# 13) Linear Discriminant Analysis

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#### Reference

Tables, Graphics, and Figures from

# An Introduction to Statistical Learning

James et al. (2017): Chapters: 4.4, 4.6.3, 4.6.4

#### **Bayes Rule**

$$P(Y = k | X = x) = \frac{P(Y=k)P(X=x|Y=k)}{P(X=x)}$$

$$= \frac{P(Y=k)P(X=x|Y=k)}{\sum_{l=1}^{K} P(Y=l)P(X=x|Y=l)}$$

$$Posterior = \frac{Prior \times Likelihood}{Marginal}$$



#### Bayes' Theorem for Classification

$$p_k(X) = Pr(Y = k | X = x)$$

$$= \frac{\pi_k f_k(x)}{\sum_{l=1}^K \pi_l f_l(x)}$$

$$f_k(x) = Pr(X = x | Y = k)$$



#### Linear Discriminant Analysis (LDA)

$$f_k(x) = \frac{1}{\sqrt{2\pi}\sigma_k} \exp\left[-\frac{1}{2\sigma_k^2}(x - \mu_k)^2\right]$$

$$p_{k}(x) = \frac{\pi_{k} \frac{1}{\sqrt{2\pi}\sigma} exp[-\frac{1}{2\sigma^{2}} (x - \mu_{k})^{2}]}{\sum_{l=1}^{K} \pi_{l} \frac{1}{\sqrt{2\pi}\sigma} exp[-\frac{1}{2\sigma^{2}} (x - \mu_{l})^{2}]}$$

$$\delta_k(x) = x \frac{\mu_k}{\sigma^2} - \frac{\mu_k^2}{2\sigma^2} + \log(\pi_k)$$

#### **K=2**, and $\pi_1 = \pi_2$

$$\delta_k(x) = x \frac{\mu_k}{\sigma^2} - \frac{\mu_k^2}{2\sigma^2} + \log(\pi_k)$$

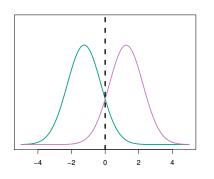
$$\delta_1 = \delta_2$$

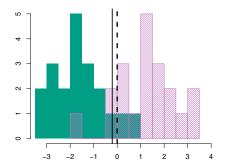
$$2x\mu_1 - \mu_1^2 = 2x\mu_2 - \mu_2^2$$

$$2x(\mu_1 - \mu_2) = \mu_1^2 - \mu_2^2$$

$$x = \frac{\mu_1^2 - \mu_2^2}{2(\mu_1 - \mu_2)} = \frac{\mu_1 + \mu_2}{2}$$

$$\mu_1 = -1.25, \ \mu_2 = 1.25, \ \sigma_1^2 = \sigma_2^2 = 1, \ \text{and} \ \pi_1 = \pi_2 = 0.5$$





#### Bayes Classifier: Linear Discriminant Analysis

$$\hat{\delta}_{k}(x) = x \frac{\hat{\mu}_{k}}{\hat{\sigma}^{2}} - \frac{\hat{\mu}_{k}^{2}}{2\hat{\sigma}^{2}} + \log(\hat{\pi}_{k})$$

$$\hat{\mu}_{k} = \frac{1}{n_{k}} \sum_{i:y_{i}=k} x_{i}$$

$$\hat{\sigma}^{2} = \frac{1}{n-K} \sum_{k=1}^{K} \sum_{i:y_{i}=k} (x_{i} - \hat{\mu}_{k})^{2}$$

$$\hat{\pi}_{k} = \frac{n_{k}}{n}$$

#### **Default Data**

|                   |       | True default status |     |        |
|-------------------|-------|---------------------|-----|--------|
|                   |       | No                  | Yes | Total  |
| Predicted         | No    | 9,644               | 252 | 9,896  |
| $default\ status$ | Yes   | 23                  | 81  | 104    |
|                   | Total | 9,667               | 333 | 10,000 |

Training Error:  $\frac{23+252}{10000} = 2.75\%$ 

Specificity:  $\frac{9644}{9667} \cong 99.8\%$ 

Sensitivity:  $\frac{81}{333} \cong 24.3\%$ 

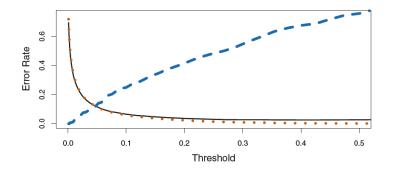
## Pr(default = Yes|X = x) > 0.2

|                   |       | True default status |     |        |
|-------------------|-------|---------------------|-----|--------|
|                   |       | No                  | Yes | Total  |
| Predicted         | No    | 9,432               | 138 | 9,570  |
| $default\ status$ | Yes   | 235                 | 195 | 430    |
|                   | Total | 9,667               | 333 | 10,000 |

Training Error:  $\frac{235+138}{10000} = 3.73\%$ 

Sensitivity:  $\frac{195}{333} \cong 58.5\%$ 

#### **Error Rates as Function of Posterior Probability**



Black: overall error rate

Blue: fraction of defaulting that are incorrectly classified

Orange: fraction of errors among the non-defaulting

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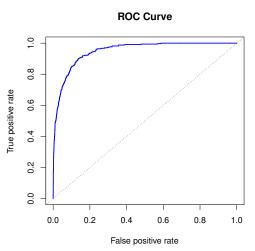
#### **Terminology**

|       |               | Predicted class |                 |       |
|-------|---------------|-----------------|-----------------|-------|
|       |               | – or Null       | + or Non-null   | Total |
| True  | – or Null     | True Neg. (TN)  | False Pos. (FP) | N     |
| class | + or Non-null | False Neg. (FN) | True Pos. (TP)  | Р     |
|       | Total         | $N^*$           | P*              |       |

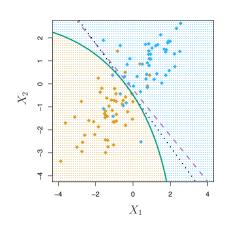
| Name             | Definition | Synonyms                                    |
|------------------|------------|---|
| False Pos. rate  | FP/N       | Type I error, 1—Specificity                 |
| True Pos. rate   | TP/P       | 1—Type II error, power, sensitivity, recall |
| Pos. Pred. value | $TP/P^*$   | Precision, 1—false discovery proportion     |
| Neg. Pred. value | $TN/N^*$   |   |

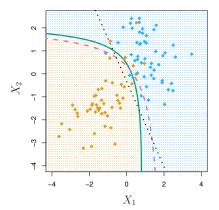
#### Receiver Operating Characteristics (ROC)

$$AUC = 0.95$$



#### LDA vs Quadratic Discriminant Analysis (QDA)





#### Linear Discriminant Analysis in R

```
library(MASS); library(ISLR); attach(Smarket)
train=(Year < 2005)
Smarket.2005=Smarket[!train,]
Direction.2005=Direction[!train]
Ida.fit=Ida(Direction~Lag1+Lag2,data=Smarket,
subset=train)
```

#### Ida.fit

```
Prior probabilities of groups:
   Down
0.491984 0.508016
Group means:
           Lag1
                      Lag2
Down 0.04279022 0.03389409
Up -0.03954635 -0.03132544
Coefficients of linear discriminants:
           1 D1
Lag1 -0.6420190
Lag2 -0.5135293
```

#### Ida.pred=predict(Ida.fit, Smarket.2005)

lda.class=lda.pred\$class table(lda.class,Direction.2005)

```
Direction.2005
lda.class Down Up
Down 35 35
Up 76 106
```

mean(Ida.class == Direction.2005)

55.95%

#### Ida.pred=predict(Ida.fit, Smarket.2005)

lda.class=lda.pred\$class
table(lda.class,Direction.2005)

```
Direction.2005
Ida.class Down Up
Down 35 35
Up 76 106
```

mean(Ida.class == Direction.2005)

55.95%

# qda.fit=qda(Direction~Lag1+Lag2,data=Smarket, subset=train)

### qda.fit

#### qda.class=predict(qda.fit,Smarket.2005)\$class

table(qda.class, Direction.2005)

```
Direction.2005
qda.class Down Up
Down 30 20
Up 81 121
```

mean(qda.class == Direction.2005)

59.92%