

# Advanced optimization methods

## Gradient descent and beyond. Part 1

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# Plan for today

- ▶ Gradient descent
- ▶ Heavy-ball method
- ▶ Nesterov accelerated GD
- ▶ Why accelerated?

# Problem statement

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

- ▶  $f$  is smooth and convex
- ▶ If  $\mu \leq f''(x) \leq L$ ,  $\mu \geq 0$ ,  $L > 0$ , then  $f'$  is Lipschitz with constant  $L$
- ▶ If  $\mu > 0$ , then  $f$  is  $\mu$ -strongly convex, and

$$f(y) \geq f(x) + \langle f'(x), y - x \rangle + \frac{\mu}{2} \|y - x\|_2^2$$

- ▶ Condition number  $\kappa = \frac{L}{\mu}$

# Gradient descent

$$x_{k+1} = x_k - \alpha_k f'(x_k)$$

- ▶ Explicit scheme for discretization of ODE

$$\frac{dx}{dt} = -f'(x), \quad x(0) = x_0$$

- ▶ Minimization of upper bound at  $x_k$

$$\min_x f(x_k) + \langle f'(x_k), x - x_k \rangle + \frac{1}{2\alpha_k} \|x - x_k\|_2^2,$$

- ▶ The best local descent direction

$$f(x_k + h_k) \approx f(x_k) + \langle f'(x_k), h_k \rangle < f(x_k)$$

## Step size selection

- ▶ Constant  $\alpha_k \equiv \text{const} < \frac{2}{L}$
- ▶ Decreasing sequence such that  $\sum_{k=1}^{\infty} \alpha_k = \infty$ , i.e.  $\frac{1}{k}$ ,  $\frac{1}{\sqrt{k}}$ , etc
- ▶ Backtracking search: Armijo, Goldstein, Wolfe rules and others
- ▶ Steepest descent: find the best possible  $\alpha_k$

## Main point

The best parameter you select gives you very gain in convergence!

## Convergence: any smooth function

$$\begin{aligned} f(x_{k+1}) &\leq f(x_k) + \langle f'(x_k), x_{k+1} - x_k \rangle + \frac{L}{2} \|x_{k+1} - x_k\|_2^2 = \\ &f(x_k) - \alpha_k \|f'(x_k)\|_2^2 + \frac{L\alpha_k^2}{2} \|f'(x_k)\|_2^2 = \\ &f(x_k) - \left( \alpha_k - \frac{L\alpha_k^2}{2} \right) \|f'(x_k)\|_2^2 \end{aligned}$$

- ▶ Descent condition:  $\alpha_k - \frac{L\alpha_k^2}{2} > 0 \Rightarrow \alpha_k < \frac{2}{L}$
- ▶ The best  $\alpha_k^* = \arg \max_{\alpha_k} \left( \alpha_k - \frac{L\alpha_k^2}{2} \right) = \frac{1}{L}$
- ▶  $f(x_k) - f(x_{k+1}) \geq \frac{1}{2L} \|f'(x_k)\|_2^2$
- ▶  $\frac{1}{2L} \sum_{k=0}^T \|f'(x_k)\|_2^2 \leq f(x_0) - f(x_{T+1}) \leq f(x_0) - f^*$
- ▶  $f$  is bounded below,  $\|f'(x_k)\|_2 \rightarrow 0, k \rightarrow \infty$

## Convergence: $L$ -smooth case

### Theorem

Let  $f$  be  $L$ -smooth convex function and  $\alpha = \frac{1}{L}$ , then GD converges as

$$f(x_{k+1}) - f^* \leq \frac{2L\|x - x_0\|_2^2}{k+4} = \mathcal{O}(1/k)$$

## Convergence: $\mu$ -strongly convex case

- ▶  $\mu$ -strong convexity implication

$$f(z) \geq f(x_k) + \langle f'(x_k), z - x_k \rangle + \frac{\mu}{2} \|z - x_k\|_2^2$$

- ▶ Minimize both side on  $z$

$$f(x^*) \geq f(x_k) - \frac{1}{2\mu} \|f'(x_k)\|_2^2, \quad \|f'(x_k)\|_2^2 \geq 2\mu(f(x_k) - f^*)$$

- ▶ Recall that for  $\alpha_k \equiv \frac{1}{L}$

$$f(x_{k+1}) \leq f(x_k) - \frac{1}{2L} \|f'(x_k)\|_2^2$$

- ▶ Finally get linear rate

$$f(x_{k+1}) - f^* \leq \left(1 - \frac{1}{\kappa}\right) (f(x_k) - f^*)$$



## More precise estimate

### Theorem

Let  $f$  be  $L$ -smooth and  $\mu$ -strongly convex and  $\alpha_k = \frac{2}{\mu+L}$ , then GD converges as

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

# Gradient descent highlights

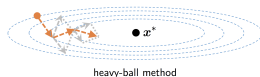
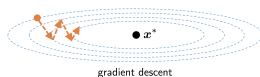
- ▶ Easy to implement
- ▶ It converges at least to stationary point
- ▶ Recent paper<sup>1</sup> shows that GD converges to a local minimizer **almost sure** with random initialization
- ▶ Linear convergence in strongly convex case
- ▶ It strongly depends on the condition number of  $f''(x)$ , random initial guess vector can help

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<sup>1</sup><https://arxiv.org/pdf/1602.04915.pdf>

# Heavy-ball method (Polyak, 1964)

$$x_{k+1} = x_k - \alpha_k f'(x_k) + \beta_k (x_k - x_{k-1})$$



Plot is from here<sup>2</sup>

- ▶ Two-step non-monotone method
- ▶ Discretization of the ODE with friction term

$$\ddot{x} + b\dot{x} + af'(x) = 0$$

- ▶ Connection between ODE and optimization methods
- ▶ CG is special case of this form

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<sup>2</sup>[http://www.princeton.edu/~yc5/ele538\\_optimization/lectures/accelerated\\_gradient.pdf](http://www.princeton.edu/~yc5/ele538_optimization/lectures/accelerated_gradient.pdf)

## Convergence: $\mu$ -strongly convex

- Rewrite method as

$$\begin{bmatrix} x_{k+1} \\ x_k \end{bmatrix} = \begin{bmatrix} (1 + \beta_k)I & -\beta_k I \\ I & 0 \end{bmatrix} \begin{bmatrix} x_k \\ x_{k-1} \end{bmatrix} + \begin{bmatrix} -\alpha_k f'(x_k) \\ 0 \end{bmatrix}$$

- Use theorem from calculus

$$\begin{bmatrix} x_{k+1} - x^* \\ x_k - x^* \end{bmatrix} = \underbrace{\begin{bmatrix} (1 + \beta_k)I - \alpha_k \int_0^1 f''(x(\tau))d\tau & -\beta_k I \\ I & 0 \end{bmatrix}}_{=A_t} \begin{bmatrix} x_k - x^* \\ x_{k-1} - x^* \end{bmatrix},$$

where  $x(\tau) = x_k + \tau(x^* - x_k)$

- Convergence depends on the spectrum of the iteration matrix  $A_t$
- Select  $\alpha_k$  and  $\beta_k$  to make spectral radius the smallest

# Parameter selection

## Theorem

Let  $f$  be  $L$ -smooth and  $\mu$ -strongly convex,  $\kappa = \frac{L}{\mu}$ . Then  $\alpha_k = \frac{4}{(\sqrt{\kappa} + 1)^2}$  and  $\beta_k = \max(|1 - \sqrt{\alpha_k L}|, |1 - \sqrt{\alpha_k \mu}|)^2$  gives

$$\left\| \begin{bmatrix} x_{k+1} - x^* \\ x_k - x^* \end{bmatrix} \right\|_2 \leq \left( \frac{\sqrt{\kappa} - 1}{\sqrt{\kappa} + 1} \right)^k \left\| \begin{bmatrix} x_1 - x^* \\ x_0 - x^* \end{bmatrix} \right\|_2$$

- ▶ Parameters depend on  $L$  and  $\mu$
- ▶ Faster than GD
- ▶ Similar to CG for  $\mu$ -strongly convex quadratic
- ▶ Can such estimate be extended to  $L$ -smooth convex function?

# Heavy-ball method highlights

- ▶ Simple two-step method
- ▶ Converges much faster than GD with appropriate  $\alpha_k, \beta_k$
- ▶ CG is particular case
- ▶ Proof only for  $\mu$ -strongly convex functions

# Nesterov accelerated GD (Nesterov, 1983)

One of possible notation variant

$$y_0 = x_0$$

$$x_{k+1} = y_k - \alpha_k f'(y_k)$$

$$y_{k+1} = y_k + \frac{k}{k+3}(x_{k+1} - x_k)$$

- ▶ Heavy-ball comparison
- ▶ ODE interpretation again
- ▶ Non-monotone, too
- ▶ More details and options see in Part 2

## Convergence: $L$ -smooth convex

### Theorem

Let  $f$  be convex and  $L$ -smooth. Assume  $\alpha_k = \frac{1}{L}$ . Then Nesterov method converges as

$$f(x_k) - f^* \leq \frac{2L\|x_0 - x^*\|_2^2}{(k+1)^2} = \mathcal{O}(1/k^2)$$

- ▶ Compare with GD convergence
- ▶ Iteration cost is almost the same



## Convergence: $\mu$ -strongly convex

### Theorem

Nesterov method for  $\mu$ -strongly convex function  $f$  (with some additional assumptions) converges as

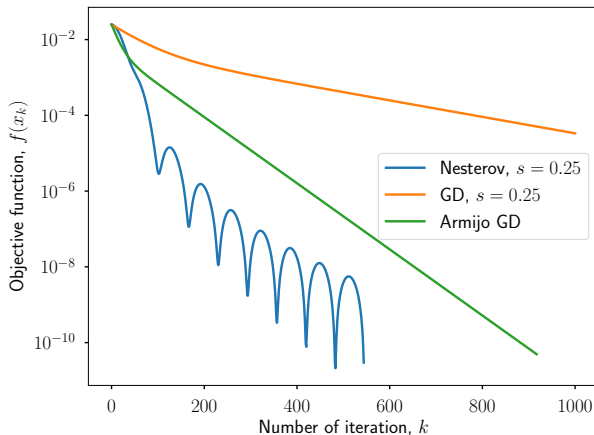
$$f(x_k) - f^* \leq L\|x_k - x_0\|_2^2 \left(1 - \frac{1}{\sqrt{\kappa}}\right)^k$$

- ▶ Faster than GD
- ▶ Similar to heavy-ball method
- ▶

## Practical issues

- Rippling behaviour and restarts

$$f(x_1, x_2) = 2 \cdot 10^{-2} x_1^2 + 5 \cdot 10^{-3} x_2^2 \rightarrow \min, \quad x_0 = (1, 1)$$



- Estimate of  $\mu$  and  $L$  is separate problem

# Why acceleration?

- ▶ It is faster than GD
- ▶ Is there even faster FOM for considered problems?

## Lower bound concept

If we have access only to (sub)gradient in any point:

Functions	Lower bound
Nonsmooth	$f(x_k) - f^* \geq \frac{G\ x^* - x_0\ _2^2}{2(1+\sqrt{k+1})}$
$L$ -smooth	$f(x_k) - f^* \geq \frac{3L\ x_0 - x^*\ _2^2}{32(k+1)^2}$
$\mu$ -strongly convex	$f(x_k) - f^* \geq \frac{\mu}{2} \left( \frac{\sqrt{\kappa}-1}{\sqrt{\kappa}+1} \right)^{2k} \ x_0 - x^*\ _2^2$

## To be discussed in part 2

- ▶ Proximal methods
- ▶ Mirror descent

## Next class announce

Stochastic modifications of the considered methods today

- ▶ SAG
- ▶ SAGA
- ▶ SVRG
- ▶ SEGA
- ▶ ...

## References

<https://epubs.siam.org/doi/book/10.1137/1.9781611974997>