# DUALITY IN QUADRATIC PROGRAMMING* $\dagger$ 

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#### Abstract

A proof, based on the duality theorem of linear programming, is given for a duality theorem for a class of quadratic programs. An illustrative application is made in the theory of elastic structures. 1. Introduction. Recent interest in quadratic programming has resulted in a series of computational methods for this type of problem. Some of these are described in [ $1,2,3,4,5]$. Little emphasis, however, has been placed thus far on the concept of duality in quadratic programs. This concept, which has proved so valuable in linear programs, is investigated briefly in what follows.

In Sec. 5 a dual problem for a class of quadratic programming problems is formulated and the equality of the two objective forms is verified. Dennis [6] has indicated previously that such a duality existed based on the Kuhn-Tucker "equivalence theorem" [7]. The proof given here rests on the duality theorem for linear programs. 2. Notation. In what follows, matrix notation will be employed. Lower case letters, $x, y, \cdots$ will denote column vectors and capital letters $A, C, \cdots$ will represent matrices. Prime denotes transpose so that $x^{\prime}, y^{\prime}, \cdots$ are row vectors. The product $x^{\prime} y$ is the inner product of the two vectors $x$ and $y$.

A vector inequality will apply to each component of the vector, i.e., $x \geq 0$ indicates that each component of $x$ is non-negative. 3. Duality in linear programming. The linear programming problem may be posed as follows. To minimize the linear form $p^{\prime} x$ over all $n$-dimensional vectors $x$ satisfying the constraints


$$
\begin{aligned}
A x & \geq b \\
x & \geq 0
\end{aligned}
$$

where $p$ is an $n \times 1$ vector, $b$ is an $m \times 1$ vector and $A$ is an $m \times n$ matrix.
The dual problem to the above is to maximize $b^{\prime} v$ over all $m$-dimensional vectors $v$ satisfying

$$
\begin{aligned}
A^{\prime} v & \leq p \\
v & \geq 0
\end{aligned}
$$

The duality theorem [8, 9] states that if a solution to either problem exists and is finite, then a solution to the other problem also exists and indeed

$$
\begin{equation*}
\text { Minimum } \quad p^{\prime} x=\text { Maximum } \quad b^{\prime} v . \tag{3.1}
\end{equation*}
$$

[^0]4. A class of quadratic programs. A class of programs which has received considerable attention $[3,5,6]$ is
\[

$$
\begin{equation*}
\text { Minimize: } f(x)=\frac{1}{2} x^{\prime} C x+p^{\prime} x \tag{4.1}
\end{equation*}
$$

\]

subject to

$$
\begin{align*}
A x & \geq b  \tag{4.2}\\
x & \geq 0 \tag{4.3}
\end{align*}
$$

where $C$ is a symmetric, positive semi-definite, $n \times n$ matrix and $p, b, A$ and $x$ are as in Sec. 3 above. This problem will be referred to as Problem I.

The symmetry restriction on $C$ results in no loss of generality, while the positive semi-definiteness requirement assures that $f(x)$ is convex and that a local minimum is also a global one [3, 5].

In order to prove a duality theorem for this class of programs the following lemma is required.

Lemma. If $C$ is a symmetric, positive semi-definite matrix then for any vectors $x$ and $y$

$$
y^{\prime} C y-x^{\prime} C x \geq 2 x^{\prime} C(y-x)
$$

Proof. From positive semi-definiteness, for any $x$ and $y$

$$
\begin{aligned}
& (y-x)^{\prime} C(y-x) \geq 0 \\
& y^{\prime} C y \geq 2 x^{\prime} C y-x^{\prime} C x
\end{aligned}
$$

Subtracting $x^{\prime} C x$ from both sides

$$
y^{\prime} C y-x^{\prime} C x \geq 2 x^{\prime} C(y-x)
$$

5. A duality theorem for quadratic programs. A dual problem to Problem I is

$$
\begin{equation*}
\text { Maximize: } \quad g(u, v)=-\frac{1}{2} u^{\prime} C u+b^{\prime} v \tag{5.1}
\end{equation*}
$$

subject to

$$
\begin{gather*}
A^{\prime} v-C u \leq p  \tag{5.2}\\
v \geq 0 \tag{5.3}
\end{gather*}
$$

where $u$ is an $n \times 1$ vector and $v$ is an $m \times 1$ vector. This problem will be referred to as Problem II.

Theorem (Dual). (i) If $x=x_{0}$ is a solution to Problem I then a solution $(u, v)=$ ( $x_{0}, v_{0}$ ) exists to Problem II. (ii) Conversely, if a solution $(u, v)=\left(u_{0}, v_{0}\right)$ to Problem II exists then a solution which satisfies $C x=C u_{0}$ to Problem I also exists. In either case

$$
\begin{equation*}
\operatorname{Max} g(u, v)=\operatorname{Min} f(x) \tag{5.4}
\end{equation*}
$$

Proof. (A) Suppose first that $x=x_{0}$ is the minimizing solution of Problem I. Consider the following linear programming problem

$$
\begin{equation*}
\text { Minimize: } \quad F(x)=-\frac{1}{2} x_{0}^{\prime} C x_{0}+x_{0}^{\prime} C x+p^{\prime} x \tag{5.5}
\end{equation*}
$$

subject to

$$
\begin{align*}
A x & \geq b  \tag{5.6}\\
x & \geq 0 \tag{5.7}
\end{align*}
$$

Denote this as Problem I'. Notice that the constraint sets for Problem I and Problem I' are identical.

Now suppose there exists an $x^{*}$ satisfying the constraints and such that

$$
\begin{equation*}
F\left(x^{*}\right)<F\left(x_{0}\right), \tag{5.8}
\end{equation*}
$$

i.e.,

$$
\left(x_{0}^{\prime} C+p^{\prime}\right)\left(x^{*}-x_{0}\right)<0
$$

It is easily verified that

$$
x_{1}=x_{0}+k\left(x-x_{0}\right), \quad 0<k<1
$$

also satisfies the constraints. Now

$$
f\left(x_{1}\right)-f\left(x_{0}\right)=k\left[\left(x_{0}^{\prime} C+p^{\prime}\right)\left(x^{*}-x_{0}\right)+\frac{1}{2} k\left(x^{*}-x_{0}\right)^{\prime} C\left(x^{*}-x_{0}\right)\right] .
$$

Choose $k$ to be

$$
k<-\frac{\left(x_{0}^{\prime} C+p^{\prime}\right)\left(x^{*}-x_{0}\right)}{\frac{1}{2}\left(x^{*}-x_{0}\right)^{\prime} C\left(x^{*}-x_{0}\right)} .
$$

It follows that the term in square brackets is negative so

$$
f\left(x_{1}\right)-f\left(x_{0}\right)<0 .
$$

But $f\left(x_{0}\right) \leq f\left(x_{1}\right)$ since $x_{0}$ is the minimizing solution of Problem I so the inequality (5.8) cannot hold for any $x$, i.e., for all $x$

$$
F(x) \geq F\left(x_{0}\right) .
$$

Thus $x_{0}$ minimizes $F(x)$ and is the optimal solution to Problem $\mathrm{I}^{\prime}$.
The dual problem to Problem $\mathrm{I}^{\prime}$ is (Sec. 3)

$$
\begin{equation*}
\text { Maximize: } \quad G(v)=-\frac{1}{2} x_{0}^{\prime} C x_{0}+b^{\prime} v \tag{5.9}
\end{equation*}
$$

subject to

$$
\begin{gather*}
A^{\prime} v \leq C x_{0}+p  \tag{5.10}\\
v \geq 0 \tag{5.11}
\end{gather*}
$$

Denote this as Problem II'. By the duality theorem for linear programs, (3.1),

$$
\operatorname{Max} G(v)=\operatorname{Min} F(x)=F\left(x_{0}\right) .
$$

If $v=v_{0}$ is a maximizing solution of Problem II' then the last equation becomes

$$
\begin{equation*}
b^{\prime} v_{0}=x_{0}^{\prime} C x_{0}+p^{\prime} x_{0} . \tag{5.12}
\end{equation*}
$$

Consider now admissible solutions ( $u, v$ ) to Problem II. In particular ( $x_{0}, v_{0}$ ) is admissible. Now from (5.1)

$$
g\left(x_{0}, v_{0}\right)-g(u, v)=-\frac{1}{2} x_{0}^{\prime} C x_{0}+b^{\prime} v_{0}+\frac{1}{2} u^{\prime} C u-b^{\prime} v
$$

by the lemma

$$
g\left(x_{0}, v_{0}\right)-g(u, v) \geq x_{0}^{\prime} C\left(u-x_{0}\right)+b^{\prime} v_{0}-b^{\prime} v
$$

and from (5.12)

$$
\begin{equation*}
g\left(x_{0}, v_{0}\right)-g(u, v) \geq x_{0}^{\prime} C u+p^{\prime} x_{0}-b^{\prime} v . \tag{5.13}
\end{equation*}
$$

Now from (5.2) and (4.3)

$$
x_{0}^{\prime} C u \geq x_{0}^{\prime}\left(A^{\prime} v-p\right)
$$

and from (4.2) and (5.3)

$$
-b^{\prime} v \geq-x_{0}^{\prime} A^{\prime} v
$$

Substituting these last two inequalities in (5.13)

$$
g\left(x_{0}, v_{0}\right)-g(u, v) \geq x_{0}^{\prime} A^{\prime} v-x_{0}^{\prime} p+p^{\prime} x_{0}-x_{0}^{\prime} A^{\prime} v=0 .
$$

Thus ( $x_{0}, v_{0}$ ) maximizes Problem II. Finally from (5.1), (5.12) and (4.1)

$$
\begin{equation*}
g\left(x_{0}, v_{0}\right)=-\frac{1}{2} x_{0}^{\prime} C x_{0}+b^{\prime} v_{0}=\frac{1}{2} x_{0}^{\prime} C x_{0}+p^{\prime} x_{0}=f\left(x_{0}\right) \tag{5.14}
\end{equation*}
$$

which verifies the equality of the objective functions (4.1) and (5.1). This completes the proof of part (i) of the theorem.
(B) The converse will be proved by applying the above result to Problem II. Suppose a maximizing solution ( $u_{0}, v_{0}$ ) of Problem II exists. Problem II may be rephrased

$$
\text { Minimize: } \quad-g(u, v)=\frac{1}{2} u^{\prime} C u-b^{\prime} v
$$

subject to

$$
\begin{aligned}
C u-A^{\prime} v & \geq-p, \\
v & \geq 0
\end{aligned}
$$

Now let

$$
u=r-s
$$

where

$$
\begin{aligned}
& r \geq 0 \\
& s \geq 0
\end{aligned}
$$

Problem II then becomes

$$
\text { Minimize: }-G(r, s, v)=\frac{1}{2}(r, s, v)^{\prime}\left(\begin{array}{rrr}
C, & -C, & 0 \\
-C, & C, & 0 \\
0, & 0, & 0
\end{array}\right)\left(\begin{array}{l}
r \\
v \\
v
\end{array}\right)+(0,0,-b)\left(\begin{array}{l}
r \\
s \\
v
\end{array}\right)
$$

subject to

$$
\begin{gathered}
\left(C,-C,-A^{\prime}\right)\binom{r}{v} \geq-p \\
r \geq 0 \\
s \geq 0 \\
v \geq 0
\end{gathered}
$$

This is now in the form of Problem I, and by part (i) of the theorem (already proved in A above) implies the existence of a solution to a dual problem which is

$$
\text { Maximize: } \quad-\frac{1}{2}(w, y, z)^{\prime}\left(\begin{array}{rrr}
C, & -C, & 0 \\
-C, & C, & 0 \\
0, & 0, & 0
\end{array}\right)\left(\begin{array}{l}
w \\
y \\
z
\end{array}\right)-p^{\prime} x
$$

subject to

$$
\begin{align*}
C x-C w+C y+0 z & \leq 0  \tag{5.15}\\
-C x+C w-C y+0 z & \leq 0  \tag{5.16}\\
-A x+0 w+0 y+0 z & \leq-b  \tag{5.17}\\
x & \geq 0
\end{align*}
$$

Moreover, the maximizing solution is required to satisfy

$$
\begin{align*}
w-y & =u_{0}  \tag{5.18}\\
z & =v_{0}
\end{align*}
$$

Inequalities (5.15) and (5.16) imply that

$$
\begin{equation*}
C x=C(w-y) \tag{5.19}
\end{equation*}
$$

so the dual problem may be rewritten

$$
\text { Maximize: } \quad-\frac{1}{2} x^{\prime} C x-p^{\prime} x=-f(x)
$$

subject to

$$
\begin{aligned}
A x & \geq b \\
x & \geq 0
\end{aligned}
$$

which is exactly the original Problem I. From (5.18) and (5.19) then the optimizing solution $x$ to Problem I must satisfy

$$
C x=C u_{0}
$$

Finally from Eq. (5.14) it follows that

$$
\operatorname{Min}-g(u, v)=\operatorname{Max}-f(x),
$$

which completes the proof of part (ii).
6. Computation of the dual variables. The proof in the preceding section also provides a means for calculating the dual variables ( $u_{0}, v_{0}$ ) once the primal variables, $x_{0}$, have been found.

The vector $u_{0}$ is identical with $x_{0}$. The vector $v_{0}$ is then a solution of a linear programming problem

$$
\text { Maximize } \quad b^{\prime} v
$$

subject to

$$
\begin{aligned}
A^{\prime} v & \leq C x_{0}+p \\
v & \geq 0
\end{aligned}
$$

7. Other classes of problems. The quadratic problem (Problem I) may be formulated in various other ways with resulting changes in its dual (Problem II). Some of these, including the original, are tabulated below for reference.

## Primal Problem

## Dual Problem

## Type I

| $\operatorname{Min} \frac{1}{2} x^{\prime} C x+p^{\prime} x$ | $\operatorname{Max}-\frac{1}{2} u^{\prime} C u+b^{\prime} v$ |
| :---: | :---: |
| $A x \geq b$ | $A^{\prime} v-C u \leq p$ |
| $x \geq 0$ | $v \geq 0$ |

## Type II

$$
\begin{array}{cc}
\operatorname{Min} \frac{1}{2} x^{\prime} C x+p^{\prime} x & \operatorname{Max}-\frac{1}{2} u^{\prime} C u+b^{\prime} v \\
A x \geq b & A^{\prime} v-C u=p \\
v \geq 0
\end{array}
$$

Type III

$$
\begin{array}{cc}
\operatorname{Min} \frac{1}{2} x^{\prime} C x+p^{\prime} x & \operatorname{Max}-\frac{1}{2} u^{\prime} C u+b^{\prime} v \\
A x=b & A^{\prime} v-C u \leq p \\
x \geq 0 &
\end{array}
$$

Type IV

$$
\begin{array}{cc}
\operatorname{Min} \frac{1}{2} x^{\prime} C x+p^{\prime} x & \operatorname{Max}-\frac{1}{2} u^{\prime} C u+b^{\prime} v \\
A x=b & A^{\prime} v-C u=p
\end{array}
$$

The Type IV problem may, of course, be treated by standard Lagrange multiplier techniques. The dual problem for a problem of this type has been given previously [10]. Indeed, $v$ are the multipliers for the original problem.

Notice that at the optimum, in all types listed above,

$$
\begin{equation*}
u=x . \tag{7.1}
\end{equation*}
$$

8. An application to elasticity. As an application of the duality theorem for quadratic programs, consider the problem of determining the elastic solution of a plane pin-jointed truss consisting of $n$ bars and $m$ joints ( $n \geq 2 m-3$ ). The truss is externally statically determinate and the applied loads lie in the plane of the truss.

The problem may be formulated as minimizing the strain energy subject to equilibrium constraints (Castigliano's Second Theorem).

If $S_{i}$ denotes the force in the $j$ th member and $A_{i}, E_{i}, L_{i}$ are its cross-sectional area, elastic modulus and length respectively, then the strain energy $U$ is

$$
U=\frac{1}{2} \sum_{i=1}^{n} \frac{L_{i}}{A_{i} E_{i}} S_{i}^{2}
$$

and the equilibrium conditions may be written [11]

$$
\sum_{i=1}^{n} a_{i i} S_{i}=F_{i} \quad(i=1,2, \cdots, 2 m-3)
$$

where $F_{i}$ is the force component at the $i$ th joint. The $a_{i i}$ depend on the geometrical configuration and are essentially direction cosines of the angles between the bars and the coordinate axes.

This is a problem of Type IV and the dual problem to this minimum problem is from Sec. 7

$$
\text { Maximize: } \quad-\frac{1}{2} \sum_{i=1}^{n} \frac{L_{j}}{A_{j} E_{j}} S_{i}^{2}+\sum_{i=1}^{2 m-3} F_{i} u_{i}
$$

subject to

$$
\sum_{i=1}^{2 m-3} a_{i j} u_{i}-\frac{L_{j}}{A_{i} E_{i}} S_{i}=0 \quad(j=1,2, \cdots, n)
$$

The use of the variables $S_{i}$ in the dual is justified by Eq. (7.1). Making use of Hooke's law which gives the elongation, $e_{j}$, of the $j$ th bar as

$$
e_{i}=\frac{L_{i}}{A_{i} E_{i}} S_{i}
$$

the problem becomes

$$
\text { Maximize: } \quad-\frac{1}{2} \sum_{i=1}^{n} \frac{A_{j} E_{i}}{L_{i}} e_{i}^{2}+\sum_{i=1}^{2 m-3} F_{i} u_{i}
$$

subject to

$$
\sum_{i=1}^{2 m-3} a_{i j} u_{i}-e_{j}=0 \quad(j=1,2, \cdots, n)
$$

If, for the moment it is assumed that the $u$, are the displacement components of the $i$ th joint, the objective function for the dual problem is the negative of the total potential energy and the constraints become the compatibility equations. The dual problem is, therefore, equivalent to the Theorem of Minimum Potential Energy. The equality of the objective functions results in a restatement of the Principle of Virtual Work.

Other applications to electrical networks containing resistors, diodes and voltage and current sources may be found in [6].

## Bibliography

1. E. M. L. Beale, On minimizing a convex function subject to linear inequalities, J. Roy. Statistical Soc. (Ser. B) 17, 173-177 (1955)
2. A. Charnes and C. E. Lemke, The continuous limit method I; minimization of convex functionals over convex polyhedra; presented at Am. Math. Soc. Meeting, Cambridge, Mass., Aug. 1958
3. M. Frank and P. Wolfe, An algorithm for quadratic programming, Naval Research Log. Quart. 3, 95-110 (March-June 1956)
4. C. Hildreth, A quadratic programming procedure, Naval Research Log. Quart. 4, 79-85 (March 1957)
5. Philip Wolfe, The simplex method for quadratic programming, RAND Rep. P-1205, Oct. 1957
6. Jack B. Dennis, A dual problem for a class of quadratic programs, MIT Research Note No. 1, Nov. 1957
7. H. W. Kuhn and A. W. Tucker, Nonlinear programming, Proc. 2nd Berkeley Symposium on Math. Statistics and Probability, 481-492, 1951
8. D. Gale, H. W. Kuhn and A. W. Tucker, Linear programming and the theory of games, Chap. XIX of Activity analysis of products and allocation, Cowles Commission Monograph 13, John Wiley and Sons, New York, 1951
9. G. B. Dantzig and A. Orden, A duality theorem based on the simplex method, Symposium on Linear Inequalities and Programming, Project SCOOP, 51-55, 1951
10. R. Courant and D. Hilbert, Methods of mathematical physics, Interscience, New York, 1953
11. J. Nielsen, Vorlesungen über elementare Mechanik, Julius Springer, Berlin, 1935

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