

EVALUATION
ONLINE LEARNING
LINKS WITH OPTIMIZATION AND GAMES
UNIVERSITÉ PARIS–SACLAY



A GENERALIZED APPROACH FOR NONSMOOTH CONVEX OPTIMIZATION

Let $f : \mathbb{R}^d \rightarrow \mathbb{R}$ be a convex function and $\mathcal{X} \subset \mathbb{R}^d$ a nonempty closed convex set, such that there exists $x_* \in \mathcal{X}$ satisfying

$$f(x_*) = \min_{x \in \mathcal{X}} f(x).$$

- 1) Prove that for all $x, x' \in \mathbb{R}^d$, $y \in \partial f(x)$ and $y' \in \partial f(x')$,

$$\langle y' - y, x' - x \rangle \geq 0.$$

- 2) Let $(x_t)_{t \geq 1}$ be a sequence in \mathbb{R}^d , $(\beta_t)_{t \geq 1}$ a sequence in $[0, 1]$, $(\gamma_t)_{t \geq 1}$ a positive sequence and for $t \geq 1$, consider

$$\Gamma_t = \sum_{s=1}^t \gamma_s, \quad \bar{x}_t = \frac{\sum_{s=1}^t \gamma_s x_s}{\Gamma_t}, \quad z_t = \beta_t \bar{x}_t + (1 - \beta_t) x_t, \quad \text{and} \quad g_t \in \partial f(z_t).$$

Let $t \geq 1$.

- a) Prove that

$$\bar{x}_t - \bar{x}_{t-1} = \frac{\gamma_t}{\Gamma_{t-1}} (x_t - \bar{x}_t) \quad \text{and} \quad x_t - z_t = \frac{\beta_t}{1 - \beta_t} (z_t - \bar{x}_t).$$

b) Prove that

$$\Gamma_t f(\bar{x}_t) - \Gamma_{t-1} f(\bar{x}_{t-1}) - \gamma_t f(x_*) \leq \langle \gamma_t g_t, x_t - x_* \rangle.$$

Indications: make $f(z_t)$ appear, introduce $\tilde{g}_t \in \partial f(\bar{x}_t)$ and use Question 1 with points \bar{x}_t and z_t .

c) Deduce that for $T \geq 1$,

$$f(\bar{x}_T) - f(x_*) \leq \frac{\sum_{t=1}^T \langle \gamma_t g_t, x_t - x_* \rangle}{\Gamma_T}.$$

- 3) Let $\|\cdot\|$ be a norm in \mathbb{R}^d and assume that f is L -Lipschitz continuous for $\|\cdot\|$. Using the tools from the course and the previous question, define algorithms for the minimization of f and derive guarantees.
- 4) Extend to *Stochastic* nonsmooth convex optimization.
- 5) Perform numerical experiments for e.g. an SVM with a moderate size dataset and compare the performance of various choices for the sequences $(\gamma_t)_{t \geq 1}$ and $(\beta_t)_{t \geq 1}$.

