

Last time:

$$\begin{cases} \text{minimize } f(x) \\ \text{s.t. } g_1(x) \leq 0 \\ \quad \vdots \\ \quad g_m(x) \leq 0 \end{cases}$$

KKT - conditions hold:

$\exists y \in \mathbb{R}^m$ s.t. the following

$$(KKT-1) \quad \nabla f(x_0) + y_1 \nabla g_1(x_0) + \dots + y_m \nabla g_m(x_0) = 0$$

$$(KKT-2) \quad \begin{cases} g_i(x_0) \leq 0 \\ g_m(x_0) \leq 0 \end{cases}$$

$$(KKT-3) \quad \begin{cases} y_i \geq 0 \\ y_m \geq 0 \end{cases}$$

$$(KKT-4) \quad \begin{cases} y_1 g_1(x_0) = 0 \\ \quad \vdots \\ y_m g_m(x_0) = 0 \end{cases}$$

x_0 local minimizer }
 and }
 x_0 regular point }

Today we will see that for convex problems, the KKT - conditions are sufficient for an optimal solution!

Recall that a problem $\left\{ \begin{array}{l} \text{minimize } f(x) \\ \text{s.t. } x \in \mathcal{F} \end{array} \right\}$ is called a convex problem

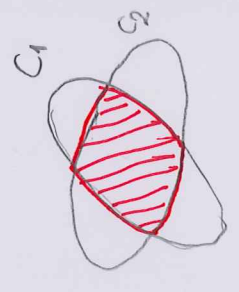
if $\mathcal{F} \subset \mathbb{R}^n$ is a convex set and $f: \mathcal{F} \rightarrow \mathbb{R}$ is a convex function.

Proposition. (P): $\left\{ \begin{array}{l} \text{minimize } f(x) \\ \text{s.t. } g_1(x) \leq 0 \\ \vdots \\ g_m(x) \leq 0 \end{array} \right\}$ is a convex problem if f, g_1, \dots, g_m are convex.

Proof. The set $C_i := \{x \in \mathbb{R}^n : g_i(x) \leq 0\}$ is convex.

$$\begin{aligned} (\because x, y \in C_i, t \in (0,1)) &\Rightarrow g_i(x) \leq 0, \text{ and so } g_i((1-t)x + ty) \\ &g_i(y) \leq 0 \leq \underbrace{(1-t)g_i(x) + tg_i(y)}_{\leq 0} \\ &\leq 0 \end{aligned}$$

So $(1-t)x + ty \in C_i$



Hence C_1, \dots, C_m are convex.

But then $\mathcal{F} := C_1 \cap \dots \cap C_m$ is also convex.

$x, y \in \mathcal{F}, t \in (0,1)$

$\because C_i$ is convex $\Rightarrow (1-t)x + ty \in C_i$

Fix i . Then $x, y \in C_i, t \in (0,1)$

Choice of i was arbitrary. Thus $(1-t)x + ty \in C_1 \cap \dots \cap C_m = \mathcal{F}$.

Finally $f: \mathcal{F} \rightarrow \mathbb{R}$ is convex (given). So (P) is a convex problem. \square

Theorem (Sufficiency of the KKT-conditions for convex problems).

Consider (P):
$$\begin{cases} \text{minimize } f(x) \\ \text{s.t. } \begin{cases} g_1(x) \leq 0 \\ \vdots \\ g_m(x) \leq 0 \end{cases} \end{cases}$$
, where f, g_1, \dots, g_m are convex functions.

Suppose that $\hat{x} \in \mathbb{R}^n$ and $\hat{y} \in \mathbb{R}^m$ satisfy:

$$(KKT-1) \quad \nabla f(\hat{x}) + \hat{y}_1 \nabla g_1(\hat{x}) + \dots + \hat{y}_m \nabla g_m(\hat{x}) = 0$$

$$(KKT-2) \quad \begin{cases} g_1(\hat{x}) \leq 0 \\ \vdots \\ g_m(\hat{x}) \leq 0 \end{cases}$$

$$(KKT-3) \quad \begin{cases} \hat{y}_1 \geq 0 \\ \vdots \\ \hat{y}_m \geq 0 \end{cases}$$

$$(KKT-4) \quad \begin{cases} \hat{y}_1 g_1(\hat{x}) = 0 \\ \vdots \\ \hat{y}_m g_m(\hat{x}) = 0 \end{cases}$$

Then \hat{x} is a global minimizer for (P).

Proof (KKT-2) $\Rightarrow \hat{x}$ is feasible.

Consider the auxiliary function $L: \mathbb{R}^n \rightarrow \mathbb{R}$ given by

$$L(x) = f(x) + \hat{y}_1 g_1(x) + \dots + \hat{y}_m g_m(x), \quad x \in \mathbb{R}^n$$

Note that $\hat{y}_1, \dots, \hat{y}_m$ are fixed numbers (given), and x is the variable.

Claim: L is convex.

If $x, y \in \mathbb{R}^n$, $t \in (0, 1)$, then:

$$\begin{aligned}
L((1-t)x + ty) &= \underbrace{f((1-t)x + ty)}_N + \sum_{i=1}^m \hat{y}_i \underbrace{g_i((1-t)x + ty)}_M \\
&\leq (1-t)f(x) + tf(y) + \sum_{i=1}^m \hat{y}_i ((1-t)g_i(x) + tg_i(y)) \\
&= (1-t) [f(x) + \sum_{i=1}^m \hat{y}_i g_i(x)] + t [f(y) + \sum_{i=1}^m \hat{y}_i g_i(y)] \\
&= (1-t)L(x) + tL(y).
\end{aligned}$$

This proves the claim.

Let us now calculate $\nabla L(\hat{x})$.

$$\nabla L(\hat{x}) = \nabla f(\hat{x}) + \sum_{i=1}^m \hat{y}_i \nabla g_i(\hat{x}) \stackrel{\text{(KKT-1)}}{=} 0 !$$

L convex and $\nabla L(\hat{x}) = 0 \iff \hat{x}$ is a global minimizer for L .

Let $x \in \mathcal{F}_e$. Then $\begin{cases} g_1(x) \leq 0 \\ \vdots \\ g_m(x) \leq 0 \end{cases}$. We will show that $f(x) \geq f(\hat{x})$.

Know: $L(x) \geq L(\hat{x})$, i.e.,

$$f(x) + \underbrace{\sum_{i=1}^m \hat{y}_i g_i(x)}_{=0 \text{ by (KKT-4)}} \geq f(\hat{x}) + \sum_{i=1}^m \hat{y}_i g_i(\hat{x})$$

$$\boxed{f(x) + \underbrace{\sum_{i=1}^m \hat{y}_i g_i(x)}_{\substack{\geq 0 \\ \geq 0 \\ \geq 0 \\ \geq 0}}}_{\geq 0} \geq f(\hat{x})$$

So $f(x) \geq f(\hat{x}) \quad \forall x \in \mathcal{F}_e$.

Hence \hat{x} is an optimal solution for (P). Done! \square

Are the conditions also necessary?

Example

$$(P) \begin{cases} \text{minimize} & f(x) \\ \text{s.t.} & g_1(x) \leq 0 \\ & g_2(x) \leq 0 \end{cases} \quad \text{where}$$

$$f(x_1, x_2) := x_1$$

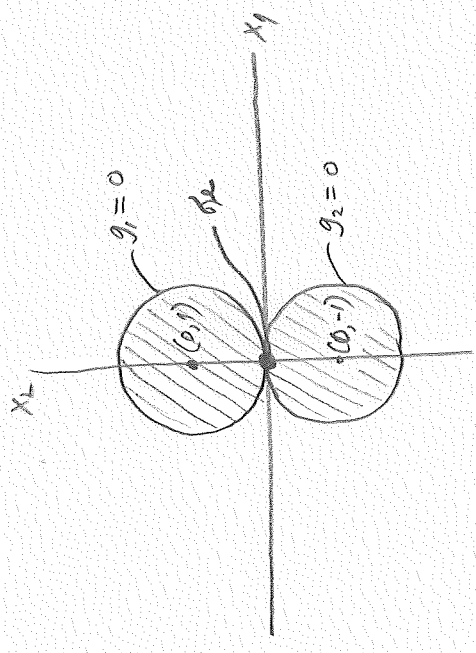
$$g_1(x_1, x_2) := x_1^2 + (x_2 - 1)^2 - 1$$

$$g_2(x_1, x_2) := x_1^2 + (x_2 + 1)^2 - 1$$

Then f, g_1, g_2 are convex. ($\because f$ is linear and the Hessians of g_1, g_2 are p.s.d.)

$$G_1(x) = \begin{bmatrix} 2 & 0 \\ 0 & 2 \end{bmatrix} \text{ is p.d.}, \quad G_2(x) = \begin{bmatrix} 2 & 0 \\ 0 & 2 \end{bmatrix} \text{ is p.d.}$$

So (P) is a convex problem.



$$dx = \{(0,0)\}$$

So $(0,0)$ is the (unique) global minimizer.

But we will now see that the KKT conditions are not satisfied with $\hat{x} := (0, 0)$:

$$\nabla f(0) = [1 \ 0]$$

$$\nabla g_1(0) = [2x_1 \ 2(x_2 - 1)] \Big|_{(x_1, x_2) = (0, 0)} = [0 \ -2]$$

$$\nabla g_2(0) = [2x_1 \ 2(x_2 + 1)] \Big|_{(x_1, x_2) = (0, 0)} = [0 \ 2]$$

So (KKT-1) becomes $\nabla f(0) + \hat{y}_1 \nabla g_1(0) + \hat{y}_2 \nabla g_2(0) = 0$ (i.e.,

$$[1 \ 0] + \hat{y}_1 [0 \ -2] + \hat{y}_2 [0 \ 2] = [0 \ 0]^*$$

a contradiction!

What went wrong? $(0, 0)$ is not a regular point.

(Recall that $x \in \mathcal{X}$ is not a regular point if \exists nonnegative v_i (i.e. $I_a(x)$), not all zeros, s.t. $\sum_{i \in I_a(x)} v_i \nabla g_i(x) = 0$.)

In our case, $I_a(0, 0) = \{1, 2\}$. With $v_1 := 1, v_2 := 1$, we have $v_1 \nabla g_1(0) + v_2 \nabla g_2(0) = 1 \cdot [0 \ -2] + 1 \cdot [0 \ 2] = 0$. So $(0, 0)$ is not regular.

Know: \hat{x} global minimizer and \hat{x} regular $\Rightarrow \hat{x}$ satisfies the KKT - conditions

② For convex problems, \hat{x} satisfies the KKT - condition $\Rightarrow \hat{x}$ is a global minimizer

It would be good to have an 'iff' statement for convex problems.

One can show the following:

Proposition: If g_1, \dots, g_m are convex and

$$\exists x_0 \text{ s.t. } \begin{cases} g_1(x) < 0 \\ \vdots \\ g_m(x) < 0 \end{cases}$$

then every feasible point is regular for

$$\begin{cases} \text{minimize } f(x) \\ \text{s.t. } g_1(x) \leq 0 \\ \vdots \\ g_m(x) \leq 0. \end{cases}$$

The problem $\left\{ \begin{array}{l} \text{minimize } f(x) \\ \text{s.t. } \left\{ \begin{array}{l} g_1(x) \leq 0 \\ \vdots \\ g_m(x) \leq 0 \end{array} \right. \end{array} \right\}$ is called a regular problem

if there exists a $x_0 \in \mathbb{R}^n$ s.t. $\left\{ \begin{array}{l} g_1(x_0) < 0 \\ \vdots \\ g_m(x_0) < 0 \end{array} \right.$

Theorem. Suppose that (P): $\left\{ \begin{array}{l} \text{minimize } f(x) \\ \text{s.t. } \left\{ \begin{array}{l} g_1(x) \leq 0 \\ \vdots \\ g_m(x) \leq 0 \end{array} \right. \end{array} \right\}$ is a regular problem,

and that f, g_1, \dots, g_m are convex functions.

Then \hat{x} is an optimal solution for (P) iff

$$\exists \hat{y} \in \mathbb{R}^m \text{ s.t. } \begin{array}{l} \text{(KKT-1)} \quad \nabla f(\hat{x}) + \hat{y}_1 \nabla g_1(\hat{x}) + \dots + \hat{y}_m \nabla g_m(\hat{x}) = 0 \\ \text{(KKT-2)} \quad \left\{ \begin{array}{l} g_1(\hat{x}) \leq 0 \\ \vdots \\ g_m(\hat{x}) \leq 0 \end{array} \right. \\ \text{(KKT-3)} \quad \left\{ \begin{array}{l} \hat{y}_1 \geq 0 \\ \vdots \\ \hat{y}_m \geq 0 \end{array} \right. \\ \text{(KKT-4)} \quad \left\{ \begin{array}{l} \hat{y}_1 g_1(\hat{x}) = 0 \\ \vdots \\ \hat{y}_m g_m(\hat{x}) = 0 \end{array} \right. \end{array}$$

Example

$$\left\{ \begin{array}{l} \text{minimize } x_1^2 - 2x_1 + x_2^2 + 1 \\ \text{s.t. } x_1 + x_2 \leq 0 \\ x_1^2 - 4 \leq 0 \end{array} \right.$$

$$\left\{ \begin{array}{l} \text{minimize } f(x) \\ \text{s.t. } g_1(x) \leq 0 \\ g_2(x) \leq 0 \end{array} \right.$$

where

$$\begin{aligned} f(x) &:= x_1^2 - 2x_1 + x_2^2 + 1 \\ g_1(x) &:= x_1 + x_2 \\ g_2(x) &:= x_1^2 - 4 \end{aligned}$$

f, g_1 is convex, since it is linear.

Hessians of f, g_2 :

$$\begin{aligned} \nabla f(x) &= [2x_1 - 2 \quad 2x_2] & F(x) &= \begin{bmatrix} 2 & 0 \\ 0 & 2 \end{bmatrix} \text{ p.d.} \\ \nabla g_2(x) &= [2x_1 \quad 0] & G_2(x) &= \begin{bmatrix} 2 & 0 \\ 0 & 0 \end{bmatrix} \text{ p.s.d.} \end{aligned}$$

So f, g_2 are convex as well.

Is the problem regular? With $x_0 := (-1, 0)$, we have

$$\begin{aligned} g_1(x_0) &= g_1(-1, 0) = -1 + 0 = -1 < 0 \\ g_2(x_0) &= g_2(-1, 0) = (-1)^2 - 4 = -3 < 0 \end{aligned}$$

So the problem is regular.

⇒ KKT conditions are necessary and sufficient.

$$\underline{\text{(KKT-1)}}: \nabla f(x) + y_1 \nabla g_1(x) + y_2 \nabla g_2(x) = 0$$

$$[2x_1 - 2 \quad 2x_2] + y_1 [1 \quad 1] + y_2 [2x_1 \quad 0] = 0$$

$$\begin{cases} 2x_1 - 2 + y_1 + 2y_2 x_1 = 0 \\ 2x_2 + y_1 = 0 \end{cases}$$

$$\underline{\text{(KKT-2)}}: \begin{cases} x_1 + x_2 \leq 0 \\ x_1^2 - 4 \leq 0 \end{cases}$$

$$\underline{\text{(KKT-3)}}: \begin{cases} y_1 \geq 0 \\ y_2 \geq 0 \end{cases}$$

$$\underline{\text{(KKT-4)}}: y_1 (x_1 + x_2) = 0$$

$$y_2 (x_1^2 - 4) = 0$$

$$\begin{cases} y_1 > 0 \\ y_2 > 0 \end{cases}$$

(KKT-4) : $\begin{cases} x_1 + x_2 = 0 \\ x_1^2 - 4 = 0 \end{cases} \Rightarrow$

$\begin{cases} x_1 = +2 \text{ or } -2 \\ x_2 = -2 \text{ or } +2 \end{cases}$

$(x_1, x_2) = (2, -2) \text{ or } (-2, 2)$

[1°]

$(x_1, x_2) = (2, -2)$: (KKT-1) : $\begin{cases} 4 - 2 + y_1 + 2y_2(-2) = 0 \\ 2(-2) + y_1 = 0 \end{cases} \Rightarrow$

$\begin{cases} y_1 = 4 \\ y_2 = -6/4 \end{cases}$

(KKT-3) violated.

[2°]

$(x_1, x_2) = (-2, 2)$: (KKT-1) : $\begin{cases} -4 - 2 + y_1 + 2y_2(-2) = 0 \\ 2(2) + y_1 = 0 \end{cases} \Rightarrow$

$\begin{cases} y_1 = -4 \\ \text{(KKT-3) violated} \end{cases}$

$$\begin{cases} y_1 > 0 \\ y_2 = 0 \end{cases}$$

(KKT-4) : $\begin{cases} x_1 + x_2 = 0 \\ 2x_1 - 2 + y_1 = 0 \\ 2x_2 + y_1 = 0 \end{cases}$

$x_1 = -x_2$

$\begin{cases} -2x_2 - 2 + y_1 = 0 \\ 2x_2 + y_1 = 0 \end{cases}$

$\begin{cases} -2 + 2y_1 = 0 \Rightarrow y_1 = 1 \\ x_2 = -\frac{1}{2} \\ x_1 = \frac{1}{2} \end{cases}$

$\begin{cases} \frac{1}{2} + (-\frac{1}{2}) = 0 \\ (\frac{1}{2})^2 - 4 < 0 \end{cases}$ so (KKT-2) is satisfied

So with $x = (\frac{1}{2}, -\frac{1}{2})$ and $y = (1, 0)$, all the KKT

conditions are satisfied.

So $x = (\frac{1}{2}, -\frac{1}{2})$ is a global minimizer.

Are there any others?

$$\begin{cases} y_1 = 0 \\ y_2 > 0 \end{cases}$$

(KKT-4): $x_1^2 - 4 = 0 \Rightarrow x_1 = +2$ or -2

[1°] $x_1 = +2$. (KKT-1): $\begin{cases} 4 - 2 + 0 + 4y_2 = 0 \\ 2x_2 + 0 = 0 \end{cases} \Rightarrow y_2 = -\frac{1}{2}$ (KKT-3) is violated.

[2°] $x_1 = -2$. (KKT-1): $\begin{cases} -4 - 2 + 0 - 4y_2 = 0 \\ -4 - 2 + 0 \end{cases} \Rightarrow y_2 = -\frac{6}{4}$ (KKT-3) is violated.

$$\begin{cases} y_1 = 0 \\ y_2 = 0 \end{cases}$$

(KKT-4): $\begin{cases} 2x_1 - 2 = 0 \\ 2x_2 = 0 \end{cases} \Rightarrow \begin{cases} x_1 = 1 \\ x_2 = 0 \end{cases}$

But then $x_1 + x_2 = 1 + 0 = 1 \neq 0$.
So (KKT-2) is violated.

So there is an optimal solution, namely $\hat{x} = \left(\frac{1}{2}, -\frac{1}{2}\right)$,

and there are no others.

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

Level curves $\{x \in \mathbb{R}^2 : f(x) = V\}$ will be circles.

Feasible set:

