Uninformed Search (Ch. 3-3.4)

PREPARING FOR A DATE:
WHAT SITUATIONS MIGHT I PREPARE FOR?
1) MEDICAL EMERGENCY
2) DANCING
3) FOOD TOO EXPENSIVE

OKAY, WHAT KINDS OF EMERGENCIES CAN HAPPEN?
1) A) SNAKEBITE
2) LIGHTNING STRIKE
3) FALL FROM CHAIR

HMM, WHICH SNAKES ARE DANGEROUS? LET'S SEE...
1) A) CORN SNAKE
2) GARTER SNAKE
3) COPPERHEAD

THE RESEARCH COMPARING SNAKE VENOMS IS SCATTERED AND INCONSISTENT. I'LL MAKE A SPREADSHEET TO ORGANIZE IT.

I'M HERE TO PICK YOU UP. YOU'RE NOT DRESSED?

BY LE, THE INLAND TAIPAN HAS THE DEADLIEST VENOM OF ANY SNAKE?

I REALLY NEED TO STOP USING DEPTH-FIRST SEARCHES.
Announcements

First homework will be posted tonight (due next Wednesday at 11:55 pm)
Review

We use words that have a general English definition in a technical sense

Rational = choose best action ($2^{nd}$ best no good)
(i.e. particle code not rational)
Goal-based = agent actually represents goals
Deterministic vs. stochastic = results of agent actions one or multiple outcomes
Known vs. unknown = agent knows what the possible outcomes of its actions are (or not)
Agent learning

For many complicated problems (facial recognition, high degree of freedom robot movement), it would be too hard to explicitly tell the agent what to do.

Instead, we build a framework to learn the problem and let the agent decide what to do.

This is less work and allows the agent to adapt if the environment changes.
Agent learning

There are four main components to learning:
1. Critic = evaluates how well the agent is doing and whether it needs to change actions (similar to performance measure)
2. Learning element = incorporate new information to improve agent
3. Performance element = selects action agent will do (exploit known best solution)
4. Problem generator = find new solutions (explore problem space for better solution)
State structure

States can be generalized into three categories:

1. Atomic (Ch. 3-5, 15, 17)
2. Factored (Ch. 6-7, 10-11, 13-16, 18, 20-21)
3. Structured (Ch. 8-9, 12, 14, 19, 22-23)

(Top are simpler, bottom are more general)

Occam's razor = if two results are identical, use the simpler approach
State structure

An **atomic** state has no sub-parts and acts as a simple unique identifier.

An example is an elevator:
Elevator = agent (actions = up/down)
Floor = state

In this example, when someone requests the elevator on floor 7, the only information the agent has is what floor it currently is on.
A factored state has a fixed number of variables/attributes associated with it.

Our simple vacuum example is factored, as each state has an id (A or B) along with a “dirty” property.

In particles, each state has a set of red balls with locations along with the blue ball location.
Structured states simply describe objects and their relationship to others

Suppose we have 3 blocks: A, B and C
We could describe: A on top of B, C next to B

A factored representation would have to enumerate all possible configurations of A, B and C to be as representative
Goal based agents need to search to find a path from their start to the goal (a path is a sequence of actions, not states)

For now we consider problem solving agents who search on atomically structured spaces

Today we will focus on uninformed searches, which only know cost between states but no other extra information
Search

In the vacuum example, the states and actions are obvious and simple.

In more complex environments, we have a choice of how to abstract the problem into simple (yet expressive) states and actions.

The solution to the abstracted problem should be able to serve as the basis of a more detailed problem (i.e. fit the detailed solution inside).
Search

Example: Google maps gives direction by telling you a sequence of roads and does not dictate speed, stop signs/lights, road lane.
In deterministic environments the search solution is a single sequence (list of actions).

Stochastic environments need multiple sequences to account for all possible outcomes of actions.

It can be costly to keep track of all of these and might be better to keep the most likely and search again if you are off the sequences.
There are 5 parts to search:
1. Initial state
2. Actions possible at each state
3. Transition model (result of each action)
4. Goal test (are we there yet?)
5. Path costs/weights (not stored in states) (related to performance measure)

After a search, the agent typically ignores its percept and blindly follows the solution
Small examples

Here is our vacuum world again:

1. initial

2. For all states, we have actions: L, R or S

3. Transition model = black arrows

4. goals

5. Path cost = ??? (from performance measure)
Small examples

8-Puzzle
1. (semi) Random
2. All states: U,D,L,R
4. As shown here
5. Path cost = 1 (move count)
3. Transition model (example):

Result([[1, 2, 3], [4, 5, 6], [7, 8, #]], D) =

(see: https://www.youtube.com/watch?v=DfVjTkzk2Ig)
Small examples

8-Puzzle is NP complete, so these type of searches are the best known methods

3x3 board = \begin{array}{ccc}
1 & 2 & 3 \\
4 & 5 & 6 \\
7 & 8 & \end{array} = 181,440 states

4x4 board = 1.3 trillion states
Solution time: milliseconds

5x5 board = $10^{25}$ states
Solution time: hours
8-Queens: how to fit 8 queens on a 8x8 board so no 2 queens can capture each other

Two ways to model this:
Incremental = each action is to add a queen to the board (1.8 x 10^{14} states)
Complete state formulation = all 8 queens start on board, action = move a queen (2057 states)
Real world examples

Directions/traveling (land or air)

Model choices: only have interstates? Add smaller roads, with increased cost? (pointless if they are never taken)
Real world examples

Touring problem: visit each place at least once, end up at starting location

Goal: Minimize distance traveled
Real world examples

Traveling salesperson problem (TSP): Visit each location exactly once and return to start

Goal: Minimize distance traveled
Search algorithm

To search, we will build a tree with the root as the initial state

```plaintext
function tree-search(root-node)
    fringe ← successors(root-node)
    while ( notempty(fringe) )
        {node ← remove-first(fringe)
         state ← state(node)
         if goal-test(state) return solution(node)
         fringe ← insert-all(successors(node), fringe) }
    return failure
end tree-search
```

Any problems with this?
Search algorithm
Search algorithm

8-queens can actually be generalized to the question:
Can you fit $n$ queens on a $z \times z$ board?

Except for a couple of small size boards, you can fit $z$ queens on a $z \times z$ board.

This can be done fairly easily with recursion

(See: nqueens.cpp)
We can remove visiting states multiple times by doing this:

```plaintext
function tree-search(root-node)
  fringe ← successors(root-node)
  explored ← empty
  while ( notempty(fringe) )
    { node ← remove-first(fringe)
      state ← state(node)
      if goal-test(state) return solution(node)
      explored ← insert(node, explored)
      fringe ← insert-all(successors(node), fringe, if node not in explored)
    }
  return failure
end tree-search
```

But this is still not necessarily all that great...
Next we will introduce and compare some tree search algorithms.

These all assume nodes have 4 properties:
1. The current state
2. Their parent state (and action for transition)
3. Children from this node (result of actions)
4. Cost to reach this node (from root)
Search algorithm

When we find a goal state, we can back track via the parent to get the sequence.

To keep track of the unexplored nodes, we will use a queue (of various types).

The explored set is probably best as a hash table for quick lookup (have to ensure similar states reached via alternative paths are the same in the has, can be done by sorting).
Search algorithm

The search algorithms metrics/criteria:
1. Completeness (does it terminate with a valid solution)
2. Optimality (is the answer the best solution)
3. Time (in big-O notation)
4. Space (big-O)

$b = \text{maximum branching factor}$
$d = \text{minimum depth of a goal}$
$m = \text{maximum length of any path}$
Today, we will focus on uninformed search, which only have the node information (4 parts) (the costs are given and cannot be computed)

Next time we will continue with informed searches that assume they have access to additional structures of the problem (i.e. if costs were distances between cities, you could also compute the distance “as the bird flies”)
Breadth first search checks all states which are reached with the fewest actions first (i.e. will check all states that can be reached by a single action from the start, next all states that can be reached by two actions, then three...)

Breadth first search checks all states which are reached with the fewest actions first (i.e. will check all states that can be reached by a single action from the start, next all states that can be reached by two actions, then three...)

Breadth first search

(see: https://www.youtube.com/watch?v=5UfMU9TsoEM)
(see: https://www.youtube.com/watch?v=nI0dT288VLs)
Breadth first search

BFS can be implemented by using a simple FIFO (first in, first out) queue to track the fringe/frontier/unexplored nodes

Metrics:
Complete
Non-optimal (unless uniform path cost)
Time complexity = $O(b^d)$
Space complexity = $O(b^d)$
Breadth first search

Exponential problems are not very fun, as seen in this picture:

<table>
<thead>
<tr>
<th>Depth</th>
<th>Nodes</th>
<th>Time</th>
<th>Memory</th>
</tr>
</thead>
<tbody>
<tr>
<td>2</td>
<td>110</td>
<td>.11 milliseconds</td>
<td>107 kilobytes</td>
</tr>
<tr>
<td>4</td>
<td>11,110</td>
<td>11 milliseconds</td>
<td>10.6 megabytes</td>
</tr>
<tr>
<td>6</td>
<td>$10^6$</td>
<td>1.1 seconds</td>
<td>1 gigabyte</td>
</tr>
<tr>
<td>8</td>
<td>$10^8$</td>
<td>2 minutes</td>
<td>103 gigabytes</td>
</tr>
<tr>
<td>10</td>
<td>$10^{10}$</td>
<td>3 hours</td>
<td>10 terabytes</td>
</tr>
<tr>
<td>12</td>
<td>$10^{12}$</td>
<td>13 days</td>
<td>1 petabyte</td>
</tr>
<tr>
<td>14</td>
<td>$10^{14}$</td>
<td>3.5 years</td>
<td>99 petabytes</td>
</tr>
<tr>
<td>16</td>
<td>$10^{16}$</td>
<td>350 years</td>
<td>10 exabytes</td>
</tr>
</tbody>
</table>

Figure 3.13 Time and memory requirements for breadth-first search. The numbers shown assume branching factor $b = 10$; 1 million nodes/second; 1000 bytes/node.
Uniform-cost search also does a queue, but uses a priority queue based on the cost (the lowest cost node is chosen to be explored)
Uniform-cost search

The only modification is when exploring a node we cannot disregard it if it has already been explored by another node.

We might have found a shorter path and thus need to update the cost on that node.

We also do not terminate when we find a goal, but instead when the goal has the lowest cost in the queue.
Uniform-cost search

UCS is..

1. Complete (if costs strictly greater than 0)
2. Optimal

However....

3&4. Time complexity = space complexity = $O(b^{1+C*/\min(path\ cost)})$, where $C^*$ cost of optimal solution (much worse than BFS)
Depth first search

DFS is same as BFS except with a FILO (or LIFO) instead of a FIFO queue
Depth first search

Metrics:
1. Might not terminate (not correct) (e.g. in vacuum world, if first expand is action L)
2. Non-optimal (just... no)
3. Time complexity = $O(b^d)$
4. Space complexity = $O(b*d)$

Only way this is better than BFS is the space complexity...
Depth limited search

DFS by itself is not great, but it has two (very) useful modifications

Depth limited search runs normal DFS, but if it is at a specified depth limit, you cannot have children (i.e. take another action)

Typically with a little more knowledge, you can create a reasonable limit and makes the algorithm correct
Depth limited search

However, if you pick the depth limit before d, you will not find a solution (not correct, but will terminate)
Iterative deepening DFS

Probably the most useful uninformed search is **iterative deepening DFS**.

This search performs depth limited search with maximum depth 1, then maximum depth 2, then 3... until it finds a solution.
Iterative deepening DFS
Iterative deepening DFS

The first few states do get re-checked multiple times in IDS, however it is not too many

When you find the solution at depth $d$, depth 1 is expanded $d$ times (at most $b$ of them)

The second depth are expanded $d-1$ times (at most $b^2$ of them)

Thus $d \cdot b + (d - 1) \cdot b^2 + \ldots + 1 \cdot b^d = O(b^d)$
Iterative deepening DFS

Metrics:
1. Complete
2. Non-optimal (unless uniform cost)
3. $O(b^d)$
4. $O(bd)$

Thus IDS is better in every way than BFS (asymptotically)

Best uninformed we will talk about
Bidirectional search

Bidirectional search starts from both the goal and start (using BFS) until the trees meet.

This is better as $2^*(b^{d/2}) < b^d$ (the space is much worse than IDS, so only applicable to small problems).
## Summary of algorithms

### Fig. 3.21, p. 91

<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 DLS</th>
<th>Bidirectional (if applicable)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Complete?</td>
<td>Yes[a]</td>
<td>Yes[a,b]</td>
<td>No</td>
<td>No</td>
<td>Yes[a]</td>
<td>Yes[a,d]</td>
</tr>
<tr>
<td>Time</td>
<td>$O(b^d)$</td>
<td>$O(b^{1+C*/\varepsilon})$</td>
<td>$O(b^m)$</td>
<td>$O(b^l)$</td>
<td>$O(b^d)$</td>
<td>$O(b^{d/2})$</td>
</tr>
<tr>
<td>Space</td>
<td>$O(b^d)$</td>
<td>$O(b^{1+C*/\varepsilon})$</td>
<td>$O(bm)$</td>
<td>$O(bl)$</td>
<td>$O(bd)$</td>
<td>$O(b^{d/2})$</td>
</tr>
<tr>
<td>Optimal?</td>
<td>Yes[c]</td>
<td>Yes</td>
<td>No</td>
<td>No</td>
<td>Yes[c]</td>
<td>Yes[c,d]</td>
</tr>
</tbody>
</table>

There are a number of footnotes, caveats, and assumptions. See Fig. 3.21, p. 91.

[a] complete if $b$ is finite  
[b] complete if step costs $\geq \varepsilon > 0$  
[c] optimal if step costs are all identical  
(also if path cost non-decreasing function of depth only)  
[d] if both directions use breadth-first search  
(also if both directions use uniform-cost search with step costs $\geq \varepsilon > 0$)

Generally the preferred uninformed search strategy