

Bayesian Decision Theory

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Bayesian Decision Theory

- ▶ Bayesian Decision Theory is a fundamental statistical approach that quantifies the tradeoffs between various decisions using probabilities and costs that accompany such decisions.
- ▶ First, we will assume that all probabilities are known.
- ▶ Then, we will study the cases where the probabilistic structure is not completely known.



Fish Sorting Example Revisited

- ▶ State of nature is a random variable.
- ▶ Define w as the type of fish we observe (state of nature, *class*) where
 - ▶ $w = w_1$ for sea bass,
 - ▶ $w = w_2$ for salmon.
 - ▶ $P(w_1)$ is the *a priori probability* that the next fish is a sea bass.
 - ▶ $P(w_2)$ is the a priori probability that the next fish is a salmon.



Prior Probabilities

- ▶ Prior probabilities reflect our knowledge of how likely each type of fish will appear before we actually see it.
- ▶ How can we choose $P(w_1)$ and $P(w_2)$?
 - ▶ Set $P(w_1) = P(w_2)$ if they are equiprobable (*uniform priors*).
 - ▶ May use different values depending on the fishing area, time of the year, etc.
- ▶ Assume there are no other types of fish

$$P(w_1) + P(w_2) = 1$$

(exclusivity and exhaustivity).



Making a Decision

- ▶ How can we make a decision with only the prior information?

$$\text{Decide } \begin{cases} w_1 & \text{if } P(w_1) > P(w_2) \\ w_2 & \text{otherwise} \end{cases}$$

- ▶ What is the *probability of error* for this decision?

$$P(\text{error}) = \min\{P(w_1), P(w_2)\}$$



Class-Conditional Probabilities

- ▶ Let's try to improve the decision using the lightness measurement x .
- ▶ Let x be a continuous random variable.
- ▶ Define $p(x|w_j)$ as the *class-conditional probability density* (probability of x given that the state of nature is w_j for $j = 1, 2$).
- ▶ $p(x|w_1)$ and $p(x|w_2)$ describe the difference in lightness between populations of sea bass and salmon.



Class-Conditional Probabilities

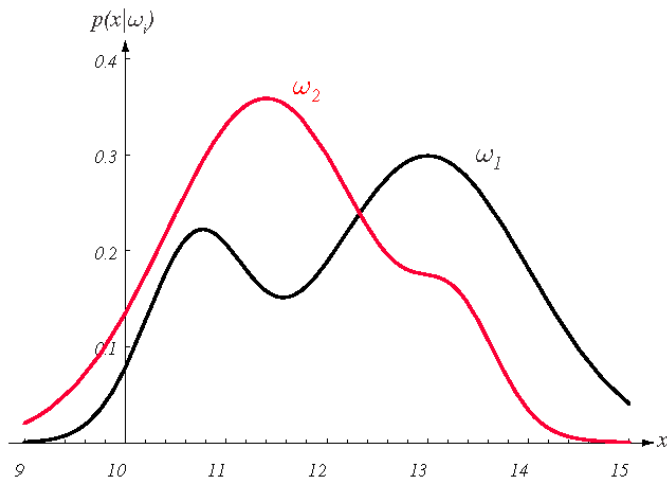


Figure 1: Hypothetical class-conditional probability density functions for two classes.



Posterior Probabilities

- ▶ Suppose we know $P(w_j)$ and $p(x|w_j)$ for $j = 1, 2$, and measure the lightness of a fish as the value x .
- ▶ Define $P(w_j|x)$ as the *a posteriori probability* (probability of the state of nature being w_j given the measurement of feature value x).
- ▶ We can use the *Bayes formula* to convert the prior probability to the posterior probability

$$P(w_j|x) = \frac{p(x|w_j)P(w_j)}{p(x)}$$

where $p(x) = \sum_{j=1}^2 p(x|w_j)P(w_j)$.



Making a Decision

- ▶ $p(x|w_j)$ is called the *likelihood* and $p(x)$ is called the *evidence*.
- ▶ How can we make a decision after observing the value of x ?

$$\text{Decide } \begin{cases} w_1 & \text{if } P(w_1|x) > P(w_2|x) \\ w_2 & \text{otherwise} \end{cases}$$

- ▶ Rewriting the rule gives

$$\text{Decide } \begin{cases} w_1 & \text{if } \frac{p(x|w_1)}{p(x|w_2)} > \frac{P(w_2)}{P(w_1)} \\ w_2 & \text{otherwise} \end{cases}$$

- ▶ Note that, at every x , $P(w_1|x) + P(w_2|x) = 1$.



Probability of Error

- What is the probability of error for this decision?

$$P(\text{error}|x) = \begin{cases} P(w_1|x) & \text{if we decide } w_2 \\ P(w_2|x) & \text{if we decide } w_1 \end{cases}$$

- What is the average probability of error?

$$P(\text{error}) = \int_{-\infty}^{\infty} p(\text{error}, x) dx = \int_{-\infty}^{\infty} P(\text{error}|x) p(x) dx$$

- *Bayes decision rule* minimizes this error because

$$P(\text{error}|x) = \min\{P(w_1|x), P(w_2|x)\}.$$



Bayesian Decision Theory

- ▶ How can we generalize to
 - ▶ more than one feature?
 - ▶ replace the scalar x by the feature vector $\mathbf{x}$
 - ▶ more than two states of nature?
 - ▶ just a difference in notation
 - ▶ allowing actions other than just decisions?
 - ▶ allow the possibility of rejection
 - ▶ different risks in the decision?
 - ▶ define how costly each action is



Bayesian Decision Theory

- ▶ Let $\{w_1, \dots, w_c\}$ be the finite set of c states of nature (*classes, categories*).
- ▶ Let $\{\alpha_1, \dots, \alpha_a\}$ be the finite set of a possible *actions*.
- ▶ Let $\lambda(\alpha_i|w_j)$ be the *loss* incurred for taking action α_i when the state of nature is w_j .
- ▶ Let $\mathbf{x}$ be the d -component vector-valued random variable called the *feature vector*.



Bayesian Decision Theory

- ▶ $p(\mathbf{x}|w_j)$ is the class-conditional probability density function.
- ▶ $P(w_j)$ is the prior probability that nature is in state w_j .
- ▶ The posterior probability can be computed as

$$P(w_j|\mathbf{x}) = \frac{p(\mathbf{x}|w_j)P(w_j)}{p(\mathbf{x})}$$

where $p(\mathbf{x}) = \sum_{j=1}^c p(\mathbf{x}|w_j)P(w_j)$.



Conditional Risk

- ▶ Suppose we observe $\mathbf{x}$ and take action α_i .
- ▶ If the true state of nature is w_j , we incur the loss $\lambda(\alpha_i|w_j)$.
- ▶ The expected loss with taking action α_i is

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

which is also called the *conditional risk*.



Minimum-Risk Classification

- ▶ The general *decision rule* $\alpha(\mathbf{x})$ tells us which action to take for observation $\mathbf{x}$.
- ▶ We want to find the decision rule that minimizes the overall risk

$$R = \int R(\alpha(\mathbf{x})|\mathbf{x}) p(\mathbf{x}) d\mathbf{x}.$$

- ▶ Bayes decision rule minimizes the overall risk by selecting the action α_i for which $R(\alpha_i|\mathbf{x})$ is minimum.
- ▶ The resulting minimum overall risk is called the *Bayes risk* and is the best performance that can be achieved.



Two-Category Classification

- ▶ Define
 - ▶ α_1 : deciding w_1 ,
 - ▶ α_2 : deciding w_2 ,
 - ▶ $\lambda_{ij} = \lambda(\alpha_i | w_j)$.
- ▶ Conditional risks can be written as

$$R(\alpha_1 | \mathbf{x}) = \lambda_{11} P(w_1 | \mathbf{x}) + \lambda_{12} P(w_2 | \mathbf{x}),$$

$$R(\alpha_2 | \mathbf{x}) = \lambda_{21} P(w_1 | \mathbf{x}) + \lambda_{22} P(w_2 | \mathbf{x}).$$



Two-Category Classification

- ▶ The *minimum-risk decision rule* becomes

$$\text{Decide } \begin{cases} w_1 & \text{if } (\lambda_{21} - \lambda_{11})P(w_1|\mathbf{x}) > (\lambda_{12} - \lambda_{22})P(w_2|\mathbf{x}) \\ w_2 & \text{otherwise} \end{cases}$$

- ▶ This corresponds to deciding w_1 if

$$\frac{p(\mathbf{x}|w_1)}{p(\mathbf{x}|w_2)} > \frac{(\lambda_{12} - \lambda_{22})}{(\lambda_{21} - \lambda_{11})} \frac{P(w_2)}{P(w_1)}$$

⇒ comparing the *likelihood ratio* to a threshold that is independent of the observation $\mathbf{x}$.



Minimum-Error-Rate Classification

- ▶ Actions are decisions on classes (α_i is deciding w_i).
- ▶ If action α_i is taken and the true state of nature is w_j , then the decision is correct if $i = j$ and in error if $i \neq j$.
- ▶ We want to find a decision rule that minimizes the probability of error.



Minimum-Error-Rate Classification

- Define the *zero-one loss function*

$$\lambda(\alpha_i | w_j) = \begin{cases} 0 & \text{if } i = j \\ 1 & \text{if } i \neq j \end{cases} \quad i, j = 1, \dots, c$$

(all errors are equally costly).

- Conditional risk becomes

$$\begin{aligned} R(\alpha_i | \mathbf{x}) &= \sum_{j=1}^c \lambda(\alpha_i | w_j) P(w_j | \mathbf{x}) \\ &= \sum_{j \neq i} P(w_j | \mathbf{x}) \\ &= 1 - P(w_i | \mathbf{x}). \end{aligned}$$



Minimum-Error-Rate Classification

- ▶ Minimizing the risk requires maximizing $P(w_i|\mathbf{x})$ and results in the *minimum-error decision rule*

Decide w_i if $P(w_i|\mathbf{x}) > P(w_j|\mathbf{x}) \quad \forall j \neq i.$

- ▶ The resulting error is called the *Bayes error* and is the best performance that can be achieved.



Minimum-Error-Rate Classification

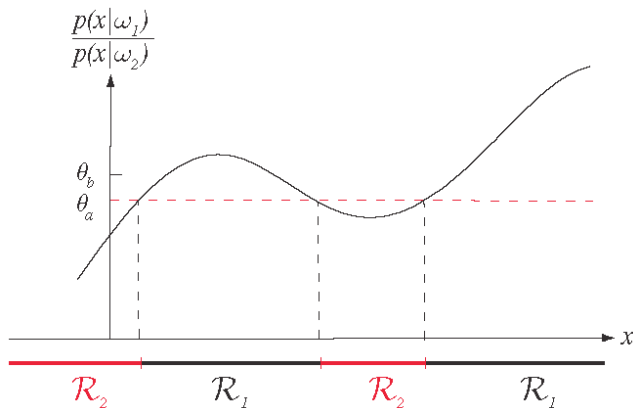


Figure 2: The likelihood ratio $p(\mathbf{x}|w_1)/p(\mathbf{x}|w_2)$. The threshold θ_a is computed using the priors $P(w_1) = 2/3$ and $P(w_2) = 1/3$, and a zero-one loss function. If we penalize mistakes in classifying w_2 patterns as w_1 more than the converse, we should increase the threshold to θ_b .



Discriminant Functions

- ▶ A useful way of representing classifiers is through *discriminant functions* $g_i(\mathbf{x})$, $i = 1, \dots, c$, where the classifier assigns a feature vector $\mathbf{x}$ to class w_i if

$$g_i(\mathbf{x}) > g_j(\mathbf{x}) \quad \forall j \neq i.$$

- ▶ For the classifier that minimizes conditional risk

$$g_i(\mathbf{x}) = -R(\alpha_i|\mathbf{x}).$$

- ▶ For the classifier that minimizes error

$$g_i(\mathbf{x}) = P(w_i|\mathbf{x}).$$



Discriminant Functions

- ▶ These functions divide the feature space into c *decision regions* ($\mathcal{R}_1, \dots, \mathcal{R}_c$), separated by *decision boundaries*.
- ▶ Note that the results do not change even if we replace every $g_i(\mathbf{x})$ by $f(g_i(\mathbf{x}))$ where $f(\cdot)$ is a monotonically increasing function (e.g., logarithm).
- ▶ This may lead to significant analytical and computational simplifications.



The Gaussian Density

- ▶ Gaussian can be considered as a model where the feature vectors for a given class are continuous-valued, randomly corrupted versions of a single typical or prototype vector.
- ▶ Some properties of the Gaussian:
 - ▶ Analytically tractable.
 - ▶ Completely specified by the 1st and 2nd moments.
 - ▶ Has the maximum entropy of all distributions with a given mean and variance.
 - ▶ Many processes are asymptotically Gaussian (Central Limit Theorem).
 - ▶ Linear transformations of a Gaussian are also Gaussian.
 - ▶ Uncorrelatedness implies independence.



Univariate Gaussian

► For $x \in \mathbb{R}$:

$$\begin{aligned} p(x) &= N(\mu, \sigma^2) \\ &= \frac{1}{\sqrt{2\pi}\sigma} \exp \left[-\frac{1}{2} \left(\frac{x - \mu}{\sigma} \right)^2 \right] \end{aligned}$$

where

$$\begin{aligned} \mu &= E[x] = \int_{-\infty}^{\infty} x p(x) dx, \\ \sigma^2 &= E[(x - \mu)^2] = \int_{-\infty}^{\infty} (x - \mu)^2 p(x) dx. \end{aligned}$$



Univariate Gaussian

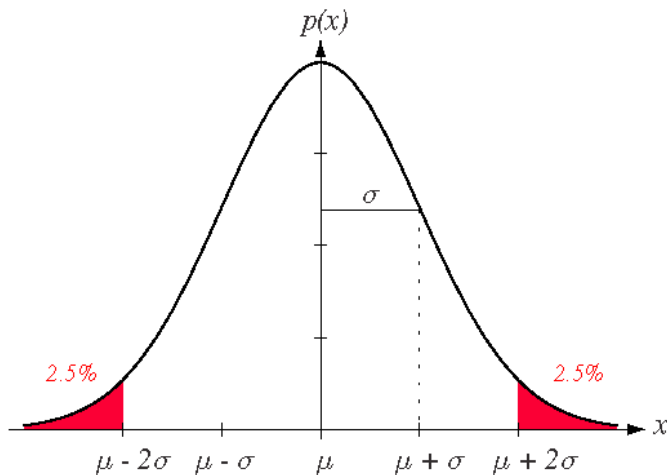


Figure 3: A univariate Gaussian distribution has roughly 95% of its area in the range $|x - \mu| \leq 2\sigma$.



Multivariate Gaussian

► For $\mathbf{x} \in \mathbb{R}^d$:

$$\begin{aligned} p(\mathbf{x}) &= N(\boldsymbol{\mu}, \boldsymbol{\Sigma}) \\ &= \frac{1}{(2\pi)^{d/2} |\boldsymbol{\Sigma}|^{1/2}} \exp \left[-\frac{1}{2} (\mathbf{x} - \boldsymbol{\mu})^T \boldsymbol{\Sigma}^{-1} (\mathbf{x} - \boldsymbol{\mu}) \right] \end{aligned}$$

where

$$\begin{aligned} \boldsymbol{\mu} &= E[\mathbf{x}] = \int \mathbf{x} p(\mathbf{x}) d\mathbf{x}, \\ \boldsymbol{\Sigma} &= E[(\mathbf{x} - \boldsymbol{\mu})(\mathbf{x} - \boldsymbol{\mu})^T] = \int (\mathbf{x} - \boldsymbol{\mu})(\mathbf{x} - \boldsymbol{\mu})^T p(\mathbf{x}) d\mathbf{x}. \end{aligned}$$



Multivariate Gaussian

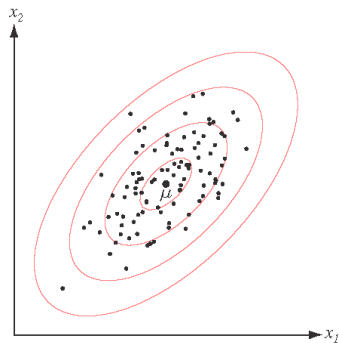


Figure 4: Samples drawn from a two-dimensional Gaussian lie in a cloud centered on the mean μ . The loci of points of constant density are the ellipses for which $(\mathbf{x} - \mu)^T \Sigma^{-1} (\mathbf{x} - \mu)$ is constant, where the eigenvectors of Σ determine the direction and the corresponding eigenvalues determine the length of the principal axes. The quantity $r^2 = (\mathbf{x} - \mu)^T \Sigma^{-1} (\mathbf{x} - \mu)$ is called the squared *Mahalanobis distance* from $\mathbf{x}$ to μ .



Linear Transformations

- ▶ Recall that, given $\mathbf{x} \in \mathbb{R}^d$, $\mathbf{A} \in \mathbb{R}^{d \times k}$, $\mathbf{y} = \mathbf{A}^T \mathbf{x} \in \mathbb{R}^k$, if $x \sim N(\boldsymbol{\mu}, \Sigma)$, then $y \sim N(\mathbf{A}^T \boldsymbol{\mu}, \mathbf{A}^T \Sigma \mathbf{A})$.
- ▶ As a special case, the *whitening transform*

$$\mathbf{A}_w = \Phi \Lambda^{-1/2}$$

where

- ▶ Φ is the matrix whose columns are the orthonormal eigenvectors of Σ ,
 - ▶ Λ is the diagonal matrix of the corresponding eigenvalues,
- gives a covariance matrix equal to the identity matrix $\mathbf{I}$.



Discriminant Functions for the Gaussian Density

- ▶ Discriminant functions for minimum-error-rate classification can be written as

$$g_i(\mathbf{x}) = \ln p(\mathbf{x}|w_i) + \ln P(w_i).$$

- ▶ For $p(\mathbf{x}|w_i) = N(\boldsymbol{\mu}_i, \boldsymbol{\Sigma}_i)$

$$g_i(\mathbf{x}) = -\frac{1}{2}(\mathbf{x} - \boldsymbol{\mu}_i)^T \boldsymbol{\Sigma}_i^{-1}(\mathbf{x} - \boldsymbol{\mu}_i) - \frac{d}{2} \ln 2\pi - \frac{1}{2} \ln |\boldsymbol{\Sigma}_i| + \ln P(w_i).$$



Case 1: $\Sigma_i = \sigma^2 \mathbf{I}$

- Discriminant functions are

$$g_i(\mathbf{x}) = \mathbf{w}_i^T \mathbf{x} + w_{i0} \quad (\text{linear discriminant})$$

where

$$\mathbf{w}_i = \frac{1}{\sigma^2} \boldsymbol{\mu}_i$$
$$w_{i0} = -\frac{1}{2\sigma^2} \boldsymbol{\mu}_i^T \boldsymbol{\mu}_i + \ln P(w_i)$$

(w_{i0} is the threshold or bias for the i 'th category).



Case 1: $\Sigma_i = \sigma^2 \mathbf{I}$

- Decision boundaries are the hyperplanes $g_i(\mathbf{x}) = g_j(\mathbf{x})$, and can be written as

$$\mathbf{w}^T (\mathbf{x} - \mathbf{x}_0) = 0$$

where

$$\begin{aligned}\mathbf{w} &= \boldsymbol{\mu}_i - \boldsymbol{\mu}_j \\ \mathbf{x}_0 &= \frac{1}{2}(\boldsymbol{\mu}_i + \boldsymbol{\mu}_j) - \frac{\sigma^2}{\|\boldsymbol{\mu}_i - \boldsymbol{\mu}_j\|^2} \ln \frac{P(w_i)}{P(w_j)} (\boldsymbol{\mu}_i - \boldsymbol{\mu}_j).\end{aligned}$$

- Hyperplane separating $\mathcal{R}_i$ and $\mathcal{R}_j$ passes through the point $\mathbf{x}_0$ and is orthogonal to the vector $\mathbf{w}$.



Case 1: $\Sigma_i = \sigma^2 \mathbf{I}$

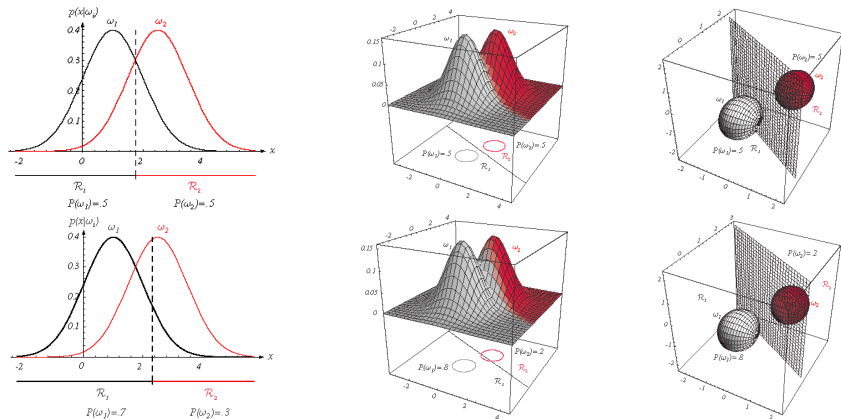


Figure 5: If the covariance matrices of two distributions are equal and proportional to the identity matrix, then the distributions are spherical in d dimensions, and the boundary is a generalized hyperplane of $d - 1$ dimensions, perpendicular to the line separating the means. The decision boundary shifts as the priors are changed.

Case 1: $\Sigma_i = \sigma^2 \mathbf{I}$

- Special case when $P(w_i)$ are the same for $i = 1, \dots, c$ is the *minimum-distance classifier* that uses the decision rule

assign $\mathbf{x}$ to w_{i^*} where $i^* = \arg \min_{i=1, \dots, c} \|\mathbf{x} - \boldsymbol{\mu}_i\|$.



Case 2: $\Sigma_i = \Sigma$

- Discriminant functions are

$$g_i(\mathbf{x}) = \mathbf{w}_i^T \mathbf{x} + w_{i0} \quad (\text{linear discriminant})$$

where

$$\mathbf{w}_i = \Sigma^{-1} \boldsymbol{\mu}_i$$

$$w_{i0} = -\frac{1}{2} \boldsymbol{\mu}_i^T \Sigma^{-1} \boldsymbol{\mu}_i + \ln P(w_i).$$



Case 2: $\Sigma_i = \Sigma$

- Decision boundaries can be written as

$$\mathbf{w}^T(\mathbf{x} - \mathbf{x}_0) = 0$$

where

$$\begin{aligned}\mathbf{w} &= \Sigma^{-1}(\boldsymbol{\mu}_i - \boldsymbol{\mu}_j) \\ \mathbf{x}_0 &= \frac{1}{2}(\boldsymbol{\mu}_i + \boldsymbol{\mu}_j) - \frac{\ln(P(w_i)/P(w_j))}{(\boldsymbol{\mu}_i - \boldsymbol{\mu}_j)^T \Sigma^{-1}(\boldsymbol{\mu}_i - \boldsymbol{\mu}_j)}(\boldsymbol{\mu}_i - \boldsymbol{\mu}_j).\end{aligned}$$

- Hyperplane passes through $\mathbf{x}_0$ but is not necessarily orthogonal to the line between the means.



Case 2: $\Sigma_i = \Sigma$

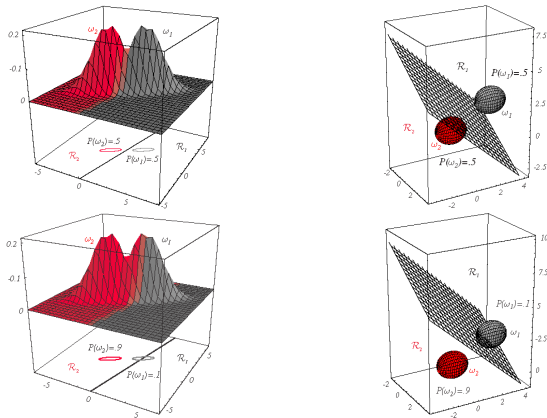


Figure 6: Probability densities with equal but asymmetric Gaussian distributions. The decision hyperplanes are not necessarily perpendicular to the line connecting the means.

Case 3: $\Sigma_i = \text{arbitrary}$

- Discriminant functions are

$$g_i(\mathbf{x}) = \mathbf{x}^T \mathbf{W}_i \mathbf{x} + \mathbf{w}_i^T \mathbf{x} + w_{i0} \quad (\text{quadratic discriminant})$$

where

$$\mathbf{W}_i = -\frac{1}{2} \Sigma_i^{-1}$$

$$\mathbf{w}_i = \Sigma_i^{-1} \boldsymbol{\mu}_i$$

$$w_{i0} = -\frac{1}{2} \boldsymbol{\mu}_i^T \Sigma_i^{-1} \boldsymbol{\mu}_i - \frac{1}{2} \ln |\Sigma_i| + \ln P(w_i).$$

- Decision boundaries are hyperquadrics.



Case 3: $\Sigma_i = \text{arbitrary}$

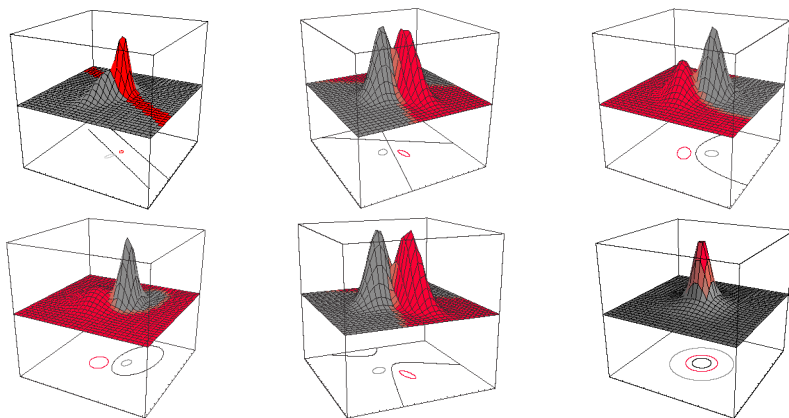


Figure 7: Arbitrary Gaussian distributions lead to Bayes decision boundaries that are general hyperquadrics.

Case 3: $\Sigma_i = \text{arbitrary}$

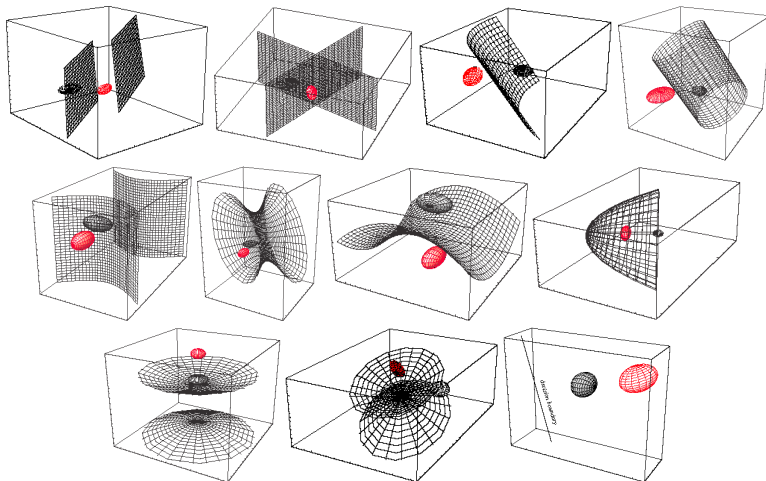


Figure 8: Arbitrary Gaussian distributions lead to Bayes decision boundaries that are general hyperquadrics.

Error Probabilities and Integrals

- For the two-category case

$$\begin{aligned}P(\text{error}) &= P(\mathbf{x} \in \mathcal{R}_2, w_1) + P(\mathbf{x} \in \mathcal{R}_1, w_2) \\&= P(\mathbf{x} \in \mathcal{R}_2|w_1)P(w_1) + P(\mathbf{x} \in \mathcal{R}_1|w_2)P(w_2) \\&= \int_{\mathcal{R}_2} p(\mathbf{x}|w_1) P(w_1) d\mathbf{x} + \int_{\mathcal{R}_1} p(\mathbf{x}|w_2) P(w_2) d\mathbf{x}.\end{aligned}$$



Error Probabilities and Integrals

- For the multcategory case

$$\begin{aligned}P(\textit{error}) &= 1 - P(\textit{correct}) \\&= 1 - \sum_{i=1}^c P(\mathbf{x} \in \mathcal{R}_i, w_i) \\&= 1 - \sum_{i=1}^c P(\mathbf{x} \in \mathcal{R}_i | w_i) P(w_i) \\&= 1 - \sum_{i=1}^c \int_{\mathcal{R}_i} p(\mathbf{x} | w_i) P(w_i) d\mathbf{x}.\end{aligned}$$



Error Probabilities and Integrals

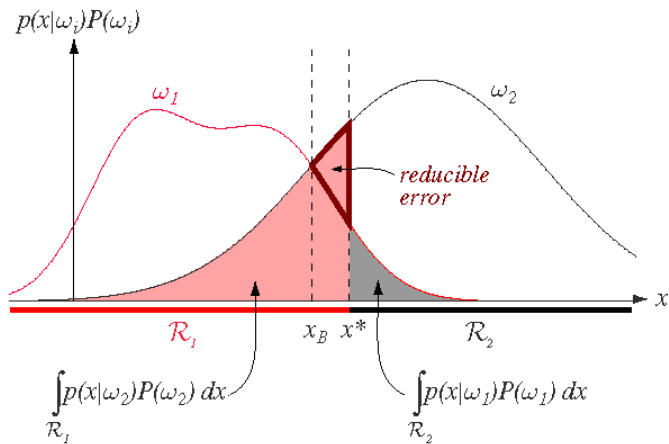


Figure 9: Components of the probability of error for equal priors and the non-optimal decision point x^* . The optimal point x_B minimizes the total shaded area and gives the Bayes error rate.

Receiver Operating Characteristics

- ▶ Consider the two-category case and define
 - ▶ w_1 : target is present,
 - ▶ w_2 : target is not present.

Table 1: *Confusion matrix.*

		Assigned	
		w_1	w_2
True	w_1	correct detection	mis-detection
	w_2	false alarm	correct rejection

- ▶ Mis-detection is also called false negative or Type I error.
- ▶ False alarm is also called false positive or Type II error.



Receiver Operating Characteristics

- If we use a parameter (e.g., a threshold) in our decision, the plot of these rates for different values of the parameter is called the *receiver operating characteristic* (ROC) curve.

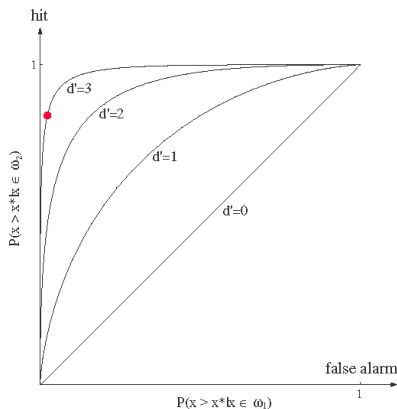


Figure 10: Example receiver operating characteristic (ROC) curves for different settings of the system.



Summary

- ▶ To minimize the overall risk, choose the action that minimizes the conditional risk $R(\alpha|\mathbf{x})$.
- ▶ To minimize the probability of error, choose the class that maximizes the posterior probability $P(w_j|\mathbf{x})$.
- ▶ If there are different penalties for misclassifying patterns from different classes, the posteriors must be weighted according to such penalties before taking action.
- ▶ Do not forget that these decisions are the optimal ones under the assumption that the “true” values of the probabilities are known.

