

# Lesson 4

## Entropy

### 4-1: Information Measures

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Math 574, Topics in Logic

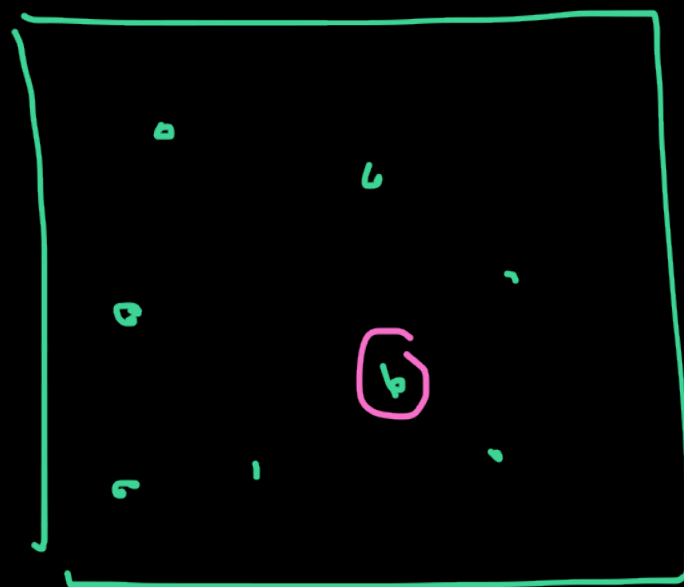
Penn State, Spring 2014

# Combinatorial Information

Suppose  $X$  is a finite, non-empty set. We choose an element in  $X$  and want to communicate the information which  $x \in X$  we chose to someone else.

**Binary channel:** We can transmit only strings of 0 and 1.

**Question:** How many bits are needed to transmit information about  $x$ , if nothing else is known about  $X$  but its cardinality?

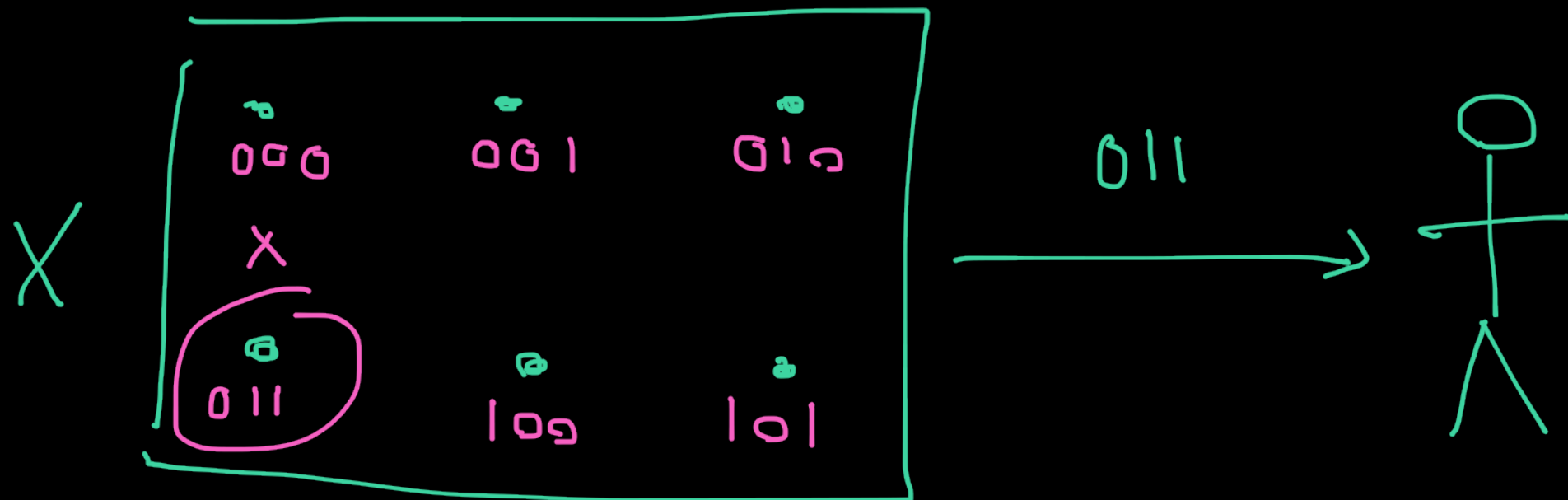


# Combinatorial Information

We assign every element in  $X$  a fixed-length binary code:

$$c : X \rightarrow \{0,1\}^n \quad (\text{one-one})$$

and transmit  $c(x)$ .



We need  $n = \lceil \log_2 |X| \rceil$  bits.

*In this lesson, unless otherwise stated, all logarithms are binary. We write  $\log_2 = \log$ .*

# Combinatorial Interpretation

Information = Bits needed to transmit =  $\log(\# \text{ of possibilities})$

$\log |X|$

# Probabilistic Information Transfer

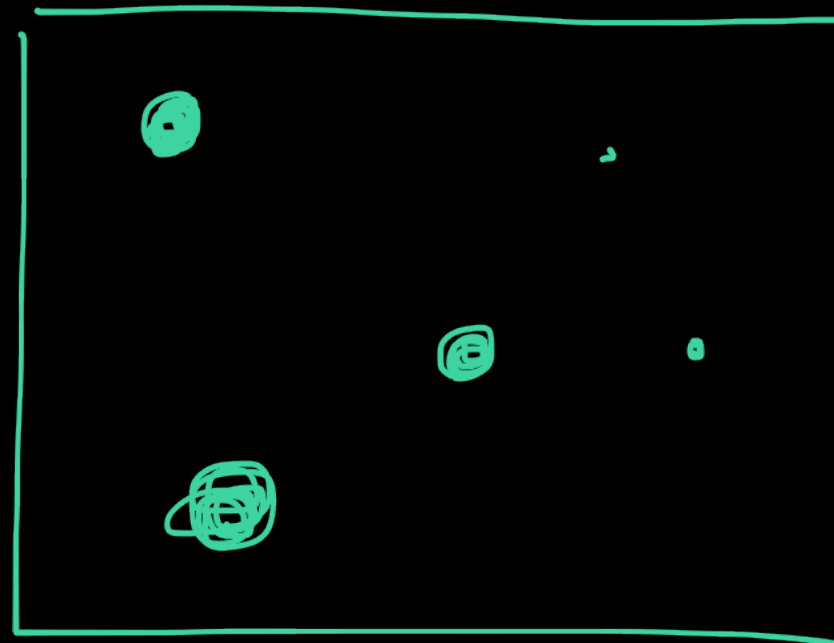
Now assume we have probability measure  $P$  on  $X$  (still finite).

We draw  $x \in X$  at random according to  $P$ .

**Question:** Can we design a **code**  $c : X \rightarrow 2^{<\mathbb{N}}$  (not necessarily of fixed length) such that

the expected length of a codeword is minimal?

→ Entropy

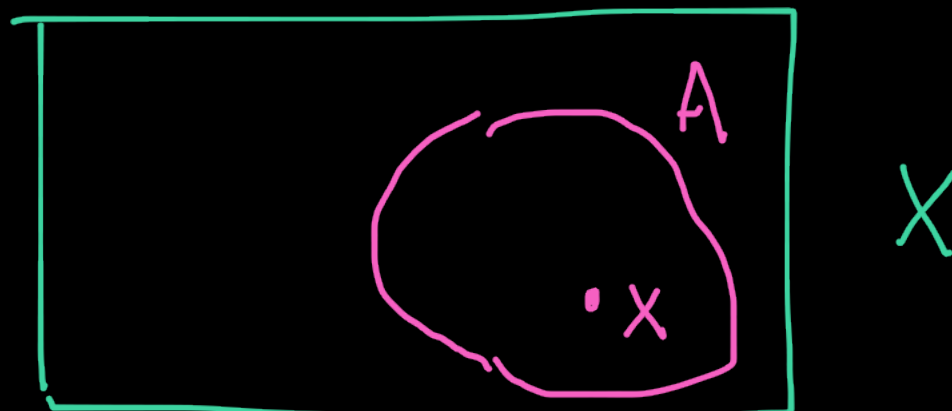


# Information Gained = Uncertainty Removed

If, in the combinatorial framework, instead of giving a full description of  $x \in X$ , we only give a set  $A \subseteq X$  with  $x \in A$ .

How much information about  $x$  do we gain from knowing  $A$ ?

- ▶ Clear: the smaller  $A$  (compared to  $X$ ), the more information gained, and the more uncertainty about  $x$  removed.
- ▶ If  $A = X$ , we gain no information at all.



# Information Functions

We are looking for a function  $I : \mathbb{Q} \cap (0, 1] \rightarrow \mathbb{R}^{\geq 0}$ . The idea is that  $I(|A|/|X|)$  measures the information content of  $A$ .

- ▶  $I(1) = 0$  (no information if  $A = X$ )
- ▶  $I$  is decreasing.

Observation:  $I(|A|/|X|)$  =  $-\log(|A|/|X|)$  has these properties

# Probabilistic Information

Now let  $(X, \mathcal{B}, \mu)$  be a probability space.

We can generalize the previous approach. We are looking for a function  $I : (0, 1] \rightarrow \mathbb{R}^{\geq 0}$  such that

(I1)  $I(1) = 0$  (no information for almost sure events)

(I2)  $I$  is decreasing in  $\mu(A)$ .

$$\frac{|A|}{|X|} \downarrow \mu(A)$$

$$I(\mu(A))$$

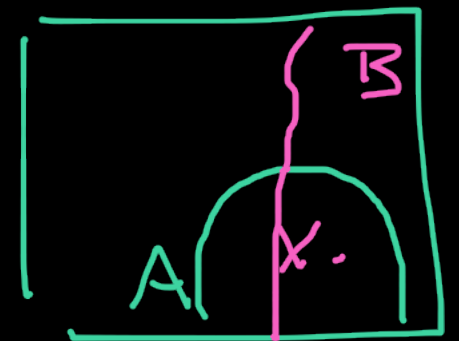
In the probabilistic setting, we have the notion of independence. With respect to information content, we would want that

information gained through independent events should behave additively,

that means

(I3) whenever  $\mu(A \cap B) = \mu(A)\mu(B)$ ,

$$\underline{I(\mu(A \cap B)) = I(\mu(A)) + I(\mu(B))}$$





# Probabilistic Information Function

**PROP:** If  $I : (0, 1] \rightarrow \mathbb{R}^{\geq 0}$  is a continuous function satisfying (I1) - (I3), there must exist a constant  $c > 0$  such that

$$\underline{I(x) = -c \log(x)}.$$

Hence  $-c \log$  is the only reasonable information function.

Entropy = expected gain  
of information