

Sensing

$$H = \frac{B}{2} Z \quad \text{for 1 qubit} \quad \text{or} \quad H = \frac{B}{2} \sum_{i=1}^n Z_i$$

$$e^{-iHt} |+\rangle = \frac{e^{-\frac{iBt}{2} |0\rangle} + e^{\frac{iBt}{2} |1\rangle}}{\sqrt{2}} \quad \phi = Bt$$

$$p = \langle + | e^{-iHt} |+\rangle = \cos^2(\phi/2)$$

outcome $X = \pm 1$

$$\mathbb{E}X = \cos^2(\phi/2) - \sin^2(\phi/2) = \cos(\phi)$$

$$\text{Var} X = 1 - (\mathbb{E}X)^2 = \sin^2 \phi \quad \text{Std}(X) = \sin(\phi) = \Delta X$$

$$N \text{ repetitions} \rightarrow \hat{X} \approx X \pm \frac{\sin \phi}{\sqrt{N}} \quad \hat{\phi} = \cos^{-1}(\hat{X})$$

$$\hat{X} = \cos(\hat{\phi})$$

$$\frac{d\hat{X}}{d\hat{\phi}} = -\sin \hat{\phi} \quad \frac{d\hat{\phi}}{d\hat{X}} = \frac{-1}{\sin \hat{\phi}} \quad \Delta \phi = \frac{\Delta X}{\sin \hat{\phi}} = \frac{1}{\sqrt{N}} \quad \text{independent of } \phi$$

$$\Delta B \approx \frac{1}{t\sqrt{N}}$$

$\frac{1}{\sqrt{N}}$ scaling called the SQL (standard quantum limit) or shot-noise limit

Is this the best we can do with N qubits?

No!

$$e^{-iHt} \frac{|0^N\rangle + |1^N\rangle}{\sqrt{2}} = \frac{e^{-\frac{iBtN}{2} |0^N\rangle} + e^{\frac{iBtN}{2} |1^N\rangle}}{\sqrt{2}}$$

$$\Delta B = \frac{1}{tN} \quad \text{called the Heisenberg limit}$$

can quantify how much information a state carries about a parameter via the Fisher information.

classical case

unknown parameter $\theta \rightarrow$ observation x via $p_\theta(x)$

goal: output $\hat{\theta} \approx \theta$

under goal: distinguish p_θ from p_0 for small θ

likelihood ratio test $W_n = \log \frac{p_\theta(x_1) \dots p_\theta(x_n)}{p_0(x_1) \dots p_0(x_n)}$

$$\mathbb{E}_{x \sim p_0} W_n = n D(p_\theta \| p_0) = n \left(0 + 0 \cdot \theta + \frac{F}{2} \theta^2 + \dots \right)$$

$D(p_\theta \| p_0) = 0$ since $D \geq 0$ def of F

$$\begin{aligned} F &= \partial_\theta^2 D(p_\theta \| p_0) \Big|_{\theta=0} \\ &= \sum_x \partial_\theta^2 p_\theta(x) \log p_\theta(x) \\ &= \sum_x p_\theta(x) \left(\partial_\theta \log p_\theta(x) \right)^2 = \sum_x \frac{(\partial_\theta p_\theta)^2}{p_\theta} \Big|_{\theta=0} \end{aligned}$$

using $\sum_x \partial_\theta p_\theta(x) = 0$ repeatedly

when can we reliably distinguish p_θ^n from p_0^n ?

need $\mathbb{E} W_n \gg \text{SD}(W_n)$ note $\mathbb{E} W_n \leq 0$
 p_θ p_0 p_0

$$\frac{1}{n} \text{Var}_{p_0} W_n = \sum_x p_0(x) \frac{\log^2 p_0(x)}{p_0(x)} - \underbrace{D(p_0 \| p_0)^2}_{\sim \theta^4}$$

$\approx \theta^2 \partial_\theta \log p_0$

$$= \theta^2 \sum_x p_0(x) \left(\partial_\theta \log p_0 \right)^2 = \theta^2 F$$

$$\frac{\mathbb{E} W_n}{\text{SD}(W_n)} = \frac{n F \theta^2 / 2}{\sqrt{n F \theta^2}} = \frac{\sqrt{n F} \theta}{2} \quad \theta_{\min} = \frac{2}{\sqrt{n F}} \quad \text{or} \quad \frac{c}{\sqrt{n F}}$$

Cramer-Rao bound

$\hat{\theta}(x^n)$ is locally unbiased near θ_0 means

$$E[\hat{\theta}] = \theta + O(\theta - \theta_0)^2$$

set $\theta_0 = 0$ for simplicity

$$\text{Var}[\hat{\theta}] = \sum_{x^n} P_{\theta_0}(x^n) \hat{\theta}^2$$

$$I = \partial_{\theta} E[\hat{\theta}] \Big|_{\theta=0} \quad (\text{unbiased condition})$$

$$I = \partial_{\theta} \left(\sum_{x^n} P_{\theta}^n(x^n) \hat{\theta}(x^n) \right) = \sum_{x^n} \hat{\theta}(x^n) \frac{\partial_{\theta} P_{\theta}^n(x^n)}{P_{\theta}^n(x^n)} = \sum_{x^n} \hat{\theta} \partial_{\theta} \log P_{\theta}^n(x^n)$$

$$\langle a(x^n), b(x^n) \rangle := \sum_{x^n} a(x^n) b(x^n)$$

then Cauchy-Schwarz \Rightarrow

$$I^2 \leq E[\hat{\theta}^2] \cdot E(\partial_{\theta} \log P_{\theta}^n(x^n))^2$$

$$= \text{Var}(\hat{\theta}) \cdot nF$$

$$\Rightarrow \text{Var}(\hat{\theta}) \geq \frac{1}{nF}$$

$$\text{saturated iff } \hat{\theta} \propto \partial_{\theta} \log P_{\theta}^n$$

Quantum Fisher Information

Assume $\rho_0 > 0$ θ near $\theta_0 = 0$

$$\text{Mult}_\rho [X] = \frac{1}{2} (\rho X + X \rho)$$

$$\text{Div}_\rho [X] = \text{Mult}_\rho^{-1} [X] \quad (\text{possible when } \rho > 0)$$

$$L_{\rho_0} = \text{Div}_{\rho_0} [\partial_\theta \rho] \quad \partial_\theta \rho = \text{Mult}_{\rho_0} [L] = \frac{1}{2} (\rho_0 L + L \rho_0)$$

L_{ρ_0} parity for $\partial_\theta \log \rho_0$

$$F_Q = \text{tr} [L_{\rho_0}^2]$$

$$\partial_\theta^2 D(\rho_\theta \| \rho_0) = \frac{F_Q \theta^2}{2} + O(\theta^3)$$

relation to classical Fisher information

$$M = \sum_x M_x \sum_{x \in X} \quad F_M = F(\beta(x) = \text{tr} M_x \rho_0) = \sum_x \text{tr} \rho_0 M_x \cdot \left(\frac{\partial_\theta \text{tr} \rho_0 M_x}{\text{tr} \rho_0 M_x} \right)^2$$

$$= \sum_x \text{tr} (\rho_0 M_x) \text{Re} \left(\frac{\text{tr} \rho_0 L M_x}{\text{tr} \rho_0 M_x} \right)^2$$

$$\leq \sum_x \frac{|\text{tr} \rho_0 L M_x|^2}{\text{tr} \rho_0 M_x} = \sum_x \frac{|\text{tr} \sqrt{\rho_0} L \sqrt{M_x} \sqrt{M_x} \sqrt{\rho_0}|^2}{\text{tr} \rho_0 M_x}$$

$$\leq \frac{\text{tr} (\sqrt{\rho_0} L \sqrt{M_x}) (\sqrt{M_x} L^* \sqrt{\rho_0})}{\text{tr} \rho_0 M_x} \cdot \text{tr} \sqrt{M_x} \rho_0 \sqrt{M_x}$$

$$= F_Q$$

saturated if $\text{Im} \text{tr} \rho_0 L M_x = 0$

and $\sqrt{M_x} L \sqrt{\rho_0} \propto \sqrt{M_x} \sqrt{\rho_0}$

$$L = \sum_x \lambda_x |\psi_x\rangle\langle\psi_x| \quad \text{take } M_x = |\psi_x\rangle\langle\psi_x| \quad (\text{or } P_x)$$

$$\Rightarrow F_M = F_Q$$

Q Cramer-Rao

A_n is unbiased if $\text{tr} A_n \rho_0^{\otimes n} = \theta$ (optimally $+O(\theta^2)$)

$$A_n = \sum_x \hat{\theta}_x |x\rangle\langle x| \quad \text{Pr}[\hat{\theta}_x] = \langle x | \rho_0^{\otimes n} | x \rangle$$

$$\text{Var} [\hat{\theta}_x] = \langle A_n^2 \rangle - \langle A_n \rangle^2 \geq \frac{1}{F(x)}$$