



(c)

$$Cost = (2)^{l_i} = C_i$$

$l_i$  = length of  $i$ th codeword

The average cost of X is

$$C = \sum_{i=1}^n p_i c_i l_i$$

which is what we would like to minimize.

We let

$$r_i = 2^{l_i}$$

$$Q = \sum_i p_i c_i$$

$$q_i = p_i c_i / Q$$

$q_i$  forms a probability distribution.

$$\begin{aligned} C &= \sum p_i c_i l_i \\ &= -\sum p_i c_i \log l_i \\ &= -\sum Q q_i \log r_i \\ &= Q \sum q_i \log \frac{1}{r_i} \\ &= Q \left[ \sum (q_i \log 1 - q_i \log r_i) \right] \\ &= Q \left( \sum q_i \log \frac{q_i}{r_i} - \sum q_i \log q_i \right) \\ &= Q(D(q||r) + H(q)) \end{aligned}$$

Since the only freedom is in the choice of  $r_i$ , we can minimize  $C$  by choosing

$$\bar{r} = \bar{q}$$

$$2^{-l_i} = \frac{p_i c_i}{\sum p_i c_i}$$

$$l_i^* = -\log \frac{p_i c_i}{\sum p_i c_i}$$

Therefore, the minimum cost  $C^*$  for the assignment of codewords is

$$C^* = Q H(q)$$

We can construct a Huffman code with minimum expected cost by using distribution  $q$  instead of distribution  $p$ .

Problem No. 2

(a)

$$C = \max_p I(X;Y) = \max_p [H(Y) - H(Y|X)] \leq \max_p [1 - H(Y|X)]$$

equally holds when the input distribution is uniform. The value of  $p$  that minimizes the capacity of the channel is  $p = 1/2$ .

$$C = 1 - 1 = 0$$

(b)

The transition probability matrix for a single binary symmetric channel is

$$A = \begin{bmatrix} 1-p & p \\ p & 1-p \end{bmatrix}$$

???????

## Problem No. 3

(a)

$$\begin{aligned}
 h(f) &= -\int_0^{\infty} f(x) \log f(x) dx \\
 &= -\int_0^{\infty} e^{-x} \ln e^{-x} dx = \int_0^{\infty} e^{-x} (-x) dx = \int_0^{\infty} x e^{-x} dx = \langle x e^{-x} - e^{-x} \rangle = 1
 \end{aligned}$$

(b)

$$\begin{aligned}
 h(f) &= \int_0^{\infty} 2e^{-2x} \ln(2e^{-2x}) dx \\
 &= \int_0^{\infty} e^{-2x} (\ln(2) + \ln(e^{-2x})) dx \\
 &= -2 \int_0^{\infty} \ln 2 e^{-2x} dx - 2 \int_0^{\infty} -2x e^{-2x} dx \\
 &= -2 \ln 2 \langle \frac{1}{-2} e^{-2x} \rangle - \langle (-x) \frac{1}{-2} e^{-2x} \rangle - \int_0^{\infty} \frac{-1}{2} e^{-2x} dx = 1.693
 \end{aligned}$$

This answer agrees with the scaling theorem.

$$\begin{aligned}\text{Scaling Theorem: } h(aX) &= h(X) + \log|a| \\ &= 1 + \log 2 = 1.693\end{aligned}$$

(c)

$$\begin{aligned}h(x) &= -\int_3^{\infty} x e^{-x} \ln e^{-x} dx = -e^3 \int_3^{\infty} e^{-x} \ln e^{-x} e^3 dx \\ &= -e^3 \left[ \int_3^{\infty} e^{-x} (\ln e^{-x} + \ln e^e) dx \right] = -e^3 \int_3^{\infty} (-x) e^{-x} dx - e^3 \int_3^{\infty} 3 e^{-x} dx \\ &= -e^3 [-\langle x e^{-x} - e^{-x} \rangle - \langle (-3) e^{-x} \rangle] = 1\end{aligned}$$

The answer agrees with the translation theorem. Part c is a translation of part a.

$$\text{Translation Theorem: } h(X+c) = h(X)$$

Translation does not change the differential entropy.

(d)

$$\begin{aligned}D(f||g) &= \int_0^{\infty} f \ln \frac{f}{g} dx = \int_0^{\infty} f (\ln f - \ln g) dx = \int_0^{\infty} f \ln f dx - \int_0^{\infty} f \ln g dx \\ &= \int_0^{\infty} e^{-x} \ln e^{-x} dx - \int_0^{\infty} e^{-x} \ln(2e^{-2x}) dx = \int_0^{\infty} e^{-x} \ln e^{-x} dx - \int_0^{\infty} e^{-x} (\ln 2 + \ln e^{-2x}) dx\end{aligned}$$

$$\begin{aligned} &= \int_0^{\infty} x e^{-x} dx - \int_0^{\infty} e^{-x} \ln 2 dx - \int_0^{\infty} (-e^{-x} \ln e^{-2x}) dx \\ &= \langle x e^{-x} - e^{-x} \rangle - \langle -\ln 2 \cdot e^{-x} \rangle - \langle -(-2x) e^{-x} \rangle = 1 - \ln 2 = 0.3069 \end{aligned}$$