Informed Search

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[Based on slides from Andrew Moore  http://www.cs.cmu.edu/~awm/tutorials ]
Main messages

• A*. Always be optimistic.
Uninformed vs. informed search

• **Uninformed search** (BFS, uniform-cost, DFS, ID etc.)
  - Knows the actual path cost $g(s)$ from start to a node $s$ in the fringe, but that’s it.

![Diagram of uninformed search](image)

• **Informed search**
  - Also has a heuristic $h(s)$ of the cost from $s$ to goal. (‘h’ = heuristic, non-negative)
  - Can be much faster than uninformed search.
Recall: Uniform-cost search

- Uniform-cost search: uninformed search when edge costs are not the same.
- Complete (will find a goal). Optimal (will find the least-cost goal).
- Always expand the node with the least $g(s)$
  - Use a priority queue:
    - Push in states with their first-half-cost $g(s)$
    - Pop out the state with the least $g(s)$ first.
- Now we have an estimate of the second-half-cost $h(s)$, how to use it?
First attempt: Best-first greedy search

• Idea 1: use $h(s)$ instead of $g(s)$
• Always expand the node with the least $h(s)$
  ▪ Use a priority queue:
    • Push in states with their second-half-cost $h(s)$
    • Pop out the state with the least $h(s)$ first.
• Known as “best first greedy” search
• How’s this idea?
Best-first greedy search looking stupid

- It will follow the path $A \rightarrow C \rightarrow G$ (why?)
- Obviously not optimal
Second attempt: A search

- Idea 2: use $g(s)+h(s)$
- Always expand the node with the least $g(s)+h(s)$
  - Use a priority queue:
    - Push in states with their first-half-cost $g(s)+h(s)$
    - Pop out the state with the least $g(s)+h(s)$ first.
- Known as “A” search
- How’s this idea?
- Works for this example
A search still not quite right

- A search is not optimal.

```
A -------- B ---- C ---- G
  1       1      1      999
h=3  h=1000 h=1    h=0
```
Third attempt: A* search

- Same as A search, but the heuristic function $h()$ has to satisfy $h(s) \leq h^*(s)$, where $h^*(s)$ is the true cost from node $s$ to the goal.

- Such heuristic function $h()$ is called **admissible**.
  - An admissible heuristic never over-estimates

- A search with admissible $h()$ is called **A* search**.

It is always optimistic
Admissible heuristic functions $h$

- 8-puzzle example

Example State:

<table>
<thead>
<tr>
<th></th>
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<th>5</th>
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<tbody>
<tr>
<td>1</td>
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Goal State:

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- Which of the following are admissible heuristics?
  - $h(n) =$ number of tiles in wrong position
  - $h(n) = 0$
  - $h(n) = 1$
  - $h(n) =$ sum of Manhattan distance between each tile and its goal location
Admissible heuristic functions $h$

- **8-puzzle example**
  - ![Example State](image)
  - ![Goal State](image)

- Which of the following are admissible heuristics?
  - $h(n)=$number of tiles in wrong position **YES**
  - $h(n)=0$ **YES**, uninformed uniform cost search
  - $h(n)=1$ **NO**, goal state
  - $h(n)=$sum of Manhattan distance between each tile and its goal location **YES**
Admissible heuristic functions $h$

- In general, which of the following are admissible heuristics? $h^*(n)$ is the true optimal cost from $n$ to goal.
  - $h(n) = h^*(n)$
  - $h(n) = \max(2, h^*(n))$
  - $h(n) = \min(2, h^*(n))$
  - $h(n) = h^*(n) - 2$
  - $h(n) = \sqrt{h^*(n)}$
Admissible heuristic functions $h$

- In general, which of the following are admissible heuristics? $h^*(n)$ is the true optimal cost from $n$ to goal.

  - $h(n) = h^*(n)$: **YES**
  - $h(n) = \max(2, h^*(n))$: **NO**
  - $h(n) = \min(2, h^*(n))$: **YES**
  - $h(n) = h^*(n) - 2$: **NO, possibly negative**
  - $h(n) = \sqrt{h^*(n)}$: **NO if $h^*(n) < 1$**
Heuristics for Admissible heuristics

• How to construct heuristic functions?

Example State

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Goal State

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• Often by relaxing the constraints
  • $h(n)=$ number of tiles in wrong position
    Allow tiles to fly to their destination in one step
  • $h(n)=$ sum of Manhattan distance between each tile and its goal location
    Allow tiles to move on top of other tiles
“my heuristic is better than yours”

• A heuristic function $h_2$ **dominates** $h_1$ if for all $s$
  
  $h_1(s) \leq h_2(s) \leq h^*(s)$

• We prefer heuristic functions as close to $h^*$ as possible, but not over $h^*$.

But

• Good heuristic function might need complex computation

• Time may be better spent, if we use a faster, simpler heuristic function and expand more nodes
Q1: When should A* stop?

- Idea: as soon as it generates the goal state?

- $h()$ is admissible
- The goal $G$ will be generated as path $A \rightarrow B \rightarrow G$, with cost 1000.
Q1: The correct A* stop rule

- A* should terminate only when a goal is popped from the priority queue.

- If you have exceedingly good memory, you’ll remember this is the same rule for uniform cost search on cyclic graphs.

- Indeed A* with \( h() = 0 \) is exactly uniform cost search!
Q2: A* revisiting expanded states

- **One more complication:** A* can revisit an expanded state, and discover a shorter path

![Diagram](image)

- Can you find the state in question?
Q2: A* revisiting expanded states

- **One more complication:** A* can revisit an expanded state, and discover a shorter path

- Can you find the state in question?

We shall put D back into the priority queue, with the smaller $g+h$.
Q3: What if A* revisits a state in the PQ?

- We’ve seen this before, with uniform cost search
- ‘promote’ D in the queue with the smaller cost

(Note the numbers are different)
The A* algorithm

1. Put the start node $S$ on the priority queue, called OPEN
2. If OPEN is empty, exit with failure
3. Remove from OPEN and place on CLOSED a node $n$ for which $f(n)$ is minimum
4. If $n$ is a goal node, exit (trace back pointers from $n$ to $S$)
5. Expand $n$, generating all its successors and attach to them pointers back to $n$. For each successor $n'$ of $n$
   1. If $n'$ is not already on OPEN or CLOSED estimate $h(n'), g(n') = g(n) + c(n,n')$, $f(n') = g(n') + h(n')$, and place it on OPEN.
   2. If $n'$ is already on OPEN or CLOSED, then check if $g(n')$ is lower for the new version of $n'$. If so, then:
      1. Redirect pointers backward from $n'$ along path yielding lower $g(n')$.
      2. Put $n'$ on OPEN.
   3. If $g(n')$ is not lower for the new version, do nothing.
A*: the dark side

- A* can use lots of memory. \(O(\text{number of states})\)
- For large problems A* will run out of memory
- We’ll look at two alternatives:
  - IDA*
  - Beam search
IDA*: iterative deepening A*

- Memory bounded search. Assume integer costs
  - Do path checking DFS, do not expand any node with $f(n) > 0$. Stop if we find a goal.
  - Do path checking DFS, do not expand any node with $f(n) > 1$. Stop if we find a goal.
  - Do path checking DFS, do not expand any node with $f(n) > 2$. Stop if we find a goal.
  - Do path checking DFS, do not expand any node with $f(n) > 3$. Stop if we find a goal.
  
  ... repeat this, increase threshold by 1 each time until we find a goal.

- This is complete, optimal, but more costly than A* in general.
Beam search

- Very general technique, not just for A*
- The priority queue has a fixed size $k$. Only the top $k$ nodes are kept. Others are discarded.
- Neither complete nor optimal, nor can maintain an ‘expanded’ node list, but memory efficient.
- Variation: The priority queue only keeps nodes that are at most $\varepsilon$ worse than the best node in the queue. $\varepsilon$ is the beam width.
- Beam search used successfully in speech recognition.
Example

(All edges are directed, pointing downwards)
Example

OPEN

S(0+8)
A(1+8) B(5+4) C(8+3)
B(5+4) C(8+3) D(4+inf) E(8+inf) G(10+0)
C(8+3) D(4+inf) E(8+inf) G(10+0) G(9+0)
C(8+3) D(4+inf) E(8+inf) G(10+0)

CLOSED

- 
S(0+8)
S(0+8) A(1+8)
S(0+8) A(1+8) B(5+4)
S(0+8) A(1+8) B(5+4) G(9+0)

Backtrack: G => B => S.
What you should know

• Know why best-first greedy search is bad.
• Thoroughly understand A*
• Trace simple examples of A* execution.
• Understand admissible heuristics.
Appendix: Proof that A* is optimal

- Suppose A* finds a suboptimal path ending in goal $G'$, where $f(G') > f^* =$ cost of optimal path
- Let’s look at the first unexpanded node $n$ on the optimal path ($n$ exists, otherwise the optimal goal would have been found)
- $f(n) \geq f(G')$, otherwise we would have expanded $n$
- $f(n) = g(n) + h(n)$ by definition
  \[= g^*(n) + h(n) \quad \text{because } n \text{ is on the optimal path}\]
  \[\leq g^*(n) + h^*(n) \quad \text{because } h \text{ is admissible}\]
  \[= f^* \quad \text{because } n \text{ is on the optimal path}\]
- $f^* \geq f(n) \geq f(G')$, contradicting the assumption at top