

Noisy Channel Coding:

Correlated Random Variables & Communication over a Noisy Channel

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Contents

- More entropy definitions
 - joint & conditional entropy
 - mutual information
- Communication over a noisy channel
 - overview
 - information conveyed by a channel
 - noisy channel coding theorem

Joint Entropy

Joint entropy of X, Y is:

$$H(X, Y) = \sum_{xy \in \mathcal{A}_X \mathcal{A}_Y} P(x, y) \log \frac{1}{P(x, y)}$$

Entropy is additive for independent random variables:

$$H(X, Y) = H(X) + H(Y) \text{ iff } P(x, y) = P(x)P(y)$$

Conditional Entropy

Conditional entropy of X given Y is:

$$H(X|Y) = \sum_{y \in \mathcal{A}_Y} P(y) \left[\sum_{x \in \mathcal{A}_X} P(x|y) \log \frac{1}{P(x|y)} \right] = \sum_{y \in \mathcal{A}_X \mathcal{A}_Y} P(x, y) \log \frac{1}{P(x|y)}$$

It measures the average uncertainty (*i.e.* information content) that remains about x when y is known.

Mutual Information

Mutual information between X and Y is:

$$I(Y; X) = I(X; Y) = H(X) - H(X|Y) \geq 0$$

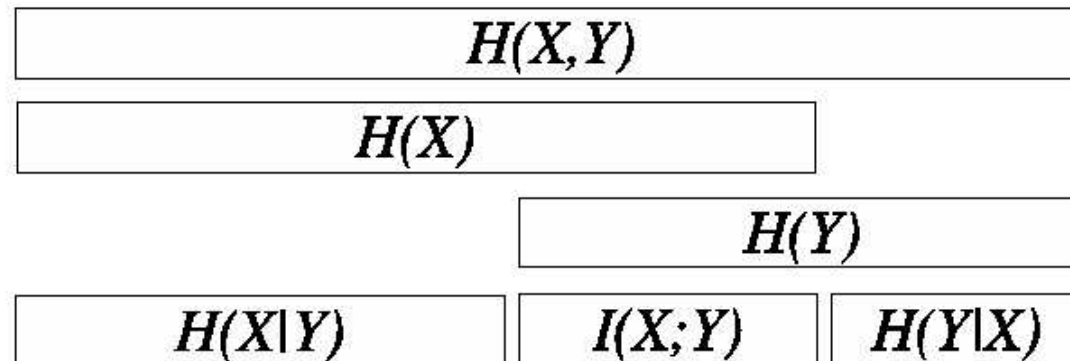
It measures the average reduction in uncertainty about x that results from learning the value of y , or vice versa.

Conditional mutual information between X and Y given Z is:

$$I(Y; X|Z) = H(X|Z) - H(X|Y, Z)$$

Breakdown of Entropy

Entropy relations:



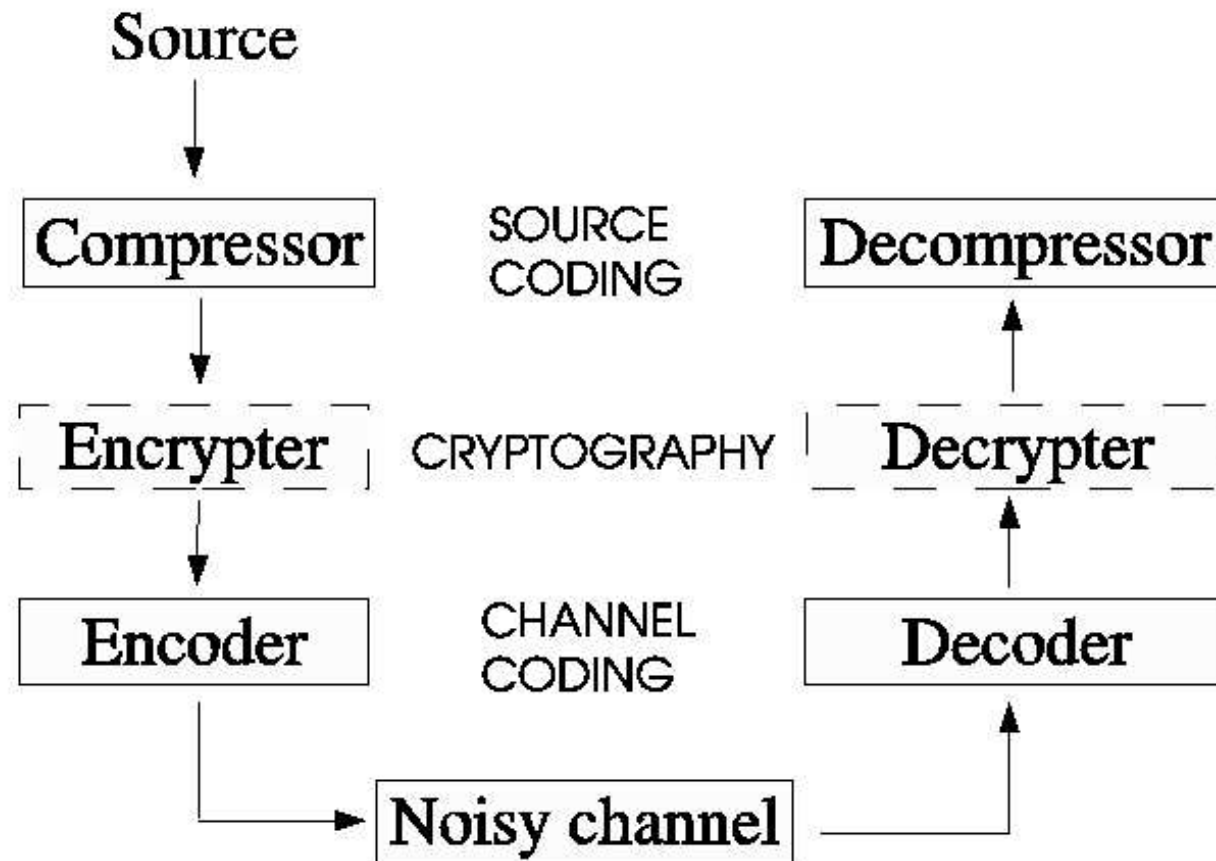
Chain rule of entropy:

$$H(X, Y) = H(X) + H(Y|X) = H(Y) + H(X|Y)$$

Noisy Channel: Overview

- Real-life communication channels are hopelessly noisy *i.e.* introduce transmission errors
- However, a solution can be achieved
 - the aim of source coding is to remove redundancy from the source data
 - the aim of channel coding is to make a noisy channel behave like a noiseless one via controlled adding of redundancy

Noisy Channel: Overview (Cont.)



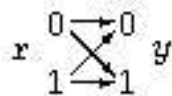
Noisy Channels

- General discrete memoryless channel is characterized by:
 - input alphabet \mathcal{A}_X
 - output alphabet \mathcal{A}_Y
 - set of conditional probability distributions $P(y|x)$, one for each $x \in \mathcal{A}_X$
- These transition probabilities can be written in a matrix form:

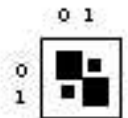
$$Q_{j|i} = P(y = b_j | x = a_i)$$

Noisy Channels: Useful Models

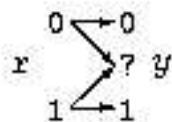
Binary symmetric channel. $\mathcal{A}_X = \{0, 1\}$. $\mathcal{A}_Y = \{0, 1\}$.



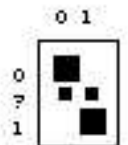
$$\begin{aligned}
 P(y=0 | r=0) &= 1 - f; & P(y=0 | r=1) &= f; \\
 P(y=1 | r=0) &= f; & P(y=1 | r=1) &= 1 - f.
 \end{aligned}$$



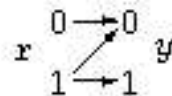
Binary erasure channel. $\mathcal{A}_X = \{0, 1\}$. $\mathcal{A}_Y = \{0, ?, 1\}$.



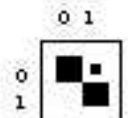
$$\begin{aligned}
 P(y=0 | r=0) &= 1 - f; & P(y=0 | r=1) &= 0; \\
 P(y=? | r=0) &= f; & P(y=? | r=1) &= f; \\
 P(y=1 | r=0) &= 0; & P(y=1 | r=1) &= 1 - f.
 \end{aligned}$$



Z channel. $\mathcal{A}_X = \{0, 1\}$. $\mathcal{A}_Y = \{0, 1\}$.



$$\begin{aligned}
 P(y=0 | r=0) &= 1; & P(y=0 | r=1) &= f; \\
 P(y=1 | r=0) &= 0; & P(y=1 | r=1) &= 1 - f.
 \end{aligned}$$



Inferring Channel Input

- If we receive symbol y , what is the probability of input symbol x ?
- Let's use the Bayes' theorem:

$$P(x|y) = \frac{P(y|x)P(x)}{P(y)} = \frac{P(y|x)P(x)}{\sum_{x'} P(y|x')P(x')}$$

Example: a Z-channel has $f = 0.15$ and the input probabilities (*i.e.* ensemble) $p(x = 0) = 0.9, p(x = 1) = 0.1$. If we observe $y = 0$,

$$P(x = 1|y = 0) = \frac{0.15 * 0.1}{0.15 * 0.1 + 1 * 0.9} = 0.26$$

Information Transmission over a Channel

- What is a suitable measure for transmitted information?
- Given what we know, the mutual information $I(X; Y)$ between the source X and the received signal Y is sufficient
 - remember that:
$$I(Y; X) = I(X; Y) = H(X) - H(X|Y)$$

= the average reduction in uncertainty about x that results from learning the value of y , or vice versa.
 - on average, y conveys information about x if $H(X|Y) < H(X)$

Information Transmission over a Channel (Cont.)

- In real life, we are interested in communicating over a channel with a negligible probability of error
- How can we combine this idea with the mathematical expression of conveyed information, i.e.

$$I(X; Y) = H(X) - H(X|Y)$$

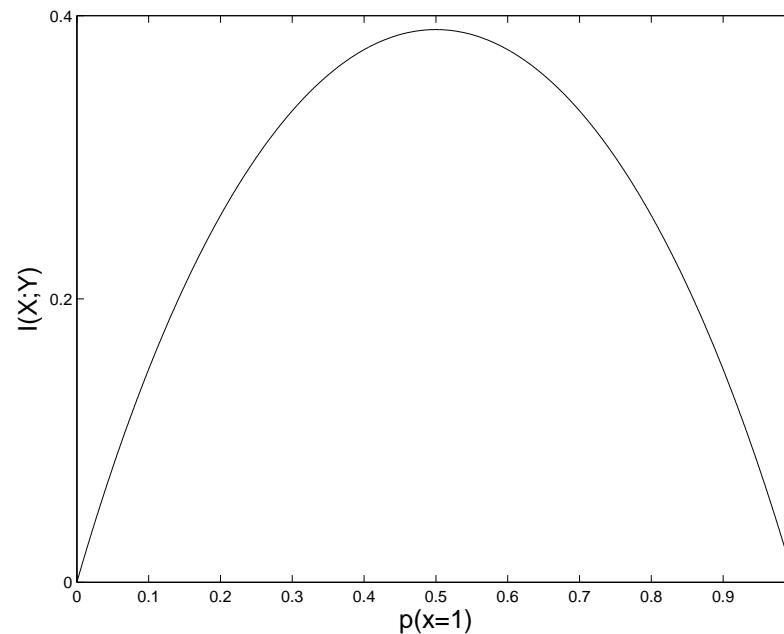
- Often it is more convenient to calculate mutual information as
- $$I(X; Y) = H(Y) - H(Y|X)$$

Information Transmission over a Channel (Cont.)

- Mutual information between the input and the output depends on the input ensemble \mathcal{P}_X
- Channel capacity is defined as the maximum of its mutual information
- The optimal input distribution maximizes mutual information

$$C(Q) = \max_{\mathcal{P}_X} I(X; Y)$$

Binary Symmetric Channel Mutual Information



$I(X;Y)$ for a binary symmetric channel with $f = 0.15$ as a function of input distribution

Noisy Channel Coding Theorem

- It seems plausible that channel capacity C can be used as a measure of information conveyed by a channel

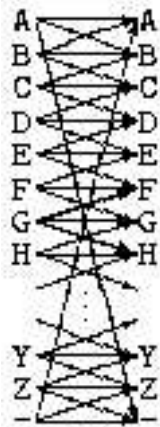
- What is not so obvious:

Shannon's noisy channel coding theorem (pt.1):

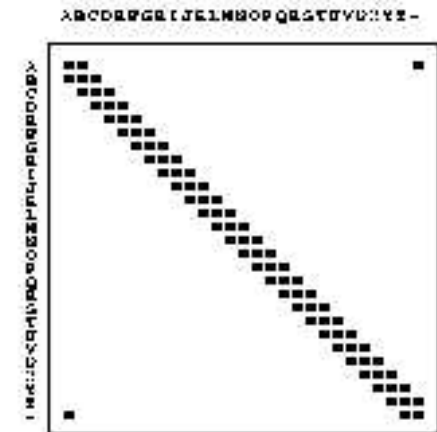
All discrete memoryless channels have non-negative capacity C . For any $\epsilon > 0$ and $R < C$, for large enough N , there exists a block code of length N and rate $\geq R$ and a decoding algorithm, such that the maximal probability of block error is $< \epsilon$

Proving the Noisy Channel Coding Theorem

Let's consider Shannon's theorem and a *noisy typewriter* channel:



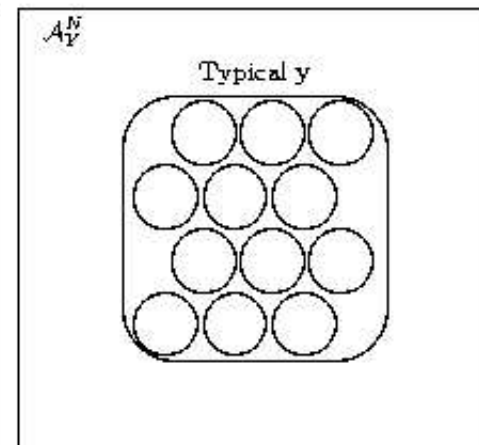
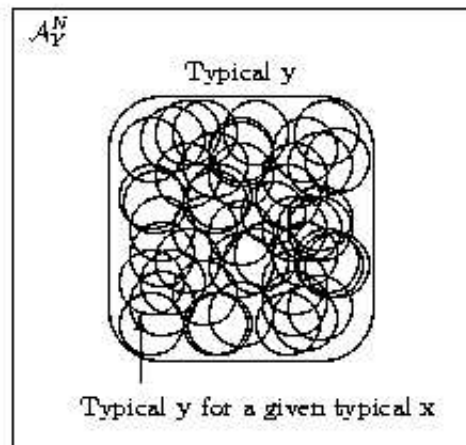
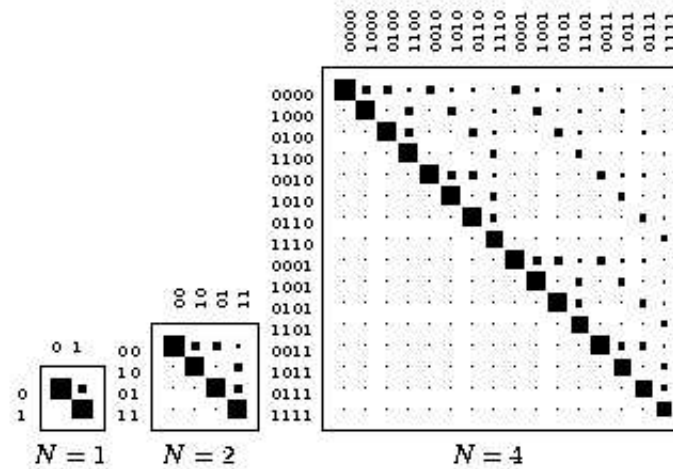
$$\begin{aligned} P(y=F | r=G) &= 1/3; \\ P(y=G | r=G) &= 1/3; \\ P(y=H | r=G) &= 1/3; \\ &\vdots \end{aligned}$$



Proving the Noisy Channel Coding Theorem (Cont.)

- Consider next *extended channels*:
 - corresponds to N uses of a single channel (block codes)
 - an extended channel has $|\mathcal{A}_x|^N$ possible inputs x and $|\mathcal{A}_y|^N$ possible outputs
- If N is large, x is likely to produce outputs only in a small subset of the output alphabet
 - extended channel looks a lot like a noisy typewriter

Example: an Extended Z-channel



Homework

- 8.10: mutual information
- 9.17: channel capacity