

Converse of the Noisy Coding Theorem (NOT in Mackay)

"If $\tilde{R} > C(Q)$: $\exists \delta > 0 \exists N_0 \forall N \geq N_0: \nexists$ code with $\frac{k}{N} \geq \tilde{R} \& P_B \leq \delta$ "

Tools: ① Data Processing Inequality (DPI) for $A \rightarrow B \rightarrow C$ Markov chain:

$$I(B:C) \geq I(A:C) \quad \& \quad H(A|B) \leq H(A|C)$$

Some for i.e. $P(a,b,c) = P(a)P(b|a)P(c|b) = P(b)P(a|b)P(c|b)$
A → C interchanged!

② If X^N arbitrary and Y^N channel output: \leftarrow i.e. $P(x^N, y^N)$

$$= P(x^N) Q(y_1|x_1) \dots Q(y_N|x_N)$$

$$I(X^N:Y^N) \leq \sum_{i=1}^N I(X_i:Y_i) \leq N \cdot C(Q)$$

HW 5

③ Fano's inequality for $S \rightarrow T \rightarrow \hat{S}$ Markov chain, $p = \Pr(S \neq \hat{S})$

$$H(\{p, 1-p\}) + p \cdot \log \#A_S \geq H(S|\hat{S}) \geq H(S|T)$$

Proof of the converse: Consider (N, k) -code with $\frac{k}{N} \geq \tilde{R} > C$.

Let $S \in \{1, \dots, 2^k\}$ uniform. Recall: $S \rightarrow X^N \rightarrow Y^N \rightarrow \hat{S}$.

Then:

$$* H(S|Y^N) = H(S) - I(S:Y^N) \stackrel{\text{DPI ①}}{\geq} H(S) - I(X^N:Y^N) \stackrel{\text{②}}{\geq} k - N \cdot C$$

$S \rightarrow X^N \rightarrow Y^N$ Markov chain

$$* H(S|Y^N) \stackrel{\text{Fano ③}}{\leq} 1 + \Pr(\hat{S} \neq S) \cdot \log \#A_S = 1 + P_B \cdot k$$

$S \rightarrow Y^N \rightarrow \hat{S}$ Markov chain

$$\Rightarrow k - N \cdot C \leq 1 + P_B \cdot k$$

$$\Rightarrow P_B \geq \frac{1}{k} (k - N \cdot C - 1) = 1 - \frac{N \cdot C}{k} - \frac{1}{k} \geq 1 - \frac{C}{\tilde{R}} - \frac{1}{N\tilde{R}}$$

Can never go below this for large enough N

Are we happy? What questions does Shannon's theorem leave unaddressed? algorithmics, large N , ... how to even compute C ?

Shannon's Theorem vs. Practice (§11)

- Need large block size N for joint typicality vs. fixed packet size
- Codebook $x^N(1), \dots, x^N(2^k)$ exponentially large in N (if $R > 0$) → HW 5
- Random codes vs predictable performance

A family of codes is "very good" if $\frac{k}{N} \rightarrow C$ & $P_B \rightarrow 0$
 "good" if $\frac{k}{N} \geq \tilde{R}$ & $P_B \rightarrow 0$ for some $\tilde{R} > 0$
 "bad" otherwise

... and "practical" if efficient encoder + decoder

Often run in embedded devices (cell phone, satellite, TV, ...)!

In practice:

- * most codes are linear (x^N linear function of s^k)
- * "easy" to come up with "plausible" encoders — but optimal decoding is in general (NP) hard! ← unlike for compression!

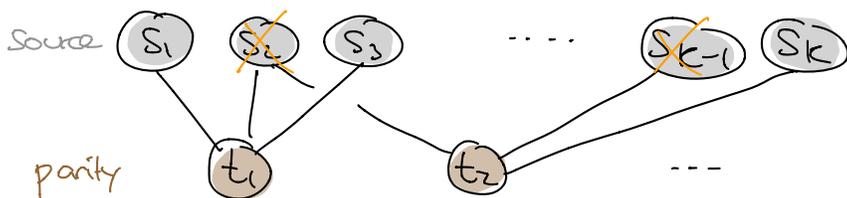
$$\sigma_{opt}(y^N) = \underset{\hat{s}}{\operatorname{argmax}} P(\hat{s} | y^N)$$

Why? If $P(s)$ arbitrary prior, want to choose σ to maximize $P(\hat{s} = s)$

$$= \sum_{y^N} \underbrace{P(\hat{s} = \sigma(y^N), Y^N = y^N)}$$

choose $s = \sigma(y^N)$ that maximizes $P(s | y^N) \propto P(s | y^N)$

e.g. imagine the following (LDPC) code:



e.g. 4 bits per parity constraint, each bit in 3 parity constraints

For erasure channel:

$$s_1 \oplus s_2 \oplus s_3 \oplus t_1 = 0$$

$$s_2 \oplus \dots \oplus s_{k-1} \oplus t_2 = 0$$

- * types of decoders: "algebraic" vs. "iterative"

Types of codes:

- * block codes: e.g. Hamming, Reed-Solomon, LDPC codes, WiFi, DVB, ...

TODAY

- * Convolutional: e.g. turbo codes
- ↳ linear streaming codes

3G/4G/LTE, Sat. comm.

