

Deep Learning

Theoretical Exercises – Week 2 – Chapter 3

Exercises on the book "Deep Learning" written by Ian Goodfellow,
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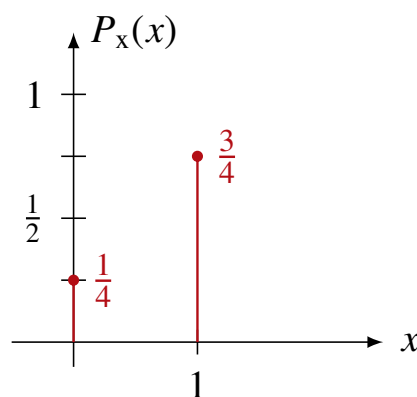
FS 2024

1 Exercises on Probability and Information Theory

1. Given a Bernoulli distributed random variable x with $P(x = 1) = \frac{3}{4}$ and $P(x = 0) = \frac{1}{4}$.
 - (a) Draw the probability mass function $P_x(x)$.
 - (b) Find the expected value of x , i.e. $\mathbb{E}_x[x]$.
 - (c) Find the variance of x , i.e. $\text{Var}_x(x)$.

Solution:

- (a) Probability mass function:



(b) Expected value:

$$\begin{aligned}\mathbb{E}_x[x] &= \sum_x x P(x = x) \\ &= 0 \cdot P(x = 0) + 1 \cdot P(x = 1) \\ &= 0 \cdot \frac{1}{4} + 1 \cdot \frac{3}{4} \\ &= \frac{3}{4}\end{aligned}$$

(c) To calculate the variance, $\mathbb{E}_x[x^2]$ has to be calculated first:

$$\begin{aligned}\mathbb{E}_x[x^2] &= \sum_x x^2 P(x = x) \\ &= 0^2 \cdot P(x = 0) + 1^2 \cdot P(x = 1) \\ &= 0^2 \cdot \frac{1}{4} + 1^2 \cdot \frac{3}{4} \\ &= \frac{3}{4},\end{aligned}$$

which results in a variance of

$$\begin{aligned}\text{Var}_x(x) &= \mathbb{E}_x[x^2] - (\mathbb{E}_x[x])^2 \\ &= \frac{3}{4} - \left(\frac{3}{4}\right)^2 \\ &= \frac{3}{16}.\end{aligned}$$

Alternatively, the variance can also be calculated as

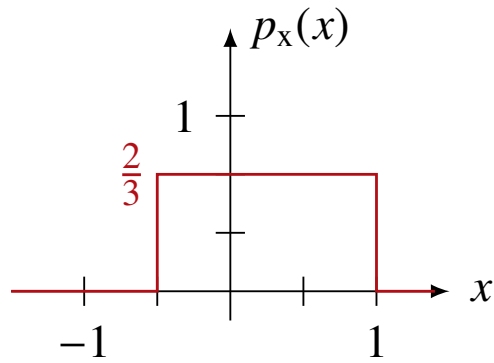
$$\begin{aligned}\text{Var}_x(x) &= \mathbb{E}[(x - \mathbb{E}_x[x])^2] \\ &= \mathbb{E}\left[\left(x - \frac{3}{4}\right)^2\right] \\ &= \left(0 - \frac{3}{4}\right)^2 \cdot P(x = 0) + \left(1 - \frac{3}{4}\right)^2 \cdot P(x = 1) \\ &= \left(0 - \frac{3}{4}\right)^2 \cdot \frac{1}{4} + \left(1 - \frac{3}{4}\right)^2 \cdot \frac{3}{4} \\ &= \frac{3}{16}.\end{aligned}$$

2. Given a uniformly distributed random variable x between -0.5 and 1 .

- (a) Draw the probability density function $f_x(x)$.
- (b) Find the expected value of x , i.e. $\mathbb{E}_x[x]$.
- (c) Find the variance of x , i.e. $\text{Var}_x(x)$.

Solution:

- (a) Probability density function:



(b) Expected value:

$$\begin{aligned}
 \mathbb{E}_x[x] &= \int x p_x(x) dx \\
 &= \int_{-0.5}^1 x \frac{2}{3} dx \\
 &= \left[\frac{x^2}{3} \right]_{-0.5}^1 \\
 &= \frac{1}{3} - \frac{1}{12} \\
 &= \frac{1}{4}
 \end{aligned}$$

(c) To calculate the variance, $\mathbb{E}_x[x^2]$ has to be calculated first:

$$\begin{aligned}
 \mathbb{E}_x[x^2] &= \int x^2 p_x(x) dx \\
 &= \int_{-0.5}^1 x^2 \frac{2}{3} dx \\
 &= \left[\frac{2x^3}{9} \right]_{-0.5}^1 \\
 &= \frac{2}{9} + \frac{1}{36} \\
 &= \frac{1}{4},
 \end{aligned}$$

which results in a variance of

$$\begin{aligned}
 \text{Var}_x(x) &= \mathbb{E}_x[x^2] - (\mathbb{E}_x[x])^2 \\
 &= \frac{1}{4} - \left(\frac{1}{4} \right)^2 \\
 &= \frac{3}{16}.
 \end{aligned}$$

3. There are 5000 yellow and 100 red cabs in a city. In a hit-and-run accident, a witness saw a red cab. What is the probability that it was actually a red cab if witnesses in 95% of the cases state the car's colour correctly?

Solution:

The probability $P(c = r | w = r)$ is sought. This is the probability that the cab (c) was red, given the witness (w) said red (r). To calculate this probability the Bayes' rule is used

$$P(c = r | w = r) = \frac{P(c = r) P(w = r | c = r)}{P(w = r)} = 27.54\%,$$

where

$$P(c = r) = \frac{100}{5000 + 100} = 0.0196,$$

$$P(w = r | c = r) = 0.95,$$

and

$$\begin{aligned} P(w = r) &= P(w = r | c = r)P(c = r) + P(w = r | c = y)P(c = y) \\ &= 0.95 \cdot \frac{100}{5000 + 100} + 0.05 \cdot \frac{5000}{5000 + 100} \\ &= 0.0676. \end{aligned} \tag{1.1}$$

4. Given are the following sets of samples of two different classes c_1 and c_2 :

$$S_1 = \{5.3, 5.7, 6.1, 6.3, 6.6\},$$

$$S_2 = \{6.2, 6.5, 6.9, 7.7, 8.0, 8.3, 8.9\}.$$

- Estimate the mean (expected value) and the variance of both classes and sketch their probability density function assuming that the samples of both classes are normally distributed.
- Estimate the prior probabilities $P(y = c_i)$ of both classes.
- Assign the new samples $x_1 = 5$ and $x_2 = 7$ to the class with the highest posterior probability.
- Calculate the entropy $H(x | y)$ of x with $y = c_1$ and $y = c_2$ respectively.

Solution:

- The mean and the variance are estimated as

$$m = \frac{1}{N} \sum_{i=1}^N x_i$$

and

$$\sigma^2 = \frac{1}{N-1} \sum_{i=1}^N (x_i - m)^2,$$

thus

$$m_1 = \frac{5.3 + 5.7 + 6.1 + 6.3 + 6.6}{5} = 6,$$

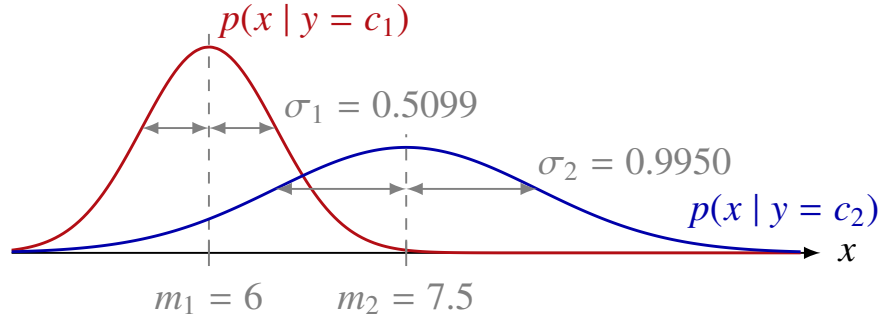
$$m_2 = \frac{6.2 + 6.5 + 6.9 + 7.7 + 8.0 + 8.3 + 8.9}{7} = 7.5,$$

$$\sigma_1^2 = \frac{(5.3 - 6)^2 + (5.7 - 6)^2 + (6.1 - 6)^2 + (6.3 - 6)^2 + (6.6 - 6)^2}{5 - 1} = 0.26,$$

and

$$\sigma_2^2 = \frac{(6.2-7.5)^2 + (6.5-7.5)^2 + (6.9-7.5)^2 + (7.7-7.5)^2 + (8.0-7.5)^2 + (8.3-7.5)^2 + (8.9-7.5)^2}{7-1}$$

$$= 0.99.$$



(b) Prior probabilities:

$$P(y = c_1) = \frac{5}{5+7} = \frac{5}{12}$$

$$P(y = c_2) = \frac{7}{5+7} = \frac{7}{12}$$

(c) If

$$P(y = c_1 | x) > P(y = c_2 | x),$$

the sample x is assigned to class c_1 otherwise x is assigned to class c_2 . Thus, to assign the new samples, $P(y = c_1 | x)$ and $P(y = c_2 | x)$ have to be determined. Since

$$P(y = c_1 | x) = \frac{P(y = c_1) p(x | y = c_1)}{p(x)}$$

and

$$P(y = c_2 | x) = \frac{P(y = c_2) p(x | y = c_2)}{p(x)},$$

the value of the term $p(x)$ does not change the assignment and can be omitted. The probabilities $P(y = c_1)$ and $P(y = c_2)$ already have been determined in (b) and the values of the probability density functions are calculated as

$$p(x | y = c_i) = \sqrt{\frac{1}{2\pi\sigma_i^2}} \exp\left(-\frac{1}{2\sigma_i^2}(x - m_i)^2\right).$$

For the first sample $x_1 = 5$ this results in

$$p(x = 5 | y = c_1) = 0.1144$$

and

$$p(x = 5 | y = c_2) = 0.0171$$

and for the second sample $x_2 = 7$ in

$$p(x = 7 | y = c_1) = 0.1144$$

and

$$p(x = 7 \mid y = c_2) = 0.3534.$$

Thus, x_1 is assigned to class c_1 , because

$$\begin{aligned} P(y = c_1) p(x = 5 \mid y = c_1) &> P(y = c_2) p(x = 5 \mid y = c_2) \\ \frac{5}{12} \cdot 0.1144 &> \frac{7}{12} \cdot 0.0171 \\ 0.0476 &> 0.0100, \end{aligned}$$

and x_2 is assigned to class c_2 , because

$$\begin{aligned} P(y = c_1) p(x = 7 \mid y = c_1) &< P(y = c_2) p(x = 7 \mid y = c_2) \\ \frac{5}{12} \cdot 0.1144 &< \frac{7}{12} \cdot 0.3534 \\ 0.0476 &< 0.2061. \end{aligned}$$

- (d) The entropy of a Gaussian distributed random variable x with mean m and variance σ^2 is

$$\begin{aligned} H(x) &= -\mathbb{E}[\log p(x)] \\ &= -\int_{-\infty}^{\infty} \log(p(x)) \cdot p(x) dx \\ &= -\int_{-\infty}^{\infty} \log\left(\frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(-\frac{(x-m)^2}{2\sigma^2}\right)\right) \cdot p(x) dx \\ &= -\int_{-\infty}^{\infty} \left[-\frac{1}{2} \log(2\pi\sigma^2) - \frac{(x-m)^2}{2\sigma^2}\right] \cdot p(x) dx \\ &= \int_{-\infty}^{\infty} \frac{1}{2} \log(2\pi\sigma^2) \cdot p(x) dx + \int_{-\infty}^{\infty} \frac{(x-m)^2}{2\sigma^2} \cdot p(x) dx \\ &= \frac{1}{2} \log(2\pi\sigma^2) \underbrace{\int_{-\infty}^{\infty} p(x) dx}_{=1} + \frac{1}{2\sigma^2} \underbrace{\int_{-\infty}^{\infty} (x-m)^2 \cdot p(x) dx}_{\sigma^2} \\ &= \frac{1}{2} \log(2\pi\sigma^2) + \frac{1}{2\sigma^2} \sigma^2 \\ &= \frac{1}{2} (\log(2\pi\sigma^2) + 1), \end{aligned}$$

which indicates that the greater the variance (uncertainty), the greater the entropy.

It follows from this that the entropy $H(x \mid y = c_1)$ is

$$\begin{aligned} H(x \mid y = c_1) &= \frac{1}{2} (\log(2\pi\sigma_1^2) + 1) \\ &= \frac{1}{2} (\log(2\pi \cdot 0.26) + 1) \\ &= 0.7454 \text{ nats} \end{aligned}$$

and the entropy of $H(x \mid y = c_2)$ is

$$\begin{aligned} H(x \mid y = c_2) &= \frac{1}{2} (\log(2\pi\sigma_2^2) + 1) \\ &= \frac{1}{2} (\log(2\pi \cdot 0.99) + 1) \\ &= 1.4139 \text{ nats}. \end{aligned}$$

Thus, the expected amount of information in a sample of class c_1 and c_2 , respectively, is 0.7454 nats¹ and 1.4139 nats, respectively.

¹The natural unit of information (nat), is a unit of information or entropy, based on natural logarithms and powers of e, rather than the powers of 2 and base 2 logarithms, which define the bit.