



Exercise 6 of October 25, 2017

<http://www.isi.ee.ethz.ch/teaching/courses/it1.html>

Problem 1

Strong Versus Weak Typicality

A sequence of chance variables X_1, \dots, X_{100} is drawn IID with X_i taking on the values “True” and “False” equiprobably. Describe the set of strongly typical sequences and the set of weakly typical sequences for $\epsilon = 0.01$.

Problem 2

Random Box Size

Let X_1, X_2, \dots, X_n be IID uniform random variables over the unit interval $[0, 1]$. An n -dimensional rectangular box with side lengths X_1, X_2, \dots, X_n is constructed. Its volume is $V_n = \prod_{i=1}^n X_i$, and the edge length L_n of an n -cube with the same volume is $L_n = V_n^{1/n}$.

- Compute $\lim_{n \rightarrow \infty} (\mathbb{E}[V_n])^{1/n}$.
- Show that $\lim_{n \rightarrow \infty} \frac{1}{n} \sum_{i=1}^n \ln X_i = -1$ in probability.
- Deduce from Part b) that $\lim_{n \rightarrow \infty} L_n = e^{-1}$ in probability.

Problem 3

From AEP to Kraft's Inequality

Let ℓ_1, \dots, ℓ_d be the codeword lengths of a uniquely decodable fixed-to-variable binary code. Use Theorem 1 to show that

$$\sum_{i=1}^d 2^{-\ell_i} \leq 1. \quad (1)$$

Theorem 1 (Converse for the Source Coding Theorem). Consider an IID source with entropy $H(X)$ and a sequence of fixed-to-fixed codes which map n source symbols to $n \rho_n$ bits. If

$$\lim_{n \rightarrow \infty} \rho_n < H(X), \quad (2)$$

then the probability of successful decoding for these codes tends to zero as n tends to infinity.

Hint: Prove the claim by contradiction. Assume that there exists a uniquely decodable code \mathcal{C} whose codeword lengths do not satisfy (1). Construct a source for which the expected codeword length of \mathcal{C} is smaller than the entropy of the source. Use the extension of \mathcal{C} to devise a coding scheme that satisfies (2) and whose probability of successful decoding tends to one as n tends to infinity, which leads to the desired contradiction.

Problem 4**Fano's Inequality**

Let X take values in the set $\mathcal{X} = \{1, \dots, m\}$ and let $p_i = \Pr[X = i]$ for $i = 1, \dots, m$.

- a) Suppose that you must guess X . Which guess would have the smallest probability of error? What is the probability of error P_e^* associated with this guess?
- b) Let \hat{x} be a fixed guess, and let P_e be the probability of error associated with this guess. Maximize $H(\tilde{X})$ over all choices of $\tilde{p}_1, \tilde{p}_2, \dots, \tilde{p}_m$ for which the guess \hat{x} has a probability of error $\tilde{P}_e = P_e$. Argue that this implies

$$H(X) \leq H_b(P_e) + P_e \log(m-1).$$

- c) Suppose that you must guess X based on the observation of a correlated chance variable Y . Given some guessing rule, let P_e be the probability of error and let E be a chance variable which is zero if the guess is correct and one otherwise. Justify the following proof of Fano's inequality:

$$\begin{aligned} H_b(P_e) + P_e \log(m-1) &\stackrel{(i)}{=} H(E) + \Pr[E=1] \log(m-1) \\ &\stackrel{(ii)}{\geq} H(E|Y) + \Pr[E=1] \log(m-1) \\ &\stackrel{(iii)}{=} \sum_{y \in \mathcal{Y}} P_Y(y) \left[H(E|Y=y) + \Pr[E=1|Y=y] \log(m-1) \right] \\ &\stackrel{(iv)}{\geq} \sum_{y \in \mathcal{Y}} P_Y(y) H(X|Y=y) \\ &\stackrel{(v)}{=} H(X|Y). \end{aligned}$$

Hint: Use the result from Part b).