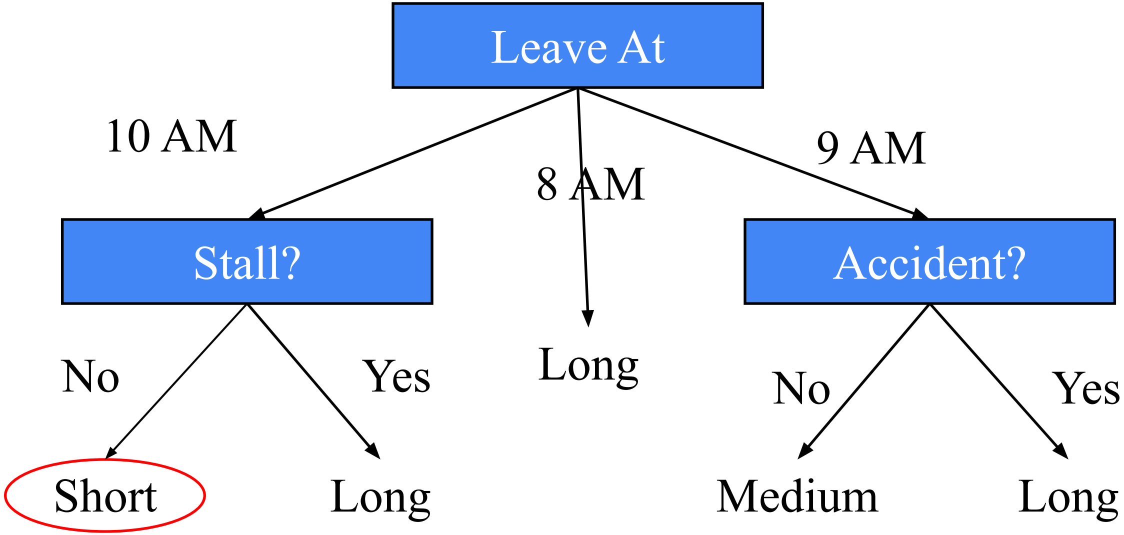
Decision Tree

Sample Experience Table

Example	Attributes				Target
	Hour	Weather	Accident	Stall	Commute
D1	8 AM	Sunny	No	No	Long
D2	8 AM	Cloudy	No	Yes	Long
D3	10 AM	Sunny	No	No	Short
D4	9 AM	Rainy	Yes	No	Long
D5	9 AM	Sunny	Yes	Yes	Long
D6	10 AM	Sunny	No	No	Short
D7	10 AM	Cloudy	No	No	Short
D8	9 AM	Rainy	No	No	Medium
D9	9 AM	Sunny	Yes	No	Long
D10	10 AM	Cloudy	Yes	Yes	Long
D11	10 AM	Rainy	No	No	Short
D12	8 AM	Cloudy	Yes	No	Long
D13	9 AM	Sunny	No	No	Medium

Predicting Commute Time



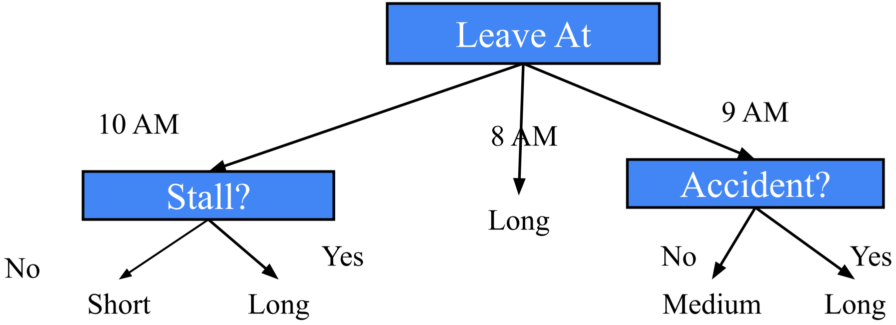
If we leave at 10 AM and there are no cars stalled on the road, what will our commute time be?

Choosing Attributes

- The previous experience decision table showed 4 attributes: hour, weather, accident and stall
- But the decision tree only showed 3 attributes: hour, accident and stall
- Why is that?
- Methods for selecting attributes (which will be described later) show that weather is not a discriminating attribute

Identifying the Best Attributes

- Refer back to our original decision tree

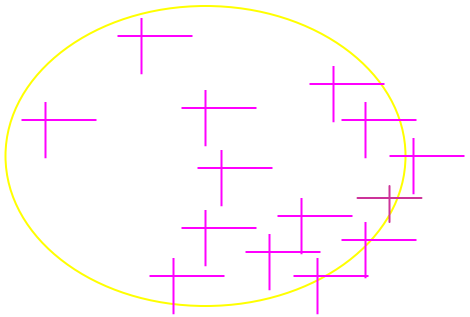


- How did we know to split on *leave at* and then on *stall* and *accident* and not *weather*?

Entropy

- Calculation of entropy
  - $Entropy(S) = \sum_{(i=1 \text{ to } l)} -|S_i|/|S| * \log_2(|S_i|/|S|)$
    - S = set of examples
    - S_i = subset of S with value v_i under the target attribute
    - l = size of the range of the target attribute

Entropy: a common way to measure impurity



- Entropy = $$\sum_i - p_i \log_2 p_i$$

  p_i is the probability of class i
  Compute it as the proportion of class i in the set.

  16/30 are green circles; 14/30 are pink crosses
  $\log_2(16/30) = -.9$; $\log_2(14/30) = -1.1$
  Entropy = $-(16/30)(-.9) - (14/30)(-1.1) = .99$

- Entropy comes from information theory. The higher the entropy the more the information content.

What does that mean for learning from examples?

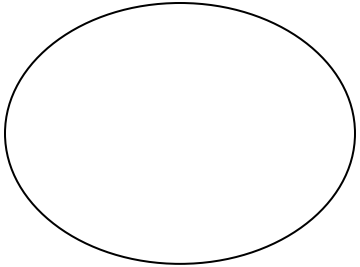
- What is the entropy of a group in which all examples belong to the same class?
  - entropy = - 1 $\log_2 1$ = 0

not a good training set for learning

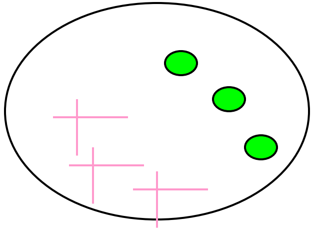
- What is the entropy of a group with 50% in either class?
  - entropy = -0.5 $\log_2 0.5$ – 0.5 $\log_2 0.5$ =1

good training set for learning

Minimum impurity



Maximum impurity

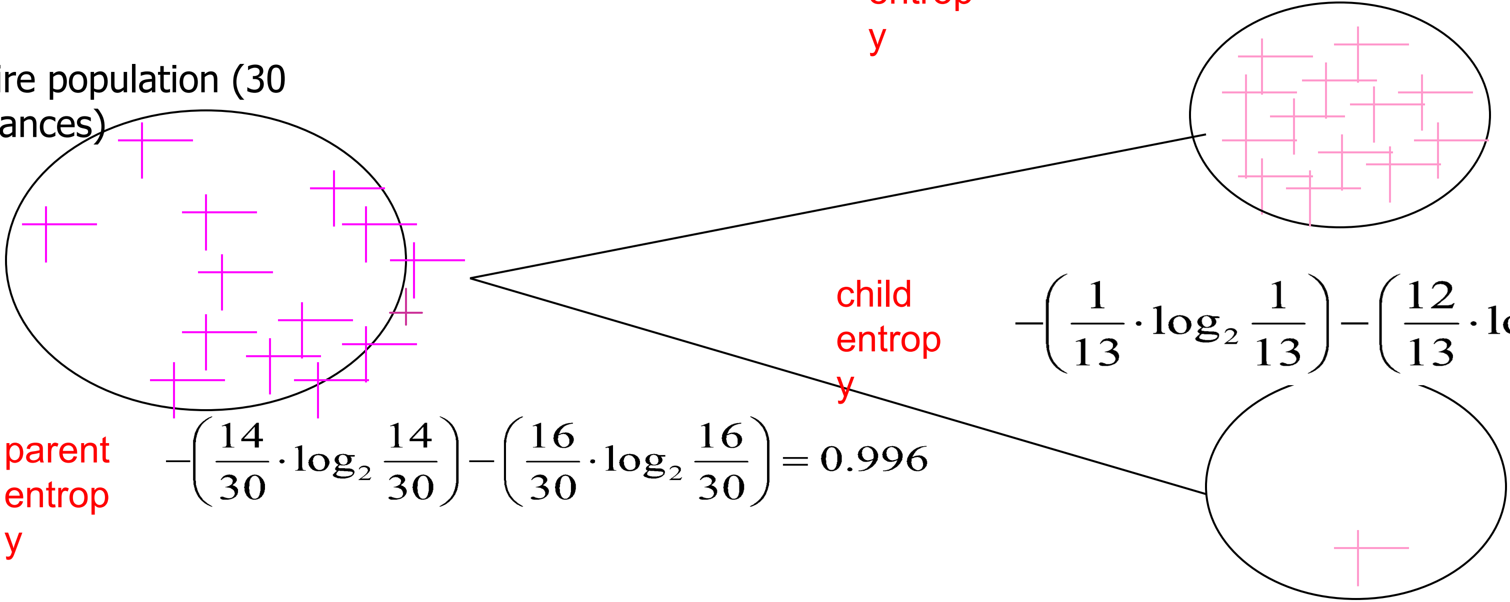


- We want to determine which attribute in a given set of training feature vectors is most useful for discriminating between the classes to be learned.
- Information gain tells us how important a given attribute of the feature vectors is.
- We will use it to decide the ordering of attributes in the nodes of a decision tree.

Calculating Information Gain

Information Gain = entropy(parent) – [average entropy(children)]

Entire population (30 instances)



child entropy

$$-\left(\frac{13}{17}\cdot\log_2\frac{13}{17}\right)-\left(\frac{4}{17}\cdot\log_2\frac{4}{17}\right)=0.787$$

17 instances

child entropy

$$-\left(\frac{1}{13}\cdot\log_2\frac{1}{13}\right)-\left(\frac{12}{13}\cdot\log_2\frac{12}{13}\right)=0.391$$

13 instances

parent entropy

$$-\left(\frac{14}{30}\cdot\log_2\frac{14}{30}\right)-\left(\frac{16}{30}\cdot\log_2\frac{16}{30}\right)=0.996$$

(Weighted) Average Entropy of Children =

$$\left(\frac{17}{30}\cdot 0.787\right)+\left(\frac{13}{30}\cdot 0.391\right)=0.615$$

Information Gain= 0.996 - 0.615 = 0.38 **for this split**

ID3

- Given our commute time sample set, we can calculate the entropy of each attribute at the root node

Attribute	Expected Entropy	Information Gain
Hour	0.6511	0.768449
Weather	1.28884	0.130719
Accident	0.92307	0.496479
Stall	1.17071	0.248842