

# Selected topics on quantum information

Mika Hirvensalo

Department of Mathematics and Statistics  
University of Turku  
mikhirve@utu.fi

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Ludwig Boltzmann (1844-1906)





$$S = k \cdot \log W,$$

where  $k$  is a constant,  $W$  is the number of microstates corresponding to a macroscopic state

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Entropy measures uncertainty

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$q$ -ary (elementary) entropy

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- List the conditions of all particles:  $c_1 c_2 \dots c_l \in \{1, 2, \dots, n\}^l$
- Assume condition (letter)  $i$  occurs  $k_i$  times, so  $k_1 + \dots + k_n = l$  and  $p_i = \frac{k_i}{l}$  is the probability (frequency) of condition  $i$

## Combinatorics:

There are

$$\frac{l!}{k_1! \dots k_n!}$$

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Per particle:

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$$\begin{aligned} & \frac{K}{I} \log \frac{I!}{k_1! \dots k_n!} \\ = & \frac{K}{I} (I \log I - I + O(\log I)) \\ & - \sum_{i=1}^n (k_i \log k_i - k_i + O(\log k_i)) \\ = & -K \sum_{i=1}^n p_i \log p_i + O\left(\frac{\log I}{I}\right). \end{aligned}$$

For a probability distribution  $(p_1, \dots, p_n)$  of events  $\{e_1, \dots, e_n\}$ , define

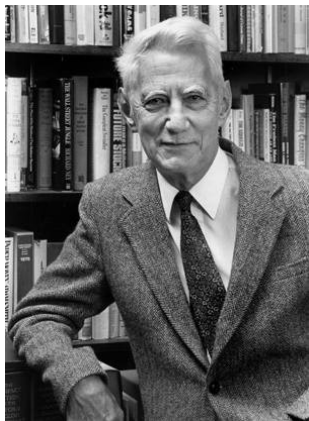
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For  $p_1 = \dots = p_n = \frac{1}{n}$

$$H\left(\frac{1}{n}, \dots, \frac{1}{n}\right) = -K \cdot n \cdot \frac{1}{n} \log \frac{1}{n} = K \log n$$



Claude Shannon (1916-2001)

- $H(p_1, \dots, p_n)$  symmetric, continuous
- $H(\frac{1}{n}, \dots, \frac{1}{n})$  non-negative, strictly increasing in  $n$
- $H(p_1, \dots, p_n) + p_n H(q_1, \dots, q_m) = H(p_1, \dots, p_{n-1}, p_n q_1, \dots, p_n q_m)$

$$\Rightarrow H(p_1, \dots, p_m) = -K \sum_{i=1}^n p_i \log p_i$$

# Joint Entropy



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be a random variable with distribution  $p(x_1), \dots, p(x_n)$ .

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If also  $Y = \{y_1, \dots, y_m\}$  is a random variable,

the *joint entropy* is

$$H(X, Y) = - \sum_{i=1}^n \sum_{j=1}^m p(x_i, y_j) \log p(x_i, y_j)$$

## Joint entropy

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# Conditional Entropy

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$$H(X, Y) = - \sum_{i=1}^n \sum_{j=1}^m p(x_i, y_j) \log p(x_i, y_j)$$

If we know  $Y = y_j$ , then

$$H(X | y_j) = - \sum_{i=1}^n p(x_i | y_j) \log p(x_i | y_j)$$

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and define

$$H(X | Y) = \sum_{j=1}^m p(y_j) H(X | y_j).$$

“Uncertainty of  $X$  when  $Y$  is known”

Lemma

$$H(X | Y) \leq H(X)$$



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(Uncertainty of  $X$  when  $Y$  is known)

## Example

Team  $A$  wins with probability  $\frac{1}{2}$ ,  $X = \{\text{win}, \text{loss}\}$ . Then  
 $H(X) = -(\frac{1}{2} \log_2 \frac{1}{2} + \frac{1}{2} \log_2 \frac{1}{2}) = 1$ .

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## Example

As a *home team*, A wins with  $\frac{3}{4}$  probability, but as *visitor*, A wins only with  $\frac{1}{3}$  probability.

$$H(X | h) = -\left(\frac{3}{4} \log_2 \frac{3}{4} + \frac{1}{4} \log_2 \frac{1}{4}\right) = 0.811278\dots,$$

$$H(X | v) = -\left(\frac{1}{3} \log_2 \frac{1}{3} + \frac{2}{3} \log_2 \frac{2}{3}\right) = 0.918296\dots$$

## Example (Continued)

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Let  $Y = \{0, 1\}$  be a fair coin toss for deciding if team  $A$  plays home. Then

$$H(X | Y) = \frac{1}{2}H(X | h) + \frac{1}{2}H(X | v) = 0.864787\dots$$

Definition (Mutual information of  $X$  and  $Y$ )

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$$I(X : Y) = H(X) - H(X | Y)$$

$$\begin{aligned} I(X : Y) &= H(X) - H(X | Y) \\ &= H(X) - (H(X, Y) - H(Y)) \\ &= H(X) + H(Y) - H(X, Y) \\ &= I(Y : X) \end{aligned}$$

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$I(X : Y)$

“Uncertainty of  $X$  minus uncertainty of  $X$  when  $Y$  known”

## Example

$X$  is the team  $A$  result,  $Y$  is the coin toss outcome. Then

$$I(X : Y) = 1 - 0.864787 \dots = 0.135213 \dots$$

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## Example

Team  $B$  wins with  $1/2$  probability, but with 99 probability as home team and only with 5 probability as visitor. Then

$$H(X | h) = -\left(\frac{99}{100} \log_2 \frac{99}{100} + \frac{1}{100} \log_2 \frac{1}{100}\right) = 0.0807931 \dots,$$

$$H(X | v) = -\left(\frac{5}{100} \log_2 \frac{5}{100} + \frac{95}{100} \log_2 \frac{95}{100}\right) = 0.286397 \dots$$

## Example (Continued)

$$H(X | Y) = \frac{1}{2}H(X | h) + \frac{1}{2}H(X | v) = 0.274894\dots$$

and

$$I(X : Y) = 1 - 0.274894\dots = 0.725106\dots$$



John von Neumann (1903–1957)

- Quantum entropy by Gedanken Experiment (1927)
- Coincides with Shannon (and Boltzmann) entropy on classical systems

$n$ -level system  $\leftrightarrow n$  perfectly distinguishable values

Formalism based on  $H_n \simeq \mathbb{C}^n$  ( $n$ -dimensional Hilbert space)

- Hermitian inner product  $\langle \mathbf{x} | \mathbf{y} \rangle = x_1^* y_1 + \dots + x_n^* y_n$
- Norm  $\|\mathbf{x}\| = \sqrt{\langle \mathbf{x} | \mathbf{x} \rangle}$
- Ket-vector  $|\mathbf{x}\rangle = \begin{pmatrix} x_1 \\ \vdots \\ x_n \end{pmatrix}$
- Bra-vector  $\langle \mathbf{x}| = (|\mathbf{x}\rangle)^* = (x_1^*, \dots, x_n^*)$
- Adjoint matrix:  $(A^*)_{ij} = A_{ji}^*$  for  $m \times n$  matrix  $A$

- Trace:  $\text{Tr}(A) = \sum_{i=1}^n A_{ii}$
- For orthonormal basis  $\{\mathbf{x}_1, \dots, \mathbf{x}_n\}$ ,  $\text{Tr}(A) = \sum_{i=1}^n \langle \mathbf{x}_i | A \mathbf{x}_i \rangle$
- Positivity:  $A \geq 0$  iff  $(\forall \mathbf{x}) \langle \mathbf{x} | A \mathbf{x} \rangle \geq 0$
- Self-adjointness:  $A^* = A$
- Unitarity:  $UU^* = U^*U = I$
- Normality:  $A^*A = AA^*$



Kronecker product (tensor product):

$$A = \begin{pmatrix} a_{11} & a_{12} & \dots & a_{1s} \\ a_{21} & a_{22} & \dots & a_{2s} \\ \vdots & \vdots & \ddots & \vdots \\ a_{r1} & a_{r2} & \dots & a_{rs} \end{pmatrix}, B = \begin{pmatrix} b_{11} & b_{12} & \dots & b_{1u} \\ b_{21} & b_{22} & \dots & b_{2u} \\ \vdots & \vdots & \ddots & \vdots \\ b_{t1} & b_{t2} & \dots & b_{tu} \end{pmatrix}$$

$$A \otimes B = \begin{pmatrix} a_{11}B & a_{12}B & \dots & a_{1s}B \\ a_{21}B & a_{22}B & \dots & a_{2s}B \\ \vdots & \vdots & \ddots & \vdots \\ a_{r1}B & a_{r2}B & \dots & a_{rs}B \end{pmatrix}$$

- $|\mathbf{x}\rangle\langle\mathbf{y}| = \begin{pmatrix} x_1 \\ \vdots \\ x_n \end{pmatrix} \otimes (y_1^*, \dots, y_n^*) =$

$$\begin{pmatrix} x_1 y_1^* & x_1 y_2^* & \dots & x_1 y_n^* \\ \vdots & \vdots & \ddots & \vdots \\ x_n y_1^* & x_n y_2^* & \dots & x_n y_n^* \end{pmatrix}$$

- $|\mathbf{x}\rangle\langle\mathbf{y}||\mathbf{z}\rangle = \langle\mathbf{y}||\mathbf{z}\rangle|\mathbf{x}\rangle$

- If especially  $\|\mathbf{x}\| = 1$ ,  $|\mathbf{x}\rangle\langle\mathbf{x}|$  is a projection onto a subspace generated by  $\mathbf{x}$ .

## Theorem (Spectral representation)

*Each normal  $A$  has spectral representation*

$$A = \lambda_1 |\mathbf{x}_1\rangle\langle\mathbf{x}_1| + \dots + \lambda_n |\mathbf{x}_n\rangle\langle\mathbf{x}_n|,$$

*where  $\{\mathbf{x}_1, \dots, \mathbf{x}_n\}$  is an orthonormal basis of  $H_n$  and  $\lambda_1, \dots, \lambda_n$  the eigenvalues of  $A$ .*

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- If  $A$  is self-adjoint, each  $\lambda_i \in \mathbb{R}$
- If  $A$  is unitary, each  $\lambda_i$  has  $|\lambda_i| = 1$
- If  $A$  is positive, each  $\lambda_i \geq 0$ .
- $\text{Tr}(A) = \lambda_1 + \dots + \lambda_n$ .

# Structure of Quantum Mechanics

State of a physical system:

Unit-trace, positive operator  $T$ :

$$T = \lambda_1 |\mathbf{x}_1\rangle\langle\mathbf{x}_1| + \dots + \lambda_n |\mathbf{x}_n\rangle\langle\mathbf{x}_n|,$$

where  $\lambda_i \geq 0$ ,  $\lambda_1 + \dots + \lambda_n = 1$  (density matrix).

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Observables:

Self-adjoint operator  $A$ :

$$A = \mu_1 |\mathbf{y}_1\rangle\langle\mathbf{y}_1| + \dots + \mu_n |\mathbf{y}_n\rangle\langle\mathbf{y}_n|,$$

where  $\mu_i \in \mathbb{R}$  are the potential values of  $A$

Minimal interpretation:

$$\mathbb{P}(\mu_i) = \text{Tr}(T |y_i\rangle\langle y_i|)$$

is the probability of seeing value  $\mu_i$  if  $A$  is observed when the system is in state  $T$ .



## Example

Let  $n = 2$  (quantum bit),  $|0\rangle = \begin{pmatrix} 1 \\ 0 \end{pmatrix}$ ,  $|1\rangle = \begin{pmatrix} 0 \\ 1 \end{pmatrix}$

$$T = \frac{1}{2} |0\rangle\langle 0| + \frac{1}{2} |1\rangle\langle 1| = \begin{pmatrix} \frac{1}{2} & 0 \\ 0 & \frac{1}{2} \end{pmatrix}$$

and

$$A = \sigma_z = 1 \cdot |0\rangle\langle 0| - 1 \cdot |1\rangle\langle 1|.$$

Then

$$\begin{aligned} \mathbb{P}(1) &= \text{Tr}(T |0\rangle\langle 0|) = \text{Tr}\left(\frac{1}{2} |0\rangle\langle 0|\right) = \frac{1}{2}, \text{ and} \\ \mathbb{P}(-1) &= \text{Tr}(T |1\rangle\langle 1|) = \text{Tr}\left(\frac{1}{2} |1\rangle\langle 1|\right) = \frac{1}{2}. \end{aligned}$$

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and

$$A = \sigma_x = \begin{pmatrix} 0 & 1 \\ 1 & 0 \end{pmatrix} = 1 \cdot |\mathbf{y}_1\rangle\langle \mathbf{y}_1| - 1 \cdot |\mathbf{y}_2\rangle\langle \mathbf{y}_2|,$$

where  $\mathbf{y}_1 = \frac{1}{\sqrt{2}}(1, 1)$  and  $\mathbf{y}_2 = \frac{1}{\sqrt{2}}(-1, 1)$ . Then

$$\mathbb{P}(1) = \text{Tr}(T |\mathbf{y}_1\rangle\langle \mathbf{y}_1|) = \frac{1}{2}, \text{ and}$$

$$\mathbb{P}(-1) = \text{Tr}(T |\mathbf{y}_2\rangle\langle \mathbf{y}_2|) = \frac{1}{2}.$$

The *expected value* of observable  $A$  in state  $T$  is

$$\begin{aligned}\mathbb{E}_T(A) &= \sum_{i=1}^n \mu_i \mathbb{P}(\mu_i) \\ &= \sum_{i=1}^n \mu_i \text{Tr}(T |y_i\rangle\langle y_i|) \\ &= \text{Tr}(TA).\end{aligned}$$

# The State Set Structure

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## Lemma

$T$  is pure if and only if  $T = |x\rangle\langle x|$  for some unit-length  $x$ .

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## Lemma

$T$  is pure if and only if  $T = |\mathbf{x}\rangle\langle\mathbf{x}|$  for some unit-length  $\mathbf{x}$ .

- For a pure state  $T = |\mathbf{x}\rangle\langle\mathbf{x}|$  and observable  $A = \sum_{i=1}^n \mu_i |\mathbf{y}_i\rangle\langle\mathbf{y}_i|$

$$\mathbb{P}(\mu_i) = \text{Tr}(T |\mathbf{y}_i\rangle\langle\mathbf{y}_i|) = \langle\mathbf{y}_i | \mathbf{x}\rangle\langle\mathbf{x} | \mathbf{y}_i\rangle\langle\mathbf{y}_i | \mathbf{y}_i\rangle = |\langle\mathbf{x} | \mathbf{y}_i\rangle|^2.$$

Let  $T = |\mathbf{x}\rangle\langle\mathbf{x}|$  be a pure state and

$$A = \mu_1 |\mathbf{y}_1\rangle\langle\mathbf{y}_1| + \dots + \mu_n |\mathbf{y}_n\rangle\langle\mathbf{y}_n|$$

an observable. In representation

$$\mathbf{x} = \alpha_1 \mathbf{y}_1 + \dots + \alpha_n \mathbf{y}_n$$

$\alpha_i = \langle\mathbf{y}_i | \mathbf{x}\rangle$  (amplitude of  $\mathbf{y}_i$ ), so

$$\mathbb{P}(\mu_i) = |\alpha_i|^2.$$

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$$A = \mu_1 |\mathbf{y}_1\rangle\langle\mathbf{y}_1| + \dots + \mu_n |\mathbf{y}_n\rangle\langle\mathbf{y}_n|$$

an observable. In representation

$$\mathbf{x} = \alpha_1 \mathbf{y}_1 + \dots + \alpha_n \mathbf{y}_n$$

$\alpha_i = \langle\mathbf{y}_i | \mathbf{x}\rangle$  (amplitude of  $\mathbf{y}_i$ ), so

$$\mathbb{P}(\mu_i) = |\alpha_i|^2.$$

## Corollary

*For each pure state  $T$  there is a nontrivial observable  $A$  such that  $\mathbb{P}(\mu_1) = 1$  for a potential value  $\mu_1$  of  $A$ .*

## Remark

For a pure state  $T = |\mathbf{x}\rangle\langle\mathbf{x}|$  the expected value of observable  $A$  is

$$\mathbb{E}_T(A) = \text{Tr}(TA) = \text{Tr}(|\mathbf{x}\rangle\langle\mathbf{x}| A) = \langle\mathbf{x} || \mathbf{x}\rangle\langle\mathbf{x}| A\mathbf{x}\rangle = \langle\mathbf{x} | A\mathbf{x}\rangle.$$

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## Remark

For any  $\theta \in \mathbb{R}$ ,

$$|e^{i\theta}\mathbf{x}\rangle\langle e^{i\theta}\mathbf{x}| = |\mathbf{x}\rangle\langle\mathbf{x}|,$$

so pure state presentation as a unit-length vector is not unique.

# Example

$$\text{Let } |0\rangle = \begin{pmatrix} 1 \\ 0 \end{pmatrix} \text{ and } |1\rangle = \begin{pmatrix} 0 \\ 1 \end{pmatrix}$$

vector  $\frac{1}{\sqrt{2}}|0\rangle + \frac{1}{\sqrt{2}}|1\rangle$  corresponds to a state

$$\begin{pmatrix} \frac{1}{\sqrt{2}} \\ \frac{1}{\sqrt{2}} \end{pmatrix} \otimes \begin{pmatrix} \frac{1}{\sqrt{2}} \\ \frac{1}{\sqrt{2}} \end{pmatrix} = \begin{pmatrix} \frac{1}{2} & \frac{1}{2} \\ \frac{1}{2} & \frac{1}{2} \end{pmatrix},$$

and

$$\mathbb{P}(1) = \text{Tr} \left( \left( \begin{pmatrix} \frac{1}{2} & \frac{1}{2} \\ \frac{1}{2} & \frac{1}{2} \end{pmatrix} \begin{pmatrix} 1 & 0 \\ 0 & 0 \end{pmatrix} \right) \right) = \text{Tr} \left( \begin{pmatrix} \frac{1}{2} & 0 \\ \frac{1}{2} & 0 \end{pmatrix} \right) = \frac{1}{2}.$$

This could be read directly from the vector presentation.

# Example

Let  $\mathbf{y}_1 = \frac{1}{\sqrt{2}}(|0\rangle + |1\rangle)$ ,  $\mathbf{y}_2 = \frac{1}{\sqrt{2}}(|0\rangle - |1\rangle)$ , and

$$A = 1 |\mathbf{y}_1\rangle\langle\mathbf{y}_1| - 1 \cdot |\mathbf{y}_2\rangle\langle\mathbf{y}_2| = \begin{pmatrix} \frac{1}{2} & \frac{1}{2} \\ \frac{1}{2} & \frac{1}{2} \end{pmatrix} - \begin{pmatrix} \frac{1}{2} & -\frac{1}{2} \\ -\frac{1}{2} & \frac{1}{2} \end{pmatrix} = \begin{pmatrix} 0 & 1 \\ 1 & 0 \end{pmatrix}$$

Then for vector  $\mathbf{x} = \frac{1}{\sqrt{2}}(|0\rangle + |1\rangle)$

$$\mathbb{P}(-1) = \text{Tr} \left( \begin{pmatrix} \frac{1}{2} & \frac{1}{2} \\ \frac{1}{2} & \frac{1}{2} \end{pmatrix} \begin{pmatrix} \frac{1}{2} & -\frac{1}{2} \\ -\frac{1}{2} & \frac{1}{2} \end{pmatrix} \right) = \text{Tr} \left( \begin{pmatrix} 0 & 0 \\ 0 & 0 \end{pmatrix} \right) = 0.$$

This could be directly read from

$$\mathbf{x} = 1 \cdot \mathbf{y}_1 + 0 \cdot \mathbf{y}_2.$$



Down  $\rightarrow$  Up:

Tensor product construction:  $T = T_1 \otimes T_2, A = A_1 \otimes A_2$

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Example

Pure state

$$\frac{1}{\sqrt{2}}(|0\rangle + |1\rangle) \otimes \frac{1}{\sqrt{2}}(|0\rangle + |1\rangle) = \frac{1}{2}(|00\rangle + |01\rangle + |10\rangle + |11\rangle)$$

Or:

$$\begin{pmatrix} \frac{1}{2} & \frac{1}{2} \\ \frac{1}{2} & \frac{1}{2} \end{pmatrix} \otimes \begin{pmatrix} \frac{1}{2} & \frac{1}{2} \\ \frac{1}{2} & \frac{1}{2} \end{pmatrix} = \begin{pmatrix} \frac{1}{4} & \frac{1}{4} & \frac{1}{4} & \frac{1}{4} \\ \frac{1}{4} & \frac{1}{4} & \frac{1}{4} & \frac{1}{4} \\ \frac{1}{4} & \frac{1}{4} & \frac{1}{4} & \frac{1}{4} \\ \frac{1}{4} & \frac{1}{4} & \frac{1}{4} & \frac{1}{4} \end{pmatrix}$$

# Compound Systems

Up  $\rightarrow$  Down:

By partial trace:  $T_1 = \text{Tr}_1(T)$

Partial trace

$T_1$  is chosen so that  $\text{Tr}(T(A_1 \otimes I)) = \text{Tr}(T_1 A_1)$  for each observable  $A_1$

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Remark

$\text{Tr}(T(A_1 \otimes I))$  is the average value of observable  $A_1 \otimes I$  in state  $T$ .  
As well,  $\text{Tr}(T_1 A_1)$  is the average value of observable  $A_1$  in state  $T_1$ .  
 $T_1$  is unique and an explicit formula for  $\text{Tr}_1(T)$  exists.

# Example

A vector

$$\frac{1}{\sqrt{2}} |00\rangle + \frac{1}{\sqrt{2}} |11\rangle$$

corresponds to a pure state

$$T = \begin{pmatrix} \frac{1}{\sqrt{2}} \\ 0 \\ 0 \\ \frac{1}{\sqrt{2}} \end{pmatrix} \otimes \left( \frac{1}{\sqrt{2}}, 0, 0, \frac{1}{\sqrt{2}} \right) = \begin{pmatrix} \frac{1}{2} & 0 & 0 & \frac{1}{2} \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ \frac{1}{2} & 0 & 0 & \frac{1}{2} \end{pmatrix}$$

Subsystem states:

$$T_1 = T_2 = \begin{pmatrix} \frac{1}{2} & 0 \\ 0 & \frac{1}{2} \end{pmatrix}$$

# Quantum Entropy

von Neumann Entropy

$$S = -K \text{Tr}(T \log T)$$



## von Neumann Entropy

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where  $f(T)$  for

$$T = p_1 |\mathbf{x}_1\rangle\langle\mathbf{x}_1| + \dots + p_n |\mathbf{x}_n\rangle\langle\mathbf{x}_n|$$

is defined as

$$\begin{aligned} f(T) &= f(\lambda_1 |\mathbf{x}_1\rangle\langle\mathbf{x}_1| + \dots + \lambda_n |\mathbf{x}_n\rangle\langle\mathbf{x}_n|) \\ &= f(\lambda_1) |\mathbf{x}_1\rangle\langle\mathbf{x}_1| + \dots + f(\lambda_n) |\mathbf{x}_n\rangle\langle\mathbf{x}_n|. \end{aligned}$$

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Hence

$$T \log T = p_1 \log p_1 |\mathbf{x}_1\rangle\langle\mathbf{x}_1| + \dots + p_n \log p_n |\mathbf{x}_n\rangle\langle\mathbf{x}_n|$$

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and

$$S(T) = -K \text{Tr}(T \log T) = -K(p_1 \log p_1 + \dots + p_n \log p_n)$$



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## Example

Let  $A$  and  $B$  be qubits with joint state  $T = |\mathbf{x}\rangle\langle\mathbf{x}|$ , where  $\mathbf{x} = \frac{1}{\sqrt{2}} |00\rangle + \frac{1}{\sqrt{2}} |11\rangle$ .

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- Conditional entropy  
 $S(T_1 | T_2) = S(T_1, T_2) - S(T_2) = 0 - 1 = -1$



For a pure state  $T = |\mathbf{x}\rangle\langle\mathbf{x}|$

$$S(T) = -1 \cdot \log 1 = 0$$

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- Conditional entropy  
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- Mutual information:

$$I(T_1 : T_2) = S(T_1) - S(T_1 | T_2) = 1 - (-1) = 2$$

## Theorem (Holevo Bound)

Let  $\rho_1, \dots, \rho_n$  be states of  $n$ -level quantum system, produced with probabilities  $p_1, \dots, p_n$ . Let also  $X$  be a random variable with value  $i$  if  $\rho_i$  is produced, and  $Y$  any observable on  $H_n$ . Then

$$I(X : Y) \leq S\left(\sum_{i=1}^n p_i \rho_i\right) - \sum_{i=1}^n p_i S(\rho_i)$$