

LECTURE 13

ALGORITHMS FOR CONVEX NONSMOOTH OPTIMIZATION

minimize $f(x)$
 $x \in \mathbb{R}^n$

$f: \mathbb{R}^n \rightarrow \mathbb{R}$, convex and nonsmooth
(Lipschitz but not continuously differentiable)

Subgradient method

(1) Choose $s_k \in \partial f(x^{(k)})$

(2) Choose a step-length $\alpha_k > 0$ s.t.

$$f\left(x^{(k)} + \alpha_k \left(\frac{-s_k}{\|s_k\|}\right)\right) < f(x^{(k)})$$

if possible

(3) $x^{(k+1)} \leftarrow x^{(k)} + \alpha_k \left(\frac{-s_k}{\|s_k\|}\right)$, $k \leftarrow k+1$

(4) Repeat 1-3

Let x_* be a ^(and global) local minimizer of f

$$\begin{aligned} \|x^{(k+1)} - x_*\|_2^2 &= \left\| x^{(k)} - x_* - \alpha_k \frac{s_k}{\|s_k\|} \right\|_2^2 \\ &= \|x^{(k)} - x_*\|_2^2 + \alpha_k^2 - \frac{2\alpha_k}{\|s_k\|} s_k^T (x^{(k)} - x_*) \end{aligned}$$

$$\leq \|x^{(k)} - x_*\|_2^2 + \alpha_k^2 + \frac{2\alpha_k}{\|s_k\|} \underbrace{(f(x_*) - f(x^{(k)}))}_{\leq 0}$$

$$\leq \|x^{(k)} - x_*\|_2^2 + \alpha_k^2$$

If $\alpha_k > 0$ are chosen such that $\alpha_k \neq 0$,
 $\sum_{k=1}^{\infty} \alpha_k^2 < \infty$

$$\left\{ \|x^{(k)} - x_*\|_2^2 \right\}$$

(i) is bounded,

(ii) indeed convergent.

THM

Let $f: \mathbb{R}^n \rightarrow \mathbb{R}$ have a global minimizer x_* .

Furthermore, ^{suppose} α_k are chosen such that

$$\sum_{k=1}^{\infty} \alpha_k = \infty \quad \text{and} \quad \sum_{k=1}^{\infty} \alpha_k^2 < \infty.$$

Then the subgradient method generates a sequence $\{x^{(k)}\}$ converging to a global minimizer x_* at a sublinear rate.

Cutting plane method

Based on the piece-wise linear model

$$\phi_k(x) := \max \{ l_j(x) \mid j=1, \dots, k \}$$

where

$$l_j(x) := f(x^{(j)}) + s_j^T (x - x^{(j)})$$

$$s_j \in \partial f(x^{(j)})$$

(1) Choose $x^{(1)}$

(2) Find the global minimizer $x^{(k+1)}$ of $\phi_k(x)$ on S (compact subset of \mathbb{R}^n containing a global min.)

(3) Define (Choose $s_{k+1} \in \partial f(x^{(k+1)})$)
$$\phi_{k+1}(x) := \max \{ \phi_k(x), f(x^{(k+1)}) + s_{k+1}^T (x - x^{(k+1)}) \}$$

(4) Let

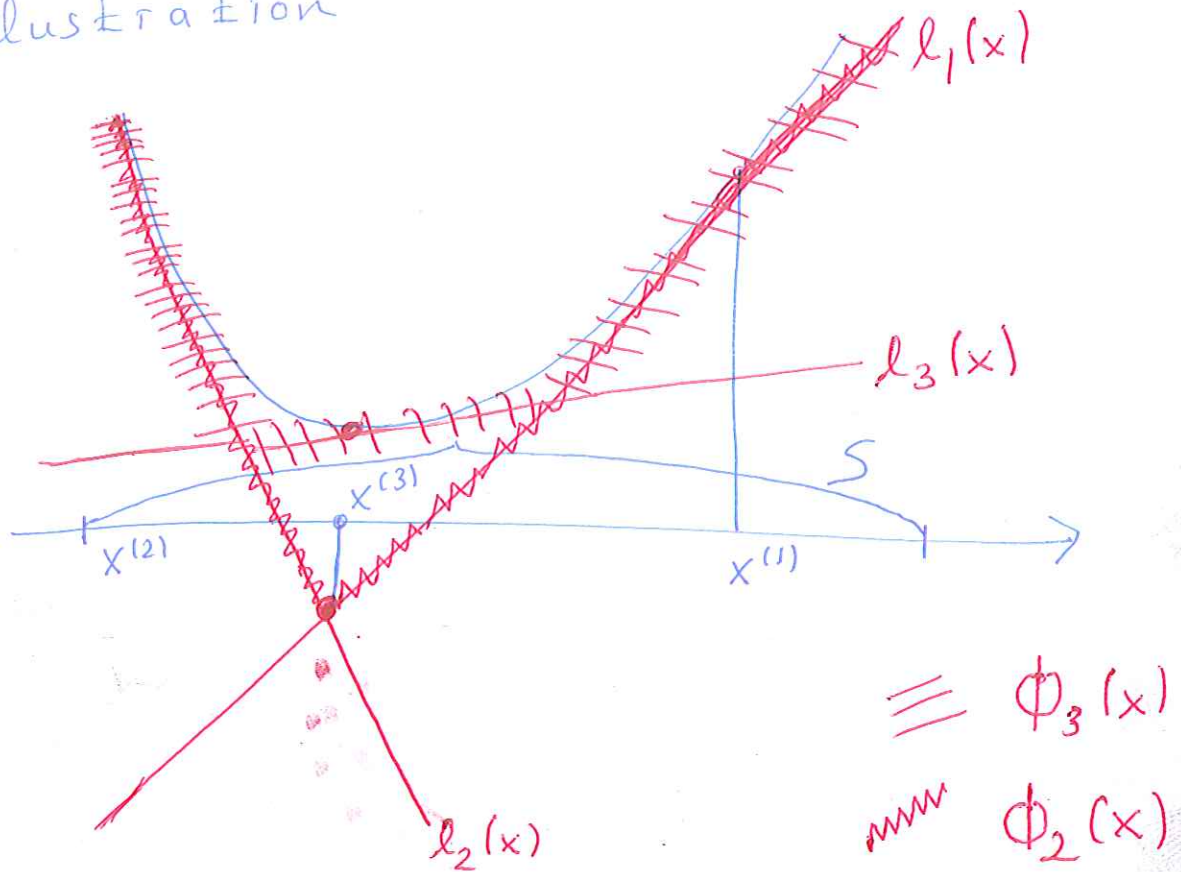
$$l_{k+1} := \min_{x \in S} \phi_k(x)$$

$$u_k := \min \{ f(x^{(j)}) \mid j=1, \dots, k \}$$

and $k \rightarrow k+1$

(5) Repeat 2-5.

Illustration



Notice

$$s_j \in \partial f(x_j) \implies$$

$$f(x) \geq \underbrace{f(x^{(j)}) + s_j^T (x - x^{(j)})}_{l_j(x)} \quad \forall x \implies$$

$$f(x) \geq \phi_k(x) \quad \forall x \implies$$

$$\min_{x \in S} f(x) \geq \min_{x \in S} \phi_k(x) = l_k$$

Moreover

$$\min_{x \in S} f(x) \leq \min \{f(x^{(j)}) \mid j=1, \dots, k\} = u_k$$

Also observe

(i) $l_k \leq l_{k+1}$ ($\{l_k\}$ is non-decreasing)

(ii) $u_k \geq u_{k+1}$ ($\{u_k\}$ is non-increasing) ④

THM

Let $f: \mathbb{R}^n \rightarrow \mathbb{R}$ have a global minimizer x_* .

Cutting plane method generates sequences

$\{l_k\}$ and $\{u_k\}$ such that

$$\lim_{k \rightarrow \infty} l_k = \lim_{k \rightarrow \infty} u_k = f(x_*).$$

(Penalized) Bundle Methods

Based on the model

$$P_k(x) := \phi_k(x) + \frac{\mu_k}{2} \|x - x^{(k)}\|_2^2$$

$\mu_k > 0$ - penalty parameter.

- (1) Choose $x^{(0)}$, $y^{(0)} \leftarrow x^{(0)}$ ($m \in \mathbb{N}$ fixed parameter)
- (2) Find the global minimizer $y^{(k+1)}$ of $P_k(x)$
- (3) $\delta_{k+1} \leftarrow f(x^{(k)}) - P_k(y^{(k+1)})$ (Note: $f(x^{(k)}) = P_k(x^{(k)}) \Rightarrow \delta_{k+1} \geq 0$)
- (4) If $f(x^{(k)}) - f(y^{(k+1)}) \geq m \cdot \delta_{k+1}$
 $x^{(k+1)} \leftarrow y^{(k+1)}$
 $K_S \leftarrow K_S \cup \{x^{(k+1)}\}$ (descent step)
else
 $x^{(k+1)} \leftarrow x^{(k)}$ (null step)
end

(5) Choose $s_{k+1} \in \partial f(y^{(k+1)})$, ^{also $\mu_{k+1} > 1$} and define

$$\phi_{k+1}(x) := \max \{ \phi_k(x), f(y^{(k+1)}) + s_{k+1}^T (x - y^{(k+1)}) \}$$

$$P_{k+1}(x) := \phi_{k+1}(x) + \frac{\mu_{k+1}}{2} \|x - x^{(k+1)}\|_2^2$$

and

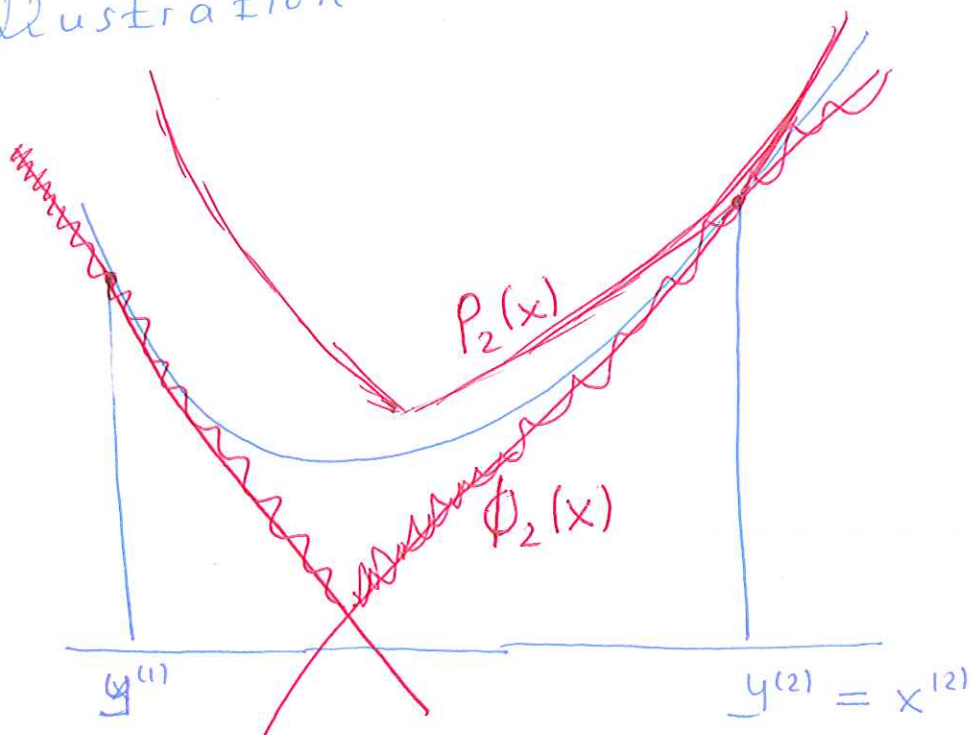
let $k \leftarrow k+1$

(6) Repeat 2-5

$\{y^{(k)}\}$ — sequence of global minimizers of $P_{k-1}(x)$

$\{x^{(k)}\}$ — sequence of descent points

Illustration



THM

Suppose $f: \mathbb{R}^n \rightarrow \mathbb{R}$ has a global minimizer, and K_s contains infinitely many integers. Let $f_* := \lim_{l \rightarrow \infty} f(x^{(k_l)})$ where $K_s = \{k_l\}$. We have $\sum_{k \in K_s} \delta_{k_l} \leq \frac{f(x^{(0)}) - f_*}{m}$.

Suppose $\{y^{(k)}\}$ is convergent. Then $\{x^{(k)}\}$ is also convergent. Thm above implies

$$\begin{aligned} \delta_{k_l} &\rightarrow 0 \text{ as } l \rightarrow \infty \\ \implies \lim_{k \rightarrow \infty} f(x^{(k)}) &= \lim_{k \rightarrow \infty} P_{k_l}(y^{(k_{l+1})}) \\ &= \lim_{k \rightarrow \infty} \phi_{k_l}(z^{(k_{l+1})}) \end{aligned}$$

where $z^{(k_{l+1})}$ is a global min of $\phi_{k_l}(x)$.

Consequently,

$$f(x^{(k)}) \geq \min_{x \in \mathbb{R}^n} f(x) \geq \phi_k(z^{(k_{l+1})})$$

$$\implies \lim_{k \rightarrow \infty} f(x^{(k)}) = \min_{x \in \mathbb{R}^n} f(x) = \lim_{k \rightarrow \infty} \phi_k(z^{(k_{l+1})})$$

$$\implies \lim_{k \rightarrow \infty} f(x^{(k)}) = \min_{x \in \mathbb{R}^n} f(x) = \lim_{k \rightarrow \infty} \phi_k(z^{(k)})$$

Proof of thm

For each l

$$f(x^{(k_l-1)}) - f(y^{(k_l)}) \geq m \cdot \delta_{k_l}$$

$$f(x^{(k_{l+1}-1)}) - f(y^{(k_{l+1})}) \geq m \cdot \delta_{k_{l+1}}$$

But notice that ~~$x^{(k_{l+1}-1)}$~~ $x^{(k_{l+1}-1)} = y^{(k_l)}$

~~and $x^{(k_l)}$~~

$$f(x^{(k_l-1)}) - f(y^{(k_{l+1})}) \geq m(\delta_{k_l} + \delta_{k_{l+1}})$$

$$\implies f(x^{(k_l-1)}) - f(y^{(k_{l+j})}) \geq m(\delta_{k_l} + \dots + \delta_{k_{l+j}})$$

Taking the limit as $j \rightarrow \infty$

$$f(x^{(0)}) - f_* \geq \sum_{k \in K_S} m \delta_k$$

□