

Applications of Information Theory

- ▶ Data compression
- ▶ Error correcting codes
- ▶ Cryptology
- ▶ Linguistics
- ▶ Statistics
- ▶ Computer science: distributed storage systems, caching, . . .
- ▶ Network information theory
- ▶ Bioinformatics: computational genomics, information flow in neural systems, . . .
- ▶ Machine learning

Machine Learning

- ▶ a large variety of machine learning and data-mining problems are about **inferring global** properties on a collection of agents by observing **local noisy** interactions of these agents.
- ▶ Examples
 - community detection in social networks,
 - image segmentation
 - data classification/clustering and information retrieval
 - protein-to protein interactions

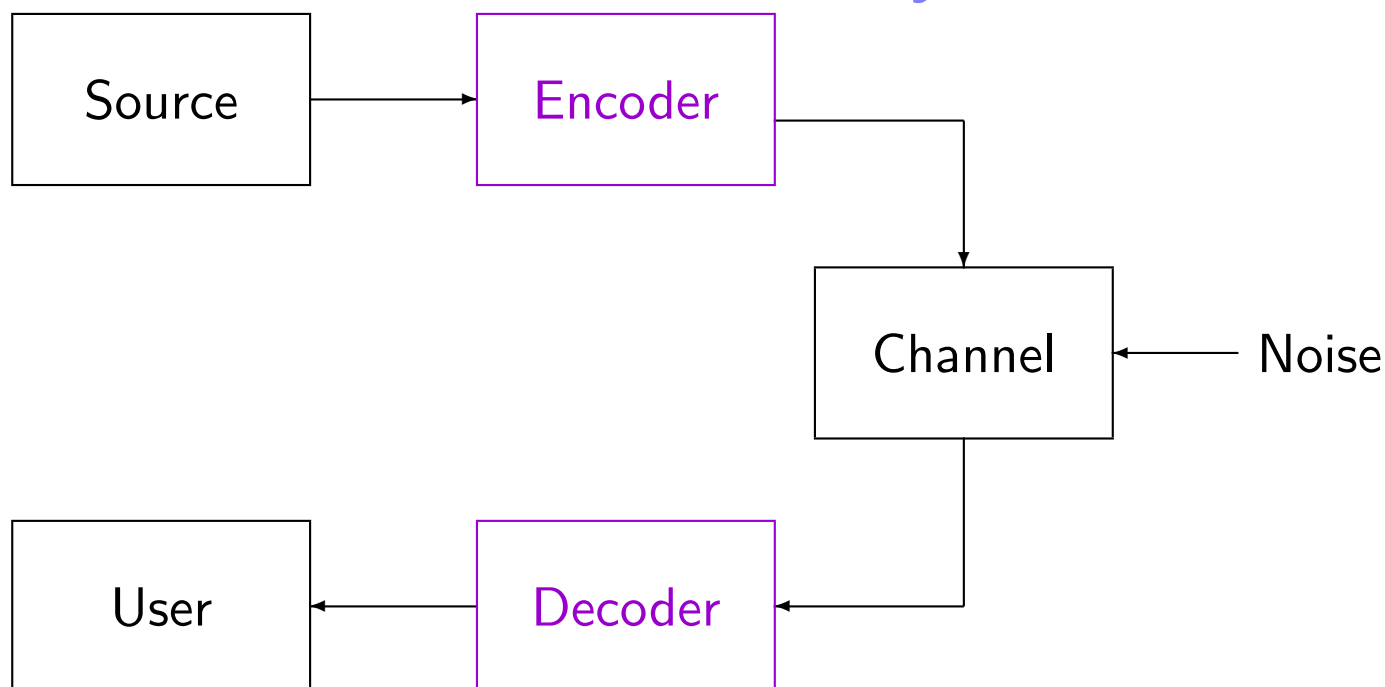
Information Theory?

- ▶ \mathcal{L}_1 and \mathcal{L}_2 two very large lists.
- ▶ Problem: find $(x_1, x_2) \in \mathcal{L}_1 \times \mathcal{L}_2$ such that $d(x_1, x_2)$ is small with time complexity $\ll |\mathcal{L}_1| \cdot |\mathcal{L}_2|$.
- ▶ Problem: given y , find whether there exists $x_1 \in \mathcal{L}_1$ such that $d(y, x_1)$ is small with time complexity $\ll |\mathcal{L}_1|$.

Content

- ▶ Upper bound on the compression rate of a source and on the information that passes through a noisy channel,
- ▶ algorithms that allow to attain these upper bounds.
- ▶ Other applications: distributed data storage.

Communication System

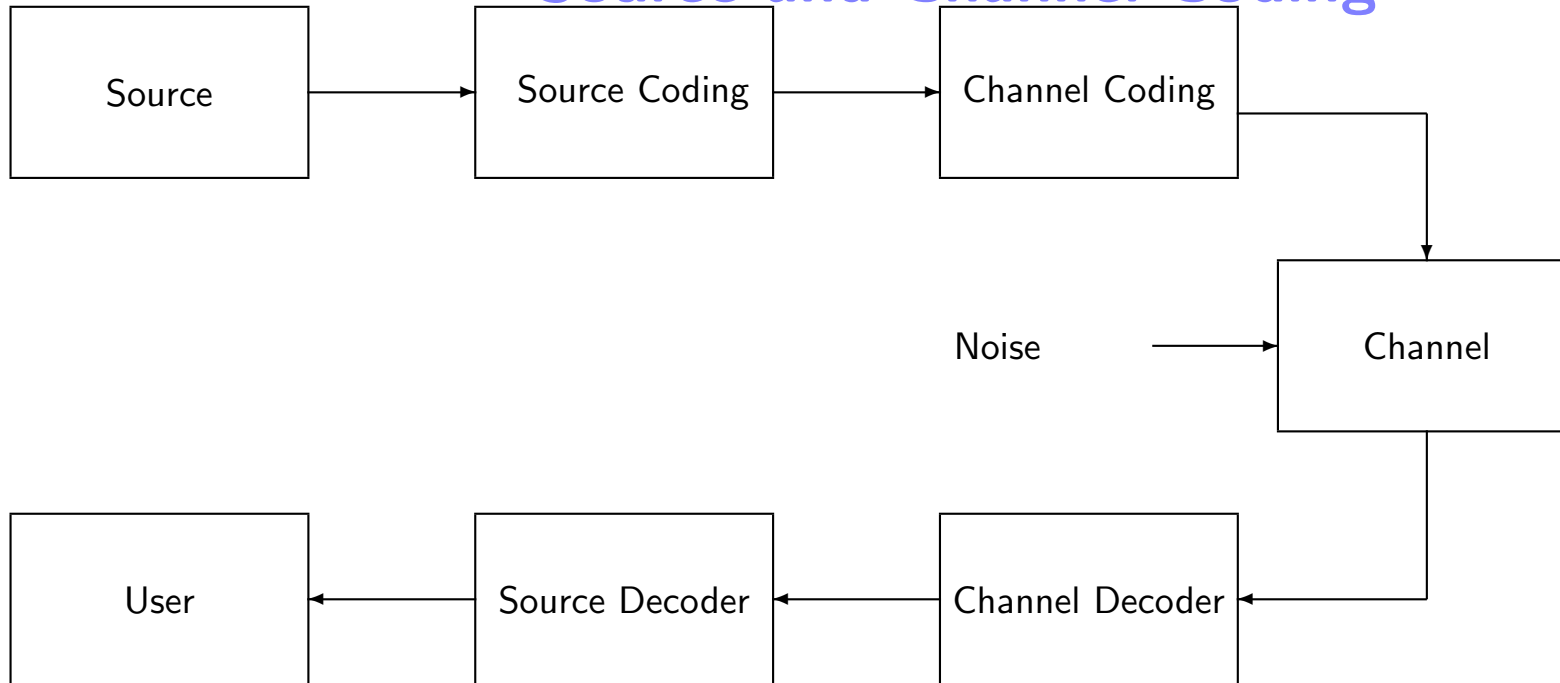


Source : voice, music, images, text, . . .

Channel : wireless communications, wire, optical fiber, flash drive,

Noise : electromagnetic perturbations, rain, inter-cell interferences, . . .

Source and Channel Coding



Efficiency: Transmit a maximum amount of information to another user by using a minimum amount of resources.

Reliability: The user should be able to recover the correct information (as much as possible)

Source/Channel Coding

Problem:

- **Source Coding:** compress efficiently a given source at a maximal compression rate. Ex:

$$\mathbf{x} = x_1 \dots x_n, \mathbf{Prob}(x_i = 1) = p.$$

- **Channel Coding:** transmit efficiently a maximum amount of information through a noisy channel. Ex:

$$\mathbf{x} = x_1 \dots x_n \xrightarrow{\text{channel}} \mathbf{y} = y_1 \dots y_n, \mathbf{Prob}(y_i \neq x_i) = p.$$

A same quantity is used in both cases : **entropy**.

Source/Channel Coding

Problem:

- **Source coding:** compress efficiently a given source at a maximal compression rate. Ex:

$$\mathbf{x} = x_1 \dots x_n, \mathbf{Prob}(x_i = 1) = p.$$

⇒ compress into a sequence of size $\approx nh(p)$ bits.

- **Channel Coding:** transmit efficiently a maximum amount of information through a noisy channel. Ex:

$$\mathbf{x} = x_1 \dots x_n \xrightarrow{\text{channel}} \mathbf{y} = y_1 \dots y_n, \mathbf{Prob}(y_i \neq x_i) = p.$$

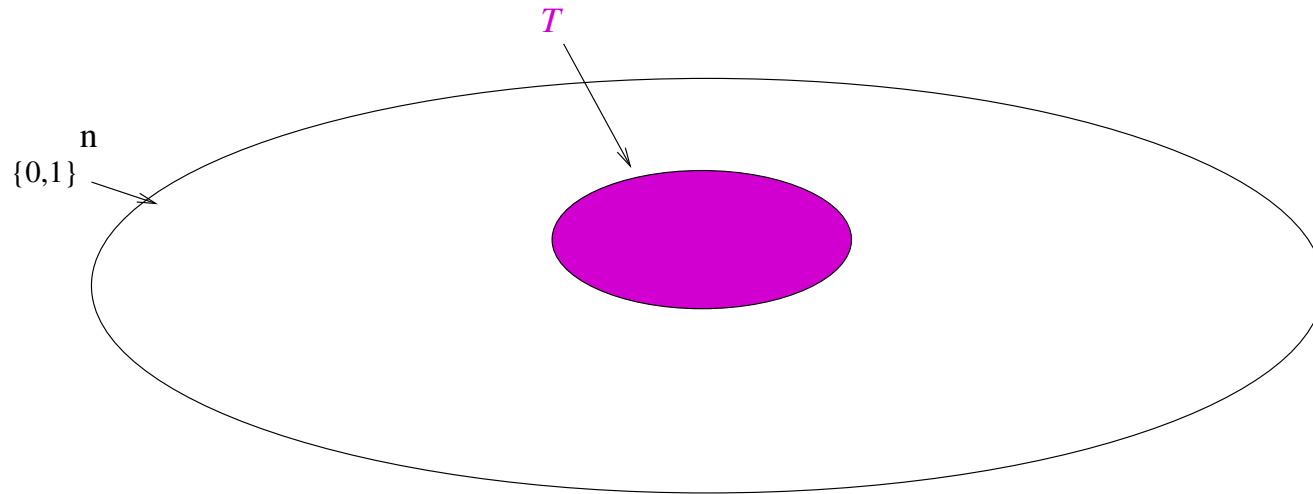
⇒ transmit $\approx n(1 - h(p))$ bits of information.

A same quantity is used in both cases : **entropy**.

$$h(p) \stackrel{\text{def}}{=} -p \log_2 p - (1 - p) \log_2(1 - p)$$

Entropy and typical sequences

A common principle : focus on typical outputs



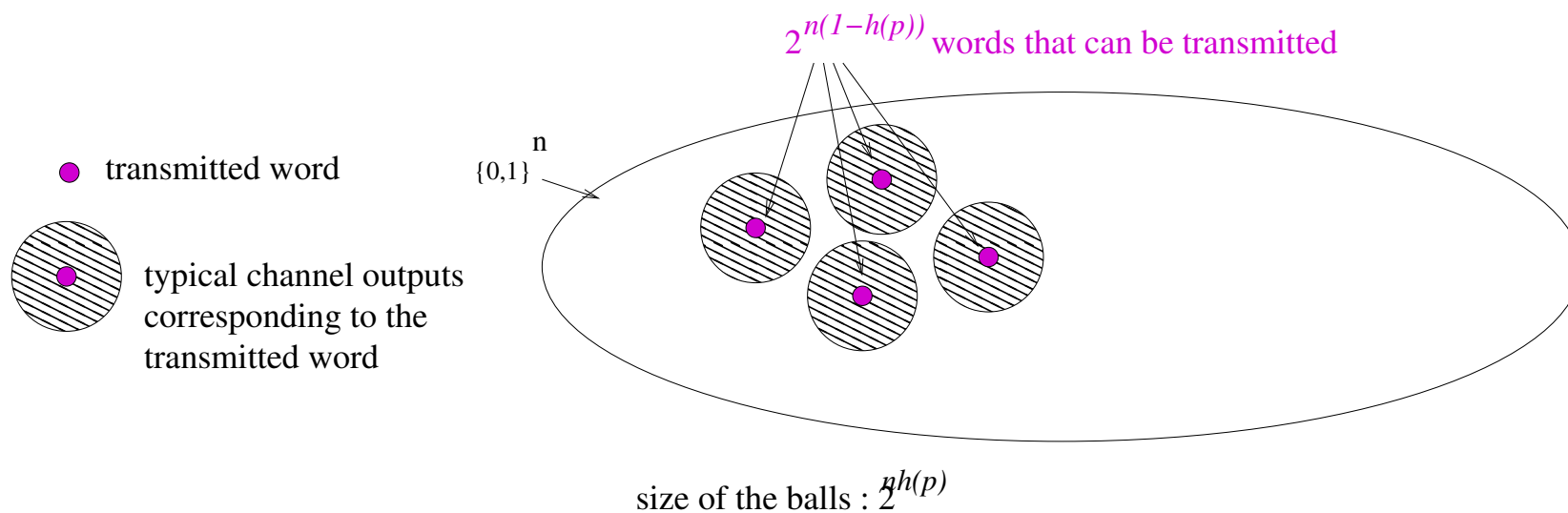
$$T = \{\mathbf{x}; |\mathbf{x}| \approx pn\}$$

$$\mathbf{Prob}(\mathbf{x} \in T) \approx 1$$

$$|T| \approx 2^{nh(p)}$$

$$\log_2 |T| \approx \text{Entropy}$$

- ▶ **Source Coding** : number with $nh(p)$ bits the elements of T and do nothing for the others.
- ▶ **Channel Coding** :



$\log(\text{number of words that can be transmitted}) = \text{number of bits of information}$

Entropy

Formula can be explained by two facts

(i) log transforms a product into a sum,

(ii) concentration of a sum of i.i.d. r.v. around their expectation.

$$\begin{aligned}\log \mathbf{Prob}(\mathbf{x}) &\stackrel{(i)}{=} \log \mathbf{Prob}(x_1) + \cdots + \log \mathbf{Prob}(x_n) \\ &\stackrel{(ii)}{\approx} n(p \log p + (1-p) \log(1-p)) = -nh(p)(a.s.) \\ \Rightarrow \mathbf{Prob}(\mathbf{x}) &\approx 2^{-nh(p)}(a.s.)\end{aligned}$$

More generally for a r.v. X taking its values in \mathcal{A} :

$$\text{Entropy}(X) \stackrel{\text{def}}{=} - \sum_{a \in \mathcal{A}} \mathbf{Prob}(X = a) \log \mathbf{Prob}(X = a).$$

Repetition Code

To fight against noise, **redundancy** is added. For instance with the repetition code of length 3

$$0 \mapsto 000$$

$$1 \mapsto 111$$

or more generally with a repetition code of length $2m + 1$.

$$0 \mapsto \overbrace{0 \dots 0}^{2m+1}$$

$$1 \mapsto \overbrace{1 \dots 1}^{2m+1}$$

Repetition Code

For an error probability of the channel $p = 0.01$, there are 0 or 1 corrupted bits with probability

$$(1 - p)^3 + 3p(1 - p)^2 \approx 0.9997$$

and 2 or 3 errors with probability

$$3p^2(1 - p) + p^3 \approx 3 \times 10^{-4}$$

Information is badly recovered with probability $\approx 3 \times 10^{-4}$. With a repetition code of length 5, this probability drops to 10^{-5} .

$$10p^3(1 - p)^2 + 5p^4(1 - p) + p^5 \approx 10^{-5}$$

The rate of this code is 0.2.

Rate of a code

The repetition code of length 3 has rate $1/3 = 0.33$ and corrects one error.

The repetition code of length 5 has rate $1/5 = 0.2$ and corrects two errors.

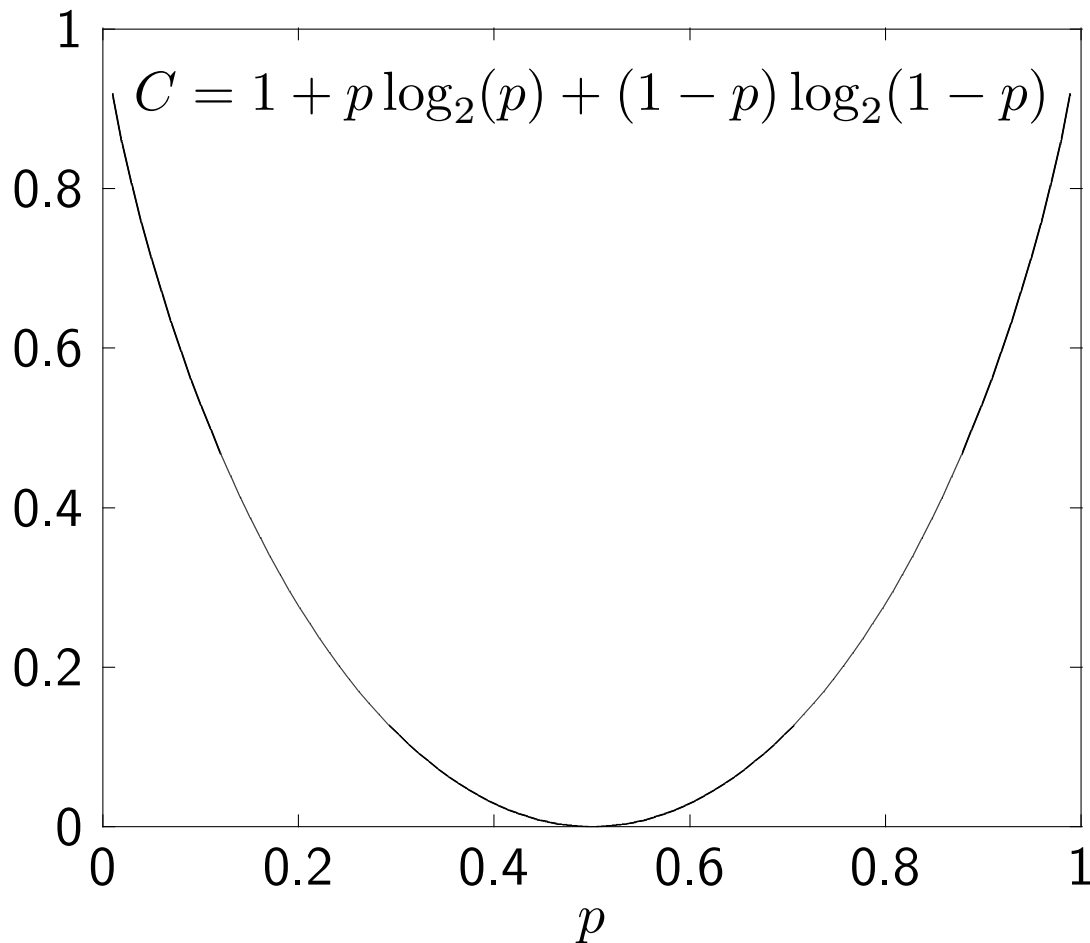
By lowering the rate, one can also lower the error probability after decoding.

Does the best transmission rate have to go to 0 ?

No ! Shannon's second theorem.

Notion of channel capacity.

Capacity of a binary symmetric channel



The capacity is the **maximum rate** at which reliable transmission is still possible.

For ex. $C(0.01) = 0.919$. It is therefore possible to improve significantly upon the repetition code.

Fundamental Results of this Course

Shannon's 1st theorem (Source Coding)

1. Every “reasonable” source can be encoded by using a number of bits per source symbol which is arbitrarily close to the source **entropy**.
2. **It is impossible to do better...**

Shannon's 2nd theorem (Channel Coding)

1. Information can be transmitted **reliably** by using an error correcting code with a rate smaller than the channel capacity.
2. **It is impossible to do better.**

TD

Today : exercise session.

Then programming algorithms in Java (4TD's on source coding, 3 TD's on channel coding, 1TD on distributed data storage).