CHAPTERS 4–5: NON-CLASSICAL AND ADVERSARIAL SEARCH

DIT411/TIN175, Artificial Intelligence

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REPETITION

UNINFORMED SEARCH (R&N 3.4)

Search problems, graphs, states, arcs, goal test, generic search algorithm, tree search, graph search, depth-first search, breadth-first search, uniform cost search, iterative deepending, bidirectional search, …

HEURISTIC SEARCH (R&N 3.5–3.6)

Greedy best-first search, A* search, heuristics, admissibility, consistency, dominating heuristics, …

LOCAL SEARCH (R&N 4.1)

Hill climbing / gradient descent, random moves, random restarts, beam search, simulated annealing, …

NON-CLASSICAL SEARCH

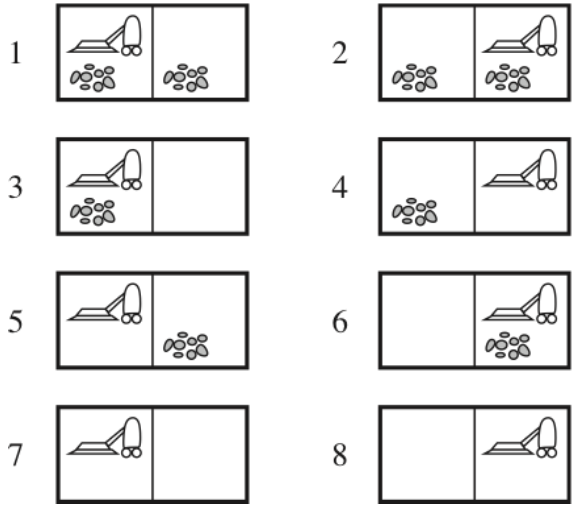
NONDETERMINISTIC SEARCH (R&N 4.3)

PARTIAL OBSERVATIONS (R&N 4.4)

NONDETERMINISTIC SEARCH (R&N 4.3)

- Contingency plan / strategy
- *And-or* search trees (not in the written exam)

AN ERRATIC VACUUM CLEANER



The eight possible states of the vacuum world; states 7 and 8 are goal states.

There are three actions: *Left, Right, Suck*.
Assume that the *Suck* action works as follows:

- if the square is dirty, it is cleaned but sometimes also the adjacent square is
- if the square is clean, the vacuum cleaner sometimes deposists dirt

NONDETERMINISTIC OUTCOMES, CONTINGENCY PLANS

Assume that the *Suck* action is nondeterministic:

- if the square is dirty, it is cleaned but sometimes also the adjacent square is
- if the square is clean, the vacuum cleaner sometimes deposists dirt

Now we need a more general *result* function:

- instead of returning a single state, it returns a set of possible outcome states
- e.g., $\text{Results}(\text{Suck}, 1) = \{5, 7\}$ and $\text{Results}(\text{Suck}, 5) = \{1, 5\}$

We also need to generalise the notion of a *solution*:

- instead of a single sequence (path) from the start to the goal, we need a *strategy* (or a *contingency plan*)
- i.e., we need **if-then-else** constructs
- this is a possible solution from state 1:
  - [*Suck*, if *State*=5 then [*Right*, *Suck*] else []]

HOW TO FIND CONTINGENCY PLANS

(will not be in the written examination)

We need a new kind of nodes in the search tree:

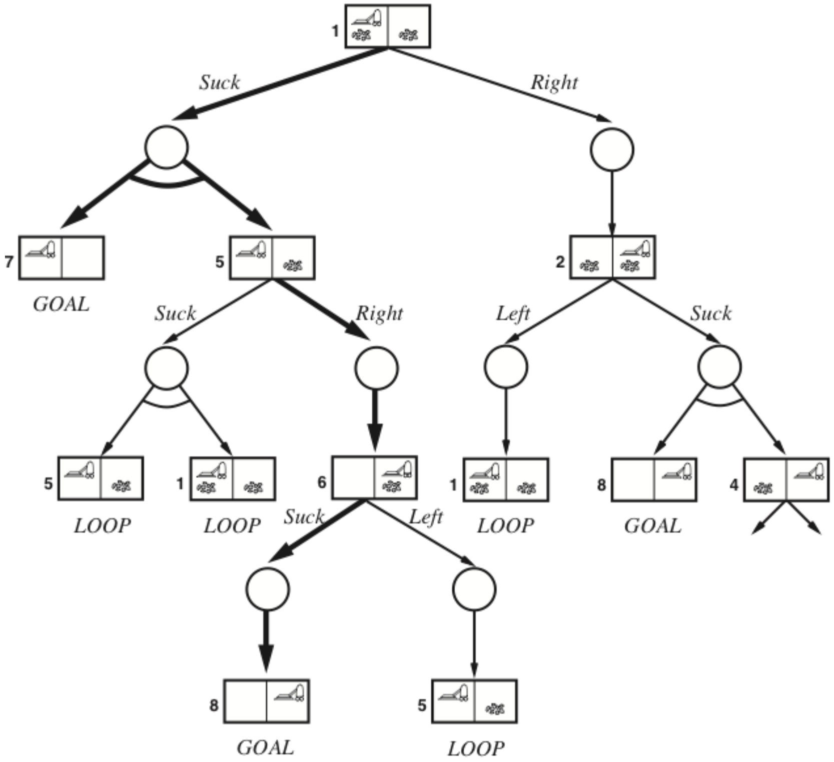
- ***and** nodes*:
  these are used whenever an action is nondeterministic
- normal nodes are called ***or** nodes*:
  they are used when we have several possible actions in a state

A solution for an ***and-or*** search problem is a subtree that:

- has a goal node at every leaf
- specifies exactly one action at each of its ***or** node*
- includes every branch at each of its ***and** node*

A SOLUTION TO THE ERRATIC VACUUM CLEANER

(will not be in the written examination)



The solution subtree is shown in bold, and corresponds to the plan:

[*Suck*, if *State*=5 then [*Right*, *Suck*] else []]

AN ALGORITHM FOR FINDING A CONTINGENCY PLAN

(will not be in the written examination)

This algorithm does a depth-first search in the *and-or* tree, so it is not guaranteed to find the best or shortest plan:

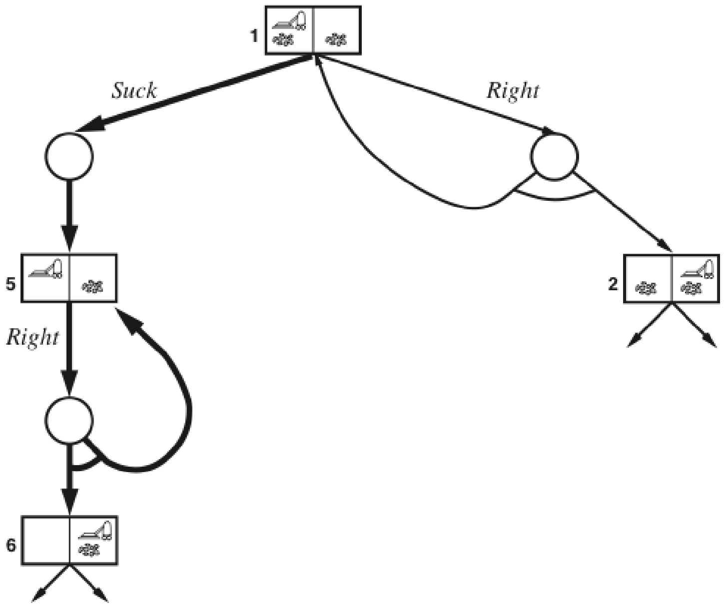
function AndOrGraphSearch(*problem*):
    return OrSearch(*problem*.InitialState, *problem*, [])

function OrSearch(*state*, *problem*, *path*):
    if *problem*.GoalTest(*state*) **then return** []
    if *state* is on *path* **then return** failure
    for each *action* in *problem*.Actions(*state*):
        plan := AndSearch(*problem*.Results(*state*, *action*), *problem*, [*state*] ++ *path*)
        if *plan* ≠ failure **then return** [*action*] ++ *plan*
    return failure

function AndSearch(*states*, *problem*, *path*):
    for each s_i in *states*:
        $plan_i$:= OrSearch(s_i, *problem*, *path*)
        if $plan_i$ = failure **then return** failure
    return [if s_1 then $plan_1$ else if s_2 then $plan_2$ else … if s_n then $plan_n$]

WHILE LOOPS IN CONTINGENCY PLANS

(will not be in the written examination)



If the search graph contains cycles, **if-then-else** is not enough in a contingency plan:

- we need **while** loops instead

In the slippery vacuum world above, the cleaner don't always move when told:

- the solution above translates to [*Suck*, while *State*=5 do *Right*, *Suck*]

PARTIAL OBSERVATIONS (R&N 4.4)

- Belief states: goal test, transitions, …
- Sensor-less (conformant) problems
- Partially observable problems

OBSERVABILITY VS DETERMINISM

A problem is *nondeterministic* if there are several possible outcomes of an action
- deterministic — nondeterministic (chance)

It is *partially observable* if the agent cannot tell exactly which state it is in
- fully observable (perfect info.) — partially observable (imperfect info.)

A problem can be either nondeterministic, or partially observable, or both:

	deterministic	**chance**
perfect information	**chess, checkers, go, othello**	**backgammon monopoly**
imperfect information	**battleships, blind tictactoe**	**bridge, poker, scrabble nuclear war**

BELIEF STATES

Instead of searching in a graph of states, we use *belief states*

- A belief state is a *set of states*

In a sensor-less (or conformant) problem, the agent has *no information at all*

- The initial belief state is the set of all problem states
    - e.g., for the vacuum world the initial state is {1,2,3,4,5,6,7,8}

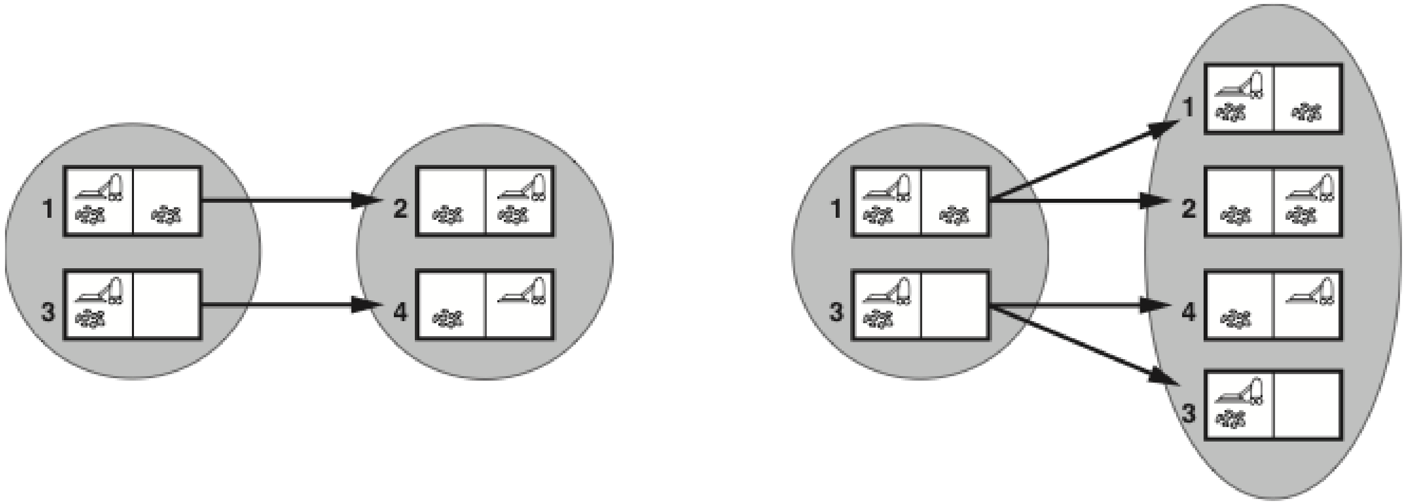
The goal test has to check that *all* members in the belief state is a goal

- e.g., for the vacuum world, the following are goal states: {7}, {8}, and {7,8}

The result of performing an action is the *union* of all possible results

- i.e., $\text{Predict}(b, a) = \{\text{Result}(s, a)$ for each $s \in b\}$
- if the problem is also nondeterministic:
    - $\text{Predict}(b, a) = \bigcup\{\text{Results}(s, a)$ for each $s \in b\}$

PREDICTING BELIEF STATES IN THE VACUUM WORLD



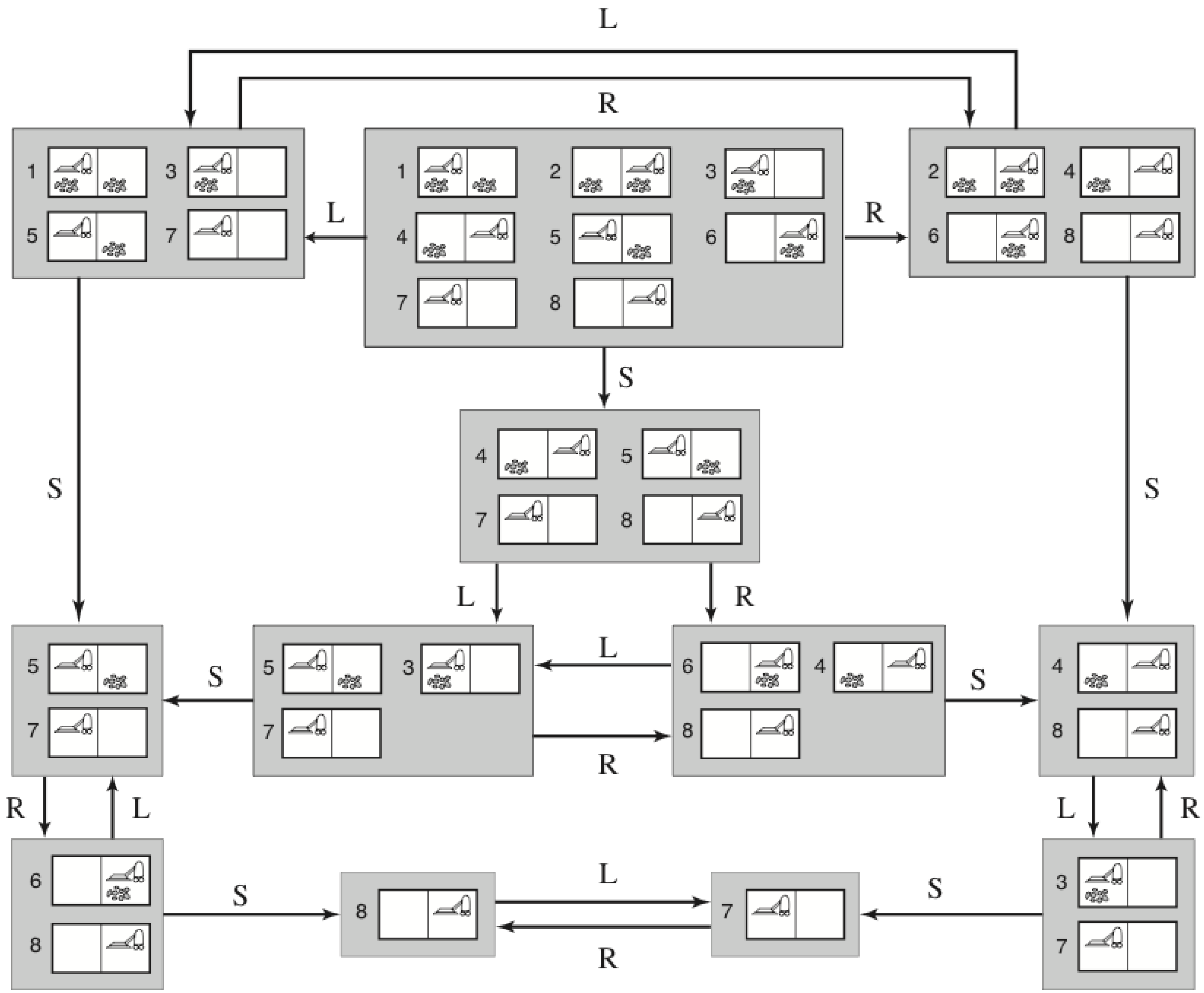
(a)

(b)

(a) Predicting the next belief state for the sensorless vacuum world with a deterministic action, *Right*.

(b) Prediction for the same belief state and action in the nondeterministic slippery version of the sensorless vacuum world.

THE DETERMINISTIC SENSORLESS VACUUM WORLD



PARTIAL OBSERVATIONS: STATE TRANSITIONS

With partial observations, we can think of belief state transitions in three stages:

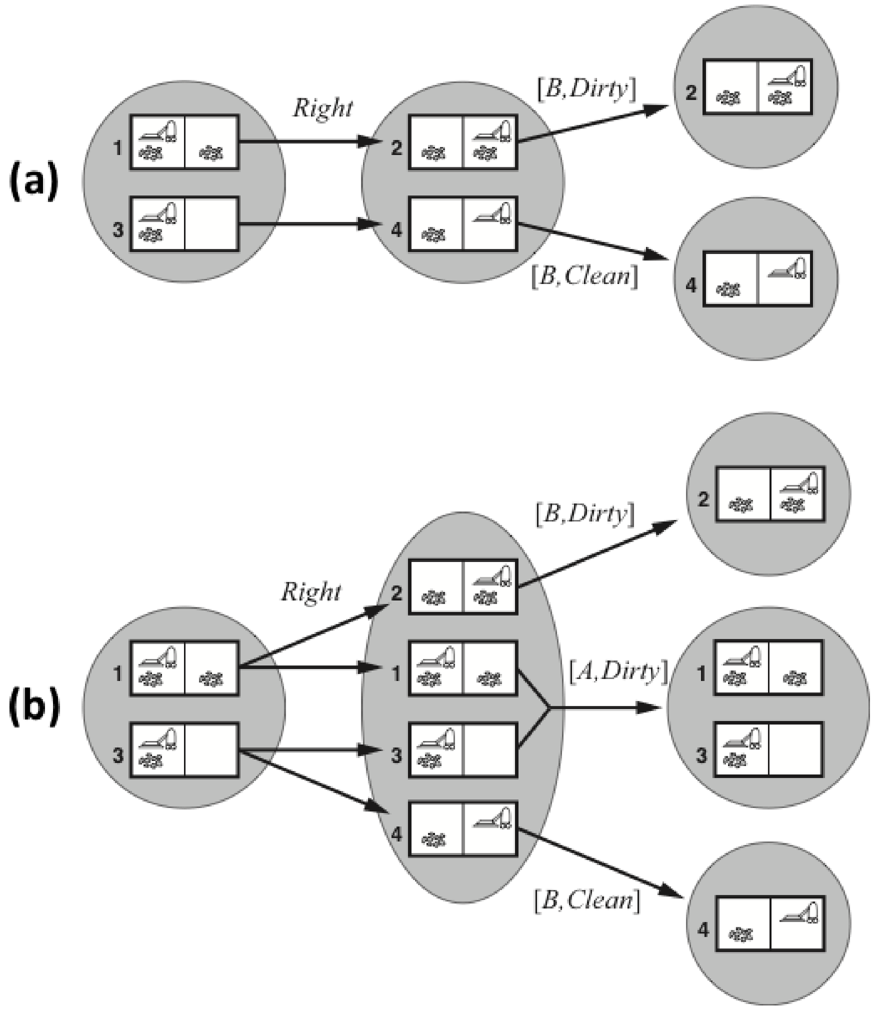
- **Prediction**, the same as for sensorless problems:
  - $b' = \text{Predict}(b, a) = \{\text{Result}(s, a) \text{ for each } s \in b\}$
- **Observation prediction**, determines the percepts that can be observed:
  - $\text{PossiblePercepts}(b') = \{\text{Percept}(s) \text{ for each } s \in b'\}$
- **Update**, filters the predicted states according to the percepts:
  - $\text{Update}(b', o) = \{s \text{ for each } s \in b' \text{ such that } o = \text{Percept}(s)\}$

Belief state transitions:

- $\text{Results}(b, a) = \{\text{Update}(b', o) \text{ for each } o \in \text{PossiblePercepts}(b')\}$
  where $b' = \text{Predict}(b, a)$

TRANSITIONS IN PARTIALLY OBSERVABLE VACUUM WORLDS

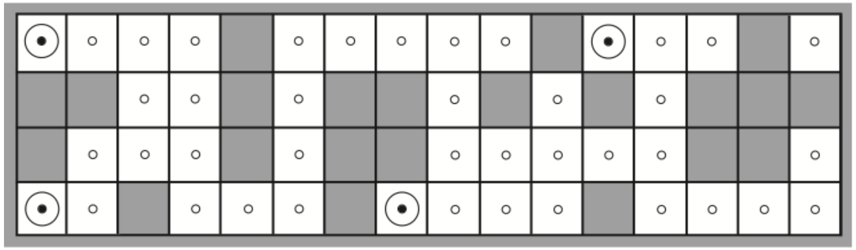
The percepts return the current position and the dirtyness of that square.



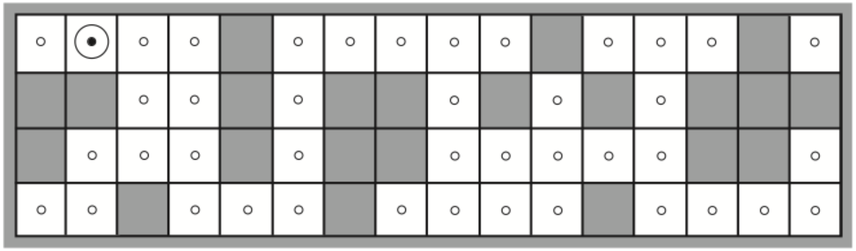
The deterministic world:
Right always succeeds.

The slippery world:
Right sometimes fails.

EXAMPLE: ROBOT LOCALISATION



(a) Possible locations of robot after $E_1 = NSW$



(b) Possible locations of robot After $E_1 = NSW, E_2 = NS$

The percepts return whether there is a wall in each of the directions.

Top: Possible initial positions of the robot, after the first observation.

- **E_1** = North, South, West

Bottom: After moving right and observing, there's only one possible position left.

- **E_1** = North, South, West; **Right**; **E_2** = North, South

ADVERSARIAL SEARCH

TYPES OF GAMES (R&N 5.1)

MINIMAX SEARCH (R&N 5.2–5.3)

IMPERFECT DECISIONS (R&N 5.4–5.4.2)

STOCHASTIC GAMES (R&N 5.5)

TYPES OF GAMES (R&N 5.1)

- cooperative, competetive, zero-sum games
- game trees, ply/plies, utility functions

MULTIPLE AGENTS

Let's consider problems with multiple agents, where:

- the agents select actions autonomously
- each agent has its own information state
    - they can have different information (even conflicting)
- the outcome depends on the actions of all agents
- each agent has its own utility function (that depends on the total outcome)

TYPES OF AGENTS

There are two extremes of multiagent systems:

- **Cooperative**: The agents share the same utility function
  - *Example*: Automatic trucks in a warehouse
- **Competetive**: When one agent wins all other agents lose
  - A common special case is when $\sum_a u_a(o) = 0$ for any outcome o. This is called a zero-sum game.
  - *Example*: Most board games

Many multiagent systems are between these two extremes.

- *Example*: Long-distance bike races are usually both cooperative (bikers form clusters where they take turns in leading a group), and competetive (only one of them can win in the end).

GAMES AS SEARCH PROBLEMS

The main difference to chapters 3–4:
now we have more than one agent that have different goals.

- All possible game sequences are represented in a game tree.
- The nodes are states of the game, e.g. board positions in chess.
- Initial state (root) and terminal nodes (leaves).
- States are connected if there is a legal move/ply.
  (a ply is a move by one player, i.e., one layer in the game tree)
- Utility function (payoff function). Terminal nodes have utility values $+x$ (player 1 wins), $-x$ (player 2 wins) and 0 (draw).

TYPES OF GAMES (AGAIN)

	deterministic	chance
perfect information	chess, checkers, go, othello	backgammon monopoly
imperfect information	battleships, blind tictactoe	bridge, poker, scrabble nuclear war

PERFECT INFORMATION GAMES: ZERO-SUM GAMES

Perfect information games are solvable in a manner similar to fully observable single-agent systems, e.g., using forward search.

If two agents compete, so that a positive reward for one is a negative reward for the other agent, we have a two-agent *zero-sum game*.

The value of a game zero-sum game can be characterized by a single number that one agent is trying to maximize and the other agent is trying to minimize.

This leads to a *minimax strategy*:

- A node is either a MAX node (if it is controlled by the maximising agent),
- or is a MIN node (if it is controlled by the minimising agent).

MINIMAX SEARCH (R&N 5.2–5.3)

- Minimax algorithm
- α-β pruning

MINIMAX SEARCH FOR ZERO-SUM GAMES

Given two players called MAX and MIN:

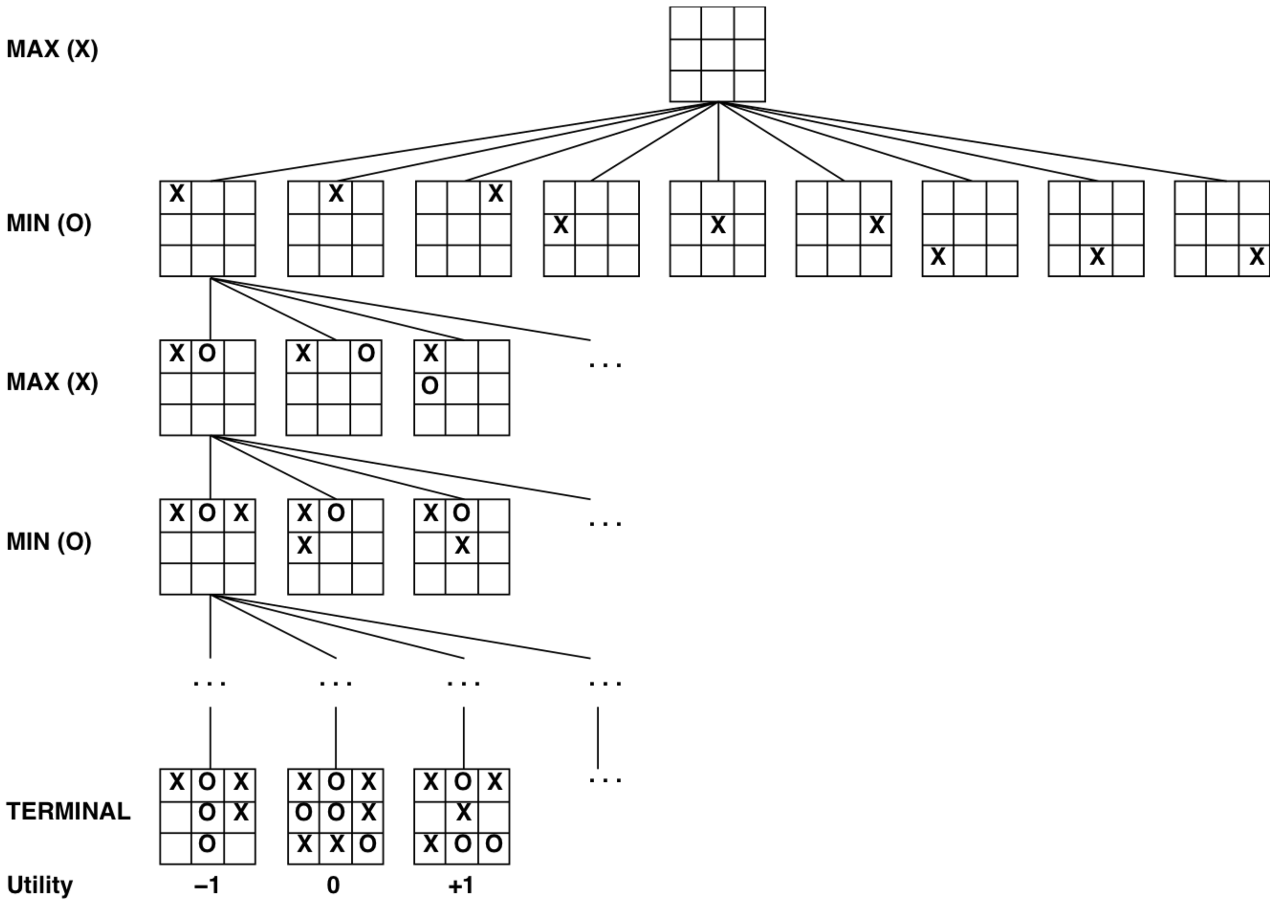
- MAX wants to maximise the utility value,
- MIN wants to minimise the same value.

$\Rightarrow$ MAX should choose the alternative that maximises, assuming MIN minimises.

Minimax gives perfect play for deterministic, perfect-information games:

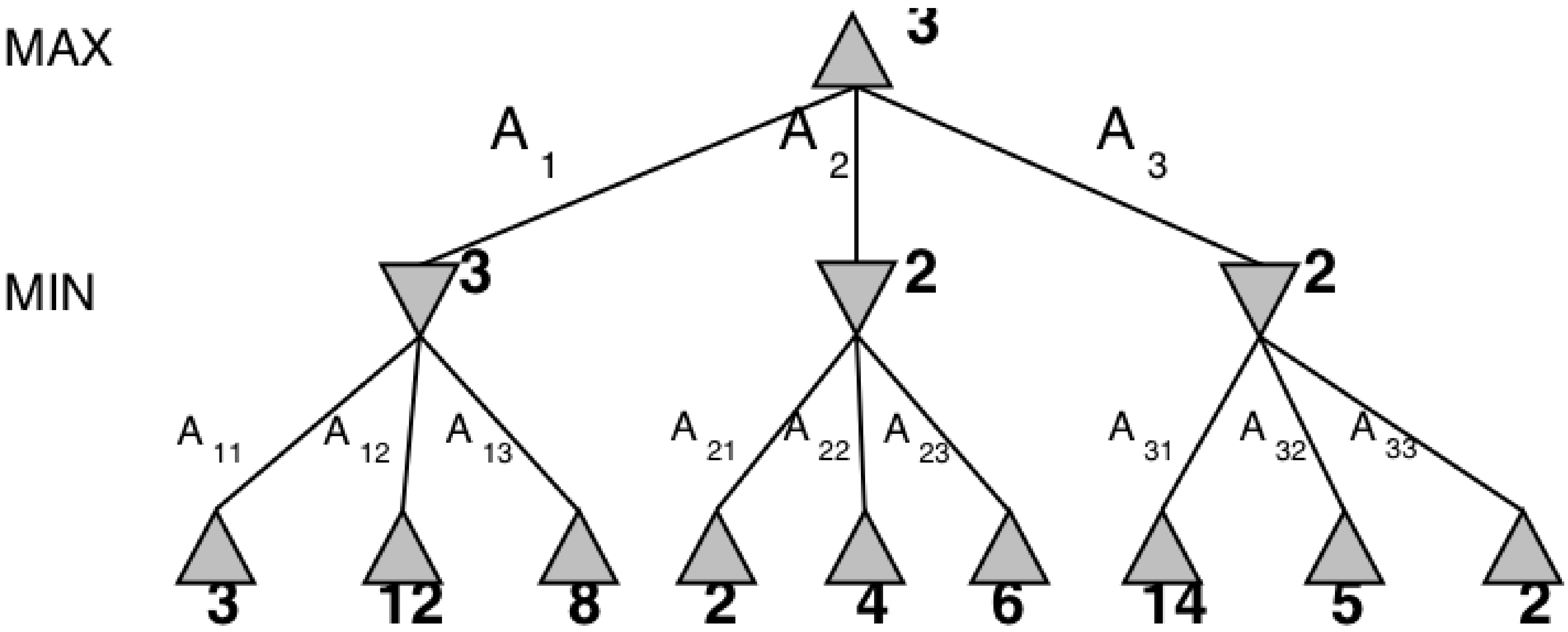
function Minimax(*state*):
    if TerminalTest(*state*) **then return** Utility(*state*)
    A := Actions(*state*)
    if *state* is a MAX node **then return** $\max_{a \in A}$ Minimax(Result(*state*, a))
    if *state* is a MIN node **then return** $\min_{a \in A}$ Minimax(Result(*state*, a))

MINIMAX SEARCH: TIC-TAC-TOE



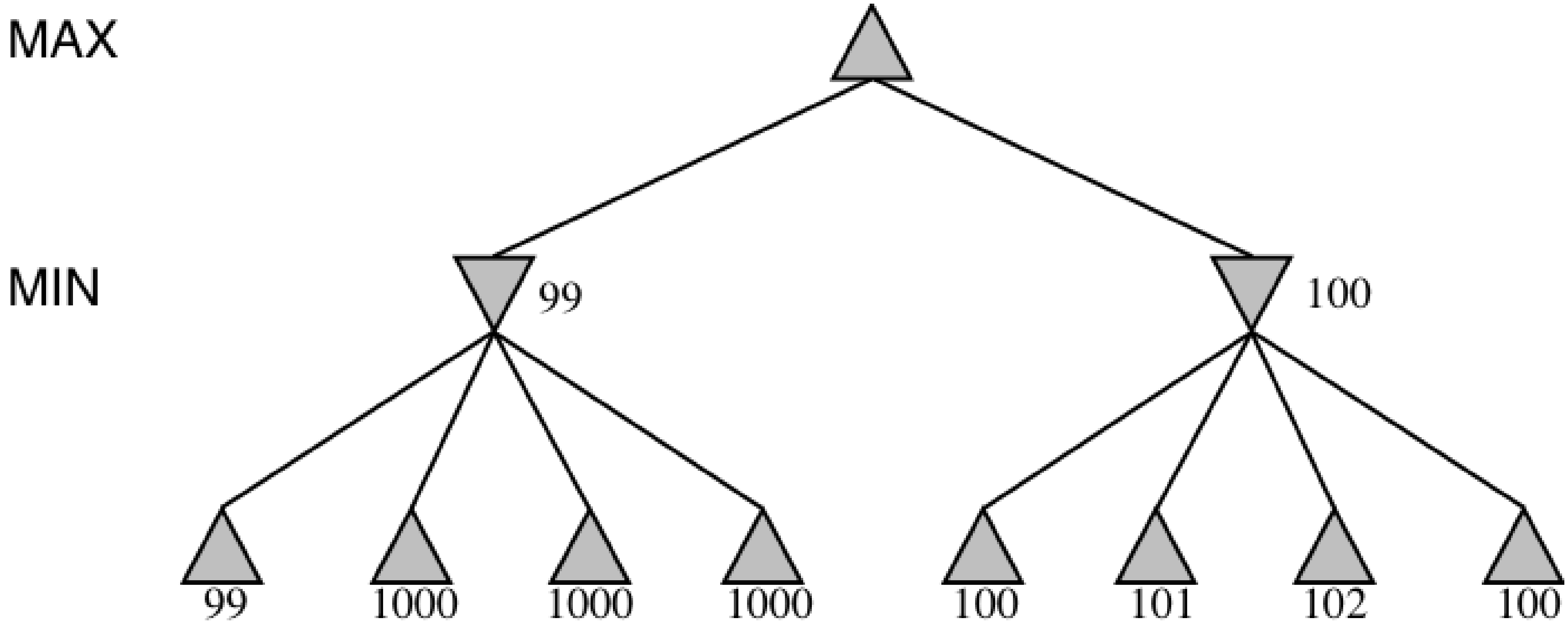
MINIMAX EXAMPLE

The Minimax algorithm gives perfect play for deterministic, perfect-information games.



CAN MINIMAX BE WRONG?

Minimax gives perfect play, but is that always the best strategy?

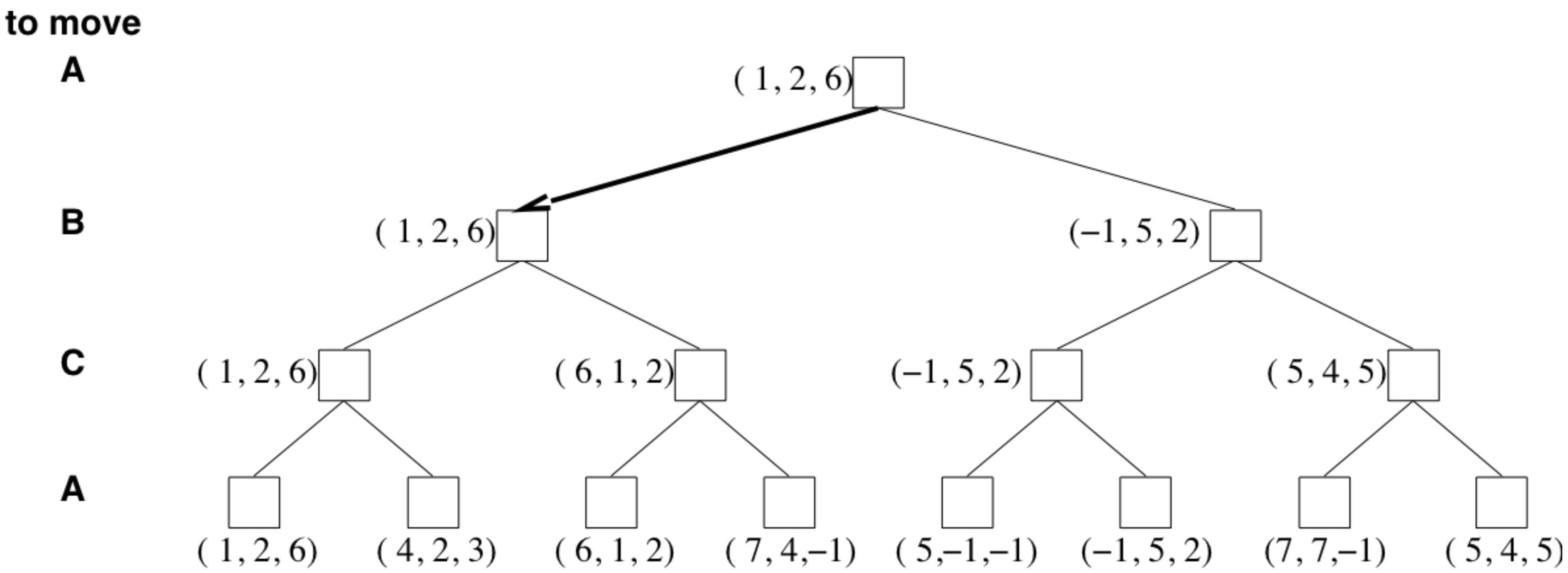


Perfect play assumes that the opponent is also a perfect player!

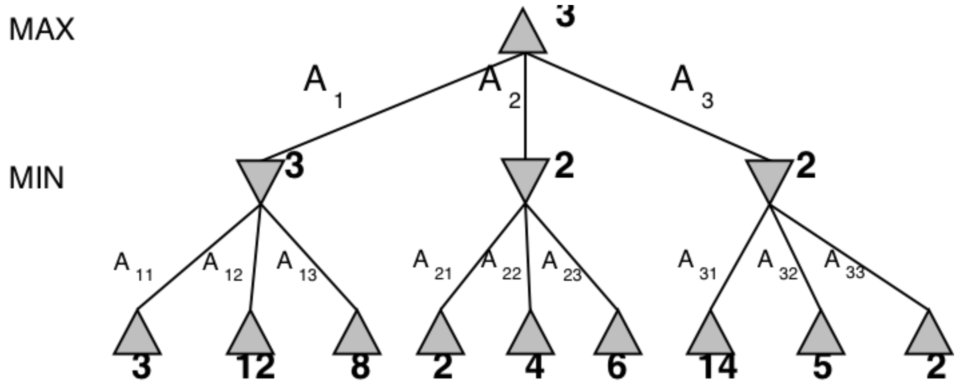
3-PLAYER MINIMAX

(will not be in the written examination)

Minimax can also be used on multiplayer games



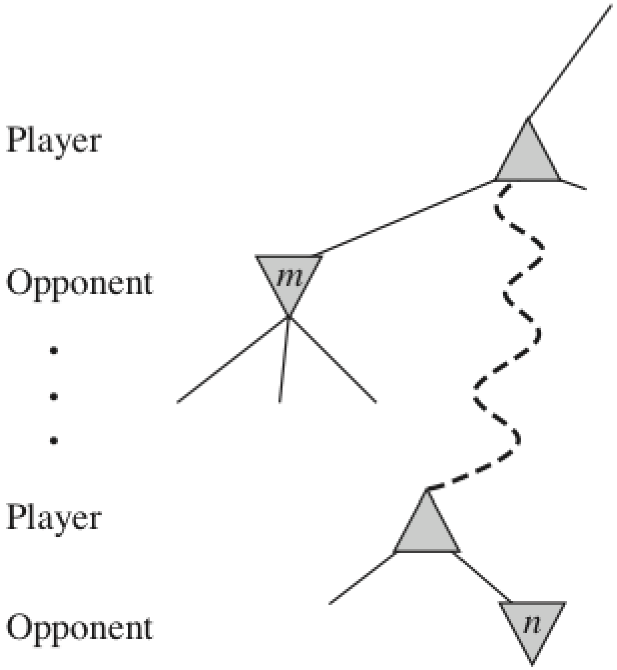
α–β PRUNING



$$
\begin{aligned}
\text{Minimax}(\textit{root}) &= \max(\min(3, 12, 8), \min(2, x, y), \min(14, 5, 2)) \\
&= \max(3, \min(2, x, y), 2) \\
&= \max(3, z, 2) \quad \text{where } z = \min(2, x, y) \leq 2 \\
&= 3
\end{aligned}
$$

I.e., we don't need to know the values of x and y!

α–β PRUNING, GENERAL IDEA

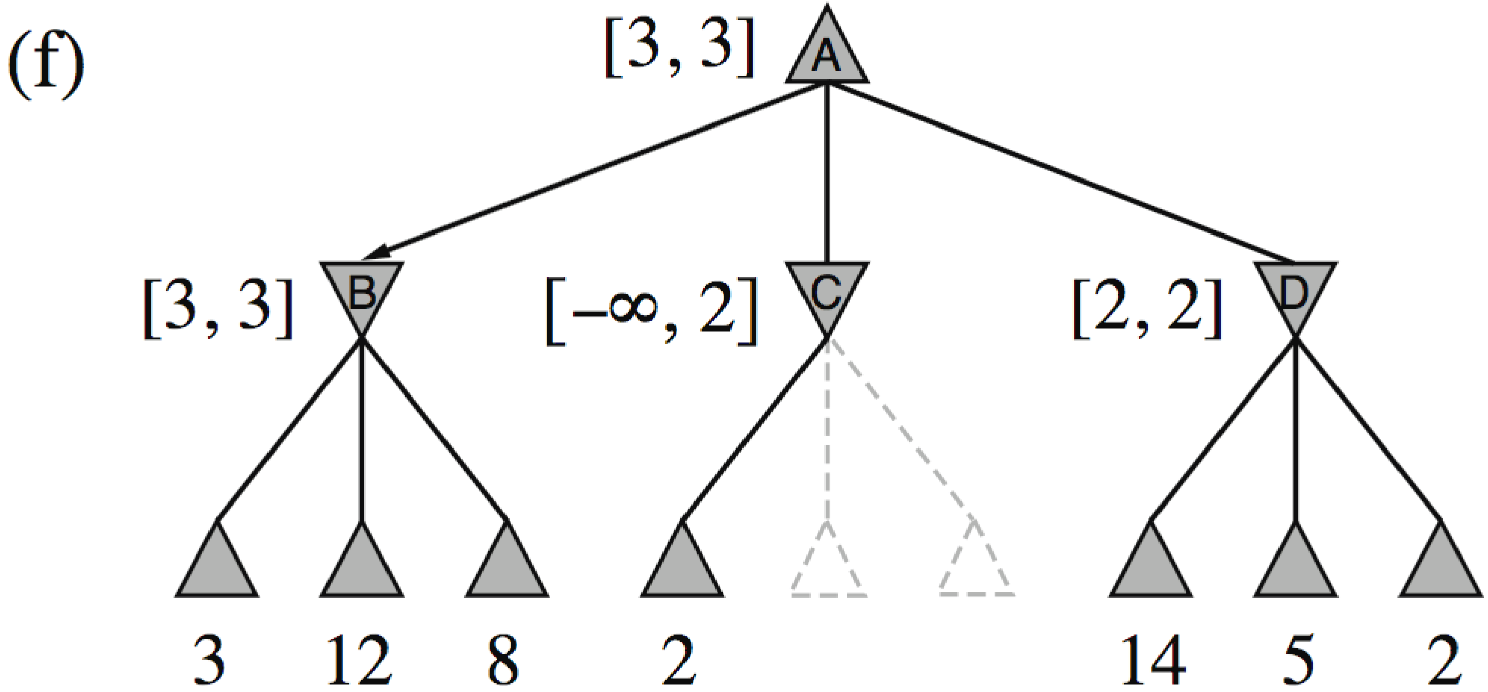


The general idea of α-β pruning is this:

- if *m* is better than *n* for Player, we don't want to pursue *n*
- so, once we know enough about *n* we can prune it
- sometimes it's enough to examine just one of *n*'s descendants

α-β pruning keeps track of the possible range of values for every node it visits; the parent range is updated when the child has been visited.

MINIMAX EXAMPLE, WITH α−β PRUNING



THE α–β ALGORITHM

function AlphaBetaSearch(*state*):
    v := MaxValue(*state*, $-\infty$, $+\infty$))
    return the *action* in Actions(*state*) that has value v

function MaxValue(*state*, α, β):
    if TerminalTest(*state*) **then return** Utility(*state*)
    $v := -\infty$
    for each *action* in Actions(*state*):
        v := max(v, MinValue(Result(*state*, *action*), α, β))
        if $v \geq \beta$ **then return** v
        α := max(α, v)
    return v

function MinValue(*state*, α, β):
    same as MaxValue but reverse the roles of α/β and *min*/*max* and $-\infty/+\infty$

HOW EFFICIENT IS $\alpha-\beta$ PRUNING?

The amount of pruning provided by the α-β algorithm depends on the ordering of the children of each node.

- It works best if a highest-valued child of a MAX node is selected first and if a lowest-valued child of a MIN node is selected first.
- In real games, much of the effort is made to optimise the search order.
- With a “perfect ordering”, the time complexity becomes $O(b^{m/2})$
    - this doubles the solvable search depth
    - however, $35^{80/2}$ (for chess) or $250^{160/2}$ (for go) is still quite large…

MINIMAX AND REAL GAMES

Most real games are too big to carry out minimax search, even with α-β pruning.

- For these games, instead of stopping at leaf nodes,
  we have to use a cutoff test to decide when to stop.
- The value returned at the node where the algorithm stops
  is an estimate of the value for this node.
- The function used to estimate the value is an evaluation function.
- Much work goes into finding good evaluation functions.
- There is a trade-off between the amount of computation required
  to compute the evaluation function and the size of the search space
  that can be explored in any given time.

IMPERFECT DECISIONS (R&N 5.4–5.4.2)

STOCHASTIC GAMES (R&N 5.5)

Note: these two sections will be presented Tuesday 6th February!