

Supplemental Material for 04/23 Book Reading Seminar

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Abstract

This is the supplemental material for the book reading seminar.
Please refer to the textbook and the whiteboard for the main content.
If necessary, please also refer to the [repository](#).

2.2

2.2.1

Lemma 1.19: For any $f \in C^2(\mathbb{R}^n)$, and any $x, y \in \mathbb{R}^n$, there exists $z \in [x, y]$ s.t.

$$f(y) = f(x) + \nabla f(x)^\top (y - x) + \frac{1}{2}(y - x)^\top \nabla^2 f(z)(y - x).$$

3 Anatomy of a lower bound

In this section we present a generic approach to proving lower bounds for optimization algorithms. The basic techniques we use are well-known and applied extensively in the literature on lower bounds for convex optimization [4, 35, 37, 45]. However, here we generalize and abstract away these techniques, showing how they apply to high-order methods, non-convex functions, and various optimization goals (e.g. ϵ -stationarity, ϵ -optimality).

3.1 Zero-chains

Nesterov [37, Chapter 2.1.2] proves lower bounds for smooth convex optimization problems using the “chain-like” quadratic function

$$f(x) := \frac{1}{2}(x_1 - 1)^2 + \frac{1}{2} \sum_{i=1}^{d-1} (x_i - x_{i+1})^2, \quad (9)$$

which he calls the “worst function in the world.” The important property of f is that for every $i \in [d]$, $\nabla_i f(x) = 0$ whenever $x_{i-1} = x_i = x_{i+1} = 0$ (with $x_0 := 1$ and $x_{d+1} := 0$). Thus, if we “know” only the first $t - 1$ coordinates of f , i.e. are able to query only vectors x such that $x_t = x_{t+1} = \dots = x_d = 0$, then any x we query satisfies $\nabla_s f(x) = 0$ for $s > t$; we only “discover” a single new coordinate t . We generalize this chain structure to higher-order derivatives as follows.

Figure 1: [15] から引用

参考文献の [15] は、[Math. Program.](#) の 2020 年の論文。

2.3

$A \succ O \iff \exists$ 直交行列 Q と対角行列 D s.t. $A = QDQ^\top$

2.4

Ex.2.15

一般に、

$$\begin{aligned} f(y) &\geq f(x) + \langle \nabla f(x), y - x \rangle + \frac{\mu}{2} \|y - x\|_2^2 \\ f(x) &\geq f(y) + \langle \nabla f(y), x - y \rangle + \frac{\mu}{2} \|y - x\|_2^2 \\ 0 &\geq \langle \nabla f(x) - \nabla f(y), y - x \rangle + \mu \|y - x\|_2^2 \end{aligned}$$

なので、

$$\begin{aligned} \langle \nabla f(x) - \nabla f(y), x - y \rangle &\geq \mu \|y - x\|_2^2 \\ \langle \nabla f(x), x - x^* \rangle &\geq \mu \|x - x^*\|_2^2 \end{aligned}$$

である。

Lemma 2.10 より、

$$\begin{aligned} \|x^{(k+1)} - x^*\|_2^2 &= \|x^{(k)} - x^*\|_2^2 - \frac{1}{L} \langle \nabla f(x^{(k)}), x^{(k)} - x^* \rangle + \frac{1}{L^2} \|\nabla f(x^{(k)})\|_2^2 \\ &= \|x^{(k)} - x^*\|_2^2 - \frac{1}{L} \langle \nabla f(x^{(k)}), x^{(k)} - x^* \rangle \\ &\quad - \frac{1}{L} \left(\langle \nabla f(x^{(k)}), x^{(k)} - x^* \rangle - \frac{1}{L} \|\nabla f(x^{(k)})\|_2^2 \right) \\ &\leq \|x^{(k)} - x^*\|_2^2 - \frac{\mu}{L} \|x^{(k)} - x^*\|_2^2 \end{aligned}$$

途中でも Lemma 2.10 の証明中の式を使っている。

Ex.2.16

特段の名前はついてない? 自信なし。

Ex.2.17

[PL 不等式](#)

Ex.2.18

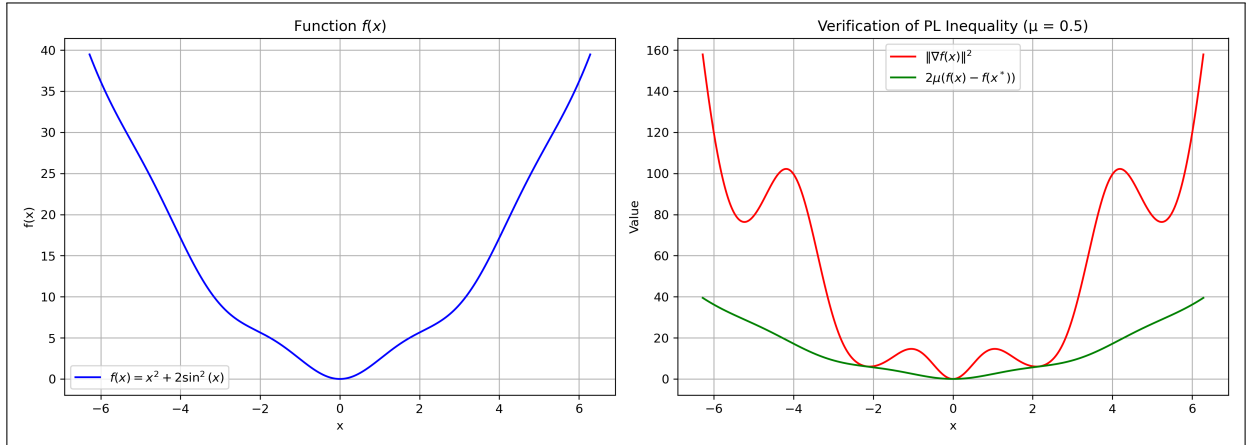


Figure 2: PL 不等式を満たすが非凸な例

2.5

直線探索

Ex.2.20

$$\begin{aligned}
 & -c_1 h \|\nabla f(x)\|_2^2 \\
 & \geq f(x - h\nabla f(x)) - f(x) \\
 & \geq \nabla f(x)^\top ((x - h\nabla f(x)) - x) + \frac{\mu}{2} \|x - h\nabla f(x) - x\|_2^2 \\
 & = -h \|\nabla f(x)\|_2^2 + \frac{\mu}{2} h^2 \|\nabla f(x)\|_2^2 \\
 \therefore \quad & -c_1 h \geq -h + \frac{\mu}{2} h^2 \iff \frac{2(1-c)}{\mu} \geq h
 \end{aligned}$$

$$\begin{aligned}
 & c_2 \|\nabla f(x)\|_2^2 \\
 & \geq \nabla f(x)^\top \nabla f(x - h\nabla f(x)) \\
 & = \nabla f(x)^\top (\nabla f(x) - \nabla^2 f(z)(h\nabla f(x))) \\
 & = \|\nabla f(x)\|_2^2 - h \nabla f(x)^\top \nabla^2 f(z) \nabla f(x) \\
 \therefore c_2 \geq & 1 - h \lambda_{\max}(\nabla^2 f(z)) \geq 1 - hL \iff h \leq \frac{1-c_2}{L}
 \end{aligned}$$

この証明は Taylor 展開と積分の平均値の定理を経由して考えないと誤りかも

2.6

Ex.2.23

不明。私の頭が悪いだけかも知れません。

$h(y/\alpha)$ と y が 0 を中心にスケールされているのが謎。 x が中心では？

Projected Gradient Descent / Proximal Gradient Descent

参考

Other assumptions

参考文献 [10] Iterative hard thresholding for compressed sensing

参考文献 [10] の参考文献 [1] Iterative Thresholding for Sparse Approximations

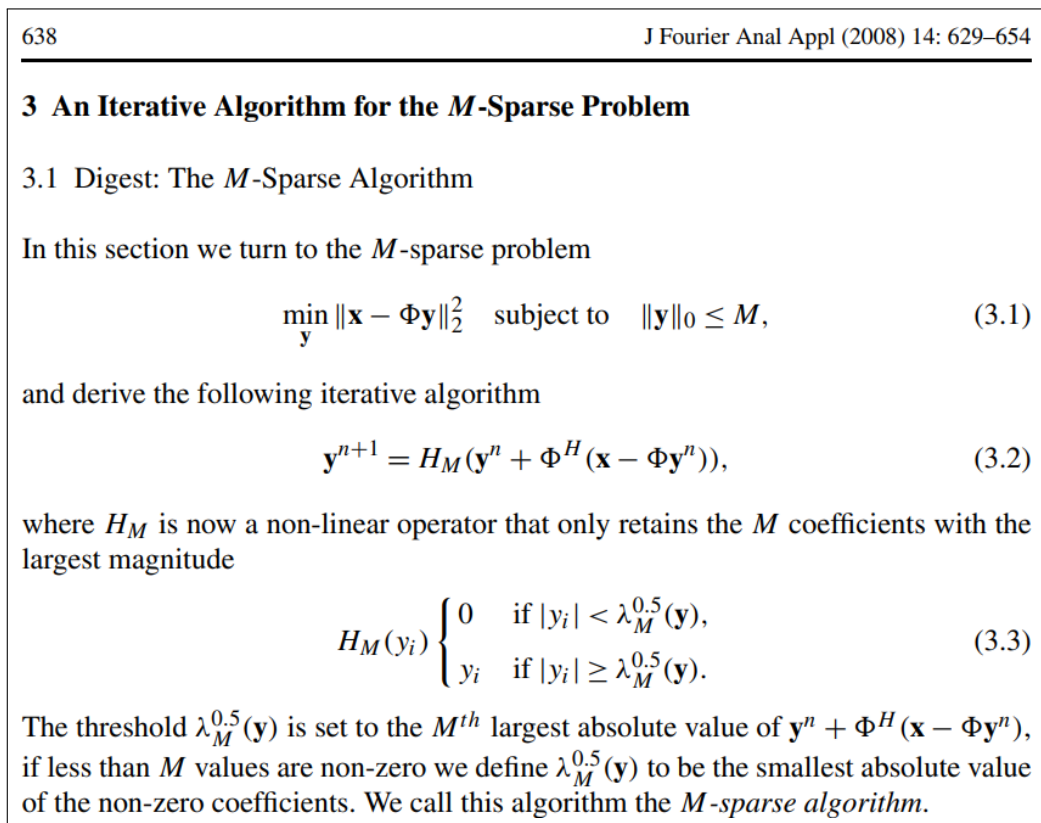


Figure 3: Iterative Hard Thresholding

3

もしここまで到達してしまっただけですいません、お詫びします。準備不足です。質問とか大事な部分の深掘りとかで時間を使います。

Appendix

Listing 1: PL

```
import numpy as np
import matplotlib.pyplot as plt
import os

os.chdir(os.path.dirname(os.path.abspath(__file__)))

x = np.linspace(-2 * np.pi, 2 * np.pi, 1000)

f = x**2 + 2 * np.sin(x) ** 2
grad_f = 2 * x + 2 * np.sin(2 * x)

mu = 0.5
lhs = grad_f**2
rhs = 2 * mu * f

fig, axes = plt.subplots(1, 2, figsize=(14, 5))

axes[0].plot(x, f, label=r"$f(x) = x^2 + 2\sin^2(x)$", color="b")
axes[0].set_title("Function  $f(x)$ ")
axes[0].set_xlabel("x")
axes[0].set_ylabel("f(x)")
axes[0].legend()
axes[0].grid(True)

axes[1].plot(x, lhs, label=r"$\|\nabla f(x)\|^2$", color="red")
axes[1].plot(x, rhs, label=r"$2\mu(f(x) - f(x^*))$", color="g")
axes[1].set_title(f"Verification of PL Inequality  $\mu$  ( $\mu = \{\mu\}$ )")
axes[1].set_xlabel("x")
axes[1].set_ylabel("Value")
axes[1].legend()
axes[1].grid(True)

plt.tight_layout()
# plt.show()
plt.savefig("PL.png", dpi=300, bbox_inches="tight")
```