Labs

**Optimization for Machine Learning**Spring 2020

**EPFL** 

School of Computer and Communication Sciences

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github.com/epfml/OptML\_course

## Problem Set 3, due March 13, 2020 (Gradient Descent, cont.)

## **Gradient Descent**

Solve Exercises 12, 14 and 16 from the lecture notes.

## **Computing Fixed Points**

Gradient descent turns up in a surprising number of situations which apriori have nothing to do with optimization. In this exercise we will see how computing the fixed point of functions can be seen as a form of gradient descent. Suppose that we have a 1-Lipschitz continuous function  $g: \mathbb{R} \to \mathbb{R}$  such that we want to solve for

$$g(x) = x$$
.

A simple strategy for finding such a fixed point is to run the following algorithm: starting from an arbitary  $x_0$ , we iteratively set

$$x_{t+1} = g(x_t). (1)$$

**Practical exercise.** We will try solve for x starting from  $x_0 = 1$  in the following two equations:

$$x = \log(1+x), \text{ and}$$
 (2)

$$x = \log(2+x). \tag{3}$$

Follow the Python notebook provided here:

 $colab.research.google.com/github/epfml/OptML\_course/blob/master/labs/ex03/template/notebook.ipynblob/master/labs/ex03/template/notebook.ipynblob/master/labs/ex03/template/notebook.ipynblob/master/labs/ex03/template/notebook.ipynblob/master/labs/ex03/template/notebook.ipynblob/master/labs/ex03/template/notebook.ipynblob/master/labs/ex03/template/notebook.ipynblob/master/labs/ex03/template/notebook.ipynblob/master/labs/ex03/template/notebook.ipynblob/master/labs/ex03/template/notebook.ipynblob/master/labs/ex03/template/notebook.ipynblob/master/labs/ex03/template/notebook.ipynblob/master/labs/ex03/template/notebook.ipynblob/master/labs/ex03/template/notebook.ipynblob/master/labs/ex03/template/notebook.ipynblob/master/notebook.ipynblob/ma$ 

What difference do you observe in the rate of convergence between the two problems? Let's understand why this occurs.

## Theoretical questions.

1. We want to re-write the update (1) as a step of gradient descent. To do this, we need to find a function f such that the gradient descent update is identical to (1):

$$x_{t+1} = x_t - \gamma f'(x_t) = g(x_t)$$
.

Derive such a function f.

- 2. Give sufficient conditions on g to ensure convergence of procedure (1). What  $\gamma$  would you need to pick? Hint: We know that gradient descent on f with fixed step-size converges if f is convex and smooth. What does this mean in terms of g?
- 3. What condition does g need to satisfy to ensure *linear* convergence? Are these satisfied for problems (2) and (3) in the exercise?