

Collaborators : None

Sources : Lecture Notes

Q3) The Uncertainty Principle

(Let) $X, Y \in \mathbb{C}^{d \times d}$ be observables, i.e. Hermitian matrices?

$$\Rightarrow X^\dagger = X \quad ; \quad Y^\dagger = Y$$

$$(a) \quad (X^2)^\dagger = (X \cdot X)^\dagger = X^\dagger \cdot X^\dagger = X \cdot X = X^2 \quad [\because (BA)^\dagger = A^\dagger B^\dagger ; X^\dagger = X]$$

$$(Y^2)^\dagger = (Y \cdot Y)^\dagger = Y^\dagger \cdot Y^\dagger = Y \cdot Y = Y^2 \quad [\because Y^\dagger = Y]$$

$\therefore X^2$ & Y^2 are Hermitian matrices

(b) Case-1 (\Rightarrow): If $XY = YX$ (Commutative), then

$$(XY)^\dagger = Y^\dagger X^\dagger = YX = XY \quad (\text{Satisfies Hermitian property})$$

Case-2 (\Leftarrow): If XY is Hermitian, i.e., $(XY)^\dagger = XY$

$$\Rightarrow Y^\dagger X^\dagger = XY$$

$$\Rightarrow YX = XY \quad (\text{Satisfies Commutation property})$$

From Case-1 & Case-2: $\{XY = YX\} \Leftrightarrow \{(XY)^\dagger = XY\}$ if X, Y are hermitian

(Commutation) (Hermitian)

(c) Let $[X, Y]$ denote $XY - YX$, then

$$\left(\frac{1}{2} [X, Y]\right)^\dagger = \left(\frac{1}{2} (XY - YX)\right)^\dagger = \left(\frac{1}{2} ((XY)^\dagger - (YX)^\dagger)\right) = \frac{1}{2} (Y^\dagger X^\dagger - X^\dagger Y^\dagger)$$

$$= \frac{1}{2} (YX - XY) = -\frac{1}{2} (XY - YX) = -\left(\frac{1}{2} [X, Y]\right)$$

$\therefore \left(\frac{1}{2} [X, Y]\right)$ is anti-Hermitian

(d) Let $[X, Y]$ denote $(XY - YX)$, then

$$\left(\frac{1}{2i} [X, Y]\right)^\dagger = \left(\frac{1}{2i} (XY - YX)\right)^\dagger = \left(\frac{-1}{2i} ((XY)^\dagger - (YX)^\dagger)\right) = \left(\frac{-1}{2i} (Y^\dagger X^\dagger - X^\dagger Y^\dagger)\right)$$

$$= \left(\frac{-1}{2i} (YX - XY)\right) = \left(\frac{1}{2i} (XY - YX)\right) = \left(\frac{1}{2i} [X, Y]\right)$$

$\therefore \frac{1}{2i} [X, Y]$ is Hermitian

$$(c) \quad \frac{1}{2} [X, Y] + i \frac{1}{2} [X, Y] = \frac{1}{2} ([X, Y] + [X, Y]) = \frac{1}{2} (XY + YX) + \frac{1}{2} (XY - YX) = XY$$

$$\therefore XY = \frac{1}{2} [X, Y] + i \frac{1}{2} [X, Y]$$

(f) Let $X' = X - E_p[X]I$ & $Y' = Y - E_p[Y]I$
 $\Rightarrow E_p[X'] = E_p[X] - E_p[X]I = 0$; $E_p[Y'] = 0$

$\sigma_p[X'] = \sqrt{E_p[(X - E_p[X]I)^+ (X - E_p[X]I - 0)]} = \sigma_p[X]$; Similarly $\sigma_p[Y'] = \sigma_p[Y]$ ①

$$\begin{aligned} [X, Y] &= XY - YX = (X' + E_p[X]I)(Y' + E_p[Y]I) - (Y' + E_p[Y]I)(X' + E_p[X]I) \\ &= (X'Y' + E_p[X]Y' + E_p[Y]X' + E_p[X]E_p[Y]I) - (Y'X' + E_p[Y]X' + E_p[X]Y' + E_p[X]E_p[Y]I) \\ &= X'Y' - Y'X' = [X', Y'] \rightarrow ② \end{aligned}$$

From ① & ②

$$\left(\sigma_p[X] \cdot \sigma_p[Y] \geq |E_p[\frac{1}{2i} [X, Y]]| \right) \Leftrightarrow \left(\sigma_p[X'] \cdot \sigma_p[Y'] \geq |E_p[\frac{1}{2i} [X', Y']]| \right) \text{ \& } E_p[X'] = E_p[Y'] = 0$$

Therefore without loss of generality, proving inequality for (X', Y') where their E_p values are 0, means proving the (inequality) for (X, Y) .

(g) Using Cauchy-Schwarz inequality:

$$|Cov_p[X, Y]|^2 \leq Var_p[X] Var_p[Y] \rightarrow ①$$

$$|Cov_p[X, Y]|^2 = |E_p[X'Y'] - E_p[X']E_p[Y']|^2 \quad \text{[From ②]}$$

$$= |E_p[XY] - 0|^2 \quad \text{[}\because X \text{ is Hermitian; } E_p[X'] = E_p[Y'] = 0 \text{ (considered)]}$$

$$= |E_p[XY]|^2 = \left| E_p\left[\frac{1}{2} [X, Y] + i \frac{1}{2} [X, Y]\right] \right|^2 \rightarrow ②$$

$$\left(\frac{1}{2} [X, Y] + i \frac{1}{2} [X, Y] \right) = \frac{1}{2} E_p[[X, Y]] + \frac{i}{2} E_p[[X, Y]]$$

$$\begin{aligned} E_P[X, Y]^* &= \text{tr}(P(X, Y))^* = \text{tr}((X, Y)P)^* \quad [\because \text{tr}(AB) = \text{tr}(BA)] \\ &= \text{tr}([(X, Y)P]^t) = \text{tr}(P^t(X, Y)^t) = \text{tr}(P(X, Y)) \end{aligned}$$

$$\Rightarrow E_P[X, Y]^* = E_P[X, Y] \text{ along } P \text{ is real } \rightarrow (3)$$

$$\Rightarrow E_P[X, Y]^* \text{ is Real } \rightarrow (3)$$

$$\begin{aligned} E_P[i(X, Y)]^* &= \text{tr}(P(i(X, Y)))^* = \text{tr}((i(X, Y))P)^* \\ &= \text{tr}([(i(X, Y))P]^t) = \text{tr}(P^t(i(X, Y))^t) = \text{tr}(P(i(X, Y))) \end{aligned}$$

$$\Rightarrow E_P[i(X, Y)]^* = E_P[i(X, Y)] \text{ is Real } \rightarrow (4)$$

$$\text{Using } (3) \text{ \& } (4) \text{ in } (2),$$

$$\begin{aligned} |\text{Cov}_P[X, Y]|^2 &= \left| \frac{1}{2} E_P[X, Y] + \frac{1}{2i} E_P[i(X, Y)] \right|^2 \geq \left| \frac{1}{2i} \right|^2 |E_P[i(X, Y)]|^2 \\ &\geq \left| \frac{1}{2i} \right|^2 |E_P[\frac{1}{2i} X, Y]|^2 \rightarrow (5) \end{aligned}$$

$$\text{Using } (1) \text{ \& } (5),$$

$$\text{Var}_P[X] \text{Var}_P[Y] \geq |\text{Cov}_P[X, Y]|^2 \geq |E_P[\frac{1}{2i} X, Y]|^2$$

$$\Rightarrow \boxed{\sigma_P[X] \cdot \sigma_P[Y] \geq |E_P[\frac{1}{2i} X, Y]|}$$