

The first part of Lec 9 is in the Lec 8 notes.

HSW converse

$$M = X^n - Q^n - \hat{M}$$

$$(1-\epsilon)_{nR-1} \leq I(M; \hat{M}) \leq I(X^n; \hat{M}) \stackrel{\text{classical}}{\leq} I(X^n; Q^n) \stackrel{\text{quantum}}{\leq} \sum_{i=1}^n I(X_i; Q_i) \stackrel{\text{same}}{\leq} \stackrel{\text{as classical}}{nC(N)}$$

$\frac{1}{n} \chi(N \otimes M)$

$$\frac{1}{n} \chi(N \otimes M) \geq \chi(N) + \chi(M)$$

sometimes = "additive"

1)  $N$  is entanglement-breaking.  
 $N(\rho) = \sum_k \text{tr}[\rho M_k] \sigma_k$

CCQ

2)  $N$  is depolarizing  
 $N(\rho) = (1-p)\rho + p \frac{I}{d}$

3) erasure  
 $N(\rho) = (1-p)\rho + p |e\rangle\langle e|$

4) unitary qubit channel  
 $N(I) = I$

5) pure loss bosonic channel

However

$$\exists N \text{ s.t. } \chi(N^{\otimes 2}) > 2\chi(N)$$

Applications of HSW converse

1) random access coding

$$X \in \{0,1\}^m \rightarrow P_X \text{ in } n \text{ qubits}$$

$$P_X \left[ \begin{array}{c} ? \\ \vdots \\ ? \\ \vdots \\ ? \end{array} \right] = \hat{X}_i$$

$$m=2, n=1 \text{ can achieve } \Pr[\hat{X}_i = x_i] = \cos^2(\pi/8) \approx 0.85 \dots$$

classically can't beat  $1/2$

However quantumly error  $\epsilon \Rightarrow n \geq m(1-H_2(\epsilon))$

Lemmas given  $\sigma_0, \sigma_1$ ,  $M_0 + M_1 = I$  s.t.  $\text{tr } M_b \sigma_b \geq 1 - \epsilon$

$$\sigma = \frac{\sigma_0 + \sigma_1}{2} \Rightarrow S(\sigma) \geq \frac{S(\sigma_0) + S(\sigma_1)}{2} + 1 - H_2(\epsilon)$$

$$\text{Pf } \rho_{xQ} = \frac{|0\rangle\langle 0| \otimes \sigma_0 + |1\rangle\langle 1| \otimes \sigma_1}{2}$$

$$\begin{aligned} I(X;Q) &= S(Q) - S(Q|X) \\ &= S(\sigma_0) - \frac{S(\sigma_0) + S(\sigma_1)}{2} \end{aligned}$$

$$\begin{aligned} &\geq I(X; b) \quad b = \text{measurement outcome} \\ &= H(X) - H(X|b) \\ &\geq 1 - H_2(\epsilon) \quad \text{#} \end{aligned}$$

R.A.C

$$g = \frac{1}{2^m} \sum_{x \in \{0,1\}^m} |x\rangle\langle x| \otimes p_x$$

$$S(Q|X_1, \dots, X_k) \geq S(Q|X_1, \dots, X_{k+1}) + 1 - H_2(\epsilon)$$

$$\Rightarrow m(1 - H_2(\epsilon)) \leq S(Q) \leq n$$

1.5) Quantum State learning  
 given state  $g$  on  $n$  qubits  
 need  $\exp(n)$  bits to describe  
 what about most measurements  $M \sim \mathcal{D}$ ?

(consider 2-outcome measurements  $\{M_1, \perp-M_1\}$  for simplicity)

Think of  $p$  as a map from  $M \rightarrow \{0,1\}$

for simplicity we will only care if  $\text{tr } M_i p \geq 1-\epsilon$  or  $\leq$   
 VC dimension ( $S$  = states) = measure of complexity

= largest set that is "scattered" by  $S$

$$\text{e.g. } \begin{matrix} / & \backslash & / & \backslash \\ \backslash & / & \backslash & / \\ \vdots & \vdots & \vdots & \vdots \end{matrix} \quad \begin{matrix} \circ & \circ \\ \times & \times \end{matrix} \quad \begin{matrix} + & + \\ - & - \end{matrix}$$

given measurements  $M_1, \dots, M_d \in M$  and outcomes  $o_1, \dots, o_d \in \{0,1\}$   
 $\exists p$  s.t.  $|\text{tr } p M_i - o_i| \leq \epsilon$

by RAC bound, this is possible only if  $d = O(n)$

$\Rightarrow p$  can be learned with  $O(n)$  samples

next time we'll see that  $\mathcal{R}(2^n)$  or  $\mathcal{R}(4^n)$   
 samples are needed to output  $\hat{p}$  s.t.  $\|p - \hat{p}\|_1 \leq \epsilon$