

Title: SDP / Quantum Lecture Series

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Date: July 15, 2019 - 10:00 AM

URL: <http://pirsa.org/19070071>

Lecture 2:

Quantum State Discrimination Problem (QSD)

Alice chooses i
with prob p_i
and creates the state



Bob wants to learn
what state he is given,
i.e., guess i

What can he do? He can measure S_k
to guess "k".

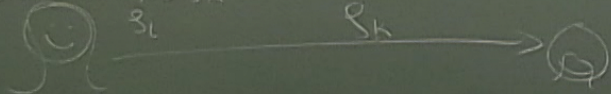
Data: The ensemble $\{(p_1, S_1), \dots, (p_n, S_n)\}$

Variables: POVM (M_1, \dots, M_n) , M_k corresponds to guess "k"
 $\sum_{k=1}^n M_k = I$, $M_k \geq 0$, $\forall k$

Lecture 2:

Quantum State Discrimination Problem (QSD)

Alice chooses ρ
with prob p_i
and creates the state



What can he do? He can measure S_k
to guess "k".

Data: The ensemble $\{(p_1, \rho_1), \dots, (p_n, \rho_n)\}$

Variables: POVM (M_1, \dots, M_n) . M_k corresponds to guess "k"
 $\sum_{k=1}^n M_k = I$, $M_k \geq 0$, $\forall k$

Bob wants to learn
what state he is given.
i.e., guess i

Optimize:

Prob [correctly guessing]

$$= \sum_{k=1}^n \underbrace{\text{Prob}[\text{getting } \rho_k]}_{P_k} \underbrace{\text{Prob}[\text{guessing } k | \text{getting } \rho_k]}_{\langle M_k, \rho_k \rangle}$$

SDP

$$\alpha = \sup \sum_{k=1}^n p_k \langle M_k, \rho_k \rangle$$

$$M_1 + \dots + M_n = I$$

$$M_1, \dots, M_n \geq 0$$

Dual
 $\inf \text{Tr}(Y)$

$$Y \geq \sum_{k=1}^n p_k \rho_k$$

$$\forall k \in \{1, \dots, n\}$$

(QSD)

Optimize:

Prob [correctly guessing]

$$= \sum_{k=1}^n \underbrace{\text{Prob}[\text{getting } s_k]}_{P_k} \cdot \underbrace{\text{Prob}[\text{guessing } k \mid \text{getting } s_k]}_{\langle M_k, s_k \rangle}$$

SDP

$$\alpha = \sup \sum_{k=1}^n P_k \langle M_k, s_k \rangle$$

$$M_1 + \dots + M_n = \mathbb{1}$$

$$M_1, \dots, M_n \geq 0$$

Dual

$$\beta = \inf \text{Tr}(Y)$$

$$Y \geq P_k s_k \quad \forall k \in \{1, \dots, n\}$$

Check:

$(M_1, \dots, M_n) = (\frac{1}{n}\mathbb{1}, \dots, \frac{1}{n}\mathbb{1})$ is primal strictly feasible

$Y = 2\mathbb{1}$ is strictly feasible

$\alpha = \beta$ and both are attained

Problem (QSD)

Optimize:

Prob [correctly guessing]

$$= \sum_{k=1}^n \underbrace{\text{Prob}[\text{getting } s_k]}_{P_k} \cdot \underbrace{\text{Prob}[\text{guessing } k \mid \text{getting } s_k]}_{\langle M_k, s_k \rangle}$$

SDP

$$\alpha = \sup \sum_{k=1}^n P_k \langle M_k, s_k \rangle$$

$$M_1 + \dots + M_n = \mathbb{1}$$

$$M_1, \dots, M_n \geq 0$$

$$\langle M_k, Y - P_k s_k \rangle = 0$$

Dual

$$\beta = \inf \text{Tr}(Y)$$

$$Y \geq P_k s_k \quad \forall k \in \{1, \dots, n\}$$

Check:

$(M_1, \dots, M_n) = (\frac{1}{n}\mathbb{1}, \dots, \frac{1}{n}\mathbb{1})$ is primal strictly feasible

$Y = 2\mathbb{1}$ is strictly feasible

$\alpha = \beta$ and both are attained

Let (M_1, \dots, M_n) be an optimal primal and Y is dual optimal

By Complementary Slackness,

$$M_k Y = P_k M_k s_k \quad \forall k$$

$$\Rightarrow \sum_{k=1}^n M_k Y = \sum_{k=1}^n P_k M_k s_k$$

Y is the unique dual opt sol'n.

$\Rightarrow Y$ is feasible

$$Y = \sum_k p_k M_k S_k \geq P_0 S_0, \text{ t.p. (1)}$$

Suppose (M_1, \dots, M_n) is a feasible primal

$$\text{If } Y = \sum_k p_k M_k S_k \geq P_0 S_0, \text{ t.p.}$$

Y is dual feasible

$$\beta \leq \text{Tr}(Y) = \sum_k p_k \langle M_k, S_k \rangle \leq \alpha \leq \beta$$

and
So $\text{Tr}(Y) = \beta$ so Y is optimal
 (M_1, \dots, M_n) is an optimal primal

let
Summary: (M_1, \dots, M_n) be a primal
 (M_1, \dots, M_n) is optimal if and only if

$\sum_k p_k M_k S_k$ is Hermitian

$$\text{d } \sum_k p_k M_k S_k \geq P_0 S_0, \text{ t.p.}$$

Y is the unique dual opt sol'n.

$\Rightarrow Y$ is feasible

$$Y = \sum_k p_k M_k S_k \geq P \& S_0, \text{ t.p. (1)}$$

Suppose (M_1, \dots, M_n) is a feasible msmt

$$\text{If } Y = \sum_k p_k M_k S_k \geq P \& S_0, \text{ t.p.}$$

Y is dual feasible

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So $\text{Tr}(Y) = \beta$ so Y is optimal
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let
Summary: (M_1, \dots, M_n) be a msmt
 (M_1, \dots, M_n) is optimal if and only if
 $\sum_k p_k M_k S_k$ is Hermitian

$$\& \sum_k p_k M_k S_k \geq P \& S_0, \text{ t.p.}$$

Remark: If instead Bob wants to guess which state
he is not given, this Quantum State Exclusion

$$\text{inf } \sum_k p_k \langle M_k, S_k \rangle$$
$$M_1 + \dots + M_n = I$$
$$M_1, \dots, M_n \geq 0$$

Lecture 2:

Trace Distance

Consider the ensemble $\left\{ \left(\frac{1}{2}, \rho \right), \left(\frac{1}{2}, \sigma \right) \right\}$

$$\text{SDP} \quad \alpha = \max \frac{1}{2} \langle M, \rho \rangle + \frac{1}{2} \langle M', \sigma \rangle$$

$$\left. \begin{array}{l} M + M' = I \\ M, M' \geq 0 \end{array} \right\} \Rightarrow \begin{array}{l} M' = I - M \\ 0 \leq M \leq I \end{array}$$

$$\begin{array}{l} M + M' = I \\ M, M' \geq 0 \end{array}$$

$$\alpha = \max \frac{1}{2} \langle M, \rho \rangle + \frac{1}{2} \langle I - M, \sigma \rangle$$
$$0 \leq M \leq I$$

$$= \max \frac{1}{2} \langle M, \rho \rangle + \frac{1}{2} - \frac{1}{2} \langle M, \sigma \rangle$$
$$0 \leq M \leq I$$

$$= \max \frac{1}{2} + \frac{1}{2} \langle M, \rho - \sigma \rangle$$
$$0 \leq M \leq I$$

$$= \frac{1}{2} + \frac{1}{2} \sum_{\lambda_k > 0} \lambda_k (\rho - \sigma)$$

Lecture 2:

Trace distance

Consider the ensemble $\left\{ \left(\frac{1}{2}, \rho \right), \left(\frac{1}{2}, \sigma \right) \right\}$

$$\text{SDP} \quad \alpha = \max \frac{1}{2} \langle M, \rho \rangle + \frac{1}{2} \langle M', \sigma \rangle$$

$$\begin{aligned} M + M' &= I \\ M, M' &\geq 0 \end{aligned}$$

$$\left. \begin{aligned} M + M' &= I \\ M, M' &\geq 0 \end{aligned} \right\} \Rightarrow \begin{aligned} M' &= I - M \\ 0 &\leq M \leq I \end{aligned}$$

$$\begin{aligned} \alpha &= \max_{0 \leq M \leq I} \frac{1}{2} \langle M, \rho \rangle + \frac{1}{2} \langle I - M, \sigma \rangle \\ &= \max_{0 \leq M \leq I} \frac{1}{2} \langle M, \rho \rangle + \frac{1}{2} - \frac{1}{2} \langle M, \sigma \rangle \\ &= \max_{0 \leq M \leq I} \frac{1}{2} + \frac{1}{2} \langle M, \rho - \sigma \rangle \end{aligned}$$

$$\begin{aligned} &= \frac{1}{2} + \frac{1}{2} \sum_{k: \lambda_k > 0} \lambda_k (\rho - \sigma) \\ &= \frac{1}{2} + \frac{1}{2} \left(\frac{1}{2} \sum_k |\lambda_k (\rho - \sigma)| \right) \\ &= \frac{1}{2} + \frac{1}{4} \|\rho - \sigma\|_1 \end{aligned}$$

where $\|\cdot\|_{\text{tr}}$ is the trace norm, 1-norm, nuclear norm
 \uparrow
 Sum of singular values

$$\|X\|_{\text{tr}} = \text{tr}(\sqrt{X^* X})$$

$\langle \mu, \sigma \rangle$
 $\in \mathbb{I}$
 $\frac{1}{2} \langle \mu, \sigma \rangle$
 $\in \mathbb{II}$

The Fidelity Function

The fidelity of 2 quantum states ρ and σ is defined as $F(\rho, \sigma) = \|\sqrt{\rho} \sigma \sqrt{\rho}\|_{tr} = \text{Tr}(\sqrt{\sqrt{\rho} \sigma \sqrt{\rho}})$

$$\|V\|_{tr} = \max_{\{ |v\rangle \}} \{ |\langle v, X \rangle|^2 \}$$

V contraction

$$\|V\|_{tr} \leq 1$$

Σ largest singular value of operator in decomposition

SDP

$$\alpha = \text{Sup} \frac{1}{2} \text{Tr}(X) + \frac{1}{2} \text{Tr}(X^*)$$

$$\beta = \text{inf} \frac{1}{2} \langle \rho, Y \rangle + \frac{1}{2} \langle \sigma, Z \rangle$$

$$A = \begin{bmatrix} 0 & I \\ I & 0 \end{bmatrix} \quad \begin{bmatrix} \rho & X \\ X^* & \sigma \end{bmatrix} \succeq 0$$

$$\begin{bmatrix} Y & I \\ I & Z \end{bmatrix} \succeq 0$$

norm, nuclear norm
 \uparrow
 of singular values

Fun

Handwritten notes on a piece of paper.

Fun Fact: Given $C \succ 0$, $\begin{bmatrix} A & B \\ B^* & C \end{bmatrix} \succ 0 \Leftrightarrow A \succ B^* C^{-1} B$

Schur Complement \nearrow

$$\begin{bmatrix} S & X \\ X^* & \sigma \end{bmatrix} \succ 0$$

$$\Leftrightarrow S \succ X^* \sigma^{-1} X$$

(assume $\sigma \succ 0, S \succ 0$)

$$\Leftrightarrow S S^{-1/2} \succ X^* \sigma^{-1} X$$

$$\Leftrightarrow I \succ S^{-1/2} X^* \sigma^{-1} X S^{-1/2}$$

(Aside: $A \succ B \Leftrightarrow X^* A X \succ X^* B X$
 X invertible)

$$\alpha = \sup \frac{1}{2} \text{Tr}(X) + \frac{1}{2} \text{Tr}(X^*)$$

$$X = \sigma^{1/2} V \rho^{1/2}$$

V contraction

$$\text{Tr}(X) = \text{Tr}(\sigma^{1/2} V \rho^{1/2}) = \langle \rho^{1/2} \sigma^{1/2}, V \rangle$$

$$\text{Tr}(X^*) = \overline{\text{Tr}(X)}$$

$$\frac{1}{2} \text{Tr}(X) + \frac{1}{2} \text{Tr}(X^*) = \text{Re}(\text{tr}(X))$$

$$= \text{Re} \langle \rho^{1/2} \sigma^{1/2}, V \rangle$$

$$\alpha = \sup_{V \text{ contraction}} \text{Re} \langle \rho^{1/2} \sigma^{1/2}, V \rangle$$

$$= \sup_V |\langle \rho^{1/2} \sigma^{1/2}, V \rangle|$$

$$= \sqrt{\text{Tr}(\rho \sigma)}$$

$$\alpha = \max_{0 \leq U \leq I} \frac{1}{2} \langle U, \rho \sigma \rangle$$

$$= \max_{0 \leq U \leq I} \frac{1}{2} \langle U, \rho \sigma \rangle$$

$$= \max_{0 \leq U \leq I} \frac{1}{2} + \frac{1}{2} \langle U, \rho \sigma \rangle$$

$$= \frac{1}{2} + \frac{1}{2} \sum_{\lambda_k > 0} \lambda_k$$

$$= \frac{1}{2} + \frac{1}{2} \left(\frac{1}{2} \sum_{\lambda_k} \lambda_k \right)$$

$$= \frac{1}{2} + \frac{1}{4} \|\rho - \sigma\|_1$$

where $\|\cdot\|_{\text{tr}}$ is the trace norm

$$\|X\|_{\text{tr}} = \text{tr}(\sqrt{X^* X})$$

X^2

Z

on

$$\langle S^{1/2} \sigma^{1/2}, V \rangle$$

$(\text{tr}(X))$

$$\langle S^{1/2} \sigma^{1/2}, V \rangle$$

\rangle

$$\beta = \inf_{Y \succ 0} \frac{1}{2} \langle S, Y \rangle + \frac{1}{2} \langle \sigma, Z \rangle$$
$$\begin{bmatrix} Y & I \\ I & Z \end{bmatrix} \succ 0$$

$$\begin{bmatrix} Y & I \\ I & Z \end{bmatrix} \succ 0 \Leftrightarrow Y \succ Z^{-1} \quad \& \quad Z \succ Y^{-1}$$

By Schur Complements

$$\beta = \inf_{Y \succ 0} \frac{1}{2} \langle S, Y \rangle + \frac{1}{2} \langle \sigma, Y^{-1} \rangle$$

$Z = Y^{-1}$ is the best choice

$$\frac{1}{2} \langle S, Y \rangle + \frac{1}{2} \langle \sigma, Y^{-1} \rangle \geq \sqrt{\langle S, Y \rangle \langle \sigma, Y^{-1} \rangle}$$

holds with equality $\Leftrightarrow \langle S, Y \rangle = \langle \sigma, Y^{-1} \rangle$

$$I + \sigma \succeq 0$$

X^2
 Z
on

$$\beta = \inf_{\begin{matrix} \frac{1}{2}\langle S, Y \rangle + \frac{1}{2}\langle \sigma, Z \rangle \\ \begin{bmatrix} Y & I \\ I & Z \end{bmatrix} \succeq 0 \end{matrix}}$$

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holds with equality $\Leftrightarrow \langle S, Y \rangle = \langle \sigma, Y^{-1} \rangle$

$$\beta = \inf_{Y \succ 0} \sqrt{\langle S, Y \rangle \langle \sigma, Y^{-1} \rangle}$$

$$\langle S^{1/2} \sigma^{1/2}, V \rangle$$

$(\text{tr}(X))$
 $\langle S^{1/2} \sigma^{1/2}, V \rangle$

$$\beta = \inf_{\begin{bmatrix} Y & I \\ I & Z \end{bmatrix} \succeq 0} \frac{1}{2} \langle S, Y \rangle + \frac{1}{2} \langle \sigma, Z \rangle$$

$$\begin{bmatrix} Y & I \\ I & Z \end{bmatrix} \succeq 0 \Leftrightarrow Y \succeq Z^{-1} \quad \text{or} \quad Z \succeq Y^{-1}$$

By Schur Complements

$$\beta = \inf_{Y \succ 0} \frac{1}{2} \langle S, Y \rangle + \frac{1}{2} \langle \sigma, Y^{-1} \rangle$$

$$\frac{1}{2} \langle S, Y \rangle + \frac{1}{2} \langle \sigma, Y^{-1} \rangle \geq \sqrt{\langle S, Y \rangle \langle \sigma, Y^{-1} \rangle}$$

↑ $Z = Y^{-1}$ is the best choice

holds with equality $\Leftrightarrow \langle S, Y \rangle = \langle \sigma, Y^{-1} \rangle$

$$\beta = \inf_{Y \succ 0} \sqrt{\langle S, Y \rangle \langle \sigma, Y^{-1} \rangle}$$

this can be equal by scaling Y
 $Y' = tY \quad t > 1$

$$\beta^2 = \inf_{Y \succ 0} \langle S, Y \rangle \langle \sigma, Y^{-1} \rangle$$

$$\beta = \inf_{\begin{bmatrix} Y & I \\ I & Z \end{bmatrix} \succeq 0} \frac{1}{2} \langle S, Y \rangle + \frac{1}{2} \langle \sigma, Z \rangle$$

$$\begin{bmatrix} Y & I \\ I & Z \end{bmatrix} \succeq 0 \Leftrightarrow Y \succeq Z^{-1} \quad \& \quad Z \succeq Y^{-1}$$

By Schur Complements

$$\beta = \inf_{Y \succ 0} \frac{1}{2} \langle S, Y \rangle + \frac{1}{2} \langle \sigma, Y^{-1} \rangle$$

$Z = Y^{-1}$ is the best choice

$$\frac{1}{2} \langle S, Y \rangle + \frac{1}{2} \langle \sigma, Y^{-1} \rangle \geq \sqrt{\langle S, Y \rangle \langle \sigma, Y^{-1} \rangle}$$

holds with equality $\Leftrightarrow \langle S, Y \rangle = \langle \sigma, Y^{-1} \rangle$

$$\beta = \inf_{Y \succ 0} \sqrt{\langle S, Y \rangle \langle \sigma, Y^{-1} \rangle}$$

this can be equal by scaling Y

$$Y' = \alpha Y \quad \alpha > 1$$

$$\beta^2 = \inf_{Y \succ 0} \langle S, Y \rangle \langle \sigma, Y^{-1} \rangle$$

let's check $\alpha = \beta$

$$(Y, Z) = (2I, 2I) \quad \& \quad X = \sqrt{S \sigma}$$

$\Rightarrow \alpha = \beta$ + α is attained $\Rightarrow \beta$ is finite

Albert's theorem

$$F(S, \sigma)^2 = \inf_{Y \succ 0} \langle S, Y \rangle \langle \sigma, Y^{-1} \rangle$$

$S \in \text{Pos}(X)$, y is a purifying system

SDP

$$\alpha = \sup \langle W, |Y\rangle\langle Y| \rangle$$

$$\text{Tr}_y(W) = \sigma$$

$$W \in \text{Pos}(X \otimes y)$$

$$\beta = \inf \langle \sigma, Z \rangle$$

(purification of σ)

$$\exists Z \geq |Y\rangle\langle Y|$$

$$\exists \in \text{Term}(X)$$

($Z \geq 0$ is implied)

$$|Y\rangle \in X \otimes y$$

$$|Y\rangle\langle Y| \in \text{Pos}(X \otimes y)$$

$$\text{Tr}_y(|Y\rangle\langle Y|) = \sigma$$

partial trace

$$(1_X \otimes \text{Tr}_y)$$

let's work with β

First, we'll assume $Z \geq 0$ and this will not change β (but it may no longer be attained)

$$Z \otimes I \succ \|X\|$$

$$\Leftrightarrow I \succ (Z^{-1/2} \otimes I) \|X\| (Z^{-1/2} \otimes I)$$

$$\Leftrightarrow I \succ \lambda_{\max} \underbrace{\left((Z^{-1/2} \otimes I) \|X\| (Z^{-1/2} \otimes I) \right)}_{\text{rank 1}}$$

So $\lambda_{\max} = \text{Trace}$

$$\Leftrightarrow I \succ \text{Tr} \left((Z^{-1/2} \otimes I) \|X\| (Z^{-1/2} \otimes I) \right)$$

$$\Leftrightarrow I \succ \langle X | (Z^{-1} \otimes I) | X \rangle$$

$$\Leftrightarrow I \succ \langle Z^{-1} \otimes I, \|X\| \rangle$$

$$\Leftrightarrow I \succ \langle Z^{-1}, \text{Tr}_Y(\|X\|) \rangle$$

$$\beta = \inf \frac{1}{2} \langle S, Y \rangle + \frac{1}{2} \langle S^{-1}, Y^{-1} \rangle$$

$$\begin{bmatrix} Y & I \\ I & Z \end{bmatrix} \succ 0$$

$$\begin{bmatrix} Y & I \\ I & Z \end{bmatrix} \succ 0 \Leftrightarrow$$

By Schur Complement

$$\beta = \inf_{Y \succ 0} \frac{1}{2} \langle S, Y \rangle$$

$$\frac{1}{2} \langle S, Y \rangle + \frac{1}{2} \langle S^{-1}, Y^{-1} \rangle$$

holds with equality \Leftrightarrow

$$Z \otimes I \succ |Y\rangle\langle Y|$$

$$\Leftrightarrow I \succ (Z^{-1/2} \otimes I) |Y\rangle\langle Y| (Z^{-1/2} \otimes I)$$

$$\Leftrightarrow I \succ \lambda_{\max} \underbrace{\left((Z^{-1/2} \otimes I) |Y\rangle\langle Y| (Z^{-1/2} \otimes I) \right)}_{\text{rank 1}}$$

So $\lambda_{\max} = \text{Trace}$

$$\Leftrightarrow I \succ \text{Tr} \left((Z^{-1/2} \otimes I) |Y\rangle\langle Y| (Z^{-1/2} \otimes I) \right)$$

$$\Leftrightarrow I \succ \langle Y | (Z^{-1} \otimes I) | Y \rangle$$

$$\Leftrightarrow I \succ \langle Z^{-1} \otimes I, |Y\rangle\langle Y| \rangle$$

$$\Leftrightarrow I \succ \langle Z^{-1}, \text{Tr}_Y(|Y\rangle\langle Y|) \rangle$$

$$\Leftrightarrow I \succ \langle Z^{-1}, \rho \rangle$$

$$\beta = \inf \left\langle \sigma, z \right\rangle$$
$$\left\langle z^{-1}, \beta \right\rangle \leq 1$$
$$z > 0$$

We can assume $\left\langle z^{-1}, \beta \right\rangle = 1$.

$$\beta = \inf \left\langle \sigma, z \right\rangle \left\langle z^{-1}, \beta \right\rangle$$
$$\left\langle z^{-1}, \beta \right\rangle = 1$$
$$z > 0$$

$(\beta, \sigma)^2$ by Alberti.

Let's check $\alpha = \beta$:

$$z \geq 1$$
$$z > 0$$

$$\langle z^{-1}, s \rangle = 1$$

$$z \geq \langle z^{-1}, s \rangle$$

~~$$\langle z^{-1}, s \rangle = 1$$~~
$$z > 0$$

Alberti

Let's check $\alpha = \beta$: $z = 21$ is strictly dual feasible

$W = \frac{1}{\dim(Y)}$ is primal feasible

$\alpha = \beta$ and α is attained

Interesting Properties

Data Processing:

- ① $\|s - \sigma\|_{tr} \geq \|\Phi(s) - \Phi(\sigma)\|_{tr}$
- ② $F(\Phi(s), \Phi(\sigma)) \geq F(s, \sigma)$.

completely positive
& trace preserving

$\mathbb{1}_{L(\mathcal{H})} \otimes \mathbb{1}_B$ is positive for all K .

$$(1) \frac{1}{2} + \frac{1}{4} \|\Phi(\rho) - \Phi(\sigma)\|_{\text{tr}} = \max_{\substack{M+M'=\mathbb{I} \\ M, M' \geq 0}} \frac{1}{2} \langle M, \Phi(\rho) \rangle + \frac{1}{2} \langle M', \Phi(\sigma) \rangle$$

$$= \max_{\substack{M+M'=\mathbb{I} \\ M, M' \geq 0}} \frac{1}{2} \langle \Phi^*(M), \rho \rangle + \frac{1}{2} \langle \Phi^*(M'), \sigma \rangle$$

$(\Phi^*(M), \Phi^*(M'))$
is a PDM

Φ^* is unital
 Φ^* is comp. pos.

$$\Phi^*(M) + \Phi^*(M')$$

$$= \Phi^*(\mathbb{I}) = \mathbb{I}$$

$$\leq \max_{\substack{N+N'=\mathbb{I} \\ N, N' \geq 0}} \frac{1}{2} \langle N, \rho \rangle + \frac{1}{2} \langle N', \sigma \rangle$$

$$= \frac{1}{2} + \frac{1}{4} \|\rho - \sigma\|_{\text{tr}}$$

□

$$(2) F(\rho, \sigma) =$$

$\langle \Phi(\sigma), \sigma \rangle$

$\langle \Phi^*(W), \sigma \rangle$

$\langle \Phi \rangle + \frac{1}{2} \langle N', \sigma \rangle$

$N + N' = I$

$N, N' \succeq 0$

Tr

□

$$(2) \quad F(\rho, \sigma) = \max \frac{1}{2} \text{Tr}(X) + \frac{1}{2} \text{Tr}(X^*) \quad (*)$$

$$\begin{bmatrix} S & X \\ X^* & \sigma \end{bmatrix} \succeq 0$$

$$\begin{bmatrix} S & X \\ X^* & \sigma \end{bmatrix} \succeq 0 \Rightarrow \begin{bmatrix} \Phi(S) & \Phi(X) \\ \Phi(X)^* & \Phi(\sigma) \end{bmatrix} \succeq 0$$

(Z-positive)

let X be an optimal sol'n for $(*)$

$$F(\rho, \sigma) = \frac{1}{2} \text{Tr}(X) + \frac{1}{2} \text{Tr}(X^*)$$

$W = \Phi(X)$ is feasible in

$$F(\Phi(\rho), \Phi(\sigma)) = \max \frac{1}{2} \text{Tr}(W) + \frac{1}{2} \text{Tr}(W^*)$$

$$\begin{bmatrix} \Phi(\rho) & W \\ W^* & \Phi(\sigma) \end{bmatrix} \succeq 0$$

$$F(\Phi(\rho), \Phi(\sigma))$$

$$\succeq \frac{1}{2} \text{Tr}(\Phi(X)) + \frac{1}{2} \text{Tr}(\Phi(X)^*)$$

$$= \frac{1}{2} \text{Tr}(X) + \frac{1}{2} \text{Tr}(X^*)$$

$$= F(\rho, \sigma)$$

Proof: For each k , let

$$F(S_k, \sigma_k) = \max \left[\frac{1}{2} \text{Tr}(X_k) + \frac{1}{2} \text{Tr}(X_k^*) \right]$$

$$\begin{bmatrix} S_k & X_k \\ X_k^* & \sigma_k \end{bmatrix} \succeq 0$$

$$\begin{bmatrix} \sum_k P_k S_k & \sum_k P_k X_k \\ \sum_k P_k X_k^* & \sum_k P_k \sigma_k \end{bmatrix}$$

$$= \sum_k P_k \begin{bmatrix} S_k & X_k \\ X_k^* & \sigma_k \end{bmatrix} \succeq 0$$

Proof: For each k , let X_k is optimal in \mathbb{Z}

$$F(S_k, \sigma_k) = \max \frac{1}{2} \text{Tr}(X_k) + \frac{1}{2} \text{Tr}(X_k^*)$$

$$\begin{bmatrix} S_k & X_k \\ X_k^* & \sigma_k \end{bmatrix} \succeq 0$$

$$\begin{bmatrix} \sum_k p_k S_k & \sum_k p_k X_k \\ \sum_k p_k S_k & \sum_k p_k \sigma_k \end{bmatrix}$$

$$= \sum_k p_k \begin{bmatrix} S_k & X_k \\ X_k^* & \sigma_k \end{bmatrix} \succeq 0$$

So, $W = \sum_k p_k X_k$ is feasible in

$$F\left(\sum_k p_k S_k, \sum_k p_k \sigma_k\right) = \sup \frac{1}{2} \text{Tr}(W) + \frac{1}{2} \text{Tr}(W^*)$$

$$\begin{bmatrix} \sum_k p_k S_k & W \\ W & \sum_k p_k \sigma_k \end{bmatrix} \succeq 0$$

$$F\left(\sum_k p_k S_k, \sum_k p_k \sigma_k\right)$$

$$\geq \frac{1}{2} \text{Tr}\left(\sum_k p_k X_k\right) + \frac{1}{2} \text{Tr}\left(\sum_k p_k X_k^*\right)$$

$$= \sum_k p_k F(S_k, \sigma_k)$$

□