

More regarding noisy channels

Information Theory Lecture 5b

Let's review what we know about entropies of two or more variables

- The joint entropy of X, Y is

$$H(X, Y) = \sum_{xy \in A_x A_y} P(x, y) \log \frac{1}{P(x, y)}$$

$$H(X, Y) = H(X) + H(Y) \text{ iff } P(x, y) = P(x)P(y)$$

Conditional Entropy

- Of X given $y=b$ is the entropy of the probability distribution $P(x|y=b)$

$$H(X | y = b) = - \sum_{x \in A_x} P(x | y = b) \log(P(x | y = b))$$

- This is the information that remains in X after y is known to be b

Condition entropy

- Of X given Y is the average of the previous expression, over all possible values of y

$$H(X | Y) = - \left[\sum_{y \in A_y} P(y) \sum_{x \in A_x} P(x | y = b) \log(P(x | y = b)) \right]$$
$$= - \sum_{xy \in A_x A_y} P(x, y) \log(P(x | y))$$

- This is the information that remains in X after we know Y in general

Chain rule for entropy

- Relating the three previous expressions

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

- The information available in X and Y is the information in X plus the information in Y given X
- or vice versa

Mutual information

- Between X and Y

- $I(X:Y) = H(X) - H(X|Y) = I(Y:X)$
- $I(X:Y) \geq 0$

- This measures the average information obtained about x given y , or vice versa

Conditional Mutual Information

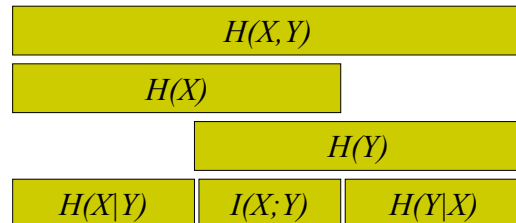
- Between X and Y given $z = C$

$$I(X; Y | z = C) = H(X | z = c) - H(X | Y, z = C)$$

- Averaging over all possible values of Z

$$I(X; Y | Z) = H(X | Z) - H(X | Y, Z)$$

The relationship



Let's return to the noisy channel

- The sender inputs symbol x , and we receive symbol y
- Our job is to infer x given y

$$P(x | y) = \frac{P(y | x)P(x)}{P(y)} = \frac{P(y | x)P(x)}{\sum_{x'} P(y | x')P(x')}$$

- But we also want to characterize average *rates* through this channel

The Capacity of a Channel \mathcal{Q}

- Is defined as the maximum information we can convey about x by reading y
- We can accomplish this by picking the best probability distribution over x (coding)

$$C(\mathcal{Q}) = \max_{P_x} I(X; Y)$$

The Noisy Typewriter Channel

- Consider a typewriter that sends one of 27 characters (A, B, ..., Z, -)
- The letters are arranged in a circle, and the typist can "miss" and hit the higher or the lower character
- We can send information *perfectly* by only using every third character on the typewriter

Shannon's Noisy Channel Coding Theorem

- Associated with each discrete, memoryless channel there is a non-negative capacity C (called the channel capacity) with the following property:
- For any $\epsilon > 0$ and $R < C$ there is a block code with block length N and rate $\geq R$ and a decoding algorithm such that the maximal probability of block error is $< \epsilon$

For the noisy typewriter

The Theorem	How it applies to the noisy typewriter
Channel capacity C	$\log_2(27/3)$
ϵ and R	We only need block length of $N=1$
Block code of length N	The block code only using every third character will require 3 characters to convey any one, so the rate is $\log_2(27/3)$
Decoding algorithm	Map the received letter to the nearest code letter
Maximal probability of block error $< \epsilon$	Zero, in this case

Another version of the proof

- (not offered here)
- Like in the noisy typewriter, we could consider blocks at x that map to non-overlapping y
- We then measure the density of these blocks in the possible input space
- This gives rate

Pattern Recognition as Noisy Communication

- Let's say we want to send symbols $A_x = \{0, 1, 2, 3, 4, \dots, 9\}$
- By writing characters in a 16 by 16 pixel box
- The input space is A_x
- The output space is $A_y = \{0, 1\}^{256}$
- Our approach to pattern recognition is

$$P(x|y) = \frac{P(y|x)P(x)}{\sum_{x'} P(y|x')P(x')}$$

Beyond perfection

- If a bit-probability of error p_b is acceptable, rates of up to $R(p_b)$ can be achieved

$$R(p_b) = \frac{C}{1 - H_2(p_b)}$$

- Rates higher than this cannot be achieved

