CSE 3401: Intro to Artificial Intelligence
Uninformed Search

- Required Readings: R & N Chapter 3, Sec. 1–4.
- Lecture slides adapted from those of Fahiem Bacchus.

Why Search

- Successful
  - Success in game playing programs based on search.
  - Many other AI problems can be successfully solved by search.

- Practical
  - Many problems don’t have a simple algorithmic solution. Casting these problems as search problems is often the easiest way of solving them. Search can also be useful in approximation (e.g., local search in optimization problems).
  - Often specialized algorithms cannot be easily modified to take advantage of extra knowledge. Heuristics in search provide a natural way of utilizing extra knowledge.
  - Some critical aspects of intelligent behaviour, e.g., planning, can be naturally cast as search.

Example, a holiday in Jamaica

- Prefer to avoid hurricane season.
- Rules of the road, larger vehicle has right of way (especially trucks).
- Want to climb up to the top of Dunns river falls.
But you want to start your climb at 8:00 am before the crowds arrive!

- Want to swim in the Blue Lagoon
- Want to hike the Cockpit Country
- No roads, need local guide and supplies.
How do we plan our holiday?

- Easier goal, climb to the top of Blue Mountain
- Near Kingston.
- Organized hikes available.
- Need to arrive on the peak at dawn, before the fog sets in.
- Can get some Blue Mountain coffee!

How do we plan our holiday?

- We must take into account various preferences and constraints to develop a schedule.
- An important technique in developing such a schedule is “hypothetical” reasoning.
  - e.g., if I fly into Kingston and drive a car to Port Antonio, I’ll have to drive on the roads at night. How desirable is this?
  - If I’m in Port Antonio and leave at 6:30am, I can arrive at Dunns river falls by 8:00am.

How do we plan our holiday?

- This kind of hypothetical reasoning involves asking
  - “what state will I be in after the following sequence of events?”
- From this we can reason about what sequence of events one should try to bring about to achieve a desirable state.
- Search is a computational method for capturing a particular version of this kind of reasoning.

Search

- There are many difficult questions that are not resolved by search. In particular, the whole question of how does an intelligent system formulate its problem as a search problem is not addressed by search.
- Search only shows how to solve the problem once we have it correctly formulated.
The formalism.

- To formulate a problem as a search problem we need the following components:
  - Formulate a state space over which to search. The state space necessarily involves abstracting the real problem.
  - Formulate actions that allow one to move between different states. The actions are abstractions of actions you could actually perform.
  - Identify the initial state that best represents your current state and the desired condition one wants to achieve.
  - Formulate various heuristics to help guide the search process.

Once the problem has been formulated as a state space search, various algorithms can be utilized to solve the problem.

- A solution to the problem will be a sequence of actions/moves that can transform your current state into state where your desired condition holds.

Example 1: Romania Travel.

Currently in Arad, need to get to Bucharest by tomorrow to catch a flight.

Example 1.

- State space.
  - States: the various cities you could be located in.
  - Note we are ignoring the low level details of driving, states where you are on the road between cities, etc.
  - Actions: drive between neighboring cities.
  - Initial state: in Arad
  - Desired condition (Goal): be in a state where you are in Bucharest. (How many states satisfy this condition?)

- Solution will be the route, the sequence of cities to travel through to get to Bucharest.
Example 2. The 8-Puzzle

- Can slide a tile into the blank spot. (Equivalently, can think of it as moving the blank around).

Example 2. The 8-Puzzle

- State space.
  - States: The different configurations of the tiles. How many different states?
  - Actions: Moving the blank up, down, left, right. Can every action be performed in every state?
  - Initial state: as shown on previous slide.
  - Desired condition (Goal): be in a state where the tiles are all in the positions shown on the previous slide.
- Solution will be a sequence of moves of the blank that transform the initial state to a goal state.

Example 2. The 8-Puzzle

- Although there are 9! different configurations of the tiles (362,880), in fact the state space is divided into two disjoint parts.
- Only when the blank is in the middle are all four actions possible.
- Our goal condition is satisfied by only a single state. But one could easily have a goal condition like
  - The 8 is in the upper left hand corner.
  - How many different states satisfy this goal?


- In the previous two examples, a state in the search space corresponded to a unique state of the world (modulo details we have abstracted away).
- However, states need not map directly to world configurations. Instead, a state could map to the agent’s mental conception of how the world is configured: the agent’s knowledge state.

- We have a vacuum cleaner and two rooms.
- Each room may or may not be dirty.
- The vacuum cleaner can move left or right (the action has no effect if there is no room to the right/left).
- The vacuum cleaner can suck; this cleans the room (even if the room was already clean).

Physical states

Goal is to have all rooms clean.


Knowledge level State Space

- The state space can consist of a set of states. The agent knows that it is in one of these states, but doesn’t know which.

Knowledge level State Space

- Complete knowledge of the world: agent knows exactly which state it is in. State space states consist of single physical states:
- Start in \{5\}: \langle right, suck \rangle

Goal is to have all rooms clean.

Knowledge level State Space

- No knowledge of the world. States consist of sets of physical states.
- Start in \{1,2,3,4,5,6,7,8\}, agent doesn’t have any knowledge of where it is.
- Nevertheless, the actions \langle right, suck, left, suck \rangle achieves the goal.

Goal is to have all rooms clean.

Initial state.
\{1,2,3,4,5,6,7,8\}

Right

Left

Suck

Suck
More complex situations.

- The agent might be able to perform some sensing actions. These actions change the agent’s mental state, not the world configuration.
- With sensing can search for a contingent solution: a solution that is contingent on the outcome of the sensing actions.
- Now the issue of interleaving execution and search comes into play.

More complex situations.

- Instead of complete lack of knowledge, the agent might think that some states of the world are more likely than others.
- This leads to probabilistic models of the search space and different algorithms for solving the problem.
- Later we will see some techniques for reasoning and making decisions under uncertainty.

Algorithms for Search.

- Inputs:
  - a specified initial state (a specific world state or a set of world states representing the agent’s knowledge, etc.)
  - a successor function \( S(x) = \{ \text{set of states that can be reached from state } x \text{ via a single action} \} \)
  - a goal test a function that can be applied to a state and returns true if the state is satisfies the goal condition.
  - A step cost function \( C(x,a,y) \) which determines the cost of moving from state \( x \) to state \( y \) using action \( a \). \( C(x,a,y) = \infty \) if \( a \) does not yield \( y \) from \( x \)

Algorithms for Search.

- Output:
  - a sequence of states leading from the initial state to a state satisfying the goal test.
  - The sequence might be
    - annotated by the name of the action used.
    - optimal in cost for some algorithms.
 Algorithms for Search

- Obtaining the action sequence.
  - The set of successors of a state $x$ might arise from different actions, e.g.,
    - $x \rightarrow a \rightarrow y$
    - $x \rightarrow b \rightarrow z$
  - Successor function $S(x)$ yields a set of states that can be reached from $x$ via a (any) single action.
  - Rather than just return a set of states, we might annotate these states by the action used to obtain them:
    - $S(x) = \{<y,a>, <z,b>\}$
      $y$ via action $a$, $z$ via action $b$.
    - $S(x) = \{<y,a>, <y,b>\}$
      $y$ via action $a$, also $y$ via alternative action $b$.

 Tree search

- Assuming search space is a tree, not a graph.
- We use the successor state function to simulate an exploration of the state space.
- Initial call has Frontier = initial state.
  - Frontier/fringe is the set of states we haven’t yet explored/expanded.

TreeSearch(Frontier, Successors, Goal?)

If Frontier is empty return failure

Curr = select state from Frontier

If( Goal?(Curr)) return Curr.

Frontier’ = (Frontier – {Curr}) U Successors(Curr)

return TreeSearch(Frontier’, Successors, Goal?)

 Tree search in Prolog

treeS([[State|Path]|_],Soln) :-
Goal?(State), reverse([[State|Path], Soln]).

TreeS([[State|Path]|Frontier],Soln) :-
GenSuccessors(State,Path,NewPaths),
merge(NewPaths,Frontier,NewFrontier),
treeS(NewFrontier,Soln).

(Arad),
(Zerind, Timisoara, Sibiu),
(Zerind, Timisoara, Arad, Oradea, Fagaras, RimnicuVilcea ),
(Zerind, Timisoara, Arad, Oradea, Sibiu, Bucharest, RimnicuVilcea ).

Solution: Arad -> Sibiu -> Fagaras -> Bucharest

Cost: 140+99+211 = 450
Selection Rule.

- The example shows that order states are selected from the frontier has a critical effect on the operation of the search.
  - Whether or not a solution is found
  - The cost of the solution found
  - The time and space required by the search.

Critical Properties of Search.

- **Completeness**: will the search always find a solution of a solution exists?
- **Optimality**: will the search always find the least cost solution? (when actions have costs)
- **Time complexity**: what is the maximum number of nodes than can be expanded or generated?
- **Space complexity**: what is the maximum number of nodes that have to be stored in memory?
Uninformed Search Strategies

- These are strategies that adopt a fixed rule for selecting the next state to be expanded.
- The rule is always the same whatever the search problem being solved.
- These strategies do not take into account any domain specific information about the particular search problem.
- Popular uninformed search techniques:
  - Breadth-First, Uniform-Cost, Depth-First, Depth-Limited, and Iterative-Deepening search.

Selecting vs. Sorting

- A simple equivalence we will exploit:
  - Order the elements on the frontier.
  - Always select the first element.
- Any selection rule can be achieved by employing an appropriate ordering of the frontier set.

Breadth First.

- Place the successors of the current state at the end of the frontier, which then behaves as a FIFO queue.
- Example:
  - let the states be the positive integers {0, 1, 2, ...}
  - let each state n have as successors n+1 and n+2
  - E.g. S(1) = {2, 3}; S(10) = {11, 12}
  - Start state 0
  - Goal state 5
  - [Draw search space graph]
Breadth First Properties

● Measuring time and space complexity.
  ■ let b be the maximum number of successors of any state.
  ■ let d be the number of actions in the shortest solution.

Breadth First Properties

● Completeness?
  ■ The length of the path from the initial state to the expanded state must increase monotonically.
  ■ we replace each expanded state with states on longer paths.
  ■ All shorter paths are expanded prior before any longer path.
  ■ Hence, eventually we must examine all paths of length d, and thus find the shortest solution.

Breadth First Properties

● Time Complexity?
  ■ # nodes generated at...
  ■ Level 0 (root): 1
  ■ Level 1: 1 * b [each node has at most b successors]
  ■ Level 2: b * b = b^2
  ■ Level 3: b * b^2 = b^3 ....
  ■ Level d: b^d
  ■ Level d + 1: b^(d+1) - b = b(b^d - 1) [when last node is successful]
  ■ Total: 1 + b + b^2 + b^3 + ... + b^(d-1) + b^d + b(b^d - 1) = O(b^(d+1))
  ■ Exponential, so can only solve small instances

Breadth First Properties

● Space Complexity?
  ■ O(b^(d+1)): If goal node is last node at level d, all of the successors of the other nodes will be on the frontier when the goal node is expanded, i.e. b(b^d - 1)
Breadth First Properties

- Optimality?
  - Will find shortest path length solution
  - Least cost solution?
    - In general no!
    - Only if all step costs are equal

Breadth First Properties

- Space complexity is a real problem.
  - E.g., let b = 10, and say 1000 nodes can be expanded per second and each node requires 100 bytes of storage:

<table>
<thead>
<tr>
<th>Depth</th>
<th>Nodes</th>
<th>Time</th>
<th>Memory</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>1</td>
<td>1 millisec.</td>
<td>100 bytes</td>
</tr>
<tr>
<td>6</td>
<td>$10^6$</td>
<td>18 mins.</td>
<td>11 GB</td>
</tr>
<tr>
<td>8</td>
<td>$10^8$</td>
<td>31 hrs.</td>
<td>11 GB</td>
</tr>
</tbody>
</table>

- Run out of space long before we run out of time in most applications.

Uniform Cost Search.

- Keep the frontier sorted in increasing cost of the path to a node; behaves like priority queue.
- Always expand the least cost node.
- Identical to Breadth First if each transition has the same cost.

- Example:
  - let the states be the positive integers \{0,1,2,\ldots\}
  - let each state n have as successors n+1 and n+2
  - Say that the n+1 action has cost 2, while the n+2 action has cost 3.
  - [Draw search space graph]

Uniform Cost Search.

\{0[0]\}
\{1[2],2[3]\}
\{2[3],2[4],3[5]\}
\{2[4],3[5],3[5],4[6]\}
\{3[5],3[5],4[6],3[6],4[7]\}
\ldots
Uniform-Cost Search

- Completeness?
  - Assume each transition has costs \( \geq \epsilon > 0 \) (otherwise can have in finite path with finite cost)
  - The previous argument used for breadth first search holds: the cost of the expanded state must increase monotonically.
  - The algorithm expands nodes in order of increasing path cost.

Uniform-Cost Search

- Time and Space Complexity?
  - \( O(b^{C^*/\epsilon}) \) where \( C^* \) is the cost of the optimal solution.
  - Difficulty is that there may be many long paths with cost \( \leq C^* \); Uniform-cost search must explore them all.

Uniform-Cost Search

- Optimality?
  - Finds optimal solution if each transition has cost \( \geq \epsilon > 0 \).
  - Explores paths in the search space in increasing order of cost. So must find minimum cost path to a goal before finding any higher costs paths.


1. Let \( c(n) \) be the cost of the path to node \( n \). If \( n_2 \) is expanded after \( n_1 \) then \( c(n_1) \leq c(n_2) \).

   **Proof:**
   - If \( n_2 \) was on the frontier when \( n_1 \) was expanded, in which case \( c(n_2) \geq c(n_1) \) else \( n_1 \) would not have been selected for expansion.
   - If \( n_2 \) was added to the frontier when \( n_1 \) was expanded, in which case \( c(n_2) \geq c(n_1) \) since the path to \( n_2 \) extends the path to \( n_1 \).
   - If \( n_2 \) is a successor of a node \( n_3 \) that was on the frontier or added when \( n_1 \) was expanded, then \( c(n_2) > c(n_3) \) and \( c(n_3) \geq c(n_1) \) by the above arguments.

2. When \( n \) is expanded every path with cost strictly less than \( c(n) \) has already been expanded (i.e., every node on it has been expanded).

Proof:
- Let \(<\text{Start}, n_0, n_1, \ldots, n_k>\) be a path with cost less than \( c(n) \). Let \( n_i \) be the last node on this path that has been expanded. \(<\text{Start}, n_0, n_1, n_i-1, n_i, n_i+1, \ldots, n_k>\).
- \( n_{i+1} \) must be on the frontier, also \( c(n_{i+1}) < c(n) \) since the cost of the entire path to \( n_k \) is \( < c(n) \).
- But then uniform-cost would have expanded \( n_{i+1} \) not \( n_i \).
- So every node on this path must already be expanded, i.e. this path has already been expanded. QED


3. The first time uniform-cost expands a state, it has found the minimal cost path to it (it might later find other paths to the same state).

Proof:
- No cheaper path exists, else that path would have been expanded before.
- No cheaper path will be discovered later, as all those paths must be at least as expensive.
- So, when a goal state is expanded, the path to it must be optimal.

Depth First Search

- Place the successors of the current state at the front of the frontier.
- Frontier behaves like a stack.

Depth First Search Example

(applied to the example of Breadth First search)

\[
\begin{align*}
\{0\} \\
\{1, 2\} \\
\{2, 3, 2\} \\
\{3, 4, 3, 2\} \\
\{4, 5, 4, 3, 2\} \\
\{5, 6, 5, 4, 3, 2\} \\
\ldots
\end{align*}
\]

*[draw search tree]*
Depth First Properties

- Completeness? No!
  - Infinite paths cause incompleteness! Typically come from cycles in search space.
  - If we prune paths with duplicate states, get completeness provided the search space is finite.

- Optimality? No!
  - Can find success along a longer branch!

Depth First Properties

- Time Complexity?
  - \(O(b^m)\) where \(m\) is the length of the longest path in the state space.
  - Why? In worst case, expands
    \[
    1 + b + b^2 + \ldots + b^{m-1} + b^m = b^{m+1} - 1/b - 1 = O(b^m)
    \]
  - Assumes no cycles.
  - Very bad if \(m\) is much larger than \(d\), but if there are many solution paths it can be much faster than breadth first.

Depth First Backtrack Points

- At each step, all nodes in the frontier (except the head) are backtrack points (see example and draw the tree for state-space).
- These are all siblings of nodes on the current branch.
Depth Limited Search

- Breadth first has computational, especially, space problems. Depth first can run off down a very long (or infinite) path.
- Depth limited search.
  - Perform depth first search but only to a pre-specified depth limit $L$.
  - No node on a path that is more than $L$ steps from the initial state is placed on the Frontier.
  - We “truncate” the search by looking only at paths of length $L$ or less.
- Now infinite length paths are not a problem.
- But will only find a solution if a solution of length $\leq L$ exists.

```
DLS(Frontier, Successors, Goal?)
If Frontier is empty return failure
Curr = select state from Frontier
If(Goal?(Curr)) return Curr.
If Depth(Curr) < L 
   Frontier' = (Frontier - {Curr}) U Successors(Curr)
Else
   Frontier' = Frontier - {Curr}
   CutOffOccured = TRUE.
return DLS(Frontier', Successors, Goal?)
```

Iterative Deepening Search.

- Take the idea of depth limited search one step further.
- Starting at depth limit $L = 0$, we iteratively increase the depth limit, performing a depth limited search for each depth limit.
- Stop if no solution is found, or if the depth limited search failed without cutting off any nodes because of the depth limit.

```
Iterative Deepening Search Example
{0} [DL = 0]   {0} [DL = 3]
{1,2}    {1,2}

{0} [DL = 1]   {0} [DL = 3]
{2,3,2}   {2,3,2}, {3,4,3,2}, {4,3,2}, {3,2}
{2}       {4,5,2}, {5,2}
Success!

{0} [DL = 2]
{1,2}
{2,3,2}, {3,2}, {2}
{3, 4}, {4}
```
Iterative Deepening Search Properties

- Completeness?
  - Yes, if solution of length \( d \) exists, will the search will find it when \( L = d \).

- Time Complexity?
  - At first glance, seems bad because nodes are expanded many times.

Time Complexity

\[
\sum_{k=0}^{d} b^k = O(b^d)
\]

[\( \text{root expanded } d+1 \text{ times, level 1 nodes expanded } d \text{ times, ...} \)]

- E.g. \( b=4, d=10 \)
  - \( 1(4^0) + 10(4^1) + 9(4^2) + \ldots + 2(4^9) = 815,555 \)
  - \( 4^{10} = 1,048,576 \)
  - Most nodes lie on bottom layer.
  - In fact IDS can be more efficient than breadth first search: nodes at limit are not expanded. BFS must expand all nodes until it expands a goal node.

Iterative Deepening Search Properties

- Space Complexity
  - \( O(bd) \) Still linear!

- Optimal?
  - Will find shortest length solution which is optimal if costs are uniform.
  - If costs are not uniform, we can use a “cost” bound instead.
    - Only expand paths of cost less than the cost bound.
    - Keep track of the minimum cost unexpanded path in each depth first iteration, increase the cost bound to this on the next iteration.
    - This can be very expensive. Need as many iterations of the search as there are distinct path costs.

Iterative Deepening Search Properties

- Consider space with three paths of length 3, but each action having a distinct cost.
Cycle Checking

- Path checking
  - Paths are stored on the frontier (this allows us to output the solution path).
  - If \(<S, n_1, \ldots, n_k, c>\) is a path to node \(n_k\), and we expand \(n_k\) to obtain child \(c\), we have:
    - \(<S, n_1, \ldots, n_k, c>\)
    - As the path to "c".
- Path checking:
  - Ensure that the state \(c\) is not equal to the state reached by any ancestor of \(c\) along this path.

Path Checking Example

Cycle Checking

- Cycle Checking.
  - Keep track of all states previously expanded during the search.
  - When we expand \(n_k\) to obtain child \(c\), ensure that \(c\) is not equal to any previously expanded state.
  - This is called cycle checking, or multiple path checking.
  - Why can’t we utilize this technique with depth-first search?
    - If we use cycle checking in depth-first search what happens to space complexity.
Cycle Checking Example

Cycle Checking

- High space complexity, only useful with breadth first search.
- There is an additional issue when we are looking for an optimal solution
  - With uniform-cost search, we still find an optimal solution
    - The first time uniform-cost expands a state it has found the minimal cost path to it.
  - This means that the nodes rejected by cycle checking can’t have better paths.
  - We will see later that we don’t always have this property when we do heuristic search.