# CSC413: Assignment 2

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# **Problem 1 Optimization**

#### 1.1 Mini-Batch Stochastic Gradient Descent

#### 1.1.1 Minimum Norm Solution

We begin by examining the update steps for both full-batch gradient descent (GD) and mini-batch SGD.

## Gradient Descent (GD)

The gradient of the loss function  $L(w) = \frac{1}{2} ||Xw - t||^2$  with respect to w is given by:

$$\nabla L(w) = X^T (Xw - t)$$

Starting from an initial point  $w_0 = 0$ , the update rule for gradient descent is:

$$w_{k+1} = w_k - \eta \nabla L(w_k)$$

Substituting the expression for the gradient, we have:

$$w_{k+1} = w_k - \eta X^T (X w_k - t)$$

Notice that the gradient  $X^T(Xw_k - t)$  lies in the row space of X. Since we start with  $w_0 = 0$ , which is in the span of X, and every update direction is also in the span of X, it follows that every iterate  $w_k$  remains in the span of X. As gradient descent converges, it converges to the minimum norm solution  $w^*$ , which lies in the span of X.

### Mini-Batch SGD

In mini-batch SGD, at each iteration, we compute the gradient using a randomly selected mini-batch of the data. Let B denote the indices of the samples in the mini-batch. The gradient for the mini-batch is:

$$\nabla L_B(w) = X_B^T (X_B w - t_B)$$

where  $X_B$  and  $t_B$  are the sub-matrix and sub-vector corresponding to the mini-batch B.

The update rule for mini-batch SGD is:

$$w_{k+1} = w_k - \eta \nabla L_B(w_k)$$

Again, since the mini-batch gradient  $\nabla L_B(w_k)$  lies in the span of the rows of X, the update step remains in the span of X. Starting from  $w_0 = 0$ , each update keeps  $w_k$  in the span of X, and the algorithm will converge to a solution  $\hat{w}$  in the span of X.

## Uniqueness of the Minimum Norm Solution

The minimum norm solution  $w^* = X^{\dagger}t$  is unique and lies in the span of X. Since both full-batch gradient descent and mini-batch SGD are confined to the span of X, and the minimum norm solution in this span is unique, it follows that:

$$\hat{w} = w^*$$

## 1.2 Adaptive Methods

#### 1.2.1 Minimum Norm Solution