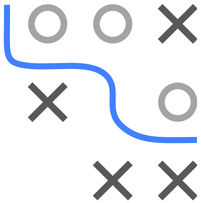
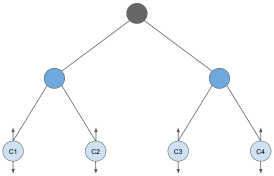
Introduction to Machine Learning

Boosting
Gradient Boosting with Trees 2

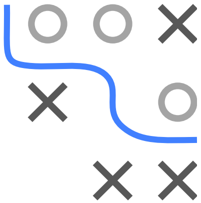




Learning goals

- Loss optimal terminal coefficients
- GB with trees for multiclass problems

ADAPTING TERMINAL COEFFICIENTS



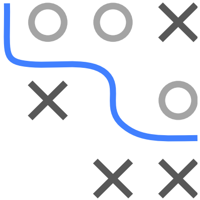
- Tree as additive model: $b(\mathbf{x}) = \sum_{t=1}^{T} c_t \mathbb{1}_{\{\mathbf{x} \in R_t\}}$,
- R_t are the terminal regions; c_t are terminal constants

The GB model is still additive in the regions:

$$\begin{aligned} f^{[m]}(\mathbf{x}) &= f^{[m-1]}(\mathbf{x}) + \alpha^{[m]} b^{[m]}(\mathbf{x}) \\ &= f^{[m-1]}(\mathbf{x}) + \alpha^{[m]} \sum_{t=1}^{T^{[m]}} c_t^{[m]} \mathbb{1}_{\{\mathbf{x} \in R_t^{[m]}\}} \\ &= f^{[m-1]}(\mathbf{x}) + \sum_{t=1}^{T^{[m]}} \tilde{c}_t^{[m]} \mathbb{1}_{\{\mathbf{x} \in R_t^{[m]}\}}. \end{aligned}$$

With $\tilde{c}_t^{[m]} = \alpha^{[m]} \cdot c_t^{[m]}$ in the case that $\alpha^{[m]}$ is a constant learning rate

GB MULTICLASS WITH TREES



- From Friedman, J. H. - Greedy Function Approximation: A Gradient Boosting Machine (1999)
- We again model one discriminant function per class.
- Determining the tree structure works just like before.
- In the estimation of the c values, i.e., the heights of the terminal regions, however, all models depend on each other because of the definition of L. Optimizing this is more difficult, so we will skip some details and present the main idea and results.