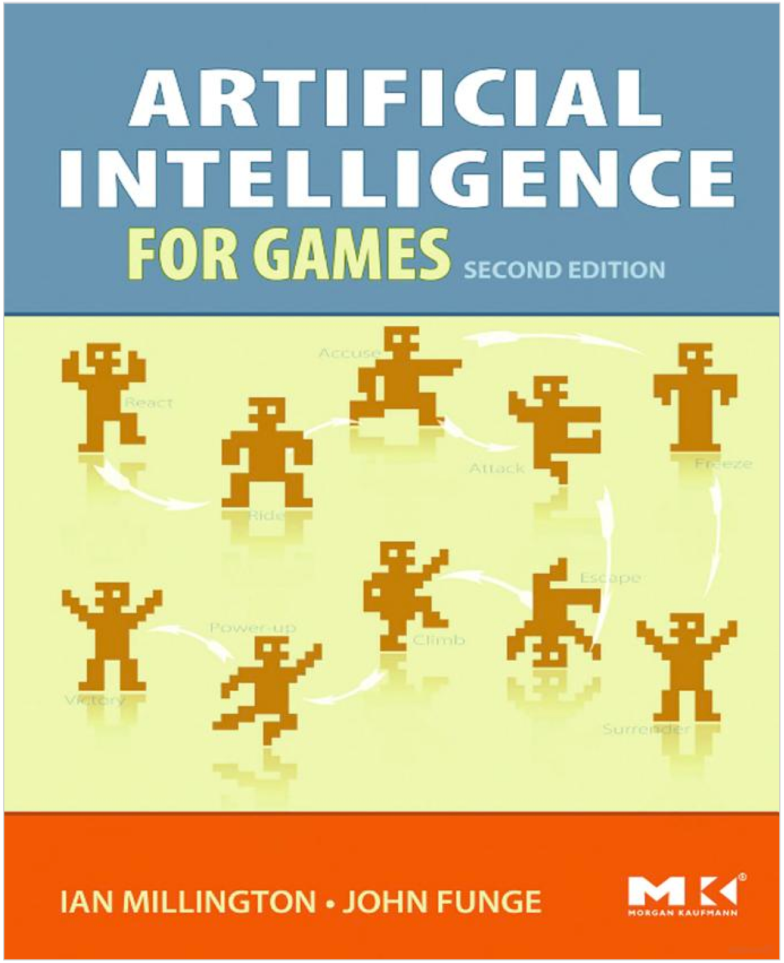
Principles of Computer Game Design and Implementation

Lecture 22

Credits

- Heavily based on
  - I. Millington and J. Funge “Artificial Intelligence for Games”, Elsevier, 2009.
  - J. Ahlquist, J. Novak “Game Artificial Intelligence”, Thomson, 2008



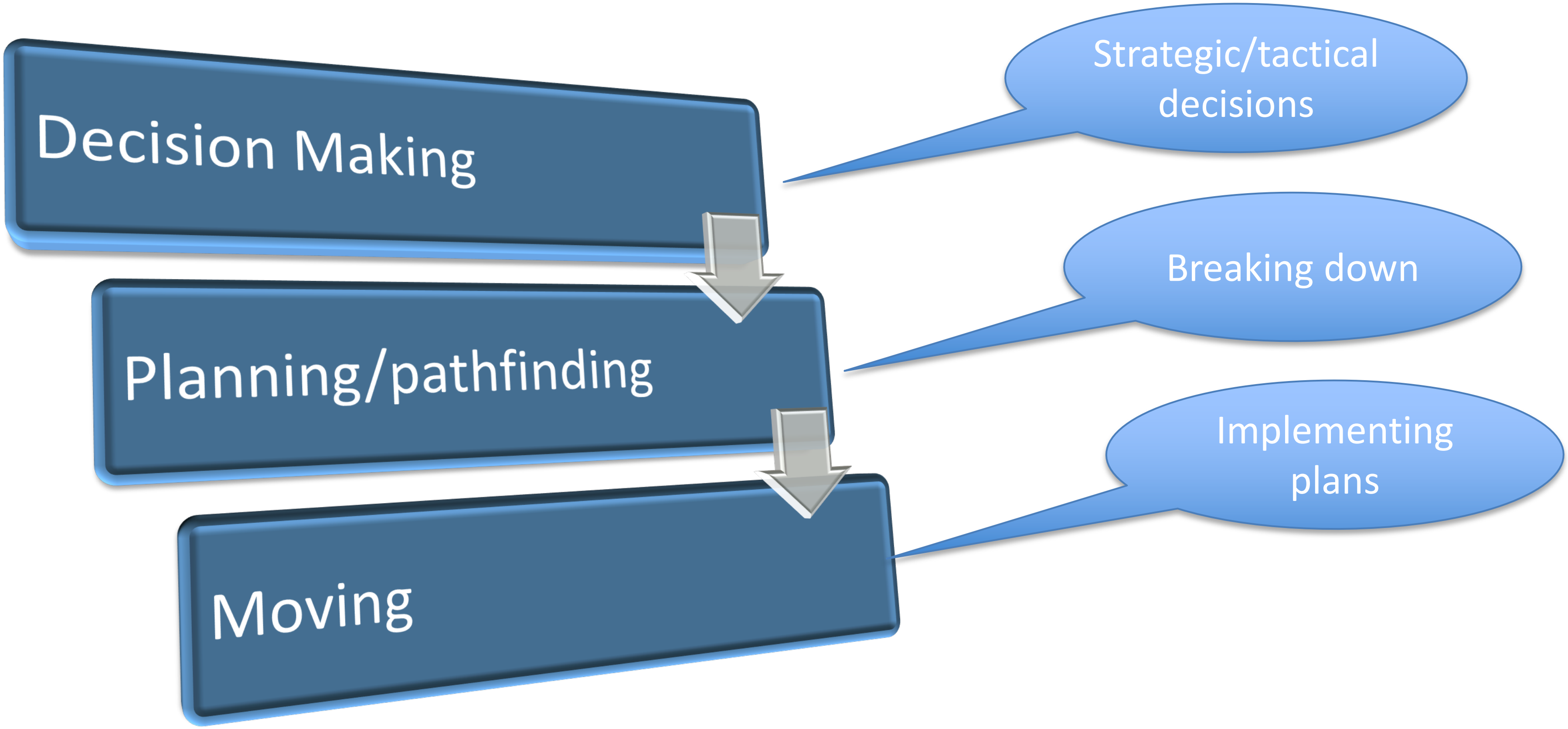
Techniques to Go Through

- Decision Tree
- Finite State Machine
- Behaviour Tree
- Planning
- Steering Behaviour
- Pathfinding (1,2)

Outline for today

- Decision tree

A Very Rough Structure of Game AI



In reality, there is no clear cut.

Major Approaches

- Reactive AI
  - Computer player reacts to human player actions
    - Event-driven
    - Pull-based
- Goal-driven AI
  - Pursuing goals
    - Hierarchy of goals
- Combinations and variations

Decision Trees and Rule-Based Systems

- Many game situations can be described as *if-then-else* cases
  - **If** see enemy **then** shoot
  - **If** (animal is enemy **or** neutral) **and** animal is not healthy **then** eat it
  - **If** animal sings and dances **then** it's friendly

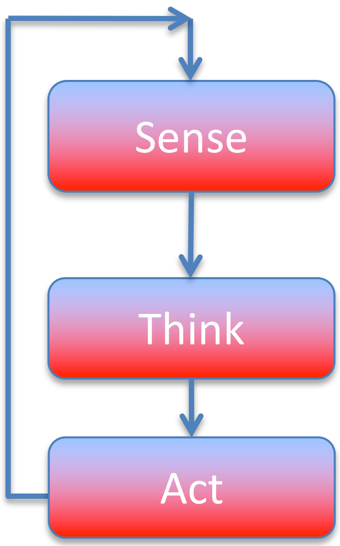
Acting on knowledge

Classification

- Decision trees
- Rule-based (production/expert) systems

Decision Trees

- Simplest decision making technique
- Easy to implement and understand
- Mostly reactive AI
- Fast execution
- Can be combined with other techniques
- Can be *learned* (using machine learning techniques)



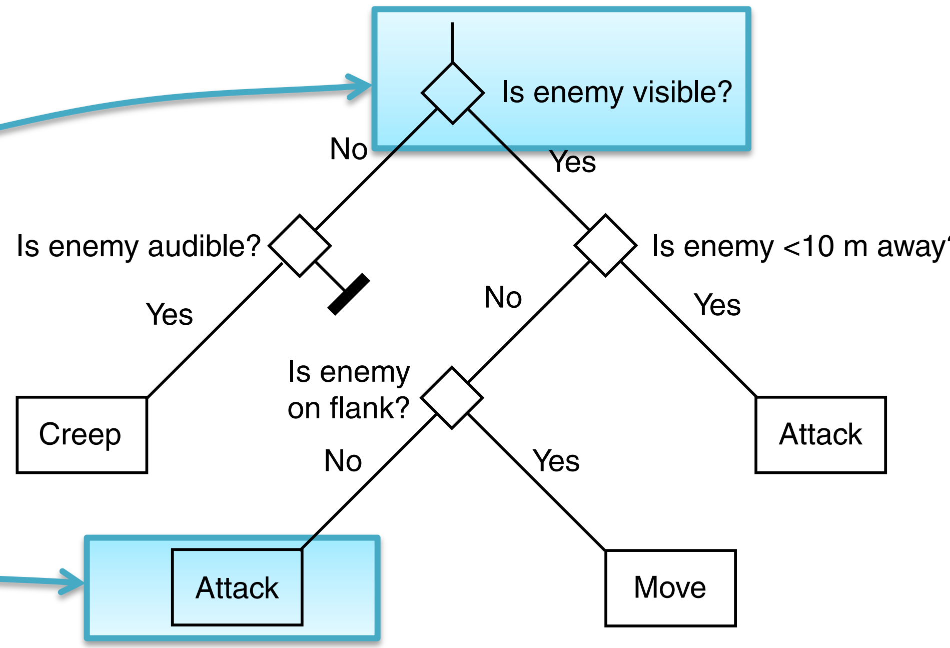
Example

Soldier decision making

- Based on perception

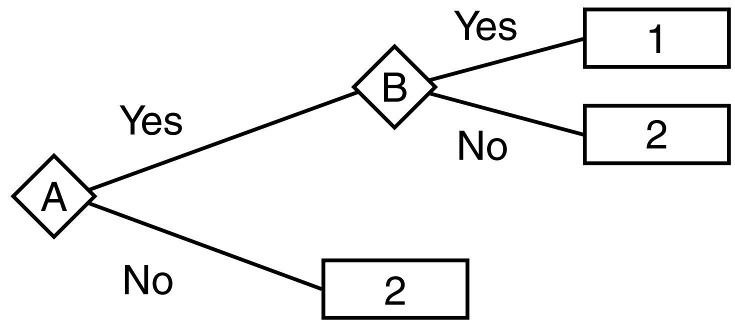
Attribute test

Action / Decision / Classification

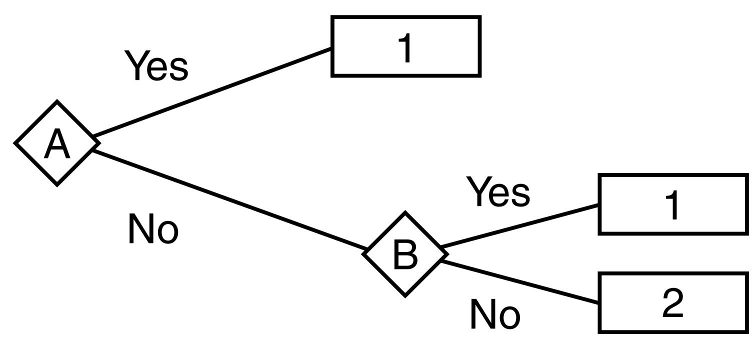


Logical Connectives

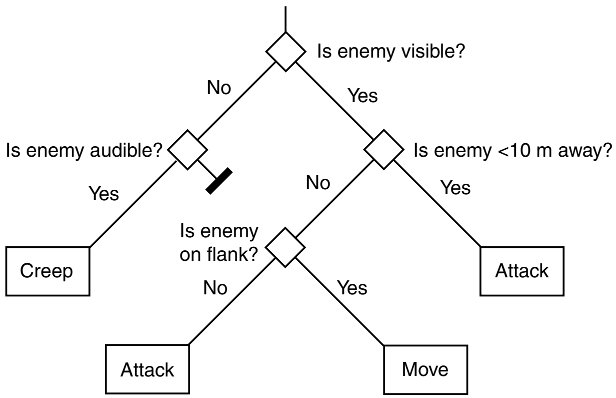
- A **and** B



- A **or** B



Easy to Implement

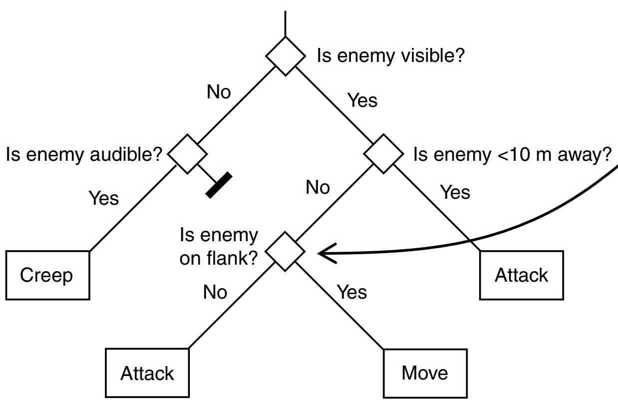



```
if(enemy.isVisible()) {
  if(distance(player, enemy) < 10){
    attack();
  }
  else{
    if(enemy.isOnFlank()){
      move();
    }
    else{
      attack();
    }
  }
}
else{ … … …
```

Hard-coded knowledge may not be a good idea

Why: Maintainability

- Why hard-coded AI is not a good idea?
  - Maintainability
    - Add an extra check *"is enemy a tank?"*

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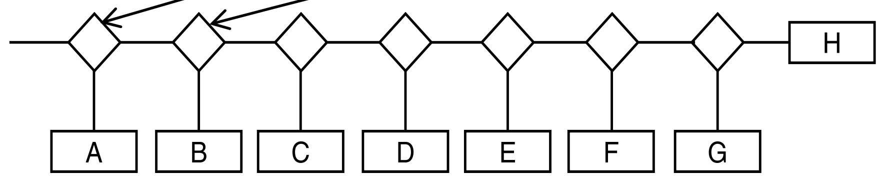
    else{
      attack();
    }
  }
}
else{ … … …
```

Which one would you choose to update?

Why: Tree Balancing

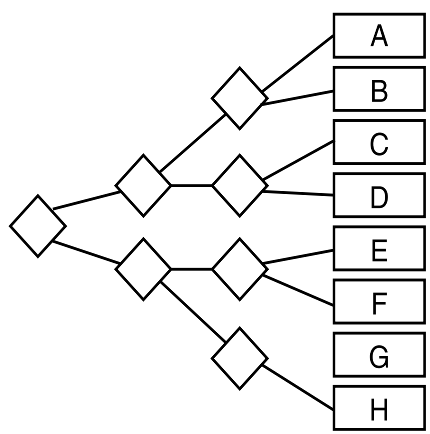
- The longer the branch the longer it takes to go along it

Unbalanced tree




```
if(…) {
      A;
}
else if(…){
      B;
   }
   else if (…){
       C;
      }
      else if(…) {
        D;
… … …
```

Balanced tree



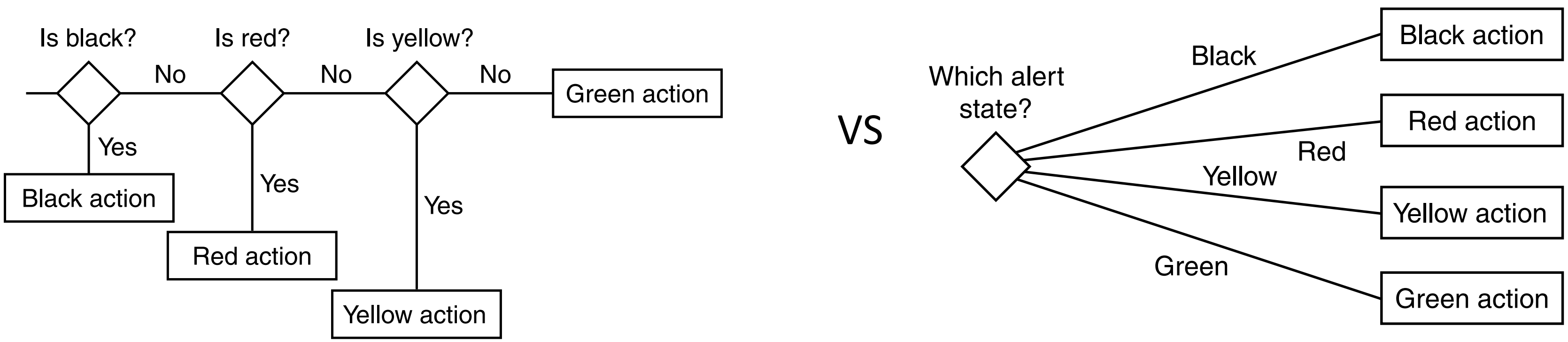
Manageable Implementation

- Special languages
  – Overkill
  – Can be done with AI scripting approaches

- A library of (C++ / Java) classes for attributes, tests and actions
  – Somewhat similar to scene graph libraries

Extensions: Split on Other Values

- Yes/No is not an answer
  - Decide on other attributes. For example,

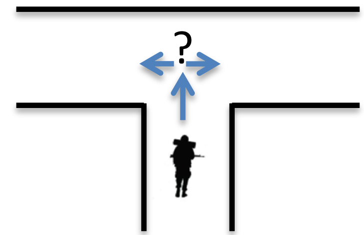


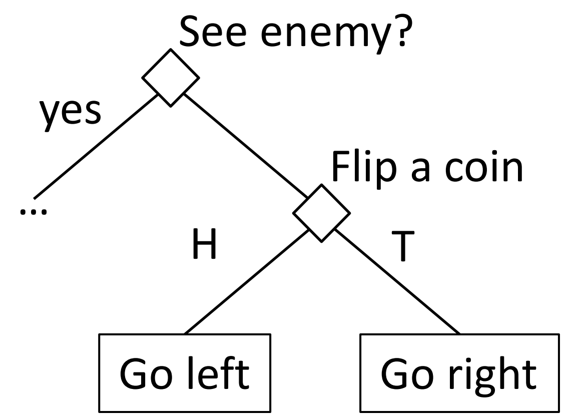
Possible data types:

- Boolean
- Enumeration
- 3D Vector (vector length within range, vector direction is given,…)
- …

Variations: Random Decisions

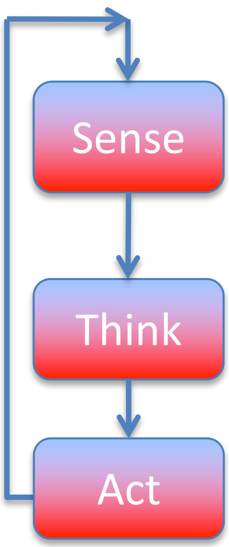
- Completely predictable behaviour is boring
- Randomness breaks the pattern
- Coin can be biased (player psychology)





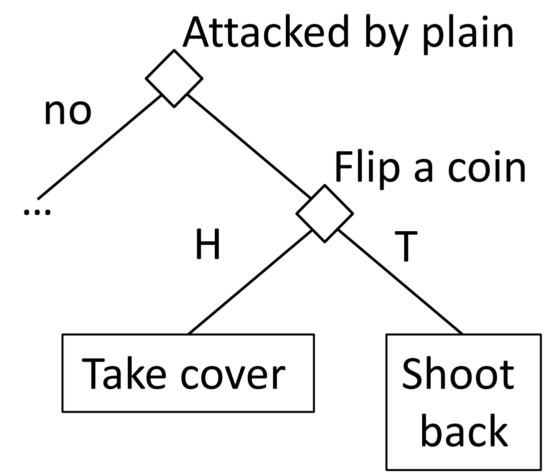
Sticking to Choice

- Marine behaviour



- Sense – Think – Act cycle navigates the decision tree every time

- Random choice every iteration will make the marine freeze



Stick to choice (for a while)

Learning Decision Trees

- Aims:
  - Better gameplay
  - Cheaper AI
  - Adaptive AI

- Not often used by game developers
  - Reproducibility and quality control
  - Increased run time
  - Can be faked

Alternatives to ML

- Pre-programmed levels of difficulty
  - Switch between behaviours
- Incremental introduction of new game entities
  - “Uncover” cleverness of AI
- Tweaking parameters at run-time
  - Reduce the number of mistakes
  - Improve aim
  - Limited form of machine learning (stats)
    - Learning user’s habits (attack from right etc.)

Faking vs Learning

- Learning (potentially) gives more options but

- With faking the AI code remains unchanged and can be tested debugged

http://heli.stanford.edu/

- On the other hand, learning gives stunning results in traditional AI (not game AI).

When to Learn

- Online learning
  - While playing
  - Input from players
  - Aim: adaptive behaviour
- Offline learning
  - Before the product is released
  - Input from designers
  - Aim: finding best behaviours

Basic Techniques

- Analysing examples
  - About 75% are used to learn
  - The rest (25%) are used to test

- Reinforcement learning
  - Rewards and punishments for actions

Decision Trees from Examples

- Given: Attributes, Decisions, Examples
- Required: Construct a tree

Health	Cover	Ammo	Decision
Healthy	In Cover	With Ammo	Attack
Hurt	In Cover	With Ammo	Attack
Healthy	In Cover	Empty	Defend
Hurt	In Cover	Empty	Defend
Hurt	Exposed	With Ammo	Defend

Example: marine behaviour

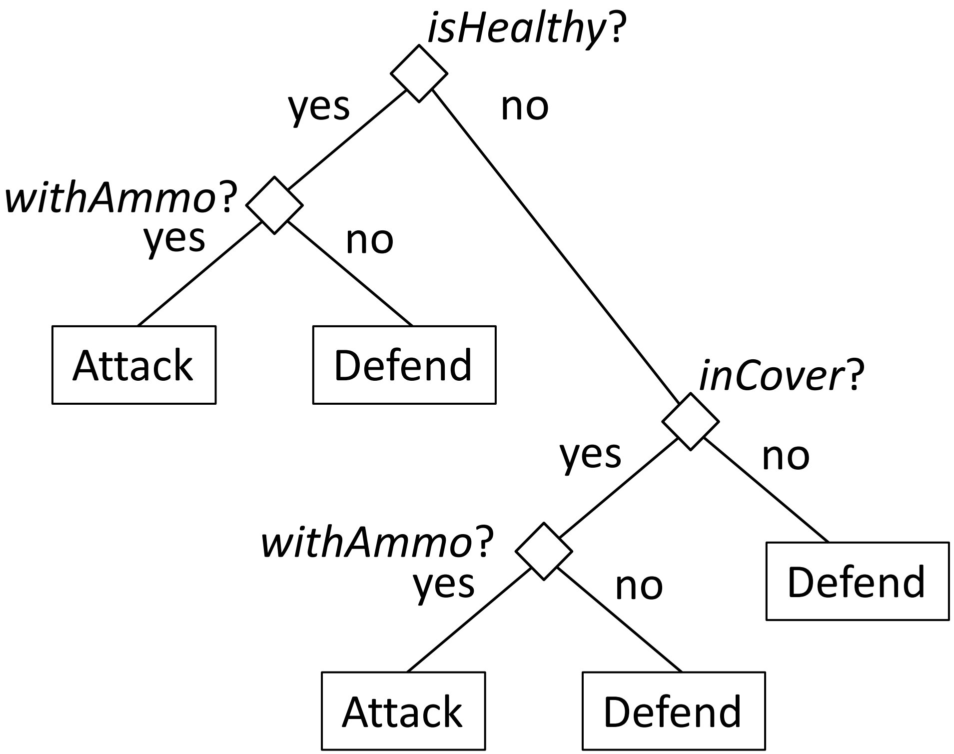
Decision Tree Learning Algorithm

Can be a majority

```
function DTL(examples, attributes, default) returns a decision tree
    if examples is empty then return default
    else if all examples have the same classification then return the classification
    else if attributes is empty then return MODE(examples)
    else
        best ← CHOOSE-ATTRIBUTE(attributes, examples)
        tree ← a new decision tree with root test best
        for each value v_i of best do
            examples_i ← {elements of examples with best = v_i}
            subtree ← DTL(examples_i, attributes − best, MODE(examples))
            add a branch to tree with label v_i and subtree subtree
        return tree
```

From S. Russel, P. Norvig "Artificial Intelligence: A modern approach", Prentice Hall

Example



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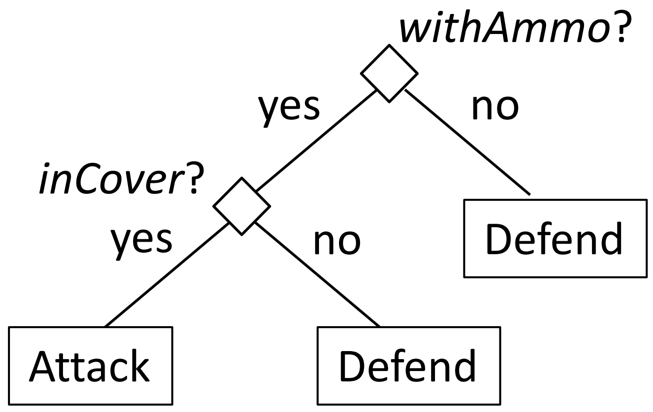
Attributes order: the column (random) order

Different Order of Attributes



Attributes order: Ammo, Cover

Health	Cover	Ammo	Decision
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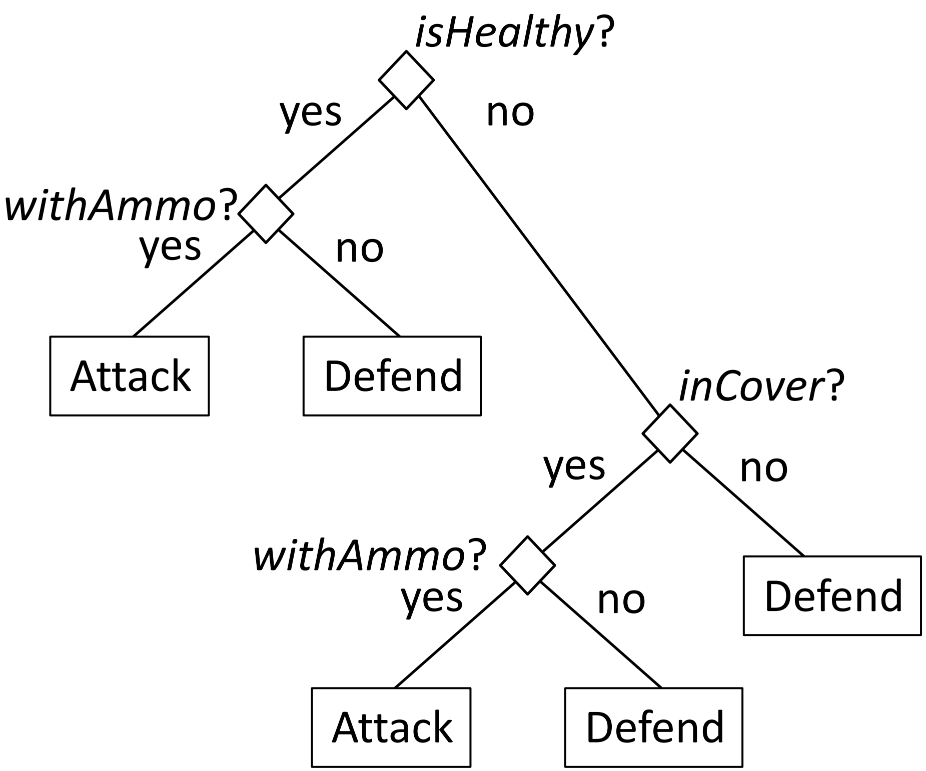
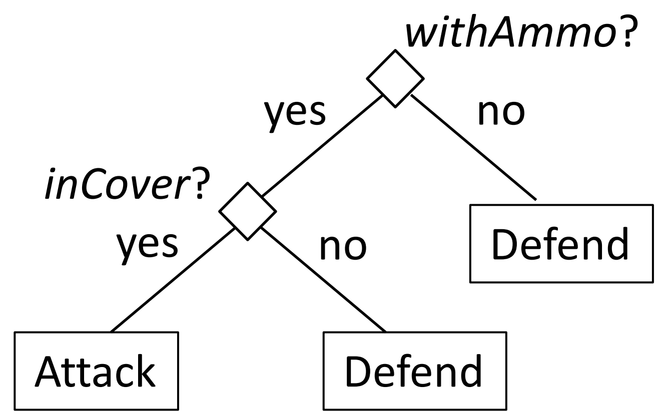
Hurt	In Cover	With Ammo	Attack
Healthy	In Cover	Empty	Defend
Hurt	In Cover	Empty	Defend
Hurt	Exposed	With Ammo	Defend

Two Learnt Trees

Attributes order: the column (random) order



Attributes order: Ammo, Cover



Health does not matter!

The Order of Attributes Matters

- Pick one best splits the cases
- Bad choice may lead to ***overfitting***: decision tree can handle ***given*** examples but not ***generalise*** from them

- First, split on the attribute that give biggest *Information Gain*
  - Information theory (Shannon, Weaver, 1949)
  - Numerical value of attribute based on statistics

Information Entropy

For a set of examples *S* let

- n_p be the number of examples with a *positive* outcome (e.g. Attack)
- n_n be the number of examples with a *negative* outcome (e.g. Defend)

Then, the entropy (a measure of uncertainty) for this set is

Total number of examples

$$E_S = -\frac{n_p}{n_p + n_n}\log_2\left(\frac{n_p}{n_p + n_n}\right) - \frac{n_n}{\boxed{n_p + n_n}}\log_2\left(\frac{n_n}{n_p + n_n}\right)$$

Information Gain

Every attribute *A* splits the set of examples *S* into two subsets

- S_A, for which the value of *A* is *true*
  - Compute the entropy E_{S_A} for S_A
- $S_{\sim A}$, for which the value of *A* is false
  - Compute the entropy $E_{S_{\sim A}}$ for $S_{\sim A}$

Number of elements in $S_{\sim A}$

$$G_A = E_S - \frac{|S_A|}{|S|} E_{S_A} - \frac{\boxed{|S_{\sim A}|}}{|S|} E_{S_{\sim A}}$$

ID3

Pick the attribute with the highest information gain

$G_{health} = 0.02$

$G_{cover} = 0.171$

$\boxed{G_{ammo} = 0.420}$

Best choice

Health	Cover	Ammo	Decision
Healthy	In Cover	With Ammo	Attack
Hurt	In Cover	With Ammo	Attack
Healthy	In Cover	Empty	Defend
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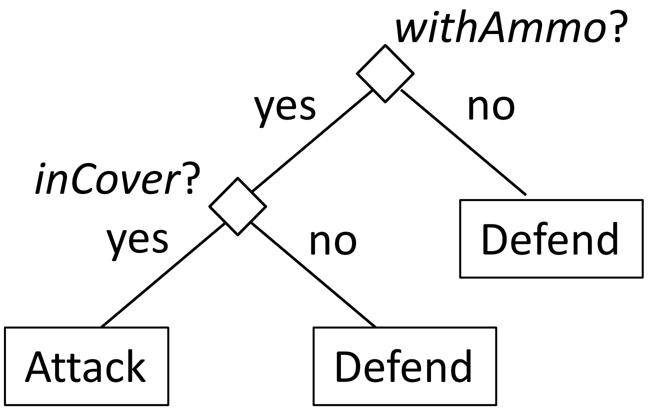
Learning with ID3



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Attributes order: Ammo, Cover

Best outcome

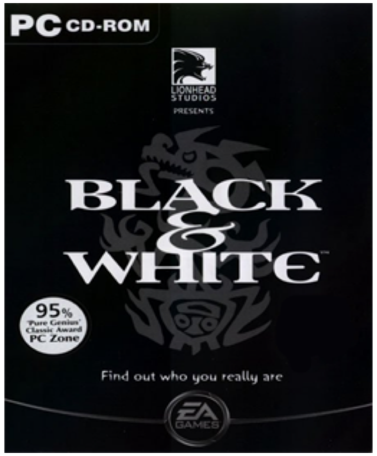
Dealing with Noise

- Data often contains "noise"
  - E.g., human player decides to attack regardless of not having any ammo
- The learnt decision tree will take *irrelevant* attributes into account
  - E.g. in our example, Health was irrelevant

- **Pruning** techniques: eliminate splitting on statistically insignificant attributes

Black & White

- Most prominent example where decision trees were learnt is Black & White.
  - Creature can be trained by users
    - If the creature behaviour is “bad”, hard to retrain
  - Very positive initial reception
    - Some critics reconsidered their opinion

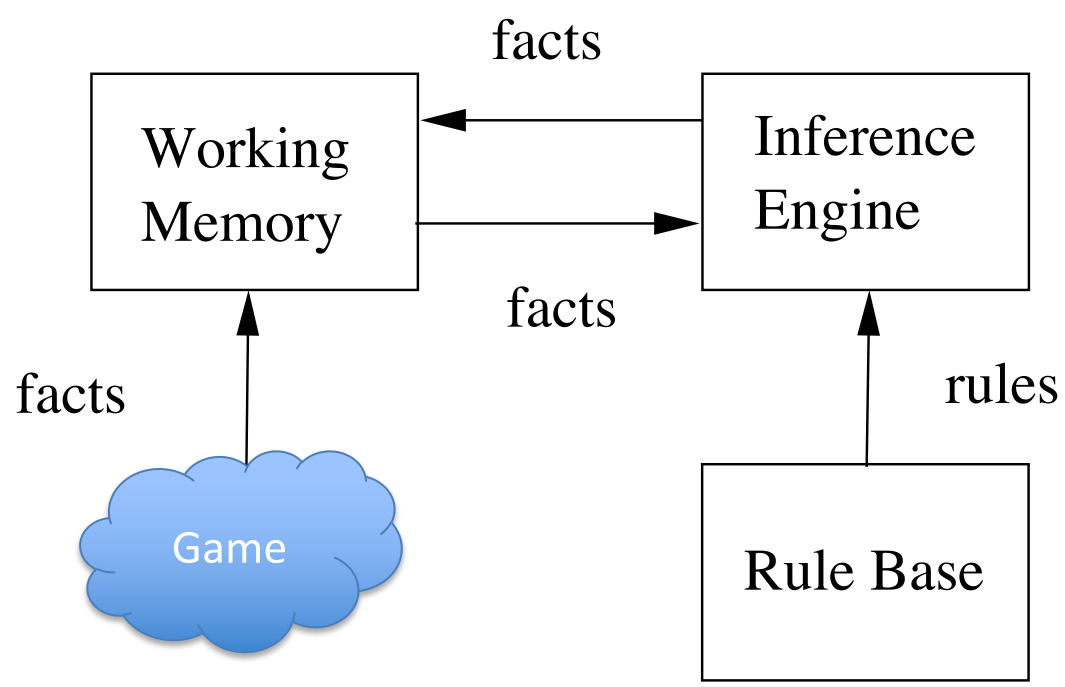


Decision Trees: Summary

- Advantages:
  - Simple, compact representation
  - Easy to create and understand
  - Decision trees can be learned
- Disadvantages:
  - Slightly more coding than other techniques (FSMs)
  - Learnt trees may contain errors

Expert (Rule-Based) Systems in Games

- Rule-based knowledge representation
  - Set of rules
  - Facts in working memory
  - Inference engine
    - *Conflict resolution*



Chaining

- Forward chaining
  - Game actions cause changes to the working memory
  - AI agent acts on the derived knowledge
  - Reactive AI
- Backward chaining
  - Pursue goals
  - Goal-driven AI
    - Other methods are more common

Example: Age of Kings

Define rule

Condition

Action

Execute only once

```
(defrule(unit-type-count
villager > 0)=>(chat-to-all "I
just made my first rule!!!!"
(disable-self);
)
```

http://aok.heavengames.com/cgi-bin/aokcgi/display.cgi?action=ct&f=26,29,,30

Larger Rule

```
(defrule(building-type-count-total
house > 0) (building-type-count-total
mill == 0) (resource-found
food) (can-build mill)=>(build mill))
```

Rules are commonly used in strategy game AI