QIC 710 Talk Notes

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December 22, 2013

Contents

1	Clas	ssical Information Theory	3
	1.1	Definitions	:
	1.2	Basic Results	3
2		antum Information Theory	
	2.1	Definitions and Properties	-
	2.2	Quantum Channels	1
		$C_{1,1}$ Single Use	ŀ
		$C_{1,\infty}$ - Infinite Use	
		C_E : Entangelement-Assisted Channels	
	2.3	Proofs	6
		2.3.1 Holevo's Bound	6

Chapter 1

Classical Information Theory

1.1 Definitions

$$C = \lim_{T \to \infty} \frac{\log(N(T))}{T} \tag{1.1}$$

$$H = \sum_{i=1}^{n} p_i \log p_i \tag{1.2}$$

$$H(x,y) = -\sum_{i} \sum_{j} p(i,j) \log p(i,j)$$
 (1.3)

$$H_x(y) = -\sum_{i} \sum_{j} p(i,j) \log p(j|i)$$
 (1.4)

$$H_y(x) = -\sum_{i} \sum_{j} p(i,j) \log p(i|j)$$
 (1.5)

1.2 Basic Results

Proof.

$$p = p_1^{p_1 N} p_2^{p_2 N} p_3^{p_3 N} \dots p_n^{p_n N}$$
(1.6)

$$\log(p) = N(p_1 \log(p_1) + p_2 \log(p_2) + p_3 \log(p_3) + \dots + p_n \log(p_n))$$
 (1.7)

$$\log(p) = -NH \tag{1.8}$$

$$p = 2^{-NH} \tag{1.9}$$

Proof.

$$\# = \frac{N!}{n_1! n_2! n_3! \dots n_n!} \tag{1.10}$$

$$\log(\#) = N\log(N) - n_1\log(n_1) - n_2\log(n_2) - \dots - n_n\log(n_n)$$
(1.11)

$$\log(\#) = N\log(N) - N(\log(N(p_1 + p_2 + \dots + p_n)) + \sum_{i} p_i \log(p_i))$$
 (1.12)

$$\log(\#) = HN \tag{1.13}$$

$$# = 2^{HN} (1.14)$$

Proof.

Talk about the rate of the channel. Talk about how it reduces to the noiseless case.

$$(1.15)$$

$$R = H(x) - H_y(x) \tag{1.16}$$

Discuss the phenemonon when $p_{fail}=1\%$. Then move on the the maximum channel capacity.

(1.17)

$$C = \max_{x} (H(x) - H_y(x)) \tag{1.18}$$

$$C_{erasure} = H(x) - H(X|Y) \tag{1.19}$$

optimal H(x) = 1

(1.20)

$$=1 - \sum_{i,j} p(i,j) \log(p(i|j))$$
 (1.21)

$$= 1 - \sum_{i,j} p(i|j)p(j)\log(p(i|j))$$
 (1.22)

$$= 1 - \left(p(0) \left(p(0|0) \log p(0|0) + p(1|0) \log p(1|0) \right)$$
 (1.23)

$$+ \, p(1) \Big(p(0|1) \log p(0|1) + p(1|1) \log p(1|1) \Big)$$

$$+ p(e) \Big(p(0|e) \log p(0|e) + p(1|e) \log p(1|e) \Big) \Big)$$

$$= 1 - \left(\frac{1-p}{2} \log 1 + 0 \log 0\right) + \frac{1-p}{2} \left(0 \log 0 + 1 \log 1\right)$$
 (1.24)

$$+p(.5 \log .5 + .5 \log .5)$$

= 1 - p (1.25)

Chapter 2

Quantum Information Theory

2.1 Definitions and Properties

$$S(\rho) = -Tr(\rho \log(\rho)) = -\sum_{i} \lambda_{i} \log \lambda_{i}$$
(2.1)

$$S(|\Psi\rangle\langle\Psi|) = 0 \tag{2.2}$$

$$\mathcal{E}(\rho) = \sum_{k} |e_{k}\rangle U[\rho \otimes |e_{0}\rangle \langle e_{0}|] U^{\dagger} |e_{k}\rangle = \sum_{k} E_{k} \rho E_{k}^{\dagger}, E_{k} \equiv \langle e_{k}| U |e_{0}\rangle \qquad (2.3)$$

2.2 Quantum Channels

2.2.1 $C_{1,1}$ Single Use

$$C_{1,1} = \max_{\rho_i} \left(H(X:Y) = H(Y) - H(Y|X) = H(X) - H(X|Y) \right)$$
 (2.4)

2.2.2 $C_{1,\infty}$ - Infinite Use

$$C_{1,\infty} = \max_{\rho_i} \left(S(\sum_i p_i \sigma_i) - \sum_i p_i S(\sigma_i) \right) = \chi$$
 (2.5)

the Holevo information

(2.6)

This is the well-known Helov-Schumacher-Westmoreland (HSW) theorem

(2.7)

2.2.3 C_E : Entangelement-Assisted Channels

Holds for noiseless channels. Defined over classical information that is sent.

$$C_E(\mathcal{N}) = \max_{\rho \in \mathcal{H}_{in}} \left(S(\rho) + S(\mathcal{N}(\rho)) - S((\mathcal{N} \otimes \mathcal{I})(\Phi_{\rho})) \right)$$
(2.8)

 Φ_{ρ} is an element of $\mathcal{H}_{i}n\otimes\mathcal{H}_{R}$ such that $Tr_{R}\Phi_{\rho}=\rho$.

2.3 Proofs

2.3.1 Holevo's Bound

$$H(X:Y) \le S(\rho) - \sum_{x} p_x S(\rho_x) \tag{2.9}$$

$$\rho^{PQM} = \sum_{x} p_x |x\rangle \langle x| \otimes \rho_x \otimes |0\rangle \langle 0|$$
 (2.10)

$$\mathcal{E}(\sigma \otimes |0\rangle \langle 0|) \equiv \sum_{y} \sqrt{E_{y}} \sigma \sqrt{E_{y}} \otimes |y\rangle \langle y|$$
(2.11)

$$S(P:Q) = S(P:Q,M) \tag{2.12}$$

since M is initially uncorrelated with P,Q

(2.13)

$$S(P:Q,M) \ge S(P':Q',M')$$
 (2.14)

applying a quantum operation can't increase mutual information between P and Q,M

(2.15)

$$S(P':Q',M') \ge S(P':M')$$
 (2.16)

tracing out Q can't increase mutual information

(2.17)

$$S(P':M') \le S(P:Q) \tag{2.18}$$

$$S(P:Q) = S(P) + S(Q) - S(P,Q) = H(p_x) + S(\rho) - (H(p_x) + \sum_{x} p_x S(\rho_x))$$

(2.19)

$$\rho^{P'Q'M'} = \sum_{xy} p_x |x\rangle \langle x| \otimes \sqrt{E_y} \rho_x \sqrt{E_y} \otimes |y\rangle \langle y|$$
(2.20)

Note that

$$p(x,y) = p_x p(y|x) = p_x tr(\sqrt{E_y} \rho_x \sqrt{E_y})$$
 (2.21)

$$\rho^{P'M'} = \sum_{xy} p(x,y) |x\rangle \langle x| \otimes |y\rangle \langle y|$$
(2.22)

$$S(\rho^{P'M'}) = -Tr\rho^{P'M'}\log\rho^{P'M'} = -\sum_{xy} p(x,y)\log p(x,y) = H(X:Y) \quad (2.23)$$

Thus,

$$H(X:Y) \le S(\rho) - \sum_{x} p_x S(\rho_x) \tag{2.24}$$