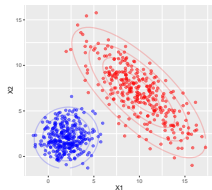


Introduction to Machine Learning

Classification: Discriminant Analysis



Learning goals

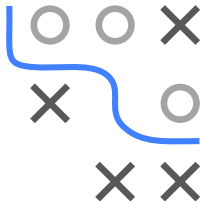
- Understand the ideas of linear and quadratic discriminant analysis
- Understand how parameters are estimated for LDA and QDA
- Understand how decision boundaries are computed for LDA and QDA

LINEAR DISCRIMINANT ANALYSIS (LDA)

LDA follows a generative approach

$$\pi_k(\mathbf{x}) = \mathbb{P}(y = k \mid \mathbf{x}) = \frac{\mathbb{P}(\mathbf{x}|y = k)\mathbb{P}(y = k)}{\mathbb{P}(\mathbf{x})} = \frac{p(\mathbf{x}|y = k)\pi_k}{\sum_{j=1}^g p(\mathbf{x}|y = j)\pi_j},$$

where we now have to pick a distributional form for $p(\mathbf{x}|y = k)$.

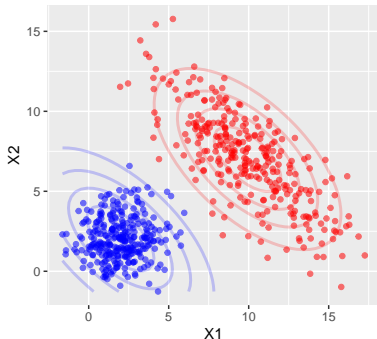


LINEAR DISCRIMINANT ANALYSIS (LDA) / 2

LDA assumes that each class density is modeled as a *multivariate Gaussian*:

$$p(\mathbf{x}|y = k) = \frac{1}{(2\pi)^{\frac{p}{2}} |\Sigma|^{\frac{1}{2}}} \exp \left(-\frac{1}{2} (\mathbf{x} - \mu_k)^T \Sigma^{-1} (\mathbf{x} - \mu_k) \right)$$

with equal covariance, i. e. $\Sigma_k = \Sigma \quad \forall k$.



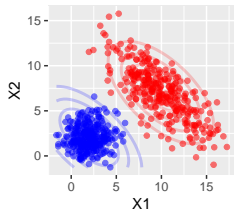
LINEAR DISCRIMINANT ANALYSIS (LDA) / 3

Parameters θ are estimated in a straightforward manner by estimating

$$\hat{\pi}_k = \frac{n_k}{n}, \text{ where } n_k \text{ is the number of class-}k \text{ observations}$$

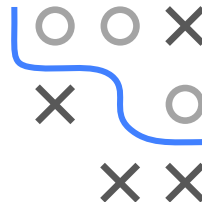
$$\hat{\mu}_k = \frac{1}{n_k} \sum_{i:y^{(i)}=k} \mathbf{x}^{(i)}$$

$$\hat{\Sigma} = \frac{1}{n-g} \sum_{k=1}^g \sum_{i:y^{(i)}=k} (\mathbf{x}^{(i)} - \hat{\mu}_k)(\mathbf{x}^{(i)} - \hat{\mu}_k)^T$$



LDA AS LINEAR CLASSIFIER

Because of the equal covariance structure of all class-specific Gaussian, the decision boundaries of LDA are linear.



LDA AS LINEAR CLASSIFIER / 2

We can formally show that LDA is a linear classifier, by showing that the posterior probabilities can be written as linear scoring functions - up to any isotonic / rank-preserving transformation.

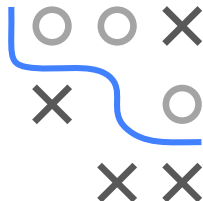
$$\pi_k(\mathbf{x}) = \frac{\pi_k \cdot p(\mathbf{x}|y = k)}{p(\mathbf{x})} = \frac{\pi_k \cdot p(\mathbf{x}|y = k)}{\sum_{j=1}^g \pi_j \cdot p(\mathbf{x}|y = j)}$$

As the denominator is the same for all classes we only need to consider

$$\pi_k \cdot p(\mathbf{x}|y = k)$$

and show that this can be written as a linear function of \mathbf{x} .





$$\begin{aligned} & \pi_k \cdot p(\mathbf{x}|y = k) \\ \propto & \pi_k \exp\left(-\frac{1}{2}\mathbf{x}^T \Sigma^{-1} \mathbf{x} - \frac{1}{2}\boldsymbol{\mu}_k^T \Sigma^{-1} \boldsymbol{\mu}_k + \mathbf{x}^T \Sigma^{-1} \boldsymbol{\mu}_k\right) \\ = & \exp\left(\log \pi_k - \frac{1}{2}\boldsymbol{\mu}_k^T \Sigma^{-1} \boldsymbol{\mu}_k + \mathbf{x}^T \Sigma^{-1} \boldsymbol{\mu}_k\right) \exp\left(-\frac{1}{2}\mathbf{x}^T \Sigma^{-1} \mathbf{x}\right) \\ = & \exp\left(\boldsymbol{\theta}_{0k} + \mathbf{x}^T \boldsymbol{\theta}_k\right) \exp\left(-\frac{1}{2}\mathbf{x}^T \Sigma^{-1} \mathbf{x}\right) \\ \propto & \exp\left(\boldsymbol{\theta}_{0k} + \mathbf{x}^T \boldsymbol{\theta}_k\right) \end{aligned}$$

by defining $\boldsymbol{\theta}_{0k} := \log \pi_k - \frac{1}{2}\boldsymbol{\mu}_k^T \Sigma^{-1} \boldsymbol{\mu}_k$ and $\boldsymbol{\theta}_k := \Sigma^{-1} \boldsymbol{\mu}_k$.

We have again left out all constants which are the same for all classes k , so the normalizing constant of our Gaussians and $\exp\left(-\frac{1}{2}\mathbf{x}^T \Sigma^{-1} \mathbf{x}\right)$.

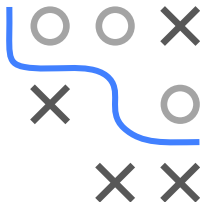
By finally taking the log, we can write our transformed scores as linear:

$$f_k(\mathbf{x}) = \boldsymbol{\theta}_{0k} + \mathbf{x}^T \boldsymbol{\theta}_k$$

QUADRATIC DISCRIMINANT ANALYSIS (QDA)

QDA is a direct generalization of LDA, where the class densities are now Gaussians with unequal covariances Σ_k .

$$p(\mathbf{x}|y = k) = \frac{1}{(2\pi)^{\frac{p}{2}} |\Sigma_k|^{\frac{1}{2}}} \exp \left(-\frac{1}{2} (\mathbf{x} - \boldsymbol{\mu}_k)^T \Sigma_k^{-1} (\mathbf{x} - \boldsymbol{\mu}_k) \right)$$



Parameters are estimated in a straightforward manner by:

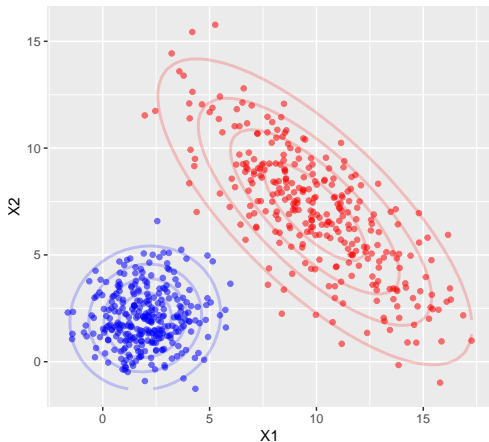
$$\hat{\pi}_k = \frac{n_k}{n}, \text{ where } n_k \text{ is the number of class-}k \text{ observations}$$

$$\hat{\boldsymbol{\mu}}_k = \frac{1}{n_k} \sum_{i:y^{(i)}=k} \mathbf{x}^{(i)}$$

$$\hat{\Sigma}_k = \frac{1}{n_k - 1} \sum_{i:y^{(i)}=k} (\mathbf{x}^{(i)} - \hat{\boldsymbol{\mu}}_k)(\mathbf{x}^{(i)} - \hat{\boldsymbol{\mu}}_k)^T$$

QUADRATIC DISCRIMINANT ANALYSIS (QDA) / 2

- Covariance matrices can differ over classes.
- Yields better data fit but also requires estimation of more parameters.



QUADRATIC DISCRIMINANT ANALYSIS (QDA) / 3

$$\begin{aligned}\pi_k(\mathbf{x}) &\propto \pi_k \cdot p(\mathbf{x}|y = k) \\ &\propto \pi_k |\Sigma_k|^{-\frac{1}{2}} \exp\left(-\frac{1}{2}\mathbf{x}^T \Sigma_k^{-1} \mathbf{x} - \frac{1}{2}\boldsymbol{\mu}_k^T \Sigma_k^{-1} \boldsymbol{\mu}_k + \mathbf{x}^T \Sigma_k^{-1} \boldsymbol{\mu}_k\right)\end{aligned}$$

Taking the log of the above, we can define a discriminant function that is quadratic in \mathbf{x} .

$$\log \pi_k - \frac{1}{2} \log |\Sigma_k| - \frac{1}{2} \boldsymbol{\mu}_k^T \Sigma_k^{-1} \boldsymbol{\mu}_k + \mathbf{x}^T \Sigma_k^{-1} \boldsymbol{\mu}_k - \frac{1}{2} \mathbf{x}^T \Sigma_k^{-1} \mathbf{x}$$



QUADRATIC DISCRIMINANT ANALYSIS (QDA) / 4

