Final Recitation – Information Theory, Application.

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Introduction

- ▶ Brief overview of the topic
- ► Importance and relevance
- Objectives of the presentation

Key Points

- ▶ Main point 1
- ► Main point 2
- ► Main point 3

Claim

Let Y be a bit given by moving X trough BSC(p), Then there is $\gamma_p < 1$ such :

$$1 - H(Y) \le \gamma \left(1 - H(X)\right)$$

Denote by δ the parameter for which X distributed as $\sim Bin(\frac{1+\delta}{2})$. First notice that:

$$\Pr(Y = 1) = \frac{1+\delta}{2}(1-p) + \frac{1-\delta}{2}p = \frac{1+\delta-2\delta p}{2}$$

So
$$Y \sim \text{Bin}(\frac{1-\delta(1-2p)}{2})$$
, Or $\delta \mapsto 1-2p\delta$.

Now expand 1 - H(X) to it's Taylor Seryias at δ gives:

$$1 - H(X) = 1 - \frac{1}{2} \left((1 + \delta) \log \left(\frac{1 + \delta}{2} \right) + (1 - \delta) \log \left(\frac{1 - \delta}{2} \right) \right)$$

$$= -\frac{1}{2} \left((1 + \delta) \log \left(\frac{1 + \delta}{2} \right) + (1 - \delta) \log \left(\frac{1 - \delta}{2} \right) \right)$$

$$= -\frac{1}{2} \cdot (1 + \delta) \sum_{i=1}^{\infty} \frac{(-1)^{n+1} \delta^n}{n} + (1 - \delta) \sum_{i=1}^{\infty} \frac{(-1)^{n+1} (-\delta)^n}{n}$$

$$= -\frac{1}{2} \cdot \sum_{i=1}^{\infty} 2 \frac{\delta^{2n}}{2n} - \sum_{i=1}^{\infty} 2 \frac{\delta^{2n}}{2n-1}$$

$$= \sum_{i=1}^{\infty} \frac{\delta^{2n}}{2n(2n-1)}$$

Denote the above by $K(\delta)$

Now, observes that:

$$1 - H(Y) = K(2p\delta) = \sum_{i=1}^{\infty} \frac{(2p\delta)^{2n}}{2n(2n-1)}$$

$$\leq (1 - 2p)^2 K(\delta) = (1 - 2p)^2 (1 - H(X))$$

And notice that since p<1 we have $\gamma<1$, noitce also that inequlity is symmetric to $p\mapsto 1-p$, in paritcular the entropy is not increase if either p=0 or p=1.

Claim

Let $Y = (Y_1, Y_2, ..., Y_m)$ be a bit given by moving each of $X_i \in X = (X_1, X_2, ..., X_m)$ trough BSC(p). Then:

$$m - H(Y) \le \gamma (m - H(X))$$

$$m - H(Y_1, Y_2, ..., Y_m) = m - \sum_{i} H(Y_i | Y_1, Y_2, ..., Y_{i-1})$$

$$\leq m - \sum_{i} H(Y_i | X_1, X_2, ..., X_{i-1})$$

$$\leq \sum_{i} 1 - H(Y_i | X_1, X_2, ..., X_{i-1})$$

$$\leq \sum_{i} \gamma (1 - H(X_i | X_1, X_2, ..., X_{i-1}))$$

$$\leq \gamma \sum_{i} (1 - H(X_i | X_1, X_2, ..., X_{i-1}))$$

$$= \gamma (m - H(X))$$

Claim

Denote b $X = (X_1, X_2, ..., X_m)$ and $Y = (Y_1, Y_2, ..., Y_m)$ the input and the output distrubtions of reversible p-noisy computation at widith m (bits) and depth d. Then, there:

$$m - H(Y) \le \gamma^d (m - H(X))$$

In particular, for $d = \Omega(\log m)$ we have $H(Y) \to m$.

Claim

Let ρ_1 be a reduce density matrix of ρ Then:

$$-\mathsf{Tr}\ \rho\log\left(\rho_1\otimes I\right)=S(\rho_1)$$

First consider the case in which ρ is a tensor of ρ_1 namely $\rho=\rho_1\otimes\rho_2$, Then clearly ρ and $\log\rho_1\otimes I$ commute. Denote by $\lambda_1,...\lambda_n$ and $\mu_1,...\mu_m$ the eigen values of ρ_1 and ρ_2 . So the trace equals:

$$\sum \lambda_i \mu_j \log(\lambda_i \cdot 1) = \left(\sum \mu_j\right) \left(\sum_i \lambda_i \log \lambda_i\right)$$

= $(\operatorname{Tr} \
ho_2) \sum_i \lambda_i \log \lambda_i = -S(
ho_1)$

Let's use the notation $\sum_{A_k} \rho|_{A_k}$ to denote the sum over all the reduced matrices over k qubits.

Claim

Let ρ be a density matrix over n qubits then:

$$\binom{n}{k}^{-1} \sum_{A_k} I(\rho|_{A_k}) \leq \frac{k}{n} I(\rho)$$

Let
$$\rho_1$$
 be $\rho^{\otimes k \binom{n}{k}}$ and let $\rho_2 = \left(\prod_{A_k} \rho|_{A_k}\right)^{\otimes n}$.
$$0 \ge S(\rho_2|\rho_1) = \operatorname{Tr} \ \left(\rho_1 \left(\log \rho_1 - \log \rho_2\right)\right) = -S(\rho_1) - \operatorname{Tr} \ \left(\rho_1 \log \rho_2\right)$$
$$= -k \binom{n}{k} S(\rho) - \sum_i \operatorname{Tr} \ \left(\rho_1 \log \left(\rho|_{A_k}\right)^n \otimes I^n\right)$$