Decision Trees

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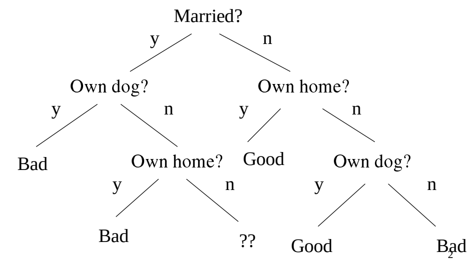
Example Decision Tree



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Applications

- Credit-card companies and banks develop DT's to decide whether to grant a card or loan.
- Medical apps, e.g., given information about patients, decide which will benefit from a new drug.
- Many others.

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Issues

- How do you use a decision tree?
  - I.e., given a record, how do you decide whether it is good or bad?
- How do you design decision trees?
  - Ad-hoc: decide yourself.
  - Training: algorithm to construct "best" DT from given data.
    - Hope future records match the training set.

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Designing a Decision Tree

- Typically, we are given data consisting of a number of records, perhaps representing individuals.
- Each record has a value for each of several attributes.
  - Often binary attributes, e.g., "has dog."
  - Sometimes numeric, e.g. "age", or discrete, multiway, like "school attended."

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Designing a Decision Tree 2

- Records are classified into "good" or "bad."
  - More generally: some number of outcomes.
- The goal is to make a small number of tests involving attributes to decide as best we can whether a record is good or bad.

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Using a Decision Tree

- Given a record to classify, start at the root, and answer the question at the root for that record.
  - E.g., is the record for a married person?
- Move next to the indicated child.
- Recursively, apply the DT rooted at that child, until we reach a decision.

Training Sets

- Decision-tree construction is today considered a type of "machine learning."
- We are given a *training set* of example records, properly classified, with which to construct our decision tree.

Example

- Here is the data on which our example DT was based:

Married?	Home?	Dog?	Rating
0	1	0	G
0	0	1	G
0	1	1	G
1	0	0	G
1	0	0	B
0	0	0	B
1	0	1	B
1	1	0	B

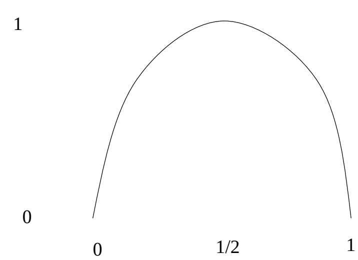
Binary Attributes

- When all attributes are binary, we can pick an attribute to place at the root by considering how nonrandom are the sets of records that go to each side.
- Branches correspond to the value of the chosen attribute.

Entropy: A Measure of Goodness

- Consider the pools of records on the "yes" and "no" sides.
- If fraction p on on a side are "good," the entropy of that side is
  $-(p \log_2 p + (1-p) \log_2(1-p))$.
  $= p \log_2(1/p) + (1-p) \log_2(1/(1-p))$
- Pick attribute that minimizes maximum entropies of the sides.

Shape of Entropy Function



Intuition

- ◆Entropy 1 = random behavior, no useful information.
- ◆Low entropy = significant information.
  - At entropy = 0, we know exactly.
- ◆Ideally, we find an attribute such that most of the "good's" are on one side, and most of the "bad's" are on the other.

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Example

- ◆Our Married, Home, Dog, Rating data:
  - 010G, 001G, 011G, 100G, 100B, 000B, 101B, 110B.
- ◆Married: 1/4 of Y is G; 1/4 of N is B.
  - Entropy = $((1/4)\log_2 4 + (3/4)\log_2(4/3))$ = .81 on both sides.

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Example, Continued

- ◆010G, 001G, 011G, 100G, 100B, 000B, 101B, 110B.
- ◆Home: 1/3 of Y is B; 2/5 of N is G.
  - Entropy is $(1/3)\log_2 3 + (2/3)\log_2(3/2) = .92$ on Y side.
  - Entropy is $(2/5)\log_2(5/2) + (3/5)\log_2(5/3) = .98$ on N side.
  - Max = .98, greater than for Married.
- ◆Dog is similar, so Married "wins."

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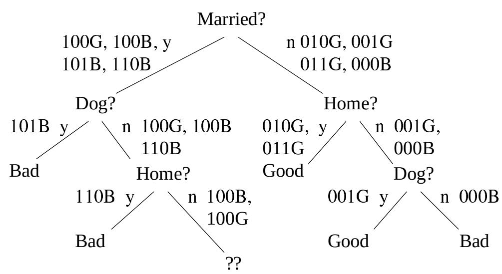
The "Training" Process



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Handling Numeric Data

- ◆While complicated tests at a node are permissible, e.g., "age = 30 or age $\leq$ 50 and age $\geq$ 42," the simplest thing is to pick one breakpoint, and divide records by value $\leq$ breakpoint and value > breakpoint.
- ◆Rate an attribute and breakpoint by min-max entropy of the two sides.

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Overfitting

- ◆A major problem in designing decision trees is that one tends to create too many levels.
  - The number of records reaching a node is small, so significance is lost.
  - Extreme example: our data was generated by coin-flips; the tree is unlikely to reflect additional data that it would be used to classify.

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Possible Solutions

1. Limit depth of tree so that each decision is based on a sufficiently large pool of training data.
2. Create several trees independently (needs randomness in choice of attribute).
   - Decision based on vote of D.T.'s.
   - Filters out irrelevant factors.

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