac{\partial A_2}{\partial Z} = \sigma(A_1)^\top \frac{\partial f}{\partial A_2}, \\ \frac{\partial f}{\partial A_1} &= \frac{\partial f}{\partial A_2} \frac{\partial A_2}{\partial A_1} = \frac{\partial f}{\partial A_2} Z^\top \odot \sigma'(A_1), \\ \frac{\partial f}{\partial Y} &= \frac{\partial f}{\partial A_1} \frac{\partial A_1}{\partial Y} = \left(\frac{\partial f}{\partial A_1} \right)^\top 1, \\ \frac{\partial f}{\partial X} &= \frac{\partial f}{\partial A_1} \frac{\partial A_1}{\partial X} = A^\top \frac{\partial f}{\partial A_1}. \end{aligned} \quad (2.3)$$