Decision Trees

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Overview

- What is a Decision Tree
- Sample Decision Trees
- How to Construct a Decision Tree
- Problems with Decision Trees
- Decision Trees in Gaming
- Summary

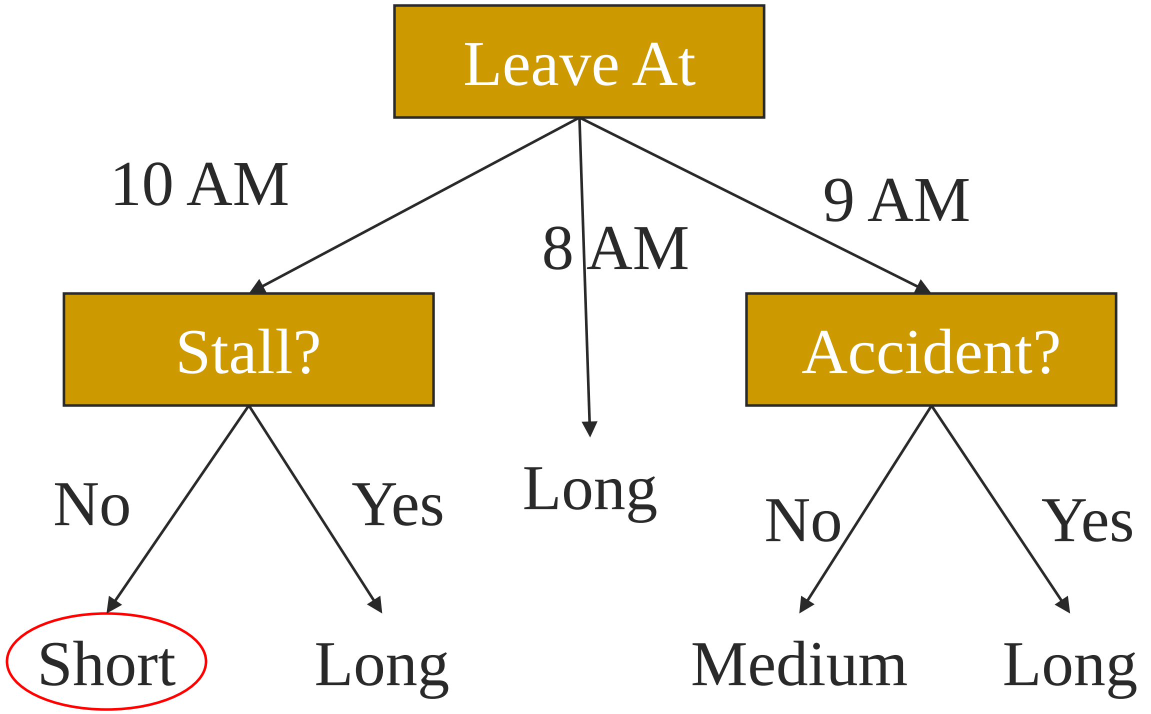
What is a Decision Tree?

- An *inductive learning task*
  - Use particular facts to make more generalized conclusions

- A predictive model based on a branching series of Boolean tests
  - These smaller Boolean tests are less complex than a one-stage classifier

- Let’s look at a sample decision tree…

Predicting Commute Time



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

Inductive Learning

- In this decision tree, we made a series of Boolean decisions and followed the corresponding branch
  - Did we leave at 10 AM?
  - Did a car stall on the road?
  - Is there an accident on the road?

- By answering each of these yes/no questions, we then came to a conclusion on how long our commute might take

Decision Trees as Rules

- We did not have represent this tree graphically

- We could have represented as a set of rules. However, this may be much harder to read…

Decision Tree as a Rule Set

```
if hour == 8am
    commute time = long
else if hour == 9am
    if accident == yes
        commute time = long
    else
        commute time = medium
else if hour == 10am
    if stall == yes
        commute time = long
    else
        commute time = short
```

- Notice that all attributes to not have to be used in each path of the decision.
- As we will see, all attributes may not even appear in the tree.

How to Create a Decision Tree

- We first make a list of attributes that we can measure
  - These attributes (for now) must be discrete
- We then choose a *target attribute* that we want to predict
- Then create an *experience table* that lists what we have seen in the past

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

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?

Choosing Attributes

- Methods for selecting attributes (which will be described later) show that weather is not a discriminating attribute
- We use the principle of *Occam's Razor*: Given a number of competing hypotheses, the simplest one is preferable

Choosing Attributes

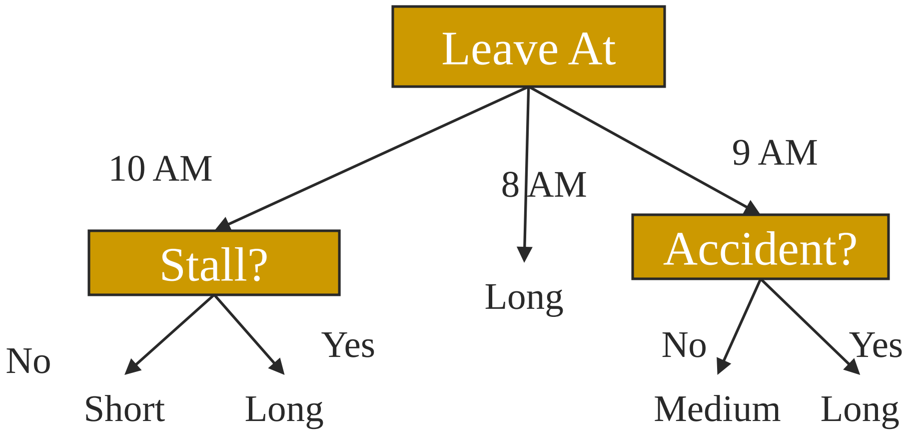
- The basic structure of creating a decision tree is the same for most decision tree algorithms
- The difference lies in how we select the attributes for the tree
- We will focus on the ID3 algorithm developed by Ross Quinlan in 1975

Decision Tree Algorithms

- The basic idea behind any decision tree algorithm is as follows:
  - Choose the *best* attribute(s) to split the remaining instances and make that attribute a decision node
  - Repeat this process for recursively for each child
  - Stop when:
    - All the instances have the same target attribute value
    - There are no more attributes
    - There are no more instances

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?

ID3 Heuristic

- To determine the best attribute, we look at the ID3 heuristic
- ID3 splits attributes based on their *entropy*.
- Entropy is the measure of disinformation…

Entropy

- Entropy is minimized when all values of the target attribute are the same.
  - If we know that commute time will always be *short*, then entropy = 0
- Entropy is maximized when there is an equal chance of all values for the target attribute (i.e. the result is random)
  - If commute time = short in 3 instances, medium in 3 instances and long in 3 instances, entropy is maximized

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

ID3

- ID3 splits on attributes with the lowest entropy
- We calculate the entropy for all values of an attribute as the weighted sum of subset entropies as follows:
  - $\sum_{(i = 1 \text{ to } k)} |S_i|/|S| \text{ Entropy}(S_i)$, where k is the range of the attribute we are testing
- We can also measure information gain (which is inversely proportional to entropy) as follows:
  - $\text{Entropy}(S) - \sum_{(i = 1 \text{ to } k)} |S_i|/|S| \text{ Entropy}(S_i)$

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

Pruning Trees

- There is another technique for reducing the number of attributes used in a tree - *pruning*
- Two types of pruning:
  - Pre-pruning (forward pruning)
  - Post-pruning (backward pruning)

Prepruning

- In prepruning, we decide during the building process when to stop adding attributes (possibly based on their information gain)

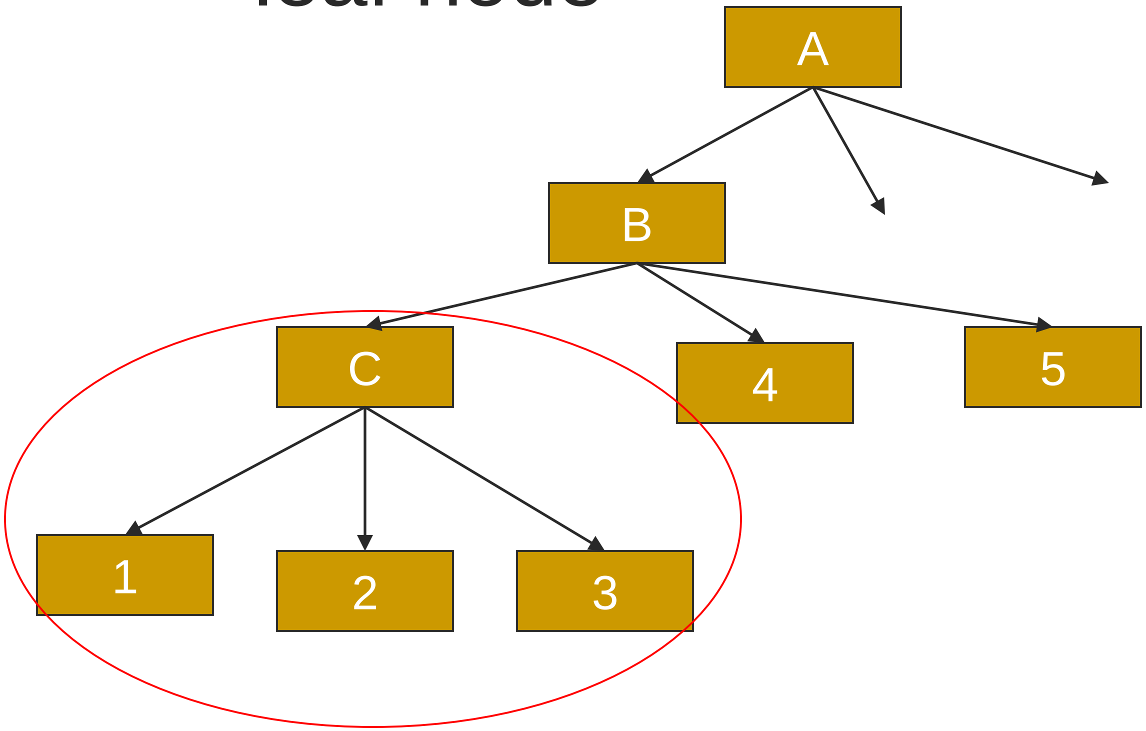
- However, this may be problematic – Why?
  - Sometimes attributes individually do not contribute much to a decision, but combined, they may have a significant impact

Postpruning

- Postpruning waits until the full decision tree has built and then prunes the attributes
- Two techniques:
  - Subtree Replacement
  - Subtree Raising

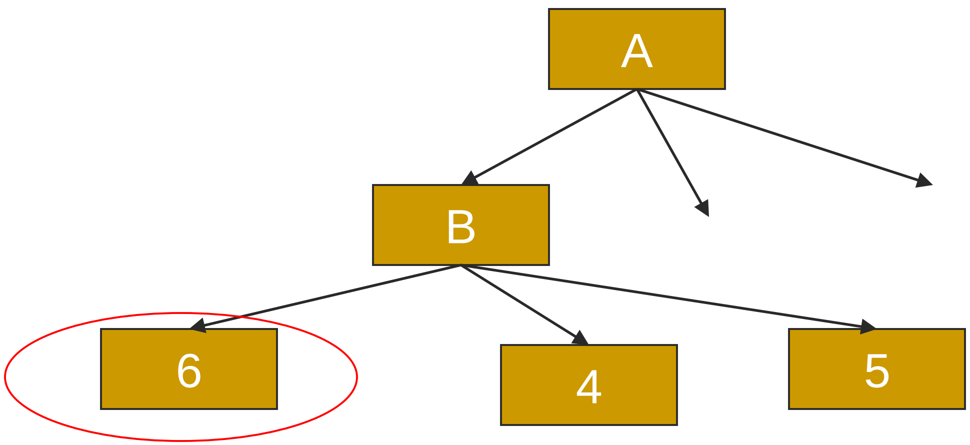
Subtree Replacement

- Entire subtree is replaced by a single leaf node



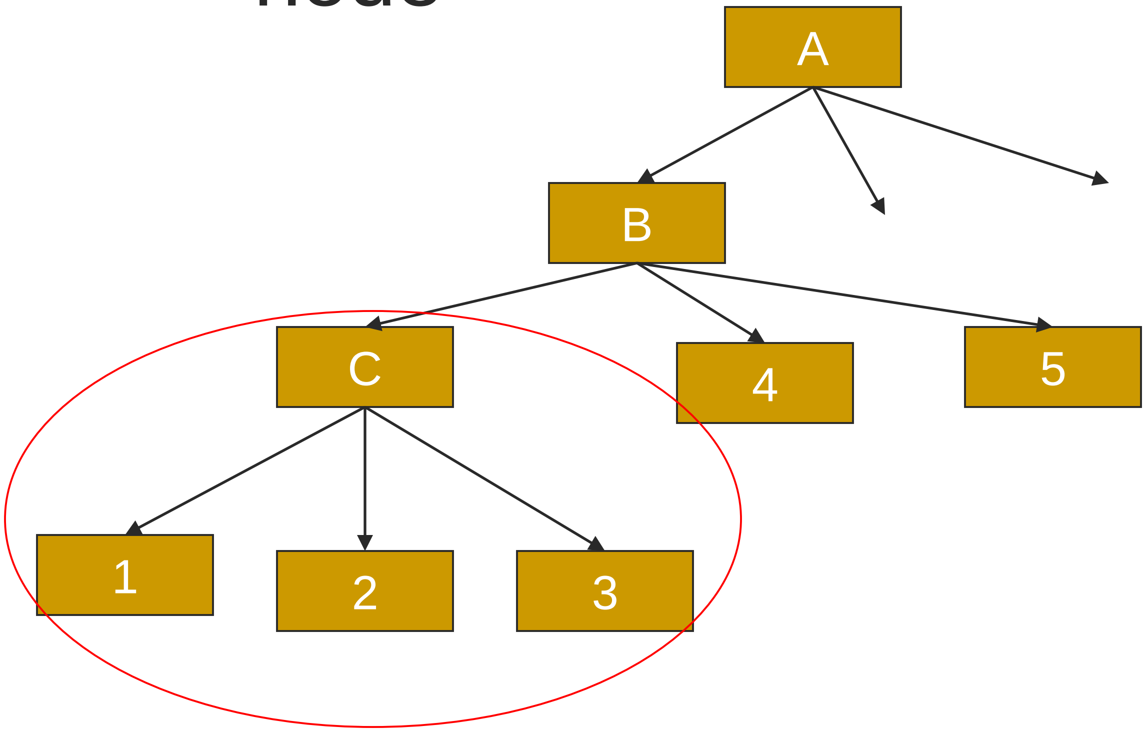
Subtree Replacement

- Node 6 replaced the subtree
- Generalizes tree a little more, but may increase accuracy



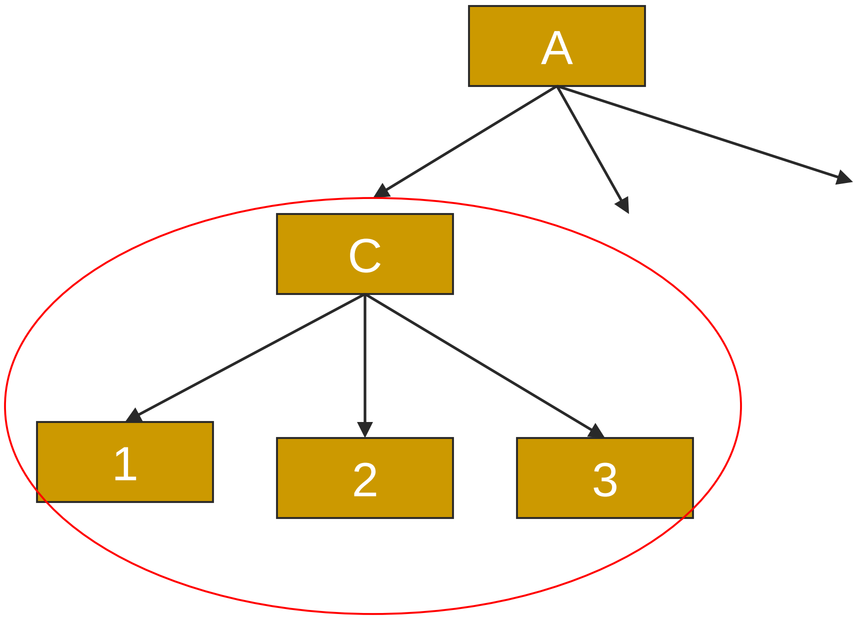
Subtree Raising

- Entire subtree is raised onto another node



Subtree Raising

- Entire subtree is raised onto another node
- This was not discussed in detail as it is not clear whether this is really worthwhile (as it is very time consuming)



Problems with ID3

- ID3 is not optimal
  - Uses *expected* entropy reduction, not actual reduction
- Must use discrete (or discretized) attributes
  - What if we left for work at 9:30 AM?
  - We could break down the attributes into smaller values…

Problems with Decision Trees

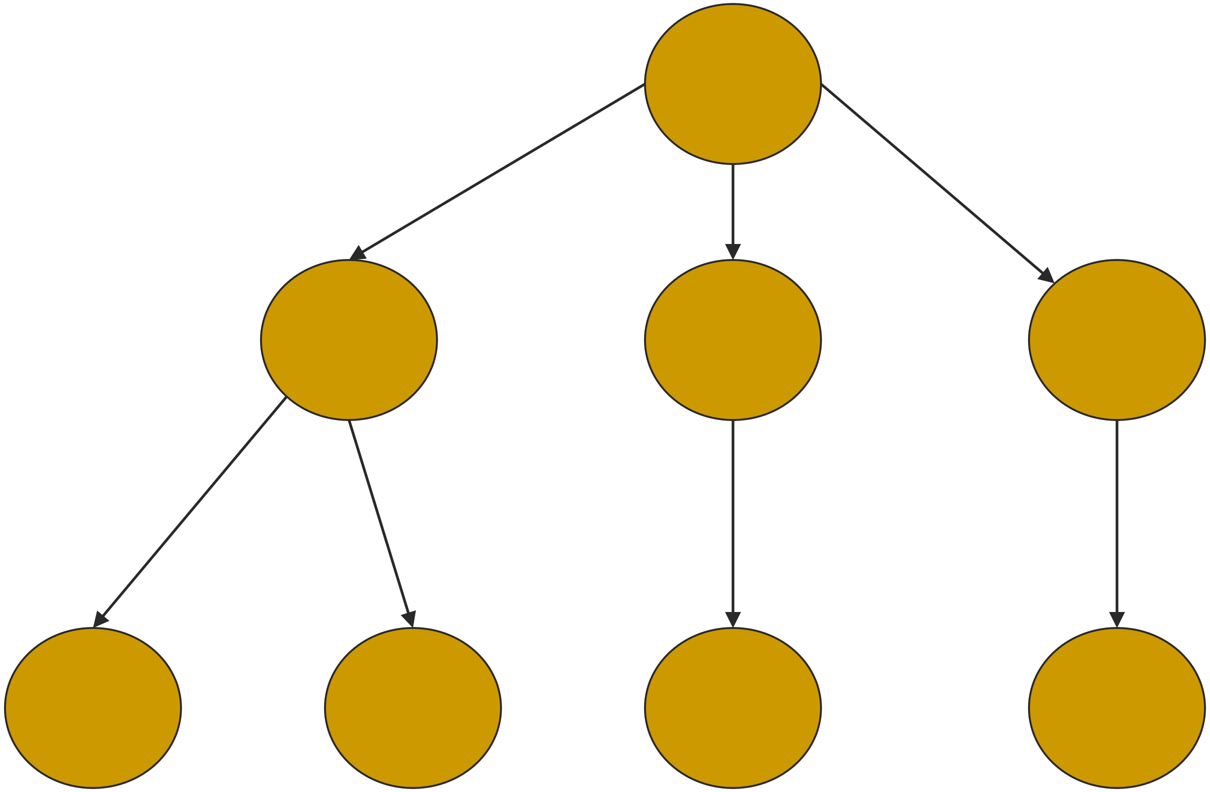
- While decision trees classify quickly, the time for building a tree may be higher than another type of classifier

- Decision trees suffer from a problem of errors propagating throughout a tree
  - A very serious problem as the number of classes increases

Error Propagation

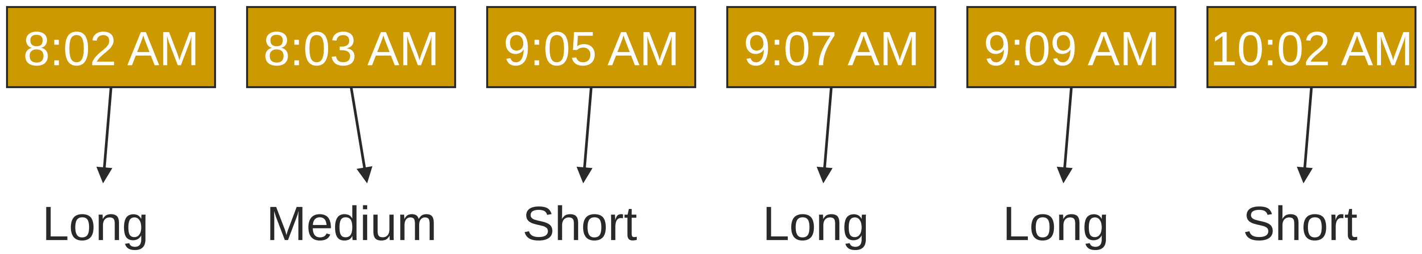
- Since decision trees work by a series of local decisions, what happens when one of these local decisions is wrong?
  - Every decision from that point on may be wrong
  - We may never return to the correct path of the tree

Error Propagation Example



Problems with ID3

- If we broke down leave time to the minute, we might get something like this:



Since entropy is very low for each branch, we have n branches with n leaves. This would not be helpful for predictive modeling.

Problems with ID3

- We can use a technique known as discretization
- We choose *cut points*, such as 9AM for splitting continuous attributes
- These cut points generally lie in a subset of *boundary points*, such that a boundary point is where two adjacent instances in a sorted list have different target value attributes

Problems with ID3

- Consider the attribute commute time

8:00 (L), 8:02 (L) | 8:07 (M), | 9:00 (S), 9:20 (S), 9:25 (S), 10:00 (S), | 10:02 (M)

When we split on these attributes, we increase the entropy so we don’t have a decision tree with the same number of cut points as leaves

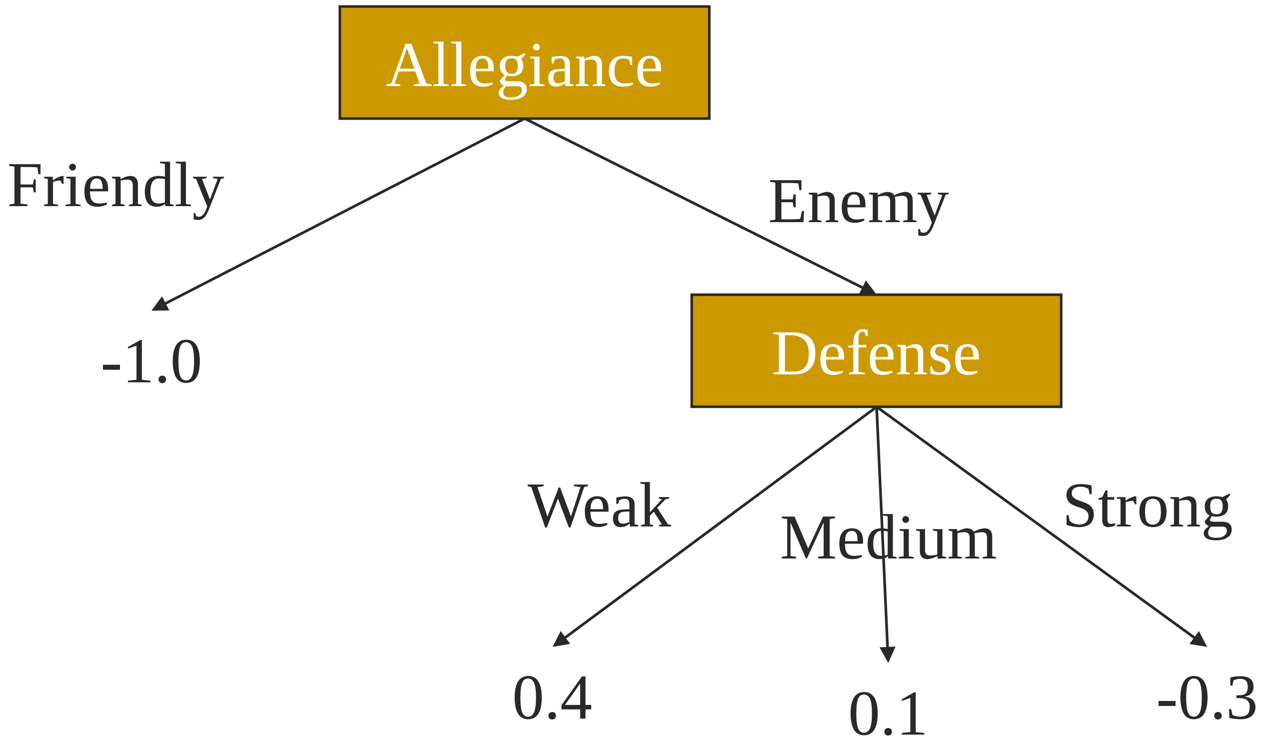
ID3 in Gaming

- Black & White, developed by Lionhead Studios, and released in 2001 used ID3
- Used to predict a player's reaction to a certain creature's action
- In this model, a greater feedback value means the creature should attack

ID3 in Black & White

Example	Attributes			Target
	Allegiance	Defense	Tribe	Feedback
D1	Friendly	Weak	Celtic	-1.0
D2	Enemy	Weak	Celtic	0.4
D3	Friendly	Strong	Norse	-1.0
D4	Enemy	Strong	Norse	-0.2
D5	Friendly	Weak	Greek	-1.0
D6	Enemy	Medium	Greek	0.2
D7	Enemy	Strong	Greek	-0.4
D8	Enemy	Medium	Aztec	0.0
D9	Friendly	Weak	Aztec	-1.0

ID3 in Black & White



Note that this decision tree does not even use the *tribe* attribute

ID3 in Black & White

- Now suppose we don't want the entire decision tree, but we just want the 2 highest feedback values
- We can create a Boolean expressions, such as
  - ((Allegiance = Enemy) ^ (Defense = Weak)) v ((Allegiance = Enemy) ^ (Defense = Medium))

Summary

- Decision trees can be used to help predict the future
- The trees are easy to understand
- Decision trees work more efficiently with discrete attributes
- The trees may suffer from error propagation