

My solutions to  
Deep Learning: Foundations and Concepts

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## 2 Probabilities

### 2.1

$$\begin{aligned} p(C = 1|T = 1) &= \frac{p(T = 1|C = 1)p(C = 1)}{p(T = 1)} && \text{Bayes' theorem} \\ &= \frac{p(T = 1|C = 1)p(C = 1)}{p(T = 1, C = 0) + p(T = 1, C = 1)} && \text{sum rule} \\ &= \frac{p(T = 1|C = 1)p(C = 1)}{p(T = 1|C = 0)p(C = 0) + p(T = 1|C = 1)p(C = 1)} && \text{product rule} \\ &= \frac{0.9 \cdot 0.001}{0.03 \cdot (1 - 0.001) + 0.9 \cdot 0.001} \\ &\approx 0.029 \end{aligned}$$

### 2.2

Let  $Y$  denote the yellow die,  $B$  the blue die,  $G$  the green die and  $R$  the red die. We consider throws of pairs of independent dice, i.e.  $p(D_1, D_2) = p(D_1)p(D_2)$ . Each die takes on a unique value in a given throw, such that e.g.  $(G = 5) := (G = 5, (B = 0 \text{ or } B = 4))$  and  $(G = 1, B = 0)$  are mutually exclusive events, hence  $p(G = 5 \text{ or } (G = 1, B = 0)) = P(G = 5) + P(G = 1, B = 0)$ .

$$\begin{aligned} p(B > Y) &= p(B = 4, Y = 3) \\ &= p(B = 4)p(Y = 3) \\ &= \frac{4}{6} \cdot \frac{6}{6} \\ &= \frac{2}{3} \end{aligned}$$

$$\begin{aligned}
p(G > B) &= p(G = 5 \text{ or } (G = 1, B = 0)) \\
&= p(G = 5) + p(G = 1)p(B = 0) \\
&= \frac{3}{6} + \frac{3}{6} \cdot \frac{2}{6} \\
&= \frac{2}{3} \\
p(R > G) &= p(R = 6 \text{ or } (R = 2, G = 1)) \\
&= p(R = 6) + p(R = 2)p(G = 1) \\
&= \frac{2}{6} + \frac{4}{6} \cdot \frac{3}{6} \\
&= \frac{2}{3} \\
p(Y > R) &= p(Y = 3, R = 2) \\
&= p(Y = 3)p(R = 2) \\
&= \frac{6}{6} \cdot \frac{4}{6} \\
&= \frac{2}{3}
\end{aligned}$$

## 2.4

$$\begin{aligned}
\int_c^d p(x)dx &= \int_c^d \frac{1}{d-c}dx \\
&= \frac{1}{d-c} \int_c^d dx \\
&= \frac{1}{d-c} [x]_c^d \\
&= \frac{1}{d-c} (d-c) \\
&= 1 \\
\mathbb{E}_p[X] &= \int_c^d xp(x)dx \\
&= \int_c^d x \frac{1}{d-c} dx \\
&= \frac{1}{d-c} \int_c^d x dx \\
&= \frac{1}{d-c} \left[ \frac{1}{2} x^2 \right]_c^d
\end{aligned}$$

$$\begin{aligned}
&= \frac{1}{2(d-c)}(d^2 - c^2) \\
&= \frac{1}{2(d-c)}(d-c)(d+c) \\
&= \frac{d+c}{2} \\
\mathbb{E}_p[X^2] &= \int_c^d x^2 p(x) dx \\
&= \int_c^d x^2 \frac{1}{d-c} dx \\
&= \frac{1}{d-c} \int_c^d x^2 dx \\
&= \frac{1}{d-c} \left[ \frac{1}{3} x^3 \right]_c^d \\
&= \frac{1}{3(d-c)}(d^3 - c^3) \\
&= \frac{1}{3(d-c)}(d-c)(d^2 + c^2 + cd) \\
&= \frac{1}{3}(d^2 + c^2 + cd) \\
\mathbb{E}_p[X]^2 &= \left( \frac{d+c}{2} \right)^2 \\
&= \frac{d^2 + 2cd + c^2}{4} \\
\mathbb{V}_p[X] &= \mathbb{E}_p[X^2] - \mathbb{E}_p[X]^2 \\
&= \frac{1}{3}(d^2 + c^2 + cd) - \frac{(d+c)^2}{2^2} \\
&= \frac{1}{3}(d^2 + c^2 + cd) - \frac{d^2 + 2cd + c^2}{4} \\
&= \frac{1}{12}(4d^2 + 4c^2 + 4cd - 3d^2 - 6cd - 3c^2) \\
&= \frac{1}{12}(d^2 - 2cd + c^2) \\
&= \frac{1}{12}(d-c)^2
\end{aligned}$$

## 2.5

### Exponential distribution

$$\begin{aligned}\int p(x|\lambda)dx &= \int_0^\infty \lambda e^{-\lambda x} dx \\&= \lambda \int_0^\infty e^{-\lambda x} dx \\&= \lambda \left[ -\frac{1}{\lambda} e^{-\lambda x} \right]_0^\infty \\&= \lambda \left[ 0 - \left( -\frac{1}{\lambda} e^{-\lambda \cdot 0} \right) \right] \\&= \lambda \cdot \frac{1}{\lambda} \\&= 1\end{aligned}$$

### Laplace distribution

$$\begin{aligned}\int p(x|\mu, \gamma) &= \int_{-\infty}^\infty \frac{1}{2\gamma} e^{-\frac{|x-\mu|}{\gamma}} dx \\&= \frac{1}{2\gamma} \int_{-\infty}^\infty e^{-\frac{|x-\mu|}{\gamma}} dx \\&= \frac{1}{2\gamma} \left( \int_{-\infty}^\mu e^{-\frac{|x-\mu|}{\gamma}} dx + \int_\mu^\infty \frac{1}{\gamma} e^{-\frac{|x-\mu|}{\gamma}} dx \right) \\&= \frac{1}{2\gamma} \left( \int_{-\infty}^\mu e^{-\frac{\mu-x}{\gamma}} dx + \int_\mu^\infty e^{-\frac{x-\mu}{\gamma}} dx \right) \\&= \frac{1}{2\gamma} \left( \int_{-\infty}^\mu e^{\frac{x-\mu}{\gamma}} dx + \int_\mu^\infty e^{\frac{\mu-x}{\gamma}} dx \right) \\&= \frac{1}{2\gamma} \left( \left[ \gamma e^{\frac{x-\mu}{\gamma}} \right]_{-\infty}^\mu + \left[ -\gamma e^{\frac{\mu-x}{\gamma}} \right]_\mu^\infty \right) \\&= \frac{1}{2\gamma} (\gamma [e^0 - 0] - \gamma [0 - (e^0)]) \\&= \frac{\gamma}{2\gamma} (1 - (-1)) \\&= \frac{1}{2} \cdot 2 \\&= 1\end{aligned}$$

## 2.6

$$\begin{aligned}
\int p(x|\mathcal{D}) &= \int_{-\infty}^{\infty} \frac{1}{N} \sum_{n=1}^N \delta(x - x_n) dx \\
&= \frac{1}{N} \sum_{n=1}^N \int_{-\infty}^{\infty} \delta(x - x_n) dx && \text{finite sum} \\
&= \frac{1}{N} \sum_{n=1}^N 1 && \text{by def. of } \delta \\
&= \frac{1}{N} \cdot N \\
&= 1
\end{aligned}$$

## 2.8

$$\begin{aligned}
\mathbb{V}[f] &= \mathbb{E} [(f(x) - \mathbb{E}[f(x)])^2] \\
&= \mathbb{E} [f(x)^2 - 2f(x)\mathbb{E}[f(x)] + \mathbb{E}[f(x)]^2] \\
&= \mathbb{E} [f(x)^2] - 2\mathbb{E}[f(x)]\mathbb{E}[f(x)] + \mathbb{E}[f(x)]^2 && \text{linearity of expectation} \\
&= \mathbb{E} [f(x)^2] - 2\mathbb{E}[f(x)]^2 + \mathbb{E}[f(x)]^2 \\
&= \mathbb{E} [f(x)^2] - \mathbb{E}[f(x)]^2
\end{aligned}$$

## 2.22

$$\begin{aligned}
f(p) &:= - \sum_{i=1}^M p_i \ln p_i \\
g(p) &:= \sum_{i=1}^M p_i - 1 \\
L(p, \lambda) &:= f(p) + \lambda g(p) \\
&= - \sum_{i=1}^M p_i \ln p_i + \lambda \left( \sum_{i=1}^M p_i - 1 \right) \\
\frac{\partial L}{\partial p_i} &= -1 \cdot \ln p_i - p_i \cdot \frac{1}{p_i} + \lambda \cdot (1 - 0) \\
&= -\ln p_i - 1 + \lambda
\end{aligned}$$

$$\begin{aligned}\frac{\partial L}{\partial \lambda} &= - \left( \sum_{i=1}^M p_i - 1 \right) \\ &= 1 - \sum_{i=1}^M p_i\end{aligned}$$

$$\begin{aligned}\frac{\partial L}{\partial p_i} &\stackrel{!}{=} 0 \\ \Leftrightarrow -\ln p_i - 1 + \lambda &= 0 \\ \Leftrightarrow -\ln p_i &= 1 - \lambda \\ \Leftrightarrow \ln p_i &= \lambda - 1 \\ \Leftrightarrow p_i &= e^{\lambda-1} \quad (1)\end{aligned}$$

$$\begin{aligned}\frac{\partial L}{\partial \lambda} &\stackrel{!}{=} 0 \\ \Leftrightarrow 1 - \sum_{i=1}^M p_i &= 0 \\ \stackrel{(1)}{\Rightarrow} 1 - \sum_{i=1}^M e^{\lambda-1} &= 0 \\ \Leftrightarrow 1 - M \cdot e^{\lambda-1} &= 0 \\ \Leftrightarrow 1 &= M \cdot e^{\lambda-1} \\ \Leftrightarrow \frac{1}{M} &= e^{\lambda-1}\end{aligned}$$

Hence for all  $i \in \{1, \dots, M\}$ :

$$p_i = \frac{1}{M}$$

and consequently

$$\begin{aligned}H[p] &= - \sum_{i=1}^M p_i \ln p_i \\ &= - \sum_{i=1}^M \frac{1}{M} \ln \frac{1}{M} \\ &= -M \cdot \frac{1}{M} (-\ln M) \\ &= \ln M\end{aligned}$$