

# GEOMETRIC PROGRAMMING: A UNIFIED DUALITY THEORY FOR QUADRATICALLY CONSTRAINED QUADRATIC PROGRAMS AND $l_p$ -CONSTRAINED $l_p$ -APPROXIMATION PROBLEMS<sup>1</sup>

BY ELMOR L. PETERSON AND J. G. ECKER

Communicated by L. Cesari, August 31, 1967

The duality theory of geometric programming as developed by Duffin, Peterson, and Zener [1] is based on abstract properties shared by certain classical inequalities, such as Cauchy's arithmetic-geometric mean inequality and Hölder's inequality. Inequalities with these abstract properties have been termed "geometric inequalities" ([1, p. 195]). We have found a new geometric inequality, which we state below, and have used it to extend the "refined duality theory" of geometric programming developed by Duffin and Peterson ([2] and [1, Chapter VI]). This extended duality theory treats both quadratically-constrained quadratic programs and  $l_p$ -constrained  $l_p$ -approximation problems. By a quadratically constrained quadratic program we mean: to minimize a positive semidefinite quadratic function, subject to inequality constraints expressed in terms of the same type of functions. By an  $l_p$ -constrained  $l_p$ -approximation problem we mean: to minimize the  $l_p$  norm of the difference between a fixed vector and a variable linear combination of other fixed vectors, subject to inequality constraints expressed by means of  $l_p$  norms.

Both the classical unsymmetrical duality theorems for linear programming (Gale, Kuhn and Tucker [3], and Dantzig and Orden [4]) and the unsymmetrical duality theorems for linearly-constrained quadratic programs (Dennis [5], Dorn [6], [7], Wolfe [8], Hanson [9], Mangasarian [10], Huard [11], and Cottle [12]) can be derived from the extended duality theorems that we state below and have proved on the basis of the new geometric inequality.

The new geometric inequality is

$$\sum_1^{N+1} x_i y_i \leq y_{N+1} \left( \sum_1^N p_i^{-1} |x_i - b_i|^{p_i} + (x_{N+1} - b_{N+1}) \right) + \sum_1^N (q_i^{-1} y_{N+1}^{(1-q_i)} |y_i|^{q_i} + b_i y_i) + b_{N+1} y_{N+1},$$

---

<sup>1</sup> Research partially supported by US-Army Research Office Durham, Grant 07701, at the University of Michigan.

which is valid for each  $\mathbf{x}$  in  $E_{N+1}$  and each  $\mathbf{y}$  in the cone

$$T = \{ \mathbf{y} \in E_{N+1} \mid y_{N+1} \geq 0, \text{ and } y_{N+1} = 0 \text{ only if } \mathbf{y} = \mathbf{0} \},$$

with the understanding that  $\sum_1^N q_i^{-1} y_{N+1}^{(1-q_i)} |y_i|^{q_i}$  is defined to be zero when  $\mathbf{y} = \mathbf{0}$ . Here  $\mathbf{b} = (b_1, b_2, \dots, b_{N+1})$  is an arbitrary, but fixed, vector in  $E_{N+1}$ , and  $p_i$  and  $q_i$  are arbitrary, but fixed, real numbers that satisfy the conditions  $p_i, q_i > 1$  and  $1/p_i + 1/q_i = 1, i = 1, 2, \dots, N$ .

Every quadratically-constrained quadratic program and every  $l_p$ -constrained  $l_p$ -approximation problem are special cases of the following program.

PRIMAL PROGRAM A. Find the infimum of  $G_0(\mathbf{x})$  subject to the following constraints on  $\mathbf{x}$ .

- (1)  $G_k(\mathbf{x}) \leq 0$  for each  $k$  in  $\{1, 2, \dots, r\}$ .
- (2)  $\mathbf{x} \in \mathcal{O}$ .

Here

$$G_k(\mathbf{x}) = \sum_{[k]} p_i^{-1} |x_i - b_i|^{p_i} + (x_{1[k]} - b_{1[k]}), \quad k = 0, 1, 2, \dots, r,$$

where

$$\begin{aligned} [k] &= \{m_k, m_k + 1, \dots, n_k\}, & k &= 0, 1, 2, \dots, r, \\ ]k[ &= n_k + 1, & k &= 0, 1, 2, \dots, r, \end{aligned}$$

and

$$m_0 = 1, m_1 = n_0 + 2, m_2 = n_1 + 2, \dots, m_r = n_{r-1} + 2, n_r + 1 = n.$$

The vector  $\mathbf{b} = (b_1, b_2, \dots, b_n)$  is an arbitrary, but fixed, vector in  $E_n$ , and the arbitrary, but fixed, constants  $p_i$  satisfy the condition  $p_i > 1$  for each  $i$  in  $[k], k = 0, 1, 2, \dots, r$ . The set  $\mathcal{O}$  is a fixed, but arbitrary, vector subspace of  $E_n$ .

To put an arbitrary quadratically-constrained quadratic program with  $m$  independent variables  $z_1, \dots, z_m$  into the form of primal program A, first observe that each positive semidefinite quadratic function  $(\frac{1}{2})\mathbf{z}^t C_z + \mathbf{c}^t \mathbf{z}$  can be factored as  $(\frac{1}{2})(D\mathbf{z})^t (D\mathbf{z}) + \mathbf{c}^t \mathbf{z}$  where  $D$  is an appropriate  $m \times m$  matrix. In particular, the objective function for such a program can be factored to give a matrix  $D_0$  and a row vector  $\mathbf{c}_0^t$ . Correspondingly, the  $k$ th constraint can be factored to give a matrix  $D_k$  and a row vector  $\mathbf{c}_k^t$ . Let  $M = [D_0, \mathbf{c}_0^t, D_1, \mathbf{c}_1^t, \dots, D_r, \mathbf{c}_r^t]^t$  and specialize primal program A by letting

$$\begin{aligned} n_k &= (k+1)m + k, & k &= 0, 1, \dots, r \\ p_i &= 2 \text{ for each } i \in [k], & k &= 0, 1, \dots, r, \\ b_i &= 0 \text{ for each } i \in [k], & k &= 0, 1, \dots, r. \end{aligned}$$

Finally, identify  $\mathcal{O}$  with the column space of the above matrix  $M$ ; that is, let  $\mathbf{x} = M\mathbf{z}$ . With these specializations, primal program A is equivalent to the quadratically-constrained quadratic program.

All linearly-constrained quadratic programs can be obtained from the most general quadratically-constrained quadratic program by choosing the  $i$ th row vector of  $M$  equal to  $\mathbf{0}$  for each  $i$  in  $[k]$ ,  $k = 1, 2, \dots, r$ . Moreover, all linear programs can be obtained by further restricting  $M$  so that its  $i$ th row vector equals  $\mathbf{0}$  for each  $i$  in  $[0]$ .

To obtain from primal program A the most general  $l_p$ -constrained  $l_p$ -approximation problem with  $m$  spanning vectors, choose  $p_i = p_k$  for each  $i$  in  $[k]$ ,  $k = 0, 1, \dots, r$ , and identify  $\mathcal{O}$  with the column space of an arbitrary  $n \times m$  matrix  $M$  with  $i$ th row vector equal to  $\mathbf{0}$  for  $k = 0, 1, 2, \dots, r$ .

The dual program corresponding to primal program A is

DUAL PROGRAM B. Find the supremum of  $v(\mathbf{y})$  subject to the following constraints on  $\mathbf{y}$ .

- (1)  $y_{j_0} = 1$ .
- (2) For each integer  $k$  in  $\{1, 2, \dots, r\}$  the vector component  $y_{j_k} \geq 0$ , and  $y_{j_k} = 0$  only if  $y_i = 0$  for each  $i$  in  $[k]$ .
- (3)  $\mathbf{y} \in \mathcal{D}$ .

Here

$$v(\mathbf{y}) = - \sum_{k=0}^r \left\{ \sum_{[k]} (q_i^{-1} y_{j_k}^{(1-q_i)} |y_i|^{q_i} + b_i y_i) + b_{j_k} y_{j_k} \right\}$$

where  $[k]$ ,  $j_k$ , and  $r$  are as defined in primal program A. The fixed vector  $\mathbf{b} = (b_1, b_2, \dots, b_n)$  is identical to the vector  $\mathbf{b}$  of primal program A, and the constants  $q_i$  are determined from the constants  $p_i$  of primal program A by the condition

$$1/p_i + 1/q_i = 1 \quad \text{for each } i \text{ in } [k], \quad k = 0, 1, 2, \dots, r.$$

The subset  $\mathcal{D}$  of  $E_n$  is the orthogonal complement of the vector subspace  $\mathcal{O}$  of primal program A.

If for primal program A we take any linearly-constrained quadratic program, or any linear program, then correspondingly dual program B reduces to the well-known dual program. To recognize this, two recollections and two elementary observations are needed. First, recall that appropriate row vectors of the matrix  $M$  must be set equal to  $\mathbf{0}$  and then observe that the dual variable  $y_i$  corresponding to such a row vector is essentially unconstrained. Second, recall that  $b_i = 0$

for each  $i$  in  $[k]$ ,  $k=0, 1, 2, \dots, r$ , and then observe from the form of the resulting dual objective function  $v$  that when the variable  $y_i$  is essentially unconstrained for some  $i$  in some  $[k]$  this variable  $y_i$  can be set equal to zero without changing the constrained supremum of  $v(\mathbf{y})$ . In the linearly-constrained quadratic case  $v$  reduces to the quadratic function

$$v(\mathbf{y}) = -\frac{1}{2} \sum_{[0]} y_i^2 - b_{j_0[} - \sum_1^r b_{j_k[y]k[}.$$

In the completely linear case  $v$  further reduces to the linear function

$$v(\mathbf{y}) = -b_{j_0[} - \sum_1^r b_{j_k[y]k[}.$$

We shall use the following standard terminology in stating our duality theorems. The *objective function* for a program is the function to be optimized ( $G_0$  or  $v$  in our theory). A program is *consistent* if there is at least one point that satisfies its constraints. Each such point is said to be a *feasible solution* to the program. The constrained infimum (supremum) of the objective function for a consistent program is termed the *infimum (supremum) of the program*. A feasible solution to a program is *optimal* if the resulting value of the objective function is actually equal to the infimum (supremum) of the program. The infimum (supremum) of a program with an optimal feasible solution is said to be the *minimum (maximum) of the program*. Thus a program can have an infimum (supremum) without having a minimum (maximum), but not conversely.

The following existence theorem relates primal program A and its dual program B.

**THEOREM 1.** *If primal program A is consistent, then it has a finite infimum  $M_A$  if, and only if, its dual program B is consistent. If dual program B is consistent, then it has a finite supremum  $M_B$  if, and only if, its primal program A is consistent.*

Unlike Theorem 1, the following duality theorem is not symmetrical relative to primal program A and its dual program B.

**THEOREM 2.** *If primal program A and its dual program B are both consistent, then*

(I) *Program A has a finite infimum  $M_A$  and program B has a finite supremum  $M_B$ , with  $M_A = M_B$ .*

(II) *The infimum  $M_A$  of program A is actually a minimum.*

(III) *The supremum  $M_B$  of program B is actually a maximum if, and only if, there are nonnegative Kuhn-Tucker (Lagrange) multipliers that solve the saddle-point problem for program A.*

Conclusion III can be strengthened so as to make Theorem 2 symmetrical relative to primal program A and its dual program B, if the class of programs is restricted to those programs for which primal program A has linear constraints. This strengthening is due to the well-known fact that each convex program with linear constraints has Kuhn-Tucker multipliers if it has a minimum.

The following duality theorem characterizes the sets of optimal feasible solutions.

**THEOREM 3.** *Given an optimal feasible solution  $x'$  to primal program A, a feasible solution  $y$  to dual program B is optimal if, and only if,  $y$  satisfies the conditions*

$$y_{1k} G_k(x') = 0, \quad k = 1, 2, \dots, r,$$

and

$$y_i = y_{1k} (\text{sgn } [x'_i - b_i] | x'_i - b_i |^{p_i-1}), \quad i \in [k], \quad k = 0, 1, \dots, r.$$

*For such an optimal feasible solution  $y'$  the numbers  $y'_{1k}$ ,  $k = 1, 2, \dots, r$ , are Kuhn-Tucker multipliers for primal program A. Given an optimal feasible solution  $y'$  to dual program B, a feasible solution  $x$  to primal program A is optimal if, and only if,  $x$  satisfies the conditions*

$$y_{1k} G_k(x) = 0, \quad k = 1, 2, \dots, r,$$

and

$$x_i = (\text{sgn } y'_i) (| y'_i / y'_{1k} |^{(q_i-1)} + b_i), \quad i \in [k], \quad k \in P,$$

where

$$P = \{k \mid y'_{1k} > 0\}.$$

Proofs for the preceding theorems will be given elsewhere. Sensitivity analyses and a computational algorithm that takes advantage of the essentially linear of the dual constraints will be described in forthcoming papers.

#### REFERENCES

1. R. J. Duffin, E. L. Peterson and C. Zener, *Geometric programming*, Wiley, New York, 1967.
2. R. J. Duffin and E. L. Peterson, *Duality theory for geometric programming*, SIAM J. Appl. Math. 14 (1966), 1307-1349.

3. D. Gale, H. W. Kuhn and A. W. Tucker, *Linear programming and the theory of games*, Cowles Commission Monograph No. 13 (1951).
4. G. B. Dantzig and A. Orden, *Duality theorems*, RAND Report RM-1265, The RAND Corporation, Santa Monica, Calif., October, 1953.
5. J. B. Dennis, *Mathematical programming and electrical networks*, Wiley, New York, 1959.
6. W. S. Dorn, *Duality in quadratic programming*, Quart. Appl. Math. 18 (1960–1961), 155–162.
7. ———, *A duality theorem for convex programs*, IBM Journal, 4 (1960), 407–413.
8. P. Wolfe, *A duality theorem for nonlinear programming*, Quart. Appl. Math. 19 (1961), 239–244.
9. M. A. Hanson, *A duality theorem in nonlinear programming with nonlinear constraints*, Australian J. of Statistics 3 (1961), 64–72.
10. O. L. Mangasarian, *Duality in nonlinear programming*, Quart. Appl. Math. 20 (1962–1963), 300–302.
11. P. Huard, “Dual programs” in *Recent advances in mathematical programming*, McGraw-Hill, New York, 1963.
12. R. W. Cottle, *Symmetric dual quadratic programs*, Quart. Appl. Math. 21 (1963–1964), 237–243.

UNIVERSITY OF MICHIGAN