
Lecture Notes 1 – Bayes Decision Theory

Probabilities and Measurements

- State of nature $\omega_1, \omega_2, \dots$
- Prior probability $P(\omega_1), P(\omega_2)$
- Measurements: $\mathbf{x} \in \mathbb{R}^d$
- Likelihood function: $p(\mathbf{x} | \omega_j)$

Bayes Theorem

- Bayes rule: $P(\omega_j | \mathbf{x}) = \frac{P(\mathbf{x} | \omega_j)P(\omega_j)}{p(\mathbf{x})} = \frac{\text{likelihood} \times \text{prior}}{\text{evidence}}$

Classification Error

- $P(\text{error} | \mathbf{x}) = \begin{cases} P(\omega_1 | \mathbf{x}) & \text{if we decide } \omega_2 \\ P(\omega_2 | \mathbf{x}) & \text{if we decide } \omega_1 \end{cases}$
- Error rate: $R = \int_{\mathbf{x}} P(\text{error} | \mathbf{x}) \cdot p(\mathbf{x}) d\mathbf{x}$

Optimal Classifiers

- Bayes decision rule: $\begin{cases} \omega_1 & \text{if } P(\omega_1 | \mathbf{x}) > P(\omega_2 | \mathbf{x}) \\ \omega_2 & \text{else} \end{cases}$
- Bayes error rate: $R = \int_{\mathbf{x}} \min\{P(\omega_1 | \mathbf{x}), P(\omega_2 | \mathbf{x})\} \cdot p(\mathbf{x}) d\mathbf{x}$

Multiclass

- Bayes decision rule: $\begin{cases} \omega_i & \text{if } \forall_{j \neq i} : P(\omega_i | \mathbf{x}) > P(\omega_j | \mathbf{x}) \end{cases}$
- Bayes error rate: $R = \int_{\mathbf{x}} \min_i (1 - P(\omega_i | \mathbf{x})) \cdot p(\mathbf{x}) d\mathbf{x}$

Discriminant functions

- Bayes decision rule: $\begin{cases} \omega_1 & \text{if } \frac{P(\mathbf{x}|\omega_1)}{P(\mathbf{x}|\omega_2)} > \theta \\ \omega_2 & \text{else} \end{cases}$
with $\theta = P(\omega_2)/P(\omega_1)$

Discriminant functions (multiclass)

- Bayes decision rule: $\begin{cases} \omega_i & \text{if } \forall_{j \neq i} : g_i(\mathbf{x}) > g_j(\mathbf{x}) \end{cases}$
with $g_i(\mathbf{x}) = f_{\text{incr}}(P(\omega_i | \mathbf{x}))$ and f_{incr} a monotonically increasing function.

Actions and Cost

- Actions $\alpha_1, \dots, \alpha_a$
- Loss $\lambda(\alpha_i \mid \omega_j)$ caused by taking action α_i given state of nature ω_j .
- Expected cost of an action: $R(\alpha_i \mid \mathbf{x}) = \sum_{j=1}^c \lambda(\alpha_i \mid \omega_j) P(\omega_j \mid \mathbf{x})$.
- Risk of optimal decider: $R = \int_{\mathbf{x}} \min_i R(\alpha_i \mid \mathbf{x}) \cdot p(\mathbf{x}) d\mathbf{x}$

Practical likelihood functions

Multivariate Density ($\mathbf{x} \in \mathbb{R}^d$)

$$p(\mathbf{x}) = \frac{1}{(2\pi)^{d/2} |\Sigma|^{1/2}} \exp \left[-\frac{1}{2} (\mathbf{x} - \boldsymbol{\mu})^\top \Sigma^{-1} (\mathbf{x} - \boldsymbol{\mu}) \right]$$

Discrete Density ($\mathbf{x} \in \{0, 1\}^d$)

$$p(\mathbf{x}) = \prod_{i=1}^d \underbrace{\Pr[x_i = 0]}_{1-p_i} \cdot 1_{x_i=0} + \underbrace{\Pr[x_i = 1]}_{p_i} \cdot 1_{x_i=1} = \prod_{i=1}^d p_i^{x_i} (1 - p_i)^{1-x_i}$$
