

Lecture 16 Channel Coding theorem for BSC

Textbook 7.5

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Outline

- 1 Definitions
- 2 Maximum-likelihood-decoding
- 3 Channel Coding theorem for BSC

Definition

A discrete channel, denoted by $(\mathcal{X}, p(y|x), \mathcal{Y})$, consists of two finite sets \mathcal{X} and \mathcal{Y} and a collection of probability mass functions $p(y|x)$, one for each $x \in \mathcal{X}$, such that for every x and y , $p(y|x) \geq 0$, and for every x , $\sum_x p(y|x) = 1$, with the interpretation that X is the input and Y is the output of the channel.

Definition

The n th extension of the discrete memoryless channel (DMC) is the channel $(\mathcal{X}^n, p(y^n|x^n), \mathcal{Y}^n)$, where

$$p(y_k|x^k, y^{k-1}) = p(y_k|x_k), \quad k = 1, 2, \dots, n.$$

Remark

If the channel is used without feedback [i.e., if the input symbols do not depend on the past output symbols, namely, $p(x_k|x^{k-1}, y^{k-1}) = p(x_k|x^{k-1})$], the channel transition function for the n th extension of the discrete memoryless channel reduces to

$$p(y^n|x^n) = \prod_{i=1}^n p(y_i|x_i).$$

When we refer to the discrete memoryless channel, we mean the discrete memoryless channel without feedback unless we state explicitly otherwise.

Definition

An (M, n) code for the channel $(\mathcal{X}, p(y|x), \mathcal{Y})$ consists of the following:

1. An index set $\{1, 2, \dots, M\}$.
2. An encoding function $X^n : \{1, 2, \dots, M\} \rightarrow \mathcal{X}^n$, yielding codewords $x^n(1), x^n(2), \dots, x^n(M)$. The set of codewords is called the cordbook.
3. A decoding function

$$g : \mathcal{Y}^n \rightarrow \{1, 2, \dots, M\},$$

which is a deterministic rule that assigns a guess to each possible received vector.

Conditional probability of error

Let

$$\lambda_i = \Pr(g(Y^n) \neq i | X^n = x^n(i)) = \sum_{y^n} p(y^n | x^n(i)) I(g(y^n) \neq i)$$

be the conditional probability of error given that index i was sent, where $I(\cdot)$ is the indicator function.

Definition

The maximal probability of error $\lambda^{(n)}$ for an (M, n) code is defined as

$$\lambda^{(n)} = \max_{i \in \{1, 2, \dots, M\}} \lambda_i.$$

Definition

The (arithmetic) average probability of error $P_e^{(n)}$ for an (M, n) code is defined as

$$P_e^{(n)} = \frac{1}{M} \sum_{i=1}^M \lambda_i.$$

Note that if the index W is chosen according to a uniform distribution over the set $\{1, 2, \dots, M\}$, and $X^n = x^n(W)$, then

$$P_e^{(n)} = \Pr(W \neq g(Y^n)).$$

Also, obviously,

$$P_e^{(n)} \leq \lambda^{(n)}.$$

Definition

The *rate* of an (M, n) code is

$$R = \frac{\log M}{n} \text{ bits per transmission.}$$

Definition

A rate R is said to be *achievable* if there exists a sequence of $(\lceil 2^{nR} \rceil, n)$ codes such that $\lambda^{(n)}$ tends to 0 as $n \rightarrow \infty$.

Definition

The *capacity* of a channel is the supremum of all achievable rates.

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If \mathbf{x} and \mathbf{y} are two tuples of 0s and 1s, then we shall say that their *Hamming-distance* is

$$d(\mathbf{x}, \mathbf{y}) := |\{i | 1 \leq i \leq n, x_i \neq y_i\}|.$$

Maximum-likelihood-decoding

If \mathbf{y} is received we try to find a codeword \mathbf{x} such that $d(\mathbf{x}, \mathbf{y})$ is minimal.

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Suppose that we use a code C consisting of M words of length n , each word occurring with equal probability. If $\mathbf{x}_1, \mathbf{x}_2, \dots, \mathbf{x}_M$ are the codewords and we use maximum-likelihood-decoding, let P_i be the probability of making an incorrect decoding of a received word is:

$$p_C := M^{-1} \sum_{i=1}^M P_i.$$

Now consider all possible codes C with the given parameters and define:

$$P^*(M, n, p) := \text{minimal value of } P_C.$$

Theorem

If $0 < R < 1 + p \log p + q \log q$ and $M_n := 2^{\lfloor Rn \rfloor}$ then $P^(M, n, p) \rightarrow 0$ if $n \rightarrow \infty$.*

The probability of an error pattern with w errors is $p^w q^{n-w}$, i.e., it depends on w only.

The number of errors in a received word is a random variable with expected value np and variance $np(1-p)$. If $b := (np(1-p)/(\epsilon/2))^{1/2}$, then by Chebyshev's inequality we have

$$P(w > np + b) \leq \frac{1}{2}\epsilon.$$

Since $p < \frac{1}{2}$, the number $\rho := \lfloor np + b \rfloor$ is less than $\frac{1}{2}n$ for sufficiently large n .

Let $B_\rho(\mathbf{x})$ be the set of words \mathbf{y} with $d(\mathbf{x}, \mathbf{y}) \leq \rho$. Then

$$|B_\rho(\mathbf{x})| = \sum_{i \leq \rho} \binom{n}{i} < \frac{1}{2} n \binom{n}{\rho} \leq \frac{1}{2} \cdot \frac{n^n}{\rho^\rho (n - \rho)^{n - \rho}}$$

The set $B_\rho(\mathbf{x})$ is usually called the *sphere* with radius ρ and center \mathbf{x} .

We shall use the following estimates:

$$\frac{\rho}{n} \log \frac{\rho}{n} = \frac{1}{n} [np + b] \log \frac{[np + b]}{n} = p \log p + O(n^{-1/2}),$$

$$\left(1 - \frac{\rho}{n}\right) \log \left(1 - \frac{\rho}{n}\right) = q \log q + O(n^{-1/2}), \quad (n \rightarrow \infty).$$

Let $\mathbf{u} \in \{0, 1\}^n$, $\mathbf{v} \in \{0, 1\}^n$. Then

$$f(\mathbf{u}, \mathbf{v}) := \begin{cases} 0, & \text{if } d(\mathbf{u}, \mathbf{v}) > \rho \\ 1, & \text{if } d(\mathbf{u}, \mathbf{v}) \leq \rho. \end{cases}$$

If $\mathbf{x}_i \in C$ and $\mathbf{y} \in \{0, 1\}^n$ then

$$g_i(\mathbf{y}) := 1 - f(\mathbf{y}, \mathbf{x}_i) + \sum_{j \neq i} f(\mathbf{y}, \mathbf{x}_j).$$

Note that if \mathbf{x}_i is the only codeword such that $d(\mathbf{x}_i, \mathbf{y}) \leq \rho$, then $g_i(\mathbf{y}) = 0$ and that otherwise $g_i(\mathbf{y}) \geq 1$.

Proof of Shannon's Theorem

We shall pick the codewords $\mathbf{x}_1, \mathbf{x}_2, \dots, \mathbf{x}_M$ at random (independently). We decode as follows. If \mathbf{y} is received and if there is exactly one codeword \mathbf{x}_i such that $d(\mathbf{x}_i, \mathbf{y}) \leq \rho$, then decode \mathbf{y} as \mathbf{x}_i . Otherwise we declare an error (or if we must decode, then we always decode as \mathbf{x}_1).

Let P_i be defined as above. We have

$$\begin{aligned} P_i &= \sum_{\mathbf{y} \in \{0,1\}^n} P(\mathbf{y}|\mathbf{x}_i) g_i(\mathbf{y}) \\ &= \sum_{\mathbf{y}} P(\mathbf{y}|\mathbf{x}_i) \{1 - f(\mathbf{y}, \mathbf{x}_i)\} + \sum_{\mathbf{y}} \sum_{j \neq i} P(\mathbf{y}|\mathbf{x}_i) f(\mathbf{y}, \mathbf{x}_j). \end{aligned}$$

Here the first term on the right-hand side is the probability that the received word \mathbf{y} is not in $B_\rho(\mathbf{x}_i)$. This probability is at most $\frac{1}{2}\epsilon$.

Hence we have

$$P_C \leq \frac{1}{2}\epsilon + M^{-1} \sum_{i=1}^M \sum_{\mathbf{y}} \sum_{j \neq i} P(\mathbf{y}|\mathbf{x}_i) f(\mathbf{y}, \mathbf{x}_j).$$

The main principle of the proof is the fact that $P^*(M, n, p)$ is less than the expected value of P_C over all possible codes C picked at random. Therefore we have

$$\begin{aligned} P^*(M, n, p) &= \frac{1}{2}\epsilon + M^{-1} \sum_{i=1}^M \sum_{\mathbf{y}} \sum_{j \neq i} \mathcal{E}(P(\mathbf{y}|\mathbf{x}_i)) \mathcal{E}(f(\mathbf{y}, \mathbf{x}_j)) \\ &= \frac{1}{2}\epsilon + M^{-1} \sum_{i=1}^M \sum_{\mathbf{y}} \sum_{j \neq i} \mathcal{E}(P(\mathbf{y}|\mathbf{x}_i)) \cdot \frac{|B_\rho|}{2^n} \\ &= \frac{1}{2}\epsilon + (M-1)2^{-n}|B_\rho|. \end{aligned}$$

So we have that

$$n^{-1} \log(P^*(M, n, p) - \frac{1}{2}\epsilon) \leq n^{-1} \log M - (1 + p \log p + q \log q) + O(n^{-1/2}).$$

Substituting $M = M_n$ on the right-hand side we find, using the restriction on R ,

$$n^{-1} \log(P^*(M, n, p) - \frac{1}{2}\epsilon) < -\beta < 0.$$

for $n > n_0$, i.e., $P^*(M, n, p) < \frac{1}{2}\epsilon + 2^{-\beta n}$.