

FORMALIZE PREVIOUS EXAMPLE

$$M_j(t) = C_j t^{d_{j1}} e^{d_{j2}} t^{d_{j3}} \dots t^{d_{jm}} \quad (C_j > 0)$$

CONSTRAINED (CP)

$$\text{(CP)} \begin{cases} \text{MINIMIZE } g_0(t) = M_1(t) + \dots + M_{m_0}(t) \\ \text{SUBJECT TO} \\ g_1(t) = M_{m_0+1}(t) + \dots + M_{m_1}(t) \leq 1 \\ \vdots \\ g_K(t) = M_{m_{K-1}+1}(t) + \dots + M_{m_K}(t) \leq 1 \\ \text{WHERE } t \geq 0 \end{cases}$$

$$\text{SET } m_K = p$$

AK:

$$\begin{aligned} g_0(t) &\geq g_0(t) \cdot g_1(t)^{\lambda_1} \cdot g_2(t)^{\lambda_2} \dots g_K(t)^{\lambda_K} \geq \\ &\geq \left(\prod_{j=1}^K \frac{C_j}{\delta_j^{\lambda_j}} \right) \prod_{i=1}^K \lambda_i^{\lambda_i} (t^0 \cdot t^0 \dots t^0) \end{aligned}$$

$$\text{(DLP)} \begin{cases} \text{MAXIMIZE } v(\delta) = \left(\prod_{j=1}^K \frac{C_j}{\delta_j^{\lambda_j}} \right) \prod_{i=1}^K \lambda_i^{\lambda_i} \\ \text{S.T. } \delta_1 + \dots + \delta_{m_0} = 1 \quad (\text{JUST AK}) \\ \alpha_1 \delta_1 + \alpha_2 \delta_2 + \dots + \alpha_{m_1} \delta_{m_1} = 0 \\ \vdots \\ \alpha_{1,m} \delta_1 + \dots + \alpha_{p,m} \delta_p = 0 \end{cases}$$

$$\begin{aligned}
 &\text{WHERE } \delta_i \geq 0 \text{ FOR } 1 \leq i \leq m_1 \\
 &\forall k \quad \delta_i \geq 0 \text{ FOR } m_{k-1}+1 \leq i \leq m_k \text{ OR} \\
 &\quad \delta_i = 0 \text{ FOR } m_k \leq i \leq m_{k+1} \\
 &\lambda_i = \delta_{m_{i-1}+1} + \dots + \delta_{m_i}
 \end{aligned}$$

DUAL OBJECTIVE FUNCTION, DUAL CONSTRAINTS,
DLP IS LINEAR .. WORKS = 1 SOLUTION

EXAMPLE:

$$\begin{aligned}
 &\text{MIN } \epsilon_1^2 \epsilon_2 \epsilon_3^{-1} \dots \delta_1 \\
 &\quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \delta_3 \\
 &\delta_1 \quad \quad \quad 2\epsilon_1 \epsilon_2^2 + \frac{1}{2} \epsilon_3^{-1} \leq 1 \quad \dots \lambda_1 \\
 &\delta_2 \quad \quad \quad \frac{1}{4} \epsilon_1^2 + \frac{1}{2} \epsilon_2^2 \epsilon_3^2 \leq 1 \quad \dots \lambda_2 \\
 &\delta_4 \quad \quad \quad \text{WHERE } \epsilon_i \geq 0 \quad \dots \delta_5
 \end{aligned}$$

$$\begin{aligned}
 &\text{MAX } \left(\frac{1}{\delta_1}\right)^{\delta_1} \left(\frac{2}{\delta_2}\right)^{\delta_2} \left(\frac{1}{2\delta_3}\right)^{\delta_3} \left(\frac{1}{4\delta_4}\right)^{\delta_4} \left(\frac{1}{2\delta_5}\right)^{\delta_5} \\
 &\lambda_1 \dots (\delta_2 + \delta_3)^{\delta_2 + \delta_3} \cdot (\delta_4 + \delta_5)^{\delta_4 + \delta_5} \quad \lambda_2 \\
 &\text{SUBJECT TO}
 \end{aligned}$$

obs.	δ_1		$= 1$
t_1	$2\delta_1 + \delta_2$	$-2\delta_4$	$= 0$
t_2	$\delta_1 - 2\delta_2$		$+2\delta_5 = 0$
t_3	$-\delta_1$	$-\delta_3$	$+2\delta_5 = 0$

$$\delta_1 > 0, \quad \delta_2 \delta_2 > 0 \text{ OR } \delta_2 = \delta_3 = 0$$

$$\delta_4 \delta_5 > 0 \text{ OR } \delta_4 = \delta_5 = 0$$

$$\delta_1 = 1$$

$$\delta_2 = \alpha$$

$$\alpha \geq 0$$

$$\delta_4 = 1 - \frac{\alpha}{2}$$

$$\alpha \leq 2$$

$$\delta_5 = -\frac{1}{2} + \alpha$$

$$\alpha \geq \frac{1}{2}$$

$$\delta_3 = -2 + 2\alpha$$

$$\alpha \geq 1$$

USING KKT FOR LP : {KKT FOR CONVEX}

$$\min f(x)$$

$$\text{s.t. } g_1(x) \leq 0, g_2(x) \leq 0, \dots, g_m(x) \leq 0$$

f, g convex, KKT convex

POLYNOMIAL IS NOT CONVEX :- $e^{-x} \dots e^{\frac{1}{2}}$

⊙ $t > 0 \Rightarrow \exists! x : x^* = t$

$$t_j = e^{x_j}$$

$$g(t) = \sum_{i=1}^m c_i t_1^{d_{i1}} t_2^{d_{i2}} \dots t_m^{d_{im}}$$

$$h(x) = \sum_{i=1}^m c_i e^{\sum_{j=1}^m d_{ij} x_j}$$

⊙ $h(x)$ IS CONVEX

$$(P) \begin{cases} \min g_0(t) \\ \text{s.t. } g_1(t) \leq 1, g_2(t) \leq 1, \dots, g_k(t) \leq 1 \\ \text{where } t > 0 \end{cases}$$

ASSOCIATED CONVEX PROGRAM IS

$$t_j \Rightarrow e^{x_j}$$

$$(P^*) \begin{cases} \min h_0(x) \\ h_1(x) - 1 \leq 0, \dots, h_k(x) - 1 \leq 0 \\ x \in \mathbb{R}^m \end{cases}$$

⊙ x^* STRICTLY INCREASING $\Rightarrow$

$t^* = (t_1^*, t_2^*, \dots, t_m^*)$ IS SOLUTION OF (P)

IFF $x^* = (x_1^*, \dots, x_m^*)$ IS SOLUTION OF (P*)

AND $t_i^* = z^* \quad \forall i$

EVENING START

THEOREM 53 (5.3.5- DUALITY OF LP)

1, LET t BE A FEASIBLE VECTOR FOR (LP)

AND δ BE A FEASIBLE VECTOR FOR
CORRESPONDING DUAL PROGRAM (DLP)

THEN

$$y_0(t) \geq v(\delta) \quad (\text{PRIMAL-DUAL INEQUALITY})$$

2, LET (LP) BE SUPERCONSISTENT AND
 t^* BE ITS SOLUTION. THEN CORRESPONDING

(DLP) IS CONSISTENT AND

HAS SOLUTION δ^* ST

$$y_0(t^*) = v(\delta^*)$$

AND

$$\delta_i^* = \begin{cases} \frac{m_i(t^*)}{y_0(t^*)} & i=1 \dots m_0 \\ \lambda_j(\delta^*) m_i(t^*) & i=m_{j-1}+1 \dots m_j \quad j=1 \dots r \end{cases}$$

CONSEQUENCES:

- (LP) SUPER CONSISTENT & (DLP) INCONSISTENT
 $\Rightarrow$ NO SOLUTION
- EXISTS CERTIFICATE THAT t^* IS A SOLUTION
($\delta^0 \dots g_0(t^*) = v(\delta^0)$)
- ALLOWS TO SOLVE (DLP) INSTEAD OF (LP)
(MAY BE DLP EASIER!)
- BOUND ERROR OF APPROXIMATE SOLUTION
 t AND δ ST.

$$g_0(t) = v(\delta) + \underbrace{\sum_i \dots}_?$$

MAX GAP (ERROR) OF SOLUTION

$\hookrightarrow$ APPROX. ALGORITHMS

- DUAL MIGHT HAVE A GOOD MEANING!

PROOF:

- 1) FROM (A9) INEQUALITY
- 2) IDEA... CHANGE TO CONVEX PROGRAM
APPLY KKT, MAKE KKT BASIC $\Rightarrow$
LET EQUATIONS FOR $t_i \dots C_2 \delta = 0 \Rightarrow \delta^*$ FEASIBLE

CONSIDER $(\text{LP})^*$ ($t_i = e^{x_i}$)

SOLUTION t^* OF $(\text{LP}) \Rightarrow \exists$ SOLUTION x^* OF $(\text{LP})^*$
($x_i = \ln t_i$)

(LP) SUPER CONSISTENT $\Rightarrow (\text{LP})^*$ SUPER CONSISTENT.

0 FUNCTIONS IN $(\text{LP})^*$ HAS CONT. FIRST PARTIAL DERIVATIVES.

$\Rightarrow$ KKT - GRADIENT FORM APPLIES (THEO - §2.14)

$\Rightarrow \exists \lambda^* = (\lambda_1^*, \dots, \lambda_k^*)$ S.T.:

a) $\lambda_i^* \geq 0$ FOR $1 \leq i \leq k$

b) $\lambda_i^* (h_i(x^*) - 1) = 0$ FOR $1 \leq i \leq k$ (COMPL-SUPPLESS)

c) $\frac{\partial h_0}{\partial x_j}(x^*) + \sum_{i=1}^k \lambda_i^* \frac{\partial h_i}{\partial x_j}(x^*) = 0$ FOR $1 \leq j \leq m$

$\hookrightarrow$ WHAT IS THIS IN g ??

$$\frac{\partial h_i}{\partial x_j} = \frac{\partial h_i}{\partial t_j} \cdot \frac{\partial t_j}{\partial x_j} = \frac{\partial y_i}{\partial t_j} e^{x_j}$$

$e^{x_j} > 0 \dots$ DIVIDE

$$(c') \quad \frac{\partial y_0}{\partial t_j}(t^*) + \sum_{i=1}^k \lambda_i^* \frac{\partial y_i}{\partial t_j}(t^*) = 0 \quad j=1, \dots, m$$

MULTIPLY BY t_j^*

$$(C'') \quad t_j^* \frac{\partial g_0}{\partial t_j}(t^*) + \sum_{i=1}^k \lambda_i^* t_j^* \frac{\partial g_i}{\partial t_j}(t^*) = 0$$

$\forall j = 1, \dots, m$

RECALL: $g_i(t) = \sum M_q(t)$

$$M_q = C_q t_1^{d_{q1}} t_2^{d_{q2}} \dots t_m^{d_{qm}}$$

→ HOW THE DERIVATIVE LOOKS LIKE

(C'') IS $\forall$ EQUIVALENT TO

$$\sum_{q=1}^{m_0} d_{qj} M_q(t^*) + \sum_{n=1}^k \sum_{q=m_{n-1}+1}^{m_n} \lambda_n^* d_{qj} M_q(t^*)$$

$$= 0$$

DIVIDE BY $g_0(t^*)$:

$$(d) \quad \sum_{q=1}^{m_0} d_{qj} \left(\frac{M_q(t^*)}{g_0(t^*)} \right) + \sum_{n=1}^k \sum_{q=m_{n-1}+1}^{m_n} d_{qj} \left(\frac{\lambda_n^* M_q(t^*)}{g_0(t^*)} \right) = 0$$

$$j^* = \begin{cases} \frac{M_q(t^*)}{g_0(t^*)} & q = 1, 2, \dots, m_0 \\ \frac{\lambda_n^* M_q(t^*)}{g_0(t^*)} & q = m_{n-1}+1, \dots, m_n \quad n = 1, \dots, k \end{cases}$$

Is δ_q^* good ??? For (DLP)

$$\delta_q^* \geq 0 \quad q=1 \dots m_0$$

• $\delta_q^* \geq 0$ for $q=m_{n-1}+1 \dots m_n$ IFF $\lambda_n^* \geq 0$

→ SO EITHER ALL ZERO OR ALL POSITIVE

• (d) SHOW THAT EXPOSURE FOR $\epsilon_j = 0$

• (AS) INEQ-CONSTRAINT

$$\sum_{q=1}^{m_0} \delta_q^* = \sum_{q=1}^{m_0} \frac{u_q(t^*)}{g_0(t^*)} = \frac{g(t^*)}{g_0(t^*)} = 1$$

⇒ $\delta^* = (\delta_1^*, \dots, \delta_{m_0}^*)$ IS FEASIBLE VECTOR FOR (DLP)

IS δ^* IN THE FORM WE PROVIDED ??

NOTE λ_n^* ... KKT MULTIPLIERS

$\lambda_n^*(\delta^*)$... FROM (DLP)

HOW $\lambda_n^*(\delta^*)$ LOOK ??

$$\lambda_n(\delta^*) = \sum_{q=m_{n-1}+1}^{m_n} \delta_q^* = \sum_{q=m_{n-1}+1}^{m_n} \lambda_n^* \frac{u_q(t^*)}{g_0(t^*)} = \lambda_n^* \frac{g_n(t^*)}{g_0(t^*)}$$

IS δ_q^* WHAT WE PROVIDED ?? KKT ⇒

$$(b') \quad \lambda_n^* (g_n(t^*) - 1) = 0 \quad n=1 \dots K$$

$$\text{So } \lambda_i^* g_i(t^*) = \lambda_i^* \lambda_i^*(5) \quad 1 \leq i \leq K$$

$$\delta_q^* = \frac{\lambda_i^* \mu_q(t^*)}{g_0(t^*)} = \frac{\lambda_i^* g_i(t^*) \mu_q(t^*)}{g_0(t^*)} = \lambda_i^*(5) \mu_q(t^*)$$

THE FORM WE PROVED!

NOW IS δ_q^* OPTIMAL??

1) $\Rightarrow g_0(t^*) \geq N(\delta^*)$ (PRIMAL-DUAL-INEQ.)
IS δ_q^* FORCING EQUALITY OF (AC),?

$$g_0(t^*) = g_0(t^*) \cdot (g_1(t^*))^{\lambda_1(5^*)} \cdot \dots \cdot (g_K(t^*))^{\lambda_K(5^*)} \geq$$

• (D') $\Rightarrow g_i(t^*) = 1$ OR $\lambda_i = \infty \Rightarrow \lambda_i(5^*) = 0$
 $\forall i = 1 \dots K$

• δ_q^* FOR $1 \leq q \leq m_0$ FORCED EQUALITY FOR (AS)
AT $g_0(t^*)$ MUST BE SAME ALL SAME

$$g_0(t^*) = \sum_{q=1}^{m_0} \mu_q = \sum_{q=1}^{m_0} \delta_q \left(\frac{\mu_q}{\delta_q} \right) = \sum_{q=1}^{m_0} \delta_q \left(\frac{\mu_q}{\frac{g_0(t^*)}{m_q}} \right)$$

□

NOTE:

LKT λ_n^* ... SENSITIVITY OF SOLUTION

$$\lambda_n(\delta^*) = \frac{\lambda_n^*}{g_n(t^*)}$$

same

$\lambda_n(\delta^*)$ ALSO PROVIDES "SENSITIVITY" TO
 n^{TH} CONSTRAINT.

[5.4] DUAL CONVEX PROGRAMS

DUALITY THEOREM FOR CONVEX PROGRAMS,

RECALL

$$P \left\{ \begin{array}{l} \min f(x) \\ \text{s.t. } g_i(x) \leq 0 \\ \vdots \\ g_m(x) \leq 0 \\ \text{WHERE } g_1, \dots, g_m \text{ ARE CONVEX AND} \\ x \in C, C \text{ CONVEX} \end{array} \right. \quad x \in C$$

$$MP = \inf_{(-\infty)} \left\{ f(x) : x \in C, g_i(x) \leq 0 \right\}$$