

# 1 Problem 1

a)

$$\begin{aligned}
 Bias(\hat{\mu}) &= E(\hat{\mu} - \mu) = E\left(\frac{1}{N} \sum_{i=1}^N X_i - \mu\right) \\
 &= E\left(\frac{1}{N} \sum_{i=1}^N X_i\right) - E(\mu) = \frac{1}{N} E\left(\sum_{i=1}^N X_i\right) - \mu \\
 &= \frac{1}{N} \sum_{i=1}^N E(X_i) - \mu \stackrel{\text{i.i.d}}{=} \frac{N}{N} \mu - \mu \\
 &= 0
 \end{aligned} \tag{1}$$

Since the  $X_i$ s are identically distributed, they have the same, true, mean  $\mu$ .

$$\begin{aligned}
 Var(\hat{\mu}) &= Var\left(\frac{1}{N} \sum_{i=1}^N X_i\right) = \frac{1}{N^2} Var\left(\sum_{i=1}^N X_i\right) \\
 &\stackrel{\text{i.i.d}}{=} \frac{1}{N^2} \sum_{i=1}^N Var(X_i) = \frac{N}{N^2} \sigma^2 \\
 &= \frac{\sigma^2}{N}
 \end{aligned} \tag{2}$$

Note that  $Cov(X_i, X_j) = 0 \forall j \neq i$  because of independence.

$$\begin{aligned}
 MSE(\hat{\mu}) &= (Bias(\hat{\mu}))^2 + Var(\hat{\mu}) \\
 &= 0^2 + \frac{\sigma^2}{N} \\
 &= \frac{\sigma^2}{N}
 \end{aligned} \tag{3}$$

b)

$$\begin{aligned}
 Bias(0) &= E(0 - \mu) \\
 &= -\mu
 \end{aligned} \tag{4}$$

$$Var(0) = 0 \tag{5}$$

Since it is a constant and therefore not random.

$$\begin{aligned}
 MSE(0) &= (Bias(0))^2 + Var(0) \\
 &= (-\mu)^2 + 0 \\
 &= \mu^2
 \end{aligned} \tag{6}$$

## 2 Problem 2

a)

$$\begin{aligned}
 Error[\hat{f}(x)] &= E[(\hat{f}(x) - f(x))^2] \\
 &= E\left[\left(\hat{f}(x)\right)^2 - 2\hat{f}(x)f(x) + (f(x))^2\right] \\
 &= E\left[\left(\hat{f}(x)\right)^2\right] - 2f(x)E[\hat{f}(x)] + (f(x))^2 \\
 &= E\left[\left(\hat{f}(x)\right)^2\right] - 2\left(E\left[\left(\hat{f}(x)\right)^2\right]\right)^2 + \left(E\left[\left(\hat{f}(x)\right)^2\right]\right)^2 \\
 &\quad + \left(E\left[\left(\hat{f}(x)\right)^2\right]\right)^2 - 2f(x)E[\hat{f}(x)] + (f(x))^2 \\
 &= E\left[\left(\hat{f}(x)\right)^2\right] - 2E[\hat{f}(x)E[\hat{f}(x)]] + E\left[E[\hat{f}(x)]\right]^2 \\
 &\quad + \left(E[\hat{f}(x)] - E[f(x)]\right)^2 \\
 &= E\left[\left(\hat{f}(x)\right)^2 - 2\hat{f}(x)E[\hat{f}(x)] + E\left[\left(\hat{f}(x)\right)^2\right]\right] \\
 &\quad + \left(\underbrace{E[\hat{f}(x)] - f(x)}_{Bias}\right)^2 \\
 &= E\left[\underbrace{\left(\hat{f}(x) - E[\hat{f}(x)]\right)^2}_{Var}\right] + Bias^2 \\
 &= Var + Bias^2
 \end{aligned} \tag{7}$$

### 3 Problem 3

a)

$$\begin{aligned}
 \min_R A &\stackrel{!}{=} \min_R E \left[ D_{KL}(R || \hat{P}) \right] \\
 &= \min_R E \left[ \sum_{i=1}^N R_i \log \left( \frac{R_i}{\hat{P}_i} \right) \right] \\
 &= \min_R \sum_{i=1}^N \left( R_i \log R_i - R_i E \left[ \log \hat{P}_i \right] \right)
 \end{aligned} \tag{8}$$

$$\begin{aligned}
 \frac{\partial A}{\partial R_i} &= \log R_i + R_i \cdot \frac{1}{R_i} - E \left[ \log \hat{P}_i \right] \\
 &= \log R_i + 1 - E \left[ \log \hat{P}_i \right] \stackrel{!}{=} 0 \\
 &\Leftrightarrow \log R_i = E \left[ \log \hat{P}_i \right] - 1 \\
 &\Leftrightarrow R_i = \frac{\exp(E \left[ \log \hat{P}_i \right])}{\exp(1)} \\
 &\Leftrightarrow R_i = \frac{\exp(E \left[ \log \hat{P}_i \right])}{\exp(\sum_{j=1}^C \hat{P}_i)}
 \end{aligned} \tag{9}$$

b)

$$\begin{aligned}
Error(\hat{P}) &= E \left[ D_{KL}(P||\hat{P}) \right] \\
&= E \left[ \sum_{i=1}^N P_i \log \left( \frac{P_i}{\hat{P}_i} \right) \right] \\
&= E \left[ \sum_{i=1}^N P_i \log \left( \frac{P_i R_i}{\hat{P}_i R_i} \right) \right] \\
&= E \left[ \sum_{i=1}^N P_i \left( \log P_i - \log R_i + \log \hat{P}_i - \log R_i \right) \right] \quad (10) \\
&= E \left[ \sum_{i=1}^N P_i \log \left( \frac{P_i}{R_i} \right) + \sum_{i=1}^N P_i \log \left( \frac{R_i}{\hat{P}_i} \right) \right] \\
&= \sum_{i=1}^N P_i \log \left( \frac{P_i}{R_i} \right) + E \left[ \sum_{i=1}^N P_i \log \left( \frac{R_i}{\hat{P}_i} \right) \right] \\
&= D_{KL}(P||R) + E \left[ D_{KL}(R||\hat{P}) \right] \\
&= Bias(\hat{P}) + Var(\hat{P})
\end{aligned}$$