

# Statistical Machine Learning

**Pier Francesco Palamara**

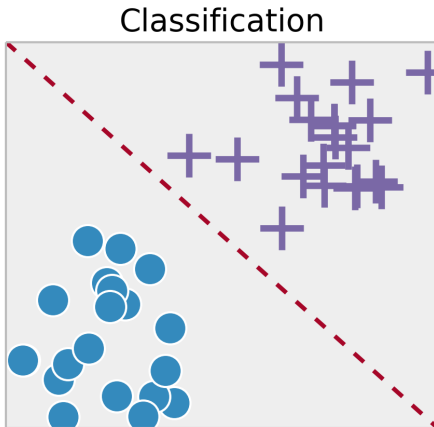
Department of Statistics

University of Oxford

Slide credits and other course material can be found at:

[http://www.stats.ox.ac.uk/~palamara/SML20\\_BDI.html](http://www.stats.ox.ac.uk/~palamara/SML20_BDI.html)

# Classification



## Recall: Loss function

- Suppose we made a prediction  $\hat{Y} = f(X) \in \mathcal{Y}$  based on observation of  $X$ .
- How good is the prediction? We can use a **loss function**  $L : \mathcal{Y} \times \mathcal{Y} \mapsto \mathbb{R}^+$  to formalize the quality of the prediction.
- Typical loss functions:

- **Squared loss** for regression

$$L(Y, f(X)) = (f(X) - Y)^2 .$$

- **Absolute loss** for regression

$$L(Y, f(X)) = |f(X) - Y| .$$

- **Misclassification loss** (or **0-1 loss**) for classification

$$L(Y, f(X)) = \begin{cases} 0 & f(X) = Y \\ 1 & f(X) \neq Y \end{cases} .$$

Many other choices are possible, e.g., **weighted misclassification loss**.

- In classification, if estimated probabilities  $\hat{p}(k)$  for each class  $k \in \mathcal{Y}$  are returned, **log-likelihood loss** (or **log loss**)  $L(Y, \hat{p}) = -\log \hat{p}(Y)$  is often used.

# The Bayes Classifier

- What is the optimal classifier if the joint distribution  $(X, Y)$  were known?
- The density  $g$  of  $X$  can be written as a mixture of  $K$  components (corresponding to each of the classes):

$$g(x) = \sum_{k=1}^K \pi_k g_k(x),$$

where, for  $k = 1, \dots, K$ ,

- $\mathbb{P}(Y = k) = \pi_k$  are the class probabilities,
- $g_k(x)$  is the conditional density of  $X$ , given  $Y = k$ .
- The **Bayes classifier**  $f_{\text{Bayes}} : x \mapsto \{1, \dots, K\}$  is the one with minimum risk:

$$\begin{aligned} R(f) &= \mathbb{E}[L(Y, f(X))] = \mathbb{E}_X [\mathbb{E}_{Y|X}[L(Y, f(X))|X]] \\ &= \int_{\mathcal{X}} \mathbb{E}[L(Y, f(X))|X = x] g(x) dx \end{aligned}$$

- The minimum risk attained by the Bayes classifier is called **Bayes risk**.
- Minimizing  $\mathbb{E}[L(Y, f(X))|X = x]$  separately for each  $x$  suffices.

# The Bayes Classifier

- Consider the 0-1 loss.
- The risk simplifies to:

$$\begin{aligned}\mathbb{E}\left[L(Y, f(X))|X = x\right] &= \sum_{k=1}^K L(k, f(x))\mathbb{P}(Y = k|X = x) \\ &= 1 - \mathbb{P}(Y = f(x)|X = x)\end{aligned}$$

- The risk is minimized by choosing the class with the greatest probability given the observation:

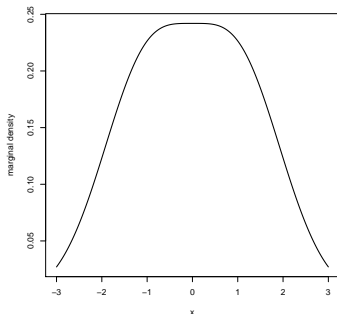
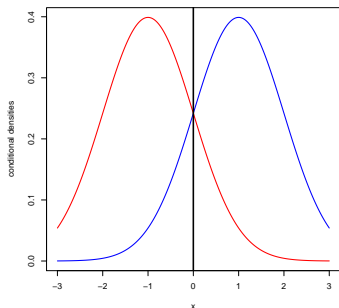
$$\begin{aligned}f_{\text{Bayes}}(x) &= \arg \max_{k=1, \dots, K} \mathbb{P}(Y = k|X = x) \\ &= \arg \max_{k=1, \dots, K} \frac{\pi_k g_k(x)}{\sum_{j=1}^K \pi_j g_j(x)} = \arg \max_{k=1, \dots, K} \pi_k g_k(x).\end{aligned}$$

- The functions  $x \mapsto \pi_k g_k(x)$  are called **discriminant functions**. The discriminant function with maximum value determines the predicted class of  $x$ .

# The Bayes Classifier: Example

A simple two Gaussians example: Suppose  $X \sim \mathcal{N}(\mu_Y, 1)$ , where  $\mu_1 = -1$  and  $\mu_2 = 1$  and assume equal class probabilities  $\pi_1 = \pi_2 = 1/2$ .

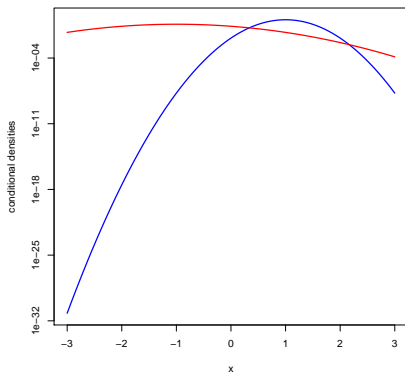
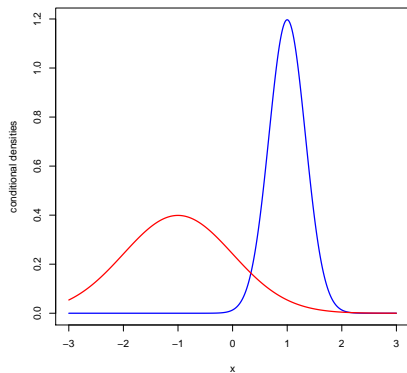
$$g_1(x) = \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{(x+1)^2}{2}\right) \quad \text{and} \quad g_2(x) = \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{(x-1)^2}{2}\right).$$



Optimal classification is  $f_{\text{Bayes}}(x) = \arg \max_{k=1, \dots, K} \pi_k g_k(x) = \begin{cases} 1 & \text{if } x < 0, \\ 2 & \text{if } x \geq 0. \end{cases}$

# The Bayes Classifier: Example

How do you classify a new observation  $x$  if now the standard deviation is still 1 for class 1 but  $1/3$  for class 2?



Looking at density in a log-scale, optimal classification is to select class 2 if and only if  $x \in [0.34, 2.16]$ .

# Plug-in Classification

- The Bayes Classifier:

$$f_{\text{Bayes}}(x) = \arg \max_{k=1, \dots, K} \pi_k g_k(x).$$

- We know neither the conditional densities  $g_k$  nor the class probabilities  $\pi_k$ !
- The **plug-in classifier** chooses the class

$$f(x) = \arg \max_{k=1, \dots, K} \hat{\pi}_k \hat{g}_k(x),$$

- where we plugged in
  - estimates  $\hat{\pi}_k$  of  $\pi_k$  and  $k = 1, \dots, K$  and
  - estimates  $\hat{g}_k(x)$  of conditional densities,
- **Linear Discriminant Analysis** is an example of plug-in classification.



# Linear Discriminant Analysis

- **LDA** is the most well-known and simplest example of plug-in classification.
- Assume multivariate normal conditional density  $g_k(x)$  for each class  $k$ :

$$X|Y = k \sim \mathcal{N}(\mu_k, \Sigma),$$

$$g_k(x) = (2\pi)^{-p/2} |\Sigma|^{-1/2} \exp\left(-\frac{1}{2}(x - \mu_k)^\top \Sigma^{-1}(x - \mu_k)\right),$$

- each class can have a **different mean**  $\mu_k$ ,
  - all classes share the **same covariance**  $\Sigma$ .
- For an observation  $x$ , the  $k$ -th log-discriminant function is

$$\log \pi_k g_k(x) = c + \log \pi_k - \frac{1}{2}(x - \mu_k)^\top \Sigma^{-1}(x - \mu_k)$$

The quantity  $(x - \mu_k)^\top \Sigma^{-1}(x - \mu_k)$  is the squared **Mahalanobis distance** between  $x$  and  $\mu_k$ .

- If  $\Sigma = I_p$  and  $\pi_k = \frac{1}{K}$ , LDA simply chooses the class  $k$  with the nearest (in the Euclidean sense) class mean.

# Linear Discriminant Analysis

- Expanding the term  $(x - \mu_k)^\top \Sigma^{-1} (x - \mu_k)$ ,

$$\begin{aligned} \log \pi_k g_k(x) &= c + \log \pi_k - \frac{1}{2} (\mu_k^\top \Sigma^{-1} \mu_k - 2\mu_k^\top \Sigma^{-1} x + x^\top \Sigma^{-1} x) \\ &= c' + \log \pi_k - \frac{1}{2} \mu_k^\top \Sigma^{-1} \mu_k + \mu_k^\top \Sigma^{-1} x \end{aligned}$$

- Setting  $a_k = \log(\pi_k) - \frac{1}{2} \mu_k^\top \Sigma^{-1} \mu_k$  and  $b_k = \Sigma^{-1} \mu_k$ , we obtain

$$\log \pi_k g_k(x) = c' + a_k + b_k^\top x$$

i.e. a **linear** discriminant function in  $x$ .

- Consider choosing class  $k$  over  $k'$ :

$$a_k + b_k^\top x > a_{k'} + b_{k'}^\top x \quad \Leftrightarrow \quad a_\star + b_\star^\top x > 0$$

where  $a_\star = a_k - a_{k'}$  and  $b_\star = b_k - b_{k'}$ .

- The Bayes classifier thus partitions  $\mathcal{X}$  into regions with the same class predictions via **separating hyperplanes**.
- The Bayes classifier under these assumptions is more commonly known as the **LDA classifier**.

# Parameter Estimation

- How to estimate the parameters of the LDA model?
- We can achieve this by maximum likelihood (EM algorithm is not needed here since the class variables  $y_i$  are observed!).
- Let  $n_k = \#\{j : y_j = k\}$  be the number of observations in class  $k$ .

$$\begin{aligned} \ell(\pi, (\mu_k)_{k=1}^K, \Sigma) &= \log p\left((x_i, y_i)_{i=1}^n \mid \pi, (\mu_k)_{k=1}^K, \Sigma\right) = \sum_{i=1}^n \log \pi_{y_i} g_{y_i}(x_i) \\ &= c + \sum_{k=1}^K \sum_{j:y_j=k} \log \pi_k - \frac{1}{2} \left( \log |\Sigma| + (x_j - \mu_k)^\top \Sigma^{-1} (x_j - \mu_k) \right) \end{aligned}$$

ML estimates:

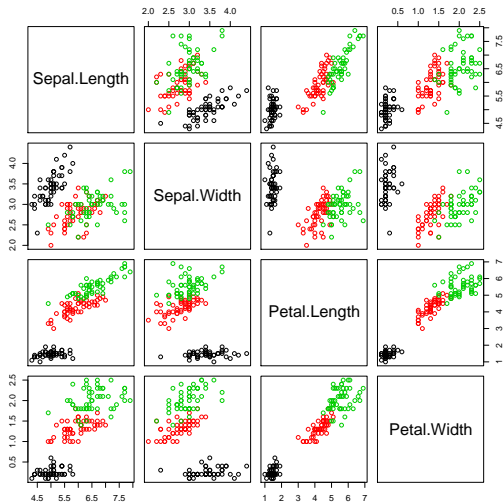
$$\hat{\pi}_k = \frac{n_k}{n} \qquad \hat{\mu}_k = \frac{1}{n_k} \sum_{j:y_j=k} x_j$$

$$\hat{\Sigma} = \frac{1}{n} \sum_{k=1}^K \sum_{j:y_j=k} (x_j - \hat{\mu}_k)(x_j - \hat{\mu}_k)^\top$$

- Note: the ML estimate of  $\Sigma$  is biased. For an unbiased estimate we need to divide by  $n - K$ .

# Iris Dataset

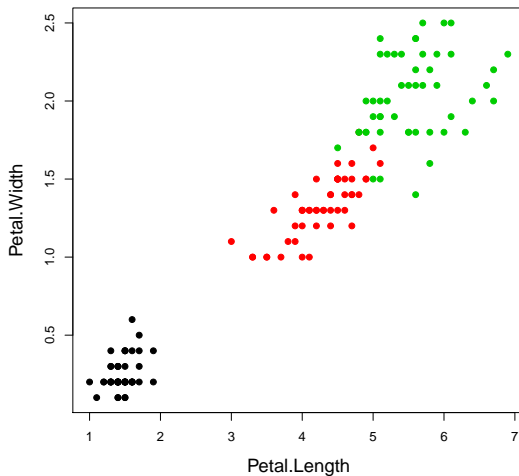
```
library(MASS)
data(iris)
##save class labels
ct <- unclass(iris$Species)
##pairwise plot
pairs(iris[,1:4],col=ct)
```



# Iris Dataset

Just focus on two predictor variables.

```
iris.data <- iris[,3:4]  
plot(iris.data,col=ct,pch=20,cex=1.5,cex.lab=1.4)
```



# Iris Dataset

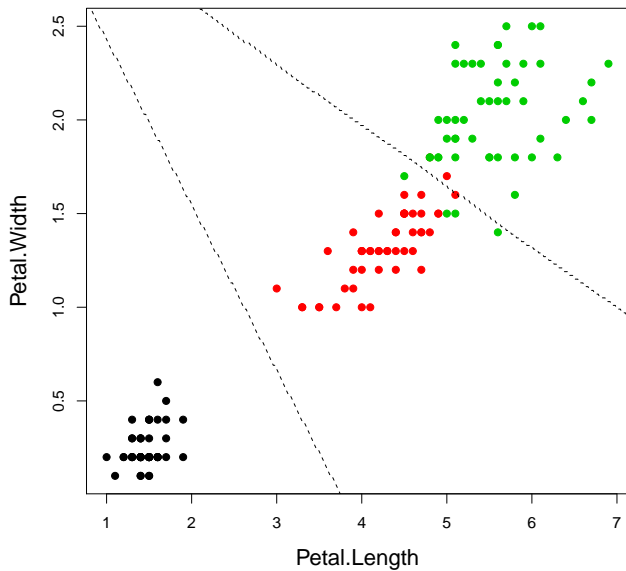
Computing and plotting the LDA boundaries.

```
##fit LDA
iris.lda <- lda(x=iris.data,grouping=ct)

##create a grid for our plotting surface
x <- seq(0,8,0.02)
y <- seq(0,3,0.02)
m <- length(x)
n <- length(y)
z <- as.matrix(expand.grid(x,y),0)
colnames(z) = colnames(iris.data)

##classes are 1,2 and 3, so set contours at 1.5 and 2.5
iris.ldp <- predict(iris.lda,z)$class
contour(x,y,matrix(iris.ldp,m,n),
        levels=c(1.5,2.5), add=TRUE, d=FALSE, lty=2)
```

# Iris Dataset



## Summary: Linear Discriminant Analysis

- **LDA**: a plug-in classifier assuming multivariate normal conditional density  $g_k(x) = g_k(x|\mu_k, \Sigma)$  for each class  $k$  sharing the **same covariance**  $\Sigma$ :

$$X|Y = k \sim \mathcal{N}(\mu_k, \Sigma),$$

$$g_k(x|\mu_k, \Sigma) = (2\pi)^{-p/2} |\Sigma|^{-1/2} \exp\left(-\frac{1}{2}(x - \mu_k)^\top \Sigma^{-1}(x - \mu_k)\right).$$

- LDA minimizes the squared **Mahalanobis distance** between  $x$  and  $\hat{\mu}_k$ , offset by a term depending on the estimated class proportion  $\hat{\pi}_k$ :

$$\begin{aligned} f_{\text{LDA}}(x) &= \operatorname{argmax}_{k \in \{1, \dots, K\}} \log \hat{\pi}_k g_k(x|\hat{\mu}_k, \hat{\Sigma}) \\ &= \operatorname{argmax}_{k \in \{1, \dots, K\}} \underbrace{\left( \log \hat{\pi}_k - \frac{1}{2} \hat{\mu}_k^\top \hat{\Sigma}^{-1} \hat{\mu}_k \right)}_{\text{terms depending on } k \text{ linear in } x} + \left( \hat{\Sigma}^{-1} \hat{\mu}_k \right)^\top x \\ &= \operatorname{argmin}_{k \in \{1, \dots, K\}} \frac{1}{2} \underbrace{(x - \hat{\mu}_k)^\top \hat{\Sigma}^{-1} (x - \hat{\mu}_k)}_{\text{squared Mahalanobis distance}} - \log \hat{\pi}_k. \end{aligned}$$



# Computations for LDA

- LDA minimizes the squared **Mahalanobis distance** between  $x$  and  $\hat{\mu}_k$ , offset by a term depending on the estimated class proportion  $\hat{\pi}_k$ :

$$f_{\text{LDA}}(x) = \operatorname{argmin}_{k \in \{1, \dots, K\}} \frac{1}{2} \underbrace{(x - \hat{\mu}_k)^\top \hat{\Sigma}^{-1} (x - \hat{\mu}_k)}_{\text{squared Mahalanobis distance}} - \log \hat{\pi}_k.$$

- Thus, LDA classification can be implemented as the following two steps:

- (1) **Sphere** the data with respect to **the common covariance estimate**

$$\hat{\Sigma} = \frac{1}{n} \sum_{k=1}^K \sum_{j: y_j = k} (x_j - \hat{\mu}_k)(x_j - \hat{\mu}_k)^\top:$$

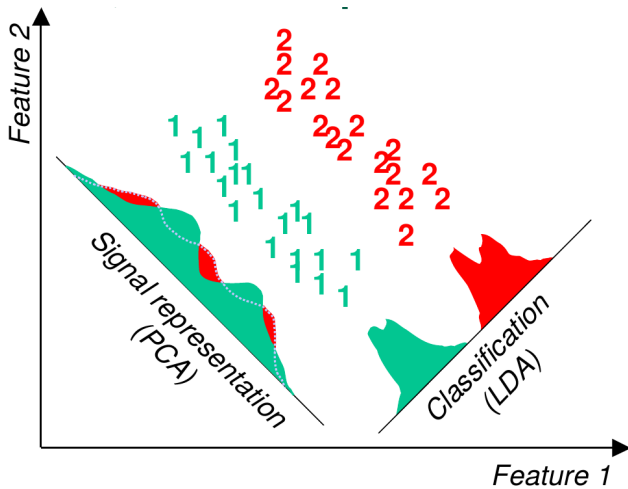
$$x^\bullet \leftarrow D^{-\frac{1}{2}} U^\top x, \quad \text{where } \hat{\Sigma} = U D U^\top.$$

- (2) Classify to the closest class mean  $\hat{\mu}_k^\bullet$  in the transformed space, modulo the effect of the estimated class proportions  $\hat{\pi}_k$ .

# Fisher's Reduced-Rank Linear Discriminant Analysis

- In LDA, data vectors are classified based on Mahalanobis distance to class means.
- There is  $K$  class means and they lie on a  $(K - 1)$ -dimensional affine subspace of ambient space  $\mathbb{R}^p$ : Decision function is unaffected by the directions orthogonal to this subspace.
- Projecting data vectors onto the subspace can be viewed as a dimensionality reduction technique that preserves discriminative information about the labels  $\{y_i\}_{i=1}^n$ : going from  $\mathbb{R}^p$  to  $\mathbb{R}^{K-1}$  and potentially  $K - 1 \ll p$ .
- Just like in PCA, we can visualise the structure in the data by choosing an appropriate basis for the subspace and projecting data onto it - immediate visualisation fully describing LDA for  $K = 3$ .
- For  $K > 3$ , Fisher proposed to look for the change of basis that finds **directions that best separate the classes** - the largest possible spread of the centroids after sphering.

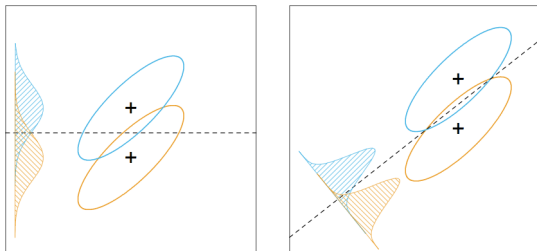
# LDA projections



## Discriminant Coordinates: 2-classes

- Centroids are  $\hat{\mu}_k = \frac{1}{n_k} \sum_{i:y_i=k} x_i$ .
- Centroids projected on a vector  $v$  are given by  $m_k = v^\top \hat{\mu}_k$ .
- Variance of projected data on  $v$  given by  $s_k^2 = \sum_{i:y_i=k} (v^\top x_i - m_k)^2$ .
- Goal: find  $v$  such that the distance between centroids is maximized, while projected clusters are “tight”:

$$\frac{(m_1 - m_2)^2}{s_1^2 + s_2^2}$$



## Discriminant Coordinates: 2-classes

- Centroids are  $\hat{\mu}_k = \frac{1}{n_k} \sum_{i:y_i=k} x_i$ .
- Centroids projected on a vector  $v$  are given by  $m_k = v^\top \hat{\mu}_k$ .
- Variance of projected data on  $v$  given by  $s_k^2 = \sum_{i:y_i=k} (v^\top x_i - m_k)^2$ .
- Goal: find  $v$  such that the distance between centroids is maximized, while projected clusters are “tight”:

$$\frac{(m_1 - m_2)^2}{s_1^2 + s_2^2} = \frac{v^\top B v}{v^\top \hat{\Sigma} v}$$

where

$$B = (\hat{\mu}_2 - \hat{\mu}_1)(\hat{\mu}_2 - \hat{\mu}_1)^\top \quad (\text{between-class covariance})$$

$$\hat{\Sigma} = \frac{1}{n} \sum_{i=1}^n (x_i - \hat{\mu}_{y_i})(x_i - \hat{\mu}_{y_i})^\top \quad (\text{within-class covariance})$$

(verify above calculations).

# Discriminant Coordinates

- More generally:

$$\frac{v^\top B v}{v^\top \hat{\Sigma} v}$$

where

$$B = \frac{1}{n} \sum_{k=1}^K n_k (\hat{\mu}_k - \bar{x})(\hat{\mu}_k - \bar{x})^\top \quad (\text{between-class covariance})$$

$$\hat{\Sigma} = \frac{1}{n} \sum_{i=1}^n (x_i - \hat{\mu}_{y_i})(x_i - \hat{\mu}_{y_i})^\top \quad (\text{within-class covariance})$$

and  $B$  has rank at most  $K - 1$ .

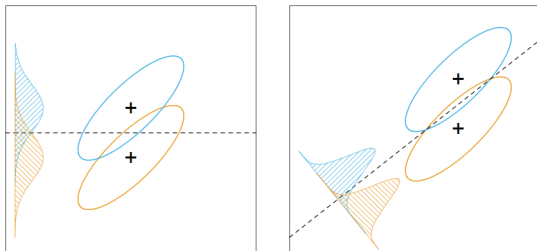


Figure from Hastie, Tibshirani and Friedman, Section 4.3.3

# Discriminant Coordinates

- To solve for the optimal  $v$ , we first reparameterize it as  $u = \widehat{\Sigma}^{\frac{1}{2}}v$ .

$$\frac{v^{\top} B v}{v^{\top} \widehat{\Sigma} v} = \frac{u^{\top} (\widehat{\Sigma}^{-\frac{1}{2}})^{\top} B \widehat{\Sigma}^{-\frac{1}{2}} u}{u^{\top} u} = \frac{u^{\top} B^{\bullet} u}{u^{\top} u}$$

where  $B^{\bullet} = (\widehat{\Sigma}^{-\frac{1}{2}})^{\top} B \widehat{\Sigma}^{-\frac{1}{2}}$ .

- We have solved something similar before. The maximization over  $u$  is achieved by the first eigenvector  $u_1$  of  $B^{\bullet}$ .
- We also look at the remaining eigenvectors  $u_l$  associated to the non-zero eigenvalues and define the **discriminant coordinates** as  $v_l = \widehat{\Sigma}^{-\frac{1}{2}} u_l$ .
- The  $v_l$ 's span exactly the affine subspace spanned by  $(\widehat{\Sigma}^{-1} \widehat{\mu}_k)_{k=1}^K$  (these vectors are given as the “linear discriminants” in the R-function `lda`).

# Crabs Dataset

```
library(MASS)
data(crabs)

## create class labels (species+sex)
crabs$spsex=factor(paste(crabs$sp,crabs$sex,sep=" "))
ct <- unclass(crabs$spsex)

## LDA on crabs in log-domain
cb.lda <- lda(log(crabs[,4:8]),ct)
```



# Crabs Dataset

```
> cb.lda
```

```
Call:
```

```
lda(log(crabs[, 4:8]), ct)
```

```
Prior probabilities of groups:
```

1	2	3	4
0.25	0.25	0.25	0.25

```
Group means:
```

	FL	RW	CL	CW	BD
1	2.564985	2.475174	3.312685	3.462327	2.441351
2	2.672724	2.443774	3.437968	3.578077	2.560806
3	2.852455	2.683831	3.529370	3.649555	2.733273
4	2.787885	2.489921	3.490431	3.589426	2.701580

```
Coefficients of linear discriminants:
```

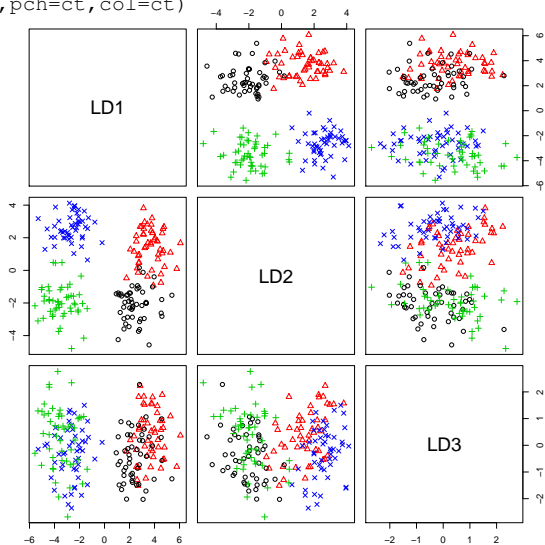
	LD1	LD2	LD3
FL	-31.217207	-2.851488	25.719750
RW	-9.485303	-24.652581	-6.067361
CL	-9.822169	38.578804	-31.679288
CW	65.950295	-21.375951	30.600428
BD	-17.998493	6.002432	-14.541487

```
Proportion of trace:
```

LD1	LD2	LD3
0.6891	0.3018	0.0091

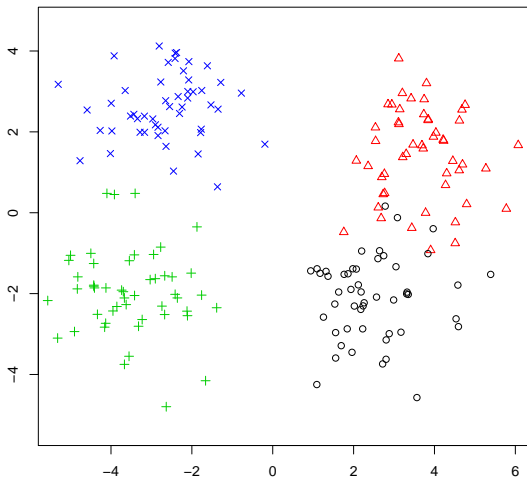
# Crabs Dataset

```
cb.ldp <- predict(cb.lda)  
pairs(cb.ldp$x, pch=ct, col=ct)
```



# Crabs Dataset

```
cb.ldp12 <- cb.ldp$x[,1:2]  
eqsplot(cb.ldp12,pch=ct,col=ct)
```



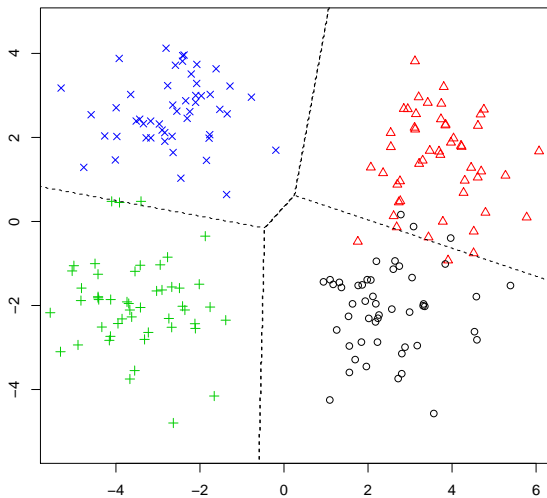
# Crabs Dataset

```
## display the decision boundaries
## take a lattice of points in LD-space
x <- seq(-6,7,0.02)
y <- seq(-6,7,0.02)
z <- as.matrix(expand.grid(x,y))
m <- length(x)
n <- length(y)

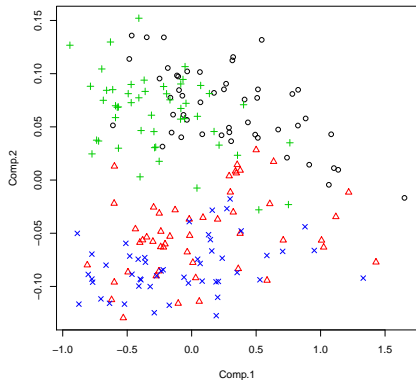
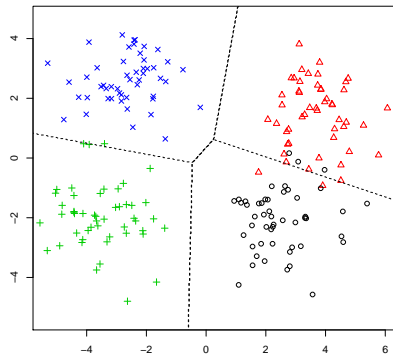
## perform LDA on first two discriminant directions
cb.lda_new <- lda(cb.ldp12,ct)
## predict onto the grid
cb.ldpp <- predict(cb.lda_new,z)$class

## classes are 1,2,3 and 4 so set contours
## at 1.5,2.5 and 3.5
contour(x,y,matrix(cb.ldpp,m,n),
        levels=c(1.5,2.5,3.5),
        add=TRUE,d=FALSE,lty=2)
```

# Crabs Dataset

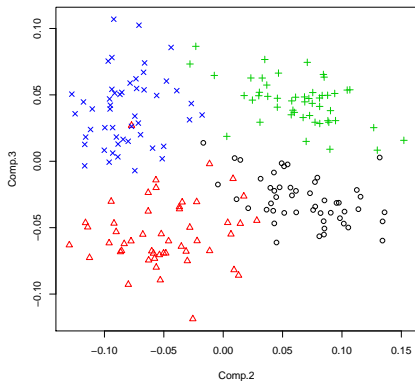
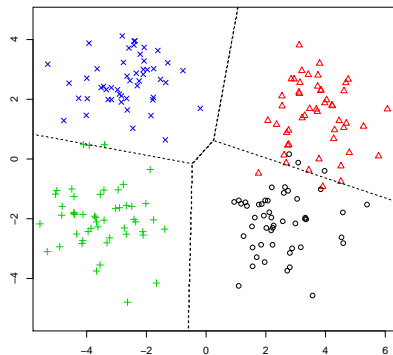


# LDA vs PCA projections



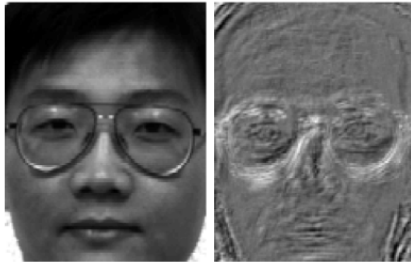
LDA separates the groups better.

# LDA vs PCA projections



LDA separates the groups better.

# Fisherfaces



Eigenfaces vs. Fisherfaces, Belhumeur et al. 1997