

# Mirror Descent

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# Recap on (sub)-gradient descent

- ◇ When we used a norm  $\|\cdot\|$  we meant the 2-norm, i.e.

$$\|x\|_2 = \sqrt{x_1^2 + x_2^2 + \cdots + x_d^2}.$$

- ◇ In **gradient descent** we used Lipschitz continuity:

$$\|\nabla f(x) - \nabla f(y)\| \leq L\|x - y\|.$$

(Lead to a complexity of  $\mathcal{O}(\frac{L}{k})$ )

- ◇ **Sub-gradient descent:** used  $\|g\| \leq G$  which lead to  $\mathcal{O}(\frac{G}{\sqrt{k}})$ .

- ◇ But there are **other norms**  $\|x\|_\infty \leq \|x\|_2 \leq \sqrt{d}\|x\|_\infty$ .  
It can happen that  $\|g\|_\infty \leq G$  but  $\|g\|_2 \approx \sqrt{d}G$ .

we lose dimension independence

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# Different norms?

*But where did we use the norm in the **method**?*

## Gradient Descent

$$x_{k+1} = x_k - \alpha \nabla f(x_k)$$

equivalently

$$x_{k+1} = \arg \min_{x \in \mathbb{R}^d} \left\{ f(x_k) + \langle \nabla f(x_k), x - x_k \rangle + \frac{1}{2\alpha} \|x - x_k\|_2^2 \right\}$$

We can replace the 2-norm with a more general **distance**.

# Bregman distance

- (i)  $h : \mathbb{R}^d \rightarrow \mathbb{R} \cup \{+\infty\}$  is convex
- (ii)  $h$  is differentiable on the interior of  $\text{dom } h$
- (iii)  $h$  is 1-strongly convex (w.r.t. given norm  $\|\cdot\|$ )

$$\mathcal{D}_h(x, y) := h(x) - h(y) - \langle \nabla h(y), x - y \rangle.$$

## Properties

- ◇ nonnegative:  $\mathcal{D}_h(x, y) \geq 0$
- ◇ not necessarily symmetric:  $\mathcal{D}_h(x, y) \neq \mathcal{D}_h(y, x)$
- ◇ From Taylor expansion we see

$$\mathcal{D}_h(x, y) \approx \frac{1}{2} \langle \nabla^2 h(y)(x - y), x - y \rangle = \frac{1}{2} \|x - y\|_{\nabla^2 h(y)}^2.$$

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# Examples

- ◇  $h(x) = \frac{1}{2} \|x\|_2^2$  gives  $\mathcal{D}_h(x, y) = \|x - y\|^2$
- ◇  $h(x) = \frac{1}{2(p-1)} \|x\|_p^2$  with  $p \in [1, 2]$
- ◇  $\Delta^d = \{x \in \mathbb{R}_+^d : \sum_{i=1}^d x_i = 1\}$  the *unit simplex* and

$$h(x) = \begin{cases} \sum_{i=1}^d x_i \log(x_i) & x_i > 0 \\ +\infty & \text{otherwise} \end{cases}$$

the **Negative entropy**.



# Negative entropy

- ◇ Negative entropy:  $h(x) = \sum_{i=1}^d x_i \log(x_i)$  for  $x_i > 0$ .
- ◇ Then  $\nabla h(x) = \log(x) + 1$  (coordinatewise) and

$$\begin{aligned}\mathcal{D}_h(x, y) &= \sum_{i=1}^d x_i \log(x_i) - y_i \log(y_i) - \langle \log(y) + 1, x - y \rangle \\ &= \sum_{i=1}^d x_i \log(x_i) - \sum_{i=1}^d x_i \log(y_i) \\ &= \sum_{i=1}^d x_i \log\left(\frac{x_i}{y_i}\right)\end{aligned}$$

Known as **Kullback-Leibler divergence**  $K(X \| Y)$ .

- ◇ Is strongly convex over  $\Delta$

$$\mathcal{D}(x, y) \geq \frac{1}{2} \|x - y\|_1^2 \quad \text{ Pinsker's ineq. }$$

# Mirror descent

Idea: replace squared Euclidian norm with more general object:

$$\begin{aligned}x_{k+1} &= \arg \min_{x \in \mathbb{R}^d} \left\{ f(x_k) + \langle \nabla f(x_k), x - x_k \rangle + \frac{1}{\alpha} \mathcal{D}_h(x, x_k) \right\} \\&= \arg \min_{x \in \mathbb{R}^d} \left\{ \langle \nabla f(x_k), x \rangle + \frac{1}{\alpha} \mathcal{D}_h(x, x_k) \right\} \\&= \arg \min_{x \in \mathbb{R}^d} \left\{ \langle \nabla f(x_k), x \rangle + \frac{1}{\alpha} (h(x) - h(x_k) - \langle \nabla h(x_k), x - x_k \rangle) \right\} \\&= \arg \min_{x \in \mathbb{R}^d} \left\{ \langle \nabla f(x_k), x \rangle + \frac{1}{\alpha} (h(x) - \langle \nabla h(x_k), x \rangle) \right\} \\&= \arg \min_{x \in \mathbb{R}^d} \left\{ \langle \alpha \nabla f(x_k) - \nabla h(x_k), x \rangle + h(x) \right\}\end{aligned}$$

Question: But why *mirror* descent?

# Mirror descent

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# The Mirror part

$$x_{k+1} = \arg \min_{x \in \mathbb{R}^d} \{ \langle \alpha \nabla f(x_k) - \nabla h(x_k), x \rangle + h(x) \}$$

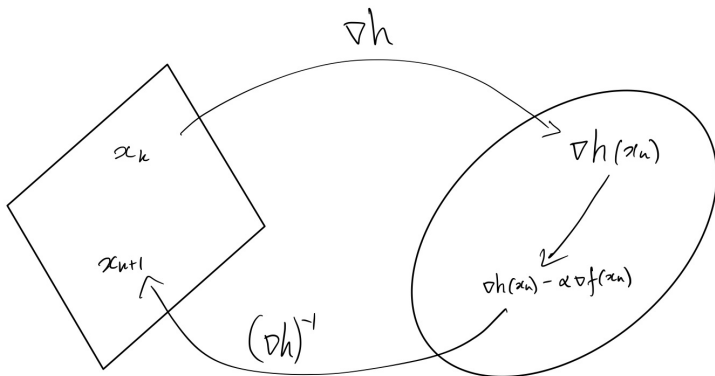
By optimality condition:

$$0 = \alpha \nabla f(x_k) - \nabla h(x_k) + \nabla h(x_{k+1})$$

Therefore

$$\nabla h(x_{k+1}) = \nabla h(x_k) - \alpha \nabla f(x_k)$$

# Why it's called mirror descent



# Mirror Descent w.r.t. negative entropy

**Negative entropy:**  $h(x) = \sum_{i=1}^d x_i \log(x_i)$  for  $x_i > 0$ .

We define  $a := \alpha \nabla f(x_k) - \nabla h(x_k)$ . Then

$$x_{k+1} = \arg \min_{x \in \Delta} \{ \langle a, x \rangle + h(x) \}$$

Results in

$$x_{k+1} = x_k \cdot * e^{-\alpha \nabla f(x_k)}$$

in a pointwise sense.

# (General) mirror descent convergence statement

Since we changed norm in the space of the variable  $x$ , we need to go to the **dual norms** in the space of the subgradients

$$\|y\|_* := \max_{\|x\|=1} \{\langle y, x \rangle\}.$$

## Theorem

*In  $(\mathbb{R}^d, \|\cdot\|)$  and subgradients bounded in dual norm  $\|g_k\|_* \leq G$ , then*

$$f(\bar{x}_k) - f^* \leq \frac{(\mathcal{D}(x^*, x_0))^{1/2} G}{\sqrt{k}},$$

*where  $\bar{x}_k$  denotes the averaged iterates, as usual.*



# Convergence w.r.t. negative entropy

It might occur that

$$\|g\|_{\infty} = (\|g\|_1)_* \leq G$$

but

$$\|g\|_2 \approx \sqrt{d}G.$$

But is are all the bounds of the previous theorem dimension independent?

**What about**  $\mathcal{D}(x^*, x_0)$ ? Let  $x_0 = (\frac{1}{d}, \dots, \frac{1}{d})$ , then

$$\mathcal{D}(x, x_0) = \sum x_i \log \left( \frac{x_i}{\frac{1}{d}} \right) = \sum x_i \log(x_i) + \log(d) \leq \log(d)$$

while  $\|x_0 - x^*\|^2 \leq 2$ .

# Proof

In the Euclidian space we used

$$\begin{aligned} & \langle x_{k+1} - x_k, x^* - x_{k+1} \rangle \\ &= \frac{1}{2} \|x^* - x_k\|^2 - \frac{1}{2} \|x^* - x_{k+1}\|^2 - \frac{1}{2} \|x_{k+1} - x_k\|^2. \end{aligned}$$

Similar **3-point identity** holds for Bregman distances:

$$\begin{aligned} & \langle \nabla h(x_{k+1}) - \nabla h(x_k), x^* - x_{k+1} \rangle = \\ &= D(x^*, x_k) - D(x^*, x_{k+1}) - D(x_{k+1}, x_k). \end{aligned}$$

Therefore

$$D(x^*, x_{k+1}) \leq D(x^*, x_k) - D(x_{k+1}, x_k) + \alpha \langle g_k, x^* - x_{k+1} \rangle.$$

## Proof II

$$D(x^*, x_{k+1}) \leq D(x^*, x_k) - D(x_{k+1}, x_k) + \alpha \langle g_k, x^* - x_{k+1} \rangle.$$

Last term is not quite right.

$$\begin{aligned} \langle g_k, x^* - x_{k+1} \rangle &= \langle g_k, x^* - x_k \rangle + \langle g_k, x_k - x_{k+1} \rangle \\ &\leq f(x^*) - f(x_k) + \|g_k\|_* \|x_k - x_{k+1}\| \\ &\leq f(x^*) - f(x_k) + \frac{\alpha \|g_k\|_*^2}{2} + \frac{\|x_k - x_{k+1}\|^2}{2\alpha}. \end{aligned}$$

Combined we get that

$$\begin{aligned} D(x^*, x_{k+1}) &\leq D(x^*, x_k) - D(x_{k+1}, x_k) + \alpha(f(x^*) - f(x_k)) \\ &\quad + \frac{\alpha^2 \|g_k\|_*^2}{2} + \frac{\|x_k - x_{k+1}\|^2}{2}. \end{aligned}$$

# Proof III

We assumed strong convexity of  $h$ :

$$D(x_{k+1}, x_k) \geq \frac{1}{2} \|x_{k+1} - x_k\|^2.$$

Yields

$$D(x^*, x_{k+1}) \leq D(x^*, x_k) + \alpha(f(x^*) - f(x_k)) + \frac{\alpha^2 \|g_k\|_*^2}{2}$$

Continue as always

$$\frac{1}{k} \sum_{i=1}^k f(x_i) - f^* \leq \frac{D(x^*, x_0)}{\alpha k} \frac{\alpha G^2}{2}$$

# What about the smooth case

- ◇ Talked about how to get better constants in the “bounded subgradients” setting
- ◇ but can't make them bounded if they are not

However,

- ◇ Can also come up with a new notion of smoothness

$$f(y) \leq f(x) + \langle \nabla f(x), y - x \rangle + LD(y, x)$$

- ◇ which might hold even if  $f$  is not smooth in classical sense