

Part III: Optimization

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= Derivatives of the Cost

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The Expression "argmin"

Consider $f: \mathbb{R} \rightarrow \mathbb{R}$ defined by

$$f(x) = (x-1)^2.$$

Then $\min_{x \in \mathbb{R}} f(x) = 0.$

That is, the minimum value of $f(x)$
is 0.

Any $\bar{x} \in \mathbb{R}$ such that $f(\bar{x}) = \min_{x \in \mathbb{R}} f(x)$
is called an optimal solution.

The set of optimal solutions is
denoted $\operatorname{argmin}_{x \in \mathbb{R}} f(x)$.

Since $\bar{x}=1$ is the only optimal solution
in this example, we have

$$\operatorname{argmin}_{x \in \mathbb{R}} f(x) = \{1\}.$$

Multivariable Calculus

If $f: \mathbb{R}^n \rightarrow \mathbb{R}$ is twice differentiable,
then

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

Where $\nabla f(x)$ is the gradient vector of f
at x and $\nabla^2 f(x)$ is the Hessian matrix
of f at x .

If $f: \mathbb{R}^n \rightarrow \mathbb{R}^m$ is differentiable, then

$$f(x + \Delta x) \approx f(x) + J(x)\Delta x$$

where $J(x)$ is the Jacobian matrix of f at x .

Here, $f(x)$ is a vector,

$$f(x) = \begin{bmatrix} f_1(x) \\ \vdots \\ f_m(x) \end{bmatrix},$$

and $J(x)$ is the matrix of all first order partial derivatives,

$$J(x) = \begin{bmatrix} \frac{\partial f_1}{\partial x_1}(x) & \dots & \frac{\partial f_1}{\partial x_n}(x) \\ \vdots & & \vdots \\ \frac{\partial f_m}{\partial x_1}(x) & \dots & \frac{\partial f_m}{\partial x_n}(x) \end{bmatrix}.$$

MXN
matrix

For example, let $f: \mathbb{R}^2 \rightarrow \mathbb{R}^3$ be given by

$$f(x) = \begin{bmatrix} x_1 x_2 \\ \sin x_1 + \cos x_2 \\ x_1^2 e^{x_2} \end{bmatrix}.$$

Then

$$J(x) = \begin{bmatrix} x_2 & x_1 \\ \cos x_1 & -\sin x_2 \\ 2x_1 e^{x_2} & x_1^2 e^{x_2} \end{bmatrix}.$$

VI. I] Minimum Problems:

Convexity and Newton's Method

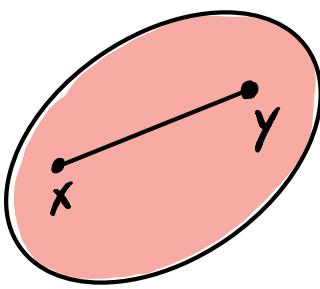
Let $f: \mathbb{R}^n \rightarrow \mathbb{R}$ and $K \subseteq \mathbb{R}^n$.

The constrained optimization problem

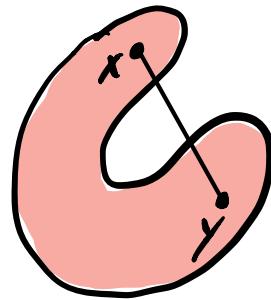
$\min f(x)$ subject to $x \in K$

is convex if f is a convex function and K is a convex set.

A set $K \subseteq \mathbb{R}^n$ is convex if the line segment between any two points $x, y \in K$ lies entirely in K .



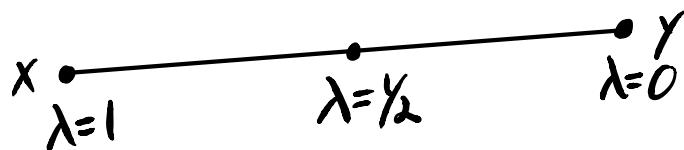
convex



not convex

The line segment between x and y can be written as

$$\{\lambda x + (1-\lambda)y : \lambda \in [0, 1]\}$$



Thus, a set $K \subseteq \mathbb{R}^n$ is convex if $\lambda x + (1-\lambda)y \in K$ for all $x, y \in K$ and $\lambda \in [0, 1]$.

Examples:

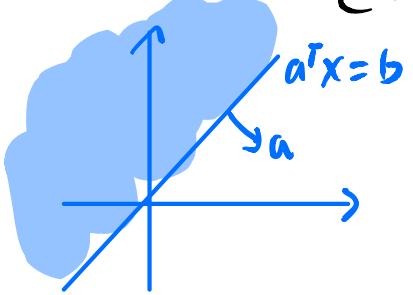
$$(1) \quad K = \{x \in \mathbb{R}^n : Ax = b\}. \quad \begin{matrix} A & m \times n \\ b & m \times 1 \end{matrix}$$

$x, y \in K, \lambda \in [0, 1] \Rightarrow \lambda x + (1-\lambda)y \in K ?$

$$A(\lambda x + (1-\lambda)y) = \lambda Ax + (1-\lambda)Ay = \lambda b + (1-\lambda)b = b$$

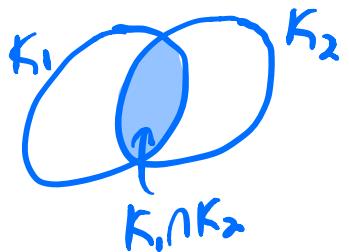
$$\therefore \lambda x + (1-\lambda)y \in K. \therefore K \text{ is convex.}$$

(2) $K = \{x \in \mathbb{R}^n : a^T x \leq b\}$. half-space



$$\begin{aligned} a^T(\lambda x + (1-\lambda)y) &= \lambda a^T x + (1-\lambda)a^T y \\ &\leq \lambda b + (1-\lambda)b = b. \\ \therefore K \text{ is convex.} \end{aligned}$$

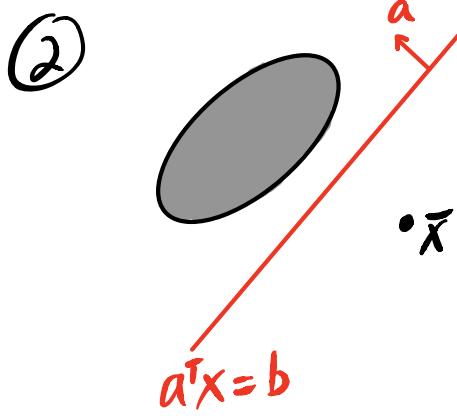
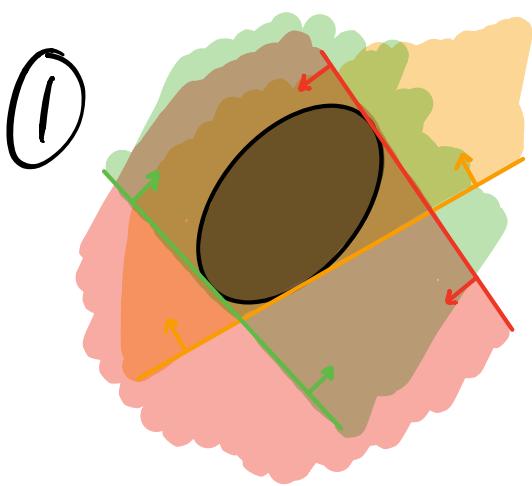
(3) $K = K_1 \cap K_2$, K_1 and K_2 convex.



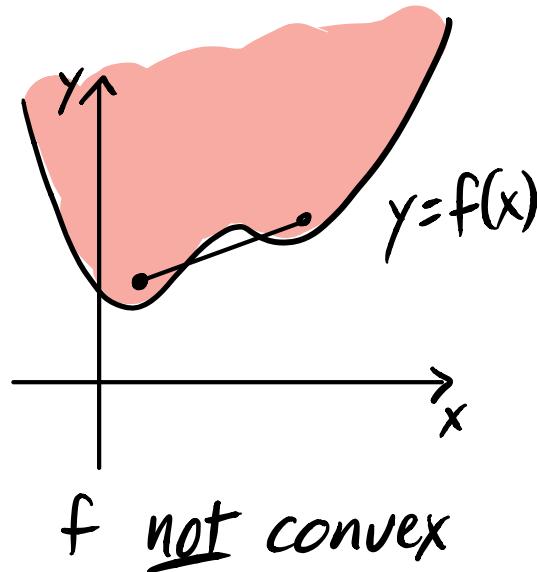
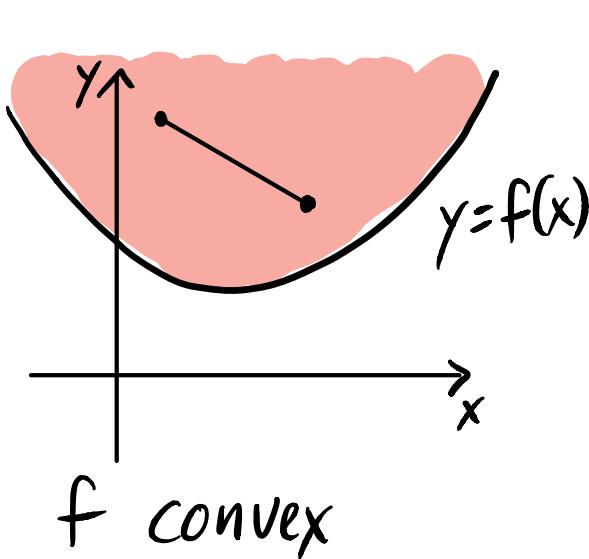
$$\begin{aligned} x, y \in K, \lambda \in [0, 1] \\ x, y \in K_1 \text{ and } x, y \in K_2 \\ \lambda x + (1-\lambda)y \in K_1 \text{ and } \lambda x + (1-\lambda)y \in K_2 \\ \therefore \lambda x + (1-\lambda)y \in K_1 \cap K_2 = K. \\ \therefore K \text{ is convex.} \end{aligned}$$

Two important properties:

- ① Every closed convex set $S \subseteq \mathbb{R}^n$ is equal to the intersection of all the half-spaces containing S .
- ② Let $S \subseteq \mathbb{R}^n$ be closed and convex and $\bar{x} \in \mathbb{R}^n$. If $\bar{x} \notin S$, then \bar{x} can be separated from S by a hyperplane.



A function $f: \mathbb{R}^n \rightarrow \mathbb{R}$ is convex if the set of points on or above the graph of f is a convex set.

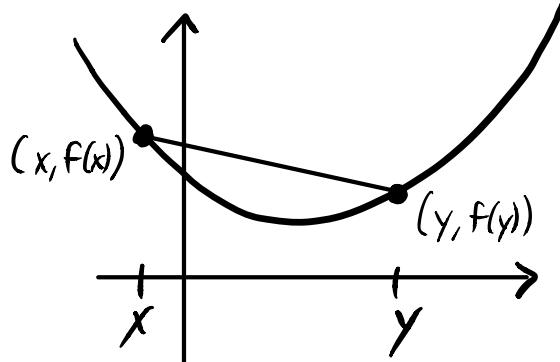


The epigraph of $f: \mathbb{R}^n \rightarrow \mathbb{R}$ is

$$\text{epi}(f) = \{(x, y) \in \mathbb{R}^n \times \mathbb{R} : f(x) \leq y\}.$$

Thus, f is a convex function iff $\text{epi}(f)$ is a convex set.

Also, a function f is convex if the line segment between $(x, f(x))$ and $(y, f(y))$ lies on or above the graph of f .



That line segment is

$$\{(\lambda x + (1-\lambda)y, \lambda f(x) + (1-\lambda)f(y)) : \lambda \in [0,1]\}.$$

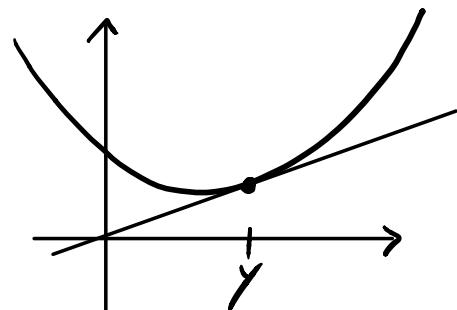
Thus, a function $f: \mathbb{R}^n \rightarrow \mathbb{R}$ is convex if $f(\lambda x + (1-\lambda)y) \leq \lambda f(x) + (1-\lambda)f(y)$ for all $x, y \in \mathbb{R}^n$ and $\lambda \in [0,1]$.

The function is strictly convex if

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

for all $x, y \in \mathbb{R}^n$, with $x \neq y$, and all $\lambda \in (0,1)$.

A differentiable convex function must be on or above all of its tangent lines.



Thus, $f(x) \geq f(y) + \nabla f(y)^T(x-y)$ for all $x, y \in \mathbb{R}^n$.

A twice differentiable function is convex iff its Hessian $\nabla^2 f(x)$ is positive semidefinite for all x .

If $\nabla^2 f(x)$ is always positive definite, then f is strictly convex.

Examples:

(1) $f(x) = c^T x$

$$(2) \quad f(x) = \frac{1}{2} x^T S x, \quad S \text{ sym. pos. def.}$$

$$(3) \quad f(x) = x_1^2 + 2x_1x_2 + x_2^2$$

$$(4) \quad f(x) = x_1^2 - x_2^2$$

$$(5) \quad f(x) = \|x\| \quad (\text{any vector norm}).$$

All optimal sol'n's are globally optimal

Suppose $f: \mathbb{R}^n \rightarrow \mathbb{R}$ is convex and $K \subseteq \mathbb{R}^n$ is convex. If $\bar{x} \in K$ is a locally optimal sol'n of the convex optimization

$$\min f(x) \text{ s.t. } x \in K$$

then there is no better sol'n in K .

Pf:

Newton's Method

Let $f: \mathbb{R}^n \rightarrow \mathbb{R}$ be twice continuously differentiable, $x^* \in \mathbb{R}^n$ be a local minimizer of f (ie $\nabla f(x^*) = 0$ and $\nabla^2 f(x^*)$ pos. def.) and $x_0 \in \mathbb{R}^n$ be our nearby initial guess. We want to find a point $x \in \mathbb{R}^n$ that is closer to x^* .

Two ideas:

- ① Replace $f(x)$ with its second order Taylor series approximation at the point x_0 and minimize that instead:

$$\left[\begin{array}{l} \min_x f(x_0) + \nabla f(x_0)^T (x - x_0) \\ \quad + \frac{1}{2} (x - x_0)^T \nabla^2 f(x_0) (x - x_0). \end{array} \right]$$

Let's call that $g(x)$. Then

$$\nabla g(x) = \nabla f(x_0) + \nabla^2 f(x_0)(x - x_0).$$

Solving $\nabla g(x) = 0$, we obtain:

$$x = x_0 - \nabla^2 f(x_0)^{-1} \nabla f(x_0).$$

② Linearize the nonlinear system

$$\nabla f(x) = 0$$

by replacing $\nabla f(x)$ with its first order Taylor series approximation at the point x_0 :

$$\nabla f(x_0) + \nabla^2 f(x_0)(x - x_0) = 0.$$

Solving this linear system for x , we obtain

$$x = x_0 - \nabla^2 f(x_0)^{-1} \nabla f(x_0).$$

Thus, we let $x_1 = x_0 + \Delta x_0$, where Δx_0 is the solution of

$$\nabla^2 f(x_0) \Delta x_0 = -\nabla f(x_0).$$

In general, we define x_{k+1} as

$$x_{k+1} = x_k + \Delta x_k, \quad \nabla^2 f(x_k) \Delta x_k = -\nabla f(x_k).$$

This is Newton's Method for minimizing a function of n variables. Since it involves the first and second derivatives of f , it is called a second-order method.

Often Newton's method converges quadratically to a point x^* :

$$\|x_{k+1} - x^*\| \leq C \|x_k - x^*\|^2.$$

Example: (Rosenbrock's banana function)

$$f(x) = (1 - x_1)^2 + 100(x_2 - x_1^2)^2$$

Example: (Himmelblau's function)

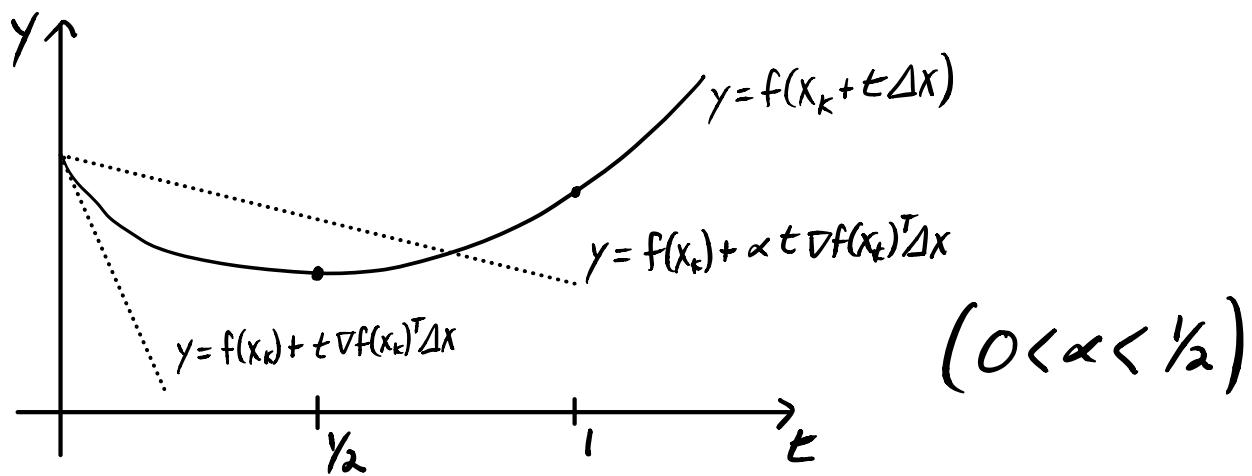
$$f(x) = (x_1^2 + x_2 - 11)^2 + (x_1 + x_2^2 - 7)^2$$

Example:

$$f(x) = (x_1 - 2)^2 + (x_1 - 2)^2 x_2^2 + (x_2 + 1)^2$$

A practical Newton's Method

To help Newton's method behave better in practice, it is important to include a line search for the step size.



Starting with $t=1$, we check if

$$f(x_k + t\Delta x) \leq f(x_k) + \alpha t \nabla f(x_k)^T \Delta x.$$

If this condition is not satisfied, we reduce t by a factor of $0 < \beta < 1$, and check the above condition again. We keep doing this until this condition is satisfied. This is a backtracking line search.

Levenburg - Marguardt for Nonlinear Least Squares

Suppose we have a nonlinear fitting function $\hat{y}: \mathbb{R}^n \rightarrow \mathbb{R}^m$ that depends on n parameters $P = (P_1, \dots, P_n)$.

We want to find the parameters P so that $\hat{y}(P)$ is as close as possible to the data points $y = (y_1, \dots, y_m)$, where the distance/error is measured by the sum of squares loss function:

$$E(P) = \frac{1}{2} \sum_{i=1}^m (y_i - \hat{y}_i(P))^2 = \frac{1}{2} \|y - \hat{y}(P)\|_2^2.$$

We want to solve the nonlinear least squares problem:

$$\min_{P \in \mathbb{R}^n} \frac{1}{2} \|y - \hat{y}(P)\|_2^2.$$

Instead of using Newton's method directly, we change the problem into a linear least squares problem by replacing $\hat{y}(p)$ with its first order Taylor series approximation:

$$\hat{y}(p_k + \Delta p) \approx \hat{y}(p_k) + J(p_k) \Delta p.$$

We find Δp by solving

$$\min_{\Delta p \in \mathbb{R}^n} \frac{1}{2} \| y - \hat{y}(p_k) - J(p_k) \Delta p \|_2^2.$$

The gradient of this objective is

$$J(p_k)^T (y - \hat{y}(p_k) - J(p_k) \Delta p).$$

We want this gradient to be zero, so we solve the linear system

$$J(p_k)^T J(p_k) \Delta p = J^T(p_k) (y - \hat{y}(p_k)).$$

Then $P_{k+1} = P_k + \Delta p$. This is the Gauss-Newton method for nonlinear least squares.

When P_k is far from an optimal P^* , it is better to use gradient descent:

$$\Delta p = -\nabla E(P_k) = J(P_k)^T(y - \hat{y}(P_k)).$$

The Levenberg - Marquardt method combines Gauss-Newton and gradient descent:

$$(J(P_k)^T J(P_k) + \lambda I) \Delta p = J(P_k)^T(y - \hat{y}(P_k)).$$

Starting with λ large, the direction Δp is more like gradient descent. We increase λ until $E(p)$ is reduced.

When $E(p_{k+1})$ is smaller than $E(p_k)$, we reduce λ . As λ approaches zero, we obtain the fast convergence of the Gauss-Newton method.

Example:

$$y = a \cos bx + b \sin ax, \quad a=100, \quad b=102$$