Solving Problems by Searching

Chapter 3
function SIMPLE-PROBLEM-SOLVING-AGENT (percept)
returns an action
inputs: percept a percept
static: seq, an action sequence, initially empty
        state, some description of the current world state
        goal, a goal, initially null
        problem, a problem formulation

state ← UPDATE-STATE (state,percept)
if seq is empty then do
    goal ← FORMULATE-GOAL (state)
    problem ← FORMULATE-PROBLEM (state,goal)
    seq ← SEARCH (problem)
    action ← FIRST (seq)
    seq ← REST (seq)
return action
Problem-solving agents (cont’d)

- Restricted form of general agent
- This is *offline* problem solving; solution executed “eyes closed”
- *Online* problem solving involves acting without complete knowledge
- Assumes: static, observable, discrete, deterministic
Example: Romania

On holiday in Romania; currently in Arad
Flight leaves tomorrow from Bucharest
Formulate goal:
be in Bucharest
Formulate problem:
states: various cities
actions: drive between cities
Find solution:
sequence of cities, e.g., Arad, Sibiu, Fagaras, Bucharest
Example: Romania
Problem types

- **Deterministic, fully observable** → *single-state problem*
  Agent knows exactly which state it will be in; solution is a sequence

- **Non-observable** → *conformant problem*
  Agent may have no idea where it is; solution (if any) is a sequence

- **Nondeterministic and/or partially observable** → *contingency problem*
  Percepts provide new information about current state
  Solution is a *tree* or *policy*
  Often *interleave* search, execution

- **Unknown state space** → *exploration problem* ("online")
Example: vacuum world

1

2

3

4

5

6

7

8
Example: vacuum world

- Single-state, start in #5.
  Solution??

- [Right, Suck]
Example: vacuum world

- Conformant, start in \{1, 2, 3, 4, 5, 6, 7, 8\}.
  e.g., *Right* goes to \{2, 4, 6, 8\}.
  Solution??

- \([Right, Suck, Left, Suck]\)
Example: vacuum world

- Contingency, start in #5 or #7
  Murphy’s Law: if a carpet can get dirty it will
  Local sensing: dirt, location only.
  Solution??

- [Right, \textbf{if dirt then Suck}]
Single-state problem formulation

A problem is defined by four items:

- **initial state** e.g., “at Arad”
- **successor function** \( S(x) = \) set of action–state pairs
  e.g., \( S(Arad) = \{ < Arad \rightarrow Zerind, Zerind >, \ldots \} \)
- **goal test**, can be
  - **explicit**, e.g., \( x = \) “at Bucharest”
  - **implicit**, e.g., \( NoDirt(x) \)
- **path cost** (additive)
  e.g., sum of distances, number of actions executed, etc.
  \( c(x, a, y) \) is the **step cost**, assumed to be \( \geq 0 \)

A solution is a sequence of actions
leading from the initial state to a goal state
Selecting a state space

- Real world is absurdly complex
  ⇒ state space must be *abstracted* for problem solving

- (Abstract) state = set of real states

- (Abstract) action = complex combination of real actions
  e.g., “Arad → Zerind” represents a complex set of possible routes, detours, rest stops, etc.
  For guaranteed realizability, any real state “in Arad” must get to some real state “in Zerind”

- (Abstract) solution = set of real paths that are solutions in the real world

- Each abstract action should be “easier” than the original problem!
Example: vacuum world state space graph
Example: vacuum world state space graph

- **states**: integer dirt and robot locations (ignore dirt amounts)
- **actions**: *Left*, *Right*, *Suck*, *NoOp*
- **goal test**: no dirt
- **path cost**: 1 per action (0 for *NoOp*)
Example: The 8-puzzle

Start State

Goal State
Example: The 8-puzzle

- **states:** integer locations of tiles (ignore intermediate positions)
- **actions:** move blank left, right, up, down (ignore unjamming etc.)
- **goal test:** = goal state (given)
- **path cost:** 1 per move
- Note: optimal solution of $n$-Puzzle family is NP-hard
Example: robotic assembly
Example: robotic assembly

- **states**: real-valued coordinates of robot joint angles
- **actions**: continuous motions of robot joints
- **goal test**: complete assembly *with no robot included*
- **path cost**: time to execute
Basic idea: offline, simulated exploration of state space by generating successors of already-explored states (a.k.a. *expanding* states)
function Tree-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 the node and add the resulting nodes to the search tree
end
(a) The initial state

(b) After expanding Arad

(c) After expanding Sibiu
Implementation: states vs. nodes

Node

- **Depth**: 6
- **Path-Cost**: 6
- **Action**: right

Parent-Node

State

```
5 4
6 1 8
7 3 2
```
A **state** is a (representation of) a physical configuration

A **node** is a data structure constituting part of a search tree includes *parent, children, depth, path cost* $g(x)$

States do not have parents, children, depth, or path cost!

The **EXPAND** function creates new nodes, filling in the various fields and using the **SUCCESSORFn** of the problem to create the corresponding states.
Implementation: general tree search

function Tree-Search (problem, fringe) returns a solution, or failure

fringe ← Insert(Make-Node(Initial-State [problem]), fringe)
loop do
  if Empty?(fringe) then return failure
  node ← Remove-First(fringe)
  if Goal-Test[problem] applied to State[node] succeeds
    then return Solution(node)
  fringe ← Insert-All(Expand(node, problem), fringe)
function \textsc{Expand} (node, problem) returns a set of nodes

\begin{verbatim}
successors ← the empty set
for each < action, result> in S\textsc{UCCESSOR-Fn} [problem(State[node])] do
    s ← a new Node
    State[s] ← result
    Parent-Node[s] ← node
    Action[s] ← action
    Path-Cost[s] ← Path-Cost[node] + Step-Cost(node, action, s)
    Depth[s] ← Depth[node] + 1
    add s to successors
return successors
\end{verbatim}
A strategy is defined by picking the order of node expansion.

Strategies are evaluated along the following dimensions:

- **completeness**—does it always find a solution if one exists?
- **time complexity**—number of nodes generated/expanded
- **space complexity**—maximum number of nodes in memory
- **optimality**—does it always find a least-cost solution?
Search strategies

Time and space complexity are 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 \( \infty \))
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
- Iterative broadening search (not in the textbook)
Breadth-first search

- Expand shallowest unexpanded node
- Implementation: *fringe* is a FIFO queue, i.e., new successors go at end
Progress of breadth-first search
Properties of breadth-first search

- **Complete:** Yes (if $b$ is finite)
- **Time:** \[ 1 + b + b^2 + b^3 + \ldots + b^d + b(b^d - 1) = O(b^{d+1}), \]
  i.e., exp. in $d$
- **Space:** $O(b^{d+1})$ (keeps every node in memory)
- **Optimal:** Yes (if cost = 1 per step); not optimal in general

*Space* is the big problem; can easily generate nodes at 10MB/sec
so 24hrs = 860GB.
Uniform-cost search

- Expand least-cost unexpanded node
- Implementation: \textit{fringe} = queue ordered by path cost
- Equivalent to breadth-first if step costs all equal
Properties of uniform-cost search

- **Complete:** Yes, if step cost $\geq \epsilon$

- **Time:** # of nodes with $g \leq$ cost of optimal solution,
  \[ O\left(b^{\lceil C^*/\epsilon \rceil}\right) \]
  where $C^*$ is the cost of the optimal solution

- **Space:** # of nodes with $g \leq$ cost of optimal solution,
  \[ O\left(b^{\lceil C^*/\epsilon \rceil}\right) \]

- **Optimal:** Yes—nodes expanded in increasing order of $g(n)$
Depth-first search

- Expand deepest unexpanded node
- Implementation: fringe = LIFO queue, i.e., put successors at front
Progress of depth-first search
Properties of depth-first search

- **Complete:** No: fails in infinite-depth spaces, spaces with loops
  Modify to avoid repeated states along path
  ⇒ complete in finite spaces

- **Time:** $O(b^m)$: terrible if $m$ is much larger than $d$
  but if solutions are dense, may be much faster than breadth-first

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

- **Optimal:** No
Depth-limited search

= depth-first search with depth limit $l$, i.e., nodes at depth $l$ have no successors

A recursive implementation is shown on the next page
Depth-limited search

function Depth-Limited-Search \((\text{problem}, \text{limit})\)
returns a solution, or failure/cutoff
return Recursive-DLS(Make-Node(Initial-State[\text{problem}]), \text{problem}, \text{limit})

function Recursive-DLS \((\text{node}, \text{problem}, \text{limit})\)
returns a solution, or failure/cutoff

cutoff-occurred? \Leftarrow \text{false}
if Goal-Test[\text{problem}](State[\text{node}]) then return Solution(\text{node})
else if Depth[\text{node}]=\text{limit} then return cutoff
else for each successor in Expand(\text{node}, \text{problem}) do
    result \Leftarrow \text{Recursive-DLS}(successor, \text{problem}, \text{limit})
    if result = cutoff then cutoff-occurred? \Leftarrow \text{true}
    else if result \neq failure then return result
    if cutoff-occurred? then return cutoff else return failure
Properties of depth-limited search

- **Complete:** No (similar to DFS)
- **Time:** $O(b^l)$, where $l$ is the depth-limit
- **Space:** $O(bl)$, i.e., linear space (similar to DFS)
- **Optimal:** No
Iterative deepening search

- Do iterations of depth-limited search starting with a limit of 0. If you fail to find a goal with a particular depth limit, increment it and continue with the iterations.

- Combines the linear space complexity of DFS with the completeness property of BFS.
Iterative deepening search

function Iterative-Deepening-Search(problem)
returns a solution, or failure
inputs: problem, a problem

for depth ← 0 to ∞ do
    result ← Depth-Limited-Search(problem, depth)
    if result ≠ cutoff then return result
Iterative deepening search

Limit = 0

Limit = 1

Limit = 2

Limit = 3
Properties of iterative deepening search

- **Complete:** Yes
- **Time:** \((d + 1)b^0 + db^1 + (d - 1)b^2 + \ldots + b^d = O(b^d)\)
- **Space:** \(O(bd)\)
- **Optimal:** Yes, if step cost = 1
  Can be modified to explore uniform-cost tree

Numerical comparison for \(b = 10\) and \(d = 5\), solution at far right:

\[
N(\text{IDS}) = 50 + 400 + 3,000 + 20,000 + 100,000
= 123,450
\]

\[
N(\text{BFS}) = 10 + 100 + 1,000 + 10,000 + 100,000 + 999,990
= 1,111,100
\]
Iterative deepening is iterations of DFS with a depth cutoff. Iterative broadening is iterations of DFS with a breadth cutoff.

Iterate $c$ from 2 to $b$, where $b$ is the maximum branching factor. At every iteration, take only $c$ children of every node expanded, simply discard the remaining children.

Algorithm??

Properties??
## Summary of Algorithms

<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>
</tr>
</thead>
<tbody>
<tr>
<td>Complete?</td>
<td>Yes*</td>
<td>Yes*</td>
<td>No</td>
<td>Yes, if $l \geq d$</td>
<td>Yes</td>
</tr>
<tr>
<td>Time</td>
<td>$b^{d+1}$</td>
<td>$b^{\lceil C^*/\epsilon \rceil}$</td>
<td>$b^m$</td>
<td>$b^l$</td>
<td>$b^d$</td>
</tr>
<tr>
<td>Space</td>
<td>$b^{d+1}$</td>
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<td>$b_m$</td>
<td>$b_l$</td>
<td>$b_d$</td>
</tr>
<tr>
<td>Optimal?</td>
<td>Yes*</td>
<td>Yes*</td>
<td>No</td>
<td>No</td>
<td>Yes</td>
</tr>
</tbody>
</table>
Repeated states

Failure to detect repeated states can turn a linear problem into an exponential one!
function \textsc{Graph-Search} (\textit{problem}, \textit{fringe})
returns a solution, or failure

closed $\leftarrow$ an empty set
fringe $\leftarrow$ \textsc{Insert}(\textsc{Make-Node}(\text{Initial-State} [\textit{problem}]), fringe)
loop do
  if \textsc{Empty?}(fringe) then return failure
  node $\leftarrow$ \textsc{Remove-First}(fringe)
  if \textsc{Goal-Test}[\textit{problem}] applied to \text{State}[\textit{node}] succeeds
      then return \text{Solution}(node)
  if \text{State}[\textit{node}] is not in closed then
    add \text{State}[\textit{node}] to closed
  fringe $\leftarrow$ \textsc{Insert-All}(\textsc{Expand}(\textit{node, problem}), fringe)
Problem formulation usually requires abstracting away real-world details to define a state space that can feasibly be explored.

Variety of uninformed search strategies.

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