Labs
Optimization for Machine Learning
Spring 2025

EPFL
School of Computer and Communication Sciences
Nicolas Flammarion
github.com/epfml/OptML_course

Problem Set 2 — Solutions (Gradient Descent)

Gradient Descent

Exercise 14. *Prove Lemma 2.4: The quadratic function $f(\mathbf{x}) = \mathbf{x}^\top Q\mathbf{x} + \mathbf{b}^\top \mathbf{x} + c$, Q symmetric, is smooth with parameter $2\|Q\|$.*

Solution: As the function $\mathbf{x} \mapsto \mathbf{b}^\top \mathbf{x} + c$ is affine and hence smooth with parameter 0, it suffices by Lemma 2.6 to restrict ourselves to the case $f(\mathbf{x}) := \mathbf{x}^\top Q\mathbf{x}$.

Because Q is symmetric, $\mathbf{x}^\top Q\mathbf{y} = \mathbf{y}^\top Q\mathbf{x}$ for any $\mathbf{x}$ and $\mathbf{y}$. Thus, a simple calculation shows that

$$\begin{aligned} f(\mathbf{y}) = \mathbf{y}^\top Q\mathbf{y} &= \mathbf{x}^\top Q\mathbf{x} + 2\mathbf{x}^\top Q(\mathbf{y}-\mathbf{x}) + (\mathbf{x}-\mathbf{y})^\top Q(\mathbf{x}-\mathbf{y}) \\ &= f(\mathbf{x}) + 2\mathbf{x}^\top Q(\mathbf{y}-\mathbf{x}) + (\mathbf{x}-\mathbf{y})^\top Q(\mathbf{x}-\mathbf{y}). \end{aligned}$$

Cauchy-Schwarz for $(\mathbf{x}-\mathbf{y})^\top Q(\mathbf{x}-\mathbf{y}) \le \|\mathbf{x}-\mathbf{y}\| \, \|Q(\mathbf{x}-\mathbf{y})\|$, and using and the definition of spectral norm for $\|Q(\mathbf{x}-\mathbf{y})\| \le \|Q\| \, \|\mathbf{x}-\mathbf{y}\|$ we get

$$f(\mathbf{y}) \le f(\mathbf{x}) + 2\mathbf{x}^\top Q(\mathbf{y}-\mathbf{x}) + \|Q\| \, \|\mathbf{x}-\mathbf{y}\|^2 ,$$

Because $\|x-y\|^2$ vanishes as $(x-y)$ goes to 0, differentiability of f (Definition 1.5) implies that $\nabla f(\mathbf{x})^\top = 2\mathbf{x}^\top Q$, so we further get

$$f(\mathbf{y}) \le f(\mathbf{x}) + \nabla f(\mathbf{x})^\top (\mathbf{y}-\mathbf{x}) + \frac{2\|Q\|}{2} \|\mathbf{x}-\mathbf{y}\|^2 ,$$

That is, f is smooth with parameter $2\|Q\|$.

Exercise 17. *Prove Lemma 2.6! (Operations which preserve smoothness)*

Solution: For (i), we sum up the weighted smoothness conditions for all the f_i to obtain

$$\sum_{i=1}^m \lambda_i f_i(\mathbf{y}) \le \sum_{i=1}^m \lambda_i f_i(\mathbf{x}) + \sum_{i=1}^m \lambda_i \nabla f_i(\mathbf{x})^\top (\mathbf{y}-\mathbf{x}) + \sum_{i=1}^m \lambda_i \frac{L_i}{2} \|\mathbf{x}-\mathbf{y}\|^2.$$

As the gradient is a linear operator, this equivalently reads as

$$f(\mathbf{y}) \le f(\mathbf{x}) + \nabla f(\mathbf{x})^\top (\mathbf{y}-\mathbf{x}) + \frac{\sum_{i=1}^m \lambda_i L_i}{2} \|\mathbf{x}-\mathbf{y}\|^2,$$

and the statement follows. For (ii), we apply smoothness of f at $\mathbf{x}' = A\mathbf{x}+\mathbf{b}$ and $\mathbf{y}' = A\mathbf{y}+\mathbf{b}$ to obtain

$$f(A\mathbf{x}+\mathbf{b}) \le f(A\mathbf{y}+\mathbf{b}) + \nabla f(A\mathbf{x}+\mathbf{b})^\top (A(\mathbf{y}-\mathbf{x})) + \frac{L}{2} \|A(\mathbf{x}-\mathbf{y})\|^2.$$

As $\nabla (f \circ g)(\mathbf{x})^\top = \nabla f(A\mathbf{x}+\mathbf{b})^\top A$ (chain rule (Lemma 1.7), using that $\nabla g(\mathbf{x}) = A$, an easy consequence of Definition 1.5). This equivalently reads as

$$(f \circ g)(\mathbf{x}) \le (f \circ g)(\mathbf{y}) + \nabla (f \circ g)(\mathbf{x})^\top (\mathbf{y}-\mathbf{x}) + \frac{L}{2} \|A(\mathbf{x}-\mathbf{y})\|^2.$$

The statement now follows from $\|A(\mathbf{x}-\mathbf{y})\| \le \|A\| \|\mathbf{x}-\mathbf{y}\|$.

Exercise 18. *In order to obtain average error at most ε in Theorem 2.8, we need to choose*

$$\gamma := \frac{1}{L}, \quad T \geq \frac{R^2 L}{2\varepsilon},$$

if $\|\mathbf{x}_0 - \mathbf{x}^\star\| \leq R$. If L is unknown, we cannot do this.

Now suppose that we know R but not L. This means, we know a concrete number R such that $\|\mathbf{x}_0 - \mathbf{x}^\star\| \leq R$; we also know that there exists a number L such that f is smooth with parameter L, but we don't know a concrete such number.

Develop an algorithm that—not knowing L—finds a vector $\mathbf{x}$ such that $f(\mathbf{x}) - f(\mathbf{x}^\star) < \varepsilon$, using at most

$$\mathcal{O}\left(\frac{R^2 L}{2\varepsilon}\right)$$

many gradient descent steps!

Solution: The idea is to guess L. The first guess is $L = 2\varepsilon/R^2$; if this guess is correct, we can choose $T = 1$. Otherwise, we keep doubling L (which keeps doubling T), until the guess is correct (which must eventually happen if some global smoothness parameter exists). How can we check that a guess is correct? We can't, but the calculations show that in order to obtain error at most ε, we only need that

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

and this *can* be checked. It follows that the successful guess will not exceed the true L by more than a factor of two, so the number of iterations for the successful guess is at most

$$2\frac{R^2 L}{2\varepsilon},$$

and the total number of iterations at most

$$4\frac{R^2 L}{2\varepsilon},$$

using that $\sum_{i=0}^{k} 2^i = 2^{k+1} - 1$.

Exercise 19. *Let $a \in \mathbb{R}$. Prove that $f(x) = x^4$ is smooth over $X = (-a, a)$ and determine a concrete smoothness parameter L.*

Solution: The required inequality reads as

$$y^4 \leq x^4 + 4x^3(y - x) + \frac{L}{2}(x - y)^2 = -3x^4 + 4x^3 y + \frac{L}{2}(x^2 - 2xy + y^2) =: r_y(x).$$

We therefore want to ensure that $r_y(x) \geq y^4$ for all $x, y \in (-a, a)$. This is the case if and only if

$$\min\{r_y(x) : x \in [-a, a]\} \geq y^4, \quad \forall y \in [-a, a].$$

To minimize $r_y(x)$, we compute derivatives and get

$$\begin{aligned} r'_y(x) &= -12x^3 + 12x^2 y + Lx - Ly, \\ r''_y(x) &= -36x^2 + 24xy + L. \end{aligned}$$

Now, if we choose a value of L for which $r_y(x)$ is convex on $(-a, a)$, the minimum is given by $r'_y(x) = 0$. There are multiple choices for L for which this works out, but here we try $L = 60a^2$: For $L = 60a^2$, we get

$$r''_y(x) \geq -36a^2 - 24a^2 + L \geq 0$$

on $(-a, a)$, so the function is convex on this interval as a consequence of Lemma 1.18. Because $r'_y(y) = 0$, $x = y$ is therefore a minimum of r_y over $(-a, a)$ by Lemma 1.22. As we have

$$r_y(y) = y^4,$$

smoothness follows with $L = 60a^2$. (Note: this constant is not necessarily tight.)