

EE 274 Lecture 3

Oct. 4, 2023

- Kraft's inequality
- Entropy
- Fundamental limit on lossless compression

Announcements

- IT Forum this Friday
 - 10/6/23, 2pm, Packard 202
 - Jouni Sirén, UCSC on genomic compression
- Code snippets on website
- SCL tutorial
 - Quick Tour
- HW 1

Why SCL?

- Efficient implementations often hard for a beginner to understand or modify
- Implementations of many basic algorithms hard to find
- Intuitively understanding the algorithm ≠ being able to implement it in practice

Why SCL?

- Provide research implementation of common data compression algorithms
- Provide convenient framework to quickly modify existing compression algorithm and to aid research in the area
- To ourselves understand these algorithms better 😊

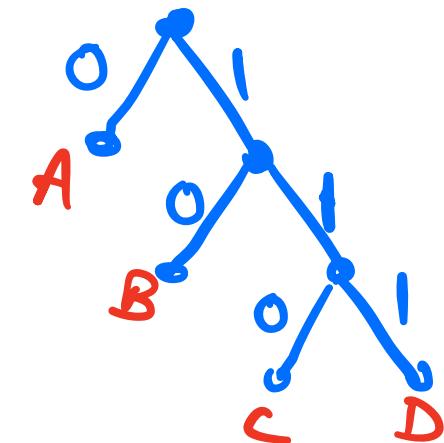
Quiz

We'll come back in a bit...

Last Time

- Prefix Codes
- Binary Tree Representation
- Good code: $l(x) \approx \log_2 \frac{1}{P(x)}$
- Shannon code:

$$l(x) = \lceil \log_2 \frac{1}{P(x)} \rceil$$

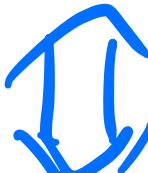


Kraft's inequality

Codewords on leaves of binary tree



Prefix Code



Lengths satisfy Kraft's
inequality

Kraft's inequality

Given a prefix code with codeword lengths l_1, l_2, \dots, l_k :

$$\sum_{i=1}^k 2^{-l_i} \leq 1$$

Conversely: Given integers $l_1, \dots, l_k \geq 1$

satisfying

$$\sum_{i=1}^k 2^{-l_i} \leq 1$$

there exists a prefix code with lengths

$$l_1, \dots, l_k$$

Proof of converse:

If $\sum_{i=1}^k 2^{-l_i} \leq 1$, you can

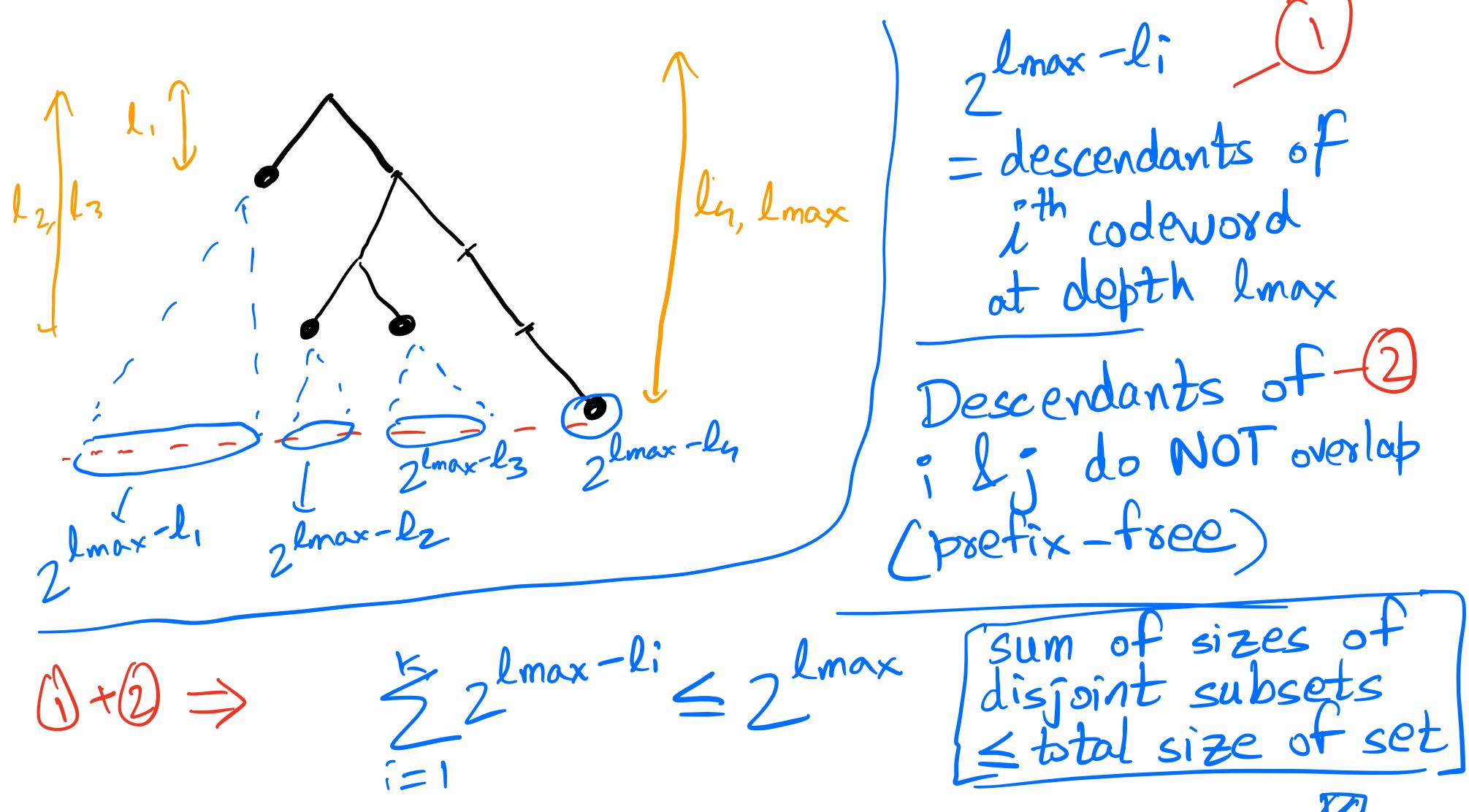
use the same code construction
as Shannon codes (check the proof!)

to get a prefix code with lengths

l_1, \dots, l_k

Proof of forward part (sketch)

Let $l_{\max} = \max \{l_1, \dots, l_k\}$



Quiz

Q1: $X = \{A, B, C, D, E\}$

1.1

x	$P(x)$	$L(x) = \lceil \log_2 \frac{1}{P(x)} \rceil$	$c(x)$
A	0.25	2	00
B	0.25	2	01
C	0.25	2	10
D	0.13	3	110
E	0.12	4	1110

1.2

$$\begin{aligned}
 E[L(x)] &= 0.25 \times 2 + 0.25 \times 2 + 0.25 \times 2 \\
 &\quad + 0.13 \times 3 + 0.12 \times 4 \\
 &= 2.37 \text{ bits/symbol}
 \end{aligned}$$

Quiz

x	P(x)	$I(x) = \lceil \log_2 \frac{1}{P(x)} \rceil$
A	0.25	2
B	0.25	2
C	0.25	2
D	0.13	3
E	0.12	4

Kraft sum:

$$\sum_{i=1}^5 2^{-I_i} = 3 \times \frac{1}{2^2} + \frac{1}{2^3} + \frac{1}{2^4}$$
$$= \frac{3}{4} + \frac{1}{8} + \frac{1}{16}$$
$$= \frac{15}{16} < 1$$

=====

Quiz
1.3

x	$P(x)$	$L(x) = \lceil \log_2 \frac{1}{P(x)} \rceil$	Better Code
A	0.25	2	00
B	0.25	2	01
C	0.25	2	10
D	0.13	3	111
E	0.12	4 3	110

$$E[L(x)] = 2.25 < 2.37$$

Kraft sum = $3 \times \frac{1}{2^2} + 2 \times \frac{1}{2^3}$
 $= \frac{3}{4} + \frac{2}{8} = 1 \leftarrow \underline{\text{Equality}}$

Quiz

2. Prefix free?

2.1

A	00
B	01
C	10
D	11 ←
E	110 ←

NO

2.2

001
011
100
111
110

YES

$$\frac{5}{8} \leq 1$$

$$\begin{aligned}\text{Kraft sum} &= \frac{1}{2^2} \times 4 + \frac{1}{2^3} \\ &= 1 + \frac{1}{8} > 1\end{aligned}$$

2.3

00 ↙
01 00 ↙
10
111
110

$$\frac{3}{4} + \frac{2}{8} = 1$$

Moving on...

- Define information-theoretic quantities
- Precisely characterize the "best" prefix code
- Justify thumb rule: $I(x) \approx \log_2 \frac{L}{P(x)}$

Entropy

Let $X = \{1, \dots, k\}$, $p_i = P(X=i)$

Entropy $H(X) = \sum_{i=1}^k p_i \log_2 \frac{1}{p_i}$ bits

Notes:

1. $H(X)$ is really $H(P)$

2. $H(X) = \mathbb{E} \left[\log_2 \frac{1}{P(X)} \right] \rightarrow \sum p_i \log_2 \frac{1}{P(X=i)}$

3. $p=0$: DEFINE $\log_2 \frac{1}{p} = 0$

Examples :

Uniform distribution:

$$X \sim \text{Unif}\{1, \dots, K\}$$

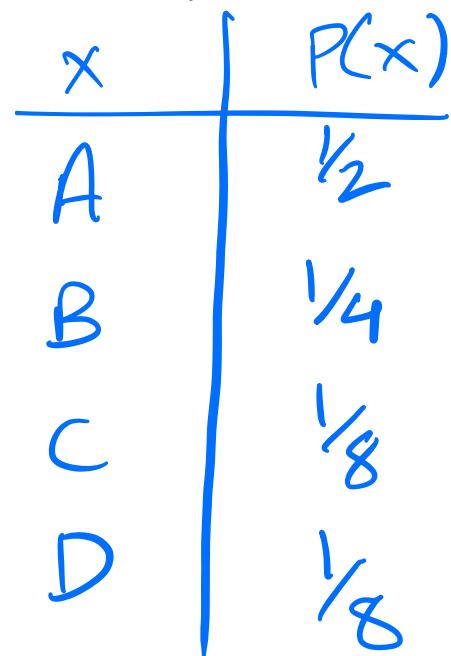
$$P(X=i) = \frac{1}{K} \quad \forall i$$

$$H(X) = \sum_{i=1}^K \frac{1}{K} \log_2 \frac{1}{K} = \log_2 K$$

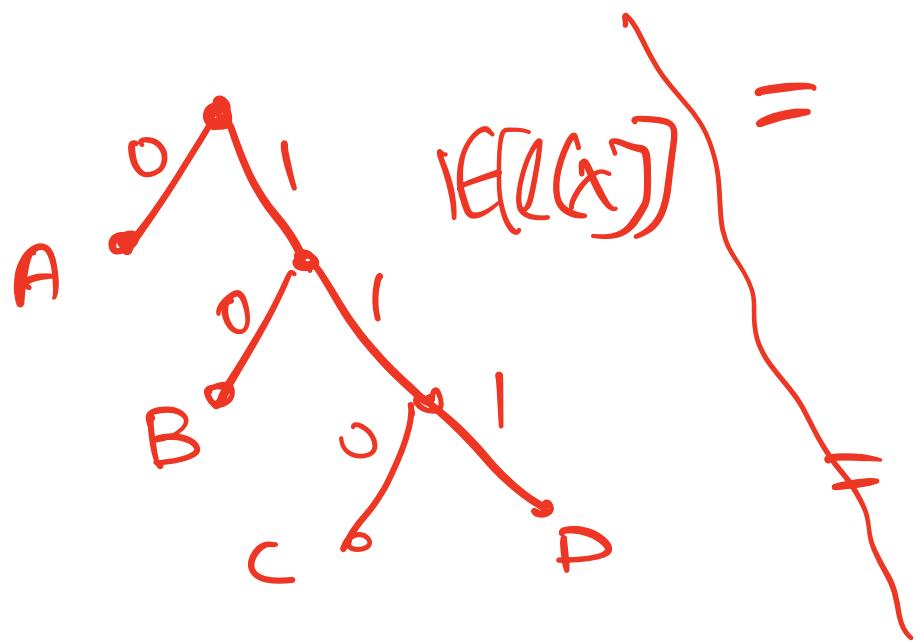
$$X \sim \text{Ber}\left(\frac{1}{2}\right) = \text{Unif}\{0, 1\}$$

$$H(X) = \log_2 2 = 1 \text{ bit}$$

Examples



$$\begin{aligned} & \frac{1}{2} \log_2 \frac{1}{\frac{1}{2}} + \frac{1}{4} \log_2 \frac{1}{\frac{1}{4}} \\ & + \frac{1}{8} \log_2 \frac{1}{\frac{1}{8}} \times 2 \end{aligned}$$



$$\begin{aligned} & \frac{1}{2} \times 1 + \frac{1}{4} \times 2 \\ & + \frac{1}{8} \times 3 + \frac{1}{8} \times 3 \\ & \frac{1}{2} + \frac{1}{2} + \frac{3}{8} = .75 \end{aligned}$$

Properties of entropy

Let $|X| = k$

$$0 \leq H(X) \leq \log_2 k$$

when
 X is deterministic

$$1 \times \log_2 \frac{1}{1} = 0$$

when
 X is uniformly distributed

$$k \times \frac{1}{k} \times \log_2 \frac{1}{k} = \log_2 k$$

What does entropy mean?

- Uncertainty / Randomness
- Amount of information contained
- How much you can compress
- Sampling from distributions & Answer to many puzzles!

Joint entropy of independent r.v.s

Just think of (X_1, X_2) as a random variable

$$\begin{aligned} H(X_1, X_2) &= \mathbb{E} \left[\log_2 \frac{1}{P(X_1, X_2)} \right] \\ &\stackrel{Y}{=} \mathbb{E} \left[\log_2 \frac{1}{P(X_1) P(X_2)} \right] \quad (?) \\ &= \mathbb{E} \log_2 \frac{1}{P(X_1)} + \mathbb{E} \log_2 \frac{1}{P(X_2)} \\ &= H(X_1) + H(X_2) \end{aligned}$$

Joint entropy of independent r.v.s

$$X_1, X_2 \text{ independent} \Rightarrow H(X_1, X_2) = H(X_1) + H(X_2)$$

For iid (independent and identically distributed)

$$X^n = (X_1, X_2, \dots, X_n) \stackrel{\text{distributed as}}{\sim} X$$

$$H(X^n) = \sum_{i=1}^n H(X_i) = n H(X)$$

For non-iid, we'll come back later

Relative entropy / KL-divergence

Let $p = (p_1, p_2, \dots, p_k)$

& $q = (q_1, q_2, \dots, q_k)$

be probability distributions on

$$\mathcal{X} = \{1, \dots, k\}$$

Then

$$D_{KL}(p||q) = \sum_{i=1}^k p_i \log_2 \frac{p_i}{q_i}$$

Examples in Quiz

Relative entropy / KL-divergence

Property: $D_{KL}(p||q) \geq 0$

with equality iff (if & only if)

$$p = q$$

Proof: Lecture notes (convexity)

Relative entropy / KL-divergence

- Measure of distance between probability distributions *in general*
- Not symmetric! $D(p||q) \neq D(q||p)$
- Comes up in ML/generative models loss functions
- Comes up in compression

Main Result of Lossless Compression

1. For every prefix code

$$E[l(x)] \geq H(x)$$

"Lower bound" / "Converse"

2. Can achieve $E[l(x)] \approx H(x)$
with prefix codes
can get arbitrarily close

"Achievability"

Main Result of Lossless Compression

- Entropy is the fundamental limit of lossless compression.
- Same result applies to class of uniquely decodable codes [HW]
- Next several lectures:
algorithms to achieve entropy efficiently
- All this assumes i.i.d. We'll study more general distributions in Lec. 8-10.

Proof of converse

"can't do better than entropy"

Let $X \sim P$ & prefix code with
lengths $(l_1, l_2, \dots, l_k) \rightarrow$ To show
 $\sum_{i=1}^k p_i l_i \geq H(P)$

Let $q_i = c2^{-l_i}$ where $c = \frac{1}{\sum 2^{-l_i}} \geq 1$ (?)

Note: $\sum_{i=1}^k q_i = c \sum_{i=1}^k 2^{-l_i} = 1$

So (q_1, \dots, q_k) is also a distribution

Proof of converse

Now $D_{KL}(p||q) \geq 0$ (?)

So

$$\sum_{i=1}^k p_i \log_2 \frac{p_i}{q_i} \geq 0$$

split
the
log

$-H(x)$
move
 $H(x)$
to RHS

$$\sum_{i=1}^k p_i \log_2 p_i + \sum_{i=1}^k p_i \log_2 \frac{1}{q_i} \geq 0$$

$$\sum_{i=1}^k p_i \log_2 \frac{1}{c2^{-l_i}} \geq H(x)$$

$$q_i = c2^{-l_i}$$

Defⁿ of $H(x)$

$$\Rightarrow E[l(x)] = \sum_{i=1}^k p_i l_i \geq \sum_{i=1}^k p_i l_i - \sum_{i=1}^k p_i \log_2 c \geq H(x)$$

(?)

Proof of converse

$$\Rightarrow \mathbb{E}[\ell(x)] = \sum_{i=1}^k p_i l_i \geq \sum_{i=1}^k p_i l_i - \sum_{i=1}^k p_i \log_2 c \geq H(x)$$

\uparrow
($c \geq 1$ by Kraft's inequality)

Thus, $\mathbb{E}[\ell(x)] \geq H(x)$.

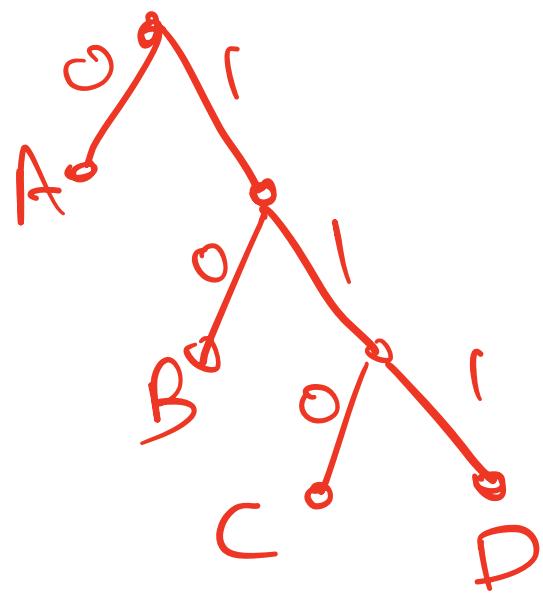
Equality when $c=1, p_i=q_i$ [Recall $D(p||q)=0$ iff $p=q$]

$$\Rightarrow p_i = 2^{-l_i} \text{ or } l_i = \log_2 \frac{1}{p}$$

Thumb rule!

What does $c=1$ signify? Kraft's with equality!

Kraft's \rightarrow no b!



$$\sum 2^{-l_i} = 1$$

	$P(x)$
A	$1/8$
B	$1/8$
C	$1/4$
D	$1/2$
<hr/>	
l_i	$\neq \log_2 1/p_i$

If $l_i = \log_2 \frac{1}{p_i}$

$$\sum_{i=1}^k 2^{-l_i} = \sum_{i=1}^k 2^{-\log_2 \frac{1}{p_i}}$$
$$= \sum_{i=1}^k p_i = 1$$

\Rightarrow Kraft's v/ equality.

Achievability

Shannon codes! $\ell(x) = \lceil \log_2 \frac{1}{p(x)} \rceil$

$$E[\ell(x)] = \sum_{i=1}^k p_i \ell_i = \sum_{i=1}^k p_i \lceil \log_2 \frac{1}{p_i} \rceil$$

Use $x \leq \lceil x \rceil < x+1$

$$\begin{aligned} E[\ell(x)] &< \sum_{i=1}^k p_i \left(\log_2 \frac{1}{p(x)} + 1 \right) \\ &= \sum_{i=1}^k p_i \log_2 \frac{1}{p(x)} + \sum_{i=1}^k p_i \\ &= H(x) + 1 \quad (?) \end{aligned}$$

$$H(x) \leq E[\ell(x)] < H(x) + 1$$

Achievability

Shannon codes!

$$l(x) = \lceil \log_2 \frac{1}{p(x)} \rceil$$

$$\mathbb{E}[l(x)] < H(x) + 1$$

Shannon code is within 1 bit of entropy!!

Special case: Dyadic distributions
(probabilities powers of 2
like $\frac{1}{2}, \frac{1}{4}$ etc.)

$$\mathbb{E}(l(x)) = H(x)$$

Achievability

Shannon codes: $E[L(x)] < H(x) + 1$

Not quite "arbitrarily close".

Shannon	
A	00
B	01
C	10

Example: $\text{Unif}(\{1,2,3\})$

$$H(x) = \log_2 3 = \underline{1.58 \text{ bits}}$$

Shannon code $E[L(x)] = \underline{2 \text{ bit}}$ $\lceil \log_2 3 \rceil$

$$\text{Bound } H(x) + 1 = 2.58 = H(x) + 1 = 2$$

Overhead $\approx 25\%$.

x	$P(x)$	$\lceil \log_2 Y_{P(x)} \rceil$	$C(x)$	$\hat{C}(x)$
A	$\frac{1}{3}$	2	00	00
B	$\frac{1}{3}$	2	01	01
C	$\frac{1}{3}$	2	10	1

$$H(x) = 1.58 \text{ bits}$$

$$A(C(x)) = 2$$

$$\frac{2}{3} + \frac{2}{3} + \frac{1}{3}$$

$\rightarrow I = 1.67 \text{ bits}$

Achievability - not quite there yet

① Shannon code often suboptimal

→ Huffman code!

② Even optimal code sometimes far from entropy.

Block codes

→ Arithmetic codes

→ ANS codes

Block coding (if time permits)

Code in blocks of n symbols:

$$H(x^n) = nH(x)$$

$$H(x^n) \leq E[\ell(x^n)] < H(x^n) + 1$$

$$nH(x) \leq E[\ell(x^n)] < nH(x) + 1$$

$$H(x) \leq \frac{E[\ell(x^n)]}{n} < H(x) + \frac{1}{n}$$

Within $\frac{1}{n}$ of entropy!

Thank you!