

OPTIMIZATION
(SI 416) – LECTURE 2

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RECAP

♣ Take a once continuously differentiable function $f : \mathbb{R}^n \rightarrow \mathbb{R}$

- ▶ Let $x, p \in \mathbb{R}^n$
- ▶ Then, there exists a $\ell \in (0, 1)$ such that

$$f(x + p) = f(x) + \langle \nabla f(x + \ell p), p \rangle$$

♣ Take a twice continuously differentiable function $f : \mathbb{R}^n \rightarrow \mathbb{R}$

- ▶ Let $x, p \in \mathbb{R}^n$
- ▶ Then, there exists a $t \in (0, 1)$ such that

$$f(x + p) = f(x) + \langle \nabla f(x), p \rangle + \frac{1}{2} \langle \nabla^2 f(x + tp) p, p \rangle$$

♣ Take a once continuously differentiable function $f : \mathbb{R}^n \rightarrow \mathbb{R}$

$\begin{array}{ccc} x_* \text{ is a} \\ \text{local minimizer} & \implies & \nabla f(x_*) = 0 \\ \text{of } f \end{array}$
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POSITIVE DEFINITENESS

♣ A $n \times n$ matrix B is called

- ▶ positive definite if

$$\langle Bv, v \rangle > 0 \quad \text{for all } v \in \mathbb{R}^n \setminus \{0\}$$

- ▶ positive indefinite (semidefinite) if

$$\langle Bv, v \rangle \geq 0 \quad \text{for all } v \in \mathbb{R}^n \setminus \{0\}$$

Theorem (Second order necessary condition)

If x_ is a local minimizer of f and if f is twice continuously differentiable in an open neighbourhood of x_* , then*

$\nabla^2 f(x_)$ is positive semidefinite.*

♣ **This isn't a sufficient condition:** again think of $f(x) = x^3$ at $x = 0$.

SECOND ORDER NECESSARY CONDITION (CONTD.)

- ♣ Suppose $\nabla^2 f(x_*)$ is not positive semidefinite
- ♣ Then there exists a $p \in \mathbb{R}^n$ such that

$$\langle \nabla^2 f(x_*)p, p \rangle < 0.$$

- ♣ As $\nabla^2 f$ is continuous at x_* , there exists a $T > 0$ such that

$$\langle \nabla^2 f(x_* + sp)p, p \rangle < 0 \quad \text{for all } s \in [0, T].$$

- ♣ Taylor's theorem says for all $t_* \in (0, T]$, there exists a $s_* \in (0, t_*)$

$$f(x_* + t_*p) = f(x_*) + t_* \langle \nabla f(x_*), p \rangle + \frac{t_*^2}{2} \langle \nabla^2 f(x_* + s_*p)p, p \rangle$$

- ♣ Recall that first order necessary condition implies that $\nabla f(x_*) = 0$
- ♣ Putting it all together, we arrive at a contradiction:

$$f(x_* + t_*p) < f(x_*) \quad \text{for all } t_* \in (0, T]$$

Theorem

Suppose f is twice continuously differentiable in an open neighbourhood of a point $x_ \in \mathbb{R}^n$.*

Suppose further that

$$\nabla f(x_*) = 0 \quad \text{and} \quad \nabla^2 f(x_*) \text{ is positive definite.}$$

Then, x_ is a strict local minimizer of f .*

- ♣ **This isn't a necessary condition:** think of $f(x) = x^4$ at $x = 0$.
- ♣ Because $\nabla^2 f$ is continuous at x_* and as it is positive definite at x_* , there exists a $r > 0$ such that

$$\nabla^2 f(z) \text{ is positive definite for all } z \in B_r(x_*).$$

- ♣ Here $B_r(x_*)$ denotes the open ball of radius r centered at x_*

SECOND ORDER SUFFICIENT CONDITION (CONTD.)

♣ Taking $p \in \mathbb{R}^n$ such that $\|p\| < r$ and using Taylor's theorem,

$$\begin{aligned} f(x_* + p) &= f(x_*) + \langle \nabla f(x_*), p \rangle + \frac{1}{2} \langle \nabla^2 f(x_* + sp)p, p \rangle \\ &= f(x_*) + \frac{1}{2} \langle \nabla^2 f(x_* + sp)p, p \rangle \end{aligned}$$

for some $s \in (0, 1)$.

♣ Using the positive definiteness of $\nabla^2 f$ in a neighbourhood of x_* implies that

$$f(x_* + p) > f(x_*)$$

for any $p \in \mathbb{R}^n$ satisfying $\|p\| < r$.

♣ Hence x_* is a strict local minimizer of f .

NOTION OF CONVEXITY

♣ A set $\Omega \subset \mathbb{R}^n$ is said to be CONVEX if

$$x, y \in \Omega \implies \alpha x + (1 - \alpha)y \in \Omega \quad \text{for all } \alpha \in [0, 1].$$

♣ Take a convex set $\Omega \subset \mathbb{R}^n$.

♣ A function $f : \Omega \rightarrow \mathbb{R}$ is said to be CONVEX on Ω if

► for any two points $x, y \in \Omega$, we have

$$f(\alpha x + (1 - \alpha)y) \leq \alpha f(x) + (1 - \alpha)f(y) \quad \text{for all } \alpha \in [0, 1].$$

♣ f is STRICTLY CONVEX if the above inequality is strict whenever $x \neq y$ and $\alpha \in (0, 1)$

♣ f is said to be CONCAVE if $-f$ is convex

Theorem

Suppose f is a convex function on \mathbb{R}^n .

Any local minimizer x_ of f is a global minimizer of f .*

- ♣ Suppose x_* is a local but not a global minimizer of f
- ♣ That is, there exists a $y \in \mathbb{R}^n$ such that

$$f(y) < f(x_*)$$

- ♣ Consider a point on the line segment joining x_* and y
- $$x = \lambda y + (1 - \lambda)x_* \quad \text{for some } \lambda \in (0, 1]$$

- ♣ By convexity of f , we have

$$f(x) \leq \lambda f(y) + (1 - \lambda)f(x_*) < f(x_*)$$

- ♣ The strict inequality is thanks to the earlier observation

CONVEX OPTIMIZATION (CONTD.)

- ♣ We have shown that for any point x on the line segment joining x_* and y ,

$$f(x) < f(x_*)$$

- ♣ Any neighbourhood of x_* contains a piece of the aforementioned line segment
- ♣ Hence x_* is not a local minimizer
- ♣ Thus a contradiction

WORDS OF CAUTION

- ♣ We are NOT claiming that every convex function has a minimizer
 - ▶ The function $f(x) = x$ doesn't have a minimum
 - ▶ A convex function bounded below need not have a minimizer.
- Consider

$$f(x) = e^x$$

SOME PROPERTIES OF CONVEX FUNCTIONS

- ♣ If $f, g : \mathbb{R}^n \rightarrow \mathbb{R}$ are convex then so is the function $f + g$
- ♣ If $f : \mathbb{R}^n \rightarrow \mathbb{R}$ is convex and if $\mu \geq 0$, then so is the function μf

DIFFERENTIABLE CONVEX FUNCTIONS

Theorem

A differentiable function $f : \mathbb{R}^n \rightarrow \mathbb{R}$ is convex if and only if

$$f(y) \geq f(x) + \langle \nabla f(x), (y - x) \rangle \quad \text{for every } x, y \in \mathbb{R}^n.$$

AN IMMEDIATE COROLLARY

Theorem (Stationarity and convexity)

Let $f : \mathbb{R}^n \rightarrow \mathbb{R}$ be a differentiable convex function on \mathbb{R}^n . A point x_ is a global minimizer of f if and only if $\nabla f(x_*) = 0$.*

STATIONARY POINT AND CONVEXITY

- ♣ If x_* is a global minimizer of f , then it is also a local minimizer
- ♣ Hence by the first order necessary condition, we have

$$\nabla f(x_*) = 0$$

- ♣ Let us now assume that for a point x_* , we have $\nabla f(x_*) = 0$
- ♣ For any point $y \in \mathbb{R}^n$, as f is convex, we have the differential inequality:

$$\begin{aligned} f(y) &\geq f(x_*) + \langle \nabla f(x_*), (y - x_*) \rangle \\ &= f(x_*) \end{aligned}$$

- ♣ Hence x_* is a global minimizer of f

Theorem

A differentiable function $f : \mathbb{R}^n \rightarrow \mathbb{R}$ is convex if and only if

$$f(y) \geq f(x) + \langle \nabla f(x), (y - x) \rangle \quad \text{for every } x, y \in \mathbb{R}^n.$$

- ♣ Let us assume that the above differential inequality is satisfied
- ♣ Our goal is to show that f is convex
- ♣ Taking $w, z \in \mathbb{R}^n$, we aim to demonstrate that

$$f(\alpha w + (1 - \alpha)z) \leq \alpha f(w) + (1 - \alpha)f(z) \quad \text{for } \alpha \in [0, 1].$$

- ♣ Let us take

$$x = \alpha w + (1 - \alpha)z \quad \text{for } \alpha \in [0, 1]$$

- ♣ Observe that $w - x = (1 - \alpha)(w - z)$ and $z - x = \alpha(z - w)$

PROOF OF THE THEOREM (CONTD.)

♣ Applying the differential inequality for w and x yields

$$f(w) \geq f(x) + \langle \nabla f(x), (w - x) \rangle$$

♣ Applying the differential inequality for z and x yields

$$f(z) \geq f(x) + \langle \nabla f(x), (z - x) \rangle$$

♣ Multiplying the first inequality by α and the second inequality by $(1 - \alpha)$ and adding the resulting inequalities yields

$$\begin{aligned} \alpha f(w) + (1 - \alpha)f(z) &\geq f(x) + \alpha \langle \nabla f(x), (w - x) \rangle \\ &\quad + (1 - \alpha) \langle \nabla f(x), (z - x) \rangle \\ &= f(x) = f(\alpha w + (1 - \alpha)z) \end{aligned}$$

Hence f is convex.

PROOF OF THE THEOREM (CONTD.)

- ♣ We have shown that the differential inequality implies convexity
- ♣ Our next objective is to show that any differentiable convex function must satisfy the following differential inequality:

$$f(y) \geq f(x) + \langle \nabla f(x), (y - x) \rangle \quad \text{for every } x, y \in \mathbb{R}^n.$$

- ♣ Pick two points $x \neq y$ in \mathbb{R}^n . Convexity of f implies that

$$f\left(\frac{x+y}{2}\right) \leq \frac{1}{2}f(x) + \frac{1}{2}f(y)$$

- ♣ Take $h := y - x$. Then the above inequality rewrites as

$$f\left(x + \frac{h}{2}\right) \leq \frac{1}{2}f(x) + \frac{1}{2}f(x+h)$$

- ♣ We can further rewrite the above inequality as

$$f(x+h) - f(x) \geq \frac{f\left(x + \frac{h}{2}\right) - f(x)}{\frac{1}{2}}$$

PROOF OF THE THEOREM (CONTD.)

♣ Observe further that

$$f\left(x + \frac{h}{4}\right) = f\left(\frac{x}{2} + \frac{1}{2}\left(x + \frac{h}{2}\right)\right) \leq \frac{1}{2}f(x) + \frac{1}{2}f\left(x + \frac{h}{2}\right)$$

♣ The above inequality can be rewritten as

$$f\left(x + \frac{h}{2}\right) - f(x) \geq \frac{f\left(x + \frac{h}{4}\right) - f(x)}{2^{-1}}$$

♣ Hence we deduce that

$$f(x + h) - f(x) \geq \frac{f\left(x + \frac{h}{4}\right) - f(x)}{2^{-2}}$$

♣ Arguing recursively, we arrive at

$$f(x + h) - f(x) \geq \frac{f\left(x + 2^{-k}h\right) - f(x)}{2^{-k}} \quad \text{for all } k \in \mathbb{N}.$$

LITTLE DETOUR

- ♣ For a function $g : \mathbb{R}^n \rightarrow \mathbb{R}$, its DIRECTIONAL DERIVATIVE at a point x in the direction p is given by

$$\lim_{s \rightarrow 0} \frac{g(x + sp) - g(x)}{s}$$

- ♣ If g is a differentiable function, then its directional derivative is

$$\langle \nabla g(x), p \rangle$$

PROOF OF THE THEOREM (CONTD.)

- ♣ Recall that we had

$$f(x + h) - f(x) \geq \frac{f(x + 2^{-k}h) - f(x)}{2^{-k}} \quad \text{for all } k \in \mathbb{N}.$$

- ♣ Letting $k \rightarrow \infty$ in the above inequality yields

$$f(y) - f(x) \geq \langle \nabla f(x), h \rangle = \langle \nabla f(x), (y - x) \rangle.$$

END OF LECTURE 2
THANK YOU FOR YOUR ATTENTION