Part II – Coding and Cryptography

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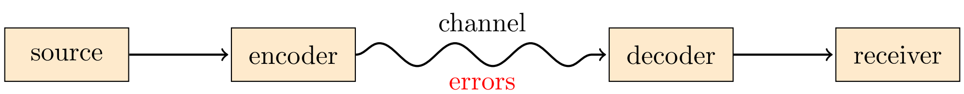
Contents

Introduction to communication channels and coding

For example, given a message m=‘Call me!’ which we wish to send by email, first encode as binary strings using ASCII. So, $f(C) = 1000011, f(a) = 1100001$, and $f^*(m) = 1000011\ 1100001 \dots 0100001$.



Basic problem: Given a source and a channel (described probabilistically) we aim to design an encoder and a decoder in order to transmit information both economically and reliably (coding) and maybe also to preserve privacy (cryptography).

Example.

- ‘economically’ Morse code: common letters have shorter codewords:
- ‘reliably’ Every book has an ISBN of form $a_1 a_2 \dots a_{10}$ where $a_i \in \{0, 1, \dots, 9\}$ for $1 \leq i \leq 9$, $a_{10} \in \{0, 1, \dots, 9, X\}$ such that

  $$10a_1 + 9a_2 + \dots + a_{10} \equiv 0 \pmod{11}$$

  so errors can be detected (but not corrected). Similarly a 13-digit ISBN has

  $$x_1 + 3x_2 + x_3 + 3x_4 + \dots + 3x_{12} + x_{13} \equiv 0 \pmod{10}$$

  for $0 \leq x_i \leq 10$, doesn’t necessarily spot transpositions.
- ‘preserve privacy’ e.g. RSA.

A **communication channel** takes letters from an input alphabet $\Sigma_1 = \{a_1, \dots, a_r\}$ and emits letters form an output alphabet $\Sigma_2 = \{b_1, \dots, b_s\}$.

A channel is determined by the probabilities

$$P(y_1 \dots y_k \text{ received} \mid x_1 \dots x_k \text{ sent})$$

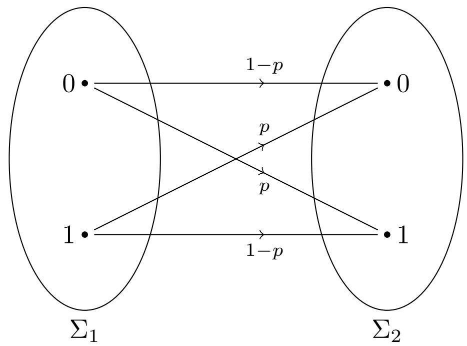
Definition (Discrete memoryless channel)**.** A **discrete memoryless channel** (DMC) is a channel for which

$$P_{ij} = P(b_j \text{ received} \mid a_i \text{ sent})$$

is the same each time the channel is used and is independent of all past and future uses.

The channel matrix is the $r \times s$ matrix with entries p_{ij} (note the rows sum to 1).

Example. Binary Symmetric Channel (BSC) has $\Sigma_1 = \Sigma_2 = \{0, 1\}$, $0 \le p \le 1$:

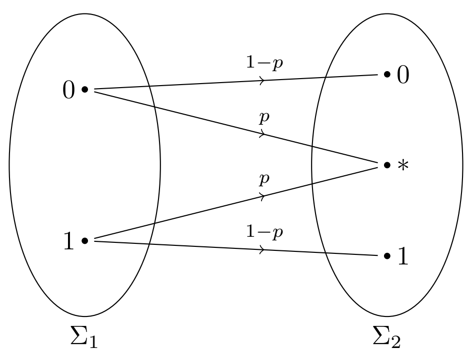


with channel matrix

$$\begin{pmatrix} 1-p & p \\ p & 1-p \end{pmatrix}$$

i.e. p is the probability a symbol is mistransmitted.

Another example is given by the Binary Erasure channel, $\Sigma_1\{0, 1\}$, $\Sigma_2 = \{0, 1, *\}$ and $0 \le p \le 1$.



with channel matrix

$$\begin{pmatrix} 1-p & p & 0 \\ 0 & p & 1-p \end{pmatrix}$$

i.e. p is the probability a symbol can't be read.

Informally, a channel's capacity is the highest rate at which information can be reliably transmitted over the channel. Rate refers to units of information per unit time, which we want to be high. Similarly, reliably means we want an arbitrarily small error probability.

I Noiseless Coding

Notation. For Σ an alphabet, let $\Sigma^* = \bigcup_{n \geq 0} \Sigma^n$ be the set of all finite strings of elements of Σ.

If $x = x_1 \dots x_r$, $y = y_1 \dots y_s$ are strings from Σ, write xy for the concatenation $x_1 \dots x_r y_1 \dots y_s$. Further, $|x_1 \dots x_r y_1 \dots y_s| = r + s$, the length of the string.

Definition (Code)**.** Let Σ_1, Σ_2 be two alphabets. A **code** is a function $f : \Sigma_1 \to \Sigma_2^*$. The strings $f(x)$ for $x \in \Sigma_1$ are called **codewords**.

Example.

1) Greek fire code:

$$\begin{aligned} \Sigma_1 &= \{\alpha, \beta, \gamma, \dots, \omega\} \qquad \text{24 letters} \\ \Sigma_2 &= \{1, 2, 3, 4, 5\} \end{aligned}$$

so, $\alpha \mapsto 11, \beta \mapsto 12, \dots, \omega \mapsto 54$.

2) $\Sigma_1 = \{\text{all words in the dictionary}\}$, and $\Sigma_2 = \{A, B, \dots, Z, [\mathit{space}]\}$ and f='spell the word and a space'.

Send a message $x_1 \cdots x_n \in \Sigma_1^*$ as $f(x_1) \cdots f(x_n) \in \Sigma_2^*$ i.e. extend f to $f^* : \Sigma_1^* \to \Sigma_2^*$.

Definition (Decipherable)**.** A code f is **decipherable** if f^* is injective, i.e. every string from Σ_2^* arises from at most one message. Clearly we need f injective, but this is not enough.

Example. Take $\Sigma_1 = \{1, 2, 3, 4\}$, $\Sigma_2 = \{0, 1\}$ with

$$f(1) = 0, f(2) = 1, f(3) = 00, f(4) = 01$$

f injective but $f^*(312) = 0001 = f^*(114)$ so f^* not decipherable.

Notation. If $|\Sigma_1| = m$, $|\Sigma_2| = a$, then we say f is an a-ary code of size m. (If $a = 2$ we say binary).

Aim. Construct decipherable codes with short word lengths.

Provided $f : \Sigma_1 \to \Sigma_2^*$ is injective, the following codes are always decipherable.

(i) A **block code** is a code with all codewords of the same length (e.g. Greek fire code).

(ii) In a **comma code**, we reserve one letter from Σ_2 that is only used to signal the end of the codeword (e.g. Example 2 above).

(iii) A **prefix-free code** is a code where no codeword is a prefix of another (if $x, y \in \Sigma_2^*$, x is a prefix of y if $y = xz$ for some $z \in \Sigma_2^*$.)

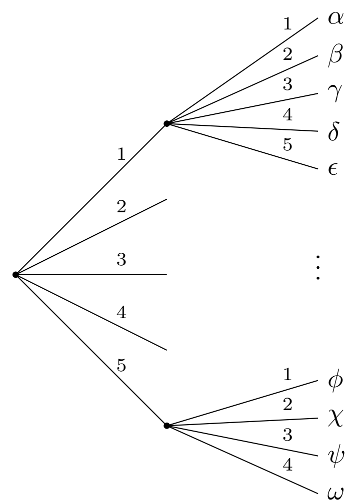
Remark. (i) and (ii) are special cases of (iii).

Prefix-free codes are also known as **instantaneous codes** (i.e. a word can be recognised as soon as it is complete) or **self-punctuating codes**.

Theorem I.1 (Kraft's inequality)**.** Let $|\Sigma_1| = m, |\Sigma_2| = a$. A prefix-free code $f : \Sigma_1 \to \Sigma_2^*$ with word lengths $s_1, \dots, s_m$ exists iff

$$\sum_{i=1}^{m} a^{-s_i} \leq 1$$

Proof. ($\Rightarrow$) Consider an infinite tree where each has a descendant, labelled by the elements of Σ_2. Each codeword corresponds to a node, the path from the root to this node spelling out the codeword. For example,



Assuming f is prefix-free, no codeword is the ancestor of any other. Now view the tree as a network with water being pumped in at a constant rate and dividing the flow equally at each node.

The total amount of water we can extract at the codewords is $\sum_{i=1}^{m} a^{-s_i}$, which is therefore ≤ 1.

($\Leftarrow$) Conversely, suppose we can construct a prefix-free code with word lengths $s_1, \dots, s_m$ wlog $s_1 \leq s_2 \leq \dots \leq s_m$. We pick codewords of lengths $s_1, s_2, \dots$ sequentially ensuring previous codewords are not prefixes. Suppose there is no valid choice for the rth codeword. Then reconstructing the tree as above gives $\sum_{i=1}^{r-1} a^{-s_i} = 1$, contradicting our assumption. So we can construct a prefix-free code. (There is a more algebraic proof in Welsh.) $\square$

Theorem I.2 (McMillan)**.** Every decipherable code satisfies Kraft's inequality.

Proof. (Karush) Let $f : \Sigma_1 \to \Sigma_2^*$ be a decipherable code with word lengths $s_1, \dots, s_m$, let $s = \max_{1 \leq i \leq m} s_i$. Let $r \in \mathbb{N}$

$$\left(\sum_{i=1}^{m} a^{-s_i} \right)^r = \sum_{l=1}^{rs} b_l a^{-l}$$

where b_l is the # of ways of choosing r codewords of total length l. f decipherable $\implies$ $b_l \leq |\Sigma_2|^l = a^l$.

Thus

$$\left(\sum_{i=1}^{m} a^{-s_i}\right)^r \le \sum_{l=1}^{rs} a^l a^{-l} = rs$$

$$\implies \sum_{i=1}^{m} a^{-s_i} \le (rs)^{\frac{1}{r}} \to 1 \text{ as } r \to \infty.$$

(As $\frac{\log r + \log s}{r} \to 0$ as $r \to \infty$).

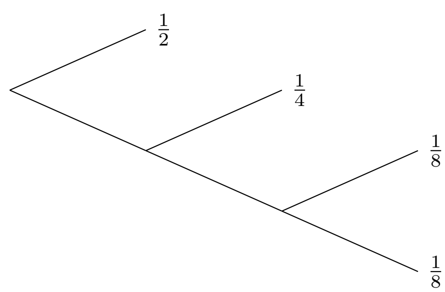
$$\therefore \sum_{i=1}^{m} a^{-s_i} \le 1.$$

□

Example.

1. Suppose $p_1 = p_2 = p_3 = p_4 = \frac{1}{4}$. We identify $\{x_1, x_2, x_3, x_4\}$ with $\{$HT, HT, TH, TT$\}$. Then $H(X) = 2$.

2. Take $(p_1, p_2, p_3, p_4) = (\frac{1}{2}, \frac{1}{4}, \frac{1}{8}, \frac{1}{8})$.



So example 1 is more random than example 2.

Definition (Entropy)**.** The entropy of X:

$$H(X) = H(p_1, \dots, p_n) = -\sum_{i=1}^{n} p_i \log p_i$$

where, in this course, $\log = \log_2$.

Remark.

(i) If $p_i = 0$, we take $p_i \log p_i = 0$.

(ii) $H(x) \ge 0$.

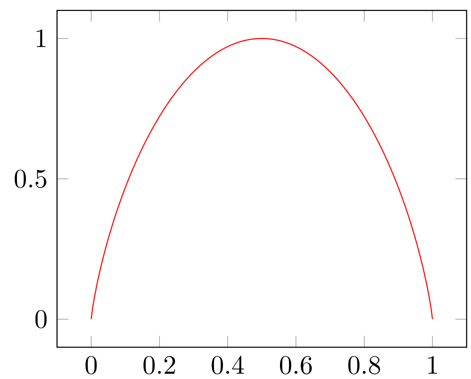
Corollary. A decipherable code with prescribed word lengths exists iff there exists a prefix-free code with the same word lengths.

So we can restrict our attention to prefix-free codes.

I.1 Mathematical Entropy

Entropy is a measure of 'randomness' or 'uncertainty'. Consider a random variable X taking values $x_1, \dots, x_n$ with probability $p_1, \dots, p_n$ ($\sum p_i = 1, 0 \le p_i \le 1$). The entropy $H(X)$ is roughly speaking the expected number of tosses of a fair coin needed to simulate X (or the expected number of yes/no questions we need to ask in order to establish the value of X).

Example. We toss a biased coin, $P(\text{heads}) = p, P(\text{tails}) = 1-p$. Write $H(p) = H(p, 1-p) = -p \log p - (1-p)\log(1-p)$. If $p = 0$ or 1, the outcome is certain and so entropy=0. Entropy is maximal where $p = \frac{1}{2}$, i.e. a fair coin.



Note the entropy can also be viewed as the expected value of the information of X, where information is given by $I(X = x) = -\log_2 P(X = x)$. For example, if a coin always lands heads we gain no information from tossing the coin. The entropy is the average amount of information conveyed by a random variable X.

Lemma I.3 (Gibbs' Inequality)**.** Let $p_1, \dots, p_n$ and $q_1, \dots, q_n$ be probability distributions. Then

$$-\sum p_i \log p_i \le -\sum p_i \log q_i$$

with equality iff $p_i = q_i$.

Proof. Since $\log x = \frac{\ln x}{\ln 2}$ it suffices to prove the inequality with log replaced with ln. Note $\ln x \le x - 1$, equality iff $x = 1$. Let $I = \{\, 1 \le i \le n \mid p_i \ne 0 \,\}$

$$\begin{aligned} \ln \frac{q_i}{p_i} &\le \frac{q_i}{p_i} - 1 \quad \forall i \in I \\ \sum_{i \in I} p_i \ln \frac{q_i}{p_i} &\le \sum q_i - \underbrace{\sum p_i}_{=1} \le 0 \\ \implies -\sum_{i \in I} p_i \ln p_i &\le -\sum_{i \in I} p_i \ln q_i \\ \implies -\sum_{i=1}^{n} p_i \ln p_i &\le -\sum_{i=1}^{n} p_i \ln q_i \end{aligned}$$

If equality holds then $\frac{q_i}{p_i} = 1 \ \forall i \in I$. So, $\sum_{i \in I} q_i = 1$ and hence $p_i = q_i$ for $1 \le i \le n$. $\square$

Corollary. $H(p_1, \ldots, p_n) \le \log n$ with equality iff $p_1 = p_2 = \cdots = p_n = \frac{1}{n}$.

Proof. Take $q_1 = q_2 = \ldots = q_n = \frac{1}{n}$ in previous lemma. □

Suppose we have two alphabets Σ_1, Σ_2 with $|\Sigma_1| = m$ and $|\Sigma_2| = a$, for $m \ge 2$ and $a \ge 2$. We model the source as a sequence of random variables $X_1, X_2, \ldots$ taking values in Σ_1.

Definition (Memoryless source)**.** A **Bernoulli** or **memoryless** source is a sequence of independently, identically distributed random variables.

That is, for each $\mu \in \Sigma_1$, $P(X_i = \mu)$ is independent of i and independent of all past and future symbols emitted. Thus

$$P(X_1 = x_1, X_2 = x_2, \ldots, X_k = x_k) = \prod_{i=1}^{k} P(X_i = x_i)$$

Let $\Sigma_1 = \{\mu_1, \ldots, \mu_n\}$, $p_i = P(X = \mu_i)$ (assume $p_i > 0$).

Definition (Expected word length)**.** The **expected word length** of a code $f : \Sigma_1 \to \Sigma_2^*$ with word lengths $s_1, \ldots, s_m$ is $E(S) = \sum_{i=1}^{m} p_i s_i$.

Definition (Optimal code)**.** A code $f : \Sigma_1 \to \Sigma_2^*$ is **optimal** if it has the shortest possible expected word length among decipherable codes.

Theorem I.4 (Shannon's Noiseless Coding Theorem)**.** The minimum expected word length of a decipherable code $f : \Sigma_1 \to \Sigma_2^*$ satisfies

$$\frac{H(X)}{\log a} \le E(S) < \frac{H(X)}{\log a} + 1$$

Proof. The lower bound is given by combining Gibbs' Inequality and Kraft's inequality. Let $q_i = \frac{a^{-s_i}}{c}$ where $c = \sum a^{-s_i} \le 1$ by Kraft's inequality. Note $\sum q_i = 1$.

$$\begin{aligned} H(X) = -\sum p_i \log p_i &\le -\sum_i p_i \log q_i \\ &= \sum p_i (s_i \log a + \log c) \\ &= \left(\sum p_i s_i\right) \log a + \underbrace{\log c}_{\le 0} \le E(S) \log a \end{aligned}$$

$$\implies \frac{H(X)}{\log a} \le E(S)$$

We get equality $\iff$ $p_i = a^{-s_i}$ for some integers s_i. For the upper bound put

$$s_i = \lceil -\log_a p_i \rceil$$

where $\lceil x \rceil$ means least integer $\ge x$.

We have

$$\begin{gathered} -\log_a p_i \le s_i < -\log_a p_i + 1 \\ \implies a^{-s_i} \le p_i \implies \sum a^{-s_i} \le \sum p_i \le 1. \end{gathered}$$

So by Theorem I.1, $\exists$ a prefix-free code with word lengths $s_1, \ldots, s_m$. Also,

$$\begin{aligned} E(S) &= \sum p_i s_i \\ &< p_i(-\log_a p_i + 1) \\ &= \frac{H(X)}{\log a} + 1 \end{aligned}$$

□

Remark. The lower bound holds for all decipherable codes.

Shannon-Fano coding

Follows from above proof. Set $s_i = \lceil -\log_a p_i \rceil$ and construct a prefix-free code with word lengths $s_1, \ldots, s_m$ by taking the s_i in increasing order ensuring that previous codewords are not prefixes. The Kraft inequality ensures there is enough room.

Example. Suppose $\mu_1, \ldots, \mu_5$ are emitted with probabilities $0.4, 0.2, 0.2, 0.1, 0.1$.
A possible Shannon-Fano code (with $a = 2$, $\Sigma_2 = \{0, 1\}$) has

p_i	$\lceil -\log_2 p_i \rceil$	
0.4	2	00
0.2	3	010
0.2	3	100
0.1	4	1100
0.1	4	1110

This has expected word length

$$\begin{aligned} &= 2 \times 0.4 + 3 \times 0.2 + 3 \times 0.2 + 4 \times 0.1 + 4 \times 0.1 \\ &= 2.8. \end{aligned}$$

compare $H(X) \approx 2.12$.

subsubsection*Huffman coding For simplicity, take $a = 2$. Take $\Sigma_1 = \{\mu_1, \ldots, \mu_m\}$ with $p_i = P(X = \mu_i)$. Without loss of generality, $p_1 \geq p_2 \geq \cdots \geq p_m$. Huffman coding is defined inductively.

If $m = 2$, assign codewords 0 and 1. If $\mu > 2$, find a Huffman coding in the case of messages $\mu_1, \mu_2, \ldots, \nu$, with probabilities $p_1, p_2, \ldots, p_{m-1} + p_m$.

Append 0 (resp, 1) to the codeword for ν to give a codeword for μ_{m-1} (resp, μ_m).

Remark.

i) This construction gives a prefix-free code.

ii) We exercise some choice when some of the p_i are equal. So Huffman codes are not unique.

Example. Use the same example probabilities as earlier.
(diagram of example)
So $\{1, 00, 011, 0101, 0100\}$ is the prefix-free code constructed. The expected word length is:

$$\begin{aligned}
&= 1 \times 0.4 + 2 \times 0.2 + 2 \times 0.2 + 4 \times 0.1 + 4 \times 0.1 \\
&= 0.4 + 0.4 + 0.6 + 0.4 + 0.4 \\
&= 2.2.
\end{aligned}$$

This is better than Shannon-Fano, which gave 2.8.

Theorem I.5. Huffman coding is optimal.

Lemma I.6. Suppose we have $\mu_1, \ldots, \mu_m \in \Sigma_1$ emitted with probabilities $p_1, \ldots, p_m$. Let f be an optimal prefix-free code, with word lengths $s_1, \ldots, s_m$. Then

i) If $p_i > p_j$, then $s_i \leq s_j$.

ii) $\exists$ two codewords of maximal length which are equal up to the last digit.

Proof.

i) If not, then swap the ith and jth codewords. This decreases the expected word length, contradicting f optimal.

ii) If not, then either only one codeword of maximal length, or any two codewords of maximal length differ before the last digit. In either case, delete the last digit of each codeword of maximal length. This maintains the prefix-free condition, contradicting f optimal.

□

Proof of Theorem I.5 ($a = 2$). We show by induction on m that any Huffman code of size m is optimal.
For $m = 2$, codewords $0, 1$ are optimal.
For $m > 2$, say source X_m emits $\mu_1, \ldots, \mu_m$ with probabilities $p_1 \geq p_2 \geq \ldots \geq p_m$ while source X_{m-1} emits $\mu_1, \ldots, \mu_{m-2}, \nu$ with probabilities $p_1, \ldots, p_{m-2}, p_{m-1} + p_m$.

We construct a Huffman coding f_{m-1} for X_{m-1} and extend to a Huffman coding for X_m. Then the expected codeword length satisfies:

$$E(s_m) = E(s_{m-1}) + p_{m-1} + p_m \tag{†}$$

Let f'_m be an optimal code for X_m, WLOG f'_m prefix-free. Lemma I.6 tells us that by shuffling codewords, we may assume that the last two codewords are of maximal length and differ only in the last digit, say y_0 and y_1 for some string y.

We define a code f'_{m-1} for X_{m-1} with

$$\begin{aligned}
f'_{m-1}(\mu_i) &= f'_m(\mu_i) \quad \forall 1 \leq i \leq m-2 \\
f'_{m-1}(\nu) &= y.
\end{aligned}$$

Then f'_{m-1} is a prefix-free code, and the expected word length satisfies

$$E(s'_m) = E(s'_{m-1}) + p_{m-1} + p_m \tag{‡}$$

Induction hypothesis tells us f_{m-1} is optimal, so $E(s_{m-1}) \leq E(s'_{m-1})$. Hence $E(s_m) \leq E(s'_m)$ by (†), (‡). So f_m optimal. □

Remark. Not all optimal codes are Huffman. For instance, take $m = 4$, and probabilities $0.3, 0.3, 0.2, 0.2$. An optimal code is given by $00, 01, 10, 11$, but this is not Huffman.

But, the previous result says that if we have a prefix-free optimal code with word lengths $s_1, \ldots, s_m$ and associated probabilites $p_1, \ldots, p_m$, $\exists$ a Huffman code with these word lengths.

Definition (Joint entropy)**.** The **joint entropy** of X and Y is

$$H(X,Y) = -\sum_{x\in\Sigma_1}\sum_{y\in\Sigma_2} P(X=x, Y=y)\log P(X=x, Y=y).$$

Lemma I.7. $H(X,Y) \le H(X) + H(Y)$, with equality $\iff$ X, Y independent.

Proof. Take $\Sigma_1 = \{x_1, \ldots, x_m\}$, $\Sigma_2 = \{y_1, \ldots, y_n\}$. Let $p_{ij} = P(X = x_i, Y = y_j)$, as well as $p_i = P(X = x_i)$, $q_i = P(Y = y_i)$. Apply Lemma to the distributions p_{ij} and $p_i q_j$:

$$\begin{aligned} -\sum p_{ij}\log(p_{ij}) &\le -\sum p_{ij}\log(p_i q_j) \\ &= -\sum_i\left(\sum_j p_{ij}\log p_i\right) - \sum_j\left(\sum_i p_{ij}\log q_j\right) \\ &= -\sum p_i\log p_i - \sum q_j \log q_j \end{aligned}$$

That is, $H(X,Y) \le H(X) + H(Y)$. Equality $\iff$ $p_{ij} = p_i q_j \forall i,j$ $\iff$ X, Y independent. $\square$

Suppose a source Ω produces a stream $X_1, X_2, \ldots$ of random variables with values in Σ. The probability mass function (p.m.f.) of $X^{(n)} = (X_1, \ldots, X_n)$ is given by

$$p_n(x_1, \ldots, x_n) = P(X_1, \ldots, X_n = x_1, \ldots, x_n) \quad \forall x_1, \ldots, x_n \in \Sigma^n$$

Now,

$$\begin{aligned} p_n &: \Sigma^n \to \mathbb{R} \\ X^{(n)} &: \Omega \to \Sigma^n \end{aligned}$$

can form

$$p(X^{(n)}) : \Sigma \xrightarrow{X^{(n)}} \Sigma^n \xrightarrow{p_n} \mathbb{R}$$

a random variable sending $\omega \mapsto p_n(X^{(n)} = X^{(n)}(\omega))$.

Example. Take $\Sigma = \{A, B, C\}$, with

$$X^{(2)} = \begin{cases} AB & p = 0.3 \\ AC & p = 0.1 \\ BC & p = 0.1 \\ BA & p = 0.2 \\ CA & p = 0.25 \\ CB & p = 0.05 \end{cases}$$

So, $p_2(AB) = 0.3$, etc, and $p_2(X^{(2)})$ takes values

$$p_2(X^{(2)}) = \begin{cases} 0.3 & p = 0.3 \\ 0.1 & p = 0.2 \\ 0.2 & p = 0.2 \\ 0.25 & p = 0.25 \\ 0.05 & p = 0.05 \end{cases}$$

Definition (Convergence in probability)**.** A sequence of random variables $X_1, X_2, \dots$ **converges in probability** to $c \in \mathbb{R}$, written $X_n \xrightarrow{p} c$ as $n \to \infty$, if

$$\forall \epsilon > 0 \quad P(|X_n - c| \leq \epsilon) \to 1 \quad \text{as } n \to \infty.$$

So, X_n and c can take very different values for large n, but only on a set with small probability.

Weak law of large numbers

$X_1, X_2, \dots$ an independent, identically distributed sequence of random variables with finite expected value μ, then

$$\frac{1}{n} \sum_{i=1}^{n} X_i \xrightarrow{p}\to \mu \quad \text{as } n \to \infty.$$

Example (Application)**.** Take $X_1, X_n, \dots$ a Bernoulli source. Then $p(X_1), p(X_2), \dots$ are i.i.d. random variables

$$\begin{aligned} & p(X_1, \dots, X_n) = p(X_1) \dots p(X_n) \\ & -\frac{1}{n} \log p(X_1, \dots, X_n) = -\frac{1}{n} \sum_{i=1}^{n} \log p(X_i) \xrightarrow{p} E(-\log p(X_1)) = H(X_1) \quad \text{as } n \to \infty. \end{aligned}$$

Definition. [Asymptotic Equipartition Property]

A source $X_1, X_2, \dots$ satisfies the **Asymptotic Equipartition Property** (AEP) if for some $H \geq 0$ we have

$$-\frac{1}{n} \log p(X_1, \dots, X_n) \xrightarrow{p} H \quad \text{as } n \to \infty.$$

Example (Motivating example)**.** Consider a coin, $p(H) = p$. If coin tossed N times, expect approximately pN heads and $(1-p)N$ tails.

$$\begin{aligned} P(\text{particular sequence of } pN \text{ heads and } (1-p)N \text{ tails}) = & \qquad p^{pN}(1-p)^{(1-p)N} \\ = 2^{N(p \log p) + (1-p)\log(1-p)} = 2^{-NH(A)} & \end{aligned}$$

where A is the result of an independent coin toss. So, with high probability we will get a typical sequence, and its probability will be close to $2^{-NH(A)}$.

Lemma I.8. A source $X_1, \dots, X_n$ satisfies AEP iff it satisfies the following:

$$\forall \epsilon > 0,\ \exists n_0(\epsilon) \text{ such that } \forall n \geq n_0(\epsilon)\ \exists \text{ a ‘typical set’} T_n \subset \Sigma^n \text{ with}$$

$$\begin{aligned} P((X_1, \dots, X_n) \in T_n) > 1 - \epsilon \\ 2^{-n(H+\epsilon)} \leq p(x_1, \dots, x_n) \leq 2^{-n(H-\epsilon)} \quad \forall (x_1, \dots, x_n) \in T^n. \end{aligned} \tag{*}$$

Sketch proof. AEP $\implies *$. Take

$$\begin{aligned} T_n &= \{\, (x_1, \dots, x_n) \in \Sigma^n \mid \left| -\frac{1}{n} \log p(x_1, \dots, x_n) - H \right| < \epsilon \,\} \\ &= \{\, (x_1, \dots, x_n) \in \Sigma^n \mid 2^{-n(H+\epsilon)} \le p(x_1, \dots, x_n) \le 2^{-n(H-\epsilon)} \,\} \end{aligned}$$

$* \implies$ AEP

$$P(\left| -\frac{1}{n} p(X_1, \dots, X_n) - H \right| < \epsilon) \ge P(T_n) \to 1 \quad \text{as } n \to \infty.$$

□

Definition (Reliably encodable)**.** A source $X_1, X_2, \dots$ is **reliably encodable** at rate r if $\exists A_n \subset \Sigma^n$ for each n such that

(i) $\frac{\log|A_n|}{n} \to r \quad \text{as } n \to \infty$

(ii) $P((X_1, \dots, X_n) \in A_n) \to 1 \quad \text{as } n \to \infty$.

So, in principle you can encode at rate almost r with negligible error for long enough strings.

So, if $|\Sigma| = a$, you can reliably encode at rate $\log a$. However you can often do better. For example, consider telegraph English with 26 letters and a space. $27 \approx 2^{4.756}$, so can encode at rate of 4.76 bits/letter. But much lower rates suffice, as there is a lot of redundancy in the English language. Hence the following definition.

Definition (Information rate)**.** The **information rate** H of a source is the infimum of all values at which it is reliably encodable.

Roughly, nH is the number of bits required to encode $(X_1, \dots, X_n)$.

Theorem I.9 (Shannon's first coding theorem)**.** If a source satisfies AEP with some constant H, then the source has information rate H.

Proof. Let $\epsilon > 0$ and let $T_n \subset \Sigma^n$ be typical sets. Then for sufficiently large $n \ge n_0(\epsilon)$,

$$p(x_1, \dots, x_n) \ge 2^{-n(H+\epsilon))} \quad \forall (x_1, \dots, x_n) \in T^n.$$

So,

$$\begin{aligned} P((X_1, \dots, X_n) \in T_n) &\ge 2^{-n(H+\epsilon)} \, |T_n| \\ \implies |T_n| &\le 2^{n(H+\epsilon)} \end{aligned}$$

therefore the source is reliably encodable at rate $H + \epsilon$.

Conversely, if $H = 0$, done. Otherwise, pick $0 < \epsilon < \frac{H}{2}$. Suppose the source is reliably encodable at rate $H - 2\epsilon$, say with sets A_n. □