Foundations of Artificial Intelligence

CS472/3 — Fall 1999
Lecture #24 & 25

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Admin

- CS672 — **Advanced Artificial Intelligence**
  - focus around case-studies of successful AI systems
  - we'll dig deeper into some of the core questions
    - e.g. "what is learnable"
  - include some more "far-out" topics, e.g., artificial life.
  - taylored towards special interests of participants
  - (field has become too broad to cover everything)

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```
function DECISION-TREE-LEARNING(examples, attributes, default) returns a decision tree
  inputs: examples, set of examples
          attributes, set of attributes
          default, default value for the goal predicate

  if examples is empty then return default
  else if all examples have the same classification then return the classification
  else if attributes is empty then return MAJORITY-VALUE(examples)
  else
      best ← CHOOSE-ATTRIBUTE(attributes, examples)
      tree ← a new decision tree with root test best
      for each value v_i of best do
          examples_i ← {elements of examples with best = v_i}
          subtree ← DECISION-TREE-LEARNING(examples_i, attributes − best,
                                           MAJORITY-VALUE(examples))
          add a branch to tree with label v_i and subtree subtree
      end
      return tree
```

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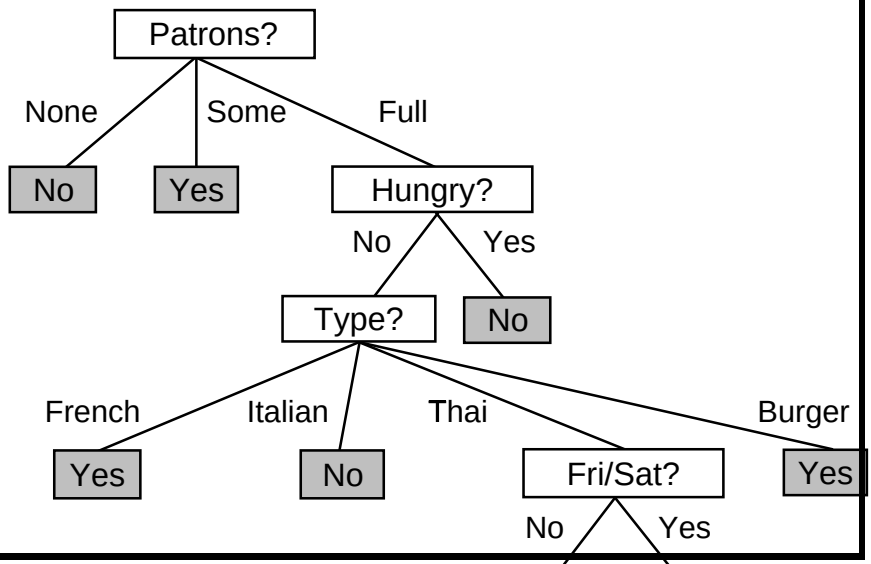

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Why does learned tree differ from original tree?

Which tree is better?

What if you run out of examples?

Aside: Can trivially find a decision tree for any set of examples?

So, what makes decision tree learning hard?

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Evaluating Performance

1. Collect large set of examples
2. Divide into disjoint sets: **training set** and the **test set**.
3. Learning alg. on **training** set generates hypothesis $h \in H$.
4. Measure percentage **test** set correctly classified by h.
5. Repeat 1 to 4 for different training and test sets / different examples.

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- a form of **cross-validation**
- measures **generalization** to unseen data
- generally considers error on the training set and error on the test set.
- **overfitting** means fits training set "too well"
  starts to degrade performance on test set.
  uses e.g. **irrelevant attributes**.

Learning Curve

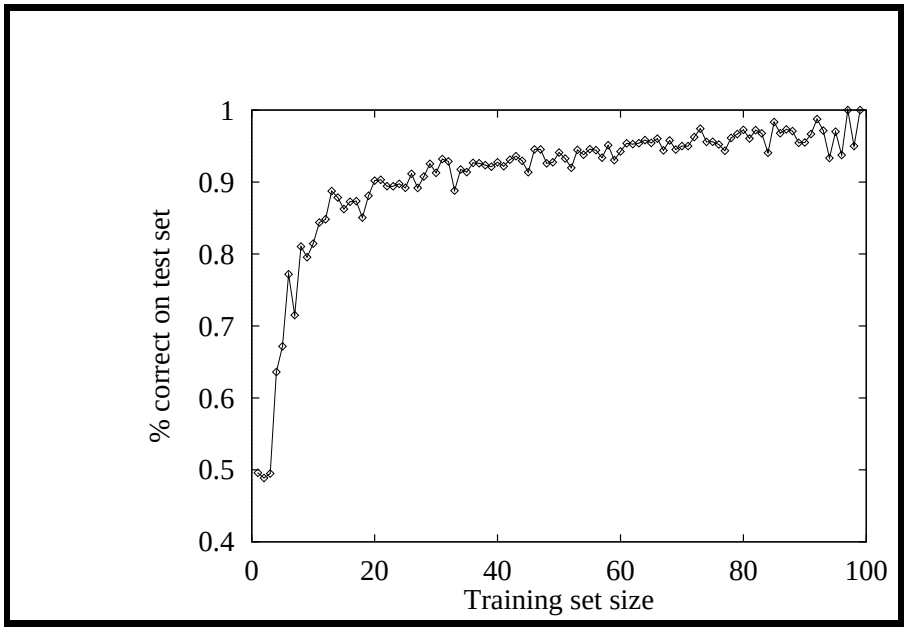

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figure for overfitting

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NOTE: often a clear optimal point:

large a enough to capture regularities but

not too large for overfitting.

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Overfitting

Consider error in hypothesis h over:

- training data: $error_{train}(h)$
- entire distr. D of data: $error_D(h)$

Hypothesis $h \in H$ **overfits** training data if

there is an alternative hypothesis $h' \in H$ such that

$$error_{train}(h) < error_{train}(h')$$

but

$$error_D(h) > error_D(h')$$

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Dealing with overfitting:

decision tree pruning — prevent splitting on attributes that are not clearly relevant.

Can test relevance with statistical techiques or using cross-validation ("watch generalization error")

(See p. 542 / 543, R&N.)

Grow full tree, then post-prune.

Rule post-pruning – later.

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How to pick best tree?

- Measure performance over training data.
- Measure performance over separate validation data set.
- MDL (minimal description length): minimize

$$size(tree) + size(misclassifications(tree))$$

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Extensions Decision Tree Learning

- Missing data (unknown values for attributes)
- Multivalued attributes (e.g. $RestaurantName$, high info gain but bad generalization).
- Continuous-values attributes.

Converting Trees to Rules

Examples:

IF $(Patrons = Full) \wedge (WaitEstimate = 0 - 10)$
THEN $(WillWait = Yes)$

IF $(Patrons = Full) \wedge (WaitEstimate > 60)$
THEN $(WillWait = No)$

Fight Overfitting Using Rule Post-Pruning

1. Grow decision tree. Fit as much data as possible. Allow overfitting.
2. Convert tree to equivalent set of rules. One rule for each path from root to leaf.
3. Prune (generalize) each rule independently of others. i.e. delete preconditions that improve its accuracy.
4. Sort final rules into desired sequence for use depending on accuracy.
5. Use ordered sequence for classification.

This is the strategy of the most successful commercial decision tree learning method (C4.5 — Quinlan 1993). Widely used in data mining.

What is advantage of rule representation over the decision tree?

Decision trees are a restricted from of general logical statements.

We can also describe our target function directly in first-order sentences.

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Example:

$$\forall WillWait(r) \Leftrightarrow Patrons(r, Some)$$
$$\vee(Patrons(r, Full) \wedge \neg Hungry(r) \wedge Type(r, French))$$
$$\vee(Patrons(r, Full) \wedge \neg Hungry(r) \wedge Type(r, Thai) \wedge Fri/Sat(r))$$
$$\vee(Patrons(r, Full) \wedge \neg Hungry(r) \wedge Type(r, Burger))$$

This is our **hyposthesis** H_r. In general, we search from among a space of hypotheses:

$$H_1 \vee H_2 \vee H_3 \vee \ldots \vee H_n.$$

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Here's an **example** in logical form:

$Alternate(X1) \wedge \neg Bar(X_1) \wedge \neg Fri/Sat(X_1) \wedge$
$Hungry(X_1) \wedge \ldots \wedge WillWait(X_1)$

We can test if this example is **consistent** with our hyposthesis. If not, we may have to **generalize** or **specialize** our hypothesis:

Current-best-hypothesis search.

See example: p. 548 R&N.