

Decision Trees



Benefits of Decision Trees

- Easy to interpret
- Easy to understand
- Extensions can add more to interpretability

But: Downside is that they are not very powerful for making good predictions.

Decision Trees

Note on terminology:

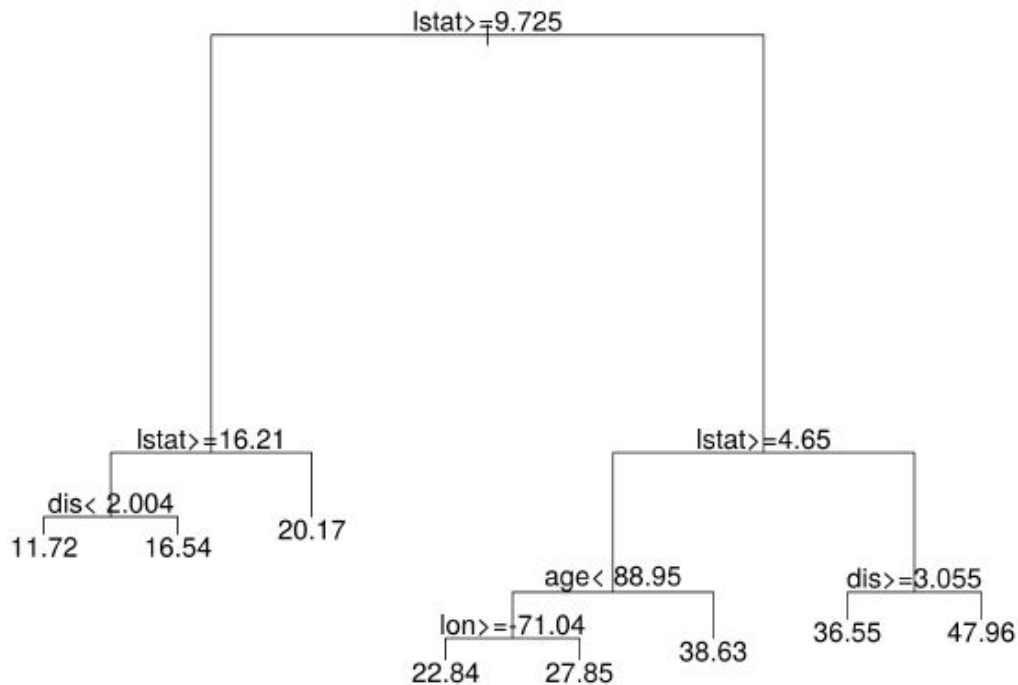
- Regression trees refer to trees used for regression (i.e., numerical outcome).
- Classification trees refer to trees used for classification (i.e., categorical outcome).

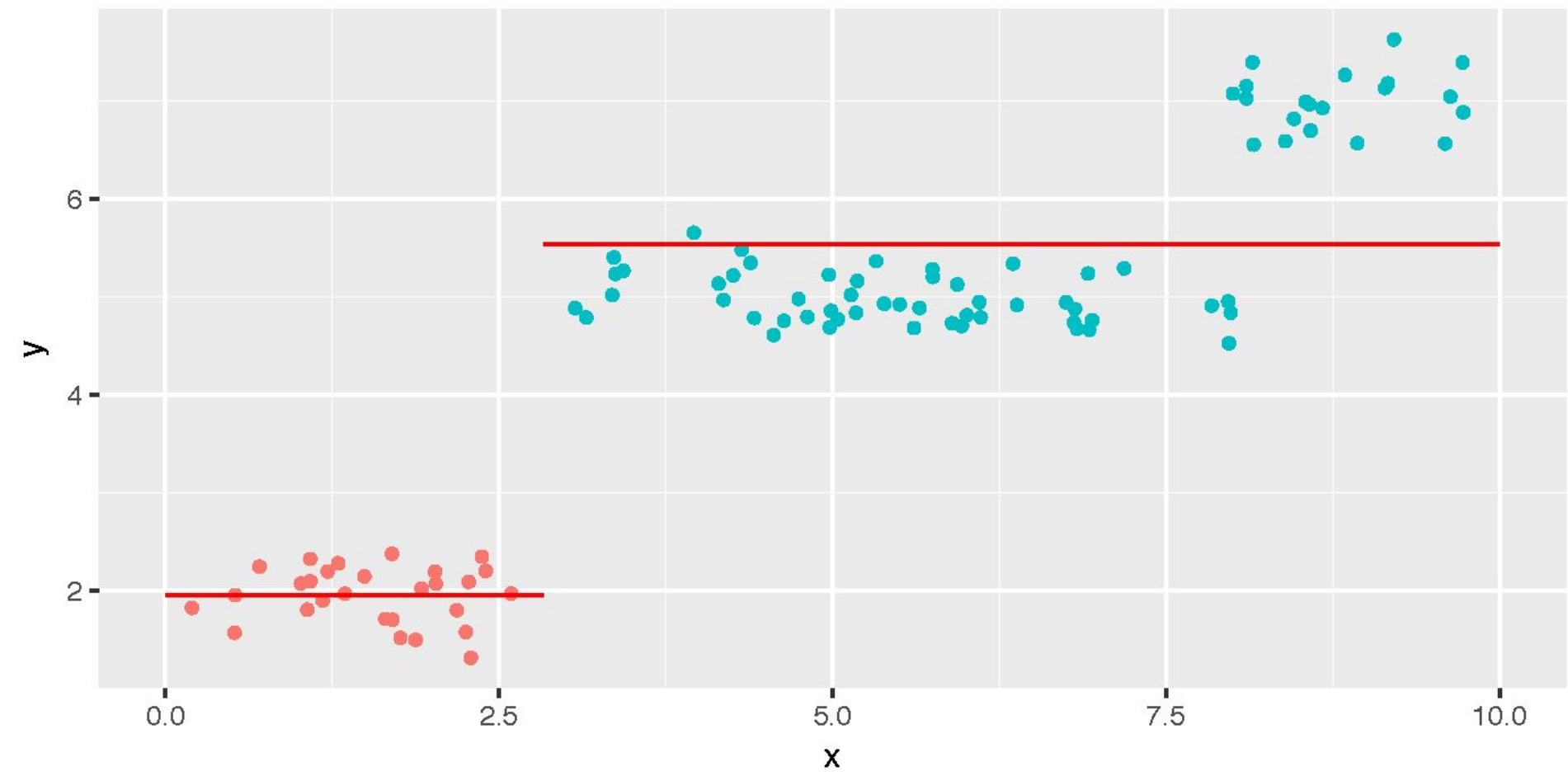
Interpreting Trees

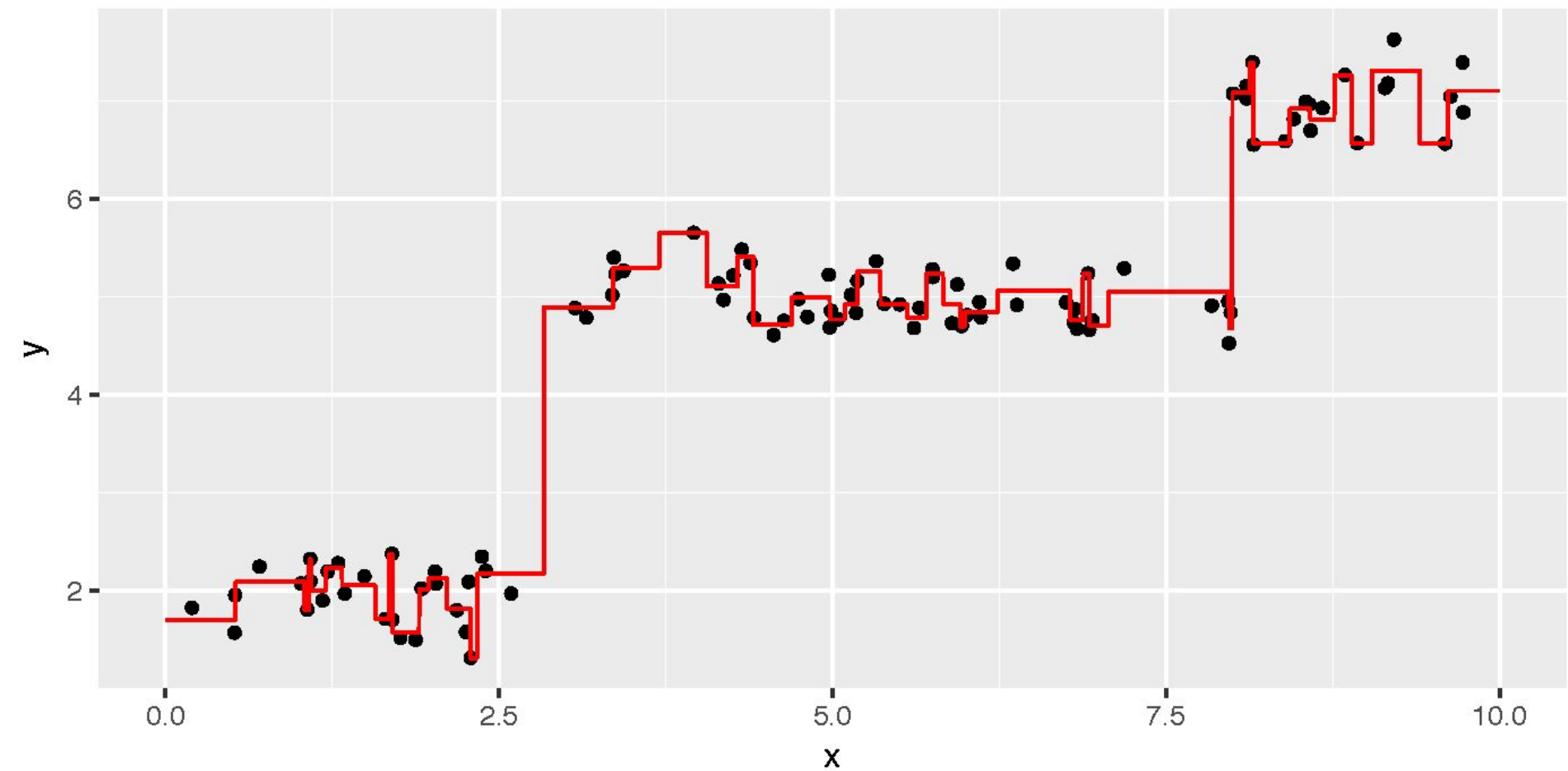
Follow the steps from the top to make a prediction for a given observation.

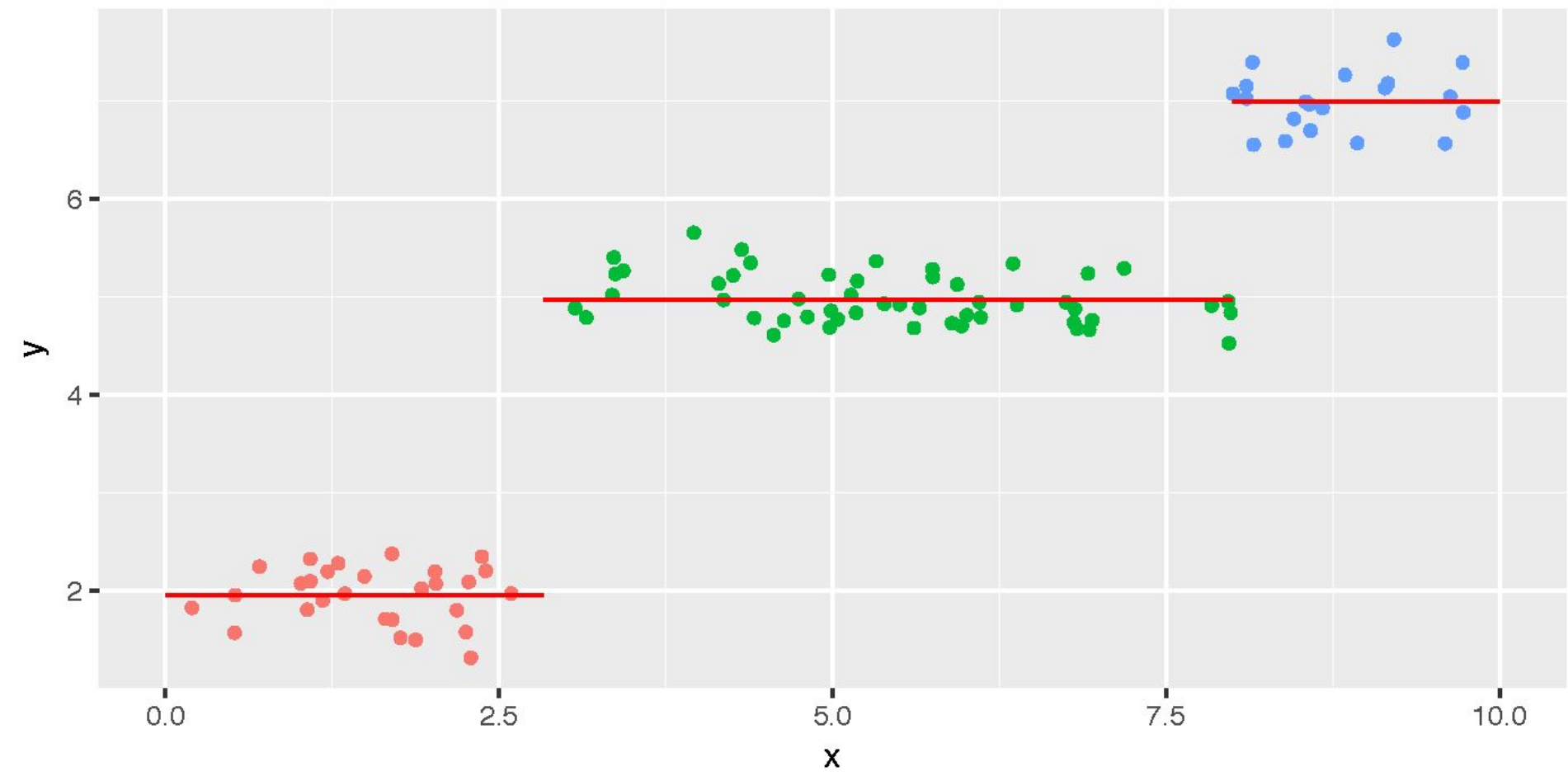
Terminal node shows estimate.

(a) Regression tree









Dealing with Correlated Predictors

We'll see how we can use the idea of decision trees and deal with correlated predictors when we get to ensemble models

General idea: We only use a few of the predictors at a time.

Surrogate Splits

Used to address issues that can arise with missing data.

Idea: Determine split, then find another variable that mimics that split. Use the other variable if there is a missing value in the original variable.

Looking Ahead

Individual trees tend to **overfit**. How can we address this to get better models?

Ensemble methods such as Random Forests tries to address some of the issues with individual trees.

- Use only a subset of predictors at a time.
- Use a bootstrap sample of observations.

Variations on Trees

Conditional Inference trees and Model based recursive partitioning aim to put more of a structure on building trees. These provide more **interpretability**.

Generally, if prediction is our primary purpose, we'll use **regular trees as base learners**.

Imbalanced Datasets

- Note: We **don't need to set the majority class** of a terminal node as our prediction. We can get scores out of the proportion in the terminal node.
- Using **different metrics (and tuning)** can help identify the best model for prediction.
- There are methods to deal with imbalance data (we will discuss later).