

## Exercises

- The probability density function of the univariate Gaussian distribution is given by:

$$p(x | \mu, \sigma^2) = \frac{1}{(2\pi\sigma^2)^{1/2}} e^{-\frac{1}{2} \frac{(x-\mu)^2}{\sigma^2}}$$

where  $x$  is the scalar random variable and  $\mu$  and  $\sigma^2$  the mean and variance, respectively.

1) Prove that  $\int_{-\infty}^{+\infty} \frac{1}{(2\pi\sigma^2)^{1/2}} e^{-\frac{1}{2} \frac{(x-\mu)^2}{\sigma^2}} dx = 1$

- 2) Given a set of samples,  $x_i$ ,  $i = 1 \dots N$ , find the values of  $\mu$  and  $\sigma^2$  for which the following function of  $\mu$  and  $\sigma^2$  (known as log-likelihood) has a maximum:

$$\sum_{i=1}^N \log p(x_i | \mu, \sigma^2)$$

- 3) Let us now assume that each sample,  $x_i$ , comes accompanied by a weight,  $w_i$ . Find the values of  $\mu$  and  $\sigma^2$  for which the following function of  $\mu$  and  $\sigma^2$  (known as weighted log-likelihood) has a maximum:

$$\sum_{i=1}^N w_i \log p(x_i | \mu, \sigma^2)$$

- 4) Let us now assume that each sample,  $x_i$ , has a normal unitary weight, but it is generated from the following pdf:

$$p(x | \mu, \sigma^2, u) = \frac{1}{\left(2\pi \frac{\sigma^2}{u}\right)^{1/2}} e^{-\frac{1}{2} \frac{(x-\mu)^2}{\sigma^2/u}}$$

For each sample,  $x_i$ , there is an accompanying value,  $u_i$ . Find the values of  $\mu$  and  $\sigma^2$  for which the following function of  $\mu$  and  $\sigma^2$  has a maximum:

$$\sum_{i=1}^N \log p(x_i | \mu, \sigma^2, u_i)$$

- The probability distribution of a discrete random variable,  $x$ , with  $K$  possible outcomes is defined by  $K$  probability values,  $0 \leq p_k \leq 1$ ,  $k = 1 \dots K$ , subject to constraint  $\sum_k p_k = 1$  (the interval where the  $p_k$  can take value is called the *simplex*). Such  $K$  probability values can be regarded as the parameters,  $\theta = [p_1, \dots, p_K]$ , of the probability distribution which can be written as  $p(x|\theta)$ .

We now want to estimate  $\theta$  with maximum likelihood from a training set,  $X$ , with  $N$  samples. We assume that the training set has  $N_1$  samples with outcome 1,  $N_2$  samples with outcome 2, ...  $N_K$  samples with outcome  $K$ , with  $\sum_k N_k = N$ . Prove that the maximum-likelihood estimate for  $\theta$  is:

$$\theta_{ML} = \left[ p_1 = \frac{N_1}{N}, \dots, p_K = \frac{N_K}{N} \right]$$

that is, nothing else than the fraction of samples of each outcome.