

Subgradient optimization methods

- Handles general nondifferentiable convex problem, Often leads to very simple algorithms
- Convergence can be very slow, no good stopping criterion
- Theoretical complexity: $O\left(\frac{1}{\epsilon^2}\right)$ iterations to find ϵ -suboptimal point
- An “optimal” first-order method: $O\left(\frac{1}{\epsilon^2}\right)$ bound cannot be improved
- So rate of optimal value decreasing is $O\left(\frac{1}{\sqrt{k}}\right)$
- $O\left(\frac{G\|x_0 - x_*\|_2}{\sqrt{k+1}}\right)$ bound cannot be improved for subgradient classical model

Gradient descend method

- Due to Y.Nesterov for any first-order method and any iterative algorithm that selects x_{k+1} in the set x_0 with span covered by gradients calculated so far.
- There is a bad function for which convergence will be bound by $O\left(\frac{1}{k^2}\right)$
- This idea suggests $1/k$ rate for gradient method is not optimal in fact
- More recent accelerated gradient methods have $O\left(\frac{1}{k^2}\right)$ convergence

Proximal gradient method

- Minimizes sums of differentiable $g(x)$ and maybe non-differentiable convex functions $h(x)$
- Useful when non-differentiable term $h(x)$ is simple (has inexpensive prox-operator)
- $prox_h(x) = \operatorname{argmin}_u (h(u) + \|u - x\|_2^2)$
- Convergence properties are similar to standard gradient method
- Less general but faster than sub gradient method, Each proximal gradient iteration is a descent step
- Sub-optimality after k iterations is $O(1/k)$
- Gradient Descend and Projected sub-gradient method can be considered as custom case of Proximal Gradient method.

Proximal Mapping

- The proximal mapping of a closed convex function f is $prox_f(x) = \operatorname{argmin}_u (f(u) + \|u - x\|_2^2)$
- The proximal mapping defines a function because for each x there is a unique u .

- Subgradient characterization $u = \text{prox}_f(x) \iff x - u \in \partial f(u)$

Nesterov momentum rate of convergence $f(x_k) - f^* \leq \frac{2L}{(k+1)^2} \|x_0 - x^*\|_2^2$