

# Non-asymptotic Equipartition Properties With Respect to Information Quantities

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# Outline

- 1 Introduction
- 2 Entropy NEP and Source Coding
- 3 Conditional Entropy NEP and Channel Coding
- 4 Mutual Information and Relative Entropy NEP

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- 1 Introduction**
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## Asymptotic Equipartition Properties (AEP)

### AEP w.r.t Entropy

For independent and identically distributed (IID) source

$$X = \{X_i\}_{i=1}^{\infty},$$

$$-\frac{1}{n} \ln p(X_1 X_2 \cdots X_n) \rightarrow H(X) \quad (1)$$

### Typicality

With high probability, the outcomes of  $X_1 X_2 \cdots X_n$  are approximately equiprobable with their respective probability

$$\text{from } e^{-n(H(X)+\epsilon)} \text{ to } e^{-n(H(X)-\epsilon)}$$

for small fixed number  $\epsilon$ . Those sequences are called **typical sequences**, and the set of typical sequences are called the **typical set**, denoted by  $\mathcal{T}^{(n)}$ .

## Application of AEP to Source Coding

### Simple Proof on Source Coding using AEP

Implication of AEP suggests that only typical sequence need to be represented, while error probability (the probability that a sequence appears with no representation) is arbitrarily small. Therefore, the rate of source code is related to  $|\mathcal{T}^{(n)}|$ , which can be easily bounded by the following argument.

$$|\mathcal{T}^{(n)}| e^{-n(H(X)+\epsilon)} \leq \sum_{x^n \in \mathcal{T}^{(n)}} p(x^n) \leq 1$$
$$\Rightarrow R_n = \frac{1}{n} \ln |\mathcal{T}^{(n)}| \leq H(X) + \epsilon$$

## Asymptotic Equipartition Properties (AEP)

### AEP w.r.t Joint Entropy

For independent and identically distributed (IID) source pair  $(X, Y) = \{(X_i, Y_i)\}_{i=1}^{\infty}$ ,

$$-\frac{1}{n} \ln p(X^n, Y^n) \rightarrow H(X, Y) \quad (2)$$

### Joint Typicality

With high probability,

$$\begin{aligned} e^{-n(H(X)+\epsilon)} &\leq p(X^n) \leq e^{-n(H(X)-\epsilon)} \\ e^{-n(H(Y)+\epsilon)} &\leq p(Y^n) \leq e^{-n(H(Y)-\epsilon)} \\ e^{-n(H(X,Y)+\epsilon)} &\leq p(X^n, Y^n) \leq e^{-n(H(X,Y)-\epsilon)} \end{aligned}$$

Call the set of those sequences as joint typical set  $\mathcal{T}_J^{(n)}$ .

## Application of AEP to Channel Coding

### Simple Proof on Channel Coding using AEP

It can be shown that while  $(X^n, Y^n) \in \mathcal{T}_J^{(n)}$  with high probability,

$$\Pr \left\{ (\tilde{X}^n, Y^n) \in \mathcal{T}_J^{(n)} \right\} \leq e^{-n(I(X;Y) - 3\epsilon)}$$

if  $\tilde{X}$  and  $Y$  are independently. Then as long as channel code rate

$$R \leq I(X;Y) - 3\epsilon$$

$\mathcal{T}_J^{(n)}$  contains only one codeword  $X^n$ .

## Impact and Limitation of AEP

### Impact

Establish asymptotic coding theorem in

- source coding;
- channel coding ;
- and multi-user information theory.

### Limitation

- AEP applies only to large block length  $n$ ;
- AEP can yield only first order results; and
- more importantly, AEP is not applicable to the non-asymptotic regime, which is the real game in practice.



## Impact and Limitation of AEP

### Impact

Establish asymptotic coding theorem in

- source coding;
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### Limitation - Solution: Non-asymptotic Equipartition Property (NEP)!

- AEP applies only to large block length  $n$ ;
- AEP can yield only first order results; and
- more importantly, AEP is not applicable to the non-asymptotic regime, which is the real game in practice.

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# Entropy NEP

Random variable:  $-\frac{1}{n} \ln p(X^n)$   
Distribution: ?

Entropy NEP  $\approx$  characterization of  
 $-\frac{1}{n} \ln p(X^n)$   
for any  $n$

## Weak Right Entropy NEP

### Chernoff Bound Result

For independent and identically distributed (IID) source

$$X = \{X_i\}_{i=1}^{\infty},$$

$$\Pr \left\{ -\frac{1}{n} \ln p(X^n) \geq H(X) + \delta \right\} \leq e^{-nr_X(\delta)} \quad (3)$$

where

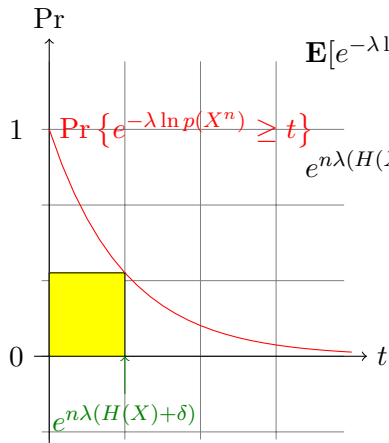
$$r_X(\delta) \triangleq \sup_{\lambda \geq 0} \left[ \lambda(H(X) + \delta) - \ln \int p^{-\lambda+1}(x) dx \right].$$

## Proof of Weak Right Entropy NEP

### Proof

$$\begin{aligned} & \Pr \left\{ -\frac{1}{n} \ln p(X_1 X_2 \cdots X_n) \geq H(X) + \delta \right\} \\ &= \Pr \{ -\ln p(X_1 X_2 \cdots X_n) \geq n(H(X) + \delta) \} \\ &\leq \inf_{\lambda \geq 0} \frac{\mathbf{E}[e^{-\lambda \ln p(X_1 X_2 \cdots X_n)}]}{e^{n\lambda(H(X) + \delta)}} \\ &= \inf_{\lambda \geq 0} e^{-n[\lambda(H(X) + \delta) - \ln \mathbf{E}[p^{-\lambda}(X_1)]]} \\ &= \inf_{\lambda \geq 0} e^{-n[\lambda(H(X) + \delta) - \ln \int p^{-\lambda+1}(x) dx]} \\ &= e^{-nr_X(\delta)}. \end{aligned} \tag{4}$$

## Graphical Interpretation



$$\begin{aligned} \mathbf{E}[e^{-\lambda \ln p(X^n)}] &= \int \Pr\{e^{-\lambda \ln p(X^n)} \geq t\} dt \\ &\geq e^{n\lambda(H(X)+\delta)} \Pr\{-\ln p(X^n) \geq n(H(X) + \delta)\} \end{aligned}$$

## Example of $r_X(\delta)$

For I.I.D binary source with  $\Pr\{X = 0\} = p \leq 0.5$ ,

$$r_{X|Y}(\delta) = D\left(p + \frac{\delta}{\ln \frac{1-p}{p}} \parallel p\right) \quad (5)$$

where

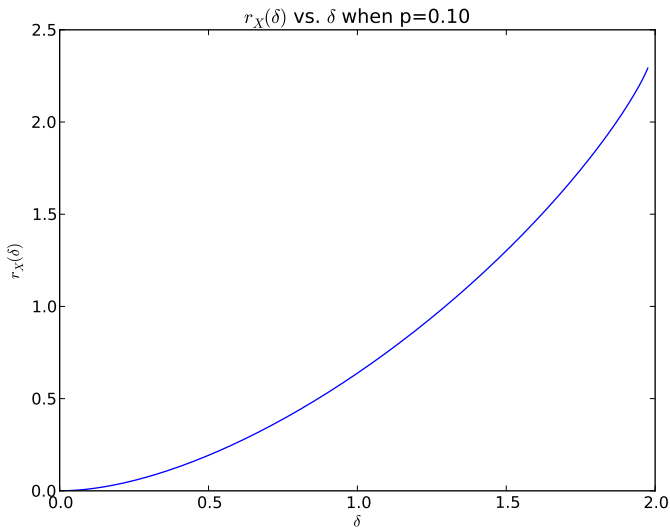
$$D(q||p) \triangleq (1-q) \ln \frac{1-q}{1-p} + q \ln \frac{q}{p}$$

- $D\left(p + \frac{\delta}{\ln \frac{1-p}{p}} \parallel p\right)$  is convex and non-decreasing.



$$D\left(p + \frac{\delta}{\ln \frac{1-p}{p}} \parallel p\right) = \frac{1}{2p(1-p) \ln^2 \frac{1-p}{p}} \delta^2 + O(\delta^3)$$

## Plot of $r_X(\delta)$





## Properties of $r_X(\delta)$

- $r_X(\delta)$  is convex and non-decreasing.
- Parametric Form

$$\delta(\lambda) = \int \frac{p^{-\lambda+1}(x)}{[\int p^{-\lambda+1}(y)dy]} [-\ln p(x)] dx - H(X) \quad (6)$$

$$r_X(\delta(\lambda)) = \lambda(H(X) + \delta(\lambda)) - \ln \int p^{-\lambda+1}(x)dx . \quad (7)$$

- $r'_X(\delta) = \lambda$ ,  $r''_X(\delta) = \frac{1}{\delta'(\lambda)}$ .



$$r_X(\delta) = \frac{1}{2\sigma_H^2(X)}\delta^2 + O(\delta^3) \quad (8)$$

## Strong Right Entropy NEP

For independent and identically distributed (IID) source

$$X = \{X_i\}_{i=1}^{\infty},$$

$$\Pr \left\{ -\frac{1}{n} \ln p(X^n) \geq H(X) + \delta \right\} \\ \leq \frac{1}{1 - e^{-\lambda}} \left[ \frac{1}{\sqrt{2\pi}\sigma_H(X, \lambda)} + \frac{2M_H(X, \lambda)}{\sigma_H^3(X, \lambda)} \right] e^{-nr_X(\delta) - \frac{1}{2} \ln n} \quad (9)$$

$$\Pr \left\{ -\frac{1}{n} \ln p(X^n) \geq H(X) + \delta \right\} \\ \geq e^{-\lambda d} \left[ \frac{de^{-\frac{d^2}{2n\sigma_H^2(X, \lambda)}}}{\sqrt{2\pi}\sigma_H(X, \lambda)} - \frac{2M_H(X, \lambda)}{\sigma_H^3(X, \lambda)} \right] e^{-nr_X(\delta) - \frac{1}{2} \ln n} \quad (10)$$

for any  $d > 0$ , where  $\lambda = r'_X(\delta) > 0$ .

## Derivation of Strong Entropy NEP

Define

$$f_\lambda(x) \triangleq \frac{p^{-\lambda}(x)}{\int p^{-\lambda+1}(y)dy} \quad (11)$$

and

$$B_k \triangleq \left\{ x^n : H(X) + \delta + \frac{k}{n} \leq -\frac{1}{n} \ln p(x^n) < H(X) + \delta + \frac{k+1}{n} \right\}.$$

Then

$$\begin{aligned} & \Pr \left\{ -\frac{1}{n} \ln p(X^n) \geq H(X) + \delta \right\} \\ &= \int_{-\frac{1}{n} \ln p(x^n) \geq H(X) + \delta} p(x^n) dx^n \\ &= \sum_{k=0}^{\infty} \int_{x^n \in B_k} p(x^n) dx^n \end{aligned}$$

## Derivation of Strong Entropy NEP

$$\begin{aligned}
 &= \sum_{k=0}^{\infty} \int_{x^n \in B_k} f_{\lambda}^{-1}(x^n) f_{\lambda}(x^n) p(x^n) dx^n \\
 &= \sum_{k=0}^{\infty} \int_{x^n \in B_k} e^{\left\{-n \left[-\frac{1}{n} \lambda \ln p(x^n) - \ln \int p^{-\lambda+1}(y) dy\right]\right\}} f_{\lambda}(x^n) p(x^n) dx^n \\
 &\leq \sum_{k=0}^{\infty} e^{\left\{-n \left[\lambda(H(X) + \delta + \frac{k}{n}) - \ln \int p^{-\lambda+1}(y) dy\right]\right\}} \int_{x^n \in B_k} f_{\lambda}(x^n) p(x^n) dx^n \\
 &= e^{-nr_X(\delta)} \sum_{k=0}^{\infty} e^{-\lambda k} \int_{x^n \in B_k} f_{\lambda}(x^n) p(x^n) dx^n \tag{12}
 \end{aligned}$$

## Central Limit Theorem

### Lemma (Berry and Esseen)

Let  $V_1, V_2, \dots$  be independent real random variables with zero means and finite third moments, and set

$$\sigma_n^2 = \sum_{i=1}^n \mathbf{E}V_i^2.$$

Then there exists a universal constant  $C < 1$  such that for any  $n \geq 1$ ,

$$\sup_{-\infty < t < +\infty} \left| \Pr\left\{ \sum_{i=1}^n V_i \leq \sigma_n t \right\} - \Phi(t) \right| \leq C \sigma_n^{-3} \sum_{i=1}^n \mathbf{E}|V_i|^3,$$

where  $\Phi(t) = (2\pi)^{-1/2} \int_{-\infty}^t e^{-u^2/2} du$ .

## Derivation of Strong Entropy NEP - Cont.

Consider  $Z_1, Z_2, \dots, Z_n$  with pmf or pdf  $f_\lambda(z)p(z)$ , and applying central limit theorem to the IID sequence

$$\{-\ln p(Z_i) - (H(X) + \delta)\}_{i=1}^n$$

yields

$$\begin{aligned} & \int_{x^n \in B_k} f_\lambda(x^n)p(x^n)dx^n \\ & \leq \frac{1}{\sqrt{2\pi}} \int_0^{\frac{1}{\sqrt{n}\sigma_H(X,\lambda)}} e^{-\frac{t^2}{2}} dt + 2C \frac{1}{\sqrt{n}} \frac{M_H(X,\lambda)}{\sigma_H^3(X,\lambda)} \\ & \leq \frac{1}{\sqrt{n}} \left( \frac{1}{\sqrt{2\pi}\sigma_H(X,\lambda)} + \frac{2M_H(X,\lambda)}{\sigma_H^3(X,\lambda)} \right) \end{aligned} \quad (13)$$

for any  $k \geq 0$ .

## Derivation of Strong Entropy NEP - Cont.

Combining (13) with (12) yields

$$\begin{aligned} & \Pr \left\{ -\frac{1}{n} \ln p(X^n) \geq H(X) + \delta \right\} \\ & \leq e^{-nr_X(\delta) - \frac{1}{2} \ln n} \left( \frac{1}{\sqrt{2\pi}\sigma_H(X, \lambda)} + \frac{2M_H(X, \lambda)}{\sigma_H^3(X, \lambda)} \right) \sum_{k=0}^{\infty} e^{-\lambda k} \\ & = \frac{1}{1 - e^{-\lambda}} \left( \frac{1}{\sqrt{2\pi}\sigma_H(X, \lambda)} + \frac{2M_H(X, \lambda)}{\sigma_H^3(X, \lambda)} \right) e^{-nr_X(\delta) - \frac{1}{2} \ln n} . \end{aligned}$$

This completes the proof of (9).

## Derivation of Strong Entropy NEP - Cont.

To prove (10), note that for any  $d > 0$

$$\begin{aligned}
 & \Pr \left\{ -\frac{1}{n} \ln p(X^n) \geq H(X) + \delta \right\} \\
 & \geq \int_{0 \leq -\frac{1}{n} \ln p(x^n) - (H(X) + \delta) < \frac{d}{n}} p(x^n) dx^n \\
 & = \int_{0 \leq -\frac{1}{n} \ln p(x^n) - (H(X) + \delta) < \frac{d}{n}} f_\lambda^{-1}(x^n) f_\lambda(x^n) p(x^n) dx^n \\
 & \geq e^{-nr_X(\delta) - \lambda d} \int_{0 \leq -\frac{1}{n} \ln p(x^n) - (H(X) + \delta) < \frac{d}{n}} f_\lambda(x^n) p(x^n) dx^n \quad (14)
 \end{aligned}$$



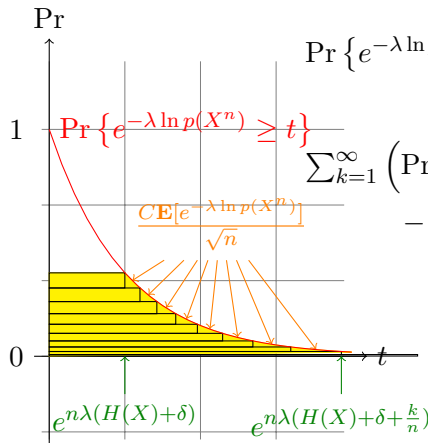
## Derivation of Strong Entropy NEP - Cont.

Applying Lemma 1 to the IID sequence  $\{-\ln p(Z_i) - (H(X) + \delta)\}_{i=1}^n$  again, we have

$$\begin{aligned}
 & \int_{0 \leq -\frac{1}{n} \ln p(x^n) - (H(X) + \delta) < \frac{d}{n}} f_\lambda(x^n) p(x^n) dx^n \\
 & \geq \frac{1}{\sqrt{2\pi}} \int_0^{\frac{d}{\sqrt{n}\sigma_H(X, \lambda)}} e^{-\frac{t^2}{2}} dt - 2C \frac{1}{\sqrt{n}} \frac{M_H(X, \lambda)}{\sigma_H^3(X, \lambda)} \\
 & \geq \frac{1}{\sqrt{n}} \left( \frac{d}{\sqrt{2\pi}\sigma_H(X, \lambda)} e^{-\frac{d^2}{2n\sigma_H^2(X, \lambda)}} - \frac{2M_H(X, \lambda)}{\sigma_H^3(X, \lambda)} \right) \quad (15)
 \end{aligned}$$

which, combined with (14), implies (10).

# Graphical Interpretation



$$\Pr \left\{ e^{-\lambda \ln p(X^n)} \geq e^{n\lambda(H(X)+\delta)} \right\}$$

$$=$$

$$\sum_{k=1}^{\infty} \left( \Pr \left\{ e^{-\lambda \ln p(X^n)} \geq e^{n\lambda(H(X)+\delta+\frac{k-1}{n}} \right\} - \Pr \left\{ e^{-\lambda \ln p(X^n)} \geq e^{n\lambda(H(X)+\delta+\frac{k}{n}} \right\} \right)$$

## Central Limit Theorem

For any  $\delta \leq c\sqrt{\frac{\ln n}{n}}$ , where  $c < \sigma_H(X)$  is a constant,

$$\begin{aligned} Q\left(\frac{\delta\sqrt{n}}{\sigma_H(X)}\right) - \frac{CM_H(X)}{\sqrt{n}\sigma_H^3(X)} &\leq \Pr\left\{-\frac{1}{n}\ln p(X^n) \geq H(X) + \delta\right\} \\ &\leq Q\left(\frac{\delta\sqrt{n}}{\sigma_H(X)}\right) + \frac{CM_H(X)}{\sqrt{n}\sigma_H^3(X)} \quad (16) \end{aligned}$$

where  $Q(t) = \frac{1}{\sqrt{2\pi}} \int_t^\infty e^{-u^2/2} du$ , and  $C < 1$  is the universal constant in the central limit theorem of Berry and Esseen.

## Application to Fixed Rate Source Coding

Given a memoryless source  $X$ , the performance of optimal fixed rate source coding for any block length  $n$  is characterized by,

$$\delta \geq R_n - H(X) \geq \delta - r_X(\delta) - \frac{\ln n}{2n} - O(n^{-1}) \quad (17)$$

whenever

$$\left| \frac{\ln \epsilon_n}{n} + r_X(\delta) + \frac{\ln n}{2n} + \frac{\ln \lambda}{n} \right| \leq O(n^{-1}) \quad (18)$$

for  $\Omega\left(\frac{1}{\sqrt{n}}\right) = \delta \leq \ln |\mathcal{X}| - H(X)$  and  $\lambda = r'_X(\delta)$ .

## Application to Fixed Rate Source Coding

(a) Let  $\delta$  be a constant with respect to  $n$ . Then

$$\begin{aligned} & r_X^{(inv)} \left( -\frac{\ln \epsilon_n}{n} - \frac{\ln n}{2n} \right) + O(n^{-1}) \\ & \geq R_n - H(X) \\ & \geq r_X^{(inv)} \left( -\frac{\ln \epsilon_n}{n} - \frac{\ln n}{2n} \right) + \frac{\ln \epsilon_n}{n} - O(n^{-1}) \end{aligned} \tag{19}$$

whenever  $\epsilon_n$  decreases exponentially with respect to  $n$ ,  
where  $r_X^{(inv)}$  is the inverse function of  $r_X$ .

## Application to Fixed Rate Source Coding

**(b)** Let  $\delta = \sigma_H(X) \sqrt{\frac{2\alpha \ln n}{n}}$  for some  $\alpha > 0$ . Then

$$\begin{aligned} & \sigma_H(X) \sqrt{\frac{2\alpha \ln n}{n}} \\ \geq & R_n - H(X) \\ \geq & \sigma_H(X) \sqrt{\frac{2\alpha \ln n}{n}} - \left(\frac{1}{2} + \alpha\right) \frac{\ln n}{n} - O(n^{-1}) \quad (20) \end{aligned}$$

whenever

$$\epsilon_n = \Theta\left(\frac{n^{-\alpha}}{\sqrt{\ln n}}\right). \quad (21)$$

## Application to Fixed Rate Source Coding

(c) Let  $\delta = \frac{c}{\sqrt{n}}$  for a constant  $c$ . Then

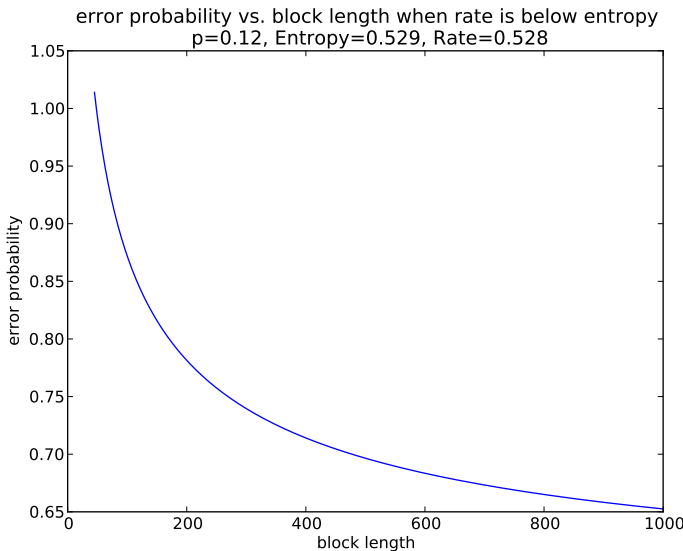
$$\frac{c}{\sqrt{n}} \geq R_n - H(X) \geq \frac{c}{\sqrt{n}} - \frac{\ln n}{2n} - O(n^{-1}) \quad (22)$$

whenever

$$\left| \epsilon_n - Q\left(\frac{c}{\sigma_H(X)}\right) \right| \leq \frac{CM_H(X)}{\sqrt{n}\sigma_H^3(X)} \quad (23)$$

where  $Q(t) = \frac{1}{\sqrt{2\pi}} \int_t^\infty e^{-u^2/2} du$ , and  $C < 1$  is the universal constant in the central limit theorem of Berry and Esseen.

## Working below Entropy!





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## Right Strong Conditional Entropy NEP

For any  $\delta \in (0, \Delta^*(X|Y))$  and any positive integer  $n$

$$\Pr \left\{ -\frac{1}{n} \ln p(X^n|Y^n) \geq H(X|Y) + \delta \right\} \\ \leq \frac{1}{1 - e^{-\lambda}} \left[ \frac{1}{\sqrt{2\pi}\sigma_H(X|Y, \lambda)} + \frac{2M_H(X|Y, \lambda)}{\sigma_H^3(X|Y, \lambda)} \right] e^{-nr_{X|Y}(\delta) - \frac{1}{2} \ln n}$$

and

$$\Pr \left\{ -\frac{1}{n} \ln p(X^n|Y^n) \geq H(X|Y) + \delta \right\} \\ \geq e^{-\lambda d} \left[ \frac{de^{-\frac{d^2}{2n\sigma_H^2(X|Y, \lambda)}}}{\sqrt{2\pi}\sigma_H(X|Y, \lambda)} - \frac{2M_H(X|Y, \lambda)}{\sigma_H^3(X|Y, \lambda)} \right] e^{-nr_{X|Y}(\delta) - \frac{1}{2} \ln n}$$

for any  $d > 0$ , where  $\lambda = r'_{X|Y}(\delta) > 0$ .

## Central Limit Theorem

For any  $\delta \leq c\sqrt{\frac{\ln n}{n}}$ , where  $c < \sigma_H(X|Y)$  is a constant,

$$\begin{aligned} & Q\left(\frac{\delta\sqrt{n}}{\sigma_H(X|Y)}\right) - \frac{CM_H(X|Y)}{\sqrt{n}\sigma_H^3(X|Y)} \\ & \leq \Pr\left\{-\frac{1}{n}\ln p(X^n|Y^n) \geq H(X|Y) + \delta\right\} \\ & \leq Q\left(\frac{\delta\sqrt{n}}{\sigma_H(X|Y)}\right) + \frac{CM_H(X|Y)}{\sqrt{n}\sigma_H^3(X|Y)} \end{aligned} \quad (24)$$

where  $Q(t) = \frac{1}{\sqrt{2\pi}} \int_t^\infty e^{-u^2/2} du$ , and  $C < 1$  is the universal constant in the central limit theorem of Berry and Esseen.

## Non-Asymptotic Channel Coding Theorem

Given a BIMC with  $C_{\text{BIMC}} \in (0, 1)$ , let  $P_e(\mathcal{C}_{n,k}^{(i)})$ ,  $i = 1, 2$ , denote the average word error probability of  $\mathcal{C}_{n,k}^{(i)}$  with respect to the random message  $q$ , the BIMC, and the random linear code  $\mathcal{C}_{n,k}^{(i)}$  itself.

- BIMC: Binary Input Memoryless Channel with Uniform Capacity-Achieving Input Distribution.
- $C_{\text{BIMC}}$ : Channel Capacity.
- $\mathcal{C}_{n,k}^{(1)}$ : Elias' Generator Ensemble.
- $\mathcal{C}_{n,k}^{(2)}$ : Gallager's Parity Check Ensemble.

## Non-Asymptotic Channel Coding Theorem

(a) For any  $\delta \in (0, \Delta^*(X|Y))$

$$P_e(\mathcal{C}_{n,k}^{(i)}) \leq 2C^{(i)}\Psi(X|Y, \lambda)e^{-nr_{X|Y}(\delta) - \frac{1}{2} \ln n} \quad (25)$$

whenever

$$\mathcal{R}(\mathcal{C}_{n,k}) \leq C_{\text{BIMC}} - \delta - r_{X|Y}(\delta) - \frac{\frac{1}{2} \ln n - \ln C^{(i)}\Psi(X|Y, \lambda)}{n} \quad (26)$$

where  $\lambda = r'_{X|Y}(\delta)$  and

$$C^{(i)} = \begin{cases} 1 & \text{if } i = 1 \\ \frac{1}{1-2^{-n}} & \text{otherwise.} \end{cases} \quad (27)$$

## Non-Asymptotic Channel Coding Theorem

(b) For any  $\alpha \geq 0.5$

$$P_e(\mathcal{C}_{n,k}^{(i)}) \leq \frac{2C^{(i)}\sigma_H(X|Y)\Psi(X|Y)}{\sqrt{2\alpha \ln n}} n^{-\alpha} + O\left(n^{-\alpha} \frac{\ln n}{\sqrt{n}}\right) \quad (28)$$

whenever

$$\mathcal{R}(\mathcal{C}_{n,k}) \leq C_{\text{BIMC}} - \sigma_H(X|Y) \sqrt{\frac{2\alpha \ln n}{n}} - \frac{\alpha \ln n}{n} - O\left(\frac{\ln \ln n}{n}\right). \quad (29)$$

## Non-Asymptotic Channel Coding Theorem

(c) For any real number  $c$

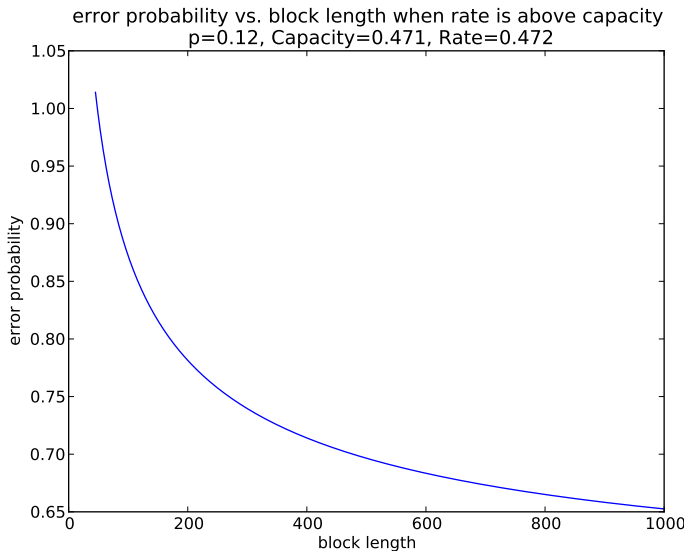
$$P_e(\mathcal{C}_{n,k}^{(i)}) \leq C^{(i)} \left( Q \left( \frac{c}{\sigma_H(X|Y)} \right) + \frac{M_H(X|Y)}{\sigma_H^3(X|Y)} \frac{1}{\sqrt{n}} \right) \quad (30)$$

whenever

$$\mathcal{R}(\mathcal{C}_{n,k}) \leq C_{\text{BIMC}} - \frac{c}{\sqrt{n}} - \frac{\ln n}{2n} + \frac{1}{n} \ln \frac{C^{(i)}(1 - C_{BE})M_H(X|Y)}{\sigma_H^3(X|Y)} \quad (31)$$

where  $0 < C_{BE} < 0.4784$  is the universal constant in the Berry-Esseen central limit theorem.

## Working above Capacity!





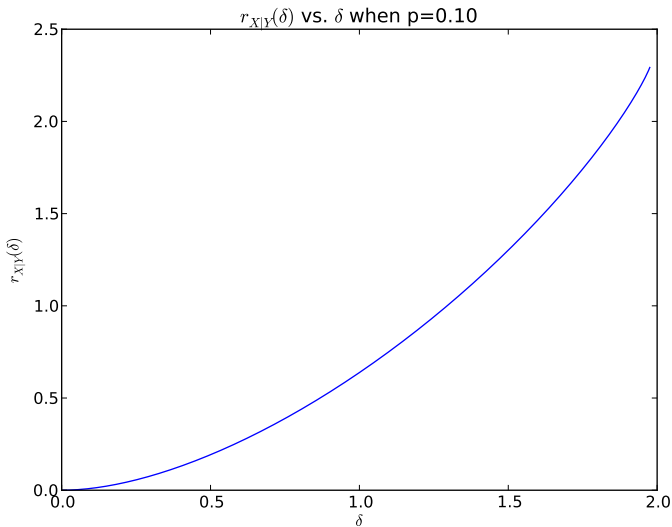
## Example of $r_{X|Y}(\delta)$ - Binary Symmetric Channel

Let  $p$  be the crossover probability of BSC,

$$r_{X|Y}(\delta) = D \left( p + \frac{\delta}{\ln \frac{1-p}{p}} \parallel p \right) \quad (32)$$

$$\sigma_H^2(X|Y) = p(1-p) \ln^2 \frac{1-p}{p} \quad (33)$$

## Plot of $r_{X|Y}(\delta)$



## Example of $r_{X|Y}(\delta)$ - Binary Input Gaussian Channel

Assume that input of channel is modulated to  $\{+1, -1\}$ , and therefore

$$p(y|x) = \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{|y-x|^2}{2\sigma^2}} \quad (34)$$

for  $x = \{+1, -1\}$ , where  $\sigma$  is the variance of the noise.

## Example of $r_{X|Y}(\delta)$ - Binary Input Gaussian Channel

Let  $U$  be gaussian random variable with mean 0 and variance 1.

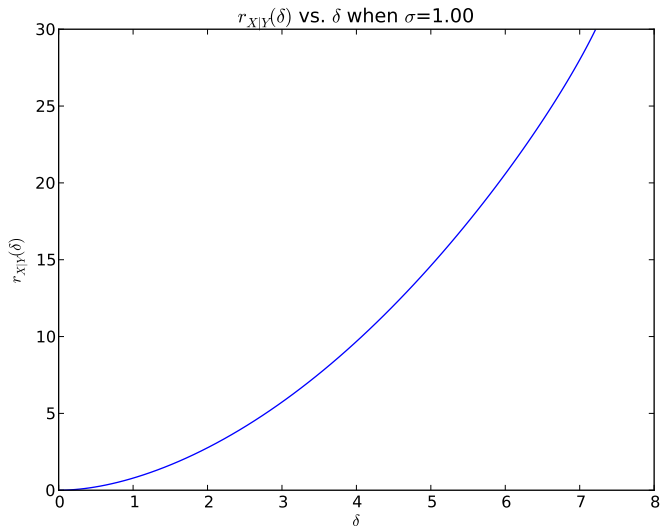
$$\delta(\lambda) = \frac{\mathbf{E} \left[ g^\lambda \left( \frac{\sigma U + 1}{\sigma^2} \right) \ln g \left( \frac{\sigma U + 1}{\sigma^2} \right) \right]}{\mathbf{E} \left[ g^\lambda \left( \frac{\sigma U + 1}{\sigma^2} \right) \right]} - \mathbf{E} \left[ \ln g \left( \frac{\sigma U + 1}{\sigma^2} \right) \right]$$

$$r_{X|Y}(\delta(\lambda)) = \lambda \frac{\mathbf{E} \left[ g^\lambda \left( \frac{\sigma U + 1}{\sigma^2} \right) \ln g \left( \frac{\sigma U + 1}{\sigma^2} \right) \right]}{\mathbf{E} \left[ g^\lambda \left( \frac{\sigma U + 1}{\sigma^2} \right) \right]} - \ln \left\{ \mathbf{E} \left[ g^\lambda \left( \frac{\sigma U + 1}{\sigma^2} \right) \right] \right\}$$

and

$$\sigma_H^2(X|Y) = \mathbf{E} \left[ \ln^2 g \left( \frac{\sigma U + 1}{\sigma^2} \right) \right] - \left\{ \mathbf{E} \left[ -\ln g \left( \frac{\sigma U + 1}{\sigma^2} \right) \right] \right\}^2$$

## Plot of $r_{X|Y}(\delta)$



# Outline

- 1 Introduction
- 2 Entropy NEP and Source Coding
- 3 Conditional Entropy NEP and Channel Coding
- 4 Mutual Information and Relative Entropy NEP**

## Left NEP on Mutual Information

For any  $\delta \in (0, \Delta_-^*(X; Y))$  and any positive integer  $n$

$$\Pr \left\{ \frac{1}{n} \ln \frac{p(Y^n|X^n)}{p(Y^n)} \leq I(X; Y) - \delta \right\} \\ \leq \frac{1}{1 - e^{-\lambda}} \left[ \frac{1}{\sqrt{2\pi}\sigma_{I,-}(X; Y, \lambda)} + \frac{2M_{I,-}(X; Y, \lambda)}{\sigma_{I,-}^3(X; Y, \lambda)} \right] e^{-nr_{X;Y,-}(\delta) - \frac{1}{2} \ln n}$$

and

$$\Pr \left\{ \frac{1}{n} \ln \frac{p(Y^n|X^n)}{p(Y^n)} \leq I(X; Y) - \delta \right\} \\ \geq e^{-\lambda d} \left[ \frac{de^{-\frac{d^2}{2n\sigma_{I,-}^2(X; Y, \lambda)}}}{\sqrt{2\pi}\sigma_{I,-}(X; Y, \lambda)} - \frac{2M_{I,-}(X; Y, \lambda)}{\sigma_{I,-}^3(X; Y, \lambda)} \right] e^{-nr_{X;Y,-}(\delta) - \frac{1}{2} \ln n}$$

for any  $d > 0$ , where  $\lambda = r'_{X;Y,-}(\delta) > 0$ .

## Central Limit Theorem

For any  $\delta \leq c\sqrt{\frac{\ln n}{n}}$ , where  $c < \sigma_I(X; Y)$  is a constant,

$$\begin{aligned} & Q\left(\frac{\delta\sqrt{n}}{\sigma_I(X; Y)}\right) - \frac{CM_I(X; Y)}{\sqrt{n}\sigma_I^3(X; Y)} \\ & \leq \Pr\left\{\frac{1}{n}\ln\frac{p(Y^n|X^n)}{p(Y^n)} \leq I(X; Y) - \delta\right\} \\ & \leq Q\left(\frac{\delta\sqrt{n}}{\sigma_I(X; Y)}\right) + \frac{CM_I(X; Y)}{\sqrt{n}\sigma_I^3(X; Y)} \end{aligned} \quad (35)$$

where  $Q(t) = \frac{1}{\sqrt{2\pi}} \int_t^\infty e^{-u^2/2} du$ , and  $C < 1$  is the universal constant in the central limit theorem of Berry and Esseen.



## Some Definition on Relative Entropy

Let  $t$  be the type of  $x^n$ , i.e.  $nt(a)$  is the number of times the symbol  $a$  appears in  $x^n$ . Define

$$q_t(y) \triangleq \sum_{x \in \mathcal{X}} t(a)p(y|x)$$

$$I(t; P) \triangleq \sum_{x \in \mathcal{X}} t(x) \int p(y|x) \ln \frac{p(y|x)}{q_t(y)} dy$$

## Left Relative Entropy NEP

For any  $\delta \in (0, \Delta_-^*(X; Y))$

$$\begin{aligned} & \Pr \left\{ \frac{1}{n} \ln \frac{p(Y^n|X^n)}{q_t(Y^n)} \leq I(t; P) - \delta \mid X^n = x^n \right\} \\ & \leq \frac{1}{1 - e^{-\lambda}} \left[ \frac{1}{\sqrt{2\pi}\sigma_{D,-}(t; P, \lambda)} + \frac{2M_{D,-}(t; P, \lambda)}{\sigma_{D,-}^3(t; P, \lambda)} \right] e^{-nr_-(t, \delta) - \frac{1}{2} \ln n} \end{aligned}$$

and

$$\begin{aligned} & \Pr \left\{ \frac{1}{n} \ln \frac{p(Y^n|X^n)}{q_t(Y^n)} \leq I(t; P) - \delta \mid X^n = x^n \right\} \\ & \geq e^{-\lambda d} \left[ \frac{de^{-\frac{d^2}{2n\sigma_{D,-}^2(t; P, \lambda)}}}{\sqrt{2\pi}\sigma_{D,-}(t; P, \lambda)} - \frac{2M_{D,-}(t; P, \lambda)}{\sigma_{D,-}^3(t; P, \lambda)} \right] e^{-nr_-(t, \delta) - \frac{1}{2} \ln n} \end{aligned}$$

for any  $d > 0$ , where  $\lambda = \frac{\partial r_-(t, \delta)}{\partial \delta} > 0$ .

## Central Limit Theorem

For any  $\delta \leq c\sqrt{\frac{\ln n}{n}}$ , where  $c < \sigma_D(t; P)$  is a constant,

$$\begin{aligned}
 & Q\left(\frac{\delta\sqrt{n}}{\sigma_D(t; P)}\right) - \frac{CM_D(t; P)}{\sqrt{n}\sigma_D^3(t; P)} \\
 & \leq \Pr\left\{\frac{1}{n}\ln\frac{p(Y^n|X^n)}{q_t(Y^n)} \leq I(t; P) - \delta \mid X^n = x^n\right\} \\
 & \leq Q\left(\frac{\delta\sqrt{n}}{\sigma_D(t; P)}\right) + \frac{CM_D(t; P)}{\sqrt{n}\sigma_D^3(t; P)}
 \end{aligned} \tag{36}$$

where  $Q(t) = \frac{1}{\sqrt{2\pi}} \int_t^\infty e^{-u^2/2} du$ , and  $C < 1$  is the universal constant in the central limit theorem of Berry and Esseen.

## Non-Asymptotic Channel Coding Theorem

Given a DIMC  $P$  with  $C_{\text{DIMC}} \in (0, |\mathcal{X}|)$ , let  $P_e(\mathcal{C}_{t,n,k})$  denote the average word error probability (under jar decoding) of  $\mathcal{C}_{t,n,k}$  with respect to the DIMC and the random code  $\mathcal{C}_{t,n,k}$  itself.

- DIMC: Discrete Input Memoryless Channel with Any Capacity-Achieving Input Distribution.
- $C_{\text{DIMC}}$ : Channel Capacity.
- $\mathcal{C}_{t,n,k}$ : Random Code Chosen within Type  $t$ .
- There always exists  $t$  such that

$$\|t - p_X\|_1 \leq \frac{|\mathcal{X}|}{n} \quad (37)$$

where  $p_X$  is the optimal input distribution.

## Non-Asymptotic Channel Coding Theorem

(a) For any  $\delta \in (0, \Delta_-^*(t))$

$$P_e(\mathcal{C}_{t,n,k}) \leq 2\Psi(t; P, \lambda) e^{-nr_-(t,\delta) - \frac{1}{2} \ln n} \quad (38)$$

whenever

$$\mathcal{R}(\mathcal{C}_{t,n,k}) \leq I(t; P) - \delta - r_-(t, \delta) - \frac{(\frac{1}{2} + |\mathcal{X}|) \ln(n+1) - \ln \Psi(t; P, \lambda)}{n} \quad (39)$$

where  $\lambda = \frac{\partial r_-(t,\delta)}{\partial \delta}$  satisfying  $\delta_-(t, \lambda) = \delta$ .

## Non-Asymptotic Channel Coding Theorem

**(b)** For any  $\alpha \geq 0.5$  and any  $t$  satisfying (37)

$$P_e(\mathcal{C}_{t,n,k}) \leq \frac{2\sigma_D(X;Y)\Psi(X;Y)}{\sqrt{2\alpha \ln n}} n^{-\alpha} + O\left(n^{-\alpha} \frac{\ln n}{\sqrt{n}}\right) \quad (40)$$

whenever

$$\begin{aligned} \mathcal{R}(\mathcal{C}_{t,n,k}) \leq & C_{\text{DIMC}} - \sigma_D(X;Y) \sqrt{\frac{2\alpha \ln n}{n}} \\ & - \frac{(\alpha + |\mathcal{X}|) \ln(n+1)}{n} - O\left(\frac{\ln \ln n}{n}\right) \end{aligned} \quad (41)$$

## Non-Asymptotic Channel Coding Theorem

(c) For any  $t$  satisfying (37)

$$P_e(\mathcal{C}_{t,n,k}) \leq Q\left(\frac{c}{\sigma_D(X;Y)}\right) + \frac{M_D(X;Y)}{\sigma_D^3(X;Y)} \frac{1}{\sqrt{n}} + O(n^{-1.5})$$

whenever

$$\begin{aligned} \mathcal{R}(\mathcal{C}_{t,n,k}) \leq & C_{\text{DIMC}} - \frac{c}{\sqrt{n}} - \left(\frac{1}{2} + |\mathcal{X}|\right) \frac{\ln(n+1)}{n} \\ & - \frac{1}{n} \ln \frac{(1 - C_{BE})M_D(X;Y)}{\sigma_D^3(X;Y)} - O(n^{-1}) \end{aligned}$$

for any real number  $c$ , where  $0 < C_{BE} < 0.56$  is the universal constant in the Berry-Esseen central limit theorem.