## Evaluation ONLINE LEARNING LINKS WITH OPTIMIZATION AND GAMES UNIVERSITÉ PARIS–SACLAY

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## COMPOSITE OPTIMIZATION

We consider a convex "composite" optimization problem where the objective function writes  $f + \phi$ , with  $f : \mathbb{R}^d \to \mathbb{R}$  being a convex differentiable function, and  $\phi : \mathbb{R}^d \to \mathbb{R} \cup \{+\infty\}$  a proper, convex, lower semicontinuous function. We assume that the proximal operator associated with  $\phi$ :

$$\operatorname{Prox}_{\phi}(x) = \operatorname*{arg\,min}_{x' \in \mathbb{R}^d} \left\{ \phi(x') + \frac{1}{2} \left\| x' - x \right\|_2^2 \right\}, \quad x \in \mathbb{R}^d.$$

is easily computable.

**EXEMPLE.** — If  $\phi = \lambda \|x\|_1$  for some  $\lambda > 0$ ,

$$\operatorname{Prox}_{\phi}(x)_{i} = \begin{cases} x_{i} - \lambda & \text{if } x_{i} \geqslant \lambda \\ 0 & \text{if } |x_{i}| \leqslant \lambda \\ x_{i} + \lambda & \text{if } x_{i} \leqslant -\lambda \end{cases}, \quad 1 \leqslant i \leqslant d, \ x \in \mathbb{R}^{d}.$$

The most popular algorithm for this setting is the *proximal gradient method*, aka *forward-backward splitting*: let  $x_0 \in \mathbb{R}^d$  such that  $\partial \phi(x_0) \neq \emptyset$ ,  $(\gamma_t)_{t \ge 0}$  a positive sequence, and

$$x_{t+1} = \operatorname{Prox}_{\gamma_t \varphi} \left( x_t - \gamma_t \nabla f(x_t) \right), \quad t \ge 0.$$

- 1) Prove that the proximal gradient method is an extension of projected gradient descent.
- 2) Prove that the proximal gradient method is an instance of UMD iterates.
- 3) L > 0. In the case where f is L-smooth for  $\|\cdot\|_2$ , using the tools from the course, establish for the proximal gradient method a convergence guarantee that extends the classical guarantee for projected gradient descent.
- 4) Let  $\|\cdot\|$  be an arbitrary norm in  $\mathbb{R}^d$  and assume that f is L-smooth for  $\|\cdot\|$ . Propose for this context an algorithm that extends the proximal gradient method and its convergence guarantee.
- 5) Propose an alternative algorithm for the context of the previous question and derive corresponding guarantees.

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