

CS5489

Lecture 3.1: Gradient Descent and Its Variants

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Slide template by courtesy of Benjamin M. Marlin
Part of slides are borrowed from Stephen P. Boyd

Generative vs Discriminative Classifiers

显示地 对**建模

- The Bayes optimal classifier, NB and LDA are said to be *generative classifiers* because they **explicitly model** the joint distribution $p(\mathbf{x}, y)$ of the feature vectors \mathbf{x} and the labels y
- To build a probabilistic classifier, all we really need to model is $p(y|\mathbf{x})$
- Classifiers based on directly estimating $p(y|\mathbf{x})$ are called **discriminative classifiers** because they don't care about the class conditional distribution $p(\mathbf{x}|y)$

Logistic Regression

- Logistic regression is a probabilistic discriminative classifier
- It directly models the decision boundary using a linear function:

$$p(y = +1|\mathbf{x}) = \frac{1}{1 + \exp(-(\mathbf{w}^T \mathbf{x} + b))}$$

$$\log \frac{p(y = +1|\mathbf{x})}{p(y = -1|\mathbf{x})} = \mathbf{w}^T \mathbf{x} + b$$

那么 $P(y = -1 | \mathbf{x})$ 呢？

- The classification function is:

$$f_{\text{LR}}(\mathbf{x}) = \arg \max_{c \in \{1, \dots, C\}} p(y = c|\mathbf{x})$$

什么叫分析方法，什么叫数值优化方法

- Learning the model parameters cannot be performed **analytically** and has to resort to **numerical optimization methods**

Optimization

- Much of machine learning can be written as an optimization problem:

$$\min_{\boldsymbol{\theta}} \ell(\mathcal{D}; \boldsymbol{\theta}) = \min_{\boldsymbol{\theta}} \frac{1}{M} \sum_{i=1}^M \ell(\mathbf{x}^{(i)}, y^{(i)}; \boldsymbol{\theta}) + r(\boldsymbol{\theta})$$

- $\boldsymbol{\theta}$ is a parameter vector to be optimized
- $\mathcal{D} = \{(\mathbf{x}^{(i)}, y^{(i)}), i = 1, \dots, M\}$ is a finite training set
- $r(\cdot)$ is a regularizer to prevent overfitting to \mathcal{D}
- In logistic regression ($\boldsymbol{\theta} = \{\mathbf{w}, b\}$)
 - $\ell(\mathbf{x}^{(i)}, y^{(i)}; \boldsymbol{\theta}) = \log(1 + \exp(-y^{(i)}(\mathbf{w}^T \mathbf{x}^{(i)} + b)))$ 这个 \log 是 logn 还是 log_2 ? 逻辑回归的公式怎么来的呢? 有没有例子说明?
 - $r(\boldsymbol{\theta}) = \frac{1}{C} \mathbf{w}^T \mathbf{w}$

Types of Optimization

- Convex optimization **凸优化**
 - The easy case
 - Includes logistic regression, linear regression, SVM
- Nonconvex optimization
 - Hard in general
 - Includes deep learning

Convex Set

- **Line segment** between $\mathbf{x}^{(1)}$ and $\mathbf{x}^{(2)}$: all points

$$\mathbf{x} = \alpha\mathbf{x}^{(1)} + (1 - \alpha)\mathbf{x}^{(2)}$$

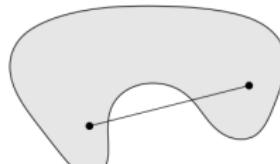
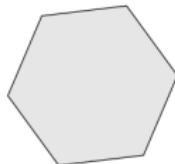
with $0 \leq \alpha \leq 1$

意思是任意两个线之间的点都在 convex set内，所以全方位凸嘛

- **Convex set**: contains line segment between any two points in the set

$$\mathbf{x}^{(1)}, \mathbf{x}^{(2)} \in \mathcal{X}, 0 \leq \alpha \leq 1 \implies \alpha\mathbf{x}^{(1)} + (1 - \alpha)\mathbf{x}^{(2)} \in \mathcal{X}$$

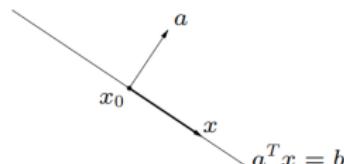
- Examples (one convex, two nonconvex sets)



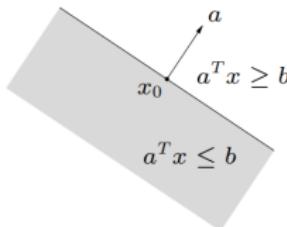
Hyperplanes and Halfspaces

- **Hyperplane:** set of the form $\{\mathbf{x} | \mathbf{a}^T \mathbf{x} = b\}$ ($\mathbf{a} \neq 0$)
 - \mathbf{a} is the normal vector

超平面不一定是平面，其核心是边界。平面中hyperplane是直线曲线。三维中hyperplane就是曲面了，以此类推（就好像逻辑回归不是回归是分类）



- **Halfspace:** set of the form $\{\mathbf{x} | \mathbf{a}^T \mathbf{x} \leq b\}$ ($\mathbf{a} \neq 0$)



- **Hyperplanes and halfspaces are convex**

这俩组成的点集是凸集合，这个用定义可以证明，老师就花了些时间在证明这个东西上

Operations that Preserve Convexity

- Practical methods for establishing convexity of a set \mathcal{X}

- 1 Apply definition

$$\mathbf{x}^{(1)}, \mathbf{x}^{(2)} \in \mathcal{X}, 0 \leq \alpha \leq 1 \implies \alpha \mathbf{x}^{(1)} + (1 - \alpha) \mathbf{x}^{(2)} \in \mathcal{X}$$

- 2 Show that \mathcal{X} is obtained from simple convex set (hyperplanes, halfspaces, etc.) by operations that preserve convexity

- Intersection
- Affine functions 仿射函数
- ...

Convex Function

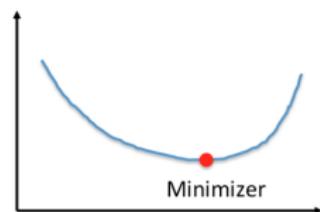
- $f : \mathbb{R}^N \mapsto \mathbb{R}$ is convex if $\text{dom}(f)$ is a convex set and

$$f(\alpha \mathbf{x}^{(1)} + (1 - \alpha) \mathbf{x}^{(2)}) \leq \alpha f(\mathbf{x}^{(1)}) + (1 - \alpha) f(\mathbf{x}^{(2)})$$

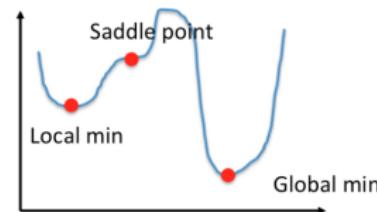
for all $\mathbf{x}^{(1)}, \mathbf{x}^{(2)} \in \text{dom}(f)$, $0 \leq \alpha \leq 1$

这一页应该是扩展了我们之前判断函数凹凸性的方法，引入了alpha， $\text{dom}(f)$ 应该是domain，自变量取值范围的意思吧

Convex



Non-Convex



- f is concave if $-f$ is convex

凹的

Examples on \mathbb{R}

■ Convex:

- Affine: $ax + b$ on \mathbb{R} , for any $a, b \in \mathbb{R}$
- Exponential: e^{ax} , for any $a \in \mathbb{R}$
- Powers: x^a on \mathbb{R}_{++} for $a \geq 1$ or $a \leq 0$
- Powers of absolute value: $|x|^p$ on \mathbb{R} , for $p \geq 1$
- Negative entropy: $x \log x$ on \mathbb{R}_{++}

exponential 是指数函数,
power 应该是幂函数,

应该是逆熵

■ Concave:

- Affine: $ax + b$ on \mathbb{R} , for any $a, b \in \mathbb{R}$
- Powers: x^a on \mathbb{R}_{++} for $0 \leq a \leq 1$
- Logarithm: $\log x$ on \mathbb{R}_{++}

只有这个函数是 both
convex and
concave 的

Examples on \mathbb{R}^N and $\mathbb{R}^{M \times N}$

■ Examples on \mathbb{R}^N

- Affine function: $\mathbf{a}^T \mathbf{x} + b$
- Norms: $\|\mathbf{x}\|_p = (\sum_{j=1}^N |x_j|^p)^{1/p}$ for $p \geq 1$; $\|\mathbf{x}\|_\infty = \max_j |x_j|$

这个 \max_j
的j打错了?

■ Examples on $\mathbb{R}^{M \times N}$ ($M \times N$ matrices)

- Affine function:

$$f(\mathbf{X}) = \sum_{i=1}^M \sum_{j=1}^N A_{ij} X_{ij} + b = \text{tr}(\mathbf{A}^T \mathbf{X}) + b$$

- Spectral norm (maximum singular value):

光譜範數 (最大奇異值)

$$f(\mathbf{X}) = \|\mathbf{X}\|_2 = \sigma_{\max}(\mathbf{X}) = (\lambda_{\max}(\mathbf{X}^T \mathbf{X}))^{1/2}$$

Example: Quadratic

- $f(x) = x^2$



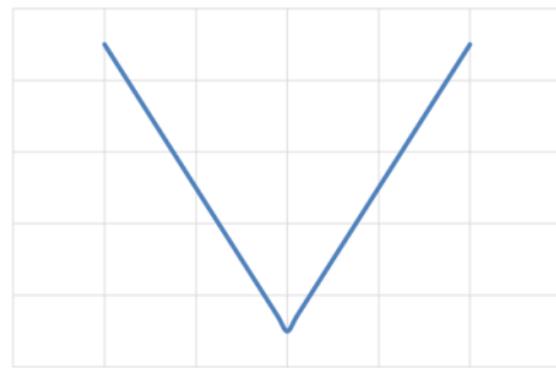
- Proof of convexity:

$$\begin{aligned}(\alpha x + (1 - \alpha)y)^2 &= \alpha^2 x^2 + 2\alpha(1 - \alpha)xy + (1 - \alpha)^2 y^2 \\&= \alpha x^2 + (1 - \alpha)y^2 - \alpha(1 - \alpha)(x^2 - 2xy + y^2) \\&\leq \alpha x^2 + (1 - \alpha)y^2\end{aligned}$$

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Example: Abs

- $f(x) = |x|$

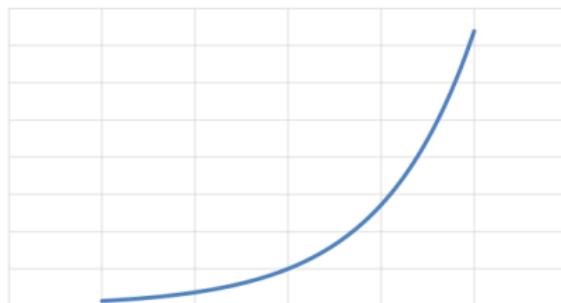


- Proof of convexity:

$$\begin{aligned} |\alpha x + (1 - \alpha)y| &\leq |\alpha x| + |(1 - \alpha)y| \\ &= \alpha|x| + (1 - \alpha)|y| \end{aligned}$$

Example: Exponential

- $f(x) = e^x$



- Proof of convexity (assuming $x > y$):

$$\begin{aligned} e^{\alpha x + (1-\alpha)y} &= e^y e^{\alpha(x-y)} \stackrel{\text{泰勒}}{=} e^y \sum_{n=0}^{\infty} \frac{1}{n!} \alpha^n (x-y)^n \\ &\leq e^y \left(1 + \alpha \sum_{n=1}^{\infty} \frac{1}{n!} (x-y)^n \right) \\ &\stackrel{\text{泰勒}}{=} e^y ((1-\alpha) + \alpha e^{x-y}) = (1-\alpha)e^y + \alpha e^x \end{aligned}$$

Properties of Convex Functions

- Any line segment we draw between two points lies above the curve
- Every local minimum is a **global** minimum
 - Why?
- This is what makes convex optimization easy
 - It **suffices** to find a local minimum because we know it will be global 足够

Properties of Convex Functions

- Non-negative combinations of convex functions are convex

$$h(\mathbf{x}) = af(\mathbf{x}) + bg(\mathbf{x})$$

- **Affine scalings** of convex functions are convex

$$h(\mathbf{x}) = f(\mathbf{Ax} + \mathbf{b})$$

- Pointwise maximum of convex functions are convex

$$h(\mathbf{x}) = \max\{f(\mathbf{x}), g(\mathbf{x})\}$$

- Compositions of convex functions are **NOT** generally convex

- Neural nets are like this $h(\mathbf{x}) = f(g(\mathbf{x}))$

First-Order Condition 一阶条件

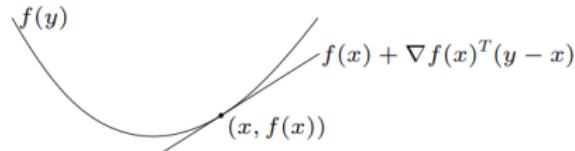
- f is **differentiable** if the gradient

$$\nabla f(\mathbf{x}) = \left[\frac{\partial f(\mathbf{x})}{\partial x_1}, \frac{\partial f(\mathbf{x})}{\partial x_2}, \dots, \frac{\partial f(\mathbf{x})}{\partial x_N} \right]^T$$

exists at each $\mathbf{x} \in \text{dom}(f)$

- **1st-order condition:** differentiable f with convex domain is **convex** iff

$$f(\mathbf{y}) \geq f(\mathbf{x}) + \nabla f(\mathbf{x})^T (\mathbf{y} - \mathbf{x}), \quad \text{for all } \mathbf{x}, \mathbf{y} \in \text{dom}(f)$$



- First-order approximation of f is global underestimator

Second-Order Condition

- f is **twice differentiable** if the **Hessian** $\nabla^2 f(\mathbf{x}) \in \mathbb{S}^N$

$$\nabla^2 f(\mathbf{x})_{ij} = \frac{\partial^2 f(\mathbf{x})}{\partial x_i \partial x_j}$$

exists at each $\mathbf{x} \in \text{dom}(f)$

- **2nd-order condition:** twice differentiable f with convex domain is convex iff

二阶条件

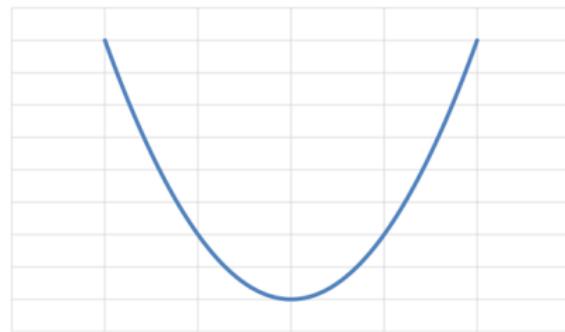
$$\nabla^2 f(\mathbf{x}) \succeq 0$$

- This means that the Hessian matrix is positive semidefinite

$$\mathbf{A} \succeq 0 \iff \forall \mathbf{x}, \mathbf{x}^T \mathbf{A} \mathbf{x} \geq 0$$

Example: Quadratic

- $f(x) = x^2$

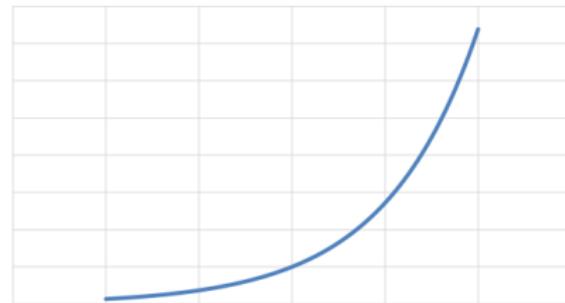


- Proof of convexity:

$$f''(x) = 2 \geq 0$$

Example: Exponential

- $f(x) = e^x$

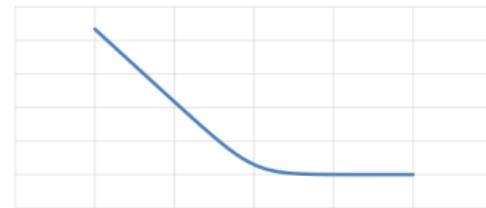


- Proof of convexity:

$$f''(x) = e^x \geq 0$$

Example: Logistic Loss

- $f(x) = \log(1 + e^{-x})$



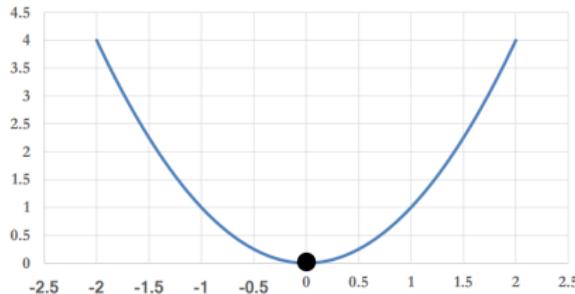
- Proof of convexity:

$$f'(x) = \frac{-e^{-x}}{1 + e^{-x}} = -\frac{1}{1 + e^x}$$

$$f''(x) = \frac{1}{(1 + e^x)(1 + e^{-x})} \geq 0$$

Parameter Estimation

- Optimization in machine learning
 - Goal is to optimize a loss function defined in a machine learning problem for parameter estimation
- Convex optimization in machine learning
 - Goal is to minimize a convex loss function with respect to parameters
 - Example: $\ell(\theta) = \theta^2$

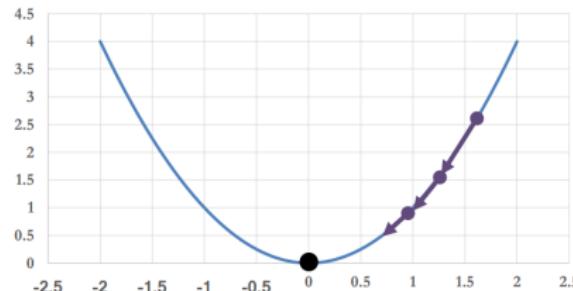


Gradient Descent

- Gradient descent (GD) uses the following update formula

$$\theta \leftarrow \theta - \alpha \nabla \ell(\theta)$$

- α is the learning rate
- $\nabla \ell(\theta)$ is the gradient of $\ell(\theta)$ evaluated at θ
- Example: $\ell(\theta) = \theta^2$, $\nabla \ell(\theta) = 2\theta$, and $\alpha = 0.125$



Gradient Descent

- **GD** first chooses an initial point $\theta^{(0)}$ and repeats:

$$\theta^{(t+1)} = \theta^{(t)} - \alpha \nabla \ell(\mathcal{D}; \theta^{(t)}) = \theta^{(t)} - \alpha \frac{1}{M} \sum_{i=1}^M \nabla \ell(\mathbf{x}^{(i)}, y^{(i)}; \theta^{(t)})$$

- How to stop?
 - $\|\theta^{(t+1)} - \theta^{(t)}\|_2 \leq \epsilon$
 - $\|\nabla \ell(\mathcal{D}; \theta^{(t)})\|_2 \leq \epsilon$
 - $\|\theta\|_2 = \sqrt{\sum_j |\theta_j|^2}$ is the ℓ_2 -norm of θ
 - ϵ is a small positive constant, e.g., 10^{-6}

Gradient Descent

- A negative gradient step can decrease the loss function

Proof. Let $\boldsymbol{\theta}^{(0)}$ be any initial point. Using the first-order Taylor expansion for the next point $\boldsymbol{\theta}^{(1)} = \boldsymbol{\theta}^{(0)} - \alpha \nabla \ell(\boldsymbol{\theta}^{(0)})$, we have

$$\begin{aligned}\ell(\boldsymbol{\theta}^{(1)}) &= \ell(\boldsymbol{\theta}^{(0)}) + \nabla \ell(\boldsymbol{\theta}^{(0)})^T (\boldsymbol{\theta}^{(1)} - \boldsymbol{\theta}^{(0)}) \\ &= \ell(\boldsymbol{\theta}^{(0)}) + \nabla \ell(\boldsymbol{\theta}^{(0)})^T (-\alpha \nabla \ell(\boldsymbol{\theta}^{(0)})) \\ &= \ell(\boldsymbol{\theta}^{(0)}) - \alpha \|\nabla \ell(\boldsymbol{\theta}^{(0)})\|_2^2\end{aligned}$$

Hence, if $\nabla \ell(\boldsymbol{\theta}^{(0)}) \neq 0$ and α is sufficiently small, we have

$$\ell(\boldsymbol{\theta}^{(1)}) - \ell(\boldsymbol{\theta}^{(0)}) = -\alpha \|\nabla \ell(\boldsymbol{\theta}^{(0)})\|_2^2 < 0$$

For sufficiently small α , $\boldsymbol{\theta}^{(1)}$ is an improvement over $\boldsymbol{\theta}^{(0)}$

Gradient Descent

- Initial point matters
 - Consider $y = f(x) = x \cos(x)$

- The final convergence point depends a lot on the initial point
- To improve optimization, run GD multiple times with different initializations, and keep the best minimum of all times (may take a long time to run)

www.charlesbordet.com/assets/images/gradient-descent/gradientdescent-f3.gif

Gradient Descent

■ Learning rate matters

- If α is too big, GD moves more quickly with a high risk that the algorithm will never converge
- If α is too small, GD moves slowly...so slowly that you might just lose patience and never reach the minimum
- Consider $y = f(x) = 2x^2 \cos(x) - 5x$

- Unfortunately, no magic bullet exists to find the perfect learning rate, and you have to test several values and pick the best

www.charlesbordet.com/assets/images/gradient-descent/gradientdescent-alpha0.001.gif
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Stochastic Gradient Descent

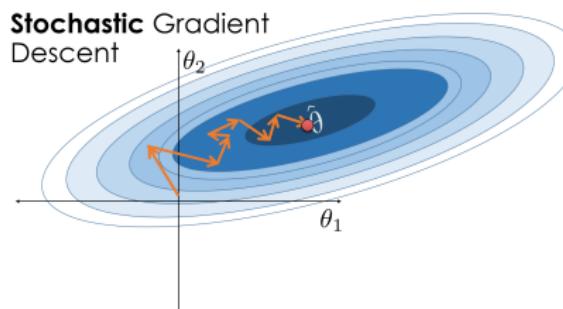
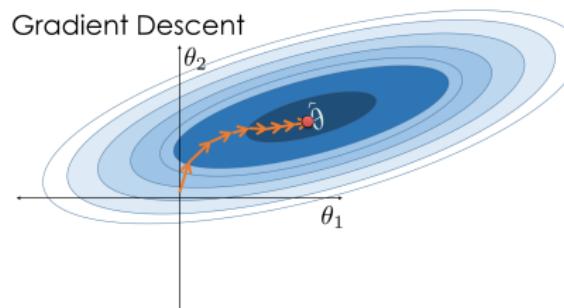
- The computational cost for GD at each iteration is $\mathcal{O}(M)$, which grows linearly with M
 - It is prohibitive to scale up to huge datasets
- Stochastic gradient descent (SGD)
 - Reduces the computational cost at each iteration to $\mathcal{O}(1)$
 - At t -th iteration, randomly sample a single training example and compute the gradient to update $\theta^{(t)}$

$$\theta^{(t+1)} = \theta^{(t)} - \alpha \nabla \ell(\mathbf{x}^{(i)}, y^{(i)}; \theta^{(t)})$$

- In expectation, SGD is just GD

$$\mathbb{E}[\nabla \ell(\mathbf{x}, y; \theta)] = \frac{1}{M} \sum_{i=1}^M \nabla \ell(\mathbf{x}^{(i)}, y^{(i)}; \theta) = \nabla \ell(\mathcal{D}; \theta)$$

Stochastic Gradient Descent



Stochastic Gradient Descent

■ Advantages:

- It is easy to fit into memory and computationally fast due to a single training sample being processed at each iteration
- The steps have oscillations, which may help the algorithm get out of bad local minima

■ Disadvantages:

- The steps are noisy. The objective does not always decrease for each step and it may take longer to achieve convergence
- It loses the advantage of vectorized operations as it deals with only a single example at a time

Mini-Batch Gradient Descent: A Compromise

- Unlike SGD, mini-batch gradient descent randomly samples a small subset of training data $\mathcal{B} \subset \mathcal{D}$ at t -th iteration, and compute the gradient to update $\theta^{(t)}$

$$\theta^{(t+1)} = \theta^{(t)} - \alpha \nabla \ell(\mathcal{B}; \theta^{(t)}) = \theta^{(t)} - \alpha \frac{1}{|\mathcal{B}|} \sum_{(\mathbf{x}, y) \in \mathcal{B}} \nabla \ell(\mathbf{x}, y; \theta^{(t)})$$

- Mini-batch gradient descent and its variants are extremely popular and extensively used in deep learning

Summary

- Convex optimization
 - Convex set:
 - $\mathbf{x}^{(1)}, \mathbf{x}^{(2)} \in \mathcal{X}, 0 \leq \alpha \leq 1 \implies \alpha\mathbf{x}^{(1)} + (1 - \alpha)\mathbf{x}^{(2)} \in \mathcal{X}$
 - Convex function:
 - $\text{dom}(f)$ is convex
 - $f(\alpha\mathbf{x} + (1 - \alpha)\mathbf{y}) \leq \alpha f(\mathbf{x}) + (1 - \alpha)f(\mathbf{y})$
 - Establish convexity
 - By definition
 - First-order condition: $f(\mathbf{y}) \geq f(\mathbf{x}) + \nabla f(\mathbf{x})^T (\mathbf{y} - \mathbf{x})$
 - Second-order condition: $\nabla^2 f(\mathbf{x}) \succeq 0$
- Numerical optimization methods
 - GD - guarantee to decrease loss; not scalable to large datasets
 - SGD - super fast to compute with noisy gradients
 - Mini-batch GD - a compromise between GD and SGD; the de facto method in deep learning