ANURAN MAKUR 2 - Density Operators: These are nxn Hermitian positive semi-definite matrices with unit trace in an n-dim quantum state space. 9: A s.t. A"=A, A>O, tr(A)=1. \rightarrow Pure-state: If $|\Psi\rangle$ is the state of a quantum system, then $p=|\Psi\rangle\langle\Psi|$ is a rank-1 pure-state density operator. -> Mixed-state: Suppose we have states 14,>,..., 14n w.p. pi,...,pn respectively. A mixed-state is: $p = \sum_{i=1}^{n} P_i | V_i \times V_i |$ \(\sim \text{useful in info. theory as we have prob. dist. over signals (source symbols)} * Why use density operators? Let IY> = [TP: IY:> be the mixed state. - Suppose [4] is an I-normal basis. Given 14>, we know the actual state we don't care or know about the distinguishable states 14>. When we do not know 14>, but only know pifor 14), we use p. -In the form $p = \sum_{i=1}^{n} p_i |\Psi_i \times \Psi_i|$, we can take an EVD of p to find $[\Psi_i]^2$ upto $[\Psi_i]^2$ upto -.. Density operators capture all information about state. quant. mech. $\rightarrow Observe: |\langle \psi | \psi_i \rangle|^2 = tr(p.|\psi_i \times \psi_i|)$ for $1-normal \{\psi_i\}$ (We have augmented vector states to matrix states & use the matrix inner product.)

(3) Classical-Quantum Channel:

- Positive operator valued measurement (POVM) ← generalization of von Neumann measurement - 141-dim Hilbert space H > state vectors 141-dim & density operators are 141×141 matrices classical quantum quantum 7 dassical-quantum channel length of codeword POVM 3 classical-quantum channel messages {Sz} Measure → m' ∈{1,..., M} [Error ⇔ m≠m']

me /1,..., Mf -M=enR encoded drannel fillion, TIM? Pelm = 1 - tr(TImSxm), Vm codebook: R = rate of code $\frac{Z}{Z_{2}^{n}} = (x_{1}, \dots, x_{n}) \in \mathcal{X}^{n}$ 2 cond. prob. of error M each codeword looks like this each codeword r state of xEX

- For each $x \in \mathcal{X}$, there is an associated density operator S_x . So, with $X_m = (X_1, ..., X_n)$ we have the associated density operator $S_{z_n} = S_{z_1} \otimes ... \otimes S_{z_n}$ (n-fold tensor product space $H^{(N-1)}$)

- POVM: Collection of M Hermitian positive semidefinite matrices [TI, ..., TIM] (each 141" x 14m) I projection to subspace I Löwner partial order

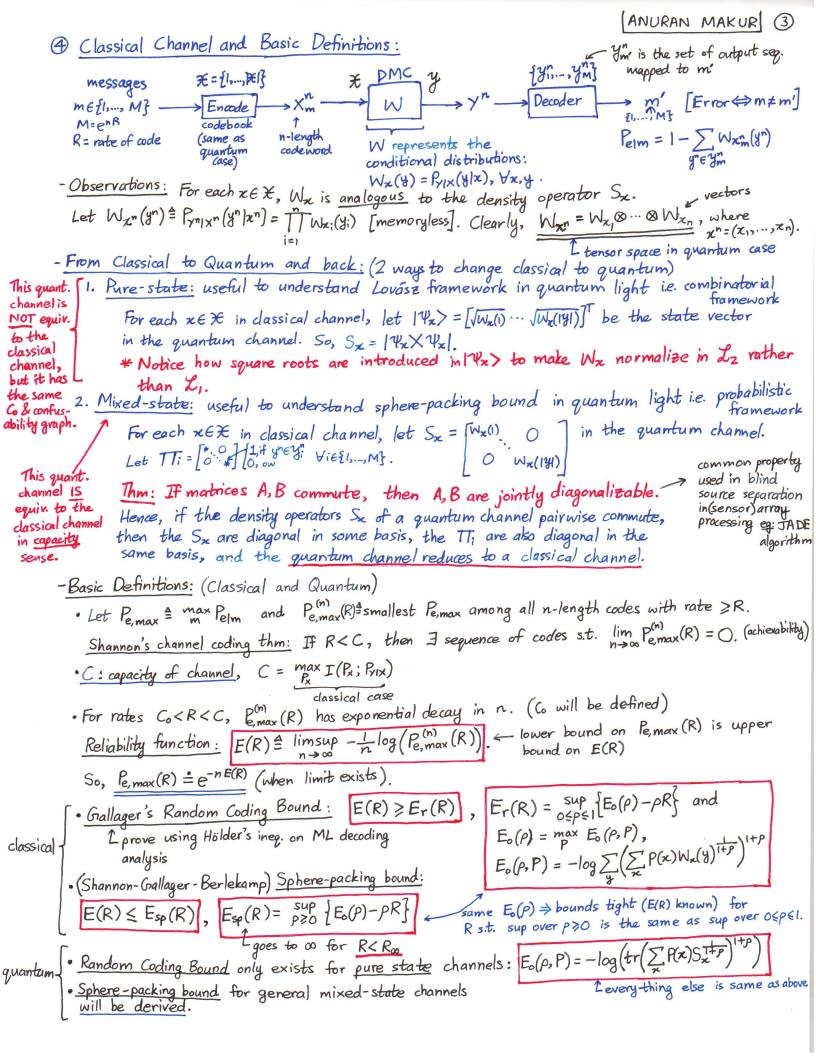
eg: 141 = enR = M. Then let STi = I and let Ti = 14:X4i, where {14:>} is an I-normal basis of Alyn If San = 14: XVII, then tr(TTiSan) = 1 and tr(TTiSan) = 0 for i = j. So, Pili = l and Pilj = 0.

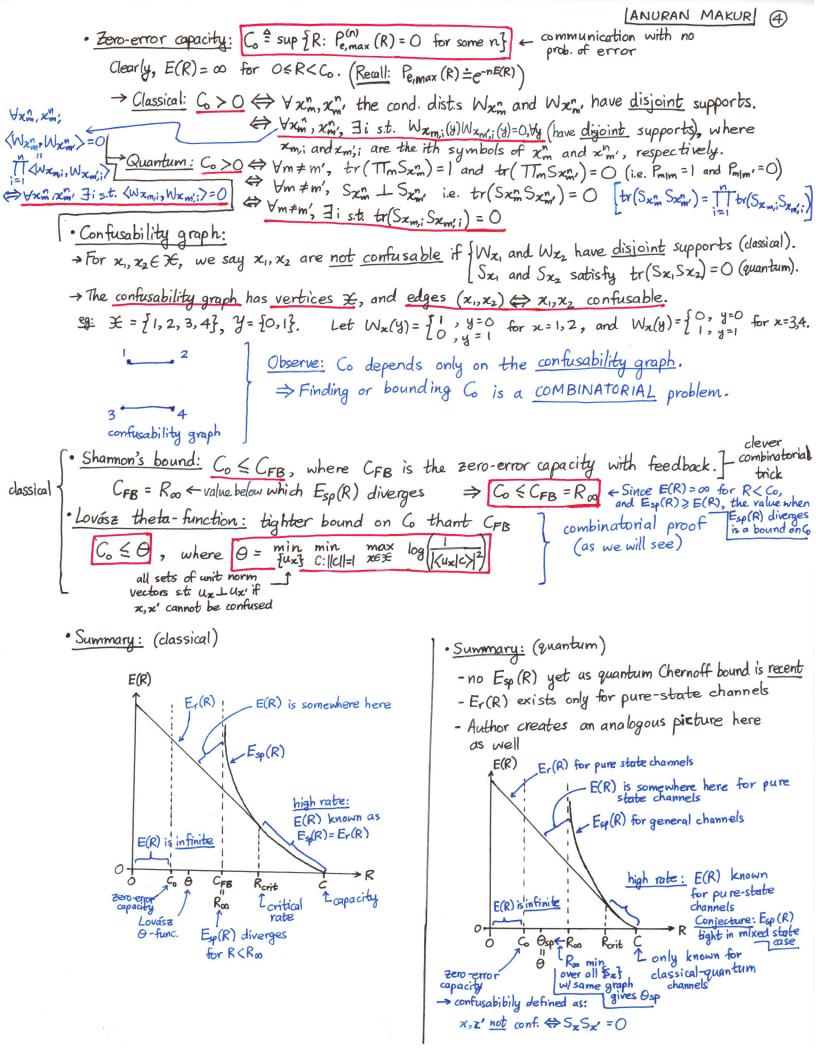
- Each Ti is a projection matrix onto a subspace $S_i \subseteq H^{[y]^n}$ When $T_i T_j = 0$, $i \neq j$ and $\sum_{i=1}^{M} T_i = I$, the S_i are orthogonal subspaces & $S_i \oplus \cdots \oplus S_m = H^{[y]^n}$. In general, the direct sum of S_i may be a subspace of $H^{[y]^n}$ (e.g. $M < |y|^n$); this is why we use $\sum_{i=1}^{M} T_i \preceq I$.

- S; is the subspace corresponding to message i. Hence, probability message m' is decoded given m is transmitted is: PMIM = tr(TTm, Sxm) => Pelm = 1-tr(TTm Sxm) } Prob of error given m sent.

-Pure-state channel: Each S_x , $x \in X$ is rank-1 i.e. $S_x = |Y_x \times Y_x|$.

⁻In general, S_x are mixed state and S_{x_m} are certainly mixed state if we use a prob. dist. on \star . eg: $S_{x_m} = S_{x_1} \otimes_{-\infty} \otimes S_{x_n}$. $S_{x_n} = \sum_{i=1}^n P_x(x_i) S_x$. $\forall i$ in random coding.





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ANURAN MAKUR (5)
    (5) Lovász's Approach in a quantum light: Umbrella bound
              -Goal: Obtain Lovász's O-bound as a consquence of bounding E(R) for classical DMC
                                                    Ly extension of Lovász's approach
                                                    -> objective is not to get tight bound on E(R)
           - Large deviations: (Classical)
                   Consider 2 distributions Po, P. on y.
                   Let the geometric mean be: Ps(y) = Po s(y) Ps(y), 06551.
                                                                                                                                                             emB.R(s) - normalization
                                                             notural parameter
                 P_s(y) = P_s(y) \exp\left[\frac{s}{s} \log\left(\frac{P_s(y)}{P_s(y)}\right) - \mu_{R,P}(s)\right] \leftarrow (\text{regular}) \text{ linear } \frac{\text{exponential}}{\text{family}}
                          base distribution natural statistic log-partition function family
                                                                                                                                                        \Rightarrow \mu_{R,R}(s) = \mathbb{E}_{R}[\log(\frac{P_{r}(y)}{B(y)})]
                 MB, P. (S)=log [ P. 1-S(4) P. 5(4)), 0≤S≤1
                                                                                                                                                           & uB, P. (5) > 0 Fisher information
                                                                                                                                                              From the figure, clearly:
                                                                                           D(BIIPO)
                                                                                                                                  D(P,11%)
                                                                                                                                                             MB,P,(5+) ≤ MB,P,(2)
                                                                                                                                                                                                                                                                                                    Analogously in the quantum
                                                                                                    MPQP, (5)
                                                                                                                                                              Also true that:
                                                                                                                                                                                                                                                                                                    case, we have:
                                                                                                                                                              MB,R(s*) > ZMB,P,(=)
                                                                                                                                                                                                                                                                                                   For density operators A, B:
                               00
                                                                                                                                                                                                                                                                                                           \mathcal{M}_{A,B}(s) = \log (tr(A^{1-s}B^s)),
                                                                                                                                                           Chernoff distance:
                                                                                                MPO,P,(S)
                                                                                                                                                     dc(Po, Pi) = - min up, Pi(s)
                                                                   At s= s*, u'p, p(s*)=0
                                                                                                                                                                                                                                                                                       d_c(A,B) \triangleq -\min_{0 \le s \le 1} M_{A,B}(s)
                                                                                                                                                          Bhattacharyya distance:
                                                               ⇒ MR, P. (3) attains its
                                                                                                                                                                                                                                                                                         dB(A,B) =-MA,B(=)
                                                                       minimum
                                                                                                                                                    dB(Po, Pi) = -从Po, Pi(立)
                  -D(PollPi)
                                               D(B*11P0) = D(Ps*11P1) = -12P0P(5)
                                                                                                                                                                                     = -log(\(\sum_{1/6}(\frac{1}{6})\text{P_6(\frac{1}{6})}\text{P_6(\frac{1}{6})}\text{P_6(\frac{1}{6})}\text{P_6(\frac{1}{6})}\text{P_6(\frac{1}{6})}\text{P_6(\frac{1}{6})}\text{P_6(\frac{1}{6})}\text{P_6(\frac{1}{6})}\text{P_6(\frac{1}{6})}\text{P_6(\frac{1}{6})}\text{P_6(\frac{1}{6})}\text{P_6(\frac{1}{6})}\text{P_6(\frac{1}{6})}\text{P_6(\frac{1}{6})}\text{P_6(\frac{1}{6})}\text{P_6(\frac{1}{6})}\text{P_6(\frac{1}{6})}\text{P_6(\frac{1}{6})}\text{P_6(\frac{1}{6})}\text{P_6(\frac{1}{6})}\text{P_6(\frac{1}{6})}\text{P_6(\frac{1}{6})}\text{P_6(\frac{1}{6})}\text{P_6(\frac{1}{6})}\text{P_6(\frac{1}{6})}\text{P_6(\frac{1}{6})}\text{P_6(\frac{1}{6})}\text{P_6(\frac{1}{6})}\text{P_6(\frac{1}{6})}\text{P_6(\frac{1}{6})}\text{P_6(\frac{1}{6})}\text{P_6(\frac{1}{6})}\text{P_6(\frac{1}{6})}\text{P_6(\frac{1}{6})}\text{P_6(\frac{1}{6})}\text{P_6(\frac{1}{6})}\text{P_6(\frac{1}{6})}\text{P_6(\frac{1}{6})}\text{P_6(\frac{1}{6})}\text{P_6(\frac{1}{6})}\text{P_6(\frac{1}{6})}\text{P_6(\frac{1}{6})}\text{P_6(\frac{1}{6})}\text{P_6(\frac{1}{6})}\text{P_6(\frac{1}{6})}\text{P_6(\frac{1}{6})}\text{P_6(\frac{1}{6})}\text{P_6(\frac{1}{6})}\text{P_6(\frac{1}{6})}\text{P_6(\frac{1}{6})}\text{P_6(\frac{1}{6})}\text{P_6(\frac{1}{6})}\text{P_6(\frac{1}{6})}\text{P_6(\frac{1}{6})}\text{P_6(\frac{1}{6})}\text{P_6(\frac{1}{6})}\text{P_6(\frac{1}{6})}\text{P_6(\frac{1}{6})}\text{P_6(\frac{1}{6})}\text{P_6(\frac{1}{6})}\text{P_6(\frac{1}{6})}\text{P_6(\frac{1}{6})}\text{P_6(\frac{1}{6})}\text{P_6(\frac{1}{6})}\text{P_6(\frac{1}{6})}\text{P_6(\frac{1}{6})}\text{P_6(\frac{1}{6})}\text{P_6(\frac{1}{6})}\text{P_6(\frac{1}{6})}\text{P_6(\frac{1}{6})}\text{P_6(\frac{1}{6})}\text{P_6(\frac{1}{6})}\text{P_6(\frac{1}{6})}\text{P_6(\frac{1}{6})}\text{P_6(\frac{1}{6})}\text{P_6(\frac{1}{6})}\text{P_6(\frac{1}{6})}\text{P_6(\frac{1}{6})}\text{P_6(\frac{1}{6})}\text{P_6(\frac{1}{6})}\text{P_6(\frac{1}{6})}\text{P_6(\frac{1}{6})}\text{P_6(\frac{1}{6})}\text{P_6(\frac{1}{6})}\text{P_6(\frac{1}{6})}\text{P_6(\frac{1}{6})}\text{P_6(\frac{1}{6})}\text{P_6(\fr
                                                                                                                                                                                                                                                                                                                       = - log (tr (JAJB))
                                                                                                                                                                                                                                                                                            d_{B}(A,B) \leq d_{c}(A,B) \leq 2d_{B}(A,B)
                                              d_B(P_0, P_1) \le d_e(P_0, P_1) \le 2d_B(P_0, P_1) (from u relations above)
          If we do Binary Hypothesis testing in Neyman-Pearson formulation:
                                                                             Hi: Yim~ iid Pi -> log-likelihood ratio test w/ 8 threshold
           Then, \lim_{n\to\infty} -\frac{1}{n} \log(\text{Re}_{1H_0}) = D(\text{Rs}_{1}|\text{R}_{0}) for some s depending on T \lim_{n\to\infty} -\frac{1}{n} \log(\text{Re}_{1H_0}) = D(\text{Rs}_{1}|\text{R}_{0}) for some s depending on T \lim_{n\to\infty} -\frac{1}{n} \log(\text{Re}_{1H_0}) = D(\text{Rs}_{1}|\text{R}_{0}) for some s depending on T
  Hence, Pe decays fastest when D(P_S||P_s) = D(P_S||P_s) = d_c(P_s,P_s): \lim_{n\to\infty} -\frac{1}{n}\log(P_s) = d_c(P_s,P_s).
    - Quantum view: (DMC) For each xEX, we have cond. dist. Wx. Def: 14x>=[Wx(1) ... JWx(191)].
            For codeword x_m^n = (x_1, ..., x_n), \sqrt{W_{x_m}(y^n)} = \sqrt{W_{x_i}(y_i)} \Rightarrow \sqrt{\psi_{x_i}(y_i)} = \sqrt{\psi_{x_i}(y_i)} \Rightarrow \sqrt{\psi_{x
             Note: Co>0 $\Rightarrow \frac{1}{2}\chi,\chi',\chi\pi' \s.t. \left(\pi_x|\pi_x') = 0. \Rightarrow \text{Codes exist s.t.} \left(\pi_m|\pi_m') = 0 \text{ for some } m \neq m'.
              dB(Wxm, Wxm,) = -log(\sum_{yn}\wideharm(yn)\wideharm(yn)) = \frac{-log(\frac{\mu_m}{y_m}\wideharm)}{\to hyp. testing framework} \to hyp. testing framework
   - Binary Hypothesis testing between m & m': - log (Pe) = dc (Wxm, Wxm,) + o(n) [see above]
          \Rightarrow -\log(P_e) \leq 2dB(W_{xm}, W_{xm}) + o(n) \Rightarrow -\log(P_e) \leq -2\log(\langle Y_m | Y_{m'} \rangle) + o(n)
       For a fixed code, -log(Pe,max) ≤ min -2 log((\4m/4m/>)+o(n) => -log(Pe,max) ≤ -2 log(max, (4m/4m/))+o(n)
         Pe,max > Prob. of error of in hyp.test_1
between 2 codewords
 - IDEA: Upper bound E(R) by lower bounding max, (4m14mi)
- Value of a representation: For P≥1, T(P)={ [Vx], x ∈ X: (V|Vx)=1, ∀x and |(Vx|Vx)| < (4x|Vx), ∀x, x'f
      V({ = 1/2}) = min max -log(|(\vec{v}_z|f)|^2) \ Lyalue of {\vec{V}_z} \ Chebyshev/minmax of Bhattacharyya distance \ (inner prod. corresp. to graph structure)
                                                                                                                                                                                         I tilted vectors (1-normal representation of degree p)
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ANURAN MAKUR 6
                                               - Theta function: \Theta(P) \triangleq \min_{\{\tilde{Y}_{\mathcal{X}}\} \in P(P)} V(\{\tilde{Y}_{\mathcal{X}}\}) = \min_{\{\tilde{Y}_{\mathcal{X}}\} \in P(P)} \min_{\{\tilde{Y}_{\mathcal{X}}\} \in P(P)\}} \max_{\{\tilde{Y}_{\mathcal{X}}\} \in P(P)\}} \max_{\{\tilde{Y}_{\mathcal{X}}\} \in P(P)\}} \min_{\{\tilde{Y}_{\mathcal{X}}\} \in P(P)\}} \max_{\{\tilde{Y}_{\mathcal{X}}\} \in P(P)\}} \sum_{\{\tilde{Y}_{\mathcal{X}}\} \in P(P)\}} \min_{\{\tilde{Y}_{\mathcal{X}}\} \in P(P)\}} \min_{\{\tilde{Y}_{\mathcal{X}}\} \in P(P)\}} \sum_{\{\tilde{Y}_{\mathcal{X}}\} \in P(P)} \sum_{\{\tilde{Y}_{\mathcal{X}}\}} \sum_{\{\tilde{Y}_{\mathcal{X}}\} \in P(P)} \sum_{\{\tilde{Y}_{\mathcal{X}}\} \in P(P)} \sum_{\{\tilde{Y}_{\mathcal{X}}\} \in P(P)} \sum_{\{\tilde{Y}_{\mathcal{X}}\}} \sum_{
                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                 UMBRELLA BOUND
                              * Theorem: For a DMC, given any P \ge 1, E(R) \le 2p\Theta(p) for R > \Theta(p)
                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                     min-max formulation
                                             Proof: (Idea: Construct auxiliary state + close to all possible states 1/2 with any sequence xn.)
                     Consider optimal \{\tilde{\psi}_{x}\} and f for \Theta(P). For \chi^{n} = (\chi_{1}, ..., \chi_{n}), |\tilde{\psi}_{x}\rangle = |\tilde{\psi}_{x}\rangle \otimes ... \otimes |\tilde{\psi}_{x}\rangle and we have: (1 \ge) |\langle \tilde{\psi}_{x}| f^{\otimes n} \rangle|^{2} = \prod_{i=1}^{n} |\langle \tilde{\psi}_{x_{i}}| f \rangle|^{2} \ge e^{-n\Theta(P)}, because |\langle \tilde{\psi}_{x_{i}}| f \rangle|^{2} \ge e^{-\Theta(P)}, \forall x.
                                            \Rightarrow M \leqslant e^{n\Theta(\rho)} \Rightarrow \underbrace{R \leqslant \Theta(\rho)}_{\text{mate}} \text{ rate of code on } \{\widehat{V}_{m}\} \text{ channel corresponds to } Co>0 \text{ into play} ]
If R > \Theta(\rho), M > e^{n\Theta(\rho)}, \exists \widehat{V}_{m}, \widehat{V}_{m'}, s.t. |(\widehat{V}_{m}|\widehat{V}_{m'})|^{2} > 0. Then |(\widehat{V}_{m}|\widehat{V}_{m'})|^{2} > |(\widehat{V}_{m}|\widehat{V}_{m'})|^{2\rho} > 0, & G=0. Hence, C_{0} \leqslant \Theta(\rho).
                                                   Lovász bound: | = ||f^{\otimes n}||_2^2 > \sum_{m} |\langle \tilde{\Psi}_m | f^{\otimes n} \rangle|^2 > Me^{-n\Theta(P)}, for \{\tilde{\Psi}_m\} L-normal [observe how idea comes
                                                    Let \Psi \triangleq \frac{1}{m} [\tilde{W} \rangle \cdots \tilde{W}]. Then, \langle f^{\otimes n} | \Psi \Psi^{+} | f^{\otimes n} \rangle \geqslant e^{-n\Theta(p)}.
                                                   Thm: For a square matrix A, \lambda_{max}(A) \leq \max_{j} |A_{ij}|. Corollary of the beautiful Gresshgorin Circle

Theorem used in numerical linear algebra.
                                                     ⇒ e-no(p) < max h∑ Kỹm lữmy
                                                 \Rightarrow \underbrace{Me^{+\theta(p)}-1}_{M-1} \leq \max_{m} \frac{1}{M-1} \sum_{m'\neq m} \underbrace{\{\psi_{m}|\psi_{m'}\}}_{\text{[Jensen]}} \leq \max_{m} \left(\frac{1}{M-1} \sum_{m'\neq m} \langle \psi_{m}|\psi_{m'} \rangle\right)^{\frac{1}{p}}
Observe that
                                                   Observe that: \max_{m \neq m'} \langle \psi_m | \psi_{m'} \rangle \geqslant \max_{m' \neq m} \frac{1}{M-1} \sum_{m' \neq m} \langle \psi_m | \psi_{m'} \rangle \geqslant \left( \frac{Me^{-n\Theta(P)} - 1}{M-1} \right)^P \geq \left( \frac{e^{-n\Theta(P)} - e^{-nR}}{M-1} \right)^P
                                                    If R > O(P), e^{-nO(P)} dominates [Laplace Principle] \Rightarrow \frac{1}{n} \log(\max_{m \neq m}, \langle \Psi_m | \Psi_{m'} \rangle) \leq \rho O(P) + o(1)
                                                     \Rightarrow E(R) = \lim_{N \to \infty} \frac{1}{N} \log(P_{e,max}) \leq 2\rho \Theta(\rho) \quad \text{(from earlier expression)}
                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                          [Q.E.D.]
                                                         · Def: Cut-off rate of channel | limiting rate for sequencial decoding practicality
                                          - Remarks:
                                                                Rout = max - \( \superprescript{P(x)P(x)}\quad \quad \
                                                               For \rho = 1, WLOG \tilde{\Psi}_x = \tilde{\Psi}_x, \forall_x \in \mathcal{X}. Since \tilde{\Psi}_z \geqslant 0, we can choose optimal f \geqslant 0. Let f = \sqrt{Q},
                                                               where Q is a probability distribution.
                                                               O(1) = \min_{x} \max_{x} -\log(|\langle \psi_{x}|f \rangle|^{2}) = \min_{x} \max_{x} -2\log(\sum_{x} \sqrt{Q(y)}W_{x}(y)) \stackrel{\text{Csiszár}}{=} \text{Rat}
                                                                                                                                                                                                                                                                                   Lover all prob. dist.s
                                                      · As p > 00, the constraint Killing) < < \/ becomes | \( \var{\psi} \) = 0 if < \( \var{\psi} \) = 0.
                                                              Hence, T(\infty) = the set of all pure state quantum channels with the same confusability.

graph as the channel W.

1 can G=0=0 for complete confusability
Quantum
interpretation
                                                                 C_0 \leq O(P) \Rightarrow \underbrace{C_0 \leq \lim_{p \to \infty} \Theta(P) = O}_{\text{min over 2423 disopposites}} \leftarrow \underbrace{\text{tightest}}_{\text{supposites}} \xrightarrow{\text{bound when } p \to \infty} \underbrace{C_0 = 0 = 0}_{\text{supposites}} \underbrace{C_0 = 0}_{\text{supposites}} \underbrace
of Lovasz
  0-bound
                                                   · Using sphere-packing bound techniques in conjunction with Lovosz's technique, an umbrella
                                                                  bound for a general classical-quantum channel can be derived.
                                                                 For classical-quartum channel \mathcal{C} with density operators S_{\varkappa}, \varkappa \in \mathcal{X}, for p \ge 1 let \Gamma(p) \triangleq \{ \tilde{S}_{\varkappa} \tilde{S}_{\varkappa} : \operatorname{tr}(\sqrt{\tilde{S}_{\varkappa}}\sqrt{\tilde{S}_{\varkappa}}) \le \operatorname{tr}(\sqrt{\tilde{S}_{\varkappa}}\sqrt{\tilde{S}_{\varkappa}}) \}. For auxiliary channel \tilde{\mathcal{C}} \in \Gamma(p), let \tilde{\mathbb{E}}_{sp}(R) be
                                                                  the sphere-packing bound (to appear next).
                                                                      Thm: E(R) \leq E_{spu}(R), where E_{spu}(R) = p_{71}, CeT(p)
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This is
  the
dassica
 proof
for test
between
Qo, QI.
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6 The Quantum Sphere-Packing Bound:

Then for O<S<1, either

 $\Rightarrow \Pi = \sum_{i} \Pi |b_{i} \times b_{j}| \Pi \quad \text{and} \quad I - \Pi = \sum_{i} (I - \Pi) |a_{i} \times a_{i}| (I - \Pi)$

* BOTH cond. Pe's cannot

decay too fast.

Exponentially tilt to get $Q_s(i,j) = \frac{Q_o^{1-s}(i,j)Q_s^s(i,j)}{e^{\mu Q_o Q_1(s)}} = e^{-\mu(s)}Q_o^{1-s}(i,j)Q_s^s(i,j), \quad \mu(s) = \mu_{Q_o,Q_1}(s)$ Let $\mathbb{Z}_s = \{(i,j): |\log\left(\frac{Q_1(i,j)}{Q_0(i,j)}\right) - \mu'(s)| \le \sqrt{2\mu''(s)}\}$, where $\mu'(s) = \mathbb{E}_{Q_s}[\log(Q_1/Q_0)]$, $\mu''(s) = VAR_{Q_s}[\log(Q_1/Q_0)]$ $Q_{s}(i,j) \leq Q_{o}(i,j) \exp[\mu(s) - s\mu'(s) - s\sqrt{2}\mu''(s)]^{-1} \quad \text{and} \quad Q_{s}(i,j) \leq Q_{i}(i,j) \exp[\mu(s) + (i-s)\mu'(s) - (i-s)\sqrt{2}\mu''(s)]$ [Chebyshev]

This choice is arbitrary.

The proof of the proof $<\sum_{(i,j)\in\mathcal{Z}_s}Q_s(i,j)$ $\leq\sum_{(i,j)\in\mathcal{Z}_s}\min\left(n_oQ_o(i,j),n_iQ_i(i,j)\right)$ trade-off between PelA & PelB [Q.E.D.] Hence, noPela + noPelB > 4 => PelA > 8 no or PelB > 8 no. * Theorem: (Sphere-packing bound) Let Si,..., Sixi be density operators for a general classical-quantum channel and E(R) be its reliabity function. Then, $\forall R > 0, \forall 0 < \epsilon < R$, $E(R) \leq E_{sp}(R - \epsilon)$, where $E_{sp}(R) = \sup_{\rho \geqslant 0} E_{o}(\rho) - \rho R$, $E_{o}(\rho) = \max_{\rho > 0} E_{o}(\rho)$ and $E_o(\rho, P) = -\log\left(tr(\sum_{x} P(x) S_x^{1+p})^{1+p}\right)$

Proof: (Idea: low rate > Pe dominated by worst pair of codewords, high rate > bound Pelm due to bulk of competitors.

So, bound Permax by looking at hypothesis test between S_{χ_m} and dummy density operator F_n .

The represents the "bulk of competitors". Author shows $\exists m, F_n$ s.t.

Pm/F = tr(TmF) is small > Fr (bulk of competitors m') are distinguishable from Sxm to

some degree

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every rate R code contains such a subcode as no. of codewords exp. in n (enR=M) but no. of compositions is poly(n).
            ANURAN MAKUR (8)
             Proof cont'd:
                WLOG assume the code is a constant composition code i.e. all codewords xm, me {1,...,M},
                 have the same empirical distribution P
                Let F be a density operator in Hom - The whole proof constructs F
                For any m E{1,..., m}, consider hypothesis test between Szm and Fi:
                                                                                                                                      1 (s) = log(tr(Szm Fs))
                From Lemma, Pelm = tr((I-TI_m)S_{xm}) > \frac{1}{8}exp[\mu(s)-s\mu'(s)-s\sqrt{2}\mu''(s)]

or Pelf = tr(TI_mF_n) > \frac{1}{8}exp[\mu(s)+(1-s)\mu'(s)-(1-s)\sqrt{2}\mu''(s)]
                 Vm, Pe, max ≥ Pelm and ∑TTm ≤ I ⇒ Im s.t. tr(TTm Fn) ≤ m = e-nR. Fix this m & let xn = xm.
          > Pe,max > fexp[u(s) - su'(s) - s\\(\frac{2}{2}u''(s)\)] or R< -\frac{1}{2}[u(s) + (1-s)u'(s) - (1-s)\\(\frac{2}{2}u''(s) - \log(8)\)] \(\tau^{\frac{1}{2}}\) trade-off
                                                                                                                                                               between R
               Remark: M(s) & M'(s) grow linearly in n but Ju"(s) will grow like In, so it will not matter in first order behaviour.
                                                                                                                                                               and Pe, max
                Want result to depend on P, not x^n = x_m^n. Let \overline{h} = F^{\otimes n}.
                Then \mu(s) = \log \left( \operatorname{tr} \left( S_{xn}^{1-s} F_{n}^{s} \right) \right) = n \sum_{x \in x} P(x) \mu_{S_{x}, F}(s) \Rightarrow \mu'(s) = n \sum_{x \in x} P(x) \mu'_{S_{x}, F}(s), \mu''(s) = n \sum_{x \in x} P(x) \mu'_{S_{x}, F}(s).
                                                                                                                                                          Juis a vin
               Let R_n(s, P, F) \triangleq -\frac{1}{n} \left[ \mu(s) + (1-s) \mu'(s) - (1-s) \sqrt{2} \mu''(s) - \log(8) \right]
          \Rightarrow \frac{1}{n} \log(R_{e,max}) < -\frac{1}{1-s} \sum_{x} P(x) \mu_{Sx,F}(s) - \frac{s}{1-s} R_n(s,P,F) + \frac{1}{n} \left(2s\sqrt{2}\mu''(s) + \frac{\log(8)}{1-s}\right) \quad \text{or} \quad R < R_n(s,P,F)
             Remark: Can we use Nussbaum-Skota mapping to make the quantum problem classical?
             Unfortunately, no. Qo and Q, depend on both Sx and F. Even if F is fixed, changing
             x to get different Sx would change both Qo and Q1. In classical proof, both distributions
              cannot enange with x.

Construct F: Let A(s,P) \triangleq \sum_{x} P(x) S_{x}^{1-s} & let P_{s} \triangleq \underset{P}{\operatorname{argmin}} \operatorname{tr}(A(s,P) \stackrel{1}{\longrightarrow} s) for 0 < s < 1.

Intuition: F_{s} \stackrel{!}{\underline{!}} \operatorname{dose} \stackrel{!}{\underline{!}} \operatorname{to all} S_{x} = \underbrace{I- U_{S_{x}}F_{s}(s)}_{s} \leq (1-s)E_{0}(\frac{s}{1-s}), \forall x
              cannot change with x.
This
section
drawn \\
from dassical Holevo: tr(Sx Ass-s) > tr(As-s), \( \text{x} \) w/ equality for x s.t. P_s(x) > 0.7

distance P_s is optimal from dassical Holevo: P_s(x) > 0.7
                 Let F_s \triangleq \frac{A_s^{V_1-s}}{tr(A_s^{V_1-s})}. Then, \mu_{S_x,F_s}(s) = \log\left(tr(S_x^{1-s}A_s^{s/1-s})\right) - s\log\left(tr(A_s^{V_1-s})\right) \geq (1-s)\log\left(tr(A_s^{V_1-s})\right) = (1-s)E_0\left(\frac{s}{1-s}\right)
         \Rightarrow -\frac{1}{n}\log(\text{Re,max}) < E_0(\frac{s}{1-s}) - \frac{s}{1-s}R_n(s,P,F_s) + \frac{2s\sqrt{2}}{\sqrt{n}}\sqrt{\sum_{x}P(x)}\mu_{x_x,F_s}^{y}(s)} + \frac{\log(8)}{(1-s)n} \quad \text{or} \quad R < R_n(s,P,F_s), \text{ where}
                                                                                                                                                  still arbitrary P, not Ps
                R_{n}(s, P, F_{s}) = -\sum_{x} P(x) \left[ u_{5x, F_{s}}(s) + (1-s) u_{5x, F_{s}}(s) \right] + \frac{1}{\sqrt{n}} (1-s) \sqrt{2} \sum_{x} P(x) u_{5x, F_{s}}^{"}(s) + \frac{1}{n} \log(8)
              By compactness argument, I sequence of codes with length n, rate Rn, composition Pn s.t.
                                                                                                                                                     A differentiable convex function
                                                         P_n \to P, R_n \to R, -\frac{1}{n} \log (P_{e,max}^{(n)}) \to E(R) as n \to \infty.
              Since \mu_{S_{20},F_{2}}(s) is nonpositive and convex for s\in(0,1): \mu_{S_{20},F_{20}}(s)+(1-s)\mu_{S_{20},F_{20}}(s)\leq\mu_{S_{20},F_{20}}(1-s)=0 lies above all its tangents.
                                                                                                                                                                its tangents.
               \Rightarrow R_n(s, P_n, F_s) \geqslant O. R_n(s, P_n, F_s) is also <u>continuous</u> in sE(0,1).
             3 Cases: (1) Rn > Rn(s, Pn, Fs), VsE(0,1) (2) Rn < Rn(s, Pn, Fs), VsE(0,1) (3) Rn = Rn(s, Pn, Fs) for some sE(0,1).
                  1) Suppose Case 1) is satisfied infinitely often for n. Focus on subsequence s.t.
                       Rn(S, Pn, Fs) < Rn, Vn. Then, - 1/n log(Pe, max) < Eo(\frac{s}{1-s}) - \frac{s}{1-s} Rn(s, Pn, Fs) + \frac{2s\Z}{\sqrt{n}} \sum_{\sqrt{x},F_s(s)} + \frac{\log(8)}{(1-s)n}
                       Fix s \in (0,1) and let n \to \infty: E(R) \leq E_0 \left(\frac{s}{1-s}\right) - \frac{s}{1-s} \underbrace{R_n(s, P_n, F_s)}_{\geq 0} \leq E_0 \left(\frac{s}{1-s}\right)
                       \therefore E(R) \leq E_0(\frac{s}{-s}), \forall s \in (0,1) \Rightarrow E(R) \leq E_0(p), p \geq 0 \quad \boxed{p = \frac{s}{1-s}}
                        So, E(R) \leq E_o(O) - O \cdot R = O \Rightarrow E(R) \leq E_{sp}(R)
             → Cases ② & ③ similar.
```

Q.E.D.

```
7 Relationships between Fundamental Quantities:
        - Rényi divergence: D_{\alpha}(U,V) \triangleq \frac{1}{\alpha-1} \mu_{U,V}(1-\alpha) = \frac{1}{\alpha-1} \log \sum_{z} U(z)^{\alpha z} V(z)^{1-\alpha z}
        (Quantum case) D_{\alpha}(A \parallel B) \triangleq \frac{1}{\alpha - 1} \log (tr(A^{\alpha} B^{+\alpha}))
       - The sphere-packing bound: Esp(R) = \sup_{\rho \geqslant 0} E_0(\rho) - \rho R, E_0(\rho) = \max_{\rho} - \log(\operatorname{tr}(\sum_{x} P(x) S_x^{1+\rho}))
          Esp(R) is the upper envelope of lines
                                                                    Eo(p)-pR. The R-axis intercept of these lines is
                                                                        As p \rightarrow 0, the gradient of E_0(p) - pR is 0
                                                                         As p \rightarrow \infty, the gradient of E_0(p) - pR is \infty
                              Eo(p)
values
                                                                           \Rightarrow R_{\infty} is where the sphere packing bound diverges
                                                             E_{sp}(R)
                                                                         Note: Co < Ro because Ro is the smallest R-value when
                                                                                E_{sp}(R) < \infty \Rightarrow E(R) < \infty and E(R) = \infty for R < G.
      - Information Radii: Recall C = min max D(WxllQ) in classical case. [Gallager's Capacity-Red.
Thm shows this is C.]
          It turns out, the right measure to look at in quantum information is Rényi divergence.
          The entire classical formulation can be done using Rényi divergence.
                                                                 As \rho \to 0 (\alpha \to 1), R_0 = C, as D\alpha \to D_{KL}.
           Rp = min max Da(Wx ||Q), a = 1+p
                                                                 As p \to \infty (\alpha \to 0), R_{\infty} = \min_{\alpha \in P^{\alpha}} \max_{x \in \mathcal{X}} -\log \left(\sum_{y: w_{\alpha}(y) \to 0} Q(y)\right)
Classical.
         Thm: For a classical-quantum channel with states Sx, x & and p>0, Rp = min max Da (Sx 11F)
          for \alpha = \frac{1}{1+p}, where min is over all density operators.
          Proof Sketch: Start with Rp = Fo(P). Use Hölder's inequality with Schatten norms to get:
                              R_p = \frac{1}{\alpha - 1} \log \left( \min_{P \in \mathbb{R}} \max_{B \in \mathbb{R}} \operatorname{tr} \left( \sum_{x} P(x) S_x^{\alpha} B \right) \right). Use von Neumann's minmax theorem.
         Remark: If Sx pairwise commute, then optimal F is diagonal in same basis as Sx. So, we recover
                    the classical Rp.
    - Connection to Lovász O-function:
       From the quantum formulation, as p \to \infty (\alpha \to 0), R_{\infty} = \min_{F} \max_{\alpha} - \log(\operatorname{tr}(S_{\alpha}^{\circ}F)).
       Assume S_x = |\Psi_x \times \Psi_x| are pure states. Restrict F = |f \times f| to be rank 1 density operator.
       Then tr(S_{\infty}^{\circ}F) = |\langle \Psi_{\infty}|f \rangle|^2 and \frac{V(\{\Psi_{\infty}\})}{f} = \min_{x \in \mathcal{X}} \max_{x \in \mathcal{X}} -\log(|\langle \Psi_{\infty}|f \rangle|^2) = R_{\infty}, \text{ constrained}.
                                                            I value of representation [42]
                                     C_0 \leq R_\infty \leq V(\{\Psi_{\mathbf{x}}\}) \Rightarrow C_0 \leq O(p) = \min_{\{\Psi_{\mathbf{x}}\} \in \Gamma(p)\}} V(\{\Psi_{\mathbf{x}}\})
       Hence, we have:
        Best bound on Co is given by min Row over all quantum channels with same
                                                                    plays role of value in Lovász O-function
       confusability graph
                                                                                      min min max -log(tr(SxF
                                                    min
                                                                 R_{\infty}(\{S_{\kappa}\}) =
                                                {Sx}: {Sx}
              analogous
                                               density operators
             to O-func.
                                               s.t. Sx Sx' = 0 if
                (Lovász)
                                               (x,x') not connected
                                                in conf. graph
                                                                    Remark: Co & Osp can also be proved using exactly
       Clearly, C_0 \leq \Theta_{sp} \leq \Theta = \lim_{p \to \infty} \Theta(p) \leq \Theta(p)
                                                                                  Lovász's argument using general density operators
                                                                                   as handles. This does not provide connection to Esp(R).
```

Llovasz-A func.

Indeed, it turns out that Osp = O.

Hence, $C_0 \le \Theta_{sp} = \Theta$.

Implication: Minimizing Row over all {5x}, F (density operators) gives the same result as minimizing Row over all {1/2}, f (pure state vectors), which we call Ros, constrained. We conclude that Esp(R) bound on classical-quantum channels (general/mixed) gives same Lovosz O bound to Co, but pure state channels suffice to give the bound. We also see that 3 a pure state channel whose optimizing F is rank 1. This is not true in general for Raffyz).

- Classical and Pure-state channels:

Consider classical-quantum channels with pure states $S_{x} = |\Psi_{x} \times \Psi_{x}|$. Then $S_{x}^{\frac{1}{1+p}} = S_{x}$. Let \$p = \(\super P(\alpha) | \psi_\alpha \times \psi_\alpha | \left \ \mixed \text{ state generated by dist. P over Sx.}

$$E_{o}(\rho, P) = -\log(tr(\bar{S}_{P}^{HP})) = -\log(\sum_{i} \lambda_{i}(\bar{S}_{P})^{HP})$$

$$\Rightarrow R_{oo} = -\log(\min_{P} \lambda_{max}(\bar{S}_{P}))$$

From "Connection to Lovász O-function",

Roo = min max - log(tr(SoxF)) = min max -log ((4x|F|4x))

 $\frac{Observe:}{E_o(\rho, P)} = -\log\left(br\left(\left(\sum_{x} P(x) S_{x}^{\frac{1}{1+\rho}}\right)^{\frac{1}{1+\rho}}\right)\right)$ $R_{p} = \frac{\max_{P} E_{o}(p, P)}{P} = -\frac{\log \left(\min_{P} \left(tr\left(\sum_{x} P(x) S_{x}^{\frac{1}{1+p}} \right)^{1+p} \right) \right)}{P}$ $\lim_{P \to \infty} R_p = -\log\left(\min_{P} \lambda_{\max}\left(\sum_{x} P(x) S_x^o\right)\right)$ eigenvalue problem

 \triangle looks like $\Theta(1)$ in Lovász section if we restrict F to be rank 1

• Fact: Optimizing F* is rank 1 if Amax (Sp*) has multiplicity 1 for optimizing P*. • Fact: For pure-state channels {4x} constructed by 14x> = VWx from classical channel,

there is always an F* with rank 1, and for [182] Ro of pure \rightarrow $R_{\infty} = \Theta(1) = R_{\text{cut}} \leftarrow \text{cutoff rate of classical channel}$ (Proof uses KKT due to technical issues with applying von Neumann's theorem.)

- · The sphere-packing bound Esp (R) produces the quantity Rp (quantum case). - Final Remarks:
 - · Rp has an information radius type description using quantum Rényi divergence which is used for the development
 - · lim Rp = C& lim Rp = Ro
 - · Minimizing Row over all {Sx} channels gives 0 Lovosz O-function.
 - · This relates C, Ro, O and Co in one unified framework in a quantum light.
 - · Key point: The Osp bound on Go is obtained using quantum probability. The O bound on Co is obtained using combinatorics. A combinatorial argument (of Lovász) shows Osp = O. So, the quantum probability view gives the same result as the combinatorial view. In this regard, quantum probability unifies the divergence between combinatorial and probabilistic techniques in information theory. ~@~