

Assignment A3 — FL Algorithms as Fixed-Point Iterations

CS-E4740 Federated Learning

Read Carefully

You do not need to submit any files. Assessment is exclusively via a MyCourses quiz.

1 Purpose

This assignment studies how a one-dimensional optimization problem

$$\min_{w \in \mathbb{R}} f(w) \quad (1)$$

can be solved via a fixed-point iteration

$$w^{(t+1)} = \mathcal{F}w^{(t)}. \quad (2)$$

In general, there are different choices for the operator \mathcal{F} such that (2) converges to a solution of (1). We focus on two constructions:

- a gradient step for a smooth and strongly convex objective function,
- a proximal operator for a convex (possibly non-smooth) objective function.

2 Part I: Gradient-Based Fixed-Point Iteration

Consider the strongly convex and smooth objective function $f : \mathbb{R} \rightarrow \mathbb{R}$ with

$$f(w) = 2w^2 - 8w.$$

Tasks

1. Compute the minimizer w^* using the zero-gradient condition

$$f'(w^*) = 0.$$

2. Consider the gradient step

$$T^{(f,\eta)}(w) = w - \eta f'(w),$$

with learning rate $\eta > 0$. Show that the iteration

$$w^{(t+1)} = T^{(f,\eta)}(w^{(t)})$$

always satisfies

$$w^{(t+1)} - w^* = q(\eta)(w^{(t)} - w^*).$$

3. Compute numerically:

- the largest number $\alpha \geq 0$ such that $T^{(f,\eta)}$ is a contractive operator for any $\eta \in (0, \alpha)$.
- the value $q(1/8)$,

4. Starting from $w^{(0)} = 18$, perform 3 iterations using $T^{(f,\eta)}$ with $\eta = 1/8$ and compute $w^{(3)} - w^*$.

3 Part II: Proximal Fixed-Point Iteration

For a continuous convex objective function f , we can define the proximal operator

$$\text{prox}_{\eta f}(w) := \arg \min_{u \in \mathbb{R}} \left(f(u) + \frac{1}{2\eta} (u - w)^2 \right) \text{ with some } \eta > 0.$$

3.1 Strongly Convex Case

Consider the strongly convex objective function

$$f(w) = 2w^2.$$

1. Try to find the corresponding proximal operator in closed-form.
2. For $\eta = 1/2$, compute the smallest number κ such that $|w^{(t+1)}| \leq \kappa |w^{(t)}|$ for all $t = 0, 1, \dots$
3. Starting from $w^{(0)} = 81$, perform 4 iterations

$$w^{(t+1)} = \text{prox}_{0.5f}(w^{(t)}).$$

and report

$$|w^{(4)}|.$$

3.2 Non-Strongly Convex Case

Now consider the convex objective function $f : \mathbb{R} \rightarrow \mathbb{R}$ with

$$f(w) = |w|.$$

Note that this function is neither differentiable nor strongly convex.

1. Compute explicitly

$$T(w) := \text{prox}_{0.5f}(w).$$

Hint: Recall that the proximal operator is defined as the minimizer of a one-dimensional convex optimization problem. For a fixed w , consider three possible cases where the minimizer lies in $(-\infty, 0)$, $\{0\}$, or $(0, \infty)$. For each possible case, simplify the objective accordingly and determine the candidate minimizer.

2. Compute the maximal ratio

$$\sup_{u \neq v} \frac{|T(u) - T(v)|}{|u - v|}.$$

4 Summary

This assignment demonstrates that:

- The gradient step for a strongly convex and smooth objective function is a contractive operator
- The proximal operator of a convex (possibly non-differentiable) function is always non-expansive.