Informed Search

Read AIMA 3.1-3.6. Some materials will not be covered in lecture, but will be on the exam.
Reminder – HW 2 has been released

• HW2 has been released. It is due on Tuesday. It covers Uninformed Search and A* Search.
• I recommend that you start early.

• Friendly reminder about the late day policy: the homework is due by 11:59pm. 1 late day = anywhere between 1 second to 24 hours late. Please don’t submit at the last minute.
Review: Search problem definition

1. **States**: a set $S$
2. An *initial state* $s_i \in S$
3. **Actions**: a set $A$
   - $\forall s \text{ Actions}(s) = \text{the set of actions that can be executed in } s$, that are *applicable* in $s$.
4. **Transition Model**: $\forall s \forall a \in \text{Actions}(s) \text{ Result}(s, a) \rightarrow s_r$
   - $s_r$ is called a *successor* of $s$
   - $\{s_i\} \cup \text{Successors}(s_i)^* = \text{state space}$
5. **Path cost (Performance Measure)**: Must be additive
   - e.g. sum of distances, number of actions executed, …
   - $c(x, a, y)$ is the step cost, assumed $\geq 0$
     - (where action $a$ goes from state $x$ to state $y$)
6. **Goal test**: $\text{Goal}(s)$
   - Can be implicit, e.g. *checkmate*(s)
   - $s$ is a *goal state* if $\text{Goal}(s)$ is true
Review: Useful Concepts

- **State space**: the set of all states reachable from the initial state by *any* sequence of actions
  - *When several operators can apply to each state, this gets large very quickly*
  - *Might be a proper subset of the set of configurations*
- **Path**: a sequence of actions leading from one state $s_j$ to another state $s_k$
- **Frontier**: those states that are available for expanding (for applying legal actions to)
- **Solution**: a path from the initial state $s_i$ to a state $s_g$ that satisfies the goal test
function TREE-SEARCH(problem, strategy) return a solution or failure
Initialize frontier to the initial state of the problem
do
  if the frontier is empty then return failure
  choose leaf node for expansion according to strategy & remove from frontier
  if node contains goal state then return solution
  else expand the node and add resulting nodes to the frontier

Determines search process!!
Review: Search Strategies

- **Strategy** = order of tree expansion
  - Implemented by different queue structures (LIFO, FIFO, priority)

- **Dimensions for evaluation**
  - **Completeness** - always find the solution?
  - **Optimality** - finds a least cost solution (lowest path cost) first?
  - **Time complexity** - # of nodes generated *(worst case)*
  - **Space complexity** - # of nodes simultaneously in memory *(worst case)*

- **Time/space complexity variables**
  - $b$, maximum branching factor of search tree
  - $d$, depth of the shallowest goal node
  - $m$, maximum length of any path in the state space (potentially $\infty$)
Breadth first search

Animation of Graph BFS algorithm set to music 'flight of bumble bee'

https://youtu.be/x-VTfcmrLEQ
Depth first search

Animation of Graph DFS algorithm
Depth First Search of Graph
set to music 'flight of bumble bee'

https://youtu.be/N UgMa5coCoE
Review: Breadth-first search

• Idea:
  • Expand *shallowest* unexpanded node

• Implementation:
  • *frontier* is FIFO (First-In-First-Out) Queue:
    —Put successors at the *end* of *frontier* successor list.

Image credit: Dan Klein and Pieter Abbeel
http://ai.berkeley.edu
Review: Depth-first search

• **Idea:**
  • Expand *deepest* unexpanded node

• **Implementation:**
  • *frontier* is LIFO (Last-In-First-Out) Queue:
    — Put successors at the *front* of *frontier* successor list.

Image credit: Dan Klein and Pieter Abbeel
http://ai.berkeley.edu
Fringe Strategies with One Queue

- These search algorithms are the same except for fringe strategies
  - DFS strategy = LIFO stack
  - BSF strategy = FIFO queue
  - Conceptually, all fringes are priority queues (i.e. collections of nodes with attached priorities)
  - You can even code one implementation that takes a variable queuing object

Slide credit: Dan Klein and Pieter Abbeel
http://ai.berkeley.edu
“Uniform Cost” Search

“In computer science, uniform-cost search (UCS) is a tree search algorithm used for traversing or searching a weighted tree, tree structure, or graph.” - Wikipedia
Motivation: Romanian Map Problem

- All our search methods so far assume \textit{step-cost = 1}
- \textit{This is only true for some problems}
**g(N): the path cost function**

- **Our assumption so far:** All moves equal in cost
  - Cost = # of nodes in path - 1
  - $g(N) = \text{depth}(N)$ in the search tree

- **More general:** Assigning a (potentially) unique cost to each step
  - $N_0, N_1, N_2, N_3$ = nodes visited on path $p$ from $N_0$ to $N_3$
  - $C(i,j)$: Cost of going from $N_i$ to $N_j$
  - If $N_0$ the root of the search tree,
    \[ g(N_3) = C(0,1) + C(1,2) + C(2,3) \]
Uniform-cost search (UCS)

• Extension of BF-search:
  • Expand node with *lowest path cost*

• Implementation:
  *frontier* = priority queue ordered by \( g(n) \)

• Subtle but significant difference from BFS:
  • Tests if a node is a goal state when it is selected for expansion, **not** when it is added to the frontier.
  • Updates a node on the frontier if a better path to the same state is found.
  • So always enqueues a node **before checking whether it is a goal.**

WHY???
When should we check for goal state?
Uniform Cost Search

Expand cheapest node first:

**Frontier is a priority queue**

No longer ply at a time, but follows **cost contours**

Therefore: Must be optimal
Complexity of UCS

- Complete!
- Optimal!
  - if the cost of each step exceeds some positive bound $\varepsilon$.
- **Time complexity:** $O(b^{C^*/\varepsilon + 1})$
- **Space complexity:** $O(b^{C^*/\varepsilon + 1})$

where $C^*$ is the cost of an optimal solution, and $\varepsilon$ is $\min(C(i,j))$

(if all step costs are equal, this becomes $O(b^{d+1})$

**NOTE:** Dijkstra’s algorithm just UCS without goal
# Summary of algorithms (for notes)

<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>
<th>Bidirectional search</th>
</tr>
</thead>
<tbody>
<tr>
<td>Complete?</td>
<td>YES</td>
<td>YES</td>
<td>NO</td>
<td>NO</td>
<td>YES</td>
<td>YES</td>
</tr>
<tr>
<td>Time</td>
<td>$b^d$</td>
<td>$b^{(C*/e)+1}$</td>
<td>$b^m$</td>
<td>$b^l$</td>
<td>$b^d$</td>
<td>$b^{d/2}$</td>
</tr>
<tr>
<td>Space</td>
<td>$b^d$</td>
<td>$b^{(C*/e)+1}$</td>
<td>$b^m$</td>
<td>$b^l$</td>
<td>$b^d$</td>
<td>$b^{d/2}$</td>
</tr>
<tr>
<td>Optimal?</td>
<td>YES</td>
<td>YES</td>
<td>NO</td>
<td>NO</td>
<td>YES</td>
<td>YES</td>
</tr>
</tbody>
</table>

**Assumes $b$ is finite**
Outline for today’s lecture

*Uninformed Search*

- Briefly: Bidirectional Search
- “Uniform Cost” Search (UCS)

*Informed Search*

- *Introduction to Informed search*
  - Heuristics
- 1\textsuperscript{st} attempt: Greedy Best-first search
Is Uniform Cost Search the best we can do? Consider finding a route from Bucharest to Arad.
Is Uniform Cost Search the best we can do? Consider finding a route from Bucharest to Arad.
A Better Idea…

- Node expansion based on *an estimate* which *includes distance to the goal*

- General approach of informed search:
  - *Best-first search*: node selected for expansion based on an *evaluation function* $f(n)$
    - $f(n)$ includes *estimate* of distance to goal (*new idea!*)

- Implementation: Sort frontier queue by this new $f(n)$.
  - Special cases: greedy search, *A** search
Simple, useful estimate heuristic: straight-line distances

<table>
<thead>
<tr>
<th>City</th>
<th>Distance</th>
</tr>
</thead>
<tbody>
<tr>
<td>Arad</td>
<td>118</td>
</tr>
<tr>
<td>Bucharest</td>
<td>0</td>
</tr>
<tr>
<td>Craiova</td>
<td>160</td>
</tr>
<tr>
<td>Dobreta</td>
<td>242</td>
</tr>
<tr>
<td>Eforie</td>
<td>161</td>
</tr>
<tr>
<td>Fagaras</td>
<td>176</td>
</tr>
<tr>
<td>Giurgiu</td>
<td>77</td>
</tr>
<tr>
<td>Hirsova</td>
<td>151</td>
</tr>
<tr>
<td>Iasi</td>
<td>226</td>
</tr>
<tr>
<td>Lugoj</td>
<td>244</td>
</tr>
<tr>
<td>Mehadia</td>
<td>241</td>
</tr>
<tr>
<td>Neamț</td>
<td>234</td>
</tr>
<tr>
<td>Oradea</td>
<td>380</td>
</tr>
<tr>
<td>Pitesti</td>
<td>100</td>
</tr>
<tr>
<td>Rimnicu Vâlcea</td>
<td>193</td>
</tr>
<tr>
<td>Sibiu</td>
<td>253</td>
</tr>
<tr>
<td>Timișoara</td>
<td>329</td>
</tr>
<tr>
<td>Urziceni</td>
<td>80</td>
</tr>
<tr>
<td>Vâlcea</td>
<td>199</td>
</tr>
<tr>
<td>Zerind</td>
<td>374</td>
</tr>
</tbody>
</table>
Heuristic (estimate) functions

Heureka! ---Archimedes

[dictionary] “A rule of thumb, simplification, or educated guess that reduces or limits the search for solutions in domains that are difficult and poorly understood.”

Heuristic knowledge is useful, but not necessarily correct.

Heuristic algorithms use heuristic knowledge to solve a problem.

A heuristic function \( h(n) \) takes a state \( n \) and returns an estimate of the distance from \( n \) to the goal.

(graphic: http://hyperbolegames.com/2014/10/20/eureka-moments/)
Breadth First for Games, Robots, …

- Pink: Starting Point
- Blue: Goal
- Teal: Scanned squares
  - Darker: Closer to starting point…

Graphics from
http://theory.stanford.edu/~amitp/GameProgramming/
(A great site for practical AI & game Programming)
vs. an optimal *informed search* algorithm (A*)

- We add a *heuristic estimate* of distance to the goal
  
- Yellow: examined nodes with *high estimated* distance
  
- Blue: examined nodes with *low estimated* distance
Breadth first in a world with obstacles
Greedy best-first search in a world with obstacles
Informed search (A*) in a world with obstacles
Outline for today’s lecture

*Uninformed Search*

- Briefly: Bidirectional Search
- “Uniform Cost” Search (UCS)

*Informed Search*

- Introduction to Informed search
  - Heuristics
- *1st attempt: Greedy Best-first search (AIMA 3.5.1)*
Review: Best-first search

Basic idea:

- **select node for expansion** with minimal evaluation function $f(n)$
  - where $f(n)$ is some function that includes *estimate heuristic* $h(n)$ of the remaining distance to goal

- Implement using priority queue
- Exactly UCS with $f(n)$ replacing $g(n)$
Greedy best-first search: \( f(n) = h(n) \)

- Expands the node that \textit{is estimated} to be closest to goal
- Completely ignores \( g(n) \): the cost to get to \( n \)
- Here, \( h(n) = h_{SLD}(n) = \) straight-line distance from to Bucharest
Greedy best-first search example

- **Initial State = Arad**
- **Goal State = Bucharest**

<table>
<thead>
<tr>
<th></th>
<th>Distance</th>
</tr>
</thead>
<tbody>
<tr>
<td>Arad</td>
<td>366</td>
</tr>
<tr>
<td>Bucharest</td>
<td>0</td>
</tr>
<tr>
<td>Craiova</td>
<td>160</td>
</tr>
<tr>
<td>Dobreta</td>
<td>242</td>
</tr>
<tr>
<td>Eforie</td>
<td>161</td>
</tr>
<tr>
<td>Fagaras</td>
<td>176</td>
</tr>
<tr>
<td>Giurgiu</td>
<td>77</td>
</tr>
<tr>
<td>Hirsova</td>
<td>151</td>
</tr>
<tr>
<td>Iasi</td>
<td>226</td>
</tr>
<tr>
<td>Lugoj</td>
<td>244</td>
</tr>
<tr>
<td>Mehadia</td>
<td>241</td>
</tr>
<tr>
<td>Neamt</td>
<td>234</td>
</tr>
<tr>
<td>Oradea</td>
<td>380</td>
</tr>
<tr>
<td>Pitesti</td>
<td>100</td>
</tr>
<tr>
<td>Rimnicu Vilcea</td>
<td>193</td>
</tr>
<tr>
<td>Sibiu</td>
<td>253</td>
</tr>
<tr>
<td>Timisoara</td>
<td>329</td>
</tr>
<tr>
<td>Urziceni</td>
<td>80</td>
</tr>
<tr>
<td>Vaslui</td>
<td>199</td>
</tr>
<tr>
<td>Zerind</td>
<td>374</td>
</tr>
</tbody>
</table>
Greedy best-first search example

Frontier queue:

Sibiu 253
Timisoara 329
Zerind 374
Greedy best-first search example

Frontier queue:
- Fagaras 176
- Rimnicu Vilcea 193
- Timisoara 329
- Arad 366
- Zerind 374
- Oradea 380

```
<table>
<thead>
<tr>
<th>City</th>
<th>Distance</th>
</tr>
</thead>
<tbody>
<tr>
<td>Arad</td>
<td>366</td>
</tr>
<tr>
<td>Bucharest</td>
<td>0</td>
</tr>
<tr>
<td>Craiova</td>
<td>160</td>
</tr>
<tr>
<td>Dobroesti</td>
<td>242</td>
</tr>
<tr>
<td>Eforie</td>
<td>161</td>
</tr>
<tr>
<td>Fagaras</td>
<td>176</td>
</tr>
<tr>
<td>Giurgiu</td>
<td>77</td>
</tr>
<tr>
<td>Hirsova</td>
<td>151</td>
</tr>
<tr>
<td>Iasi</td>
<td>226</td>
</tr>
<tr>
<td>Lugoj</td>
<td>244</td>
</tr>
<tr>
<td>Mehadia</td>
<td>241</td>
</tr>
<tr>
<td>Neamti</td>
<td>234</td>
</tr>
<tr>
<td>Oradea</td>
<td>380</td>
</tr>
<tr>
<td>Pitesti</td>
<td>100</td>
</tr>
<tr>
<td>Rimnicu Vilcea</td>
<td>193</td>
</tr>
<tr>
<td>Sibiu</td>
<td>253</td>
</tr>
<tr>
<td>Timisoara</td>
<td>329</td>
</tr>
<tr>
<td>Urziceni</td>
<td>80</td>
</tr>
<tr>
<td>Vaslui</td>
<td>199</td>
</tr>
<tr>
<td>Zerind</td>
<td>374</td>
</tr>
</tbody>
</table>
```
Greedy best-first search example

Frontier queue:
Bucharest 0
Rimnicu Vilcea 193
Sibiu 253
Timisoara 329
Arad 366
Zerind 374
Oradea 380

Goal reached!!
Properties of greedy best-first search

- **Optimal?**
  - No!

  — Found: **Arad → Sibiu → Fagaras → Bucharest (450km)**
  — Shorter: **Arad → Sibiu → Rimnicu Vilcea → Pitesti → Bucharest (418km)**
Properties of greedy best-first search

- **Complete?**
  - No – can get stuck in loops,
  - e.g., Iasi → Neamt → Iasi → Neamt → …
Properties of greedy best-first search

- **Complete?** No – can get stuck in loops,
  - e.g., Iasi → Neamt → Iasi → Neamt → …

- **Time?** $O(b^m)$ – worst case (like Depth First Search)
  - But a good heuristic can give dramatic improvement of average cost

- **Space?** $O(b^m)$ – priority queue, so worst case: keeps all (unexpanded) nodes in memory

- **Optimal?** No
IF TIME

- **Optimal informed search:** A* (AIMA 3.5.2)
A* search

- Best-known form of best-first search.
- Key Idea: avoid expanding paths that are already expensive, but expand most promising first.
- **Simple idea:** \( f(n) = g(n) + h(n) \)
  - \( g(n) \) the actual cost (so far) to *reach* the node
  - \( h(n) \) estimated cost to *get from the node to the goal*
  - \( f(n) \) estimated *total cost* of path through \( n \) to goal
- Implementation: Frontier queue as priority queue by increasing \( f(n) \) *(as expected...)*
Key concept: Admissible heuristics

- A heuristic $h(n)$ is **admissible** if it *never overestimates* the cost to reach the goal; i.e. it is **optimistic**
  - Formally: $\forall n$, $n$ a node:
    1. $h(n) \leq h^*(n)$ where $h^*(n)$ is the true cost from $n$
    2. $h(n) \geq 0$ so $h(G)=0$ for any goal $G$.

- Example: $h_{SLD}(n)$ never overestimates the actual road distance

**Theorem:** If $h(n)$ is **admissible**, A* using Tree Search is **optimal**
Idea: Admissibility

Inadmissible (pessimistic) heuristics break optimality by trapping good plans on the fringe

Admissible (optimistic) heuristics slow down bad plans but never outweigh true costs

Slide credit: Dan Klein and Pieter Abbeel
http://ai.berkeley.edu
A* search example

Frontier queue:

Arad 366
A* search example

Frontier queue:
Sibiu 393
Timisoara 447
Zerind 449

We add the three nodes we found to the Frontier queue.
We sort them according to the $g() + h()$ calculation.
A* search example

Frontier queue:
Rimricu Vicea 413
Fagaras 415
Timisoara 447
Zerind 449
Arad 646
Oradea 671

When we expand Sibiu, we run into Arad again. Note that we’ve already expanded this node once; but we still add it to the Frontier queue again.
A* search example

Frontier queue:
Fagaras 415
Pitesti 417
Timisoara 447
Zerind 449
Craiova 526
Sibiu 553
Arad 646
Oradea 671

We expand Rimricu Vicea.
A* search example

Frontier queue:
- Pitesti 417
- Timisoara 447
- Zerind 449
- **Bucharest 450**
- Craiova 526
- Sibiu 553
- Sibiu 591
- Arad 646
- Oradea 671

When we expand Fagaras, we find Bucharest, but we’re not done. The algorithm doesn’t end until we “expand” the goal node – it has to be at the top of the Frontier queue.
A* search example

Frontier queue:
Bucharest 418
Timisoara 447
Zerind 449
**Bucharest 450**
Craiova 526
Sibiu 553
Sibiu 591
Rimnicu Vilea 607
Craiova 615
Arad 646
Oradea 671

Note that we just found a better value for Bucharest!

Now we expand this better value for Bucharest since it’s at the top of the queue.

We’re done and we know the value found is optimal!
Outline for today’s lecture

**Informed Search**

- Optimal informed search: A*
- *Creating good heuristic functions (AIMA 3.6)*
- Hill Climbing
Heuristic functions

- For the 8-puzzle
  - Avg. solution cost is about 22 steps
    -(branching factor $\leq 3$)
  - Exhaustive search to depth 22: $3.1 \times 10^{10}$ states
  - A good heuristic function can reduce the search process
Example Admissible heuristics

For the 8-puzzle:

- \( h_{oop}(n) = \) number of out of place tiles

- \( h_{md}(n) = \) total Manhattan distance (i.e., \# of moves from desired location of each tile)

\[
\begin{align*}
\text{Start State} & \quad \text{Goal State} \\
7 & | 1 & 2 & | 1 & 2 \\
5 & | 3 & 6 & | 4 & 5 \\
8 & | 3 & 1 & | 6 & 7 & 8 \\
\end{align*}
\]

- \( h_{oop}(S) = 8 \)
- \( h_{md}(S) = 3+1+2+2+2+3+3+2 = 18 \)
Relaxed problems

- A problem with fewer restrictions on the actions than the original is called a *relaxed problem*.

- *The cost of an optimal solution to a relaxed problem is an admissible heuristic for the original problem.*

- If the rules of the 8-puzzle are relaxed so that a tile can move *anywhere*, then $h_{oop}(n)$ gives the shortest solution.

- If the rules are relaxed so that a tile can move to *any adjacent square*, then $h_{md}(n)$ gives the shortest solution.
Defining Heuristics: $h(n)$

- Cost of an exact solution to a *relaxed* problem (fewer restrictions on operator)

- **Constraints on Full Problem:**
  
  A tile can move from square A to square B *if* A is adjacent to B *and* B is blank.

- **Constraints on relaxed problems:**
  
  — A tile can move from square A to square B *if* A is adjacent to B. ($h_{md}$)
  
  — A tile can move from square A to square B *if* B is blank.
  
  — A tile can move from square A to square B. ($h_{oop}$)
Dominance: A metric on better heuristics

- If \( h_2(n) \geq h_1(n) \) for all \( n \) (both admissible)
  - then \( h_2 \) dominates \( h_1 \)
- So \( h_2 \) is optimistic, but more accurate than \( h_1 \)
  - \( h_2 \) is therefore better for search
  - Notice: \( h_{md} \) dominates \( h_{oop} \)

- Typical search costs (average number of nodes expanded):
  - \( d=12 \)
    - Iterative Deepening Search = 3,644,035 nodes
    - \( A^*(h_{oop}) = 227 \) nodes
    - \( A^*(h_{md}) = 73 \) nodes
  - \( d=24 \)
    - IDS = too many nodes
    - \( A^*(h_{oop}) = 39,135 \) nodes
    - \( A^*(h_{md}) = 1,641 \) nodes
The best and worst admissible heuristics

\( h^*(n) \) - the (unachievable) Oracle heuristic
- \( h^*(n) = \) the true distance from the root to \( n \)

\( h_{\text{we're here already}}(n) = h_{\text{teleportation}}(n) = 0 \)

- Admissible: both yes!!!
- \( h^*(n) \) dominates all other heuristics
- \( h_{\text{teleportation}}(n) \) is dominated by all heuristics
Optimality of A* Tree Search
Admissibility

Inadmissible (pessimistic) heuristics break optimality by trapping good plans on the fringe

Admissible (optimistic) heuristics slow down bad plans but never outweigh true costs

Slide credit: Dan Klein and Pieter Abbeel
http://ai.berkeley.edu
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

• Is Manhattan Distance admissible?

• 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
Optimality of A* Tree Search: Blocking

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. \( f(n) \) is less or equal to \( f(A) \)

\[
f(n) = g(n) + h(n)
\]
Definition of f-cost

\[
f(n) \leq g(A)
\]
Admissibility of \( h \)

\[
g(A) = f(A)
\]
h = 0 at a goal

Slide credit: Dan Klein and Pieter Abbeel
http://ai.berkeley.edu
Optimality of A* Tree Search: Blocking

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. $f(n)$ is less or equal to $f(A)$
  2. $f(A)$ is less than $f(B)$

$g(A) < g(B)$ \quad B is suboptimal

$f(A) < f(B)$ \quad h = 0 at a goal

Slide credit: Dan Klein and Pieter Abbeel
http://ai.berkeley.edu
Optimality of A* Tree Search: Blocking

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. $f(n)$ is less or equal to $f(A)$
  2. $f(A)$ is less than $f(B)$
  3. $n$ expands before B
• All ancestors of A expand before B
• A expands before B
• A* search is optimal

$\text{Slide credit: Dan Klein and Pieter Abbeel}
\text{http://ai.berkeley.edu}$
Properties of A*
Properties of A*
UCS vs A* Contours

- Uniform-cost expands equally in all “directions”

- A* expands mainly toward the goal, but does hedge its bets to ensure optimality

Slide credit: Dan Klein and Pieter Abbeel
http://ai.berkeley.edu
A* Applications

- Video games
- Pathing / routing problems (A* is in your GPS!)
- Resource planning problems
- Robot motion planning
- ...

Slide credit: Dan Klein and Pieter Abbeel
http://ai.berkeley.edu
Optimality of A* (intuitive)

- **Lemma**: A* expands nodes on frontier in order of increasing $f$ value

- Gradually adds "$f$-contours" of nodes
- Contour $i$ has all nodes with $f=f_i$, where $f_i < f_{i+1}$
- (After all, A* is just a variant of uniform-cost search....)
**Optimality of A** using Tree-Search (proof idea)

- **Lemma:** A* expands nodes on frontier in order of increasing \( f \) value

- Suppose some suboptimal goal \( G_2 \) (i.e. a goal on a suboptimal path) has been generated and is in the frontier along with an optimal goal \( G \).

  Must prove: \( f(G_2) > f(G) \)

  (Why? Because if \( f(G_2) > f(n) \), then \( G_2 \) will never get to the front of the priority queue.)

**Proof:**

1. \( g(G_2) > g(G) \) since \( G_2 \) is suboptimal

2. \( f(G_2) = g(G_2) \) since \( f(G_2) = g(G_2) + h(G_2) \) & \( h(G_2) = 0 \), since \( G_2 \) is a goal

3. \( f(G) = g(G) \) similarly

4. \( f(G_2) > f(G) \) from 1, 2, 3

Also must show that \( G \) is added to the frontier before \( G_2 \) is expanded – see AIMA for argument in the case of Graph Search
**A* search, evaluation**

- **Completeness:** YES
  - Since bands of increasing $f$ are added
  - As long as $b$ is finite
    - (guaranteeing that there aren’t infinitely many nodes $n$ with $f(n) < f(G)$)

- **Time complexity:** Same as UCS worst case
  - Number of nodes expanded is still exponential in the length of the solution.

- **Space complexity:** Same as UCS worst case
  - It keeps all generated nodes in memory so exponential
  - Hence space is the major problem not time

- **Optimality:** YES
  - Cannot expand $f_{i+1}$ until $f_i$ is finished.
  - $A^*$ expands all nodes with $f(n) < f(G)$
  - $A^*$ expands one node with $f(n) = f(G)$
  - $A^*$ expands no nodes with $f(n) > f(G)$
Consistency

- A heuristic is **consistent** if

\[ h(n) \leq c(n,a,n') + h(n') \]

- Consistency enforces that \( h(n) \) is optimistic

Theorem: if \( h(n) \) is consistent, **A* using Graph-Search is optimal**

See book for details