

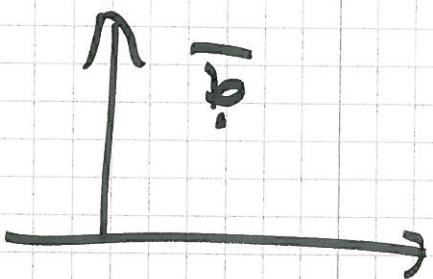
~~14.10.11~~ 14.10.11

HELLO!

"PROBLEM TYPE"	CANDIDATES	DIAGNOSTICS
NO CONSTRAINTS	$\frac{\partial f}{\partial x_i} = 0$	H (HESSIAN)
BINDING = CONSTRAINTS	$\frac{\partial g}{\partial x_i} = 0$	bH (BORDERED HESSIANS)
NOT BINDING CONSTRAINTS	$\frac{\partial g}{\partial x_i}$ KUHN — + TUCKER CONDIT.	HARDER... USUALLY L CONCAVE

CONSIDER THE FOLLOWING:

$$\text{Fix } b = \bar{b}$$



LET \bar{x} BE THE

POINT THAT GIVE THE MAX VALUE.

$$f(\bar{x}) = f^*(\bar{b})$$

$$\Rightarrow f(x) \leq f^*(g(x))$$

$\stackrel{\alpha}{=}$

\bar{b}

AND DEFINE

$$\varphi(x) = f(x) - f^*(g(x))$$

THE POINT $\varphi(x)$ IS MAX IN \bar{x} .

WHY? LESS THAN OR EQUAL TO
ZERO AND ZERO IN \bar{x} .

$$\Rightarrow \frac{\partial \varphi}{\partial x_i}(\bar{x}) = \frac{\partial f}{\partial x}(x)$$

$$\sum_{j=1}^n \frac{\partial f^*(\bar{b})}{\partial b_j} \frac{\partial g_j}{\partial x_i}$$

$$= \frac{\partial f}{\partial x} - \sum_{j=1}^n \frac{\partial g_j}{\partial x_i}$$

$$\boxed{\frac{\partial g}{\partial x_i}(x)}$$

INTERPRETATION OF THE LAGRANGE MULTIPLICATOR

Consider

$$\max f(x) \quad \text{subject to} \\ \left[g_j(x) = b_j; j = 1, \dots, m \right]$$

Assume that

$$f^*(b) = \max \{ f(x) : g_j(x) \in b_j \}$$

THIS IS JUST THE SOLUTION TO
THE MAX PROBLEM VIEVED
AS A FUNCTION OF THE
(BINDING) CONSTRAINTS

FURTHERMORE, ASSUME THAT
THIS FUNCTION IS DIFFERENTIABLE
IN THE b_j . (THIS IS JUST A
TECHNICAL ASSUMPTION, FOR VS
ALWAYS THE CASE.)

WOW!

$$\gamma_i = \frac{\partial f^*(b)}{\partial b_i}$$

THE γ 's ARE JUST THE PARTIAL DERIVATIVES OF THE VALUE FUNCTION $f^*(b)$!

WHY DO WE CARE?

ECONOMIC INTERPRETATION.

QUASI EXAMPLE

f PROFIT

$g(x) \leq b$:

BOUND ON INPUT FACTORS
(SAY METAL,

IRON, COPPER ..)

THEN $\frac{\partial f^*}{\partial b_i}$ IS NUMBER \underline{I} IS NUMBER

IS THE INCREASE ATTRIBUTED TO AN INCREASE OF ONE UNIT IRON.

MORE INTERESTINGLY, IT IS
LIMIT ALSO THE MAX PRICE FOR
IRON THAT MAKES AN
INCREASE IN INPUT OF IRON
PROFITABLE.

IN SOME SENSE ~~THIS~~ IS
 $\frac{\partial f^*}{\partial b_1}$ THE INTERNAL PRICE
OF IRON FOR THE FIRM.
(TYPICALLY NOT MARKET PRICE)
THIS IS WHY $\frac{\partial f^*}{\partial b_1}$ (or λ_1)
IS CALLED THE SHADOW
PRICE.

$$\frac{\partial \mathcal{L}}{\partial x_i} = \frac{\partial f}{\partial x_i} - \sum_{j=1}^m \gamma_j \frac{\partial g_j}{\partial x_i}$$

$$\gamma_j = \frac{\partial f}{\partial b_j}$$

HELLO! ?

A REMARK ABOUT THE VALUE
FUNCTION $f^*(b) = \max \{f(x) \text{ sub. } g_j(x) = b_j\}$
 $= \max \{f(x) \text{ sub. } g_j(x) = b_j\}$

BUT REALIZE THAT

THIS VALUE FUNCTION IS
"BORN" NATURALLY WHEN
WE "DO" $\max f(x) \text{ s.t. } g(x) = a$

THEN WE TYPICALLY GET

$$x = \frac{a}{n} \text{ AND THEN}$$

THE VALUE FUNCTION IS $f\left(\frac{a}{n}\right)$

THE ENVELOPE THEOREM

IN THE PROBLEM

$$\max_{x \in S} f(x, r)$$

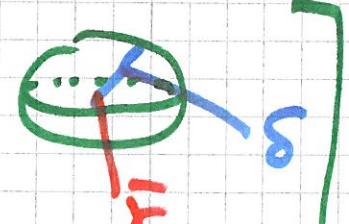
$$S \subseteq \mathbb{R}^n$$

$$r = (r_1, \dots, r_n)$$

ASSUME THAT THE SOLUTIONS

$$x^*(r) \in \text{int}(S)$$

FOR EVERY r in $B(\bar{r}, \delta)$

$[B(\bar{r}, \delta)$ IS A BALL ]

ASSUME

$$r \mapsto f(x^*(\bar{r}), r)$$

$$r \mapsto f^*(r)$$

CORRESPONDS TO THE VALUE
FUNCTION IN OUR DISCUSSION
OF THE λ 's IN LAGRANGIANS

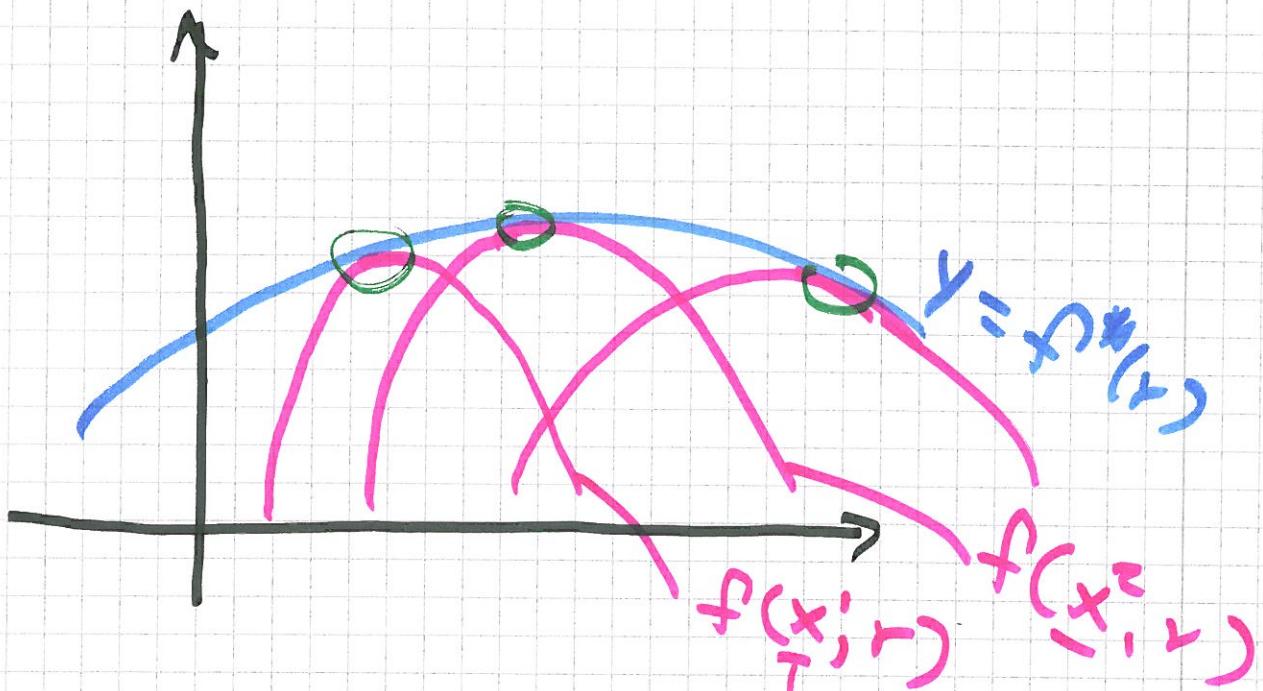
ARE DIFFERENTIABLE.

THEN

$$\frac{\partial f^*(r)}{\partial r_j} = \frac{\partial f(x, r)}{\partial r_j} \quad (x = x^*(r) \\ r = \bar{r})$$

THIS IS THE ENVELOPE
THEOREM.

WHAT DOES THIS MEAN?



THE ENVELOPE THEOREM
TELLS US THAT $f^*(r)$
CREATES A BORDER OF THIS
TYPE)

WHY IS THIS TRUE?

SAME PROOF AS IN THE
 \neq CASE:

$$\text{DO } \varphi(r) = f(x^*(r), r) - f^*(r)$$

SMALL EXAMPLE OF USE:

CONSIDER

$$\max f(x; a) = -x^2 + 2ax + 4a^2$$

WHAT IS THE EFFECT OF AN
INCREASE IN a ?

SOLUTION:

$$f'(x) = -2x + 2a = 0$$

$$x = a$$

$$x^*(a) = a$$

$$f^*(a) = -a^2 + 2a \cdot a + 4a^2 = 5a^2$$

D

$$\frac{\partial f^*}{\partial a}(a) = 10a$$

DIFF THIS

$$x^* = a$$

$$\frac{\partial f}{\partial a}(x^*(a), a) = 2x^* + 8a = 10a$$

THIS IS A CHECK OF ENVELOPE THEOREM

BORDERED HESSIANS

MOTIVATION / INTUITION:

WHAT ABOUT "LOCAL
SECOND ORDER CONDITIONS"
WITH CONSTRAINTS?

WE HAVE DIAGNOSTICS
IN THE CASE WITHOUT
CONSTRAINTS... NOW WE
WANT DIAGNOSTICS
WITH CONSTRAINTS!

FIRST IDEA:

DO HESSIAN FOR
 \mathcal{L} IN CONTRAST TO f

$$\mathcal{H} = \begin{bmatrix} \mathcal{L}_{11} & \mathcal{L}_{12} & \dots \\ \vdots & \ddots & \mathcal{L}_{1n} \end{bmatrix}$$

IT IS A GOOD IDEA, BUT
TO STRONG.

WHY?

WE DONT NEED CONVEXITY
(OK CONCAVITY) EVERY WHERE
WE NEED IT IN THE
DIRECTIONS DEFINED BY
THE CONSTRAINTS).

LESS CRYPTIC, BUT HORRIBLE
CONSIDER

$$\max_{\text{min}} f(x) \quad \text{SUB.} \quad g_j(x) = b_j \\ j=1, \dots, m$$

$$\mathcal{L} = f(x) - \sum_{j=1}^m \lambda_j (g_j(x) - b_j)$$

DEFINE THE FOLLOWING
MONSTER:

$$H = \begin{vmatrix} 0 & \cdots & 0 & \frac{\partial g_1(x^*)}{\partial x_1} & \cdots & \frac{\partial g_1(x^*)}{\partial x_r} \\ \vdots & \ddots & \vdots & \vdots & \ddots & \vdots \\ 0 & \cdots & 0 & \frac{\partial g_m(x^*)}{\partial x_1} & \cdots & \frac{\partial g_m(x^*)}{\partial x_r} \\ \mathcal{L}_1''(x) & \cdots & \mathcal{L}_r''(x) & \cdots & \cdots & \mathcal{L}_n''(x) \\ \vdots & & \vdots & & & \vdots \\ \mathcal{L}_{r_1}''(x) & \cdots & \mathcal{L}_{r_n}''(x) & \cdots & \cdots & \mathcal{L}_n''(x) \end{vmatrix}$$

A green arrow points from the top row to the first column. A pink arrow points from the bottom row to the second column.

THIS IS THE DEFINITION OF
THE BORDER HESSIAN

THE RESULT IS:

f SUB $g_1 \dots g_m$ $S \subseteq \mathbb{R}^m$

$x^* \in \text{INT}(S)$

~~satisfying~~ satisfying THE
NEG. CONDITIONS (Th.3.3)

$$\left[\frac{\partial g_1}{\partial x_1} \dots \frac{\partial g_1}{\partial x_n} \right] \text{ rank } m$$

THEN

a. $(-1)^m B_r(x) > 0 \quad r = m+1, \dots, n$
THEN x^* SOLVES LOC. MIN

b. $(-1)^r B_r(x) > 0 \quad r = m+1, \dots, n$
THEN x^* SOLVES SOLVES
LOC. MAX.

NOTE INDEPENDENT OF r. THAT
IS ALL NEG. OR POS.

EXAMPLE

Loc. $\max_{\min} f(x, y, z) = x^2 + y^2 + z^2$

$$g_1(x, y, z) = \underline{x + 2y + z = 30}$$

$$g_2(x, y, z) = \underline{2x - y - 3z = 10}$$

SOLUTION

$$\mathcal{L} = \underline{x^2 + y^2 + z^2} - \lambda_1(x + 2y + z - 30)$$

$$- \lambda_2(2x - y - 3z - 10)$$

WE WILL NOT SPEND TIME ON
FINDING THE STAT. POINT
JUST STATE IT

$P(10, 10, 0)$

DOUBLE DERIVATIVES

THE POINT IS DIAGNOSTICS:

$$m = 2$$

$$n = 3$$

$$bH = \left[\begin{array}{ccc|ccc} 0 & 0 & 1 & 2 & 1 \\ 0 & 0 & 2 & -1 & -3 \\ \hline 1 & 2 & | & 2 & 0 & 0 \\ 2 & -1 & | & 0 & 2 & 0 \\ \hline 1 & -3 & | & 0 & 0 & 2 \end{array} \right]$$

$$\det(bH) = 150$$

COMPUTATION

NOTE: $m+1$ TO n IN THIS

$$m = 2, n = 3,$$

KUHN - TUCKER

CONCERN THE MOST GENERAL
AND INTERESTING CASE WHERE
CONSTRAINTS ARE JUST AN
UPPER LIMIT.

$$\max f(x_1, \dots, x_m) \text{ SUBJ. } \begin{cases} g_1(x_1, \dots, x_n) \leq b_1 \\ \vdots \\ g_m(x_1, \dots, x_n) \leq b_m \end{cases}$$

(x_1, \dots, x_m) THAT SATISFY THESE
CONSTRAINTS ARE CALLED
ADMISSIBLE.

AS SEEN MANY TIMES BEFORE

① $\mathcal{L} = f(x) - \sum_i \lambda_i (g_i(x) - b_i)$

LEADS TO 1. ORDER EQU.

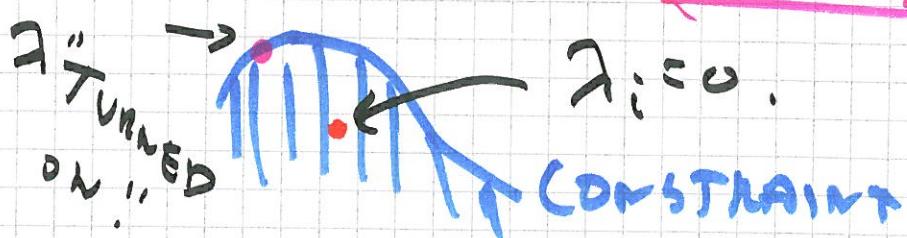
② $\frac{\partial \mathcal{L}}{\partial x_i} = \frac{\partial f}{\partial x_i} - \sum_{j=1}^m \lambda_j \frac{\partial g_j}{\partial x_i} = 0$

NEW THING: COMPLEMENTARY SLACKNESS CONDITION

③ $\lambda_i \geq 0$ WITH $\lambda_i = 0 \Rightarrow g_i(x) \leq b_i$

~~INTERPRETATION: IF THE CONSTRAINT IS NOT BINDING, THEN~~

~~IF $\lambda_i = 0$ THEN THE CONSTRAINT IS NOT BINDING.~~



② + ③ IS CALLED KUHN TUCKER CONDITIONS.

AN ALTERNATIVE WAY TO
WRITE ③:

$$\lambda_j \geq 0 \quad \lambda_j(g_j(x) - b_j) = 0$$

~~λ_j~~ $j = 1, 2, \dots, m$

ONLY ONE OF THESE
CAN BE ~~NOT~~ ZERO
AT THE TIME.

ILLUSTRATION ON HOW TO
USE THE KUHN-TUCKER
CONDITIONS.

NEXT LECTURE ...

- OTHER THINGS:
- BOUNDED HESSIAN
- KUHN-TUCKER & DIAGNOSTICS.