# EE376A - Information Theory Midterm, Monday February 12th

#### **Instructions:**

- You have two hours, 6:00PM 8:00PM
- The exam has 3 questions, totaling 100 points. (There are additional 20 points bonus)
- Please start answering each question on a new page of the answer booklet.
- You are allowed to carry the textbook, your own notes and other course related material with you. Electronic reading devices [including kindles, laptops, ipads, etc.] are allowed, provided they are used solely for reading pdf files already stored on them and not for any other form of communication or information retrieval.
- Calculators are allowed for numerical computations.
- You are required to provide a sufficiently detailed explanation of how you arrived at your answers.
- You can use previous parts of a problem even if you did not solve them.
- ullet As throughout the course, entropy (H) and Mutual Information (I) are specified in bits.
- log is taken in base 2.
- Throughout the exam 'prefix code' refers to a variable length code satisfying the prefix condition.
- Good Luck!

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### 1. Universal Prefix Codes (35 points)

In this problem we consider binary prefix codes over the set of non-negative natural numbers  $\mathbb{N} = \{1, 2, 3, ...\}$ . We do not know the probability distribution  $P \equiv (p_j, j \in \mathbb{N})$ , but we do know that it is a monotone distribution, i.e.  $p_j \geq p_{j+1} \forall j \in \mathbb{N}$ . We wish to construct prefix codes which perform well irrespective of the source probabilities. For a given code  $c_j, j \in \mathbb{N}$  (where each  $c_j$  is a binary codeword), we denote the code lengths by  $l_j^c, j \in \mathbb{N}$  and the expected code length by  $\bar{L}_c := \sum_{j=1}^{\infty} p_j l_j^c$ . Also,  $0^j$  denotes a sequence of j zeros.

- (a) (6 points) Consider the code  $u_j = 0^j 1$ . Is this code prefix free? Justify.
- (b) (Bonus, 5 points) Find a monotone distribution P, such that  $H(P) < \infty$ , but  $\bar{L}_u = \infty$ . (it is fine to specify  $p_j$  up to a normalizing factor).
- (c) (8 points) Consider now the code  $b_j$ , which is the binary representation of j (Eg:  $b_5 = 101$ ). Note that the codelength of  $b_j$  is given by:  $l_j^b = \lfloor \log_2 j \rfloor + 1$ . Is this code prefix free?
- (d) (8 points) For any monotone distribution P, show that the binary code  $b_j$  in (c) has expected code length  $\bar{L}_b \leq H(P) + 1$ .
- (e) (8 points) Now, consider the code  $c_j = 0^{\lfloor \log_2 j \rfloor + 1} 1b_j$  with  $l_j^c = 2 \lfloor \log_2 j \rfloor + 3$ . Argue that this code is prefix free.
- (f) (5 points) For the code in (e), show that  $\bar{L}_c \leq 2H(P) + 3$  for all monotone distributions P.
- (g) (Bonus, 5 points) Can you suggest prefix codes which improve on the performance of the code from part (e), i.e., achieve performance  $\bar{L}_c \leq c_1 H(P) + c_2$ , where  $c_1 < 2$  ( $c_1$  is a constant,  $c_2$  is a lower-order term of H(P))?

#### Solution to Problem 1

- (a) This is a prefix code. Different codes  $u_j$  have different number of zeros before 1.
- (b) Choose  $p_j \propto (j+1)^{-2}$ . This is well-defined since  $\sum_{n=1}^{\infty} n^{-2} < \infty$ . Also,  $H(P) < \infty$  since  $\sum_{j=1}^{\infty} (j+1)^{-2} \log(j+1) < \infty$  (the integral  $\int_{1}^{\infty} \frac{\log x}{x^2} dx$  is finite). However,

$$\bar{L}_u = \sum_{j=1}^{\infty} p_j(j+1) \propto \sum_{j=1}^{\infty} \frac{1}{j+1} = \infty$$

for the integral  $\int_1^\infty \frac{dx}{x}$  diverges.

- (c) This code is not prefix-free. For example,  $b_1 = 1$  is a prefix of  $b_3 = 11$ .
- (d) For monotone distributions, we have  $p_j \leq \frac{1}{j} \sum_{k=1}^{j} p_k \leq \frac{1}{j}$  for any j. Hence,

$$\bar{L}_b \le \sum_{j=1}^{\infty} p_j(\log_2 j + 1) \le \sum_{j=1}^{\infty} p_j(\log_2 \frac{1}{p_j} + 1) = H(P) + 1.$$

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- (e) Assume by contradiction that  $c_j$  is a prefix of  $c_{j'}$  for  $j \neq j'$ . Comparing the number of zeros in the front, we must have  $\lfloor \log_2 j \rfloor = \lfloor \log_2 j' \rfloor$ . Hence,  $b_j$  and  $b_{j'}$  must have the same length, and the prefix assumption implies  $b_j = b_{j'}$ . Since  $b_j$  is the binary representation of j, we then have j = j', a contradiction!
- (f) Similar to (d), we have  $jp_i \leq 1$ . Hence,

$$\bar{L}_c \le \sum_{j=1}^{\infty} p_j (2\log_2 j + 3) \le \sum_{j=1}^{\infty} p_j (2\log_2 \frac{1}{p_j} + 3) = 2H(P) + 3.$$

(g) For  $l_j^c = \lfloor \log_2 j + A \log_2 \log_2 j + B \rfloor$ , since  $\int_1^\infty \frac{dx}{x(\log x)^\alpha} < \infty$  for any  $\alpha > 1$ , suitable choices of A, B give  $\sum_{j=1}^\infty 2^{-l_j^c} < 1$ . By Kraft's inequality, there exist a prefix code  $c_j$  with codelength  $l_j^c$ . Using  $jp_j \leq 1$  again, the average codelength for this code is

$$\bar{L}_c \leq \sum_{j=1}^{\infty} p_j \left( \log_2 j + A \log_2 \log_2 j + B \right) 
\leq \sum_{j=1}^{\infty} p_j \left( \log_2 \frac{1}{p_j} + A \log_2 \log_2 \frac{1}{p_j} + B \right) 
\leq H(P) + A \sum_{j=1}^{\infty} \log_2 \left( \sum_{j=1}^{\infty} p_j \log_2 \frac{1}{p_j} \right) + B 
= H(P) + A \log_2 H(P) + B.$$

#### 2. Perfect Secrecy (30 points)

Alice wishes to communicate a message M to Bob, where M is chosen randomly from some alphabet  $\mathcal{M}$ . To prevent an eavesdropping adversary from reading the message, Alice encrypts the message using a deterministic function C = E(K, M) to obtain the ciphertext  $C \in \mathcal{C}$ , where  $K \in \mathcal{K}$  is a secret random key known to both Alice and Bob, and is independent of the message. Bob receives the ciphertext and decrypts it back to M using another deterministic function M = D(K, C). We say that this system is perfectly secure if I(M; C) = 0.

- (a) (6 points) Explain intuitively why a perfectly secure system is safe from an eavesdropping adversary.
- (b) (9 points) Show that  $H(M|C) \leq H(K|C)$  (under any system, secure or not).
- (c) (9 points) Using part (b), show that  $I(M;C) \ge H(M) H(K)$ .
- (d) (6 points) Part (c) suggests that a perfectly secure system must have  $H(K) \ge H(M)$ . Do you think this is practical? Explain.
- (e) (Bonus, 5 points) Now, assume that  $\mathcal{M} = \mathcal{K} = \mathcal{C} = \{0,1\}^n$  with M and K uniformly and independently distributed in  $\{0,1\}^n$ . Can you suggest perfectly secure encryption and decryption functions E(K,M) and D(K,C)?

#### Solution to Problem 2

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- (a) For a perfectly secure system, M and C are independent. Hence, an eavesdropper who observes the ciphertext C cannot infer any information of M from C.
- (b) We have

$$H(M|C) = H(M, K|C) - H(K|M, C)$$

$$\leq H(M, K|C)$$

$$= H(K|C) + H(M|K, C)$$

$$= H(K|C)$$

where the last step follows from H(M|K,C) = 0, for M = D(K,C) is a deterministic function of K,C.

(c) We have

$$I(M; C) = H(M) - H(M|C) \ge H(M) - H(K|C) \ge H(M) - H(K).$$

The first inequality follows from (b); the second inequality is due to the fact that conditioning reduces entropy.

- (d) Under a perfectly secure system,  $0 = I(M; C) \ge H(M) H(K)$ , thus  $H(K) \ge H(M)$ . This is not practical: usually the message is very long (i.e., H(M) is large), but we need to transmit/store the key which is as long as the message in a perfectly secure system.
- (e) Consider  $E(K, M) = K \oplus M, D(K, C) = K \oplus C$ , where  $\oplus$  denotes the coordinate-wise modulo-2 sum. Clearly D(K, E(K, M)) = M. Moreover,

$$I(M; C) = H(C) - H(C|M) = H(C) - H(K \oplus M|M)$$
  
=  $H(C) - H(K|M) = H(C) - H(K) = 0$ 

where the last step follows from the fact that both M, C are uniformly distributed on  $\{0,1\}^n$ . Hence, this is a perfectly secure system.

#### 3. Mix of Problems (35 points)

(a) Pairwise Independence (12 points)

We say random variables  $X_1, X_2, \ldots, X_n$  are pairwise independent if any pair of random variables  $(X_i, X_j)$ ,  $j \neq i$  are independent.

- i. Let  $X_1, X_2, X_3$  be pairwise independent random variables, distributed identically as Bern(0.5). Then:
  - A. (6 points) Show that:  $H(X_1, X_2, X_3) \leq 3$ . When is equality achieved?
  - B. (6 points) Show that:  $H(X_1, X_2, X_3) \ge 2$ . When is equality achieved?
- ii. (Bonus, 5 points) Let  $Z_1, Z_2, \ldots, Z_k$  be i.i.d Bern(0.5) random variables. Show that using the  $Z_i$ 's, you can generate  $2^k 1$  pairwise independent random variables, identically distributed as Bern(0.5).

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## (b) Individual Sequences (12 points)

Let  $x^n$  be a given arbitrary binary sequence, with  $n_0$  0's and  $n_1$  1's  $(n_1 = n - n_0)$ . You are also provided a compressor C which takes in any arbitrary i.i.d distribution q(x) as a parameter, and encodes  $x^n$  using:

$$\bar{L}_q = \frac{1}{n} \log \frac{1}{q(x^n)}$$

bits per symbol (ignoring integer constraints).

- i. (6 points) Given the sequence  $x^n$ , what distribution q(x) will you choose as a parameter (in terms of  $n_0$ ,  $n_1$ ) to the compressor C, so that  $\bar{L}_q$  is minimized. Justify.
- ii. (6 points) When compressing any given individual sequence  $x^n$ , we also need to store the parameter distribution q(x) (as it is required for decoding). Show that you can represent the parameter distribution q(x) using  $\log(n+1)$  bits. Find the effective compression ratio.

# (c) **AEP**(11 points)

Let p(x) and q(x) be two distinct distributions supported on the same alphabet  $\mathcal{X}$ .

i. (5 points) Let  $X^n$  be distributed i.i.d according to distribution p(x). Then, for what distributons p(x), q(x) is the following relationship satisfied for all  $\epsilon > 0$ ?

$$P\left(\left\{x^n \in \mathcal{X}^n : \left|\frac{1}{n}\log\frac{1}{p(x^n)} - H(q)\right| < \epsilon\right\}\right) \to 1, \text{ as } n \to \infty$$

ii. (6 points) Let  $X^n$  be distributed i.i.d according to distribution p(x). Show that for any  $\epsilon > 0$ :

$$P\left(\left\{x^n \in \mathcal{X}^n : \left|\frac{1}{n}\log\frac{1}{q(x^n)} - (H(p) + D(p||q))\right| < \epsilon\right\}\right) \to 1, \text{ as } n \to \infty$$

#### Solution to Problem 3

(a) i. A. We have

$$H(X_1, X_2, X_3) = H(X_1, X_2) + H(X_3 | X_1, X_2)$$

$$\leq H(X_1, X_2) + H(X_3)$$

$$= H(X_1) + H(X_2) - I(X_1; X_2) + H(X_3) = 3.$$

Equality holds if and only if  $X_3$  is independent of  $(X_1, X_2)$ , which together with the pairwise independence implies that  $X_1, X_2, X_3$  are mutually independent.

B. We have

$$H(X_1, X_2, X_3) = H(X_1, X_2) + H(X_3 | X_1, X_2)$$
  
 
$$\geq H(X_1, X_2)$$

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$$= H(X_1) + H(X_2) - I(X_1; X_2) = 2.$$

Equality holds if  $X_3$  is a deterministic function of  $(X_1, X_2)$ . We also require  $X_3$  to have the correct marginal distribution of Bern(0.5), and satisfy pairwise independent properties. The only functions possible are:  $X_3 = X_1 \oplus X_2$  and  $X_3 = 1 \oplus X_1 \oplus X_2$ .

- ii. For any non-empty subset  $S \subset \{1, \dots, k\}$ , we define a random variable  $X_S = \sum_{i \in S} Z_i$ . There are  $2^k 1$  random variables in total. To show  $X_S \sim Bern(0.5)$ , pick any  $i_0 \in S$  and note that  $X_S|(Z_i)_{i \neq i_0} \sim Bern(0.5)$ . For pairwise independence, suppose  $S \neq S'$  are two different non-empty subsets. By symmetry, assume that we can pick  $i_0 \in S S'$ , then  $X_S|(Z_i)_{i \neq i_0} \sim Bern(0.5)$  and  $X_{S'}$  is a deterministic function of  $(Z_i)_{i \neq i_0}$ . This shows that  $X_S$  and  $X_{S'}$  are independent.
- (b) i. For q(0) = 1 q, q(1) = q, we have

$$\bar{L}_q = \frac{1}{n} \log \frac{1}{(1-q)^{n_0} q^{n_1}} = -\frac{n_0}{n} \log(1-q) - \frac{n_1}{n} \log(q).$$

We see that  $\bar{L}_q$  is convex in q, and taking derivative w.r.t q gives  $q^* = \frac{n_1}{n}$ .

ii. By the previous part, it suffices to store  $n_1 \in \{0, 1, \dots, n\}$  for full knowledge of q(x). Hence,  $\log(n+1)$  bits are enough. The effective compression ratio is

$$\bar{L}_q + \frac{\log(n+1)}{n} = H(\frac{n_1}{n}) + \frac{\log(n+1)}{n}.$$

- (c) i. By AEP, H(q) = H(p) suffices. This is also necessary, for a sequence of random variables cannot converge in probability to two different limits.
  - ii. By LLN, we have

$$\frac{1}{n}\log\frac{1}{q(x^n)} = \frac{1}{n}\sum_{i=1}^n\log\frac{1}{q(x_i)}$$

$$\to \mathbb{E}_P[\log\frac{1}{q(x)}] = \sum_x p(x)\log\frac{1}{q(x)} = H(p) + D(p||q)$$

in probability under P, which is exactly the desired statement.

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