CS221 Problem Workout

Week 1

1) Problem 1: Gradient and Gradient Descent

(i) Let $\phi(x) : \mathbb{R} \mapsto \mathbb{R}^d$, $\mathbf{w} \in \mathbb{R}^d$. Consider the following objective function (a.k.a. loss function).

$$\text{Loss}(x, y, \mathbf{w}) = \begin{cases} 1 - 2(\mathbf{w} \cdot \phi(x))y & \text{if } (\mathbf{w} \cdot \phi(x))y \leq 0 \\ (1 - (\mathbf{w} \cdot \phi(x))y)^2 & \text{if } 0 < (\mathbf{w} \cdot \phi(x))y \leq 1 \\ 0 & \text{if } (\mathbf{w} \cdot \phi(x))y > 1, \end{cases}$$

where $y \in \mathbb{R}$. Compute the gradient $\nabla_{\mathbf{w}} \text{Loss}(x, y, \mathbf{w})$.

(ii) Write out the Gradient Descent update rule for some function $\text{TrainLoss}(\mathbf{w}) : \mathbb{R}^d \mapsto \mathbb{R}$.

(iii) Let $d = 2$ and $\phi(x) = [1, x]$. Consider the following loss function.

$$\text{TrainLoss}(\mathbf{w}) = \frac{1}{2}\Big(\text{Loss}(x_1, y_1, \mathbf{w}) + \text{Loss}(x_2, y_2, \mathbf{w})\Big). \tag{1}$$

Compute $\nabla_w \text{TrainLoss}(\mathbf{w})$ for the following values of $x_1, y_1, x_2, y_2, \mathbf{w}$.

$$\mathbf{w} = \left[0, \frac{1}{2}\right],$$
$$x_1 = -2, \quad y_1 = 1,$$
$$x_2 = -1, \quad y_2 = -1.$$

(iv) Perform two iterations of Gradient Descent to minimize the objective function $\text{TrainLoss}(\mathbf{w}) = \frac{1}{2}\Big(\text{Loss}(x_1, y_1, w) + \text{Loss}(x_2, y_2, w)\Big)$ with values for x_1, y_1, x_2, y_2 as above. Use initialization $\mathbf{w}^0 = \left[0, \frac{1}{2}\right]$ and step size $\eta = \frac{1}{2}$.

2) Problem 2: Gradient computation

(i) Let $\phi(x) : \mathbb{R} \mapsto \mathbb{R}^d$, $\mathbf{w} \in \mathbb{R}^d$, and $f(x, \mathbf{w}) = \mathbf{w} \cdot \phi(x)$. Consider the following loss function.

$$\text{Loss}(x, y, \mathbf{w}) = \frac{1}{2} \max\{2 - (\mathbf{w} \cdot \phi(x))y, 0\}^2. \tag{2}$$

Compute its gradient $\nabla_{\mathbf{w}} \text{Loss}(x, y, \mathbf{w})$.

3) **Problem 3: Vector visualization**

Recall that we can visualize a vector $\mathbf{w} \in \mathbb{R}^d$ as a point in d-dimensional space. Let us now visualize some vectors in 2 dimensions on pen and paper.

(i) Consider $\mathbf{x} \in \mathbb{R}^2$. Draw the line (i.e. the "decision boundary") that separates between vectors having a positive dot product with weights $\mathbf{w} = [3, -2]$ and those having a negative dot product. Shade the part of the 2D plane that contains vectors satisfying $\mathbf{w} \cdot \mathbf{x} > 0$.

Hint: It might help to write out the expression for the dot product and seeing the relation between x_1 and x_2 that leads to a positive dot product. You could also use the geometric interpretation of the dot product.

(ii) Repeat the above for $\mathbf{w} = [2, 0]$ and $\mathbf{w} = [0, 2]$.

(iii) A small twist: visualize the set of vectors where $\mathbf{w} \cdot \mathbf{x} \geq 1$ for $\mathbf{w} = [3, -2]$.

(iv) Consider the following element-wise inequality notation. For two vectors $\mathbf{a}, \mathbf{b} \in \mathbb{R}^d$,

$$\mathbf{a} \leq \mathbf{b} \iff a_i \leq b_i \ \forall i = 1, 2, \ldots d. \tag{3}$$

Suppose we have a matrix $A \in \mathbb{R}^{2\times 2}$ and a vector $\mathbf{b} \in \mathbb{R}^2$ as follows.

$$A = \begin{bmatrix} 3 & -2 \\ 2 & 0 \end{bmatrix}, \mathbf{b} = [1, 0]. \tag{4}$$

Visualize the set of vectors where $A\mathbf{x} \geq \mathbf{b}$. Hint: A matrix vector product is a collection of dot products, and the above set can be obtained by the intersection of two of the sets constructed in the previous questions.

4) Problem 4: More gradient computations

(i) Compute the gradient of the loss function below.

$$\text{Loss}(x, y, \mathbf{w}) = \sigma(-(\mathbf{w} \cdot \phi(x))y), \tag{5}$$

where $\sigma(z) = (1 + \exp(-z))^{-1}$ is the logistic function.

(ii) Suppose we have the following loss function.

$$\text{Loss}(x, y, \mathbf{w}) = \max\{1 - \lfloor(\mathbf{w} \cdot \phi(x))y\rfloor, 0\}, \tag{6}$$

where $\lfloor a \rfloor$ returns a rounded down to the nearest integer. Determine what the gradient of this function looks like, and whether gradient descent is suitable to optimize this loss function.