

Introduction to Machine Learning

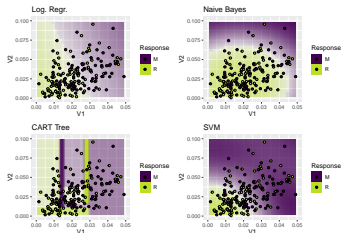
Classification

Basic Definitions



Learning goals

- Understand why classification models have a score / probability as output and not a class
- Understand the difference between scoring and probabilistic classifiers
- Know the concept of decision regions and boundaries
- Know the difference between generative and discriminant approach



CLASSIFICATION TASKS

In classification, we aim at predicting a discrete output

$$y \in \mathcal{Y} = \{C_1, \dots, C_g\}$$

with $2 \leq g < \infty$, given data \mathcal{D} .

In this course, we assume the classes to be encoded as

- $\mathcal{Y} = \{0, 1\}$ or $\mathcal{Y} = \{-1, +1\}$ (in the binary case $g = 2$)
- $\mathcal{Y} = \{1, \dots, g\}$ (in the multiclass case $g \geq 3$)



SCORING CLASSIFIERS

- Construct g **discriminant / scoring functions** $f_1, \dots, f_g : \mathcal{X} \rightarrow \mathbb{R}$
- Scores $f_1(\mathbf{x}), \dots, f_g(\mathbf{x})$ are transformed into classes by choosing the class with the maximum score

$$h(\mathbf{x}) = \arg \max_{k \in \{1, \dots, g\}} f_k(\mathbf{x}).$$

- For $g = 2$, a single discriminant function $f(\mathbf{x}) = f_1(\mathbf{x}) - f_{-1}(\mathbf{x})$ is sufficient (note that it would be natural here to label the classes with $\{-1, +1\}$)
- Class labels are constructed by $h(\mathbf{x}) = \text{sgn}(f(\mathbf{x}))$
- $|f(\mathbf{x})|$ is called “confidence”



PROBABILISTIC CLASSIFIERS

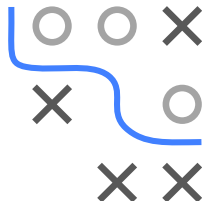
- Construct g probability functions

$$\pi_1, \dots, \pi_g : \mathcal{X} \rightarrow [0, 1], \sum_i \pi_i = 1$$

- Probabilities $\pi_1(\mathbf{x}), \dots, \pi_g(\mathbf{x})$ are transformed into labels by predicting the class with the maximum probability

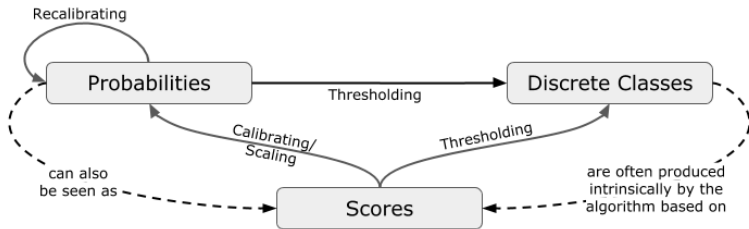
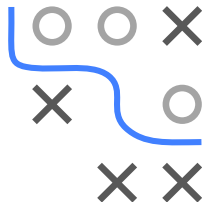
$$h(\mathbf{x}) = \arg \max_{k \in \{1, \dots, g\}} \pi_k(\mathbf{x})$$

- For $g = 2$ one $\pi(\mathbf{x})$ is constructed (note that it would be natural here to label the classes with $\{0, 1\}$)
- Probabilistic classifiers can also be seen as scoring classifiers
- If we want to emphasize that our model outputs probabilities, we denote the model as $\pi(\mathbf{x}) : \mathcal{X} \rightarrow [0, 1]^g$; if we are talking about models in a general sense, we write f , comprising both probabilistic and scoring classifiers (context will make this clear!)



PROBABILISTIC CLASSIFIERS / 2

- Both scoring and probabilistic classifiers can output classes by thresholding (binary case) / selecting the class with the maximum score (multiclass)
- Thresholding: $h(\mathbf{x}) := [\pi(\mathbf{x}) \geq c]$ or $h(\mathbf{x}) = [f(\mathbf{x}) \geq c]$ for some threshold c .
- Usually $c = 0.5$ for probabilistic, $c = 0$ for scoring classifiers.
- There are also versions of thresholding for the multiclass case



DECISION REGIONS AND BOUNDARIES

- A **decision region** for class k is the set of input points \mathbf{x} where class k is assigned as prediction of our model:

$$\mathcal{X}_k = \{\mathbf{x} \in \mathcal{X} : h(\mathbf{x}) = k\}$$

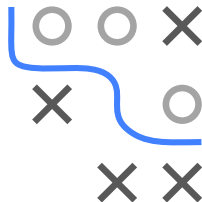
- Points in space where the classes with maximal score are tied and the corresponding hypersurfaces are called **decision boundaries**

$$\begin{aligned} \{\mathbf{x} \in \mathcal{X} : & \exists i \neq j \text{ s.t. } f_i(\mathbf{x}) = f_j(\mathbf{x}) \\ & \text{and } f_i(\mathbf{x}), f_j(\mathbf{x}) \geq f_k(\mathbf{x}) \forall k \neq i, j\} \end{aligned}$$

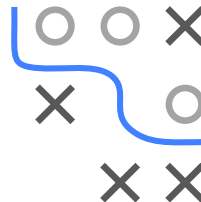
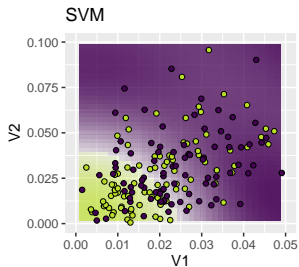
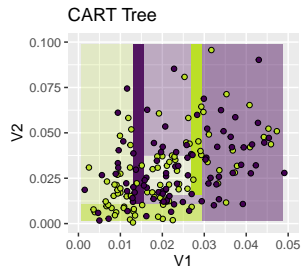
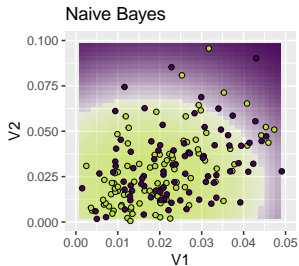
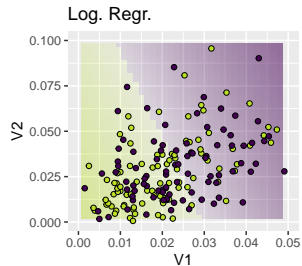
In the binary case we can simplify and generalize to the decision boundary for general threshold c :

$$\{\mathbf{x} \in \mathcal{X} : f(\mathbf{x}) = c\}$$

If we set $c = 0$ for scores and $c = 0.5$ for probabilities, this is consistent with the definition above.



DECISION BOUNDARY EXAMPLES



CLASSIFICATION APPROACHES

Two fundamental approaches exist to construct classifiers:

The **generative approach** and the **discriminant approach**.

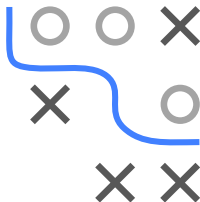
They tackle the classification problem from different angles:

- **Generative** classification approaches assume a data-generating process in which the distribution of the features \mathbf{x} is different for the various classes of the output y , and try to learn these conditional distributions:

“Which y tends to have \mathbf{x} like these?”

- **Discriminant** approaches use **empirical risk minimization** based on a suitable loss function:

“What is the best prediction for y given these \mathbf{x} ?”



GENERATIVE APPROACH

The **generative approach** models $p(\mathbf{x}|y = k)$, usually by making some assumptions about the structure of these distributions, and employs the Bayes theorem:

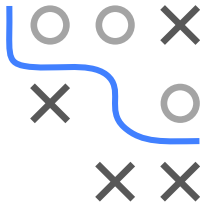
$$\pi_k(\mathbf{x}) = \mathbb{P}(y = k | \mathbf{x}) = \frac{\mathbb{P}(\mathbf{x}|y = k)\mathbb{P}(y = k)}{\mathbb{P}(\mathbf{x})} = \frac{p(\mathbf{x}|y = k)\pi_k}{\sum_{j=1}^g p(\mathbf{x}|y = j)\pi_j}$$

Prior class probabilities π_k are easy to estimate from the training data.

Examples:

- Naive Bayes classifier
- Linear discriminant analysis (generative, linear)
- Quadratic discriminant analysis (generative, not linear)

Note: LDA and QDA have 'discriminant' in their name, but are generative models! (... sorry.)



DISCRIMINANT APPROACH

The **discriminant approach** tries to optimize the discriminant functions directly, usually via empirical risk minimization.

$$\hat{f} = \arg \min_{f \in \mathcal{H}} \mathcal{R}_{\text{emp}}(f) = \arg \min_{f \in \mathcal{H}} \sum_{i=1}^n L \left(y^{(i)}, f \left(\mathbf{x}^{(i)} \right) \right).$$

Examples:

- Logistic regression (discriminant, linear)
- Neural networks
- Support vector machines

