

## Problem Set 2, Sept 26, 2019 (Solutions to Theory Questions)

$$\nabla (y_n - \mathbf{x}_n^\top \mathbf{w}) = -\mathbf{x}_n^\top$$

### 1 MAE Subgradient (Exercise 6)

$$\partial h =$$

The subgradient for the function  $h : \mathbb{R} \rightarrow \mathbb{R}, h(e) := |e|$  is given as

$$g : \mathbb{R} \rightarrow \{-1, 0, 1\}, g(e) := \text{sign}(e).$$

$$x_1^1 w^1 + x_1^2 w^2 \dots$$

The MAE cost function is defined as  $\mathcal{L}(\mathbf{w}) = \frac{1}{N} \sum_{n=1}^N |y_n - \mathbf{x}_n^\top \mathbf{w}|$ .

As given in the annotated lecture notes 2, we can use the **chain-rule for subgradients**, for  $\mathcal{L}(\mathbf{w}) := h(q(\mathbf{w}))$ , when the outer function  $h$  is not differentiable, but  $q$  is differentiable. We write  $\partial h(\mathbf{y})$  for the set of all subgradients of  $h$  at  $\mathbf{y}$ . Then any vector  $\mathbf{g}$  of the following form is a subgradient of  $\mathcal{L}$  at  $\mathbf{w}$ :

$$\mathbf{g} \in \partial h(q(\mathbf{w})) \cdot \nabla q(\mathbf{w})$$

where we can pick any element of the left, and multiply with the vector on the right (the gradient).

We now find the (sub)gradient update for a single component  $w_i$  and conclude by generalizing to the whole vector  $\mathbf{w}$ . In our case here,  $\partial h$  is the sign function. Then for  $\frac{\partial \mathcal{L}(\mathbf{w})}{\partial w_i} = \frac{1}{N} \sum_{n=1}^N \frac{\partial |y_n - \mathbf{x}_n^\top \mathbf{w}|}{\partial w_i}$  we have that:

$$\frac{\partial \mathcal{L}(\mathbf{w})}{\partial w_i} = \frac{1}{N} \sum_{n=1}^N -(x_n)_i \text{sign}(y_n - \mathbf{x}_n^\top \mathbf{w}).$$

Finally we can conclude that  $\frac{-1}{N} \mathbf{X}^\top \cdot \text{sign}(\mathbf{e})$  is a subgradient to  $\mathcal{L}$  at  $\mathbf{w}$ , where  $\mathbf{e} := \mathbf{y} - \mathbf{X} \cdot \mathbf{w}$  and  $\text{sign}$  applied element-wise to  $\mathbf{e}$ , and  $\mathbf{X}$  is the matrix collecting all datapoints as its rows.