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) $h : \mathbb{R}^d \to \mathbb{R} \cup \{+\infty\}$ is convex
(ii) h is differentiable on the interior of 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

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

- $\mathcal{D}_h(x, y) \geq \frac{1}{2}\|x - y\|^2$ (1-strong convexity)

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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 Δ

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

Mirror descent

Idea: replace squared Euclidian norm with more general object:

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

Question: But why *mirror* descent?

Mirror descent

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&= \arg\min_{x \in \mathbb{R}^d} \{ \langle \nabla f(x_k), x \rangle + \frac{1}{\alpha} (h(x) - h(x_k) - \langle \nabla h(x_k), x - x_k \rangle) \} \\
&= \arg\min_{x \in \mathbb{R}^d} \{ \langle \nabla f(x_k), x \rangle + \frac{1}{\alpha} (h(x) - \langle \nabla h(x_k), x \rangle) \} \\
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\end{aligned}
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Question: But why *mirror* descent?

The Mirror part

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

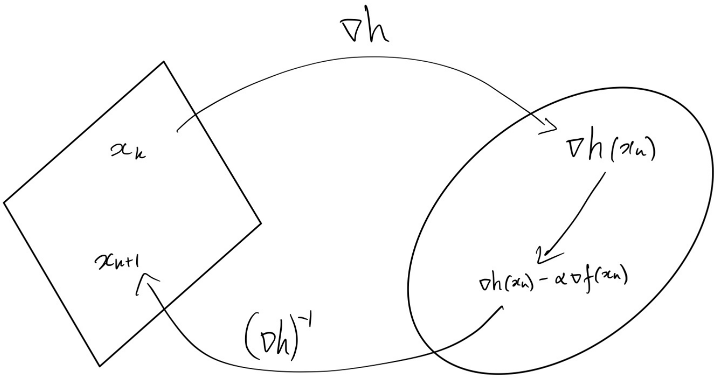
By optimality condition:

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

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

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

in a componentwise sense.

$$x_{k+1}[i] = x_k[i] e^{-\alpha [\nabla f(x_k)]_i}, \quad \forall i = 1, \ldots, d.$$

(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 are all the bounds of the previous theorem dimension independent?
What about $\mathcal{D}(x^*, x_0)$? Let $x_0 = (\frac{1}{d}, \cdots, \frac{1}{d})$, 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

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

Similar 3-point identity holds for Bregman distances:

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

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

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

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