

ÉCOLE POLYTECHNIQUE FÉDÉRALE DE LAUSANNE

School of Computer and Communication Sciences

Handout 9

Solutions to Homework 4

Information Theory and Coding

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PROBLEM 1.

- (a) We have $H(f(U)) \leq H(f(U), U) = H(U) + H(f(U)|U) = H(U) + 0 = H(U)$.
- (b) Notice that $U \leftrightarrow V \leftrightarrow f(V)$ is a Markov chain. The data processing inequality implies that $H(U) - H(U|f(V)) = I(U; f(V)) \leq I(U; V) = H(U) - H(U|V)$. Therefore, $H(U|V) \leq H(U|f(V))$.

PROBLEM 2.

- (a) We have:

$$\begin{aligned} H(U|\hat{U}) &\leq H(U, W|\hat{U}) = H(W|\hat{U}) + H(U|\hat{U}, W) \leq H(W) + H(U|\hat{U}, W) \\ &= H(W) + H(U|\hat{U}, W=0) \cdot \mathbb{P}[W=0] + H(U|\hat{U}, W=1) \cdot \mathbb{P}[W=1] \\ &\stackrel{(*)}{\leq} h_2(p_e) + 0 \cdot (1-p_e) + \log(|\mathcal{U}|-1) \cdot p_e = h_2(p_e) + p_e \log(|\mathcal{U}|-1), \end{aligned}$$

where (*) follows from the following facts:

- $H(W) = h_2(p_e)$.
 - $H(U|\hat{U}, W=0) = 0$: conditioned on $W=0$, we know that $U = \hat{U}$ and so the conditional entropy $H(U|\hat{U}, W=0)$ is equal to 0.
 - $H(U|\hat{U}, W=1) \leq \log(|\mathcal{U}|-1)$: conditioned on $W=1$, we know that $U \neq \hat{U}$ and so there are at most $|\mathcal{U}|-1$ values for U . Therefore, the conditional entropy $H(U|\hat{U}, W=1)$ is at most $\log(|\mathcal{U}|-1)$.
- (b) Let $\hat{U} = f(V)$. We have $H(U|\hat{U}) \leq h_2(p_e) + p_e \log(|\mathcal{U}|-1)$ from (a). On the other hand, from Problem 1(b) we have $H(U|V) \leq H(U|f(V)) = H(U|\hat{U})$. We conclude that $H(U|V) \leq h_2(p_e) + p_e \log(|\mathcal{U}|-1)$.

PROBLEM 3.

- (a) Since

$$P(U=u, Z=z) = \begin{cases} p(u) & \text{if } z=1, \\ q(u) & \text{if } z=2, \end{cases}$$

one can immediately see that the distribution of U is $r(u) = \theta p(u) + (1-\theta)q(u)$.

- (b) $H(U) = h(r)$, and

$$H(U|Z) = \sum_z P(Z=z)H(U|Z=z) = \theta h(p) + (1-\theta)h(q).$$

The last equality follows since given $z=1$ (resp. $z=2$) U has distribution p (resp. q). Since $H(U) \geq H(U|Z)$, we have proved that $h(r) \geq \theta h(p) + (1-\theta)h(q)$.

PROBLEM 4.

(a) We have:

$$\begin{aligned} S &= \sum_{u \in \mathcal{U}} \max\{P_1(u), P_2(u)\} \stackrel{(*)}{\leq} \sum_{u \in \mathcal{U}} (P_1(u) + P_2(u)) \\ &= \sum_{u \in \mathcal{U}} P_1(u) + \sum_{u \in \mathcal{U}} P_2(u) = 1 + 1 = 2, \end{aligned}$$

It is easy to see from (*) that $S = 2$ if and only if $\max\{P_1(u), P_2(u)\} = P_1(u) + P_2(u)$ for all $u \in \mathcal{U}$, which is equivalent to say that there is no $u \in \mathcal{U}$ for which we have $P_1(u) > 0$ and $P_2(u) > 0$. In other words, $S = 2$ if and only if

$$\{u \in \mathcal{U} : P_1(u) > 0\} \cap \{u \in \mathcal{U} : P_2(u) > 0\} = \emptyset.$$

(b) Let $l_i = \lceil \log_2 \frac{S}{\max\{P_1(a_i), P_2(a_i)\}} \rceil$, and let us compute the Kraft sum:

$$\sum_{i=1}^M 2^{-l_i} \leq \sum_{i=1}^M 2^{-\log_2 \frac{S}{\max\{P_1(a_i), P_2(a_i)\}}} = \sum_{i=1}^M \frac{\max\{P_1(a_i), P_2(a_i)\}}{S} = 1.$$

Since the Kraft sum is at most 1, there exists a prefix-free code where the length of the codeword associated to a_i is l_i .

(c) Since the code constructed in (b) is prefix free, it must be the case that $\bar{l} \geq H(U)$. In order to prove the upper bounds, let P^* be the true distribution (which is either P_1 or P_2). It is easy to see that $P^*(a_i) \leq \max\{P_1(a_i), P_2(a_i)\}$ for all $1 \leq i \leq M$. We have:

$$\begin{aligned} \bar{l} &= \sum_{i=1}^M P^*(a_i) \cdot l_i = \sum_{i=1}^M P^*(a_i) \cdot \left\lceil \log_2 \frac{S}{\max\{P_1(a_i), P_2(a_i)\}} \right\rceil \\ &< \sum_{i=1}^M P^*(a_i) \cdot \left(1 + \log_2 \frac{S}{\max\{P_1(a_i), P_2(a_i)\}} \right) \\ &= \sum_{i=1}^M P^*(a_i) \cdot \left(1 + \log S + \log_2 \frac{1}{\max\{P_1(a_i), P_2(a_i)\}} \right) \\ &= 1 + \log S + \sum_{i=1}^M P^*(a_i) \cdot \log_2 \frac{1}{\max\{P_1(a_i), P_2(a_i)\}} \\ &\stackrel{(*)}{\leq} 1 + \log S + \sum_{i=1}^M P^*(a_i) \cdot \log_2 \frac{1}{P^*(a_i)} = H(U) + \log S + 1 \leq H(U) + 2, \end{aligned}$$

where the inequality (*) uses the fact that $P^*(a_i) \leq \max\{P_1(a_i), P_2(a_i)\}$ for all $1 \leq i \leq M$.

(d) Now let $l_i = \lceil \log_2 \frac{S}{\max\{P_1(a_i), \dots, P_k(a_i)\}} \rceil$, and let us compute the Kraft sum:

$$\sum_{i=1}^M 2^{-l_i} \leq \sum_{i=1}^M 2^{-\log_2 \frac{S}{\max\{P_1(a_i), \dots, P_k(a_i)\}}} = \sum_{i=1}^M \frac{\max\{P_1(a_i), \dots, P_k(a_i)\}}{S} = 1.$$

Since the Kraft sum is at most 1, there exists a prefix-free code where the length of the codeword associated to a_i is l_i . Since the code is prefix free, it must be the case that $\bar{l} \geq H(U)$. In order to prove the upper bounds, let P^* be the true distribution (which is either P_1 or \dots or P_k). It is easy to see that $P^*(a_i) \leq \max\{P_1(a_i), \dots, P_k(a_i)\}$ for all $1 \leq i \leq M$. We have:

$$\begin{aligned}
\bar{l} &= \sum_{i=1}^M P^*(a_i) \cdot l_i = \sum_{i=1}^M P^*(a_i) \cdot \left\lceil \log_2 \frac{S}{\max\{P_1(a_i), \dots, P_k(a_i)\}} \right\rceil \\
&< \sum_{i=1}^M P^*(a_i) \cdot \left(1 + \log_2 \frac{S}{\max\{P_1(a_i), \dots, P_k(a_i)\}}\right) \\
&= \sum_{i=1}^M P^*(a_i) \cdot \left(1 + \log_2 S + \log_2 \frac{1}{\max\{P_1(a_i), \dots, P_k(a_i)\}}\right) \\
&= 1 + \log_2 S + \sum_{i=1}^M P^*(a_i) \cdot \log_2 \frac{1}{\max\{P_1(a_i), \dots, P_k(a_i)\}} \\
&\stackrel{(*)}{\leq} 1 + \log_2 S + \sum_{i=1}^M P^*(a_i) \cdot \log_2 \frac{1}{P^*(a_i)} = H(U) + \log_2 S + 1,
\end{aligned}$$

where the inequality (*) uses the fact that $P^*(a_i) \leq \max\{P_1(a_i), \dots, P_k(a_i)\}$ for all $1 \leq i \leq M$. Now notice that $\max\{P_1(a_i), \dots, P_k(a_i)\} \leq \sum_{j=1}^k P_j(a_i)$ for all $1 \leq i \leq M$. Therefore, we have

$$S = \sum_{i=1}^M \max\{P_1(a_i), \dots, P_k(a_i)\} \leq \sum_{i=1}^M \sum_{j=1}^k P_j(a_i) = \sum_{j=1}^k \sum_{i=1}^M P_j(a_i) = \sum_{j=1}^k 1 = k.$$

We conclude that $H(U) \leq \bar{l} \leq H(U) + \log S + 1 \leq H(U) + \log k + 1$.

PROBLEM 5.

- (a) We prove the identity by induction on $n \geq 1$. For $n = 1$, the identity is trivial. Let $n > 1$ and suppose that the identity is true up to $n - 1$. We have:

$$\begin{aligned}
I(Y_1^{n-1}; X_n) &= I(Y_1^{n-2}, Y_{n-1}; X_n) \stackrel{(*)}{=} I(Y_1^{n-2}; X_n) + I(X_n; Y_{n-1} | Y_1^{n-2}) \\
&\stackrel{(**)}{=} \left(\sum_{i=1}^{n-2} I(X_n; Y_i | Y_1^{i-1}) \right) + I(X_n; Y_{n-1} | Y_1^{n-2}) = \sum_{i=1}^{n-1} I(X_n; Y_i | Y_1^{i-1}).
\end{aligned}$$

The identity (*) is by the chain rule for mutual information, and the identity (**) is by the induction hypothesis.

- (b) For every $0 \leq i \leq n$, define $a_i = I(X_{i+1}^n; Y_1^i)$, and for every $1 \leq i \leq n$, define $b_i = I(X_{i+1}^n; Y_1^{i-1})$. It is easy to see that $a_0 = a_n = 0$. We have:

$$\begin{aligned}
\sum_{i=1}^n I(X_{i+1}^n; Y_i | Y_1^{i-1}) &\stackrel{(*)}{=} \sum_{i=1}^n \left(I(X_{i+1}^n; Y_1^i) - I(X_{i+1}^n; Y_1^{i-1}) \right) = \left(\sum_{i=1}^n a_i \right) - \left(\sum_{i=1}^n b_i \right) \\
&\stackrel{(**)}{=} \left(\sum_{i=0}^{n-1} a_i \right) - \left(\sum_{i=1}^n b_i \right) = \left(\sum_{i=1}^n a_{i-1} \right) - \left(\sum_{i=1}^n b_i \right) = \sum_{i=1}^n (a_{i-1} - b_i) \\
&= \sum_{i=1}^n \left(I(X_i^n; Y_1^{i-1}) - I(X_{i+1}^n; Y_1^{i-1}) \right) \stackrel{(***)}{=} \sum_{i=1}^n I(Y_1^{i-1}; X_i | X_{i+1}^n).
\end{aligned}$$

The identities (*) and (***) are by the chain rule for mutual information. The identity (**) follows from the fact that $a_0 = a_n = 0$, which implies that $\sum_{i=1}^n a_i = \sum_{i=0}^{n-1} a_i$.

PROBLEM 6.

(a) We can write the following chain of inequalities:

$$Q^n(\mathbf{x}) \stackrel{1}{=} \prod_{i=1}^n Q(x_i) \stackrel{2}{=} \prod_{a \in \mathcal{X}} Q(a)^{N(a|\mathbf{x})} \stackrel{3}{=} \prod_{a \in \mathcal{X}} Q(a)^{nP_{\mathbf{x}}(a)} = \prod_{a \in \mathcal{X}} 2^{nP_{\mathbf{x}}(a) \log Q(a)} \quad (1)$$

$$= \prod_{a \in \mathcal{X}} 2^{n(P_{\mathbf{x}}(a) \log Q(a) - P_{\mathbf{x}}(a) \log P_{\mathbf{x}}(a) + P_{\mathbf{x}}(a) \log P_{\mathbf{x}}(a))} \quad (2)$$

$$= 2^{n \sum_{a \in \mathcal{X}} (-P_{\mathbf{x}}(a) \log \frac{P_{\mathbf{x}}(a)}{Q(a)} + P_{\mathbf{x}}(a) \log P_{\mathbf{x}}(a))} = 2^{n(-D(P_{\mathbf{x}}\|Q) + H(P_{\mathbf{x}}))},$$

where 1 follows because the sequence is i.i.d., grouping symbols gives 2, and 3 is the definition of type.

(b) Upper bound: We know that

$$\sum_{k=0}^n \binom{n}{k} p^k (1-p)^{n-k} = 1.$$

Consider one term and set $p = k/n$. Then,

$$1 \geq \binom{n}{k} \left(\frac{k}{n}\right)^k \left(1 - \frac{k}{n}\right)^{n-k} = \binom{n}{k} 2^{n\left(\frac{k}{n} \log \frac{k}{n} + \frac{n-k}{n} \log \frac{n-k}{n}\right)} = \binom{n}{k} 2^{-nh_2\left(\frac{k}{n}\right)}$$

Lower bound: Define $S_j = \binom{n}{j} p^j (1-p)^{n-j}$. We can compute

$$\frac{S_{j+1}}{S_j} = \frac{n-j}{j+1} \frac{p}{1-p}.$$

One can see that this ratio is a decreasing function in j . It equals 1, if $j = np + p - 1$, so $\frac{S_{j+1}}{S_j} < 1$ for $j = \lfloor np + p \rfloor$ and $\frac{S_{j+1}}{S_j} \geq 1$ for any smaller j . Hence, S_j takes its maximum value at $j = \lfloor np + p \rfloor$, which equals k in our case. From this we have that

$$\begin{aligned} 1 &= \sum_{j=0}^n \binom{n}{j} p^j (1-p)^{n-j} \leq (n+1) \max_j \binom{n}{j} p^j (1-p)^j \\ &\leq (n+1) \binom{n}{k} \left(\frac{k}{n}\right)^k \left(1 - \frac{k}{n}\right)^{n-k} = (n+1) \binom{n}{k} 2^{-nh_2\left(\frac{k}{n}\right)}. \end{aligned} \quad (3)$$

The last equality comes from the derivation we had when proving the upper bound.

(c) Since for every $\mathbf{x} \in T(P)$, $Q^n(\mathbf{x}) = 2^{-n(H(P) + D(P\|Q))}$ (by part (a)) and $\frac{1}{n+1} 2^{nH(P)} \leq |T(P)| \leq 2^{nH(P)}$ (by part (b)), we have

$$\frac{1}{n+1} 2^{-nD(P\|Q)} \leq Q^n(T(P)) \leq 2^{-nD(P\|Q)}$$