

Optimization for Machine Learning

CS-439

Lecture 2: Gradient Descent

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Chapter 2

Gradient Descent

The Algorithm

Get near to a minimum \mathbf{x}^* / close to the optimal value $f(\mathbf{x}^*)$?

(Assumptions: $f : \mathbb{R}^d \rightarrow \mathbb{R}$ convex, differentiable, has a global minimum \mathbf{x}^*)

Goal: Find $\mathbf{x} \in \mathbb{R}^d$ such that

$$f(\mathbf{x}) - f(\mathbf{x}^*) \leq \varepsilon.$$

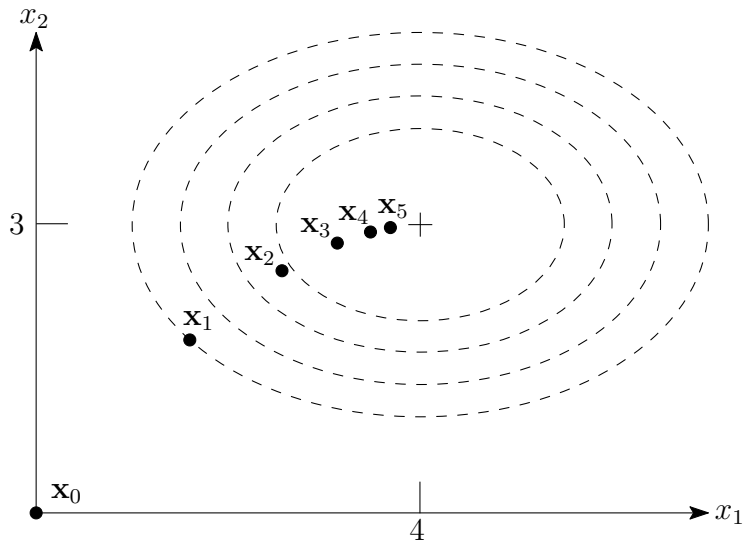
Note that there can be several global minima $\mathbf{x}_1^* \neq \mathbf{x}_2^*$ with $f(\mathbf{x}_1^*) = f(\mathbf{x}_2^*)$.

Iterative Algorithm: choose $\mathbf{x}_0 \in \mathbb{R}^d$.

$$\mathbf{x}_{t+1} := \mathbf{x}_t - \gamma \nabla f(\mathbf{x}_t),$$

for **timesteps** $t = 0, 1, \dots$, and **stepsize** $\gamma \geq 0$.

Example



$$f(x_1, x_2) := 2(x_1 - 4)^2 + 3(x_2 - 3)^2, \mathbf{x}_0 := (0, 0), \gamma := 0.1$$

Intuition

Continuous-time analysis

Vanilla analysis

How to bound $f(\mathbf{x}_t) - f(\mathbf{x}^*)$?

- ▶ Abbreviate $\mathbf{g}_t := \nabla f(\mathbf{x}_t)$ (gradient descent: $\mathbf{g}_t = (\mathbf{x}_t - \mathbf{x}_{t+1})/\gamma$).

$$\mathbf{g}_t^\top (\mathbf{x}_t - \mathbf{x}^*) = \frac{1}{\gamma} (\mathbf{x}_t - \mathbf{x}_{t+1})^\top (\mathbf{x}_t - \mathbf{x}^*).$$

- ▶ Apply $2\mathbf{v}^\top \mathbf{w} = \|\mathbf{v}\|^2 + \|\mathbf{w}\|^2 - \|\mathbf{v} - \mathbf{w}\|^2$ to rewrite

$$\begin{aligned}\mathbf{g}_t^\top (\mathbf{x}_t - \mathbf{x}^*) &= \frac{1}{2\gamma} (\|\mathbf{x}_t - \mathbf{x}_{t+1}\|^2 + \|\mathbf{x}_t - \mathbf{x}^*\|^2 - \|\mathbf{x}_{t+1} - \mathbf{x}^*\|^2) \\ &= \frac{\gamma}{2} \|\mathbf{g}_t\|^2 + \frac{1}{2\gamma} (\|\mathbf{x}_t - \mathbf{x}^*\|^2 - \|\mathbf{x}_{t+1} - \mathbf{x}^*\|^2)\end{aligned}$$

- ▶ Sum this up over the first T iterations:

$$\sum_{t=0}^{T-1} \mathbf{g}_t^\top (\mathbf{x}_t - \mathbf{x}^*) = \frac{\gamma}{2} \sum_{t=0}^{T-1} \|\mathbf{g}_t\|^2 + \frac{1}{2\gamma} (\|\mathbf{x}_0 - \mathbf{x}^*\|^2 - \|\mathbf{x}_T - \mathbf{x}^*\|^2)$$

Vanilla analysis II

Use first-order characterization of convexity: $f(\mathbf{y}) \geq f(\mathbf{x}) + \nabla f(\mathbf{x})^\top (\mathbf{y} - \mathbf{x}), \forall \mathbf{x}, \mathbf{y}$

- ▶ with $\mathbf{x} = \mathbf{x}_t, \mathbf{y} = \mathbf{x}^*$:

$$f(\mathbf{x}_t) - f(\mathbf{x}^*) \leq \mathbf{g}_t^\top (\mathbf{x}_t - \mathbf{x}^*)$$

giving

$$\sum_{t=0}^{T-1} (f(\mathbf{x}_t) - f(\mathbf{x}^*)) \leq \frac{\gamma}{2} \sum_{t=0}^{T-1} \|\mathbf{g}_t\|^2 + \frac{1}{2\gamma} \|\mathbf{x}_0 - \mathbf{x}^*\|^2,$$

an upper bound for the **average error** $f(\mathbf{x}_t) - f(\mathbf{x}^*)$ over the steps

- ▶ last iterate is not necessarily the best one
- ▶ stepsize is crucial

Lipschitz convex functions: $\mathcal{O}(1/\varepsilon^2)$ steps

Assume that all gradients of f are bounded in norm.

- ▶ Equivalent to f being Lipschitz (Theorem 1.9; **Exercise 12**).
- ▶ Rules out many interesting functions (for example, the “supermodel” $f(x) = x^2$)

Theorem

Let $f : \mathbb{R}^d \rightarrow \mathbb{R}$ be convex and differentiable with a global minimum \mathbf{x}^* ; furthermore, suppose that $\|\mathbf{x}_0 - \mathbf{x}^*\| \leq R$ and $\|\nabla f(\mathbf{x})\| \leq B$ for all \mathbf{x} . Choosing the stepsize

$$\gamma := \frac{R}{B\sqrt{T}},$$

gradient descent yields

$$\frac{1}{T} \sum_{t=0}^{T-1} f(\mathbf{x}_t) - f(\mathbf{x}^*) \leq \frac{RB}{\sqrt{T}}.$$

Lipschitz convex functions: $\mathcal{O}(1/\varepsilon^2)$ steps II

Proof.

- ▶ Plug $\|\mathbf{x}_0 - \mathbf{x}^*\| \leq R$ and $\|\mathbf{g}_t\| \leq B$ into Vanilla Analysis II:

$$\sum_{t=0}^{T-1} (f(\mathbf{x}_t) - f(\mathbf{x}^*)) \leq \frac{\gamma}{2} \sum_{t=0}^{T-1} \|\mathbf{g}_t\|^2 + \frac{1}{2\gamma} \|\mathbf{x}_0 - \mathbf{x}^*\|^2 \leq \frac{\gamma}{2} B^2 T + \frac{1}{2\gamma} R^2.$$

- ▶ choose γ such that

$$q(\gamma) = \frac{\gamma}{2} B^2 T + \frac{R^2}{2\gamma}$$

is minimized.

- ▶ Solving $q'(\gamma) = 0$ yields the minimum $\gamma = \frac{R}{B\sqrt{T}}$, and $q(R/(B\sqrt{T})) = RB\sqrt{T}$.
- ▶ Dividing by T , the result follows.



Lipschitz convex functions: $\mathcal{O}(1/\varepsilon^2)$ steps III

$$T \geq \frac{R^2 B^2}{\varepsilon^2} \quad \Rightarrow \quad \text{average error} \leq \frac{RB}{\sqrt{T}} \leq \varepsilon.$$

Advantages:

- ▶ dimension-independent (no d in the bound)!
- ▶ holds for both average, or best iterate

In Practice:

What if we don't know R and B ? \rightarrow **Exercise 16** (having to know R can't be avoided)

Smooth functions

“Not too curved”

Definition

Let $f : \text{dom}(f) \rightarrow \mathbb{R}$ be differentiable, $X \subseteq \text{dom}(f)$, $L \in \mathbb{R}_+$. f is called **smooth** (with parameter L) over X if

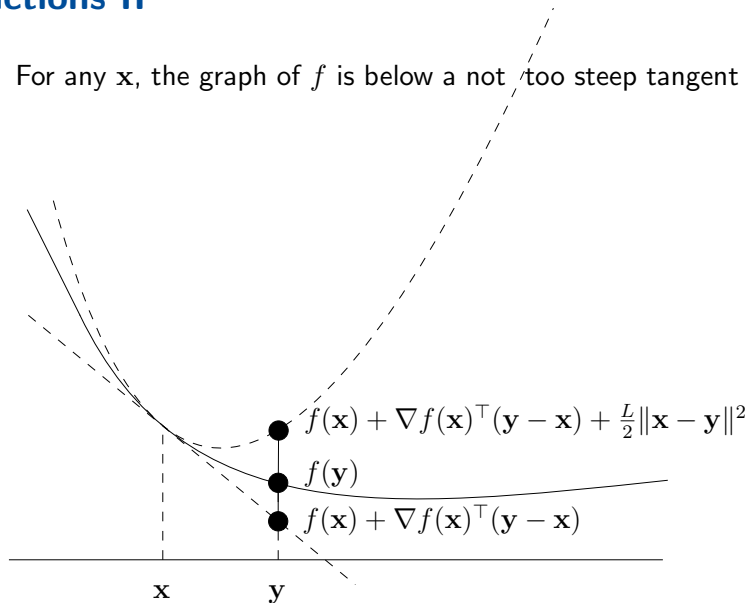
$$f(\mathbf{y}) \leq f(\mathbf{x}) + \nabla f(\mathbf{x})^\top (\mathbf{y} - \mathbf{x}) + \frac{L}{2} \|\mathbf{x} - \mathbf{y}\|^2, \quad \forall \mathbf{x}, \mathbf{y} \in X.$$

f smooth $:\Leftrightarrow f$ smooth over \mathbb{R}^d .

Definition does not require convexity (useful later)

Smooth functions II

Smoothness: For any \mathbf{x} , the graph of f is below a not too steep tangent paraboloid at $(\mathbf{x}, f(\mathbf{x}))$:



Smooth functions III

- ▶ In general: quadratic functions are smooth (**Exercise 14**).
- ▶ Operations that preserve smoothness (the same that preserve convexity):

Lemma (Exercise 17)

- (i) *Let f_1, f_2, \dots, f_m be functions that are smooth with parameters L_1, L_2, \dots, L_m , and let $\lambda_1, \lambda_2, \dots, \lambda_m \in \mathbb{R}_+$. Then the function $f := \sum_{i=1}^m \lambda_i f_i$ is smooth with parameter $\sum_{i=1}^m \lambda_i L_i$.*
- (ii) *Let f be smooth with parameter L , and let $g(\mathbf{x}) = A\mathbf{x} + \mathbf{b}$, for $A \in \mathbb{R}^{d \times m}$ and $\mathbf{b} \in \mathbb{R}^d$. Then the function $f \circ g$ is smooth with parameter $L\|A\|^2$, where $\|A\|$ is the **spectral norm** of A (Definition 1.2).*

Smooth vs Lipschitz

- ▶ Bounded gradients \Leftrightarrow Lipschitz continuity of f
- ▶ Smoothness \Leftrightarrow Lipschitz continuity of ∇f (in the convex case).

Lemma

Let $f : \mathbb{R}^d \rightarrow \mathbb{R}$ be convex and differentiable. The following two statements are equivalent.

- (i) *f is smooth with parameter L .*
- (ii) *$\|\nabla f(\mathbf{x}) - \nabla f(\mathbf{y})\| \leq L\|\mathbf{x} - \mathbf{y}\|$ for all $\mathbf{x}, \mathbf{y} \in \mathbb{R}^d$.*

Proof in lecture slides of L. Vandenberghe, <http://www.seas.ucla.edu/~vandenbe/236C/lectures/gradient.pdf>.

Sufficient decrease

Lemma

Let $f : \mathbb{R}^d \rightarrow \mathbb{R}$ be differentiable and smooth with parameter L . With stepsize

$$\gamma := \frac{1}{L},$$

gradient descent satisfies

$$f(\mathbf{x}_{t+1}) \leq f(\mathbf{x}_t) - \frac{1}{2L} \|\nabla f(\mathbf{x}_t)\|^2, \quad t \geq 0.$$

Remark

More specifically, this already holds if f is smooth with parameter L over the line segment connecting \mathbf{x}_t and \mathbf{x}_{t+1} .

Sufficient decrease II

$$f(\mathbf{x}_{t+1}) \leq f(\mathbf{x}_t) - \frac{1}{2L} \|\nabla f(\mathbf{x}_t)\|^2.$$

Proof.

Use smoothness and definition of gradient descent ($\mathbf{x}_{t+1} - \mathbf{x}_t = -\nabla f(\mathbf{x}_t)/L$):

$$\begin{aligned} f(\mathbf{x}_{t+1}) &\leq f(\mathbf{x}_t) + \nabla f(\mathbf{x}_t)^\top (\mathbf{x}_{t+1} - \mathbf{x}_t) + \frac{L}{2} \|\mathbf{x}_t - \mathbf{x}_{t+1}\|^2 \\ &= f(\mathbf{x}_t) - \frac{1}{L} \|\nabla f(\mathbf{x}_t)\|^2 + \frac{1}{2L} \|\nabla f(\mathbf{x}_t)\|^2 \\ &= f(\mathbf{x}_t) - \frac{1}{2L} \|\nabla f(\mathbf{x}_t)\|^2. \end{aligned}$$



Smooth convex functions: $\mathcal{O}(1/\varepsilon)$ steps

Theorem

Let $f : \mathbb{R}^d \rightarrow \mathbb{R}$ be convex and differentiable with a global minimum \mathbf{x}^\star ; furthermore, suppose that f is smooth with parameter L . Choosing stepsize

$$\gamma := \frac{1}{L},$$

gradient descent yields

$$f(\mathbf{x}_T) - f(\mathbf{x}^\star) \leq \frac{L}{2T} \|\mathbf{x}_0 - \mathbf{x}^\star\|^2, \quad T > 0.$$

Smooth convex functions: $\mathcal{O}(1/\varepsilon)$ steps II

$$f(\mathbf{x}_T) - f(\mathbf{x}^\star) \leq \frac{L}{2T} \|\mathbf{x}_0 - \mathbf{x}^\star\|^2, \quad T > 0.$$

Proof.

Vanilla Analysis II:

$$\sum_{t=0}^{T-1} (f(\mathbf{x}_t) - f(\mathbf{x}^\star)) \leq \frac{\gamma}{2} \sum_{t=0}^{T-1} \|\nabla f(\mathbf{x}_t)\|^2 + \frac{1}{2\gamma} \|\mathbf{x}_0 - \mathbf{x}^\star\|^2.$$

This time, we can bound the squared gradients by sufficient decrease:

$$\frac{1}{2L} \sum_{t=0}^{T-1} \|\nabla f(\mathbf{x}_t)\|^2 \leq \sum_{t=0}^{T-1} (f(\mathbf{x}_t) - f(\mathbf{x}_{t+1})) = f(\mathbf{x}_0) - f(\mathbf{x}_T).$$

Smooth convex functions: $\mathcal{O}(1/\varepsilon)$ steps III

Putting it together with $\gamma = 1/L$:

$$\begin{aligned}\sum_{t=0}^{T-1} (f(\mathbf{x}_t) - f(\mathbf{x}^*)) &\leq \frac{1}{2L} \sum_{t=0}^{T-1} \|\nabla f(\mathbf{x}_t)\|^2 + \frac{L}{2} \|\mathbf{x}_0 - \mathbf{x}^*\|^2 \\ &\leq f(\mathbf{x}_0) - f(\mathbf{x}_T) + \frac{L}{2} \|\mathbf{x}_0 - \mathbf{x}^*\|^2.\end{aligned}$$

Rewriting:

$$\sum_{t=1}^T (f(\mathbf{x}_t) - f(\mathbf{x}^*)) \leq \frac{L}{2} \|\mathbf{x}_0 - \mathbf{x}^*\|^2.$$

As last iterate is the best (sufficient decrease!):

$$f(\mathbf{x}_T) - f(\mathbf{x}^*) \leq \frac{1}{T} \left(\sum_{t=1}^T (f(\mathbf{x}_t) - f(\mathbf{x}^*)) \right) \leq \frac{L}{2T} \|\mathbf{x}_0 - \mathbf{x}^*\|^2.$$

Smooth convex functions: $\mathcal{O}(1/\varepsilon)$ steps IV

$$R^2 := \|\mathbf{x}_0 - \mathbf{x}^\star\|^2.$$

$$T \geq \frac{R^2 L}{2\varepsilon} \quad \Rightarrow \quad \text{error} \leq \frac{L}{2T} R^2 \leq \varepsilon.$$

- ▶ $50 \cdot R^2 L$ iterations for error 0.01 ...
- ▶ ... as opposed to $10,000 \cdot R^2 B^2$ in the Lipschitz case

In Practice:

What if we don't know the smoothness parameter L ?

→ **Exercise 18**