“A good decision is based on knowledge and not on numbers.” – Plato

“Once you make a decision, the universe conspires to make it happen.” – Ralph Waldo Emerson

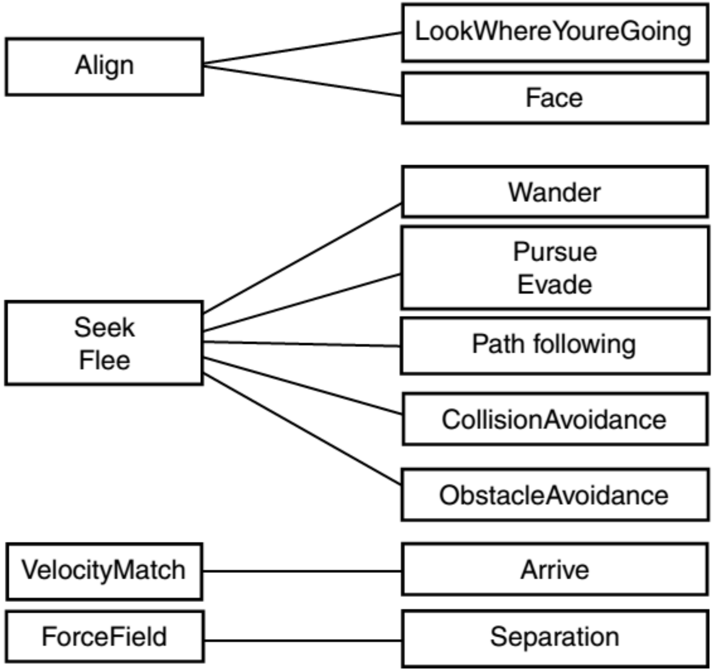
“The quality of decision is like the well-timed swoop of a falcon which enables it to strike and destroy its victim.” – Sun Tzu

Class N-3

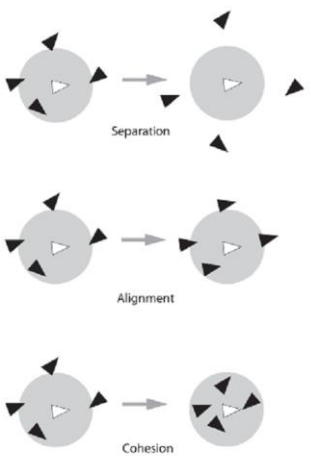
1. When might you precompute paths?
2. This is a single-source, multi-target shortest path algorithm for arbitrary directed graphs with non-negative weights. Question?
3. This is a all-pairs shortest path algorithm.
4. How can a designer allow static paths in a dynamic environment?
5. When will we typically use heuristic search?
6. What is an admissible heuristic?
7. When/Why might we use hierarchical pathing?
8. Does path smoothing work with hierarchical?
9. How might we combat fog-of-war?

Class N-2

1. Steering vs flocking?
2. Steering Family Tree
3. How might we combine behaviors?
4. What three steering mechanisms enable flocking?



Millington Fig 3.29



Buckland Fig 3.16

Class N-1

1. How can we describe decision making?
2. What makes FSMs so attractive?
3. What might make us not choose an FSM?
4. Two drawbacks of FSMs, and how to fix?
5. What are the performance dimensions we tend to assess?
6. What are two methods we discussed to learn about changes in the world state?

OOB

- Decision Making: f(knowledge) → action
  - N+2: Planning
  - N+1: Rule-based Agents, Fuzzy, Markov
  - N-0: Decision & Behavior Trees (M Ch5.2, 5.4)
  - N-1: FSMs
  - N-2: Steering
  - N-3: Graphs, Search, and Movement

Decision Making: Trees

2016-06-07

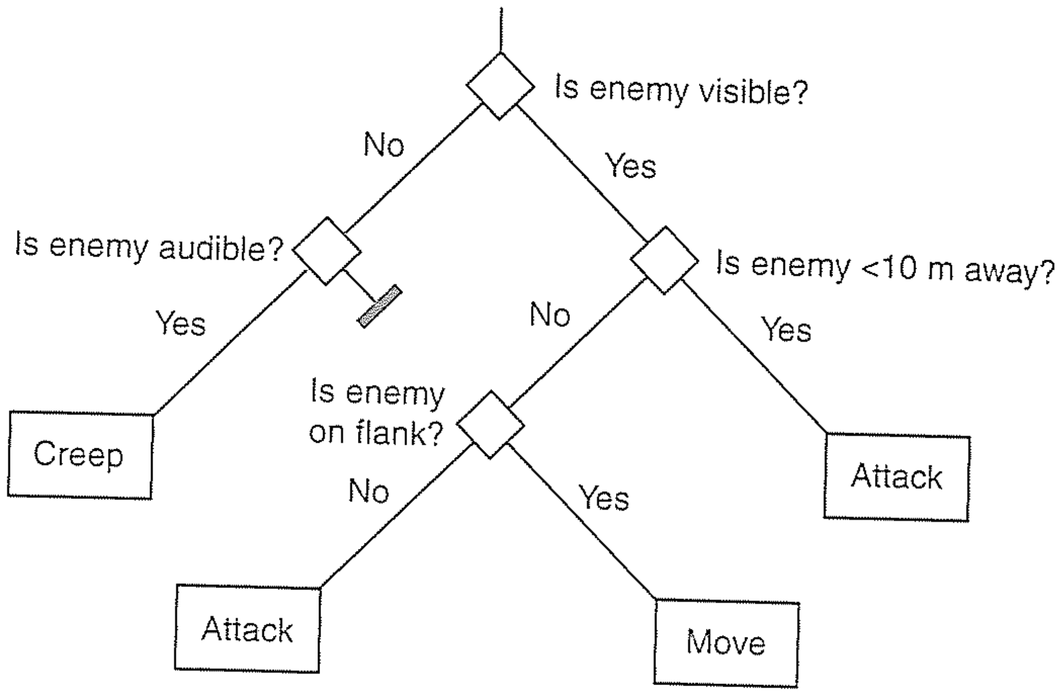
DECISION TREES (M CH 5.2)

Decision Trees

- Fast, simple, easily implemented, easy to grok
- Modular
- Simplest decision making technique
- Used extensively to control
  - Characters
  - In-game decision making (eg animation)
- Can be learned (rare in games)
  - Learned tree still easy to grok

D-Tree Structure

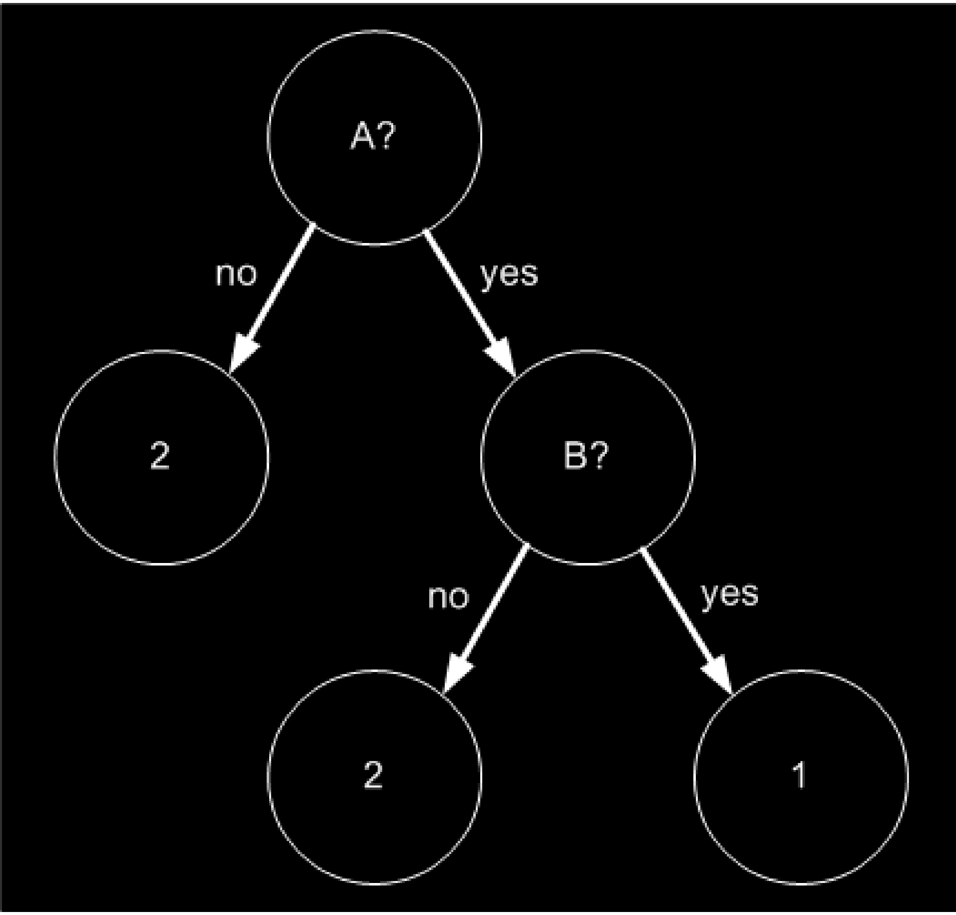
- Dtree made of connected decision points
  - root == starting decision
  - leaves == actions
- For each decision, one of 2+ options is selected
- Typically use global game state

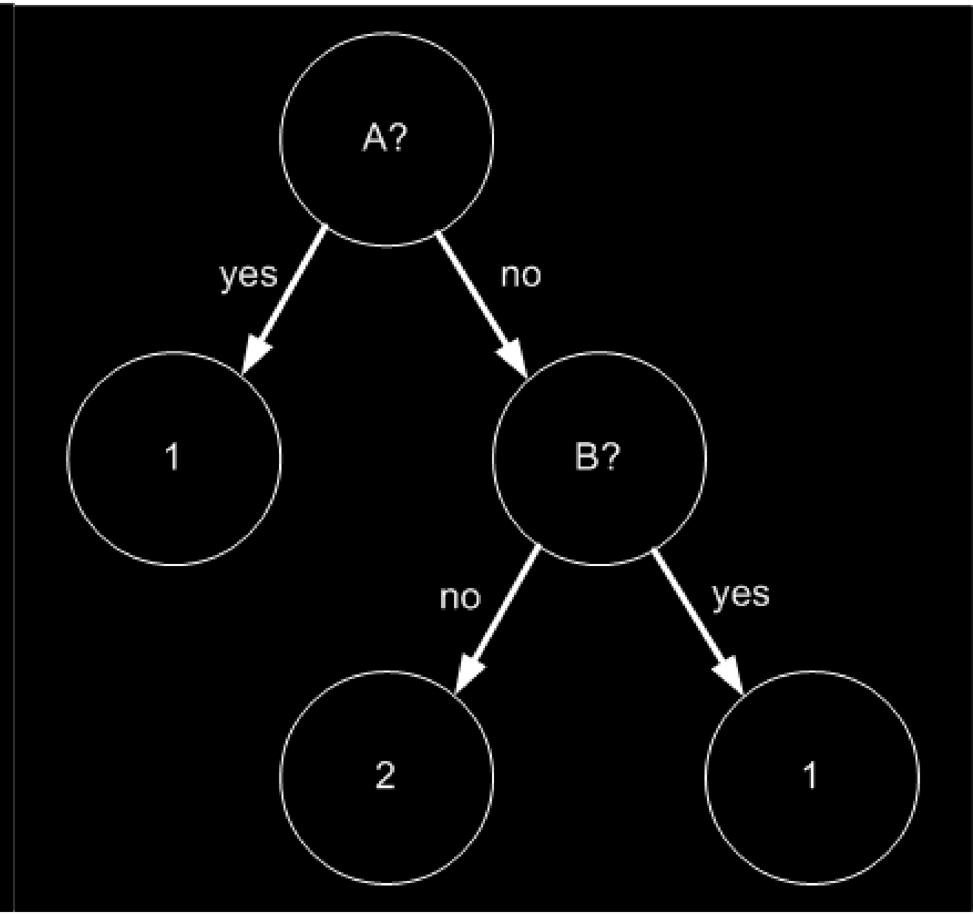


Decisions

- Can be of multiple types
  - Boolean
  - Enumeration
  - Numeric range
  - etc.
- No explicit AND or OR, but representable
  - Tree structure represents combinations

AND / OR in D-Tree





Branching

- N-ary trees
  - Usually ends up as if/then statements
  - Can be faster if using enums w/ array access
  - Speedup often marginal & not worth the effort
- Binary trees
  - Easier to optimize
  - ML techniques typically require binary trees
  - Can be a graph, so long as it’s a DAG

Knowledge Representation

- Typically work directly w/ primitive types
- Requires no translation of knowledge
  - Access game state directly
  - Can cause HARD-TO-FIND bugs
    - Rare decisions
    - Structure of game-state changes
  - Cons avoidable w/ careful world interface
    - See Millington CH 10

Tree Balancing

- More balanced → faster (theory)
  - Balance ~= same number of leaves on each branch
  - O(N) vs O(Log_2 N)
- Short path to likely action → faster (practice)
  - O(1)
  - Defer time consuming decisions 'til last
- Performance tuning
  - Dark art – since fast anyway, rarely important
  - Balance, but keep common paths short & bury long decisions

See M Ch 5.2

```
class DecisionTreeNode:
   def makeDecision() #recursively walk tree

class Action:
   def makeDecision():
      return this

class FloatDecision(Decision):
   minValue
   maxValue
   def getBranch():
      if max >= test >= min:
         return trueNode
      else:
         return falseNode
```

```
class Decision(DecisionTreeNode):
   trueNode
   falseNode
   testValue
   def getBranch()
   def makeDecision() :
      branch = getBranch()
      return branch.makeDecision()
```

Randomness

- Predictable == bad
- Can add a random decision node
- Keep track of decision from last cycle
- Reset after a timeout or new decision
- See M 5.2.10 for implementation deets

Learning Decision Trees

- Real power of D-trees comes from learning
- Problem: Construct a decision tree from examples of inputs and actions
- Sol'n: Quinlan's "Induction of Decision Trees"
  - ID3, C4.5, See5
    - http://en.wikipedia.org/wiki/ID3_algorithm
  - J48 (GPL java implementation)
    - http://www.opentox.org/dev/documentation/components/j48
    - See Weka (GNU GPL)

Learning Decision Trees

- A simple technique whereby the computer learns to predict human decision-making
- Can also be used to learn to classify
  - A decision can be thought of as a classification problem
- An object or situation is described as a set of attributes
  - Attributes can have discrete or continuous values
- Predict an outcome (decision or classification)
  - Can be discrete or continuous
  - We assume positive (true) or negative (false)

Basic Concept

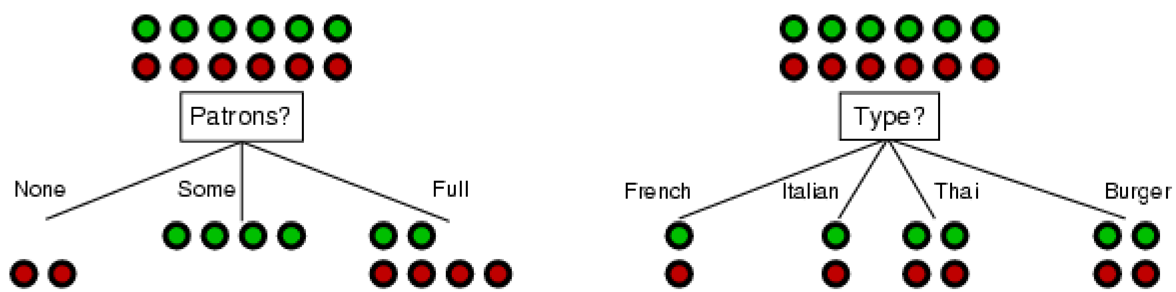
- Given the current set of decisions, what attribute can best split them?
- Choose the “best one” and create a new decision node
  - Best == most information gained
- Good attributes make homogeneous sets
- Recursively go down each edge

Example

Example	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	10-60	**T**

Choosing an Attribute

- Idea: A good attribute splits the examples into subsets that are (ideally) "all positive" or "all negative"

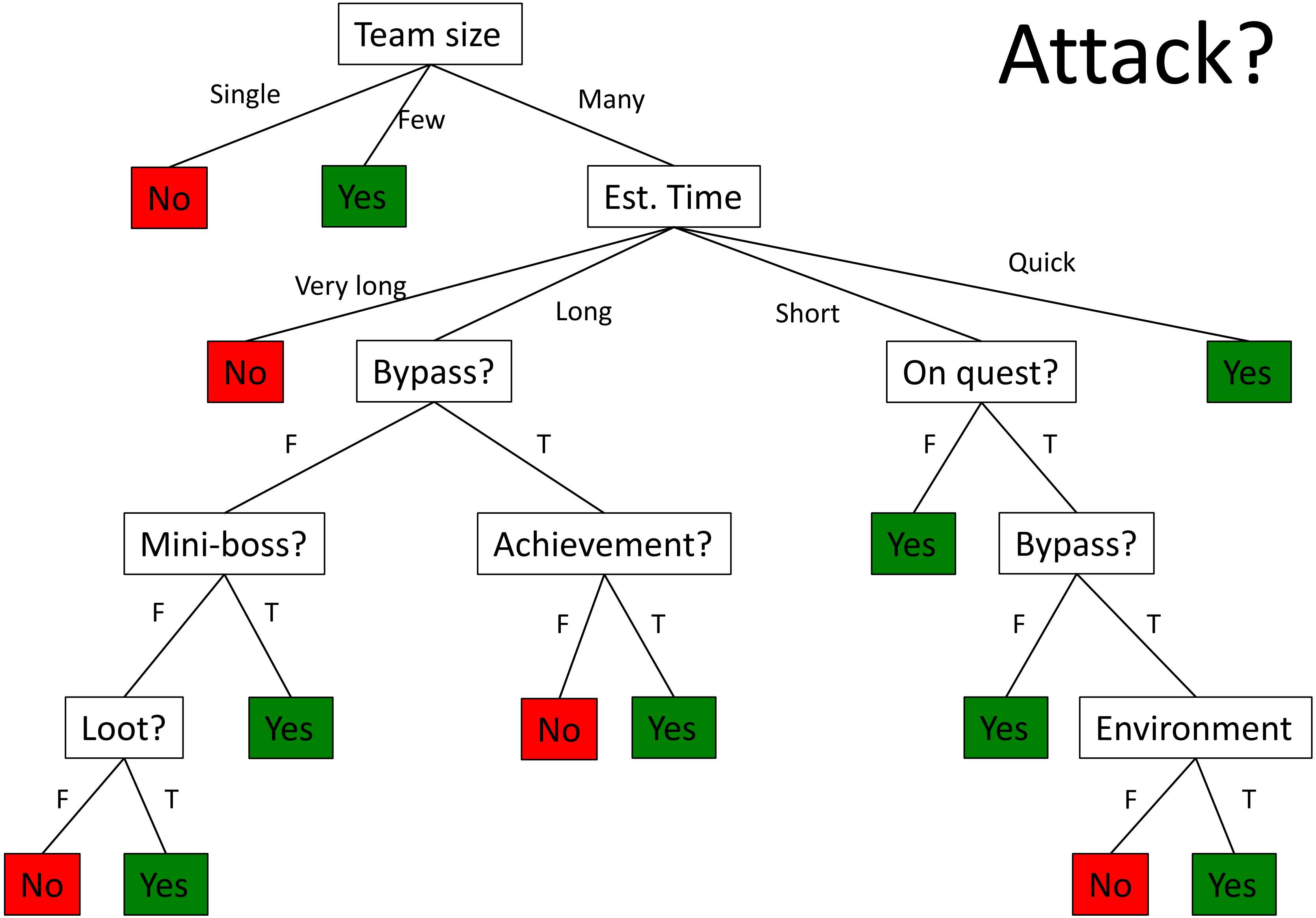


- *Patrons?* is a better choice

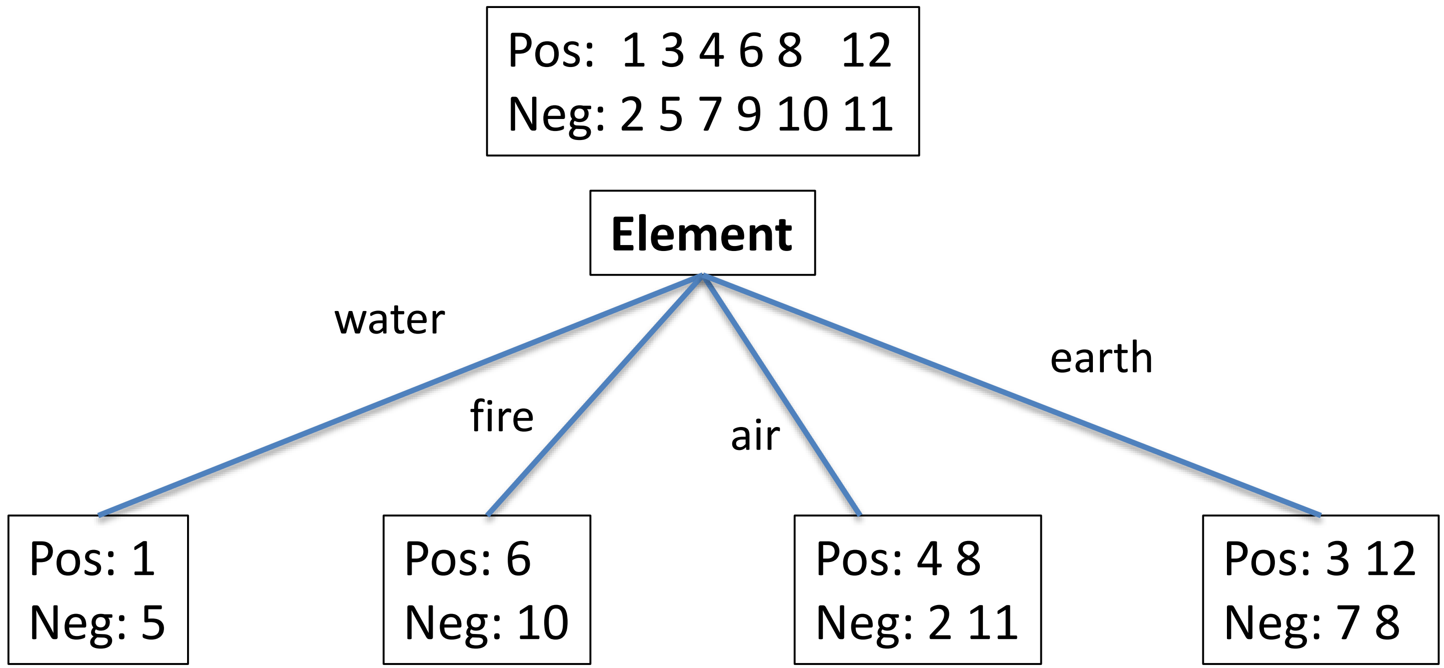
Attack?

- Attributes:
  - Bypass? Can be bypassed
  - Loot? Has valuable items/treasure
  - Achievement? Will unlock an achievement if you win
  - On Quest? You are on a quest
  - Experience. How much experience points you get
  - Environment. How favorable is the terrain?
  - Mini-boss? Is this a mini-boss, preventing further progress?
  - Element. The elemental properties (earth, air, fire, water)
  - Estimated Time. How long will this combat take (quick, short, long, very long)?
  - Team size. How many monsters in the team (none, small, large)?

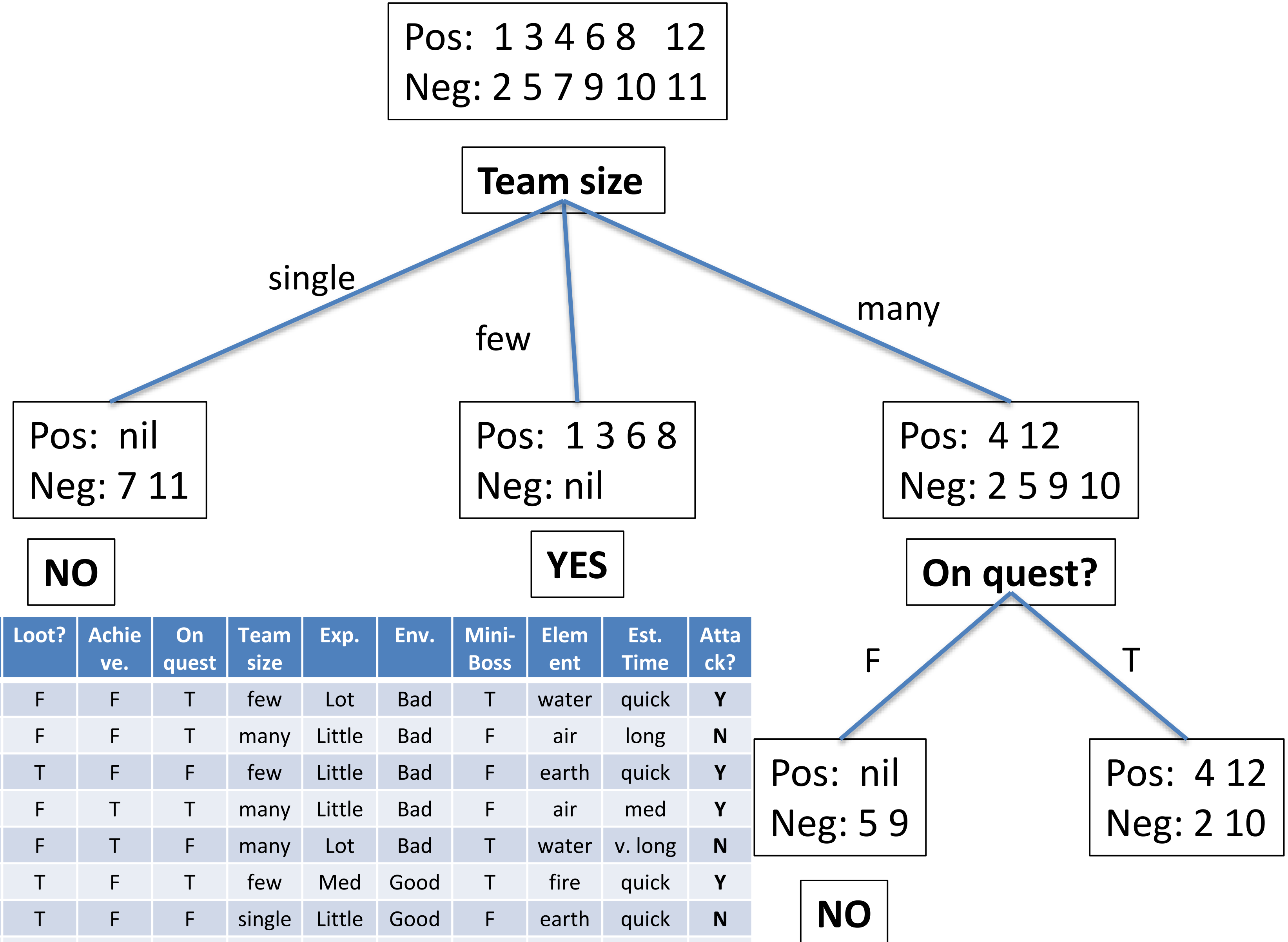
Attack?


Team size
Single
Few
Many
No
Yes
Est. Time
Very long
Long
Short
Quick
No
Bypass?
On quest?
Yes
F
T
Mini-boss?
Achievement?
Yes
Bypass?
F
T
Loot?
Yes
No
Yes
Yes
Environment
F
T
No
Yes
No
Yes

#	Bypass?	Loot?	Achieve.	On quest	Team size	Exp.	Env.	Mini-Boss	Element	Est. Time	Attack?
1	T	F	F	T	few	Lot	Bad	T	water	quick	**Y**
2	T	F	F	T	many	Little	Bad	F	air	long	**N**
3	F	T	F	F	few	Little	Bad	F	earth	quick	**Y**
4	T	F	T	T	many	Little	Bad	F	air	med	**Y**
5	T	F	T	F	many	Lot	Bad	T	water	v. long	**N**
6	F	T	F	T	few	Med	Good	T	fire	quick	**Y**
7	F	T	F	F	single	Little	Good	F	earth	quick	**N**
8	F	F	F	T	few	Med	Good	T	air	quick	**Y**
9	F	T	T	F	many	Little	Good	F	earth	v. long	**N**
10	T	T	T	T	many	Lot	Bad	T	fire	med	**N**
11	F	F	F	F	single	Little	Bad	F	air	quick	**N**
12	T	T	T	T	many	Little	Bad	F	earth	long	**Y**

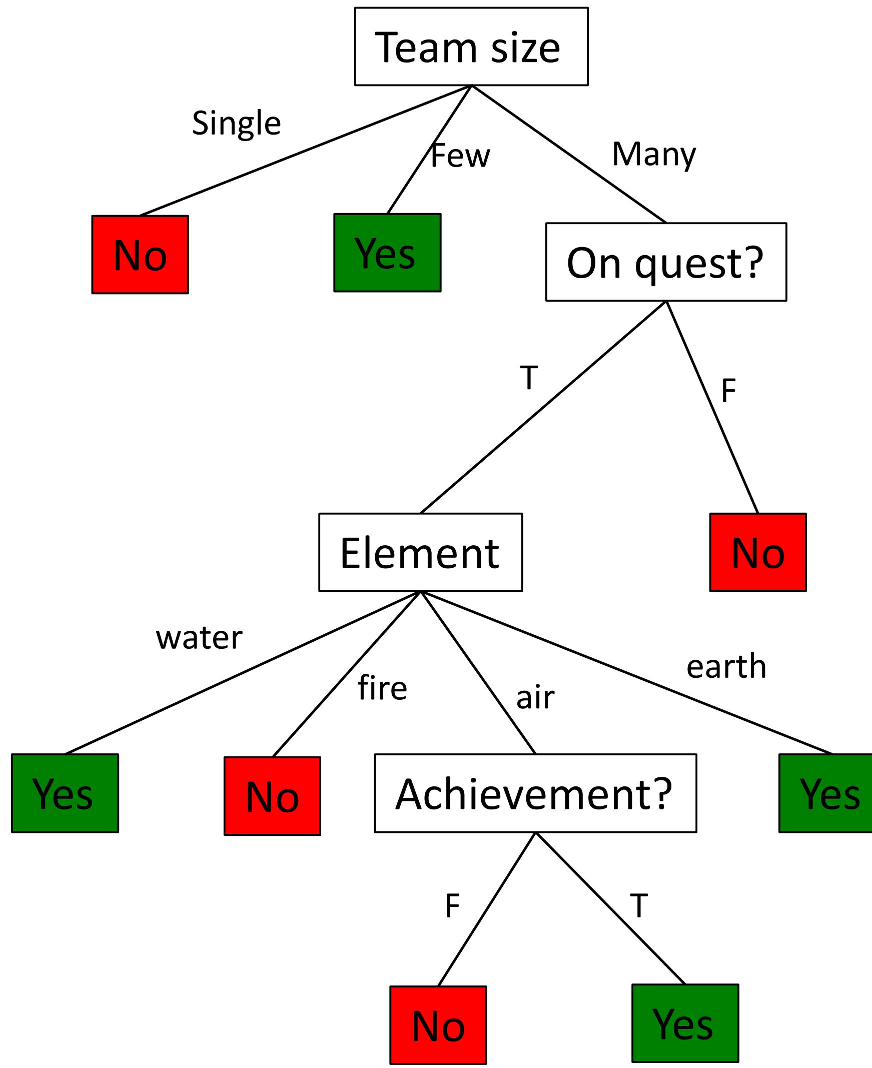


#	Bypass?	Loot?	Achieve.	On quest	Team size	Exp.	Env.	Mini-Boss	Element	Est. Time	Attack?
1	T	F	F	T	few	Lot	Bad	T	water	quick	**Y**
2	T	F	F	T	many	Little	Bad	F	air	long	**N**
3	F	T	F	F	few	Little	Bad	F	earth	quick	**Y**
4	T	F	T	T	many	Little	Bad	F	air	med	**Y**
5	T	F	T	F	many	Lot	Bad	T	water	v. long	**N**
6	F	T	F	T	few	Med	Good	T	fire	quick	**Y**
7	F	T	F	F	single	Little	Good	F	earth	quick	**N**
8	F	F	F	T	few	Med	Good	T	air	quick	**Y**
9	F	T	T	F	many	Little	Good	F	earth	v. long	**N**
10	T	T	T	T	many	Lot	Bad	T	fire	med	**N**
11	F	F	F	F	single	Little	Bad	F	air	quick	**N**
12	T	T	T	T	many	Little	Bad	F	earth	long	**Y**



#	Bypass?	Loot?	Achieve.	On quest	Team size	Exp.	Env.	Mini-Boss	Element	Est. Time	Attack?
1	T	F	F	T	few	Lot	Bad	T	water	quick	**Y**
2	T	F	F	T	many	Little	Bad	F	air	long	**N**
3	F	T	F	F	few	Little	Bad	F	earth	quick	**Y**
4	T	F	T	T	many	Little	Bad	F	air	med	**Y**
5	T	F	T	F	many	Lot	Bad	T	water	v. long	**N**
6	F	T	F	T	few	Med	Good	T	fire	quick	**Y**
7	F	T	F	F	single	Little	Good	F	earth	quick	**N**
8	F	F	F	T	few	Med	Good	T	air	quick	**Y**
9	F	T	T	F	many	Little	Good	F	earth	v. long	**N**
10	T	T	T	T	many	Lot	Bad	T	fire	med	**N**
11	F	F	F	F	single	Little	Bad	F	air	quick	**N**
12	T	T	T	T	many	Little	Bad	F	earth	long	**Y**

- Learned from the 12 examples
- Why doesn't it look like the previous tree?
  - Not enough examples
  - No reason to use environment or mini-boss
  - Hasn't seen all cases
- Learning is only as good as your training data
- Supervised learning
  - Training set
  - Test set



Which attribute to choose?

- The one that gives you the most information (aka the most diagnostic)
- Information theory
  - Answers the question: how much information does something contain?
  - Ask a question
  - Answer is information
  - Amount of information depends on how much you already knew (information gain)
- Example: flipping a coin

Entropy

- Measure of information in set of examples
  - That is, amount of agreement between examples
  - All examples are in the same action, E = 0
  - Even distributed and different, E = 1
- If there are n possible answers, $v_1 \ldots v_n$ and v_i has probability $P(v_i)$ of being the right answer, then the amount of information is:

$$H\left(P(v_1), \ldots, P(v_n)\right) = -\sum_{i=1}^{n} P(v_i) \log_2 P(v_i)$$

- For a training set:

  p = # of positive examples

  n = # of negative examples

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

Probability of
a positive example

Probability of
a negative example

- For our attack behavior
  - p = n = 6
  - H() = 1
  - Would not be 1 if training set weren't 50/50 yes/no, but the point is to arrange attributes to increase gain (decrease entropy)

Pos:	1 3 4 6 8 12
Neg:	2 5 7 9 10 11

Measuring attributes

- Remainer(A) is amount of entropy remaining after applying an attribute
  - If I use attribute A next, how much less entropy will I have?
  - Use this to compare attributes

Instances of the attribute

Positive examples for this answer to A

Negative examples for this answer to A

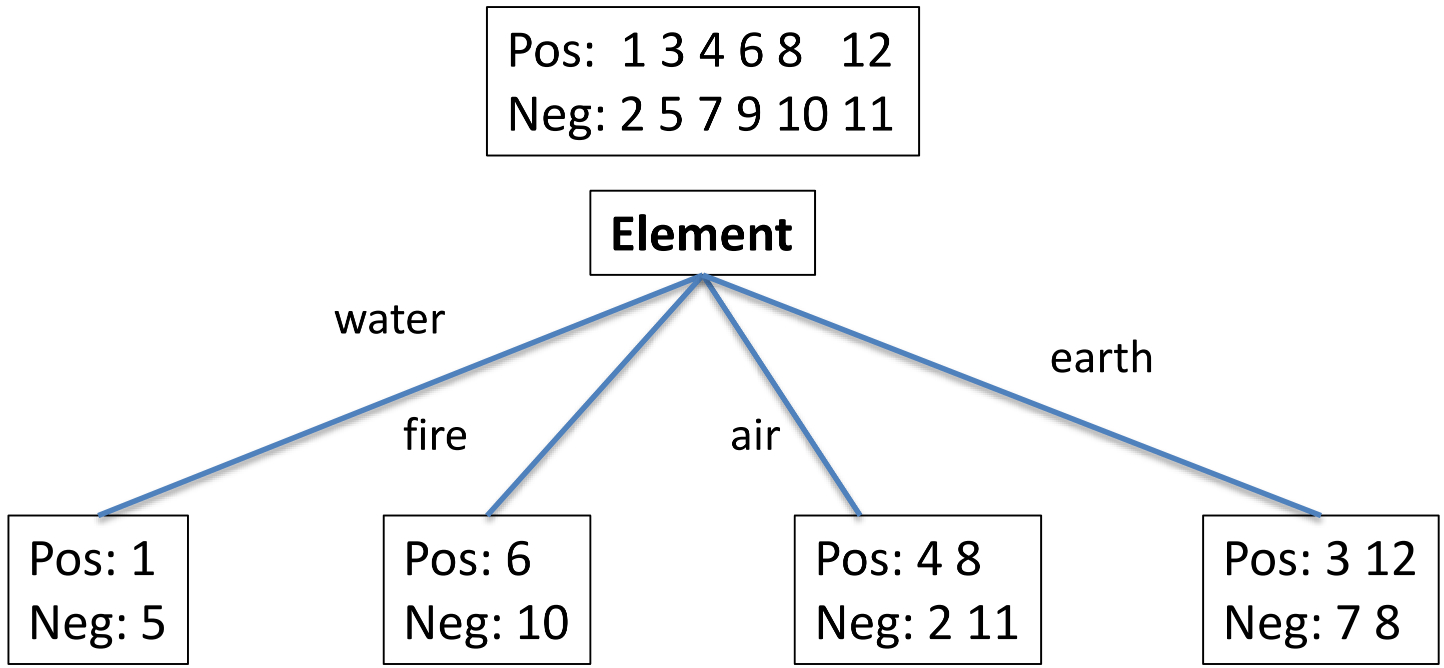
$$\text{Remainder(A)} = \sum_{i=1}^{v} \frac{p_i + n_i}{p + n} H\left(\frac{p_i}{p_i + n_i}, \frac{n_i}{p_i + n_i} \right)$$

attribute

Different answers

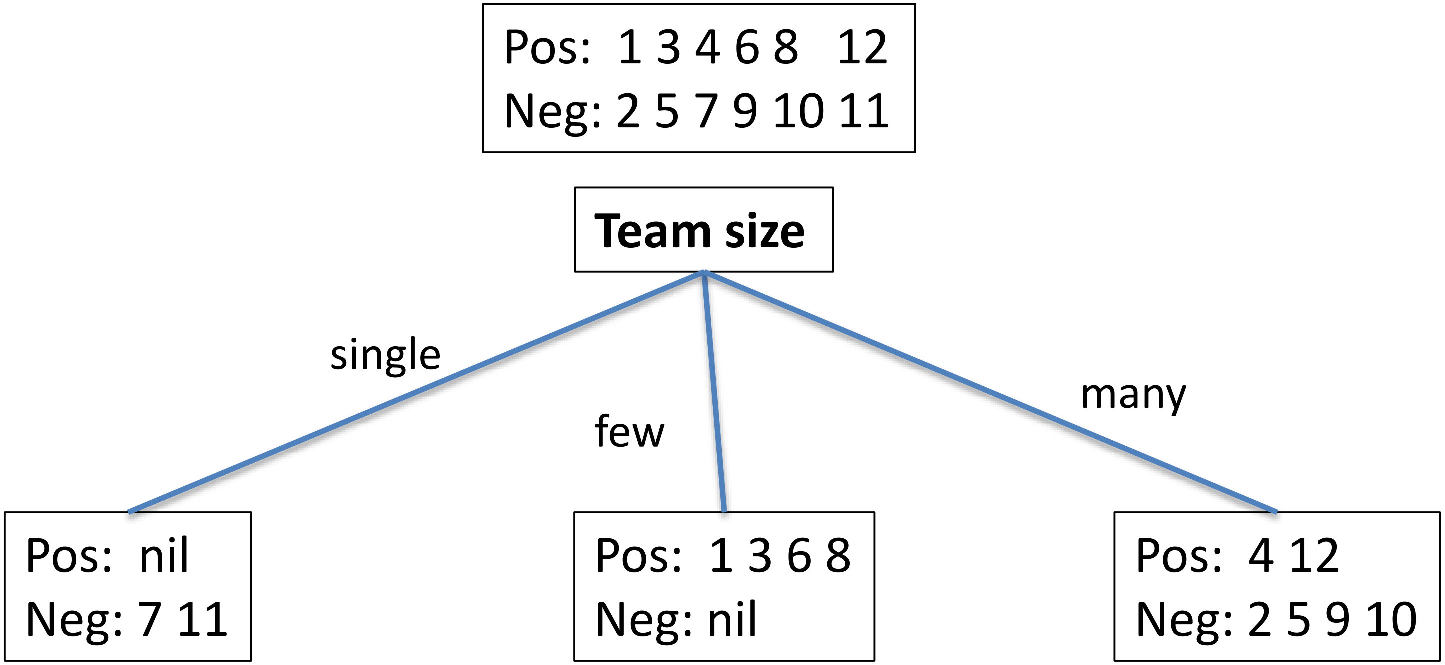
Total answers

Examples classified by A



$$\text{Remainder(element)} = \frac{2}{12} I\left(\frac{1}{2}, \frac{1}{2}\right) + \frac{2}{12} I\left(\frac{1}{2}, \frac{1}{2}\right) + \frac{4}{12} I\left(\frac{2}{4}, \frac{2}{4}\right) + \frac{4}{12} I\left(\frac{2}{4}, \frac{2}{4}\right) = 1 \text{ bit}$$

water fire air earth



$$\text{Remainder(teamsize)} = \underbrace{\frac{2}{12} I\left(\frac{0}{2}, \frac{2}{2}\right)}_{\text{single}} + \underbrace{\frac{4}{12} I\left(\frac{4}{4}, \frac{0}{4}\right)}_{\text{few}} + \underbrace{\frac{6}{12} I\left(\frac{2}{6}, \frac{4}{6}\right)}_{\text{many}} \approx 0.459 \text{ bit}$$

- Not done yet
- Need to measure information **gained** by an attribute

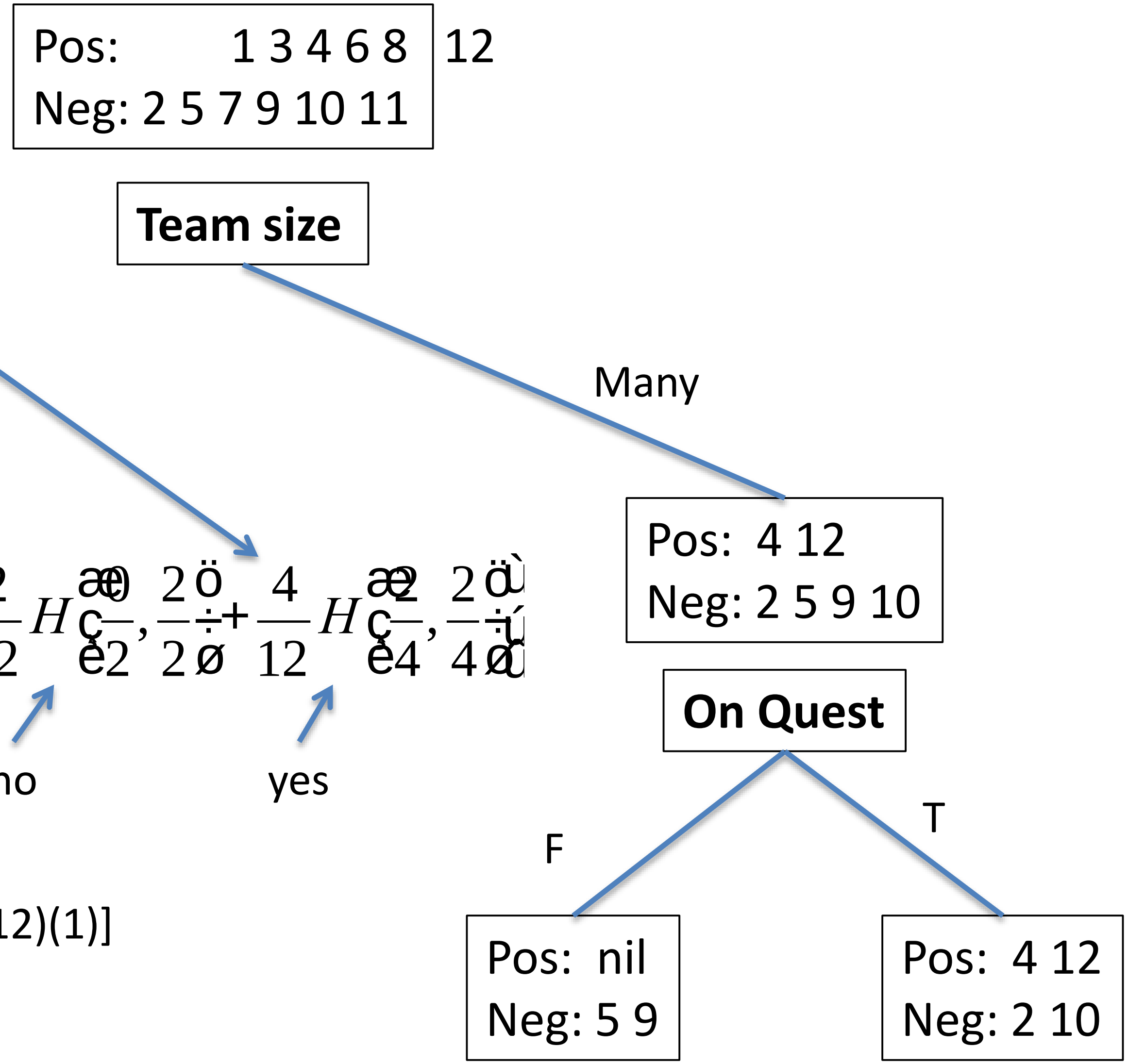
$$\text{Gain(A)} = H\left(\frac{p}{p+n}, \frac{n}{p+n}\right) - \text{remainder(A)}$$

- Pick the biggest
- Example:
  - Gain(element) = H(½,½) – $\left[\frac{2}{12}H\left(\frac{1}{2},\frac{1}{2}\right)+\frac{2}{12}H\left(\frac{1}{2},\frac{1}{2}\right)+\frac{4}{12}H\left(\frac{2}{4},\frac{2}{4}\right)+\frac{4}{12}H\left(\frac{2}{4},\frac{2}{4}\right)\right]$

    = 0 bits

  - Gain(teamsize) = H(½,½) – $\left[\frac{2}{12}H\left(\frac{0}{2},\frac{2}{2}\right)+\frac{4}{12}H\left(\frac{4}{4},\frac{0}{4}\right)+\frac{6}{12}H\left(\frac{2}{6},\frac{4}{6}\right)\right]$

    ≈ 0.541 bits



teamsize=many, onquest=T

teamsize=many, onquest=F

$$\text{Gain(quest)} = H\left(\frac{2}{12}, \frac{4}{12}\right) - \left[\frac{2}{12} H\left(\frac{0}{2}, \frac{2}{2}\right) + \frac{4}{12} H\left(\frac{2}{4}, \frac{2}{4}\right)\right]$$

no

yes

= 0.959 – [0 + (4/12)(1)]

≈ 0.626 bits

Decision-tree-learning (examples, attributes, default)

IF examples is empty THEN RETURN default

ELSE IF all examples have same classification THEN RETURN classification

ELSE IF attributes is empty RETURN majority-value(examples)

ELSE

best = choose(attributes, example) ← Where gain happens

tree = new decision tree with best as root

m = majority-value(examples)

FOREACH answer v_i of best DO

examples$_i$ = {elements of examples with best=v_i}

subtree$_i$ = decision-tree-learning(examples$_i$, attributes-{best}, m)

add a branch to tree based on v_i and subtree$_i$

RETURN tree

How many hypotheses?

- How many distinct trees?
  - N attributes

    = # of boolean functions

    = # of distinct truth tables with 2^n rows

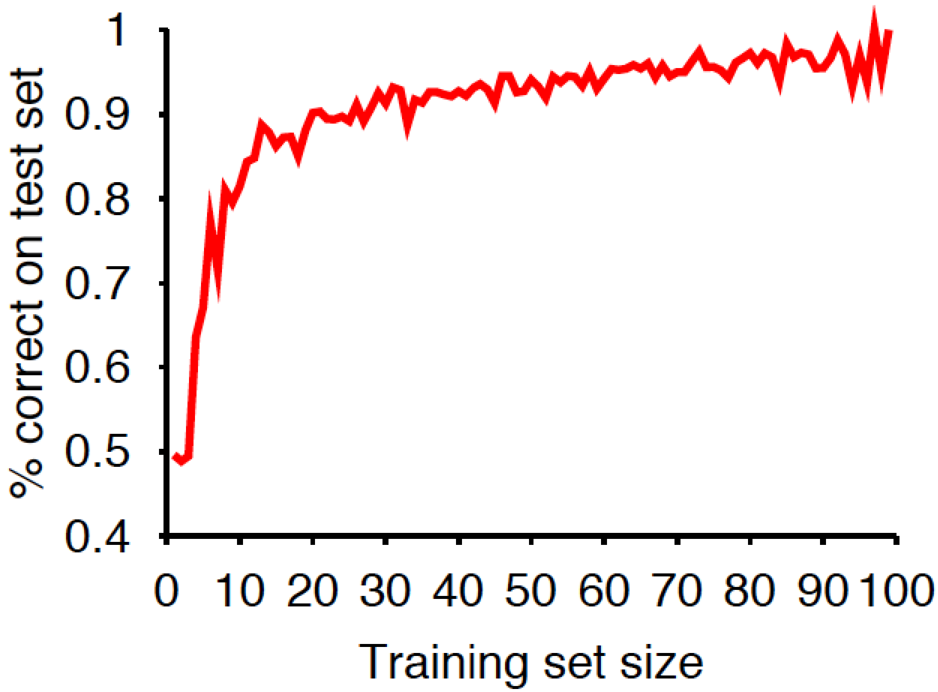
    = 2^2^n
  - With 6 attributes: > 18 quintillion possible trees

How do we assess?

- How do we know hypothesis ≈ true decision function?
- A learning algorithm is good if it produces hypotheses that do a good job of predicting decisions/classifications from unseen examples

1. Collect a large set of examples (with answers)
2. Divide into training set and test set
3. Use training set to produce hypothesis h
4. Apply h to test set (w/o answers)
   – Measure % examples that are correctly classified
5. Repeat 2-4 for different sizes of training sets, randomly selecting examples for training and test
   – Vary size of training set m
   – Vary which m examples are training

- Plot a learning curve
  - % correct on test set, as a function of training set size



- As training set grows, prediction quality should increase
  - Called a “happy graph”
  - There is a pattern in the data AND the algorithm is picking it up!

Noise

- Suppose 2 or more examples with same description (Same assignment of attributes) have different answers
- Examples: on two identical* situations, I do two different things
- You can’t have a consistent hypothesis (it must contradict at least one example)
- Report majority classification or report probability

Overfitting

- Learn a hypothesis that is consistent using irrelevant attributes
  - Coincidental circumstances result in spurious distinctions among examples
  - Why does this happen?
    - You gave a bunch of attributes because you didn’t know what would be important
    - If you knew which attributes were important, you might not have had to do learning in the first place
- Example: Day, month, or color of die in predicting a die roll
  - As long as no two examples are identical, we can find an exact hypothesis
  - Should be random 1-6, but if I roll once every day and each day results in a different number, the learning algorithm will conclude that day determines the roll
- **Applies to all learning algorithms**

Black and White

Black and White

- Creature must learn what to do in different situations
- Player can reward or punish the creature
  - Tells the creature whether they made the right choice of action or not
- Creature learns to predict the feedback it will receive from the player

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

Continuous DTs must discretize the variables by deciding where to split the continuous range.

No Free Lunch

- ID3
  - Must discretize continuous attributes
  - Offline only (online = adjust to new examples)
  - Too inefficient with many examples
- Incremental methods (C4.5, See5, ITT, etc)
  - Starts with a d-tree
  - Each node holds examples that reach that node
  - Any node can update self given new example
  - Can be unstable (new trees every cycle; rare in practice)