

LECTURE 25

LECTURE OUTLINE

- Incremental Subgradient Methods
- Convergence Rate Analysis and Randomized Methods

- Incremental subgradient method for problem $\min_{x \in X} \sum_{i=1}^m f_i(x)$

$$x_{k+1} = \psi_{m,k}, \quad \psi_{i,k} = [\psi_{i-1,k} - \alpha_k g_{i,k}]^+, \quad i = 1, \dots, m$$

starting with $\psi_{0,k} = x_k$, where $g_{i,k}$ is a subgradient of f_i at $\psi_{i-1,k}$.

- **Key Lemma:** For all $y \in X$ and k ,

$$\|x_{k+1} - y\|^2 \leq \|x_k - y\|^2 - 2\alpha_k (f(x_k) - f(y)) + \alpha_k^2 C^2,$$

where $C = \sum_{i=1}^m C_i$ and

$$C_i = \sup_k \{ \|g\| \mid g \in \partial f_i(x_k) \cup \partial f_i(\psi_{i-1,k}) \}$$

CONSTANT STEPSIZE

- For $\alpha_k \equiv \alpha$, we have

$$\liminf_{k \rightarrow \infty} f(x_k) \leq f^* + \frac{\alpha C^2}{2}.$$

- Sharpness of the estimate:
 - Consider the problem

$$\min_x \sum_{i=1}^M C_0 (|x + 1| + 2|x| + |x - 1|)$$

with the worst component processing order

- Lower bound on the error. There is a problem, where even with best processing order,

$$f^* + \frac{\alpha m C_0^2}{2} \leq \liminf_{k \rightarrow \infty} f(x_k)$$

where

$$C_0 = \max\{C_1, \dots, C_m\}$$

COMPLEXITY ESTIMATE FOR CONSTANT STEP

- For any $\epsilon > 0$, we have

$$\min_{0 \leq k \leq K} f(x_k) \leq f^* + \frac{\alpha C^2 + \epsilon}{2}$$

where

$$K = \left\lceil \frac{(d(x_0, X^*))^2}{\alpha \epsilon} \right\rceil.$$

RANDOMIZED ORDER METHODS

$$x_{k+1} = [x_k - \alpha_k g(\omega_k, x_k)]^+$$

where ω_k is a random variable taking equiprobable values from the set $\{1, \dots, m\}$, and $g(\omega_k, x_k)$ is a subgradient of the component f_{ω_k} at x_k .

- Assumptions:

- (a) $\{\omega_k\}$ is a sequence of independent random variables. Furthermore, the sequence $\{\omega_k\}$ is independent of the sequence $\{x_k\}$.
- (b) The set of subgradients $\{g(\omega_k, x_k) \mid k = 0, 1, \dots\}$ is bounded, i.e., there exists a positive constant C_0 such that with prob. 1

$$\|g(\omega_k, x_k)\| \leq C_0, \quad \forall k \geq 0.$$

- Stepsize Rules:

- Constant: $\alpha_k \equiv \alpha$
- Diminishing: $\sum_k \alpha_k = \infty, \sum_k (\alpha_k)^2 < \infty$
- Dynamic

RANDOMIZED METHOD W/ CONSTANT STEP

- With probability 1

$$\inf_{k \geq 0} f(x_k) \leq f^* + \frac{\alpha m C_0^2}{2}$$

(with $\inf_{k \geq 0} f(x_k) = -\infty$ when $f^* = -\infty$).

Proof: By adapting key lemma, for all $y \in X$, k

$$\|x_{k+1} - y\|^2 \leq \|x_k - y\|^2 - 2\alpha (f_{\omega_k}(x_k) - f_{\omega_k}(y)) + \alpha^2 C_0^2$$

Take conditional expectation with $\mathcal{F}_k = \{x_0, \dots, x_k\}$

$$\begin{aligned} E\{\|x_{k+1} - y\|^2 \mid \mathcal{F}_k\} &\leq \|x_k - y\|^2 \\ &\quad - 2\alpha E\{f_{\omega_k}(x_k) - f_{\omega_k}(y) \mid \mathcal{F}_k\} + \alpha^2 C_0^2 \\ &= \|x_k - y\|^2 - 2\alpha \sum_{i=1}^m \frac{1}{m} (f_i(x_k) - f_i(y)) + \alpha^2 C_0^2 \\ &= \|x_k - y\|^2 - \frac{2\alpha}{m} (f(x_k) - f(y)) + \alpha^2 C_0^2, \end{aligned}$$

where the first equality follows since ω_k takes the values $1, \dots, m$ with equal probability $1/m$.

PROOF CONTINUED I

- Fix $\gamma > 0$, consider the level set L_γ defined by

$$L_\gamma = \left\{ x \in X \mid f(x) < f^* + \frac{2}{\gamma} + \frac{\alpha m C_0^2}{2} \right\}$$

and let $y_\gamma \in L_\gamma$ be such that $f(y_\gamma) = f^* + \frac{1}{\gamma}$. Define a new process $\{\hat{x}_k\}$ as follows

$$\hat{x}_{k+1} = \begin{cases} [\hat{x}_k - \alpha g(\omega_k, \hat{x}_k)]^+ & \text{if } \hat{x}_k \notin L_\gamma, \\ y_\gamma & \text{otherwise,} \end{cases}$$

where $\hat{x}_0 = x_0$. We argue that $\{\hat{x}_k\}$ (and hence also $\{x_k\}$) will eventually enter each of the sets L_γ .

Using key lemma with $y = y_\gamma$, we have

$$E\{\|\hat{x}_{k+1} - y_\gamma\|^2 \mid \mathcal{F}_k\} \leq \|\hat{x}_k - y_\gamma\|^2 - z_k,$$

where

$$z_k = \begin{cases} \frac{2\alpha}{m} (f(\hat{x}_k) - f(y_\gamma)) - \alpha^2 C_0^2 & \text{if } \hat{x}_k \notin L_\gamma, \\ 0 & \text{if } \hat{x}_k = y_\gamma. \end{cases}$$

PROOF CONTINUED II

- If $\hat{x}_k \notin L_\gamma$, we have

$$\begin{aligned} z_k &= \frac{2\alpha}{m} (f(\hat{x}_k) - f(y_\gamma)) - \alpha^2 C_0^2 \\ &\geq \frac{2\alpha}{m} \left(f^* + \frac{2}{\gamma} + \frac{\alpha m C_0^2}{2} - f^* - \frac{1}{\gamma} \right) - \alpha^2 C_0^2 \\ &= \frac{2\alpha}{m\gamma}. \end{aligned}$$

Hence, as long as $\hat{x}_k \notin L_\gamma$, we have

$$E\{\|\hat{x}_{k+1} - y_\gamma\|^2 \mid \mathcal{F}_k\} \leq \|\hat{x}_k - y_\gamma\|^2 - \frac{2\alpha}{m\gamma}.$$

This, cannot happen for an infinite number of iterations, so that $\hat{x}_k \in L_\gamma$ for sufficiently large k . Hence, in the original process we have

$$\inf_{k \geq 0} f(x_k) \leq f^* + \frac{2}{\gamma} + \frac{\alpha m C_0^2}{2}$$

with probability 1. Letting $\gamma \rightarrow \infty$, we obtain $\inf_{k \geq 0} f(x_k) \leq f^* + \alpha m C_0^2 / 2$. **Q.E.D.**

CONVERGENCE RATE

- Let $\alpha_k \equiv \alpha$ in the randomized method. Then, for any positive scalar ϵ , we have with prob. 1

$$\min_{0 \leq k \leq N} f(x_k) \leq f^* + \frac{\alpha m C_0^2 + \epsilon}{2},$$

where N is a random variable with

$$E\{N\} \leq \frac{m(d(x_0, X^*))^2}{\alpha \epsilon}$$

- Compare w/ the deterministic method. It is guaranteed to reach after processing no more than

$$K = \frac{m(d(x_0, X^*))^2}{\alpha \epsilon}$$

components the level set

$$\left\{ x \mid f(x) \leq f^* + \frac{\alpha m^2 C_0^2 + \epsilon}{2} \right\}$$

BASIC TOOL FOR PROVING CONVERGENCE

• **Supermartingale Convergence Theorem:** Let Y_k , Z_k , and W_k , $k = 0, 1, 2, \dots$, be three sequences of random variables and let \mathcal{F}_k , $k = 0, 1, 2, \dots$, be sets of random variables such that $\mathcal{F}_k \subset \mathcal{F}_{k+1}$ for all k . Suppose that:

- (a) The random variables Y_k , Z_k , and W_k are nonnegative, and are functions of the random variables in \mathcal{F}_k .
- (b) For each k , we have

$$E\{Y_{k+1} \mid \mathcal{F}_k\} \leq Y_k - Z_k + W_k$$

- (c) There holds $\sum_{k=0}^{\infty} W_k < \infty$.

Then, $\sum_{k=0}^{\infty} Z_k < \infty$, and the sequence Y_k converges to a nonnegative random variable Y , with prob. 1.

• Can be used to show convergence of randomized subgradient methods with diminishing and dynamic stepsize rules.