CS434a/541a: Pattern Recognition
Prof. Olga Veksler

Lecture 4

Normal Random Variable and its discriminant functions

1

Announcement

- Assignment 1 has been posted
  - Note changes to problem 3 and 6 made today
  - Problem 3(d) corrections to 0.99 and 0.01
  - Problem 6, c = number of classes

2

Outline

- Normal Random Variable
  - Properties
  - Discriminant functions

3

Why Normal Random Variables?

- Analytically tractable
- Works well when observation comes form a corrupted single prototype (μ)
- Is an optimal distribution of data for many classifiers used in practice

4

The Univariate Normal Density

- ***x*** is a scalar (has dimension 1)

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

Where:

μ = mean (or expected value) of x

σ^2 = variance

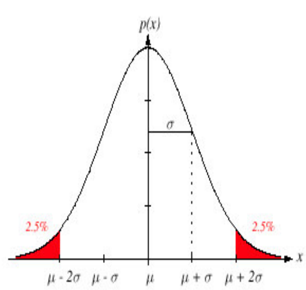


FIGURE 2.7. A univariate normal distribution has roughly 95% of its area in the range $|x - \mu| \le 2\sigma$, as shown. The peak of the distribution has value $p(\mu) = 1/\sqrt{2\pi}\sigma$. From: Richard O. Duda, Peter E. Hart, and David G. Stork, *Pattern Classification*. Copyright © 2001 by John Wiley & Sons, Inc.

Several Features

- What if we have several features $x_1, x_2, \ldots, x_d$
  - each normally distributed
  - may have different means
  - may have different variances
  - may be dependent or independent of each other
- How do we model their joint distribution?

The Multivariate Normal Density

- Multivariate normal density in ***d*** dimensions is:

inverse of Σ

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

determinant of Σ

$$\Sigma = \begin{bmatrix} \sigma_1^2 & \cdots & \sigma_{1d} \\ \vdots & \ddots & \vdots \\ \sigma_{d1} & \cdots & \sigma_d^2 \end{bmatrix}$$

covariance of x_1 and x_d

$x = [x_1, x_2, \ldots, x_d]^t$

$\mu = [\mu_1, \mu_2, \ldots, \mu_d]^t$

- Each x_i is $N(\mu_i, \sigma_i^2)$
  - to prove this, integrate out all other features from the joint density

More on Σ

- $\Sigma = \begin{bmatrix} \sigma_1^2 & \cdots & \sigma_{1d} \\ \vdots & \ddots & \vdots \\ \sigma_{d1} & \cdots & \sigma_d^2 \end{bmatrix}$ plays role similar to the role that σ^2 plays in one dimension

- From Σ we can find out
  1. The individual variances of features $x_1, x_2, \ldots, x_d$
  2. If features x_i *and* x_j are
     - independent $\sigma_{ij}=0$
     - have positive correlation $\sigma_{ij}>0$
     - have negative correlation $\sigma_{ij}<0$

9

The Multivariate Normal Density

- If Σ is diagonal $\begin{bmatrix} \sigma_1^2 & 0 & 0 \\ 0 & \sigma_2^2 & 0 \\ 0 & 0 & \sigma_3^2 \end{bmatrix}$ then the features $x_i, \ldots, x_j$ are independent, and

$$p(x) = \prod_{i=1}^{d} \frac{1}{\sigma_i \sqrt{2\pi}} \exp\left[-\frac{(x_i - \mu_i)^2}{2\sigma_i^2}\right]$$

10

The Multivariate Normal Density

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

$$p(x) = \underbrace{c}_{\text{normalizing constant}} \cdot \exp\left[-\frac{1}{2} \underbrace{\begin{bmatrix} x_1-\mu_1 & x_2-\mu_2 & x_3-\mu_3 \end{bmatrix} \begin{bmatrix} \sigma_1^2 & \sigma_{12} & \sigma_{13} \\ \sigma_{12} & \sigma_2^2 & \sigma_{23} \\ \sigma_{13} & \sigma_{23} & \sigma_3^2 \end{bmatrix}^{-1} \begin{bmatrix} x_1-\mu_1 \\ x_2-\mu_2 \\ x_3-\mu_3 \end{bmatrix}}_{\text{scalar } s \text{ (single number), the closer } s \text{ to 0 the larger is } p(x)}\right]$$

- Thus $P(x)$ is larger for smaller $(x-\mu)^t \Sigma^{-1} (x-\mu)$

11

$(x-\mu)^t \Sigma^{-1} (x-\mu)$

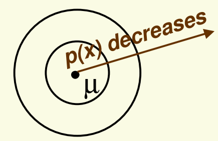
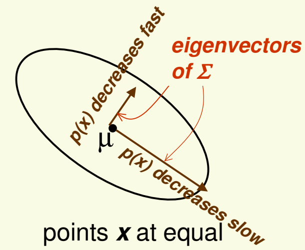
- Σ is positive semi definite ($x^t \Sigma x >= 0$)
- If $x^t \Sigma x = 0$ for nonzero x then det(Σ)=0. This case is not interesting, $p(x)$ is not defined
  1. one feature vector is a constant (has zero variance)
  2. or two components are multiples of each other
- so we will assume Σ is positive definite ($x^t \Sigma x > 0$)
- If Σ is positive definite then so is Σ^{-1}

$(x-\mu)^t \Sigma^{-1} (x-\mu)$

- Positive definite matrix of size ***d*** by ***d*** has ***d*** distinct real eigenvalues and its ***d*** eigenvectors are orthogonal
- Thus if Φ is a matrix whose columns are normalized eigenvectors of Σ, then $\Phi^{-1} = \Phi^t$
- $\Sigma\Phi = \Phi\Lambda$ where Λ is a diagonal matrix with corresponding eigenvalues on the diagonal
- Thus $\Sigma = \Phi\Lambda\Phi^{-1}$ and $\Sigma^{-1} = \Phi\Lambda^{-1}\Phi^{-1}$
- Thus if $\Lambda^{-1/2}$ denotes matrix s.t. $\Lambda^{-1/2}\Lambda^{-1/2} = \Lambda^{-1}$

$$\Sigma^{-1} = \left(\Phi\Lambda^{-\frac{1}{2}}\right)\left(\Phi\Lambda^{-\frac{1}{2}}\right)^t = MM^t$$

$(x-\mu)^t \Sigma^{-1} (x-\mu)$

$(x-\mu)^t(x-\mu)$ *usual (Eucledian) distance between x and μ*	$(x-\mu)^t \sum^{-1} (x-\mu)$ *Mahalanobis distance between x and μ*
	
points ***x*** at equal Eucledian distance from μ lie on a circle	points ***x*** at equal Mahalanobis distance from μ lie on an ellipse: Σ stretches circles to ellipses

$(x-\mu)^t \Sigma^{-1} (x-\mu)$

- Thus

$$(x-\mu)^t \Sigma^{-1} (x-\mu) = (x-\mu)^t MM^t (x-\mu) =$$
$$= \left(M^t(x-\mu)\right)^t \left(M^t(x-\mu)\right) = \left|M^t(x-\mu)\right|^2$$

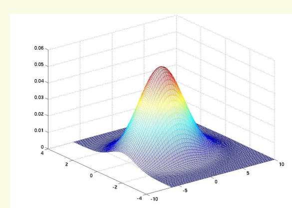
- Thus $\boxed{(x-\mu)^t \Sigma^{-1} (x-\mu) = \left|M^t(x-\mu)\right|^2}$

  where $M^t = \underbrace{\Lambda^{-\frac{1}{2}}}_{\text{scaling matrix}} \underbrace{\Phi^{-1}}_{\text{rotation matrix}}$

- Points x which satisfy $\left|M^t(x-\mu)\right|^2 = const$ lie on an ellipse

2-d Multivariate Normal Density

- Can you see much in this graph?

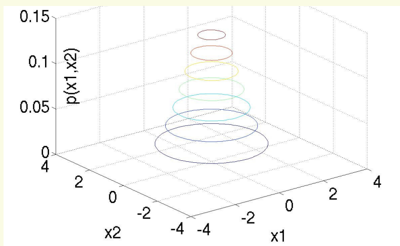


- At most you can see that the mean is around [0,0], but can't really tell if x_1 and x_2 are correlated

16

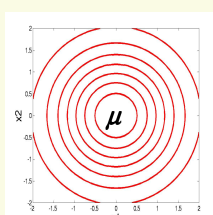
2-d Multivariate Normal Density

- How about this graph?



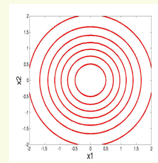
2-d Multivariate Normal Density

- Level curves graph
  - $p(x)$ is constant along each contour
  - topological map of 3-d surface

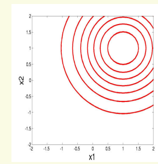


- Now we can see much more
  - x_1 and x_1 are independent
  - σ_1^2 and σ_2^2 are equal

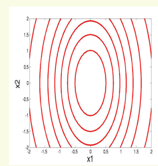
2-d Multivariate Normal Density



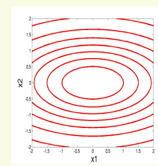
$\Sigma = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$ $\mu = [0,0]$



$\Sigma = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$ $\mu = [1,1]$

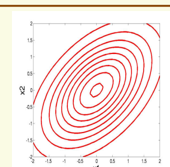


$\Sigma = \begin{bmatrix} 1 & 0 \\ 0 & 4 \end{bmatrix}$ $\mu = [0,0]$

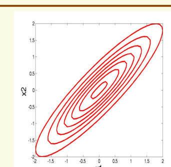


$\Sigma = \begin{bmatrix} 4 & 0 \\ 0 & 1 \end{bmatrix}$ $\mu = [0,0]$

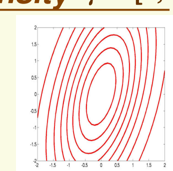
2-d Multivariate Normal Density $\mu = [0,0]$



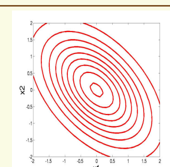
$\Sigma = \begin{bmatrix} 1 & 0.5 \\ 0.5 & 1 \end{bmatrix}$



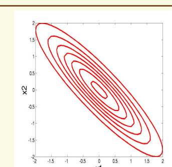
$\Sigma = \begin{bmatrix} 1 & 0.9 \\ 0.9 & 1 \end{bmatrix}$



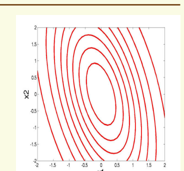
$\Sigma = \begin{bmatrix} 1 & 0.9 \\ 0.9 & 4 \end{bmatrix}$



$\Sigma = \begin{bmatrix} 1 & -0.5 \\ -0.5 & 1 \end{bmatrix}$



$\Sigma = \begin{bmatrix} 1 & -0.9 \\ -0.9 & 1 \end{bmatrix}$

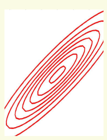


$\Sigma = \begin{bmatrix} 1 & -0.9 \\ -0.9 & 4 \end{bmatrix}$

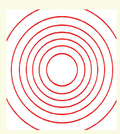
The Multivariate Normal Density

- If X has density $N(\mu,\Sigma)$ then AX has density $N(A^t\mu, A^t\Sigma A)$
  - Thus X can be transformed into a spherical normal variable (covariance of spherical density is the identity matrix I) with whitening transform

X **AX**



$$A_w = \Phi\Lambda^{-\frac{1}{2}}$$



$\Sigma = \begin{bmatrix} 1 & 0.9 \\ 0.9 & 1 \end{bmatrix}$ $\Sigma = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$

Discriminant Functions

- The minimum error-rate classification is achieved by the discriminant function

$$g_i(x) = P(c_i\,|x) = P(x|c_i)P(c_i)/P(x)$$

- Since the observation x is independent of the class, the equivalent discriminant function is

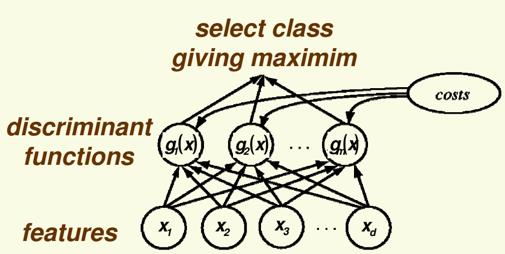
$$g_i(x) = P(x|c_i)P(c_i)$$

- For normal density, convinient to take logarithms. Since logarithm is a monotonically increasing function, the equivalent discriminant function is

$$g_i(x) = \ln P(x|c_i) + \ln P(c_i)$$

Discriminant Functions

- Classifier can be viewed as network which computes m discriminant functions and selects category corresponding to the largest discriminant



- $g_i(x)$ can be replaced with any monotonically increasing function, the results will be unchanged

Discriminant Functions for the Normal Density

- Suppose we for class c_i its class conditional density $p(x|c_i)$ is $N(\mu_i,\Sigma_i)$

$$p(x\,|\,c_i) = \frac{1}{\boxed{(2\pi)^{d/2}}\boxed{|\Sigma_i|^{1/2}}}\exp\boxed{\left[-\frac{1}{2}(x-\mu_i)^t\Sigma_i^{-1}(x-\mu_i)\right]}$$

- Discriminant function $g_i(x) = \ln P(x|c_i) + \boxed{\ln P(c_i)}$

- Plug in $p(x|c_i)$ and $P(c_i)$ get

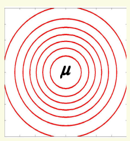
constant for all i

$$g_i(x) = \boxed{-\frac{1}{2}(x-\mu_i)^t\Sigma_i^{-1}(x-\mu_i)}\boxed{\cancel{-\frac{d}{2}\ln 2\pi}}\boxed{-\frac{1}{2}\ln|\Sigma_i|} + \boxed{\ln P(c_i)}$$

$$\boxed{g_i(x) = -\frac{1}{2}(x-\mu_i)^t\Sigma_i^{-1}(x-\mu_i) - \frac{1}{2}\ln|\Sigma_i| + \ln P(c_i)}$$

Case $\Sigma_i = \sigma^2 I$

- That is $\Sigma_i = \begin{bmatrix} \sigma^2 & 0 & 0 \\ 0 & \sigma^2 & 0 \\ 0 & 0 & \sigma^2 \end{bmatrix} = \sigma^2 \cdot \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}$
- In this case, features $x_1, x_2, \ldots, x_d$ are independent with different means and equal variances σ^2



25

Case $\Sigma_i = \sigma^2 I$

- Discriminant function

$$g_i(x) = -\frac{1}{2}(x-\mu_i)^t \Sigma^{-1}(x-\mu_i) - \frac{1}{2}\ln|\Sigma_i| + \ln P(c_i)$$

- $\mathrm{Det}(\Sigma_i) = \sigma^{2d}$ and $\Sigma_i^{-1} = (1/\sigma^2) I = \begin{bmatrix} \frac{1}{\sigma^2} & 0 & 0 \\ 0 & \frac{1}{\sigma^2} & 0 \\ 0 & 0 & \frac{1}{\sigma^2} \end{bmatrix}$
- Can simplify discriminant function

$$g_i(x) = -\frac{1}{2}(x-\mu_i)^t \frac{I}{\sigma^2}(x-\mu_i) - \cancel{\frac{1}{2}\ln(\sigma^{2d})} + \ln P(c_i)$$

constant for all i

$$g_i(x) = -\frac{1}{2\sigma^2}(x-\mu_i)^t(x-\mu_i) + \ln P(c_i) =$$

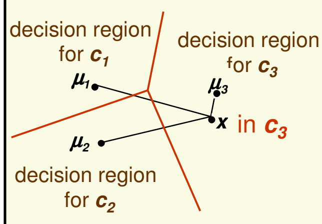
$$= -\frac{1}{2\sigma^2}|x-\mu_i|^2 + \ln P(c_i)$$

26

Case $\Sigma_i = \sigma^2 I$ Geometric Interpretation

If $\ln P(c_i) = \ln P(c_j)$, then

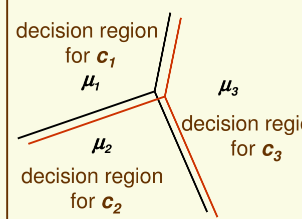
$$g_i(x) = -|x-\mu_i|^2$$



voronoi diagram: *points in each cell are closer to the mean in that cell than to any other mean*

If $\ln P(c_i) \neq \ln P(c_j)$, then

$$g_i(x) = -\frac{1}{2\sigma^2}|x-\mu_i|^2 + \ln P(c_i)$$



Case $\Sigma_i = \sigma^2 I$

$$g_i(x) = -\frac{1}{2\sigma^2}(x-\mu_i)^t(x-\mu_i) + \ln P(c_i) =$$

$$= -\frac{1}{2\sigma^2}(\cancel{x^t x} - \mu_i^t x - x^t\mu_i + \mu_i^t\mu_i) + \ln P(c_i)$$

constant for all classes

$$g_i(x) = -\frac{1}{2\sigma^2}(-2\mu_i^t x + \mu_i^t\mu_i) + \ln P(c_i) = \frac{\mu_i^t}{\sigma^2} x + \left(-\frac{\mu_i^t\mu_i}{2\sigma^2} + \ln P(c_i)\right)$$

$$g_i(x) = w_i^t x + w_{i0}$$

discriminant function is linear

28

Case $\Sigma_i = \sigma^2 I$

$$g_i(x) = w_i^t x + w_{i0}$$

constant in x

linear in x: $w_i^t x = \sum_{i=1}^{d} w_i x_i$

- Thus discriminant function is linear,
- Therefore the decision boundaries $g_i(\mathbf{x})=g_j(\mathbf{x})$ are linear
  - lines if $\mathbf{x}$ has dimension 2
  - planes if $\mathbf{x}$ has dimension 3
  - hyper-planes if $\mathbf{x}$ has dimension larger than 3

Case $\Sigma_i = \sigma^2 I$: Example

- Need to find out when $g_i(\mathbf{x}) < g_j(\mathbf{x})$ for i,j=1,2,3
- Can be done by solving $g_i(\mathbf{x}) = g_j(\mathbf{x})$ for i,j=1,2,3
- Let's take $g_1(\mathbf{x}) = g_2(\mathbf{x})$ first

$$\frac{[1\ 2]}{3}x + \left(-\frac{5}{6} - 1.38\right) = \frac{[4\ 6]}{3}x + \left(-\frac{52}{6} - 1.38\right)$$

- Simplifying, $\frac{[-3\ -4]}{3}\begin{bmatrix} x_1 \\ x_2 \end{bmatrix} = -\frac{47}{6}$

$$-x_1 - \frac{4}{3}x_2 = -\frac{47}{6}$$

line equation

Case $\Sigma_i = \sigma^2 I$: Example

- 3 classes, each 2-dimensional Gaussian with

$$\mu_1 = \begin{bmatrix} 1 \\ 2 \end{bmatrix} \quad \mu_2 = \begin{bmatrix} 4 \\ 6 \end{bmatrix} \quad \mu_3 = \begin{bmatrix} -2 \\ 4 \end{bmatrix} \qquad \Sigma_1 = \Sigma_2 = \Sigma_3 = \begin{bmatrix} 3 & 0 \\ 0 & 3 \end{bmatrix}$$

- Priors $P(c_1) = P(c_2) = \frac{1}{4}$ and $P(c_3) = \frac{1}{2}$
- Discriminant function is $g_i(x) = \frac{\mu_i^t}{\sigma^2}x + \left(-\frac{\mu_i^t \mu_i}{2\sigma^2} + \ln P(c_i)\right)$
- Plug in parameters for each class

$$g_1(x) = \frac{[1\ 2]}{3}x + \left(-\frac{5}{6} - 1.38\right) \qquad g_2(x) = \frac{[4\ 6]}{3}x + \left(-\frac{52}{6} - 1.38\right)$$

$$g_3(x) = \frac{[-2\ 4]}{3}x + \left(-\frac{20}{6} - 0.69\right)$$

Case $\Sigma_i = \sigma^2 I$: Example

- Next solve $g_2(\mathbf{x}) = g_3(\mathbf{x})$

$$2x_1 + \frac{2}{3}x_2 = 6.02$$

- Almost finally solve $g_1(\mathbf{x}) = g_3(\mathbf{x})$

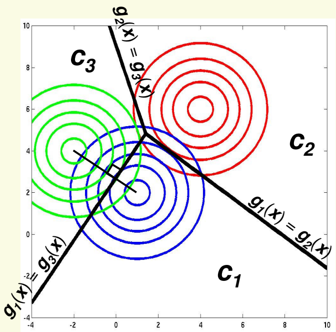
$$x_1 - \frac{2}{3}x_2 = -1.81$$

- And finally solve $g_1(\mathbf{x}) = g_2(\mathbf{x}) = g_3(\mathbf{x})$

$$x_1 = 1.4 \quad \text{and} \quad x_2 = 4.82$$

Case $\Sigma_i = \sigma^2 I$: Example

- Priors $P(c_1) = P(c_2) = \frac{1}{4}$ and $P(c_3) = \frac{1}{2}$



lines connecting means are perpendicular to decision boundaries

33

Case $\Sigma_i = \Sigma$

- Discriminant function

$$g_i(x) = -\frac{1}{2}(x-\mu_i)^t \Sigma^{-1}(x-\mu_i) - \cancel{\frac{1}{2}\ln|\Sigma_i|} + \ln P(c_i)$$

constant for all classes

- Discriminant function becomes

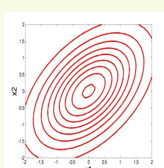
$$g_i(x) = -\frac{1}{2}\underbrace{(x-\mu_i)^t \Sigma^{-1}(x-\mu_i)}_{\text{squared Mahalanobis Distance}} + \ln P(c_i)$$

- Mahalanobis Distance $\|x-y\|^2_{\Sigma^{-1}} = (x-y)^t \Sigma^{-1}(x-y)$
- If $\Sigma = I$, Mahalanobis Distance becomes usual Eucledian distance

$$\|x-y\|^2_{I^{-1}} = (x-y)^t (x-y)$$

Case $\Sigma_i = \Sigma$

- Covariance matrices are equal but arbitrary
- In this case, features $x_1, x_2, \ldots, x_d$ are not necessarily independent

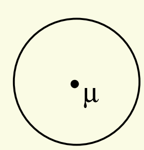


$$\Sigma = \begin{bmatrix} 1 & 0.5 \\ 0.5 & 1 \end{bmatrix}$$

34

Eucledian vs. Mahalanobis Distances

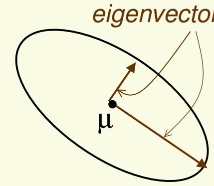
$$|x-\mu|^2 = (x-\mu)^t (x-\mu)$$



points x at equal Eucledian distance from μ lie on a circle

$$\|x-\mu\|^2_{\Sigma^{-1}} = (x-\mu)^t \Sigma^{-1}(x-\mu)$$

eigenvectors of Σ

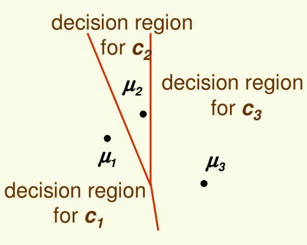


points x at equal Mahalanobis distance from μ lie on an ellipse: Σ stretches cirles to ellipses

Case $\Sigma_i = \Sigma$ Geometric Interpretation

If $\ln P(c_i) = \ln P(c_j)$, **then**

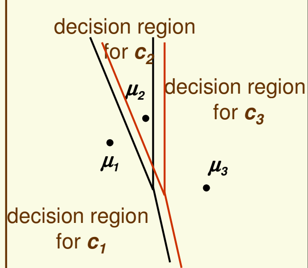
$$g_i(x) = -\|x-\mu_i\|_{\Sigma^{-1}}$$



points in each cell are closer to the mean in that cell than to any other mean under Mahalanobis distance

If $\ln P(c_i) \neq \ln P(c_j)$, **then**

$$g_i(x) = -\frac{1}{2}\|x-\mu_i\|_{\Sigma^{-1}} + \ln P(c_i)$$



Case $\Sigma_i = \Sigma$: Example

- 3 classes, each 2-dimensional Gaussian with

$$\mu_1 = \begin{bmatrix}1\\2\end{bmatrix} \quad \mu_2 = \begin{bmatrix}-1\\5\end{bmatrix} \quad \mu_3 = \begin{bmatrix}-2\\4\end{bmatrix} \quad \Sigma_1 = \Sigma_2 = \Sigma_3 = \begin{bmatrix}1 & -1.5\\-1.5 & 4\end{bmatrix}$$

$$P(c_1) = P(c_2) = \frac{1}{4} \qquad P(c_3) = \frac{1}{2}$$

- Again can be done by solving $g_i(x) = g_j(x)$ for i,j=1,2,3

Case $\Sigma_i = \Sigma$

- Can simplify discriminant function:

$$g_i(x) = -\frac{1}{2}(x-\mu_i)^t\Sigma^{-1}(x-\mu_i) + \ln P(c_i) =$$

$$= -\frac{1}{2}\left(x^t\Sigma^{-1}x - \mu_i^t\Sigma^{-1}x - x^t\Sigma^{-1}\mu_i + \mu_i^t\Sigma^{-1}\mu_i\right) + \ln P(c_i) =$$

$$= -\frac{1}{2}\left(\underbrace{\cancel{x^t\Sigma^{-1}x}}_{\text{constant for all classes}} - 2\mu_i^t\Sigma^{-1}x + \mu_i^t\Sigma^{-1}\mu_i\right) + \ln P(c_i) =$$

$$= -\frac{1}{2}\left(-2\mu_i^t\Sigma^{-1}x + \mu_i^t\Sigma^{-1}\mu_i\right) + \ln P(c_i)$$

$$= \mu_i^t\Sigma^{-1}x + \left(\ln P(c_i) - \frac{1}{2}\mu_i^t\Sigma^{-1}\mu_i\right) = w_i^t x + w_{i0}$$

- Thus in this case discriminant is also linear

Case $\Sigma_i = \Sigma$: Example

- Let's solve in general first

$$g_j(x) = g_i(x)$$

$$\mu_j^t\Sigma^{-1}x + \left(\ln P(c_j) - \frac{1}{2}\mu_j^t\Sigma^{-1}\mu_j\right) = \mu_i^t\Sigma^{-1}x + \left(\ln P(c_i) - \frac{1}{2}\mu_i^t\Sigma^{-1}\mu_i\right)$$

- Let's regroup the terms

$$\left(\mu_j^t\Sigma^{-1} - \mu_i^t\Sigma^{-1}\right)x = -\left(\ln P(c_j) - \frac{1}{2}\mu_j^t\Sigma^{-1}\mu_j\right) + \left(\ln P(c_i) - \frac{1}{2}\mu_i^t\Sigma^{-1}\mu_i\right)$$

- We get the line where $g_j(x) = g_i(x)$

$$\underbrace{\left(\mu_j^t - \mu_i^t\right)\Sigma^{-1}}_{\text{row vector}}x = \underbrace{\left(\ln\frac{P(c_i)}{P(c_j)} + \frac{1}{2}\mu_j^t\Sigma^{-1}\mu_j - \frac{1}{2}\mu_i^t\Sigma^{-1}\mu_i\right)}_{\text{scalar}}$$

Case $\Sigma_i = \Sigma$: Example

$$(\mu_j^t - \mu_i^t)\Sigma^{-1}x = \left(\ln\frac{P(c_i)}{P(c_j)} + \frac{1}{2}\mu_j^t\Sigma^{-1}\mu_j - \frac{1}{2}\mu_i^t\Sigma^{-1}\mu_i \right)$$

- Now substitute for i,j=1,2

$$[-2 \quad 0]x = 0$$
$$x_1 = 0$$

- Now substitute for i,j=2,3

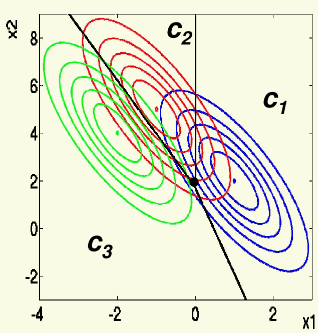
$$[-3.14 \quad -1.4]x = -2.41$$
$$3.14x_1 + 1.4x_2 = 2.41$$

- Now substitute for i,j=1,3

$$[-5.14 \quad -1.43]x = -2.41$$
$$5.14x_1 + 1.43x_2 = 2.41$$

Case $\Sigma_i = \Sigma$: Example

- Priors $P(c_1) = P(c_2) = \frac{1}{4}$ and $P(c_3) = \frac{1}{2}$

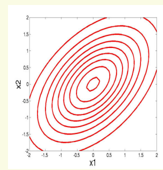


*lines connecting means are **not** in general perpendicular to decision boundaries*

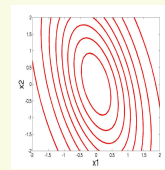
42

General Case Σ_i are arbitrary

- Covariance matrices for each class are arbitrary
- In this case, features x_1, x_2, …, x_d are not necessarily independent



$\Sigma_i = \begin{bmatrix} 1 & 0.5 \\ 0.5 & 1 \end{bmatrix}$



$\Sigma_i = \begin{bmatrix} 1 & -0.9 \\ -0.9 & 4 \end{bmatrix}$

43

General Case Σ_i are arbitrary

- From previous discussion,

$$\boxed{g_i(x) = -\frac{1}{2}(x-\mu_i)^t\Sigma_i^{-1}(x-\mu_i) - \frac{1}{2}\ln|\Sigma_i| + \ln P(c_i)}$$

- This can't be simplified, but we can rearrange it:

$$g_i(x) = -\frac{1}{2}\left(x^t\Sigma_i^{-1}x - 2\mu_i^t\Sigma_i^{-1}x + \mu_i^t\Sigma_i^{-1}\mu_i\right) - \frac{1}{2}\ln|\Sigma_i| + \ln P(c_i)$$

$$g_i(x) = x^t\left(-\frac{1}{2}\Sigma_i^{-1}\right)x + \mu_i^t\Sigma_i^{-1}x + \left(-\frac{1}{2}\mu_i^t\Sigma_i^{-1}\mu_i - \frac{1}{2}\ln|\Sigma_i| + \ln P(c_i)\right)$$

$$g_i(x) = x^tWx + w^tx + w_{i0}$$

44

General Case Σ_i are arbitrary

linear in x

constant in x

$$g_i(x) = x^t W x + w^t x + w_{i0}$$

quadratic in x since

$$x^t W x = \sum_{j=1}^{d}\sum_{i=1}^{d} w_{ij} x_i x_j = \sum_{i,j=1}^{d} w_{ij} x_i x_j$$

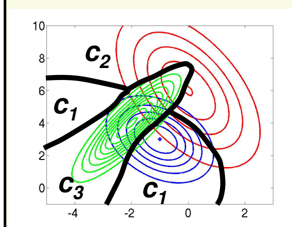
- Thus the discriminant function is quadratic
- Therefore the decision boundaries are quadratic (ellipses and parabolloids)

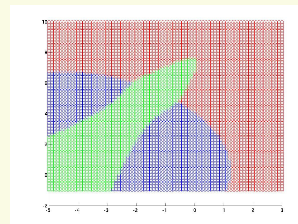
45

General Case Σ_i are arbitrary: Example

$\mu_1 = \begin{bmatrix}-1\\3\end{bmatrix}$ $\mu_2 = \begin{bmatrix}0\\6\end{bmatrix}$ $\mu_3 = \begin{bmatrix}-2\\4\end{bmatrix}$ $\Sigma_1 = \begin{bmatrix}1 & -0.5\\-0.5 & 2\end{bmatrix}$ $\Sigma_2 = \begin{bmatrix}2 & -2\\-2 & 7\end{bmatrix}$ $\Sigma_3 = \begin{bmatrix}1 & 1.5\\1.5 & 3\end{bmatrix}$

$P(c_1) = P(c_2) = \frac{1}{4}$ $P(c_3) = \frac{1}{2}$





General Case Σ_i are arbitrary: Example

- 3 classes, each 2-dimensional Gaussian with

$$\mu_1 = \begin{bmatrix}-1\\3\end{bmatrix} \quad \mu_2 = \begin{bmatrix}0\\6\end{bmatrix} \quad \mu_3 = \begin{bmatrix}-2\\4\end{bmatrix}$$

$$\Sigma_1 = \begin{bmatrix}1 & -0.5\\-0.5 & 2\end{bmatrix} \quad \Sigma_2 = \begin{bmatrix}2 & -2\\-2 & 7\end{bmatrix} \quad \Sigma_3 = \begin{bmatrix}1 & 1.5\\1.5 & 3\end{bmatrix}$$

- Priors: $P(c_1) = P(c_2) = \frac{1}{4}$ and $P(c_3) = \frac{1}{2}$
- Again can be done by solving $g_i(x) = g_j(x)$ for i,j=1,2,3

$$g_i(x) = x^t\left(-\frac{1}{2}\Sigma_i^{-1}\right)x + \mu_i^t\Sigma_i^{-1}x + \left(-\frac{1}{2}\mu_i^t\Sigma_i^{-1}\mu_i - \frac{1}{2}\ln|\Sigma_i| + \ln P(c_i)\right)$$

- Need to solve a bunch of quadratic inequalities of 2 variables

Important Points

- The Bayes classifier when classes are normally distributed is in general quadratic
  - If covariance matrices are equal and proportional to identity matrix, the Bayes classifier is linear
    - If, in addition the priors on classes are equal, the Bayes classifier is the minimum Eucledian distance classifier
  - If covariance matrices are equal, the Bayes classifier is linear
    - If, in addition the priors on classes are equal, the Bayes classifier is the minimum Mahalanobis distance classifier
- Popular classifiers (Euclidean and Mahalanobis distance) are optimal only if distribution of data is appropriate (normal)