Learning from Observations

Chapter 18, Sections 1–3

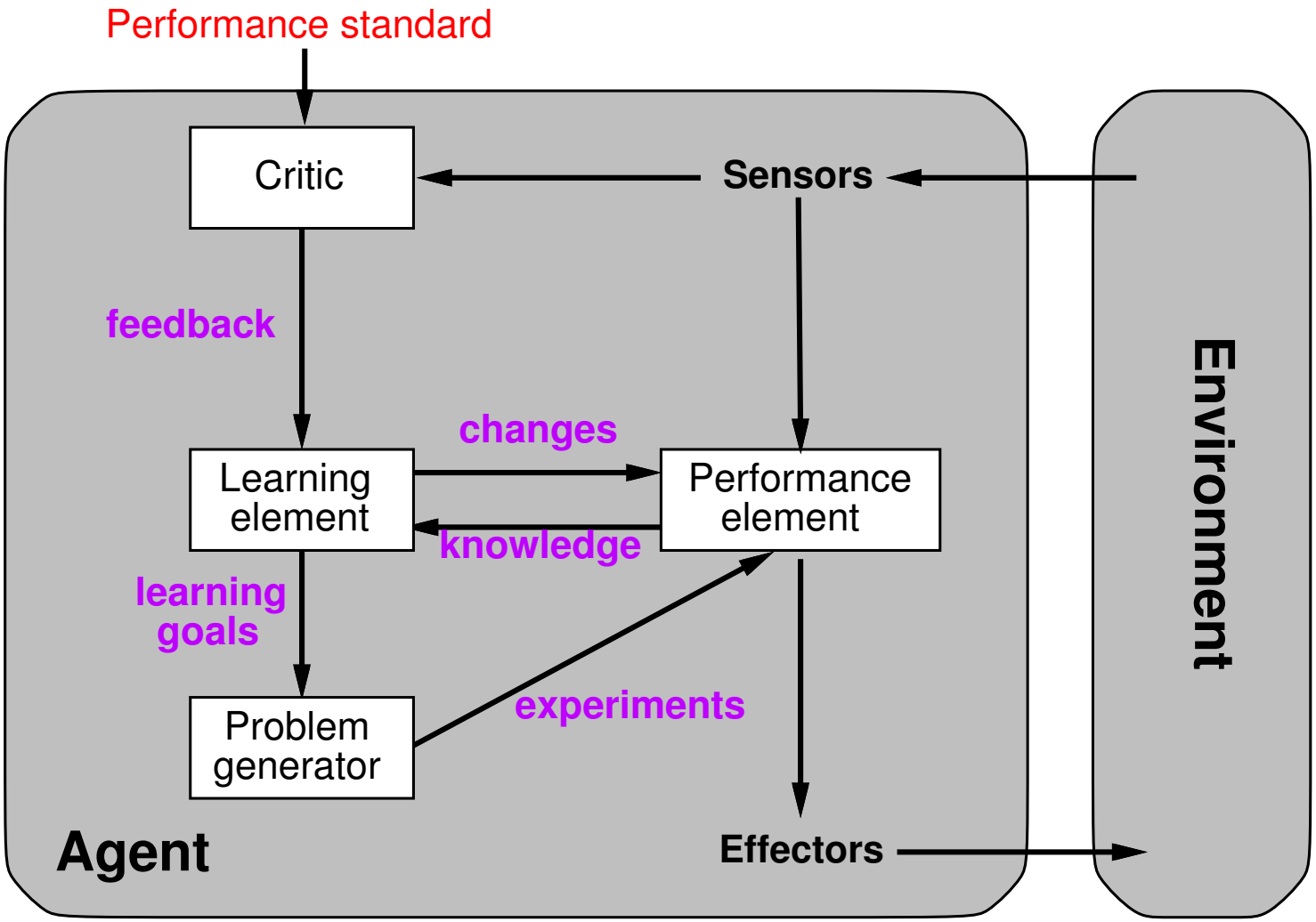
Outline

- Learning agents
- Inductive learning
- Decision tree learning
- Measuring learning performance

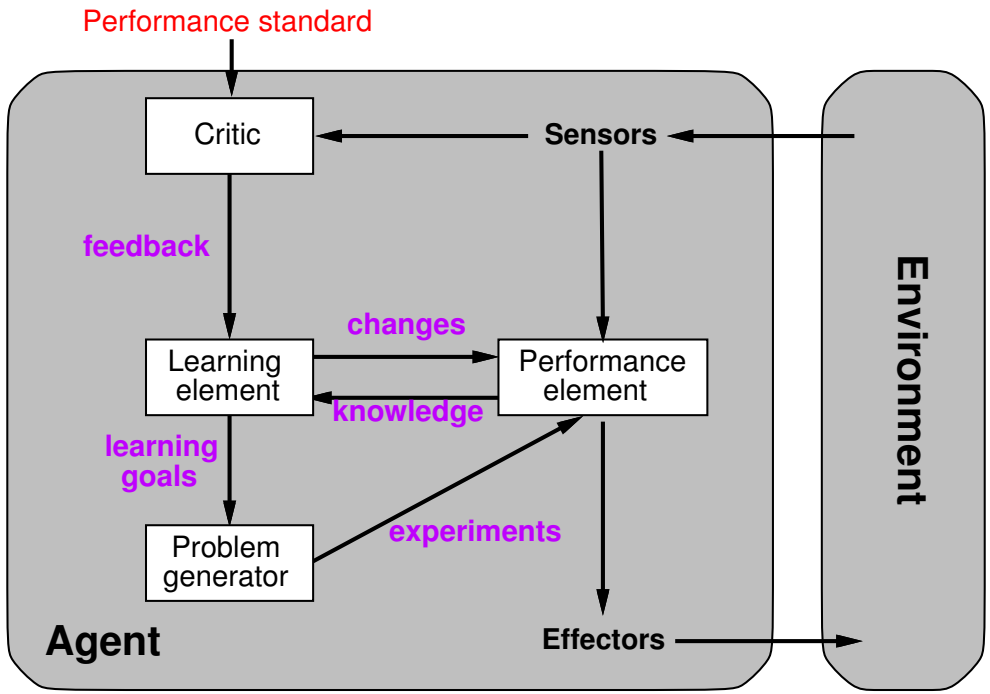
Learning

- Learning modifies the agent's decision mechanisms to improve performance
- Learning is essential for unknown or uncertain environments,
  - I.e., when designer lacks omniscience
- Learning is useful as a *system-construction* method
  - I.e., expose the agent to reality rather than trying to write it down
  - E.g. neural nets, where learning is essential

Learning agents: General architecture



Learning agents



- Performance element is what we have called the "agent"
- Critic/LearningElement/ProblemGenerator do the "improving"
- Performance standard is fixed
- Learning may require experimentation - actions an agent might not normally consider.

Learning element

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  - what type of performance element is used
  - which functional component is to be learned
  - how that functional component is represented
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α/β search	Eval. function	Weighted linear function	Win/Loss

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Reflex agent	Percept-action function	Neural net	Correct action

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- *Unsupervised learning*:
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- *Supervised learning*:
  - Agent is given examples and their classification
  - Requires a "teacher"
  - Early example: Winston, with examples and "near misses".

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- This is a *highly* simplified model of real learning:
  - ignores prior knowledge
  - assumes a deterministic, observable "environment"
  - assumes examples are *given*

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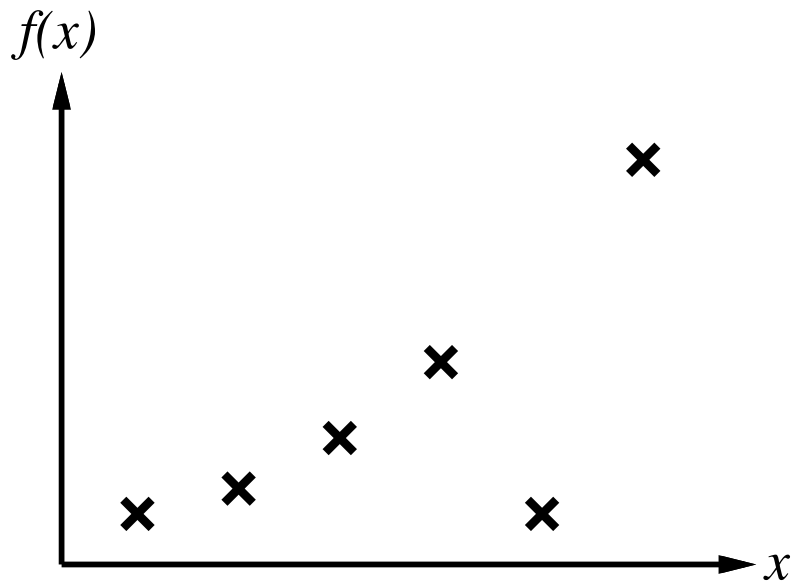

- Q: What's an appropriate function to fit to the known points?

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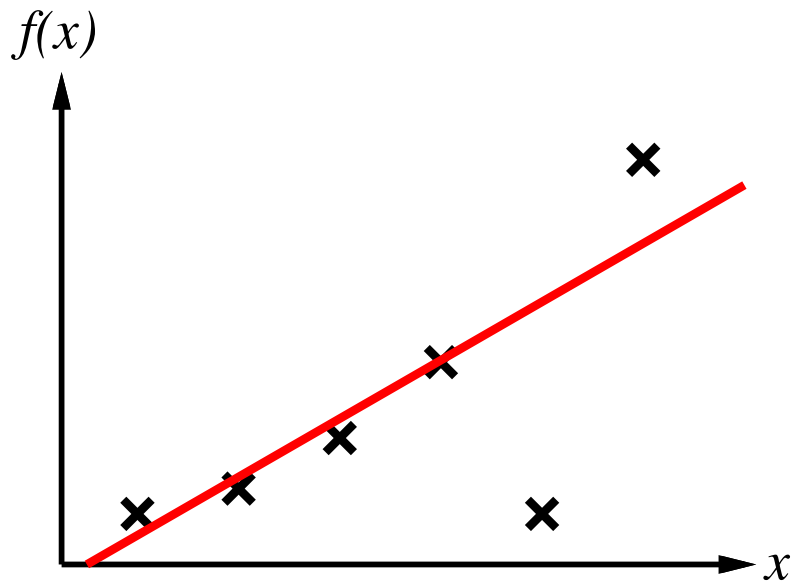

- A straight line is the simplest curve.

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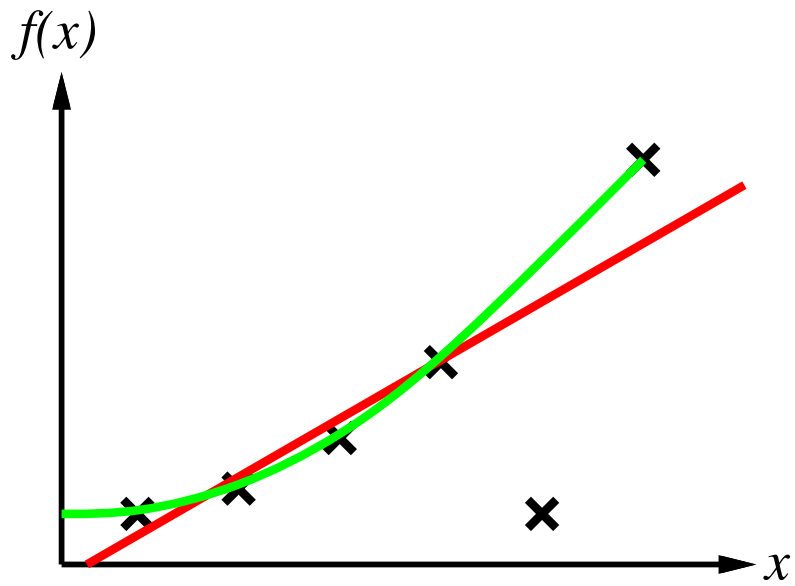

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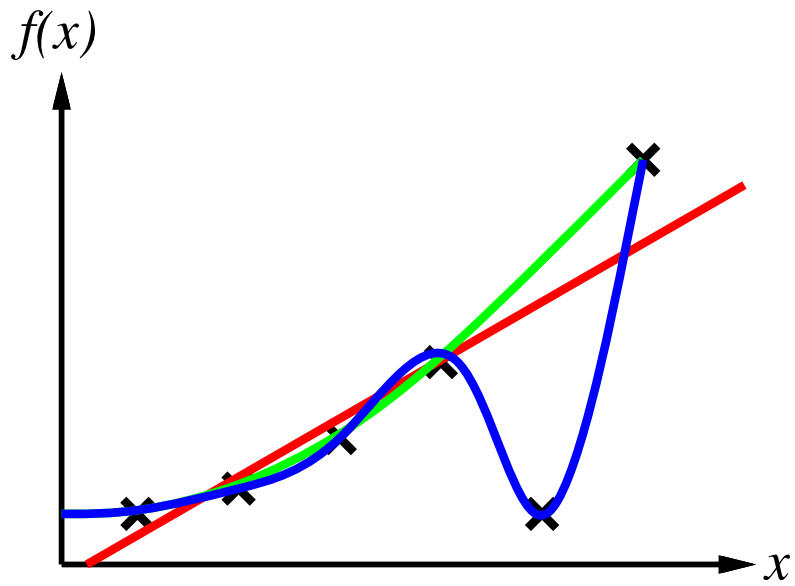

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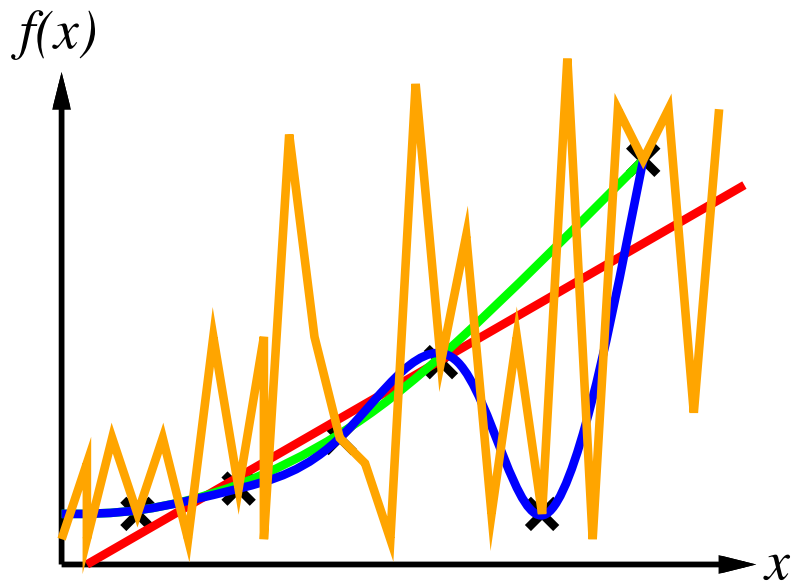

- In fact, any number of functions will fit the data.
- Q: How do we choose between different hypotheses that are consistent with the data?

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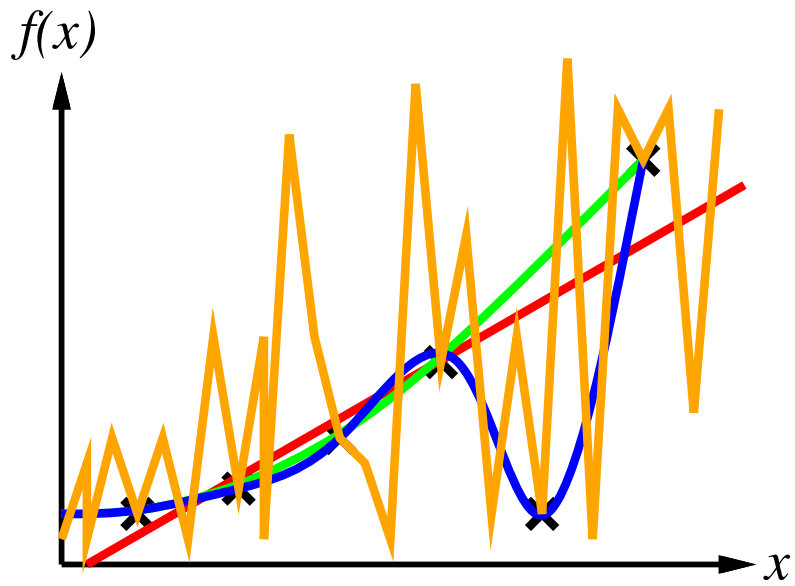

- *Ockham's razor*: Choose the *simplest* hypothesis
  - But defining simplicity isn't easy.

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    I.e. the root is the best *predictor* of the outcome.
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☞ A *decision tree* is a tree where a node is labelled by an attribute and the edges from the node are labelled with the attribute's values.

Decision tree learning

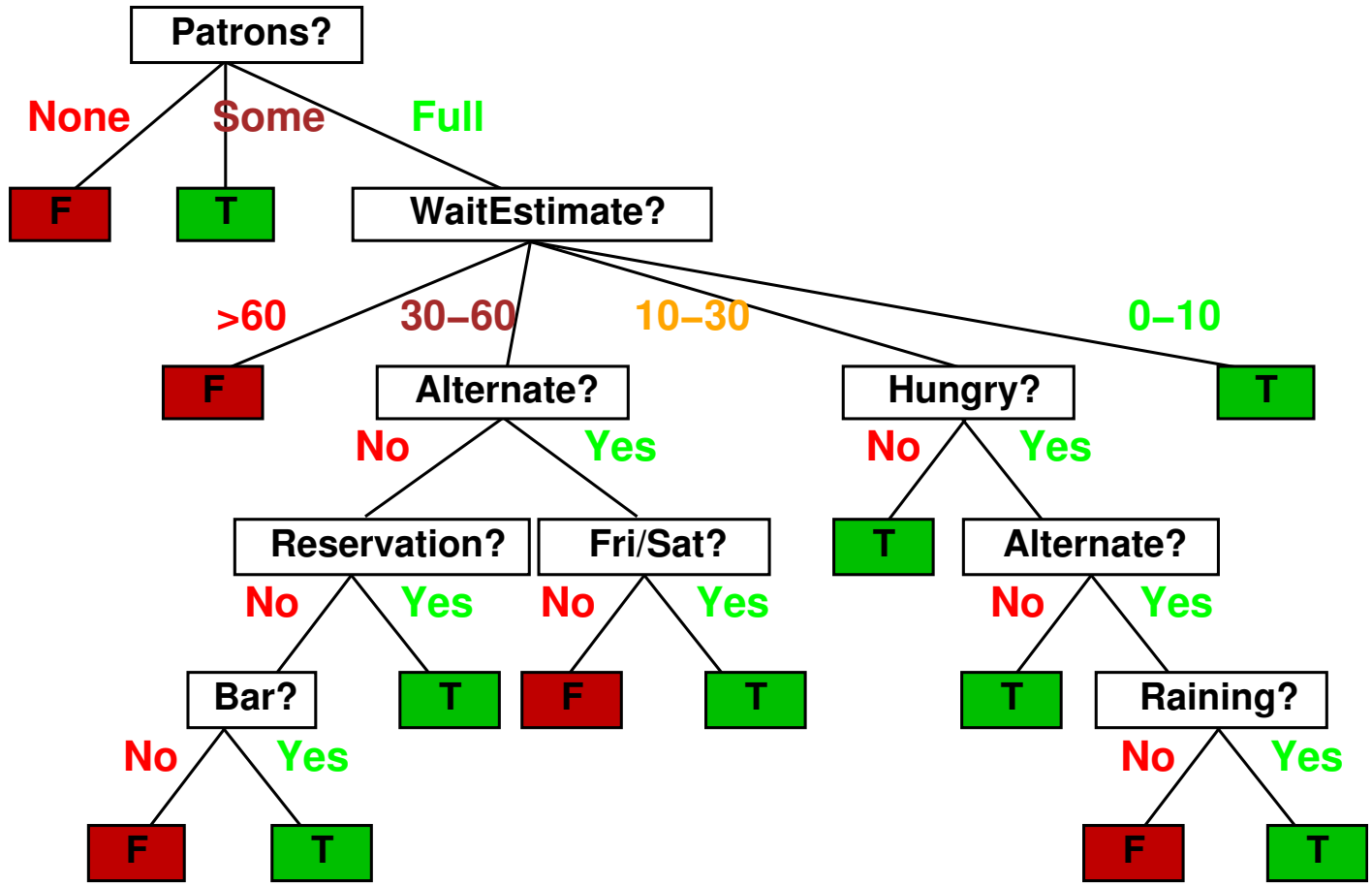
- Examples given by *attribute values* (Boolean, discrete, continuous, etc.)
  - E.g., situations where I will/won't wait for a restaurant table:

Ex.	Attributes										Target:
	Alt	*Bar*	*Fri*	*Hun*	*Pat*	*Price*	*Rain*	*Res*	*Type*	*Est*	*Wait?*
X_1	*T*	*F*	*F*	*T*	*Some*	*$$$*	*F*	*T*	*French*	*0–10*	*T*
X_2	*T*	*F*	*F*	*T*	*Full*	*$*	*F*	*F*	*Thai*	*30–60*	*F*
X_3	*F*	*T*	*F*	*F*	*Some*	*$*	*F*	*F*	*Burger*	*0–10*	*T*
X_4	*T*	*F*	*T*	*T*	*Full*	*$*	*F*	*F*	*Thai*	*10–30*	*T*
X_5	*T*	*F*	*T*	*F*	*Full*	*$$$*	*F*	*T*	*French*	*>60*	*F*
X_6	*F*	*T*	*F*	*T*	*Some*	*$$*	*T*	*T*	*Italian*	*0–10*	*T*
X_7	*F*	*T*	*F*	*F*	*None*	*$*	*T*	*F*	*Burger*	*0–10*	*F*
X_8	*F*	*F*	*F*	*T*	*Some*	*$$*	*T*	*T*	*Thai*	*0–10*	*T*
X_9	*F*	*T*	*T*	*F*	*Full*	*$*	*T*	*F*	*Burger*	*>60*	*F*
X_{10}	*T*	*T*	*T*	*T*	*Full*	*$$$*	*F*	*T*	*Italian*	*10–30*	*F*
X_{11}	*F*	*F*	*F*	*F*	*None*	*$*	*F*	*F*	*Thai*	*0–10*	*F*
X_{12}	*T*	*T*	*T*	*T*	*Full*	*$*	*F*	*F*	*Burger*	*30–60*	*T*

- *Classification* of examples is *positive* (T) or *negative* (F)

Decision trees

- One possible representation for hypotheses
- E.g., the author's "personal" tree for deciding whether to wait:



Decision trees

- A decision tree reaches its decision by making a series of tests on an example, beginning at the root.
- Note that all attributes may not be used in the tree.
- An attribute may occur in > 1 place in the tree.
  - An attribute never appears twice along a branch. (Why not?)
- Different attributes may appear at the same depth on the tree
- Issue: There are lots of trees that will classify the same data. How to choose a "good" tree?

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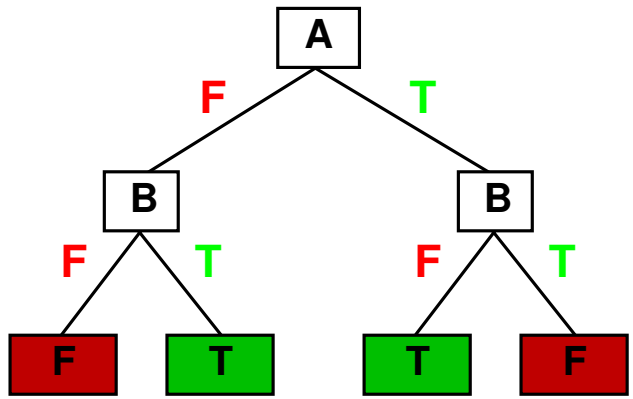

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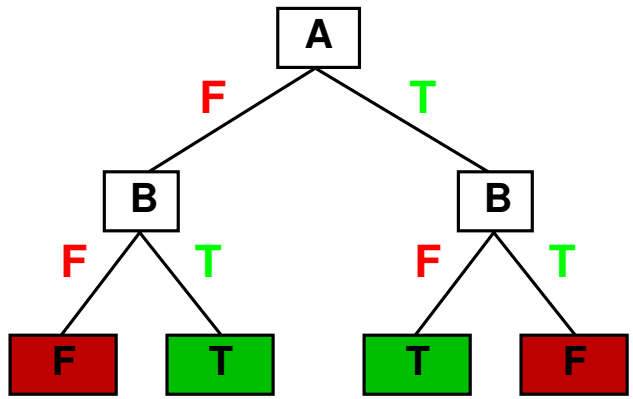

- Trivially, there is a consistent DT for any consistent training set, with one path to a leaf for each example
  ☞ but it probably won't generalize to new examples
- Prefer to find more *compact* decision trees
- Consider this as a search problem, searching the space of decision trees (next) ...

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- A more expressive hypothesis space
  - increases chance that target function can be expressed (good!)
  - increases number of hypotheses consistent with training set
    $\Rightarrow$ makes searching the space harder (bad!)
    $\Rightarrow$ may get worse predictions (bad!)

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- Stop if all examples have the same value (or if you run out of examples).
- Otherwise,
  - choose an attribute to split on, and
  - for each of that attribute's values build a subtree for those examples with that attibute value.

Decision tree learning

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- Idea: (recursively) choose "best" attribute as root of (sub)tree

Function DTL(examples, attributes, default) returns a decision tree
  if examples is empty then return default
  if all examples have the same classification
    then return the classification
  if attributes is empty then return Mode(examples)
  best $\leftarrow$ Choose-Attribute(attributes, examples)
  tree $\leftarrow$a new decision tree with root test best
  for each value v_i of best do
    $examples_i \leftarrow$ {elements of examples with $best = v_i$}
    subtree $\leftarrow$ DTL($examples_i$,attributes $-$ best, Mode(examples))
    add a branch to tree with label v_i and subtree subtree
  return tree

Choosing an attribute

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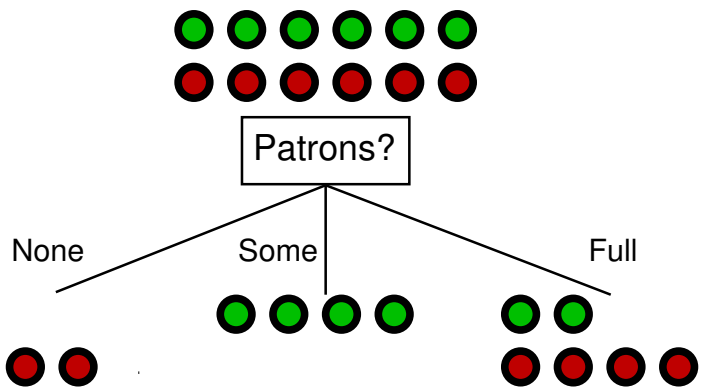
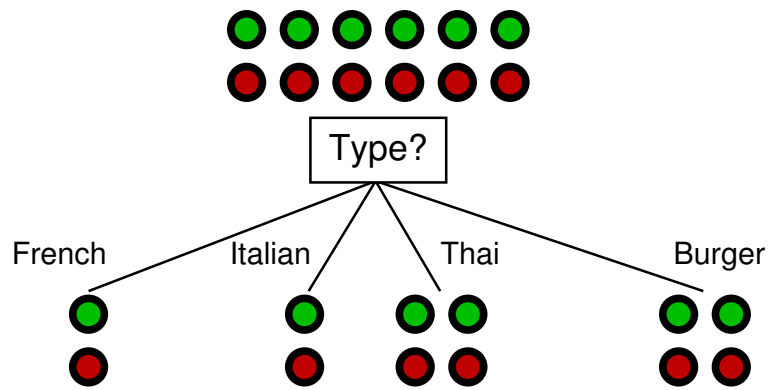
- Below, *Patrons* is a better choice since it gives *information* about the classification





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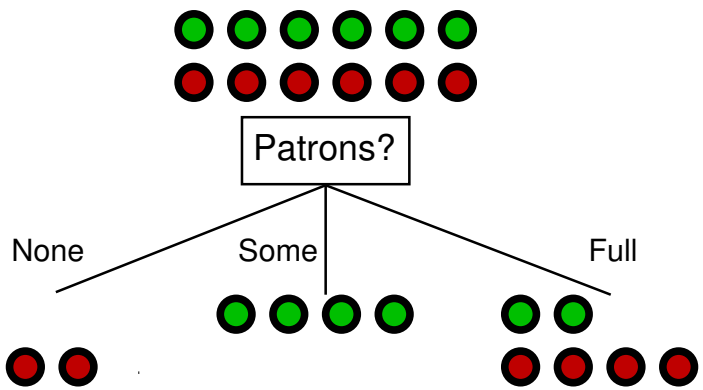

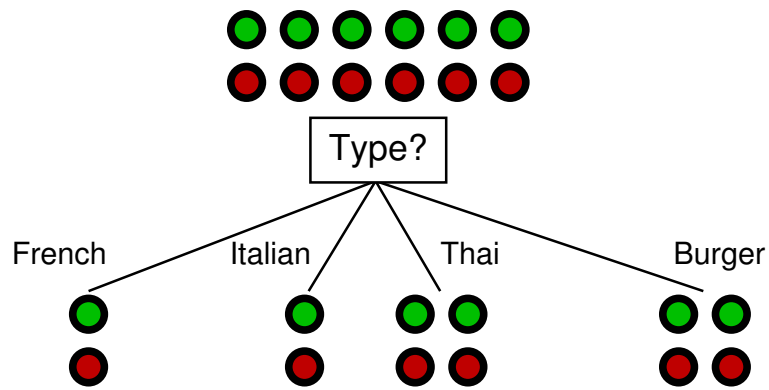

- Problem: How to formalise this?

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- Or (the same thing):

  1 bit lets you distinguish 2 items.

  2 bits lets you distinguish 4 items;

  n bits lets you distinguish 2^n items.

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- The *information* in an answer when the prior is $\langle P_1, \ldots, P_n \rangle$ is

$$I(\langle P_1, \ldots, P_n \rangle) = -\sum_{i=1}^{n} P_i \log_2 P_i$$

  (also called *entropy* of the prior)
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- A RV with prior $\langle 0.5, 0.5 \rangle$ has lower entropy than one with $\langle 0.25, 0.25, 0.25, 0.25 \rangle$.
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  RV with prior $\langle 0.95, 0.05 \rangle$ has entropy about .08.

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- $I(\langle \frac{p}{p+n}, \frac{n}{p+n} \rangle)$ bits needed to classify a new example
- I.e.:

$$I(\langle \frac{p}{p+n}, \frac{n}{p+n} \rangle) = -\frac{p}{p+n} \log_2 \left(\frac{p}{p+n} \right) - \frac{n}{p+n} \log_2 \left(\frac{n}{p+n} \right)$$

- E.g., 12 restaurant examples: $p = n = 6$ so we need 1 bit

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- Choose the attribute with the largest information gain.

Information contd.

- For the training set, $p = n = 6$ and $I(6/12, 6/12) = 1$ bit.

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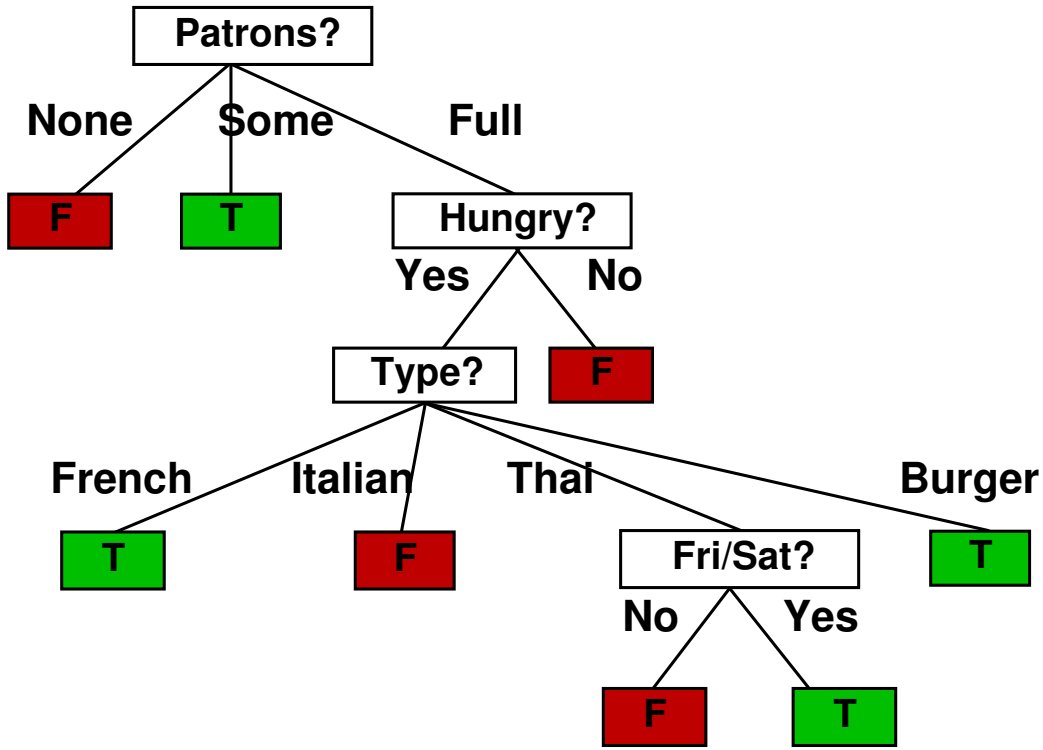
Information contd.

- For the training set, $p = n = 6$ and $I(6/12, 6/12) = 1$ bit.
- $IG(Patrons) = 1 - 0.459 = .541$
  $IG(Type) = 1 - 1 = 0$
- *Patrons* has the highest IG of all attributes and so is chosen by the DTL algorithm as the root.

Example contd.

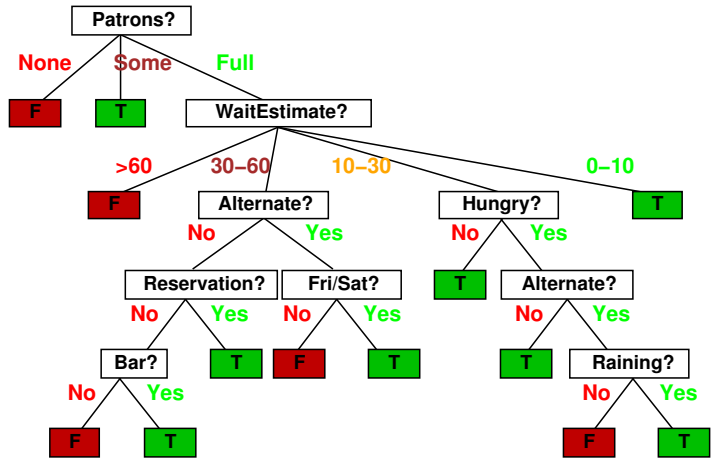
- Decision tree learned from the 12 examples:



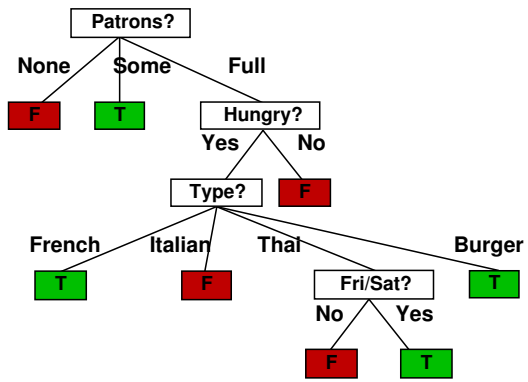
- Much simpler than "true" tree (next slide)

Example contd.

Compare:



vs:



Performance Measurement

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  - Answer: Test it on other examples

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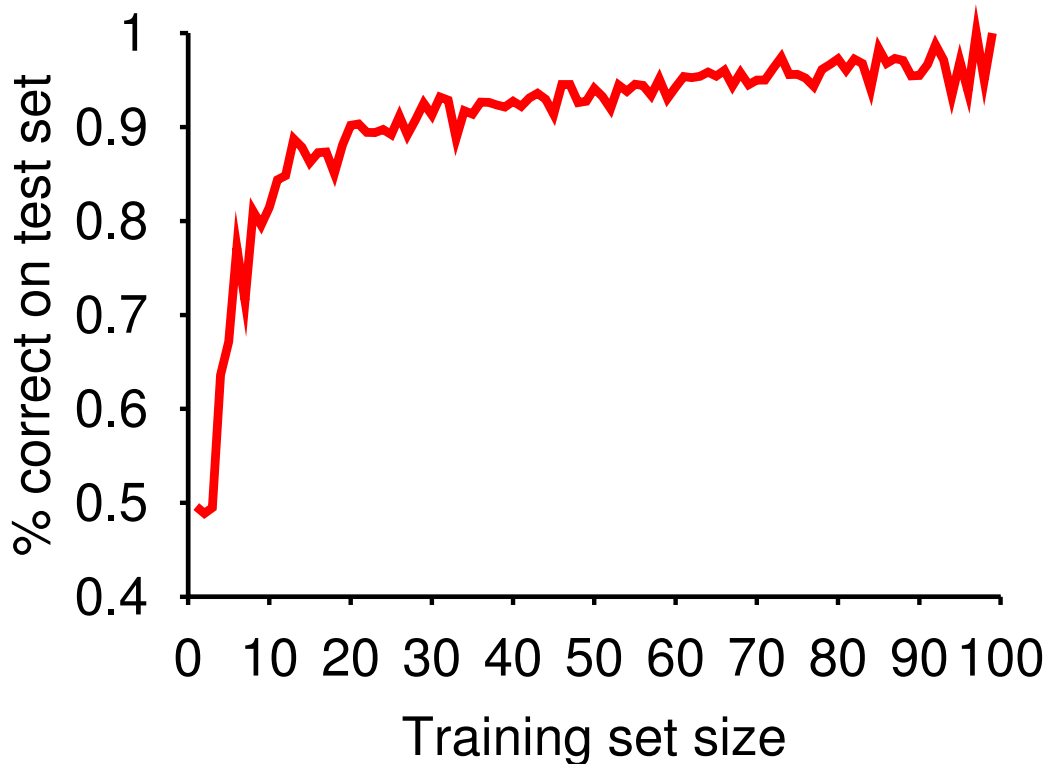
- How do we know if the result of learning is "reasonable"?
  - Answer: Test it on other examples
- Methodology for assessing performance:
  1. Collect a large set of examples.
  2. Divide into two sets: a training set and a test set.
  3. Apply the learning algorithm to the training set.
     - E.g. generate a decision tree
  4. Measure the proportion of examples in the test set that are correctly classified.
  5. Repeat the above steps for different sizes of training sets and different training sets for each size.
- Intuition: Small training sets will tend to be inaccurate; large training sets will be more work.
  - Try to find a good balance.

Performance Measurement

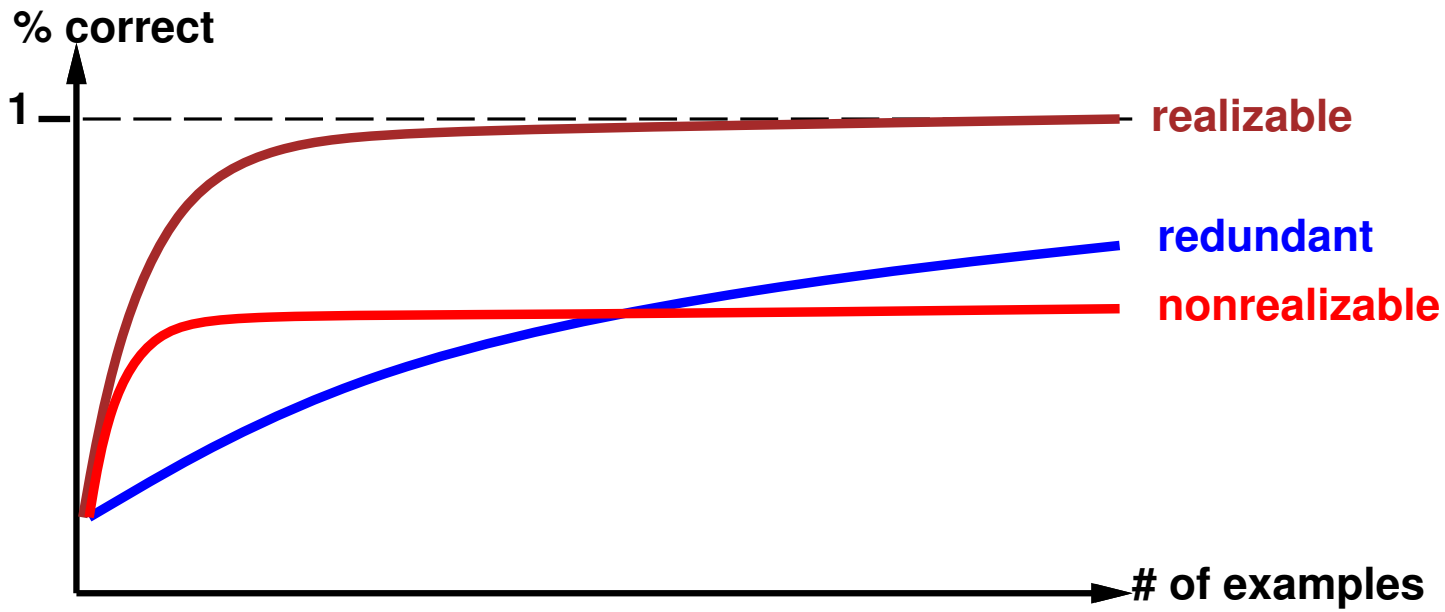
- Plotting the results gives a *learning curve*:



- So big gains when a small training set is increased in size, after which it tapers off.

Performance measurement contd.

- Learning curve depends on
  - *realizable* vs. *non-realizable* learning problem.
    - realizable: can express target function
    - non-realizability can be due to missing attributes or restricted hypothesis class (e.g., thresholded linear function)
  - *redundant* expressiveness (e.g., loads of irrelevant attributes)



Summary

- Learning needed for unknown environments, "lazy" designers
- Learning agent = performance element + learning element
- Learning method depends on type of performance element, available feedback, type of component to be improved, and its representation
- For supervised learning, the aim is to find a simple hypothesis that is approximately consistent with training examples
- Decision tree learning uses information gain
- Learning performance = prediction accuracy on test sets