

## Homework 3

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**HW 1** We consider the following optimization problem:

$$\min_{\mathbf{x}} f(\mathbf{x}) = \frac{1}{m} \sum_{i=1}^m f_i(\mathbf{x}).$$

And assume that  $f$  is  $\beta$ -smooth and  $\alpha$ -strong convex. Using mini-batch SGD with fixed learning rate to solve it as

$$\mathbf{x}^{t+1} = \mathbf{x}^t - \frac{s}{n_b} \sum_{i_t \in D_t} \nabla f_{i_t}(\mathbf{x}^t),$$

where  $D_t \subset \{1, 2, \dots, m\}$  are drawn randomly and  $|D_t| = n_b$  is the size of  $D_t$ . We further suppose that

- (1) The index  $D_t$  does not depend from the previous  $D_0, D_1, \dots, D_{t-1}$ .
- (2)  $\mathbb{E}_{i_t \in D_t} [\nabla f_{i_t}(\mathbf{x}^t)] = \nabla f(\mathbf{x}^t)$  (Unbiased Estimation).
- (3)  $\mathbb{E}_{i_t \in D_t} [\|\nabla f_{i_t}(\mathbf{x}^t)\|^2] = \sigma^2 + \|\nabla f(\mathbf{x}^t)\|^2$  (control the variance).

Prove

$$(i) \mathbb{E}_{D_t} \|g^t\|^2 = \frac{\sigma^2}{n_b} + \|\nabla f(\mathbf{x}^t)\|^2, \text{ where } \mathbf{g}^t = \frac{1}{n_b} \sum_{i \in D_t} \nabla f_i(\mathbf{x}^t).$$

(ii)

$$\mathbb{E}_{D_t} [f(\mathbf{x}^{t+1})] \leq f(\mathbf{x}^t) - s \nabla f(\mathbf{x}^t)^\top \mathbb{E}_{D_t} [\mathbf{g}^t] + \frac{\beta s^2}{2} \mathbb{E}_{D_t} [\|\mathbf{g}^t\|^2].$$

(iii)

$$\mathbb{E}_{D_t} [f(\mathbf{x}^{t+1}) - f(\mathbf{x}^t)] \leq -\left(s - \frac{\beta s^2}{2}\right) \|\nabla f(\mathbf{x}^t)\|^2 + \frac{\beta s^2}{2n_b} \sigma^2.$$

(iv) Then

$$\mathbb{E}[f(\mathbf{x}^{t+1}) - f^*] - \frac{\beta s}{2n_b \alpha (2 - \beta s)} \sigma^2 \leq (1 - \alpha s (2 - \beta s)) \left[ \mathbb{E}[f(\mathbf{x}^t) - f^*] - \frac{\beta s}{2n_b \alpha (2 - \beta s)} \sigma^2 \right].$$

**HW 2** Derive BCD algorithm for LASSO problem.**HW 3** Derive ADMM algorithm for Fused LASSO problem.**HW 4** Consider the following Basis Pursuit problem as:

$$\begin{aligned} \min_{\mathbf{x}} \quad & \|\mathbf{x}\|_1 \\ \text{s.t.} \quad & \mathbf{Ax} = \mathbf{b}. \end{aligned}$$

Derive ADMM algorithm for it.

Hit: using the indicator function of  $\Omega = \{\mathbf{x} | \mathbf{Ax} = \mathbf{b}\}$ .

## References