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FENCHEL'S DUALITY THEOREM IN  
GENERALIZED GEOMETRIC PROGRAMMING

by

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Abstract. Fenchel's duality theorem is extended to generalized geometric programming with explicit constraints -- an extension that also generalizes and strengthens Slater's version of the Kuhn-Tucker theorem.

Key words: Fenchel's duality theorem, generalized geometric programming, convex programming, ordinary programming, Slater's constraint qualification, Kuhn-Tucker theorem.

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1. Introduction. Although many implications of this extension have already been discussed in the author's recent survey paper [1], a proof of it is given here for the first time.

This proof utilizes the unconstrained version that has already been established by independent and somewhat different arguments in [2] and [3]. In doing so, it exploits the main result from [4] and also requires some of the convexity theory in [3]--especially the theory having to do with the "relative interior" (ri  $S$ ) of an arbitrary convex set  $S \subseteq E_N$  ( $N$ -dimensional Euclidean space).

2. The unconstrained case. We begin with the following notation and hypotheses:

$\mathcal{X}$  is a nonempty closed convex cone in  $E_n$ ,

$g$  is a (proper) closed convex function with a nonempty (effective) domain  $\mathcal{C} \subseteq E_n$ .

Now, given  $\mathcal{X}$  and  $g$ , consider the resulting "geometric programming problem"  $\mathcal{A}$ .

PROBLEM  $\mathcal{A}$ . Using the feasible solution set

$$\mathcal{d} \stackrel{\Delta}{=} \mathcal{X} \cap \mathcal{C},$$

calculate both the problem infimum

$$\varphi \stackrel{\Delta}{=} \inf_{x \in \mathcal{d}} g(x)$$

and the optimal solution set

$$\mathcal{d}^* \stackrel{\Delta}{=} \{x \in \mathcal{d} \mid g(x) = \varphi\}.$$

Geometric duality is defined in terms of both the "dual cone"

$$\mathcal{Y} \triangleq \{y \in E_n \mid 0 \leq \langle x, y \rangle \text{ for each } x \in \mathcal{X}\}$$

and the "conjugate transform function"  $h$  whose (effective) domain

$$\mathcal{D} \triangleq \{y \in E_n \mid \sup_{x \in \mathcal{C}} [\langle y, x \rangle - g(x)] \text{ is finite}\}$$

and whose functional value

$$h(y) \triangleq \sup_{x \in \mathcal{C}} [\langle y, x \rangle - g(x)].$$

In particular, given the geometric programming problem  $\mathcal{A}$ , consider the resulting "geometric dual problem"  $\mathcal{B}$ .

PROBLEM  $\mathcal{B}$ . Using the feasible solution set

$$\mathcal{J} \triangleq \mathcal{Y} \cap \mathcal{D},$$

calculate both the problem infimum

$$\psi \triangleq \inf_{y \in \mathcal{J}} h(y)$$

and the optimal solution set

$$\mathcal{J}^* \triangleq \{y \in \mathcal{J} \mid h(y) = \psi\}.$$

Fenchel's duality theorem in the context of dual problems  $\mathcal{A}$  and  $\mathcal{B}$  is one of the most important theorems in geometric programming. It can be stated in the following way.

Theorem 1. If problem  $\mathcal{B}$  has both a feasible solution  $y^0 \in (\text{ri } \mathcal{A}) \cap (\text{ri } \mathcal{B})$  and a finite infimum  $\psi$ , then

(I) problem  $\mathcal{C}$  has both a nonempty feasible solution set  $\mathcal{S}$  and a finite infimum  $\varphi$ , and

$$0 = \varphi + \psi,$$

(II) problem  $\mathcal{C}$  has a nonempty optimal solution set  $\mathcal{S}^*$ .

This theorem is established as Theorem 31.4 on page 335 of [3].

The implications of Theorem 1 are given on page 26 of [1]. An important extension of it is established in the next section.

3. The constrained case. To incorporate explicit constraints into generalized geometric programming, we introduce the following notation and hypotheses:

I and J are two nonintersecting (possibly empty) positive-integer index sets with finite cardinality  $o(I)$  and  $o(J)$  respectively;

$x^k$  and  $y^k$  are independent vector variables in  $E_{n_k}$  for  $k \in \{0\} \cup I \cup J$ , and  $x^I$  and  $y^I$  denote the respective Cartesian products of the vector variables  $x^i$ ,  $i \in I$ , and  $y^i$ ,  $i \in I$  while  $x^J$  and  $y^J$  denote the respective Cartesian products of the vector variables  $x^j$ ,  $j \in J$ , and  $y^j$ ,  $j \in J$ ; so the Cartesian products  $(x^0, x^I, x^J) \stackrel{\Delta}{=} x$  and  $(y^0, y^I, y^J) \stackrel{\Delta}{=} y$  are independent vector variables in  $E_n$ , where

$$n \stackrel{\Delta}{=} n_0 + \sum_I n_i + \sum_J n_j;$$

$\alpha$  and  $\lambda$  are independent vector variables with respective components  $\alpha_i$  and  $\lambda_i$  for  $i \in I$ , and  $\beta$  and  $\kappa$  are independent vector variables with

respective components  $\beta_j$  and  $\kappa_j$  for  $j \in J$ ;

$X$  and  $Y$  are nonempty closed convex dual cones in  $E_n$ , and  $g_k$  and  $h_k$  are (proper) closed convex conjugate functions with respective (effective) domains  $C_k \subseteq E_{n_k}$  and  $D_k \subseteq E_{n_k}$  for  $k \in \{0\} \cup I \cup J$ .

Now, let

$$\mathcal{X} \stackrel{\Delta}{=} \{(x^0, x^I, \alpha, x^J, \kappa) \in E_n \mid (x^0, x^I, x^J) \in X; \alpha = 0; \kappa \in E_{o(J)}\},$$

where  $n + o(I) + o(J) = n$ . In addition, let

$$\mathcal{C} \stackrel{\Delta}{=} \{(x^0, x^I, \alpha, x^J, \kappa) \in E_n \mid x^0 \in C_0; x^i \in C_i, \alpha_i \in E_1, \text{ and} \\ g_i(x^i) + \alpha_i \leq 0, i \in I; (x^j, \kappa_j) \in C_j^+, j \in J\},$$

and let

$$g(x^0, x^I, \alpha, x^J, \kappa) \stackrel{\Delta}{=} g_0(x^0) + \sum_J g_j^+(x^j, \kappa_j),$$

where the (closed convex) function  $g_j^+$  has a domain

$$C_j^+ \stackrel{\Delta}{=} \{(x^j, \kappa_j) \mid \text{either } \kappa_j = 0 \text{ and } \sup_{d^j \in D_j} \langle x^j, d^j \rangle < +\infty, \text{ or } \kappa_j > 0 \text{ and } x^j \in \kappa_j C_j\}$$

and functional values

$$g_j^+(x^j, \kappa_j) \stackrel{\Delta}{=} \begin{cases} \sup_{d^j \in D_j} \langle x^j, d^j \rangle & \text{if } \kappa_j = 0 \text{ and } \sup_{d^j \in D_j} \langle x^j, d^j \rangle < +\infty \\ \kappa_j g_j(x^j / \kappa_j) & \text{if } \kappa_j > 0 \text{ and } x^j \in \kappa_j C_j. \end{cases}$$

The resulting problem  $\mathcal{Q}$  can clearly be stated in the following way.

PROBLEM A. Consider the objective function G whose domain

$$C \stackrel{\Delta}{=} \{(x, \kappa) \mid x^k \in C_k, k \in \{0\} \cup I, \text{ and } (x^j, \kappa_j) \in C_j^+, j \in J\}$$

and whose functional value

$$G(x, \kappa) \stackrel{\Delta}{=} g_0(x^0) + \sum_J g_j^+(x^j, \kappa_j).$$

Using the feasible solution set

$$S \stackrel{\Delta}{=} \{(x, \kappa) \in C \mid x \in X, \text{ and } g_i(x^i) \leq 0, i \in I\},$$

calculate both the problem infimum

$$\varphi \stackrel{\Delta}{=} \inf_{(x, \kappa) \in S} G(x, \kappa)$$

and the optimal solution set

$$S^* \stackrel{\Delta}{=} \{(x, \kappa) \in S \mid G(x, \kappa) = \varphi\}.$$

Now, section 3 of [4] shows that

$$\mathcal{Y} = \{(y^0, y^I, \lambda, y^J, \beta) \in E_n \mid (y^0, y^I, y^J) \in Y; \beta = 0; \lambda \in E_{o(I)}\}.$$

Section 3 of [4] also shows that

$$\mathcal{D} = \{(y^0, y^I, \lambda, y^J, \beta) \in E_n \mid y^0 \in D_0; (y^i, \lambda_i) \in D_i^+, i \in I; y^j \in D_j,$$

$$\beta_j \in E_1, \text{ and } h_j(y^j) + \beta_j \leq 0, j \in J\},$$

and that

$$h(y^0, y^I, \lambda, y^J, \beta) = h_0(y^0) + \sum_I h_i^+(y^i, \lambda_i),$$

where the (closed convex) function  $h_i^+$  has a domain

$$D_i^{+\Delta} = \{(y^i, \lambda_i) \mid \text{either } \lambda_i = 0 \text{ and } \sup_{c^i \in C_i} \langle y^i, c^i \rangle < +\infty, \text{ or } \lambda_i > 0 \text{ and } y^i \in \lambda_i D_i\}$$

and functional values

$$h_i^+(y^i, \lambda_i) \stackrel{\Delta}{=} \begin{cases} \sup_{c^i \in C_i} \langle y^i, c^i \rangle & \text{if } \lambda_i = 0 \text{ and } \sup_{c^i \in C_i} \langle y^i, c^i \rangle < +\infty \\ \lambda_i h_i(y^i/\lambda_i) & \text{if } \lambda_i > 0 \text{ and } y^i \in \lambda_i D_i. \end{cases}$$

The resulting problem  $\mathcal{B}$  can clearly be stated in the following way.

PROBLEM B. Consider the objective function  $H$  whose domain

$$D = \{(y, \lambda) \mid y^k \in D_k, k \in \{0\} \cup J, \text{ and } (y^i, \lambda_i) \in D_i^+, i \in I\}$$

and whose functional value

$$H(y, \lambda) \stackrel{\Delta}{=} h_0(y^0) + \sum_I h_i^+(y^i, \lambda_i).$$

Using the feasible solution set

$$T \stackrel{\Delta}{=} \{(y, \lambda) \in D \mid y \in Y, \text{ and } h_j(y^j) \leq 0, j \in J\},$$

calculate both the problem infimum

$$\psi \stackrel{\Delta}{=} \inf_{(y, \lambda) \in T} H(y, \lambda)$$

and the optimal solution set

$$T^* \stackrel{\Delta}{=} \{(y, \lambda) \in T \mid H(y, \lambda) = \psi\}.$$



It is worth noting that dual problems A and B provide the only completely symmetric duality that is presently known for general (closed) convex programming with explicit constraints. Moreover, [1] and some of the references cited therein show that all other duality in convex programming can be viewed as a special case. For the fundamental relations between geometric duality and ordinary Lagrangian duality see [5].

Fenchel's duality theorem in the context of dual problems A and B is one of the most important theorems, as well as one of the deepest theorems, in geometric programming. It can be stated in the following way.

Theorem 2. If

(i) problem B has a feasible solution  $(y', \lambda')$  such that

$$h_j(y'^j) < 0 \quad j \in J,$$

(ii) problem B has a finite infimum  $\psi$ ,

(iii) there exists a vector  $(y^+, \lambda^+)$  such that

$$y^+ \in (\text{ri } Y),$$

$$y^{+k} \in (\text{ri } D_k) \quad k \in \{0\} \cup J,$$

$$(y^{+i}, \lambda_i^+) \in (\text{ri } D_i^+) \quad i \in I,$$

then

(I) problem A has both a nonempty feasible solution set S and a finite infimum  $\varphi$ , and

$$0 = \varphi + \psi,$$

(II) problem A has a nonempty optimal solution set  $S^*$ .

Proof. We obviously need only show that the Fenchel hypothesis in Theorem 1 (i.e. the hypothesis that there exists a vector  $y^0 \in (\text{ri } \mathcal{Y}) \cap (\text{ri } \mathcal{D})$ ) is equivalent to hypotheses (i) and (iii) in Theorem 2.

Toward that end, we first use the formulas for  $\mathcal{Y}$  and  $\mathcal{D}$  to derive comparable formulas for  $(\text{ri } \mathcal{Y})$  and  $(\text{ri } \mathcal{D})$  -- two derivations that make crucial use of the following basic facts:

(A)  $(\text{ri } U) = U$  when  $U$  is a vector space,

(B)  $(\text{ri } V) = \times_{k=1}^{\eta} (\text{ri } V_k)$  when  $V = \times_{k=1}^{\eta} V_k$  and the sets  $V_k$  are convex,

and

(C)  $(\text{ri } W) = (\text{int } W)$ , the "interior" of  $W$ , when  $W$  is a convex set with the same "dimension" as the space in which it is embedded.

Fact (A) is established on page 44 of [3]; fact (B) can be obtained inductively from the formula at the top of page 49 of [3]; and fact (C) is explained on page 44 of [3].

Now, the formula for  $\mathcal{Y}$  along with facts (A) and (B) implies that

$$(\text{ri } \mathcal{Y}) = \{ (y^0, y^I, \lambda, y^J, \beta) \in E_n \mid (y^0, y^I, y^J) \in (\text{ri } Y); \lambda \in E_{o(I)}; \beta = 0 \}.$$

Moreover, the formula for  $\mathcal{D}$  along with facts (A) and (B) implies that

$$(\text{ri } \mathcal{D}) = \{ (y^0, y^I, \lambda, y^J, \beta) \in E_n \mid y^0 \in (\text{ri } D_0); \lambda_i > 0 \text{ and } y^i \in \lambda_i (\text{ri } D_i), \\ i \in I; y^j \in (\text{ri } D_j), \beta_j \in E_1, \text{ and } h_j(y^j) + \beta_j < 0, j \in J \},$$

by virtue of both the equation

$$(\text{ri } D_i^+) = \{(y^i, \lambda_i) \mid \lambda_i > 0 \text{ and } y^i \in \lambda_i (\text{ri } D_i)\}$$

and the equation

$$\begin{aligned} (\text{ri } \{(y^j, \beta_j) \mid y^j \in D_j \text{ and } h_j(y^j) + \beta_j \leq 0\}) = \\ \{(y^j, \beta_j) \mid \beta_j \in E_1, y^j \in (\text{ri } D_j), \text{ and } h_j(y^j) + \beta_j < 0\}. \end{aligned}$$

To derive the latter equation, simply use Theorem 6.8 on page 49 of [3] along with fact (C). To derive the former equation, first consider the point-to-set mapping  $Y_i^+ : \Lambda_i^+$  where

$$Y_i^+[\lambda_i] \stackrel{\Delta}{=} \{y^i \mid (y^i, \lambda_i) \in D_i^+\}$$

and

$$\Lambda_i^{+\Delta} = \{\lambda_i \mid Y_i^+[\lambda_i] \text{ is not empty}\}.$$

Now, Corollary 6.8.1 on page 50 of [3] implies that

$$(\text{ri } D_i^+) = \{(y^i, \lambda_i) \mid \lambda_i \in (\text{ri } \Lambda_i^+) \text{ and } y^i \in (\text{ri } Y_i^+[\lambda_i])\}.$$

Moreover, the definition of  $D_i^+$  clearly shows that  $\Lambda_i^+ = \{\lambda_i \geq 0\}$ , which means of course that

$$(\text{ri } \Lambda_i^+) = \{\lambda_i > 0\}.$$

Furthermore, for  $\lambda_i > 0$  the definition of  $D_i^+$  clearly shows that  $Y_i^+[\lambda_i] = \lambda_i D_i$ , which means that

$$(\text{ri } Y_i^+[\lambda_i]) \equiv \lambda_i (\text{ri } D_i) \text{ for } \lambda_i \in (\text{ri } \Lambda_i^+),$$

by virtue of Corollary 6.6.1 on page 48 of [3]. Consequently, our derivation of the preceding formula for (ri  $D$ ) is complete.

In particular then, the Fenchel hypothesis in Theorem 1 simply asserts that

$$\begin{aligned} &\text{there exists a vector } (y^0, y^I, \lambda, y^J, 0) = y^0 \\ &\text{such that } (y^0, y^I, y^J) \in (\text{ri } Y); \quad y^0 \in (\text{ri } D_0); \\ &\lambda_i > 0 \text{ and } y^i \in \lambda_i (\text{ri } D_i), \quad i \in I; \quad y^j \in (\text{ri } D_j) \\ &\text{and } h_j(y^j) < 0, \quad j \in J. \end{aligned}$$

To complete our proof, we now show that this hypothesis is in fact equivalent to the hypothesis

$$\begin{aligned} &\text{there exists a vector } (y'^0, y'^I, \lambda', y'^J) \\ &\text{such that } (y'^0, y'^I, y'^J) \in Y; \quad y'^0 \in D_0; \\ &(y'^i, \lambda'_i) \in D_i^+, \quad i \in I; \quad y'^j \in D_j \text{ and } h_j(y'^j) < 0, \quad j \in J \end{aligned}$$

--- and there exists a vector

$$\begin{aligned} &(y^{+0}, y^{+I}, \lambda^+, y^{+J}) \text{ such that} \\ &(y^{+0}, y^{+I}, y^{+J}) \in (\text{ri } Y); \quad y^{+0} \in (\text{ri } D_0); \quad \lambda_i^+ > 0 \\ &\text{and } y^{+i} \in \lambda_i^+ (\text{ri } D_i), \quad i \in I; \quad y^{+j} \in (\text{ri } D_j), \quad j \in J. \end{aligned}$$

Obviously, a vector  $(y^0, y^I, \lambda, y^J)$  that satisfies the former hypothesis satisfies both parts of the latter hypothesis. On the other hand,

Theorem 6.1 on page 45 of [3] and Theorem 7.1 on page 51 of [3] imply that a convex combination  $\alpha(y'^0, y'^I, \lambda', y'^J) + \beta(y^{+0}, y^{+I}, \lambda^+, y^{+J})$  of vectors  $(y'^0, y'^I, \lambda', y'^J)$  and  $(y^{+0}, y^{+I}, \lambda^+, y^{+J})$  that satisfy the latter hypothesis will satisfy the former hypothesis for sufficiently small  $\beta > 0$ . q.e.d.

Although the condition  $h_j(y'^j) < 0, j \in J$  in hypothesis (i) of Theorem 2 resembles the well-known "Slater constraint qualification", it is of course to be deleted when  $J$  is empty -- which is the situation in most applications. However, the analogous condition  $g_i(x'^i) < 0, i \in I$  in hypothesis (i) of the (unstated) dual of Theorem 2 (obtained from Theorem 2 by interchanging the symbols  $A$  and  $B$ , the symbols  $x$  and  $y$ , the symbols  $\kappa$  and  $\lambda$ , the symbols  $g$  and  $h$ , the symbols  $i$  and  $j$ , the symbols  $I$  and  $J$ , the symbols  $\varphi$  and  $\psi$ , the symbols  $X$  and  $Y$ , the symbols  $C$  and  $D$ , the symbols  $S$  and  $T$ , and the symbols  $S^*$  and  $T^*$ ) is essentially the Slater constraint qualification. In fact, we shall now see that the "ordinary programming" case of the dual of Theorem 2 actually strengthens Slater's version of the "Kuhn-Tucker theorem".

The ordinary programming case occurs when

$$J = \emptyset,$$

$$n_k = m \text{ and } C_k \stackrel{\Delta}{=} C_0 \text{ for some set } C_0 \subseteq E_m \quad k \in \{0\} \cup I,$$

and

$$X \stackrel{\Delta}{=} \text{column space of } \begin{bmatrix} U \\ U \\ \cdot \\ \cdot \\ \cdot \\ U \end{bmatrix} \text{ where there is a total of } 1 + o(I) \text{ identity matrices } U \text{ that are } m \times m.$$

In particular, an explicit elimination of the vector space condition  $x \in X$  by the linear transformation

$$\begin{pmatrix} x^0 \\ x^I \end{pmatrix} = \begin{bmatrix} U \\ U \\ \cdot \\ \cdot \\ \cdot \\ U \end{bmatrix} z$$

shows that the resulting problem A is equivalent to the very general ordinary programming problem

Minimize  $g_0(z)$  subject to

$$g_i(z) \leq 0 \quad i \in I$$

$$z \in C_0.$$

Now, the Slater constraint qualification for the preceding problem simply requires the existence of a feasible solution  $z'$  such that  $g_i(z') < 0$ ,  $i \in I$ . Moreover, Slater's version of the Kuhn-Tucker theorem asserts that the existence of such a "Slater solution"  $z'$  and the existence of a finite infimum  $\varphi$  are sufficient to guarantee the existence of a Kuhn-Tucker (Lagrange) multiplier vector  $\lambda^*$ .

To strengthen the preceding theorem with the aid of the dual of Theorem 2, first note that the image  $x' = (z', z', \dots, z')$  of a Slater solution  $z'$  under the given linear transformation satisfies hypothesis (i) of the dual of Theorem 2. Then, note that the existence of a finite infimum  $\varphi$  is simply hypothesis (ii) of the dual of Theorem 2. Now, the convexity of  $C_0$  implies the existence of a vector  $z^+ \in (\text{ri } C_0)$ , by virtue of Theorem 6.2 on page 45 of [3]. Moreover, its image  $x^+ = (z^+, z^+, \dots, z^+)$  under the given linear transformation clearly satisfies hypothesis (iii)

of the dual of Theorem 2 -- because  $(ri X) = X$  by virtue of fact (A), and because  $J = \emptyset$ . Consequently, the dual of Theorem 2 implies that both  $T$  and  $T^*$  are nonempty and that  $0 = \varphi + \psi$ . In view of Corollary 7A of [6], we conclude from the nonemptiness of  $T^*$  that a Kuhn-Tucker (Lagrange) vector  $\lambda^*$  exists. Finally, note that we have also shown the existence of another vector  $y^*$ ; so the Slater version of the Kuhn-Tucker theorem has actually been strengthened.

More significant implications of Theorem 2 are given on page 47 of [1].

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