

Math 5251 Hamming distance & decoding (§4.4)

If we send codewords $C \subset \{0,1\}^*$ of length l
 $\{x_1, \dots, x_m\}$

through a BSC with error probability $p < \frac{1}{2}$

safe to assume;
Why?

and receive the word y , which
word x_i should we decode it as?

You would think we should pick an x_i
that minimizes this...

DEF'N: Given two words in Σ^* of same length l

$x = x^{(1)} x^{(2)} \dots x^{(l)}$ their Hamming distance is
 $y = y^{(1)} y^{(2)} \dots y^{(l)}$

$$d(x, y) := \# \{ p = 1, 2, \dots, l : x^{(p)} \neq y^{(p)} \}$$

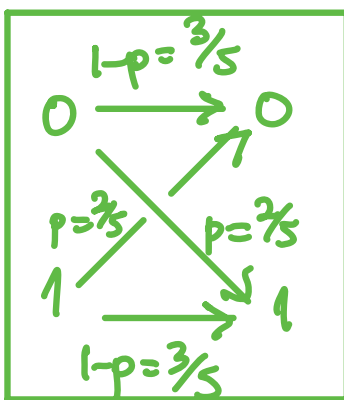
EXAMPLES $d(101, 000) = 2,$
 $d(102, 000) = 2$
 $d(101, 010) = 3$
 $d(101, 101) = 0$

If we don't know much about the source word probabilities, this is a good rule to follow and called **maximum likelihood estimation**,

in that it picks x_i maximizing

$$P(\text{received } y \mid \text{sent } x_i) = p^{d(x_i, y)} (1-p)^{l-d(x_i, y)}$$

EXAMPLE If we send words in $\{0,1\}^*$ of length 2 via repetition code of length $l=4$ through a BSC of error prob $p = \frac{2}{5}$

$$C = \begin{array}{l} x_1 \\ x_2 \\ x_3 \\ x_4 \end{array} \begin{array}{cccc} 0000 \\ 0101 \\ 1010 \\ 1111 \end{array}$$


receiving
 $y = 0111$

then how should we decode?

$$P(y=0111 \text{ rec'd} \mid x_1=0000 \text{ sent}) = \left(\frac{2}{5}\right)^3 \left(\frac{3}{5}\right)^1 = \frac{24}{625}$$

$$x_2=0101 \quad = \left(\frac{2}{5}\right)^1 \left(\frac{3}{5}\right)^3 = \frac{54}{625}$$

$$x_3=1010 \quad = \left(\frac{2}{5}\right)^3 \left(\frac{3}{5}\right)^1 = \frac{24}{625}$$

$$x_4=1111 \quad = \left(\frac{2}{5}\right)^1 \left(\frac{3}{5}\right)^3 = \frac{54}{625}$$

decode y as
one of these
two

What would be an alternative? If we had more info about source probabilities p_1, \dots, p_n , then one could use **ideal decoder/minimum error rule**, maximizing $P(x_i \text{ sent} | y \text{ received})$ via a Bayesian calculation:

$$P(x_i \text{ sent} | y \text{ received}) = \frac{P(x_i \text{ sent} \cap y \text{ received})}{P(y \text{ received})}$$

$$= \frac{P(y \text{ received} | x_i \text{ sent}) \cdot P(x_i \text{ sent})}{P(y \text{ received})}$$

$$= \frac{p^{d(y, x_i)} (1-p)^{l-d(y, x_i)} \cdot p_i}{P(y \text{ received})}$$

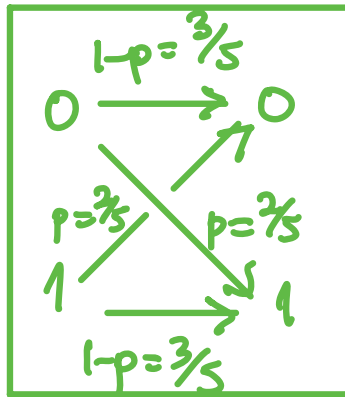
Pick x_i maximizing this numerator

EXAMPLE What if in previous example we had these source probabilities?:

"OK" $\left\{ \begin{array}{l} p_i \\ \frac{1}{2} \\ \frac{1}{6} \\ \frac{1}{6} \\ \frac{1}{6} \end{array} \right.$

various distress signals?

$x_1 = 0000$
 $x_2 = 0101$
 $x_3 = 1010$
 $x_4 = 1111$



receiving
 $y = 0111$

Then the ideal observer maximizes the numerator in

$$P(x_i \mid \text{received}) = \frac{\left(\frac{2}{5}\right)^{d(x_i, 0110)} \cdot \left(\frac{3}{5}\right)^{4-d(x_i, 0110)} \cdot P_i}{P(\text{received})}$$

This numerator is

$\left(\frac{2}{5}\right)^3 \left(\frac{3}{5}\right)^1 \cdot \frac{1}{2} = \frac{12}{625}$	for $x_1 = 0000$
$\left(\frac{2}{5}\right)^1 \left(\frac{3}{5}\right)^3 \cdot \frac{1}{6} = \frac{9}{625}$	for $x_2 = 0101$
$\left(\frac{2}{5}\right)^3 \left(\frac{3}{5}\right)^1 \cdot \frac{1}{6} = \frac{4}{625}$	for $x_3 = 1010$
$\left(\frac{2}{5}\right)^1 \left(\frac{3}{5}\right)^3 \cdot \frac{1}{6} = \frac{9}{625}$	for $x_4 = 1111$

The ideal observer decoding

Channel capacity & Shannon's Noisy Coding Theorem (§4.4, 4.5)

As with $\text{avglength}(f)$ for u.d. codes, is there a limit on the **rate** $\frac{\log_2(|C|)}{l}$ of a choice of length l binary codewords $C \subset \{0,1\}^*$ being sent through a noisy channel

if we would like the probability of undetected error to be made arbitrarily small?

EXAMPLE

Note that if we began with codewords being all 2^l words w_i of length l in $\{0,1\}^*$, and encoding them with the **r -fold repetition code**

$$C = \{w_1, w_2, \dots, w_r\} \subset \{0,1\}^* \text{ with words of length } rl$$

then the **max error probability** $\rightarrow 0$ as $r \rightarrow \infty$ but also

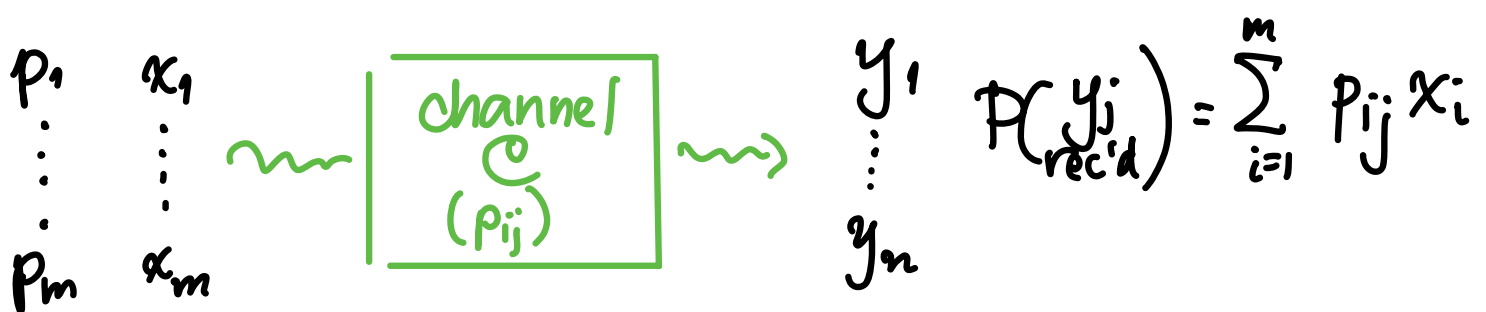
$$\text{rate}(C) = \frac{\log_2(|C|)}{rl} = \frac{\log_2(2^l)}{rl} = \frac{1}{r} \rightarrow 0 \text{ as } r \rightarrow \infty.$$

Q: Can we do better with the rate,
still having error probability $\rightarrow 0$?

Yes, and how much better again
relates to quantifying **information/entropy**

of the source $X = \{x_1, \dots, x_m\}$
probs p_1, \dots, p_m

and the **new source** $Y = \{y_1, \dots, y_n\}$, that has
probabilities calculable from the channel
probabilities matrix $p_{ij} := \mathcal{P}(\text{rec'd } y_j \mid \text{sent } x_i)$



For each event $\{y_j \text{ received}\}$, one can calculate $P(x_i \text{ sent} \mid y_j \text{ received})$ for $j=1, 2, \dots, n$ and use it to define ...

DEFIN: The conditional entropies

$$H(X \mid y_j \text{ received}) := \sum_{i=1}^m P(x_i \text{ sent} \mid y_j \text{ rec'd}) \log_2 \left(\frac{1}{P(x_i \text{ sent} \mid y_j \text{ rec'd})} \right)$$

and then the entropy of X given Y ,

$$H(X \mid Y) = \sum_{j=1}^n P(y_j \text{ rec'd}) H(X \mid y_j \text{ rec'd})$$

and finally the information about X given by Y

$$I(X \mid Y) = H(X) - H(X \mid Y).$$

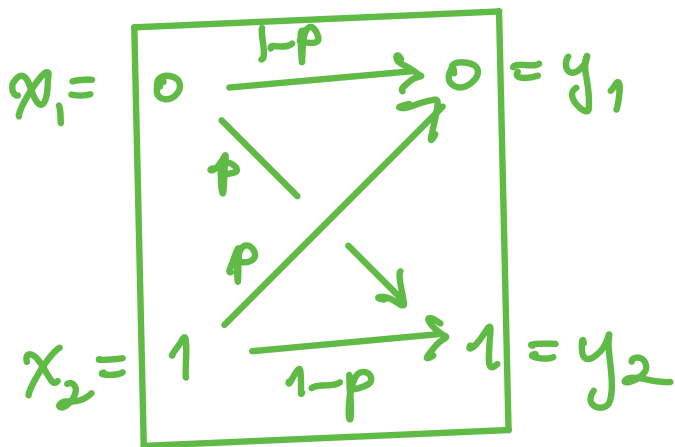
That is, we expect that despite the noise, knowing Y should decrease our surprise about X , by $I(X \mid Y)$ bits.

Finally, we can define ...

DEF'N: The channel capacity of C

$$\text{capacity}(C) := \max \left\{ I(X|Y) : \begin{array}{l} \text{source probabilities} \\ p_1, \dots, p_m \text{ for} \\ X = \{x_1, \dots, x_m\} \end{array} \right\}$$

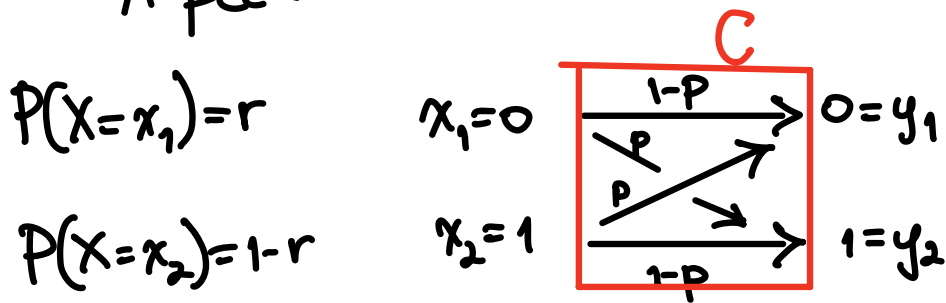
EXAMPLE Garrett calculates with some easy calculus that the BSC with error prob p



$$\text{capacity}(C) = 1 + p \log_2(p) + (1-p) \log_2(1-p)$$

(and max of $I(X|Y)$ is achieved for $P(x_1) = P(x_2) = \frac{1}{2}$, regardless of the BSC error probability p)

A peek inside that calculation of $\text{cap}(C)$ for BSC...



leads to (with some straightforward algebra)

$$f(r) := I(X|Y) = H(X) - H(X|Y)$$

$$= p \log_2(p) + (1-p) \log_2(1-p) - [A \log_2 A + B \log_2 B]$$

where $A = r(1-p) + (1-r)p$
 $B = rp + (1-r)(1-p)$

Want to compute

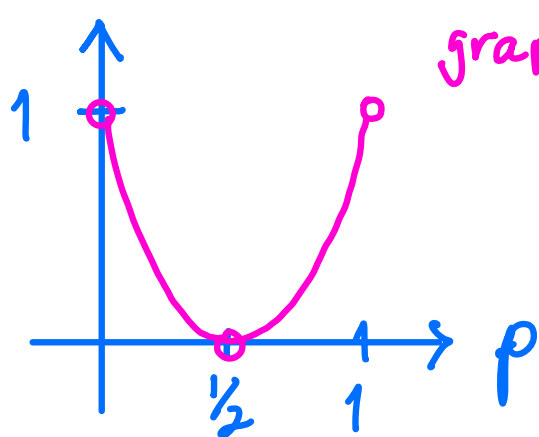
$$\text{cap}(C) = \max_{\substack{(p_1, p_2) \\ r'' \quad 1-r''}} I(X|Y) = \max_r f(r)$$

so set $0 = f'(r) = \frac{d}{dr} f(r)$, and find that it is maximized when $r = \frac{1}{2}$, regardless of p .

But then when $r = \frac{1}{2}$, $A = \frac{1}{2}(1-p) + (1-\frac{1}{2})p = \frac{1}{2}(1-p+p) = \frac{1}{2}$
 $B = \frac{1}{2}p + (1-\frac{1}{2})(1-p) = \frac{1}{2}(p+1-p) = \frac{1}{2}$

$$\text{and } \text{cap}(C) = p \log_2(p) + (1-p) \log_2(1-p) - \left[\frac{1}{2} \log_2\left(\frac{1}{2}\right) + \frac{1}{2} \log_2\left(\frac{1}{2}\right) \right]$$

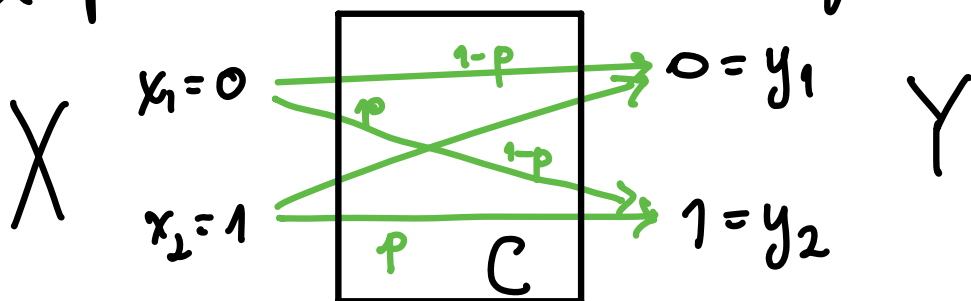
$$= p \log_2(p) + (1-p) \log_2(1-p) + 1$$



graph of $y = \text{capacity (BSC with error prob } p)$
 $= 1 + p \log_2(p) + (1-p) \log_2(1-p)$

EXAMPLE Note BSC with error prob $p = 1/2$ has capacity $1 + \frac{1}{2} \log_2(\frac{1}{2}) + \frac{1}{2} \log_2(\frac{1}{2}) = 1 - \frac{1}{2} - \frac{1}{2} = 0$

It's a special case of this family of **useless** channels:



where one can check that for any choice of source probabilities $X = \{x_1, x_2\}$, one has

probs: p_1, p_2

$$X, Y \text{ independent} \Rightarrow H(X | y_j \text{ occurs}) = H(X) \quad \forall y_j \in Y$$

$$\Rightarrow H(X|Y) = H(X)$$

$$\text{i.e. } I(X|Y) = 0$$

$$\Rightarrow \text{capacity}(C) = 0.$$

No way to detect errors, even with long repetition codes and very low rates!

Shannon's Noisy Coding Thm (§4.5)

Let C be a memoryless channel, and pick any R in the range $0 < R < \text{capacity}(C)$.

Then one can find a sequence of codes

$$C_n \subset \{0,1\}^* \text{ for } n=1,2,3,\dots$$

with

- C_n consists of words of length n

- $\text{rate}(C_n) \rightarrow R$ as $n \rightarrow \infty$

- using max likelihood (=min Hamming distance)

decoding, the max probability of a word in C_n being decoded wrong

$\rightarrow 0$ as $n \rightarrow \infty$.

Roman §3.4.4 states it, but both he and Garrett prove it only for the BSC with error probability p .

An interesting feature of the proof is, using fairly easy probabilistic estimates, one can pick C_n with high probability to be

$2^{\lfloor R \cdot n \rfloor}$ randomly chosen (!) words
of length n

(so $\text{rate}(C_n) = \frac{\lfloor R \cdot n \rfloor}{n} \rightarrow R$ as $n \rightarrow \infty$)

DRAWBACK: Efficiently doing minimum-distance decoding with C chosen randomly is hard.

Roman also proves an accompanying result:

THEOREM (Weak Converse to Shannon's Noisy Coding Thm.)

[Roman
Thm. 3.3.6]

Let C be a discrete memoryless channel,
and pick any $R > \text{cap}(C)$.

Let $\mathcal{C}_n \subset \{0,1\}^n$ for $n=1,2,3,\dots$ be **any** sequence of
length n binary codes that have $|\mathcal{C}_n| \approx 2^{nR}$
(so that $\text{rate}(\mathcal{C}_n) = \frac{\log_2(|\mathcal{C}_n|)}{n} \approx \frac{\log_2(2^{nR})}{n} = \frac{nR}{n} = R$).

Then assuming codewords from \mathcal{C}_n are chosen
uniformly at random, when passing them through C
and doing minimum distance decoding,

$$\left(\begin{array}{l} \text{probability} \\ \text{of error} \\ \text{in decoding} \\ \text{from } \mathcal{C}_n \end{array} \right) \geq 1 - \frac{1}{nR} - \frac{\text{cap}(C)}{R}$$

↓ as $n \rightarrow \infty$

$$1 - \frac{\text{cap}(C)}{R} \geq 0.$$

↑ since $R > \text{cap}(C)$

BAD!