

CHAPTER 13 ^{SBO} SUFFICIENCY (OUR BEST CONTRIBUTION)

13.1 THE FUNDAMENTAL THEOREM OF NONLINEAR PROGRAMMING

RECALL:

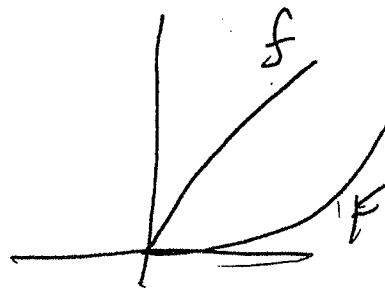
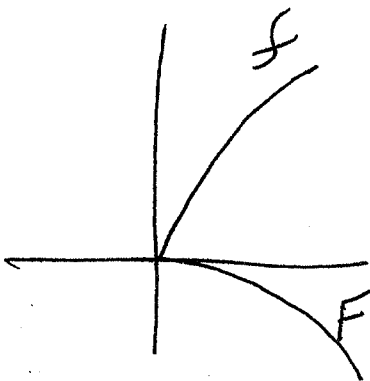
DEF 3.10.3 (LOCAL SUPPORT FUNCTION)

F LOWER SUPPORT FUNCTION FOR f AT x^* IF

(i) $F(x) \leq f(x) \quad \forall x \in S \cap N(x^*)$

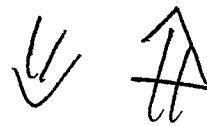
(ii) $F(x^*) = f(x^*)$

(iii) $F'(x^*) = 0$



OBSERVATION:

x^* MINIMIZES F



x^* MINIMIZES f

2

PROPOSITION 13.1.1

~~Let (x^*, λ^*, μ^*) be a KKT of PROBLP~~ LET (x^*, λ^*, μ^*) be a KKT of PROBLP

THEN $F(x) = l(x, \lambda^*, \mu^*)$ IS A LOCAL SUPPORT

FUNCTION FOR f .

PROOF.

$$l(x, \lambda^*, \mu^*) = f(x) + \sum \lambda_i h_i(x) - \sum \mu_i g_i(x) \stackrel{=0}{=} f(x) \stackrel{=0}{=} f(x)$$

$$\leq f(x)$$

$$l(x^*, \lambda^*, \mu^*) = f(x^*)$$

$$l'_x(x^*, \lambda^*, \mu^*) = 0$$

~~THEOREM~~ 13.1.2 (THE FUNDAMENTAL THEOREM OF NONLINEAR PROG)

LET (x^*, λ^*, μ^*) BE A KKT POINT OF PROB NLP.

IF x^* IS A (LOCAL, GLOBAL, STRICT)

MINIMIZER OF $F(x) = \mathcal{L}(x, \lambda^*, \mu^*)$

THEN x^* IS A (LOCAL, GLOBAL, STRICT)

MINIMIZER OF f OVER S .

Proof

$$f(x^*) = F(x^*) \leq F(x) \leq f(x)$$

4

SECTION 13.2 SUFFICIENCY FOR NONLINEAR PROGRAMMING.
Recall:

3.12 Fundamental Principles for Second-Order Sufficiency

Theorem 3.12.1 (Fundamental Principles for Second-Order Sufficiency). Consider Problem (3.1) and $x^* \in S$.

Assume

- (a) X is a normed linear space.
- (b) f is Fréchet differentiable in a neighborhood of x^* and has a second Fréchet derivative at x^* .
- (c) There exists a local lower support function F for f at x^* .

Then

- (i) The condition that for each $\{x_k \neq x^*\} \subset S$ converging to x^* satisfying

$$\lim_k f'(x^*) \left(\frac{x_k - x^*}{\|x_k - x^*\|} \right) = 0, \quad (3.62)$$

it follows that

$$\liminf_k F''(x^*) \left(\frac{x_k - x^*}{\|x_k - x^*\|}, \frac{x_k - x^*}{\|x_k - x^*\|} \right) > 0, \quad (3.63)$$

is sufficient for x^* to be a strict local minimizer of f in S .

Moreover, if $X = \mathbb{R}^n$, then statement (i) is equivalent to the statement

- (ii) The condition that for each nonzero $z \in T_s(S, x^*)$ satisfying

$$f'(x^*)(z) = 0 \quad (3.64)$$

it follows that

$$F''(x^*)(z, z) > 0, \quad (3.65)$$

is sufficient for x^* to be a strict local minimizer of f in S .

Example 3.12.2. We wish to see what our fundamental principle for second-order sufficiency, Theorem 3.12.1, gives with respect to unconstrained minimization in \mathbb{R}^n . Consider $f : \mathbb{R}^n \rightarrow \mathbb{R}$ and $x^* \in \mathbb{R}^n$. Assume that f has a Fréchet derivative in a neighborhood of x^* and has a second Fréchet derivative at x^* . Our first-order necessary condition is that $\nabla f(x^*) = 0$. Hence, we let f serve as its own support function. This means that one of our assumptions must be $\nabla f(x^*) = 0$. This assumption is not restrictive since it must hold if sufficiency holds. It is clear that $T_\ell(\mathbb{R}^n, x^*) = \mathbb{R}^n$; hence $T_s(\mathbb{R}^n, x^*) = \mathbb{R}^n$, since the latter tangent cone contains the former. We see from part (ii) of Theorem 3.12.1 that x^* will be a strict local minimizer if

$$f''(x^*)(z, z) = \langle \nabla^2 f(x^*)z, z \rangle > 0 \quad \text{for all } z \neq 0.$$

Hence, sufficiency conditions for x^* to be a strict local minimizer of $f : \mathbb{R}^n \rightarrow \mathbb{R}$ are

- (i) f is Fréchet differentiable in a neighborhood of x^* and has a second Fréchet derivative at x^* ,
- (ii) $\nabla f(x^*) = 0$, and
- (iii) $\nabla^2 f(x^*)$, the Hessian matrix of f at x^* , is positive definite.

RECALL PROPOSITION 13.1.1 THAT SAYS
~~THE~~ THAT ~~IN~~ FOR PROBLEM NLP,
 IF (x^*, λ^*, μ^*) IS A KKT POINT,
 THEN THE LAGRANGIAN

$$F(x) = l(x, \lambda^*, \mu^*)$$

IS A LOWER SUPPORT FUNCTION
 FOR f .

Sufficiency For Nonlinear Programming Problems in \mathbb{R}^n

Theorem 3.2.1 Application Theorem One: Sufficiency for Constrained Optimization in \mathbb{R}^n . Consider Problem (NLP), where $f, h_i, g_i : \mathbb{R}^n \rightarrow \mathbb{R}$ and are twice continuously differentiable. Sufficient conditions for x^* to be a strict local solution of Problem (NLP) are:

(i) There exists λ^*, μ^* such that (x^*, λ^*, μ^*) is a KKT point.

(ii) Whenever $z \neq 0$ is such that

$$z^T \nabla g_i(x^*) \geq 0 \text{ for } i \in B(x^*)$$

$$z^T \nabla g_i(x^*) = 0 \text{ for } i \in B(x^*) \setminus \{i \mid \mu_i^* > 0\}$$

$$z^T \nabla h_i(x^*) = 0 \text{ for } i = 1, \dots, m,$$

then $z^T \nabla_x^2 \mathcal{L}(x^*, \lambda^*, \mu^*) z > 0$.

PROOF. OUR TASK IS TO SHOW THAT THE IMPLICATION GIVEN IN (i) OF OUR FUNDAMENTAL PRINCIPLE FOR SECOND-ORDER SUFFICIENCY, THEOREM 3.12.1, HOLDS USING THE LAGRANGIAN AS SUPPORT FUNCTION WHEN ~~THE~~ THE CONDITIONS GIVEN IN THEOREM 3.2.1 HOLD.

SO WE ASSUME THE CONDITIONS OF THE LATTER THEOREM AND CONSIDER THE HYPOTHESIS IN (i) OF THE FORMER THEOREM. SPECIFICALLY CONSIDER $\exists \in T_0(S, X^*)$ SATISFYING $\exists T \psi(x^*) = 0$.

§ 8

WE KNOW THAT

~~WE KNOW THAT~~
$$\beta = \lim_{n \rightarrow \infty} \frac{\|g_n\|}{\|x_n - x^*\|}$$

FOR A SEQUENCE $\{x_n\}$ SATISFYING

(a) x_n IS FEASIBLE

(b) $x_n \neq x^*$

(c) $x_n \rightarrow x^*$.

WITHOUT LOSS OF GENERALITY ~~WE~~ ASSUME $\|\beta\| = 1$.

LET $z_k = \frac{(x_k - x^*)}{\|x_k - x^*\|}$ AND LET $\delta_k = \|x_k - x^*\|$, SO THAT

$$\delta_k z_k = x_k - x^*.$$

NOW

$$\frac{g_i(x^* + \delta_k z_k) - g_i(x^*)}{\delta_k} \geq 0,$$

therefore $\nabla g_i(x^*)^T z \geq 0$ for $i \in B(x^*)$. Also,

$$\frac{h_i(x^* + \delta_k z_k) - h_i(x^*)}{\delta_k} = 0,$$

so $\nabla h_i(x^*)^T z = 0$ for $i = 1, \dots, m$. It follows that

$$0 = \nabla f(x^*)^T z = \sum_{i \in B(x^*)} \mu_i \nabla g_i(x^*)^T z.$$

Thus, $\nabla g_i(x^*)^T z = 0$ for $i \in B(x^*)$ and ~~and~~ all of the ~~assumptions~~ ^{conditions} in (ii) of Theorem 12.2.1 are satisfied. Hence, we have

$$z^T \nabla_x^2 \phi(x^*, \lambda^*, \mu^*) z > 0$$

and

Our general principle for sufficiency holds. \square

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13.3 Sufficiency For Nonlinear Programming Problems in Hilbert Space

In this section, we study sufficiency results in infinite dimensions. First, we consider the case of an unconstrained optimization problem.

Theorem 13.3.1 Application Theorem Two: Sufficiency for Unconstrained Optimization in Hilbert Space. Consider $f : H \rightarrow \mathbb{R}$, where H is a Hilbert space. Assume that $f \in C^2$. Sufficient conditions for x^* to be a strict local minimizer of f are

$$(i) \quad \nabla f(x^*) = 0.$$

$$(ii) \quad \eta^T \nabla^2 f(x^*) \eta \geq c \|\eta\|^2 \quad \text{for all } \eta \neq 0 \text{ in } H \text{ and some } c > 0.$$

Proof: Clearly (i) and (ii) of Theorem 13.2.1 are satisfied. \square

Remark 13.3.2 If $H = \mathbb{R}^n$, then (ii) of Theorem 13.3.1 is implied by $\eta^T \nabla^2 f(x^*) \eta \geq 0$ for all $\eta \neq 0$. This fact follows directly from the fact that the Rayleigh quotient $(\eta^T \nabla^2 f(x^*) \eta) / (\eta^T \eta)$ is minimized by the smallest eigenvalue of $\nabla^2 f(x^*)$, which is necessarily positive.

Consider Problem ~~(1.1)~~^{NLP}, where f, h_i , and g_i all have their domains in H . Problem ~~(1.1)~~^{NLP} is now an infinite-dimensional constrained nonlinear program. For the remainder of this section we use the notation

$$B^* = \{i : g_i(x^*) = 0\}$$

$$D^* = \{i : g_i(x^*) = 0, \mu_i^* > 0\} = \mathcal{B}(x^*, \mu^*)$$

$$T^* = \{d \in H : \nabla h_i(x^*)^T d = 0, i = 1, \dots, m;$$

$$\nabla g_i(x^*)^T d = 0, i \in D^*;$$

$$\nabla g_i(x^*)^T d \geq 0, i \in B^*\}. = \mathcal{Q}(x^*, \mu^*)$$

To the best of my knowledge, the following result is new and not in previous literature.

Theorem 13.3.2 Application Theorem Three: Sufficiency for Constrained Optimization in Hilbert Space. Assume Problem ~~(1.1)~~^{NLP} $\in C^2$. Sufficient conditions for x^* to be a strict local solution of Problem ~~(1.1)~~^{NLP} are

- (i) There exist λ^*, μ^* such that ~~$\nabla_{\lambda, \mu} L(x^*, \lambda^*, \mu^*) = 0$ and $\mu_i^* g_i(x^*) = 0$~~ .
 (x^*, λ^*, μ^*) IS A KKT POINT.
- (ii) $d^T \nabla_x^2 L(x^*, \lambda^*, \mu^*) d \geq \alpha \|d\|^2$ for all $d \in T^*$.

PROOF. OUR TASK IS TO SHOW THAT THE IMPLICATION GIVEN IN (c) OF OUR FUNDAMENTAL PRINCIPLE FOR SECOND-ORDER SUFFICIENCY, THEOREM 3.12.1, HOLDS USING THE LAGRANGIAN AS SUPPORT FUNCTION WHEN THE CONDITIONS GIVEN IN THEOREM 13.2.2 HOLD.

WE BEGIN BY ASSUMING that there exist λ^*, μ^* such that (x^*, λ^*, μ^*) IS A KKT POINT.
 ~~that $\nabla_{\lambda, \mu} L(x^*, \lambda^*, \mu^*) = 0$.~~ NOW WE ~~ASSUME~~ CONSIDER THE FRONT-END OF THE IMPLICATION (c) IN THEOREM 3.12.1.

Let $\{x_k\}$ be a feasible sequence such that $x_k \neq x^*$, $x_k \rightarrow x^*$, and $\lim_k \nabla f(x^*)^T d_k = 0$, where $d_k = (x_k - x^*) / \|x_k - x^*\|$. Let $\sigma_k = \|x_k - x^*\|$.

OUR OBJECTIVE IS TO ESTABLISH ~~(3.6)~~ THAT (3.63)

$$\liminf_k d_k^T \nabla_x^2 l(x^*, \lambda^*, \mu^*) d_k > 0.$$

MUST HOLD FOR THIS d_k SEQUENCE. WE ACCOMPLISH THIS BY CONTRADICTION. WE SUPPOSE THAT FOR SOME SUBSEQUENCE OF $\{d_k\}$, ALSO CALLED $\{d_k\}$, WE HAVE

$$\lim_{k \rightarrow \infty} d_k^T \nabla_x^2 l(x_k, \lambda^*, \mu^*) d_k \leq 0. \quad (13.1)$$

BUT THIS NOW BECOMES TO SHOW THAT THE SUPPOSITION (13.1) CONTRADICTS (ii) OF THEOREM 13.3.2.

128

(I) We know $\frac{h_i(x^* + \overset{0}{\sigma_k} d_k) - h_i(x^*)}{\sigma_k} = 0.$

Therefore,

$$\nabla h_i(x^*)(d_k) \rightarrow 0.$$

BY FRECHET DIFFERENTIATION

(II) We also have

$$\frac{g_i(x^* + \sigma_k d_k) - g_i(x^*)}{\sigma_k} \geq 0.$$

Thus,

$$\liminf \nabla g_i(x^*) d_k \geq 0 \quad \text{for } i \in B^*.$$

(III) For $i \in D^*$ (i.e. $\mu_i^* > 0$), we have by definition

$$\begin{aligned} \nabla_x \mathcal{L}(x^*, \lambda^*, \mu^*)^T d_k &= \nabla f(x^*)^T d_k + \sum_{i=1}^m \lambda_i^* \nabla h_i(x^*)^T d_k \\ &\quad - \sum_{i \in D^*} \mu_i^* \nabla g_i(x^*)^T d_k. \end{aligned}$$

However, since

$$\nabla_x \mathcal{L}(x^*, \lambda^*, \mu^*) = 0, \quad \nabla f(x^*)^T d_k \neq 0,$$

$$\text{and } \sum_{i=1}^m \lambda_i^* \nabla h_i(x^*)^T d_k \neq 0,$$

we know that

$$\sum_{i \in D^*} \mu_i^* \nabla g_i(x^*)^T d_k \rightarrow 0.$$

Thus, $\nabla g_i(x^*)^T d_k \rightarrow 0$ for all $i \in D^*$.

(IV) By choosing a subsequence, we have

$$\nabla g_i(x_k)^T d_k \rightarrow \beta_i \geq 0 \quad \text{for all } i \in B^* - D^*.$$

Let

$$\begin{aligned} \Psi &= \{\nabla h_i(x^*) : i = 1, \dots, m\} \cup \{\nabla g_i(x^*) : i \in D^*\} \\ &\quad \cup \{\nabla g_i(x^*) : i \in B^* - D^* \text{ and } \beta_i = 0\}, \end{aligned}$$

and let $\psi = \text{span}(\Psi)$.

13

(V) Define $\nu : \psi \rightarrow \mathbb{R}^{|\Psi|}$ so that the components of the vector space $\nu(d)$ are

$$\nabla h_i(x^*)^T d \quad \text{for } i = 1, \dots, m,$$

$$\nabla g_i(x^*)^T d \quad \text{for } i \in D^*, \text{ and}$$

$$\nabla g_i(x^*)^T d \quad \text{for } i \in B^* - D^* \text{ and } \beta_i = 0.$$

Notice that ν is one-to-one, since

$$\nu d = 0 \implies \nu^T d = 0 \text{ for all } \nu \in \psi \implies d^T d = 0 \implies d = 0.$$

Therefore, $\dim(\psi) = \dim(\mathbb{R}(\nu))$, and ν is a map between the finite-dimensional spaces ψ and $\mathbb{R}(\nu)$. Then, there exists $\alpha > 0$ such that $\|\nu d\| \geq \alpha \|d\|$ for all $d \in \psi$. (Note that $\|\nu(\cdot)\|$ achieves its minimum on the unit sphere.)

(VI) Consider the decomposition $H = \psi \oplus \psi^\perp$. We can write $d_k = d_k^1 + d_k^2$ uniquely, where $d_k^1 \in \psi$ and $d_k^2 \in \psi^\perp$. Now,

$$\nu(d_k) = \nu(d_k^1) + \nu(d_k^2).$$

However, $\nu(d_k^2) = 0$. From (I), (II), (III), and (IV), we have $\nu(d_k) \rightarrow 0$, and so $\nu(d_k^1) \rightarrow 0$. Also, since $d_k^1 \in \psi$, $\|\nu(d_k^1)\| \geq \alpha \|d_k^1\|$. Then, $d_k^1 \rightarrow 0$.

(VII) Now, for $i \in B^* - D^*$ and $\beta_i \neq 0$, we have

$$\nabla g_i(x^*) d_k \rightarrow \beta_i \implies \nabla g_i(x^*) d_k^2 \rightarrow \beta_i > 0.$$

(Recall $\nabla g_i(x^*)^T d_k^1 \rightarrow 0$.) Thus, for k large, $\nabla g_i(x^*)^T d_k^2 > 0$ and $d_k^2 \in T^*$ for k sufficiently large.

(VIII) We have

$$(d_k^2)^T \nabla_x^2 \mathcal{L}(x_*, \lambda^*, \mu^*) d_k^2 \geq \alpha \|d_k^2\|^2$$

for k large. In the following equations, we use the shortened notation $\nabla_x^2 \mathcal{L}(x_*, \lambda^*, \mu^*) = \nabla_x^2 \mathcal{L}^*$. Then,

$$\begin{aligned} d_k^T (\nabla_x^2 \mathcal{L}^*) d_k &= (d_k^1)^T (\nabla_x^2 \mathcal{L}^*) d_k^1 + 2(d_k^1)^T (\nabla_x^2 \mathcal{L}^*) d_k^2 + (d_k^2)^T (\nabla_x^2 \mathcal{L}^*) d_k^2 \\ &\geq \alpha \|d_k^2\|^2 - 2 \|\nabla_x^2 \mathcal{L}^*\| \|d_k^1\| \|d_k^2\| - \|\nabla_x^2 \mathcal{L}^*\| \|d_k^1\|^2 \\ &= \alpha \|d_k^2\|^2 - \|\nabla_x^2 \mathcal{L}^*\| \{2\|d_k^1\| \|d_k^2\| + \|d_k^1\|^2\} \\ &\geq \frac{\alpha}{2} \text{ for } k \text{ large.} \end{aligned}$$

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162

[Draft - distribution restricted to CAAM 460 students]

To obtain this result we used the fact that $d_k^1 \rightarrow 0$.

Our conclusion $d_k^T \nabla_x^2 \theta(x^*, \lambda^*, \mu^*) d_k \geq \alpha/2$ for k large contradicts the supposition

$$\lim_{k \rightarrow \infty} d_k^T \nabla_x^2 \theta(x_k, \lambda^*, \mu^*) d_k \leq 0.$$

Thus, our theorem holds. \square

REMARK 1.

THIS BEAUTIFUL PROOF IS DUE

TO MY FORMER STUDENT

RICHARD BYRD

REMARK 2. STATEMENTS IN THE LITERATURE SAY THAT THIS THEOREM DOES NOT HOLD

WITHOUT FURTHER ASSUMPTIONS.