TD 1 – Shannon Theory

Exercises

We recall the definition of the entropy (in bits): $H(p) \overset{\text{def.}}{=} -\sum_k p_k \log_2 p_k$ with the convention $0\log(0) = 0$. This definition extends to matrices by replacing k with (i, j).
For $(a, b) \in \mathbb{R}_+^n \times \mathbb{R}_+^m$, we define $a \otimes b \overset{\text{def.}}{=} (a_i b_j)_{ij}$. Finally, we introduce the simplex $\Sigma_n \overset{\text{def.}}{=} \left\{p \in \mathbb{R}_+^n : \sum_k p_k = 1\right\}$.

Entropic coding (adapted from exam 2021)

We consider the alphabet $(s_1, s_2, s_3, s_4, s_5)$. The probabilities of appearance of the symbols s_k are $p_1 = 1/3$, $p_2 = 1/4$, $p_3 = 1/6$, $p_4 = 1/6$, $p_5 = 1/12$. You may use $\log_2(3) \approx 1.6$.

1. Compute the entropy $H(p)$ for the distribution of the considered alphabet.
2. If one were to define a fixed length code for this alphabet, how many bits would be needed to code each symbol?
3. What is the optimal average number of bits per symbol for a code on this alphabet? Why is a fixed-length code inefficient?
4. Draw a binary prefix coding tree, following the proof of Shannon's theorem. What is the average number of bits per symbol for the associated code?
5. Draw the Huffman tree for the considered alphabet, explaining each step. Write the associated code. What is the average number of bits per symbol for the associated code?

Entropic coding by blocks (adapted from exam 2020)

We assume X is a discrete random variable with values in $\{1, \ldots, k\}$ with probablity distribution $p = (p_1, \ldots, p_k)$.

1. What is the probability distribution $q = (q_{i_1,\ldots,i_n})_{i_1,\ldots,i_n}$ of the random vector $(X_1, \ldots, X_n)$ on $\{1, \ldots, k\}^n$, where the X_i are independent copies of X?
2. Compute the entropy $H(q)$ of q as a function of $H(p)$.
3. We assume an infinite sequence of symbols with distribution p. Show that by using a Huffman code by blocks of n consecutive symbols, the average number of bits per symbol tends to $H(p)$ as $n \to \infty$.

Entropy function

1. Show that $H : p \in \mathbb{R}_+^n \to -\sum_k p_k \log_2 p_k$ is a strictly concave function.
2. For what value of $p \in \mathbb{R}_+^n$ is H maximal?
3. Show that for all $p, q \in \Sigma_n$, $H(p) \leq -\sum_i p_i \log_2 q_i$. Then, show that $H(p) \leq \log_2(n)$. Finally, find for which $p \in \Sigma_n$ the function H is maximal. For what value of $p \in \Sigma_n$ is H maximal?
4. For $(a, b) \in \Sigma_n \times \Sigma_m$, compute $H(a \otimes b)$.

Kullback-Leibler divergence (adapted from exam 2017)

For $q \in \mathbb{R}_{+,*}^n$ (strictly positive) and $r \in \mathbb{R}_+^n$, we define the Kulback-Leibler divergence between the two vectors as

$$\mathrm{KL}(r|q) \overset{\text{def.}}{=} \sum_i r_i \log\left(\frac{r_i}{q_i}\right) - r_i + q_i.$$

The same expression holds also for matrices, where the sum is on (i, j) instead of just i.

1. Show that the function $\mathrm{KL}(\cdot|q)$ is strictly convex and compute its minimizer.
2. Deduce that KL is "distance-like", i.e. that $\mathrm{KL}(r|q) > 0$ and $\mathrm{KL}(r|q) = 0$ if and only if $r = q$.
3. Show that, if $(a, b) \in \Sigma_n \times \Sigma_m$, $(a', b') \in \mathbb{R}_{+,*}^n \times \mathbb{R}_{+,*}^m$ and $P \in \mathbb{R}_+^{n\times m}$ such that $P\mathbb{1}_m = a$ and $P^\top \mathbb{1}_n = b$, then one has

$$\mathrm{KL}(P|a' \otimes b') = \mathrm{KL}(P|a \otimes b) + \mathrm{KL}(a \otimes b|a' \otimes b').$$