

Quantum Information Theory

quinten tupker

January 22 2021 - February 14, 2021

Introduction

These notes are based on the course lectured by Professor S Strelchuk in Lent 2020. This was lectured online due to measures taken to counter the spread of Covid-19 in the UK. These are not necessarily an accurate representation of what was lectures, and represent solely my personal notes on the content of the course, combined with probably, very very many personal notes and digressions... Of course, any corrections/comments would be appreciated.

Information theory is the theory of information storage and transmission. It provides the theoretical limits on what is possible with information technologies in much of our world, and a framework to study many other fields, such as animal communication as well. This is the quantum version of that theory.

1 Classical Information Theory

We begin by observing that information is closely related to uncertainty. In particular, what might be able to say it is the opposite of uncertainty, and so then, it is no surprise that we build our theory of information using concepts from probability theory. As such we define

Definition 1. The **surprisal** of random variable X taking values in discrete finite **alphabet** J according to distribution $p(x)$ is

$$\mathcal{I}(x) = -\ln(p(x))$$

Definition 2. The **Shannon entropy** of a random variable X is

$$H(X) = -\sum_{x \in J} p(x) \ln(p(x))$$

(the logarithm is base 2)

This may appear to be a somewhat arbitrary definition, but it has a strong theoretical basis given that

Theorem 1. *The **Shannon Source Coding Theorem** states (informally) that the limit that information can be compressed so that it can be reliably retrieved is the Shannon entropy of the source.*

Here a basic example of a source is a **memoryless source** which is an object producing a sequence of signals, but since it is memoryless, each signal is completely independent from any other, so $\mathbb{P}(u_1, \dots, u_n) = \mathbb{P}(u_1) \dots \mathbb{P}(u_n)$. It is also known as an **i.i.d. information source**.

But how do we actually compress information? Conceptually there are two ways

- a **variable length encoding** stores higher probability signals in shorter codes, and lower probability signals in longer codes.
- a **fixed length encoding** stores higher probability signals in unique fixed length codes, and lower probability signals in the same fixed code.

Example 1. *An example of a fixed length code for the numbers $1, \dots, 8$ are their binary representations, but if we also know that $p(1, \dots, 8) = 1/2, 1/4, 1/8, 1/16, 1/64, 1/64, 1/64, 1/64$ then the code $C(1, \dots, 8) = 0, 10, 110, 1110, 111100, 111101, 111110, 111111$ has an average length 2 compared to the fixed length of 3. Furthermore, the Shannon entropy of this source is 2 as well, so this is maximally efficient.*

1.1 Classical Data Compression

Let's start making the definitions necessary to formalise compression.

Definition 3. A **compression map** is a map $C^n : u^{(n)} = (u_1, \dots, u_n) \mapsto x(x_1, \dots, x_{nR})$ sending a **message** u to a **code** x .

Definition 4. A **decompression map** D^n sends $D^n : x \in \{0, 1\}^{[nR]} \mapsto u'^{(n)}$ with probability $\mathbb{P}(u^{(n)}|x)$.

Definition 5. A **code** of rate R and blocklength n is the triple (C^n, D^n, R) .

Here we can compute the **probability of error** as

$$P_{av}^{(n)}(C_n) = \sum_{u^{(n)} \in J^n} \mathbb{P}(u^{(n)}) \mathbb{P}(D^n(C^n(u^{(n)})) \neq u^{(n)}). \quad (1)$$

[End of lecture 1]

Definition 6. A compression/decompression scheme is **reliable** iff $\forall \epsilon > 0 \exists$ sequence of codes C_n such that $\lim_{n \rightarrow \infty} P_{av}^{(n)}(C_n) = 0$

(does this require the code to i.i.d?) As such one could define the data compression rate as

$$\inf\{R : \exists C_n = \{C^n, D^n, R\} : \lim_{n \rightarrow \infty} P_{av}^{(n)}(C_n) = 0\} \quad (2)$$

1.2 Typical Sequences

It is honestly surprising how easy it is to prove Shannon's source coding theorem, since we find we in fact only need one simple, and honestly rather crude tool to do so. That tool is

Definition 7. a **typical set**, denoted $T_\epsilon^{(n)}$, which is the set of sequences $u = (u_1, \dots, u_n)$ satisfying

$$2^{-n(H(u)+\epsilon)} \leq \mathbb{P}(u) \leq 2^{-n(H(u)-\epsilon)} \quad (3)$$

Why “typical”? Because if we have a memoryless source generating a sequence of length n , then a “typical” sequence occurs with probability

$$\prod_{u \in J} \mathbb{P}(u)^{n\mathbb{P}(u)} = 2^{-nH(u)} \quad (4)$$

(a typical sequence would have the expected value as the number of occurrences of each letter in the alphabet). We consequently find the following theorem (not proven)

Theorem 2. $\forall \epsilon, \delta > 0, \exists n$ such that

1. $u \in T_\epsilon^{(n)} \implies H(u) - \epsilon \leq \frac{-1}{n} \log(\mathbb{P}(u)) \leq H(u) + \epsilon$
2. $\mathbb{P}(T_\epsilon^{(n)}) > 1 - \delta$
3. $|T_\epsilon^{(n)}| \leq 2^{n(H(u)+\epsilon)}$
4. $|T_\epsilon^{(n)}| > (1 - \delta)2^{n(H(u)-\epsilon)}$

and so

Corollary 1. $\forall \epsilon, \delta > 0, \exists n_0, \forall n > n_0, J^n$ decomposes into the disjoint **atypical** and **typical sets** $A_\epsilon^{(n)}, T_\epsilon^{(n)}$ satisfying

1. $\mathbb{P}(A_\epsilon^{(n)}) < \delta$
2. $2^{-n(H(u)+\epsilon)} \leq \mathbb{P}(u) \leq 2^{-n(H(u)-\epsilon)}$ (on the typical set?)

That allows us to formally state

Theorem 3. Shannon's source coding theorem, which claims that for a i.i.d. source U , if $R > H(U)$, then we can find a reliable compression scheme and if $R < H(U)$ there are no reliable compression schemes.

Proof. If $R > H(U)$ then pick $\epsilon > 0$ such that $H(U) + \epsilon < R$ and n such that $T_\epsilon^{(n)}$ satisfies our typical set theorem conditions. Then for $\delta > 0$ there are at most $2^{n(H(U)+\epsilon)} < 2^{nR}$ ϵ -typical sequences. Our compression scheme then works according to

1. Split J^n into typical and atypical sequences
2. order typical sequences somehow (say lexicographically), assigning each sequence a binary index.
3. typical sequences are sent to their binary code, prefixed with a 1, leading to a total length of $\lceil nR \rceil + 1$
4. atypical sequences are all sent to the fixed string $00 \dots 0$ of length $\lceil nR \rceil + 1$

If $R < H(U)$ there does not exist a reliable compression scheme (see lemma below). \square

Lemma 1. *For a collection of strings of length n , $S(n)$, with $|S(n)| \leq 2^{nR}$, $R < H(U)$. Then, $\forall \delta > 0, \exists n, \sum_{u \in S(n)} \mathbb{P}(u) < \delta$*

Basically, when $R < H(U)$ we will always get some typical sets that are indistinguishable after compression. Assume $S(n)$ is a set of such indistinguishables. This lemma states that these become less significant?

Proof. Again, we split $S(n)$ into its typical and atypical part and then observe

$$\begin{aligned}
\mathbb{P}(S(n)) &= \sum_{u \in S(n)} \mathbb{P}(u) \\
&= \sum_{u \in S(n) \cap T_\epsilon^{(n)}} \mathbb{P}(u) + \sum_{u \in S(n) \cap A_\epsilon^{(n)}} \mathbb{P}(u) \\
&\leq |S(n)| 2^{-n(H(n) - \epsilon)} + \mathbb{P}(A_\epsilon^{(n)}) \\
&\leq 2^{-n(H(n) - R)} + \mathbb{A}_\epsilon^{(\kappa)}
\end{aligned}$$

\square

which completes the proof of Shannon's source coding theorem. Finally, we note that using a variable length encoding scheme or something like that does not fundamentally change this result. [End of lecture 2]

Today we discuss the types of relationships one can have between various types of entropy. As such,

Definition 8. the **joint entropy** of X, Y is

$$H(X, Y) = - \sum_{x \in J_X} \sum_{y \in J_Y} p(x, y) \log(p(x, y)) \quad (5)$$

Definition 9. the **conditional entropy** is

$$H(Y|X) = - \sum_{x \in J_X} \sum_{y \in J_Y} p(x, y) \log(p(y|x)) = - \sum_{x \in J_X} p(x) H(Y|X = x) \quad (6)$$

where we note the “chain rule”

$$H(X, Y) = H(Y|X) + H(X) \quad (7)$$

which generalises nicely as

$$H(X, Y, Z) = H(X) + H(Y|X) + H(Z|Y, X) \quad (8)$$

and similar for higher numbers of variables.

Definition 10. We further define p to be **absolutely continuous** wrt q iff $q(x) = 0 \implies p(x) = 0$ or equivalently $\text{supp}(p) \subseteq \text{supp}(q)$ which we can denote as $p \ll q$.

and

Definition 11. the **relative entropy** or **Kullback-Leibler divergence** of $p \ll q$ to be

$$D(p||q) = \sum_{x \in J} p(x) \log(p(x)/q(x)) \quad (9)$$

Note that if $q(x) = 1 \forall x \in J$ then $D(p||q) = -H(X)$ so this is stronger than the Shannon entropy.

This measures how different two distributions are in a certain sense, however, it certainly is not a metric (not symmetric, and no triangle inequality).

Definition 12. We similarly define the **mutual information** between X, Y to be

$$I(X : Y) = H(X) + H(Y) - H(X, Y) = H(X) - H(X|Y) \quad (10)$$

Definition 13. and the **conditional mutual information** (CMI)

$$I(X : Y|Z) = H(X|Z) - H(X|Y, Z) \quad (11)$$

Intuition wise, one can think of $H(X, Y)$ as adding entropy, $I(X : Y)$ as taking the intersection between the two, $D(p||q)$ as measuring the difference between one distribution contained in another, and $H(Y|X)$ as removing the overlap of one distribution into another ($H(Y|X) = H(Y) - I(Y : X)$). This also explains the commutativity of these various operations. I’m not sure about the CMI yet...

From here we can state

Theorem 4. *the data processing inequality for Markov Chain $X \rightarrow Y \rightarrow Z$:*

$$I(X : Y) \geq I(X : Z). \quad (12)$$

If we imagine X as a perfect source, Y as an observed, noisy signal, and Z as a “cleaned up” version of Y after some data processing, then this states that no matter the data processing used to clean up Y , Z can never contain more information about X than Y .

We finally have the following theorem.

- Theorem 5.**
1. $p \ll q \implies D(p||q) \geq 0$ with equality iff $p = q$
 2. $H(x) \geq 0$ with equality iff X deterministic
 3. $H(X|Y) \geq 0$ or equivalently $H(X, Y) \geq H(Y)$
 4. $H(X) \leq \log(|J|)$
 5. $H(X, Y) \leq H(X) + H(Y)$ or equivalently $H(Y) \geq H(Y|X)$ with equality iff $X \perp Y$
 6. H is concave meaning $H(\lambda p_x + (1 - \lambda)p_y) \geq \lambda H(p_x) + (1 - \lambda)H(p_y)$
 7. $I(X : Y) \geq 0$ and equal iff $X \perp Y$

All of these are exercises on the example sheet. [End of lecture 4]

1.3 Classical Information Transmission

Let's build the infrastructure for a bound on reliable information transmission.

Definition 14. A **discrete channel** is a combination of

- discrete alphabets J_X, J_Y
- a set of conditional probabilities $\mathbb{P}(y_1, \dots, y_n | x_1, \dots, x_m)$

Definition 15. A memoryless channel is one satisfying

$$\mathbb{P}(y_1, \dots, y_n | x_1, \dots, x_n) = \prod_{i=1}^n \mathbb{P}(y_i | x_i) \quad (13)$$

These are completely characterised by the so-called **channel matrix** $P = \mathbb{P}(y|x)$.

Example 2. For example we can consider a **binary symmetric channel** for $\mathbb{P}(0|0) = \mathbb{P}(1|1) = 1 - p$ where $p_{err} = 3p^2(1 - p) + p^3 = 3p^2 - 2p^3$ if we use the redundant coding $0 \mapsto 000, 1 \mapsto 111$.

Definition 16. Now for messages $m = x_1, \dots, x_n$ and $m' = y_1, \dots, y_m$ and $m \in [M] = \{1, \dots, M\}$ we **encoding** $E_n : [M] \rightarrow J_X^n$, **decoder** $D_n : [M] \rightarrow J_X^n$, and rate of encoding R such that $M = \lfloor 2^{nR} \rfloor$. The triple $C_n = (E_n, D_n, R)$ is then called an **error correcting code**.

Definition 17. and unlike the average error probabilities consider in information storage, here the error probability is the maximum

$$P_{err}(C_n) = \max_{m \in [M]} \mathbb{P}(D_n(Y^{(n)}) \neq m | X^{(n)} = E_n(m)) \quad (14)$$

Definition 18. and rate R is called **achievable** if there exists an error correcting code such that

$$\lim_{n \rightarrow \infty} P_{err}(C_n) = 0 \quad (15)$$

and so quite naturally

Definition 19. the **capacity** of a discrete memoryless channel is $C(N) = \sup\{R : R \text{ is achievable}\}$.

for which

Theorem 6. *Shannon's noisy channel coding theorem states that*

$$C(N) = \max_{p(x)} I(X : Y) \quad (16)$$

(note that the maximum is only taken over the input, not the output distribution)

Theorem 7. *which has the properties*

- $C(N) \geq 0$
- $C(X) \leq \log |J_X|, \log |J_Y|$

rigorous proof of which is found in the 1991 book *Elements of Information Theory*.

Example 3. *Finally, in the binary symmetric channel from before we find that*

$$I(X : Y) = H(Y) - H(Y|X) = H(Y) - h(p) \implies C(N) = 1 - h(p) \quad (17)$$

[End of lecture 4]

2 Quantum Information Theory

2.1 Quantum States

The lecturer reviews quantum states and how they are represented using linear algebra. Here we note that the **Hemming space** is the space \mathbb{C}^{2^n} , and use $B(H)$ to represent the space of bounded linear operators on H . We also mention the **Pauli Matrices** and their properties

- $\sigma_\alpha^2 = I$
- $\sigma_\alpha \sigma_\beta = i\epsilon_{\alpha\beta\gamma} \sigma_\gamma$
- $\{\sigma_\alpha, \sigma_\beta\} = 0$ for $\alpha \neq \beta$

2.2 Open Quantum Systems

We generalise our formalism a bit to account for external noise. As such, the lecturer reviews the postulates of quantum mechanics. Then we define

Definition 20. a **density matrix** to be a matrix representing a combination states

$$\rho = \sum p_i |\psi_i\rangle \langle \psi_i| \quad (18)$$

which can be equivalently be defined by the properties that

- $\rho \geq 0$ (positive semi-definite) which implies ρ Hermitian
- $\text{tr } \rho = 1$

which serves as a more abstract definition density matrices. If we let $\mathcal{D}(H)$ represent the **set of density matrices** over space H then we notice the property that $\sigma_i \in \mathcal{D}(H), \sum p_i = 1 \implies \sum p_i \sigma_i \in \mathcal{D}(H)$. [End of lecture 5]

Introducing some vocabulary, we say

Definition 21. a state ρ is a **pure state** if $\rho = |\psi\rangle\langle\psi|$ or equivalently that $\rho^2 = \rho$ or $\text{tr } \rho^2 = 1$. If not, we call ρ a **mixed state**

Definition 22. and we can define the **purity** of ρ to be $\text{tr } \rho^2$ which is 1 for a pure state and strictly less than 1 for a mixed state. It is minimised for I/d .

Definition 23. For a product space $H_A \otimes H_B$ we find it useful to define the **partial trace** tr_B that sends an operator

$$X_{AB} \mapsto X_A = \text{tr}_B X_{AB} = \sum \langle e_i^B | X_{AB} | e_i^B \rangle \quad (19)$$

for an orthonormal basis e_i^B .

We can then define $\text{tr}_{AB} = \text{tr}_A \circ \text{tr}_B$. For observable $M_{AB} = M_A \otimes I_B$ we then find that the expectation value

$$\langle M_{AB} \rangle = \text{tr}(M_{AB} \rho_{AB}) = \text{tr}(M_A \rho_A) \quad (20)$$

where

$$\rho_{AB} = \sum_{i,j,\alpha,\beta} a_{i\alpha,j\beta} |i\rangle\langle j|_A \otimes |\alpha\rangle\langle\beta|_B \implies \rho_A = \sum_{i,j,\alpha} a_{i\alpha,j\alpha} |i\rangle\langle j| \quad (21)$$

We then see that $\text{tr}_B(\rho_A \otimes \rho_B) = \rho_A$ for states ρ_A, ρ_B (called a **bipartite system**), while for maximally entangled states such as the **Bell states** or **EPR pairs**

$$|\phi^\pm\rangle = \frac{1}{\sqrt{2}}(|00\rangle \pm |11\rangle) \quad (22)$$

$$|\chi^\pm\rangle = \frac{1}{\sqrt{2}}(|01\rangle \pm |10\rangle) \quad (23)$$

have $\text{tr}_B \rho_{AB} = I_A/2$ meaning that the qubits are maximally mixed, even though the global state is known! For both density matrices and state vectors, we define them to be **separable** if they can be written as tensor products $|\psi\rangle = |\phi\rangle_A \otimes |\chi\rangle_B$ or $\rho_{AB} = \sum_i p_i \omega_i^A \otimes \sigma_i^B$ and if not we call them **entangled**. [End of lecture 6]

2.3 Schmidt Decomposition

The lecturer gives the following special case of the Schmidt decomposition theorem:

Theorem 8. *The **Schmidt decomposition theorem** states that a pure state $|\Psi_{AB}\rangle$ with $d_A = \dim(\mathcal{H}_A)$, $d_B = \dim(\mathcal{H}_B)$ where the spaces $\mathcal{H}_A, \mathcal{H}_B$ has Schmidt bases $|i_A\rangle, |i_B\rangle$ and nonnegative real **Schmidt coefficients** λ_i such that*

$$\sum_{i=1}^{\min(d_A, d_B)} \lambda_i^2 = 1 \quad (24)$$

and note here that $\rho_A = \sum_i \lambda_i^2 |i_A\rangle \langle i_A|$ and the same for ρ_B .

Proof. The lecturer provides a proof using the Singular Value Decomposition (SVD), and uses the fact that $\text{tr } \rho_A = 1 = \text{tr } \rho_B$ to get $\sum \lambda_i^2 = 1$. \square

From here we note that if ρ_A, ρ_B have no degenerate eigenvalues other than 0, the $|\Psi_{AB}\rangle$ is determined uniquely by ρ_A, ρ_B since one can

1. diagonalise ρ_A, ρ_B
2. and then match up eigenvectors corresponding to the same eigenvalues

We also define

Definition 24. the Schmidt rank of pure bipartite state $|\Psi_{AB}\rangle$ to be the non-zero coefficients in its Schmidt decomposition. This is denoted by $n(\Psi_{AB})$.

This provides a simple way of checking whether or not $|\Psi_{AB}\rangle$ is entangled since it is entangled iff $n(\Psi_{AB}) > 1$.

2.4 Purification

A useful mathematical trick is to represent mixed states as pure states. In particular, for density ρ_A on system A we can introduce a **reference system** R and pure state $|\Psi_{AR}\rangle$ such that

$$\rho_A = \text{tr}_R(|\Psi_{AR}\rangle \langle \Psi_{AR}|) \quad (25)$$

In particular, we can do so for $\mathcal{H}_R \simeq \mathcal{H}_A$ by considering for

$$\rho_A = \sum_i p_i |i_A\rangle \langle i_A| \quad (26)$$

the pure state

$$|\Psi_{AR}\rangle = \sum_i \sqrt{p_i} |i_A\rangle \otimes |i_R\rangle \quad (27)$$

(which is just the Schmidt decomposition of $|\Psi_{AR}\rangle$. More generally, we can use the **canonical purification**

$$|\Psi_{AR}\rangle = \sqrt{d}(\sqrt{\rho_A} \otimes I_R) |\Omega\rangle \quad (28)$$

where

$$|\Omega\rangle = \frac{1}{\sqrt{d}} \sum_{i=1}^d |i\rangle |i\rangle \in \mathcal{H}_A \otimes \mathcal{H}_R \quad (29)$$

Also, we note that any pure state $|\Psi_{AR}\rangle$ with reduced state ρ_A can be written as

$$|\Psi_{AR}\rangle = \sqrt{d}(\sqrt{\rho_A} \otimes V) |\Omega\rangle \quad (30)$$

where V is an isometry rotating $|i\rangle$ into the Schmidt basis of $|\Psi_{AR}\rangle$. [End of lecture 7]

2.5 The no cloning theorem

Although it shows up in part II, we review the no cloning theorem.

Theorem 9. *The **no cloning theorem** states that there is no quantum process that universally clones quantum states. More precisely, one can only design a quantum process that clones orthogonal states.*

Proof. Suppose that for two states $|\psi\rangle, |\phi\rangle$ we have that for any state $|s\rangle$

$$\begin{aligned} U(|\psi\rangle \otimes |s\rangle) &= |\psi\rangle \otimes |\psi\rangle \\ U(|\phi\rangle \otimes |s\rangle) &= |\phi\rangle \otimes |\phi\rangle \end{aligned}$$

meaning that by taking the inner product we have $\langle\phi|\psi\rangle = \langle\phi|\psi\rangle^2$ meaning that ϕ, ψ are either identical or orthogonal. Now, one might argue that this assumes that we are in a pure state, and also assumes that any operation we use is unitary. However, by considering the purification of a non-pure state this generalises to non-pure states. Also, by adding an ancilla we can make (any?) state unitary so we this generalises to copying any quantum state. \square

2.6 Time evolution of open systems

2.7 Quantum operations

To describe changes in open quantum systems, we use **quantum operations** which we define to be **linear completely positive trace preserving** maps or CPTP maps. These describe discrete changes in a system, and have the advantage that they do not explicitly introduce time. Specifically, we consider these maps to be maps of densities

$$\Lambda : \mathcal{D}(\mathcal{H}) \rightarrow \mathcal{D}(\mathcal{H}); \rho \mapsto \rho' \quad (31)$$

satisfying the properties that Λ is

- linear (allowing us to interpret mixed states probabilistically)
- trace-preserving (we need to preserve total probability)

- positive (meaning that $\rho \geq 0 \implies \lambda(\rho) \geq 0$. Here $\rho \geq 0$ means ρ is positive semi-definite.
- **complete positivity** which means that \forall ancillas B the map $\Lambda \otimes \text{id}_B$ is positive too. This is a stronger statement than positivity, since in particular we note that $\rho \mapsto \rho^T$ is not completely positive.

Theorem 10. *A map $\Lambda : \mathcal{B}(\mathcal{H}) \rightarrow \mathcal{B}(\mathcal{K})$ for $\mathcal{H} \simeq \mathbb{C}^d$ is completely positive if and only if*

$$(\Lambda \otimes \text{id}_d) |\Omega\rangle \langle \Omega| \geq 0$$

where $|\Omega\rangle = \frac{1}{\sqrt{d}} \sum |ii\rangle \in \mathbb{C}^d \times \mathbb{C}^d$ is the maximally entangled state of Schmidt rank d .

Proof. Necessity of this condition is clear. To prove sufficiency we observe that $\forall k \geq 1$ we have that $\rho \in \mathcal{D}(\mathcal{H} \otimes \mathbb{C}^k)$ so we that if $\rho = \sum p_i |\phi_i\rangle \langle \phi_i|$ then

$$\forall (\Lambda \otimes \text{id}_k) |\phi_i\rangle \langle \phi_i| \geq 0 \implies (\Lambda \otimes \text{id}_k) \rho \geq 0$$

From the last lecture we know that any pure state can be written in the form $(I_d \otimes R) |\Omega\rangle$ for $R \in \mathcal{B}(\mathbb{C}^d, \mathbb{C}^k)$ so in particular we see that $(\Lambda \otimes \text{id}_k) |\phi_i\rangle \langle \phi_i| \geq 0$ can be written in the forms

$$\begin{aligned} (\Lambda \otimes \text{id}_k) (I_d \otimes R_i) |\Omega\rangle \langle \Omega| (I_d \otimes R_i^\dagger) &\geq 0 \\ (I_{d'} \otimes R_i) (\Lambda \otimes \text{id}_d) |\Omega\rangle \langle \Omega| (I_{d'} \otimes R_i^\dagger) &\geq 0 \end{aligned}$$

meaning that since the outside conjugation is invertible, we are positive iff

$$(\Lambda \otimes \text{id}_d) |\Omega\rangle \langle \Omega| \geq 0$$

as required □

Note that here we call $J(\Lambda) = J = (\Lambda \otimes \text{id}_d) |\Omega\rangle \langle \Omega|$ the **Choi matrix** or the **Choi state** of Λ . [End of lecture 8]