

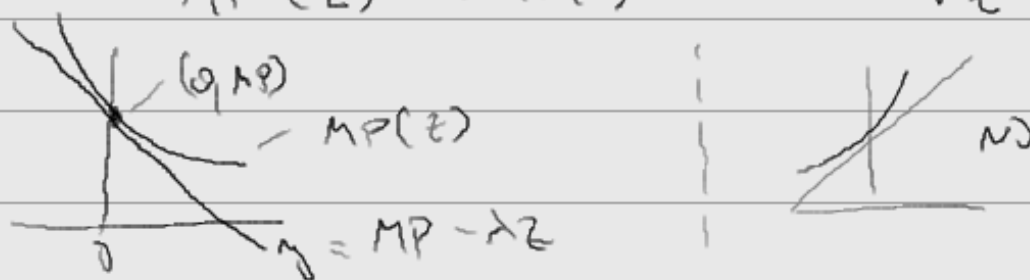
•  $\exists z \in D^\circ : MP(z) \in \mathbb{R}$  THEN  
 $MP(z) \in \mathbb{R} \quad \forall z \in D$

### THEOREM 47 (S. 2.8)

LET  $(P)$  BE SUPPORT CONSISTENT & CONVEX

LET  $MP(0) \in \mathbb{R}$ , THEN  $\exists \lambda \geq 0 \in \mathbb{R}^m$

$$MP(z) \geq MP(0) - \lambda \cdot z \quad \forall z \in D$$



PROOF: ( $z < 0$  STRICT CONVEX,  $z > 0$  RECURSIVE)

SUPPORT THEOREM (45)  $\Rightarrow \exists \lambda \in \mathbb{R}^m$

$$MP(z) \geq MP(0) - \lambda \cdot z \quad \text{COORDINATE}$$

FOR CONTRADICTION LET  $\lambda_i < 0$ .

946:  $0 \in D^\circ \Rightarrow \exists r > 0$  ST  $B(0, r) \subseteq D^\circ$

$$z^i = (0, \dots, \underbrace{\frac{r}{2}}_{i\text{-TH}}, \dots) \in B(0, r)$$

$$MP(z^i) \geq MP(0) - \lambda \cdot z^{(i)} = MP - \frac{r}{2} \lambda_i$$

$$MP(z^i) < MP$$

BUT  $z' \geq 0 \Rightarrow$  WE ADDED CONSTRAINTS  
IN  $(P(z)) \Rightarrow MP(z) \leq MP(0) = MP$

□

DEF:

$\lambda \in \mathbb{R}^m$ ,  $\lambda \geq 0$  IS SENSITIVITY VECTOR  
OF A CONVEX  $(P)$  IF

$$MP(z) \geq MP(0) - \lambda \cdot z \quad \forall z \in D$$

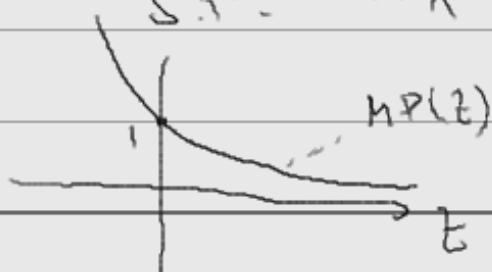
NOTE:  $\lambda$  IS  $OMP(0)$  IF EXISTS

THM 47 -  $\lambda$  ALWAYS EXISTS FOR SUPERCONSISTENT  $(P)$

EXAMPLES

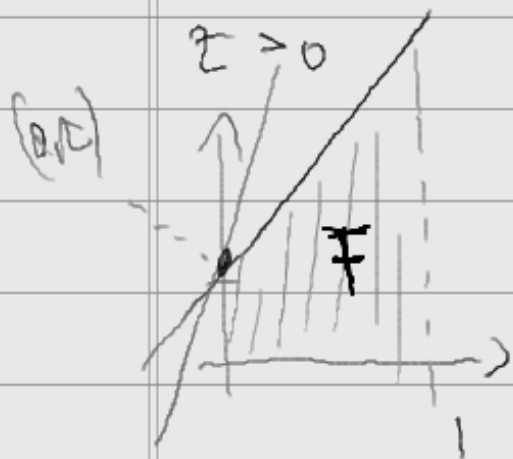
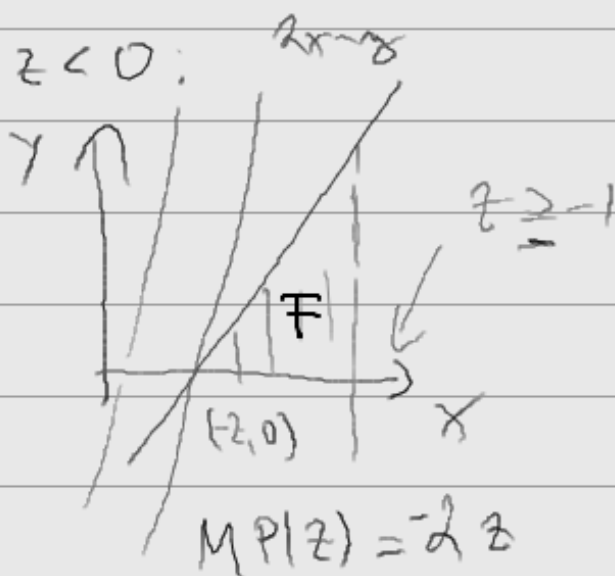
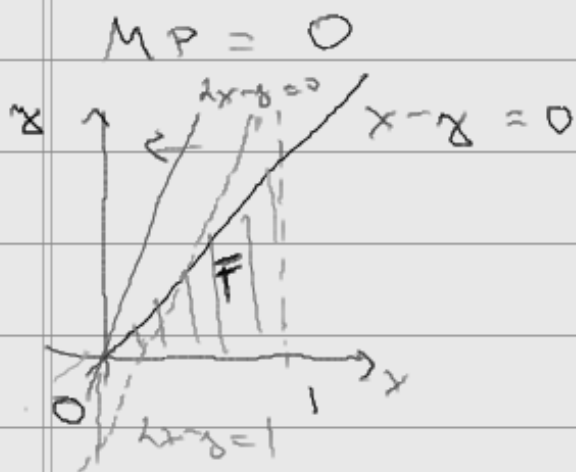
$$(P) \begin{cases} \text{MINIMIZE } e^{x+y} \\ \text{S.T. } -x - y \leq 0 \end{cases}$$

$$(P(z)) \begin{cases} \text{MINIMIZE } e^{x+y} \\ \text{S.T. } -x - y \leq z \quad (x+y \geq -z) \end{cases}$$

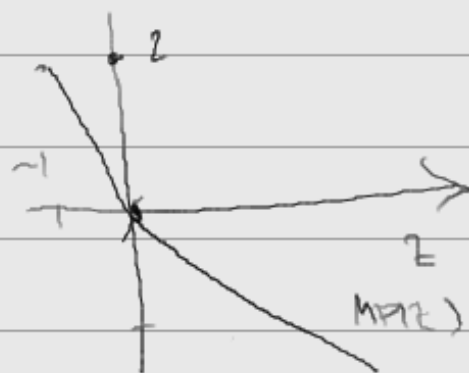


$$(P) \begin{cases} \text{MINIMIZE } 2x - y \\ \text{S.T. } -x + y \leq 0 \\ \text{WHERE } y \geq 0 \\ 0 \leq x \leq 1 \end{cases}$$

$$(P(z)) \begin{cases} \text{MINIMIZE } 2x - y \\ \text{S.T. } -x + y \leq z \\ y \geq 0, 0 \leq x \leq 1 \end{cases}$$



$$\begin{aligned} -x + y &= z \\ y &= z \\ MP(z) &= -z \end{aligned}$$



ex (NOT CONTINUOUS MP(z))

$$(P) \begin{cases} \text{MINIMIZE } e^{-y} \\ \text{s.t. } \sqrt{x^2 + y^2} - x \leq 0 \end{cases}$$

$$\lim_{y \rightarrow 0} \sqrt{x^2 + y^2} \geq x \Rightarrow y = 0$$

$$MP(0) = e^{-0} = 1 \in F = \{(x, 0) : x \geq 0\}$$

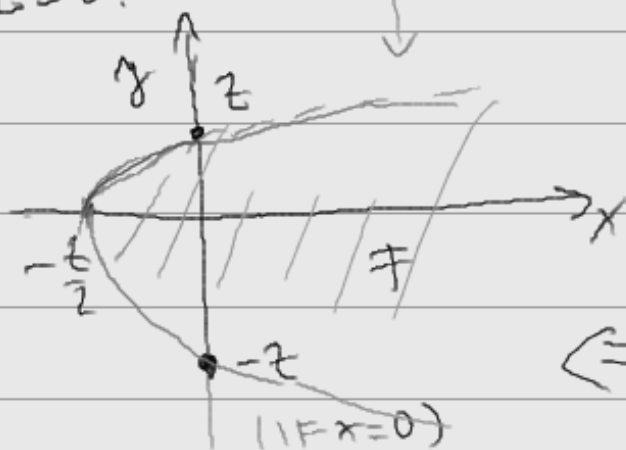
$$(P(z)) \begin{cases} \text{MIN } e^{-y} \\ \text{s.t. } \sqrt{x^2 + y^2} - x \leq z \Rightarrow \boxed{z \geq 0} \end{cases}$$

$$\sqrt{x^2 + y^2} \leq z + x$$

$$x^2 + y^2 \leq z^2 + 2xz + x^2$$

$$y^2 \leq z^2 + 2xz$$

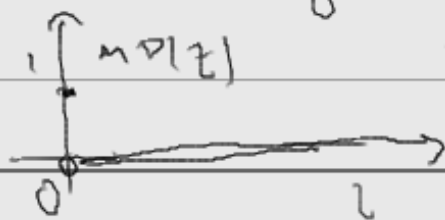
$z > 0$ :



$$\begin{aligned} y^2 &= z^2 \\ z &\leq 2x \\ x &= \frac{y^2 - z^2}{2z} \end{aligned}$$

$\Leftarrow y$  IS NOT BOUNDED

$$MP(z) = \inf_{y \in F} e^{-y} = 0$$



## EXAMPLE FOR $\lambda$

$$(P) \begin{cases} \text{MINIMIZE } f(x) \\ \text{S.T. } g_1(x) \leq 0, g_2(x) \leq 0, g_3(x) \leq 0 \end{cases}$$

LET SENSITIVITY VECTOR  $\lambda = (100, 1, 0)$

THEM 47:  $z = (z_1, z_2, z_3)$

$$MP(z) \geq MP(0) - \lambda \cdot z = MP - 100z_1 - z_2$$

$$MP((1, 0, 0)) \geq MP - 100 \leftarrow \text{IMPORTANT}$$

$$MP((0, 1, 0)) \geq MP - 1$$

$$MP((0, 0, 1)) \geq MP \leftarrow \text{USELESS}$$

## THEOREM 48 (S.2.11)

LET

$$(P) \begin{cases} \text{MINIMIZE } f(x) \\ \text{S.T. } g_1(x) \leq 0, \dots, g_m(x) \leq 0 \\ \text{WHERE } x \in C \end{cases}$$

$C$  BE CONVEX AND  $\lambda \in \mathbb{R}^m$  ITS SENSITIVITY

VECTOR. THEN

$$MP = \inf_{x \in C} \left\{ f(x) + \sum_{i=1}^m \lambda_i g_i(x) \right\}$$

UNCONSTRAINED OPTIMIZATION DATA

PROOF:  $[MP \leq \inf]$

BY DEFINITION  $MP(z) \geq MP - \lambda, z$

NOTE  $\lambda \in \mathbb{C}$ ,  $z = (g_1(x), \dots, g_m(x))$  THEN  
 $x$  IN DOMAIN OF  $MP(z)$ .

$$MP(z) + \sum \lambda_i g_i(x) \geq MP$$

BY DEF (MP IS  $\inf$ )  $f(x) \geq MP(z)$

$$f(x) + \sum \lambda_i g_i(x) \geq MP \quad \leftarrow \forall x \in \mathbb{C}$$

$$\inf_{x \in \mathbb{C}} \left\{ f(x) + \sum_{i=1}^m \lambda_i g_i(x) \right\} \geq MP$$

$[MP \geq \inf]$

$$\inf_{x \in \mathbb{C}} \left\{ f(x) + \sum_{i=1}^m \lambda_i g_i(x) \right\} \leq \inf_{\substack{x \in \mathbb{C} \\ g(x) \leq 0}} \left\{ f(x) + \sum_{i=1}^m \lambda_i g_i(x) \right\} \leq$$

$\lambda_i \geq 0$

$$\leq \inf_{x \in \mathbb{C}} \{ f(x) \}$$

□

"(P) SUPERCONSISTENT  $\xrightarrow{T47}$   $\downarrow$  SENSITIVE VERM  $\xrightarrow{T48}$

CAN BE TRANSLATED AS UNCONSTRAINED OPT.  $\checkmark$

# THEOREM 4.9 (5.2.13 - KARUSH-KUHN-TUCKER, SADDLE POINT FORM)

LET (P) BE A SUPERCONSISTENT CONVEX PROGRAM. THEN  $x^* \in C$  IS A SOLUTION OF (P) IFF  $\exists \lambda^* \in \mathbb{R}^m$  ST.

(1)  $\lambda^* \geq 0$

(2)  $L(x^*, \lambda) \leq L(x^*, \lambda^*) \leq L(x, \lambda^*) \quad \forall \lambda \geq 0, \forall x \in C$

SADDLE POINT

(3)  $\lambda_i^* g_i(x^*) = 0 \quad \forall i = 1, 2, \dots, m$

PROOF:

$(\implies) x^*$  IS A SOLUTION OF (P) (1)

$x^* \in C, g(x^*) \leq 0, f(x^*) = \text{OPT}, \text{T47} \implies \exists \lambda^* \geq 0$

SENSITIVITY VECTOR, T48:

$$f(x^*) = \inf_{x \in C} L(x, \lambda^*)$$

NEXT

$$f(x^*) \geq f(x^*) + \sum \lambda_i^* g_i(x^*) = L(x^*, \lambda^*)$$

$\lambda_i \geq 0$                        $g_i(x^*) \leq 0$

$$L(x^*, \lambda^*) \leq L(x, \lambda^*) \quad \iff \quad \lambda_i^* g_i(x^*) = 0 \quad (3)$$

MISSING  $L(x^*, \lambda) \leq L(x^0, \lambda^0) \quad \forall \lambda \geq 0$

$$L(x^0, \lambda^0) - L(x^*, \lambda) =$$

$$= f(x^0) + \sum \lambda_i^0 g_i(x^0) - f(x^*) - \sum \lambda_i g_i(x^*) =$$

$$= - \sum_{\substack{\lambda_i \geq 0 \\ g_i(x^*) \leq 0}} \lambda_i g_i(x^*) \geq 0$$

↓

$$L(x^*, \lambda^*) \geq L(x^0, \lambda) \quad \forall \lambda$$

(⇐)

LET  $x^* \in C$  AND  $\lambda^* \in \mathbb{R}^m$  SATISFY (1), (2) & (3)

DEF  $\lambda^{(i)}$  ST  $\lambda_j^{(i)} = \begin{cases} \lambda_j^* & \text{IF } j \neq i \\ \lambda_{j+1}^* & \text{IF } j = i \end{cases}$

(SHIFT  $i^{\text{TH}}$  COORDINATE)  $\lambda^{(i)} \geq 0$

$$(2) \Rightarrow 0 \geq L(x^*, \lambda^{(i)}) - L(x^0, \lambda^*) =$$

$$= f(x^*) + \sum \lambda_j^{(i)} g_j(x^*) - f(x^0) - \sum \lambda_j^* g_j(x^0) = g_i(x^*)$$

$$\Rightarrow x^* \text{ IS A FEASIBLE SOLUTION}$$



$$(3) \Rightarrow J(x^*) = J(x^*) + \sum_{i=1}^m \lambda_i^* g_i(x^*) = L(x^*, \lambda^*)$$

$$L(x^*, \lambda^*) \stackrel{(2)}{=} \inf \{ L(x, \lambda^*) : x \in C \} \leq \\ \leq \inf \{ L(x, \lambda^*) : x \in F \} = \\ = \inf \{ J(x) + \sum_{\substack{\lambda_i \geq 0 \\ \lambda_i \leq 0}} \lambda_i g_i(x) : x \in F \}$$

$$\leq \inf \{ J(x) : x \in F \} = \text{MP}$$

□

NOTE: (3) CAN BE PROVED FROM (2)

DEF:

- $(x^*, \lambda^*) ; x^* \in C, \lambda^* \geq 0 ; \text{ s.t.}$
- $L(x^*, \lambda) \leq L(x^*, \lambda^*) \leq L(x, \lambda^*) \quad \forall x \in C, \lambda \geq 0$
- IS CALLED THE SADDLE POINT OF THE LAGRANGIAN
- CONDITION  $\lambda_i^* g_i(x^*) = 0, i = 1, 2, \dots, m$  IS COMPLEMENTARY SLACKNESS CONDITION.

REPHRASE THE 4<sup>th</sup> USING SLACKNESS & SADDLE POINT