

Answer Key for Practice Quiz - 1

CS 591Q/791V - Pattern Recognition

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1. a. Bayes Risk: [pp. 24-25] Consider the problem of designing a pattern classification system where the goal is to assign a d-dimensional feature vector \mathbf{x} to one of c classes, $\omega_1, \dots, \omega_c$, resulting in one of a actions, $\alpha_1, \dots, \alpha_a$. Denote as $\lambda(\alpha_i|\omega_j)$ the cost of taking action α_i when the true class of the input pattern \mathbf{x} is ω_j . Then the conditional risk of taking action α_i upon encountering feature vector \mathbf{x} is

$$R(\alpha_i|\mathbf{x}) = \sum_{j=1}^c \lambda(\alpha_i|\omega_j)P(\omega_j|\mathbf{x}),$$

for $i = 1, \dots, a$. Thus, the decision policy would be to select that action α_i for which $R(\alpha_i|\mathbf{x})$ is minimum. The resulting minimum overall risk is called the Bayes Risk.

- b. Minimum Distance Classifier: [p. 39] Given a feature vector \mathbf{x} and a set of mean vectors μ_1, \dots, μ_c corresponding to c classes, $\omega_1, \dots, \omega_c$, the minimum distance classifier assigns x to that class whose mean vector is located at the smallest Euclidean distance from \mathbf{x} . Thus,

$$\text{Assign } \mathbf{x} \text{ to class } \omega_{j^*}, \text{ where } j^* = \arg \min_{j=1, \dots, c} \|\mathbf{x} - \mu_j\|.$$

2. [see Figure 2.13 in p. 41 to view a similar problem]

The decision boundary can be computed as:

$$\begin{aligned} P(\omega_1|x) &= P(\omega_2|x) \\ \Rightarrow p(x|\omega_1) &= p(x|\omega_2), \quad (\text{since } P(\omega_1) = P(\omega_2)) \\ \Rightarrow \frac{1}{\sqrt{2\pi}1} \exp\left(-\frac{1}{2}x^2\right) &= \frac{1}{\sqrt{2\pi}4} \exp\left(-\frac{1}{2}\frac{(x-\frac{1}{2})^2}{4}\right) \end{aligned}$$

Applying ln on both sides and multiplying by -1, we have:

$$\begin{aligned} \frac{x^2}{2} &= \ln 2 + \frac{(x-\frac{1}{2})^2}{8} \\ \Rightarrow \frac{x^2}{2} &= \ln 2 + \frac{1}{8}\left(x^2 - x + \frac{1}{4}\right) \\ \Rightarrow 4x^2 &= 8\ln 2 + (x^2 - x + \frac{1}{4}) \\ \Rightarrow 3x^2 + x - 5.79 &= 0 \\ \Rightarrow x &= -1.56 \quad \text{or} \quad x = 1.23 \end{aligned}$$

Thus the decision rule will be,

$$\begin{cases} x \in \omega_1, & \text{if } -1.56 < x < 1.23, \\ x \in \omega_2, & \text{otherwise.} \end{cases}$$

3. [see section 2.7]

Note that $\omega_{max}(\mathbf{x})$ denotes the class that \mathbf{x} is assigned to by the Bayes classifier. It could be one of $\omega_1, \dots, \omega_c$ depending on the feature vector \mathbf{x} . So, $P(correct|\mathbf{x}) = P(\omega_{max}|\mathbf{x})$. Thus,

$$\begin{aligned}P(correct|\mathbf{x}) &= P(\omega_{max}|\mathbf{x}) \\ \Rightarrow P(correct) &= \int P(\omega_{max}|\mathbf{x})p(\mathbf{x})d\mathbf{x} \\ \Rightarrow P(error) &= 1 - \int P(\omega_{max}|\mathbf{x})p(\mathbf{x})d\mathbf{x}.\square\end{aligned}$$

4. [see section 2.5.1]

The entropy of a distribution $p(x)$ is given by

$$H(p(x)) = - \int p(x) \ln[p(x)] dx,$$

where the integral is in the interval $[-\infty, \infty]$. In this case,

$$p(x) = \frac{1}{\sqrt{(2\pi\sigma^2)}} e^{-\frac{x^2}{2\sigma^2}},$$

and

$$\ln[p(x)] = -\ln[\sqrt{(2\pi\sigma^2)}] - \frac{x^2}{2\sigma^2} = -(\ln[\sqrt{(2\pi\sigma^2)}] - \frac{x^2}{2\sigma^2}).$$

Thus,

$$\begin{aligned}H(p(x)) &= - \int p(x) \ln[p(x)] dx \\ &= \int p(x) (\ln[\sqrt{(2\pi\sigma^2)}] + \frac{x^2}{2\sigma^2}) dx \\ &= \int p(x) \ln[\sqrt{(2\pi\sigma^2)}] dx + \int p(x) \frac{x^2}{2\sigma^2} dx \\ &= \ln[\sqrt{(2\pi\sigma^2)}] \int p(x) dx + \frac{1}{2\sigma^2} \int x^2 p(x) dx \\ &= \ln[\sqrt{(2\pi\sigma^2)}] + \frac{1}{2\sigma^2} \sigma^2 \\ &\quad (\text{since } \int p(x) dx = 1, \text{ and } \int x^2 p(x) dx \text{ is the formula for the variance of a 0-mean gaussian distribution}) \\ &= \ln[\sqrt{(2\pi\sigma^2)}] + \frac{1}{2} \\ &= \ln[\sqrt{(2\pi\sigma^2)}] + \frac{1}{2} \ln(e) \\ &= \ln[\sqrt{(2e\pi\sigma^2)}].\square \\ &\quad (\text{since } \frac{1}{2} \ln(e) = \ln(\sqrt{e}))\end{aligned}$$
