

# Assignment 1

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## Question 1

$$\begin{aligned}
 E(\mathbf{w}) &= \frac{1}{2} \sum_{n=1}^N [y(x_n, \mathbf{w}) - t_n]^2 \\
 &= \frac{1}{2} \sum_{n=1}^N (\mathbf{w}^T \mathbf{x}_n - t_n)^2
 \end{aligned}$$

w.r.t  $\mathbf{x}_n = [x_n^0 \ \dots \ x_n^M]^T$ ,  $n$  is the index of sample. To minimize the error function, find its partial derivative about  $\mathbf{w}$ .

$$\begin{aligned}
 \frac{\partial}{\partial \mathbf{w}} E(\mathbf{w}) &= \frac{1}{2} \sum_{n=1}^N \left[ \frac{\partial}{\partial \mathbf{w}} (\mathbf{w}^T \mathbf{x}_n - t_n)^2 \right] \\
 &= \frac{1}{2} \sum_{n=1}^N \left\{ 2 (\mathbf{w}^T \mathbf{x}_n - t_n) \begin{bmatrix} \frac{\partial}{\partial w_0} (w_0 x_n^0 + \dots + w_M x_n^M - t_n) \\ \vdots \\ \frac{\partial}{\partial w_M} (w_0 x_n^0 + \dots + w_M x_n^M - t_n) \end{bmatrix} \right\} \\
 &= \frac{1}{2} \sum_{n=1}^N \left\{ 2 (\mathbf{w}^T \mathbf{x}_n - t_n) \begin{bmatrix} x_n^0 \\ \vdots \\ x_n^M \end{bmatrix} \right\} \\
 &= \sum_{n=1}^N (\mathbf{w}^T \mathbf{x}_n - t_n) \mathbf{x}_n = \mathbf{0}
 \end{aligned}$$

We can figure out that for the  $i^{\text{th}}$  row in the column vector, such equation establishes:

$$\begin{aligned}
 \sum_{m=0}^M \sum_{n=0}^N w_m x_n^m x_n^i &= \sum_{n=0}^N t_n x_n^i \\
 \text{Denoting } X &= \left[ \sum_n x_n^{(i+j)} \right]_{M \times M} \text{ where } i, j \text{ is the row/col index of matrix element; } Y = \left[ \sum_n t_n x_n^i \right]_{M \times 1}: \\
 X \mathbf{w} &= Y \\
 X^T X \mathbf{w} &= X^T Y \Rightarrow \mathbf{w} = (X^T X)^{-1} X^T Y
 \end{aligned}$$

## Question 2

$$\begin{aligned}
 p(\text{apple}) &= p(\text{apple}|r) \cdot p(r) + p(\text{apple}|g) \cdot p(g) + p(\text{apple}|b) \cdot p(b) \\
 &= \frac{3}{3+4+3} \cdot 0.2 + \frac{3}{3+3+4} \cdot 0.6 + \frac{1}{1+1+0} \cdot 0.2 \\
 &= 0.34
 \end{aligned}$$

$$\begin{aligned}
p(g|\text{orange}) &= \frac{p(\text{orange}|g) \cdot p(g)}{p(\text{orange})} \\
&= \frac{p(\text{orange}|g) \cdot p(g)}{p(\text{orange}|r) \cdot p(r) + p(\text{orange}|g) \cdot p(g) + p(\text{orange}|b) \cdot p(b)} \\
&= \frac{3/(3+3+4) \cdot 0.6}{4/(3+4+3) \cdot 0.2 + 3/(3+3+4) \cdot 0.6 + 1/(1+1+0) \cdot 0.2} \\
&= 0.5
\end{aligned}$$

### Question 3

$$\begin{aligned}
\mathbb{E}[x+z] &= \iint (x+z)p(x,z) dx dz \\
&\stackrel{\text{indep.}}{=} \iint_{x,z} (x+z)p(x)p(z) dx dz \\
&= \iint xp(x)p(z) dx dz + \iint zp(z)p(x) dx dz \\
&= \int \left[ \int p(z) dz \right] xp(x) dx + \int \left[ \int p(x) dx \right] zp(z) dz \\
&= \int 1 \cdot xp(x) dx + \int 1 \cdot zp(z) dz \\
&= \mathbb{E}[x] + \mathbb{E}[z]
\end{aligned}$$

$$\begin{aligned}
\text{var}[x] + \text{var}[z] &= \int \{x - \mathbb{E}[x]\}^2 p(x) dx + \int \{z - \mathbb{E}[z]\}^2 p(z) dz \\
&\stackrel{\int p(x) dx=1}{\stackrel{\int p(z) dz=1}{=}} \int \left\{ \int p(z) dz \right\} \{x - \mathbb{E}[x]\}^2 p(x) dx + \int \left\{ \int p(x) dx \right\} \{z - \mathbb{E}[z]\}^2 p(z) dz \\
&= \iint \{x - \mathbb{E}[x]\}^2 p(x)p(z) dx dz + \iint \{z - \mathbb{E}[z]\}^2 p(x)p(z) dx dz \\
&= \iint \{ \{(x+z) - \mathbb{E}[x+z]\}^2 - 2xz - 2\mathbb{E}[x]\mathbb{E}[z] + 2x\mathbb{E}[z] + 2z\mathbb{E}[x] \} p(x)p(z) dx dz \\
&= \text{var}[x+z] - 2 \iint \{xz + \mathbb{E}[x]\mathbb{E}[z] - x\mathbb{E}[z] - z\mathbb{E}[x]\} p(x)p(z) dx dz \\
&= \text{var}[x+z] - 2 \left\{ \int \left[ \int zp(z) dz \right] xp(x) dx + \mathbb{E}[x]\mathbb{E}[z] \iint p(x)p(z) dx dz \right. \\
&\quad \left. - \mathbb{E}[z] \int \left[ \int xp(x) dx \right] p(z) dz - \mathbb{E}[x] \int \left[ \int zp(z) dz \right] p(x) dx \right\} \\
&= \text{var}[x+z] - 2 \{ \mathbb{E}[x]\mathbb{E}[z] + \mathbb{E}[x]\mathbb{E}[z] - \mathbb{E}[x]\mathbb{E}[z] - \mathbb{E}[x]\mathbb{E}[z] \} \\
&= \text{var}[x+z]
\end{aligned}$$

### Question 4

**Poisson Distribution** Having its likelihood function, consider the partial derivation about  $\lambda$  of its log-likelihood:

$$\begin{aligned}
p(\mathcal{D}|\lambda) &= \prod_{i=1}^n \frac{\lambda^{X_i} e^{-\lambda}}{X_i!} \\
\ln p(\mathcal{D}|\lambda) &= \sum_{i=1}^n \ln \frac{\lambda^{X_i} e^{-\lambda}}{X_i!} = \sum_{i=1}^n [X_i \ln \lambda - \lambda - \ln(X_i!)] \\
\frac{\partial}{\partial \lambda} \ln p(\mathcal{D}|\lambda) &= \frac{\sum_{i=1}^n X_i}{\lambda} - n = 0 \Rightarrow \lambda_{\text{ML}} = \frac{1}{n} \sum_{i=1}^n X_i
\end{aligned}$$

**Exponential Distribution** By the definition of exponential distribution, all the sample points in  $\mathcal{D}$  are greater than 0 (otherwise,  $p(\mathcal{D}|\lambda)$  gotta be 0):

$$\begin{aligned} p(\mathcal{D}|\lambda) &= \prod_{i=1}^n \frac{1}{\lambda} e^{-X_i/\lambda} \\ \ln p(\mathcal{D}|\lambda) &= \sum_{i=1}^n \ln \left( \frac{1}{\lambda} e^{-X_i/\lambda} \right) = \sum_{i=1}^n \left( -\frac{X_i}{\lambda} - \ln \lambda \right) \\ \frac{\partial}{\partial \lambda} \ln p(\mathcal{D}|\lambda) &= \frac{\sum_{i=1}^n X_i}{\lambda^2} - \frac{n}{\lambda} = 0 \Rightarrow \lambda_{\text{ML}} = \frac{1}{n} \sum_{i=1}^n X_i \end{aligned}$$

## Question 5

$$\begin{aligned} p(\text{correct}) &= p(x \in \mathcal{R}_1, C_1) + p(x \in \mathcal{R}_2, C_2) = \int_{\mathcal{R}_1} p(x, C_1) dx + \int_{\mathcal{R}_2} p(x, C_2) dx \\ p(\text{mistake}) &= p(x \in \mathcal{R}_2, C_1) + p(x \in \mathcal{R}_1, C_2) = \int_{\mathcal{R}_2} p(x, C_1) dx + \int_{\mathcal{R}_1} p(x, C_2) dx \end{aligned}$$

The calculus of variations' way can be repretated as:

$$\begin{aligned} \frac{\delta \mathbb{E}[L]}{\delta y(\mathbf{x})} &= 2 \int \{y(\mathbf{x}) - \mathbf{t}\} p(\mathbf{x}, \mathbf{t}) d\mathbf{t} = 0 \\ y(\mathbf{x}) \int p(\mathbf{x}, \mathbf{t}) d\mathbf{t} &= \int \mathbf{t} p(\mathbf{x}, \mathbf{t}) d\mathbf{t} \\ y(\mathbf{x}) &= \frac{\int \mathbf{t} p(\mathbf{x}, \mathbf{t}) d\mathbf{t}}{\int p(\mathbf{x}, \mathbf{t}) d\mathbf{t}} = \frac{\int \mathbf{t} p(\mathbf{x}, \mathbf{t}) d\mathbf{t}}{p(\mathbf{x})} = \int \mathbf{t} p(\mathbf{t}|\mathbf{x}) d\mathbf{t} = \mathbb{E}_{\mathbf{t}}[\mathbf{t}|\mathbf{x}] \end{aligned}$$

## Question 6

$$\begin{aligned} \mathbf{H}[\mathbf{X}] &= - \int p(x) \ln \left[ \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{(x-\mu)^2}{2\sigma^2}} \right] dx \\ &= \int \ln(\sqrt{2\pi}\sigma) p(x) + \frac{(x-\mu)^2}{2\sigma^2} p(x) dx \\ &= \ln(\sqrt{2\pi}\sigma) \int p(x) dx + \frac{1}{2\sigma^2} \left[ \int x^2 p(x) dx - 2\mu \int x p(x) dx + \mu^2 \int p(x) dx \right] \\ &= \ln(\sqrt{2\pi}\sigma) \cdot 1 + \frac{1}{2\sigma^2} \{ \mathbb{E}[x^2] - 2\mu \mathbb{E}[x] + \mu^2 \cdot 1 \} \\ &= \ln(\sqrt{2\pi}\sigma) \cdot 1 + \frac{1}{2\sigma^2} \{ \text{var}[x] + \mathbb{E}^2[x] - 2\mu \mathbb{E}[x] + \mu^2 \} \\ &\stackrel{x \sim \mathcal{N}(\mu, \sigma^2)}{=} \ln(\sqrt{2\pi}\sigma) + \frac{1}{2\sigma^2} \{ \sigma^2 + \mu^2 - 2\mu \cdot \mu + \mu^2 \} \\ &= \ln(\sqrt{2\pi}\sigma) + \frac{1}{2} \end{aligned}$$

$$\begin{aligned} \mathbf{I}[\mathbf{x}, \mathbf{y}] &\equiv \mathbf{KL}(p(\mathbf{x}, \mathbf{y}) || p(\mathbf{x})p(\mathbf{y})) \\ &= - \iint p(\mathbf{x}, \mathbf{y}) \ln \left( \frac{p(\mathbf{x})p(\mathbf{y})}{p(\mathbf{x}, \mathbf{y})} \right) d\mathbf{x} d\mathbf{y} \end{aligned}$$

$$\begin{aligned}
\mathbf{I}[\mathbf{x}, \mathbf{y}] &= - \iint p(\mathbf{x}, \mathbf{y}) \ln \left( \frac{p(\mathbf{x})}{p(\mathbf{x}, \mathbf{y})/p(\mathbf{y})} \right) d\mathbf{x} d\mathbf{y} \\
&= - \iint p(\mathbf{x}, \mathbf{y}) \left[ \ln p(\mathbf{x}) - \ln \left( \frac{p(\mathbf{x}, \mathbf{y})}{p(\mathbf{y})} \right) \right] d\mathbf{x} d\mathbf{y} \\
&= - \iint p(\mathbf{x}, \mathbf{y}) \ln p(\mathbf{x}) d\mathbf{x} d\mathbf{y} + \iint p(\mathbf{x}, \mathbf{y}) \ln p(\mathbf{x}|\mathbf{y}) d\mathbf{x} d\mathbf{y} \\
&= - \int \left[ \int p(\mathbf{x}, \mathbf{y}) d\mathbf{y} \right] \ln p(\mathbf{x}) d\mathbf{x} + \mathbf{H}[\mathbf{x}|\mathbf{y}] \\
&= - \int p(\mathbf{x}) \ln p(\mathbf{x}) d\mathbf{x} - \mathbf{H}[\mathbf{x}|\mathbf{y}] \\
&= \mathbf{H}[\mathbf{x}] - \mathbf{H}[\mathbf{x}|\mathbf{y}]
\end{aligned}$$

$$\begin{aligned}
\mathbf{I}[\mathbf{x}, \mathbf{y}] &= - \iint p(\mathbf{x}, \mathbf{y}) \ln \left( \frac{p(\mathbf{y})}{p(\mathbf{x}, \mathbf{y})/p(\mathbf{x})} \right) d\mathbf{x} d\mathbf{y} \\
&= - \iint p(\mathbf{x}, \mathbf{y}) \left[ \ln p(\mathbf{y}) - \ln \left( \frac{p(\mathbf{x}, \mathbf{y})}{p(\mathbf{x})} \right) \right] d\mathbf{x} d\mathbf{y} \\
&= - \iint p(\mathbf{x}, \mathbf{y}) \ln p(\mathbf{y}) d\mathbf{x} d\mathbf{y} + \iint p(\mathbf{x}, \mathbf{y}) \ln p(\mathbf{y}|\mathbf{x}) d\mathbf{x} d\mathbf{y} \\
&= - \int \left[ \int p(\mathbf{x}, \mathbf{y}) d\mathbf{x} \right] \ln p(\mathbf{y}) d\mathbf{y} + \mathbf{H}[\mathbf{y}|\mathbf{x}] \\
&= - \int p(\mathbf{y}) \ln p(\mathbf{y}) d\mathbf{y} - \mathbf{H}[\mathbf{y}|\mathbf{x}] \\
&= \mathbf{H}[\mathbf{y}] - \mathbf{H}[\mathbf{y}|\mathbf{x}]
\end{aligned}$$