

# Econ 508-A

## KT Sufficient Conditions

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# INTRODUCTION

Given the problem

$$\begin{aligned} & \max_x f(\mathbf{x}) \\ & \text{s.t. } g_k(\mathbf{x}) \leq 0 \end{aligned}$$

The KT conditions are also sufficient for a maximum when:

- ▶ The objective function  $f$  is concave.
- ▶ The constraint set  $X$  is convex  
(the constraints  $g_k$  are convex).

We'll develop weaker conditions in the following sections.

# INTERIOR LOCAL OPTIMA

**THEOREM:** Let  $f : X \rightarrow \mathbb{R}$  be differentiable, where  $X \subseteq \mathbb{R}^N$ . Given  $\mathbf{x}^* \in X$ , suppose that  $X$  is locally convex (there is  $\varepsilon$  s.t.  $N_\varepsilon(\mathbf{x}^*) \cap X$  is convex). Suppose that the following conditions hold:

1.  $Df(\mathbf{x}^*) = 0$
2.  $f$  is locally concave at  $\mathbf{x}^*$ .

Then  $\mathbf{x}^*$  is a local maximum.

Moreover, if  $f$  is locally strictly concave, then  $\mathbf{x}^*$  is a local strict maximum.

# PROOF

By contradiction:

Suppose that  $f$  is locally concave at  $\mathbf{x}^*$  but  $\mathbf{x}^*$  is not a local maximum.

Choose any  $\varepsilon > 0$  s.t.  $f$  is concave on  $N_\varepsilon(\mathbf{x}^*)$ .

Since  $\mathbf{x}^*$  is not a local maximum,  $\exists \hat{\mathbf{x}} \in N_\varepsilon(\mathbf{x}^*)$  s.t.  $f(\hat{\mathbf{x}}) > f(\mathbf{x}^*)$ .

Take any  $\alpha \in (0, 1)$  and let  $\mathbf{x}^\alpha = \alpha\hat{\mathbf{x}} + (1 - \alpha)\mathbf{x}^*$ .

By concavity of  $f(\mathbf{x})$ ,

$$f(\mathbf{x}^\alpha) \geq \alpha f(\hat{\mathbf{x}}) + (1 - \alpha)f(\mathbf{x}^*) = f(\mathbf{x}^*) + \alpha(f(\hat{\mathbf{x}}) - f(\mathbf{x}^*))$$

# PROOF (CONTINUED)

Rewriting  $\mathbf{x}^\alpha = \mathbf{x}^* + \alpha(\hat{\mathbf{x}} - \mathbf{x}^*)$  and dividing by  $\alpha$ ,

$$\frac{f(\mathbf{x}^* + \alpha(\hat{\mathbf{x}} - \mathbf{x}^*)) - f(\mathbf{x}^*)}{\alpha} \geq \frac{\alpha(f(\hat{\mathbf{x}}) - f(\mathbf{x}^*))}{\alpha} = f(\hat{\mathbf{x}}) - f(\mathbf{x}^*) > 0$$

Taking limits as  $\alpha \rightarrow 0$ , this implies that

$$D_{(\hat{\mathbf{x}} - \mathbf{x}^*)}f(\mathbf{x}^*) = Df(\mathbf{x}^*)(\hat{\mathbf{x}} - \mathbf{x}^*) > 0, \text{ so } Df(\mathbf{x}^*) \neq 0 \quad \blacksquare$$

For strict, do the same with strict inequality.

## COROLLARY OF PREVIOUS THEOREM

Let  $f : X \rightarrow \mathbb{R}$  be  $C^2$ , where  $X \subseteq \mathbb{R}^N$ . Given  $\mathbf{x}^* \in X$ , suppose that  $X$  is locally convex. Suppose that the following conditions hold:

1.  $Df(\mathbf{x}^*) = 0$  (sufficiency FOC)
2.  $D^2 f(\mathbf{x}^*)$  is ND (sufficiency SOC)

Then  $\mathbf{x}^*$  is a strict local maximum.

Notice that  $D^2 f(\mathbf{x}^*)$  being ND is sufficient for strict concavity of  $f$  at  $\mathbf{x}^*$ .

# NECESSARY CONDITIONS

THEOREM: Let  $f : X \rightarrow \mathbb{R}$  be  $C^2$ , where  $X \subseteq \mathbb{R}^N$ . If  $\mathbf{x}^*$  is interior and a local maximum, then the following conditions hold:

1.  $Df(\mathbf{x}^*) = 0$  (Necessity FOC)
2.  $D^2 f(\mathbf{x}^*)$  is NSD (Necessity SOC)

# PROOF

If  $\mathbf{x}^*$  is an interior local maximum, then there is  $\varepsilon > 0$  such that for  $N_\varepsilon(\mathbf{x}^*) \subseteq X$  and  $\forall \mathbf{x} \in N_\varepsilon(\mathbf{x}^*)$ ,  $f(\mathbf{x}^*) \geq f(\mathbf{x})$ . Note that  $N_\varepsilon(\mathbf{x}^*)$  is convex.

1. Already proved.
2. Suppose  $Df(\mathbf{x}^*) = 0$  but  $D^2 f(\mathbf{x}^*)$  is not negative semidefinite.

Then for some  $\mathbf{v} \in \mathbb{R}^N$ ,  $\mathbf{v} \neq \mathbf{0}$ ,  $\mathbf{v}' D^2 f(\mathbf{x}^*) \mathbf{v} > 0$ .

Thus, the function is locally strictly convex on the line through  $\mathbf{x}^*$  in the direction  $\mathbf{v}$ .

So along this line  $\mathbf{x}^*$  is a local strict minimum, and, hence, cannot be a local strict maximum.





# EXAMPLE

Note that there is a discrepancy between the necessity and sufficiency SOC. We need strict negative definiteness at  $x^*$  to guarantee negative definiteness in  $N_\varepsilon(x^*)$ .

Consider the following example:

Let  $f : \mathbb{R} \rightarrow \mathbb{R}$  be  $f(x) = x^4$ .

$Df(0) = 0$  and  $D^2f(0) = 0$ , so the necessary conditions for a maximum are satisfied.

However,  $x = 0$  is a minimum, since  $f$  is strictly convex.

# CONSTRAINED LOCAL OPTIMA

**THEOREM:** Let  $f : X \rightarrow \mathbb{R}$  be  $C^2$ , where  $X \subseteq \mathbb{R}^N$ . Given  $\mathbf{x}^* \in X$ , suppose that  $X$  is locally convex. Assuming the following:

1. The KT conditions hold.
2.  $f$  is locally concave at  $\mathbf{x}^*$

Then  $\mathbf{x}^*$  is a local maximum.

Moreover, if  $f$  is locally strictly concave, then  $\mathbf{x}^*$  is a local strict maximum.

**PROOF:** omitted (similar to the proof of the first theorem: there would exist some feasible direction in which  $f$  increases and the  $g_k$  are not increasing).

# NECESSARY CONDITIONS

THEOREM: Let  $f$  and  $g$  be  $C^2$ . Fix  $\mathbf{x}^*$  and let

$$T = \{ \mathbf{v} \in \mathbb{R}^N : \nabla g_k(\mathbf{x}^*) \cdot \mathbf{v} = 0 \forall k \text{ binding} \}$$

1. Suppose that constraint qualification holds. Suppose that  $\mathbf{x}^*$  is a local maximum. Then there are unique numbers  $\lambda_k \geq 0$  such that the following conditions hold:

(a) i.  $\nabla f(\mathbf{x}^*) = \sum_k \lambda_k \nabla g_k(\mathbf{x}^*)$

ii.  $\lambda_k g_k(\mathbf{x}^*) = 0$  for all  $k$ .

(b)  $D^2 f(\mathbf{x}^*) - \sum_k \lambda_k D^2 g_k(\mathbf{x}^*)$  is negative semidefinite on  $T$ .

# SUFFICIENT CONDITIONS

2. Suppose that at a feasible point  $\mathbf{x}^*$  there exist numbers  $\lambda_k \geq 0$  such that the following conditions hold:

(a) i.  $\nabla f(\mathbf{x}^*) = \sum_k \lambda_k \nabla g_k(\mathbf{x}^*)$

ii.  $\lambda_k > 0$  iff  $g_k(\mathbf{x}^*) = 0 \forall k$ .

(b)  $D^2f(\mathbf{x}^*) - \sum_k \lambda_k D^2g_k(\mathbf{x}^*)$  is negative definite on  $T$ .

Then  $\mathbf{x}^*$  is a strict local maximum.

PROOF: omitted. ■

Note that condition 2(a)ii is stronger than KT(2), since it requires that active constraints be binding.

# GLOBAL OPTIMIZATION

A local maximum is a global maximum if  $f$  is concave.

THEOREM: Let  $X \subseteq \mathbb{R}^N$  be convex. Let  $f : X \rightarrow \mathbb{R}$ .

1. Let  $\mathbf{x}^*$  be a local maximum.
  - (a) If  $f$  is concave on  $X$ , then  $\mathbf{x}^*$  is a global maximum.
  - (b) If  $f$  is strictly quasiconcave on  $X$ , then  $\mathbf{x}^*$  is a global strict maximum.
2. Let  $\mathbf{x}^*$  be a local strict maximum. If  $f$  is quasiconcave on  $X$ , then  $\mathbf{x}^*$  is a global strict maximum.

# PROOF

1. (a) Suppose  $\mathbf{x}^*$  is not a global maximum.

Then there is  $\mathbf{x} \in X$  such that  $f(\mathbf{x}) > f(\mathbf{x}^*)$ .

For  $\alpha \in (0, 1)$ , let  $\mathbf{x}^\alpha = \alpha\mathbf{x} + (1 - \alpha)\mathbf{x}^*$ .

By concavity,  $f(\mathbf{x}^\alpha) \geq \alpha f(\mathbf{x}) + (1 - \alpha)f(\mathbf{x}^*) > f(\mathbf{x}^*)$ .

Since  $\alpha$  is arbitrary, this implies that  $\mathbf{x}^*$  is not a local maximum.

# PROOF (CONTINUED)

1. (b) Suppose  $\mathbf{x}^*$  is not a global strict maximum.

Then there is  $\mathbf{x} \in X$  such that  $f(\mathbf{x}) \geq f(\mathbf{x}^*)$ .

For  $\alpha \in (0, 1)$ , let  $\mathbf{x}^\alpha = \alpha\mathbf{x} + (1 - \alpha)\mathbf{x}^*$ .

By strict quasiconcavity,  $f(\mathbf{x}^\alpha) > f(\mathbf{x}^*)$ .

Since  $\alpha$  is arbitrary, this implies that  $\mathbf{x}^*$  is not a local maximum.

## PROOF (CONTINUED)

2. Suppose  $\mathbf{x}^*$  is not a global strict maximum.

Then there is  $\mathbf{x} \in X$  such that  $f(\mathbf{x}) \geq f(\mathbf{x}^*)$ .

For  $\alpha \in (0, 1)$ , let  $\mathbf{x}^\alpha = \alpha\mathbf{x} + (1 - \alpha)\mathbf{x}^*$ .

By quasiconcavity,  $f(\mathbf{x}^\alpha) \geq f(\mathbf{x}^*)$ .

Since  $\alpha$  is arbitrary, this implies that  $\mathbf{x}^*$  is not a local maximum.