

4.1 Non-negativity

$$H(x) = \sum p \log(1/p)$$

Clearly $p > 0$ and $p < 1$

$\therefore 1/p > 1$ and $\log(1/p) > 0$

$\therefore p \log(1/p) > 0 \Rightarrow \underline{\underline{\sum p \log(1/p) > 0}}$

Monotonicity

Continuity: Since sum of continuous function is continuous
Let $F = p \log(p)$, where $F = F(p)$ let's take $p \log p$.

F is continuous if for $c - \delta < p < c + \delta$

$$F(c) - \delta < F(p) < F(c) + \delta$$

$$\Rightarrow -\delta < F(p) - F(c) < \delta$$

$$|F(p) - F(c)| < \delta \quad \text{--- (1)}$$

Let $p \in P'$ and

~~we~~ we have $c - \delta < p < c + \delta$.

$$(c - \delta) \log p < p \log p < (c + \delta) \log p$$

$$\text{clearly } c \log p - \delta < p \log p < c \log p + \delta \quad \text{--- (2)}$$

$$|p \log p| < \delta$$

From (1) and (2) $H(x)$ is continuous.

Monotonicity : $H(x) = \sum_{i=1}^n p \log(1/p)$

Consider $p \log p$.

~~For small δ $(p+\delta) \log(p+\delta)$~~

For small δ we have $(p+\delta) \log(1/(p+\delta))$

If δ is positive $p+\delta > p \Rightarrow 1/(p+\delta) < 1/p$

\Rightarrow But p and $p+\delta$ are less than 1.

$$4.2. I(x, y) = \sum_x \sum_y p(x, y) \log \frac{p(x, y)}{p(x)p(y)}$$

$$= \sum_x \sum_y p(x, y) \log p(x, y) - \sum_x \sum_y p(x, y) \log p(x) - \sum_x \sum_y p(x, y) \log p(y)$$

$$= \sum_x \sum_y p(x, y) \log p(x, y) - \sum_x p(x) \log p(x) - \sum_y p(y) \log p(y)$$

$$= -H(x, y) + H(x) + H(y)$$

Also $H(x, y) = H(x|y) + H(y)$

$$\therefore I(x, y) = H(x) - H(x|y)$$

Similarly $H(x, y) = H(y|x) + H(x)$

$$\therefore I(x, y) = H(y) - H(y|x)$$

$$\begin{aligned}
4.3 \text{ (a)} \quad & \text{Probability of error} \\
& \text{with majority voting} = P(\text{at least two erroneous bits}) \\
& = 3P(\text{two erroneous bits}) \\
& \quad + P(\text{3 erroneous bits}) \\
& = 3\epsilon^2(1-\epsilon) + \epsilon^3 \\
& = \epsilon^2 [3 - 3\epsilon + \epsilon] \\
& = \epsilon^2 [3 - 2\epsilon]
\end{aligned}$$

$$\begin{aligned}
\text{(b)} \quad & \text{Probability of error} = \epsilon'^2 [3 - 2\epsilon'] \\
& \text{where } \epsilon' = \epsilon^2 [3 - 2\epsilon] \\
& = [\epsilon^2 (3 - 2\epsilon)]^2 [3 - 2\epsilon^2 (3 - 2\epsilon)] \\
& = \epsilon^4 (9 + 4\epsilon^2 - 12\epsilon) (3 - 6\epsilon^2 + 4\epsilon^3)
\end{aligned}$$

wh) Differential entropy = $-\int_{-\infty}^{\infty} p(x) \log(p(x)) dx$

For a gaussian process $p(x) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(x-\mu)^2}{2\sigma^2}}$

where μ = mean σ^2 = variance

$$-\int_{-\infty}^{\infty} p(x) \log p(x) dx = -\int_{-\infty}^{\infty} p(x) \log \left[\frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(x-\mu)^2}{2\sigma^2}} \right] dx$$

$$= -\int_{-\infty}^{\infty} p(x) \log \left(\frac{1}{\sqrt{2\pi\sigma^2}} \right) dx - \int_{-\infty}^{\infty} p(x) \left(-\frac{(x-\mu)^2}{2\sigma^2} \right) dx$$

$$= \int_{-\infty}^{\infty} p(x) \log(\sqrt{2\pi\sigma^2}) dx + \int_{-\infty}^{\infty} p(x) \frac{(x^2 + \mu^2 - 2\mu x)}{2\sigma^2} dx$$

$$= \log(\sqrt{2\pi\sigma^2}) + \int_{-\infty}^{\infty} \frac{p(x) x^2 dx}{2\sigma^2} + \int_{-\infty}^{\infty} \frac{p(x) \mu^2 dx}{2\sigma^2} - \int_{-\infty}^{\infty} \frac{p(x) \cdot 2\mu x dx}{2\sigma^2}$$

$$= \log(\sqrt{2\pi\sigma^2}) + \frac{1}{2\sigma^2} \langle x^2 \rangle + \frac{\mu^2}{2\sigma^2} - \frac{2\mu}{2\sigma^2} \langle x \rangle$$

$$= \log(\sqrt{2\pi\sigma^2}) + \frac{1}{2\sigma^2} (\langle x \rangle + \sigma^2) + \frac{\mu^2}{2\sigma^2} - \frac{2\mu^2}{2\sigma^2}$$

$$= \log(\sqrt{2\pi\sigma^2}) + \frac{\mu + \sigma^2 - \mu^2}{2\sigma^2}$$

=

$$= - \int_{-\infty}^{\infty} P(x) \log \left(\frac{1}{\sqrt{2\pi\sigma^2}} \right) dx + \int_{-\infty}^{\infty} P(x) \frac{(x-\mu)^2}{2\sigma^2} dx$$

$$= \log(\sqrt{2\pi\sigma^2}) + \frac{1}{2\sigma^2} \int_{-\infty}^{\infty} P(x) (x-\mu)^2 dx$$

$$= \log(\sqrt{2\pi\sigma^2}) + \frac{1}{2\sigma^2} \langle (x-\mu)^2 \rangle$$

$$= \log(\sqrt{2\pi\sigma^2}) + \frac{1}{2\sigma^2} \sigma^2$$

$$= \log_e(\sqrt{2\pi\sigma^2}) + \frac{1}{2}$$

$$= \frac{1}{2} \log(2\pi\sigma^2) + \frac{1}{2} \log e$$

$$= \underline{\underline{\frac{1}{2} \log(2\pi e\sigma^2)}}$$

$$4.5(a) \quad \Delta F = 3300 \text{ Hz} \quad \text{SNR} = 20 \text{ dB} = 10 \log(S/N).$$

$$\text{Capacity} = \Delta F \log_2 \left(1 + \frac{S}{N} \right) \quad \text{bits/second}$$

$$= 3300 \log_2(1 + 10^2) \quad \text{bits/second}$$

$$= 21945 \quad \text{bits/second.}$$

$$(b) \quad \text{Capacity} = 1 \text{ Gbit/s} = 10^9 \text{ bit/s} = 3300 \log_2(1 + S/N)$$

$$\log_2(1 + S/N) = \frac{10^9}{3.3 \times 10^3}$$

$$\log_{10}(1 + S/N) = \frac{10^9 \times \log_{10} 2}{3.3 \times 10^3} = \frac{10^9 \times 3 \times 10^{-1}}{3.3 \times 10^3}$$

$$= 10^5$$

$$10 \log(S/N) \approx 10^6 \text{ dB}$$

$$\underline{\underline{\text{SNR} = 10^6 \text{ dB}}}$$

$$4.6) F(x_1, x_2, \dots, x_n) = \frac{1}{n} \sum_{i=1}^n x_i$$

$$\begin{aligned} \langle F(x_1, x_2, \dots, x_n) \rangle &= \left\langle \frac{1}{n} \sum_{i=1}^n x_i \right\rangle = \frac{1}{n} \sum_{i=1}^n \langle x_i \rangle \\ &= \frac{1}{n} \sum_{i=1}^n x_0 = \frac{1}{n} \cdot n \cdot x_0 = \underline{\underline{x_0}} \end{aligned}$$

Hence the estimator is biased.

Cramer-Rao Inequality states $\sigma^2(F) \geq 1/J(x)$.

Here $x = x_0$

$$\text{Variance of estimator} = \sigma^2(F) = \left\langle \left[\frac{1}{n} \sum_{i=1}^n (x_i - x_0) \right]^2 \right\rangle$$

$$= \frac{1}{n^2} \sum_{i=1}^n \langle (x_i - x_0)^2 \rangle$$

$$= \frac{1}{n^2} \cdot n \cdot \frac{1}{n^2} \sum_{i=1}^n \sigma^2$$

$$= \frac{1}{n^2} \cdot n \cdot \sigma^2 = \underline{\underline{\sigma^2/n}}$$