Optimization

Wenxiao Yang[*]

[*]Department of Mathematics, University of Illinois at Urbana-Champaign

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目录

1 Unconstrained Optimization

1.1 Conditions for Optimality

Function: $f : \mathbb{R}^n \to \mathbb{R}^n$, $x \in \&$, $\& \subseteq \mathbb{R}^n$.
Terminology: x^* will always be the optimal input at some function.

1.2 Global minimizer, Local minimizer

Definition 1.
Say x^* is a global minimizer(minimum) of f if $f(x^*) \leq f(x), \forall x \in \&$.
Say x^* is a unique global minimizer(minimum) of f if $f(x^*) < f(x), \forall x \neq x^*$.
Say x^* is a local minimizer(minimum) of f if $\exists r > 0$ so that $f(x^*) \leq f(x)$ when $\|x - x^*\| < r$.

A minimizer is strict if $f(x^*) < f(x)$ for all relevant x.

1.3 Optimization in $\mathbb{R}$

1.3.1 Theorem 1: differentiable f, x^* is a local minimizer $\Rightarrow f'(x^*) = 0$

Theorem 1. *If $f(x)$ is differentiable function and x^* is a local minimizer, then $f'(x^*) = 0$.*

证明.
Def of $f'(x) = \lim_{h \to 0} \frac{f(x+h)-f(x)}{h}$
Def of local minimizer: $f(x^*) - f(x) \geq 0, |x^* - x| < r$
when $0 < h < r$, $\frac{f(x+h)-f(x)}{h} \geq 0$; when $-r < h < 0$, $\frac{f(x+h)-f(x)}{h} \leq 0$. Then $f'(x) = 0$. □

1.3.2 Theorem 2: $f'(x^*) = 0, f''(x^*) \geq 0,\ \forall x \in [a, b] \Rightarrow x^*$ is a global minimizer on $[a, b]$; $f'(x^*) = 0, f''(x^*) \geq 0 \Rightarrow x^*$ is a local minimizer

Theorem 2. *If $f : \mathbb{R} \to \mathbb{R}$ is a function with a continuous second derivative and x^* is a critical point of f (i.e. $f'(x) = 0$), then:*
(1): If $f''(x) \geq 0,\ \forall x \in \mathbb{R}$, then x^* is a global minimizer on $\mathbb{R}$.
(2): If $f''(x) \geq 0,\ \forall x \in [a, b]$, then x^* is a global minimizer on $[a, b]$.
(3): If we only know $f''(x^*) \geq 0$, x^* is a local minimizer.

proof of theorem 2.
(1)$f(x) = f(x^*) + f'(x^*)(x - x^*) + \frac{1}{2} f''(\xi)(x - x^*)^2 = f(x^*) + 0 + \textit{something non negative} \geq f(x^*)\ \forall x$
(2) Similar to (1)
(3)$f''(x^*) \geq 0,\ f''$ continuous $\Rightarrow \exists r$ s.t. $f''(x) \geq 0\ \forall x \in [x^* - \frac{r}{2}, x^* + \frac{r}{2}]$, then x is a local minimizer. □

1.4 Optimization in $\mathbb{R}^n$

1.4.1 Necessary Conditions for Optimality: Local Minimum $\Rightarrow \nabla f(x^*) = 0$

A base point x, we consider an arbitrary direction u. $\{x + tu | t \in \mathbb{R}\}$
For $\alpha > 0$ sufficiently small:

1. $f(x^*) \leq f(x^* + \alpha u)$
2. $g(\alpha) = f(x^* + tu) - f(x^*) \geq 0$
3. $g(\beta)$ is continuously differentiable for $\beta \in [0, \alpha]$

By chain rule,

$$g'(\beta) = \sum_{i=1}^{n} \frac{\partial f}{\partial x_i}(x^* + \beta u)u_i$$

By Mean Value Theorem,

$$g(\alpha) = g(0) + g'(\beta)\alpha \text{ for some } \beta \in [0, \alpha]$$

Thus

$$g(\alpha) = \alpha \sum_{i=1}^{n} \frac{\partial f}{\partial x_i}(x^* + \beta u)u_i \geq 0$$

$$\Rightarrow \sum_{i=1}^{n} \frac{\partial f}{\partial x_i}(x^* + \beta u)u_i \geq 0$$

Letting $\alpha \to 0$ and hence $\beta \to 0$, we get

$$\sum_{i=1}^{n} \frac{\partial f}{\partial x_i}(x^*)u_i \geq 0 \text{ for all } u \in \mathbb{R}^n$$

By choosing $u = [1, 0, ..., 0]^T$, $u = [-1, 0, ..., 0]^T$, we get

$$\frac{\partial f(x^*)}{\partial x_1} \geq 0, \ \frac{\partial f(x^*)}{\partial x_1} \leq 0 \Rightarrow \frac{\partial f(x^*)}{\partial x_1} = 0$$

Similarly, we can get

$$\nabla f(x^*) = [\frac{\partial f(x^*)}{\partial x_1}, \frac{\partial f(x^*)}{\partial x_2}, ..., \frac{\partial f(x^*)}{\partial x_n}]^T = 0$$

A base point x, we consider an arbitrary direction u. $\{x + tu | t \in \mathbb{R}\}$
We define the restriction of f to the line through x in the direction of u to be the function:

$$\phi_u(t) = f(x + tu)$$

Lemma 1. *x^* is a global minimizer of f iff for all u, $t = 0$ is the global minimizer of $\phi_u(t)$*

证明.
$(\Rightarrow)$ $\phi_u(0) = f(x^*) \leq f(x^* + tu) = \phi_u(t)$
$(\Leftarrow)$ Let $X \in \mathbb{R}^n$, $u = X - x^*$. $\phi_u(0) \leq \phi_u(1) \Rightarrow f(x^*) \leq f(x^* + u) = f(x)$ □

1.4.2 The first-derivative test in $\mathbb{R}^n$: $\phi_u'(t) = \nabla f(x+tu) \cdot u$

First derivative of $f : \mathbb{R}^n \to \mathbb{R}$, Easier: $\phi_u'(t)$?
Suppose $f : \mathbb{R}^n \to \mathbb{R}$ and $\mathtt{g} : \mathbb{R} \to \mathbb{R}^n$:

$$\frac{\partial f(\mathtt{g}(t))}{\partial t} = \sum_{i=1}^{n} \frac{\partial f}{\partial x_i}(\mathtt{g}(t)) \frac{d}{dt} g_i(t)$$

$$\frac{\partial \phi_u(t)}{\partial t} = \sum_{i=1}^{n} \frac{\partial f}{\partial x_i}(x+tu) u_i$$

The gradient of f: $\nabla f(x) = (\frac{\partial f}{\partial x_1}, ..., \frac{\partial f}{\partial x_d})^T \Rightarrow \phi_u'(t) = \nabla f(x+tu) \cdot u$
Fine print: Chain rule only works when all $\frac{\partial f}{\partial x_k}$ exists and are continuous.

Example 1. $f(x,y) = x^2 + 3xy - 1$, $x^* = (0,0)$, $u = (3,2)$
$\phi_u(t) = f(x^* + tu) = f(3t, 2t) = 27t^2 - 1$
$\phi_u'(t) = 54t$
$\nabla f(x,y) = (2x+3y, 3x)$
$\phi_u'(t) = \nabla f(x+tu) \cdot u = 54t$

1.4.3 Theorem 4: ∇f is continuous, x^* is a global minimizer of $f \Rightarrow \nabla f(x^*) = 0$

Theorem 3 (Theorem 2.1)**.** *Given a function $f : \mathbb{R}^n \to \mathbb{R}$, if ∇f is continuous and x^* is a global minimizer of f, then $\nabla f(x^*) = 0$. (When $\nabla f(x^*) = 0$, we call x^* a critical point of f.)*

x^* is a global minimizer $\Rightarrow$ x^* is a critical point, inverse may not true.

1.4.4 The second-derivative test in $\mathbb{R}^n$

$$\phi_u'(t) = \sum_{i=1}^{n} \frac{\partial f}{\partial x_i}(x+tu) u_i$$

$$\phi_u''(t) = \sum_{i=1}^{n} \sum_{j=1}^{n} u_i u_j \frac{\partial^2 f}{\partial x_i \partial x_j}(x+tu)$$

1.4.5 Hessian matrix

Define Hessian matrix of f and write Hf. That is,

$$\phi_u''(t) = u^T Hf(x+tu) u$$

Fine print: Chain rule only works when all $\frac{\partial^2 f}{\partial x_i \partial x_j}$ exists and are continuous. ($\Rightarrow Hf$ is continuous)

1.4.6 Theorem 5: Hf is continuous, $\nabla f(x^*) = 0$, $u^T Hf(x^*)u \geq 0, \forall u \Rightarrow x^*$ is a global minimizer of f

Theorem 4. *Given a function $f : \mathbb{R}^n \to \mathbb{R}$, if Hf is continuous and x^* is a critical point of f. If for any u, that $u^T Hf(x^*)u \geq 0$. Then x^* is a global minimizer of f.*

proved by Taylor

Theorem 5 (Taylor)**.** *Given a function $f : \mathbb{R}^n \to \mathbb{R}$, if Hf is continuous and x^* is a critical point of f, then*

$$f(x) = f(x^*) = \nabla f(x^*)(x - x^*) + \frac{1}{2}(x - x^*)^T Hf(z)(x - x^*)$$

for some z on the line between x and x^*

1.5 Minimizing over other sets

What if the domain of f: $D \subset \mathbb{R}^n$
(1): want x^* to be in the interior of D, not on the boundary (want to be able to "look" from x^* in any direction.)
(2): want x^* to "see" all other points in D using straight line u.
Convexity
good domain e.g. Ball: $B(x^*, r) = \{x || |x - x^*|| < r\}$

1.5.1 Theorem 7: ∇f is continuous, x^*(interior of D) is a local minimizer of $f \Rightarrow \nabla f(x^*) = 0$

Theorem 6 (Theorem 4.1, 类似 Theorem 2.1)**.** *Suppose $f : D \to \mathbb{R}$ has continuous ∇f and x^* is not on the boundary of D. If x^* is a local minimizer of f, then x^* is a critical point of f: $\nabla f(x^*) = 0$*

1.5.2 Theorem 8: Hf is continuous, x^*(interior of D) $\nabla f(x^*) = 0$, $\exists r$ s.t. $u^T Hf(x^*)u \geq 0, \forall x \in B(x^*, r), \forall u \Rightarrow x^*$ is a local minimizer of f

Theorem 7. *Given a function $f : D \to \mathbb{R}$, if Hf is continuous and x^* is a critical point of f in the interior of D. Suppose $\exists r$ s.t. for any u, that $u^T Hf(x^*)u \geq 0$ whenever $x \in B(x^*, r) \subset D$. Then x^* is a local minimizer of f.*