Information and Coding Theory

Solutions to Exercise Sheet 1

Exercise 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) 6 bits are needed since $2^6 = 64$.
- (d) 3 symbols are needed since $4^3 = 64$.
- (e) Define the Lagrangian $L(\{p_i\}) = H(X) + \lambda [\sum_{i=0}^{m-1} p_i 1].$ 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:

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

It follows that $p_i = 2^{\lambda - \frac{1}{\ln 2}}$, i.e. p_i is a constant. If the constraint is applied, then $p_i = \frac{1}{m}$.

Exercise 2.

- (a) $H(X_p) = 1.75$ bits.
- (b) $H(X_a) = 2$ 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; therefore it is impossible to compress that source.

Exercise 3. (a) H(X) = 2 bits.

(b) Sequence of questions:

Did "head" come up on the first flip?

Did "head" come up on the second flip??

:

Did "head" come up on the *n*th flip?

One bit can be associated with the answer to each question. The answers to n questions are therefore encoded in n bits. The expected number of "yes/no" questions is given by $\sum_{n=1}^{\infty} p(n)n = H(X) = 2$. It is equal to the entropy, which shows that the sequence of questions is optimal.

Exercise 4.

- (a) H(Y) = H(X) = 1.875 bits, because the function is bijective (i.e. fixing Y also fixes X).
- (b) The function is not bijective, so 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 $H(X|f(X)) \ge 0$.

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.

Exercise 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 $H(X) \le H(Z)$, and similarly $H(Y) \le H(Z)$.

(b) Example:

XY	-1	-2	-3	-4	P(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)	1/4	1/4	1/4	1/4	

How to compute H(X) and H(Y):

 $H(Y) = H(X) = H(1/4, 1/4, 1/4, 1/4) = \log_2 4 = 2$ bits.

We have $\mathcal{Z} = \{3, 2, 1, 0, -1, -2, -3\}$ with P(Z = 0) = 3/4, P(Z = 1) = 1/8 and P(Z = -1) = 1/8.

All other probabilities are zero.

How to compute of H(Z):

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

(c) We require that X and Y are independent and all $z_{i,j} = x_i + y_j$ are distinct for all pairs (i,j). If these conditions are satisfied then $p_z(i,j) = p_x(i)p_y(j)$, which gives us the solution (after substituting it in the definition 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.

Exercise 6. Optional

YX	-1	0	1	P(Y)
-2	0	1/3	0	1/3
1	1/3	0	1/3	2/3
P(X)	1/3	1/3	1/3	

In this example, $\langle X \rangle = \langle Y \rangle = \langle XY \rangle = 0$, which makes r = 0.

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