Information Theory Lecture 4

- Discrete channels, codes and capacity: CT7
 - Channels: CT7.1–2
 - Capacity and the coding theorem: CT7.3–7 and CT7.9
 - Combining source and channel coding: CT7.13

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Discrete Channels

$$X \longrightarrow \begin{array}{c} \text{channel} \\ p(y|x) \end{array} \longrightarrow Y$$

- Let \mathcal{X} and \mathcal{Y} be finite sets.
- A discrete channel is a random mapping p(y|x): $\mathcal{X} \mapsto \mathcal{Y}$.
- The *nth extension of the discrete channel* is a random mapping $p(y_1^n|x_1^n)$: $\mathcal{X}^n \mapsto \mathcal{Y}^n$, defined for all $n \ge 1$, $x_1^n \in \mathcal{X}^n$ and $y_1^n \in \mathcal{Y}^n$.
 - A pmf $p(x_1^n)$ induces a pmf $p(y_1^n)$ via the channel,

$$p(y_1^n) = \sum_{x_1^n} p(y_1^n | x_1^n) p(x_1^n)$$

• The channel is *stationary* if for any *n*

$$p(y_1^n | x_1^n) = p(y_{1+k}^{n+k} | x_{1+k}^{n+k}), \quad k = 1, 2, \dots$$

• A stationary channel is *memoryless* if

$$p(y_m | x_1^m y_1^{m-1}) = p(y_m | x_m), \quad m = 2, 3, \dots$$

That is, the channel output at time m does not depend on past inputs or outputs.

• Furthermore, if the channel is used *without feedback*

$$p(y_1^n|x_1^n) = \prod_{m=1}^n p(y_m|x_m), \quad n = 2, 3, \dots$$

That is, each time the channel is used its effect on the output is independent of previous and future uses.

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- A *discrete memoryless channel* (DMC) is completely described by the triple $(\mathcal{X}, p(y|x), \mathcal{Y})$.
- The binary symmetric channel (BSC) with crossover probability ε,

• a DMC with
$$\mathcal{X} = \mathcal{Y} = \{0, 1\}$$
 and $p(1|0) = p(0|1) = \varepsilon$



- The binary erasure channel (BEC) with erasure probability ε ,
 - a DMC with $\mathcal{X}=\{0,1\}$, $\mathcal{Y}=\{0,1,e\}$ and $p(e|0)=p(e|1)=\varepsilon$



A Block Channel Code



- An (M, n) block channel code for a DMC (X, p(y|x), Y) is defined by:
 - 1 An index set $\mathcal{I}_M \triangleq \{1, \ldots, M\}$.
 - **2** An encoder mapping $\alpha : \mathcal{I}_M \longmapsto \mathcal{X}^n$. The set

$$C_n \triangleq \left\{ x_1^n : x_1^n = \alpha(i), \ \forall \, i \in \mathcal{I}_M \right\}$$

of codewords is called the codebook.

- **3** A decoder mapping $\beta : \mathcal{Y}^n \longmapsto \mathcal{I}_M$.
- The *rate* of the code is

$$R \triangleq \frac{\log M}{n} \quad \text{[bits per channel use]}$$

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Why?

- *M* different codewords $\{x_1^n(1), \ldots, x_1^n(M)\}$ can convey $\log M$ bits of *information* per codeword, or *R* bits per channel use.
- Consider M = 2^k, |X| = 2, and assume that k < n. Then k "information bits" are mapped into n > k "coded bits." Introduces redundancy; can be employed by the decoder to correct channel errors.



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Error Probabilities

• Information symbol $\omega \in \mathcal{I}_M$, with $p(i) = \Pr(\omega = i)$. Then, for a given DMC and a given code

 $\omega \ \longrightarrow \ X_1^n = \alpha(\omega) \ \longrightarrow \ Y_1^n \ \longrightarrow \ \hat{\omega} = \beta(Y_1^n)$

- Define:
 - **1** The *conditional* error probability: $\lambda_i = \Pr(\hat{\omega} \neq i | \omega = i)$
 - **2** The maximal error probability: $\lambda^{(n)} = \max \{\lambda_1, \dots, \lambda_M\}$
 - **3** The *average* error probability:

$$P_e^{(n)} = \Pr(\hat{\omega} \neq \omega) = \sum_{i=1}^M \lambda_i p(i)$$

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Jointly Typical Sequences

The set $A_{\varepsilon}^{(n)}$ of *jointly typical sequences* with respect to a pmf p(x, y) is the set $\{(x_1^n, y_1^n)\}$ of sequences for which

$$\begin{vmatrix} -\frac{1}{n} \log p(x_1^n) - H(X) \end{vmatrix} < \varepsilon \\ \begin{vmatrix} -\frac{1}{n} \log p(y_1^n) - H(Y) \end{vmatrix} < \varepsilon \\ -\frac{1}{n} \log p(x_1^n, y_1^n) - H(X, Y) \end{vmatrix} < \varepsilon$$

where

$$p(x_1^n, y_1^n) = \prod_{m=1}^n p(x_m, y_m)$$
$$p(x_1^n) = \sum_{y_1^n} p(x_1^n, y_1^n), \qquad p(y_1^n) = \sum_{x_1^n} p(x_1^n, y_1^n)$$

and where the entropies are computed based on p(x, y).

The joint AEP

Let (X_1^n, Y_1^n) drawn according to $p(x_1^n, y_1^n) = \prod_{m=1}^n p(x_m, y_m)$

- $\Pr((X_1^n, Y_1^n) \in A_{\varepsilon}^{(n)}) > 1 \varepsilon$ for sufficiently large n.
- $|A_{\varepsilon}^{(n)}| \le 2^{n(H(X,Y)+\varepsilon)}$.
- $|A_{\varepsilon}^{(n)}| \ge (1-\varepsilon)2^{n(H(X,Y)-\varepsilon)}$ for sufficiently large n.
- If \tilde{X}_1^n and \tilde{Y}_1^n are drawn independently according to $p(x_1^n) = \sum_{y_1^n} p(x_1^n, y_1^n)$ and $p(y_1^n) = \sum_{x_1^n} p(x_1^n, y_1^n)$, then

$$\Pr\left((\tilde{X}_1^n, \tilde{Y}_1^n) \in A_{\varepsilon}^{(n)}\right) \le 2^{-n(I(X;Y)-3\varepsilon)}$$

and for sufficiently large \boldsymbol{n}

$$\Pr\left((\tilde{X}_1^n, \tilde{Y}_1^n) \in A_{\varepsilon}^{(n)}\right) \ge (1 - \varepsilon)2^{-n(I(X;Y) + 3\varepsilon)}$$

with I(X;Y) computed for the pmf p(x,y).

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Channel Capacity

- For a fixed n, a code can convey more information for large M ⇒ we would like to maximize the rate R = ¹/_n log M without sacrificing performance
 - Which is the largest R that allows for a (very) low $P_e^{(n)}$??
- For a given channel we say that the rate R is *achievable* if there exists a sequence of (M, n) codes, with $M = \lceil 2^{nR} \rceil$, such that the maximal probability of error $\lambda^{(n)} \to 0$ as $n \to \infty$.

The capacity C of a channel is the supremum of all rates that are achievable over the channel.

Random Code Design

- Choose a joint pmf $p(x_1^n)$ on \mathcal{X}^n .
- Random code design: Draw M codewords $x_1^n(i)$, i = 1, ..., M, i.i.d. according to $p(x_1^n)$ and let these define a codebook

$$\mathcal{C}_n = \left\{ x_1^n(1), \dots, x_1^n(M) \right\}.$$

 Note: The interpretation here is that the codebook is "designed" in a random fashion. When the resulting code then is used, the codebook must, of course, be fixed and known...

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A Lower Bound for C of a DMC

- A DMC $(\mathcal{X}, p(y|x), \mathcal{Y}).$
- Fix a pmf p(x) for $x \in \mathcal{X}$. Generate $\mathcal{C}_n = \{x_1^n(1), \dots, x_1^n(M)\}$ using $p(x_1^n) = \prod p(x_m)$.
- A data symbol ω is generated according to a *uniform* distribution on \mathcal{I}_M , and $x_1^n(\omega)$ is transmitted.
- The channel produces a corresponding output sequence Y_1^n .
- Let $A_{\varepsilon}^{(n)}$ be the typical set w.r.t. p(x,y) = p(y|x)p(x). At the receiver, the decoder then uses the following decision rule. Index $\hat{\omega}$ was sent if:
 - $(x_1^n(\hat{\omega}), Y_1^n) \in A_{\varepsilon}^{(n)}$ for some small ε ;
 - no other ω corresponds to a jointly typical $(x_1^n(\omega), Y_1^n)$.

Now study

$$\pi_n = \Pr(\hat{\omega} \neq \omega)$$

where "Pr" is over the random codebook selection, the data variable ω and the channel.

- Symmetry $\implies \pi_n = \Pr(\hat{\omega} \neq 1 | \omega = 1)$
- Let

$$E_i = \{ (x_1^n(i), Y_1^n) \in A_{\varepsilon}^{(n)} \}$$

then for a sufficiently large n,

$$\pi_n = P(E_1^c \cup E_2 \cup \dots \cup E_M) \leq P(E_1^c) + \sum_{i=2}^M P(E_i)$$

$$\leq \varepsilon + (M-1)2^{-n(I(X;Y)-3\varepsilon)} \leq \varepsilon + 2^{-n(I(X;Y)-R-3\varepsilon)}$$

because of the union bound and the joint AEP.

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Note that

$$I(X;Y) = \sum_{x,y} p(y|x)p(x)\log\frac{p(y|x)}{p(y)}$$

with $p(y) = \sum_{x} p(y|x)p(x)$, where p(x) generated the random codebook and p(y|x) is given by the channel.

• Let C_{tot} be the set of all possible codebooks that can be generated by $p(x_1^n) = \prod p(x_m)$, then at least one $C_n \in C_{tot}$ must give

$$P_e^{(n)} \le \pi_n \le \varepsilon + 2^{-n(I(X;Y) - R - 3\varepsilon)}$$

 \implies as long as $R < I(X;Y) - 3\varepsilon$ there exists at least one $\mathcal{C}_n \in \mathcal{C}_{\text{tot}}$, say \mathcal{C}_n^* , that can give $P_e^{(n)} \to 0$ as $n \to \infty$.

- Order the codewords in C_n^* according to the corresponding λ_i 's and throw away the worst half \Longrightarrow
 - new rate $R' = R n^{-1}$
 - for the remaining codewords

$$\frac{\lambda^{(n)}}{2} \le \varepsilon + 2^{-n(I(X;Y) - R - 3\varepsilon)}$$

 \implies for any p(x), all rates $R < I(X;Y) - 3\varepsilon$ achievable

 \implies all rates $R < \max_{p(x)} I(X;Y) - 3\varepsilon$ achievable \implies

$$C \ge \max_{p(x)} I(X;Y)$$

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An Upper Bound for C of a DMC

- Let $C_n = \{x_1^n(1), \ldots, x_1^n(M)\}$ be any sequence of codes that can achieve $\lambda^{(n)} \to 0$ at a fixed rate $R = \frac{1}{n} \log M$.
- Note that $\lambda^{(n)} \to 0 \implies P_e^{(n)} \to 0$ for any $p(\omega)$. We can assume \mathcal{C}_n encodes equally probable $\omega \in \mathcal{I}_M$.
- Fano's inequality \implies

$$R \le \frac{1}{n} + P_e^{(n)}R + \frac{1}{n}I(x_1^n(\omega); Y_1^n) \le \frac{1}{n} + P_e^{(n)}R + \max_{p(x)}I(X; Y)$$

That is, for any fixed achievable R

$$\lambda^{(n)} \to 0 \implies R \le \max_{p(x)} I(X;Y) \implies C \le \max_{p(x)} I(X;Y)$$

The Channel Coding Theorem for DMC's

Theorem (the channel coding theorem) For a given DMC $(\mathcal{X}, p(y|x), \mathcal{Y})$, let p(x) be a pmf on \mathcal{X} and let

$$C = \max_{p(x)} I(X;Y)$$
$$= \max_{p(x)} \left\{ \sum_{x \in \mathcal{X}} \sum_{y \in \mathcal{Y}} p(y|x) p(x) \log \frac{p(y|x)}{\sum_{x \in \mathcal{X}} p(y|x) p(x)} \right\}$$

Then C is the capacity of the channel. That is, <u>all</u> rates R < C and <u>no</u> rates R > C <u>are achievable</u>.

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The Joint Source–Channel Coding Theorem

- A (stationary and ergodic) discrete source S with entropy rate H(S) [bits/source symbol].
 - A length-L block of source symbols can be coded into k bits, and then reconstructed without errors as long as k/L > H(S) and as $L \to \infty$.
- A DMC $(\mathcal{X}, p(y|x), \mathcal{Y})$ with capacity C [bits/channel use].
 - If k/n < C a channel code exists that can convey k bits of information per n channel uses without errors as n → ∞.
- L source symbols → k information bits → n channel symbols;
 will convey the source symbols without errors as long as

$$H(\mathcal{S}) < \frac{k}{L} < \frac{n}{L} \cdot C$$

- Hence, as long as H(S) < C [bits/source symbol] the source can be transmitted without errors, as both $L \to \infty$ and $n \to \infty$ (assuming n/L = 1).
- If H(S) > C there is no way of constructing a system with an error probability that is not bounded away from zero.
 (Fano's inequality, etc.)
- No system exists that can communicate a source without errors for H(S) > C. One way of achieving error-free performance, for H(S) < C, is to use separate source and channel coding.

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