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# On Decision Trees

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# The Decision Tree Hypothesis

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## Decision Tree Hypotheses

Propose a function representing the mapping for *(input, output)* pairs in the training data.

- **Classification:** (attributes, class), e.g. 'restaurant'
- **Regression:** (attributes, value), e.g. \$ prediction

## Geometry of Decision Boundaries

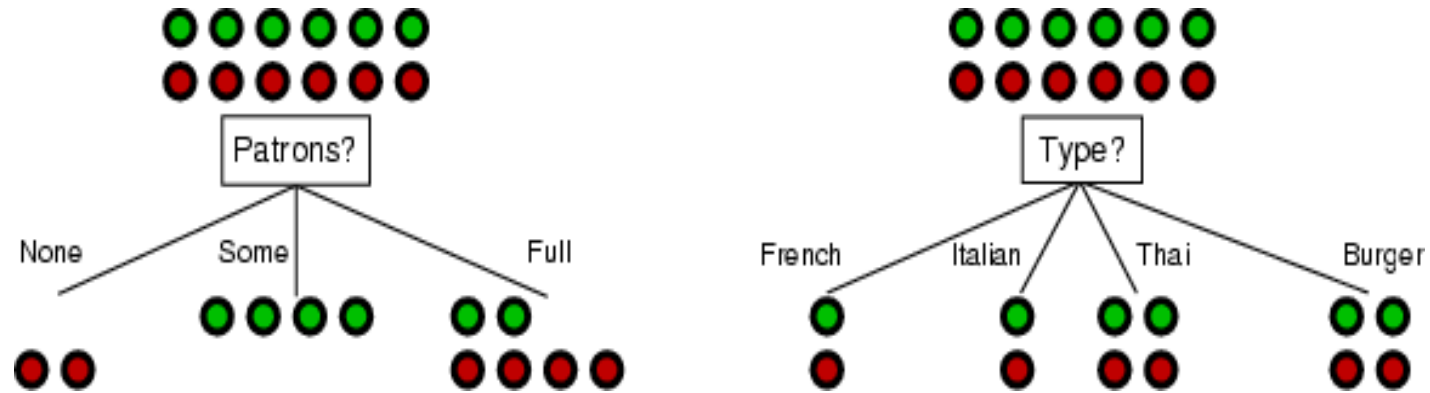
Our decision trees *split* individual attribute domains, producing axis-aligned rectangular decision regions

Some attributes are *correlated* (i.e. vary together), leading to non-rectangular regions (e.g. for classes)

However, even with an arbitrary linear separator, we cannot always represent the target function  $f$ .

# Attribute Selection for Decision Tree Learning

- A Good Attribute
  - Splits examples into (*ideally*) "all positive" or "all negative" subsets



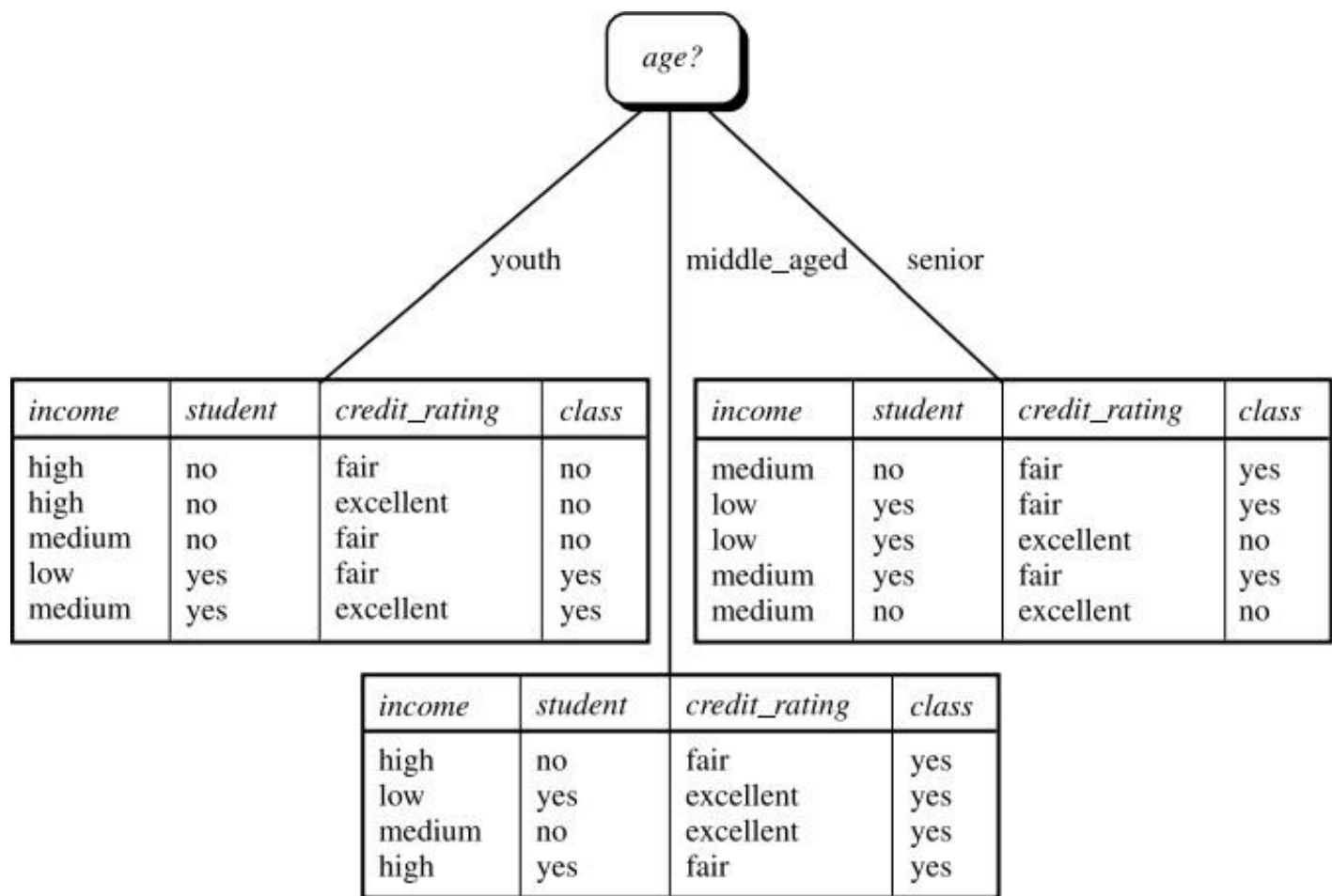
- For Example Above (Selecting Tree Root Node)
  - *Patrons?* is a better choice than *Type?* as attribute to select



*It's white board time! Crafting **top-down induction** for decision trees!*

Class-Labeled Training Tuples from the *AllElectronics* Customer Database

| <i>RID</i> | <i>age</i>  | <i>income</i> | <i>student</i> | <i>credit_rating</i> | <i>Class: buys_computer</i> |
|------------|-------------|---------------|----------------|----------------------|-----------------------------|
| 1          | youth       | high          | no             | fair                 | no                          |
| 2          | youth       | high          | no             | excellent            | no                          |
| 3          | middle_aged | high          | no             | fair                 | yes                         |
| 4          | senior      | medium        | no             | fair                 | yes                         |
| 5          | senior      | low           | yes            | fair                 | yes                         |
| 6          | senior      | low           | yes            | excellent            | no                          |
| 7          | middle_aged | low           | yes            | excellent            | yes                         |
| 8          | youth       | medium        | no             | fair                 | no                          |
| 9          | youth       | low           | yes            | fair                 | yes                         |
| 10         | senior      | medium        | yes            | fair                 | yes                         |
| 11         | youth       | medium        | yes            | excellent            | yes                         |
| 12         | middle_aged | medium        | no             | excellent            | yes                         |
| 13         | middle_aged | high          | yes            | fair                 | yes                         |
| 14         | senior      | medium        | no             | excellent            | no                          |



# The Top-Down Induction Algorithm

**Algorithm: Generate\_decision\_tree.** Generate a decision tree from the training tuples of data partition,  $D$ .

**Input:**

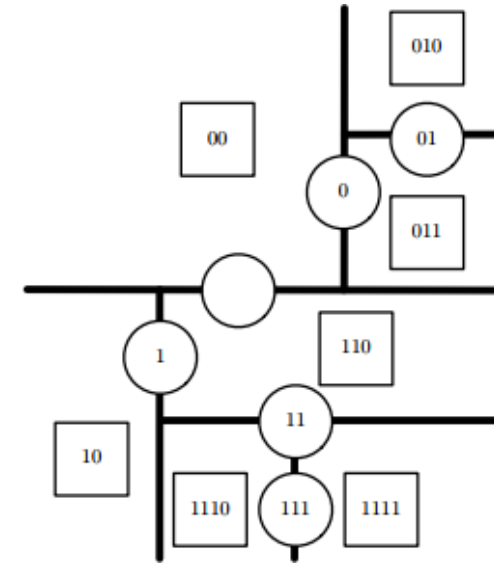
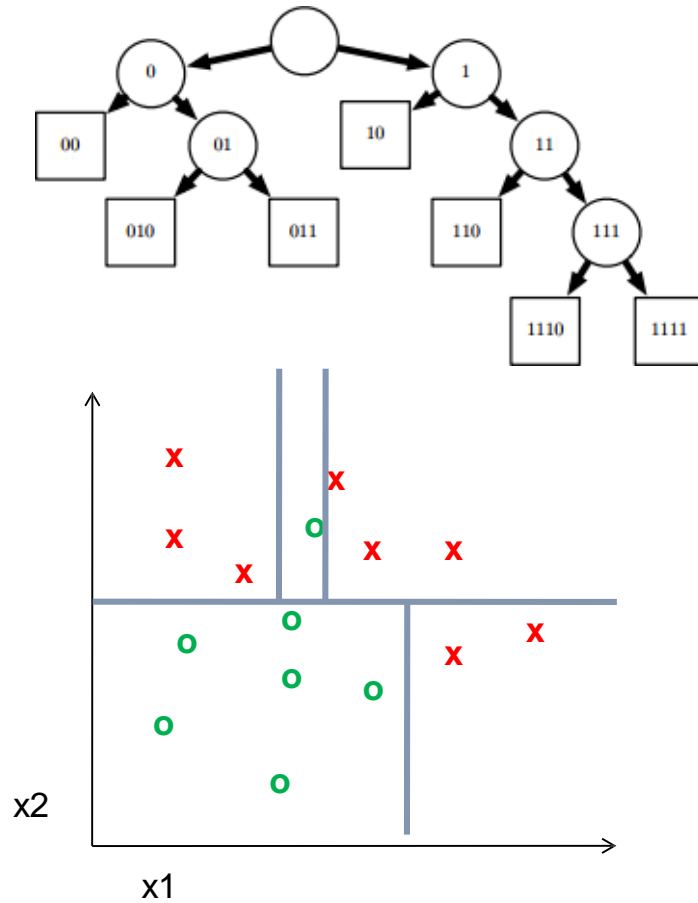
- Data partition,  $D$ , which is a set of training tuples and their associated class labels;
- *attribute\_list*, the set of candidate attributes;
- *Attribute\_selection\_method*, a procedure to determine the splitting criterion that “best” partitions the data tuples into individual classes. This criterion consists of a *splitting\_attribute* and, possibly, either a *split-point* or *splitting\_subset*.

**Output:** A decision tree.

**Method:**

- (1) create a node  $N$ ;
  - (2) **if** tuples in  $D$  are all of the same class,  $C$ , **then**
  - (3)     return  $N$  as a leaf node labeled with the class  $C$ ;
  - (4) **if** *attribute\_list* is empty **then**
  - (5)     return  $N$  as a leaf node labeled with the majority class in  $D$ ; // majority voting
  - (6) apply **Attribute\_selection\_method**( $D$ , *attribute\_list*) to **find** the “best” *splitting\_criterion*;
  - (7) label node  $N$  with *splitting\_criterion*;
  - (8) **if** *splitting\_attribute* is discrete-valued **and**  
      multiway splits allowed **then** // not restricted to binary trees
  - (9)     *attribute\_list*  $\leftarrow$  *attribute\_list* – *splitting\_attribute*; // remove *splitting\_attribute*
  - (10) **for each** outcome  $j$  of *splitting\_criterion*  
      // partition the tuples and grow subtrees for each partition
  - (11)     let  $D_j$  be the set of data tuples in  $D$  satisfying outcome  $j$ ; // a partition
  - (12)     **if**  $D_j$  is empty **then**
  - (13)         attach a leaf labeled with the majority class in  $D$  to node  $N$ ;
  - (14)     **else** attach the node returned by **Generate\_decision\_tree**( $D_j$ , *attribute\_list*) to node  $N$ ;
  - endfor**
  - (15) return  $N$ ;
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# Decision Trees – Aggregated Piecewise Functions



Divides (input) space into regions (nodes on lines categorize samples, leaf nodes on regions correspond to examples received). Piecewise-constant function (cannot learn function with more local maxima than number of training samples).



QUESTIONS?

