CME 307 / MS&E 311: Optimization

Gradient descent

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Outline

Unconstrained minimization

$$\text{minimize} \quad f(x)$$

- $f : \mathbf{R}^n \to \mathbf{R}$ differentiable
- assume optimal value $f^\star = \inf_x f(x)$ is attained (and finite)
- assume a starting point $x^{(0)}$ is known

unconstrained minimization methods

- produce sequence of points $x^{(k)}$, $k = 0, 1, \ldots$ with

$$f(x^{(k)}) \to f^\star$$

(we hope)

Solution of an optimization problem

$$\text{minimize} \quad f(x)$$

for $f : \mathcal{D} \to \mathbf{R}$. $x^\star$ is a

- **local minimizer** if there is a neighborhood $\mathcal{N}$ around $x^\star$ so that $f(x) \geq f(x^\star)$ for all $x \in \mathcal{N}$.
- **global minimizer** if $f(x) \geq f(x^\star)$ for all $x \in \mathcal{D}$.
- **strict local minimizer** if there is a neighborhood $\mathcal{N}$ around $x^\star$ so that $f(x) > f(x^\star)$ for all $x \in \mathcal{N}$.
- **isolated local minimizer** if the neighborhood $\mathcal{N}$ contains no other local minimizers.
- **unique minimizer** if it is the only global minimizer.

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pictures!

First order optimality condition

Theorem

If $x^\star \in \mathbf{R}^n$ is a local minimizer of a differentiable function $f : \mathbf{R}^n \to \mathbf{R}$, then $\nabla f(x^\star) = 0$.

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If $x^\star \in \mathbf{R}^n$ is a local minimizer of a differentiable function $f : \mathbf{R}^n \to \mathbf{R}$, then $\nabla f(x^\star) = 0$.

proof: suppose by contradiction that $\nabla f(x^\star) \neq 0$. consider points of the form $x_\alpha = x^\star - \alpha \nabla f(x^\star)$ for $\alpha > 0$. by definition of the gradient,

$$\lim_{\alpha \to 0} \frac{f(x_\alpha) - f(x^\star)}{\alpha} = -\nabla f(x^\star)^\top \nabla f(x^\star) = -\|nablaf(x^\star)\|^2 < 0$$

so for any sufficiently small $\alpha > 0$, we have $f(x_\alpha) < f(x^\star)$, which contradicts the fact that $x^\star$ is a local minimizer.

Second order optimality condition

Theorem

If $x^\star \in \mathbf{R}^n$ is a local minimizer of a twice differentiable function $f : \mathbf{R}^n \to \mathbf{R}$, then $\nabla^2 f(x^\star) \succeq 0$.

Second order optimality condition

Theorem

If $x^\star \in \mathbf{R}^n$ is a local minimizer of a twice differentiable function $f : \mathbf{R}^n \to \mathbf{R}$, then $\nabla^2 f(x^\star) \succeq 0$.

proof: similar to the previous proof. use the fact that the second order approximation

$$f(x_\alpha) \approx f(x^\star) + \nabla f(x^\star)^\top (x_\alpha - x^\star) + \frac{1}{2}(x_\alpha - x^\star)^\top \nabla^2 f(x^\star)(x_\alpha - x^\star)$$

is accurate locally to show a contradiction unless $\nabla^2 f(x^\star) \succeq 0$: if not, there is a direction v such that $v^T \nabla^2 f(x^\star) v < 0$. then $f(x + \alpha v) < f(x^\star)$ for α arbitrarily small, which contradicts the fact that $x^\star$ is a local minimizer.

Outline

Gradient descent

$$\text{minimize} \quad f(x)$$

idea: go downhill

Algorithm Gradient descent

Given: $f : \mathbf{R}^d \to \mathbf{R}$, stepsize t, maxiters
Initialize: $x = 0$ (or anything you'd like)
For: $k = 1, \ldots,$ maxiters

- update x:

$$x \leftarrow x - t\nabla f(x)$$

Gradient descent: choosing a step-size

- **constant step-size.** $t^{(k)} = t$ (constant)
- **decreasing step-size.** $t^{(k)} = 1/k$
- **line search.** try different possibilities for $t^{(k)}$ until objective at new iterate

$$f(x^{(k)}) = f(x^{(k-1)} - t^{(k)} \nabla f(x^{(k-1)}))$$

  decreases enough.

tradeoff: line search requires evaluating $f(x)$ (can be expensive)

Line search

define $x^+ = x - t\nabla f(x)$

- exact line search: find t to minimize $f(x^+)$
- the **Armijo rule** requires t to satisfy

$$f(x^+) \leq f(x) - ct\|\nabla f(x)\|^2$$

for some $c \in (0,1)$, *e.g.*, $c = .01$.

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a simple **backtracking line search** algorithm:

- set $t = 1$
- if step decreases objective value sufficiently, accept x^+:

$$f(x^+) \leq f(x) - ct\|\nabla f(x)\|^2 \quad \Longrightarrow \quad x \leftarrow x^+$$

  otherwise, halve the stepsize $t \leftarrow t/2$ and try again

Demo: gradient descent

https://colab.research.google.com/github/stanford-cme-307/demos/blob/main/gradient-descent.ipynb

Outline

Unconstrained minimization

Gradient descent

What functions?

Analysis via Polyak-Lojasiewicz condition

How well does GD work?

for $x \in \mathbf{R}^n$,

- $f(x) = x^T x$
- $f(x) = x^T Ax$ for $A \succeq 0$
- $f(x) = \|x\|_1$ (nonsmooth but differentiable **almost** everywhere)
- $f(x) = 1/x$ on $x > 0$ (strictly convex but not strongly convex)

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A: No.
Q: Is a stationary point always a global minimum?
A: No.
Q: ... for convex functions?
A: Yes.

$\nabla f(x^\star) = 0$ is the **first-order (necessary) condition** for optimality.

Invex function

Definition

A function $f : \mathbf{R}^n \to \mathbf{R}$ is **invex** if for some vector-valued function $\eta : \mathbf{R}^n \times \mathbf{R}^n \to \mathbf{R}^n$,

$$f(x) - f(u) \geq \eta(x, u)^\top \nabla f(u) \qquad \forall u \in \mathbf{R}^n,\ x \in \mathbf{dom}\, f$$

Theorem (Craven and Glover, Ben-Israel and Mond)

A function is invex iff every stationary point is a global minimum.

Quadratic approximation

Suppose $f : \mathbf{R} \to \mathbf{R}$ is twice differentiable. For any $x \in \mathbf{R}$, approximate f about x:

$$f(y) \approx f(x) + \nabla f(x)^T (y - x) + \frac{1}{2}(y - x)^T \nabla^2 f(x)(y - x).$$

If f is a quadratic function, $\nabla^2 f(x) = H$ is constant.

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Quadratic approximations are useful because quadratics are easy to minimize:

$$\begin{aligned} y^\star &= \operatorname*{argmin}_y f(x) + \nabla f(x)^T(y-x) + \frac{1}{2}(y-x)^T H(y-x) \\ &\implies \nabla f(x) + H(y^\star - x) = 0 \\ y^\star &= x - H^{-1}(\nabla f(x)). \end{aligned}$$

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If we approximate the Hessian of f by $H = \frac{1}{t}I$ for some $t > 0$ and choose x^+ to minimize the quadratic approximation, we obtain the **gradient descent** update with step size t:

$$x^+ = x + -t\nabla f(x)$$

Quadratic upper bound

Definition (Smooth)

A function $f : \mathbf{R} \to \mathbf{R}$ is L-**smooth** if for all $x, y \in \mathbf{R}$,

$$f(y) \leq f(x) + \nabla f(x)^T (y - x) + \frac{L}{2}\|y - x\|^2.$$

Equivalently, assuming the derivatives exist,

- the operator $\frac{1}{L}\nabla f$ is L-**Lipschitz continuous**:

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

- $\nabla^2 f(x) \preceq LI$ for all $x \in \mathbf{dom}\, f$.

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A: $\lambda_{\max}(A)$-smooth

Quadratic lower bound

Definition (Strongly convex)

A function $f : \mathbf{R} \to \mathbf{R}$ is μ-**strongly convex** if for all $x, y \in \mathbf{R}$,

$$f(y) \geq f(x) + \nabla f(x)^T (y - x) + \frac{\mu}{2} \|y - x\|^2.$$

Equivalently, assuming the derivatives exist,

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A: $\lambda_{\min}(A)$-strongly convex

Optimizing the upper bound

start at $x^{(0)}$. suppose f is L-smooth, so for all $y \in \mathbf{R}$,

$$f(y) \leq f(x^{(0)}) + \nabla f(x)^T (y - x^{(0)}) + \frac{L}{2}\|y - x^{(0)}\|^2$$

let's choose next iterate $x^{(1)}$ to minimize this upper bound:

$$\begin{aligned} x^{(1)} &= \operatorname*{argmin}_y f(x) + \nabla f(x)^T (y - x) + \frac{L}{2}\|y - x\|^2 \\ &\implies \nabla f(x^{(0)}) + L(x^{(1)} - x^{(0)}) = 0 \\ x^{(1)} &= x^{(0)} - \frac{1}{L}\nabla f(x^{(0)}) \end{aligned}$$

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- **gradient descent** update with step size $t = \frac{1}{L}$
- lower bound ensures true optimum can't be too far away...

Outline

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Gradient descent

What functions?

Analysis via Polyak-Lojasiewicz condition

Some important functions

for $A \in \mathbf{R}^{m \times n}$, $b \in \mathbf{R}^m$, $x \in \mathbf{R}^n$,

- **Quadratic loss.** $\|Ax - b\|^2$
- **Logistic loss.** $f(x) = \sum_{i=1}^m \log(1 + \exp\left(b_i a_i^T x\right))$
  where a_i is ith row of A

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Q: Which of these are strongly convex? Under what conditions?
A: Quadratic loss is strongly convex if A is rank n. Logistic loss is strongly convex on a compact domain if A is rank n.

The Polyak-Lojasiewicz condition

Definition (Polyak-Lojasiewicz condition)

A function $f : \mathbf{R} \to \mathbf{R}$ satisfies the **Polyak-Lojasiewicz condition** if

$$\frac{1}{2}\|\nabla f(x)\|^2 \geq \mu(f(x) - f^\star)$$

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Suppose $f(x) = g(Ax)$ where $g : \mathbf{R}^m \to \mathbf{R}$ is strongly convex and $A : \mathbf{R}^n \to \mathbf{R}^m$ is linear. Then f is Polyak-Lojasiewicz.

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so logistic loss (on a compact set) and quadratic loss are Polyak-Lojasiewicz even when $m < n$ **karimi2016linear**.

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Q: Are all Polyak-Lojasiewicz functions convex?
A: No. A river valley is Polyak-Lojasiewicz but not convex.
why use Polyak-Lojasiewicz? Polyak-Lojasiewicz is weaker than strong convexity but yields simpler proofs

PL and invexity

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proof: if $\nabla f(\bar{x}) = 0$, then

$$0 = \frac{1}{2}\|\nabla f(x)\|^2 \geq \mu(f(\bar{x}) - f^\star) \geq 0$$

$\implies f(\bar{x}) = f^\star$ is the global optimum.

strong convexity $\implies$ Polyak-Lojasiewicz

Theorem

If f is μ-strongly convex, then f is μ-Polyak-Lojasiewicz.

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proof: minimize the strong convexity condition over y:

$$\begin{aligned} \min_y f(y) &\geq \min_y \left(f(x) + \nabla f(x)^T (y - x) + \frac{\mu}{2} \|y - x\|^2 \right) \\ f^\star &\geq f(x) - \frac{1}{2\mu} \|y - x\|^2 \end{aligned}$$

Types of convergence

- objective converges

$$f(x^{(k)}) \to f^\star$$

- iterates converge

$$x^{(k)} \to x^\star$$

under

- strong convexity: objective converges $\implies$ iterates converge
  proof: use strong convexity with $x = x^\star$ and $y = x^{(k)}$:

$$f(x^{(k)}) - f^\star \geq \frac{\mu}{2}\|x^{(k)} - x^\star\|^2$$

- Polyak-Lojasiewicz: not necessarily true ($x^\star$ may not be unique)

Rates of convergence

- linear convergence with rate c

$$f(x^{(k)}) - f^\star \leq c^k(f(x^{(0)}) - f^\star)$$

  - looks like a line on a semi-log plot
  - example: gradient descent on smooth strongly convex function
- sublinear convergence
  - looks slower than a line (curves up) on a semi-log plot
  - example: $1/k$ convergence

$$f(x^{(k)}) - f^\star \leq \mathcal{O}(1/k)$$

  - example: gradient descent on smooth convex function
  - example: stochastic gradient descent

Gradient descent converges linearly

Theorem

If $f : \mathbf{R}^n \to \mathbf{R}$ is μ-Polyak-Lojasiewicz, L-smooth, and $x^\star = \mathrm{argmin}_x f(x)$ exists, then gradient descent with stepsize L

$$x^{(k+1)} = x^{(k)} - \frac{1}{L}\nabla f(x^{(k)})$$

converges linearly to $f^\star$ with rate $(1 - \frac{\mu}{L})$.

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proof: plug in update rule to L-smoothness condition

$$\begin{aligned}
f(x^{(k+1)}) - f(x^{(k)}) &\leq \nabla f(x^{(k)})^T(x^{(k+1)} - x^{(k)}) + \frac{L}{2}\|x^{(k+1)} - x^{(k)}\|^2 \\
&\leq (-\frac{1}{L} + \frac{1}{2L})\|\nabla f(x^{(k)})\|^2 \\
&\leq -\frac{1}{2L}\|\nabla f(x^{(k)})\|^2 \\
&\leq -\frac{\mu}{L}(f(x^{(k)}) - f^\star) \triangleright \text{(using PL)}
\end{aligned}$$

Practical convergence

- Gradient descent with optimal stepsize converges even faster.

$$f(x^{(k+1)}) = \inf_{\alpha} f(x^{(k)} - \alpha \nabla f(x^{(k)})) \leq f(x^{(k)} - \frac{1}{L} \nabla f(x^{(k)}))$$

Practical convergence

- Gradient descent with optimal stepsize converges even faster.

$$f(x^{(k+1)}) = \inf_{\alpha} f(x^{(k)} - \alpha \nabla f(x^{(k)})) \leq f(x^{(k)} - \frac{1}{L} \nabla f(x^{(k)}))$$

- Local vs global convergence

Quiz

- A strongly convex function always satisfies the Polyak-Lojasiewicz condition
  A. true
  B. false
- Suppose $f : \mathbf{R} \to \mathbf{R}$ is L-smooth and satisfies the Polyak-Lojasiewicz condition. Then any stationary point $\nabla f(x) = 0$ of f is a global optimum: $f(x) = \mathrm{argmin}_y f(y) =: f^\star$.
  A. true
  B. false
- Suppose $f : \mathbf{R} \to \mathbf{R}$ is L-smooth and satisfies the Polyak-Lojasiewicz condition. Then gradient descent on f converges linearly from any starting point.
  A. true
  B. false