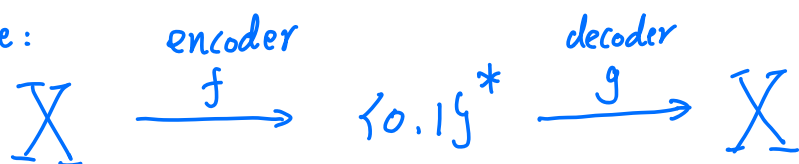


Almost lossless / errorless. Coding

Coding scheme:



Idea: If we want perfect (errorless) code, then $k \geq \log_2 |X|$

But any physics process is subjected to noise,
the transmission is erroneous.

In reality, we do things with certain accuracy / error tolerance.

Def: A pair (f, g) is called a (k, ϵ) -code for X if

$$f: X \rightarrow \{0,1\}^k \quad g: \{0,1\}^k \rightarrow X$$

such that $P(g(f(x)) \neq x) \leq \epsilon$ — k bits sent.
— undetectable error

Remark: Alternative setting with detectable error

$$f: X \rightarrow \{0,1\}^k \quad g: \{0,1\}^k \rightarrow X \cup \{e\}$$

such that $\exists S \subseteq X$ s.t.

$$g(f(x)) = \begin{cases} x & x \in S \\ e & x \notin S \end{cases}$$

$$P(g(f(X)) \neq X) = P(g(f(X)) = e) = P_X(S)$$

S lossless part. e detectable error

Def: (Optimal error probability)

$$\varepsilon^*(X, k) := \inf \{ \varepsilon : \exists (k, \varepsilon) \text{ - code for } X \}$$

Smallest error that a length k code can achieve.

Thm: $\varepsilon^*(X, k) = P[\log_2(f^*(X)) \geq k] = 1 - \sum_{i=1}^{2^{k-1}} P_X(i)$

(Recall that we assume $P_X(i) \geq P_X(i+1)$ decreasing)

Pf: We assign a code word to each of $\underbrace{2^{k-1} \text{ most likely realizations of } X}_S$ and all the rest to one word "error"

$$\varepsilon^*(X, k) = P[X \notin S] = P[\log_2(f^*(X)) \geq k]$$

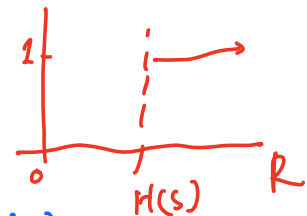
Actual code book: Variable length $\{ \emptyset, 0, 1, 00, 01, \dots, \underbrace{11 \dots 1}_{k-1} \}$
 fixed length $\{ (00 \dots 00) \quad (00 \dots 01) \quad \dots \quad (11 \dots 10) \}$
 $(11 \dots 11)$ for "error". 2^{k-1}

Shannon's Source coding Thm (948)

Let S^n be i.i.d. Then

$$\lim_{n \rightarrow \infty} \varepsilon^*(S^n, nR) = \begin{cases} 0 & \text{if } R > H(S) \\ 1 & \text{if } R < H(S) \end{cases}$$

Rate
↓



Lemma (Achievability)

$$\varepsilon^*(X, k) \leq P[\log_2 \frac{1}{P_X(X)} \geq k]$$

Indeed, $\varepsilon^*(X, k) = \sum_{m \geq 2^k} P_X(m) = \sum 1_{\{m \geq 2^k\}} P_X(m) \leq \sum 1_{\{\frac{1}{P_X(m)} \geq 2^k\}} P_X(m)$

$$= E 1_{\{\log_2 \frac{1}{P_X(X)} \geq k\}}$$

Lemma (converse)

$$\Sigma^*(X, k) \geq P[\log \frac{1}{P_X(X)} > k + \tau] - 2^{-\tau}, \quad \forall \tau > 0$$

Denote, $L = \log^*$. $L(m) = \lfloor \log m \rfloor \leq \log m \leq \log \frac{1}{P_X(m)}$

$$1 - \Sigma^*(X, k) = P[L \leq k]$$

$$= P[L \leq k, \log_2 \frac{1}{P_X} \leq k + \tau] + P[L \leq k, \log_2 \frac{1}{P_X} > k + \tau]$$

$$\leq P[\log_2 \frac{1}{P_X} \leq k + \tau] + \sum_m P_X(m) \mathbb{1}_{\{L(m) \leq k\}} \mathbb{1}_{\{P_X(m) \leq 2^{-(k+\tau)}\}}$$

$$\leq P[\log_2 \frac{1}{P_X} \leq k + \tau] + (2^{k+1} - 1) \cdot 2^{-k-\tau}$$

(Pf of Thm)

$$P[\log_2 \frac{1}{P_X} > k + \tau] - 2^{-\tau} \leq \Sigma^*(X, k) \leq P[\log \frac{1}{P_X} \geq k]$$

Now take $X = S^n$, $P_{S^n}(s_1, \dots, s_n) = P_S(s_1) \cdot P_S(s_2) \cdot \dots \cdot P_S(s_n)$
 By WLLN, $\frac{1}{n} \log \frac{1}{P_{S^n}} = \frac{1}{n} (\log \frac{1}{P_{S_1}} + \log \frac{1}{P_{S_2}} + \dots + \log \frac{1}{P_{S_n}})$

$$\xrightarrow{P} \mathbb{E}(\log \frac{1}{P_S}) = H(S)$$

Then

$$\begin{aligned} \Sigma^*(S^n, nR) &\leq P[\log \frac{1}{P_{S^n}} > nR] \\ &= P[\frac{1}{n} \log \frac{1}{P_{S^n}} > R] \xrightarrow{\text{concentrate}} P[H(S) > R] = 0 \end{aligned}$$

if $R > H(S)$

$$\begin{aligned} \Sigma^*(S^n, nR) &\geq P[\log \frac{1}{P_{S^n}} > nR - \sqrt{n}] - 2^{-\sqrt{n}} \\ &\geq P[\frac{1}{n} \log \frac{1}{P_{S^n}} > R - \frac{1}{\sqrt{n}}] - 2^{-\sqrt{n}} \\ &\geq P[\frac{1}{n} \log \frac{1}{P_{S^n}} > R] - 2^{-\sqrt{n}} \end{aligned}$$

$$\begin{aligned}
\lim_{n \rightarrow \infty} \sum^*(S^n, nR) &\geq \lim_{n \rightarrow \infty} P\left[\frac{1}{n} \log \frac{1}{P_S^n} > R\right] = \lim_{n \rightarrow \infty} 2^{-\sqrt{n}} \\
&\geq P[H(S) > R] = 1 \\
&\quad \text{if } H(S) > R,
\end{aligned}$$

A Direct argument. Typical Sequence

Let \mathcal{X} be a finite alphabet.

For a sequence $x^n = x_1 \cdots x_n \in \mathcal{X}^n$, we can define

$$N_{x^n}(a) = \# \{i \mid x_i = a\}$$

Then $\frac{N_{x^n}(a)}{n}$ is the frequency "a" appears in x^n

$$P_{x^n}(a) := \frac{N_{x^n}(a)}{n} \text{ empirical distribution of } x^n.$$

Now

$X \sim P$ R.V. on \mathcal{X} , $x^n = x_1 \cdots x_n$ i.i.d

x^n is a random sequence.

What would be most likely sequence?

$$P_{x^n} \approx P_X$$

A sequence x^n is strong (n, ε) -typical for P if

$$|P_{x^n}(a) - P_X(a)| < \frac{\varepsilon}{|X|} \quad \forall a \in X$$

is weak (n, ε) -typical if

$$H(P) + \varepsilon < \frac{1}{n} \log \frac{1}{P_{x^n}(x^n)} < H(P) - \varepsilon$$

We denote $T_\varepsilon^n(P) \subseteq X^n$ be the set of strong typical sequence of P

$A_\varepsilon^n(P) \subseteq X^n$ --- weak --- of P

Theorem (Typicality) ① $T_\varepsilon^n(P) \subseteq A_\varepsilon^n(P)$

$$② (1-\varepsilon) 2^{n(H(P)-\varepsilon)} \leq |A_\varepsilon^n(P)| \leq 2^{n(H(P)+\varepsilon)}$$

$$③ 2^{n(H(P)-\delta(\varepsilon))} |T_\varepsilon^n(P)| \leq 2^{n(H(P)+\delta(\varepsilon))}$$

where $\delta(\varepsilon) \rightarrow 0$ as $\varepsilon \rightarrow 0$

$$④ P_{X^n}(X^n \in A_\varepsilon^n) \rightarrow 1$$

$$P_{X^n}(X^n \in T_\varepsilon^n) \rightarrow 1 \text{ as } n \rightarrow \infty$$

$$X^n \in A_\varepsilon^n(P) \Leftrightarrow 2^{n(H(P)-\varepsilon)} < P_{X^n}(X^n) < 2^{n(H(P)+\varepsilon)}$$

$$P_{X^n}(X^n \in A_\varepsilon^n) = P_{X^n}\left(\left|\frac{1}{n} \sum_{i=1}^n \log \frac{1}{P_{X_i}} - H(X)\right| \leq \varepsilon\right) \rightarrow 1$$

by W.L.L.N

Alternative proof for Shannon's Coding Theorem.

Choose error free set $S(n) = A_\varepsilon^n$. Assign a codeword to each $x^n \in S(n)$.

need $|S(n)| \leq 2^{n(H(X) + \varepsilon)}$ codeword

word length $\leq \lfloor n(H(X) + \varepsilon) \rfloor$

error probability $\varepsilon(n) = 1 - P(S(n)) \rightarrow 0$

□