

Unified analysis of gradient/subgradient descent

APPM 5630 Spring 2021

Advanced Convex Optimization

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We'll solve $\min_{\mathbf{x}} f(\mathbf{x})$ via the following generic algorithm, with $R = \|\mathbf{x}_1 - \mathbf{x}^*\|$,

Require: \mathbf{x}_1

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1: for  $k = 1, 2, \dots, K$  do  
2:    $\mathbf{x}_{k+1} = \mathbf{x}_k - t\mathbf{v}_k$   
3: end for
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where \mathbf{v} is “gradient-like” (e.g., a gradient, subgradient, or a gradient in expectation, like $\mathbb{E} \mathbf{v}_k = \nabla f(\mathbf{x}_k)$).

Lemma 1 (Lemma 14.1 in Shalev-Shwartz and Ben-David). *Let $\{\mathbf{v}_k\}_{k=1}^K$ be arbitrary. No assumptions on f (need not be convex or smooth). The generic algorithm sequence satisfies*

$$\sum_{k=1}^K \langle \mathbf{x}_k - \mathbf{x}^*, \mathbf{v}_k \rangle \leq \frac{\|\mathbf{x}_1 - \mathbf{x}^*\|^2}{2t} + \frac{t}{2} \sum_{k=1}^K \|\mathbf{v}_k\|^2 \quad (1)$$

Proof. (Sketch: just the good parts)

$$\begin{aligned} \sum_{k=1}^K \langle \mathbf{x}_k - \mathbf{x}^*, \mathbf{v}_k \rangle &= \frac{1}{2t} \sum_{k=1}^K (-\|\mathbf{x}_{k+1} - \mathbf{x}^*\|^2 + \|\mathbf{x}_k - \mathbf{x}^*\|^2 + \|\mathbf{v}_k\|^2) \quad \text{complete-the-square and algebra} \\ &= \frac{1}{2t} (\|\mathbf{x}_1 - \mathbf{x}^*\|^2 - \|\mathbf{x}_{K+1} - \mathbf{x}^*\|^2) + \frac{1}{2t} \sum_{k=1}^K \|\mathbf{v}_k\|^2 \quad \text{via telescoping sum} \\ &\leq \frac{1}{2t} \|\mathbf{x}_1 - \mathbf{x}^*\|^2 + \frac{1}{2t} \sum_{k=1}^K \|\mathbf{v}_k\|^2. \end{aligned}$$

□

Corollary 2. *If $\|\mathbf{v}_k\| \leq \rho$ (e.g., if f is ρ -Lipschitz) and $t = \frac{R}{\rho\sqrt{K}}$ then*

$$\frac{1}{K} \sum_{k=1}^K \langle \mathbf{x}_k - \mathbf{x}^*, \mathbf{v}_k \rangle \leq \rho \frac{R}{\sqrt{K}}$$

Now we'll see how to use these results

1 f is convex but not smooth

Assume f is ρ -Lipschitz so the corollary applies. If f is convex, then we have a well-defined subdifferential, so we'll choose $\mathbf{v}_k \in \partial f(\mathbf{x}_k)$ to give us **subgradient descent**. By convexity and definition of subgradients,

$$f(\mathbf{x}_k) - f^* \leq \langle \mathbf{x}_k - \mathbf{x}^*, \mathbf{v}_k \rangle \quad (2)$$

so combining this with Corollary 2 immediately yields

Corollary 3 (sub-gradient descent). *If f is convex and ρ -Lipschitz, then subgradient descent yields*

$$\frac{1}{K} \sum_{k=1}^K (f(\mathbf{x}_k) - f^*) \leq \rho \frac{R}{\sqrt{K}}$$

hence

$$f(\mathbf{x}_{\text{best}}) - f^* \leq \rho \frac{R}{\sqrt{K}} \quad (3)$$

and

$$f(\bar{\mathbf{x}}) - f^* \leq \rho \frac{R}{\sqrt{K}} \quad (4)$$

where $\mathbf{x}_{\text{best}} \in \operatorname{argmin}_{\mathbf{x} \in \{\mathbf{x}_1, \mathbf{x}_2, \dots, \mathbf{x}_K\}} f(\mathbf{x})$ and $\bar{\mathbf{x}} = \frac{1}{K} \sum_{k=1}^K \mathbf{x}_k$. If possible, we should use \mathbf{x}_{best} , but in some situations this is not easy. Subgradient descent is not a descent method, so it's not necessarily true that $\mathbf{x}_{\text{best}} = \mathbf{x}_K$. Couldn't we just evaluate $f(\mathbf{x}_k)$ and record the best iterate seen so far? Often we can do this, but sometimes f is very expensive to evaluate (as will especially be the case when we do *stochastic* gradients which sample, and the true loss function f is a population expectation that we can never calculate). In these case, we can do iterate averaging to get $\bar{\mathbf{x}}$, and this result follows because $f(\bar{\mathbf{x}}) \leq \frac{1}{K} \sum_{k=1}^K f(\mathbf{x}_k)$ via Jensen's inequality.

Commentary Unlike gradient descent in the smooth case, here we have slower convergence $1/\sqrt{K}$ vs $1/K$ in the smooth case (or $1/K^2$ for Nesterov acceleration). Furthermore, we need to know the maximum number of iterations K in advance in order to set the stepsize. In practice, like stochastic gradient methods, one might use a constant stepsize for a while, then reduce it: a stepsize “schedule.”

2 f is smooth (∇f is L -Lipschitz continuous)

We use the descent Lemma, which applies whenever ∇f is L -Lipschitz continuous, regardless of convexity:

$$f(\mathbf{y}) \leq f(\mathbf{x}) + \langle \nabla f(\mathbf{x}), \mathbf{y} - \mathbf{x} \rangle + \frac{L}{2} \|\mathbf{y} - \mathbf{x}\|_2^2$$

so when applied to $\mathbf{y} = \mathbf{x}_k - t\mathbf{v}_k$ with $\mathbf{v}_k = \nabla f(\mathbf{x}_k)$ and $t = L^{-1}$ (this is **gradient descent**) which after a bit of algebra gives

$$f(\mathbf{x}_{k-1}) \leq f(\mathbf{x}_k) - \frac{1}{2L} \underbrace{\|\nabla f(\mathbf{x}_k)\|_2^2}_{\mathbf{v}_k} \quad (5)$$

If we don't assume f is convex, we can't expect to converge to the global minimizer, so there isn't a result about $f(\mathbf{x}_k) - f^* \rightarrow 0$. Instead, we show convergence to a stationary point, meaning $\|\nabla f(\mathbf{x}_k)\| \rightarrow 0$.

Corollary 4 (gradient descent, non-convex). *If ∇f is L -Lipschitz, then gradient descent with $t = L^{-1}$ yields*

$$\min_{k=1, \dots, K} \|\nabla f(\mathbf{x}_k)\|^2 \leq \frac{2L}{K} (f(\mathbf{x}_1) - f^*)$$

Proof. Sum Eq. (5) from $k = 1, \dots, K$ after re-arranging to get

$$\frac{1}{2L} \sum_{k=1}^K \|\nabla f(\mathbf{x}_k)\|^2 \leq \sum_{k=1}^K f(\mathbf{x}_k) - f(\mathbf{x}_{k-1}) = f(\mathbf{x}_1) - f(\mathbf{x}_{K+1}) \leq f(\mathbf{x}_1) - f^*$$

since we had a telescoping series, and use $\min_{k=1, \dots, K} \|\nabla f(\mathbf{x}_k)\|^2 \leq \frac{1}{K} \sum_{k=1}^K \|\nabla f(\mathbf{x}_k)\|^2$ since the min is less than the average. \square

In the convex case, we expect to converge to the global minimizer:

Corollary 5 (gradient descent, convex). *If ∇f L -Lipschitz, and f is convex, then gradient descent with $t = L^{-1}$ yields*

$$f(\mathbf{x}_K) - f^* \leq \frac{L}{2K} \|\mathbf{x}_1 - \mathbf{x}^*\|^2.$$

Proof. Using the main Lemma (Eq. 1) and replacing $\langle \mathbf{x}_k - \mathbf{x}^*, \mathbf{v}_k \rangle$ with the bound in Eq. (2) (since gradients are subgradients) gives

$$\sum_{k=1}^K f(\mathbf{x}_k) - f^* \leq \frac{1}{2t} \|\mathbf{x}_1 - \mathbf{x}^*\|^2 + \frac{t}{2} \sum_{k=1}^K \underbrace{\|\nabla f(\mathbf{x}_k)\|}_{\mathbf{v}_k}^2 \quad (6)$$

and the descent lemma Eq. (5) gives $f(\mathbf{x}_{k-1}) + \frac{1}{2L} \|\nabla f(\mathbf{x}_k)\|^2 \leq f(\mathbf{x}_k)$, so combining with the above equation gives

$$\begin{aligned} \sum_{k=1}^K \left(f(\mathbf{x}_{k-1}) + \frac{1}{2L} \|\nabla f(\mathbf{x}_k)\|^2 - f^* \right) &\leq \sum_{k=1}^K f(\mathbf{x}_k) - f^* \quad \text{via descent lemma} \\ &\leq \frac{L}{2} \|\mathbf{x}_1 - \mathbf{x}^*\|^2 + \frac{1}{2L} \sum_{k=1}^K \|\nabla f(\mathbf{x}_k)\|^2 \quad \text{via Eq. (6)} \end{aligned}$$

where we used $t = 1/L$. Now canceling the $\frac{1}{2L} \sum_{k=1}^K \|\nabla f(\mathbf{x}_k)\|^2$ from both sides gives

$$\sum_{k=1}^K f(\mathbf{x}_k) - f^* \leq \frac{L}{2} \|\mathbf{x}_1 - \mathbf{x}^*\|^2$$

hence

$$f(\mathbf{x}_K) = f(\mathbf{x}_{\text{best}}) \leq \frac{1}{K} \sum_{k=1}^K f(\mathbf{x}_k) - f^* \leq \frac{L}{2K} \|\mathbf{x}_1 - \mathbf{x}^*\|^2$$

where $\mathbf{x}_K = \mathbf{x}_{\text{best}}$ follows because the descent lemma implies that this is a descent method. \square

Our last case to consider is if we're strongly convex, in which case we expect faster convergence, and \mathbf{x}^* is unique, and we expect a bound on $\|\mathbf{x}_k - \mathbf{x}^*\|$. Note that if f is μ strongly convex, then f satisfies the μ Polyak-Lojasiewicz (PL) inequality

$$\frac{1}{2} \|\nabla f(\mathbf{x})\|^2 \geq \mu(f(\mathbf{x}) - f^*) \quad (7)$$

(see Nesterov's 2018 book, Thm 2.1.5 and Eq 2.1.10 for a proof). Our result is

Corollary 6 (gradient descent, strongly convex). *If ∇f L -Lipschitz, and f is μ strongly convex, then gradient descent with $t = L^{-1}$ yields*

$$f(\mathbf{x}_{K+1}) - f^* \leq \underbrace{\left(1 - \frac{\mu}{L}\right)}_c^{K-1} (f(\mathbf{x}_1) - f^*).$$

This is linear convergence, which is asymptotically better than sublinear convergence. We think of $\kappa = \frac{L}{\mu}$ as the condition number, so $c = 1 - \kappa^{-1}$. We won't show it here, but Nesterov acceleration can improve c to $c \approx 1 - \kappa^{-1/2}$ when $\kappa \gg 1$.

Proof.

$$f(\mathbf{x}_{k+1}) - f(\mathbf{x}_k) \leq \frac{-1}{2L} \|\nabla f(\mathbf{x}_k)\|^2 \leq \frac{-\mu}{L} (f(\mathbf{x}_k) - f^*)$$

using the descent lemma for the first inequality and the PL inequality for the second inequality. Re-arranging and recursing gives

$$f(\mathbf{x}_{k+1}) - f^* \leq \left(1 - \frac{\mu}{L}\right) (f(\mathbf{x}_k) - f^*) \leq \left(1 - \frac{\mu}{L}\right)^{t-1} (f(\mathbf{x}_1) - f^*).$$

\square