

Corrections and Notes for  
CONVEX OPTIMIZATION ALGORITHMS

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- p. 11 (+4) Change “ $x_2 \in \mathfrak{R}^n$ ” to “ $x_2 \in \mathfrak{R}^m$ ”
- p. 11 (-12) Change “at  $f$  at  $x$ ” to “of  $f$  at  $x$ ”
- p. 11 (-3) Change “ $z \in \mathfrak{R}^n$ ” to “ $z \in \mathfrak{R}^m$ ”
- p. 15 (-5) Change “ $S$ ” to “ $S^\perp$ ”
- p. 46 (+5) Change the statement and proof of Prop. 1.5.3 as follows:

**Proposition 1.5.3:** Let  $f : Y \mapsto \mathfrak{R}$  be a function defined on a subset  $Y$  of  $\mathfrak{R}^n$ , and let  $X_i$ ,  $i = 1, \dots, m$ , be closed subsets of  $Y$  with nonempty intersection. Assume that  $f$  is Lipschitz continuous over  $Y$  with constant  $L$ , and that for some scalar  $\beta > 0$ , we have

$$\text{dist}(x; X_1 \cap \dots \cap X_m) \leq \beta \sum_{i=1}^m \text{dist}(x; X_i), \quad \forall x \in Y.$$

Let  $c$  be a scalar such that  $c > \beta L$ . Then the set of minima of  $f$  over  $\bigcap_{i=1}^m X_i$  coincides with the set of minima of

$$f(x) + c \sum_{i=1}^m \text{dist}(x; X_i)$$

over  $Y$ .

**Proof:** The proof is similar to the proof of Prop. 1.5.2, using the given additional condition to modify the main inequality. Denote  $F(x) = f(x) + c \sum_{i=1}^m \text{dist}(x; X_i)$  and  $X = X_1 \cap \dots \cap X_m$ . For a vector  $x \in Y$ , let  $\hat{x}_i$

denote a vector of  $X_i$  that is at minimum distance from  $x$ , and let  $\hat{x}$  denote a vector of  $X$  that is at minimum distance from  $x$ . If  $c > \beta L$ , we have for all  $x \in Y$ ,

$$\begin{aligned} F(x) &= f(x) + c \sum_{i=1}^m \|x - \hat{x}_i\| \\ &\geq f(\hat{x}) + (f(x) - f(\hat{x})) + \frac{c}{\beta} \|x - \hat{x}\| \\ &\geq f(\hat{x}) + \left(\frac{c}{\beta} - L\right) \|x - \hat{x}\| \\ &\geq F(\hat{x}), \end{aligned}$$

with strict inequality if  $x \neq \hat{x}$ . The proof now proceeds as in the proof of Prop. 1.5.2. **Q.E.D.**

**p. 92 (+8)** For clarity change

“More specifically, instead of the gradient sum

$$s_k = \sum_{\ell=0}^{m-1} \nabla f_{i_{k-\ell}}(x_{k-\ell}),$$

in Eq. (2.35), these methods use

$$\tilde{s}_k = \nabla f_{i_k}(x_k) - \nabla f_{i_k}(\tilde{x}_k) + \sum_{\ell=0}^{m-1} \nabla f_{i_{k-\ell}}(\tilde{x}_k),$$

where  $\tilde{x}_k$  is the most recent point where the full gradient has been calculated. To calculate  $\tilde{s}_k$  one only needs to compute the difference of the two gradients

$$\nabla f_{i_k}(x_k) - \nabla f_{i_k}(\tilde{x}_k)$$

and add it to the full gradient  $\sum_{\ell=0}^{m-1} \nabla f_{i_{k-\ell}}(\tilde{x}_k)$ .”

to

“For an example, instead of the gradient sum

$$s_k = \sum_{\ell=0}^{m-1} \nabla f_{i_{k-\ell}}(x_{k-\ell}),$$

in Eq. (2.35), such a method may use  $\tilde{s}_k$ , updated according to

$$\tilde{s}_k = \nabla f_{i_k}(x_k) - \nabla f_{i_k}(\tilde{x}_k) + \tilde{s}_{k-1},$$

where  $\tilde{s}_0$  is the full gradient computed at the start of the current cycle, and  $\tilde{x}_k$  is the point at which this full gradient has been calculated. Thus to obtain  $\tilde{s}_k$  one only needs to compute the difference of the two gradients

$$\nabla f_{i_k}(x_k) - \nabla f_{i_k}(\tilde{x}_k)$$

and add it to the current approximation of the full gradient  $\tilde{s}_{k-1}$ .”

**p. 113 (-13)** Change “Lagrangian” to “Lagrangian method”

**p. 206 (+13)** Change “ $\tilde{\lambda} \in \partial f(x_{\tilde{\lambda}})$ ” to “ $\tilde{\lambda} \in \partial f(x)$ ”

**p. 255 (-5)** Change “ $-\|\bar{x}_1 - \bar{x}_2\|^2$ ” to “ $-\frac{1}{c}\|\bar{x}_1 - \bar{x}_2\|^2$ ”

**p. 283 (+15)** Change “(5.83)” to “(5.87)”

**p. 283 (+18)** Change “ $Ax = z$ ” to “ $Ax + Bz = d$ ”

**p. 284 (+2)** Change “ $\lambda_{k+1}^1$ ” and “ $\lambda_{k+1}^m$ ” to “ $\lambda_k^1$ ” and “ $\lambda_k^m$ ”, respectively

**p. 293 (+2)** Change “Example 3.4” to “Section 3.4, Example 3.4”

**p. 293 (+4)** Change Eq. (5.107) and the following line to

$$\lambda_{k+1}^j = \lambda_k^j + \frac{c}{m_j} \left( \sum_{i=1}^m A_{ji} x_{k+1}^i - b^j \right), \quad j = 1, \dots, r, \quad (5.107)$$

where  $A_{ji}$ ,  $b^j$ , and  $r$  are the components and row dimension of  $A_i$  and  $b$ , respectively, and  $m_j$  is the number of

**p. 298 (+8)** Change “ $z \in \mathfrak{R}^n$ ” to “ $z \in \mathfrak{R}^m$ ”

**p. 299 (-5)** Change “ $\lambda - cv$ ” to “ $\lambda + cv$ ”

**p. 300 (-6)** Change “ $f_1$  (or  $f_2$ , respectively)” to “ $f_2$  (or  $f_1$ , respectively)”

**p. 308 (-9)** Change “ $y \in \mathfrak{R}^n$ ” to “ $y \in X$ ”

**p. 314 (+9 to +22)** Replace the part of the proof starting just after the equation  $\phi(x) = f(x) - \frac{\sigma}{2}\|x\|^2$ . and ending just before the statement “Using the expression (6.25) ...” with the following:

We will show that  $\nabla\phi$ , which is given by

$$\nabla\phi(x) = \nabla f(x) - \sigma x, \quad (6.25)$$

is Lipschitz continuous with constant  $L - \sigma$ . To this end, based on the equivalence of statements (i) and (v) of Exercise 6.1, it is sufficient to show that

$$(\nabla\phi(x) - \nabla\phi(y))'(x - y) \leq (L - \sigma)\|x - y\|^2, \quad \forall x, y \in \mathfrak{R}^n,$$

or, using the expression (6.25) for  $\nabla\phi$ ,

$$(\nabla f(x) - \nabla f(y) - \sigma(x - y))'(x - y) \leq (L - \sigma)\|x - y\|^2, \quad \forall x, y \in \mathfrak{R}^n.$$

This relation is equivalently written as

$$(\nabla f(x) - \nabla f(y))'(x - y) \leq L\|x - y\|^2, \quad \forall x, y \in \mathfrak{R}^n,$$

and is true by (iii) of part (a).

Having shown that  $\nabla\phi$  is Lipschitz continuous with constant  $L - \sigma$ , we apply (ii) of part (a) to the function  $\phi$  and obtain

$$(\nabla\phi(x) - \nabla\phi(y))'(x - y) \geq \frac{1}{L - \sigma} \|\nabla\phi(x) - \nabla\phi(y)\|^2.$$

**p. 316 (-17)** Change “ $\nabla f(\bar{x}) = 0$ ” to “the optimality condition  $\nabla f(\bar{x})'(x - \bar{x}) \geq 0$ , for all  $x \in X$ ”

**p. 318 (-13)** Change “ $\beta^m$ ” to “ $\sigma\beta^m$ ”

**p. 323 (+7)** Change “gradient [cf. Eq. (6.6)]” to “gradient within  $\mathfrak{R}^n$ ”

**p. 323 (+12)** Change “ $\beta_k \in (0, 1)$ ” to “ $\beta_k \in [0, 1)$ ”

**p. 323 (-11)** Change “ $\theta_0 = \theta_1 \in (0, 1]$ ” to “ $\theta_{-1} = \theta_0 = 1$ ”

**p. 323 (-10)** In Eq. (6.33) add the additional condition  $\theta_k \leq 2/(k + 2)$ , which is used in the proof of Prop. 6.2.1 [p. 326, (-16)]. So Eq. (6.33) should now read

$$\frac{1 - \theta_{k+1}}{\theta_{k+1}^2} \leq \frac{1}{\theta_k^2}, \quad \theta_k \leq \frac{2}{k + 2}, \quad k = 0, 1, \dots \quad (6.33)$$

**p. 323 (-1)** Change “ $x_{k+1} = P_X(x_k - \alpha\nabla f(x_k))$ ,” to “ $x_{k+1} = P_X(y_k - \alpha\nabla f(y_k))$ ,”

**p. 324 (-8)** Change “ $\nabla f$  satisfies the Lipschitz condition (6.6)” to “ $\nabla f$  is Lipschitz continuous within  $\mathfrak{R}^n$  with Lipschitz constant  $L$ ,”

**p. 336 (-16)** Change “ $x \in \mathfrak{R}^n$ ” to “ $x \in \mathfrak{R}^m$ ”

**p. 365 (-5)** Change the statement of Prop. 6.4.9 in accordance with the correction to Prop. 1.5.3.

**p. 383 (+10)** Change “whwew” to “where”

**p. 428 (-19)** Change “3.3” to “Section 3.3”

**p. 437 (+13)** Change “Note:” to “Notes: If Eq. (6.238) holds with  $\gamma = 1$  it holds for all  $\gamma \in (1, 2)$ , so this exercise shows arbitrarily fast superlinear convergence for the case of a sharp minimum, even when  $X^*$  contains multiple points (cf. Exercise 6.4).”

**p. 461 (+7)** Change “ $\beta_k \geq 0, \gamma_k > 0$ ” to “ $0 \leq \beta_k, 0 < \gamma_k \leq 1$ ”

**p. 471 (-12)** Change “ $\text{dom}(f)$ ” to “ $\mathfrak{R}^n$ ”

**p. 485 (-7,-8)** Erase these two lines

**p. 488 (+8)** Change “By the Conjugacy Theorem [Prop. 1.6.1(c)]  $C^*$  is equal to  $\text{cl}\delta_C$ . Thus the polar cone of  $C^*$  is  $\text{cl}(C)$ .” to “By the Conjugacy Theorem [Prop. 1.6.1(d)], the polar cone of  $C^*$  is  $\text{cl}(C)$ .”

**p. 511 (+3)** Change “ $z \in \mathfrak{R}^n$ ” to “ $z \in \mathfrak{R}^m$ ”