CMPT 409/981: Optimization for Machine Learning

Lecture 6

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Recap

- **Gradient Descent**: $w_{k+1} = w_k - \eta \nabla f(w_k)$.
- **Nesterov Acceleration**: $w_{k+1} = [w_k + \beta_k(w_k - w_{k-1})] - \eta \nabla f(w_k + \beta_k(w_k - w_{k-1}))$.
- Nesterov acceleration can be interpreted as doing GD on "extrapolated" points where β_k can be interpreted as the "momentum" in the previous direction $(w_k - w_{k-1})$.

Minimizing Smooth, Strongly-Convex Functions

- Recall that for smooth, convex functions, GD is sub-optimal (convergence rate of $O(1/\epsilon)$) and can be improved by using Nesterov acceleration (convergence rate of $\Theta(1/\sqrt{\epsilon})$).
- For smooth, strongly-convex functions, the convergence rate of GD is $O\left(\kappa \log\left(1/\epsilon\right)\right)$.
- Is GD optimal when minimizing smooth, strongly-convex functions, or can we do better?

Lower Bound: For any initialization, there exists a smooth, strongly-convex function such that any first-order method requires $\Omega\left(\sqrt{\kappa} \log\left(1/\epsilon\right)\right)$ iterations.

- GD is sub-optimal for minimizing smooth, convex functions. Using Nesterov acceleration is optimal and requires $\Theta\left(\sqrt{\kappa} \log\left(1/\epsilon\right)\right)$ iterations

Nesterov Acceleration for Smooth, Strongly-Convex Functions

Nesterov acceleration results in the $O\left(\sqrt{\kappa}\log(1/\epsilon)\right)$ rate for smooth, strongly-convex functions.

In order to obtain this rate, the algorithm requires the following parameter settings: $\eta = \frac{1}{L}$ and,

$$\beta_k = \frac{\sqrt{\kappa} - 1}{\sqrt{\kappa} + 1}$$

Refer to Bubeck, 3.7.1 for the analysis.

- Compared to the smooth, convex setting for which β_k varies, the strongly-convex setting requires a constant β_k in order to attain the accelerated rate.
- Compared to GD, for smooth, strongly-convex functions, Nesterov acceleration requires knowledge of κ (and hence μ) in order to set β_k.
- Unlike estimating L, estimating μ is difficult, and misestimating it can result in bad empirical performance. Common trick that results in decent performance is to use the convex parameters with restarts.

Summary

Function class	L-smooth	L-smooth + convex	L-smooth + μ-strongly convex
Gradient Descent	$\Theta\left({}^{1}/_{\epsilon}\right)$	$O\left({}^{1}/_{\epsilon}\right)$	$O\left(\kappa \log\left({}^{1}/_{\epsilon}\right)\right)$
Nesterov Acceleration	-	$\Theta\left({}^{1}/_{\sqrt{\epsilon}}\right)$	$\Theta\left(\sqrt{\kappa} \log\left({}^{1}/_{\epsilon}\right)\right)$

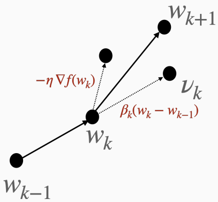
Table 1: Optimization Zoo

- For all cases, $\eta = \frac{1}{L}$ for both GD and Nesterov acceleration, and we can use Armijo line-search to estimate L and set the step-size.
- Gradient Descent is adaptive to strong-convexity, however, Nesterov acceleration requires knowledge of μ to set β_k.

Questions?

Heavy-Ball Momentum

- Heavy Ball or Polyak momentum is often used as an alternative to Nesterov acceleration, especially in ML.
- It is one of the building blocks of commonly used methods such as Adam.
- **Nesterov Acceleration**: $v_k = w_k + \beta_k(w_k - w_{k-1})$; $w_{k+1} = v_k - \eta\nabla f(v_k)$ i.e. extrapolate and compute the gradient at the extrapolated point v_k.
- **Polyak Momentum**: Compute the gradient at w_k and then extrapolate: $v_k = w_k + \beta_k(w_k - w_{k-1})$; $w_{k+1} = v_k - \eta\nabla f(w_k)$.



- When minimizing quadratics: $f(w) = \frac{1}{2}w^\intercal Aw - bw + c$ where A is symmetric, positive semi-definite, or equivalently solve linear systems of the form: $Aw = b$, using Polyak momentum with *optimal* values of (η, β) is equivalent to conjugate gradient.

Heavy-Ball Momentum

Brief History

- *Quadratics*: HB momentum with a specific (η, β) can achieve the accelerated rate and obtain a dependence on $\sqrt{\kappa}$ asymptotically [Pol64].
- *Quadratics*: HB momentum with a different (η, β) can achieve a non-asymptotic accelerated rate after certain number of burn-in iterations (that depends on κ) [WLA21].
- *General smooth, SC functions*: Using Polyak's (η, β) parameters can result in cycling and HB momentum is not guaranteed to converge [LRP16].
- *General smooth, SC functions*: Using a different (η, β), HB momentum can converge and match the GD rate (no acceleration) [GFJ15].
- *General smooth, SC functions + Diagonal Hessian + Lipschitz-continuity of Hessian*: Using a different (η, β), HB momentum matches the GD rate at the beginning, but achieves the accelerated rate after $O(\kappa)$ iterations [WLWH22].
- *General smooth, SC functions + Lipschitz-continuity of Hessian*: HB momentum with any (η, β) will either result in a non-accelerated rate or will not converge [GTD23].

Heavy-Ball Momentum

- We will focus on minimizing strongly-convex quadratics: $f(w) = \frac{1}{2} w^\intercal A w - bw + c$, where A is a symmetric positive definite matrix.

Claim: For L-smooth, μ-strongly convex quadratics, HB momentum with $\eta = \frac{4}{(\sqrt{L}+\sqrt{\mu})^2}$ and $\beta = \frac{\sqrt{\kappa}-1}{\sqrt{\kappa}+1}$ achieves the following convergence rate:

$$\|w_T - w^*\| \leq \sqrt{2} \left(\frac{\sqrt{\kappa}-1}{\sqrt{\kappa}+1} + \epsilon_T \right)^T \|w_0 - w^*\|$$

where $\epsilon_T \geq 0$ and $\lim_{T\to\infty} \epsilon_T = 0$.

- HB momentum with $\eta = \frac{1}{L}$ and $\beta = \left(1 - \frac{1}{2\sqrt{\kappa}}\right)^2$ achieves a slightly-worse, but accelerated non-asymptotic rate [WLA21].

$$\|w_T - w^*\| \leq 4\sqrt{\kappa} \left(1 - \frac{1}{2\sqrt{\kappa}}\right)^T \|w_0 - w^*\|$$

Minimizing strongly-convex quadratics with GD

- As a warm-up, let us first prove the optimal GD rate for smooth, strongly-convex quadratics.

Claim: For L-smooth, μ-strongly convex quadratics, GD with $\eta = \frac{2}{\mu+L}$ achieves the following convergence rate:

$$\|w_T - w^*\| \leq \left(\frac{\kappa - 1}{\kappa + 1}\right)^T \|w_0 - w^*\|$$

Proof: For quadratics, $\nabla f(w) = Aw - b$,

$$\begin{aligned} w_{k+1} &= w_k - \eta \nabla f(w_k) = w_k - \eta [A w_k - b] \\ \implies \|w_{k+1} - w^*\| &= \|w_k - w^* - \eta [A w_k - b]\| \\ &= \|w_k - w^* - \eta [A w_k - A w^*]\| \qquad (\text{Since } \nabla f(w^*) = 0 \implies A w^* = b) \\ \implies \|w_{k+1} - w^*\| &= \|(I_d - \eta A)(w_k - w^*)\| \leq \|I_d - \eta A\|_2 \, \|w_k - w^*\| \end{aligned}$$

(By definition of the matrix norm: for matrix B, $\|B\|_2 = \max \left\{ \frac{\|Bv\|_2}{\|v\|_2} \right\}$ for all vectors $v \neq 0$)

We have thus reduced the problem to bounding $\|I_d - \eta A\|_2$.

Minimizing strongly-convex quadratics with GD

Recall that $\|w_{k+1} - w^*\| \leq \|I_d - \eta A\|_2 \, \|w_k - w^*\|$. Since f is L-smooth and μ-strongly convex, $\mu I_d \preceq \nabla^2 f(w) = A \preceq L I_d$.

If $A = U \Lambda U^\intercal$ is the eigen-decomposition of A, and $\lambda_1, \lambda_2, \ldots, \lambda_d$ are the eigenvalues of A, then, $I_d - \eta A = U S U^\intercal$ where $S_{i,i} = 1 - \eta \lambda_i$.

Since U is an orthonormal matrix, $\|I_d - \eta A\|_2 = \|S\|_2$. By definition of the matrix norm, for symmetric matrices,

$$\|B\|_2 = \rho(B) := \max\{|\lambda_1[B]|, |\lambda_2[B]|, \ldots, |\lambda_d[B]|\}$$

where $\rho(B)$ is the spectral radius of B.

Let us choose a step-size $\eta \in \left[\frac{1}{L}, \frac{1}{\mu}\right]$. Hence,

$$\|I_d - \eta A\|_2 = \|S\|_2 = \rho(S) = \max\{|\lambda_1[S]|, |\lambda_2[S]|, \ldots, |\lambda_d[S]|\} \leq \max_{\lambda \in [\mu, L]} \{|1 - \eta\lambda|\}$$

$$\|I_d - \eta A\|_2 = \max\{|1 - \eta\mu|, |1 - \eta L|\} \qquad \text{(Since } 1 - \eta\lambda \text{ is linear in } \lambda\text{)}$$

Minimizing strongly-convex quadratics with GD

Recall that $\|w_{k+1} - w^*\| \leq \|I_d - \eta A\|_2 \|w_k - w^*\|$ and $\|I_d - \eta A\|_2 \leq \max\{|1 - \eta\mu|, |1 - \eta L|\}$.

Since $\eta \in \left[\frac{1}{L}, \frac{1}{\mu}\right]$,

$$\|I_d - \eta A\|_2 \leq \max\{1 - \eta\mu, \eta L - 1\} = \frac{L - \mu}{L + \mu}$$

(By setting $\eta = \frac{2}{\mu + L}$, we minimize $\max\{1 - \eta\mu, \eta L - 1\}$)

Putting everything together,

$$\|w_{k+1} - w^*\| \leq \frac{L - \mu}{L + \mu} \|w_k - w^*\| = \frac{\kappa - 1}{\kappa + 1} \|w_k - w^*\|$$

Recursing from $k = 0$ to $T - 1$,

$$\|w_T - w^*\| \leq \left(\frac{\kappa - 1}{\kappa + 1}\right)^T \|w_0 - w^*\|.$$

Questions?

References i

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