



**Lower bounds for gradient descent.
Accelerated gradient descent. Momentum.
Nesterov's acceleration**

Daniil Merkulov

Optimization for ML. Faculty of Computer Science. HSE University

Recap of Gradient Descent convergence

Gradient Descent:

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

$$x^{k+1} = x^k - \alpha^k \nabla f(x^k)$$

convex (non-smooth)	smooth (non-convex)	smooth & convex	smooth & strongly convex (or PL)
$f(x^k) - f^* \sim \mathcal{O}\left(\frac{1}{\sqrt{k}}\right)$ $k_\varepsilon \sim \mathcal{O}\left(\frac{1}{\varepsilon^2}\right)$	$\ \nabla f(x^k)\ ^2 \sim \mathcal{O}\left(\frac{1}{k}\right)$ $k_\varepsilon \sim \mathcal{O}\left(\frac{1}{\varepsilon}\right)$	$f(x^k) - f^* \sim \mathcal{O}\left(\frac{1}{k}\right)$ $k_\varepsilon \sim \mathcal{O}\left(\frac{1}{\varepsilon}\right)$	$\ x^k - x^*\ ^2 \sim \mathcal{O}\left(\left(1 - \frac{\mu}{L}\right)^k\right)$ $k_\varepsilon \sim \mathcal{O}\left(\mu \log \frac{1}{\varepsilon}\right)$

$$\begin{aligned} f(x) - f^* &= \varepsilon \\ \varepsilon &= \frac{1}{k} \\ k &= \frac{1}{\varepsilon} \end{aligned}$$

Recap of Gradient Descent convergence

Gradient Descent:

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

$$x^{k+1} = x^k - \alpha^k \nabla f(x^k)$$

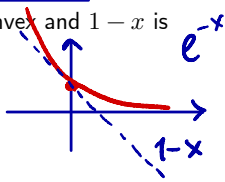
convex (non-smooth)	smooth (non-convex)	smooth & convex	smooth & strongly convex (or PL)
$f(x^k) - f^* \sim \mathcal{O}\left(\frac{1}{\sqrt{k}}\right)$	$\ \nabla f(x^k)\ ^2 \sim \mathcal{O}\left(\frac{1}{k}\right)$	$f(x^k) - f^* \sim \mathcal{O}\left(\frac{1}{k}\right)$	$\ x^k - x^*\ ^2 \sim \mathcal{O}\left(\left(1 - \frac{\mu}{L}\right)^k\right)$
$k_\varepsilon \sim \mathcal{O}\left(\frac{1}{\varepsilon^2}\right)$	$k_\varepsilon \sim \mathcal{O}\left(\frac{1}{\varepsilon}\right)$	$k_\varepsilon \sim \mathcal{O}\left(\frac{1}{\varepsilon}\right)$	$k_\varepsilon \sim \mathcal{O}\left(\frac{1}{\mu} \log \frac{1}{\varepsilon}\right)$

For smooth strongly convex we have:

$$f(x^k) - f^* \leq \left(1 - \frac{\mu}{L}\right)^k (f(x^0) - f^*).$$

Note also, that for any x , since e^{-x} is convex and $1 - x$ is its tangent line at $x = 0$, we have:

$$1 - x \leq e^{-x}$$



Recap of Gradient Descent convergence

Gradient Descent:

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

$$x^{k+1} = x^k - \alpha^k \nabla f(x^k)$$

convex (non-smooth)	smooth (non-convex)	smooth & convex	smooth & strongly convex (or PL)
$f(x^k) - f^* \sim \mathcal{O}\left(\frac{1}{\sqrt{k}}\right)$	$\ \nabla f(x^k)\ ^2 \sim \mathcal{O}\left(\frac{1}{k}\right)$	$f(x^k) - f^* \sim \mathcal{O}\left(\frac{1}{k}\right)$	$\ x^k - x^*\ ^2 \sim \mathcal{O}\left(\left(1 - \frac{\mu}{L}\right)^k\right)$
$k_\varepsilon \sim \mathcal{O}\left(\frac{1}{\varepsilon^2}\right)$	$k_\varepsilon \sim \mathcal{O}\left(\frac{1}{\varepsilon}\right)$	$k_\varepsilon \sim \mathcal{O}\left(\frac{1}{\varepsilon}\right)$	$k_\varepsilon \sim \mathcal{O}\left(\kappa \log \frac{1}{\varepsilon}\right)$

For smooth strongly convex we have:

$$f(x^k) - f^* \leq \left(1 - \frac{\mu}{L}\right)^k (f(x^0) - f^*).$$

Note also, that for any x , since e^{-x} is convex and $1 - x$ is its tangent line at $x = 0$, we have:

$$1 - x \leq e^{-x}$$

Finally we have

$$1 - \frac{\mu}{L} \leq \exp\left(-\frac{\mu}{L}\right)$$

$$\begin{aligned} \varepsilon &= f(x^{k_\varepsilon}) - f^* \leq \left(1 - \frac{\mu}{L}\right)^{k_\varepsilon} (f(x^0) - f^*) \\ &\leq \exp\left(-k_\varepsilon \frac{\mu}{L}\right) (f(x^0) - f^*) \end{aligned}$$

$$k_\varepsilon \geq \kappa \log \frac{f(x^0) - f^*}{\varepsilon} = \mathcal{O}\left(\kappa \log \frac{1}{\varepsilon}\right)$$

Recap of Gradient Descent convergence

Gradient Descent:

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

$$x^{k+1} = x^k - \alpha^k \nabla f(x^k)$$

convex (non-smooth)	smooth (non-convex)	smooth & convex	smooth & strongly convex (or PL)
$f(x^k) - f^* \sim \mathcal{O}\left(\frac{1}{\sqrt{k}}\right)$	$\ \nabla f(x^k)\ ^2 \sim \mathcal{O}\left(\frac{1}{k}\right)$	$f(x^k) - f^* \sim \mathcal{O}\left(\frac{1}{k}\right)$	$\ x^k - x^*\ ^2 \sim \mathcal{O}\left(\left(1 - \frac{\mu}{L}\right)^k\right)$
$k_\varepsilon \sim \mathcal{O}\left(\frac{1}{\varepsilon^2}\right)$	$k_\varepsilon \sim \mathcal{O}\left(\frac{1}{\varepsilon}\right)$	$k_\varepsilon \sim \mathcal{O}\left(\frac{1}{\varepsilon}\right)$	$k_\varepsilon \sim \mathcal{O}\left(\kappa \log \frac{1}{\varepsilon}\right)$

For smooth strongly convex we have:

$$f(x^k) - f^* \leq \left(1 - \frac{\mu}{L}\right)^k (f(x^0) - f^*).$$

Note also, that for any x , since e^{-x} is convex and $1 - x$ is its tangent line at $x = 0$, we have:

$$1 - x \leq e^{-x}$$

Finally we have

$$\varepsilon = f(x^{k_\varepsilon}) - f^* \leq \left(1 - \frac{\mu}{L}\right)^{k_\varepsilon} (f(x^0) - f^*)$$

$$\leq \exp\left(-k_\varepsilon \frac{\mu}{L}\right) (f(x^0) - f^*)$$

$$k_\varepsilon \geq \kappa \log \frac{f(x^0) - f^*}{\varepsilon} = \mathcal{O}\left(\kappa \log \frac{1}{\varepsilon}\right)$$

Question: Can we do faster, than this using the first-order information?

Recap of Gradient Descent convergence

Gradient Descent:

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

$$x^{k+1} = x^k - \alpha^k \nabla f(x^k)$$

convex (non-smooth)	smooth (non-convex)	smooth & convex	smooth & strongly convex (or PL)
$f(x^k) - f^* \sim \mathcal{O}\left(\frac{1}{\sqrt{k}}\right)$	$\ \nabla f(x^k)\ ^2 \sim \mathcal{O}\left(\frac{1}{k}\right)$	$f(x^k) - f^* \sim \mathcal{O}\left(\frac{1}{k}\right)$	$\ x^k - x^*\ ^2 \sim \mathcal{O}\left(\left(1 - \frac{\mu}{L}\right)^k\right)$
$k_\varepsilon \sim \mathcal{O}\left(\frac{1}{\varepsilon^2}\right)$	$k_\varepsilon \sim \mathcal{O}\left(\frac{1}{\varepsilon}\right)$	$k_\varepsilon \sim \mathcal{O}\left(\frac{1}{\varepsilon}\right)$	$k_\varepsilon \sim \mathcal{O}\left(\kappa \log \frac{1}{\varepsilon}\right)$

For smooth strongly convex we have:

$$f(x^k) - f^* \leq \left(1 - \frac{\mu}{L}\right)^k (f(x^0) - f^*).$$

Note also, that for any x , since e^{-x} is convex and $1 - x$ is its tangent line at $x = 0$, we have:

$$1 - x \leq e^{-x}$$

Finally we have

$$\varepsilon = f(x^{k_\varepsilon}) - f^* \leq \left(1 - \frac{\mu}{L}\right)^{k_\varepsilon} (f(x^0) - f^*)$$

$$\leq \exp\left(-k_\varepsilon \frac{\mu}{L}\right) (f(x^0) - f^*)$$

$$k_\varepsilon \geq \kappa \log \frac{f(x^0) - f^*}{\varepsilon} = \mathcal{O}\left(\kappa \log \frac{1}{\varepsilon}\right)$$

Question: Can we do faster, than this using the first-order information? **Yes, we can.**

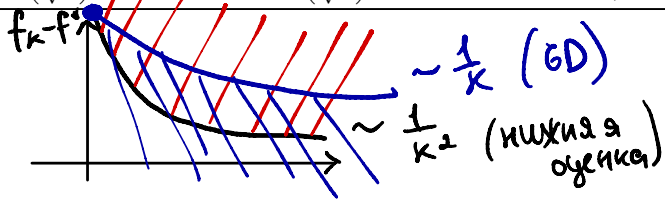
Lower bounds

Lower bounds

НИЖНИЕ
ОЦЕНКИ

Для заданного класса функций
 $\exists$ такая $f(x) \in$, что $\forall$ метод 1 порядка
 будет сходиться не быстрее

convex (non-smooth)	smooth (non-convex) ¹	smooth & convex	smooth & strongly convex (or PL)
$\mathcal{O}\left(\frac{1}{\sqrt{k}}\right)$	$\mathcal{O}\left(\frac{1}{k^2}\right)$	$\mathcal{O}\left(\frac{1}{k^2}\right)$	$\mathcal{O}\left(\left(1 - \sqrt{\frac{\mu}{L}}\right)^k\right)$
$k_\epsilon \sim \mathcal{O}\left(\frac{1}{\epsilon^2}\right)$	$k_\epsilon \sim \mathcal{O}\left(\frac{1}{\sqrt{\epsilon}}\right)$	$k_\epsilon \sim \mathcal{O}\left(\frac{1}{\sqrt{\epsilon}}\right)$	$k_\epsilon \sim \mathcal{O}\left(\sqrt{n} \log \frac{1}{\epsilon}\right)$



¹Carmon, Duchi, Hinder, Sidford, 2017

²Nemirovski, Yudin, 1979

Black box iteration

The iteration of gradient descent:

$$\begin{aligned}x^{k+1} &= x^k - \alpha^k \nabla f(x^k) \\&= x^{k-1} - \alpha^{k-1} \nabla f(x^{k-1}) - \alpha^k \nabla f(x^k) \\&\vdots \\&= x^0 - \sum_{i=0}^k \alpha^{k-i} \nabla f(x^{k-i})\end{aligned}$$

Black box iteration

The iteration of gradient descent:

$$\begin{aligned}x^{k+1} &= x^k - \alpha^k \nabla f(x^k) \\&= x^{k-1} - \alpha^{k-1} \nabla f(x^{k-1}) - \alpha^k \nabla f(x^k) \\&\vdots \\&= x^0 - \sum_{i=0}^k \alpha^{k-i} \nabla f(x^{k-i})\end{aligned}$$

Consider a family of first-order methods, where

$$\begin{aligned}x^{k+1} &\in x^0 + \text{span} \{ \nabla f(x^0), \nabla f(x^1), \dots, \nabla f(x^k) \} && f - \text{smooth} \\x^{k+1} &\in x^0 + \text{span} \{ g_0, g_1, \dots, g_k \}, \text{ where } g_i \in \partial f(x^i) && f - \text{non-smooth}\end{aligned}\tag{1}$$

Black box iteration

The iteration of gradient descent:

$$\begin{aligned}x^{k+1} &= x^k - \alpha^k \nabla f(x^k) \\&= x^{k-1} - \alpha^{k-1} \nabla f(x^{k-1}) - \alpha^k \nabla f(x^k) \\&\vdots \\&= x^0 - \sum_{i=0}^k \alpha^{k-i} \nabla f(x^{k-i})\end{aligned}$$

Consider a family of first-order methods, where

$$\begin{aligned}x^{k+1} &\in x^0 + \text{span} \{ \nabla f(x^0), \nabla f(x^1), \dots, \nabla f(x^k) \} && f - \text{smooth} \\x^{k+1} &\in x^0 + \text{span} \{ g_0, g_1, \dots, g_k \}, \text{ where } g_i \in \partial f(x^i) && f - \text{non-smooth}\end{aligned} \tag{1}$$

In order to construct a lower bound, we need to find a function f from corresponding class such that any method from the family 1 will work at least as slow as the lower bound.

Smooth case

huxhsg oyekka

Theorem

There exists a function f that is L -smooth and convex such that any method 1 satisfies for any $k : 1 \leq k \leq \frac{n-1}{2}$:

$$f(x^k) - f^* \geq \frac{3L\|x^0 - x^*\|_2^2}{32(k+1)^2}$$

$$\sim \frac{1}{k^2}$$

Smooth case

Theorem

There exists a function f that is L -smooth and convex such that any method 1 satisfies for any $k : 1 \leq k \leq \frac{n-1}{2}$:

$$f(x^k) - f^* \geq \frac{3L\|x^0 - x^*\|_2^2}{32(k+1)^2}$$

- No matter what gradient method you provide, there is always a function f that, when you apply your gradient method on minimizing such f , the convergence rate is lower bounded as $\mathcal{O}\left(\frac{1}{k^2}\right)$.

Smooth case

Theorem

There exists a function f that is L -smooth and convex such that any method 1 satisfies for any $k : 1 \leq k \leq \frac{n-1}{2}$:

$$f(x^k) - f^* \geq \frac{3L\|x^0 - x^*\|_2^2}{32(k+1)^2}$$

- No matter what gradient method you provide, there is always a function f that, when you apply your gradient method on minimizing such f , the convergence rate is lower bounded as $\mathcal{O}\left(\frac{1}{k^2}\right)$.
- The key to the proof is to explicitly build a special function f .

Smooth case

Theorem

There exists a function f that is L -smooth and convex such that any method 1 satisfies for any $k : 1 \leq k \leq \frac{n-1}{2}$:

$$f(x^k) - f^* \geq \frac{3L\|x^0 - x^*\|_2^2}{32(k+1)^2}$$

- No matter what gradient method you provide, there is always a function f that, when you apply your gradient method on minimizing such f , the convergence rate is lower bounded as $\mathcal{O}\left(\frac{1}{k^2}\right)$.
- The key to the proof is to explicitly build a special function f .
- Note, that this bound $\mathcal{O}\left(\frac{1}{k^2}\right)$ does not match the rate of gradient descent $\mathcal{O}\left(\frac{1}{k}\right)$. Two options possible:

Smooth case

Theorem

There exists a function f that is L -smooth and convex such that any method 1 satisfies for any $k : 1 \leq k \leq \frac{n-1}{2}$:

$$f(x^k) - f^* \geq \frac{3L\|x^0 - x^*\|_2^2}{32(k+1)^2}$$

- No matter what gradient method you provide, there is always a function f that, when you apply your gradient method on minimizing such f , the convergence rate is lower bounded as $\mathcal{O}\left(\frac{1}{k^2}\right)$.
- The key to the proof is to explicitly build a special function f .
- Note, that this bound $\mathcal{O}\left(\frac{1}{k^2}\right)$ does not match the rate of gradient descent $\mathcal{O}\left(\frac{1}{k}\right)$. Two options possible:
 - a. The lower bound is not tight.

Smooth case



i Theorem

There exists a function f that is L -smooth and convex such that any method 1 satisfies for any $k : 1 \leq k \leq \frac{n-1}{2}$:

$$f(x^k) - f^* \geq \frac{3L\|x^0 - x^*\|_2^2}{32(k+1)^2}$$

$$\geq \sim \frac{1}{k}$$

- No matter what gradient method you provide, there is always a function f that, when you apply your gradient method on minimizing such f , the convergence rate is lower bounded as $\mathcal{O}\left(\frac{1}{k^2}\right)$.
- The key to the proof is to explicitly build a special function f .
- Note, that this bound $\mathcal{O}\left(\frac{1}{k^2}\right)$ does not match the rate of gradient descent $\mathcal{O}\left(\frac{1}{k}\right)$. Two options possible:
 - a. The lower bound is not tight.
 - b. The gradient method is not optimal for this problem.

Smooth case

Theorem

There exists a function f that is L -smooth and convex such that any method 1 satisfies for any $k : 1 \leq k \leq \frac{n-1}{2}$:

$$f(x^k) - f^* \geq \frac{3L\|x^0 - x^*\|_2^2}{32(k+1)^2}$$

- No matter what gradient method you provide, there is always a function f that, when you apply your gradient method on minimizing such f , the convergence rate is lower bounded as $\mathcal{O}\left(\frac{1}{k^2}\right)$.
- The key to the proof is to explicitly build a special function f .
- Note, that this bound $\mathcal{O}\left(\frac{1}{k^2}\right)$ does not match the rate of gradient descent $\mathcal{O}\left(\frac{1}{k}\right)$. Two options possible:
 - a. The lower bound is not tight.
 - b. **The gradient method is not optimal for this problem.**

Nesterov's worst function

- Let $n = 2k + 1$ and $A \in \mathbb{R}^{n \times n}$.

$$A = \begin{bmatrix} 2 & -1 & 0 & 0 & \cdots & 0 \\ -1 & 2 & -1 & 0 & \cdots & 0 \\ 0 & -1 & 2 & -1 & \cdots & 0 \\ 0 & 0 & -1 & 2 & \cdots & 0 \\ \vdots & \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & 0 & \cdots & 2 \end{bmatrix}$$

Nesterov's worst function

- Let $n = 2k + 1$ and $A \in \mathbb{R}^{n \times n}$.

$$A = \begin{bmatrix} 2 & -1 & 0 & 0 & \cdots & 0 \\ -1 & 2 & -1 & 0 & \cdots & 0 \\ 0 & -1 & 2 & -1 & \cdots & 0 \\ 0 & 0 & -1 & 2 & \cdots & 0 \\ \vdots & \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & 0 & \cdots & 2 \end{bmatrix}$$

- Notice, that

$$x^T A x = x_1^2 + x_n^2 + \sum_{i=1}^{n-1} (x_i - x_{i+1})^2,$$

Therefore, $x^T A x \geq 0$. It is also easy to see that $0 \preceq A \preceq 4I$.

Nesterov's worst function

- Let $n = 2k + 1$ and $A \in \mathbb{R}^{n \times n}$.

$$A = \begin{bmatrix} 2 & -1 & 0 & 0 & \cdots & 0 \\ -1 & 2 & -1 & 0 & \cdots & 0 \\ 0 & -1 & 2 & -1 & \cdots & 0 \\ 0 & 0 & -1 & 2 & \cdots & 0 \\ \vdots & \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & 0 & \cdots & 2 \end{bmatrix}$$

- Notice, that

$$x^T A x = x_1^2 + x_n^2 + \sum_{i=1}^{n-1} (x_i - x_{i+1})^2,$$

Therefore, $x^T A x \geq 0$. It is also easy to see that $0 \preceq A \preceq 4I$.

Nesterov's worst function

- Let $n = 2k + 1$ and $A \in \mathbb{R}^{n \times n}$.

$$A = \begin{bmatrix} 2 & -1 & 0 & 0 & \cdots & 0 \\ -1 & 2 & -1 & 0 & \cdots & 0 \\ 0 & -1 & 2 & -1 & \cdots & 0 \\ 0 & 0 & -1 & 2 & \cdots & 0 \\ \vdots & \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & 0 & \cdots & 2 \end{bmatrix}$$

- Notice, that

$$x^T A x = x_1^2 + x_n^2 + \sum_{i=1}^{n-1} (x_i - x_{i+1})^2,$$

Therefore, $x^T A x \geq 0$. It is also easy to see that $0 \preceq A \preceq 4I$.

Example, when $n = 3$:

$$A = \begin{bmatrix} 2 & -1 & 0 \\ -1 & 2 & -1 \\ 0 & -1 & 2 \end{bmatrix}$$

Nesterov's worst function

- Let $n = 2k + 1$ and $A \in \mathbb{R}^{n \times n}$.

$$A = \begin{bmatrix} 2 & -1 & 0 & 0 & \cdots & 0 \\ -1 & 2 & -1 & 0 & \cdots & 0 \\ 0 & -1 & 2 & -1 & \cdots & 0 \\ 0 & 0 & -1 & 2 & \cdots & 0 \\ \vdots & \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & 0 & \cdots & 2 \end{bmatrix}$$

- Notice, that

$$x^T A x = x_1^2 + x_n^2 + \sum_{i=1}^{n-1} (x_i - x_{i+1})^2,$$

Therefore, $x^T A x \geq 0$. It is also easy to see that $0 \preceq A \preceq 4I$.

Example, when $n = 3$:

$$A = \begin{bmatrix} 2 & -1 & 0 \\ -1 & 2 & -1 \\ 0 & -1 & 2 \end{bmatrix}$$

Lower bound:

$$\begin{aligned} x^T A x &= 2x_1^2 + 2x_2^2 + 2x_3^2 - 2x_1x_2 - 2x_2x_3 \\ &= x_1^2 + x_1^2 - 2x_1x_2 + x_2^2 + x_2^2 - 2x_2x_3 + x_3^2 + x_3^2 \\ &= x_1^2 + (x_1 - x_2)^2 + (x_2 - x_3)^2 + x_3^2 \geq 0 \end{aligned}$$

Nesterov's worst function

- Let $n = 2k + 1$ and $A \in \mathbb{R}^{n \times n}$.

$$A = \begin{bmatrix} 2 & -1 & 0 & 0 & \cdots & 0 \\ -1 & 2 & -1 & 0 & \cdots & 0 \\ 0 & -1 & 2 & -1 & \cdots & 0 \\ 0 & 0 & -1 & 2 & \cdots & 0 \\ \vdots & \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & 0 & \cdots & 2 \end{bmatrix}$$

- Notice, that

$$x^T A x = x_1^2 + x_n^2 + \sum_{i=1}^{n-1} (x_i - x_{i+1})^2,$$

Therefore, $x^T A x \geq 0$. It is also easy to see that $0 \preceq A \preceq 4I$.

Example, when $n = 3$:

$$A = \begin{bmatrix} 2 & -1 & 0 \\ -1 & 2 & -1 \\ 0 & -1 & 2 \end{bmatrix}$$

Lower bound:

$$\begin{aligned} x^T A x &= 2x_1^2 + 2x_2^2 + 2x_3^2 - 2x_1x_2 - 2x_2x_3 \\ &= x_1^2 + x_1^2 - 2x_1x_2 + x_2^2 + x_2^2 - 2x_2x_3 + x_3^2 + x_3^2 \\ &= x_1^2 + (x_1 - x_2)^2 + (x_2 - x_3)^2 + x_3^2 \geq 0 \end{aligned}$$

Upper bound

$$\begin{aligned} x^T A x &= 2x_1^2 + 2x_2^2 + 2x_3^2 - 2x_1x_2 - 2x_2x_3 \\ &\leq 4(x_1^2 + x_2^2 + x_3^2) \\ 0 &\leq 2x_1^2 + 2x_2^2 + 2x_3^2 + 2x_1x_2 + 2x_2x_3 \\ 0 &\leq x_1^2 + x_1^2 + 2x_1x_2 + x_2^2 + x_2^2 + 2x_2x_3 + x_3^2 + x_3^2 \\ 0 &\leq x_1^2 + (x_1 + x_2)^2 + (x_2 + x_3)^2 + x_3^2 \end{aligned}$$

Nesterov's worst function

- Define the following L -smooth convex function: $f(x) = \frac{L}{4} \left(\frac{1}{2} x^T A x - e_1^T x \right) = \frac{L}{8} x^T A x - \frac{L}{4} e_1^T x$.

Nesterov's worst function

- Define the following L -smooth convex function: $f(x) = \frac{L}{4} \left(\frac{1}{2} x^T A x - e_1^T x \right) = \frac{L}{8} x^T A x - \frac{L}{4} e_1^T x$.
- The optimal solution x^* satisfies $Ax^* = e_1$, and solving this system of equations gives:

$$\begin{bmatrix} 2 & -1 & 0 & 0 & \cdots & 0 \\ -1 & 2 & -1 & 0 & \cdots & 0 \\ 0 & -1 & 2 & -1 & \cdots & 0 \\ 0 & 0 & -1 & 2 & \cdots & 0 \\ \vdots & \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & 0 & \cdots & 2 \end{bmatrix} \begin{bmatrix} x_1^* \\ x_2^* \\ x_3^* \\ \vdots \\ x_n^* \end{bmatrix} = \begin{bmatrix} 1 \\ 0 \\ 0 \\ \vdots \\ 0 \end{bmatrix} \quad \begin{cases} 2x_1^* - x_2^* = 1 \\ -x_i^* + 2x_{i+1}^* - x_{i+2}^* = 0, \quad i = 2, \dots, n-1 \\ -x_{n-1}^* + 2x_n^* = 0 \end{cases}$$

Nesterov's worst function

- Define the following L -smooth convex function: $f(x) = \frac{L}{4} \left(\frac{1}{2} x^T A x - e_1^T x \right) = \frac{L}{8} x^T A x - \frac{L}{4} e_1^T x$.
- The optimal solution x^* satisfies $Ax^* = e_1$, and solving this system of equations gives:

$$\begin{bmatrix} 2 & -1 & 0 & 0 & \cdots & 0 \\ -1 & 2 & -1 & 0 & \cdots & 0 \\ 0 & -1 & 2 & -1 & \cdots & 0 \\ 0 & 0 & -1 & 2 & \cdots & 0 \\ \vdots & \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & 0 & \cdots & 2 \end{bmatrix} \begin{bmatrix} x_1^* \\ x_2^* \\ x_3^* \\ \vdots \\ x_n^* \end{bmatrix} = \begin{bmatrix} 1 \\ 0 \\ 0 \\ \vdots \\ 0 \end{bmatrix} \quad \begin{cases} 2x_1^* - x_2^* = 1 \\ -x_i^* + 2x_{i+1}^* - x_{i+2}^* = 0, \quad i = 2, \dots, n-1 \\ -x_{n-1}^* + 2x_n^* = 0 \end{cases}$$

- The hypothesis: $x_i^* = a + bi$ (inspired by physics). Check, that the second equation is satisfied, while a and b are computed from the first and the last equations.

Nesterov's worst function

- Define the following L -smooth convex function: $f(x) = \frac{L}{4} \left(\frac{1}{2} x^T A x - e_1^T x \right) = \frac{L}{8} x^T A x - \frac{L}{4} e_1^T x$.
- The optimal solution x^* satisfies $Ax^* = e_1$, and solving this system of equations gives:

$$\begin{bmatrix} 2 & -1 & 0 & 0 & \cdots & 0 \\ -1 & 2 & -1 & 0 & \cdots & 0 \\ 0 & -1 & 2 & -1 & \cdots & 0 \\ 0 & 0 & -1 & 2 & \cdots & 0 \\ \vdots & \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & 0 & \cdots & 2 \end{bmatrix} \begin{bmatrix} x_1^* \\ x_2^* \\ x_3^* \\ \vdots \\ x_n^* \end{bmatrix} = \begin{bmatrix} 1 \\ 0 \\ 0 \\ \vdots \\ 0 \end{bmatrix} \quad \begin{cases} 2x_1^* - x_2^* = 1 \\ -x_i^* + 2x_{i+1}^* - x_{i+2}^* = 0, \quad i = 2, \dots, n-1 \\ -x_{n-1}^* + 2x_n^* = 0 \end{cases}$$

- The hypothesis: $x_i^* = a + bi$ (inspired by physics). Check, that the second equation is satisfied, while a and b are computed from the first and the last equations.
- The solution is:

$$x_i^* = 1 - \frac{i}{n+1},$$

Nesterov's worst function

- Define the following L -smooth convex function: $f(x) = \frac{L}{4} \left(\frac{1}{2} x^T A x - e_1^T x \right) = \frac{L}{8} x^T A x - \frac{L}{4} e_1^T x$.
- The optimal solution x^* satisfies $Ax^* = e_1$, and solving this system of equations gives:

$$\begin{bmatrix} 2 & -1 & 0 & 0 & \cdots & 0 \\ -1 & 2 & -1 & 0 & \cdots & 0 \\ 0 & -1 & 2 & -1 & \cdots & 0 \\ 0 & 0 & -1 & 2 & \cdots & 0 \\ \vdots & \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & 0 & \cdots & 2 \end{bmatrix} \begin{bmatrix} x_1^* \\ x_2^* \\ x_3^* \\ \vdots \\ x_n^* \end{bmatrix} = \begin{bmatrix} 1 \\ 0 \\ 0 \\ \vdots \\ 0 \end{bmatrix} \quad \begin{cases} 2x_1^* - x_2^* = 1 \\ -x_i^* + 2x_{i+1}^* - x_{i+2}^* = 0, \quad i = 2, \dots, n-1 \\ -x_{n-1}^* + 2x_n^* = 0 \end{cases}$$

- The hypothesis: $x_i^* = a + bi$ (inspired by physics). Check, that the second equation is satisfied, while a and b are computed from the first and the last equations.
- The solution is:

$$x_i^* = 1 - \frac{i}{n+1},$$

- And the objective value is

$$f(x^*) = \frac{L}{8} x^{*T} A x^* - \frac{L}{4} \langle x^*, e_1 \rangle = -\frac{L}{8} \langle x^*, e_1 \rangle = -\frac{L}{8} \left(1 - \frac{1}{n+1} \right).$$

Smooth case (proof)

- Suppose, we start from $x^0 = 0$. Asking the oracle for the gradient, we get $g_0 = -e_1$. Then, x^1 must lie on the line generated by e_1 . At this point all the components of x^1 are zero except the first one, so

$$x^1 = \begin{bmatrix} \bullet \\ 0 \\ \vdots \\ 0 \end{bmatrix}.$$

Smooth case (proof)

- Suppose, we start from $x^0 = 0$. Asking the oracle for the gradient, we get $g_0 = -e_1$. Then, x^1 must lie on the line generated by e_1 . At this point all the components of x^1 are zero except the first one, so

$$x^1 = \begin{bmatrix} \bullet \\ 0 \\ \vdots \\ 0 \end{bmatrix}.$$

- At the second iteration we ask the oracle again and get $g_1 = Ax^1 - e_1$. Then, x^2 must lie on the line generated by e_1 and $Ax^1 - e_1$. All the components of x^2 are zero except the first two, so

$$\begin{bmatrix} 2 & -1 & 0 & \cdots & 0 \\ -1 & 2 & -1 & \cdots & 0 \\ 0 & -1 & 2 & \cdots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & \cdots & 2 \end{bmatrix} \begin{bmatrix} \bullet \\ 0 \\ \vdots \\ 0 \end{bmatrix} \Rightarrow x^2 = \begin{bmatrix} \bullet \\ \bullet \\ 0 \\ \vdots \\ 0 \end{bmatrix}.$$

Smooth case (proof)

- Suppose, we start from $x^0 = 0$. Asking the oracle for the gradient, we get $g_0 = -e_1$. Then, x^1 must lie on the line generated by e_1 . At this point all the components of x^1 are zero except the first one, so

$$x^1 = \begin{bmatrix} \bullet \\ 0 \\ \vdots \\ 0 \end{bmatrix}.$$

- At the second iteration we ask the oracle again and get $g_1 = Ax^1 - e_1$. Then, x^2 must lie on the line generated by e_1 and $Ax^1 - e_1$. All the components of x^2 are zero except the first two, so

$$\begin{bmatrix} 2 & -1 & 0 & \cdots & 0 \\ -1 & 2 & -1 & \cdots & 0 \\ 0 & -1 & 2 & \cdots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & \cdots & 2 \end{bmatrix} \begin{bmatrix} \bullet \\ 0 \\ \vdots \\ 0 \end{bmatrix} \Rightarrow x^2 = \begin{bmatrix} \bullet \\ \bullet \\ 0 \\ \vdots \\ 0 \end{bmatrix}.$$

Smooth case (proof)

- Suppose, we start from $x^0 = 0$. Asking the oracle for the gradient, we get $g_0 = -e_1$. Then, x^1 must lie on the line generated by e_1 . At this point all the components of x^1 are zero except the first one, so

$$x^1 = \begin{bmatrix} \bullet \\ 0 \\ \vdots \\ 0 \end{bmatrix}.$$

- At the second iteration we ask the oracle again and get $g_1 = Ax^1 - e_1$. Then, x^2 must lie on the line generated by e_1 and $Ax^1 - e_1$. All the components of x^2 are zero except the first two, so

$$\begin{bmatrix} 2 & -1 & 0 & \cdots & 0 \\ -1 & 2 & -1 & \cdots & 0 \\ 0 & -1 & 2 & \cdots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & \cdots & 2 \end{bmatrix} \begin{bmatrix} \bullet \\ 0 \\ \vdots \\ 0 \end{bmatrix} \Rightarrow x^2 = \begin{bmatrix} \bullet \\ \bullet \\ 0 \\ \vdots \\ 0 \end{bmatrix}.$$

- Due to the structure of the matrix A one can show using induction that after k iterations we have all the last $n - k$ components of x^k to be zero.

$$x^{(k)} = \begin{bmatrix} \bullet \\ \bullet \\ \vdots \\ \bullet \\ 0 \\ \vdots \\ 0 \end{bmatrix} \begin{matrix} 1 \\ 2 \\ \vdots \\ k \\ k+1 \\ \vdots \\ n \end{matrix}$$

Smooth case (proof)

- Suppose, we start from $x^0 = 0$. Asking the oracle for the gradient, we get $g_0 = -e_1$. Then, x^1 must lie on the line generated by e_1 . At this point all the components of x^1 are zero except the first one, so

$$x^1 = \begin{bmatrix} \bullet \\ 0 \\ \vdots \\ 0 \end{bmatrix}.$$

- At the second iteration we ask the oracle again and get $g_1 = Ax^1 - e_1$. Then, x^2 must lie on the line generated by e_1 and $Ax^1 - e_1$. All the components of x^2 are zero except the first two, so

$$\begin{bmatrix} 2 & -1 & 0 & \cdots & 0 \\ -1 & 2 & -1 & \cdots & 0 \\ 0 & -1 & 2 & \cdots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & \cdots & 2 \end{bmatrix} \begin{bmatrix} \bullet \\ 0 \\ \vdots \\ 0 \end{bmatrix} \Rightarrow x^2 = \begin{bmatrix} \bullet \\ \bullet \\ 0 \\ \vdots \\ 0 \end{bmatrix}.$$

- Due to the structure of the matrix A one can show using induction that after k iterations we have all the last $n - k$ components of x^k to be zero.

$$x^{(k)} = \begin{bmatrix} \bullet \\ \bullet \\ \vdots \\ \bullet \\ 0 \\ \vdots \\ 0 \end{bmatrix} \begin{matrix} 1 \\ 2 \\ \vdots \\ k \\ k+1 \\ \vdots \\ n \end{matrix}$$

- However, since every iterate x^k produced by our method lies in $S_k = \text{span}\{e_1, e_2, \dots, e_k\}$ (i.e. has zeros in the coordinates $k+1, \dots, n$), it cannot “reach” the full optimal vector x^* . In other words, even if one were to choose the best possible vector from S_k , denoted by

$$\tilde{x}^k = \arg \min_{x \in S_k} f(x),$$

its objective value $f(\tilde{x}^k)$ will be strictly worse than $f(x^*)$.

Smooth case (proof)

- Because $x^k \in S_k = \text{span}\{e_1, e_2, \dots, e_k\}$ and $\tilde{x}^k$ is the best possible approximation to x^* within S_k , we have

$$f(x^k) \geq f(\tilde{x}^k).$$

Smooth case (proof)

- Because $x^k \in S_k = \text{span}\{e_1, e_2, \dots, e_k\}$ and $\tilde{x}^k$ is the best possible approximation to x^* within S_k , we have

$$f(x^k) \geq f(\tilde{x}^k).$$

- Thus, the optimality gap obeys

$$f(x^k) - f(x^*) \geq f(\tilde{x}^k) - f(x^*).$$

Smooth case (proof)

- Because $x^k \in S_k = \text{span}\{e_1, e_2, \dots, e_k\}$ and $\tilde{x}^k$ is the best possible approximation to x^* within S_k , we have

$$f(x^k) \geq f(\tilde{x}^k).$$

- Thus, the optimality gap obeys

$$f(x^k) - f(x^*) \geq f(\tilde{x}^k) - f(x^*).$$

- Similarly, to the optimum of the original function, we have $\tilde{x}_i^k = 1 - \frac{i}{k+1}$ and $f(\tilde{x}^k) = -\frac{L}{8} \left(1 - \frac{1}{k+1}\right)$.

Smooth case (proof)

- Because $x^k \in S_k = \text{span}\{e_1, e_2, \dots, e_k\}$ and $\tilde{x}^k$ is the best possible approximation to x^* within S_k , we have

$$f(x^k) \geq f(\tilde{x}^k).$$

- Thus, the optimality gap obeys

$$f(x^k) - f(x^*) \geq f(\tilde{x}^k) - f(x^*).$$

- Similarly, to the optimum of the original function, we have $\tilde{x}_i^k = 1 - \frac{i}{k+1}$ and $f(\tilde{x}^k) = -\frac{L}{8} \left(1 - \frac{1}{k+1}\right)$.
- We now have:

$$f(x^k) - f(x^*) \geq f(\tilde{x}^k) - f(x^*)$$

(2)

Smooth case (proof)

- Because $x^k \in S_k = \text{span}\{e_1, e_2, \dots, e_k\}$ and $\tilde{x}^k$ is the best possible approximation to x^* within S_k , we have

$$f(x^k) \geq f(\tilde{x}^k).$$

- Thus, the optimality gap obeys

$$f(x^k) - f(x^*) \geq f(\tilde{x}^k) - f(x^*).$$

- Similarly, to the optimum of the original function, we have $\tilde{x}_i^k = 1 - \frac{i}{k+1}$ and $f(\tilde{x}^k) = -\frac{L}{8} \left(1 - \frac{1}{k+1}\right)$.
- We now have:

$$\begin{aligned} f(x^k) - f(x^*) &\geq f(\tilde{x}^k) - f(x^*) \\ &= -\frac{L}{8} \left(1 - \frac{1}{k+1}\right) - \left(-\frac{L}{8} \left(1 - \frac{1}{n+1}\right)\right) \end{aligned}$$

(2)

Smooth case (proof)

- Because $x^k \in S_k = \text{span}\{e_1, e_2, \dots, e_k\}$ and $\tilde{x}^k$ is the best possible approximation to x^* within S_k , we have

$$f(x^k) \geq f(\tilde{x}^k).$$

- Thus, the optimality gap obeys

$$f(x^k) - f(x^*) \geq f(\tilde{x}^k) - f(x^*).$$

- Similarly, to the optimum of the original function, we have $\tilde{x}_i^k = 1 - \frac{i}{k+1}$ and $f(\tilde{x}^k) = -\frac{L}{8} \left(1 - \frac{1}{k+1}\right)$.
- We now have:

$$\begin{aligned} f(x^k) - f(x^*) &\geq f(\tilde{x}^k) - f(x^*) \\ &= -\frac{L}{8} \left(1 - \frac{1}{k+1}\right) - \left(-\frac{L}{8} \left(1 - \frac{1}{n+1}\right)\right) \\ &= \frac{L}{8} \left(\frac{1}{k+1} - \frac{1}{n+1}\right) = \frac{L}{8} \left(\frac{n-k}{(k+1)(n+1)}\right) \end{aligned} \tag{2}$$

Smooth case (proof)

- Because $x^k \in S_k = \text{span}\{e_1, e_2, \dots, e_k\}$ and $\tilde{x}^k$ is the best possible approximation to x^* within S_k , we have

$$f(x^k) \geq f(\tilde{x}^k).$$

- Thus, the optimality gap obeys

$$f(x^k) - f(x^*) \geq f(\tilde{x}^k) - f(x^*).$$

- Similarly, to the optimum of the original function, we have $\tilde{x}_i^k = 1 - \frac{i}{k+1}$ and $f(\tilde{x}^k) = -\frac{L}{8} \left(1 - \frac{1}{k+1}\right)$.
- We now have:

$$\begin{aligned} f(x^k) - f(x^*) &\geq f(\tilde{x}^k) - f(x^*) \\ &= -\frac{L}{8} \left(1 - \frac{1}{k+1}\right) - \left(-\frac{L}{8} \left(1 - \frac{1}{n+1}\right)\right) \\ &= \frac{L}{8} \left(\frac{1}{k+1} - \frac{1}{n+1}\right) = \frac{L}{8} \left(\frac{n-k}{(k+1)(n+1)}\right) \\ &\stackrel{n=2k+1}{=} \frac{L}{16(k+1)} \end{aligned} \tag{2}$$

Smooth case (proof)

- Now we bound $R = \|x^0 - x^*\|_2$:

$$\|x^0 - x^*\|_2^2 = \|0 - x^*\|_2^2 = \|x^*\|_2^2 = \sum_{i=1}^n \left(1 - \frac{i}{n+1}\right)^2$$

We observe, that

$$\begin{aligned}\sum_{i=1}^n i &= \frac{n(n+1)}{2} \\ \sum_{i=1}^n i^2 &= \frac{n(n+1)(2n+1)}{6} \\ &\leq \frac{(n+1)^3}{3}\end{aligned}$$

Smooth case (proof)

- Now we bound $R = \|x^0 - x^*\|_2$:

$$\begin{aligned}\|x^0 - x^*\|_2^2 &= \|0 - x^*\|_2^2 = \|x^*\|_2^2 = \sum_{i=1}^n \left(1 - \frac{i}{n+1}\right)^2 \\ &= n - \frac{2}{n+1} \sum_{i=1}^n i + \frac{1}{(n+1)^2} \sum_{i=1}^n i^2\end{aligned}$$

We observe, that

$$\begin{aligned}\sum_{i=1}^n i &= \frac{n(n+1)}{2} \\ \sum_{i=1}^n i^2 &= \frac{n(n+1)(2n+1)}{6} \\ &\leq \frac{(n+1)^3}{3}\end{aligned}$$

Smooth case (proof)

- Now we bound $R = \|x^0 - x^*\|_2$:

$$\begin{aligned}\|x^0 - x^*\|_2^2 &= \|0 - x^*\|_2^2 = \|x^*\|_2^2 = \sum_{i=1}^n \left(1 - \frac{i}{n+1}\right)^2 \\ &= n - \frac{2}{n+1} \sum_{i=1}^n i + \frac{1}{(n+1)^2} \sum_{i=1}^n i^2 \\ &\leq n - \frac{2}{n+1} \cdot \frac{n(n+1)}{2} + \frac{1}{(n+1)^2} \cdot \frac{(n+1)^3}{3}\end{aligned}$$

We observe, that

$$\begin{aligned}\sum_{i=1}^n i &= \frac{n(n+1)}{2} \\ \sum_{i=1}^n i^2 &= \frac{n(n+1)(2n+1)}{6} \\ &\leq \frac{(n+1)^3}{3}\end{aligned}$$

Smooth case (proof)

- Now we bound $R = \|x^0 - x^*\|_2$:

$$\begin{aligned}\|x^0 - x^*\|_2^2 &= \|0 - x^*\|_2^2 = \|x^*\|_2^2 = \sum_{i=1}^n \left(1 - \frac{i}{n+1}\right)^2 \\&= n - \frac{2}{n+1} \sum_{i=1}^n i + \frac{1}{(n+1)^2} \sum_{i=1}^n i^2 \\&\leq n - \frac{2}{n+1} \cdot \frac{n(n+1)}{2} + \frac{1}{(n+1)^2} \cdot \frac{(n+1)^3}{3} \\&= \frac{n+1}{3} \stackrel{n=2k+1}{=} \frac{2(k+1)}{3}.\end{aligned}$$

We observe, that

$$\begin{aligned}\sum_{i=1}^n i &= \frac{n(n+1)}{2} \\ \sum_{i=1}^n i^2 &= \frac{n(n+1)(2n+1)}{6} \\ &\leq \frac{(n+1)^3}{3}\end{aligned}$$

Smooth case (proof)

- Now we bound $R = \|x^0 - x^*\|_2$:

$$\begin{aligned}\|x^0 - x^*\|_2^2 &= \|0 - x^*\|_2^2 = \|x^*\|_2^2 = \sum_{i=1}^n \left(1 - \frac{i}{n+1}\right)^2 \\&= n - \frac{2}{n+1} \sum_{i=1}^n i + \frac{1}{(n+1)^2} \sum_{i=1}^n i^2 \\&\leq n - \frac{2}{n+1} \cdot \frac{n(n+1)}{2} + \frac{1}{(n+1)^2} \cdot \frac{(n+1)^3}{3} \\&= \frac{n+1}{3} \stackrel{n=2k+1}{=} \frac{2(k+1)}{3}.\end{aligned}$$

- Thus,

$$k+1 \geq \frac{3}{2} \|x^0 - x^*\|_2^2 = \frac{3}{2} R^2 \quad (3)$$

We observe, that

$$\begin{aligned}\sum_{i=1}^n i &= \frac{n(n+1)}{2} \\ \sum_{i=1}^n i^2 &= \frac{n(n+1)(2n+1)}{6} \\ &\leq \frac{(n+1)^3}{3}\end{aligned}$$

Smooth case (proof)

Finally, using (2) and (3), we get:

$$\begin{aligned} f(x^k) - f(x^*) &\geq \frac{L}{16(k+1)} = \frac{L(k+1)}{16(k+1)^2} \\ &\geq \frac{L}{16(k+1)^2} \frac{3}{2} R^2 \\ &= \frac{3LR^2}{32(k+1)^2} \end{aligned}$$

Smooth case (proof)

Finally, using (2) and (3), we get:

$$\begin{aligned} f(x^k) - f(x^*) &\geq \frac{L}{16(k+1)} = \frac{L(k+1)}{16(k+1)^2} \\ &\geq \frac{L}{16(k+1)^2} \frac{3}{2} R^2 \\ &= \frac{3LR^2}{32(k+1)^2} \end{aligned}$$

Which concludes the proof with the desired $\mathcal{O}\left(\frac{1}{k^2}\right)$ rate.

Smooth case lower bound theorems

i Smooth convex case

There exists a function f that is L -smooth and convex such that any method 1 satisfies for any $k : 1 \leq k \leq \frac{n-1}{2}$:

$$f(x^k) - f^* \geq \frac{3L\|x^0 - x^*\|_2^2}{32(k+1)^2}$$



$$\sim \frac{1}{k^2}$$

$$\sim \frac{1}{k}$$

Общ. μ -сильно вып.

обычная СХ-ТБ

$$1/k$$

$$\sim \frac{1}{k}$$

у скоренной СХ-ТБ

$$1/k^2$$

$$\sim \sqrt{\frac{1}{k}}$$

i Smooth strongly convex case

For any x^0 and any $\mu > 0, \kappa = \frac{L}{\mu} > 1$, there exists a function f that is L -smooth and μ -strongly convex such that for any method of the form 1 holds:

$$\|x^k - x^*\|_2 \geq \left(\frac{\sqrt{\kappa} - 1}{\sqrt{\kappa} + 1} \right)^k \|x^0 - x^*\|_2$$

$$f(x^k) - f^* \geq \frac{\mu}{2} \left(\frac{\sqrt{\kappa} - 1}{\sqrt{\kappa} + 1} \right)^{2k} \|x^0 - x^*\|_2^2$$



$$\sim \frac{1}{k}$$

$$\sqrt{\frac{1}{k}}$$

Acceleration for quadratics

Convergence result for quadratics

Suppose, we have a strongly convex quadratic function minimization problem solved by the gradient descent method:

$$f(x) = \frac{1}{2}x^T Ax - b^T x$$

$$x^{k+1} = x^k - \alpha_k \nabla f(x^k).$$

Theorem

The gradient descent method with the learning rate $\alpha_k = \frac{2}{\mu+L}$ converges to the optimal solution x^* with the following guarantee:

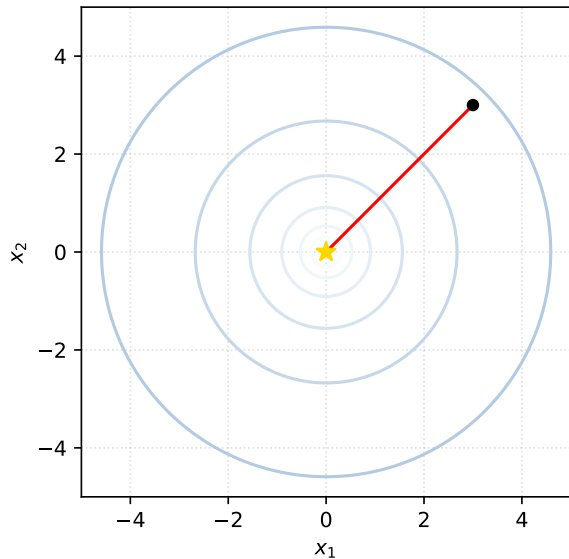
$$\|x^{k+1} - x^*\|_2 = \left(\frac{\varkappa - 1}{\varkappa + 1}\right)^k \|x^0 - x^*\|_2$$

$$f(x^{k+1}) - f(x^*) = \left(\frac{\varkappa - 1}{\varkappa + 1}\right)^{2k} (f(x^0) - f(x^*))$$

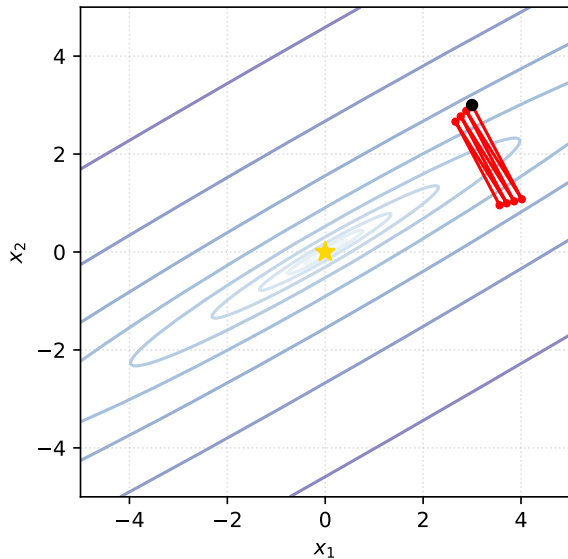
where $\varkappa = \frac{L}{\mu}$ is the condition number of A .

Condition number κ

$\kappa = 1.0$



$\kappa = 100.0$



Convergence from the first principles

$$e_k = x_k - x^* \quad Ax^* = b$$

$$f(x) = \frac{1}{2}x^T Ax - b^T x \quad x_{k+1} = x_k - \alpha_k \nabla f(x_k).$$

Let x^* be the unique solution of the linear system $Ax = b$ and put $e_k = x_k - x^*$ where $x_{k+1} = x_k - \alpha_k (Ax_k - b)$ is defined recursively starting from some x_0 , and α_k is a step size we'll determine shortly.

$$e_{k+1} = (I - \alpha_k A) e_k.$$

$$(I - \alpha_k A)(I - \alpha_{k-1} A) \cdot (I - \alpha_{k-2} A) \dots$$

$$= (I - \alpha_k A)^2 e_{k-1} = (I - \alpha_k A)^3 e_{k-2}$$

Полином степени k = 0 $\Rightarrow$ после k итераций

Polynomials

The above calculation gives us $e_k = p_k(A) e_0$, where p_k is the polynomial

$$p_k(a) = \prod_{i=1}^k (1 - \alpha_i a).$$

We can upper bound the norm of the error term as

$$\|e_k\| \leq \|p_k(A)\| \cdot \|e_0\|.$$

Convergence from the first principles

ПОЛУКОМ = МЕТОД

$$f(x) = \frac{1}{2}x^T Ax - b^T x \quad x_{k+1} = x_k - \alpha_k \nabla f(x_k).$$

Let x^* be the unique solution of the linear system $Ax = b$ and put $e_k = \|x_k - x^*\|$, where $x_{k+1} = x_k - \alpha_k (Ax_k - b)$ is defined recursively starting from some x_0 , and α_k is a step size we'll determine shortly.

$$e_{k+1} = (I - \alpha_k A)e_k.$$

Polynomials

The above calculation gives us $e_k = p_k(A)e_0$, where p_k is the polynomial

$$p_k(a) = \prod_{i=1}^k (1 - \alpha_i a).$$

We can upper bound the norm of the error term as

$$\|e_k\| \leq \|p_k(A)\| \cdot \|e_0\|.$$

спектр:

Since A is a symmetric matrix with eigenvalues in $[\mu, L]$,

$$\|p_k(A)\| \leq \max_{\mu \leq a \leq L} |p_k(a)|.$$

This leads to an interesting problem: Among all polynomials that satisfy $p_k(0) = 1$ we're looking for a polynomial whose magnitude is as small as possible in the interval $[\mu, L]$.

Naive polynomial solution

A naive solution is to choose a uniform step size $\alpha_k = \frac{2}{\mu+L}$ in the expression. This choice makes $|p_k(\mu)| = |p_k(L)|$.

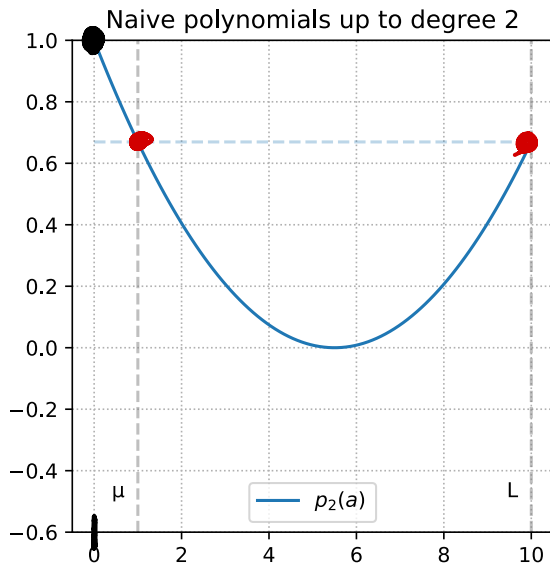
$$\|e_k\| \leq \left(1 - \frac{1}{\kappa}\right)^k \|e_0\|$$

This is exactly the rate we proved in the previous lecture for any smooth and strongly convex function.

Let's look at this polynomial a bit closer. On the right figure we choose $\alpha = 1$ and $\beta = 10$ so that $\kappa = 10$. The relevant interval is therefore $[1, 10]$.

Can we do better? The answer is yes.

$$p(a) = \prod_{i=1}^k (1 - \alpha_i \cdot a)$$



Naive polynomial solution

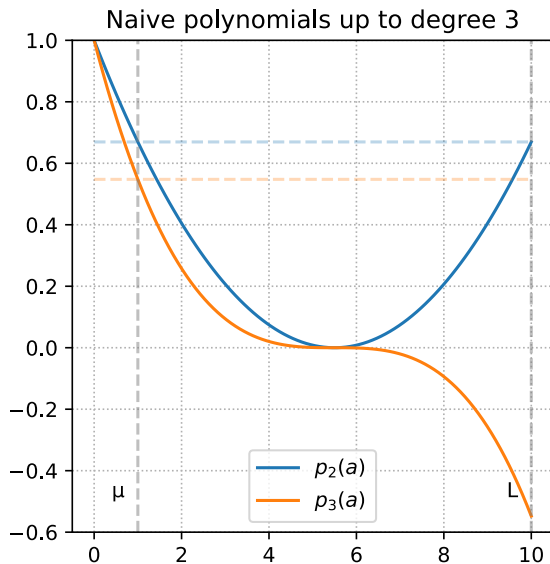
A naive solution is to choose a uniform step size $\alpha_k = \frac{2}{\mu+L}$ in the expression. This choice makes $|p_k(\mu)| = |p_k(L)|$.

$$\|e_k\| \leq \left(1 - \frac{1}{\kappa}\right)^k \|e_0\|$$

This is exactly the rate we proved in the previous lecture for any smooth and strongly convex function.

Let's look at this polynomial a bit closer. On the right figure we choose $\alpha = 1$ and $\beta = 10$ so that $\kappa = 10$. The relevant interval is therefore $[1, 10]$.

Can we do better? The answer is yes.



Naive polynomial solution

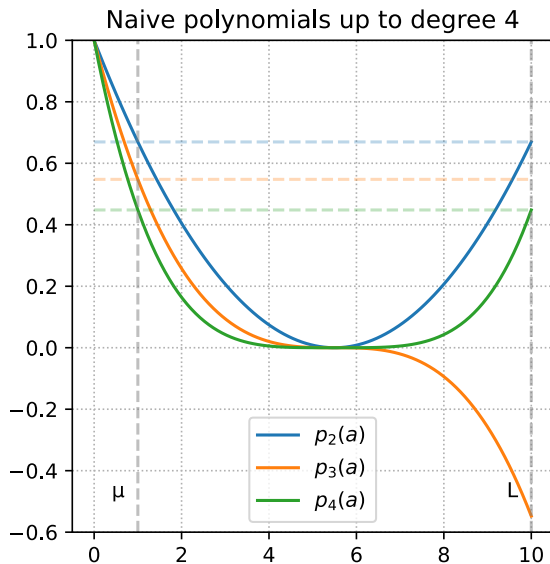
A naive solution is to choose a uniform step size $\alpha_k = \frac{2}{\mu+L}$ in the expression. This choice makes $|p_k(\mu)| = |p_k(L)|$.

$$\|e_k\| \leq \left(1 - \frac{1}{\kappa}\right)^k \|e_0\|$$

This is exactly the rate we proved in the previous lecture for any smooth and strongly convex function.

Let's look at this polynomial a bit closer. On the right figure we choose $\alpha = 1$ and $\beta = 10$ so that $\kappa = 10$. The relevant interval is therefore $[1, 10]$.

Can we do better? The answer is yes.



Naive polynomial solution

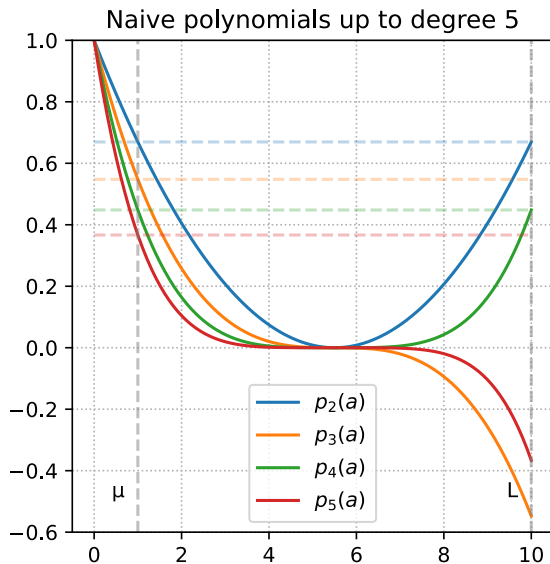
A naive solution is to choose a uniform step size $\alpha_k = \frac{2}{\mu+L}$ in the expression. This choice makes $|p_k(\mu)| = |p_k(L)|$.

$$\|e_k\| \leq \left(1 - \frac{1}{\kappa}\right)^k \|e_0\|$$

This is exactly the rate we proved in the previous lecture for any smooth and strongly convex function.

Let's look at this polynomial a bit closer. On the right figure we choose $\alpha = 1$ and $\beta = 10$ so that $\kappa = 10$. The relevant interval is therefore $[1, 10]$.

Can we do better? The answer is yes.



Naive polynomial solution

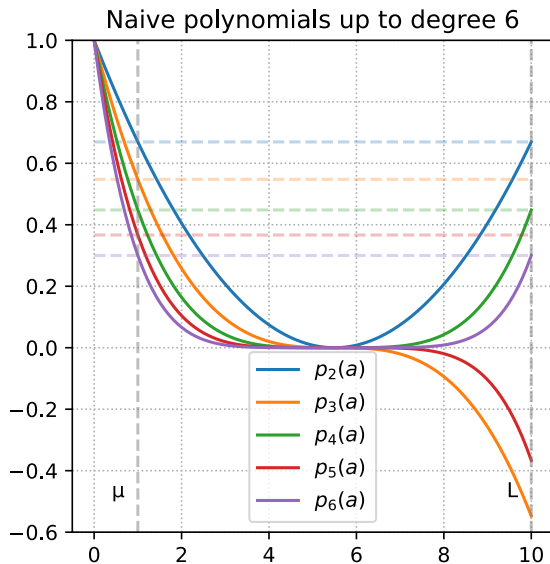
A naive solution is to choose a uniform step size $\alpha_k = \frac{2}{\mu+L}$ in the expression. This choice makes $|p_k(\mu)| = |p_k(L)|$.

$$\|e_k\| \leq \left(1 - \frac{1}{\kappa}\right)^k \|e_0\|$$

This is exactly the rate we proved in the previous lecture for any smooth and strongly convex function.

Let's look at this polynomial a bit closer. On the right figure we choose $\alpha = 1$ and $\beta = 10$ so that $\kappa = 10$. The relevant interval is therefore $[1, 10]$.

Can we do better? The answer is yes.



Chebyshev polynomials

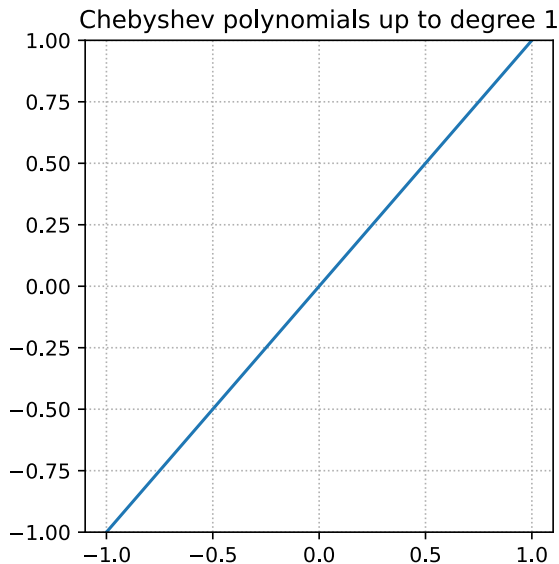
Chebyshev polynomials turn out to give an optimal answer to the question that we asked. Suitably rescaled, they minimize the absolute value in a desired interval $[\mu, L]$ while satisfying the normalization constraint of having value 1 at the origin.

$$T_0(x) = 1$$

$$T_1(x) = x$$

$$T_k(x) = 2xT_{k-1}(x) - T_{k-2}(x), \quad k \geq 2.$$

Let's plot the standard Chebyshev polynomials (without rescaling):



Chebyshev polynomials

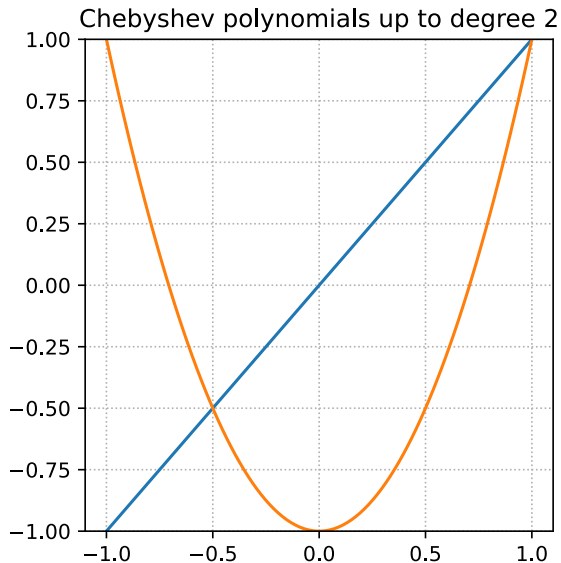
Chebyshev polynomials turn out to give an optimal answer to the question that we asked. Suitably rescaled, they minimize the absolute value in a desired interval $[\mu, L]$ while satisfying the normalization constraint of having value 1 at the origin.

$$T_0(x) = 1$$

$$T_1(x) = x$$

$$T_k(x) = 2xT_{k-1}(x) - T_{k-2}(x), \quad k \geq 2.$$

Let's plot the standard Chebyshev polynomials (without rescaling):



Chebyshev polynomials

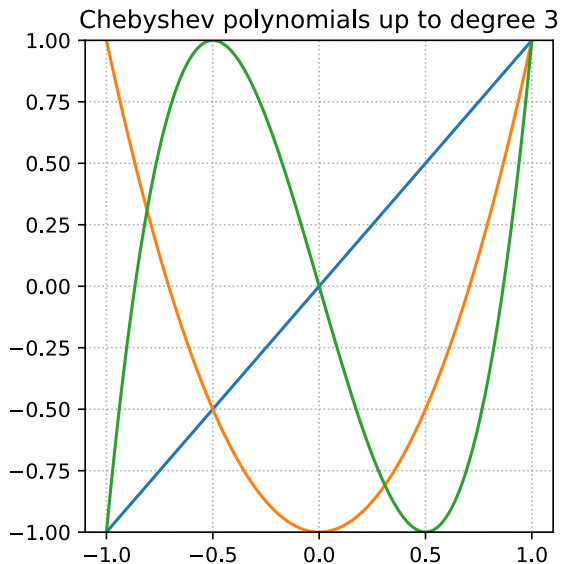
Chebyshev polynomials turn out to give an optimal answer to the question that we asked. Suitably rescaled, they minimize the absolute value in a desired interval $[\mu, L]$ while satisfying the normalization constraint of having value 1 at the origin.

$$T_0(x) = 1$$

$$T_1(x) = x$$

$$T_k(x) = 2xT_{k-1}(x) - T_{k-2}(x), \quad k \geq 2.$$

Let's plot the standard Chebyshev polynomials (without rescaling):



Chebyshev polynomials

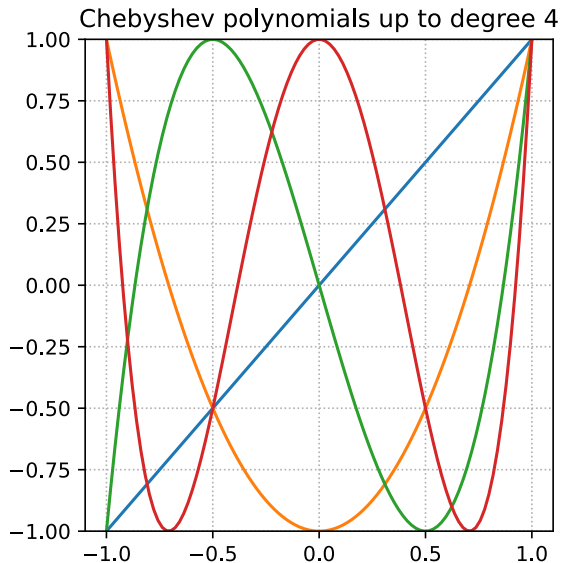
Chebyshev polynomials turn out to give an optimal answer to the question that we asked. Suitably rescaled, they minimize the absolute value in a desired interval $[\mu, L]$ while satisfying the normalization constraint of having value 1 at the origin.

$$T_0(x) = 1$$

$$T_1(x) = x$$

$$T_k(x) = 2xT_{k-1}(x) - T_{k-2}(x), \quad k \geq 2.$$

Let's plot the standard Chebyshev polynomials (without rescaling):



Chebyshev polynomials

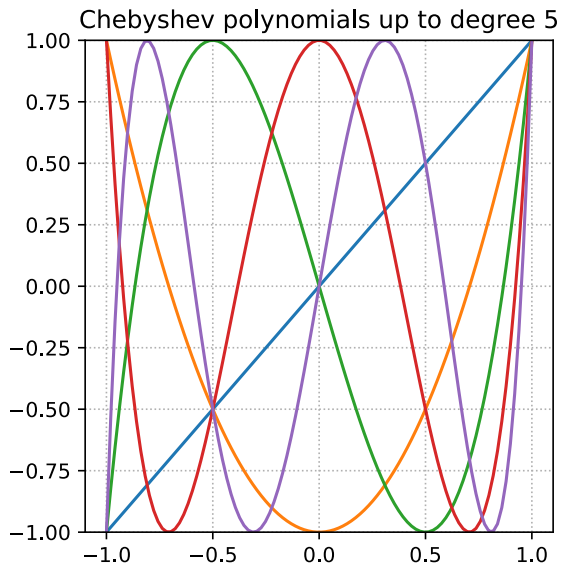
Chebyshev polynomials turn out to give an optimal answer to the question that we asked. Suitably rescaled, they minimize the absolute value in a desired interval $[\mu, L]$ while satisfying the normalization constraint of having value 1 at the origin.

$$T_0(x) = 1$$

$$T_1(x) = x$$

$$T_k(x) = 2xT_{k-1}(x) - T_{k-2}(x), \quad k \geq 2.$$

Let's plot the standard Chebyshev polynomials (without rescaling):



Rescaled Chebyshev polynomials

Original Chebyshev polynomials are defined on the interval $[-1, 1]$. To use them for our purposes, we need to rescale them to the interval $[\mu, L]$.

Rescaled Chebyshev polynomials

Original Chebyshev polynomials are defined on the interval $[-1, 1]$. To use them for our purposes, we need to rescale them to the interval $[\mu, L]$.

We will use the following affine transformation:

$$x = \frac{L + \mu - 2a}{L - \mu}, \quad a \in [\mu, L], \quad x \in [-1, 1].$$

Note, that $x = 1$ corresponds to $a = \mu$, $x = -1$ corresponds to $a = L$ and $x = 0$ corresponds to $a = \frac{\mu+L}{2}$. This transformation ensures that the behavior of the Chebyshev polynomial on $[-1, 1]$ is reflected on the interval $[\mu, L]$

Rescaled Chebyshev polynomials

Original Chebyshev polynomials are defined on the interval $[-1, 1]$. To use them for our purposes, we need to rescale them to the interval $[\mu, L]$.

We will use the following affine transformation:

$$x = \frac{L + \mu - 2a}{L - \mu}, \quad a \in [\mu, L], \quad x \in [-1, 1].$$

Note, that $x = 1$ corresponds to $a = \mu$, $x = -1$ corresponds to $a = L$ and $x = 0$ corresponds to $a = \frac{\mu+L}{2}$. This transformation ensures that the behavior of the Chebyshev polynomial on $[-1, 1]$ is reflected on the interval $[\mu, L]$

In our error analysis, we require that the polynomial equals 1 at 0 (i.e., $p_k(0) = 1$). After applying the transformation, the value T_k takes at the point corresponding to $a = 0$ might not be 1. Thus, we multiply by the inverse of T_k evaluated at

$$\frac{L + \mu}{L - \mu}, \quad \text{ensuring that} \quad P_k(0) = T_k\left(\frac{L + \mu - 0}{L - \mu}\right) \cdot T_k\left(\frac{L + \mu}{L - \mu}\right)^{-1} = 1.$$

Rescaled Chebyshev polynomials

Original Chebyshev polynomials are defined on the interval $[-1, 1]$. To use them for our purposes, we need to rescale them to the interval $[\mu, L]$.

We will use the following affine transformation:

$$x = \frac{L + \mu - 2a}{L - \mu}, \quad a \in [\mu, L], \quad x \in [-1, 1].$$

Note, that $x = 1$ corresponds to $a = \mu$, $x = -1$ corresponds to $a = L$ and $x = 0$ corresponds to $a = \frac{\mu+L}{2}$. This transformation ensures that the behavior of the Chebyshev polynomial on $[-1, 1]$ is reflected on the interval $[\mu, L]$

In our error analysis, we require that the polynomial equals 1 at 0 (i.e., $p_k(0) = 1$). After applying the transformation, the value T_k takes at the point corresponding to $a = 0$ might not be 1. Thus, we multiply by the inverse of T_k evaluated at

$$\frac{L + \mu}{L - \mu}, \quad \text{ensuring that} \quad P_k(0) = T_k\left(\frac{L + \mu - 0}{L - \mu}\right) \cdot T_k\left(\frac{L + \mu}{L - \mu}\right)^{-1} = 1.$$

Let's plot the rescaled Chebyshev polynomials

$$P_k(a) = T_k\left(\frac{L + \mu - 2a}{L - \mu}\right) \cdot T_k\left(\frac{L + \mu}{L - \mu}\right)^{-1}$$

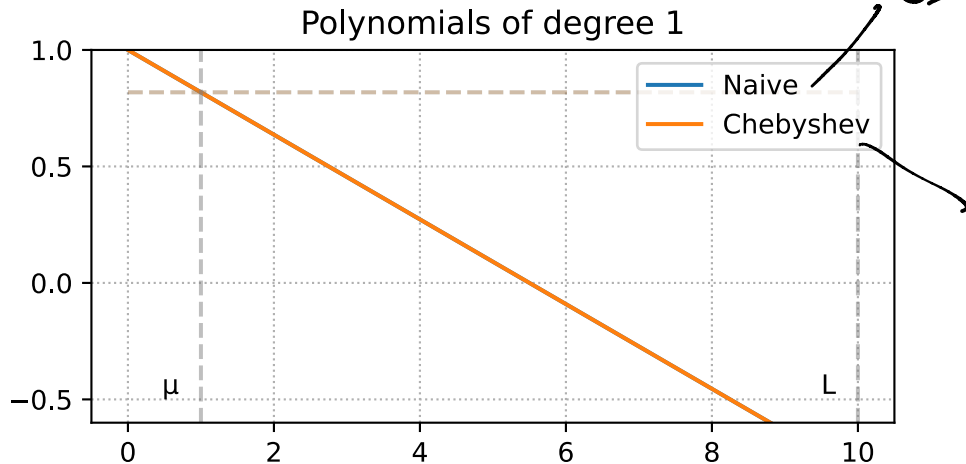
$T_k(x)$ - монотон
убывающая

and observe, that they are much better behaved than the naive polynomials in terms of the magnitude in the interval $[\mu, L]$.

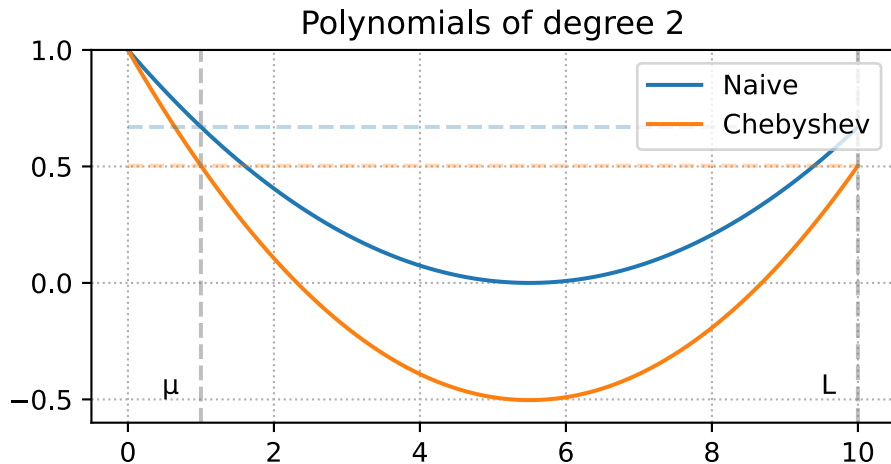
$[-1; 1] \leftrightarrow [\mu; L]$

но промывка
 $P_k(0) = 1$

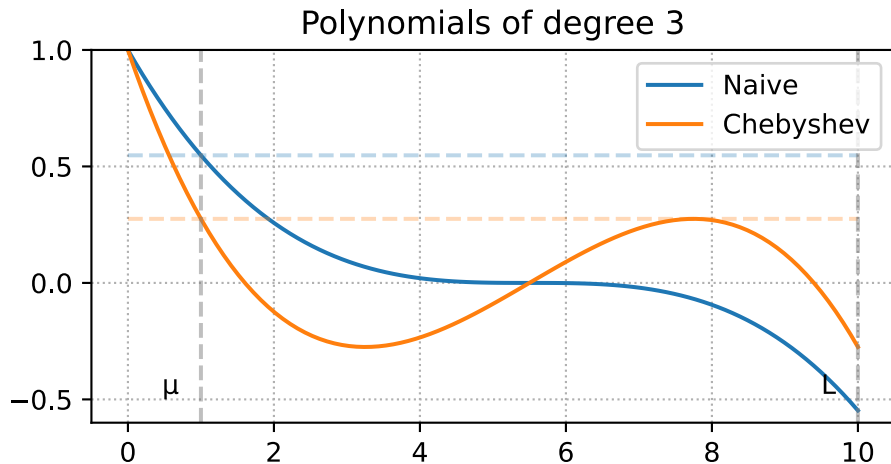
Rescaled Chebyshev polynomials



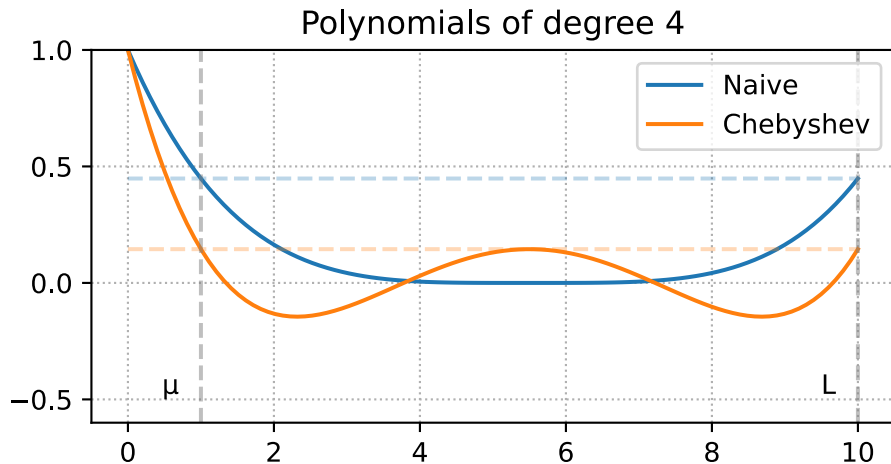
Rescaled Chebyshev polynomials



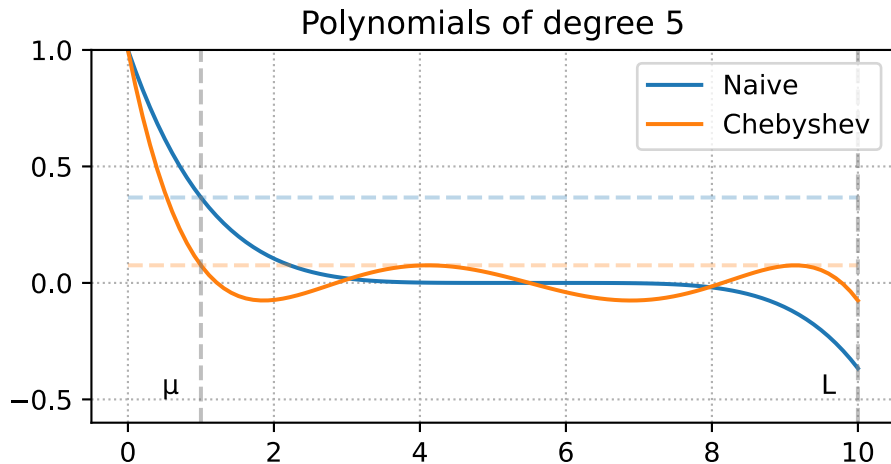
Rescaled Chebyshev polynomials



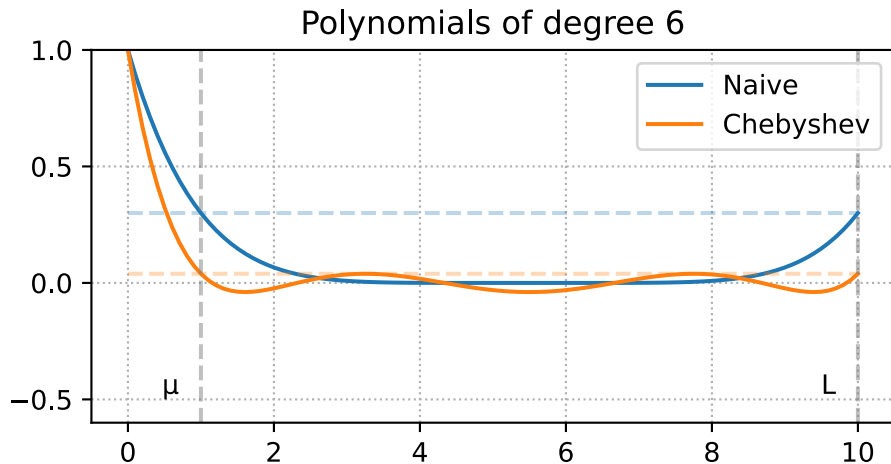
Rescaled Chebyshev polynomials



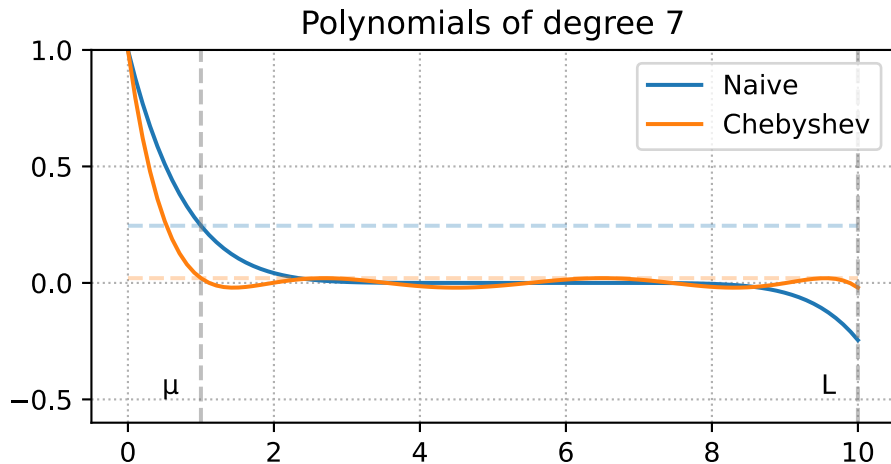
Rescaled Chebyshev polynomials



Rescaled Chebyshev polynomials

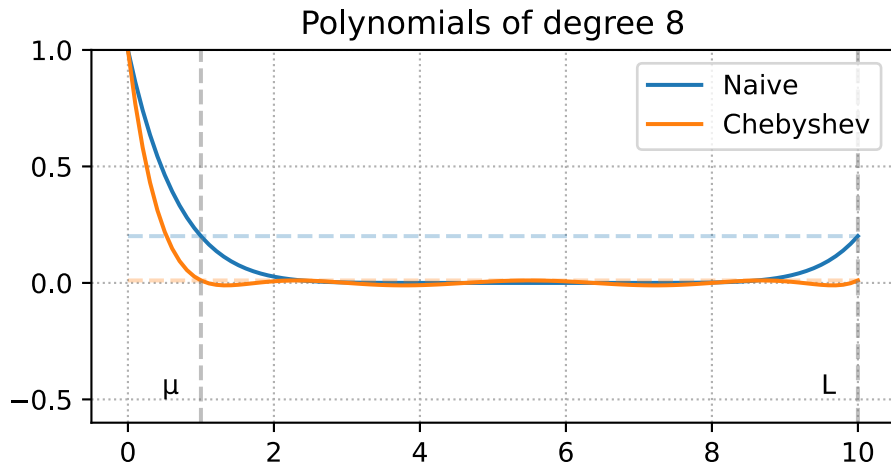


Rescaled Chebyshev polynomials

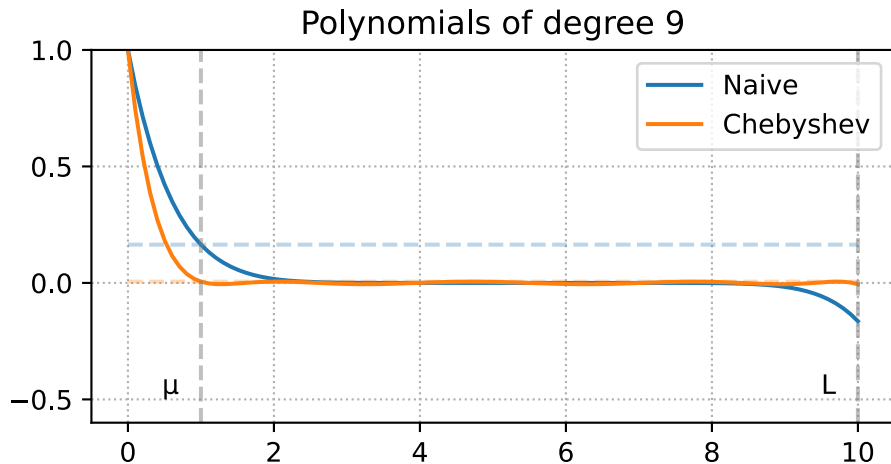


Rescaled Chebyshev polynomials

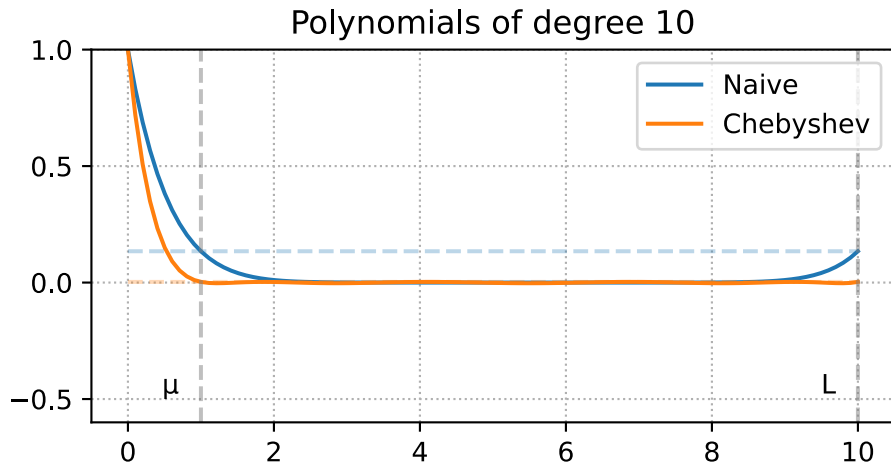
$$p(a) = (1 - d_1 a)(1 - d_2 a)$$



Rescaled Chebyshev polynomials



Rescaled Chebyshev polynomials



Chebyshev polynomials upper bound

We can see, that the maximum value of the Chebyshev polynomial on the interval $[\mu, L]$ is achieved at the point $a = \mu$. Therefore, we can use the following upper bound:

$$\|P_k(A)\|_2 \leq P_k(\mu) = T_k\left(\frac{L + \mu - 2\mu}{L - \mu}\right) \cdot T_k\left(\frac{L + \mu}{L - \mu}\right)^{-1} = T_k(1) \cdot T_k\left(\frac{L + \mu}{L - \mu}\right)^{-1} = T_k\left(\frac{L + \mu}{L - \mu}\right)^{-1}$$

Chebyshev polynomials upper bound

We can see, that the maximum value of the Chebyshev polynomial on the interval $[\mu, L]$ is achieved at the point $a = \mu$. Therefore, we can use the following upper bound:

$$\|P_k(A)\|_2 \leq P_k(\mu) = T_k\left(\frac{L + \mu - 2\mu}{L - \mu}\right) \cdot T_k\left(\frac{L + \mu}{L - \mu}\right)^{-1} = T_k(1) \cdot T_k\left(\frac{L + \mu}{L - \mu}\right)^{-1} = T_k\left(\frac{L + \mu}{L - \mu}\right)^{-1}$$

Using the definition of condition number $\kappa = \frac{L}{\mu}$, we get:

$$\|P_k(A)\|_2 \leq T_k\left(\frac{\kappa + 1}{\kappa - 1}\right)^{-1} = T_k\left(1 + \frac{2}{\kappa - 1}\right)^{-1} = T_k(1 + \epsilon)^{-1}, \quad \epsilon = \frac{2}{\kappa - 1}.$$

Chebyshev polynomials upper bound

We can see, that the maximum value of the Chebyshev polynomial on the interval $[\mu, L]$ is achieved at the point $a = \mu$. Therefore, we can use the following upper bound:

$$\|P_k(A)\|_2 \leq P_k(\mu) = T_k\left(\frac{L + \mu - 2\mu}{L - \mu}\right) \cdot T_k\left(\frac{L + \mu}{L - \mu}\right)^{-1} = T_k(1) \cdot T_k\left(\frac{L + \mu}{L - \mu}\right)^{-1} = T_k\left(\frac{L + \mu}{L - \mu}\right)^{-1}$$

Using the definition of condition number $\kappa = \frac{L}{\mu}$, we get:

$$\|P_k(A)\|_2 \leq T_k\left(\frac{\kappa + 1}{\kappa - 1}\right)^{-1} = T_k\left(1 + \frac{2}{\kappa - 1}\right)^{-1} = T_k(1 + \epsilon)^{-1}, \quad \epsilon = \frac{2}{\kappa - 1}.$$

Therefore, we only need to understand the value of T_k at $1 + \epsilon$. This is where the acceleration comes from. We will bound this value with $\mathcal{O}\left(\frac{1}{\sqrt{\epsilon}}\right)$.

Chebyshev polynomials upper bound

To upper bound $|P_k|$, we need to lower bound $|T_k(1 + \epsilon)|$.

Chebyshev polynomials upper bound

To upper bound $|P_k|$, we need to lower bound $|T_k(1 + \epsilon)|$.

1. For any $x \geq 1$, the Chebyshev polynomial of the first kind can be written as

$$T_k(x) = \cosh(k \operatorname{arccosh}(x))$$
$$T_k(1 + \epsilon) = \cosh(k \operatorname{arccosh}(1 + \epsilon)).$$

Chebyshev polynomials upper bound

To upper bound $|P_k|$, we need to lower bound $|T_k(1 + \epsilon)|$.

1. For any $x \geq 1$, the Chebyshev polynomial of the first kind can be written as

$$\begin{aligned}T_k(x) &= \cosh(k \operatorname{arccosh}(x)) \\T_k(1 + \epsilon) &= \cosh(k \operatorname{arccosh}(1 + \epsilon)).\end{aligned}$$

2. Recall that:

$$\cosh(x) = \frac{e^x + e^{-x}}{2} \quad \operatorname{arccosh}(x) = \ln(x + \sqrt{x^2 - 1}).$$

Chebyshev polynomials upper bound

To upper bound $|P_k|$, we need to lower bound $|T_k(1 + \epsilon)|$.

1. For any $x \geq 1$, the Chebyshev polynomial of the first kind can be written as

$$\begin{aligned}T_k(x) &= \cosh(k \operatorname{arccosh}(x)) \\T_k(1 + \epsilon) &= \cosh(k \operatorname{arccosh}(1 + \epsilon)).\end{aligned}$$

2. Recall that:

$$\cosh(x) = \frac{e^x + e^{-x}}{2} \quad \operatorname{arccosh}(x) = \ln(x + \sqrt{x^2 - 1}).$$

3. Now, letting $\phi = \operatorname{arccosh}(1 + \epsilon)$,

$$e^\phi = 1 + \epsilon + \sqrt{2\epsilon + \epsilon^2} \geq 1 + \sqrt{\epsilon}.$$

Chebyshev polynomials upper bound

To upper bound $|P_k|$, we need to lower bound $|T_k(1 + \epsilon)|$.

1. For any $x \geq 1$, the Chebyshev polynomial of the first kind can be written as

$$T_k(x) = \cosh(k \operatorname{arccosh}(x))$$

$$T_k(1 + \epsilon) = \cosh(k \operatorname{arccosh}(1 + \epsilon)).$$

2. Recall that:

$$\cosh(x) = \frac{e^x + e^{-x}}{2} \quad \operatorname{arccosh}(x) = \ln(x + \sqrt{x^2 - 1}).$$

3. Now, letting $\phi = \operatorname{arccosh}(1 + \epsilon)$,

$$e^\phi = 1 + \epsilon + \sqrt{2\epsilon + \epsilon^2} \geq 1 + \sqrt{\epsilon}.$$

4. Therefore,

$$\begin{aligned} T_k(1 + \epsilon) &= \cosh(k \operatorname{arccosh}(1 + \epsilon)) \\ &= \cosh(k\phi) \\ &= \frac{e^{k\phi} + e^{-k\phi}}{2} \geq \frac{e^{k\phi}}{2} \\ &= \frac{(1 + \sqrt{\epsilon})^k}{2}. \end{aligned}$$

Chebyshev polynomials upper bound

To upper bound $|P_k|$, we need to lower bound $|T_k(1 + \epsilon)|$.

1. For any $x \geq 1$, the Chebyshev polynomial of the first kind can be written as

$$\begin{aligned}T_k(x) &= \cosh(k \operatorname{arccosh}(x)) \\T_k(1 + \epsilon) &= \cosh(k \operatorname{arccosh}(1 + \epsilon)).\end{aligned}$$

2. Recall that:

$$\cosh(x) = \frac{e^x + e^{-x}}{2} \quad \operatorname{arccosh}(x) = \ln(x + \sqrt{x^2 - 1}).$$

3. Now, letting $\phi = \operatorname{arccosh}(1 + \epsilon)$,

$$e^\phi = 1 + \epsilon + \sqrt{2\epsilon + \epsilon^2} \geq 1 + \sqrt{\epsilon}.$$

4. Therefore,

$$\begin{aligned}T_k(1 + \epsilon) &= \cosh(k \operatorname{arccosh}(1 + \epsilon)) \\&= \cosh(k\phi) \\&= \frac{e^{k\phi} + e^{-k\phi}}{2} \geq \frac{e^{k\phi}}{2} \\&= \frac{(1 + \sqrt{\epsilon})^k}{2}.\end{aligned}$$

5. Finally, we get:

$$\begin{aligned}\frac{\|e_k\| \leq \underbrace{\|P_k(A)\|}_{\leq} \|e_0\|}{(1 + \sqrt{\epsilon})^k} &\leq \frac{2}{(1 + \sqrt{\epsilon})^k} \|e_0\| \\&\leq 2 \left(1 + \sqrt{\frac{2}{n-1}}\right)^{-k} \|e_0\| \\&\leq 2 \exp\left(-\sqrt{\frac{2}{n-1}} k\right) \|e_0\|\end{aligned}$$

Accelerated method [1/2]

Due to the recursive definition of the Chebyshev polynomials, we directly obtain an iterative acceleration scheme. Reformulating the recurrence in terms of our rescaled Chebyshev polynomials, we obtain:

$$T_{k+1}(x) = 2xT_k(x) - T_{k-1}(x)$$

Given the fact, that $x = \frac{L+\mu-2a}{L-\mu}$, and:

non-linear

[-1;1]

[μ;L]

$$P_k(a) = T_k\left(\frac{L+\mu-2a}{L-\mu}\right) T_k\left(\frac{L+\mu}{L-\mu}\right)^{-1}$$

$$T_k\left(\frac{L+\mu-2a}{L-\mu}\right) = P_k(a) T_k\left(\frac{L+\mu}{L-\mu}\right)$$

Accelerated method [1/2]

Due to the recursive definition of the Chebyshev polynomials, we directly obtain an iterative acceleration scheme. Reformulating the recurrence in terms of our rescaled Chebyshev polynomials, we obtain:

$$T_{k+1}(x) = 2xT_k(x) - T_{k-1}(x)$$

Given the fact, that $x = \frac{L+\mu-2a}{L-\mu}$, and:

$$P_k(a) = T_k\left(\frac{L+\mu-2a}{L-\mu}\right) T_k\left(\frac{L+\mu}{L-\mu}\right)^{-1}$$

$$T_k\left(\frac{L+\mu-2a}{L-\mu}\right) = P_k(a) T_k\left(\frac{L+\mu}{L-\mu}\right)$$

$$T_{k-1}\left(\frac{L+\mu-2a}{L-\mu}\right) = P_{k-1}(a) T_{k-1}\left(\frac{L+\mu}{L-\mu}\right)$$

$$T_{k+1}\left(\frac{L+\mu-2a}{L-\mu}\right) = P_{k+1}(a) T_{k+1}\left(\frac{L+\mu}{L-\mu}\right)$$

$$P_{k+1}(a)t_{k+1} = 2\frac{L+\mu-2a}{L-\mu}P_k(a)t_k - P_{k-1}(a)t_{k-1}, \text{ where } t_k = T_k\left(\frac{L+\mu}{L-\mu}\right)$$

$$P_{k+1}(a) = 2\frac{L+\mu-2a}{L-\mu}P_k(a)\frac{t_k}{t_{k+1}} - P_{k-1}(a)\frac{t_{k-1}}{t_{k+1}}$$

Accelerated method [1/2]

Due to the recursive definition of the Chebyshev polynomials, we directly obtain an iterative acceleration scheme. Reformulating the recurrence in terms of our rescaled Chebyshev polynomials, we obtain:

$$T_{k+1}(x) = 2xT_k(x) - T_{k-1}(x)$$

Given the fact, that $x = \frac{L+\mu-2a}{L-\mu}$, and:

$$P_k(a) = T_k\left(\frac{L+\mu-2a}{L-\mu}\right) T_k\left(\frac{L+\mu}{L-\mu}\right)^{-1}$$

$$T_k\left(\frac{L+\mu-2a}{L-\mu}\right) = P_k(a) T_k\left(\frac{L+\mu}{L-\mu}\right)$$

$$T_{k-1}\left(\frac{L+\mu-2a}{L-\mu}\right) = P_{k-1}(a) T_{k-1}\left(\frac{L+\mu}{L-\mu}\right)$$

$$T_{k+1}\left(\frac{L+\mu-2a}{L-\mu}\right) = P_{k+1}(a) T_{k+1}\left(\frac{L+\mu}{L-\mu}\right)$$

$$P_{k+1}(a)t_{k+1} = 2\frac{L+\mu-2a}{L-\mu}P_k(a)t_k - P_{k-1}(a)t_{k-1}, \text{ where } t_k = T_k\left(\frac{L+\mu}{L-\mu}\right)$$

$$P_{k+1}(a) = 2\frac{L+\mu-2a}{L-\mu}P_k(a)\frac{t_k}{t_{k+1}} - P_{k-1}(a)\frac{t_{k-1}}{t_{k+1}}$$

Since we have $P_{k+1}(0) = P_k(0) = P_{k-1}(0) = 1$, we can find the method in the following form:

$$P_{k+1}(a) = (1 - \alpha_k a)P_k(a) + \beta_k (P_k(a) - P_{k-1}(a)).$$

Accelerated method [2/2]

Rearranging the terms, we get:

$$P_{k+1}(a) = (1 + \beta_k)P_k(a) - \alpha_k a P_k(a) - \beta_k P_{k-1}(a),$$
$$P_{k+1}(a) = 2 \frac{L + \mu}{L - \mu} \frac{t_k}{t_{k+1}} P_k(a) - \frac{4a}{L - \mu} \frac{t_k}{t_{k+1}} P_k(a) - \frac{t_{k-1}}{t_{k+1}} P_{k-1}(a)$$

Accelerated method [2/2]

Rearranging the terms, we get:

$$P_{k+1}(a) = (1 + \beta_k)P_k(a) - \alpha_k a P_k(a) - \beta_k P_{k-1}(a),$$

$$P_{k+1}(a) = 2 \frac{L + \mu}{L - \mu} \frac{t_k}{t_{k+1}} P_k(a) - \frac{4a}{L - \mu} \frac{t_k}{t_{k+1}} P_k(a) - \frac{t_{k-1}}{t_{k+1}} P_{k-1}(a)$$

$$\begin{cases} \beta_k = \frac{t_{k-1}}{t_{k+1}}, \\ \alpha_k = \frac{4}{L - \mu} \frac{t_k}{t_{k+1}}, \\ 1 + \beta_k = 2 \frac{L + \mu}{L - \mu} \frac{t_k}{t_{k+1}} \end{cases}$$

Accelerated method [2/2]

Rearranging the terms, we get:

$$\begin{aligned} P_{k+1}(a) &= (1 + \beta_k)P_k(a) - \alpha_k a P_k(a) - \beta_k P_{k-1}(a), \\ P_{k+1}(a) &= 2 \frac{L + \mu}{L - \mu} \frac{t_k}{t_{k+1}} P_k(a) - \frac{4a}{L - \mu} \frac{t_k}{t_{k+1}} P_k(a) - \frac{t_{k-1}}{t_{k+1}} P_{k-1}(a) \end{aligned} \quad \left\{ \begin{aligned} \beta_k &= \frac{t_{k-1}}{t_{k+1}}, \\ \alpha_k &= \frac{4}{L - \mu} \frac{t_k}{t_{k+1}}, \\ 1 + \beta_k &= 2 \frac{L + \mu}{L - \mu} \frac{t_k}{t_{k+1}} \end{aligned} \right.$$

We are almost done :) We remember, that $e_{k+1} = P_{k+1}(A)e_0$. Note also, that we work with the quadratic problem, so we can assume $x^* = 0$ without loss of generality. In this case, $e_0 = x_0$ and $e_{k+1} = x_{k+1}$.

$$\begin{aligned} x_{k+1} &= P_{k+1}(A)x_0 = (I - \alpha_k A)P_k(A)x_0 + \beta_k (P_k(A) - P_{k-1}(A))x_0 \\ &= (I - \alpha_k A)x_k + \beta_k (x_k - x_{k-1}) \end{aligned}$$

Accelerated method [2/2]

Rearranging the terms, we get:

$$P_{k+1}(a) = (1 + \beta_k)P_k(a) - \alpha_k a P_k(a) - \beta_k P_{k-1}(a),$$

$$P_{k+1}(a) = 2 \frac{L + \mu}{L - \mu} \frac{t_k}{t_{k+1}} P_k(a) - \frac{4a}{L - \mu} \frac{t_k}{t_{k+1}} P_k(a) - \frac{t_{k-1}}{t_{k+1}} P_{k-1}(a)$$

$$\begin{cases} \beta_k = \frac{t_{k-1}}{t_{k+1}}, \\ \alpha_k = \frac{4}{L - \mu} \frac{t_k}{t_{k+1}}, \\ 1 + \beta_k = 2 \frac{L + \mu}{L - \mu} \frac{t_k}{t_{k+1}} \end{cases}$$

We are almost done :) We remember, that $e_{k+1} = P_{k+1}(A)e_0$. Note also, that we work with the quadratic problem, so we can assume $x^* = 0$ without loss of generality. In this case, $e_0 = x_0$ and $e_{k+1} = x_{k+1}$.

$$\begin{aligned} x_{k+1} &= P_{k+1}(A)x_0 = (I - \alpha_k A)P_k(A)x_0 + \beta_k (P_k(A) - P_{k-1}(A))x_0 \\ &= (I - \alpha_k A)x_k + \beta_k (x_k - x_{k-1}) \end{aligned}$$

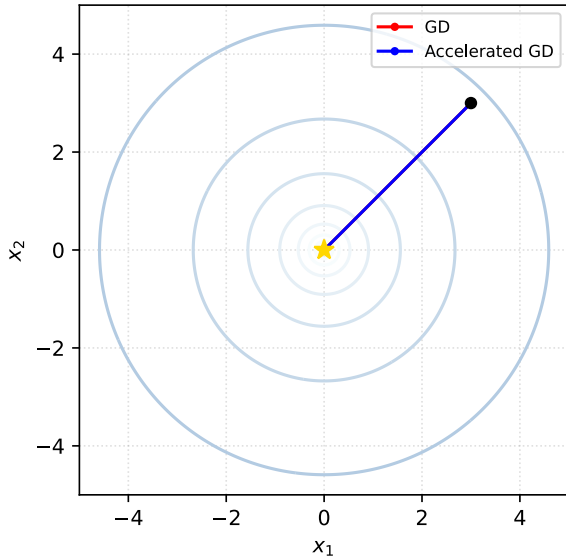
For quadratic problem, we have $\nabla f(x_k) = Ax_k$, so we can rewrite the update as:

$$x_{k+1} = \underbrace{x_k - \alpha_k \nabla f(x_k)}_{GD} + \underbrace{\beta_k (x_k - x_{k-1})}_{\text{Momentum}}$$

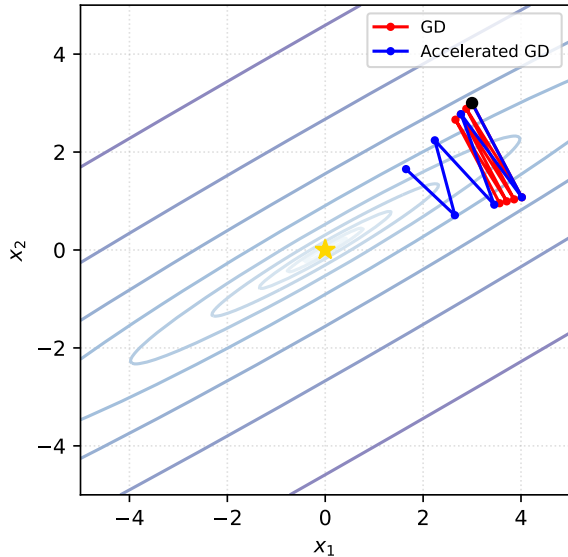
ускоренный метод

Acceleration from the first principles

$\kappa = 1.0$



$\kappa = 100.0$



Heavy ball

Oscillations and acceleration

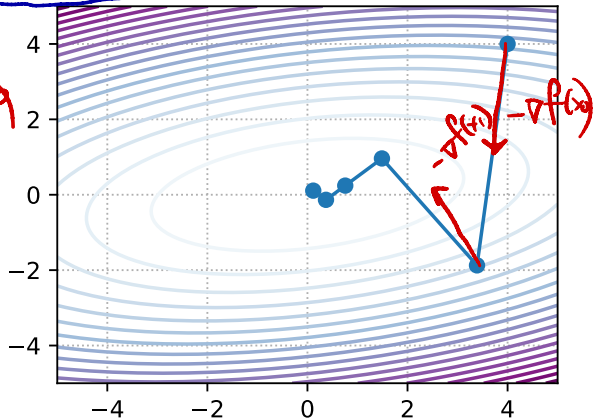
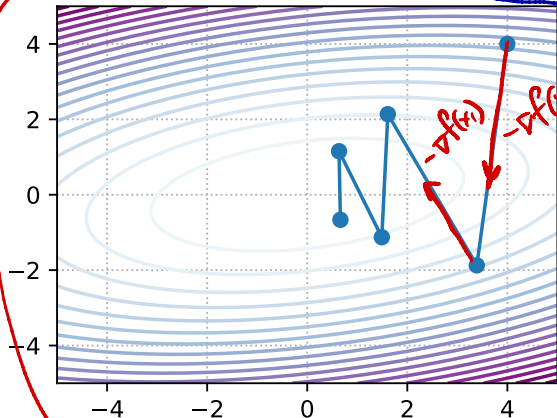
$$x_{k+1} = x_k - \alpha \nabla f(x_k) + \beta (x_k - x_{k-1}) \quad 0 < \beta < 1$$

$$x_k = x_{k-1} - \alpha \nabla f(x_{k-1}) + \beta (x_{k-1} - x_{k-2})$$

$$x_k - x_{k-1} = -\alpha \nabla f(x_{k-1}) + \beta (x_{k-1} - x_{k-2})$$

Heavy Ball

Gradient Descent



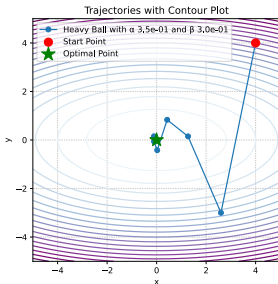
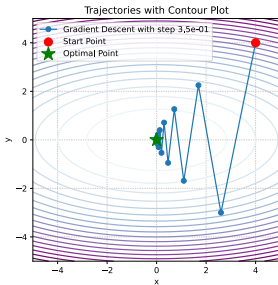
$$x_{k+1} = x_k - \alpha \nabla f(x_k) - \beta \cdot \alpha \nabla f(x_{k-1}) + \beta^2 (x_{k-1} - x_{k-2}) =$$

$$= x_k - \alpha \nabla f(x_k) - \beta \alpha \nabla f(x_{k-1}) - \beta^2 \alpha \nabla f(x_{k-2}) + \beta^3 (x_{k-2} - x_{k-3})$$

Polyak Heavy ball method

Let's introduce the idea of momentum, proposed by Polyak in 1964. Recall that the momentum update is

$$x^{k+1} = x^k - \alpha \nabla f(x^k) + \beta(x^k - x^{k-1}).$$



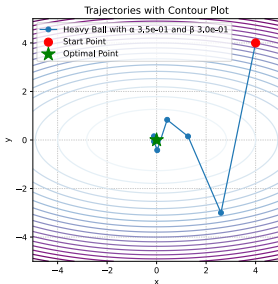
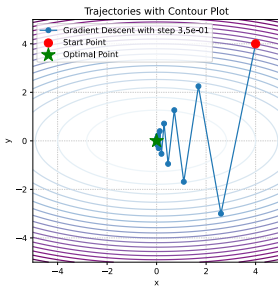
Polyak Heavy ball method

Let's introduce the idea of momentum, proposed by Polyak in 1964. Recall that the momentum update is

$$x^{k+1} = x^k - \alpha \nabla f(x^k) + \beta(x^k - x^{k-1}).$$

Which is in our (quadratics) case is

$$\hat{x}_{k+1} = \hat{x}_k - \alpha \Lambda \hat{x}_k + \beta(\hat{x}_k - \hat{x}_{k-1}) = (I - \alpha \Lambda + \beta I) \hat{x}_k - \beta \hat{x}_{k-1}$$



Polyak Heavy ball method

Let's introduce the idea of momentum, proposed by Polyak in 1964. Recall that the momentum update is

$$x^{k+1} = x^k - \alpha \nabla f(x^k) + \beta(x^k - x^{k-1}).$$

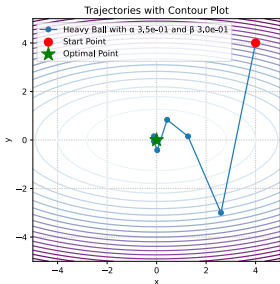
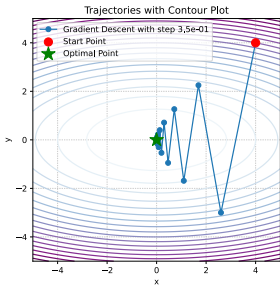
Which is in our (quadratics) case is

$$\hat{x}_{k+1} = \hat{x}_k - \alpha \Lambda \hat{x}_k + \beta(\hat{x}_k - \hat{x}_{k-1}) = (I - \alpha \Lambda + \beta I) \hat{x}_k - \beta \hat{x}_{k-1}$$

This can be rewritten as follows

$$\hat{x}_{k+1} = (I - \alpha \Lambda + \beta I) \hat{x}_k - \beta \hat{x}_{k-1},$$

$$\hat{x}_k = \hat{x}_k.$$



Polyak Heavy ball method

Let's introduce the idea of momentum, proposed by Polyak in 1964. Recall that the momentum update is

$$x^{k+1} = x^k - \alpha \nabla f(x^k) + \beta(x^k - x^{k-1}).$$

Which is in our (quadratics) case is

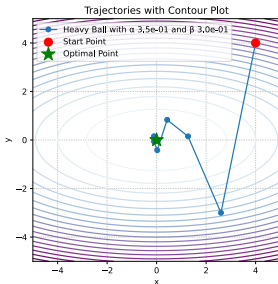
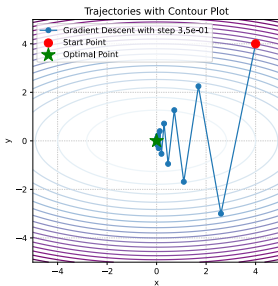
$$\hat{x}_{k+1} = \hat{x}_k - \alpha \Lambda \hat{x}_k + \beta(\hat{x}_k - \hat{x}_{k-1}) = (I - \alpha \Lambda + \beta I) \hat{x}_k - \beta \hat{x}_{k-1}$$

This can be rewritten as follows

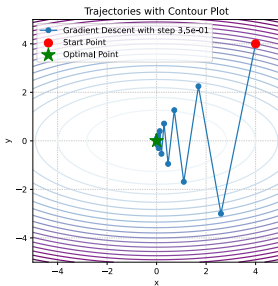
$$\hat{x}_{k+1} = (I - \alpha \Lambda + \beta I) \hat{x}_k - \beta \hat{x}_{k-1},$$

$$\hat{x}_k = \hat{x}_k.$$

Let's use the following notation $\hat{z}_k = \begin{bmatrix} \hat{x}_{k+1} \\ \hat{x}_k \end{bmatrix}$. Therefore $\hat{z}_{k+1} = M \hat{z}_k$, where the iteration matrix M is:



Polyak Heavy ball method



Let's introduce the idea of momentum, proposed by Polyak in 1964. Recall that the momentum update is

$$x^{k+1} = x^k - \alpha \nabla f(x^k) + \beta(x^k - x^{k-1}).$$

Which is in our (quadratics) case is

$$\hat{x}_{k+1} = \hat{x}_k - \alpha \Lambda \hat{x}_k + \beta(\hat{x}_k - \hat{x}_{k-1}) = (I - \alpha \Lambda + \beta I) \hat{x}_k - \beta \hat{x}_{k-1}$$

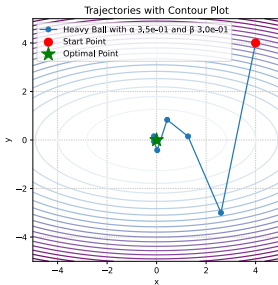
This can be rewritten as follows

$$\hat{x}_{k+1} = (I - \alpha \Lambda + \beta I) \hat{x}_k - \beta \hat{x}_{k-1},$$

$$\hat{x}_k = \hat{x}_k.$$

Let's use the following notation $\hat{z}_k = \begin{bmatrix} \hat{x}_{k+1} \\ \hat{x}_k \end{bmatrix}$. Therefore $\hat{z}_{k+1} = M \hat{z}_k$, where the iteration matrix M is:

$$M = \begin{bmatrix} I - \alpha \Lambda + \beta I & -\beta I \\ I & 0_d \end{bmatrix}.$$



Reduction to a scalar case

Note, that M is $2d \times 2d$ matrix with 4 block-diagonal matrices of size $d \times d$ inside. It means, that we can rearrange the order of coordinates to make M block-diagonal in the following form. Note that in the equation below, the matrix M denotes the same as in the notation above, except for the described permutation of rows and columns. We use this slight abuse of notation for the sake of clarity.

Reduction to a scalar case

Note, that M is $2d \times 2d$ matrix with 4 block-diagonal matrices of size $d \times d$ inside. It means, that we can rearrange the order of coordinates to make M block-diagonal in the following form. Note that in the equation below, the matrix M denotes the same as in the notation above, except for the described permutation of rows and columns. We use this slight abuse of notation for the sake of clarity.

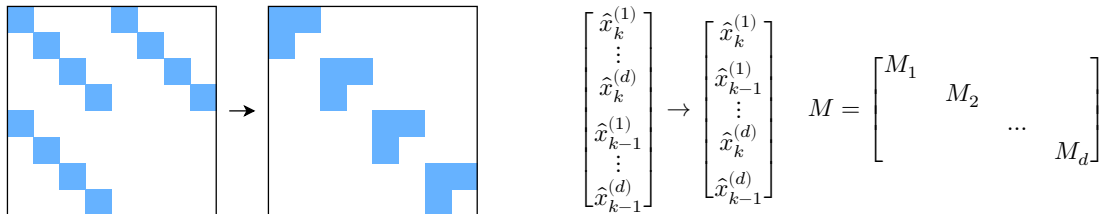


Figure 1: Illustration of matrix M rearrangement

where $\hat{x}_k^{(i)}$ is i -th coordinate of vector $\hat{x}_k \in \mathbb{R}^d$ and M_i stands for 2×2 matrix. This rearrangement allows us to study the dynamics of the method independently for each dimension. One may observe, that the asymptotic convergence rate of the $2d$ -dimensional vector sequence of $\hat{z}_k$ is defined by the worst convergence rate among its block of coordinates. Thus, it is enough to study the optimization in a one-dimensional case.

Reduction to a scalar case

For i -th coordinate with λ_i as an i -th eigenvalue of matrix W we have:

$$M_i = \begin{bmatrix} 1 - \alpha\lambda_i + \beta & -\beta \\ 1 & 0 \end{bmatrix}.$$

Reduction to a scalar case

For i -th coordinate with λ_i as an i -th eigenvalue of matrix W we have:

$$M_i = \begin{bmatrix} 1 - \alpha\lambda_i + \beta & -\beta \\ 1 & 0 \end{bmatrix}.$$

The method will be convergent if $\rho(M) < 1$, and the optimal parameters can be computed by optimizing the spectral radius

$$\alpha^*, \beta^* = \arg \min_{\alpha, \beta} \max_i \rho(M_i) \quad \alpha^* = \frac{4}{(\sqrt{L} + \sqrt{\mu})^2}; \quad \beta^* = \left(\frac{\sqrt{L} - \sqrt{\mu}}{\sqrt{L} + \sqrt{\mu}} \right)^2.$$

Reduction to a scalar case

For i -th coordinate with λ_i as an i -th eigenvalue of matrix W we have:

$$M_i = \begin{bmatrix} 1 - \alpha\lambda_i + \beta & -\beta \\ 1 & 0 \end{bmatrix}.$$

The method will be convergent if $\rho(M) < 1$, and the optimal parameters can be computed by optimizing the spectral radius

$$\alpha^*, \beta^* = \arg \min_{\alpha, \beta} \max_i \rho(M_i) \quad \alpha^* = \frac{4}{(\sqrt{L} + \sqrt{\mu})^2}; \quad \beta^* = \left(\frac{\sqrt{L} - \sqrt{\mu}}{\sqrt{L} + \sqrt{\mu}} \right)^2.$$

It can be shown, that for such parameters the matrix M has complex eigenvalues, which forms a conjugate pair, so the distance to the optimum (in this case, $\|z_k\|$), generally, will not go to zero monotonically.

Heavy ball quadratic convergence

We can explicitly calculate the eigenvalues of M_i :

$$\lambda_1^M, \lambda_2^M = \lambda \left(\begin{bmatrix} 1 - \alpha\lambda_i + \beta & -\beta \\ 1 & 0 \end{bmatrix} \right) = \frac{1 + \beta - \alpha\lambda_i \pm \sqrt{(1 + \beta - \alpha\lambda_i)^2 - 4\beta}}{2}.$$

Heavy ball quadratic convergence

We can explicitly calculate the eigenvalues of M_i :

$$\lambda_1^M, \lambda_2^M = \lambda \left(\begin{bmatrix} 1 - \alpha\lambda_i + \beta & -\beta \\ 1 & 0 \end{bmatrix} \right) = \frac{1 + \beta - \alpha\lambda_i \pm \sqrt{(1 + \beta - \alpha\lambda_i)^2 - 4\beta}}{2}.$$

When α and β are optimal (α^*, β^*) , the eigenvalues are complex-conjugated pair $(1 + \beta - \alpha\lambda_i)^2 - 4\beta \leq 0$, i.e. $\beta \geq (1 - \sqrt{\alpha\lambda_i})^2$.

Heavy ball quadratic convergence

We can explicitly calculate the eigenvalues of M_i :

$$\lambda_1^M, \lambda_2^M = \lambda \left(\begin{bmatrix} 1 - \alpha\lambda_i + \beta & -\beta \\ 1 & 0 \end{bmatrix} \right) = \frac{1 + \beta - \alpha\lambda_i \pm \sqrt{(1 + \beta - \alpha\lambda_i)^2 - 4\beta}}{2}.$$

When α and β are optimal (α^*, β^*) , the eigenvalues are complex-conjugated pair $(1 + \beta - \alpha\lambda_i)^2 - 4\beta \leq 0$, i.e. $\beta \geq (1 - \sqrt{\alpha\lambda_i})^2$.

$$\operatorname{Re}(\lambda^M) = \frac{L + \mu - 2\lambda_i}{(\sqrt{L} + \sqrt{\mu})^2}; \quad \operatorname{Im}(\lambda^M) = \frac{\pm 2\sqrt{(L - \lambda_i)(\lambda_i - \mu)}}{(\sqrt{L} + \sqrt{\mu})^2}; \quad |\lambda^M| = \frac{L - \mu}{(\sqrt{L} + \sqrt{\mu})^2}.$$

Heavy ball quadratic convergence

We can explicitly calculate the eigenvalues of M_i :

$$\lambda_1^M, \lambda_2^M = \lambda \left(\begin{bmatrix} 1 - \alpha\lambda_i + \beta & -\beta \\ 1 & 0 \end{bmatrix} \right) = \frac{1 + \beta - \alpha\lambda_i \pm \sqrt{(1 + \beta - \alpha\lambda_i)^2 - 4\beta}}{2}.$$

When α and β are optimal (α^*, β^*) , the eigenvalues are complex-conjugated pair $(1 + \beta - \alpha\lambda_i)^2 - 4\beta \leq 0$, i.e. $\beta \geq (1 - \sqrt{\alpha\lambda_i})^2$.

$$\operatorname{Re}(\lambda^M) = \frac{L + \mu - 2\lambda_i}{(\sqrt{L} + \sqrt{\mu})^2}; \quad \operatorname{Im}(\lambda^M) = \frac{\pm 2\sqrt{(L - \lambda_i)(\lambda_i - \mu)}}{(\sqrt{L} + \sqrt{\mu})^2}; \quad |\lambda^M| = \frac{L - \mu}{(\sqrt{L} + \sqrt{\mu})^2}.$$

And the convergence rate does not depend on the stepsize and equals to $\sqrt{\beta^*}$.

Heavy Ball quadratics convergence

i Theorem

Assume that f is quadratic μ -strongly convex L -smooth quadratics, then Heavy Ball method with parameters

$$\alpha = \frac{4}{(\sqrt{L} + \sqrt{\mu})^2}, \beta = \left(\frac{\sqrt{L} - \sqrt{\mu}}{\sqrt{L} + \sqrt{\mu}} \right)^2$$

converges linearly:

$$\|x_k - x^*\|_2 \leq \left(\frac{\sqrt{\kappa} - 1}{\sqrt{\kappa} + 1} \right)^{\kappa} \|x_0 - x^*\|$$

Heavy Ball Global Convergence³

i Theorem

Assume that f is smooth and convex and that

$$\beta \in [0, 1), \quad \alpha \in \left(0, \frac{2(1-\beta)}{L}\right).$$

Then, the sequence $\{x_k\}$ generated by Heavy-ball iteration satisfies

$$f(\bar{x}_T) - f^* \leq \begin{cases} \frac{\|x_0 - x^*\|^2}{2(T+1)} \left(\frac{L\beta}{1-\beta} + \frac{1-\beta}{\alpha} \right), & \text{if } \alpha \in \left(0, \frac{1-\beta}{L}\right], \\ \frac{\|x_0 - x^*\|^2}{2(T+1)(2(1-\beta) - \alpha L)} \left(L\beta + \frac{(1-\beta)^2}{\alpha} \right), & \text{if } \alpha \in \left[\frac{1-\beta}{L}, \frac{2(1-\beta)}{L}\right), \end{cases}$$

~ 1/k

where $\bar{x}_T$ is the Cesaro average of the iterates, i.e.,

$$\bar{x}_T = \frac{1}{T+1} \sum_{k=0}^T x_k.$$

³Global convergence of the Heavy-ball method for convex optimization, Euhanna Ghadimi et.al.

Heavy Ball Global Convergence ⁴

i Theorem

Assume that f is smooth and strongly convex and that

$$\alpha \in (0, \frac{2}{L}), \quad 0 \leq \beta < \frac{1}{2} \left(\frac{\mu\alpha}{2} + \sqrt{\frac{\mu^2\alpha^2}{4} + 4(1 - \frac{\alpha L}{2})} \right).$$

Then, the sequence $\{x_k\}$ generated by Heavy-ball iteration converges linearly to a unique optimizer x^* . In particular,

$$f(x_k) - f^* \leq q^k(f(x_0) - f^*),$$

where $q \in [0, 1)$.

⁴Global convergence of the Heavy-ball method for convex optimization, Euhanna Ghadimi et.al.

Heavy ball method summary

- Ensures accelerated convergence for strongly convex quadratic problems

Heavy ball method summary

- Ensures accelerated convergence for strongly convex quadratic problems
- Local accelerated convergence was proved in the original paper.

ЛОКАЛЬНАЯ СХ-ТЬ : $\forall x_0 \in \mathbb{R}^n : \|x_0 - x^*\| \leq R$

сходимость есть только

в некоторой окр-ти
оптимального
решения

ГЛОБАЛЬНАЯ

СХ-ТЬ: не зависит
от x_0

Heavy ball method summary

- Ensures accelerated convergence for strongly convex quadratic problems
- Local accelerated convergence was proved in the original paper.
- Recently ⁵ was proved, that there is no global accelerated convergence for the method.

⁵Provable non-accelerations of the heavy-ball method

Heavy ball method summary

- Ensures accelerated convergence for strongly convex quadratic problems
- Local accelerated convergence was proved in the original paper.
- Recently ⁵ was proved, that there is no global accelerated convergence for the method.
- Method was not extremely popular until the ML boom

⁵Provable non-accelerations of the heavy-ball method

Heavy ball method summary

- Ensures accelerated convergence for strongly convex quadratic problems
- Local accelerated convergence was proved in the original paper.
- Recently ⁵ was proved, that there is no global accelerated convergence for the method.
- Method was not extremely popular until the ML boom
- Nowadays, it is de-facto standard for practical acceleration of gradient methods, even for the non-convex problems (neural network training)

⁵Provable non-accelerations of the heavy-ball method

Nesterov accelerated gradient

The concept of Nesterov Accelerated Gradient method

GD

$$\underline{x_{k+1} = x_k - \alpha \nabla f(x_k)}$$

HB

$$\underline{x_{k+1} = x_k - \alpha \nabla f(x_k) + \beta(x_k - x_{k-1})}$$

$$\begin{cases} y_{k+1} = x_k + \beta(x_k - x_{k-1}) \\ x_{k+1} = y_{k+1} - \alpha \nabla f(y_{k+1}) \end{cases}$$

The concept of Nesterov Accelerated Gradient method

$$x_{k+1} = x_k - \alpha \nabla f(x_k) \quad x_{k+1} = x_k - \alpha \nabla f(x_k) + \beta(x_k - x_{k-1})$$

Let's define the following notation

$$x^+ = x - \alpha \nabla f(x)$$

Gradient step

$$d_k = \beta_k(x_k - x_{k-1})$$

Momentum term

Then we can write down:

$$x_{k+1} = x_k^+$$

Gradient Descent

$$x_{k+1} = x_k^+ + d_k$$

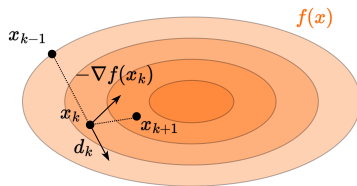
Heavy Ball

$$x_{k+1} = (x_k + d_k)^+$$

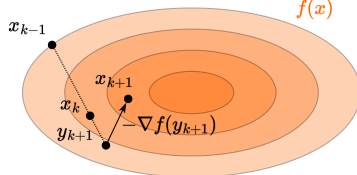
Nesterov accelerated gradient

$$\begin{cases} y_{k+1} = x_k + \beta(x_k - x_{k-1}) \\ x_{k+1} = y_{k+1} - \alpha \nabla f(y_{k+1}) \end{cases}$$

Polyak momentum



Nesterov momentum



General case convergence

i Theorem

Let $f : \mathbb{R}^n \rightarrow \mathbb{R}$ is convex and L -smooth. The Nesterov Accelerated Gradient Descent (NAG) algorithm is designed to solve the minimization problem starting with an initial point $x_0 = y_0 \in \mathbb{R}^n$ and $\lambda_0 = 0$. The algorithm iterates the following steps:

Gradient update: $y_{k+1} = x_k - \frac{1}{L} \nabla f(x_k)$

Extrapolation: $x_{k+1} = (1 - \gamma_k) y_{k+1} + \gamma_k y_k$

Extrapolation weight: $\lambda_{k+1} = \frac{1 + \sqrt{1 + 4\lambda_k^2}}{2}$

Extrapolation weight: $\gamma_k = \frac{1 - \lambda_k}{\lambda_{k+1}}$

The sequences $\{f(y_k)\}_{k \in \mathbb{N}}$ produced by the algorithm will converge to the optimal value f^* at the rate of $\mathcal{O}\left(\frac{1}{k^2}\right)$, specifically:

$$f(y_k) - f^* \leq \frac{2L\|x_0 - x^*\|^2}{k^2}$$

$$\sim \frac{1}{k^2}$$

General case convergence

i Theorem

Let $f : \mathbb{R}^n \rightarrow \mathbb{R}$ is μ -strongly convex and L -smooth. The Nesterov Accelerated Gradient Descent (NAG) algorithm is designed to solve the minimization problem starting with an initial point $x_0 = y_0 \in \mathbb{R}^n$ and $\lambda_0 = 0$. The algorithm iterates the following steps:

$$\begin{aligned}\text{Gradient update:} \quad & y_{k+1} = x_k - \frac{1}{L} \nabla f(x_k) \\ \text{Extrapolation:} \quad & x_{k+1} = (1 + \gamma_k) y_{k+1} - \gamma_k y_k \\ \text{Extrapolation weight:} \quad & \gamma_k = \frac{\sqrt{L} - \sqrt{\mu}}{\sqrt{L} + \sqrt{\mu}}\end{aligned}$$

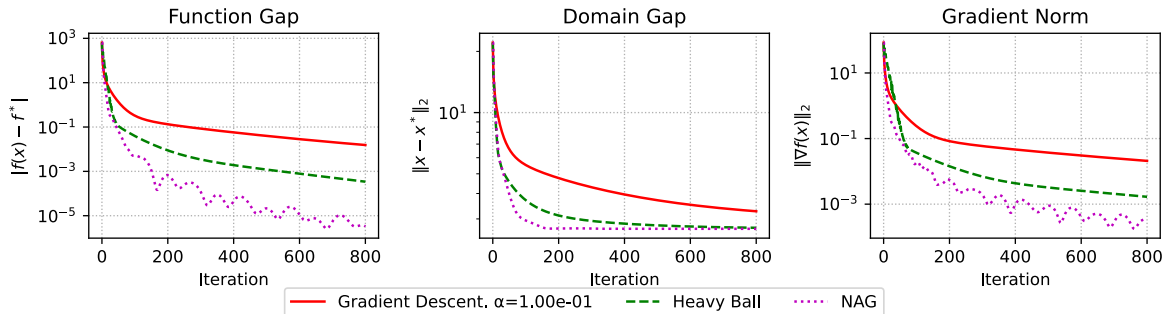
The sequences $\{f(y_k)\}_{k \in \mathbb{N}}$ produced by the algorithm will converge to the optimal value f^* linearly:

$$f(y_k) - f^* \leq \frac{\mu + L}{2} \|x_0 - x^*\|_2^2 \exp\left(-\frac{k}{\sqrt{\kappa}}\right)$$

Numerical experiments

Convex quadratics (aka linear regression)

Convex quadratics: $n=60$, random matrix, $\mu=0$, $L=10$

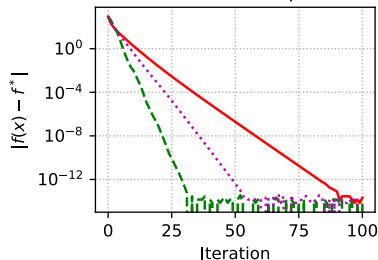


$\beta=0.8$

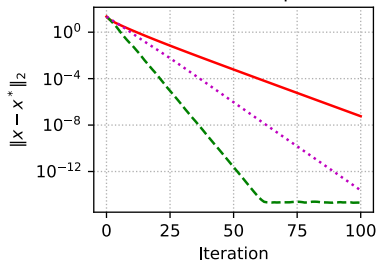
Strongly convex quadratics (aka regularized linear regression)

Strongly convex quadratics: $n=60$, random matrix, $\mu=1$, $L=10$

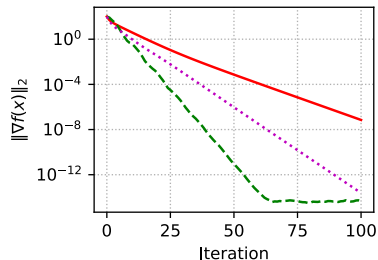
Function Gap



Domain Gap



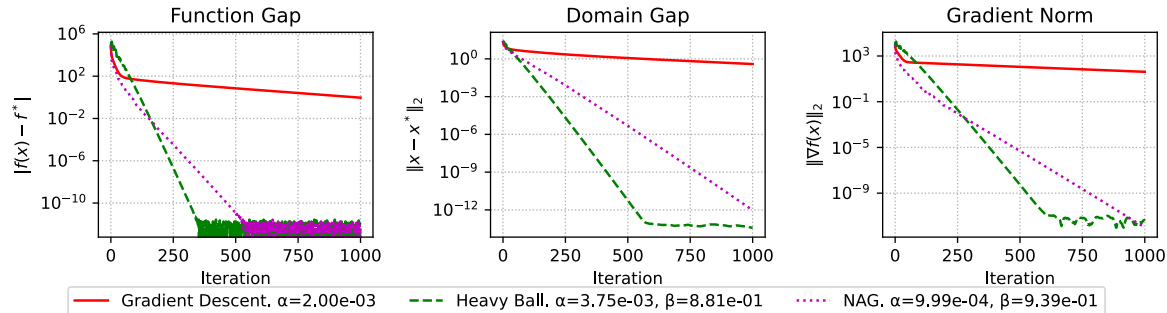
Gradient Norm



— Gradient Descent. $\alpha=1.67\text{e-}01$ - - - Heavy Ball. $\alpha=2.15\text{e-}01$, $\beta=2.88\text{e-}01$... NAG. $\alpha=9.09\text{e-}02$, $\beta=5.37\text{e-}01$

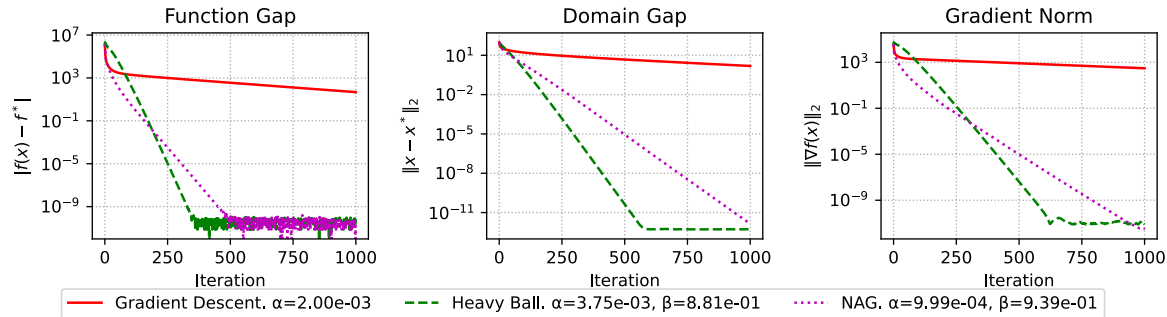
Strongly convex quadratics (aka regularized linear regression)

Strongly convex quadratics: $n=60$, random matrix, $\mu=1$, $L=1000$



Strongly convex quadratics (aka regularized linear regression)

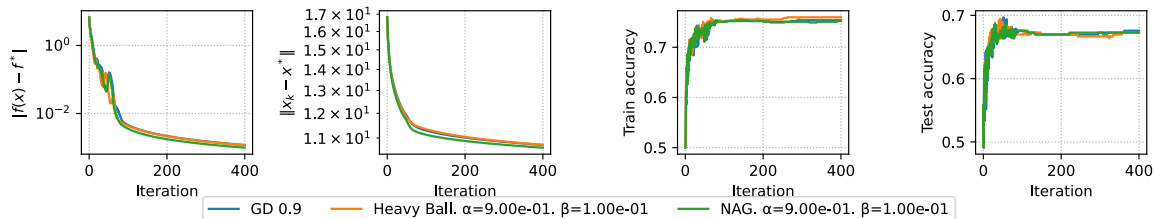
Strongly convex quadratics: $n=1000$, random matrix, $\mu=1$, $L=1000$



Convex binary logistic regression

$$\beta = 0.1$$

Convex binary logistic regression, $\mu=0$.

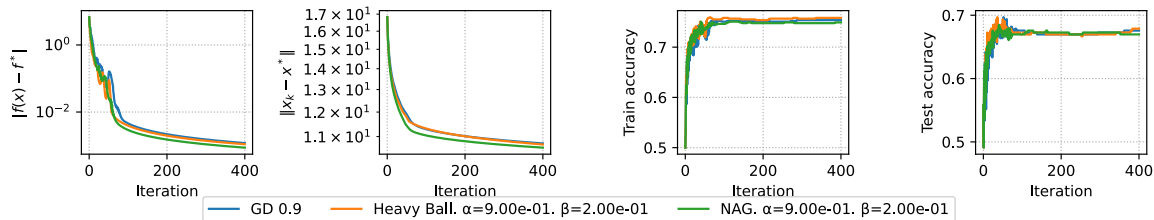


$$\beta = 0$$

HB = GD
NAG = GD

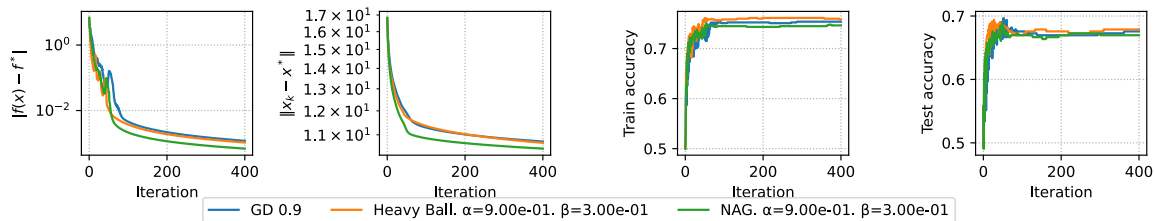
Convex binary logistic regression

Convex binary logistic regression, $\mu=0$.



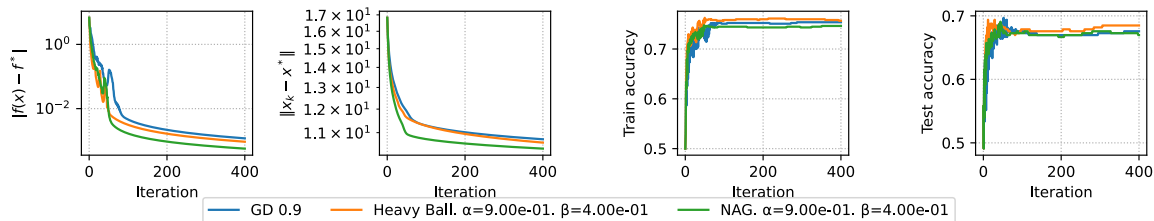
Convex binary logistic regression

Convex binary logistic regression, $\mu=0$.



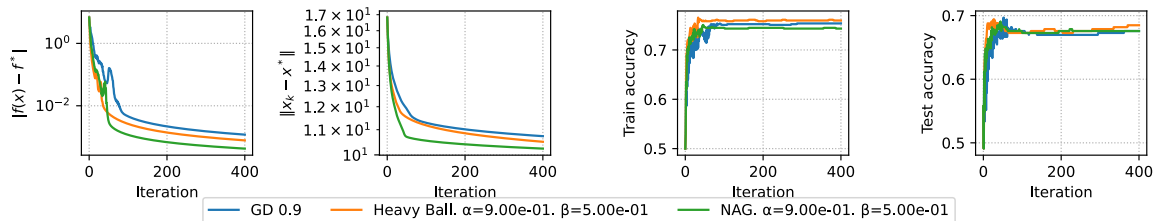
Convex binary logistic regression

Convex binary logistic regression, $\mu=0$.



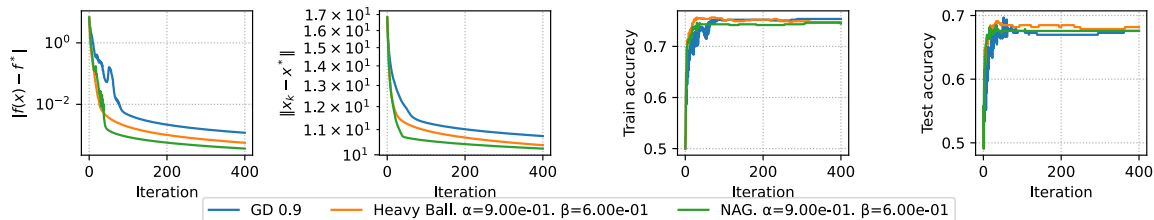
Convex binary logistic regression

Convex binary logistic regression, $\mu=0$.



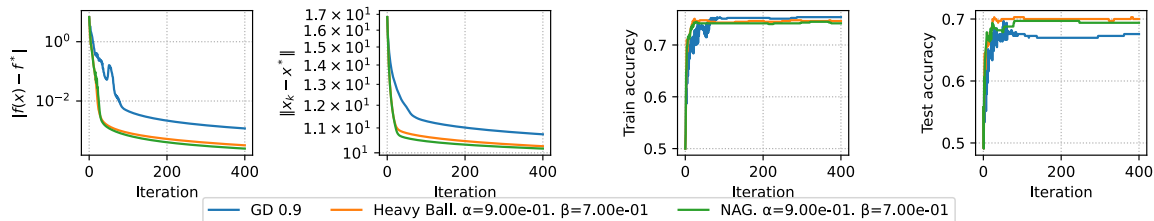
Convex binary logistic regression

Convex binary logistic regression, $\mu=0$.



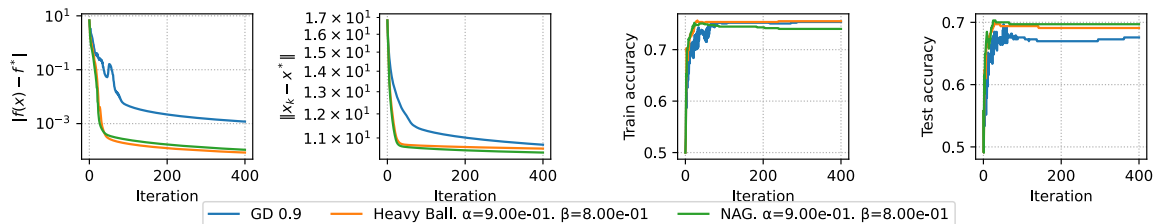
Convex binary logistic regression

Convex binary logistic regression, $\mu=0$.



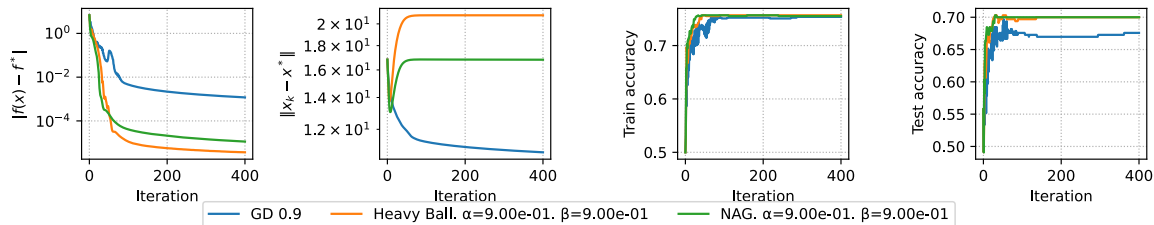
Convex binary logistic regression

Convex binary logistic regression, $\mu=0$.



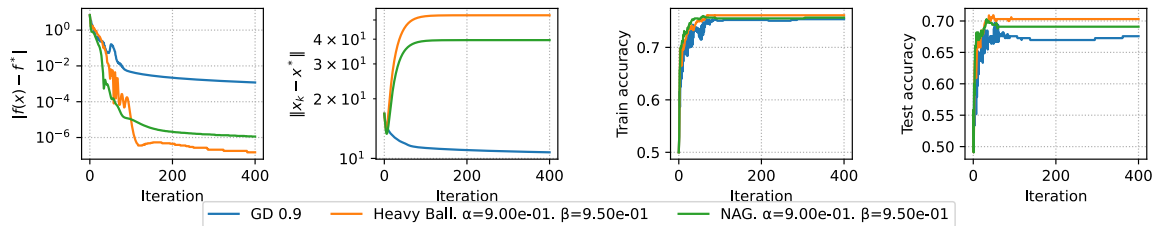
Convex binary logistic regression

Convex binary logistic regression, $\mu=0$.



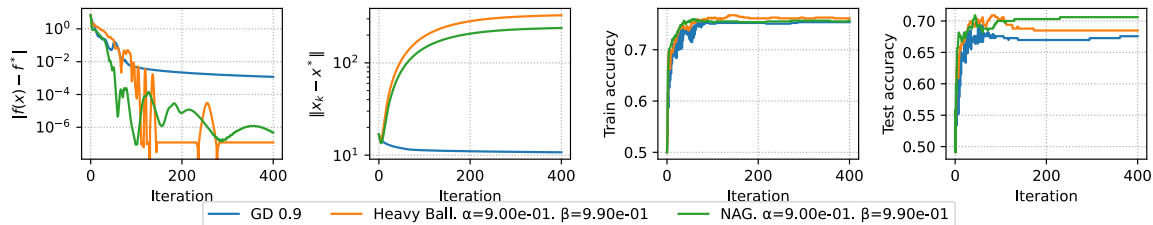
Convex binary logistic regression

Convex binary logistic regression, $\mu=0$.



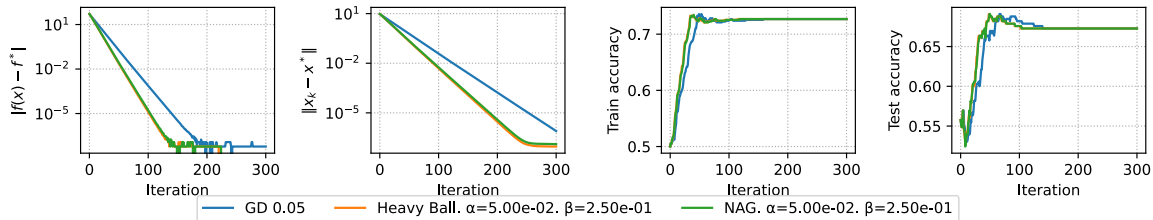
Convex binary logistic regression

Convex binary logistic regression, $\mu=0$.



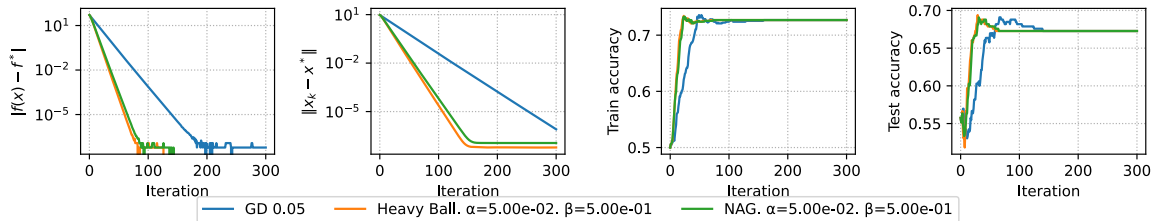
Strongly convex binary logistic regression

Strongly convex binary logistic regression. $\mu=1$.



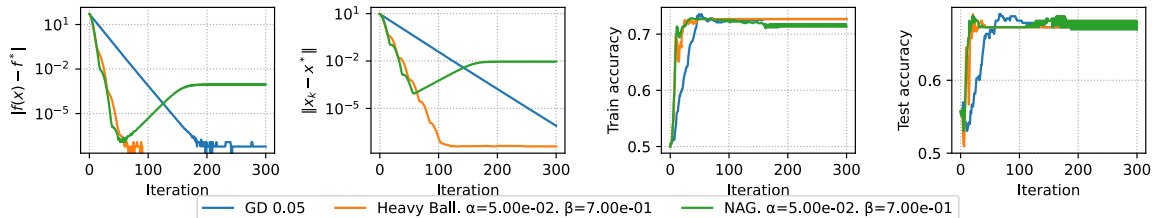
Strongly convex binary logistic regression

Strongly convex binary logistic regression. $\mu=1$.



Strongly convex binary logistic regression

Strongly convex binary logistic regression. $\mu=1$.



Strongly convex binary logistic regression

Strongly convex binary logistic regression. $\mu=1$.

