

This homework is due at **2pm, October 18**.

Problem 1

Recall that the logistic regression corresponds to the optimization problem

$$w^* \in \arg \min_w \{ f(w) \mid w \in \mathbb{R}^p \},$$

where

$$f(w) := \frac{1}{n} \sum_{i=1}^n \log(1 + e^{-y_i \langle x_i, w \rangle}),$$

for given data $(x_1, y_1), \dots, (x_n, y_n) \in \mathbb{R}^p \times \{-1, +1\}$.

- (10 points) Suppose that the data satisfies

$$P(y_i = 1) = 1 - P(y_i = -1) = \frac{1}{1 + e^{-\langle x_i, w^\dagger \rangle}}, \quad \forall 1 \leq i \leq n,$$

for some $w^\dagger \in \mathbb{R}^p$, and that y_1, \dots, y_n are independent random variables. **Show that w^* is a maximum-likelihood estimator of w^\dagger .**

- (10 points) Let $X \in \mathbb{R}^{n \times p}$, whose i -th row is given by x_i . Denote by $\text{var}(y_i)$ the variance of y_i for every i . **Show that**

$$\nabla^2 f(w) = \frac{1}{4n} X^T D X,$$

where $D \in \mathbb{R}^{n \times n}$ is a diagonal matrix given by

$$D := \begin{bmatrix} \text{var}(y_1) & 0 & \cdots & 0 \\ 0 & \text{var}(y_2) & \ddots & \vdots \\ \vdots & \ddots & \ddots & 0 \\ 0 & \cdots & 0 & \text{var}(y_n) \end{bmatrix}.$$

- (10 points) **Show that $\text{var}(y_i) \leq 1$ for all $1 \leq i \leq n$.**
- (10 points) **Show that the function f is L -smooth for some $L > 0$. Specify the corresponding parameter L .**
(HINT: The parameter L may depend on, for example, the matrix X .)
(HINT: You do not need to find the best value of L .)
- (10 points) **Give an algorithm that, for any given $\varepsilon > 0$, computes some w_ε such that**

$$f(w_\varepsilon) \leq f(w^*) + \varepsilon$$

with $O(\varepsilon^{-1/2})$ calls to the first-order oracle.

Problem 2

Let $\mathcal{X} \subseteq \mathbb{R}^p$ be a closed convex set. Let $f : \mathcal{X} \rightarrow \mathbb{R}$ be differentiable, L -Lipschitz, and μ -strongly convex with respect to the ℓ_2 -norm, for some strictly positive real numbers L and μ . Consider solving the optimization problem

$$f^* = \min_x \{ f(x) \mid x \in \mathcal{X} \}.$$

via the following algorithm.

- 1: Set $x_1 \in \mathcal{X}$ and $T \in \mathbb{N}$.
- 2: **for** $t = 2, \dots, T$ **do**
- 3: $x_t \leftarrow \text{proj}_{\mathcal{X}}(x_{t-1} - \eta_t \nabla f(x_{t-1}))$
- 4: **end for**

Of course, the step sizes η_t should be properly chosen. The projection is defined with respect to the ℓ_2 -norm, i.e.,

$$\text{proj}_{\mathcal{X}}(y) := \arg \min_x \{ \|y - x\|_2 \mid x \in \mathcal{X} \}.$$

1. (10 points) **Show that**

$$2(f(x_t) - f(x^*)) \leq 2\langle \nabla f(x_t), x_t - x^* \rangle - \mu \|x_t - x^*\|_2^2, \quad \forall t \in \mathbb{N}.$$

2. (10 points) **Show that projection onto \mathcal{X} is a non-expansive mapping.** That is, show that

$$\|\text{proj}_{\mathcal{X}}(y) - \text{proj}_{\mathcal{X}}(x)\|_2 \leq \|y - x\|_2, \quad \forall x, y \in \mathbb{R}^p.$$

3. (10 points) **Show that**

$$2\langle \nabla f(x_t), x_t - x^* \rangle \leq \frac{\|x_t - x^*\|_2^2 - \|x_{t+1} - x^*\|_2^2}{\eta_{t+1}} + \eta_{t+1} L^2, \quad \forall t \in \mathbb{N}.$$

4. (20 points) Set

$$\eta_{t+1} := \frac{1}{\mu t}, \quad \forall t \in \mathbb{N}.$$

Show that

$$\min\{f(x_1), \dots, f(x_t)\} - f^* \leq \frac{L^2(1 + \log t)}{2\mu t}, \quad \forall t \in \mathbb{N}.$$