

HA NOI UNIVERSITY OF SCIENCE AND TECHNOLOGY SCHOOL OF INFORMATION AND COMMUNICATION TECHNOLOGY



FUNDAMENTALS OF OPTIMIZATION

Mathematical foundation

Optimization problems

- Maximize or minimize some function relative to some set (range of choices)
- The function represents the quality of the choice, indicating which is the "best"
- Example
 - A shipper need to find the shortest route to deliver packages to customers 1, 2, ..., N



Notations

- $x \in \mathbb{R}^n$: vector of decision variables $x_{i,j} = 1, 2, ..., n$
- $f: \mathbb{R}^n \to \mathbb{R}$ is the objective function (**dom** $f = \mathbb{R}^n$)
- $g_i: \mathbb{R}^n \to \mathbb{R}$ is the constraint function defining restriction on x, i = 1, 2, ..., m

minimize f(x) over $x = (x_1, x_2, ..., x_n) \in X \subset \mathbb{R}^n$ satisfying a property P:

$$g_i(x) \le b_i$$
, $i = 1, 2, ..., s$
 $g_i(x) = d_i$, $i = s + 1, 2, ..., m$

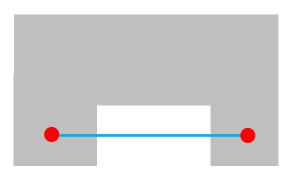


Convex sets

• S is called a convex set if: $\forall u_1, u_2, ..., u_k$ in S, \forall non-negative numbers $\lambda_1, \lambda_2, ..., \lambda_k$ such that $\sum_{i=1}^k \lambda_i = 1$, then $\sum_{i=1}^k u_i \lambda_i$ is in S



Convex set



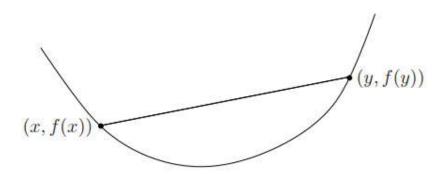
Non Convex set

- Linear function: f(x) = Ax
- Affine function: f(x) = Ax + b
- Convex function
 - f is called convex if $\forall x_1, x_2$ and $\forall \lambda \in [0,1]$:

$$f(\lambda x_1 + (1 - \lambda)x_2) \le \lambda f(x_1) + (1 - \lambda)f(x_2)$$

• *f* is called strictly convex if $\forall x_1 \neq x_2$ and $\forall \lambda \in (0,1)$:

$$f(\lambda x_1 + (1 - \lambda)x_2) < \lambda f(x_1) + (1 - \lambda)f(x_2)$$



• Example: f(x) = 2x + 3

•
$$f(\lambda x_1 + (1 - \lambda)x_2) = 2(\lambda x_1 + (1 - \lambda)x_2) + 3$$

$$= (2\lambda x_1 + 3\lambda) + (2(1-\lambda)x_2) + (1-\lambda)3)$$

$$= \lambda f(x_1) + (1 - \lambda)f(x_2)$$

- Examples
 - $f(x) = x^2$
 - $f(x) = x^n$, n is a constant is convex on x > 0
 - Is convex if $n \ge 1$ or $n \le 0$
 - Is concave is $0 \le n \le 1$
 - $f(x) = e^{ax}$, a is a constant
 - $f(x) = x \ln x$

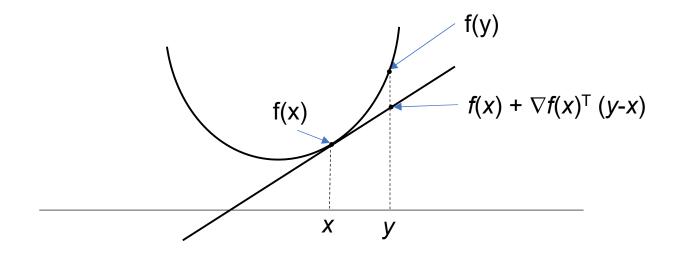
Basis

•
$$f(x_1, x_2, ..., x_n)$$
 is a multivariable function
$$\nabla f(x) \text{ (or } f'(x)) = \frac{\frac{\partial f}{\partial x_1}(x)}{\frac{\partial f}{\partial x_2}(x)}$$
...
$$\frac{\partial f}{\partial x_n}(x)$$

$$\nabla^2 f(x) \text{ (or } f''(x)) = \boxed{\frac{\partial^2 f}{\partial x_i \partial x_j}}(x)$$
 called Hessian matrix



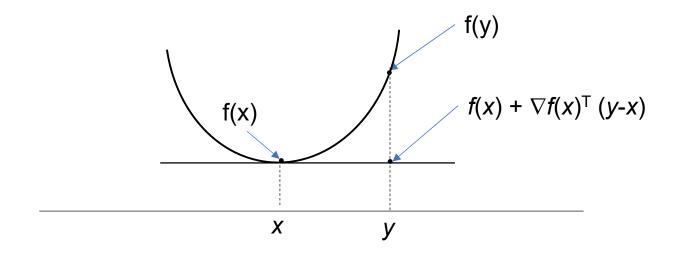
- First-order condition
 - Suppose f is differentiable (i.e., its gradient exists at all points in **dom** f, which is open). f is convex if and only if **dom** f is convex and $f(x) + \nabla f(x)^{\mathsf{T}} (y-x) \leq f(y), \ \forall x,y \in \mathbf{dom} \ f$





Basis

• If $\nabla f(x) = 0$, then $f(y) \ge f(x)$, $\forall y \in \text{dom } f \rightarrow x$ is global minimizer of the function f



Norms

- Norm: A real-valued function f(x) on \mathbb{R}^n is called a norm, if
 - $f(x) \geq 0$
 - $\lambda f(x) = f(\lambda x)$
 - $f(x + y) \le f(x) + f(y)$ (triangle inequality)
- Examples
 - $||x||_p = (|x_1|^p + |x_2|^p + \dots + |x_n|^p)^{1/p}$
 - $||x||_1 = (|x_1| + |x_2| + \ldots + |x_n|)$
 - $||x||_{\infty} = \max\{|x_1|, |x_2|, \dots, |x_n|\}$

Taylor approximation

Single variable Taylor series

$$f(x) = f(a) + \frac{f'(a)}{1!}(x - a) + \frac{f''(a)}{2!}(x - a)^2 + \cdots$$

First-order Taylor approximation

$$f(x + h) \approx f(x) + h^{\mathsf{T}} \nabla(x)$$

Second-order Taylor approximation

$$f(x+h) \approx f(x) + h^{\mathsf{T}} \nabla f(x) + \frac{1}{2} h^{\mathsf{T}} \nabla^2 f(x) h$$



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Thank you for your attentions!

