

CS 4700: Foundations of Artificial Intelligence

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**Machine Learning:
Decision Trees
R&N 18.3**

Big Picture of Learning

Learning can be seen as **fitting a function** to the data. We can consider **different target functions** and therefore different hypothesis spaces.

Examples:

Propositional if-then rules

Decision Trees

First-order if-then rules

First-order logic theory

Linear functions

Polynomials of degree at most k

Neural networks

Java programs

Turing machine

Etc

A learning problem
is **realizable** if its **hypothesis space**
contains the true function.

*Tradeoff between expressiveness of
a hypothesis space and the
complexity of finding simple, consistent hypotheses
within the space.*

Decision Tree Learning

Task:

- Given: collection of examples $(x, f(x))$
- Return: a function h (*hypothesis*) that approximates f
- h is a *decision tree*

Input: an object or situation described by a set of attributes (or features)

Output: a “decision” – the predicts output value for the input.

The *input* attributes and the *outputs* can be *discrete* or *continuous*.

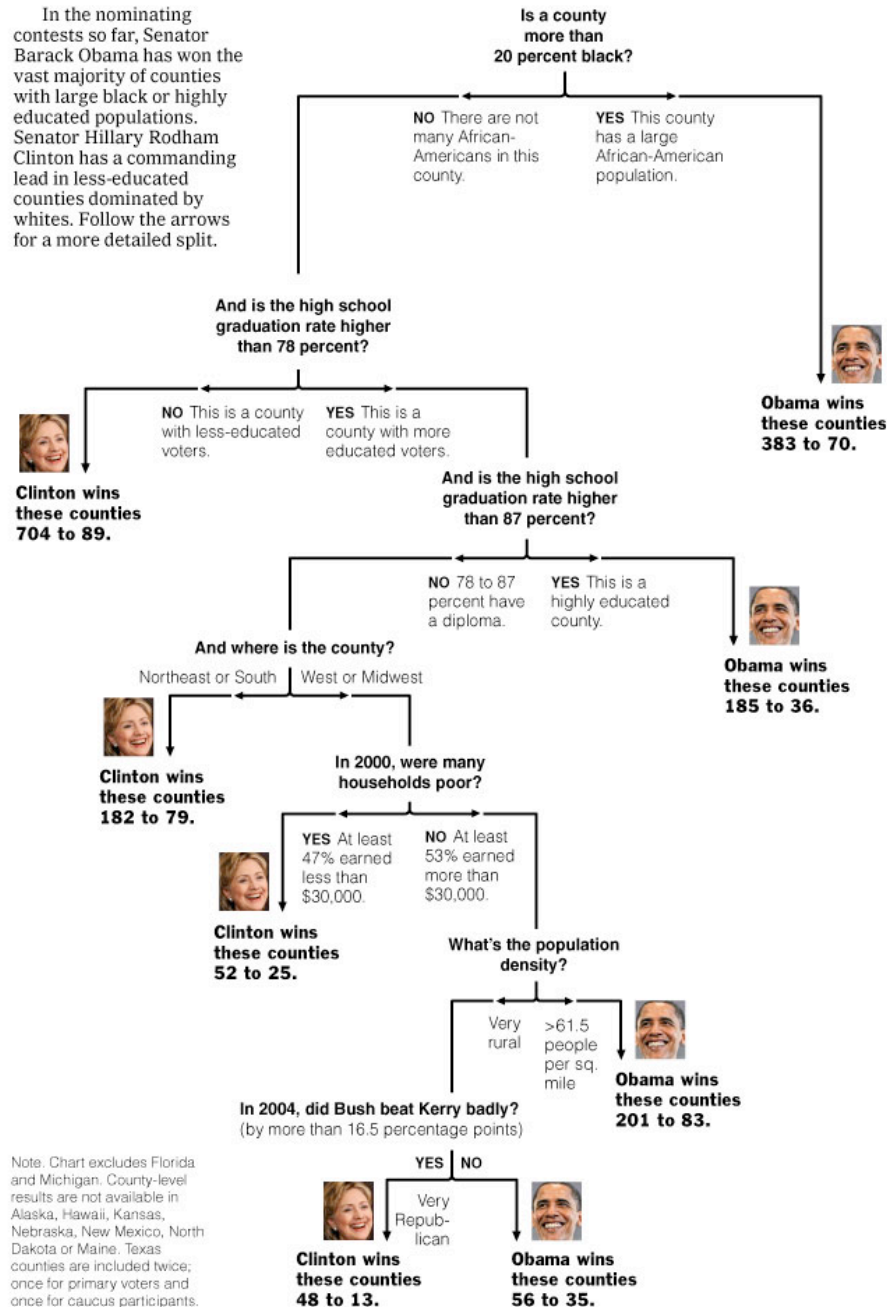
We will focus on decision trees for **Boolean classification**:
each example is classified as *positive* or *negative*.

Decision Tree: The Obama-Clinton Divide

Can we learn
how counties vote?

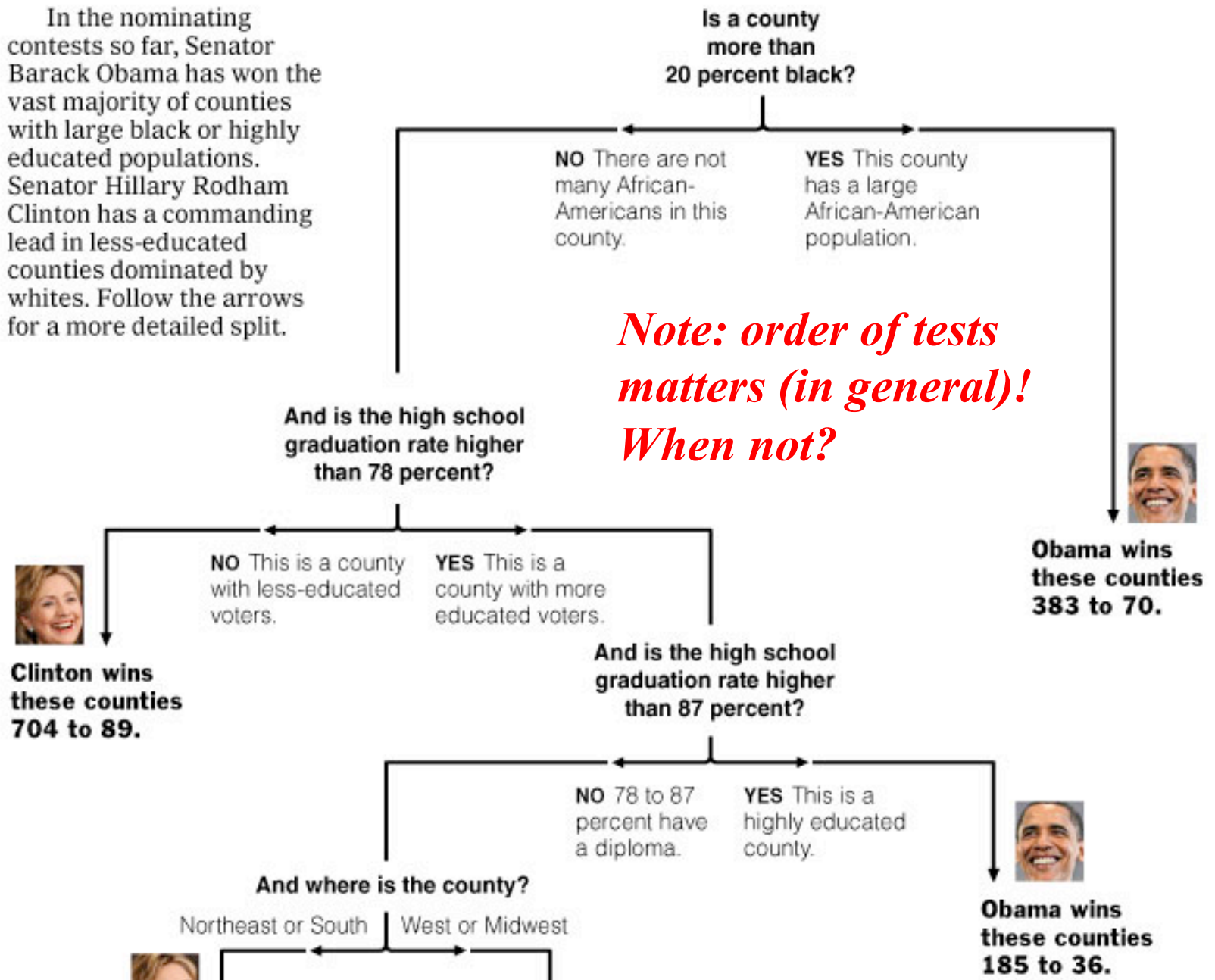
New York Times
April 16, 2008

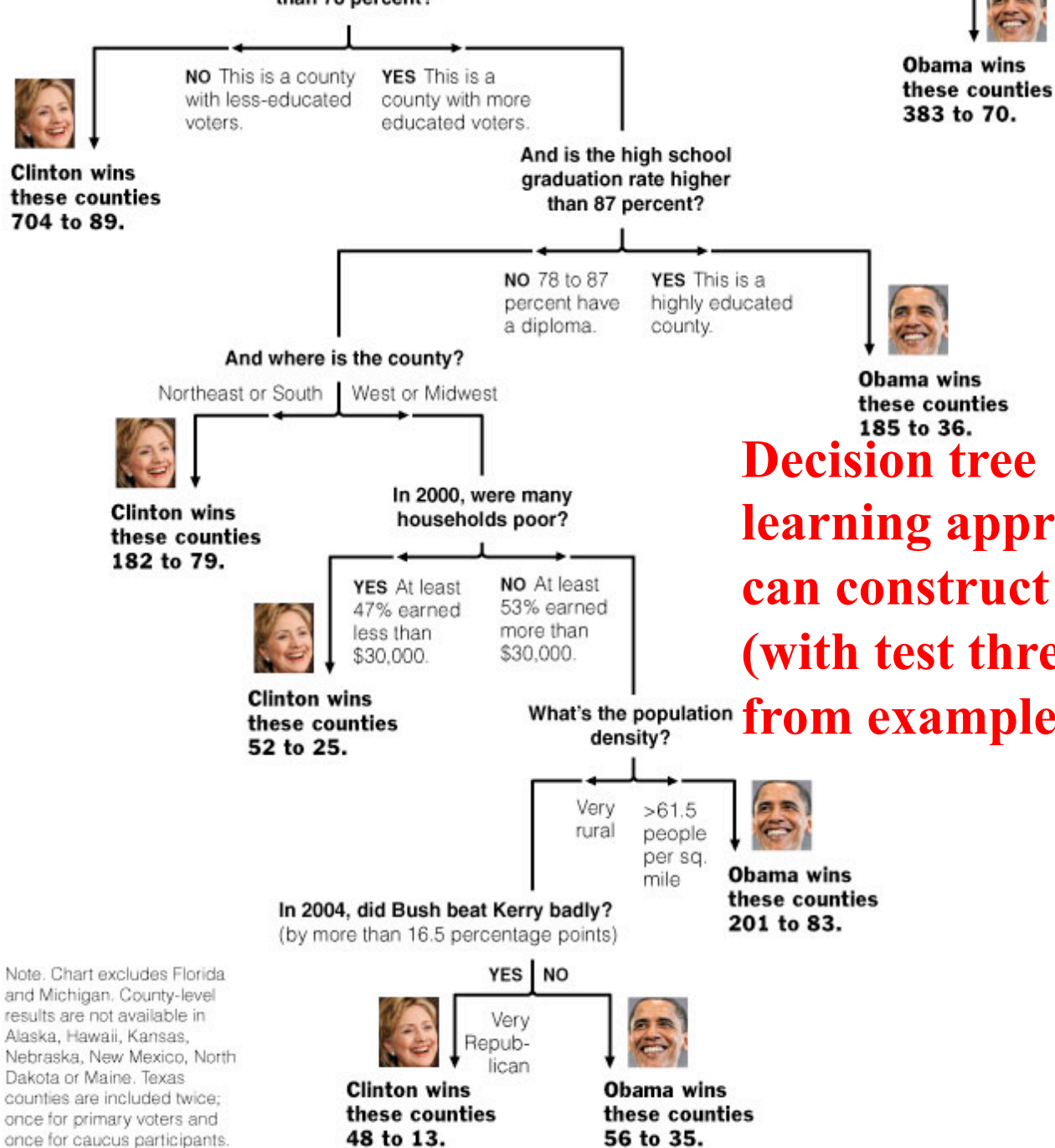
Decision Trees:
a sequence of tests.
Representation very natural for
humans.
Style of many “How to” manuals
and trouble-shooting
procedures.



Decision Tree: The Obama-Clinton Divide

In the nominating contests so far, Senator Barack Obama has won the vast majority of counties with large black or highly educated populations. Senator Hillary Rodham Clinton has a commanding lead in less-educated counties dominated by whites. Follow the arrows for a more detailed split.





**Decision tree
learning approach
can construct tree
(with test thresholds)
from example counties.**

Note: Chart excludes Florida and Michigan. County-level results are not available in Alaska, Hawaii, Kansas, Nebraska, New Mexico, North Dakota or Maine. Texas counties are included twice; once for primary voters and once for caucus participants.

Decision Tree

What is a decision tree?

A tree with two types of nodes:

Decision nodes

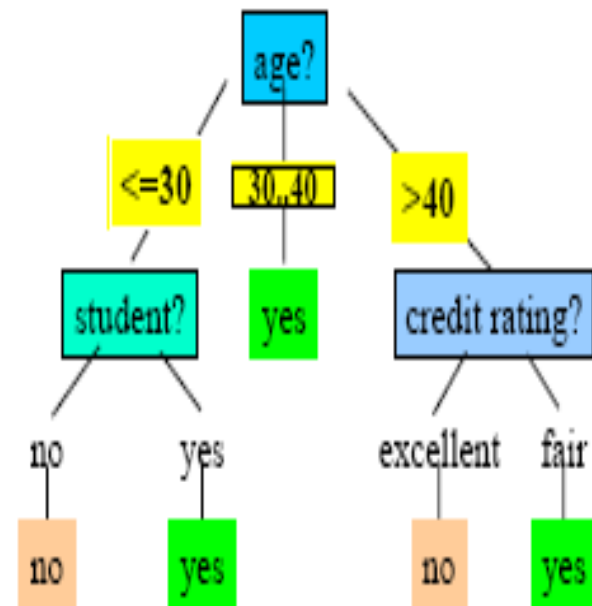
Leaf nodes

Decision node: Specifies a choice or test of some attribute with 2 or more alternatives;

→ every **decision node** is part of a path to a **leaf node**

Leaf node: Indicates classification of an example

- Decision Tree example (is a customer going to buy a computer or not):



Inductive Learning Example

Food (3)	Chat (2)	Fast (2)	Price (3)	Bar (2)	BigTip
great	yes	yes	normal	no	yes
great	no	yes	normal	no	yes
mediocre	yes	no	high	no	no
great	yes	yes	normal	yes	yes

Etc.

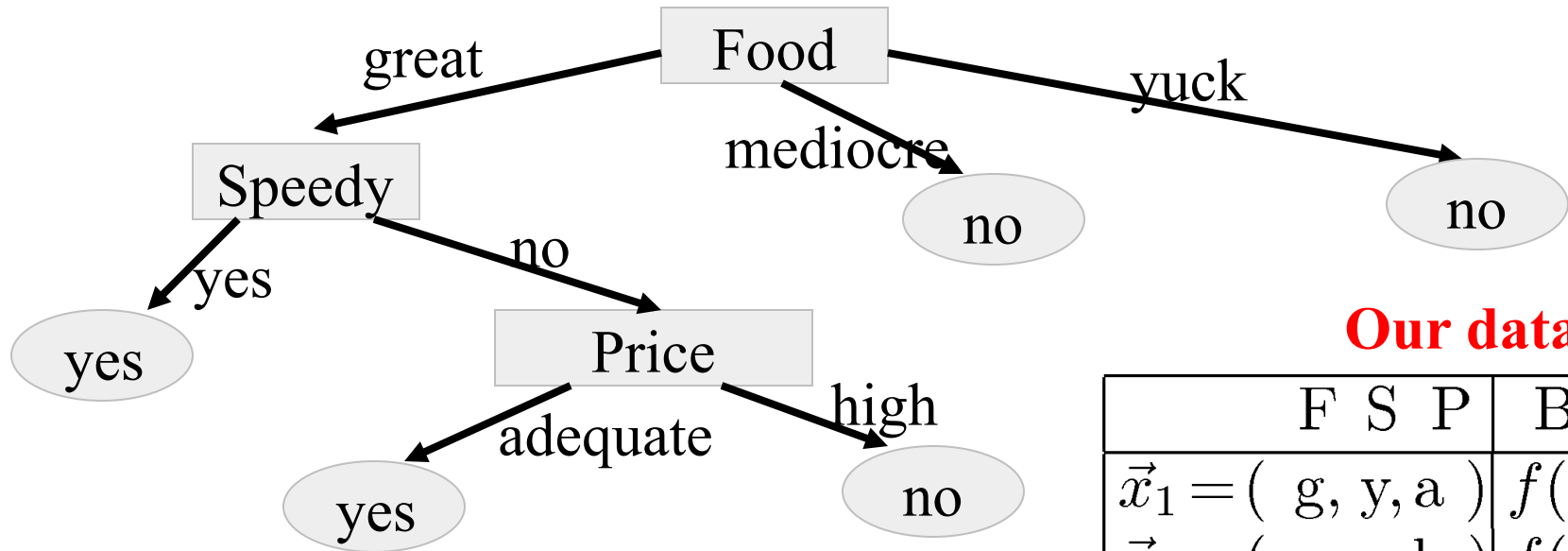
Instance Space X: Set of all possible objects described by attributes (often called features).

Target Function f: Mapping from Attributes to Target Feature (often called label) (f is unknown)

Hypothesis Space H: Set of all classification rules h_i we allow.

Training Data D: Set of instances labeled with Target Feature

Decision Tree Example: “BigTip”



Our data

	F	S	P	BigTip
$\vec{x}_1 = (g, y, a)$	g	y	a	$f(\vec{x}_1) = 1$
$\vec{x}_2 = (g, n, h)$	g	n	h	$f(\vec{x}_2) = 0$
$\vec{x}_3 = (g, y, h)$	g	y	h	$f(\vec{x}_3) = 1$
$\vec{x}_4 = (g, n, a)$	g	n	a	$f(\vec{x}_4) = 1$
$\vec{x}_5 = (m, y, a)$	m	y	a	$f(\vec{x}_5) = 0$
$\vec{x}_6 = (y, y, a)$	y	y	a	$f(\vec{x}_6) = 0$
$\vec{x}_7 = (g, y, a)$	g	y	a	$f(\vec{x}_7) = 1$
$\vec{x}_8 = (g, y, h)$	g	y	h	$f(\vec{x}_8) = 1$
$\vec{x}_9 = (m, y, a)$	m	y	a	$f(\vec{x}_9) = 0$
$\vec{x}_{10} = (g, y, a)$	g	y	a	$f(\vec{x}_{10}) = 1$

Is the decision tree we learned consistent?

Yes, it agrees with all the examples!

Data: Not all $2 \times 2 \times 3 = 12$ tuples
Also, some repeats! These are
literally “observations.”

Learning decision trees:

An example

Problem: decide whether to wait for a table at a restaurant. What attributes would you use?

Attributes used by R&N

1. Alternate: is there an alternative restaurant nearby?
2. Bar: is there a comfortable bar area to wait in?
3. Fri/Sat: is today Friday or Saturday?
4. Hungry: are we hungry?
5. Patrons: number of people in the restaurant (None, Some, Full)
6. Price: price range (\$, \$\$, \$\$\$)
7. Raining: is it raining outside?
8. Reservation: have we made a reservation?
9. Type: kind of restaurant (French, Italian, Thai, Burger)
10. WaitEstimate: estimated waiting time (0-10, 10-30, 30-60, >60)

**What about
restaurant name?**

**It could be great for
generating a small tree
but ...**

Goal predicate: WillWait?

It doesn't generalize!

Attribute-based representations

Examples described by **attribute values** (Boolean, discrete, continuous)

E.g.

Example	Attributes										Target
	<i>Alt</i>	<i>Bar</i>	<i>Fri</i>	<i>Hun</i>	<i>Pat</i>	<i>Price</i>	<i>Rain</i>	<i>Res</i>	<i>Type</i>	<i>Est</i>	<i>Wait</i>
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

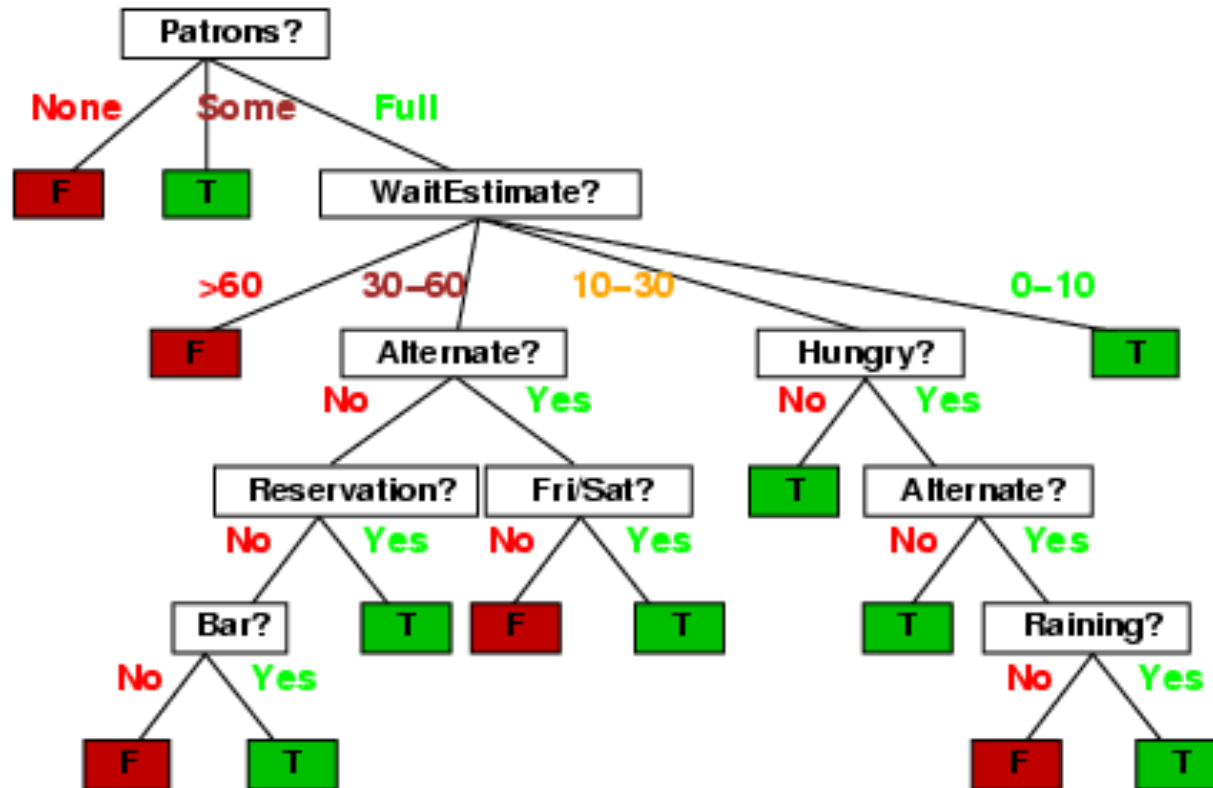
12 examples
6 +
6 -

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

Decision trees

One possible representation for hypotheses

E.g., here is a tree for deciding whether to wait:



Expressiveness of Decision Trees

Any particular decision tree hypothesis for WillWait goal predicate can be seen as **a disjunction of a conjunction of tests**, i.e., an assertion of the form:

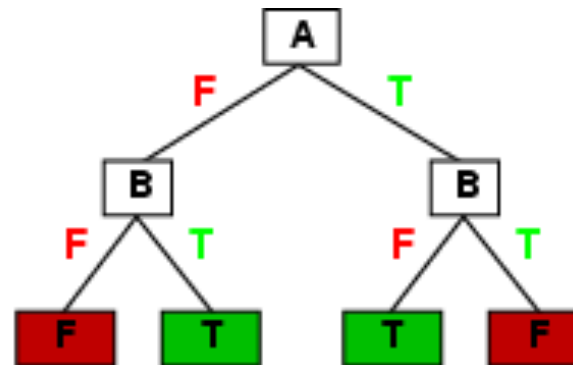
$$\forall s \text{ WillWait}(s) \leftrightarrow (P1(s) \vee P2(s) \vee \dots \vee Pn(s))$$

Where each condition $P_i(s)$ is a **conjunction of tests** corresponding to the path from the root of the tree to a leaf with a positive outcome.

Expressiveness

Decision trees can **express any Boolean function** of the input attributes.
E.g., for Boolean functions, truth table row \rightarrow path to leaf:

A	B	A xor B
F	F	F
F	T	T
T	F	T
T	T	F



Number of Distinct Decision Trees

How many distinct decision trees with 10 Boolean attributes?

= number of Boolean functions with 10 propositional symbols

Input features

Output

0 0 0 0 0 0 0 0 0 0

0/1

0 0 0 0 0 0 0 0 0 1

0/1

0 0 0 0 0 0 0 0 1 0

0/1

0 0 0 0 0 0 0 1 0 0

0/1

...

1 1 1 1 1 1 1 1 1 1

0/1

How many entries does this table have?

$$2^{10}$$

So how many Boolean functions
with 10 Boolean attributes are there,
given that each entry can be 0/1?

$$= 2^{2^{10}}$$

Hypothesis spaces

How many distinct decision trees with n Boolean attributes?

= number of Boolean functions

= number of distinct truth tables with 2^n rows $= 2^{2^n}$

E.g. how many Boolean functions on 6 attributes? A lot...

With 6 Boolean attributes, there are 18,446,744,073,709,551,616 possible trees!

Googles calculator could not handle 10 attributes ☺!

There are even more decision trees! (see later)

Decision tree learning Algorithm

Decision trees can **express any Boolean function**.

Goal: Finding a **decision tree that agrees with training set**.

We could construct a decision tree that has **one path to a leaf for each example**, where the **path tests sets each attribute value to the value of the example**.

What is the problem with this from a learning point of view?

Problem: This approach would just memorize example.
How to deal with new examples? **It doesn't generalize!**

(But sometimes hard to avoid --- e.g. parity function, 1, if an even number of inputs, or majority function, 1, if more than half of the inputs are 1).

We want a compact/smallest tree.

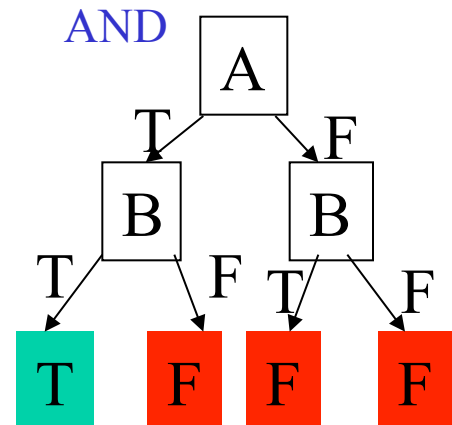
But finding the smallest tree consistent with the examples is NP-hard!

Overall Goal: get a good classification with a **small number of tests**.

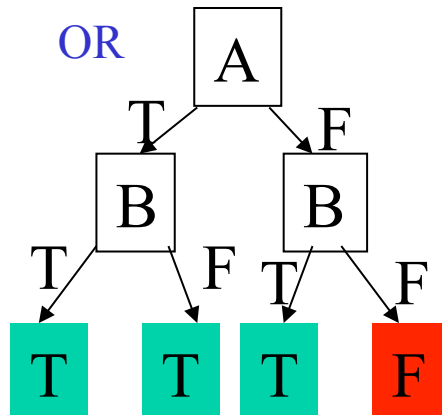
Expressiveness:

Boolean Function with 2 attributes $\rightarrow 2^{2^2}$ DTs

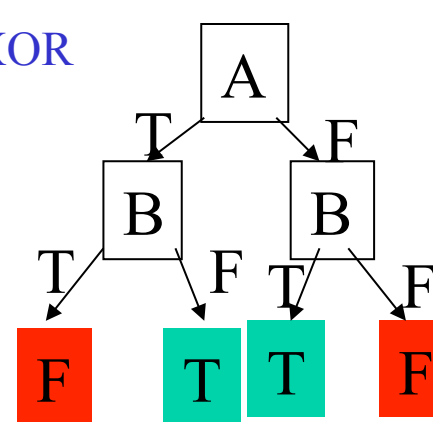
AND



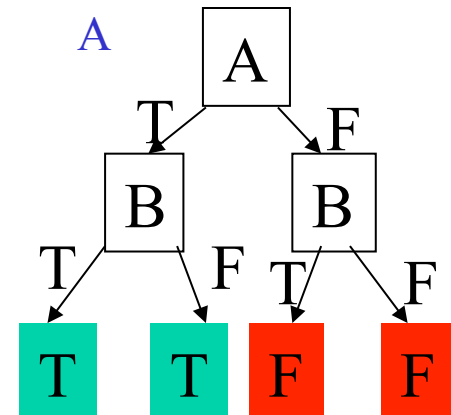
OR



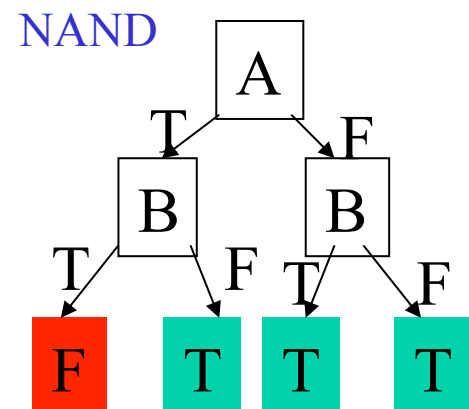
XOR



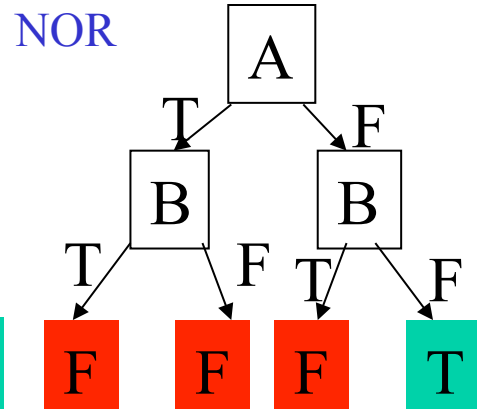
A



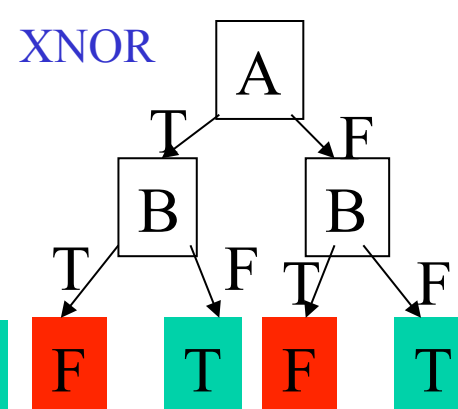
NAND



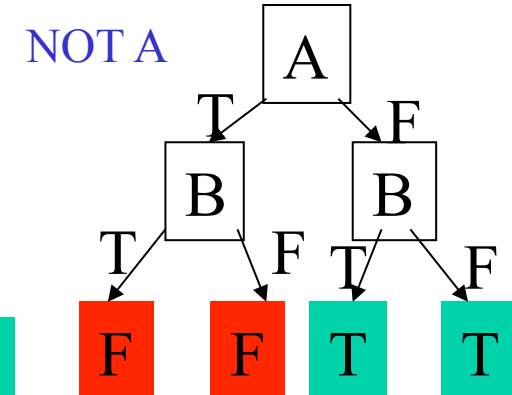
NOR



XNOR



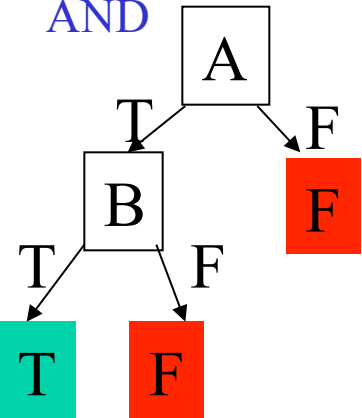
NOT A



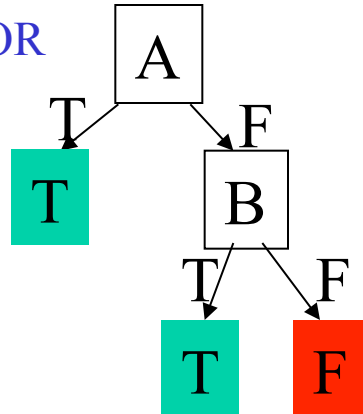
Expressiveness:

2 attribute $\rightarrow 2^{2^2}$ DTs

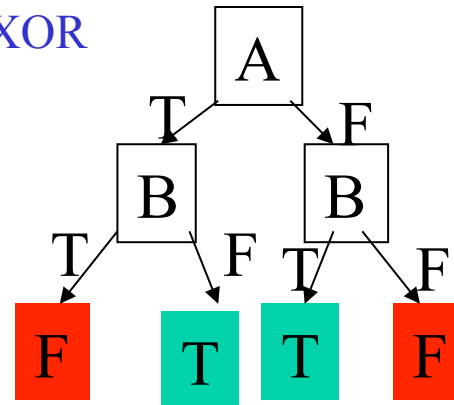
AND



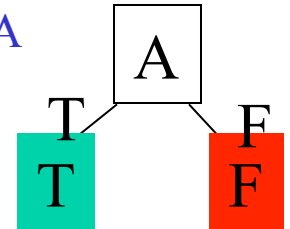
OR



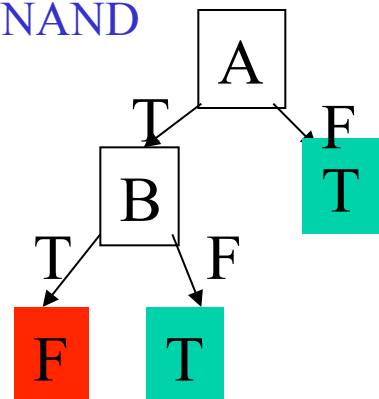
XOR



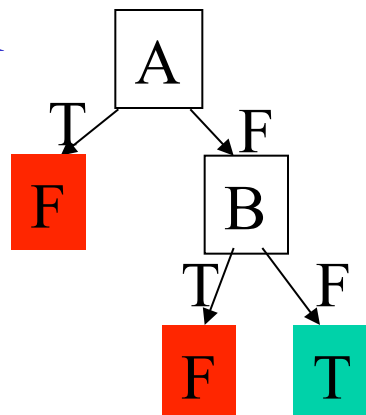
A



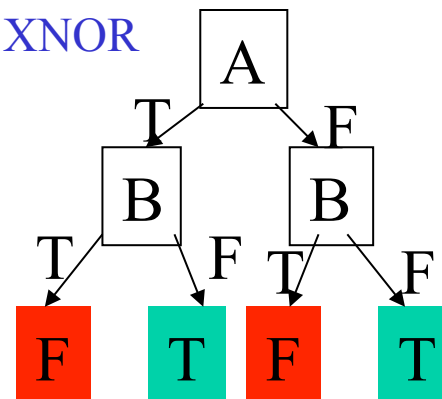
NAND



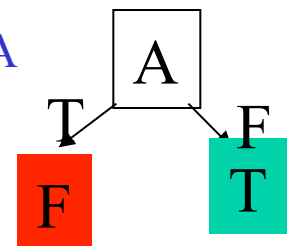
NOR



XNOR

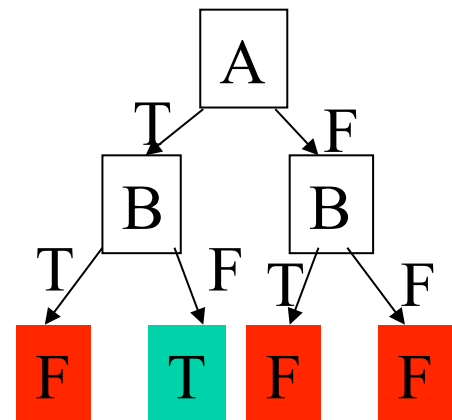


NOT A

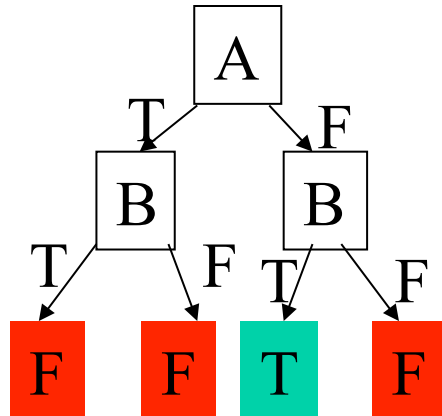


Expressiveness: 2 attribute $\rightarrow 2^{2^2}$ DTs

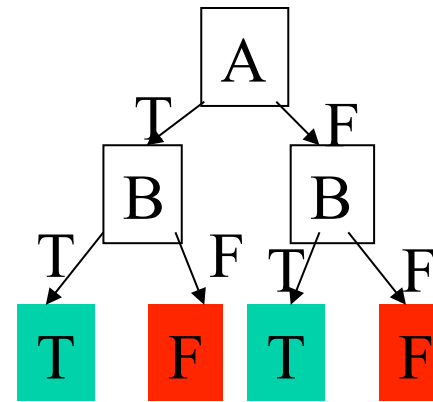
A AND-NOT B



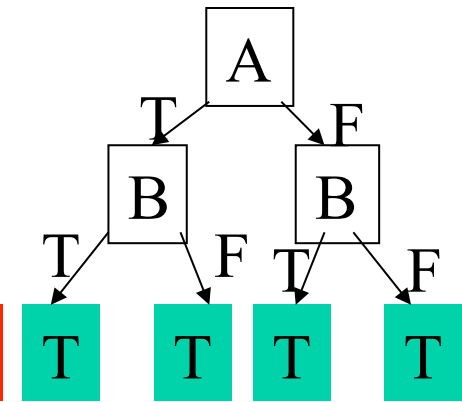
NOT A AND B



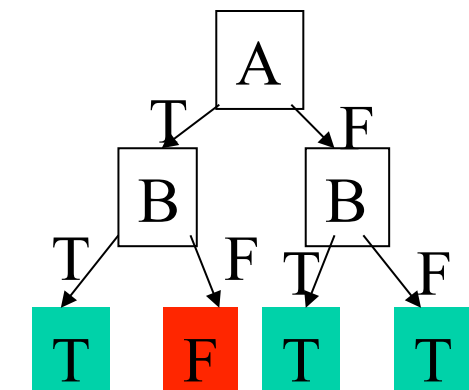
B



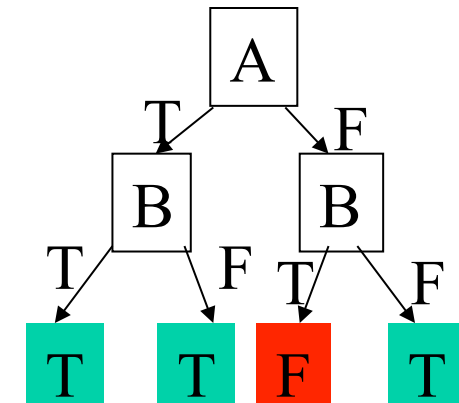
TRUE



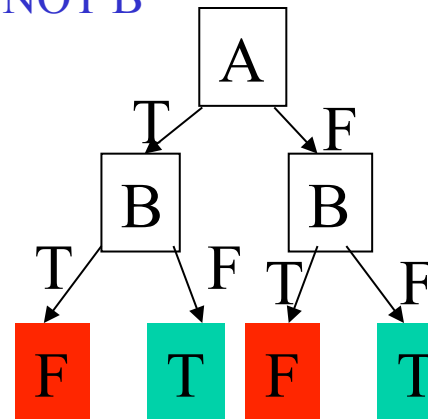
A OR NOT B



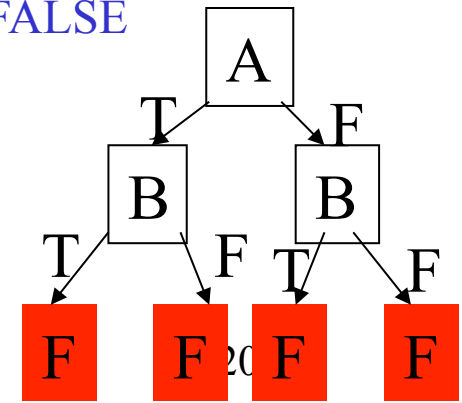
NOR A OR B



NOT B

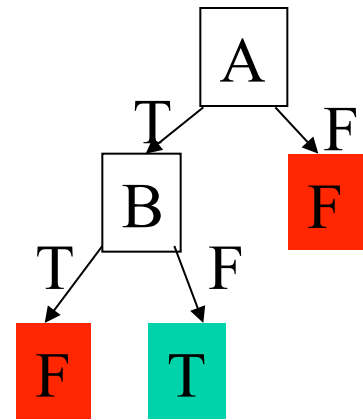


FALSE

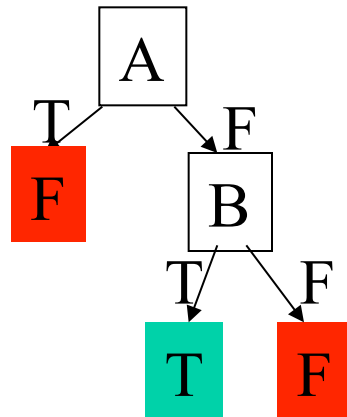


Expressiveness: 2 attribute $\rightarrow 2^{2^2}$ DTs

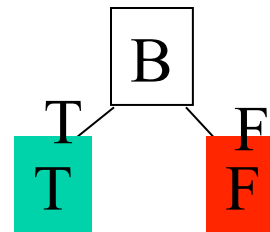
A AND-NOT B



NOT A AND B



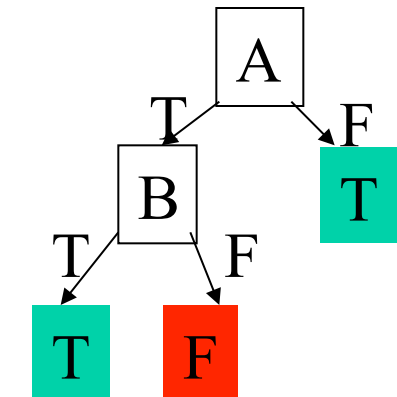
B



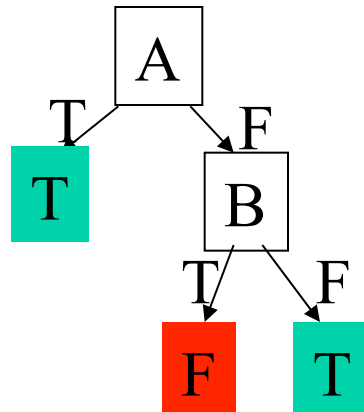
TRUE



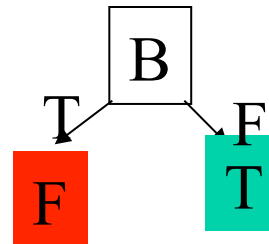
A OR NOT B



NOR A OR B



NOT B



FALSE



“most significant”

In what sense?

Basic DT Learning Algorithm

Goal: find a *small* tree consistent with the training examples

Idea: (recursively) choose “most significant” attribute as root of (sub)tree;

Use a **top-down greedy search** through the space of possible decision trees.

Greedy because there is **no backtracking**. It picks highest values first.

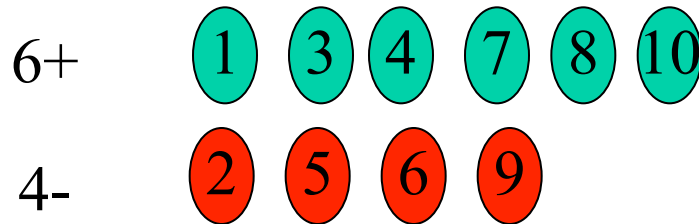
Variations of known algorithms ID3, C4.5 (Quinlan -86, -93)

Top-down greedy construction

- Which **attribute should be tested?** (ID3 Iterative Dichotomiser 3)
 - **Heuristics and Statistical testing with current data**
- **Repeat for descendants**

Big Tip Example

10 examples:



Attributes:

- Food with values g,m,y
- Speedy? with values y,n
- Price, with values a, h



Let's build our decision tree
starting with the attribute Food,
(3 possible values: g, m, y).

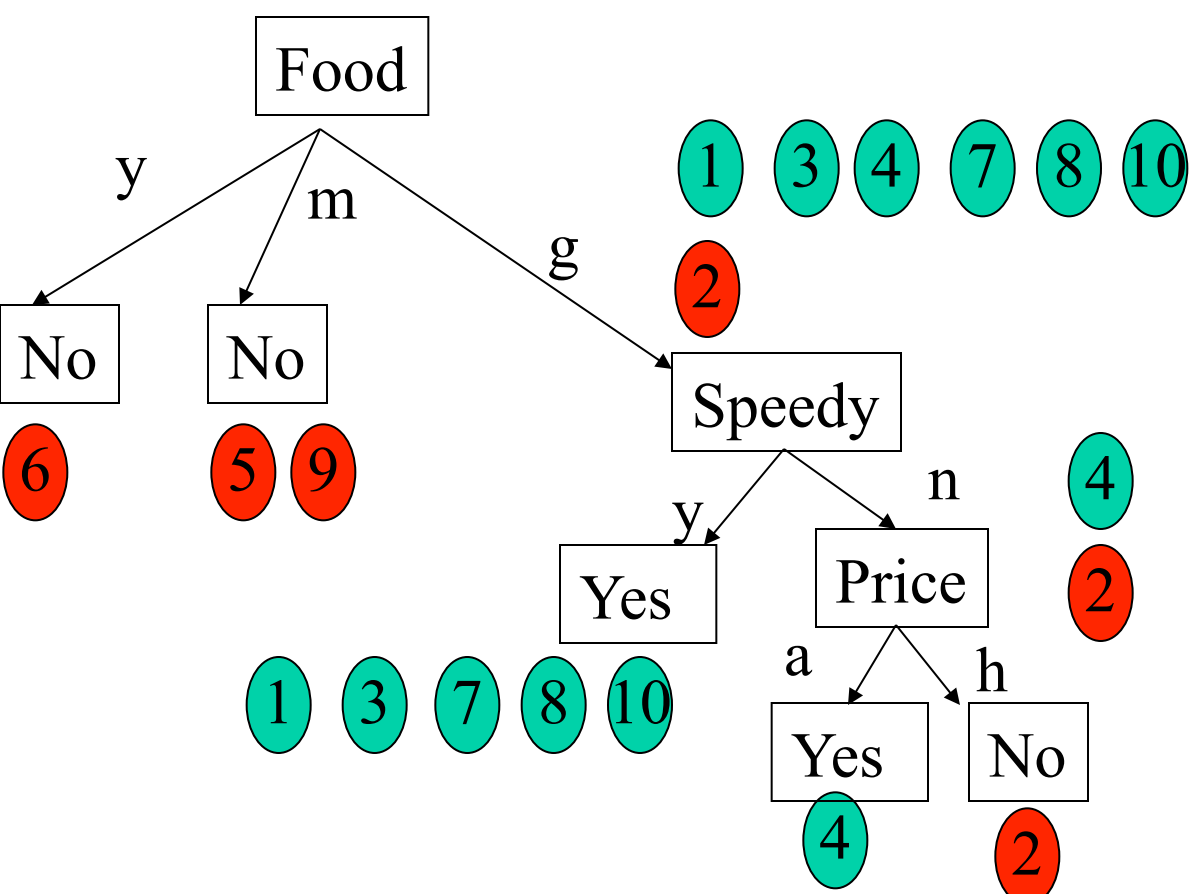
	F S P	BigTip
$\vec{x}_1 = (g, y, a)$		$f(\vec{x}_1) = 1$
$\vec{x}_2 = (g, n, h)$		$f(\vec{x}_2) = 0$
$\vec{x}_3 = (g, y, h)$		$f(\vec{x}_3) = 1$
$\vec{x}_4 = (g, n, a)$		$f(\vec{x}_4) = 1$
$\vec{x}_5 = (m, y, a)$		$f(\vec{x}_5) = 0$
$\vec{x}_6 = (y, y, a)$		$f(\vec{x}_6) = 0$
$\vec{x}_7 = (g, y, a)$		$f(\vec{x}_7) = 1$
$\vec{x}_8 = (g, y, h)$		$f(\vec{x}_8) = 1$
$\vec{x}_9 = (m, y, a)$		$f(\vec{x}_9) = 0$
$\vec{x}_{10} = (g, y, a)$		$f(\vec{x}_{10}) = 1$

Node “done”
when uniform
label or “no
further
uncertainty.”

Top-Down Induction of Decision Tree: Big Tip Example

- 1 3 4 7 8 10
- 2 5 6 9

10 examples:
 6+
 4-

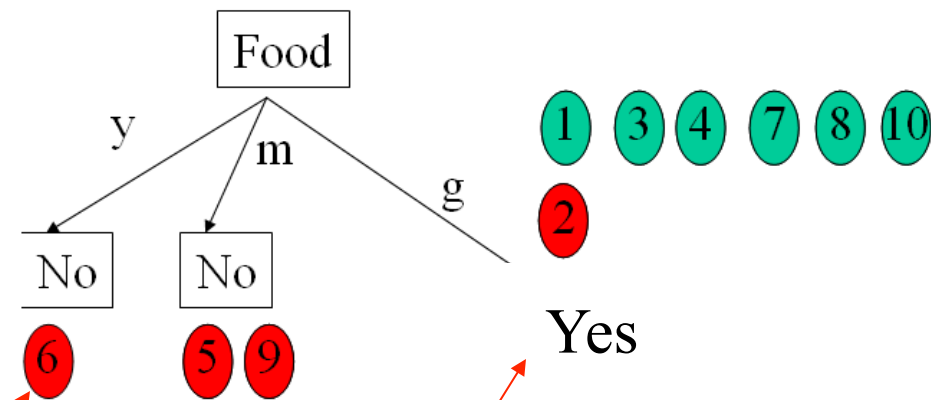


How many + and - examples per subclass, starting with y?

Let's consider next the attribute Speedy

	F	S	P	BigTip
$\vec{x}_1 = (g, y, a)$				$f(\vec{x}_1) = 1$
$\vec{x}_2 = (g, n, h)$				$f(\vec{x}_2) = 0$
$\vec{x}_3 = (g, y, h)$				$f(\vec{x}_3) = 1$
$\vec{x}_4 = (g, n, a)$				$f(\vec{x}_4) = 1$
$\vec{x}_5 = (m, y, a)$				$f(\vec{x}_5) = 0$
$\vec{x}_6 = (y, y, a)$				$f(\vec{x}_6) = 0$
$\vec{x}_7 = (g, y, a)$				$f(\vec{x}_7) = 1$
$\vec{x}_8 = (g, y, h)$				$f(\vec{x}_8) = 1$
$\vec{x}_9 = (m, y, a)$				$f(\vec{x}_9) = 0$
$\vec{x}_{10} = (g, y, a)$				$f(\vec{x}_{10}) = 1$

Top-Down Induction of DT (simplified)



TDIDF(D, c_{def})

IF(all examples in D have same class c)

- Return leaf with class c (or class c_{def} , if D is empty)

ELSE IF(no attributes left to test)

- Return leaf with class c of majority in D

ELSE

- Pick A as the “best” decision attribute for next node
- FOR each value v_i of A create a new descendent of node
 - $D_i = \{(\vec{x}, y) \in D : \text{attribute } A \text{ of } \vec{x} \text{ has value } v_i\}$
 - Subtree t_i for v_i is $\text{TDIDT}(D_i, c_{\text{def}})$

- RETURN tree with A as root and t_i as subtrees

Training Data: $D = \{(\vec{x}_1, y_1), \dots, (\vec{x}_n, y_n)\}$

Picking the Best Attribute to Split

Ockham's Razor:

- All other things being equal, choose the **simplest explanation**

Decision Tree Induction:

- Find **the smallest tree** that classifies the training data correctly

Problem

- Finding the smallest tree is **computationally hard ☹!**

Approach

- Use heuristic search (**greedy search**)

Key Heuristics:

- Pick attribute that *maximizes information (Information Gain)* 
i.e. “most informative”
- Other statistical tests

Attribute-based representations

Examples described by **attribute values** (Boolean, discrete, continuous)

E.g.

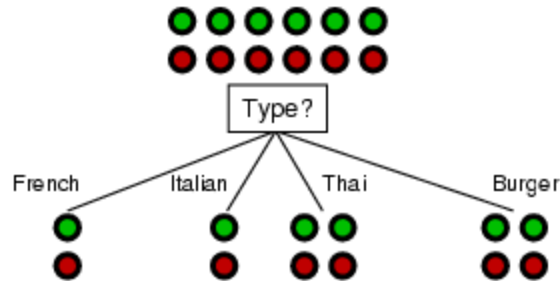
Example	Attributes										Target
	<i>Alt</i>	<i>Bar</i>	<i>Fri</i>	<i>Hun</i>	<i>Pat</i>	<i>Price</i>	<i>Rain</i>	<i>Res</i>	<i>Type</i>	<i>Est</i>	<i>Wait</i>
X_1	T	F	F	T	Some	\$\$\$	F	T	French	0-10	T
X_2	T	F	F	T	Full	\$	F	F	Thai	30-60	F
X_3	F	T	F	F	Some	\$	F	F	Burger	0-10	T
X_4	T	F	T	T	Full	\$	F	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

12 examples
6 +
6 -

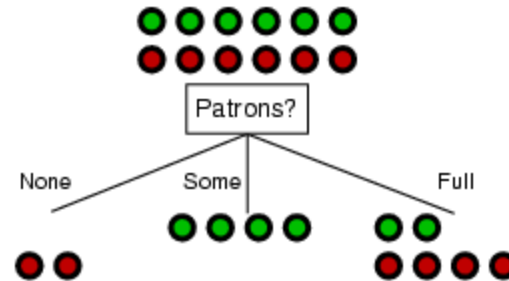
Classification of examples is **positive** (T) or **negative** (F)

Choosing an attribute: Information Gain

Goal: trees with short paths to leaf nodes



Is this a good attribute
to split on?



Which one should we pick?

A perfect attribute would **ideally** divide the examples into sub-sets that are **all positive or all negative**...
i.e. maximum information gain.

Information Gain

Most useful in classification

- how to measure the ‘worth’ of an attribute *information gain*
- how well attribute separates examples according to their classification

Next

- precise definition for gain

→ measure from Information Theory

Shannon and Weaver 49

One of the most successful and impactful mathematical theories known.

Information

“Information” answers questions.

The **more clueless** I am about a question, the **more information** the **answer to the question** contains.

Example – fair coin \rightarrow prior $\langle 0.5, 0.5 \rangle$

By definition **Information of the prior** (or **entropy of the prior**):

$$I(P1, P2) = -P1 \log_2(P1) - P2 \log_2(P2) =$$

$$I(0.5, 0.5) = -0.5 \log_2(0.5) - 0.5 \log_2(0.5) = 1$$

We need 1 bit to convey the outcome of the flip of a fair coin.

Scale: 1 bit = answer to Boolean question with prior $\langle 0.5, 0.5 \rangle$

Why does a biased coin have less information?

(How can we code the outcome of a biased coin sequence?)

Information (or Entropy)

Information in an answer given possible answers v_1, v_2, \dots, v_n :

$$I(P(v_1), \dots, P(v_n)) = \sum_{i=1}^n -P(v_i) \log_2(P(v_i))$$

— v_1, \dots, v_n possible answers

— $P(v_i)$ probability of answer v_i

(Also called **entropy** of the prior.)

Example – biased coin \rightarrow prior $\langle 1/100, 99/100 \rangle$

$$\begin{aligned} I(1/100, 99/100) &= -1/100 \log_2(1/100) - 99/100 \log_2(99/100) \\ &= 0.08 \text{ bits (so not much information gained from “answer.”)} \end{aligned}$$

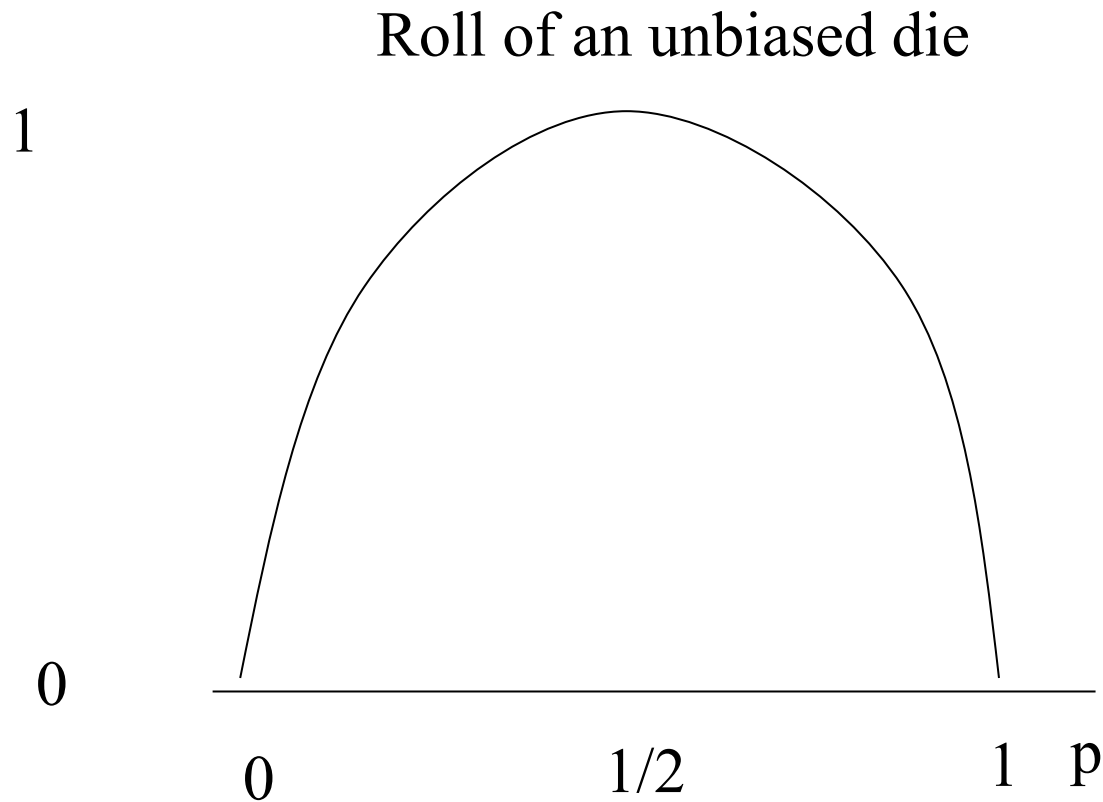
Example – fully biased coin \rightarrow prior $\langle 1, 0 \rangle$

$$I(1, 0) = -1 \log_2(1) - 0 \log_2(0) = 0 \text{ bits}$$

$$0 \log_2(0) = 0$$

i.e., no uncertainty left in source!

Shape of Entropy Function



The **more uniform** the probability distribution,
the **greater is its entropy**.

Information or Entropy

Information or Entropy measures the “randomness” of an arbitrary collection of examples.

We don't have exact probabilities but our training data provides an estimate of the probabilities of positive vs. negative examples given a set of values for the attributes.

For a collection S, entropy is given as:

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

For a collection S having positive and negative examples

p - # positive examples;

n - # negative examples

Attribute-based representations

Examples described by **attribute values** (Boolean, discrete, continuous)

E.g., situations where I will/won't wait for a table:

Example	Attributes										Target
	<i>Alt</i>	<i>Bar</i>	<i>Fri</i>	<i>Hun</i>	<i>Pat</i>	<i>Price</i>	<i>Rain</i>	<i>Res</i>	<i>Type</i>	<i>Est</i>	<i>Wait</i>
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

12 examples

6 +

6 -

What's the entropy of this collection of examples?

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

$$p = n = 6; I(0.5,0.5) = -0.5 \log_2(0.5) - 0.5 \log_2(0.5) = 1$$

So, we need 1 bit of info to classify a randomly picked example, assuming no other information is given about the example.

Choosing an attribute:

Information Gain

Intuition: Pick the attribute that **reduces the entropy** (the uncertainty) the most.

So we measure the **information gain** after **testing a given attribute A**:

$$Gain(A) = I\left(\frac{p}{p+n}, \frac{n}{p+n}\right) - \text{Remainder}(A)$$

$\text{Remainder}(A) \rightarrow$ gives us **the remaining uncertainty** after getting info on attribute A.

Choosing an attribute: Information Gain

Remainder(A)

→ gives us the amount information we still need after testing on A.

Assume A divides the training set E into E_1, E_2, \dots, E_v , corresponding to the different v distinct values of A.

Each subset E_i has p_i positive examples and n_i negative examples.

So for total information content, we need to weigh the contributions of the different subclasses induced by A

Weight (relative size) of each subclass

$$\text{Remainder}(A) = \sum_{i=1}^v \overset{\text{Weight (relative size) of each subclass}}{\frac{p_i + n_i}{p + n}} I\left(\frac{p_i}{p_i + n_i}, \frac{n_i}{p_i + n_i}\right)$$

Choosing an attribute: Information Gain

Measures the **expected reduction in entropy**. The higher the Information Gain (IG), or just Gain, with respect to an attribute A , the more is the expected reduction in entropy.

$$Gain(S, A) = Entropy(S) - \sum_{v \in Values(A)} \underbrace{\frac{|S_v|}{|S|}}_{\text{Weight of each subclass}} Entropy(S_v)$$

where $Values(A)$ is the set of all **possible values** for attribute A ,
 S_v is the subset of S for which attribute A has value v .

Interpretations of gain

Gain(S,A)

- expected reduction in entropy caused by knowing A
- information provided about the target function value given the value of A
- number of bits saved in the coding a member of S knowing the value of A

Used in ID3 (Iterative Dichotomiser 3) Ross Quinlan

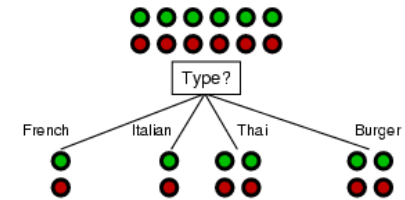
What if we used attribute “example label” uniquely specifying the answer? Info gain? Issue?

High branching: can correct with “info gain ratio”

Information gain

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

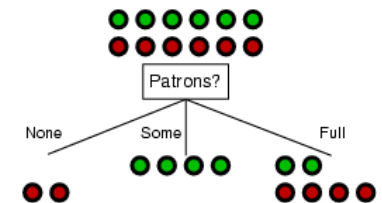
Consider the attributes *Type* and *Patrons*:



Info gain?

$$IG(\text{Type}) = 1 - \left[\frac{2}{12} I\left(\frac{1}{2}, \frac{1}{2}\right) + \frac{2}{12} I\left(\frac{1}{2}, \frac{1}{2}\right) + \frac{4}{12} I\left(\frac{2}{4}, \frac{2}{4}\right) + \frac{4}{12} I\left(\frac{2}{4}, \frac{2}{4}\right) \right] = 0 \text{ bits}$$

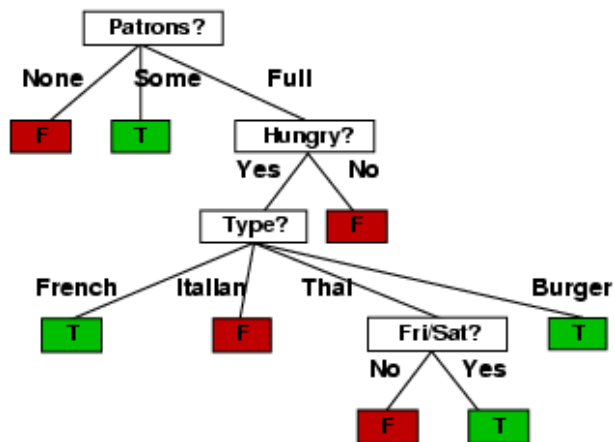
$$IG(\text{Patrons}) = 1 - \left[\frac{2}{12} I(0,1) + \frac{4}{12} I(1,0) + \frac{6}{12} I\left(\frac{2}{6}, \frac{4}{6}\right) \right] = .0541 \text{ bits}$$



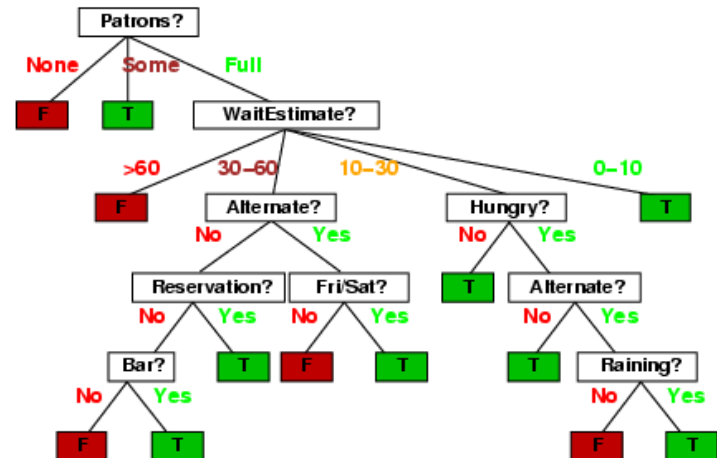
***Patrons* has the highest IG of all attributes and so is chosen by the DTL algorithm as the root.**

Example contd.

Decision tree learned from the 12 examples:



“personal R&N Tree”



Substantially simpler than “true” tree ---
but a more complex hypothesis isn't justified
from just the data.

Inductive Bias

Roughly: prefer

- shorter trees over deeper/more complex ones
- ones with high gain attributes near root

Difficult to characterize precisely

- attribute selection heuristics
- interacts closely with given data

Evaluation Methodology General for Machine Learning

Evaluation Methodology

How to evaluate the quality of a learning algorithm, i.e.,:

How good are the hypotheses produce by the learning algorithm?

How good are they at classifying unseen examples?

Standard methodology (“**Holdout Cross-Validation**”):

1. Collect a large set of examples.
2. Randomly divide collection into two disjoint sets: **training set** and **test set**.
3. Apply learning algorithm to training set generating hypothesis h
4. Measure performance of h w.r.t. test set (a form of cross-validation)
→ measures generalization to unseen data

Important: keep the training and test sets disjoint! “No peeking”!

Note: The first two questions about any learning result: Can you describe your training and your test set? What’s your error on the test set?

Example of peeking:

We generate four different hypotheses – for example by using different criteria to pick the next attribute to branch on.

We test the performance of the four different hypothesis on the test set and we select the best hypothesis.

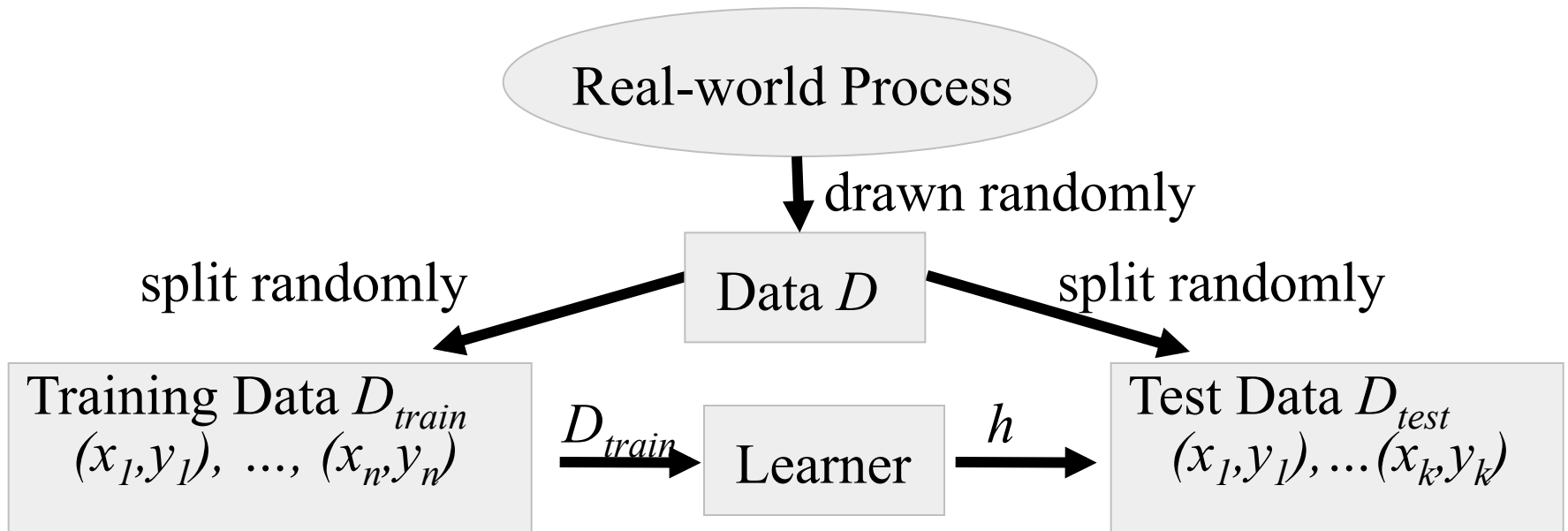
Voila: Peeking occurred! Why?

The hypothesis was selected on the basis of its performance on the **test set**, so information about the test set has leaked into the learning algorithm.

So a new (separate!) test set would be required!

Note: In competitions, such as the “Netflix \$1M challenge,” test set is not revealed to the competitors. (Data is held back.)

Test/Training Split



Measuring Prediction Performance

Definition: The **training error** $Err_{D_{train}}(h)$ on training data $D_{train} = ((\vec{x}_1, y_1), \dots, (\vec{x}_n, y_n))$ of a hypothesis h is $Err_{D_{train}}(h) = \frac{1}{n} \sum_{i=1}^n \Delta(h(\vec{x}_i), y_i)$.

Definition: The **test error** $Err_{D_{test}}(h)$ on test data $D_{test} = ((\vec{x}_1, y_1), \dots, (\vec{x}_k, y_k))$ of a hypothesis h is $Err_{D_{test}}(h) = \frac{1}{k} \sum_{i=1}^k \Delta(h(\vec{x}_i), y_i)$.

Definition: The **prediction/generalization/true error** $Err_P(h)$ of a hypothesis h for a learning task $P(X, Y)$ is

$$Err_P(h) = \sum_{\vec{x} \in X, y \in Y} \Delta(h(\vec{x}), y) P(X = \vec{x}, Y = y).$$

Definition: The zero/one-loss function $\Delta(a, b)$ returns 1 if $a \neq b$ and 0 otherwise.

Performance Measures

Error Rate

- Fraction (or percentage) of false predictions

Accuracy

- Fraction (or percentage) of correct predictions

Precision/Recall

Example: binary classification problems (classes pos/neg)

- Precision: Fraction (or percentage) of correct predictions among all examples predicted to be positive
- Recall: Fraction (or percentage) of correct predictions among all real positive examples

(Can be generalized to multi-class case.)

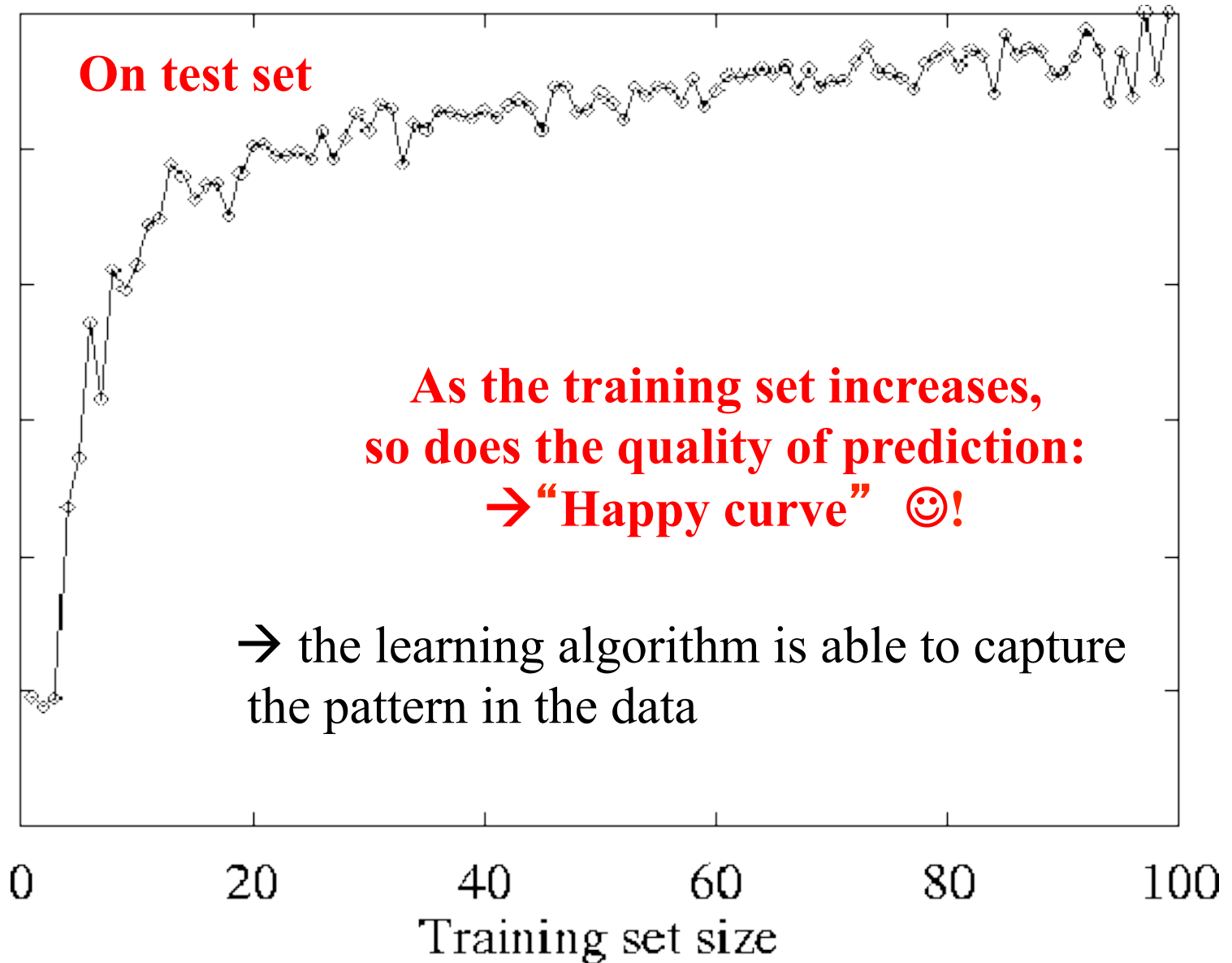
Learning Curve Graph

Learning curve graph

**average prediction quality – proportion correct on test set –
as a function of the size of the training set..**

Restaurant Example: Learning Curve

Prediction quality:
Average Proportion correct on **test set**



How well does it work?

Many case studies have shown that decision trees are at least as accurate as human experts.

- A study for **diagnosing breast cancer** had **humans** correctly classifying the examples **65%** of the time, and the **decision tree** classified **72%** correct.
- **British Petroleum** designed a **decision tree** for **gas-oil separation for offshore oil platforms** that replaced an earlier rule-based expert system.
- **Cessna** designed an **airplane flight controller** using **90,000 examples** and **20 attributes** per example.

Summary

Decision tree learning is a particular case of **supervised learning**,

For **supervised learning**, the aim is to find a **simple hypothesis**
approximately consistent with training examples

Decision tree learning using **information gain**

Learning performance = **prediction accuracy measured on test set**

Extensions of the Decision Tree Learning Algorithm (Briefly)

Noisy data

Overfitting and Model Selection

Cross Validation

Missing Data (R&N, Section 18.3.6)

Using gain ratios (R&N, Section 18.3.6)

Real-valued data (R&N, Section 18.3.6)

Generation of rules and pruning

Noisy data

Many kinds of "noise" that could occur in the examples:

- Two examples have **same attribute/value pairs, but different classifications**
 - report **majority classification** for the examples corresponding to the node deterministic hypothesis.
 - report **estimated probabilities of each classification** using the relative frequency (if considering stochastic hypotheses)
- Some values of **attributes are incorrect** because of errors in the data acquisition process or the preprocessing phase
- The **classification is wrong** (e.g., + instead of -) because of some error

One important reason why you don't want to "overfit" your learned model.

Overfitting

Ex.: Problem of trying to predict the roll of a die. The experiment data include:

Day of the week; (2) Month of the week; (3) Color of the die;

....

DTL may find an hypothesis that fits the data but with irrelevant attributes.

Some attributes are irrelevant to the decision-making process, e.g., color of a die is irrelevant to its outcome but they are used to differentiate examples
→ Overfitting.

Overfitting means fitting the **training set** “too well”
→ **performance on the test set degrades.**

Example overfitting risk: Using restaurant name.

If the hypothesis space has many dimensions because of a large number of attributes, we may find **meaningless regularity** in the data that is irrelevant to the true, important, distinguishing features.

- **Fix by pruning to lower # nodes in the decision tree or put a limit on number of nodes created.**
- **For example, if Gain of the best attribute at a node is below a threshold, stop and make this node a leaf rather than generating children nodes.**

Overfitting is a key problem in learning. There are formal results on the number of examples needed to properly train an hypothesis of a certain complexity (“number of parameters” or # nodes in DT). The more params, the more data is needed. We’ll see some of this in our discussion of PAC learning.

Overfitting

Let's consider **D**, the entire **distribution of data**, and **T**, the **training set**.

Hypothesis $h \in H$ overfits **D** if

$\exists h' \neq h \in H$ such that

$\text{error}_T(h) < \text{error}_T(h')$ but

$\text{error}_D(h) > \text{error}_D(h')$

Note: estimate error on full distribution by using test data set.

Data overfitting is the arguably the most common pitfall in machine learning.

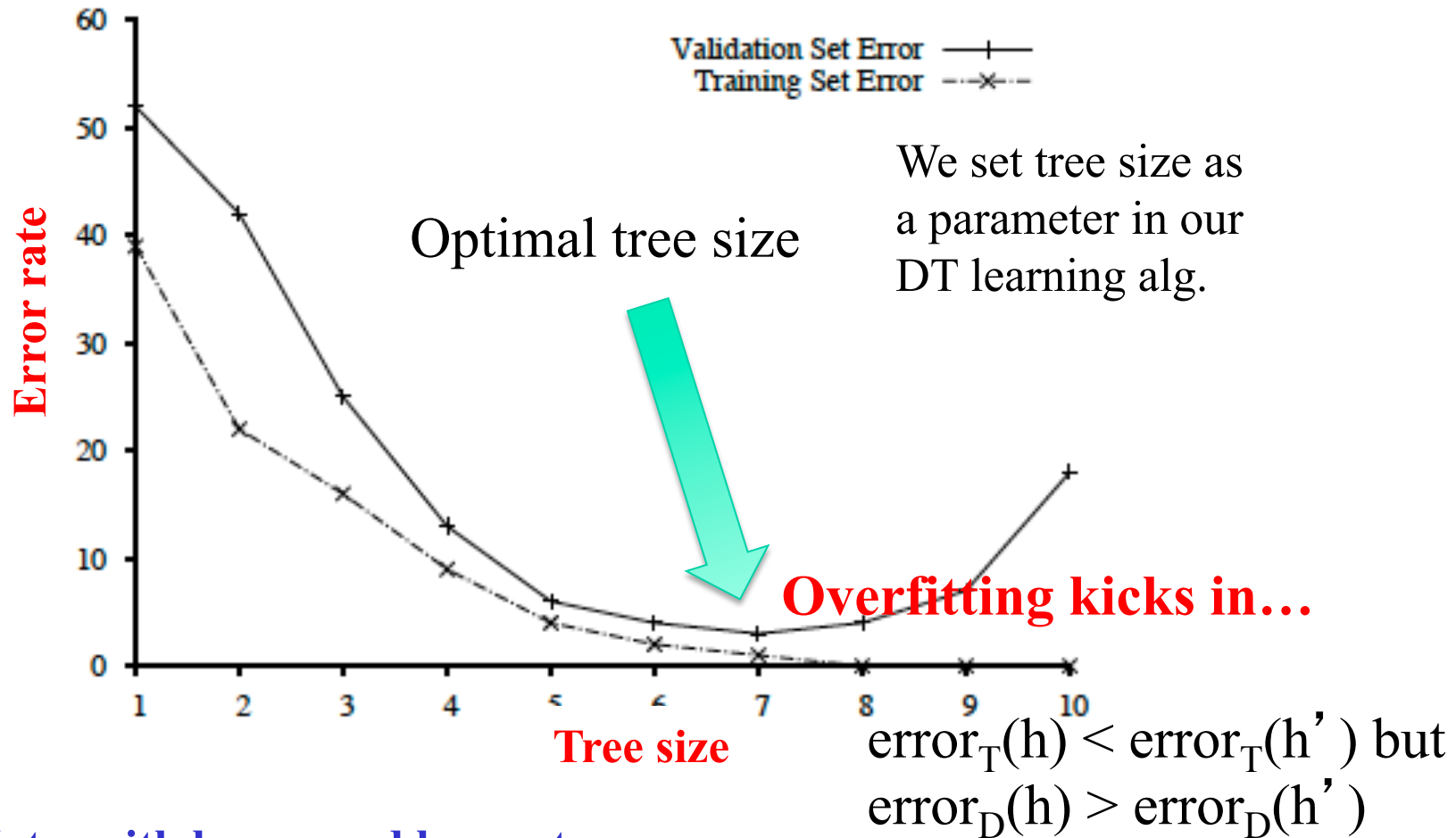
Why?

- 1) Temptation to use as much data as possible to train on. (“Ignore test till end.” Test set too small.) Data “peeking” not noticed.**
- 2) Temptation to fit very complex hypothesis (e.g. large decision tree). In general, the larger the tree, the better the fit to the training data.**

It’s hard to think of a better fit to the training data as a “worse” result. Often difficult to fit training data well, so it seems that “a good fit to the training data means a good result.”

Note: Modern “savior:” Massive amounts of data to train on! Somewhat characteristic of ML AI community vs. traditional statistics community. Anecdote: Netflix competition.

Key figure in machine learning



Note: with larger and larger trees,
we just do better and better on the training set!

But note the performance on the validation set...

**Procedure for finding the optimal tree size is called “model selection.”
See section 18.4.1 R&N and Fig. 18.8.**

**To determine validation error for each tree size, use k-fold cross-validation. (Uses the data better than “holdout cross-validation.”)
Uses “all data - test set” --- k times splits that set into a training set and a validation set.**

After right decision tree size is found from the error rate curve on validation data, train on all training data to get final decision tree (of the right size).

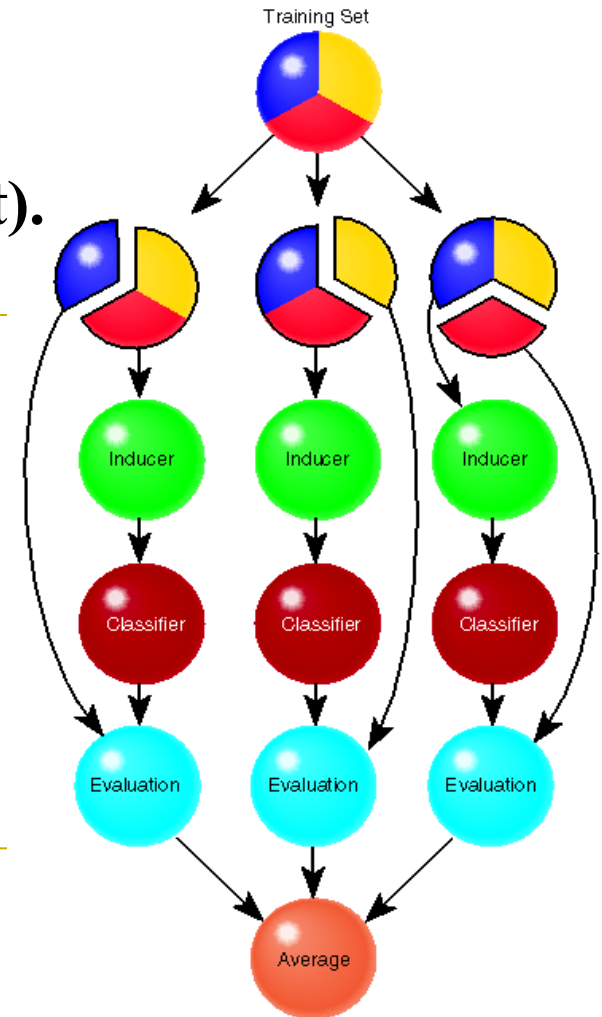
Finally, evaluate tree on the test data (not used before) to get true generalization error (to unseen examples).

Learner L is e.g. DT learner for “tree with 7 nodes” max.

A method for estimating the accuracy (or error) of a learner (using validation set).

Cross Validation

```
CV( data S, alg L, int k )  
  Divide S into k disjoint sets { S1, S2, ..., Sk }  
  For i = 1..k do  
    Run L on S-i = S - Si  
    obtain L(S-i) = hi  
    Evaluate hi on Si  
    errSi(hi) = 1/|Si| ∑⟨x,y⟩ ∈ Si I(hi(x) ≠ y)  
  Return Average 1/k ∑i errSi(hi)
```



Specific techniques for dealing with overfitting

(Model selection provides general framework)

- 1) **Decision tree pruning** or grow only up to certain size.
Prevent splitting on features that are not clearly relevant.

Testing of relevance of features --- “does split provide new information”:

statistical tests ---> Section 18.3.5 R&N χ^2 test.

- 2) **Grow full tree, then post-prune rule post-pruning**

- 3) **MDL (minimal description length):**

minimize

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

Converting Trees to Rules

Every decision tree corresponds to set of rules:

- IF (Patrons = None)
THEN WillWait = No
- IF (Patrons = Full)
 & (Hungry = No)
 & (Type = French)
THEN WillWait = Yes
- ...



Fighting 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?

Logical aside

Decision trees are a restricted form of general logical statements.

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

Example:

$$\forall WillWait(r) \Leftrightarrow Patrons(r, Some)$$

$$\vee (Patrons(r, Full) \wedge \neg Hungry(r) \wedge Type(r, French))$$

$$\vee (Patrons(r, Full) \wedge \neg Hungry(r) \wedge Type(r, Thai) \wedge Fri/Sat)$$

$$\vee (Patrons(r, Full) \wedge \neg Hungry(r) \wedge Type(r, Burger))$$

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

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

End logical aside

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

$$\textit{Alternate}(X_1) \wedge \neg \textit{Bar}(X_1) \wedge \neg \textit{Fri/Sat}(X_1) \wedge \\ \textit{Hungry}(X_1) \wedge \dots \wedge \textit{WillWait}(X_1)$$

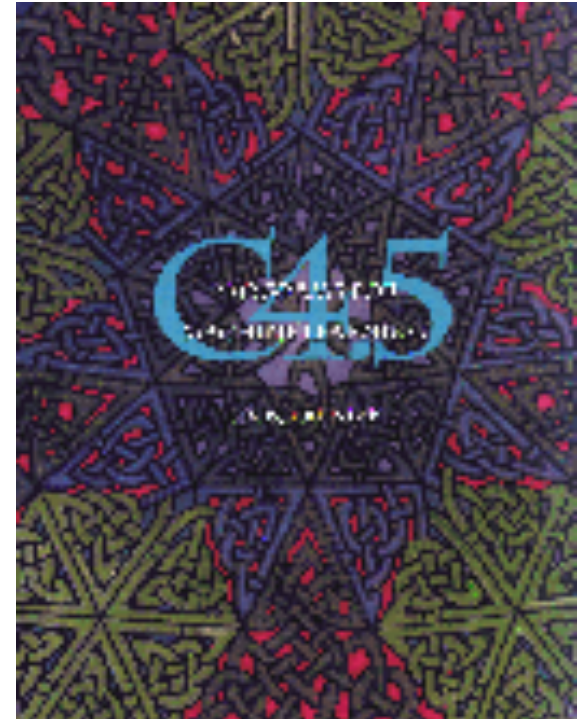
We can test if this example is **consistent** with our hypothesis. If not, we may have to **generalize** or **specialize** our hypothesis:

Current-best-hypothesis search.

C4.5 is an extension of ID3 that accounts for unavailable values, C4.5 continuous attribute value ranges, pruning of decision trees, rule derivation, and so on.

C4.5: Programs for Machine Learning

**J. Ross Quinlan, The Morgan Kaufmann Series
in Machine Learning, Pat Langley.**



Summary:

When to use Decision Trees

Instances presented as **attribute-value pairs**

Method of approximating discrete-valued functions

Target function has discrete values: **classification problems**

Robust to **noisy data**:

Training data may contain

- errors
- missing attribute values

Typical bias: prefer smaller trees (**Ockham's razor**)

Widely used, practical and easy to interpret results

Inducing decision trees is one of the most widely used learning methods in practice

Can outperform human experts in many problems

Strengths include

- Fast
- simple to implement
- human readable
- can convert result to a set of easily interpretable rules
- empirically valid in many commercial products
- handles noisy data

Can be a legal requirement! Why?

Weaknesses include:

- "Univariate" splits/partitioning using only one attribute at a time so limits types of possible trees
- large decision trees may be hard to understand
- requires fixed-length feature vectors
- non-incremental (i.e., batch method)