Introduction

- What is AI?
- Contributions to AI
- History of AI
- Modern AI

Reading: Russel and Norvig, Chapter 1
1.1 AI in the Media - the glitz and glamour

- sci-fi
  - Kubric, Spielberg, . . .
- “science” programs
  - “Towards 2000”
- news/current affairs
  - Kasparov
- advertisements
  - washing machines, TVs, cars, . . .

Don’t believe a word you hear!

(. . . without proof)
# 1.2 The AI Literature

| “[The automation of] activities that we associate with human thinking, activities such as decision-making, problem solving, learning . . .” (Bellman, 1978) | “The study of mental faculties through the use of computational models” (Charniak+McDermott, 1985) |
| ———————————————————————————————————————————————————————————————————— | ———————————————————————————————————————————————————————————————————— |
| “The study of how to make computers do things at which, at the moment, people are better” (Rich+Knight, 1991) | “The branch of computer science that is concerned with the automation of intelligent behavior” (Luger+Stubblefield, 1993) |

Views of AI fall into four categories:

| Thinking humanly | Thinking rationally |
| ———————————————————— | ———————————————————— |
| Acting humanly | Acting rationally |

1.3 Thinking humanly: cognitive modelling

- determine how humans think
- develop theory of human mind — psychological experiments
- model theory using computer programs

  eg. General Problem Solver (GPS) [Newel & Simon, 1961]

Requires scientific theories of internal activities of the brain

- What level of abstraction? "Knowledge" or "circuits"?
- How to validate?

1. Predicting and testing behavior of human subjects (top-down)
   ⇒  *Cognitive Science*

2. Direct identification from neurological data (bottom-up)
   ⇒  *Cognitive Neuroscience*
1.4 Acting humanly: The Turing test

Alan Turing (1950) “Computing machinery and intelligence”:

◊ “Can machines think?” → “Can they behave intelligently?”

intelligence = ability to act indistinguishably from a human in cognitive tasks

◊ Operational test for intelligent behavior ⇒ Turing Test

- human interrogates computer via teletype
- passes test if human cannot tell if there’s a human or computer at the other end

What else might today’s turing test include...?
1.4 Acting humanly: The Turing test

◊ Predicted that by 2000, a machine might have a 30% chance of fooling a lay person for 5 minutes

◊ Anticipated all major arguments against AI in following 50 years

◊ Suggested major components of AI: knowledge, reasoning, language understanding, learning

Problem: Turing test is not reproducible, constructive, or amenable to mathematical analysis
1.5 Thinking rationally: Laws of Thought

Began with Greeks in 4th century BC (1st century BE)
— e.g. Aristotle’s logical syllogisms

\[
\begin{align*}
&\text{All men are mortal,} \\
&\text{Socrates is a man,} \\
&\text{therefore Socrates is mortal}
\end{align*}
\]

Several Greek schools developed various forms of logic: notation and rules of derivation for thoughts;
— may or may not have proceeded to the idea of mechanization
1.5 Thinking rationally: Laws of Thought

Direct line through mathematics and philosophy to modern AI, e.g.

- Boole (1815–1864, *Laws of Thought* 1854, *Boolean logic*)
- Frege (1848–1925, *Begriffsschrift* 1879, *first-order logic*)
- Hilbert (1862–1943), (*Hilbert systems*)
- Russell & Whitehead (*Principia Mathematica* 1918)

Problems:

1. **Normative** (or prescriptive) rather than descriptive
2. Not all intelligent behavior is mediated by logical deliberation
1.6 Acting rationally

⇒ act in such a way to achieve goals, given beliefs

(Doesn’t necessarily involve thinking—e.g., blinking reflex. Is a thermostatically controlled heater “intelligent”?)

Define agent — entity that perceives surroundings and acts accordingly

\[ \text{AI} = \text{study and construction of rational agents.} \]

AI as intelligent agent design

• incorporates aspects from the other three approaches
• currently the dominant view of AI
“a bunch of methodologies, inspired by socio-biological analogy, for getting machines to do stuff”
2. Pre-history — Contributions to AI

Philosophy (428 BC → present)

- logic, methods of reasoning
- mind as a physical system
- foundations of learning, language, rationality

Mathematics (c. 800 → present)

- formal representation and proof
- computation, (un)decidability, (in)tractability
- probability

Psychology (1879 → present)

- perception and motor control
- cognitive neuroscience
- learning (reinforcement)
2. Pre-history — Contributions to AI

*Computing* (1940 → present)

- provision of programmable machines
- algorithms
- declarative languages (*Prolog* and *Lisp*)
- neural computing

*Linguistics* (1957 → present)

- language theory: grammar, semantics
3. The Chequered History of AI

In the beginning...

1943 McCulloch & Pitts: Boolean circuit model of brain on/off neurons, corresponding to propositions even suggested networks could learn! 
⇒ forerunner of symbolic and connectionist traditions

1950 Turing’s “Computing Machinery and Intelligence” 
Turing and Shannon writing chess programs — with no computers!

1951 Minsky & Edmonds, first neural net computer, SNARK

1950s Newell & Simon’s Logic Theorist (machine coded by hand!) 
“We have created a computer program capable of thinking non-numerically, and thereby solved the venerable mind-body problem.” — Simon
Able to prove theorems in Russell and Whitehead’s Principia Mathematica — even came up with a shorter proof!

1956 McCarthy’s Dartmouth meeting: “Artificial Intelligence”
“Look, Ma, no hands!” era

1952 Samuel’s checker playing programs
    — eventually tournament level
    ⇒ disproved computers can only do what they are told

1958 McCarthy
    — defined LISP ⇒ dominant AI programming language
    — he and others invented time-sharing ⇒ birth of DEC
    — published “Programs with Common Sense”
    ⇒ defined hypothetical program Advice Taker
    AI program that includes general knowledge, axioms
    forerunner to knowledge representation and reasoning today

1959 McCarthy & Hayes “Philisophical Investigations from
    the Standpoint of AI” ⇒ KR, reasoning, planning,…

1961 Newell and Simon’s General Problem Solver (GPS)
    imitate human problem solving — “thinking humanly”
3. The Chequered History of AI

1965 Robinson’s *resolution principle*
complete theorem proving algorithm for 1st-order logic
made **Prolog** possible

1971 **STAIRS** — practical logic-based planning system
**SHAKEY** — integration of logical reasoning and
physical activity
3. The Chequered History of AI

Falling off the bike

Bold predictions prove elusive...

◊ Lack of domain knowledge

eg. machine translation

US government funding to translate Russian to English after Sputnik in 1957

Initially thought syntactic transformations using grammar and electronic dictionary

“the spirit is willing but the flesh is weak”

“the vodka is good but the meat is rotten”

1966 report — no immediate prospect of success

All government funding cancelled
3. The Chequered History of AI

◊ Intractibility — early solutions did not scale up!

development of computational complexity theory and NP-completeness

\[ \text{program finds solution in principle} \not\Rightarrow \text{has any of the mechanisms needed to find it in practice} \]

difficulties of combinatorial explosion one of main criticisms in Lighthill Report in 1973

⇒ British government decision to end support for AI research in all but 2 universities

◊ limitations of basic AI structures

1969 Minsky and Papert’s book *Perceptrons*

— two-input perceptron could not be trained to recognise when its two inputs were different (*exclusive-or* problem)

⇒ research funding for neural nets all but disappeared
3. The Chequered History of AI

**AI goes specialist**


1976 **MYCIN** — diagnosis of blood infections. ~ 450 rules. Performed as well as some experts, better than junior doctors. No theoretical model — acquired rules from interviewing experts. Early attempt to deal with *uncertainty*. 

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3. The Chequered History of AI

1979  Duda et al., Prospector
Probabilistic reasoning system — recommended drilling at geological site that proved to contain large molybdenum deposit!!

1970s Recognition that language understanding also required knowledge and a means of using it. (Charniak)
“There is no such thing as syntax.” — Schank

1973  Woods’ Lunar system — allowed geologists to ask questions in English about Apollo’s rock samples.
— first NLP program used by others for real work.
3. The Chequered History of AI

Expert systems industry booms...

1982 McDermott’s R.1 began operation at DEC — first successful commercial expert system. Helped configure orders for new systems — saved estimated $40 million a year.

1988 DEC: 40 deployed expert systems
Du Pont: 100 in use, 500 in development, est $100m year

Increased demand for AI languages — eg Prolog

1980s Japanese ambitious “Fifth Generation” project.
“Prolog machines” — millions of inferences per sec.

US funding increased accordingly.
British Alvey report reinstated funding cut by Lighthill report (under new name “Intelligent Knowledge-Based Systems”)

Boom in Expert System development tools, dedicated Lisp workstations (eg Symbolics), etc...

few million sales in 1980 —— $2 billion in 1988
3. The Chequered History of AI

and busts...?

~1986 Recognition of limitations and some disillusionment — buying expert system shell and filling it with rules not enough.


⇒ predictions of “AI winter”.

4. Modern AI

AI matures (at least a bit!)

- Better understanding of difficulty!
- Increase in technical and theoretical depth.
- Recognition (by most) of the need for both symbolic and sub-symbolic approaches, working together.
- Resurgence and incorporation of probabilistic and decision-theoretic methods.

⇒ emphasis on solid foundations and a more wholistic approach

The new environment!

- Fast distributed hardware
- New languages (eg Java), distributed programs
- Increased communications (WWW).
- New possibilities, eg ALife, GAs, . . .
- Advances in understanding of biological and neural systems (biologically-inspired computing)
- New applications, eg Web agents, Mars rovers, . . .

⇒ emphasis on intelligent “agents”, incorporating a range of AI technologies
CITS 7210 Algorithms for Artificial Intelligence

Topic 2

Intelligent Agents

- What are agents?
- Rational agents
- Agent functions and programs
- Types of agents

Reading: Russell and Norvig, Chapter 2
1. What are agents?

agent — perceives environment through sensors
— acts on the environment through effectors

Examples...

<table>
<thead>
<tr>
<th>Perceps</th>
<th>light, sound, solidity, ...</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sensors</td>
<td></td>
</tr>
<tr>
<td>human</td>
<td>eyes, ears, skin, ...</td>
</tr>
<tr>
<td>robot</td>
<td>infra-red detectors, cameras, microphone, accelerometers, ...</td>
</tr>
<tr>
<td>Effectors</td>
<td></td>
</tr>
<tr>
<td>human</td>
<td>hands, legs, voice, ...</td>
</tr>
<tr>
<td>robot</td>
<td>grippers, wheels, speakers, ...</td>
</tr>
<tr>
<td>Actions</td>
<td>pickup, throw, speak, ...</td>
</tr>
</tbody>
</table>
2. Rational agents

Recall: rational agent tries to . . .
   — “do the right thing”
   — act to achieve goals

The “right thing” can be specified by a *performance measure* defining a numerical value for any environment history

**Rational action:** whichever action maximizes the expected value of the performance measure **given the percept sequence to date**

- Rational ≠ omniscient
- Rational ≠ clairvoyant
- Rational ≠ successful
3. Agent functions and programs

An agent can be completely specified by an agent function mapping percept sequences to actions

(In principle, one can supply each possible sequence to see what it does. Obviously, a lookup table would usually be immense.)

One agent function (or a small equivalence class) is rational

Aim: find a way to implement the rational agent function concisely and efficiently

An agent program implements and agent function: takes a single percept as input, keeps internal state, returns an action:

```
function Skeleton-Agent(percept) returns action
    static: memory, the agent's memory of the world
    memory ← Update-Memory(memory, percept)
    action ← Choose-Best-Action(memory)
    memory ← Update-Memory(memory, action)
    return action
```

In OO-speak • • • ⇒
3.1 Agents in Java

class Player implements Agent {
    ...

    Action getAction(Percept percept) {
        Move myNextMove;
        // my selection algorithm
        return myNextMove;
    }
    ...

}
4. Types of Agents

An *agent program* accepts percepts, combines them with any stored knowledge, and selects actions.

A *rational agent* will choose actions so as to maximise some *performance measure*. (In practice try to achieve “good” performance.)

Four basic types in order of increasing generality:

- simple reflex agents
- reflex agents with state
- goal-based agents
- utility-based agents
4.1 Simple Reflex Agents

⇒ choose responses using *condition-action* rules (or *production rules*).

**if** you see the car in front’s brake lights **then** apply the brakes

Some researches claim this is how simple life-forms (eg. insects) behave.
4.2 Agents that keep track of the world

While simply reacting to the current state of the world is adequate in some circumstances, most intelligent action requires more knowledge to work from:

- memory of the past
- knowledge about the effects of actions — how the world evolves
- requires internal state

eg. You notice someone ahead signal to the bus. You know that this will cause the bus driver to stop (ideally), and conclude that you should change lanes.
4.3 Goal-based agents

Reacting to evolving world may keep you from crashing your car, but it doesn’t tell you where to go!

Intelligent beings act in such a way as to try to achieve some **goals**.

![Diagram of agent-environment interaction](image)

Some goals are pretty simple. eg. Star Trek — “to go where no-one has gone before”

Some are more complex and require **planning** to achieve them. eg. Star Wars — *to defeat the Empire* — find a potential Jedi knight, ship him off to see Yoda, teach him to use the force, etc

Planning is a fundamental problem of AI. Usually requires **search** through the available actions to find an appropriate sequence.

Some people even say AI is really search!
4.4 Utility-based agents

Two views:

1. A successful agent is only required to satisfy objective goals (emotions are a hindrance)
2. Subjective measures such as happiness, security (safety), etc are important for success

E.g. Luke could maximise his material benefits by turning to the dark side of the force, but he’d be very unhappy :-(

Researchers call this measure of happiness utility (since it sounds more scientific)
5. Next... 

- Conceptualising the environment
  — states, actions (operators), goals

- The fundamental skills of an intelligent agent
  — problem solving and search
Problem Solving and Search

- Problem-solving and search
- Search algorithms
  - uninformed search algorithms
    - breadth-first search
    - uniform-cost search
    - depth-first search
    - iterative deepening search
    - bidirectional search

Reading: Russell and Norvig, Chapter 3
1. Problem Solving and Search

Seen that an intelligent agent has:

- knowledge of the *state* of the “world”
- a notion of how actions or *operations* change the world
- some *goals*, or states of the world, it would like to bring about

Finding a sequence of operations that changes the state of the world to a desired goal state is a *search problem* (or basic *planning problem*).

*Search algorithms are the cornerstone of AI*

In this section we see some examples of how the above is encoded, and look at some common *search strategies*. 
1.1 States, Operators, Graphs and Trees

**state** — description of the world at a particular time
  — impossible to describe the whole world
  — need to abstract those attributes or properties that are important.

**Examples**

**Example 1:** Say we wish to drive from Arad to Bucharest. First we “discretise” the problem:

- **states** — map of cities + our location
- **operators** — drive from one city to the next
- **start state** — driver located at Arad
- **goal state** — driver located at Bucharest

**Find solution:**
  sequence of cities, e.g., Arad, Sibiu, Fagaras, Bucharest
1.1 States, Operators, Graphs and Trees

The states and operators form a graph — states form nodes, operators form arcs or edges...
### Example 2: The *eight puzzle*

<table>
<thead>
<tr>
<th>States — description of the positions of the numbered squares</th>
</tr>
</thead>
<tbody>
<tr>
<td>Operators — some alternatives. . .</td>
</tr>
<tr>
<td>(a) move a numbered square to an adjacent place, or</td>
</tr>
<tr>
<td>(b) move blank left, right, up or down — far fewer operators</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Start State</th>
<th>Goal State</th>
</tr>
</thead>
<tbody>
<tr>
<td>5</td>
<td>4</td>
</tr>
<tr>
<td>6</td>
<td>1</td>
</tr>
<tr>
<td>7</td>
<td>3</td>
</tr>
<tr>
<td>1</td>
<td>2</td>
</tr>
<tr>
<td>8</td>
<td>4</td>
</tr>
<tr>
<td>7</td>
<td>6</td>
</tr>
</tbody>
</table>

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Example 3: *Missionaries and Cannibals*

**start state** — 3 missionaries, 3 cannibals, and a boat that holds two people, on one side of river

**goal state** — all on other side

**states** — description of legal configurations (ie. where no-one gets eaten) of where the missionaries, cannibals, and boat are

**operators** — state changes possible using 2-person boat
1.1 States, Operators, Graphs and Trees

\[
\begin{align*}
\langle\{\text{MMMCCCB}\},\{\}\rangle & \\
\langle\{\text{MMCC}\},\{\text{MCB}\}\rangle & \quad \langle\{\text{MMMC}\},\{\text{CCB}\}\rangle & \quad \langle\{\text{MMMCC}\},\{\text{CB}\}\rangle \\
\langle\{\text{MMMCCB}\},\{\text{C}\}\rangle & \\
\langle\{\text{MMM}\},\{\text{CCCBB}\}\rangle & \\
\langle\{\text{MMMCCB}\},\{\text{C}\}\rangle & \\
\langle\{\text{MC}\},\{\text{MMCCB}\}\rangle & \\
\langle\{\text{MMCCB}\},\{\text{MC}\}\rangle & \\
\langle\{\text{CC}\},\{\text{MMMCB}\}\rangle & \\
\langle\{\text{CCBB}\},\{\text{MM}\}\rangle & \\
\langle\{\text{C}\},\{\text{MMMCCB}\}\rangle & \\
\langle\{\text{CCB}\},\{\text{MMMMC}\}\rangle & \quad \langle\{\text{MCB}\},\{\text{MMCC}\}\rangle \\
\langle\{\},\{\text{MMMCCB}\}\rangle
\end{align*}
\]
1.2 Operator costs

Graphs may also contain the cost of getting from one node to another (ie. associated with each operator, or each arc).

*cost of path = sum of the costs of arcs making up the path*

Usually concerned not just with finding a path to the goal, but finding a cheap path.

*shortest path problem* — find the cheapest path from a start state to a goal state

Where operator costs are not given, all operators are assumed to have unit cost.
A problem is defined by four items:

- **Initial state**: e.g., “at Arad”
- **Operators** (or successor function $S(x)$)
  - e.g., Arad $\rightarrow$ Zerind, Arad $\rightarrow$ Sibiu, etc.
- **Goal test**, can be
  - *explicit*, e.g., $x$ = “at Bucharest”
  - *implicit*, e.g., “world peace”
- **Path cost** (additive)
  - e.g., sum of distances, number of operators executed, etc.

A solution is a sequence of operators leading from the initial state to a goal state.
1.4 Example: robotic assembly

**states??:** real-valued coordinates of robot joint angles

**operators??:** continuous motions of robot joints

**goal test??:** complete assembly *with no robot included!*

**path cost??:** time to execute
2. Search algorithms

Basic idea:
offline, simulated exploration of state space by generating successors of already-explored states (a.k.a. expanding states)

```
function General-Search(problem, strategy) returns a solution, or failure
    initialize the search tree using the initial state of problem
    loop do
        if there are no candidates for expansion
            then return failure
        choose a leaf node for expansion according to strategy
        if the node contains a goal state
            then return the corresponding solution
        else expand node and add resulting nodes to the search tree
    end
```
2.1 General search example
2.2 General search in more detail

General search algorithm

Given a start state $s_0 \in S$, a goal function $g(s) \rightarrow \{\text{true}, \text{false}\}$, and an (optional) terminal condition $t(s) \rightarrow \{\text{true}, \text{false}\}$:

Initialise a set $U = \{s_0\}$ of unvisited nodes containing just the start state, and an empty set $V = \{\}$ of visited nodes.
1. If $U$ is empty halt and report no goal found.
2. Select, according to some (as yet undefined) strategy, a node $s$ from $U$.
3. (Optional) If $s \in V$ discard $s$ and repeat from 1.
4. If $g(s) = \text{true}$ halt and report goal found.
5. (Optional) If $t(s) = \text{true}$ discard $s$ and repeat from 1.
6. Otherwise move $s$ to the set $V$, and add to $U$ all the nodes reachable from $s$. Repeat from 1.

Step 3 is an occurs check for cycles.

- Some search strategies will still work without this trade-off — work to check if visited vs work re-searching same nodes again.
- Others may cycle forever.

With these cycles removed, the graph becomes a search tree.
2.3 Comparing search strategies

The *search strategy* is crucial — determines in which order the nodes are expanded. Concerned with:

- **completeness** — does the strategy guarantee finding a solution if there is one
- **time complexity** — how long does it take
- **space complexity** — how much memory is needed to store states
- **optimality** — does it guarantee finding the best solution

Time and space complexity are often measured in terms of

- $b$ — maximum *branching factor* of the search tree
- $d$ — *depth* of the *least-cost solution*
- $m$ — *maximum depth* of the state space (may be $\infty$)
Many strategies can be implemented by placing unvisited nodes in a queue (Step 6) and always selecting the next node to expand from the front of the queue (Step 2)

⇒ the way the children of expanded nodes are placed in the queue determines the search strategy.

Many different strategies have been proposed. We’ll look at some of the most common ones...
3. Uninformed search strategies

*Uninformed* strategies use only the information available in the problem definition

- Breadth-first search
- Uniform-cost search
- Depth-first search
- Depth-limited search
- Iterative deepening search
- Bidirectional search

Later we will look at *informed* strategies that use additional information.
3.1 Breadth-first search

Expand shallowest unexpanded node

Implementation:

\[ \text{QueueingFn} = \text{put successors at end of queue} \]

⇒ expand all nodes at one level before moving on to the next
3.1 Breadth-first search

**Complete?** Yes (if $b$ is finite)

**Time?** $O(1 + b + b^2 + b^3 + \ldots + b^d) = O(b^d)$, i.e., exponential in $d$

**Space?** $O(b^d)$ (all leaves in memory)

**Optimal?** *Yes (if cost = 1 per step); not optimal in general*

*Space* is the big problem; can easily generate nodes at 1MB/sec so 24hrs $= 86$GB.

Good example of computational explosion...

Assume branching factor of 10, 1000 nodes/sec, 100 bytes/node.

<table>
<thead>
<tr>
<th>Depth</th>
<th>Nodes</th>
<th>Time</th>
<th>Memory</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>1</td>
<td>1 millisecond</td>
<td>100 bytes</td>
</tr>
<tr>
<td>2</td>
<td>111</td>
<td>.1 seconds</td>
<td>11 kilobytes</td>
</tr>
<tr>
<td>4</td>
<td>11,111</td>
<td>11 seconds</td>
<td>1 megabyte</td>
</tr>
<tr>
<td>6</td>
<td>$10^6$</td>
<td>18 minutes</td>
<td>111 megabytes</td>
</tr>
<tr>
<td>8</td>
<td>$10^8$</td>
<td>31 hours</td>
<td>11 gigabytes</td>
</tr>
<tr>
<td>10</td>
<td>$10^{10}$</td>
<td>128 days</td>
<td>1 terabyte</td>
</tr>
<tr>
<td>12</td>
<td>$10^{12}$</td>
<td>35 years</td>
<td>111 terabytes</td>
</tr>
<tr>
<td>14</td>
<td>$10^{14}$</td>
<td>3500 years</td>
<td>11,111 terabytes</td>
</tr>
</tbody>
</table>

*Welcome to AI!*

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3.2 Uniform-cost search

**Problem:** Varying cost operations

e.g. Romania with step costs in km...
3.2 Uniform-cost search

Expand least total cost unexpanded node

Implementation:

\[ \text{QUEUEINGFN} = \text{insert in order of increasing path cost} \]
3.2 Uniform-cost search

**Complete?** Yes (if step cost $\geq 0$)

**Time?** # of nodes with path cost $g \leq$ cost of optimal solution

**Space?** # of nodes with $g \leq$ cost of optimal solution

**Optimal?** Yes *(if step cost $\geq 0$)*
3.3 Depth-first search

Follow one path until you can go no further, then backtrack to last choice point and try another alternative.

Implementation:

\[ \text{\textsc{QueueingFn}} = \text{insert successors at front of queue} \]
\[ \text{or use } \textit{recursion} — \text{“queueing” performed automatically by internal stack} \]

Occurs check or terminal condition needed to prevent infinite cycling.

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Finite tree example...
3.3 Depth-first search

**Complete?** No: fails in infinite-depth spaces. — complete for finite tree (in particular, require cycle check).

**Time?** $O(b^m)$.
— may do very badly if $m$ is much larger than $d$
— may be much faster than breadth-first if solutions are dense

**Space?** $O(bm)$, i.e., linear space!

**Optimal?** No

*Space performance is big advantage.*

*Time, completeness and optimality can be big disadvantages.*
3.4 Depth-limited search

= depth-first search with depth limit $l$

**Implementation:**

Nodes at depth $l$ have no successors.
Can be implemented by our *terminal condition*.

Sometimes used to apply depth-first to infinite (or effectively infinite) search spaces. Take “best” solution found with limited resources. (See Game Playing...)

Also in...
“Probe” deeper and deeper (often bounded by available resources).
3.5 Iterative deepening search

Summary view...
3.5 Iterative deepening search

Complete? Yes
Time? \((d + 1)b^0 + db^1 + (d - 1)b^2 + \ldots + b^d \rightarrow O(b^d)\)
Space? \(O(bd)\)
Optimal? Yes, if step cost = 1

Can also be modified to explore uniform-cost tree

How do the above compare with

- breadth-first?
- depth-first?
3.6 Bidirectional search

Tends to expand fewer nodes than unidirectional, but raises other difficulties — eg. how long does it take to check if a node has been visited by other half of search?
4. Summary

Problem formulation usually requires abstracting away real-world details to define a state space that can feasibly be explored.

- Abstraction reveals states and operators.
- Evaluation by goal or utility function.
- Strategy implemented by queuing function (or similar).

Variety of uninformed search strategies...

<table>
<thead>
<tr>
<th>Criterion</th>
<th>Breadth-First</th>
<th>Uniform-Cost</th>
<th>Depth-First</th>
<th>Depth-Limited</th>
<th>Iterative Deepening</th>
<th>Bidirectional (if applicable)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Time</td>
<td>$b^d$</td>
<td>$b^d$</td>
<td>$b^m$</td>
<td>$b^l$</td>
<td>$b^d$</td>
<td>$b^{d/2}$</td>
</tr>
<tr>
<td>Space</td>
<td>$b^d$</td>
<td>$b^d$</td>
<td>$bm$</td>
<td>$bl$</td>
<td>$bd$</td>
<td>$b^{d/2}$</td>
</tr>
<tr>
<td>Optimal?</td>
<td>Yes</td>
<td>Yes</td>
<td>No</td>
<td>No</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Complete?</td>
<td>Yes</td>
<td>Yes</td>
<td>No</td>
<td>Yes, if $l \geq d$</td>
<td>Yes</td>
<td>Yes</td>
</tr>
</tbody>
</table>

Iterative deepening search uses only linear space and not much more time than other uninformed algorithms.
Informed search algorithms

- Best-first search
- Greedy search
- A* search
- Admissible heuristics
- Memory-bounded search
- IDA*
- SMA*

Reading: Russell and Norvig, Chapter 4, Sections 1–3
1. Informed (or best-first) search

Recall uninformed search:

- select nodes for expansion on basis of distance from start
- uses only information contained in the graph
- no indication of distance to go!

Informed search:

- select nodes on basis of some estimate of *distance to goal*!
- requires additional information — *evaluation function*, or *heuristic rules*
- choose “best” (most promising) alternative ⇒ *best-first search*.

Implementation:

\[ \text{QUEUEINGFN} = \text{insert successors in decreasing order of desirability} \]

Examples:

- greedy search
- A* search
2. **Greedy search**

Assume we have an estimate of the distance to the goal.

For example, in our travelling to Bucharest problem, we may know straight-line distances to Bucharest...

Greedy search always chooses to visit the candidate node with the smallest estimate

⇒ that which *appears* to be closest to goal

Evaluation function $h(n)$ (*heuristic*)

$=\text{estimate of cost from } n \text{ to goal}$

E.g., $h_{\text{SLD}}(n) = \text{straight-line distance from } n \text{ to Bucharest}$
2. Greedy search
2. Greedy search

**Complete?** No, in general. e.g. can get stuck in loops,
Iasi → Neamt → Iasi → Neamt →
Complete in finite space with repeated-state checking

**Time?** $O(b^m)$, but a good heuristic can give dramatic improvement

**Space?** $O(b^m)$—keeps all nodes in memory

**Optimal?** *No*
2.1 Means-ends Analysis

Example of greedy search. (Used in SOAR problem solver.)

**Heuristic:** Pick operations that reduce as much as possible the “difference” between the intermediate state and goal state.

eg. Missionaries and cannibals

Indicates best choice in all states except for $\langle \{MC\}, \{MMCCB\} \rangle$ and $\langle \{MMCCB\}, \{MC\} \rangle$ (though no other choices).

3. A* search

Greedy search minimises estimated cost to goal, and thereby (hopefully) reduces search cost, but is neither optimal nor complete.

Uniform-cost search minimises path cost so far and is optimal and complete, but is costly.

Can we get the best of both worlds...?

Yes! Just add the two together to get *estimate of total path length* of solution as our evaluation function...

Evaluation function

\[ f(n) = g(n) + h(n) \]

- \( g(n) \) = cost so far to reach \( n \)
- \( h(n) \) = estimated cost to goal from \( n \)
- \( f(n) \) = estimated total cost of path through \( n \) to goal
3. **A* search**

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3. **A* search**

A heuristic $h$ is *admissible* iff

$$h(n) \leq h^*(n) \quad \text{for all } n$$

where $h^*(n)$ is the *true* cost from $n$.

i.e. $h(n)$ *never overestimates*

e.g., $h_{SLD}(n)$ never overestimates the actual road distance

Can prove:

*if $h(n)$ is admissible, $f(n)$ provides a complete and optimal search!*

$\Rightarrow$ called A* search.
3.1 Optimality of A*

**Theorem:** A* search is optimal

**Proof**

Suppose some suboptimal goal $G_2$ has been generated and is in the queue. Let $n$ be an unexpanded node on a shortest path to an optimal goal $G_1$.

\[
f(G_2) = g(G_2) \quad \text{since } h(G_2) = 0
\]

\[
> g(G_1) \quad \text{since } G_2 \text{ is suboptimal}
\]

\[
\geq g(n) + h(n) \quad \text{since } h \text{ is admissible}
\]

\[
= f(n)
\]

Since $f(G_2) > f(n)$, A* will not select $G_2$ for expansion.
3.2 Monotonicity and the pathmax equation

To get a more intuitive view, we consider the \( f \)-values along any path.

For most admissible heuristics, \( f \)-values increase \textit{monotonically} (see Romania problem).

For some admissible heuristics, \( f \) may be nonmonotonic — ie it may \textit{decrease} at some points.

\begin{itemize}
  \item e.g., suppose \( n' \) is a successor of \( n \)
  \begin{itemize}
    \item \( n \): \( g=5 \), \( h=4 \), \( f=9 \)
    \item \( n' \): \( g'=6 \), \( h'=2 \), \( f'=8 \)
  \end{itemize}
\end{itemize}

But \( f' = 8 \) is redundant!

\[
f(n) = 9 \quad \Rightarrow \quad \text{true cost of a path through } n \text{ is } \geq 9
\]
\[
\Rightarrow \quad \text{true cost of a path through } n' \text{ is } \geq 9
\]

\textit{Pathmax} modification to A*:

\[
f(n') = \max(g(n') + h(n'), f(n))
\]

With pathmax, \( f \) is always increases monotonically \( \cdots \sim \)
Lemma: A* (with pathmax) expands nodes in order of increasing $f$ value

Gradually adds “$f$-contours” of nodes (cf. breadth-first/uniform-cost adds layers or “circles”—A* “stretches” towards goal)

If $f^*$ is cost of optimal solution path:

- A* expands all nodes with $f(n) < f^*$
- A* expands some nodes with $f(n) = f^*$

Can see intuitively that A* is complete and optimal.
3.4 Properties of A*

**Complete** Yes, unless there are infinitely many nodes with $f \leq f(G)$

**Time** Exponential in [relative error in $h \times$ length of soln.]

**Space** Keeps all nodes in memory (see below)

**Optimal** Yes—cannot expand $f_{i+1}$ until $f_i$ is finished

Among optimal algorithms of this type A* is optimally efficient!

ie. no other algorithm is guaranteed to expand fewer nodes.

“Proof”

Any algorithm that does not expand all nodes in each contour may miss an optimal solution.
4. Admissible heuristics

Straight line distance is an obvious heuristic for distance planning. What about other problems?

This section examine heuristics in more detail.

E.g., two heuristics for the 8-puzzle:

\[
\begin{array}{ccc}
5 & 4 & \text{Grayed tile}\\
6 & 1 & 8 \\
7 & 3 & 2 \\
\end{array}
\]

Start State

\[
\begin{array}{ccc}
1 & 2 & 3 \\
8 & \text{Grayed tile} & 4 \\
7 & 6 & 5 \\
\end{array}
\]

Goal State

\(h_1(n) = \text{number of misplaced tiles}\)

\(h_2(n) = \text{total Manhattan distance}\)

(i.e., no. of squares from desired location of each tile)

\(h_1(S) = ??\)

\(h_2(S) = ??\)

Are both admissible?
4.1 Measuring performance

Quality of heuristic can be characterised by *effective branching factor* $b^\ast$.

Assume:

- $A^\ast$ expands $N$ nodes
- solution depth $d$

$b^\ast$ is branching factor of uniform tree, depth $d$ with $N$ nodes:

$$N = 1 + b^\ast + (b^\ast)^2 + \cdots + (b^\ast)^d$$

- tends to remain fairly constant over problem instances
- can be determined empirically
  - $\Rightarrow$ fairly good guide to heuristic performance

*a good heuristic would have $b^\ast$ close to 1*
### Example

Effective branching factors for iterative deepening search and A* with $h_1$ and $h_2$ (averaged over 100 randomly generated instances of 8-puzzle for each solution length):

<table>
<thead>
<tr>
<th>d</th>
<th>IDS</th>
<th>$A^*(h_1)$</th>
<th>$A^*(h_2)$</th>
<th>IDS</th>
<th>$A^*(h_1)$</th>
<th>$A^*(h_2)$</th>
</tr>
</thead>
<tbody>
<tr>
<td>2</td>
<td>10</td>
<td>6</td>
<td>6</td>
<td>2.45</td>
<td>1.79</td>
<td>1.79</td>
</tr>
<tr>
<td>4</td>
<td>112</td>
<td>13</td>
<td>12</td>
<td>2.87</td>
<td>1.48</td>
<td>1.45</td>
</tr>
<tr>
<td>6</td>
<td>680</td>
<td>20</td>
<td>18</td>
<td>2.73</td>
<td>1.34</td>
<td>1.30</td>
</tr>
<tr>
<td>8</td>
<td>6384</td>
<td>39</td>
<td>25</td>
<td>2.80</td>
<td>1.33</td>
<td>1.24</td>
</tr>
<tr>
<td>10</td>
<td>47127</td>
<td>93</td>
<td>39</td>
<td>2.79</td>
<td>1.38</td>
<td>1.22</td>
</tr>
<tr>
<td>12</td>
<td>364404</td>
<td>227</td>
<td>73</td>
<td>2.78</td>
<td>1.42</td>
<td>1.24</td>
</tr>
<tr>
<td>14</td>
<td>3473941</td>
<td>539</td>
<td>113</td>
<td>2.83</td>
<td>1.44</td>
<td>1.23</td>
</tr>
<tr>
<td>16</td>
<td>–</td>
<td>1301</td>
<td>211</td>
<td>–</td>
<td>1.45</td>
<td>1.25</td>
</tr>
<tr>
<td>18</td>
<td>–</td>
<td>3056</td>
<td>363</td>
<td>–</td>
<td>1.46</td>
<td>1.26</td>
</tr>
<tr>
<td>20</td>
<td>–</td>
<td>7276</td>
<td>676</td>
<td>–</td>
<td>1.47</td>
<td>1.27</td>
</tr>
<tr>
<td>22</td>
<td>–</td>
<td>18094</td>
<td>1219</td>
<td>–</td>
<td>1.48</td>
<td>1.28</td>
</tr>
<tr>
<td>24</td>
<td>–</td>
<td>39135</td>
<td>1641</td>
<td>–</td>
<td>1.48</td>
<td>1.26</td>
</tr>
</tbody>
</table>

- informed better than uninformed
- $h_2$ better than $h_1$

Is $h_2$ always better than $h_1$?
4.2 Dominance

Yes!

We say $h_2$ dominates $h_1$ if $h_2(n) \geq h_1(n)$ for all $n$ (both admissible).

$$\text{dominance } \Rightarrow \text{ better efficiency}$$

— $h_2$ will expand fewer nodes on average than $h_1$

“Proof”

$A^*$ will expand all nodes $n$ with $f(n) < f^*$.

$$\Rightarrow \quad A^* \text{ will expand all nodes with } h(n) < f^* - g(n)$$

But $h_2(n) \geq h_1(n)$ so all nodes expanded with $h_2$ will also be expanded with $h_1$ ($h_1$ may expand others as well).

always better to use an (admissible) heuristic function with higher values
4.3 Inventing heuristics — relaxed problems

- How can we come up with a heuristic?
- Can the computer do it automatically?

A problem is *relaxed* by reducing restrictions on operators

*cost of exact solution of a relaxed problem is often a good heuristic for original problem*

**Example**

- if the rules of the 8-puzzle are relaxed so that a tile can move *anywhere*, then $h_1(n)$ gives the shortest solution
- if the rules are relaxed so that a tile can move to *any adjacent square*, then $h_2(n)$ gives the shortest solution

**Note:** Must also ensure heuristic itself is not too expensive to calculate.

Extreme case: perfect heuristic can be found by carrying out search on original problem.

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4.4 Automatic generation of heuristics

If problem is defined in suitable formal language ⇒ may be possible to construct relaxed problems automatically.

eg. 8-puzzle operator description

\[ A \text{ is adjacent to } B \quad \& \quad B \text{ is blank} \rightarrow \text{can move from } A \text{ to } B \]

Relaxed rules

\[ A \text{ is adjacent to } B \rightarrow \text{can move from } A \text{ to } B \]

\[ B \text{ is blank} \rightarrow \text{can move from } A \text{ to } B \]

\[ \text{can move from } A \text{ to } B \]

**Absolver** (Prieditis 1993)

- new heuristic for 8-puzzle better than any existing one
- first useful heuristic for Rubik’s cube!
5. Memory-bounded Search

Good heuristics improve search, but many problems are still too hard.

Usually memory restrictions that impose a hard limit.

(eg. recall estimates for breadth-first search

<table>
<thead>
<tr>
<th>Depth</th>
<th>Nodes</th>
<th>Time</th>
<th>Memory</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>1</td>
<td>1 millisecond</td>
<td>100 bytes</td>
</tr>
<tr>
<td>2</td>
<td>111</td>
<td>.1 seconds</td>
<td>11 kilobytes</td>
</tr>
<tr>
<td>4</td>
<td>11,111</td>
<td>11 seconds</td>
<td>1 megabyte</td>
</tr>
<tr>
<td>6</td>
<td>10^6</td>
<td>18 minutes</td>
<td>111 megabytes</td>
</tr>
<tr>
<td>8</td>
<td>10^8</td>
<td>31 hours</td>
<td>11 gigabytes</td>
</tr>
<tr>
<td>10</td>
<td>10^{10}</td>
<td>128 days</td>
<td>1 terabyte</td>
</tr>
<tr>
<td>12</td>
<td>10^{12}</td>
<td>35 years</td>
<td>111 terabytes</td>
</tr>
<tr>
<td>14</td>
<td>10^{14}</td>
<td>3500 years</td>
<td>11,111 terabytes</td>
</tr>
</tbody>
</table>

This section — algorithms designed to save memory.

- IDA*
- SMA*
Recall uninformed search

- uniform-cost/breadth-first search
  - completeness, optimality
  - exponential space usage
- depth-first
  - linear space usage
  - incomplete, suboptimal

**Solution:** iterative-deepening \( \Rightarrow \) explores “uniform-cost trees”, or “contours”, using linear space.
5.1 Iterative Deepening A* (IDA*)

Can we do the same with A*?

Contours more directed, but same technique applies!

Modify depth-limited search to use $f$-cost limit, rather than depth limit $\Rightarrow$ IDA*

**Complete?** Yes (with admissible heuristic)

**Optimal?** Yes (with admissible heuristic)

**Space?** Linear in path length

**Time?** ?
5.1 Iterative Deepening A* (IDA*)

Time complexity of IDA*

Depends on number of different values $f$ can take on.

- small number of values, few iterations
eg. 8-puzzle
- many values, many iterations
eg. Romania example, each state has different heuristic $\Rightarrow$ only one extra town in each contour

Worst case: $A^*$ expands $N$ nodes, IDA* goes through $N$ iterations

\[ 1 + 2 + \cdots + N \Rightarrow O(N^2) \]

A solution: increase $f$-cost limit by fixed amount $\epsilon$ in each iteration

$\Rightarrow$ returns solutions at worst $\epsilon$ worse than optimal

Called $\epsilon$-admissible.

IDA* was first memory-bounded optimal heuristic algorithm and solved many practical problems.
5.2 Simplified memory-bounded A* (SMA*)

- Uses all available memory.
- Complete if available memory is sufficient to store the shallowest solution path.
- Optimal if available memory is sufficient to store the shallowest solution path. Otherwise best solution given available memory.

How does it work?

- Needs to generate successor nodes but no memory left ⇒ drop, or “forget”, least promising nodes.
- Keep record of best $f$-cost of forgotten nodes in ancestor.
- Only regenerate nodes if all more promising options are exhausted.

Example (values of forgotten nodes in parentheses) $\ldots \Rightarrow$
5.2 Simplified memory-bounded A* (SMA*)
5.2 Simplified memory-bounded A* (SMA*)

- Solves significantly more difficult problems than A*.
- Performs well on highly-connected state spaces and real-valued heuristics on which A* has difficulty.
- Susceptible to continual “switching” between candidate solution paths.
  ie. limit in memory can lead to intractible computation time
Game playing

- broadening our world view — dealing with incompleteness
- why play games?
- perfect decisions — the Minimax algorithm
- dealing with resource limits
  - evaluation functions
  - cutting off search
- alpha-beta pruning
- game-playing agents in action

Reading: Russell and Norvig, Chapter 5
1. Broadening our world view

We have assumed we are dealing with world descriptions that are:

- **complete** — all necessary information about the problem is available to the search algorithm
- **deterministic** — effects of actions are uniquely determined

Real-world problems are rarely complete and deterministic...

**Sources of Incompleteness**

- **sensor limitations** — not possible to gather enough information about the world to completely know its state — includes the future!
- **intractability** — full state description is too large to store, or search tree too large to compute

**Sources of (Effective) Nondeterminism**

- humans, the weather, stress fractures, dice, ...

**Aside...**

Debate: incompleteness $\leftrightarrow$ nondeterminism
1.1 Approaches for Dealing with Incompleteness

**contingency planning**
- build all possibilities into the plan
- may make the tree very large
- can only guarantee a solution if the number of contingencies is finite and tractable

**interleaving or adaptive planning**
- alternate between planning, acting, and sensing
- requires extra work during execution — planning cannot be done in advance (or “off-line”)

**strategy learning**
- learn, from looking at examples, strategies that can be applied in any situation
- must decide on parameterisation, how to evaluate states, how many examples to use, . . . black art??
2. Why Play Games?

- abstraction of real world
- well-defined, clear state descriptions
- limited operations, clearly defined consequences

but!

- provide a mechanism for investigating many of the real-world issues outlined above
  - more like the real world than examples so far

Added twist — the domain contains hostile agents (also making it like the real world...?)
2.1 Examples

Tractable Problem with Complete Information

Noughts and crosses (tic-tac-toe) for control freaks — you get to choose moves for both players!

Stop when you get to a goal state.

- What uninformed search would you select? How many states visited?
- What would be an appropriate heuristic for an informed search? How many states visited?
2.1 Examples

Tractable Contingency Problem

Noughts and crosses — allow for all the opponents moves. (Opponent is non-deterministic.)

How many states?

Intractable Contingency Problem

Chess

- average branching factor 35, approx 50 operations
  \[ \Rightarrow \text{search tree has about } 35^{100} \text{ nodes (although only about } 10^{40} \text{ different legal positions)}! \]
- cannot solve by brute force, must use other approaches, eg.
  - interleave time- (or space-) limited search with moves
    \[ \Rightarrow \text{this section} \]
    * algorithm for perfect play (Von Neumann, 1944)
    * finite horizon, approximate evaluation (Zuse, 1945; Shannon, 1950; Samuel, 1952–57)
    * pruning to reduce costs (McCarthy, 1956)
  - learn strategies that determine what to do based on some aspects of the current position
    \[ \Rightarrow \text{later in the course} \]
3. Perfect Decisions — **Minimax Algorithm**

Perfect play for deterministic, perfect-information games

- two players, **Max** and **Min**, both try to win
- **Max** moves first
  - can **Max** find a strategy that *always wins*?

Define a game as a kind of search problem with:

- initial state
- set of legal moves (operators)
- terminal test — is the game over?
- utility function — how good is the outcome for each player?

eg. Tic-tac-toe — can **Max** choose a move that always results in a terminal state with a utility of +1?
Even for this simple game the search tree is large.

Try an even simpler game...
3. Perfect Decisions — **Minimax Algorithm**

eg. Two-ply (made-up game)

Max

<table>
<thead>
<tr>
<th>1</th>
<th>2</th>
<th>3</th>
</tr>
</thead>
</table>

Min

<table>
<thead>
<tr>
<th>4</th>
<th>5</th>
<th>6</th>
</tr>
</thead>
</table>

(one move deep, two *ply*)

- **Max**’s aim — maximise utility of terminal state
- **Min**’s aim — minimise it
- What is **Max**’s optimal strategy, *assuming* **Min** makes the best possible moves?
3. Perfect Decisions — Minimax Algorithm

function Minimax-Decision(game) returns an operator

   for each op in Operators[game] do
      Value[op] ← Minimax-Value(Apply(op, game), game)
   end

   return the op with the highest Value[op]

function Minimax-Value(state, game) returns a utility value

   if Terminal-Test(game)(state) then
      return Utility(game)(state)
   else if MAX is to move in state then
      return the highest Minimax-Value of Successors(state)
   else
      return the lowest Minimax-Value of Successors(state)

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3. **Perfect Decisions — Minimax Algorithm**

**Complete** Yes, if tree is finite (chess has specific rules for this)

**Optimal** Yes, against an optimal opponent. Otherwise??

**Time complexity** $O(b^m)$

**Space complexity** $O(bm)$ (depth-first exploration)

For chess, $b \approx 35, m \approx 100$ for “reasonable” games  
$\Rightarrow$ exact solution completely infeasible

**Resource limits**

Usually time: suppose we have 100 seconds, explore $10^4$ nodes/second  
$\Rightarrow 10^6$ nodes per move

Standard approach:

- **cutoff test**  
e.g., depth limit (perhaps add quiescence search)

- **evaluation function**  
  $=$ estimated desirability of position
4. Evaluation functions

Instead of stopping at terminal states and using utility function, cut off search and use a heuristic *evaluation function*.

Chess players have been doing this for years...

**simple** — 1 for pawn, 3 for knight/bishop, 5 for rook, etc

**more involved** — centre pawns, rooks on open files, etc

Can be expressed as *linear weighted sum* of *features*

\[ \text{Eval}(s) = w_1f_1(s) + w_2f_2(s) + \ldots + w_nf_n(s) \]

e.g., \( w_1 = 9 \) with

\( f_1(s) = (\text{number of white queens}) - (\text{number of black queens}) \)
4.1 Quality of evaluation functions

Success of program depends *critically* on quality of evaluation function.

- agree with utility function on terminal states
- time efficient
- reflect chances of winning

**Note: Exact values don’t matter**

![Diagram](image)

Behaviour is preserved under any *monotonic* transformation of Eval

Only the order matters:
- payoff acts as an *ordinal utility* function
5. Cutting off search

Options...

- fixed depth limit
- iterative deepening (fixed time limit) — more robust

Problem — inaccuracies of evaluation function can have disastrous consequences.
5.1 Non-quiescence problem

Consider chess evaluation function based on material advantage. White’s depth limited search stops here... Looks like a win to white — actually a win to black.

Want to stop search and apply evaluation function in positions that are quiescent. May perform quiescence search in some situations — eg. after capture.
5.2 Horizon problem

Black to move

Win for white, but black may be able to chase king for extent of its depth-limited search, so does not see this. Queening move is “pushed over the horizon”.

No general solution.
6. Alpha-beta pruning

Consider $\text{MINIMAX}$ with reasonable evaluation function and quiescent cut-off. Will it work in practice?

Assume can search approx 5000 positions per second. Allowed approx 150 seconds per move. Order of $10^6$ positions per move.

$$b^m = 10^6, \quad b = 35 \quad \Rightarrow \quad m = 4$$

4-ply lookahead is a hopeless chess player!

4-ply $\approx$ human novice  
8-ply $\approx$ typical PC, human master  
12-ply $\approx$ Deep Blue, Kasparov

But do we need to search all those positions? Can we eliminate some before we get there — prune the search tree?

One method is $alpha$-$beta$ pruning. . .
6.1 $\alpha-\beta$ pruning example

\[ \text{MAX} \]

\[ \text{MIN} \]

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6.2 Why is it called $\alpha$–$\beta$?

$\alpha$ is the best value (to MAX) found so far off the current path
If $V$ is worse than $\alpha$, MAX will avoid it $\Rightarrow$ prune that branch
Define $\beta$ similarly for MIN
6.3 The $\alpha$–$\beta$ algorithm

Basically **MINIMAX** + keep track of $\alpha$, $\beta$ + prune

```plaintext
function Max-Value(state, game, $\alpha$, $\beta$) returns the minimax value of state
  inputs: state, current state in game
           game, game description
           $\alpha$, the best score for MAX along the path to state
           $\beta$, the best score for MIN along the path to state
  if Cutoff-Test(state) then return Eval(state)
  for each s in Successors(state) do
    $\alpha \leftarrow$ Max($\alpha$, Min-Value(s, game, $\alpha$, $\beta$))
    if $\alpha \geq \beta$ then return $\beta$
  end
  return $\alpha$

function Min-Value(state, game, $\alpha$, $\beta$) returns the minimax value of state
  if Cutoff-Test(state) then return Eval(state)
  for each s in Successors(state) do
    $\beta \leftarrow$ Min($\beta$, Max-Value(s, game, $\alpha$, $\beta$))
    if $\beta \leq \alpha$ then return $\alpha$
  end
  return $\beta$
```

6.4 Properties of $\alpha-\beta$

Pruning does not affect final result.

Good move ordering improves effectiveness of pruning.

With “perfect ordering,” time complexity $= O(b^{m/2})$

$\Rightarrow$ doubles depth of search

$\Rightarrow$ can easily reach depth 8 and play good chess.

Perfect ordering is unknown, but a simple ordering (captures first, then threats, then forward moves, then backward moves) gets fairly close.

Can we learn appropriate orderings? $\Rightarrow$ speedup learning

(Note complexity results assume idealized tree model:

- nodes have same branching factor $b$
- all paths reach depth limit $d$
- leaf evaluations randomly distributed

Ultimately resort to empirical tests.)
7. Game-playing agents in practice

Games that don’t include chance

**Checkers**: Chinook became world champion in 1994 after 40-year-reign of human world champion Marion Tinsley (who retired due to poor health). Used an endgame database defining perfect play for all positions involving 8 or fewer pieces on the board, a total of 443,748,401,247 positions.

**Chess**: Deep Blue defeated human world champion Gary Kasparov in a six-game match (not a World Championship) in 1997. Deep Blue searches 200 million positions per second, uses very sophisticated evaluation, and undisclosed methods for extending some lines of search up to 40 ply.

**Othello**: human champions refuse to compete against computers, who are too good.

**Go**: human champions refuse to compete against computers, who are too bad. In go, \( b > 300 \), so most programs use pattern knowledge bases to suggest plausible moves.
7. Game-playing agents in practice

Games that include an element of chance

Dice rolls increase $b$: 21 possible rolls with 2 dice

**Backgammon** $\approx 20$ legal moves (can be 6,000 with 1-1 roll)

$$\text{depth 4} = 20 \times (21 \times 20)^3 \approx 1.2 \times 10^9$$

As depth increases, probability of reaching a given node shrinks

$\Rightarrow$ value of lookahead is diminished

$\alpha-\beta$ pruning is much less effective

**TDGammon** uses depth-2 search + very good **Eval**

$\approx$ world-champion level
8. Summary

Games are fun to work on! (and can be addictive)

They illustrate several important points about AI

◊ problems raised by
  — incomplete knowledge
  — resource limits

◊ perfection is unattainable ⇒ must approximate

Games are to AI as grand prix racing is to automobile design
Agents that Learn

- why learn?
- general model of learning agents
- inductive learning
- learning decision trees

Reading: Russell & Norvig, Chapter 18
1. Why Learn?

So far, all intelligence comes from the designer:

- time consuming for designer
- restricts capabilities of agent

Learning agents can:

- act autonomously
- deal with unknown environments
- synthesise rules/patterns from large volumes of data
- handle complex data
- improve their own performance
2. General Model of Learning Agents

Idea: percepts used not just for acting, but for improving future performance.

Four basic components...

**Performance element**
- responsible for selecting actions for good agent performance
- agent function considered previously: percepts → actions

**Learning element**
- responsible for improving performance element
- requires feedback on how the agent is doing

**Critic element**
- responsible for providing feedback
- comparison with objective performance standard (outside agent)

**Problem generator**
- responsible for generating new experience
- requires *exploration* — taking suboptimal actions
2. General Model of Learning Agents

E.g. taxi driver agent

*performance element* — Lets take Winthorp Ave, I know it works.

*problem generator* — Nah, lets try Mounts Bay Rd for a change. You never know, it may be quicker.

*critic* — Wow, it was 5 mins quicker, and what a lovely view!

*learning element* — Yeh, in future we’ll take Mounts Bay Rd.
2.1 The Learning Element

Two separate goals:

1. Improve *outcome* of performance element
   — how good is the solution
2. Improve *time performance* of performance element
   — how fast does it reach a solution
   — known as *speedup learning*

Learning systems may work on one or both tasks.

Design of a learning element is affected by four issues:

1. the components of the performance element to be improved
2. representation of those components
3. feedback available
4. prior information available
2.1 The Learning Element

Components of the performance element

Can use:

1. direct mapping from states to actions
2. means to infer properties (model) of the world from percept sequence
3. information on how the world evolves
4. information about how actions change the world
5. utility information about desirability of states
6. action-value information about desirability of actions in states
7. goals whose achievement maximises utility

Each component can be learned, given appropriate feedback.

E.g. our taxi driver agent

- Mounts Bay Rd has a nicer view (5)
- Taking Mounts Bay Rd → arrive more quickly (4,7)
- If travelling from Perth to UWA, always take Mounts Bay Rd (6)
2.1 The Learning Element

Representation of components

Examples:

- utility functions, eg linear weighted polynomials for game-playing agent
- logical sentences for reasoning agent
- probabilistic descriptions, eg belief networks for decision-theoretic agent

Available feedback

**supervised learning**
- agent provided with both inputs and correct outputs
- usually by a “teacher”

**reinforcement learning**
- agent chooses actions
- receives some *reward* or *punishment*

**unsupervised learning**
- no hint about correct outputs
- can only learn relationships between percepts
2.1 The Learning Element

Prior knowledge

- agent begins with a *tabula rasa* (empty slate)
- agent makes use of background knowledge

In practice learning is hard \( \Rightarrow \) use background knowledge if available.

**Learning = Function approximation**

All components of performance element can be described mathematically by a function. eg.

- how the world evolves: \( f: \text{state} \mapsto \text{state} \)
- goal: \( f: \text{state} \mapsto \{0,1\} \)
- utilities: \( f: \text{state} \mapsto [-\infty, \infty] \)
- action values: \( f: (\text{state}, \text{action}) \mapsto [-\infty, \infty] \)

*all learning can be seen as learning a function*
3. Inductive Learning

Assume $f$ is function to be learned.

Learning algorithm supplied with sample inputs and corresponding outputs $\Rightarrow$ supervised learning

Define example (or sample): pair $(x, f(x))$

Task:

given a set of examples of $f$, return a function $h$ that approximates $f$.

$h$ is called a hypothesis

Task is called pure inductive inference or induction.

Many choices for $h$

A preference for one over another is called a bias.

3. Inductive Learning

Example: Simple reflex agent

Sample is a pair \((\text{percept}, \text{action})\)

eg. \(\text{percept} \) — chess board position

\(\text{action} \) — best move supplied by friendly grandmaster

Algorithm:

\[
\begin{align*}
\text{global } & \text{} \quad \text{examples} \leftarrow \{\}\quad \\
\text{function } & \text{} \quad \text{Reflex-Performance-Element}(\text{percept}) \quad \text{returns} \\ & \text{an action} \\
& \quad \text{if } (\text{percept}, a) \text{ in examples then return } a \\
& \quad \text{else} \\
& \quad \quad h \leftarrow \text{INDUCE}(\text{examples}) \\
& \quad \quad \text{return } h(\text{percept})
\end{align*}
\]

\[
\begin{align*}
\text{procedure } & \text{} \quad \text{Reflex-Learning-Element}(\text{percept}, \text{action}) \\
& \quad \text{inputs: } \text{percept}, \text{ feedback percept} \\
& \quad \quad \text{action}, \text{ feedback action} \\
& \quad \quad \text{examples} \leftarrow \text{examples} \cup \{(\text{percept}, \text{action})\}
\end{align*}
\]
3. Inductive Learning

Many variations possible, eg.

- *incremental learning* — learning element updates $h$ with each new sample
- *reinforcement* — agent receives feedback on quality of action

Many possible representations of $h$ — choice of representation is critical

- type of learning algorithm that can be used
- whether learning problem is feasible
- expressiveness vs tractability
4. Learning Decision Trees

**Decision tree**

- **input** — description of a situation
  - abstracted by set of *properties*, *parameters*, *attributes*, *features*, ...
- **output** — boolean (yes/no) decision
  - can also be thought of as defining a *categorisation*, *classification* or *concept*
  - set of situations with a positive response

\[ f: \text{situation} \mapsto \{0, 1\} \]

We consider

1. decision trees as performance elements
2. inducing decision trees (learning element)
4.1 Decision Trees as Performance Elements

Example

Problem: decide whether to wait for a table at a restaurant

Aim: provide a definition, expressed as a decision tree, for the goal concept “Will Wait”

First step: identify attributes

— what factors are necessary to make a rational decision

For example:

1. alternative nearby?
2. bar?
3. Friday/Saturday?
4. hungry?
5. patrons?
6. price?
7. raining?
8. reservation?
9. type of food?
10. estimated wait?

Example of a decision tree ⋯ ⋯ ⋯

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Choice of attributes is critical \( \Rightarrow \) determines whether an appropriate function can be learned ("garbage-in, garbage-out")

No matter how good a learning algorithm is, it will fail if appropriate features cannot be identified (\(c.f.\) neural nets)

In real world problems feature selection is often the hardest task!

(black art?)
4.1 Decision Trees as Performance Elements

Expressiveness of Decision Trees

- limited to propositional (boolean) problems
  - cannot input arbitrary number of restaurants and ask to choose
  - cannot handle continuous information
- fully expressive within class of propositional problems
- may be exponentially large w.r.t. no. inputs

Number of trees (size of hypothesis space)

\[
\begin{align*}
  n \text{ attributes} & \quad \downarrow \\
  2^n \text{ combinations of inputs} & \quad \downarrow \\
  2^{2^n} \text{ different functions}
\end{align*}
\]

eg. 6 attributes, approx. \(2 \times 10^{19}\) functions to choose from

⇒ lots of work for learning element!
4.2 Decision Tree Induction

Terminology...

**example** — \(\{\text{attributes}\}, \text{value}\)

**positive example** — \(\text{value} = \text{true}\)

**negative example** — \(\text{value} = \text{false}\)

**training set** — set of examples used for learning

Example training set:

<table>
<thead>
<tr>
<th>Example</th>
<th>Attributes</th>
<th>Goal</th>
<th>WillWait</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Alt</td>
<td>Bar</td>
<td>Fri</td>
</tr>
<tr>
<td>X_1</td>
<td>Yes</td>
<td>No</td>
<td>No</td>
</tr>
<tr>
<td>X_2</td>
<td>Yes</td>
<td>No</td>
<td>No</td>
</tr>
<tr>
<td>X_3</td>
<td>No</td>
<td>Yes</td>
<td>No</td>
</tr>
<tr>
<td>X_4</td>
<td>Yes</td>
<td>No</td>
<td>Yes</td>
</tr>
<tr>
<td>X_5</td>
<td>Yes</td>
<td>No</td>
<td>Yes</td>
</tr>
<tr>
<td>X_6</td>
<td>No</td>
<td>Yes</td>
<td>No</td>
</tr>
<tr>
<td>X_7</td>
<td>No</td>
<td>Yes</td>
<td>No</td>
</tr>
<tr>
<td>X_8</td>
<td>No</td>
<td>No</td>
<td>No</td>
</tr>
<tr>
<td>X_9</td>
<td>No</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>X_{10}</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>X_{11}</td>
<td>No</td>
<td>No</td>
<td>No</td>
</tr>
<tr>
<td>X_{12}</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
</tbody>
</table>

Goal: find a decision tree that agrees with all the examples in the training set
4.2 Decision Tree Induction

Trivial Solution

Branch on each attribute in turn, until you reach a distinct leaf for each example.

Problems

- tree is bigger than needed — does not find patterns that “summarise” or “simplify” information
- cannot answer for examples that haven’t been seen ⇒ cannot generalise

Two sides of the same coin!

Ockham’s razor: the most likely hypothesis is the simplest one that is consistent with the examples

Finding smallest tree is intractable, but can use heuristics to generate reasonably good solution.

Basic idea: recursively select the most “important”, or discriminating, attribute for successive branch points

(discriminating — formally requires information theory, but humans do it intuitively ⇒ sort the “men from the boys”, “sheep from the lambs”, “oats from the chaff” . . .)
### 4.2 Decision Tree Induction

(a) 

**Patrons?**

- **None**
  - +: $X_1, X_3, X_4, X_6, X_8, X_{12}$
  - -: $X_7, X_{11}$
- **Some**
  - +: $X_1, X_3, X_6, X_8$
  - -: $X_7, X_{11}$
- **Full**
  - +: $X_4, X_{12}$
  - -: $X_2, X_5, X_9, X_{10}$

(b) 

**Type?**

- **French**
  - +: $X_1$
  - -: $X_5$
- **Italian**
  - +: $X_6$
  - -: $X_{10}$
- **Thai**
  - +: $X_4, X_8$
  - -: $X_2, X_{11}$
- **Burger**
  - +: $X_3, X_{12}$
  - -: $X_7, X_9$

(c) 

**Patrons?**

- **None**
  - +: $X_1, X_3, X_6, X_8, X_{12}$
  - -: $X_7, X_{11}$
- **Some**
  - +: $X_1, X_3, X_6, X_8$
  - -: $X_7, X_{11}$
- **Full**
  - +: $X_4, X_{12}$
  - -: $X_2, X_5, X_9, X_{10}$

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4.2 Decision Tree Induction

Recursive algorithm

**Base cases**
- remaining examples all +ve or all −ve — stop and label “yes” or “no”
- no examples left — no relevant examples have been seen, return majority in parent node
- no attributes left — problem: either data is inconsistent (“noisy”, or nondeterministic) or attributes chosen were insufficient to adequately discriminate (start again, or use majority vote)

**Recursive case**
- both +ve and −ve examples — choose next most discriminating attribute and repeat
4.2 Decision Tree Induction

Algorithm...

function Decision-Tree-Learning(examples, attributes, default)
returns a decision tree

inputs: examples, set of examples
        attributes, set of attributes
        default, default value for the goal predicate

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 Majority-Value(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 ← Decision-Tree-Learning(examples_i,
                                           attributes − best, Majority-Value(examples))
        add a branch to tree with label v_i and subtree subtree
    end
    return tree
Applied to our training set gives:

Note: different to original tree, despite using data generated from that tree. Is the tree (hypothesis) wrong?

- No — *with respect to seen examples!*
  In fact more concise, and highlights new patterns.
- *Probably — w.r.t. unseen examples...*
4.3 Assessing Performance

A good hypothesis = predicts the classifications of unseen examples

To assess performance we require further examples with known outcomes — test set

Usual methodology:

1. Collect large set of examples.
2. Divide into two disjoint sets: training set and test set.
3. Apply learning algorithm to training set to generate hypothesis $H$.
5. Repeat for different training sets of different sizes.

Plot prediction quality against training set size...
4.3 Assessing Performance

Learning curve (or “Happy Graph”)

Despite representational limitations, decision-tree learning has been used successfully in a wide variety of applications. e.g.

**Designing Oil Platform Equipment**

**Gasoil** — BP, deployed 1986 (Michie)
- designs complex gas-oil separation systems for offshore oil platforms
- attributes include relative proportions of gas, oil and water, flow rate, pressure, density, viscosity, temperature and susceptibility to waxing
- largest commercial expert system in the world at that time
- approx. 2500 rules
- building by hand would have taken \( \sim 10 \) person-years
- decision-tree learning applied to database of existing designs
  \[ \Rightarrow \text{developed in 100 person-days} \]
- outperformed human experts
- said to have saved BP millions of dollars!
4.4 Practical Uses of Decision-Tree Learning

Learning to Fly

C4.5 — 1992 (Sammut et al)

— one approach — learn correct mapping from state to action
— Cessna on flight simulator
— training: 3 skilled human pilots, assigned flight plan, 30 times each
— training example for each action taken by pilot ⇒ 90000 examples
— 20 state variables
— decision tree generated and fed back into simulator to fly plane
— Results: flies better than its teachers!
⇒ generalisation process “cleans out” mistakes by teachers
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Topic 7

Sequential Decision Problems

◊ Introduction to sequential decision problems
◊ Value iteration
◊ Policy iteration
◊ Longevity in agents

Reading: Russell and Norvig, Chapter 17, Sections 1–3
1. Sequential decision problems

Previously concerned with single decisions, where utility of each action’s outcome is known.

This section — *sequential decision problems* — utility depends on a sequence of decisions

Sequential decision problems which include utilities, uncertainty, and sensing, generalise search and planning problems...
1.1 From search algorithms to policies

Sequential decision problems in known, accessible, deterministic domains

**tools** — search algorithms

**outcome** — sequence of actions that leads to good state

Sequential decision problems in *uncertain* domains

**tools** — techniques originating from control theory, operations research, and decision analysis

**outcome** — *policy*

\[ \text{policy} = \text{set of state-action "rules"} \]

• tells agent what is the best (MEU) action to try in any situation

• derived from utilities of states

This section is about finding optimal policies.
Consider the environment:

```
  3
  2
  1

START
```

**Problem**

Utilities only known for terminal states

⇒ even for deterministic actions, depth-limited search fails!

Utilities for other states will depend on sequence (or environment history) that leads to terminal state.
1.2 From search algorithms to policies – example

Indeterminism

**deterministic version** — each action (N,S,E,W) moves one square in intended direction (bumping into wall results in no change)

**stochastic version** — actions are unreliable...

**transition model** — probabilities of actions leading to transitions between states

\[ M_{ij}^a \equiv P(j|i,a) = \text{probability that doing } a \text{ in } i \text{ leads to } j \]

Cannot be certain which state an action leads to (cf. game playing).

⇒ generating sequence of actions in advance then executing unlikely to succeed
1.2 From search algorithms to policies – example

Policies

But, if

- we know what state we’ve reached (accessible)
- we can calculate best action for each state

⇒ always know what to do next!

Mapping from states to actions is called a policy

eg. Optimal policy for step costs of 0.04...

Note: small step cost ⇒ conservative policy (eg. state (3,1))
1.2 From search algorithms to policies – example

Expected Utilities

Given a policy, can calculate expected utilities...

Aim is therefore not to find action sequence, but to find optimal policy — ie. policy that maximises expected utilities.
Policy represents agent function explicitly

utility-based agent $\mapsto$ simple reflex agent!

function \textsc{Simple-Policy-Agent}(percept) returns an action

static: $M$, a transition model
$U$, a utility function on environment histories
$P$, a policy, initially unknown

if $P$ is unknown then $P \leftarrow$ the optimal policy given $U$, $M$

return $P[\text{percept}]

Problem of calculating an optimal policy in an accessible, stochastic environment with a known transition model is called a \textit{Markov decision problem}.

\textit{Markov property} — transition probabilities from a given state depend only on the state (not previous history)

How can we calculate optimal policies...?
2. Value Iteration

Basic idea:

- calculate utility of each state \( U(state) \)
- use state utilities to select optimal action

Sequential problems usually use an additive utility function (c.f. path cost in search problems):

\[
U([s_1, s_2, \ldots, s_n]) = R(s_1) + R(s_2) + \cdots + R(s_n) \\
= R(s_1) + U([s_2, \ldots, s_n])
\]

where \( R(i) \) is reward in state \( i \) (eg. +1, -1, -0.04).

Utility of a state (a.k.a. its value):

\[
U(s_i) = \text{expected sum of rewards until termination assuming optimal actions}
\]

Difficult to express mathematically. Easier is recursive form...

\[
\text{expected sum of rewards} = \text{current reward} + \text{expected sum of rewards after taking best action}
\]
2.1 Dynamic programming

Bellman equation (1957)

\[ U(i) = R(i) + \max_a \sum_j M^a_{ij} U(j) \]

eg.

\[ U(1, 1) = -0.04 + \max \{ 0.8U(1, 2) + 0.1U(2, 1) + 0.1U(1, 1), \]
\[ \quad \quad 0.9U(1, 1) + 0.1U(1, 2), \]
\[ \quad \quad 0.9U(1, 1) + 0.1U(2, 1), \]
\[ \quad \quad 0.8U(2, 1) + 0.1U(1, 2) + 0.1U(1, 1) \} \]

One equation per state = \( n \) nonlinear equations in \( n \) unknowns

Given utilities of the states, choosing best action is just maximum expected utility (MEU) — choose action such that the expected utility of the immediate successors is highest.

\[ policy(i) = \arg \max_a \sum_j M^a_{ij} U(j) \]

Proven optimal (Bellman & Dreyfus, 1962).

How can we solve

\[ U(i) = R(i) + \max_a \sum_j M^a_{ij} U(j) \]
2.2 Value iteration algorithm

Idea

- start with arbitrary utility values
- update to make them locally consistent with Bellman eqn.
- repeat until “no change”

Everywhere locally consistent $\Rightarrow$ global optimality

```plaintext
function Value-Iteration(M, R) returns a utility function
  inputs: M, a transition model
           R, a reward function on states
  local variables: U, utility function, initially identical to R
                  U', utility function, initially identical to R
  repeat
    U ← U'
    for each state i do
      U'[i] ← R[i] + max_a Σ_j M^i_a j U[j]
    end
  until Close-Enough(U, U')
  return U
```

Applying to our example: $\cdots \Rightarrow$

2.2 Value iteration algorithm
2.3 Assessing performance

Under certain conditions utility values are guaranteed to converge.

Do we require convergence?

Two measures of progress:

1. **RMS (root mean square) Error of Utility Values**

![Graph showing the RMS error decreasing with the number of iterations.](image-url)
2.3 Assessing performance

2. Policy Loss

Actual utility values less important than the policy they imply

⇒ measure difference between expected utility obtained from policy and expected utility from optimal policy

Note: policy is optimal before RMS error converges.
3. Policy iteration

- policies may not be highly sensitive to exact utility values
  ⇒ may be less work to iterate through policies than utilities!

**Policy Iteration Algorithm**

\[ \pi \leftarrow \text{an arbitrary initial policy} \]

repeat until no change in \( \pi \)

  compute utilities given \( \pi \) (**value determination**)
  update \( \pi \) as if utilities were correct (i.e., local MEU)

```plaintext
function Policy-Iteration(M, R) returns a policy
  inputs: M, a transition model
          R, a reward function on states
  local variables: U, a utility function, initially identical to R
                  P, a policy, initially optimal with respect to U
  repeat
    U ← Value-Determination(P, U, M, R)
    unchanged? ← true
    for each state i do
      if \( \max_a \sum_j M_{ij} U[j] > \sum_j M_{ij}^{P[i]} U[j] \) then
        P[i] ← arg \( \max_a \sum_j M_{ij}^{P[i]} U[j] \)
        unchanged? ← false
    until unchanged?
  return P
```

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3.1 Value determination

⇒ simpler than value iteration since action is fixed

Two possibilities:

1. Simplification of value iteration algorithm.

\[ U'(i) \leftarrow R(i) + \sum_j M_{ij}^{\pi(i)} U(j) \]

May take a long time to converge.

2. Direct solution.

\[ U(i) = R(i) + \sum_j M_{ij}^{\pi(i)} U(j) \quad \text{for all } i \]

i.e., \( n \) simultaneous linear equations in \( n \) unknowns, solve in \( O(n^3) \) (eg. Gaussian elimination)

Can be most efficient method for small state spaces.
4. What if I live forever?

Agent continues to exist — using the additive definition of utilities

- $U(i)$s are infinite!
- value iteration fails to terminate

How should we compare two infinite lifetimes?

How can we decide what to do?

One method: *discounting*

Future rewards are discounted at rate $\gamma \leq 1$

$$U([s_0, \ldots s_\infty]) = \sum_{t=0}^{\infty} \gamma^t R(s_t)$$

Intuitive justification:

1. purely pragmatic
   - smoothed version of limited horizons in game playing
   - smaller $\gamma$, shorter horizon
2. model of animal and human preference behaviour
   - *a bird in the hand is worth two in the bush!*
   - eg. widely used in economics to value investments
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Topic 8

**Reinforcement Learning**

- passive learning in a known environment
- passive learning in unknown environments
- active learning
- exploration
- learning action-value functions
- generalisation

Reading: Russell & Norvig, Chapter 20, Sections 1–7.
1. Reinforcement Learning

Previous learning examples

- supervised — input/output pairs provided
  eg. chess — given game situation and best move

Learning can occur in much less generous environments

- no examples provided
- no model of environment
- no utility function
  eg. chess — try random moves, gradually build model of environment and opponent

Must have some (absolute) feedback in order to make decision.
  eg. chess — comes at end of game

⇒ called reward or reinforcement

Reinforcement learning — use rewards to learn a successful agent function
1. Reinforcement Learning

Harder than supervised learning

eg. reward at end of game — which moves were the good ones?

... but ...

only way to achieve very good performance in many complex domains!

Aspects of reinforcement learning:

• *accessible* environment — states identifiable from percepts
  
  *inaccessible* environment — must maintain internal state

• model of environment known or learned (in addition to utilities)

• rewards only in terminal states, or in any states

• rewards components of utility — eg. dollars for betting agent or hints — eg. “nice move”

• passive learner — watches world go by

  *active learner* — act using information learned so far, use problem generator to explore environment
1. Reinforcement Learning

Two types of reinforcement learning agents:

*utility learning*

- agent learns utility function
- selects actions that maximise expected utility

**Disadvantage:** must have (or learn) model of environment — need to know where actions lead in order to evaluate actions and make decision

**Advantage:** uses “deeper” knowledge about domain

*Q-learning*

- agent learns *action-value* function
  — expected utility of taking action in given state

**Advantage:** no model required

**Disadvantage:** shallow knowledge

  — cannot look ahead
  — can restrict ability to learn

We start with utility learning...
2. Passive Learning in a Known Environment

Assume:

- accessible environment
- effects of actions known
- actions are selected *for* the agent ⇒ *passive*
- known model $M_{ij}$ giving probability of transition from state $i$ to state $j$

Example:

(a) environment with utilities (rewards) of terminal states
(b) transition model $M_{ij}$

Aim: *learn utility values for non-terminal states*
2. Passive Learning in a Known Environment

Terminology

*Reward-to-go* = sum of rewards from state to terminal state

*additive* utility function: utility of sequence is sum of rewards accumulated in sequence

Thus for additive utility function and state $s$:

$$\text{expected utility of } s = \text{expected reward-to-go of } s$$

**Training sequence** eg.

$$(1,1) \rightarrow (2,1) \rightarrow (3,1) \rightarrow (3,2) \rightarrow (3,1) \rightarrow (4,1) \rightarrow (4,2) \ [-1]$$
$$(1,1) \rightarrow (1,2) \rightarrow (1,3) \rightarrow (1,2) \rightarrow \cdots \rightarrow (3,3) \rightarrow (4,3) \ [1]$$
$$(1,1) \rightarrow (2,1) \rightarrow \cdots \rightarrow (3,2) \rightarrow (3,3) \rightarrow (4,3) \ [1]$$

**Aim:** use *samples* from training sequences to *learn* (an approximation to) expected reward for all states.

ie. generate an *hypothesis* for the utility function

Note: similar to sequential decision problem, except rewards initially unknown.
2.1 A generic passive reinforcement learning agent

Learning is iterative — successively update estimates of utilities

function PASSIVE-RL-AGENT(e) returns an action

static:  
U, a table of utility estimates
N, a table of frequencies for states
M, a table of transition probabilities from state to state
percepts, a percept sequence (initially empty)

add e to percepts
increment N[STATE[e]]
U ← UPDATE(U, e, percepts, M, N)
if TERMINAL?[e] then percepts ← the empty sequence
return the action Observe

Update

• after transitions, or
• after complete sequences

update function is one key to reinforcement learning

Some alternatives •••→
2.2 Naïve Updating — LMS Approach

From Adaptive Control Theory, late 1950s

Assumes:

observed rewards-to-go → actual expected reward-to-go

At end of sequence:

- calculate (observed) reward-to-go for each state
- use observed values to update utility estimates

eg, utility function represented by table of values — maintain running average . . .

function LMS-Update(U, e, percepts, M, N) returns an updated U
    if Terminal?[e] then reward-to-go ← 0
    for each eᵢ in percepts (starting at end) do
        reward-to-go ← reward-to-go + Reward[eᵢ]
        U[State[eᵢ]] ← Running-Average(U[State[eᵢ]], reward-to-go, N[State[eᵢ]])
    end

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2.2 Naïve Updating — LMS Approach

Exercise

Show that this approach minimises mean squared error (MSE) (and hence root mean squared (RMS) error) w.r.t. observed data.

That is, the hypothesis values $x_h$ generated by this method minimise

$$\sum_i \left( x_i - x_h \right)^2$$

where $x_i$ are the sample values.

For this reason this approach is sometimes called the least mean squares (LMS) approach.

In general wish to learn utility function (rather than table).

Have examples with:

- input value — state
- output value — observed reward

⇒ inductive learning problem!

Can apply any techniques for inductive function learning — linear weighted function, neural net, etc...
Problem:

LMS approach ignores important information

⇒ interdependence of state utilities!

Example (Sutton 1998)

![Diagram]

New state awarded estimate of +1. Real value $\sim -0.8$. 
Leads to slow convergence...
2.3 Adaptive Dynamic Programming

Take into account relationship between states...

utility of a state = probability weighted average of its successors' utilities + its own reward

Formally, utilities are described by set of equations:

\[ U(i) = R(i) + \sum_j M_{ij} U(j) \]

(passive version of Bellman equation — no maximisation over actions)

Since transition probabilities \( M_{ij} \) known, once enough training sequences have been seen so that all reinforcements \( R(i) \) have been observed:

- problem becomes well-defined sequential decision problem
- equivalent to value determination phase of policy iteration

\[ \Rightarrow \] above equation can be solved exactly
Refer to learning methods that solve utility equations using dynamic programming as *adaptive dynamic programming (ADP)*.

Good benchmark, but intractable for large state spaces

eg. backgammon: $10^{50}$ equations in $10^{50}$ unknowns
2.4 Temporal Difference Learning

Can we get the best of both worlds — use constraints without solving equations for all states?

⇒ use observed transitions to adjust locally in line with constraints

\[ U(i) \leftarrow U(i) + \alpha(R(i) + U(j) - U(i)) \]

\( \alpha \) is learning rate

Called \textit{temporal difference (TD) equation} — updates according to \textit{difference} in utilities between successive states.

Note: compared with

\[ U(i) = R(i) + \sum_j M_{ij} U(j) \]

— only involves observed successor rather than all successors

However, average value of \( U(i) \) converges to correct value.

Step further — replace \( \alpha \) with function that decreases with number of observations

\[ \Rightarrow U(i) \text{ converges to correct value} \ (\text{Dayan, 1992}). \]
2.4 Temporal Difference Learning

```
function TD-Update(U, e, percepts, M, N) returns utility table U

    if Terminal?[e] then
        U[State[e]] ← Running-Average(U[State[e]], Reward[e],
                                           N[State[e]])
    else if percepts contains more than one element then
        e' ← the penultimate element of percepts
        i, j ← State[e'], State[e]
        U[i] ← U[i] + α(N[i])(Reward[e'] + U[j] - U[i])
```

Example runs ⋯ →

Notice:

• values more erratic
• RMS error significantly lower than LMS approach after 1000 epochs
2.4 Temporal Difference Learning

Utility estimates versus Number of epochs for different configurations.

RMS error in utility versus Number of epochs for a single configuration.

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3. Passive Learning, Unknown Environments

- LMS and TD learning don’t use model directly
  ⇒ operate unchanged in unknown environment
- ADP requires estimate of model
- All utility-based methods use model for action selection

Estimate of model can be updated during learning by observation of transitions

- each percept provides input/output example of transition function

eg. for tabular representation of M, simply keep track of percentage of transitions to each neighbour

Other techniques for learning stochastic functions — not covered here.
4. **Active Learning in Unknown Environments**

Agent must decide which actions to take.

Changes:

- agent must include *performance element* (and *exploration element*) $\Rightarrow$ choose action
- model must incorporate probabilities *given action* $M_{i,j}^a$
- constraints on utilities must take account of choice of action

$$U(i) = R(i) + \max_a \sum_j M_{i,j}^a U(j)$$

(Bellman’s equation from sequential decision problems)

**Model Learning and ADP**

- Tabular representation — accumulate statistics in 3 dimensional table (rather than 2 dimensional)
- Functional representation — input to function includes action taken

ADP can then use value iteration (or policy iteration) algorithms

4. Active Learning in Unknown Environments

function \textsc{Active-ADP-Agent}(e) returns an action

static: \( U \), a table of utility estimates
\( M \), a table of transition probabilities from state to state
for each action
\( R \), a table of rewards for states
percepts, a percept sequence (initially empty)
last-action, the action just executed

add \( e \) to percepts
\( R[\text{STATE}[e]] \leftarrow \text{REWARD}[e] \)
\( M \leftarrow \text{Update-Active-Model}(M, \text{percepts}, \text{last-action}) \)
\( U \leftarrow \text{Value-Iteration}(U, M, R) \)
if \( \text{Terminal?}[e] \) then percepts \( \leftarrow \) the empty sequence
last-action \( \leftarrow \text{Performance-Element}(e) \)
return last-action

Temporal Difference Learning

Learn model as per ADP.

Update algorithm...?

No change! Strange rewards only occur in proportion to probability of strange action outcomes

\[
U(i) \leftarrow U(i) + \alpha (R(i) + U(j) - U(i))
\]
5. Exploration

How should performance element choose actions?

Two outcomes:

- gain rewards on current sequence
- observe new percepts for learning, and improve rewards on future sequences

*trade-off between immediate and long-term good*

- not limited to automated agents!

Non trivial

- too conservative $\Rightarrow$ get stuck in a rut
- too inquisitive $\Rightarrow$ inefficient, never get anything done

eg. taxi driver agent
5. Exploration

Example

Two extremes:

**whacky** — acts randomly in hope of exploring environment
  ⇒ learns good utility estimates
  ⇒ never gets better at reaching positive reward

**greedy** — acts to maximise utility given current estimates
  ⇒ finds a path to positive reward
  ⇒ never finds optimal route

Start whacky, get greedier?

Is there an optimal exploration policy?

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5. Exploration

Optimal is difficult, but can get close...

— give weight to actions that have not been tried often, while tending to avoid low utilities

Alter constraint equation to assign higher utility estimates to relatively unexplored action-state pairs

\[ \Rightarrow \text{optimistic "prior" — initially assume everything is good.} \]

Let

\[ U^+(i) \quad \text{— optimistic estimate} \]
\[ N(a, i) \quad \text{— number of times action } a \text{ tried in state } i \]

ADP update equation

\[ U^+(i) \leftarrow R(i) + \max_a f(\sum_j M_{ij}^a U^+(j), N(a, i)) \]

where \( f(u, n) \) is exploration function.

Note \( U^+ \) (not \( U \)) on r.h.s. — propagates tendency to explore from sparsely explored regions through densely explored regions
5. Exploration

\( f(u, n) \) determines \textit{trade-off} between “greed” and “curiosity”

\[ \Rightarrow \text{ should increase with } u, \text{ decrease with } n \]

Simple example

\[ f(u, n) = \begin{cases} R^+ & \text{if } n < N_e \\ u & \text{otherwise} \end{cases} \]

where \( R^+ \) is optimistic estimate of best possible reward, \( N_e \) is fixed parameter

\[ \Rightarrow \text{ try each state at least } N_e \text{ times.} \]

Example for ADP agent with \( R^+ = 2 \) and \( N_e = 5 \)

Note policy converges on optimal very quickly

(\text{wacky} — best policy loss \( \approx 2.3 \)

\text{greedy} — best policy loss \( \approx 0.25 \))

Utility estimates take longer — after exploratory period further exploration only by “chance”

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5. Exploration

Utility estimates

RMS error, policy loss (exploratory policy)

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6. Learning Action-Value Functions

Action-value functions

- assign expected utility to taking action $a$ in state $i$
- also called $Q$-values
- allow decision-making without use of model

Relationship to utility values

$$U(i) = \max_a Q(a, i)$$

Constraint equation

$$Q(a, i) = R(i) + \sum_j M_{ij}^{a} \max_{a'} Q(a', j)$$

Can be used for iterative learning, but need to learn model.

Alternative $\Rightarrow$ temporal difference learning

TD Q-learning update equation

$$Q(a, i) \leftarrow Q(a, i) + \alpha (R(i) + \max_{a'} Q(a', j) - Q(a, i))$$
6. Learning Action-Value Functions

Algorithm:

```plaintext
function Q-LEARNING-AGENT(e) returns an action
    static:  Q, a table of action values
             N, a table of state-action frequencies
             a, the last action taken
             i, the previous state visited
             r, the reward received in state i

    j ← STATE[e]
    if i is non-null then
        N[a, i] ← N[a, i] + 1
        Q[a, i] ← Q[a, i] + α(r + max_{a'}^{} Q[a', j] − Q[a, i])
    if TERMINAL?[e] then
        i ← null
    else
        i ← j
        r ← REWARD[e]
        a ← arg max_{a'}^{} f(Q[a', j], N[a', j])
    return a
```

Example ⋄ ⋄ ⋄

Note: slower convergence, greater policy loss

Consistency between values not enforced by model.
6. Learning Action-Value Functions

Utility estimates

Number of iterations

RMS error, policy loss (TD Q-learning)

Number of epochs

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7. Generalisation

So far, algorithms have represented hypothesis functions as tables — *explicit representation*

eg. state/utility pairs

OK for small problems, impractical for most real-world problems.

eg. chess and backgammon $\rightarrow 10^{50} - 10^{120}$ states.

Problem is not just storage — *do we have to visit all states to learn?*

Clearly humans don’t!

Require *implicit representation* — compact representation, rather than storing value, allows value to be calculated

eg. weighted linear function of features

$$U(i) = w_1 f_1(i) + w_2 f_2(i) + \cdots + w_n f_n(i)$$

From say $10^{120}$ states to 10 weights $\Rightarrow$ *whopping compression!*

But more importantly, returns estimates for unseen states

$\Rightarrow$ *generalisation!!*
7. Generalisation

Very powerful. eg. from examining 1 in $10^{44}$ backgammon states, can learn a utility function that can play as well as any human.

On the other hand, may fail completely...

* hypothesis space must contain a function close enough to actual utility function

Depends on

- type of function used for hypothesis
eg. linear, nonlinear (neural net), etc
- chosen features

Trade off:

larger the hypothesis space

⇒ better likelihood it includes suitable function, but
⇒ more examples needed
⇒ slower convergence

7. Generalisation

And last but not least...
CITS 7210 Algorithms for Artificial Intelligence

Topic 9

Planning

- Search vs. planning
- Planning Languages and STRIPS
- State Space vs. Plan Space
- Partial-order Planning

Reading: Russell & Norvig, Chapter 11
1. Search vs. Planning

Consider the task *get milk, bananas, and a cordless drill*

Standard search algorithms seem to fail miserably:

After-the-fact heuristic/goal test inadequate
1. **Search vs. Planning**

Planning systems do the following:

1. open up action and goal representation to allow selection
2. divide-and-conquer by subgoaling
3. relax requirement for sequential construction of solutions

<table>
<thead>
<tr>
<th></th>
<th><strong>Search</strong></th>
<th><strong>Planning</strong></th>
</tr>
</thead>
<tbody>
<tr>
<td>States</td>
<td>internal state of Java objects</td>
<td>descriptive (logical) sentences</td>
</tr>
<tr>
<td></td>
<td>encoded in Java methods</td>
<td>preconditions/outcomes</td>
</tr>
<tr>
<td>Actions</td>
<td>encoded in Java methods</td>
<td>descriptive sentence</td>
</tr>
<tr>
<td></td>
<td>sequence from ( s_0 )</td>
<td>constraints on actions</td>
</tr>
<tr>
<td>Goal</td>
<td>( \Rightarrow \text{ implicit} )</td>
<td>( \Rightarrow \text{ explicit} )</td>
</tr>
<tr>
<td>Plan</td>
<td>( \Rightarrow \text{ hard to decompose} )</td>
<td>( \Rightarrow \text{ easier to decompose} )</td>
</tr>
</tbody>
</table>
2. Planning Languages and STRIPS

Require *declarative language* — *declarations or statements* about world.

Range of logics have been proposed — best descriptive languages we have, but can be difficult to use in practice.

\[ more \text{ descriptive power} \rightarrow more \text{ difficult to compute (reason) automatically} \]

STRIPS (STanford Research Institute Problem Solver) first to suggest suitable compromise

- restricted form of logic
- restricted language \( \Rightarrow \) efficient algorithm

Basis of many subsequent languages and planners.

**States**

\[ \text{At(Home), } \neg \text{Have(Milk), } \neg \text{Have(Bananas), } \neg \text{Have(Drill)} \]

(conjunctions of function-free ground literals)
2. Planning Languages and STRIPS

Goals

\[ \text{At(Home)}, \ \text{Have(Milk)}, \ \text{Have(Bananas)}, \ \text{Have(Drill)} \]

Can have variables

\[ \text{At}(x), \ \text{Sells}(x, \text{Milk}) \]

(conjunctions of function-free literals)

Actions

\textbf{ACTION (NAME):} \textit{Buy}(x)

\textbf{PRECONDITION:} \textit{At}(p), \textit{Sells}(p, x)

\textbf{EFFECT:} \textit{Have}(x)

(Precondition: conjunction of positive literals
Effect: conjunction of literals)
3. State Space vs. Plan Space

Standard search: node = concrete world state
Planning search: node = \textit{partial plan}

Definition: \textit{open condition} is a precondition of a step not yet fulfilled

Operators on partial plans, eg:

- add a step to fulfill an open condition
- order one step wrt another
- instantiate an unbound variable

Gradually move from incomplete/vague plans to complete, correct plans
4. Partial-order planning

Example

Goal: $RightShoeOn, LeftShoeOn$

Operators:

$Op$(Action: $RightShoe$, Precond: $RightSockOn$, Effect: $RightShoeOn$)

$Op$(Action: $RightSock$, Effect: $RightSockOn$)


$Op$(Action: $LeftSock$, Effect: $LeftSockOn$)

Consider partial plans:

1. $LeftShoe, RightShoe$ — ordering unimportant
2. $RightSock, RightShoe$ — ordering important
3. $RightSock, LeftShoe, RightShoe$ — ordering between some actions important

partial order planner $\Rightarrow$ planner that can represent steps in which some are ordered (in sequence) and others not (in “parallel”)

least commitment planner — partial order planner that delays commitment to order between steps for as long as possible

⇒ less backtracking

A plan is complete iff every precondition is achieved

A precondition is achieved iff it is the effect of an earlier step and no possibly intervening step undoes it
4. Partial-order planning

*linearisation* — obtaining a totally ordered plan from a partially ordered plan by imposing ordering constraints

---

**Partial Order Plan:**

- Start
  - Left Sock
    - LeftSockOn
      - Left Shoe
      - LeftShoeOn
  - Right Sock
    - RightSockOn
      - Right Shoe
      - RightShoeOn
- Finish

**Total Order Plans:**

- Start
  - Right Sock
    - RightSockOn
      - Right Shoe
      - RightShoeOn
    - Left Sock
      - LeftSockOn
        - Left Shoe
        - LeftShoeOn
  - Left Sock
    - LeftSockOn
      - Left Shoe
      - LeftShoeOn
    - Right Sock
      - RightSockOn
        - Right Shoe
        - RightShoeOn
    - Finish
      - Finish
      - Finish
- Start
  - Right Sock
    - RightSockOn
      - Right Shoe
      - RightShoeOn
    - Left Sock
      - LeftSockOn
        - Left Shoe
        - LeftShoeOn
    - Right Sock
      - RightSockOn
        - Right Shoe
        - RightShoeOn
    - Finish
      - Finish
      - Finish
- Start
  - Right Sock
    - RightSockOn
      - Right Shoe
      - RightShoeOn
    - Left Sock
      - LeftSockOn
        - Left Shoe
        - LeftShoeOn
    - Right Sock
      - RightSockOn
        - Right Shoe
        - RightShoeOn
    - Left Sock
      - LeftSockOn
        - Left Shoe
        - LeftShoeOn
    - Finish
      - Finish
      - Finish
- Start
  - Right Sock
    - RightSockOn
      - Right Shoe
      - RightShoeOn
    - Left Sock
      - LeftSockOn
        - Left Shoe
        - LeftShoeOn
    - Right Sock
      - RightSockOn
        - Right Shoe
        - RightShoeOn
    - Right Sock
      - RightSockOn
        - Right Shoe
        - RightShoeOn
    - Finish
      - Finish
      - Finish

4. Partial-order planning

In addition to orderings we must record

- variable bindings: eg. \( x = \text{LocalStore} \)
- causal links: \( S_i \xrightarrow{c} S_j \) (\( S_i \) achieves precondition \( c \) for \( S_j \))

Thus our initial plan might be:

\[
\text{Plan(Steps):}\{ \begin{align*}
S_1: \text{Op(Action: Start)}, \\
S_2: \text{Op(Action: Finish, Precond: RightShoeOn, LeftShoeOn)}
\end{align*}\},
\]

\[
\text{Orderings:}\{ \begin{align*}
S_1 \prec S_2
\end{align*}\},
\]

\[
\text{Bindings:}\{\}
\]

\[
\text{Links:}\{\}
\]

Algorithm \( \cdots \leadsto \)
4.1 POP algorithm sketch

```
function POP(initial, goal, operators) returns plan

    plan ← MAKE-MINIMAL-PLAN(initial, goal)

loop do
    if SOLUTION?(plan) then return plan
    S_need, c ← SELECT-SUBGOAL(plan)
    CHOOSE-OPERATOR(plan, operators, S_need, c)
    RESOLVE-THREATS(plan)
end

function SELECT-SUBGOAL(plan) returns S_need, c

    pick a plan step S_need from STEPS(plan)
    with a precondition c that has not been achieved

    return S_need, c
```

continued...
4.1 POP algorithm sketch

\[\text{procedure } \text{CHOOSE-OPERATOR}(\text{plan, operators, } S_{\text{need}}, c)\]

\begin{enumerate}
\item choose a step \(S_{\text{add}}\) from \text{operators} or \text{STEPS(plan)} that has \(c\) as an effect
\item if there is no such step then fail
\item add the causal link \(S_{\text{add}} \xrightarrow{c} S_{\text{need}}\) to \text{LINKS(plan)}
\item add the ordering constraint \(S_{\text{add}} \prec S_{\text{need}}\) to \text{ORDERINGS(plan)}
\item if \(S_{\text{add}}\) is a newly added step from \text{operators} then
  \begin{enumerate}
  \item add \(S_{\text{add}}\) to \text{STEPS(plan)}
  \item add Start \(\prec S_{\text{add}} \prec \text{Finish}\) to \text{ORDERINGS(plan)}
  \end{enumerate}
\end{enumerate}

\[\text{procedure } \text{RESOLVE-THREATS}(\text{plan})\]

\begin{enumerate}
\item for each \(S_{\text{threat}}\) that threatens a link \(S_i \xrightarrow{c} S_j\) in \text{LINKS(plan)} do
\item choose either
  \begin{enumerate}
  \item Demotion: Add \(S_{\text{threat}} \prec S_i\) to \text{ORDERINGS(plan)}
  \item Promotion: Add \(S_j \prec S_{\text{threat}}\) to \text{ORDERINGS(plan)}
  \end{enumerate}
\item if not \text{CONSISTENT(plan)} then fail
\end{enumerate}

POP is sound, complete, and \underline{systematic} (no repetition)

Extensions for more expressive languages (eg disjunction, etc)
A *clobberer* is a potentially intervening step that destroys the condition achieved by a causal link. E.g., *Go(Home)* clobbers *At(HWS)*:

**Demotion**: put before *Go(HWS)*

**Promotion**: put after *Buy(Drill)*
4.3 Example: Blocks world

On(C,A) On(A,Table) Cl(B) On(B,Table) Cl(C)

On(C,z) Cl(C)

PutOnTable(C)

Cl(A) On(A,z) Cl(B)

PutOn(A,B)

On(A,B) On(B,C)

FINISH

PutOn(A,B)
clobbers Cl(B)

PutOn(B,C)
clobbers Cl(C)

PutOnTable(C)

The real world
Conditional planning
Monitoring and replanning
Integrated planning and acting

Reading: Russell & Norvig, Chapter 13
1. The real world

- Flat(Spare) Intact(Spare) Off(Spare)
- On(Tire1) Flat(Tire1)

START

~Flat(Spare) Intact(Spare) Off(Spare)
On(Tire1) Flat(Tire1)

On(x) ~Flat(x)

FINISH

On(x) Remove(x)
Off(x) Puton(x)
Intact(x) Inflate(x)

Off(x) ClearHub
On(x) ~ClearHub
~Flat(x)

1.1 Incomplete/incorrect information

Incomplete information

- Unknown preconditions, e.g., $\text{Intact}($Spare$)$?
- Disjunctive effects, e.g., $\text{Inflate}(x)$ causes $\text{Inflated}(x)$ or $\text{SlowHiss}(x)$ or $\text{Burst}(x)$ or $\text{BrokenPump}$ or . . .

Incorrect information

- Current state incorrect, e.g., spare NOT intact
- Missing/incorrect postconditions in operators

“Qualification problem”

$\Rightarrow$ can never finish listing all the required preconditions and possible conditional outcomes of actions
1.2 Solutions

**Conditional planning**

- Plan to obtain information ⇒ *observation actions*
- Subplan for each contingency, e.g.,

  
  \[ \text{Check(Tire1), If (Intact(Tire1),[Inflate(Tire1)], [CallRAC])} \]

  ⇒ Expensive because it plans for many unlikely cases

**Monitoring/Replanning**

⇒ Unanticipated outcomes may lead to failure (e.g., no RAC card)

- Assume normal states, outcomes
  - Check progress *during execution*, replan if necessary

In general, some monitoring is unavoidable
2. Conditional planning

\[ \ldots, \text{If}(p, [\text{then plan}], [\text{else plan}]), \ldots \]

**Execution:**

check \( p \) against current KB, execute “then” or “else”

**Conditional planning:** just like POP except

- if an open condition can be established by observation action
  - add the action to the plan
  - complete plan for each possible observation outcome
  - insert conditional step with these subplans

```
CheckTire(x)
KnowsIf(Intact(x))
```
2.1 Conditional planning example

Start

On(Tire1)
Flat(Tire1)
Inflated(Spare)

Finish

On( x )
Inflated( x )
(True)
### 2.1 Conditional planning example

```
Start
- On(Tire1)
- Flat(Tire1)
- Inflated(Spare)

Check(Tire1)
- Intact(Tire1)

Inflate(Tire1)
- Inflated(Tire1)

Finish
- On(Tire1)

On(x)  Inflated(x)
```

2.1 Conditional planning example

On(Tire1)  Inflated(Spare)  On(Tire1)  Inflated(Spare)

Check(Tire1)  Flat(Tire1)  Intact(Tire1)  Inflate(Tire1)

Remove(Tire1)  Flat(Tire1)  Intact(Tire1)

Puton(Spare)  Inflat(Tire1)  Intact(Tire1)

Start  Finish  Intact(Tire1)  Intact(Tire1)  Intact(Tire1)  Intact(Tire1)
3. Monitoring

**Execution monitoring**

- “failure” = preconditions of *remaining plan* not met
- preconditions = *causal links at current time*

**Action monitoring**

- “failure” = preconditions of *next action* not met
  (or action itself fails, e.g., robot bump sensor)

In both cases, need to *replan*
3.1 Preconditions for remaining plan

At(SM)  Have(Milk)  At(Home)  Have(Ban.)  Have(Drill)

Buy(Drill)

Buy(Milk)

Buy(Ban.)

Go(Home)

At(SM)  Sells(SM,Ban.)  Sells(SM,Milk)

At(HWS)  Sells(HWS,Drill)

At(HWS)  Sells(HWS,Milk)

At(HWS)  At(Home)  Have(Ban.)  Have(Drill)

Start

Go(HWS)

Go(SM)

3.2 Replanning

Simplest: on failure, replan from scratch

Better (but harder): plan to get back on track by reconnecting to best continuation

⇒ “loop until done” behavior (with no explicit loop)

```
START
Color(Chair,Blue) ~Have(Red)

Get(Red)

Have(Red)
Paint(Red)

Have(Red)

Color(Chair,Red)
FINISH
```

<table>
<thead>
<tr>
<th>PRECONDITIONS</th>
<th>FAILURE RESPONSE</th>
</tr>
</thead>
<tbody>
<tr>
<td>none</td>
<td>N/A</td>
</tr>
<tr>
<td>Have(Red)</td>
<td>Fetch more red</td>
</tr>
<tr>
<td>Color(Chair,Red)</td>
<td>Repaint</td>
</tr>
</tbody>
</table>
Instead of planning and execution monitoring as separate processes...

- execute a plan step
- monitor the world
- fix deficiencies in plan (open conditions, clobbering, etc)
- refine plan in light of new information (execution errors, actions by other agents, etc)
Agent wishes to achieve goal state $On(C,D), On(D,B)$

(a) start state
(b) another agent has put D on B
(c) our agent has executed $Move(C,D)$ but failed, dropping C on A
(d) goal state achieved
4.1 Situated Planning Example

Initial plan (a).

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4.1 Situated Planning Example

(a)  
(b)  
(c)  
(d)  

External agent changes environment (b).
4.1 Situated Planning Example

Redundant action removed.

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4.1 Situated Planning Example

Move executed...

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4.1 Situated Planning Example

...but failed (c). Replan.
Move executed and succeeded (d).
The End
<table>
<thead>
<tr>
<th>Monday Week 11</th>
<th>Seminar Room 2.28</th>
</tr>
</thead>
<tbody>
<tr>
<td>3pm — 4pm</td>
<td>Seminars</td>
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<tr>
<td>4pm — 5pm</td>
<td>CheX World Cup</td>
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<td>Wednesday Week 11</td>
<td>Seminar Room 1.24</td>
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