## ECE 776 - Information theory (Spring 2012) <br> Final

P1 (1 point). Consider the random process $X_{i}=U Z_{i}$, where $U$ equals -1 or 1 with equal probability and $Z_{i}$ are i.i.d. over index $i$ and distributed as $Z_{i} \sim f(z)=\lambda e^{-\lambda z}$, with $z \geq 0$ (and $f(z)=0$ otherwise).
a. What can we say about the limit $\lim _{n \rightarrow \infty} 1 / n \sum_{i=1}^{n} X_{i}$ ?
b. Calculate the differential entropy rate $\lim _{n \rightarrow \infty} \frac{1}{n} h\left(X^{n}\right)$.
$\mathbf{P 2}$ (1 point). For any random variables $X_{1}, \ldots, X_{n}$, prove the equality

$$
H\left(X_{1}, \ldots, X_{n}\right) \leq \frac{1}{n-1} \sum_{i=1}^{n} H\left(X_{1}, \ldots, X_{i-1}, X_{i+1}, \ldots, X_{n}\right)
$$

(Hint: Note that the equality is equivalent to $n H\left(X_{1}, \ldots, X_{n}\right) \leq \sum_{i=1}^{n} H\left(X_{1}, \ldots, X_{i-1}, X_{i+1}, \ldots, X_{n}\right)+$ $\left.H\left(X_{1}, \ldots, X_{n}\right)\right)$.

P3 (1 point). Derive the equation that describes the typical set for a Gaussian distribution with mean $\mu$ and variance $\sigma^{2}$.
$\mathbf{P} 4$ (1 point). Suppose that $X$ is a random variable with support $[1, \infty)$ and $Y$ is a random variable with support $[0,1]$. Moroever, we have $E[X]=\mu_{X} \geq 0$ and $E[Y]=\mu_{Y} \geq 0$. Prove the inequality

$$
h(X \mid Y) \leq \log _{2}\left(e\left(\mu_{X}-\mu_{Y}\right)\right) .
$$

P5 (2 points). Generate two random codebooks $\mathcal{C}_{1}$ and $\mathcal{C}_{2}$ with $2^{n R_{1}}$ and $2^{n R_{2}}$ codewords of length $n$ symbols, where the symbols are generated i.i.d. with probabilities $p\left(x_{1}\right)$ and $p\left(x_{2}\right)$, respectively. Define the set

$$
\mathcal{B}=\left\{\left(x_{1}^{n}, x_{2}^{n}\right): x_{1}^{n} \in \mathcal{C}_{1}, x_{2}^{n} \in \mathcal{C}_{2},\left(x_{1}^{n}, x_{2}^{n}\right) \in A_{\epsilon}^{(n)}\right\}
$$

where $A_{\epsilon}^{(n)}$ is the set of jointly typical sequences with respect to a joint $\operatorname{pmf} p\left(x_{1}, x_{2}\right)$ with marginal pmfs $p\left(x_{1}\right)$ and $p\left(x_{2}\right)$. Show that

$$
2^{n\left(R_{1}+R_{1}-I\left(X_{1} ; X_{2}\right)-3 \epsilon\right)} \leq E[|\mathcal{B}|] \leq 2^{n\left(R_{1}+R_{1}-I\left(X_{1} ; X_{2}\right)+3 \epsilon\right)}
$$

for $n$ large enough. Please provide all the details of the proof (you can use the theorems proved in class).

P6 (1 point). We wish to transmit a $\operatorname{Ber}(p)$ process $V^{n}$ over $n$ channel uses of a binary symmetric channel with crossover probability 0.3 . Find necessary and sufficient conditions on $p$ such that $V^{n}$ can be estimated with vanishing error probability at the receiver.

P7 (1 point). We have the two independent random variables $X_{1}$ and $X_{2}$ with pmfs $p(x)$ and $q(x)$, respectively, with $x \in \mathcal{X}$. Prove that

$$
\operatorname{Pr}\left[X_{1}=X_{2}\right] \geq 2^{-(H(p(x))+D(p(x) \| q(x)))} .
$$

(Hint: $p(x)=2^{\log _{2} p(x)}$ ).
P8 (1 point) For any source (not necessarily Gaussian) with differential entropy $h(X)$, prove the following bound:

$$
R(D) \geq h(X)-\frac{1}{2} \log _{2}(2 \pi e D)
$$

When do we have equality? Therefore, is a Gaussian source with the same differential entropy $h(X)$ easier or more difficult to compress?

P9 (2 points) Consider the Gaussian channel with received signal $Y=\left(Y_{1}, Y_{2}\right)$, where

$$
\begin{aligned}
& Y_{1}=X+Z_{1} \\
& Y_{2}=X+Z_{2}
\end{aligned}
$$

the power constraint is $P$ and the noises $\left(Z_{1}, Z_{2}\right)$ are independent and with variances $N_{1}$ and $N_{2}$.
a. Calculate the capacity.
b. Can we simplify the decoder so that it operates on a single received symbol rather than two for each channel use?

Sol.:
P1. a. The process is stationary but not ergodic. We have that the quantity $1 / n \sum_{i=1}^{n} X_{i}$ tends to $1 / \lambda$ with probability $1 / 2$ and $-1 / \lambda$ with probability $1 / 2$ by the (strong) law of large numbers.
b. We have

$$
\begin{aligned}
\lim _{n \rightarrow \infty} \frac{1}{n} h\left(X^{n}\right) & =\lim _{n \rightarrow \infty} \frac{1}{n} h\left(X^{n}, U\right) \\
= & \lim _{n \rightarrow \infty} \frac{1}{n} h\left(X^{n} \mid U\right)+\mathbb{1}_{\bigotimes} \\
& =\log _{2}\left(\frac{e}{\lambda}\right)+1
\end{aligned}
$$

where the first equality holds since $U$ is a function of $X^{n}$ (except on a set of measure zero).
P2. We have

$$
\begin{aligned}
H\left(X_{1}, \ldots, X_{n}\right) & =H\left(X_{1}, \ldots, X_{i-1}, X_{i+1}, \ldots, X_{n}\right)+H\left(X_{i} \mid X_{1}, \ldots, X_{i-1}, X_{i+1}, \ldots, X_{n}\right) \\
& \leq H\left(X_{1}, \ldots, X_{i-1}, X_{i+1}, \ldots, X_{n}\right)+H\left(X_{i} \mid X_{1}, \ldots, X_{i-1}\right) .
\end{aligned}
$$

Summing over $i$, we get

$$
n H\left(X_{1}, \ldots, X_{n}\right) \leq \sum_{i=1}^{n} H\left(X_{1}, \ldots, X_{i-1}, X_{i+1}, \ldots, X_{n}\right)+H\left(X_{1}, \ldots, X_{n}\right)
$$

which is the desired result.
P3. Please see lecture notes.

P4. We have

$$
\begin{aligned}
h(X \mid Y) & =\int h(X \mid Y=y) f(y) d y \\
& =\int h(X-y \mid Y=y) f(y) d y \\
& =h(X-Y \mid Y) \\
& \leq h(X-Y) \\
& \leq \log _{2}\left(e\left(\mu_{X}-\mu_{Y}\right)\right),
\end{aligned}
$$

where the second inequality follows by the maximum entropy theorem since $X-Y$ has support $[0, \infty)$ and mean $E[X-Y]=\mu_{X}-\mu_{Y}$.

P5. Observe that for given codebooks, we have

$$
|\mathcal{B}|=\sum_{w_{1}=1}^{2^{n R_{1}}} \sum_{w_{1}=1}^{2^{n R_{2}}} 1\left\{\left(x_{1}^{n}\left(w_{1}\right), x_{2}^{n}\left(w_{2}\right)\right) \in A_{\epsilon}^{(n)}\right\},
$$

where $1\{x\}=0$ if $x$ is false and 1 otherwise. We can then write

$$
\begin{aligned}
E[|\mathcal{B}|] & =\sum_{w_{1}=1}^{2^{n R_{1}}} \sum_{w_{1}=1}^{2^{n R_{2}}} E\left[1\left\{\left(X_{1}^{n}\left(w_{1}\right), X_{2}^{n}\left(w_{2}\right)\right) \in A_{\epsilon}^{(n)}\right\}\right] \\
& =\sum_{w_{1}=1}^{2^{n R_{1}}} \sum_{w_{1}=1}^{2^{n R_{2}}} \operatorname{Pr}\left\{\left(X_{1}^{n}\left(w_{1}\right), X_{2}^{n}\left(w_{2}\right)\right) \in A_{\epsilon}^{(n)}\right\}
\end{aligned}
$$

But we know that

$$
(1-\epsilon) 2^{-n\left(I\left(X_{1} ; X_{2}\right)+3 \epsilon\right)} \leq \operatorname{Pr}\left\{\left(X_{1}^{n}\left(w_{1}\right), X_{2}^{n}\left(w_{2}\right)\right) \in A_{\epsilon}^{(n)}\right\} \leq 2^{-n\left(I\left(X_{1} ; X_{2}\right)-3 \epsilon\right)}
$$

where the first inequality holds for $n$ large enough. The desired result follows immediately.
P6. The necessary and sufficient conditions on $p$ is

$$
H(0.3) \leq 1-H(p)
$$

from which we can derive the condition on $p$.
P7. We have

$$
\begin{aligned}
\operatorname{Pr}\left[X_{1}\right. & \left.=X_{2}\right]=\sum_{x} p(x) q(x) \\
& =\sum_{x} p(x) 2^{\log _{2} q(x)} \\
& \leq 2^{\sum_{x} p(x) \log _{2} q(x)} \\
& =2^{\sum_{x} p(x) \log _{2}\left(q(x) \frac{p(x)}{p(x)}\right)} \\
& =2^{\sum_{x} p(x) \log _{2}\left(q(x) \frac{p(x)}{p(x)}\right)} \\
& =2^{-H(p(x))-D(p(x) \| q(x))} .
\end{aligned}
$$

P8. The result follows from the inequality

$$
\begin{aligned}
I(X ; \hat{X}) & =h(X)-h(X \mid \hat{X}) \\
& \geq h(X)-\frac{1}{2} \log _{2}(2 \pi e D)
\end{aligned}
$$

where the inequality can be derived as seen in class. We have equality if $X$ is Gaussian. Therefore, a Gaussian source with the same differential entropy $h(X)$ is easier to compress.

P9. Following the same steps seen in class we get

$$
C=\frac{1}{2} \log _{2}\left(1+\frac{P}{N_{1}}+\frac{P}{N_{2}}\right) .
$$

Moreover, it can be checked that a decoder that operates with the received signal $\frac{1}{\sqrt{N_{1}}} Y_{1}+$ $\frac{1}{\sqrt{N_{2}}} Y_{2}$ achieves the same capacity.

