



The Homogeneous Self-Dual Method

Robert J. Vanderbei

December 14, 2005
ORF 522

[Home Page](#)

[Title Page](#)

[Contents](#)



Page 1 of 16

[Go Back](#)

[Full Screen](#)

[Close](#)

[Quit](#)

Operations Research and Financial Engineering, Princeton University

<http://www.princeton.edu/~rvdb>

The Homogeneous Self-Dual Problem



Primal-Dual Pair

$$\begin{array}{ll} \text{maximize} & c^T x \\ \text{subject to} & Ax \leq b \\ & x \geq 0 \end{array}$$

$$\begin{array}{ll} \text{minimize} & b^T y \\ \text{subject to} & A^T y \geq c \\ & y \geq 0 \end{array}$$

Homogeneous Self-Dual Problem

$$\begin{array}{ll} \text{maximize} & 0 \\ \text{subject to} & -A^T y + c\phi \leq 0 \\ & Ax - b\phi \leq 0 \\ & -c^T x + b^T y \leq 0 \\ & x, \quad y, \quad \phi \geq 0 \end{array}$$

[Home Page](#)

[Title Page](#)

[Contents](#)



Page 2 of 16

[Go Back](#)

[Full Screen](#)

[Close](#)

[Quit](#)

In Matrix Notation

$$\begin{array}{ll} \text{maximize} & 0 \\ \text{subject to} & \begin{bmatrix} 0 & -A^T & c \\ A & 0 & -b \\ -c^T & b^T & 0 \end{bmatrix} \begin{bmatrix} x \\ y \\ \phi \end{bmatrix} \leq \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix} \\ & x, y, \phi \geq 0. \end{array}$$

HSD is self-dual (constraint matrix is skew symmetric).

HSD is feasible ($x = 0, y = 0, \phi = 0$).

HSD is homogeneous—i.e., multiplying a feasible solution by a positive constant yields a new feasible solution.

Any feasible solution is optimal.

If ϕ is a null variable, then either primal or dual is infeasible (see text).



[Home Page](#)

[Title Page](#)

[Contents](#)



[Page 3 of 16](#)

[Go Back](#)

[Full Screen](#)

[Close](#)

[Quit](#)

Theorem. Let (x, y, ϕ) be a solution to HSD. If $\phi > 0$, then

- $x^* = x/\phi$ is optimal for primal, and
- $y^* = y/\phi$ is optimal for dual.

Proof.

x^* is primal feasible—obvious.

y^* is dual feasible—obvious.

Weak duality theorem implies that $c^T x^* \leq b^T y^*$.

3rd HSD constraint implies reverse inequality.

Primal feasibility, plus dual feasibility, plus no gap implies optimality.



[Home Page](#)

[Title Page](#)

[Contents](#)



Page 4 of 16

[Go Back](#)

[Full Screen](#)

[Close](#)

[Quit](#)

Change of Notation

$$\begin{bmatrix} 0 & -A^T & c \\ A & 0 & -b \\ -c^T & b^T & 0 \end{bmatrix} \longrightarrow A \quad \begin{bmatrix} x \\ y \\ \phi \end{bmatrix} \longrightarrow x \quad n + m + 1 \longrightarrow n$$

In New Notation:

$$\begin{array}{ll} \text{maximize} & 0 \\ \text{subject to} & Ax + z = 0 \\ & x, z \geq 0 \end{array}$$



[Home Page](#)

[Title Page](#)

[Contents](#)



Page 5 of 16

[Go Back](#)

[Full Screen](#)

[Close](#)

[Quit](#)



More Notation

$$\begin{aligned} \text{Infeasibility:} \quad & \rho(x, z) = Ax + z \\ \text{Complementarity:} \quad & \mu(x, z) = \frac{1}{n}x^T z \end{aligned}$$

Nonlinear System

$$\begin{aligned} A(x + \Delta x) + (z + \Delta z) &= \delta(Ax + z) \\ (X + \Delta X)(Z + \Delta Z)e &= \delta\mu(x, z)e \end{aligned}$$

Linearized System

$$\begin{aligned} A\Delta x + \Delta z &= -(1 - \delta)\rho(x, z) \\ Z\Delta x + X\Delta z &= \delta\mu(x, z)e - XZe \end{aligned}$$

[Home Page](#)[Title Page](#)[Contents](#)[Page 6 of 16](#)[Go Back](#)[Full Screen](#)[Close](#)[Quit](#)

Algorithm

Solve linearized system for $(\Delta x, \Delta z)$.

Pick step length θ .

Step to a new point:

$$\bar{x} = x + \theta \Delta x, \quad \bar{z} = z + \theta \Delta z.$$

Even More Notation

$$\bar{\rho} = \rho(\bar{x}, \bar{z}), \quad \bar{\mu} = \mu(\bar{x}, \bar{z})$$



[Home Page](#)

[Title Page](#)

[Contents](#)



Page 7 of 16

[Go Back](#)

[Full Screen](#)

[Close](#)

[Quit](#)

Theorem 2

1. $\Delta z^T \Delta x = 0.$
2. $\bar{\rho} = (1 - \theta + \theta\delta)\rho.$
3. $\bar{\mu} = (1 - \theta + \theta\delta)\mu.$
4. $\bar{X}\bar{Z}e - \bar{\mu}e = (1 - \theta)(XZe - \mu e) + \theta^2\Delta X\Delta Ze.$

Proof.

1. Tedious but not hard (see text).
- 2.

$$\begin{aligned}\bar{\rho} &= A(x + \theta\Delta x) + (z + \theta\Delta z) \\ &= Ax + z + \theta(A\Delta x + \Delta z) \\ &= \rho - \theta(1 - \delta)\rho \\ &= (1 - \theta + \theta\delta)\rho.\end{aligned}$$



[Home Page](#)

[Title Page](#)

[Contents](#)



Page 8 of 16

[Go Back](#)

[Full Screen](#)

[Close](#)

[Quit](#)



3.

$$\begin{aligned}\bar{x}^T \bar{z} &= (x + \theta \Delta x)^T (z + \theta \Delta z) \\ &= x^T z + \theta (z^T \Delta x + x^T \Delta z) + \theta^2 \Delta x^T \Delta z \\ &= x^T z + \theta e^T (\delta \mu e - X Z e) \\ &= (1 - \theta + \theta \delta) x^T z.\end{aligned}$$

Now, just divide by n .

4.

$$\begin{aligned}\bar{X} \bar{Z} e - \bar{\mu} e &= (X + \theta \Delta X)(Z + \theta \Delta Z) e - (1 - \theta + \theta \delta) \mu e \\ &= X Z e - \mu e + \theta (X \Delta z + Z \Delta x + (1 - \delta) \mu e) + \theta^2 \Delta X \Delta Z e \\ &= (1 - \theta)(X Z e - \mu e) + \theta^2 \Delta X \Delta Z e.\end{aligned}$$

[Home Page](#)

[Title Page](#)

[Contents](#)



Page 9 of 16

[Go Back](#)

[Full Screen](#)

[Close](#)

[Quit](#)

Neighborhoods of $\{(x, z) > 0 : x_1 z_1 = x_2 z_2 = \cdots = x_n z_n\}$

$$\mathcal{N}(\beta) = \{(x, z) > 0 : \|XZe - \mu(x, z)e\| \leq \beta\mu(x, z)\}$$

Note: $\beta < \beta'$ implies $\mathcal{N}(\beta) \subset \mathcal{N}(\beta')$.

Predictor-Corrector Algorithm

Odd Iterations–Predictor Step

Assume $(x, z) \in \mathcal{N}(1/4)$.

Compute $(\Delta x, \Delta z)$ using $\delta = 0$.

Compute θ so that $(\bar{x}, \bar{z}) \in \mathcal{N}(1/2)$.

Even Iterations–Corrector Step

Assume $(x, z) \in \mathcal{N}(1/2)$.

Compute $(\Delta x, \Delta z)$ using $\delta = 1$.

Put $\theta = 1$.

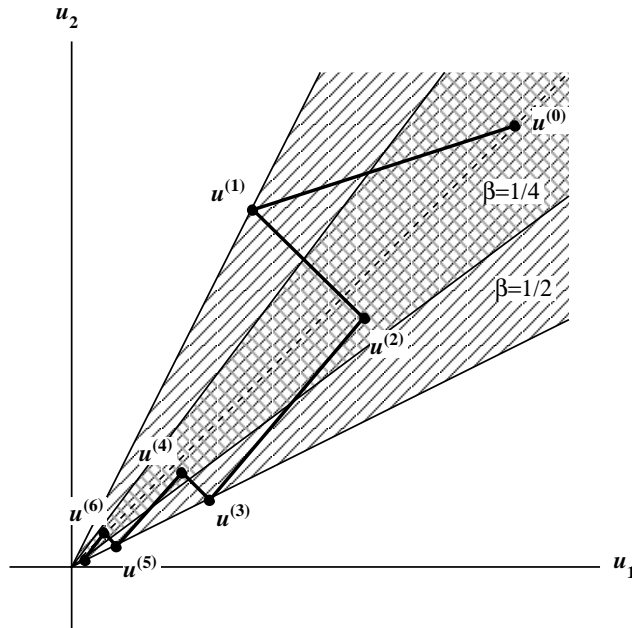
[Home Page](#)[Title Page](#)[Contents](#)[Page 10 of 16](#)[Go Back](#)[Full Screen](#)[Close](#)[Quit](#)

Predictor-Corrector Algorithm

In Complementarity Space

Let

$$u_j = x_j z_j \quad j = 1, 2, \dots, n.$$



[Home Page](#)

[Title Page](#)

[Contents](#)



Page 11 of 16

[Go Back](#)

[Full Screen](#)

[Close](#)

[Quit](#)

Well-Definedness of Algorithm



[Home Page](#)

[Title Page](#)

[Contents](#)



Page 12 of 16

[Go Back](#)

[Full Screen](#)

[Close](#)

[Quit](#)

Must check that preconditions for each iteration are met.

Technical Lemma.

1. If $\delta = 0$, then $\|\Delta X \Delta Z e\| \leq \frac{n}{2} \mu$.

2. If $\delta = 1$ and $(x, z) \in \mathcal{N}(\beta)$, then $\|\Delta X \Delta Z e\| \leq \frac{\beta^2}{1-\beta} \mu / 2$.

Proof. Tedious **and** tricky. See text.

Theorem.

1. After a predictor step, $(\bar{x}, \bar{z}) \in \mathcal{N}(1/2)$ and $\bar{\mu} = (1 - \theta)\mu$.
2. After a corrector step, $(\bar{x}, \bar{z}) \in \mathcal{N}(1/4)$ and $\bar{\mu} = \mu$.

Proof.

1. $(\bar{x}, \bar{z}) \in \mathcal{N}(1/2)$ by definition of θ .

$$\bar{\mu} = (1 - \theta)\mu \text{ since } \delta = 0.$$

2. $\theta = 1$ and $\beta = 1/2$. Therefore,

$$\|\bar{X}\bar{Z}e - \bar{\mu}e\| = \|\Delta X \Delta Z e\| \leq \mu/4.$$

Need to show also that $(\bar{x}, \bar{z}) > 0$. Intuitively clear (see earlier picture) but proof is tedious. See text.



[Home Page](#)

[Title Page](#)

[Contents](#)



Page 13 of 16

[Go Back](#)

[Full Screen](#)

[Close](#)

[Quit](#)

Complexity Analysis

Progress toward optimality is controlled by the stepsize θ .

Theorem. In predictor steps, $\theta \geq \frac{1}{2\sqrt{n}}$.

Proof.

Consider taking a step with step length $t \leq 1/2\sqrt{n}$:

$$x(t) = x + t\Delta x, \quad z(t) = z + t\Delta z.$$

From earlier theorems and lemmas,

$$\begin{aligned} \|X(t)Z(t)e - \mu(t)e\| &\leq (1-t)\|XZe - \mu e\| + t^2\|\Delta X\Delta Ze\| \\ &\leq (1-t)\frac{\mu}{4} + t^2\frac{n\mu}{2} \\ &\leq (1-t)\frac{\mu}{4} + \frac{\mu}{8} \\ &\leq (1-t)\frac{\mu}{4} + (1-t)\frac{\mu}{4} \\ &= \frac{\mu(t)}{2}. \end{aligned}$$

Therefore $(x(t), z(t)) \in \mathcal{N}(1/2)$ which implies that $\theta \geq 1/2\sqrt{n}$.



[Home Page](#)

[Title Page](#)

[Contents](#)



Page 14 of 16

[Go Back](#)

[Full Screen](#)

[Close](#)

[Quit](#)

Since

$$\mu^{(2k)} = (1 - \theta^{(2k-1)})(1 - \theta^{(2k-3)}) \dots (1 - \theta^{(1)})\mu^{(0)}$$

and $\mu^{(0)} = 1$, we see from the previous theorem that

$$\mu^{(2k)} \leq \left(1 - \frac{1}{2\sqrt{n}}\right)^k.$$

Hence, to get a small number, say 2^{-L} , as an upper bound for $\mu^{(2k)}$ it suffices to pick k so that:

$$\left(1 - \frac{1}{2\sqrt{n}}\right)^k \leq 2^{-L}.$$

This inequality is implied by the following simpler one:

$$k \geq 2 \log(2) L \sqrt{n}.$$

Since the number of iterations is $2k$, we see that $4 \log(2) L \sqrt{n}$ iterations will suffice to make the final value of μ be less than 2^{-L} .

Of course,

$$\rho^{(k)} = \mu^{(k)} \rho^{(0)}$$

so the same bounds guarantee that the final infeasibility is small too.



[Home Page](#)

[Title Page](#)

[Contents](#)



Page 15 of 16

[Go Back](#)

[Full Screen](#)

[Close](#)

[Quit](#)

Back to Original Primal-Dual Setting

Just a final remark: If primal and dual problems are feasible, then algorithm will produce a solution to HSD with $\phi > 0$ from which a solution to original problem can be extracted.

See text for details.



[Home Page](#)

[Title Page](#)

[Contents](#)



Page 16 of 16

[Go Back](#)

[Full Screen](#)

[Close](#)

[Quit](#)