# CSE 5819 Assignment #2

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This assignment is organized as follows:

- 1. ChatGPT pg 1-6
- 2. Problems pg 3-10

## 1 Part 1: ChatGPT Self-Learning (20pts)

You can start from the following prompts, but you need to create subsequent questions that attempt to understand the basic concepts of machine learning.

### 2 Problems

[Convex Optimization, Mean/Medium/Mode, Preparation for Learning Loss Functions]

Take the training data set  $D = \{(x_i, y_i): 1 \le i \le n\}$ . Now consider the following hypothesis class (i.e., the set of constant functions)

$$H = \{h_z(x) = z, \forall x \in R\}$$

We will choose a model from this hypothesis class in our machine learning task.

#### 2.1 Question One

1. [20 pts] Let us use  $L_2$  vector norm to measure the discrepancy between the observed y and the model output  $h_z(x)$ . In other words, the squared loss is defined as

$$L_{sq}(h) = \frac{1}{n} \sum_{i=1}^{n} (h(x_i) - y_i)^2$$

Prove that if we set the constant z equal to the mean of y

$$m = \frac{1}{n} \sum_{i=1}^{n} y_i$$

this constant function  $h_m(\cdot)$  minimizes the squared loss, and in other words,

$$h_m = \arg\min_{\mathbf{h} \in \mathbf{H}} L_{sq}(\mathbf{h})$$

#### 2.2 Question Two

2. [20 pts] Let us use the  $L_1$  vector norm to measure the discrepancy between the observed y and the model output  $h_z(x)$ . In other words, the absolute loss is defined as

$$L_{abs}(h) = \frac{1}{n} \sum_{i=1}^{n} |h(x_i) - y_i|$$

Prove that if we set the constant z equal to the median of y

$$m = median(\{y_i, 1 \le i \le n\})$$

this constant function  $h_m(\cdot)$  minimizes the absolute loss, and in other words,

$$h_m = \arg\min_{\mathbf{h} \in \mathbf{H}} L_{abs}(\mathbf{h})$$

#### 2.3 Question Three

3. [20 pts] Let us use the  $L_0$  vector norm to measure the discrepancy between the observed y and the model output  $h_z(x)$ . In other words, the binary loss is defined as

$$L_{bin}(h) = \frac{1}{n} \sum_{i=1}^{n} 1\{h(x_i) \neq y_i\}$$

where  $1\{h(x_i) \neq y_i\}$  returns 1 if  $h(x_i) \neq y_i$ ; or otherwise return 0. In other words, this loss counts how many times the model output  $h(x_i)$  is not equal to the observed  $y_i$ . Then normalize the sum by n.

Prove that if we set the constant z equal to the mode of y

$$m = mode(\{y_i, 1 \le i \le n\})$$

where the mode is the most common number in the observed y's,

this constant function  $h_m(\cdot)$  minimizes the binary loss, and in other words,

$$h_m = \arg\min_{\mathbf{h} \in \mathbf{H}} L_{bin}(h)$$