



# (lossy) source coding theorem for binary sources

given  $X^N = (X_1 X_2 \dots X_N)$ , where each  $X_i \sim \text{Bernoulli}(p)$

## $\delta$ -lossy compression

$L = \phi(X^N)$  defined only for  $X^N \in \mathcal{S}_\delta$  s.t.  $\mathbb{P}[\mathcal{S}_\delta] \geq 1 - \delta$

Good tix (typical seq)      Bad tix

$\left. \begin{array}{l} 00 \dots 00 \\ 00 \dots 01 \end{array} \right\} 1 \text{ '1'}$

$(\leq 9 \text{ '1's})$

$\left. \begin{array}{l} 01 \dots 0 \end{array} \right\} 9 \text{ '1's'}$

$( > 9 \text{ '1's} )$

$\leftarrow 2^{N(1 - H_2(p))}$

but  $\mathbb{P}[\text{bad tix}] \leq \delta$

$\leftarrow \approx 2^{N H_2(p + \frac{\sigma}{\sqrt{8N}})} \Rightarrow N H_2(p + \frac{\sigma}{\sqrt{8N}})$  bits

$\mathbb{P}[\text{good tix}] \geq 1 - \delta$

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- $\delta$ -sufficient subset  $\mathcal{S}_\delta$ : smallest subset of  $\{0, 1\}^N$  s.t.  $\mathbb{P}[\mathcal{S}_\delta] \geq 1 - \delta$
- essential information content in  $X^N$ :  $H_\delta(X^N) \triangleq \log_2 |\mathcal{S}_\delta|$

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- essential information content in  $X^N$ :  $H_\delta(X^N) \triangleq \log_2 |\mathcal{S}_\delta| \approx N H_2\left(p + \frac{1-\delta}{2N}\right)$

### Shannon's source coding theorem (lossy version)

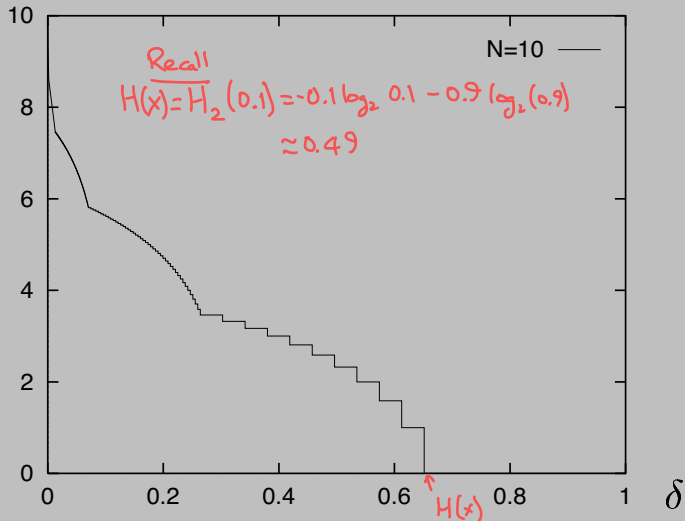
if  $X$  has entropy  $H(X)$ , then for any  $\epsilon > 0$  and  $0 < \delta < 1$ , there exists  $N_0$  s.t. for all  $N > N_0$ , we have

$$\left| \frac{H_\delta(X^N)}{N} - H(X) \right| \leq \epsilon$$

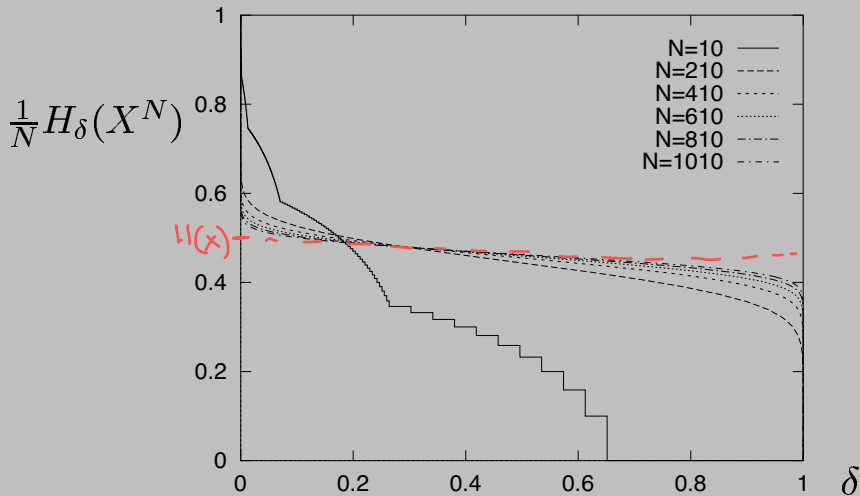
# (lossy) source coding for binary sources: intuition

$$H_\delta(X^{10})$$

$$= \log_2 |S_\delta|$$



## (lossy) source coding for binary sources: intuition



## Next

- lossy  $\rightarrow$  lossless
- 'practical' codes
  - symbol codes (Huffman code)
  - stream codes 'not practical'
- lower bounds

## lossless source coding

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## from lossy to lossless compression

given  $X^N = (X_1 X_2 \dots X_N)$ , where each  $X_i \sim \text{Bernoulli}(p)$

$$S_\delta \equiv \{D_1, D_2, \dots, D_{|S_\delta|}\}, \quad |S_\delta| \approx 2^{NH(x)}$$

Lossy scheme: - use  $\log_2 |S_\delta| = NH(x)$  bits to encode each  $D_i \in S_\delta$

- If  $D_i \notin S_\delta$ , send arbitrary symbol

wp  $\geq 1 - \delta$ , can decode  $D$  using  $NH(x)$  bits

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Lossless scheme - use 'prefix' 0 to indicate  $D \in S_\delta$ , 1 to indicate  $D \notin S_\delta$

- code:  $\hat{L}(D) = \underbrace{0}_{NH(x) \text{ bits}} \tilde{L} \text{ if } D \in S_\delta \left. \vphantom{\hat{L}(D)} \right\} D \in S_\delta$   
 $\underbrace{1}_{N \text{ bits}} \tilde{L} \text{ if } D \notin S_\delta \left. \vphantom{\hat{L}(D)} \right\} D \notin S_\delta$



## from lossy to lossless compression

given  $X^N = (X_1 X_2 \dots X_N)$ , where each  $X_i \sim \text{Bernoulli}(p)$

### Shannon's source coding theorem

if  $X$  has entropy  $H(X)$ , then for any  $\epsilon > 0$  and  $0 < \delta < 1$ , there exists  $N_0$  s.t. for all  $N > N_0$ , we have a lossless code  $L = \phi(X^N)$  s.t.

$$\left| \frac{\mathbb{E}[L]}{N} - H(X) \right| \leq \epsilon$$

From last slide

$$\begin{aligned} \mathbb{E}[\hat{L}(D)] &= (N H_\delta(x)) \cdot \overbrace{(1-\delta)}^{\mathbb{P}[D \in S_\delta]} + N \cdot \overbrace{(\delta)}^{\mathbb{P}[D \notin S_\delta]} \\ &= N H_\delta(x) + N \delta (1 - H_\delta(x)) \\ &\approx N H(x) \quad \begin{array}{l} \underbrace{\hspace{10em}}_{\substack{\rightarrow 0 \text{ as } \delta \rightarrow 0 \\ \text{(from lossy coding thm)}}} \end{array} \end{aligned}$$

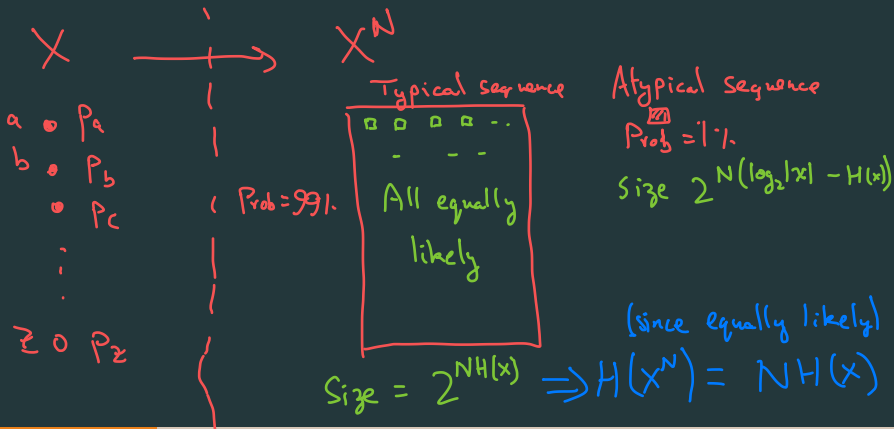
# lossless compression via **typical set** encoding

## typical set

$$\mathcal{X} = \{a, b, \dots, z\}$$

iid source produces  $X^N = (X_1 X_2 \dots X_n)$ ; each  $X_i \in \mathcal{X}$  has entropy  $H(X)$

then  $X^N$  is **very likely** to be one of  $\approx 2^{NH(X)}$  typical strings, (typicality)  
all of which have probability  $\approx 2^{-NH(X)}$  (asymptotic equipartition)

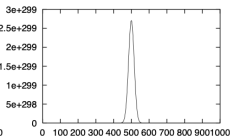
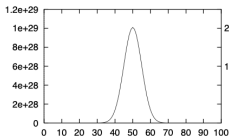


# visualizing the typical set

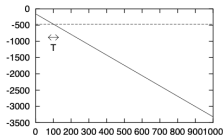
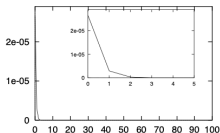
$N = 100$

$N = 1000$

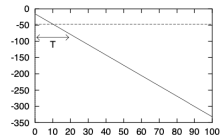
$$n(r) = \binom{N}{r}$$



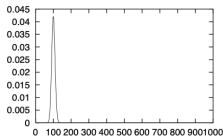
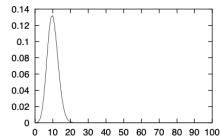
$$P(\mathbf{x}) = p_1^r (1 - p_1)^{N-r}$$



$$\log_2 P(\mathbf{x})$$



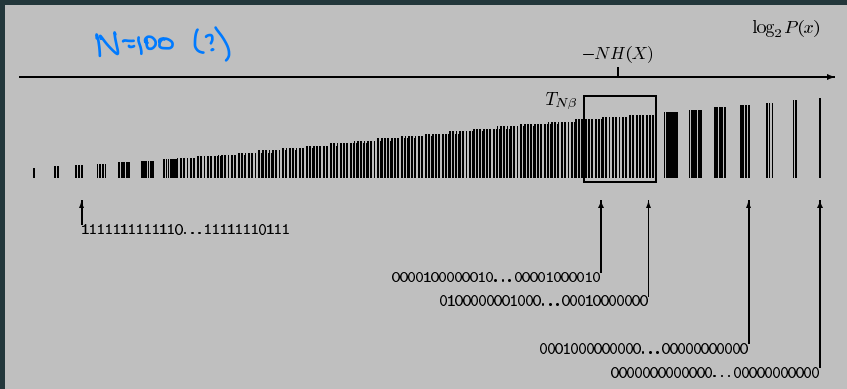
$$n(r)P(\mathbf{x}) = \binom{N}{r} p_1^r (1 - p_1)^{N-r}$$



$r$

$r$

# visualizing 'asymptotic equipartition'



# practical source coding solutions

## symbol codes

$$X_1 X_2 \dots X_n \rightarrow \phi(X_1) \phi(X_2) \dots \phi(X_n)$$

Each letter gets its own codeword

## stream codes

$$X_1 X_2 \dots X_n \rightarrow \phi(X_1) \phi(X_2 | X_1) \phi(X_3 | X_1 X_2) \dots \phi(X_n | X_1 X_2 \dots X_{n-1})$$

Entire dataset gets its own codeword



Eg - LZW, arithmetic codes  
Lempel-Ziv-Welch

Reading Assignment

symbol codes (Mackay chapter 5)

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## symbol codes

### expected length of symbol code

let  $X \sim \{p(x)\}_{x \in \mathcal{X}}$ , and consider code  $C(\cdot)$ , and let  $\ell(x) = |C(x)|$   
the expected length of  $C$  is  $\mathbb{E}[L(C, X)] = \sum_x p(x)\ell(x)$

what we want from symbol code  $C$ :

- **unique decodability**:  $\forall x_1 x_2 \dots x_n \neq y_1 y_2 \dots y_n$ , we have  $C(x_1)C(x_2) \dots C(x_n) \neq C(y_1)C(y_2) \dots C(y_n)$   $\Leftrightarrow$  lossless
- easy to decode
- small  $\mathbb{E}[L(C, X)]$

# types of symbol codes

$$H(x) = 1.75$$

1 2 3 3

consider source producing  $X \sim \{a, b, c, d\}$  with prob  $\{\frac{1}{2}, \frac{1}{4}, \frac{1}{8}, \frac{1}{8}\}$

Symbol $x$	info content $(h(x))$	(one-hot encoding)		(binary encoding)	
		Code 1	$l(x)$	Code 2	$l(x)$
a	1	1000	4	00	2
b	2	0100	4	01	2
c	3	0010	4	10	2
d	3	0001	4	11	2
	<u>                    </u> $H(x) = 1.75$		<u>                    </u> $E[l(x)] = 4$		<u>                    </u> 2



prefix codes

(variable length, greedy encoding/decoding)

Symbol	info content $(h(x))$	prefix-free		uniquely decodable	
		Code 3	$l(x)$	Code 4	$l(x)$
a	1	0	1	0	1
b	2	10	2	01	2
c	3	110	3	011	3
d	3	111	3	111	3
			$E[l(x)] = 1.75$		1.75

$H(x) = 1.75$



# the limits of unique decodability

Kraft-McMillan inequality (conservation laws)

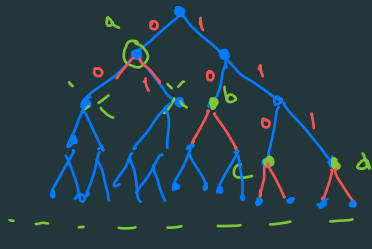
for any  $C \equiv$  uniquely decodable binary code over  $\mathcal{X}$ , with  $l(x) = |C(x)|$

$$\sum_{x \in \mathcal{X}} \underbrace{2^{-l(x)}}_{\text{fraction of leaf nodes in partition } \mathcal{X}} \leq 1$$

moreover, for any  $\{l(x)\}$  satisfying this, we can find a prefix code

- (Kraft's Ineq) Special case for prefix-free

Every prefix free code  $\equiv$  subset of nodes in a binary tree



$2^{L_{\max}}$  'leaf node' partitioned  
among  $|\mathcal{X}|$  symbols