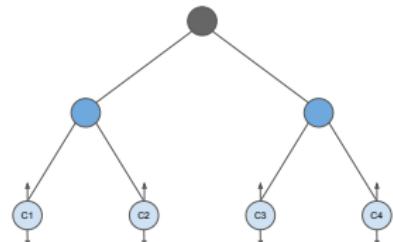


Introduction to Machine Learning

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.

