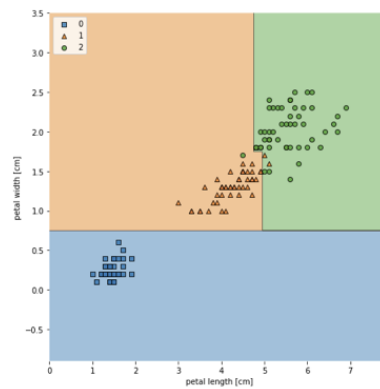


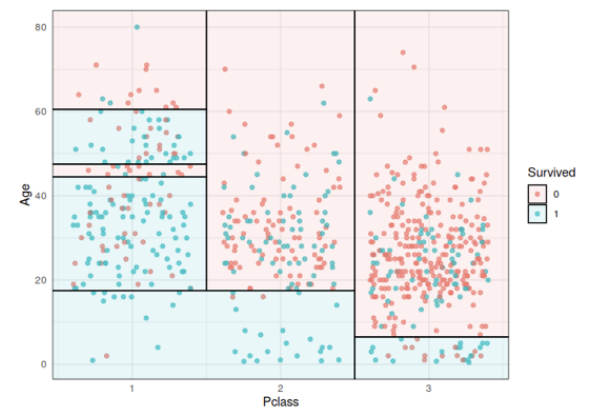
## Supervised Learning III

### 1. Tree Complexity

- a. Trees can get crazy big
  - i. The bigger the tree: the more complex the decision surface
- b. Last time: more complex functions = more likely to memorize
- c. How can we build in a way to keep things “simple”
  - i. Only make a bigger tree if absolutely necessary
- d. Tree pruning!



i.



### 2. Decision Tree Pruning

- a. Two flavors of pruning:
  - i. Pre-pruning:
    1. Prune while the decision tree is being constructed
    2. Stop growing the tree when some criteria is met
  - ii. Post-pruning
    1. Make a decision tree
    2. Prune subtrees afterwards
    3. Two flavors of this:
      - a. Top-down pruning
      - b. Bottom-up pruning

### 3. Top-Down Post Pruning

- a. Pessimistic Error Pruning:
  - i. When at node 'n' that has children c1, c2, ..., ck
  - ii. Delete a child one at a time
    1. Measure the % error
      - a. If the % error increases: leave this child alone
      - b. If the % error decreases: prune this child
  - iii. Repeat for all surviving child nodes

#### 4. Bottom-Up Post Pruning

- a. Reduced Error Pruning
- b. Minimum Error Pruning
- c. Minimum Cost Complexity Pruning
  - i. Also build sequence of trees (from initial tree)
  - ii. Each tree (in sequence) created by removing a subtree (from prev. tree in sequence)
    - 1. How to pick subtree to remove?
    - 2. Pick subtree 'n' that minimizes:

$$\frac{e(\text{prune}(T, n), \cdot) - e(T, \cdot)}{|n \in \text{leaves}(T)| - |\text{leaves}(\text{prune}(T, n))|}$$

iii.

#### 5. Minimum Description Length (MDL)

- a. Often used to measure complexity of a function:

$$MDL(h) = \# \text{ bits}(h) + \# \text{ bits}(\underline{D} \mid h)$$

- b. For decision trees:

$$MDL(T) = \text{size}(T) + \# \text{ misclassifications}(T)$$

- c. Can use MDL as a criteria!
  - i. Tradeoff between tree size and training errors!
  - ii. Prefers smaller trees (when # misclassifications is constant)