First abstract setup: two random variables: X and Y

Let X - (Source) and Y (Destination) be two random variables ranging over collections. Both can be interpreted in many ways, but for cognitive science applications Source will be an external (internal) source having some variability H (entropy) and Destination a collection of possible objects, such as types, actions, etc.

In any abstract setup there always is symetrical measure of information relation between the two. Mutual information $I(X;Y)$ as reduction in uncertainty

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

Mutual information is the drop in entropy of one variable once the other is known.

This way of speaking about introduces the psychological aspect of theory of information (uncertainty , surprise, knowledge) Mutual information as expectation over the joint distribution

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

Computed directly from the joint and marginal probabilities of the variables.

First causal setup of pipeline

To model some aspects of cognition (e.g perception) the abstract pair of random variables of X and Y is interpreted causally:

There is a causal relationship between the source and the destination, i.e. the is a directed physical (e.g. biophysical) relationship between the two.

This causal, mechanists interpretation immediately solves the symmetry problem appearing: the destination information is such and such because the source information is such and such.

Let X - "Source" and Y = "Destination" be two random variables. There can be interpreted in many ways, here Source will be an external source having some variability (entropy) and Destination a collection of possible objects, such as types, actions, etc.

A first relation between these variables is mutual information

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

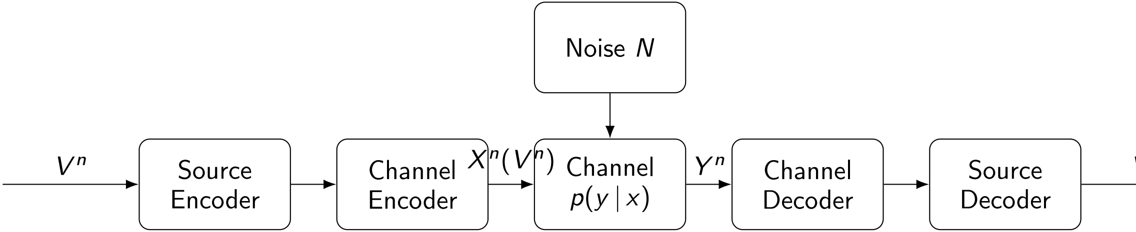
where:

- $I(X;Y)$ is the mutual information between random variables X and Y,
- $p(x,y)$ is the joint probability distribution of X and Y,
- $p(x)$ and $p(y)$ are the marginal probability distributions of X and Y, respectively.

Mutual information quantifies the amount of information obtained about one random variable

Shannon pipeline with source and channel coding separation

The Shannon pipeline with source and channel encoding / decoding parts: communication model



Cover and Thomas, 2006