18.440: Lecture 34

Entropy

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Outline

Entropy

Noiseless coding theory

Conditional entropy

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What is entropy?

- Entropy is an important notion in thermodynamics, information theory, data compression, cryptography, etc.
- Familiar on some level to everyone who has studied chemistry or statistical physics.
- Kind of means amount or randomness or disorder.
- But can we give a mathematical definition? In particular, how do we define the entropy of a random variable?

Information

- Suppose we toss a fair coin k times.
- Then the state space S is the set of 2^k possible heads-tails sequences.
- If X is the random sequence (so X is a random variable), then for each $x \in S$ we have $P\{X = x\} = 2^{-k}$.
- In information theory it's quite common to use log to mean $\log_2$ instead of $\log_e$. We follow that convention in this lecture. In particular, this means that

$$\log P\{X = x\} = -k$$

for each $x \in S$.
- Since there are 2^k values in S, it takes k "bits" to describe an element $x \in S$.
- Intuitively, could say that when we learn that $X = x$, we have learned $k = -\log P\{X = x\}$ "bits of information".

Shannon entropy

- Shannon: famous MIT student/faculty member, wrote *The Mathematical Theory of Communication* in 1948.
- Goal is to define a notion of how much we "expect to learn" from a random variable or "how many bits of information a random variable contains" that makes sense for general experiments (which may not have anything to do with coins).
- If a random variable X takes values $x_1, x_2, \dots, x_n$ with positive probabilities $p_1, p_2, \dots, p_n$ then we define the **entropy** of X by

$$H(X) = \sum_{i=1}^{n} p_i(-\log p_i) = -\sum_{i=1}^{n} p_i \log p_i.$$

- This can be interpreted as the expectation of $(-\log p_i)$. The value $(-\log p_i)$ is the "amount of surprise" when we see x_i.

Twenty questions with Harry

- Harry always thinks of one of the following animals:

x	$P\{X = x\}$	$-\log P\{X = x\}$
Dog	$1/4$	2
Cat	$1/4$	2
Cow	$1/8$	3
Pig	$1/16$	4
Squirrel	$1/16$	4
Mouse	$1/16$	4
Owl	$1/16$	4
Sloth	$1/32$	5
Hippo	$1/32$	5
Yak	$1/32$	5
Zebra	$1/64$	6
Rhino	$1/64$	6

- Can learn animal with $H(X) = \frac{47}{16}$ questions on average.

Other examples

- Again, if a random variable X takes the values $x_1, x_2, \dots, x_n$ with positive probabilities $p_1, p_2, \dots, p_n$ then we define the **entropy** of X by

$$H(X) = \sum_{i=1}^{n} p_i(-\log p_i) = -\sum_{i=1}^{n} p_i \log p_i.$$

- If X takes one value with probability 1, what is $H(X)$?
- If X takes k values with equal probability, what is $H(X)$?
- What is $H(X)$ if X is a geometric random variable with parameter $p = 1/2$?

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Coding values by bit sequences

- If X takes four values A, B, C, D we can code them by:

$$A \leftrightarrow 00$$

$$B \leftrightarrow 01$$

$$C \leftrightarrow 10$$

$$D \leftrightarrow 11$$

- Or by

$$A \leftrightarrow 0$$

$$B \leftrightarrow 10$$

$$C \leftrightarrow 110$$

$$D \leftrightarrow 111$$

- No sequence in code is an extension of another.
- What does 100111110010 spell?
- A coding scheme is equivalent to a twenty questions strategy.

Twenty questions theorem

- **Noiseless coding theorem:** Expected number of questions you need is at least the entropy.
- Precisely, let X take values $x_1, \ldots, x_N$ with probabilities $p(x_1), \ldots, p(x_N)$. Then if a valid coding of X assigns n_i bits to x_i, we have

$$\sum_{i=1}^{N} n_i p(x_i) \geq H(X) = -\sum_{i=1}^{N} p(x_i) \log p(x_i).$$

- **Data compression:** suppose we have a sequence of n independent instances of X, called $X_1, X_2, \ldots, X_n$. Do there exist encoding schemes such that the expected number of bits required to encode the entire sequence is about $H(X)n$ (assuming n is sufficiently large)?
- Yes, but takes some thought to see why.

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Entropy for a pair of random variables

- Consider random variables X, Y with joint mass function $p(x_i, y_j) = P\{X = x_i, Y = y_j\}$.
- Then we write

$$H(X, Y) = -\sum_i \sum_j p(x_i, y_j) \log p(x_i, y_i).$$

- $H(X, Y)$ is just the entropy of the pair (X, Y) (viewed as a random variable itself).
- Claim: if X and Y are independent, then

$$H(X, Y) = H(X) + H(Y).$$

Why is that?

Conditional entropy

- Let's again consider random variables X, Y with joint mass function $p(x_i, y_j) = P\{X = x_i, Y = y_j\}$ and write

$$H(X, Y) = -\sum_i \sum_j p(x_i, y_j) \log p(x_i, y_i).$$

- But now let's not assume they are independent.
- We can define a **conditional entropy** of X *given* $Y = y_j$ by

$$H_{Y=y_j}(X) = -\sum_i p(x_i|y_j) \log p(x_i|y_j).$$

- This is just the entropy of the conditional distribution. Recall that $p(x_i|y_j) = P\{X = x_i|Y = y_j\}$.
- We similarly define $H_Y(X) = \sum_j H_{Y=y_j}(X)p_Y(y_j)$. This is the *expected* amount of conditional entropy that there will be in Y after we have observed X.

Properties of conditional entropy

- Definitions: $H_{Y=y_j}(X) = -\sum_i p(x_i|y_j) \log p(x_i|y_j)$ and $H_Y(X) = \sum_j H_{Y=y_j}(X) p_Y(y_j)$.
- **Important property one:** $H(X,Y) = H(Y) + H_Y(X)$.
- In words, the expected amount of information we learn when discovering (X,Y) is equal to expected amount we learn when discovering Y *plus* expected amount when we subsequently discover X (given our knowledge of Y).
- To prove this property, recall that $p(x_i, y_j) = p_Y(y_j) p(x_i|y_j)$.
- Thus, $H(X,Y) = -\sum_i \sum_j p(x_i, y_j) \log p(x_i, y_j) =$ $-\sum_i \sum_j p_Y(y_j) p(x_i|y_j) [\log p_Y(y_j) + \log p(x_i|y_j)] =$ $-\sum_j p_Y(y_j) \log p_Y(y_j) \sum_i p(x_i|y_j) -$ $\sum_j p_Y(y_j) \sum_i p(x_i|y_j) \log p(x_i|y_j) = H(Y) + H_Y(X)$.

Properties of conditional entropy

- Definitions: $H_{Y=y_j}(X) = -\sum_i p(x_i|y_j) \log p(x_i|y_j)$ and $H_Y(X) = \sum_j H_{Y=y_j}(X) p_Y(y_j)$.
- **Important property two:** $H_Y(X) \le H(X)$ with equality if and only if X and Y are independent.
- In words, the expected amount of information we learn when discovering X *after* having discovered Y can't be more than the expected amount of information we would learn when discovering X *before* knowing anything about Y.
- Proof: note that $\mathcal{E}(p_1, p_2, \ldots, p_n) := -\sum p_i \log p_i$ is concave.
- The vector $v = \{p_X(x_1), p_X(x_2), \ldots, p_X(x_n)\}$ is a weighted average of vectors $v_j := \{p_X(x_1|y_j), p_X(x_2|y_j), \ldots, p_X(x_n|y_j)\}$ as j ranges over possible values. By (vector version of) Jensen's inequality, $H(X) = \mathcal{E}(v) = \mathcal{E}(\sum p_Y(y_j)v_j) \ge \sum p_Y(y_j)\mathcal{E}(v_j) = H_Y(X)$.

18.440 Probability and Random Variables
Spring 2014