Recap: Search

- **Search problem:**
  - States (configurations of the world)
  - Successor function: a function from states to lists of (state, action, cost) triples; drawn as a graph
  - Start state and goal test

- **Search tree:**
  - Nodes: represent plans for reaching states
  - Plans have costs (sum of action costs)

- **Search Algorithm:**
  - Systematically builds a search tree
  - Chooses an ordering of the fringe (unexplored nodes)

Example: Pancake Problem

Action: Flip over the top $n$ pancakes

Cost: Number of pancakes flipped

Example: Pancake Problem

State space graph with costs as weights
General Tree Search

Action: flip top two
Cost: 2

Path to reach goal:
Flip four, flip three
Total cost: 7

Example: Heuristic Function
Heuristic: the largest pancake that is still out of place

What is a Heuristic?

- An estimate of how close a state is to a goal
- Designed for a particular search problem

Examples: Manhattan distance: 10+5 = 15
Euclidean distance: 11.2

Greedy Search

Strategy: expand a node that you think is closest to a goal state
- Heuristic: estimate of distance to nearest goal for each state

A common case:
- Best-first takes you straight to the (wrong) goal

Worst-case: like a badly-guided DFS
Greedy Search

- Expand the node that seems closest...
- What can go wrong?

A* Search

Combining UCS and Greedy

- Uniform-cost orders by path cost, or backward cost \( g(n) \)
- Greedy orders by goal proximity, or forward cost \( h(n) \)
- A* Search orders by the sum: \( f(n) = g(n) + h(n) \)

Is A* Optimal?

- What went wrong?
- Actual bad goal cost < estimated good path cost
- We need estimates to be less than or equal to actual costs!

When should A* terminate?

- Should we stop when we enqueue a goal?
- No: only stop when we dequeue a goal

Admissible Heuristics

- A heuristic \( h \) is admissible (optimistic) if:
  \[ 0 \leq h(n) \leq h^*(n) \]
  where \( h^*(n) \) is the true cost to a nearest goal
- Examples:
  - Coming up with admissible heuristics is most of what’s involved in using A* in practice.
Optimality of A* Tree Search

Assume:
- A is an optimal goal node
- B is a suboptimal goal node
- h is admissible

Claim:
- A will exit the fringe before B

Proof:
- Imagine B is on the fringe
- Some ancestor n of A is on the fringe, too (maybe A!)
- Claim: n will be expanded before B
  1. $f(n) \leq f(A)$
  2. $f(A) < f(B)$

B is suboptimal

$h = 0$ at a goal

UCS vs A* Contours

- Uniform-cost expanded in all directions
- A* expands mainly toward the goal, but hedges its bets to ensure optimality

Which Algorithm?

- Uniform cost search (UCS):
- A* search is optimal
Which Algorithm?

- A*, Manhattan Heuristic:

Creating Admissible Heuristics

- Most of the work in solving hard search problems optimally is in coming up with admissible heuristics
- Often, admissible heuristics are solutions to relaxed problems, where new actions are available
- Inadmissible heuristics are often useful too

Creating Heuristics

8-puzzle:

- What are the states?
- How many states?
- What are the actions?
- What states can I reach from the start state?
- What should the costs be?

8 Puzzle I

- Heuristic: Number of tiles misplaced
- $h(\text{start}) = 8$
- Is it admissible?

<table>
<thead>
<tr>
<th>Average nodes expanded when optimal path has length...</th>
<th>4 steps</th>
<th>8 steps</th>
<th>12 steps</th>
</tr>
</thead>
<tbody>
<tr>
<td>UCS</td>
<td>112</td>
<td>6,300</td>
<td>$3.6 \times 10^6$</td>
</tr>
<tr>
<td>TILES</td>
<td>13</td>
<td>39</td>
<td>227</td>
</tr>
</tbody>
</table>

8 Puzzle II

- What if we had an easier 8-puzzle where any tile could slide any direction at any time, ignoring other tiles?
- Total Manhattan distance: $h(\text{start}) = 3 + 1 + 2 + \ldots = 18$

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<td>39</td>
<td>227</td>
</tr>
<tr>
<td>MANHATTAN</td>
<td>12</td>
<td>25</td>
<td>73</td>
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</tbody>
</table>

Is it admissible?
8 Puzzle III

- How about using the actual cost as a heuristic?
  - Would it be admissible?
  - Would we save on nodes expanded?
- What’s wrong with it?
- With A*: a trade-off between quality of estimate and work per node!

Trivial Heuristics, Dominance

- Dominance: $h_a \geq h_b$ if $\forall n : h_a(n) \geq h_b(n)$
- Heuristics form a semi-lattice:
  - Max of admissible heuristics is admissible
  - $h(n) = \max(h_a(n), h_b(n))$
- Trivial heuristics
  - Bottom of lattice is the zero heuristic (what does this give us?)
  - Top of lattice is the exact heuristic

A* Applications

- Pathing / routing problems
- Resource planning problems
- Robot motion planning
- Language analysis
- Machine translation
- Speech recognition
- …

Tree Search: Extra Work!

- Failure to detect repeated states can cause exponentially more work. Why?

Graph Search

- In BFS, for example, we shouldn’t bother expanding some nodes (which, and why?)

Graph Search

- Idea: never expand a state twice
- How to implement:
  - Tree search + set of expanded states ("closed set")
  - Expand the search tree node-by-node, but...
  - Before expanding a node, check to make sure its state has never been expanded before
  - If not new, skip it, if new add to closed set
- Hint: in python, store the closed set as a set, not a list
- Can graph search wreck completeness? Why/why not?
- How about optimality?
A* Graph Search Gone Wrong

State space graph

Search tree

Consistency of Heuristics

Optimality of A* Graph Search

Optimality

Summary: A*

- A* uses both backward costs and (estimates of) forward costs
- A* is optimal with admissible / consistent heuristics
- Heuristic design is key: often use relaxed problems