

“Information is the resolution of uncertainty.”

Shannon

Erfan Mirzaei

Information Theory Mini-Course

Sep 2022



---

# Session 1

Information  
Entropy

---

# Information

- What is information?
  - Philosophical question
  - All animals, humans, even plants communicate information. [Language]
  - What is **conveyed** or **represented** by a particular arrangement or sequence of things.
- Can we measure information? [What is our intuition?]
- You are lost in an island and can not hear the voice of each other:
-  OR  [You have enough of them.]
- Persian Language: 32 letters

Sol: Send All the letters respectively, with how many stones?

# Information

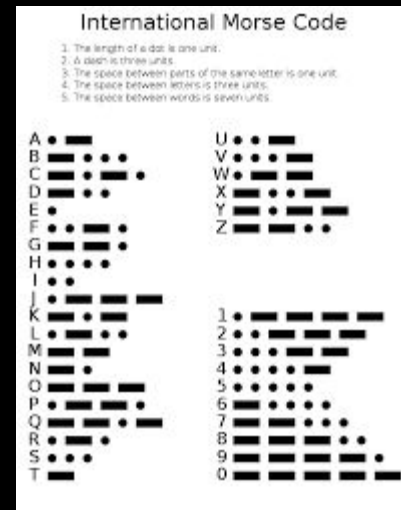
- Can you do better?
  - Yes, you can :)
  - $\text{Log}_2 26 = 4.8$  vs. 4.1257
- Underlying Assumption:

# bits =  $\text{Log } N \longrightarrow$  They're equiprobable.

# bits =  $\text{Log } 1/(1/N) = \text{Log } 1/p$

\*Note: Base of logarithm depends on your language.

Probability of a random event is reciprocal proportional with number of bits needed to **represent** it.



# Information vs. Probability vs. Surprise

- Imagine yourself in the describe situation, and now think you didn't receive stones. Now you should guess that what had been the letter?
- It is easier to guess in Persian or English?
- If an oracle say the right answer to you, in which case you gain more information?
- Less probable events  $\rightarrow$  **more surprising events**  $\rightarrow$  events which contain more information if happen/reveal  $\rightarrow$  # bits need to describe events

# Information measure: Entropy

- Properties of Information
  - Deterministic Outcome  $\rightarrow$  zero information
  - Probability is Decreasing  $\rightarrow$  information increasing
  - Information content of independent random variables is additive.
- 1948: “Mathematical Theory of communication”, Shannon

$$H(X = x) = \log_2 1/P(X=x) = - \log_2 P(X = x)$$

I think our example can explain why we should use log  
for information measure and its relation to bits.

Do you agree with me?



Claude Shannon



John von Neumann

# Information measure: Entropy

- Def of Entropy of a random variable  $X$  is: [Expected Value of  $\log_2 -P(X)$ ]

$$\begin{aligned} H(X) &= -\sum_x P(x) \cdot \log P(x) \\ &= \sum_x \underbrace{P(x)}_{\text{The prob. of event } x} \cdot \underbrace{\log\left(\frac{1}{P(x)}\right)}_{\text{WHAT IS THIS?}} \end{aligned}$$

$$X = \{1, 2, 3, 4, 5, 6\}$$

$$H(X) = 6 * \log(1/6) = 2.48 \text{ bits}$$

# Entropy properties

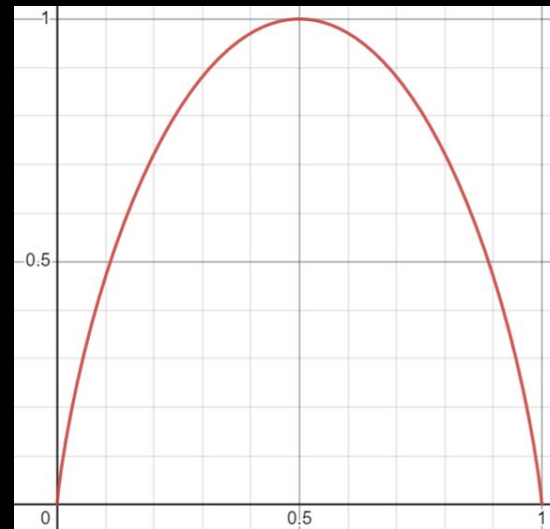
- $H(X) \geq 0$
- $H(X) = H(2X) \rightarrow H(X)$ ,  $g$  is one-2-one func.  $\rightarrow H(g(X)) = H(X)$
- $X = \{0 \text{ with } p, 1 \text{ with } 1-p\} \rightarrow$

$$H(X) = -p * \log_2 p - (1-p) * \log_2 (1-p)$$

Its argmax is 0.5. When events are equiprobable.

i.e when probability distribution is uniform.

$$p = 0, p = 1 \rightarrow H(X) = 0$$





# Thanks for your attention

Erfan Mirzaei  
erfunmirzaei@gmail.com