## Optimization for Learning - FRTN50 Assignment 1

Written by: Martin Morin

Latest update: October 18, 2019

## Introduction

The goal of this hand-in is to become familiar with some of the steps involved in solving an optimization problem. This include forming Fenchel-dual problems and finding gradients and/or proximal operators. Most of these steps will not need to be repeated every time a new problem is encountered and one can often rely on previous work by you or others. However, it is still important to be aware of and understand them.

**Problem** The problem we will solve is the following constrained problem

$$\min_{x \in S} f(x) = \min_{x} f(x) + \iota_{S}(x)$$

where  $\iota_S$  is the indicator function for the set S. In this case we let f be a quadratic,  $f(x) = \frac{1}{2}x^TQx + q^Tx$  where  $Q \succ 0$ , and S be the box,  $S = \{x : \forall i, a_i \leq x_i \leq b_i\}$  where  $a_i$  and  $b_i$  are the lower and upper bounds on the i:th coordinate of x.

**Solution Method** To solve the optimization problem we will use the *proximal gradient* method. Proximal gradient solves problems of the form

$$\min_{x} \phi(x) + h(x) \tag{1}$$

where  $\phi$  is differentiable and h is proximable, i.e.  $\operatorname{prox}_h$  can be cheaply computed. Proximal gradient is a method that, starting from some arbitrary initial guess  $x^0$ , iteratively performs the following update

$$x^{k+1} = \operatorname{prox}_{\gamma h}(x^k - \gamma \nabla \phi(x^k))$$
 (2)

until  $x^k$  is deemed to have converged. In this hand-in we simply run it a large fixed number of iterations and plot the norm of the step-length/residual,  $\|x^{k+1} - x^k\|$ , of each step to make sure it converge to zero.

The iteration (2) has a positive step-size parameter  $\gamma$  that will affect the convergence. It should be tuned to the problem or chosen based on the properties of  $\phi$  and h. In the closed convex case with  $\phi$  being L-smooth, i.e.  $\nabla \phi$  is L-Lipschitz continuous, the maximal step-size to guarantee convergence is  $\gamma < \frac{2}{L}$ . The proximal gradient method is one of the fundamental building blocks of modern optimization methods and will be covered in more detail later in the course.

## Assignment

Solve the following tasks.

- **Task 1** Derive  $f^*$  and  $\iota_S^*$  and write down the Fenchel-dual problem.
- **Task 2** Show that f and  $f^*$  are L-, and  $L^*$ -smooth respectively. Find L and  $L^*$ .
- **Task 3** Derive expressions for  $\nabla f$ ,  $\nabla f^*$ ,  $\operatorname{prox}_{\gamma \iota_S}$  and  $\operatorname{prox}_{\gamma \iota_S^*}$ .
- **Task 4** Let  $y^*$  be a solution to the dual problem, derive an expression that gives a solution to the primal problem given  $y^*$ .
- Task 5 The file functions.jl contains empty Julia-functions for evaluating the functions, gradients, proximal operators, and primal solution from the previous tasks. Use your results to fill in the functions.
- **Task 6** The file problem.jl contains a function for generating Q, q, a, and b that define the quadratic f and the box constraint set S. Use Task 5 to solve the primal problem using the proximal gradient method.

Try a range of different step-sizes. What seems to be the best choice? Does the upper bound  $\gamma < \frac{2}{L}$  seem reasonable?

Test different initial points for the algorithm, does this affect the solution the algorithm converge to? Reason about why/why not it affects the solution? Does your solution satisfy the constraint  $x^* \in S$ ? What about the iterates, do they always satisfy the constraint,  $x^k \in S$ ? Why/why not?

Task 7 Solve the dual problem. Similar to the previous task, find/verify the upper bound on the step-size and find a good step-size choice.

Compare the solutions from the primal and the one extracted from the dual, are they the same? Do they satisfy the constraint  $x^* \in S$ ? Let  $y^k$  be the iterates of the dual method, using the expression from Task 4, extract the primal iterates  $\hat{x}^k$  from  $y^k$ . Does  $\hat{x}^k$  always satisfy the constraint  $\hat{x}^k \in S$ ?

How does the function values,  $f(\hat{x}^k)$ , develop over the iterations? What about  $f(\hat{x}^k) + \iota_S(\hat{x}^k)$ ?

## **Submission**

See the latest version of the course program for instruction on how to submit the assignment. Your submission should contain the following files.

- Your filled in version of functions.jl from Task 5.
- Your code that solves the problems from Task 6 and 7.
- A single pdf containing the following:
  - Your derivations and final expressions from Task 1-4.

 A couple of paragraphs explaining and commenting on your findings from Task 6 and 7. Answer the questions raised in the tasks and motivate them with plots whenever possible.