

Exercise 2.

$$(a). \text{Error}(\hat{f}(x)) = E[(\hat{f}(x) - f(x))^2], \quad \text{Bias}(\hat{f}(x)) = E[\hat{f}(x) - f(x)], \\ \text{Var}(\hat{f}(x)) = E[(\hat{f}(x) - E[\hat{f}(x)])^2]$$

$$\begin{aligned} \text{Error}(\hat{f}(x)) &= E[(\hat{f}(x) - f(x))^2] \\ &= E[(\hat{f}(x) - E[\hat{f}(x)] + E[\hat{f}(x)] - f(x))^2] \\ &= E\{[\hat{f}(x) - E[\hat{f}(x)]]^2 + 2[\hat{f}(x) - E[\hat{f}(x)]] [E[\hat{f}(x)] - f(x)] + [E[\hat{f}(x)] - f(x)]^2\} \\ &= E[(\hat{f}(x) - E[\hat{f}(x)])^2] + 2E[\hat{f}(x) - E[\hat{f}(x)]] [E[\hat{f}(x)] - f(x)] + E[E[\hat{f}(x)] - f(x)]^2 \\ &= \text{Var}(\hat{f}(x)) + 2 \times 0 + [E[\hat{f}(x)] - f(x)]^2 \quad (\because E[E[\hat{f}(x)]] = E[\hat{f}(x)], E[\hat{f}(x)] = f(x)) \\ &= \text{Var}(\hat{f}(x)) + \text{Bias}(\hat{f}(x))^2 \end{aligned}$$

Exercise 3.

$$(a). D_{KL}(R \| \hat{P}) = \sum_{i=1}^C R(i) \log \frac{R(i)}{\hat{P}(i)} \\ \min_R E[D_{KL}(R \| \hat{P})] = \min_R \left[\sum_{i=1}^C R(i) \log \frac{R(i)}{\hat{P}(i)} \right] \\ \text{s.t. } \sum_{i=1}^C R(i) = 1.$$

$$\mathcal{L} = \sum_{i=1}^C R(i) \log R(i) - \sum_{i=1}^C R(i) \log(\hat{P}(i)) + \lambda \left[\sum_{i=1}^C R(i) - 1 \right]$$

$$\frac{\partial \mathcal{L}}{\partial R(i)} = \log R(i) + 1 - \log(\hat{P}(i)) + \lambda = 0 \quad (*), \quad i=1, 2, \dots, C.$$

$$\frac{\partial \mathcal{L}}{\partial \lambda} = \sum_{i=1}^C R(i) - 1 = 0. \quad (**)$$

From (*), we have $R(i) = \exp[\log(\hat{P}(i)) - \lambda - 1] = \frac{\exp[\log \hat{P}(i)]}{\exp(\lambda + 1)}$

plug it into (**), we can obtain

$$\sum_{i=1}^C \exp(\log(\hat{P}(i)) / \exp(\lambda + 1)) = 1$$

$$\Rightarrow \exp(\lambda + 1) = \sum_{i=1}^C \exp \log(\hat{P}(i))$$

plug it back into (***), we have the solution to the optimization problem

$$R(i) = \frac{\exp E[\log \hat{P}(i)]}{\sum_j \exp E[\log \hat{P}(j)]}$$