

Interior-Point Method.

Suppose $X^{(0)}, (y^{(0)}, S^{(0)})$ are given Slater points for (P) and (D) respectively. Will generate $\{X^{(k)}, (y^{(k)}, S^{(k)})\}$ pair of primal-dual Slater points such that $\langle X^{(k)}, S^{(k)} \rangle \rightarrow 0$.

To remove the "difficult part" of SDP, we treat the constraint $X \succeq 0$ as a barrier function

$$f(X) = -\ln(\det(X)) = \sum_{j=1}^n -\ln(x_j),$$

domain of f will be

$$\text{dom}(f) = \{X \in \mathcal{S}_+^n; X \succ 0\}.$$

If we have a sequence $\{X^{(k)}\} \subset \mathcal{S}_+^n$ such that $X^{(k)} \rightarrow \bar{X} \in \text{bd}(\mathcal{S}_+^n)$ then $f(X^{(k)}) \rightarrow \infty$.

$f(X)$ is finite on \mathcal{S}_{++}^n .

For every $\mu > 0$, consider

$$(P_\mu) \quad \begin{aligned} & \inf_{\mu} \langle C, X \rangle + f(X) \\ & A(X) = b. \end{aligned}$$

We hope as $\mu \rightarrow 0^+$, optimal solutions of (P_μ) converge to an optimal solution of (P).

Proposition 4.1: With the above definition for f , for every $X \in \mathcal{S}_{++}^n$ and every $H \in \mathcal{S}_+^n$, we have:

$$(a) \quad \langle f'(X), H \rangle = -\langle X^{-1}, H \rangle;$$

$$(b) \quad f''(X)[H, H] = \text{Tr}((X^{-1/2} H X^{-1/2})^2);$$

$$(c) \quad f'''(X)[H, H, H] = -2 \text{Tr}((X^{-1/2} H X^{-1/2})^3).$$

(see textbook)

Think about LP:

$$\min_{\mu} \langle C, X \rangle - \sum_{j=1}^n \mu \ln(x_j)$$

$$A X = b$$

$$f(x_j) = -\ln(x_j)$$

$$f'(x_j) = -1/x_j$$

$$f''(x_j) = 1/x_j^2$$

$$f'''(x_j) = -2/x_j^3$$

By the previous proposition, $f(X)$ is strictly convex on \mathcal{S}_{++}^n ($f''(X)$ is positive definite).

Under our assumptions, (P_μ) has a unique solution for every $\mu > 0$.

Apply KKT to (P_μ) . The unique optimal solution is characterized by

$$\begin{cases} A(X) = b, & X \succ 0 \\ \mu C + f'(X) - A^*(y) = 0, \end{cases}$$

$$\Leftrightarrow \begin{cases} A(X) = b, & X \succ 0 \\ A^*(\mu y) + \mu X^{-1} = C. \end{cases}$$

Redefine $y \leftarrow \mu y$

$$\Leftrightarrow \begin{cases} A(X) = b, & X \succ 0 \\ A^*(y) + S = C, & S = \mu X^{-1}. \end{cases}$$

If $\mu \rightarrow 0^+$, then
 $\langle X, S \rangle = \mu \langle X^{-1}, X \rangle = n\mu \rightarrow 0$

Under the assumptions that both (P) & (D) have Slater points, and A is onto,
 for every $\mu > 0$,

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$$(P_\mu) \quad \inf \frac{1}{\mu} \langle C, X \rangle - \ln \det X$$

$$A(X) = b, \quad (X \in \mathcal{S}_{++}^n)$$

has a unique solution $X(\mu)$ which corresponds to a unique solution
 $(X(\mu), y(\mu), S(\mu))$ of

$$\begin{aligned} A(X) &= b, \quad X \succ 0 \\ A^T(y) + S &= C \\ S &= \mu X^{-1} \end{aligned}$$

$\{(X(\mu), y(\mu), S(\mu)); \mu > 0\}$ ← primal-dual central path

(goes off to ∞ if feasibility region unbd)

We can follow this path approximately as $\mu \rightarrow 0^+$. If we have a point $(X(\mu), S(\mu))$ on
 the central path, then

$$S(\mu) = \mu X(\mu)^{-1}$$

and

$$\langle X(\mu), S(\mu) \rangle = n\mu.$$

We will extend this to arbitrary pairs $X, S \in \mathcal{S}_+^n$ and define "their μ " by

$$\mu := \frac{\langle X, S \rangle}{n}.$$

Given $X, S \in \mathcal{S}_{++}^n$, a measure of centrality is

$$\psi(X, S) := n \ln \left(\frac{\langle X, S \rangle}{n} \right) - \ln \det X - \ln \det S$$

Theorem 4.2: For every $X, S \in \mathcal{S}_{++}^n$, we have $\psi(X, S) \geq 0$. The equality holds if and
 only if $S = \mu X^{-1}$, where

$$\mu = \frac{\langle X, S \rangle}{n}.$$

Proof: Note

$$\langle X, S \rangle - \text{Indet } X \geq \inf_{X \in \mathcal{S}_{++}^n} \{ \langle S, X \rangle - \text{Indet}(X) \}$$

for all $X, S \in \mathcal{S}_{++}^n$. Hence attained at $X = S^{-1}$

$$\langle X, S \rangle - \text{Indet } X \geq \langle S, S^{-1} \rangle - \text{Indet}(S^{-1})$$

for all $X, S \in \mathcal{S}_{++}^n$, and inequality holds if and only if $S = X^{-1}$. \square

$$\langle X, S \rangle - \text{Indet } X - \text{Indet } S - n \geq 0$$

for all $X, S \in \mathcal{S}_{++}^n$. \square

$$\langle \alpha_1 X, \alpha_2 S \rangle - \text{Indet}(\alpha_1 X) - \text{Indet}(\alpha_2 S) - n \geq 0$$

for all $X, S \in \mathcal{S}_{++}^n$, $\alpha_1, \alpha_2 > 0$, and equality holds iff $\alpha_1 \alpha_2 X = S^{-1}$. \square

$$\alpha_1 \alpha_2 \langle X, S \rangle - n \ln(\alpha_1 \alpha_2) - \text{Indet}(X) - \text{Indet}(S) - n \geq 0$$

Define $t = \alpha_1 \alpha_2 > 0$, and minimize the LHS w.r.t t . Well $t \langle X, S \rangle - n \ln t$ is strictly convex, and is uniquely minimized at $t = \frac{n}{\langle X, S \rangle}$. Therefore (substituting $t = \frac{n}{\langle X, S \rangle}$),

$$\frac{n}{\langle X, S \rangle} \langle X, S \rangle + n \ln \left(\frac{\langle X, S \rangle}{n} \right) - \text{Indet } X - \text{Indet } S - n \geq 0,$$

and equality holds if and only if $tX = S^{-1}$ if and only if $S = \mu X^{-1}$. \square

This result, among other things, gives a spectral generalization of arithmetic-geometric mean inequalities applied to eigenvalues of $X^{1/2} S X^{1/2}$.

To design some algorithms, we can focus on two criteria:

- We want $\langle X, S \rangle$ to be small.
- We want to be close to the central path, i.e. we want $\sqrt{\langle X, S \rangle}$ small.

We consider putting them together in a single function

$$\psi(X, S) = \sqrt{n} \ln \langle X, S \rangle + \sqrt{\langle X, S \rangle},$$

potential function

Theorem 4.5: Suppose $X^{(0)}, S^{(0)}$ Slater points for (P) & (D) respectively are given such that for given $\epsilon > 0$ and $\epsilon \in (0, 1)$, $\sqrt{\langle X^{(0)}, S^{(0)} \rangle} \leq \sqrt{n} \ln(1/\epsilon)$. Further assume that in each iteration, we decrease the value of $\psi(X, S)$ by an absolute constant $\delta > 0$, then for some $\bar{k} = O(\sqrt{n} \ln(1/\epsilon))$, we have

$$\langle X^{(k)}, S^{(k)} \rangle \leq \epsilon \langle X^{(0)}, S^{(0)} \rangle \quad \forall k \geq \bar{k}.$$

Proof: Suppose $\varphi(X^{(k+1)}, S^{(k+1)}) \leq \varphi(X^{(k)}, S^{(k)}) - \delta \quad \forall k \geq 0$. After k iterations,

$$\varphi(X^{(k)}, S^{(k)}) \leq \varphi(X^{(0)}, S^{(0)}) - k\delta$$

$$\Leftrightarrow \sqrt{n} \ln \left(\frac{\langle X^{(k)}, S^{(k)} \rangle}{\langle X^{(0)}, S^{(0)} \rangle} \right) + \underbrace{\psi(X^{(k)}, S^{(k)}) - \psi(X^{(0)}, S^{(0)})}_{\geq 0 \text{ by thm 4.2}} \leq -k\delta$$

$\geq -\sqrt{n} \ln(1/\epsilon)$

$$\Rightarrow \sqrt{n} \ln \left(\frac{\langle X^{(k)}, S^{(k)} \rangle}{\langle X^{(0)}, S^{(0)} \rangle} \right) \leq -k\delta + \sqrt{n} \ln(1/\epsilon)$$

For $k \geq 3$,

$$k \geq 3 \frac{\sqrt{n}}{\delta} \ln(1/\epsilon),$$

we obtain the desired ~~conclusion~~ result

Our task is reduced to finding a way of updating $(X^{(k)}, S^{(k)}) \rightarrow (X^{(k+1)}, S^{(k+1)})$ st $\varphi(\cdot, \cdot)$ decreases.

We have Slater points X, S for (P) & (D). We want an algorithm that will be invariant under the automorphisms of the cones S_+^n and under switching the roles of (P) & (D). Let $T \in \text{Aut}(S_+^n)$ (self-adjoint). Given (P), consider

$$\begin{array}{l} \text{Dual} \\ \text{Primal} \end{array} \quad \begin{array}{l} S_+^n \rightarrow T(S_+^n) = S_+^n \\ S_+^n \rightarrow T^{-1}(S_+^n) = S_+^n \end{array}$$

$$X \rightarrow T^{-1}(X), \quad \bar{A}(\cdot) = A(T(\cdot)), \quad \bar{C} = T(C)$$

(P) becomes (\bar{P})

(D) becomes (\bar{D})

$$\begin{array}{l} \inf \langle \bar{C}, X \rangle \\ \bar{A}(X) = b \\ X \in S_+^n \end{array}$$

$$\begin{array}{l} \sup b^T y \\ \bar{A}^*(y) + S = \bar{C} \\ S \in S_+^n \end{array}$$

Given any pair $X, S \in \mathcal{S}_{++}^n$, we want to construct $T: \mathcal{S}_{++}^n \rightarrow \mathcal{S}_{++}^n$ linear, self-adjoint (symmetric matrix), positive definite, and

$$(i) T(S) = T^{-1}(X) =: V$$

$$(ii) T(X^{-1}) = T^{-1}(S^{-1}) = V^{-1}$$

$$(iii) T \in \text{Aut}(\mathcal{S}_{++}^n)$$

Such T exists!

Consider $T(\cdot) = W \cdot W$ for some $W \in \mathcal{S}_{++}^n$.

(iii) ✓

$$(i) WSW = W^{-1}XW^{-1} \Leftrightarrow W^2SW^2 = X$$

$$\Leftrightarrow S^{1/2}W^2SW^2S^{1/2} = S^{1/2}XS^{1/2}$$

$$\Leftrightarrow (S^{1/2}W^2S^{1/2})(S^{1/2}W^2S^{1/2}) = S^{1/2}XS^{1/2}$$

$$\Leftrightarrow S^{1/2}W^2S^{1/2} = (S^{1/2}XS^{1/2})^{1/2}$$

$$\Leftrightarrow W^2 = S^{-1/2}(S^{1/2}XS^{1/2})^{1/2}S^{-1/2}$$

To verify (ii), note

$$\begin{aligned} WSW = W^{-1}XW^{-1} &\Leftrightarrow \underbrace{W^{-1}S^{-1}W^{-1}}_{T^{-1}(S^{-1})} = \underbrace{WX^{-1}W}_{T(X^{-1})} = V^{-1} \\ \Downarrow & \\ \Downarrow & \end{aligned}$$

$$(X, S) \rightarrow (T^{-1}(X), T(S)) = (V, V)$$

We have $(X^{(k)}, S^{(k)})$ we want to compute $(X^{(k+1)}, S^{(k+1)})$.

$$D_x := X^{(k+1)} - X^{(k)}, \quad D_s := S^{(k+1)} - S^{(k)}$$

$$A(X^{(k)}) = A(X^{(k+1)}) = b \Leftrightarrow D_x \in \text{Null}(A)$$

$$A^*(y^{(k)}) + S^{(k)} = A^*(y^{(k+1)}) + S^{(k+1)} = c \Leftrightarrow D_s \in \text{Range}(A^*)$$

$$\Rightarrow \langle D_x, D_s \rangle = 0$$

We want $(X^{(k+1)}, S^{(k+1)})$ to have a smaller potential function value.

(i) We want smaller $\langle X, S \rangle$

$$X(\alpha) := X^{(k)} + \alpha D_x, \quad S(\alpha) := S^{(k)} + \alpha D_s$$

$$\langle X(\alpha), S(\alpha) \rangle = \langle X, S \rangle + \alpha(\langle D_x, S \rangle + \langle X, D_s \rangle) + \alpha^2 \langle D_x, D_s \rangle$$

Consider T : Primal Space is mapped under T^{-1}

Dual Space $\quad \quad \quad T$

$$\begin{aligned} \bar{D}_x &:= T^{-1}(D_x), \quad \bar{D}_s := T^{-1}(D_s) \\ \langle X(\alpha), S(\alpha) \rangle &= \langle X, S \rangle + \alpha \left(\underbrace{\langle T^{-1}(D_x), T(S) \rangle}_{=V} + \underbrace{\langle T^{-1}(X), T(D_x) \rangle}_{=V} \right) \\ &= \langle X, S \rangle + \alpha \langle V, \bar{D}_x + \bar{D}_s \rangle \end{aligned}$$

Largest decrease in the duality gap is obtained by setting $\bar{D}_x + \bar{D}_s = -V$.

(ii) The potential function has a "barrier part" $f(x) + f(s)$

Lemma 4.6: Let $X \in \mathcal{S}_{++}^n$. Suppose $D \in \mathcal{S}^n$ satisfies

$$\|D\|_X := \langle D, X^{-1}DX^{-1} \rangle^{1/2} < 1.$$

Then

$$f(x) + \langle f'(x), D \rangle \leq f(x+D) \leq f(x) + \langle f'(x), D \rangle + \frac{\|D\|_X^2}{2(1-\|D\|_X)^2}.$$

\uparrow is in $\text{dom}(f)$ by below

Note that

$$\|D\|_X \leq 1 \Rightarrow X \pm D \in \mathcal{S}_+^n$$

$$\|D\|_X < 1 \Rightarrow X \pm D \in \mathcal{S}_{++}^n$$

$$\|D\|_X^2 = \|X^{-1/2}DX^{-1/2}\|_F^2$$

$$\|D\|_X \leq 1 \Rightarrow \|X^{1/2}DX^{1/2}\|_2 \leq 1 \Rightarrow I \mp X^{1/2}DX^{1/2} \succeq 0$$

$$\Leftrightarrow X \mp D \succeq 0 \quad \text{or} \quad X^{1/2} \cdot X^{1/2} \in \text{Aut}(\mathcal{S}_+^n)$$

Let's analyze how the barrier terms change as we move $(X, S) \rightarrow (X(\alpha), S(\alpha))$.

Let's use the first-order estimate given by Lemma 4.6:

$$\begin{aligned} \langle f'(X), D_x \rangle + \langle f'(S), D_s \rangle &= \langle -X^{-1}, D_x \rangle + \langle -S^{-1}, D_s \rangle \\ &= -\langle \underbrace{T(X^{-1})}_{V^{-1}}, \underbrace{T^{-1}(D_x)}_{\bar{D}_x} \rangle - \langle \underbrace{T^{-1}(S^{-1})}_{V^{-1}}, \underbrace{T(D_s)}_{\bar{D}_s} \rangle \\ &= \langle -V^{-1}, \bar{D}_x + \bar{D}_s \rangle \end{aligned}$$

To have the largest rate of decrease with respect to first-order estimate of the change in the barrier part, we pick $\bar{D}_x + \bar{D}_s = -V^{-1}$.

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Recall $\bar{A}(\cdot) = A(T(\cdot))$. Then (\bar{D}_x, \bar{D}_s) is the unique solution of

$$\begin{aligned}\bar{A}(\bar{D}_x) &= 0 \\ \bar{A}'(\bar{D}_x) + \bar{D}_s &= 0 \\ \bar{D}_x + \bar{D}_s &= \tilde{u},\end{aligned}$$

where

$$\tilde{u} = -\left(\frac{n+\sqrt{n}}{\langle X, S \rangle}\right) V + V^{-1}$$

We need one more tool.

$$\tilde{\mu} = \frac{\langle X^{-1}, S^{-1} \rangle}{n}$$

Note

$$\mu = \frac{\langle X, S \rangle}{n} = \frac{\langle T^{-1}(X), T(S) \rangle}{n} = \frac{\langle V, V \rangle}{n}$$

$$\tilde{\mu} = \frac{\langle X^{-1}, S^{-1} \rangle}{n} = \frac{\langle T(X^{-1}), T(S^{-1}) \rangle}{n} = \frac{\langle V^{-1}, V^{-1} \rangle}{n}$$

Theorem 4.8: For every pair $X, S \in \mathbb{S}_{++}^n$, $\mu \tilde{\mu} \geq 1$. Moreover, equality holds if and only if $S = \mu X^{-1}$.

$$\begin{aligned}\text{Proof: } 0 &\leq \frac{\langle T(S - \mu X^{-1}), T(S - \mu X^{-1}) \rangle}{n\mu} = \frac{\langle V - \mu V^{-1}, V - \mu V^{-1} \rangle}{n\mu} \\ &= \frac{1}{n\mu} (n\mu - 2n\mu + \mu^2 n\tilde{\mu}) = \mu \tilde{\mu} - 1.\end{aligned}$$

Equality holds if and only if $T(S - \mu X^{-1}) = 0 \Leftrightarrow S = \mu X^{-1}$. \square

$$\begin{aligned}\|\tilde{u}\|_F^2 &= \langle \tilde{u}, \tilde{u} \rangle = \left\langle -\frac{n+\sqrt{n}}{\langle X, S \rangle} V + V^{-1}, -\frac{n+\sqrt{n}}{\langle X, S \rangle} V + V^{-1} \right\rangle \\ &= \frac{1}{\mu} \left(\underbrace{n(\mu\tilde{\mu}-1)}_{>0} + \underbrace{1}_{>0 \text{ by 4.8}} \right) > 0.\end{aligned}$$

$$u := \frac{\tilde{u}}{\|\tilde{u}\|_F}, \text{ so that } \|u\|_F = 1.$$

Redefine (\bar{D}_x, \bar{D}_s) as the unique solution of

$$\begin{cases} \bar{D}_x \in \text{Null}(\bar{A}), \bar{D}_s \in \text{Range}(\bar{A}^*) \\ \bar{D}_x + \bar{D}_s = u \end{cases}$$

Note $\|u\|_F = 1 \Rightarrow \|\bar{D}_x\|_F, \|\bar{D}_s\|_F \leq 1$.

Primal Dual Interior Point Algorithm

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Given $X^{(0)} \succ 0, S^{(0)} \succ 0$ feasible in (P) and (D) respectively, such that for given $\epsilon \in (0, 1)$ we have

$$\psi(X^{(0)}, S^{(0)}) \leq \sqrt{n} \ln(1/\epsilon).$$

Set

$$k := 0$$

WHILE

$$\langle X^{(k)}, S^{(k)} \rangle > \epsilon \langle X^{(0)}, S^{(0)} \rangle$$

DO

side-notes:

$$X := X^{(k)}$$

$$S := S^{(k)}$$

$$W^2 := S^{-1/2} (S^{1/2} X S^{1/2})^{1/2} S^{-1/2}$$

$$\bar{A}(\cdot) = A(W \cdot W)$$

$$[\bar{A}_i = W A_i W]$$

$$V := W S W$$

$$\tilde{u} := - \left(\frac{n + \sqrt{n}}{\langle X, S \rangle} \right) V + V^{-1}$$

$$u := \frac{1}{\|u\|_F} \tilde{u}$$

Solve the system

$$\begin{cases} \bar{A}(\bar{D}_x) = 0 \\ \bar{A}^*(\bar{D}_s) + \bar{D}_s = 0 \\ \bar{D}_x + \bar{D}_s = u \end{cases}$$

$$\varphi_n = \varphi - \sqrt{n} \ln \langle X, S \rangle + \psi$$

Compute

$$\bar{\alpha} := \operatorname{argmin} \{ \varphi_n(X + \alpha W \bar{D}_x W, S + \alpha W^{-1} \bar{D}_s W^{-1}); \alpha > 0 \}$$

$$X^{(k+1)} := X + \bar{\alpha} W \bar{D}_x W$$

$$S^{(k+1)} := S + \bar{\alpha} W^{-1} \bar{D}_s W^{-1}$$

$$k := k + 1$$

END WHILE

(#)

For the analysis of

$$\frac{\|D_x\|_X^2}{2(1-\|D_x\|_X)^2}$$

we estimate

$$\begin{aligned} \|D_x\|_X^2 &= \langle D_x, X^{-1} D_x X^{-1} \rangle \\ &= \langle W^{-1} D_x W^{-1}, (W X^{-1} W)(W^{-1} D_x W^{-1})(W X^{-1} W) \rangle \\ &= \langle \bar{D}_x, V^{-1} \bar{D}_x V^{-1} \rangle \\ &\leq \|V^{-1} \cdot V^{-1}\|_2 \|\bar{D}_x\|_F^2 \quad (\leq \|V^{-1} \cdot V^{-1}\|_2) \\ &\leq \frac{1}{\lambda_n(V)^2} \end{aligned}$$

and similarly

$$\begin{aligned} \|D_s\|_S^2 &= \langle D_s, S^{-1} D_s S^{-1} \rangle \\ &= \langle \bar{D}_s, V^{-1} \bar{D}_s V^{-1} \rangle \\ &\leq \|V^{-1} \cdot V^{-1}\|_2 \|\bar{D}_s\|_F^2 \\ &\leq \frac{1}{\lambda_n(V)^2} \end{aligned}$$

Lemma 4.11: Let \tilde{u}, V be as before. Then

$$\|\tilde{u}\|_F \geq \frac{\sqrt{3}}{2\lambda_n(V)}.$$

Proof: Note that

$$\tilde{u} = -\left(\frac{n+\sqrt{n}}{\langle X, S \rangle}\right) V + V^{-1} = \left(V^{-1} - \frac{1}{\mu} V\right) - \frac{1}{\sqrt{n}\mu} V$$

and

$$\langle V, V^{-1} - \frac{1}{\mu} V \rangle = 0.$$

Thus

$$\begin{aligned} \|\tilde{u}\|_F^2 &= \|V^{-1} - \frac{1}{\mu} V\|_F^2 + \frac{1}{n\mu^2} \|V\|_F^2, \\ \|V^{-1} - \frac{1}{\mu} V\|_F^2 &= \sum_{k=1}^n \left(\frac{1}{\lambda_k(V)} - \frac{1}{\mu} \lambda_k(V) \right)^2 \\ &\geq \left(\frac{1}{\lambda_n(V)} - \frac{\lambda_n(V)}{\mu} \right)^2 \\ &= \frac{1}{\lambda_n(V)^2} - \frac{2}{\mu} + \frac{\lambda_n(V)^2}{\mu^2}. \end{aligned}$$

So

$$\begin{aligned}
 \|\tilde{\alpha}\|_F^2 &\geq \frac{1}{\lambda_n(V)^2} - \frac{2}{\mu} + \frac{\lambda_n(V)^2}{\mu^2} + \frac{1}{\mu} \\
 &= \frac{1}{\lambda_n(V)^2} - \frac{1}{\mu} + \frac{\lambda_n(V)^2}{\mu^2} \\
 &= \frac{1}{\lambda_n(V)^2} \left(\left(\frac{\lambda_n(V)^4}{\mu^2} - \frac{\lambda_n(V)^2}{\mu} + \frac{1}{4} \right) + \frac{3}{4} \right) \\
 &= \frac{1}{\lambda_n(V)^2} \left(\left(\frac{\lambda_n(V)^2}{\mu} - \frac{1}{2} \right)^2 + \frac{3}{4} \right) \\
 &\geq \frac{3}{4\lambda_n(V)^2}
 \end{aligned}$$

Taking square-roots yields the desired result.

Let's prove that the potential function decreases:

$$\begin{aligned}
 \varphi(X(\alpha), S(\alpha)) - \varphi(X, S) &\stackrel{\text{lemma 4.6}}{\leq} (n+\sqrt{n}) \ln \left(\frac{\langle X(\alpha), S(\alpha) \rangle}{\langle X, S \rangle} \right) - \alpha \langle U, V^{-1} \rangle \\
 &\quad + \alpha^2 \left(\frac{\|D_x\|_x^2}{2(1-\|D_x\|_x)^2} + \frac{\|D_s\|_s^2}{2(1-\|D_s\|_s)^2} \right) \\
 &\stackrel{\text{front of this page}}{\leq} (n+\sqrt{n}) \ln \left(\frac{\langle X, S \rangle + \alpha \langle U, V \rangle}{\langle X, S \rangle} \right) - \alpha \langle U, V^{-1} \rangle + \alpha^2 \left(\frac{1/\lambda_n(V)^2}{(1-1/\lambda_n(V))^2} \right) \\
 &\stackrel{\text{lemma 4.6}}{\leq} (n+\sqrt{n}) \left(\alpha \frac{\langle U, V \rangle}{\langle X, S \rangle} \right) - \alpha \langle U, V^{-1} \rangle + \frac{\alpha^2}{(\lambda_n(V)-1)^2} \\
 &\quad \text{linear estimate of } \ln \\
 &\leq -\alpha \left\langle U, -\left(\frac{n+\sqrt{n}}{\langle X, S \rangle} \right) V + V^{-1} \right\rangle + \frac{\alpha^2}{(\lambda_n(V)-1)^2} \\
 &\quad \underbrace{\hspace{10em}}_{\tilde{\alpha}} \\
 &\quad \|\tilde{\alpha}\|_F
 \end{aligned}$$

So choosing $\alpha = \lambda_n(V)/8 > 0$ yields

$$\varphi(X(\alpha), S(\alpha)) - \varphi(X, S) \leq -\alpha \left(\frac{\sqrt{3}}{2\lambda_n(V)} \right) + \frac{\alpha^2}{(\lambda_n(V)-1)^2} = \frac{-\sqrt{3}}{16} + \frac{1}{49} < -\frac{1}{12}.$$

Now we have all the components for

Theorem 4.13: The Interior Point Algorithm terminates in at most
 $O(m \ln(1/\epsilon))$
 iterations with a primal-dual feasible pair X, S such that
 $\langle X, S \rangle \leq \epsilon \langle X^{(0)}, S^{(0)} \rangle$.

How do we find the initial Slater points?

1) Convert optimization problem to a feasibility problem.

$(P), (D)$ have optimal solutions and optimal objective values are the same

\Leftrightarrow

$$\begin{cases} Ax = b, X \succeq 0 \\ A^*(y) + S = C, S \succeq 0 \\ \langle C, X \rangle - b^T y = 0 \end{cases} \text{ is feasible}$$

2) Given a feasibility problem, we can construct an optimization problem to solve it

$$\begin{cases} Ax = b, X \succeq 0 \\ \text{has feasible solutions} \end{cases}$$

\Leftrightarrow

$$\begin{cases} \inf y \\ Ax + y(b - A(I)) = b \\ X \succeq 0 \\ y \in \mathbb{R}^m \end{cases}$$

has optimal value 0, and it's attained

Notice that $(I, y=1)$ is a Slater point.