Labs

**Optimization for Machine Learning**Spring 2023

**EPFL** 

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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

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

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

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

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

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

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

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

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

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

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

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

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  $\varepsilon$  in Theorem 2.8, we need to choose

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

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  $\|\mathbf{x}_0 - \mathbf{x}^\star\| \le R$ ; 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  $f(\mathbf{x}) - f(\mathbf{x}^*) < \varepsilon$ , using at most

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

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  $\varepsilon$ , we only need that

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

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

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

and the total number of iterations at most

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

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

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

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

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

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

$$r'_y(x) = -12x^3 + 12x^2y + Lx - Ly,$$
  
 $r''_y(x) = -36x^2 + 24xy + L.$ 

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

$$r_y''(x) \ge -36a^2 - 24a^2 + L \ge 0$$

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.)