

Chapter 1: The Science of Information

April 18, 2020

Two Basic Concepts

- Information is **uncertainty**: modeled by random variable
- Information is **digital**: transmission should be 0's and 1's (bits) w/o reference to what they really represent.

Two Fundamental Theorem

- **Source Coding Theorem**
 - No matter how smart the **compression system** designed, there is a fundamental limit the data compression.
- **Channel Coding Theorem**
 - No matter how smart the **communication system** designed, for reliable communication, there exists a maximum rate that information can be transmitted through the channel.
 - This quality is called the **communication capacity**.
 - P.S. data storage can also be a form a data communication (from the past to the future).

Links

Wikipedia: [Information Theory](#)

> Information Theory

- **Bit**: the most fundamental unit of information.
- **Important quantities of information**:
 - **Entropy**: a measure of information in a single random variable.
 - Gives a limit on the rate at which data can be reliably compressed.
 - **Mutual Information**: a measure of information in common for two random variables.
 - Gives a limit on the rate of reliable communication across a noisy channel.
- **Terms**:
 - **Entropy**:
 - $H = \mathbb{E}_X[-\log p(x)] = -\sum_i p_i \log_2(p_i)$
 - This equation gives the entropy in the units of "bits" (per symbol) because it uses a logarithm of base 2.
 - $H(X) = \mathbb{E}_X[I(x)] = -\sum_{x \in \mathbb{X}} p(x) \log p(x)$

- $I(x)$ is the self-information, which is the entropy contribution of an individual message.
- **Joint Entropy:**
 - $H(X, Y) = \mathbb{E}_{X,Y}[-\log p(x, y)] = -\sum_{x,y} p(x, y) \log p(x, y)$
- **Conditional Entropy:**
 - $H(X|Y) = \mathbb{E}_Y[H(X|y)] = -\sum_{y \in Y} p(y) \sum_{x \in X} p(x|y) \log p(x|y) = -\sum_{x,y} p(x, y) \log p(x|y)$
 - $H(X|Y) = H(X, Y) - H(Y)$
- **Mutual Information:**
 - Measures the amount of information that can be obtained about one *r.v.*, by observing another (e.g. the mutual information of x relative to y).
 - It can be used to maximize the information shared between sent and received signals.
 - $I(X; Y) = \mathbb{E}_{X,Y}[SI(x, y)] = \sum_{x,y} p(x, y) \log \frac{p(x,y)}{p(x)p(y)}$
 - $I(X; Y) = H(X) - H(X|Y)$
 - $I(X; Y) = I(Y; X) = H(X) + H(Y) - H(X, Y)$
 - $I(X; Y) = \mathbb{E}_{p(y)} [D_{\text{KL}}(p(X|Y=y) \| p(X))]$
 - $I(X; Y) = D_{\text{KL}}(p(X, Y) \| p(X)p(Y))$
- **KL-Divergence / Information Gain:**
 - KL-Divergence is the number of average additional bits per datum necessary for compression.
 - "Unnecessary surprise" by the prior from the truth:
 - $D_{\text{KL}}(p(X) \| q(X)) = \sum_{x \in X} -p(x) \log q(x) - \sum_{x \in X} -p(x) \log p(x)$
 - $D_{\text{KL}}(p(X) \| q(X)) = \sum_{x \in X} p(x) \log \frac{p(x)}{q(x)}$

> Coding Theory

- **Coding theory** is concerned with **finding explicit methods**, called *codes*, for *increasing the efficiency* and *reducing the error rate* of **data communication** over noisy channels to near the *channel capacity*.
 - Data compression: Source coding.
 - Any process that generates successive messages can be considered as a **source** of information.
 - Error correction: Channel coding.
- **Classification**
 - **Source Coding** (Data Compression)
 - **Lossless Data Compression**
 - **Lossy Data Compression / Rate-Distortion Theory**
 - **Channel Coding** (Error Correcting)
- Compression followed by transmission is optimal for only one transmitter and one receiver. When there are multiple, we will use network information theory.
- **Information rate** is the average entropy per symbol.
 - $r = \lim_{n \rightarrow \infty} \frac{1}{n} H(X_1, X_2, \dots, X_n)$

- The rate of a source of information is related to its *redundancy* and how well it can be *compressed*.
- **Channel capacity:**
 - $C = \max_f I(X; Y)$

Wikipedia: Claude Shannon

- Shannon's mouse appears to have been the first artificial learning device of its kind.
- Shannon developed Alzheimer's disease and spent the last few years of his life in a nursing home.