Information and coding theory

Solution to exercise sheet $n^{\circ} 1$:

1-1.

(a) Example $\mathcal{X} = \{0, 1, \dots m - 1\}$. With $p(x) = \frac{1}{m}$ for $x \in \mathcal{X}$.

(b) $H(X) = -\sum_{i=0}^{m-1} p_i \log_2 p_i = \log_2 m = 6$ bits.

(c) One needs 6 bits, since $2^6 = 64$.

(d) One needs 3 symbols, since $4^3 = 64$.

(e) One defines the Lagrangian L(

$$L({p_i}) = H(X) - \lambda [\sum_{i=0}^{m-1} p_i - 1].$$

Condition for an extremum:

$$\forall i, \frac{\partial L}{\partial p_i} = 0.$$

The distribution that maximizes H(X) (note that H(X) is concave) satisfies:

$$-\log_2 p_i - \frac{1}{\ln 2} + \lambda = 0 \qquad \forall i.$$

One finds $p_i = 2^{\lambda - \frac{1}{\ln 2}}$, i.e. p_i is a constant. With the constraint one finds $p_i = \frac{1}{m}$.

1-2.

(a) $H(X_P) = 1.75$ bits.

(b) $H(X_Q) = 2$ bits.

(c) The expected length of the codewords is 1.75 bits for the distribution P and 2.25 bits for the distribution Q.

(d) The entropy gives the minimal expected length of codewords one can obtain. The binary code C is optimal for the distribution P, since its expected length $L_P = H(X_P)$. For the distribution Q we find $L_Q > H(X_Q)$ and $L_Q > L_P$, which implies that the code is not optimal. The optimal code for Q is given by a simple enumeration of the elements of X; it is thus, impossible to compress that source.

1-3.

(a) H(X) = 2 bits.

(b) Sequence of questions :

Did one obtain "head" with the first flip?

Did one obtain "head" with the second flip?

. . .

Did one obtain "head" with the *n*th flip?

One can associate the answer to each question with a separate bit, and thus the answers to n questions are encoded in n bits. We obtain the expected number of "yes/no" questions: $\sum_{n=1}^{\infty} p(n)n = H(X) = 2$. It is equal to the entropy, which shows that the sequence of questions is optimal.

1-4.

- (a) H(Y) = H(X) = 1.875 bits, because the function is bijective (i.e. if one fixes Y, one knows X).
- (b) The function is not bijective. One obtains H(Y) < H(X) with H(X) = 2.085 bits and H(Y) = 1,325 bits.
- (c) H(X, f(X)) = H(X) + H(f(X)|X) but H(f(X)|X) = 0, because knowing X fixes f(X). H(f(X), X) = H(f(X)) + H(X|f(X)) but H(X|f(X)) > 0.

Finally: H(f(X), X) = H(X, f(X)) implies $H(f(X)) \le H(X)$.

It is saturated if H(X|f(X)) = 0, i.e. if the function Y = f(X) is bijective.

1-5.

(a) Definition of the conditional entropy : $H(Y|X) = \sum_{x \in \mathcal{X}} p(x)H(Y|X=x)$.

$$H(Z|Y) = \sum_{y \in \mathcal{Y}} p(y)H(Z|Y=y) = \sum_{y \in \mathcal{Y}} p(y)H(X+Y|Y=y) = \sum_{y \in \mathcal{Y}} p(y)H(X|Y=y) = H(X|Y).$$

If X and Y are independent, then H(X|Y) = H(X).

As conditioning can only reduce the entropy : $H(Z|Y) \leq H(Z)$.

We finally obtain $H(X) \leq H(Z)$, and similarly $H(Y) \leq H(Z)$.

(b) Example

P(X = x, Y = y)		Y = -1	-2	-3	-4	P(X=x)
X =	1	1/4	0	0	0	1/4
	2	0	1/4	0	0	1/4
	3	0	0	1/8	1/8	1/4
	4	0	0	1/8	1/8	1/4
	P(Y=y)	1/4	1/4	1/4	1/4	1

Calculation of H(X) and H(Y): $H(Y) = H(X) = H(1/4, 1/4, 1/4, 1/4) = \log_2 4 = 2$ bits. One obtains $\mathcal{Z} = \{3, 2, 1, 0, -1, -2, -3\}$ with P(Z = 0) = 3/4, P(Z = 1) = 1/8 et P(Z = 1)-1) = 1/8 and the other probabilities are zero.

Calculation of H(Z): $H(Z) = -\frac{3}{4} \log_2 \frac{3}{4} - \frac{1}{4} \log_2 \frac{1}{8} = 1.061$ bits. One verifies that H(X) > H(Z) and H(Y) > H(Z).

(c) We require that X and Y are independent and that all $z_{i,j} = x_i + y_j$ are distinct for any couple (i, j). If these conditions are satisfied one obtains $p_z(i, j) = p_x(i)p_y(j)$, which gives us the solution (after insertion in the defintion of H(Z)).

Example: $\mathcal{X} = \{1, 2, 3\}$ and $\mathcal{Y} = \{10, 20, 30, 40\}$ for any probability distribution of X and Y, where X and Y are independently distributed.

Optional.

P(X,Y)		X = -1	0	1	P(Y)
Y =	-2	0	1/3	0	1/3
	1	1/3	0	1/3	2/3
P(X)		1/3	1/3	1/3	1

In this example, one verifies $\langle X \rangle = \langle Y \rangle = \langle XY \rangle = 0$, thus r = 0.

H(X:Y) = H(X) + H(Y) - H(X,Y) = 0.918 bit.