Artificial Intelligence

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CHAPTER 9: LEARNING FROM EXAMPLES

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9.3 Learning Decision Trees
9.4 Evaluating And Choosing The Best Hypothesis
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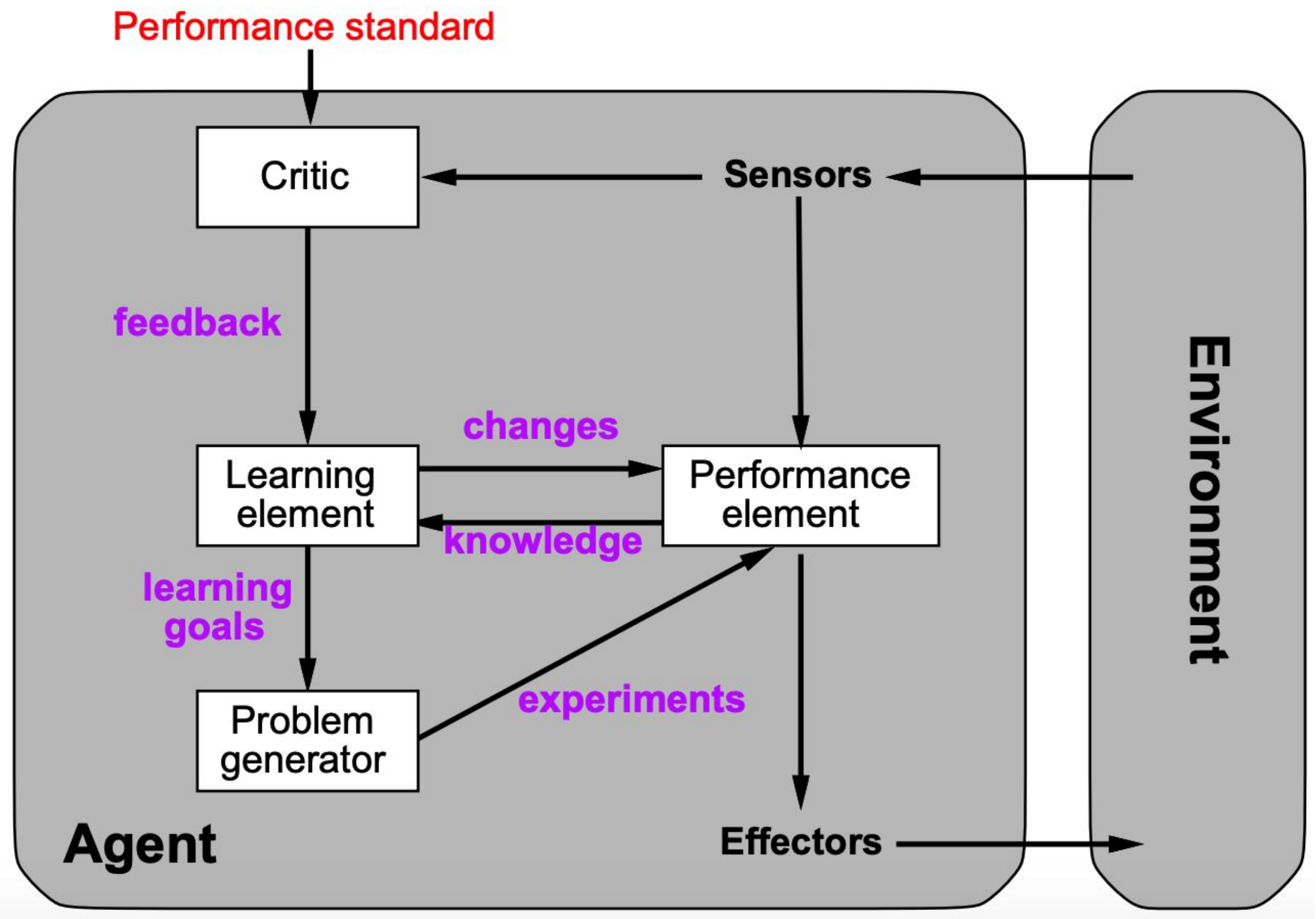
9.1 Forms Of Learning

Learning agents



Learning element

Design of learning element is dictated by

- what type of performance element is used
  - E.g., logical agent
- how that functional component is represented
  - E.g., state transition model
- which functional component is to be learned
  - E.g., logic language
- what kind of feedback is available
  - E.g., outcome

9.1 Forms Of Learning

- What feedback is available to learn from: it depends on three types of feedback
  - In **reinforcement learning** the agent learns from a series of reinforcements - rewards or punishments.
    - E.g.: the points for a win at the end of a chess game tells the agent it did something right.
  - In **unsupervised learning** the agent learns patterns in the input even though no explicit feedback is supplied.
    - E.g.: a taxi agent might gradually develop a concept of “good traffic days” and “bad traffic days” without ever being given labeled examples of each by a teacher.
  - In **supervised learning** the agent observes some example input–output pairs and learns a function that maps from input to output.

9.2 Supervised Learning

9.2 Supervised Learning

- The task of supervised learning:

  Given a **training set** of N example input–output pairs

  $(x_1,y_1), (x_2,y_2),\ldots(x_N,y_N)$,

  where each y_j was generated by an unknown function $y = f(x)$,

  Problem: find a **hypothesis** h

  such that $h \approx f$

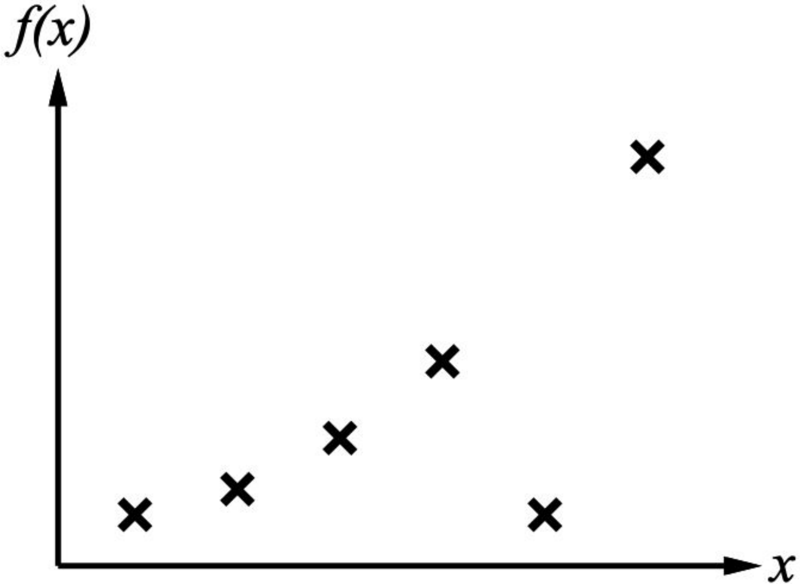
  given a training set of examples

9.2 Supervised Learning

Inductive learning method

Construct/adjust h to agree with f on training set

(h is **consistent** if it agrees with f on all examples)



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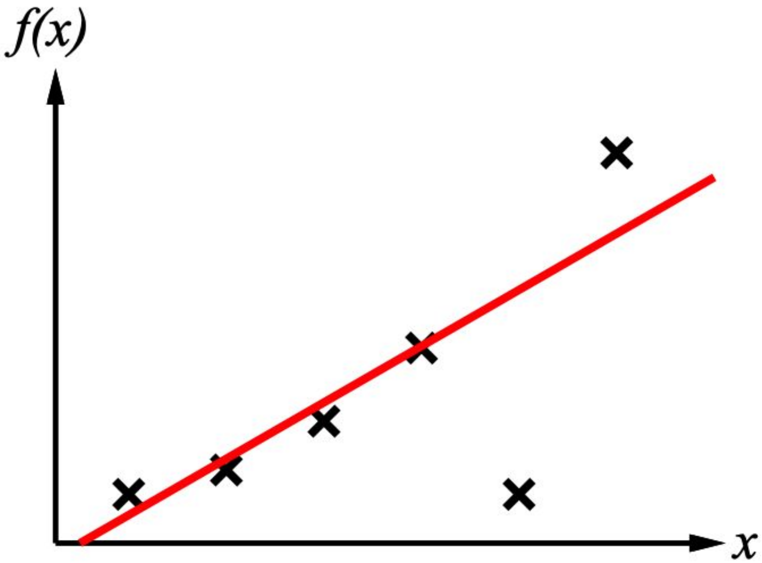

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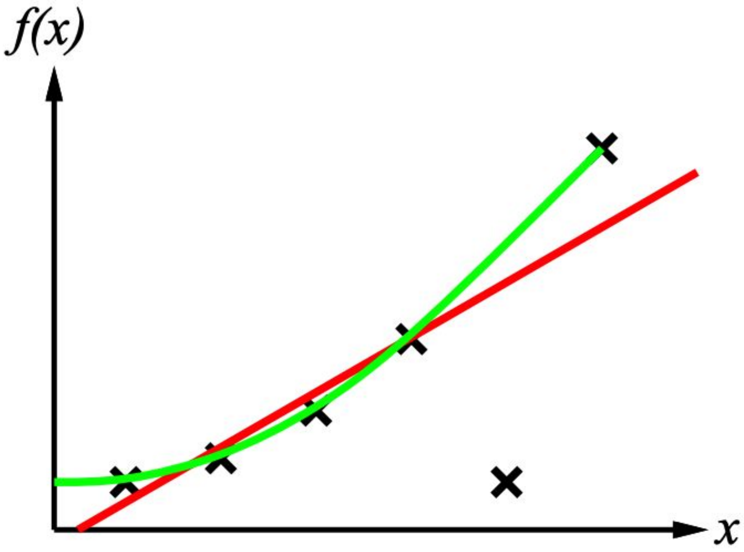

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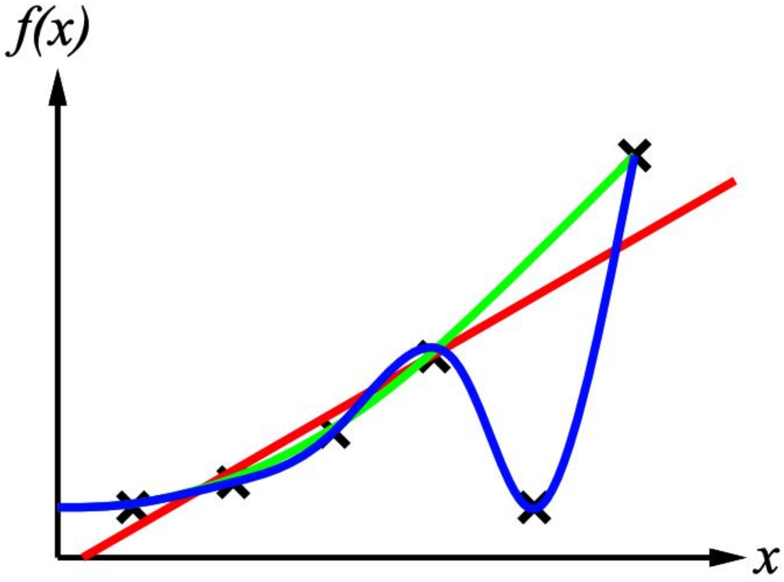

9.2 Supervised Learning

Inductive learning method

Construct/adjust h to agree with f on training set

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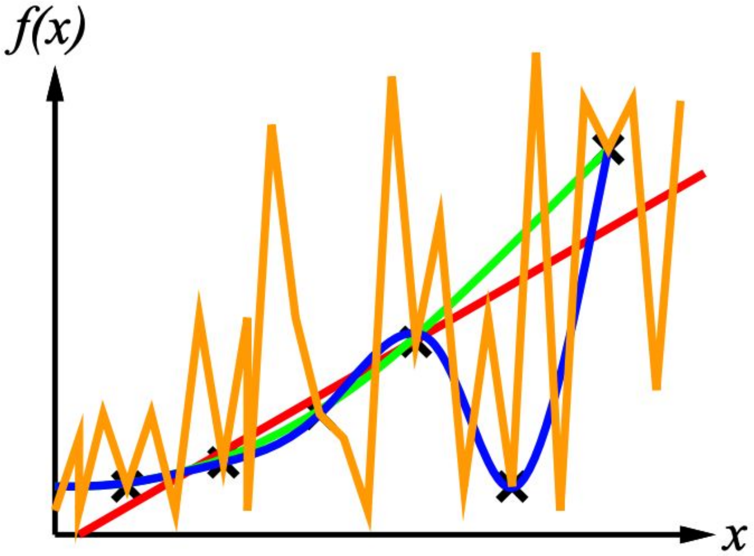
Ockham's razor: maximize a combination of consistency and simplicity



9.2 Supervised Learning

- To measure the accuracy of a hypothesis h, we give it a **test set** of examples that are distinct from the training set.
- A hypothesis **generalizes** h well if it correctly predicts the value of y for novel examples.

9.2 Supervised Learning

- Types of supervised learning:
  - **Classification**: **y** is one of a finite set of values (e.g., sunny, cloudy or rainy)
  - **Regression**: **y** is a number, the learning problem is called regression.

9.3 Learning Decision Trees

9.3 The decision tree representation

A decision tree represents a function that takes as input a vector of attribute values and returns a "decision"—a single output value.

9.3 The decision tree representation

A decision tree reaches its decision by performing a sequence of tests.

- Each internal node: a test of the values of the attribute, A_i
- The branches from the node: the values of the attribute, $A_i = v_{ik}$.
- Each leaf node: a value to be returned by the function.

Expressiveness of decision trees: $Goal \Leftrightarrow (Path_1 \lor Path_2 \lor \cdots)$

9.3 Inducing decision trees from examples

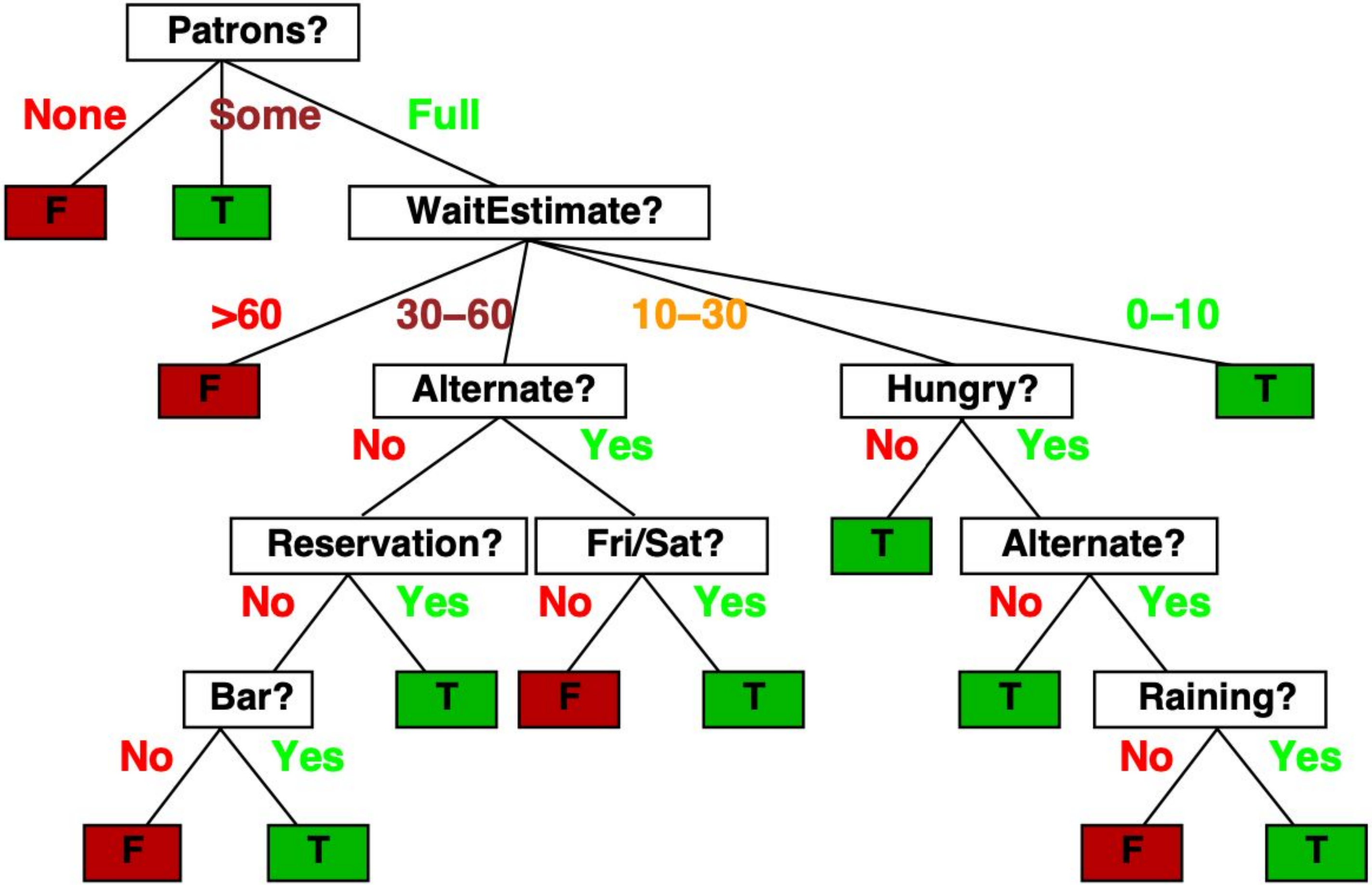
Build a decision tree to decide whether to wait for a table at a restaurant with the following attributes:

1. Alternate: whether there is a suitable alternative restaurant nearby.
2. Bar: whether the restaurant has a comfortable bar area to wait in.
3. Fri/Sat: true on Fridays and Saturdays.
4. Hungry: whether we are hungry.
5. Patrons: how many people are in the restaurant (values are None, Some, and Full).
6. Price: the restaurant's price range ($, $$, $$$).
7. Raining: whether it is raining outside.
8. Reservation: whether we made a reservation.
9. Type: the kind of restaurant (French, Italian, Thai, or burger).
10. WaitEstimate: the wait estimated by the host (0–10 minutes, 10–30, 30–60, or >60).

9.3 Attribute-based representations

Example	Attributes										Target
	Alt	*Bar*	*Fri*	*Hun*	*Pat*	*Price*	*Rain*	*Res*	*Type*	*Est*	*WillWait*
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

9.3 Inducing decision trees from examples



9.3 Decision tree learning

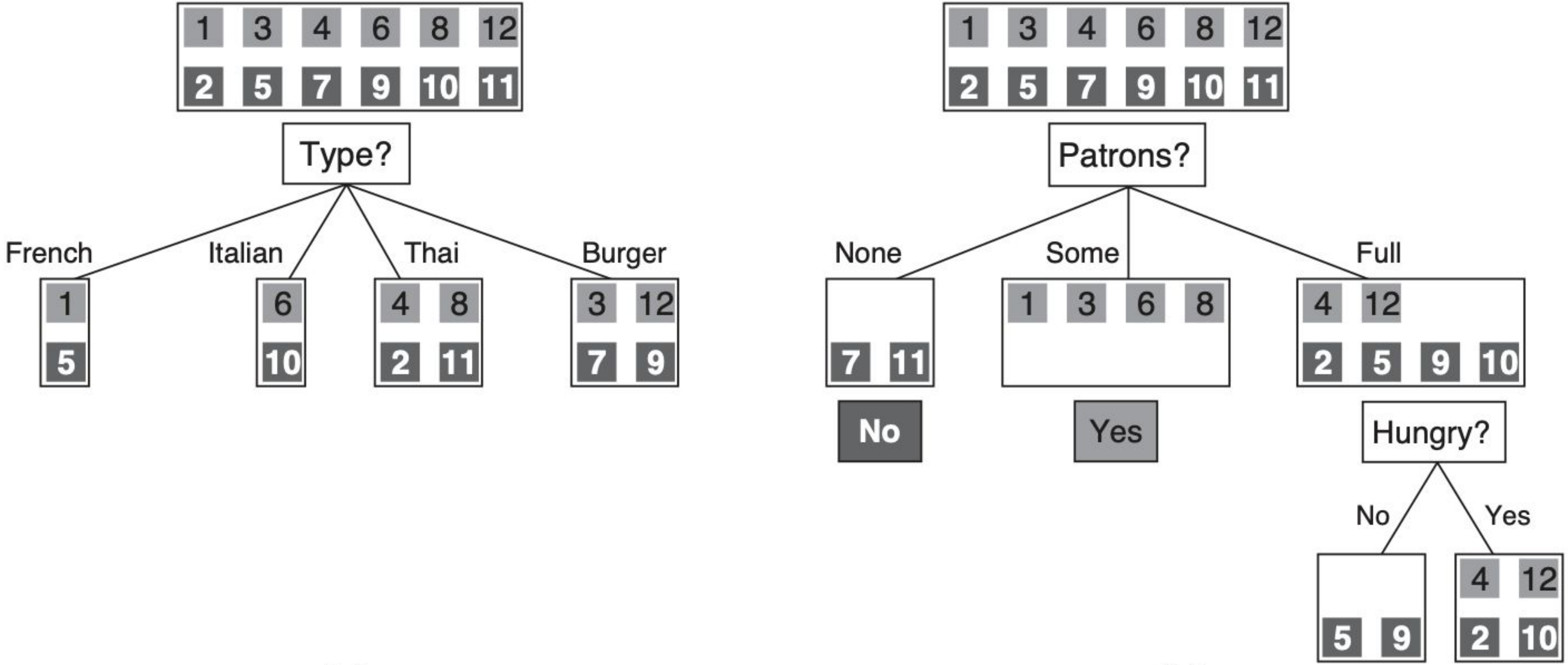
- Aim: find a small tree consistent with the training examples
- Idea: (recursively) choose "most significant" attribute as root of (sub)tree
- PLURALITY-VALUE: selects the most common output value among a set of examples.

function DECISION-TREE-LEARNING(*examples*, *attributes*, *parent_examples*) **returns** a tree

if *examples* is empty **then return** PLURALITY-VALUE(*parent_examples*)
else if all *examples* have the same classification **then return** the classification
else if *attributes* is empty **then return** PLURALITY-VALUE(*examples*)
else
  $A \leftarrow \operatorname{argmax}_{a \in attributes}$ IMPORTANCE(a, *examples*)
  tree ← a new decision tree with root test A
  for each value v_k of A **do**
    $exs \leftarrow \{e : e \in examples$ **and** $e.A = v_k\}$
    subtree ← DECISION-TREE-LEARNING(*exs*, *attributes* − A, *examples*)
    add a branch to *tree* with label $(A = v_k)$ and subtree *subtree*
  return *tree*

9.3 Choosing attribute tests

- Idea: a good attribute splits the examples into subsets that are "all positive" or "all negative"
- Patrons? is a better choice—gives information about the classification



(a) (b)

9.3 Choosing attribute tests

- *The more clueless I am about the answer initially, the more information is contained in the answer*
- Scale: 1 bit = an answer to Boolean question with prior probability $\langle 0.5, 0.5\rangle$
- *Information in an answer* or *entropy of the prior* when prior probability is $\langle P_1, \ldots, P_n\rangle$:

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

9.3 Choosing attribute tests

Suppose we have p positive and n negative examples at the root

⇒ bits needed to classify a new example

$$H(\langle p/(p+n), n/(p+n)\rangle)$$

An attribute splits the examples E into subsets E_i, each E_i has p_i positive and n_i negative examples

⇒ bits needed to classify a new example

$$H(\langle p_i/(p_i+n_i), n_i/(p_i+n_i)\rangle)$$

⇒ expected number of bits per example over all branches:

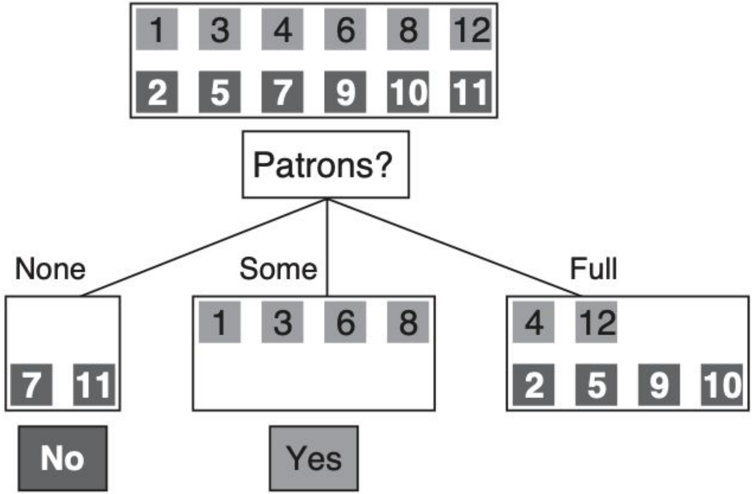
$$\Sigma_i \; \frac{p_i + n_i}{p + n} H(\langle p_i/(p_i + n_i), n_i/(p_i + n_i)\rangle)$$

9.3 Choosing attribute tests

For Patrons?, this is 0.459 bits, for Type this is (still) 1 bit

$\Rightarrow$ choose the attribute that minimizes the remaining information needed

$$\frac{2}{12}H(<0,1>) + \frac{4}{12}H(<1,0>) + \frac{6}{12}H(<\frac{2}{6},\frac{4}{6}>)$$
$$= -\frac{1}{2}(\frac{1}{3}log_2\frac{1}{3} + \frac{2}{3}log_2\frac{2}{3})$$
$$= 0.4591$$

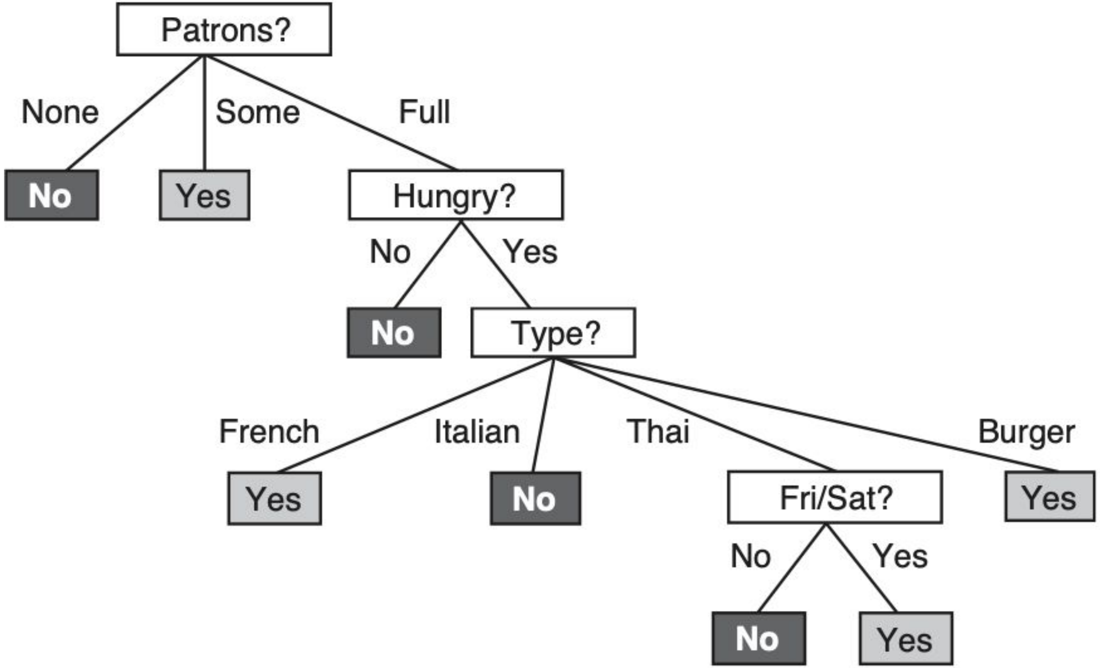


$$\Sigma_i \; \frac{p_i + n_i}{p+n} \; H(\langle p_i/(p_i+n_i), n_i/(p_i+n_i)\rangle)$$

(b)

9.3 Choosing attribute tests

- Decision tree learned from the 12 examples:

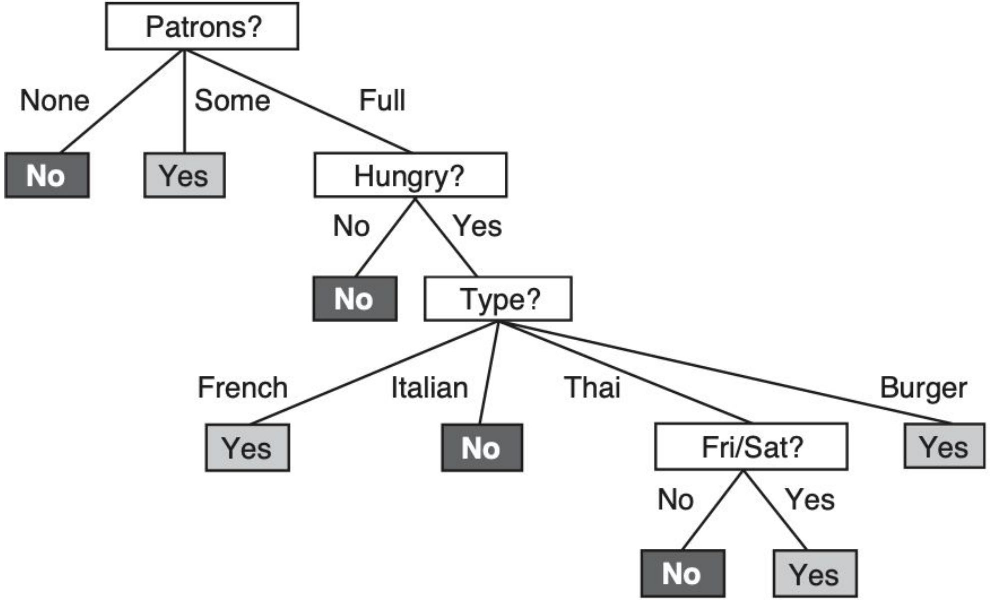


9.3 Choosing attribute tests

- Predict label of new example: X13

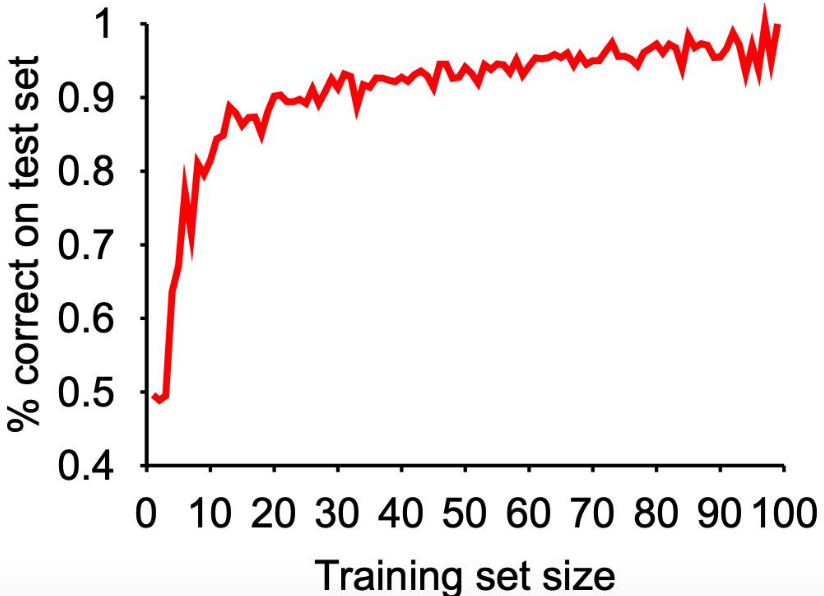
Attributes									
Alt	*Bar*	*Fri*	*Hun*	*Pat*	*Price*	*Rain*	*Res*	*Type*	*Est*

X13 = [T, T, F, F, Full, $$, F, F, Thai, 10-30]



Performance measurement

- How do we know that h ≈ f?
  - Try h on a new test set of examples
  - (use same distribution over example space as training set)
- **Learning curve** = % correct on test set as a function of training set size



9.3 Broadening the applicability of decision trees

- Overfitting: the model corresponds too closely or exactly to a particular set of data, => it fails to fit to additional data or predict future observations
    - For decision trees, a technique called decision tree pruning combats overfitting
- Missing data: not all the attribute values will be known for every example
- Multivalued attributes: an attribute has many possible values
- Continuous and integer-valued input attributes: find the split point that gives the highest information gain

9.4 Evaluating And Choosing The Best Hypothesis

9.4 Evaluating And Choosing The Best Hypothesis

- We want to learn a hypothesis that fits the future data best.
- "Best fit":
  - the **error rate** of a hypothesis:
    - the proportion of mistakes it makes
    - the proportion of times that $h(x) \neq y$ for an (x, y) example.
  - Lowest error rate on a new data

9.4 Evaluating And Choosing The Best Hypothesis

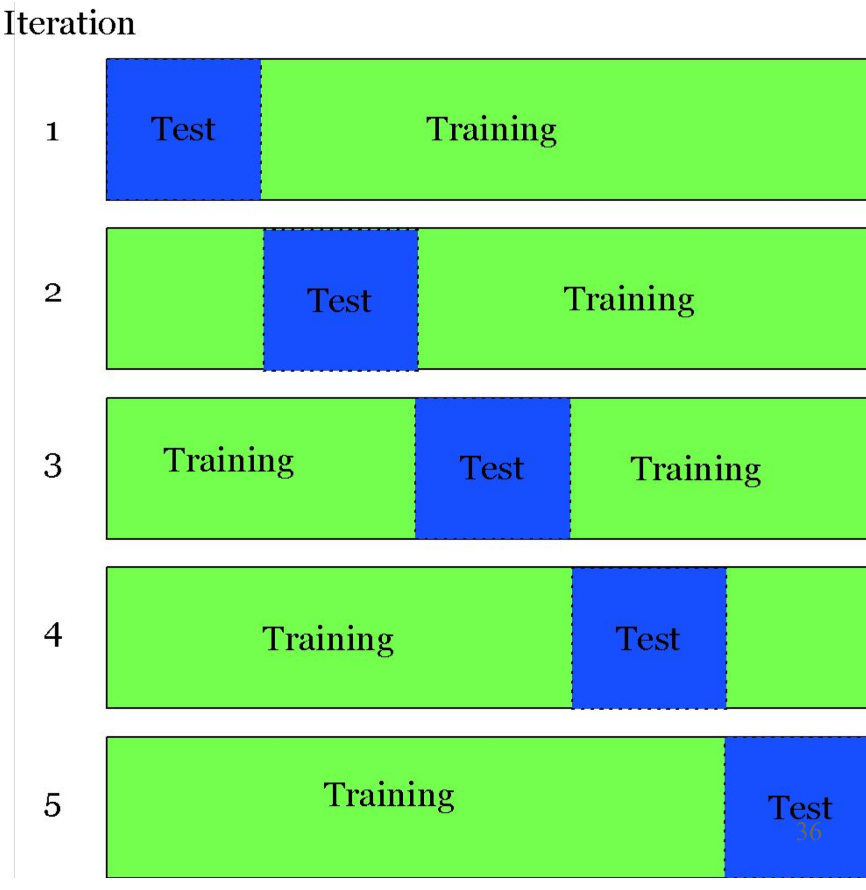
- Rather large number of examples: split examples into 3 sets:
  - training set: train h
  - validation set (development set): choose the best h
  - test set: evaluate h on the unseen data

9.4 Evaluating And Choosing The Best Hypothesis

- Small number of examples: k-fold cross-validation
    - split the data into k equal subsets
    - perform k rounds of learning
    - on each round:
        - $1/k$ of the data is held out as a test set,
        - the remaining examples are used as training data

9.4 Evaluating And Choosing The Best Hypothesis

- Break up data into 10 folds
  - Equal positive and negative inside each fold?
- For each fold
  - Choose the fold as a temporary test set
  - Train on 9 folds, compute performance on the test fold
- Report average performance of the 10 runs



9.4 Model selection

An algorithm to select the model that has the lowest error rate on validation data by

- building models of increasing complexity
- choosing the one with best empirical error rate on validation data.

9.4 From error rates to loss

- It is traditional to express utilities by a loss function.
- The loss function L(x, y, ŷ) is defined as the amount of utility lost by predicting h(x) = ŷ when the correct answer is f(x) = y:

$$
\begin{aligned}
L(x, y, \hat{y}) &= \mathit{Utility}(\text{result of using } y \text{ given an input } x) \\
&- \mathit{Utility}(\text{result of using } \hat{y} \text{ given an input } x)
\end{aligned}
$$

$$
\begin{array}{ll}
\text{Absolute value loss:} & L_1(y, \hat{y}) = |y - \hat{y}| \\
\text{Squared error loss:} & L_2(y, \hat{y}) = (y - \hat{y})^2 \\
\text{0/1 loss:} & L_{0/1}(y, \hat{y}) = 0 \text{ if } y = \hat{y}, \text{ else } 1
\end{array}
$$

NONPARAMETRIC MODELS

NONPARAMETRIC MODELS

- A learning model that summarizes data with a set of parameters of fixed size (independent of the number of training examples) is called a **parametric model**.
- A **nonparametric model** is one that cannot be characterized by a bounded set of parameters.

Nearest neighbor models

- Given a query x_q , find the k examples that are nearest to x_q.
- $NN(k, x_q)$ to denote the set of k nearest neighbors.
- Classification:
  - find $NN(k, x_q)$
  - take the plurality vote of the neighbors
- Regression
  - find $NN(k, x_q)$
  - take the mean or median of the k neighbors
- 5-nearest-neighbors decision boundary is good; higher k would underfit.
- Cross-validation can be used to select the best value of k.

Nearest neighbor models

- Distance metric:

  Minkowski distance or L^p norm

$$L^p(\mathbf{x}_j, \mathbf{x}_q) = (\sum_i |x_{j,i} - x_{q,i}|^p)^{1/p}$$

With $p = 2$ this is Euclidean distance and with $p = 1$ it is Manhattan distance

$(|x_{11} - x_{21}|^2 + |x_{12} - x_{22}|^2)^{½}$

$(|x_{11} - x_{21}|^1 + |x_{12} - x_{22}|^1)^1$

d(A, B)

$((x_A - x_B)^2 + (y_A - y_B)^2)^{1/2}$

Nearest neighbor models

- Low-dimensional spaces with plenty of data, nearest neighbors works very well.
- High-dimensional spaces: the nearest neighbors are usually not very near!
- kNN algorithm:
  - Input: given a set of N examples and a query x_q,
  - Output: NN (k, x_q)
  - kNN algorithm:
    - iterate through the examples
      - measure the distance to xq from each one
    - keep the best k.

Nearest neighbor models

- Predict label of new example: X13

Attributes									
Alt	*Bar*	*Fri*	*Hun*	*Pat*	*Price*	*Rain*	*Res*	*Type*	*Est*

X13 = [T, T, F, F, Full, $$, F, F, Thai, 10-30]

Fri={F:0, T:1}; Hun = {F:0, T:1}; Pat = {0:Full, 1:None, 2:Some};

Type={0:Burger, 1:French, 2:Italy, 3:Thai}

Example	Attributes										Target
	Alt	*Bar*	*Fri*	*Hun*	*Pat*	*Price*	*Rain*	*Res*	*Type*	*Est*	*WillWait*
X_1	T	F	F	T	Some	$$$	F	T	French	0–10	T

$L^2(X_{13}, X_1) = (|0-0|^2 + |0-1|^2 + |0-2|^2 + |3-1|^2)^{1/2} = 3$

$L^2(X_{13}, X_2)$

Naive Bayes models

Naive Bayes models

- Naive Bayes is a probabilistic classifier
- Given a document d, out of all classes c ∈ C, the classifier returns the class ĉ which has the maximum posterior probability given the document.

$$\hat{c} = \underset{c \in C}{\operatorname{argmax}} P(c|d)$$

Naive Bayes models

$$\hat{c} = \underset{c \in C}{\operatorname{argmax}} P(c|d)$$

$$\hat{c} = \underset{c \in C}{\operatorname{argmax}} P(c|d) = \underset{c \in C}{\operatorname{argmax}} \frac{P(d|c)P(c)}{P(d)}$$

$$\hat{c} = \underset{c \in C}{\operatorname{argmax}} P(c|d) = \underset{c \in C}{\operatorname{argmax}} P(d|c)P(c)$$

Naive Bayes models

Without loss of generality, we can represent a document d as a set of features f_1, f_2,..., f_n:

$$\hat{c} = \underset{c \in C}{\operatorname{argmax}} P(c|d) = \underset{c \in C}{\operatorname{argmax}} P(d|c)P(c)$$

$$\hat{c} = \underset{c \in C}{\operatorname{argmax}} \overbrace{P(f_1, f_2, \ldots, f_n|c)}^{\text{likelihood}} \; \overbrace{P(c)}^{\text{prior}}$$

Naive Bayes models

- 1st assumption: position doesn't matter.
- 2nd assumption, Naive Bayes assumption: this is the conditional independence assumption that the probabilities $P(f_i|c)$ are independent given the class c

$$\hat{c} = \underset{c \in C}{\operatorname{argmax}} \overbrace{P(f_1, f_2, \ldots, f_n|c)}^{\text{likelihood}} \; \overbrace{P(c)}^{\text{prior}}$$

$$c_{NB} = \underset{c \in C}{\operatorname{argmax}} P(c) \prod_{f \in F} P(f|c)$$

Naive Bayes models

- Apply the naive Bayes classifier to text, each word in the documents as a feature

$$c_{NB} = \underset{c \in C}{\operatorname{argmax}} P(c) \prod_{f \in F} P(f|c)$$

$$c_{NB} = \underset{c \in C}{\operatorname{argmax}} P(c) \prod_{i \in positions} P(w_i|c)$$

Boolean Multinomial Naïve Bayes: Learning

- Calculate $P(c_j)$ terms
  - For each c_j in C do

    $docs_j \leftarrow$ all docs with class $=c_j$

$$P(c_j) \leftarrow \frac{|docs_j|}{|\text{total \# documents}|}$$

- From training corpus, extract *Vocabulary*

  Remove duplicates in each doc:

  For each word type w in doc_j

  Retain only a single instance of w

Boolean Multinomial Naïve Bayes: Learning

- Calculate $P(w_k \mid c_j)$ terms

  $Text_j \leftarrow$ single doc containing all $docs_j$

  For each word w_k in *Vocabulary*

  $n_k \leftarrow$ # of occurrences of w_k in $Text_j$

$$P(w_k \mid c_j) \leftarrow \frac{n_k + \alpha}{n + \alpha \mid Vocabulary \mid}$$

Boolean Multinomial Naïve Bayes: Testing

- First remove all duplicate words from *d*
- Then compute NB using the same equation:

$$c_{NB} = \underset{c_j \in C}{\operatorname{argmax}} P(c_j) \prod_{i \in positions} P(w_i \mid c_j)$$

Let's do a worked sentiment example!

	Cat	Documents
Training	-	just plain boring
	-	entirely predictable and lacks energy
	-	no surprises and very few laughs
	+	very powerful
	+	the most fun film of the summer
Test	?	predictable with no fun

An Example with add-1 smoothing

	Cat	Documents
Training	-	just plain boring
	-	entirely predictable and lacks energy
	-	no surprises and very few laughs
	+	very powerful
	+	the most fun film of the summer
Test	?	predictable ~~with~~ no fun

1. Prior from training:

$$\hat{P}(c_j) = \frac{N_{c_j}}{N_{total}}$$

P(-) = 3/5
P(+) = 2/5

2. Drop "with"

An Example with add-1 smoothing

	Cat	Documents
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	-	no surprises and very few laughs
	+	very powerful
	+	the most fun film of the summer
Test	?	predictable ~~with~~ no fun

3. Likelihoods from training:

$$p(w_i|c) = \frac{count(w_i, c) + 1}{(\sum_{w \in V} count(w, c)) + |V|}$$

$$P(\text{“predictable”}|-) = \frac{1+1}{14+20} \qquad P(\text{“predictable”}|+) = \frac{0+1}{9+20}$$

$$P(\text{“no”}|-) = \frac{1+1}{14+20} \qquad P(\text{“no”}|+) = \frac{0+1}{9+20}$$

$$P(\text{“fun”}|-) = \frac{0+1}{14+20} \qquad P(\text{“fun”}|+) = \frac{1+1}{9+20}$$

An Example with add-1 smoothing

	Cat	Documents
Training	-	just plain boring
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4. Scoring the test set:

$$\boxed{P(-)P(S|-) = \frac{3}{5} \times \frac{2 \times 2 \times 1}{34^3} = 6.1 \times 10^{-5}}$$

$$P(+)P(S|+) = \frac{2}{5} \times \frac{1 \times 1 \times 2}{29^3} = 3.2 \times 10^{-5}$$

Example	Attributes										Target
	Alt	*Bar*	*Fri*	*Hun*	*Pat*	*Price*	*Rain*	*Res*	*Type*	*Est*	*WillWait*
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

X13 = [T, T, F, F, Full, $$, F, F, Thai, 10-30]