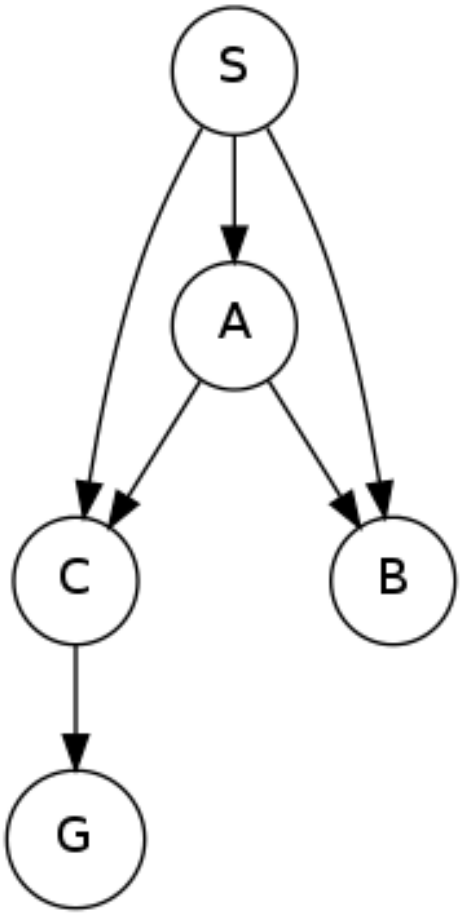
Warm-up: DFS Graph Search

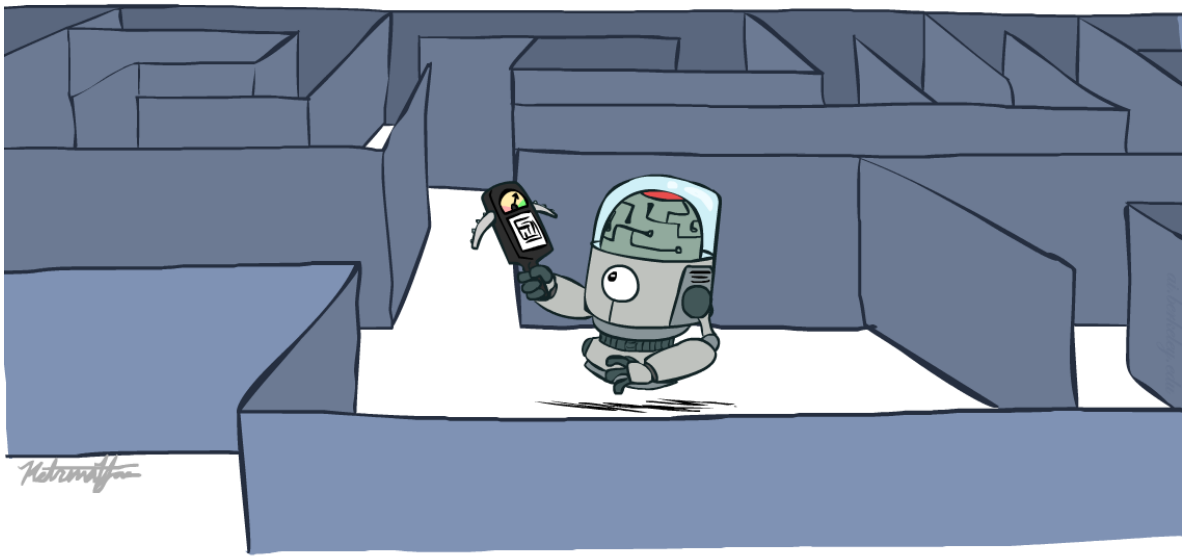
In HW1 Q4.1, why was the answer S->C->G, not S->A->C->G?

After all, we were doing DFS and breaking ties alphabetically.



AI: Representation and Problem Solving

Informed Search



Instructors: Pat Virtue & Stephanie Rosenthal

Slide credits: CMU AI, http://ai.berkeley.edu

Announcements

Assignments:

- HW1 (online) due last night, 10 pm
  - Slip days available until Thursday 10pm
- HW2 (written) out now
  - Due Tue 1/28, 10 pm
- P0: Python & Autograder Tutorial
  - Due TOMORROW Thu 1/23, 10 pm
- P1: Search & Games
  - Out tomorrow
  - Due in 2 weeks Thu 2/5, 10 pm
  - Partners!

Announcements

Who's lecturing?

- Prof. Rosenthal for Search through 1/27
- Prof. Virtue starts 1/29 for 2 weeks

Warm-up: DFS Graph Search

In HW1 Q4.1, why was the answer S->C->G, not S->A->C->G?

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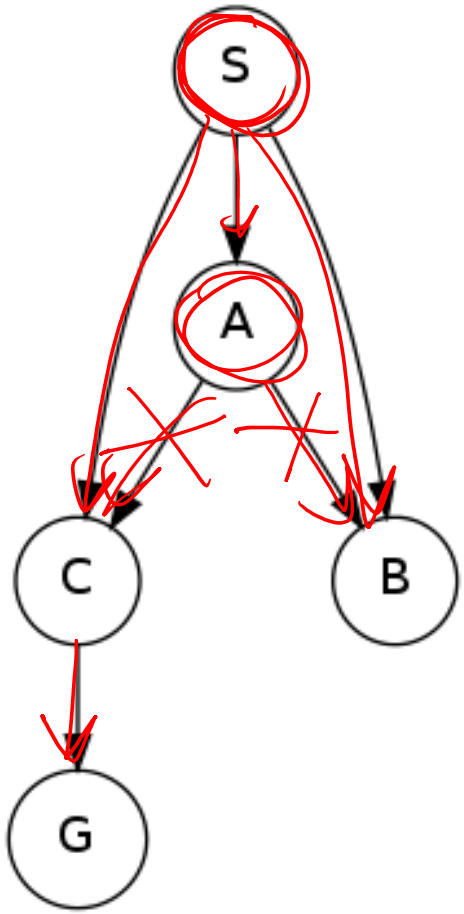
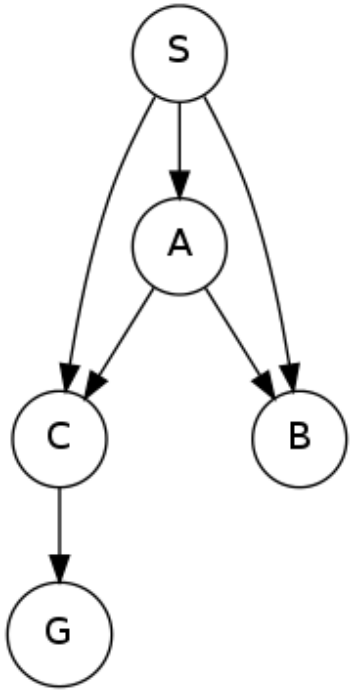


```
function GRAPH_SEARCH(problem) returns a solution, or failure
    initialize the explored set to be empty
    initialize the frontier as a specific work list (stack, queue, priority queue)
    add initial state of problem to frontier
    loop do
        if the frontier is empty then
            return failure
        choose a node and remove it from the frontier
        if the node contains a goal state then
            return the corresponding solution
        add the node state to the explored set
        for each resulting child from node
            if the child state is not already in the frontier or explored set then
                add child to the frontier
```

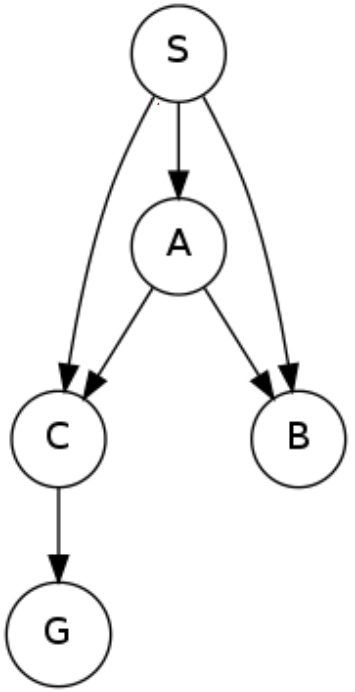


function TREE_SEARCH(problem) returns a solution, or failure

initialize the frontier as a specific work list (stack, queue, priority queue)
add initial state of problem to frontier
loop do
if the frontier is empty then
return failure
choose a node and remove it from the frontier
if the node contains a goal state then
return the corresponding solution

for each resulting child from node
add child to the frontier

S - A
S - B
S - C
S - A - B
S - A - C



function UNIFORM-COST-SEARCH(problem) returns a solution, or failure

initialize the explored set to be empty

initialize the frontier as a **priority queue using node path_cost as the priority**

add initial state of problem to frontier **with path_cost = 0**

loop do

if the frontier is empty then

return failure

choose a node and remove it from the frontier

if the node contains a goal state then

return the corresponding solution

add the node state to the explored set

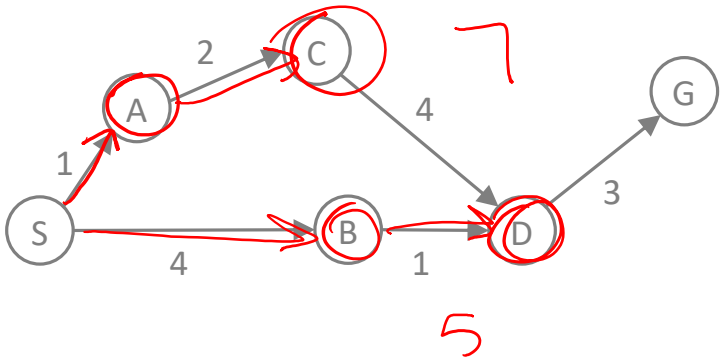
for each resulting child from node

if the child state is not already in the frontier or explored set then

add child to the frontier

else if the child is already in the frontier with higher path_cost then

replace that frontier node with child



Recall: Depth-First Search (DFS) Properties

What nodes does DFS expand?

- Some left prefix of the tree.
- Could process the whole tree!
- If m is finite, takes time $O(b^m)$

How much space does the frontier take?

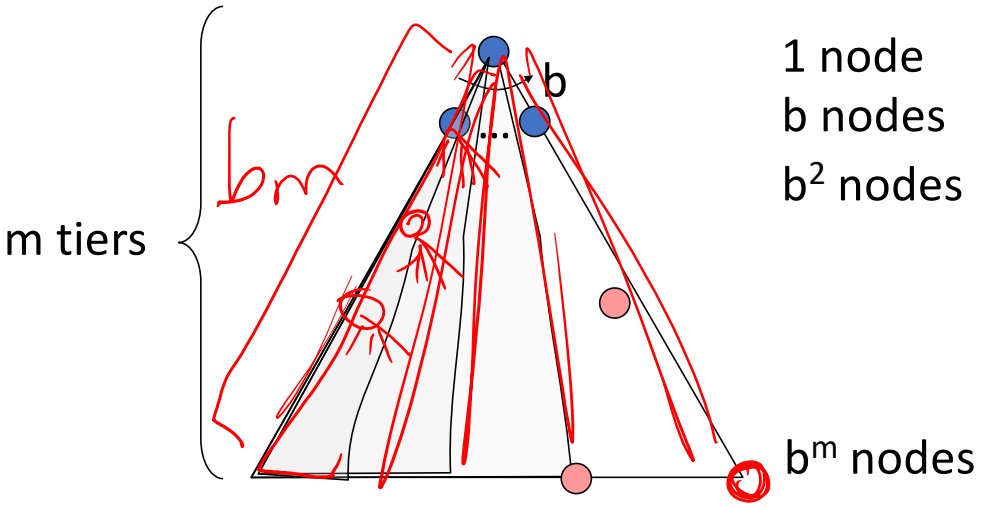
- Only has siblings on path to root, so O(bm)

Is it complete?

- m could be infinite, so only if we prevent cycles (graph search)

Is it optimal?

- No, it finds the "leftmost" solution, regardless of depth or cost



Recall: Breadth-First Search (BFS) Properties

What nodes does BFS expand?

- Processes all nodes above shallowest solution
- Let depth of shallowest solution be s
- Search takes time $O(b^s)$

How much space does the frontier take?

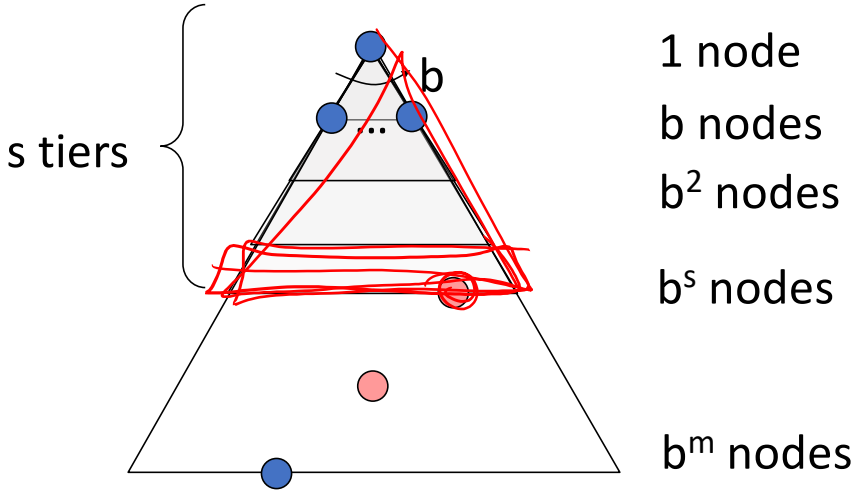
- Has roughly the last tier, so $O(b^s)$

Is it complete?

- s must be finite if a solution exists, so yes!

Is it optimal?

- Only if costs are all the same



Uniform Cost Search (UCS) Properties

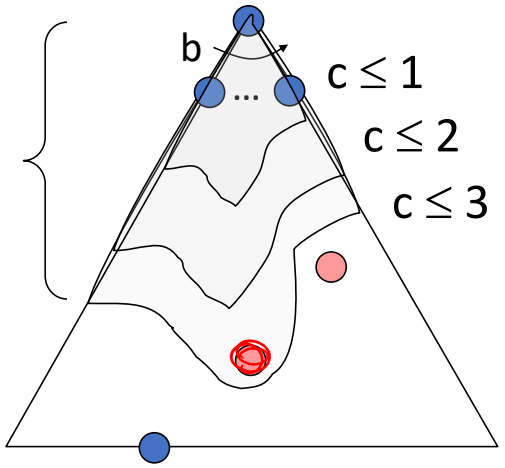
What nodes does UCS expand?

- Processes all nodes with cost less than cheapest solution
- If that solution costs C^* and step costs are at least ε, then the "effective depth" is roughly C^*/ε
- Takes time $O(b^{C^*/\varepsilon})$ (exponential in effective depth)

How much space does the frontier take?

- Has roughly the last tier, so $O(b^{C^*/\varepsilon})$

C^*/ε "tiers"



Is it complete?

- Assuming best solution has a finite cost and minimum step cost is positive, yes!

Is it optimal?

- Yes! (Proof via A*)

Uniform Cost Issues

Strategy:

- Explore (expand) the lowest path cost on frontier

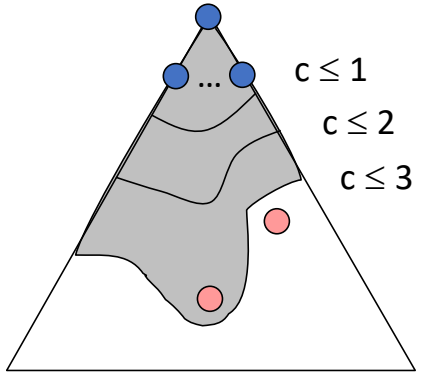
The good:

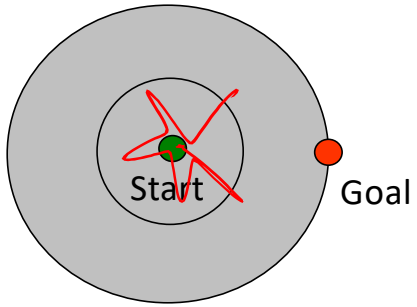
- UCS is complete and optimal!

The bad:

- Explores options in every “direction”
- No information about goal location

We’ll fix that today!





[Demo: contours UCS empty (L3D1)]
[Demo: contours UCS pacman small maze (L3D3)]

Demo Contours UCS Empty

Demo Contours UCS Pacman Small Maze

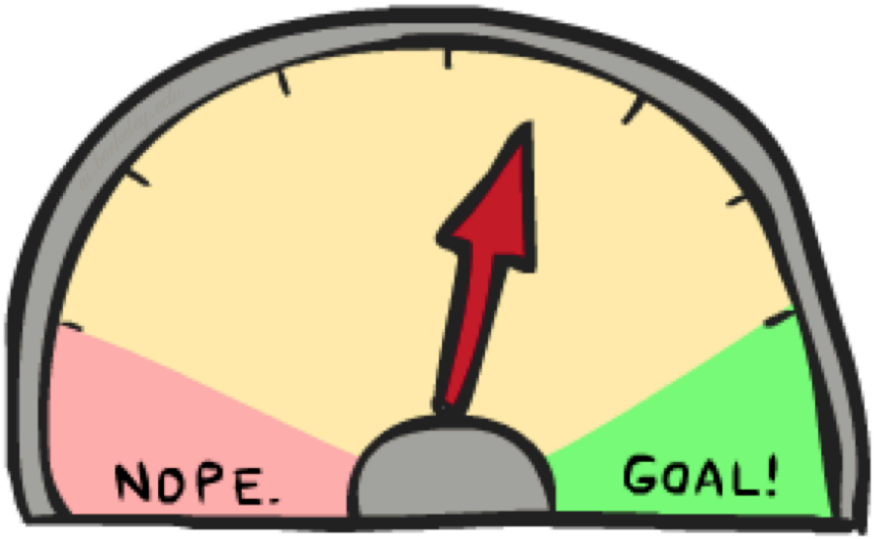
Uninformed vs Informed Search

Today

Informed Search

- Heuristics
- Greedy Search
- A* Search

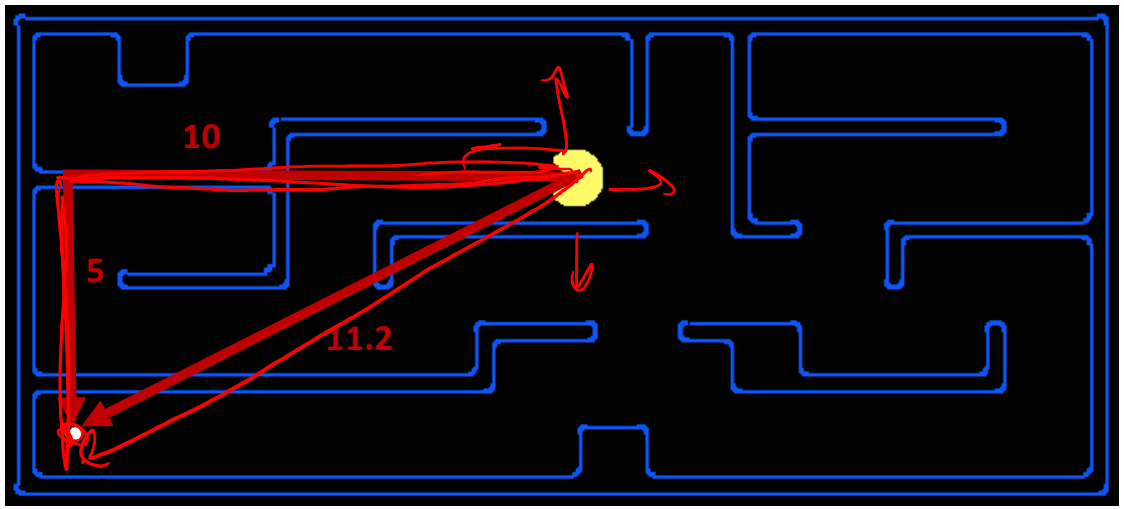
Informed Search

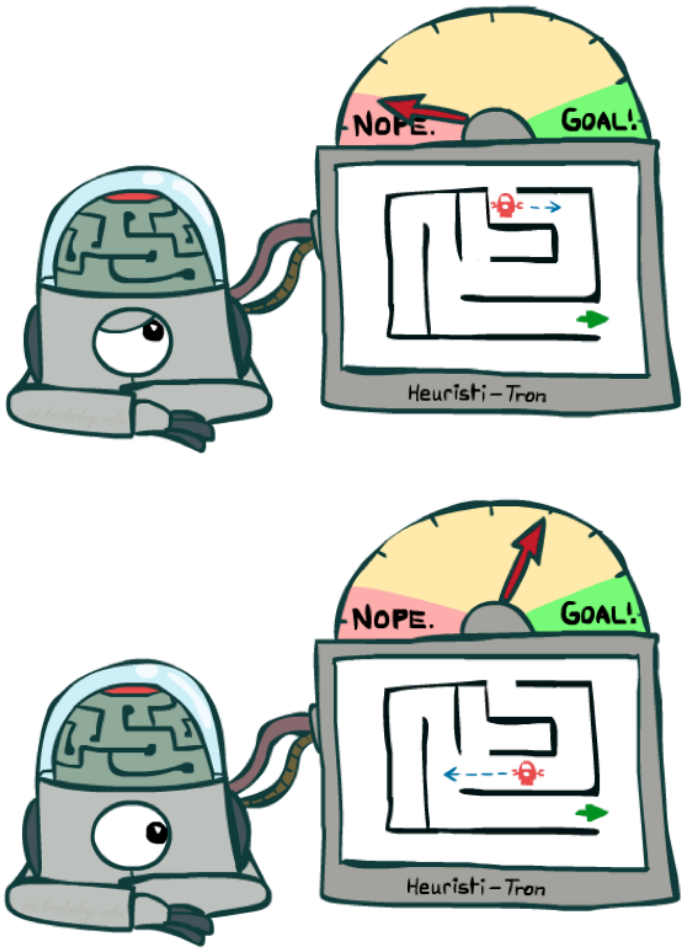


Search Heuristics

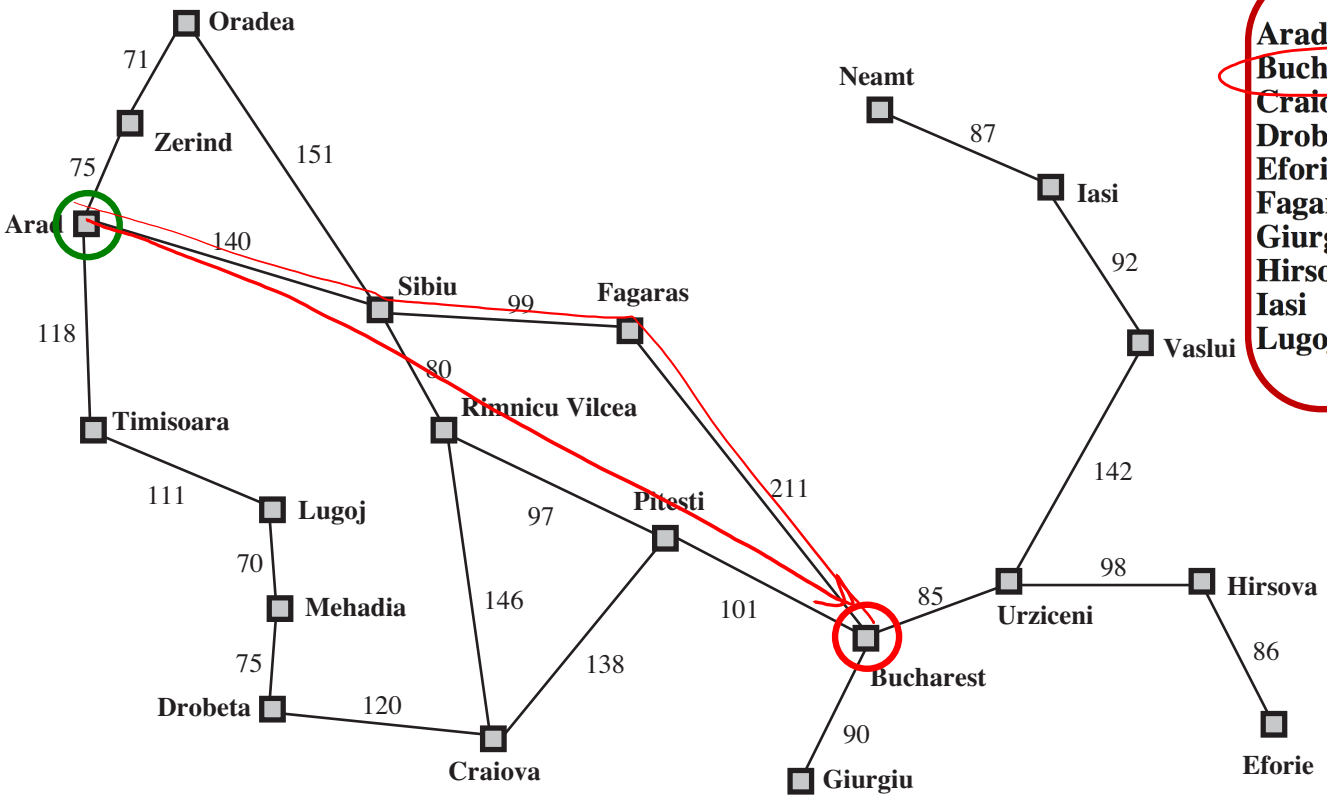
A heuristic is:

- A function that *estimates* how close a state is to a goal
- Designed for a particular search problem
- Examples: Manhattan distance, Euclidean distance for pathing





Example: Euclidean distance to Bucharest

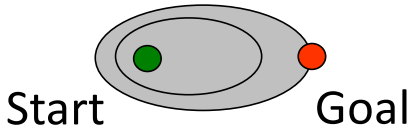


Arad	366	**Mehadia**	241
Bucharest	0	**Neamt**	234
Craiova	160	**Oradea**	380
Drobeta	242	**Pitesti**	100
Eforie	161	**Rimnicu Vilcea**	193
Fagaras	176	**Sibiu**	253
Giurgiu	77	**Timisoara**	329
Hirsova	151	**Urziceni**	80
Iasi	226	**Vaslui**	199
Lugoj	244	**Zerind**	374

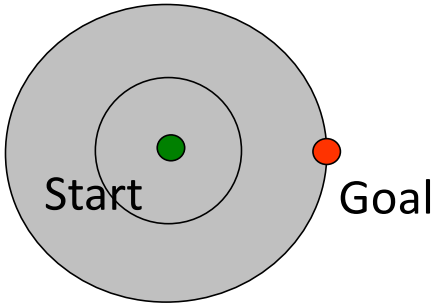
h(state) → value

Effect of heuristics

Guide search ***towards the goal*** instead of ***all over the place***



Informed

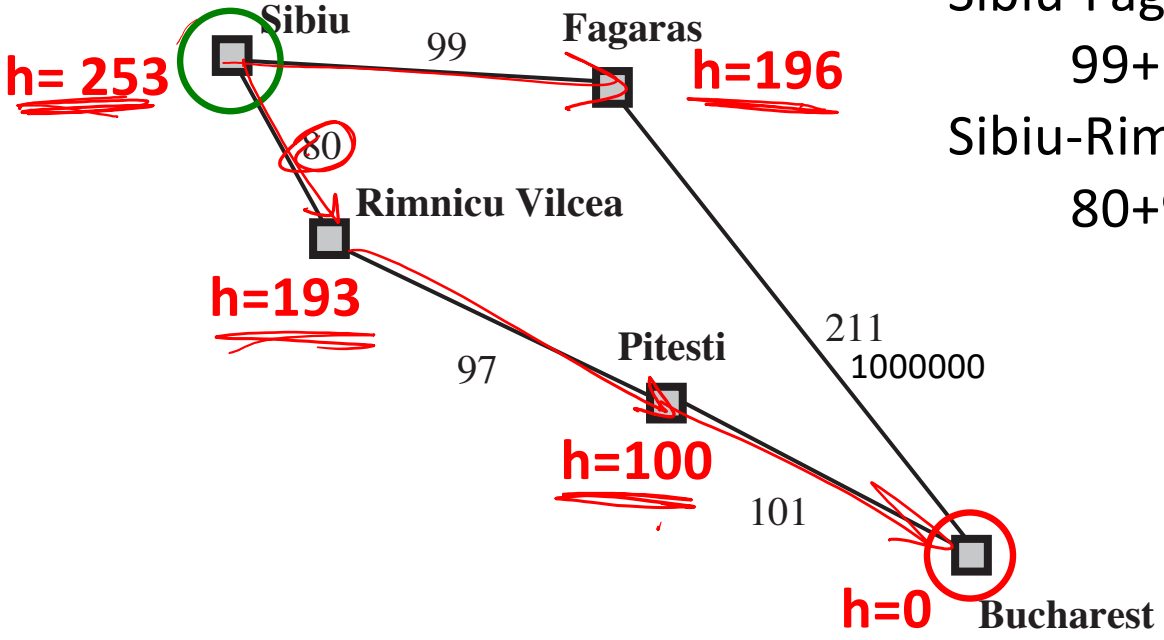


Uninformed

Greedy Search

Greedy Search

Expand the node that seems closest…(order frontier by h)



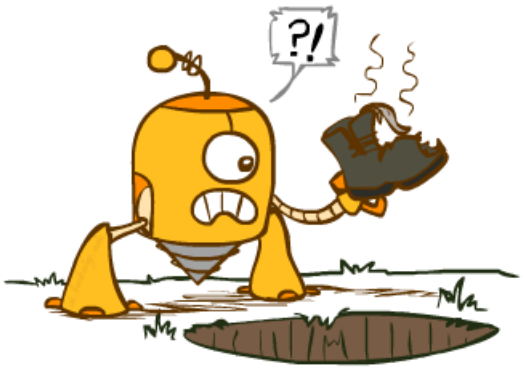
heuristic is lowest

Sibiu-Fagaras-Bucharest =

99+211 = **310**

Sibiu-Rimnicu Vilcea-Pitesti-Bucharest =

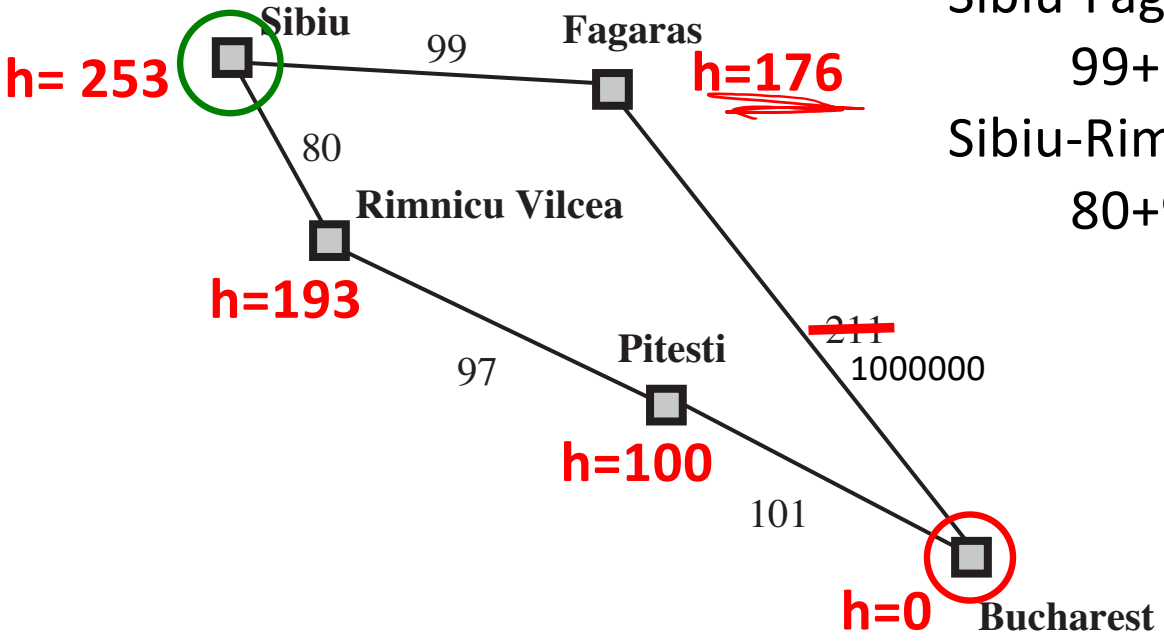
80+97+101 = **278**



Greedy Search

Expand the node that seems closest…(order frontier by h)

What can possibly go wrong?



Sibiu-Fagaras-Bucharest =
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Sibiu-Rimnicu Vilcea-Pitesti-Bucharest =
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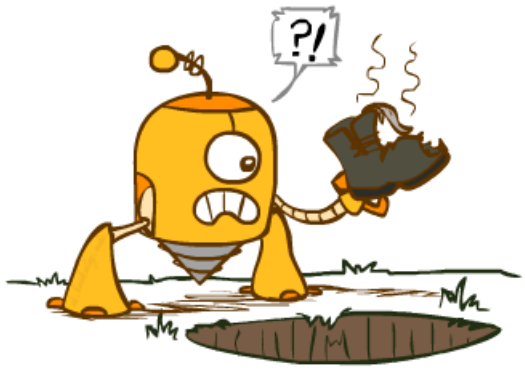
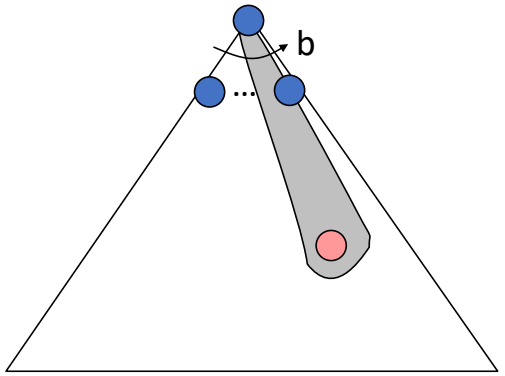


Greedy Search

Strategy: expand a node that ***seems*** closest to a goal state, according to h



Problem 1: it chooses a node even if it's at the end of a very long and winding road

Problem 2: it takes h literally even if it's completely wrong

Demo Contours Greedy (Empty)

Demo Contours Greedy (Pacman Small Maze)

A* Search

A* Search

UCS

Greedy

A*

A* Applications

Pathing / routing problems

Resource planning problems

Robot motion planning

Language analysis

Video games

Machine translation

Speech recognition

…

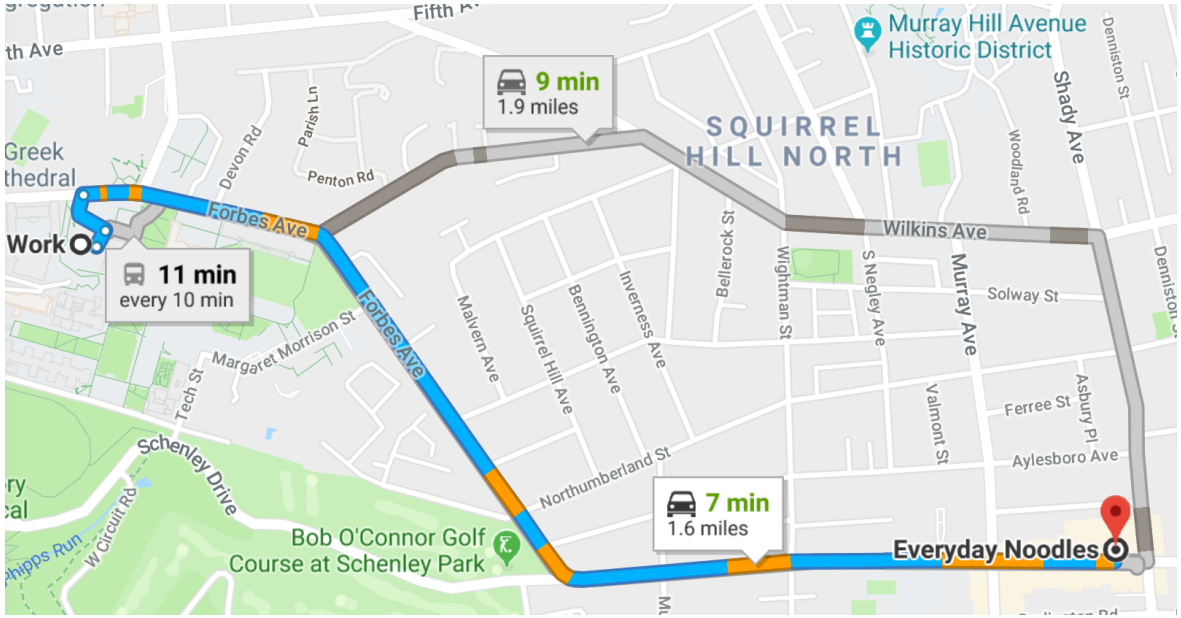
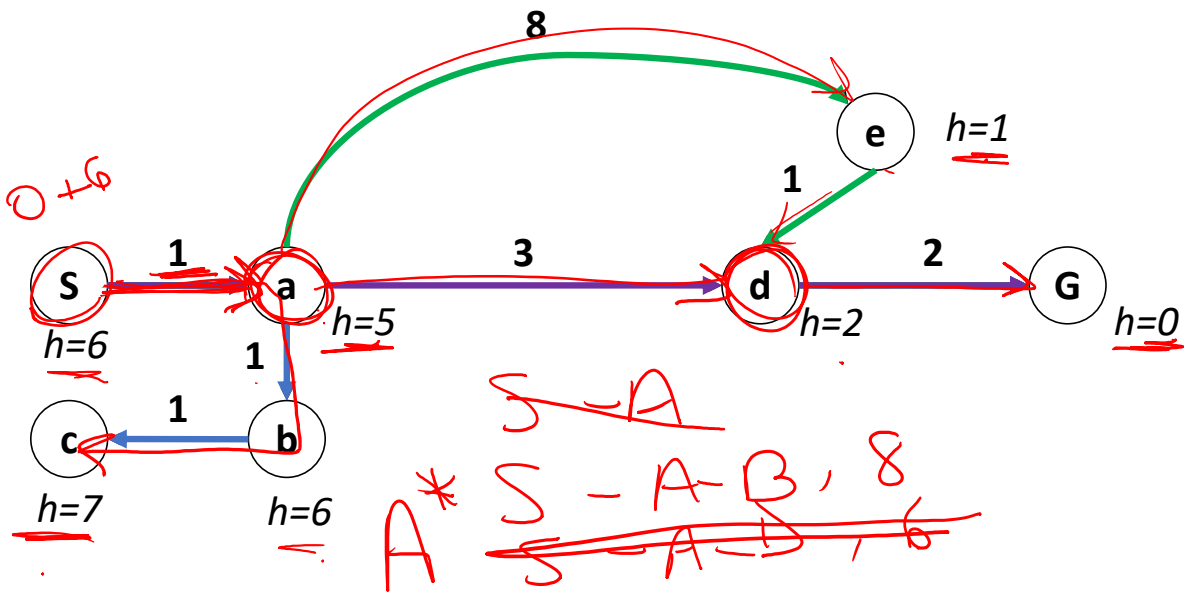


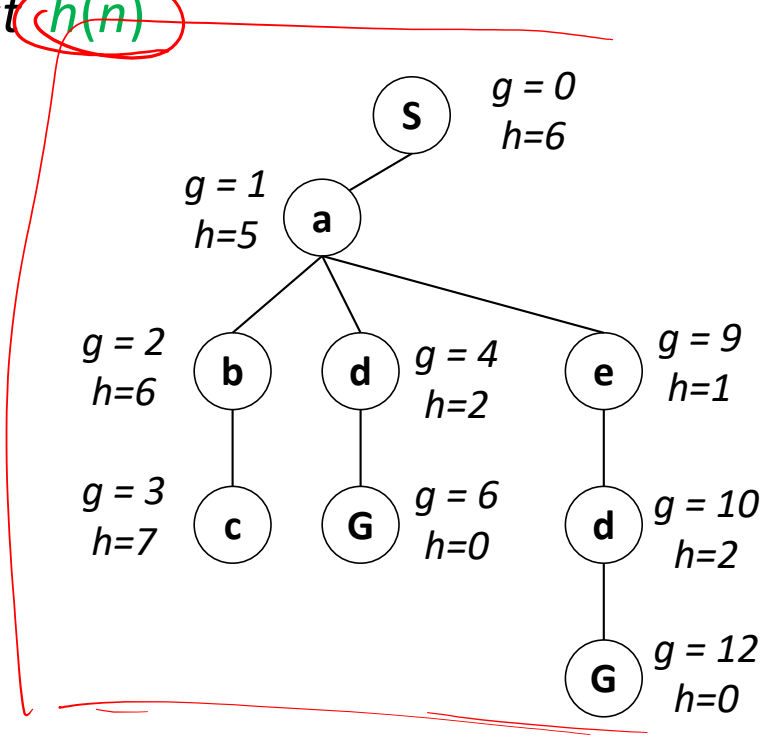
Image: maps.google.com

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: $f(n) = g(n) + h(n)$

Example: Teg Grenager

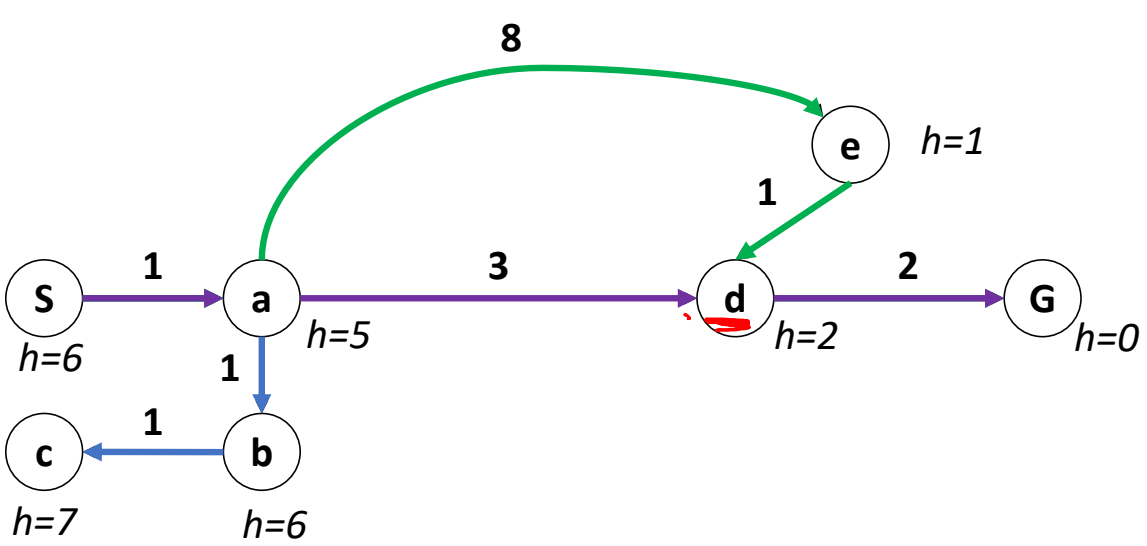
Notation

Uniform-cost orders by path cost, or *backward cost* $g(n)$

g(n) = cost from start to n, could write g(s-…-n)

Greedy orders by goal proximity, or *forward cost* $h(n)$

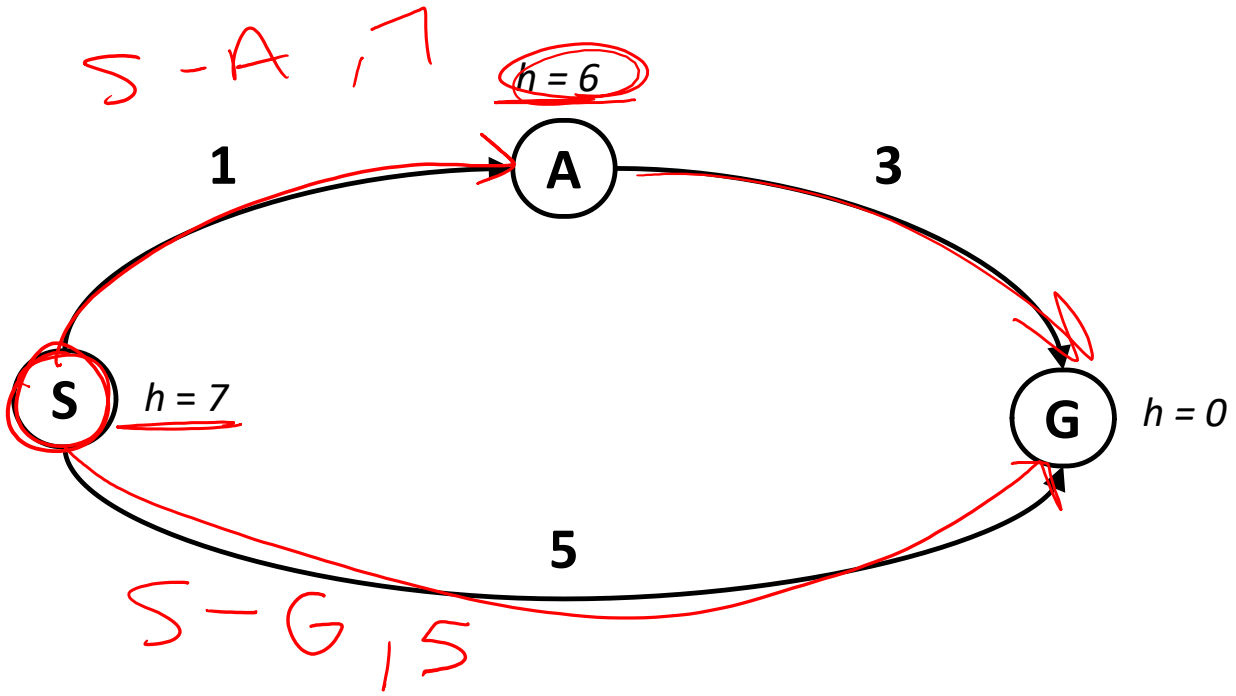
h(n) = estimate of n to goal, could write h(n-…-g)



S - A - D

Example: Teg Grenager

Is A* Optimal?



What went wrong?

Actual bad goal cost < ***estimated*** good goal cost

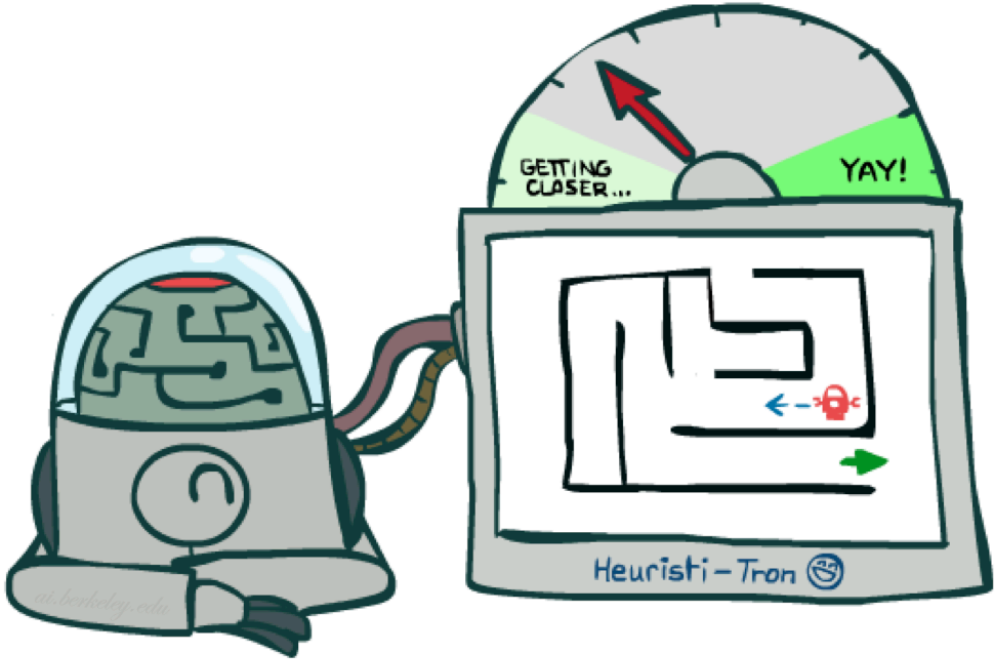
We need estimates to be less than actual costs!

The Price is Wrong…

Closest bid without going over…

https://www.youtube.com/watch?v=9B0ZKRurC5Y

Admissible Heuristics



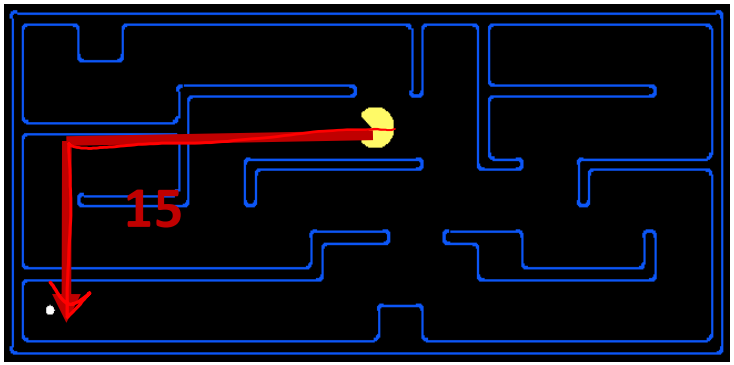
Admissible Heuristics

A heuristic h is *admissible* (optimistic) if:

$$0 \leq h(n) \leq h^*(n)$$

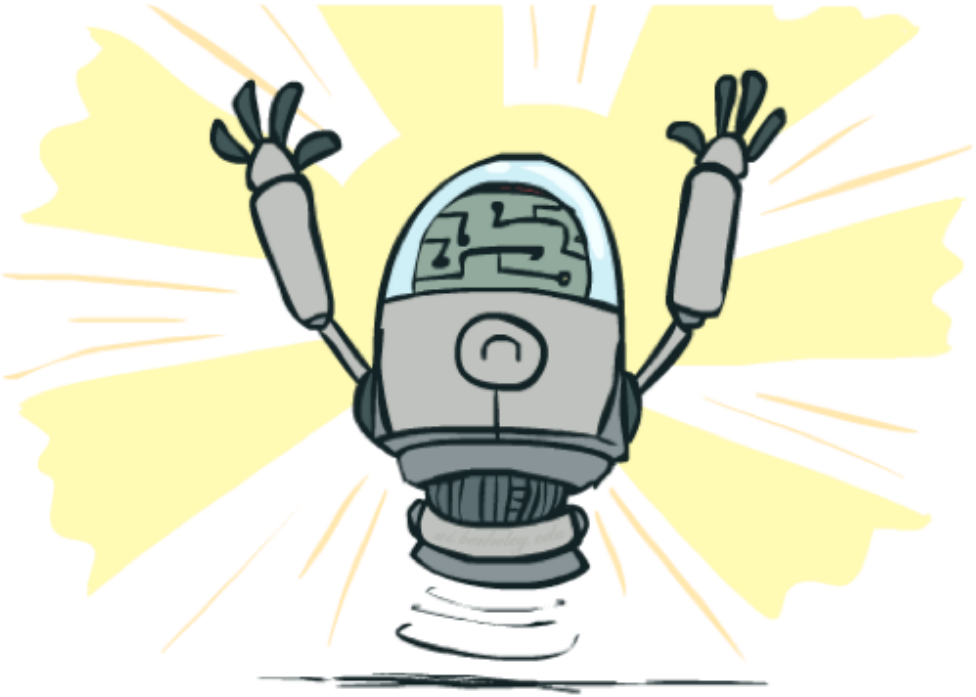
where $h^*(n)$ is the true cost to a nearest goal

Example:



Coming up with admissible heuristics is most of what's involved in using A* in practice.

Optimality of A* Tree Search



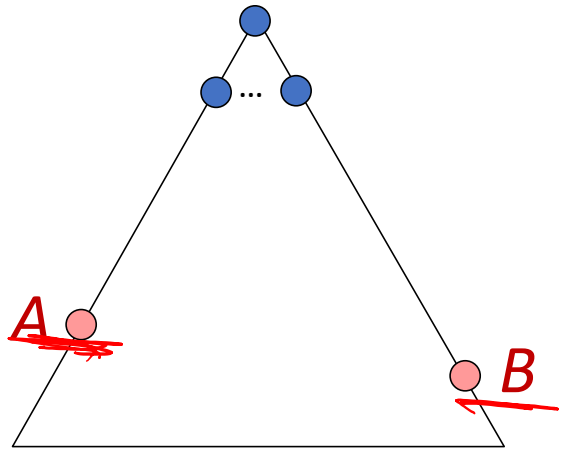
Optimality of A* Tree Search

Assume:

A is an optimal goal node

B is a suboptimal goal node

h is admissible



Claim:

A will be chosen for exploration (popped off the frontier) before *B*

Optimality of A* Tree Search: Blocking

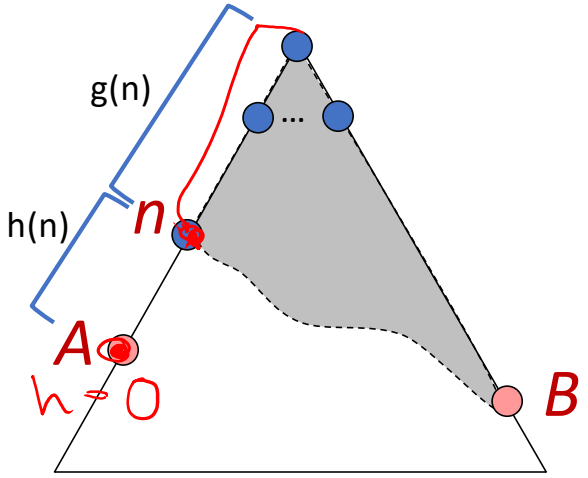
Proof:

Imagine *B* is on the frontier

Some ancestor *n* of *A* is on the frontier, too

(Maybe the start state; maybe *A* itself!)

Claim: *n* will be explored before *B*



1. $f(n) = g(n) + h(n)$ — *Definition of f*
2. $g(A) = g(n) + c(n, \ldots, A)$ — *Definition of g*
3. $g(A) = g(n) + h^*(n)$ — *Definition of h**
4. $g(n) + h(n) \leq g(n) + h^*(n)$ — *Admissibility of h*
5. $f(n) \leq g(A)$ — *Substitution*
6. $g(A) = f(A)$ — *h=0 at A (admissibility)*
7. $f(n) \leq f(A)$ — *Substitution*

Optimality of A* Tree Search: Blocking

Proof:

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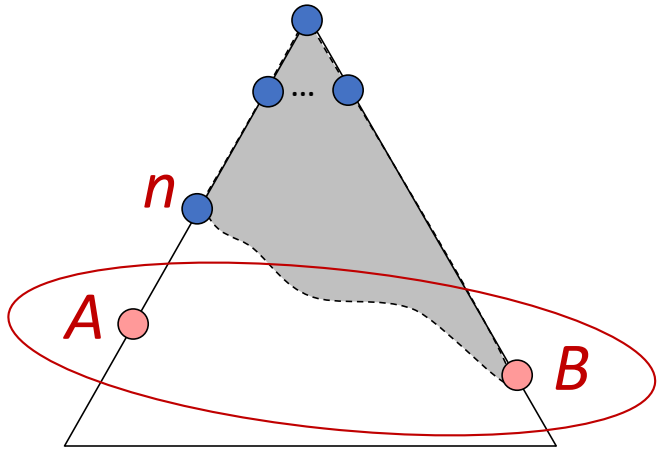


7. $f(n) \leq f(A)$ — *Previous page*

8. $g(A) < g(B)$ — *Suboptimality of B*

9. $f(A) < f(B)$ — *h=0 at goal*

10. $f(n) \leq f(A) < f(B)$

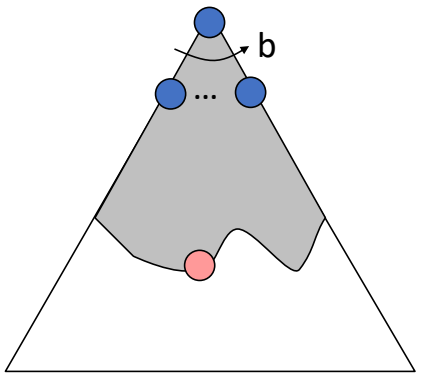
All ancestors n are explored before B

A is explored before B

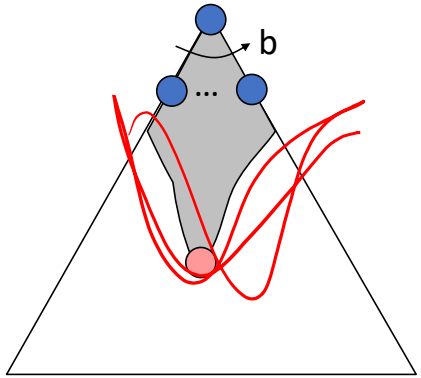
A search is optimal!*

Properties of A*

Uniform-Cost

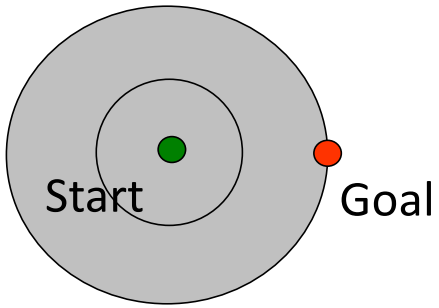


A*

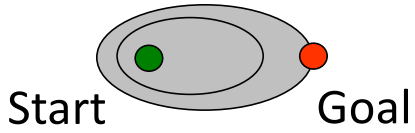


UCS vs A* Contours

Uniform-cost expands equally in all "directions"

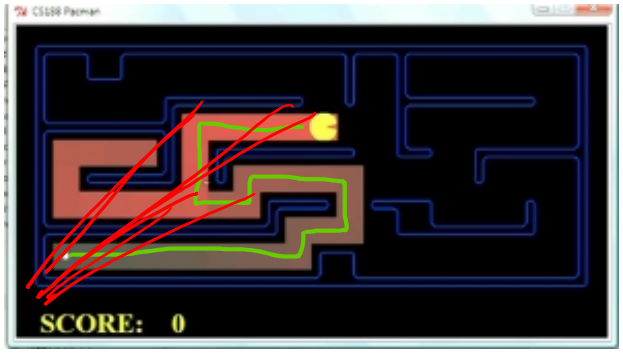


A* expands mainly toward the goal, but does hedge its bets to ensure optimality

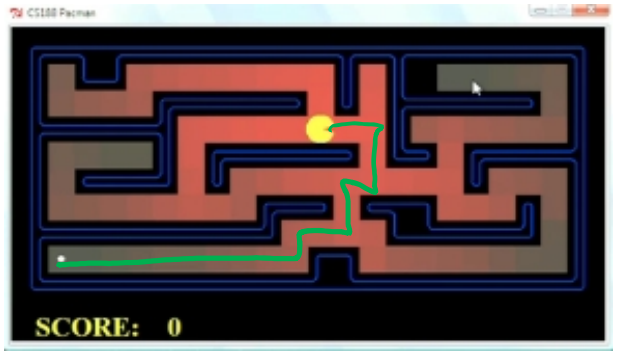


Demo Contours (Pacman Small Maze) – A*

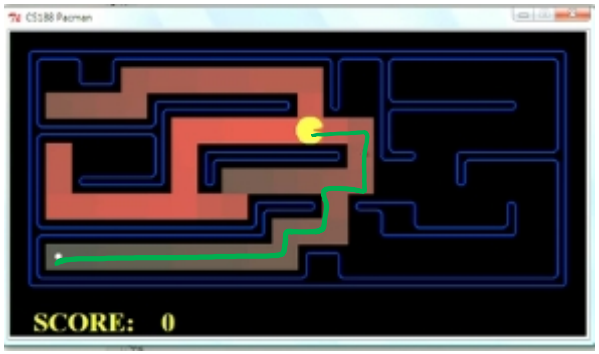
Comparison



Greedy



Uniform Cost



A*

Demo Empty Water Shallow/Deep – Guess Algorithm

A* Search Algorithms

A* Tree Search

- Same tree search algorithm as before but with a frontier that is a priority queue using priority $f(n) = g(n) + h(n)$

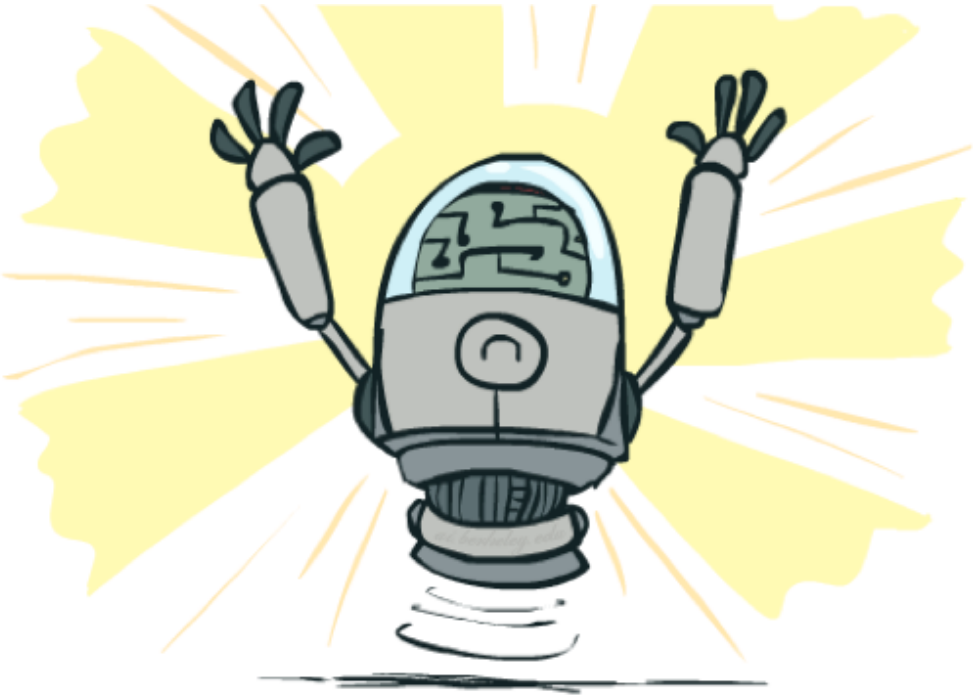
A* Graph Search

- Same as **UCS** graph search algorithm but with a frontier that is a priority queue using priority $f(n) = g(n) + h(n)$

```
function UNIFORM-COST-SEARCH(problem) returns a solution, or failure
    initialize the explored set to be empty
    initialize the frontier as a priority queue using g(n) as the priority
    add initial state of problem to frontier with priority g(S) = 0
    loop do
        if the frontier is empty then
            return failure
        choose a node and remove it from the frontier
        if the node contains a goal state then
            return the corresponding solution
        add the node state to the explored set
        for each resulting child from node
            if the child state is not already in the frontier or explored set then
                add child to the frontier
            else if the child is already in the frontier with higher g(n) then
                replace that frontier node with child
```

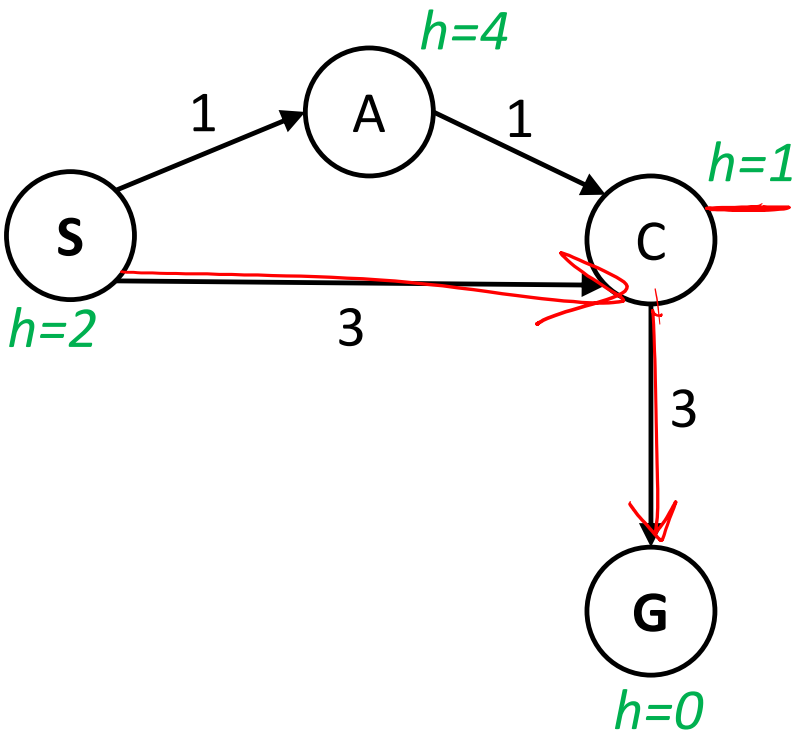
```
function A-STAR-SEARCH(problem) returns a solution, or failure
    initialize the explored set to be empty
    initialize the frontier as a priority queue using f(n) = g(n) + h(n) as the priority
    add initial state of problem to frontier with priority f(S) = 0 + h(S)
    loop do
        if the frontier is empty then
            return failure
        choose a node and remove it from the frontier
        if the node contains a goal state then
            return the corresponding solution
        add the node state to the explored set
        for each resulting child from node
            if the child state is not already in the frontier or explored set then
                add child to the frontier
            else if the child is already in the frontier with higher f(n) then
                replace that frontier node with child
```

Optimality of A* Graph Search

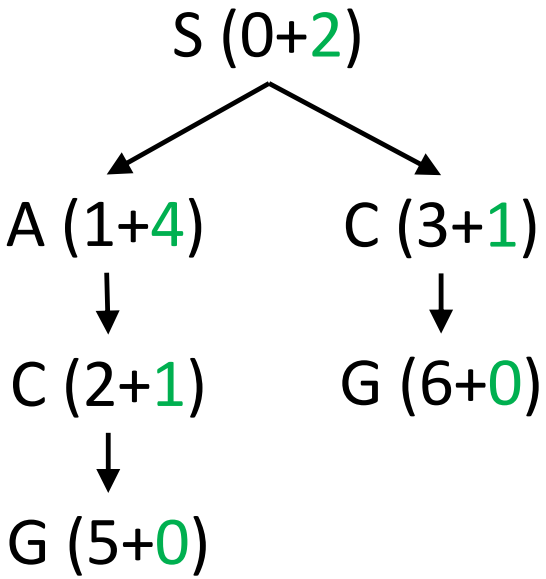


A* Tree Search

State space graph

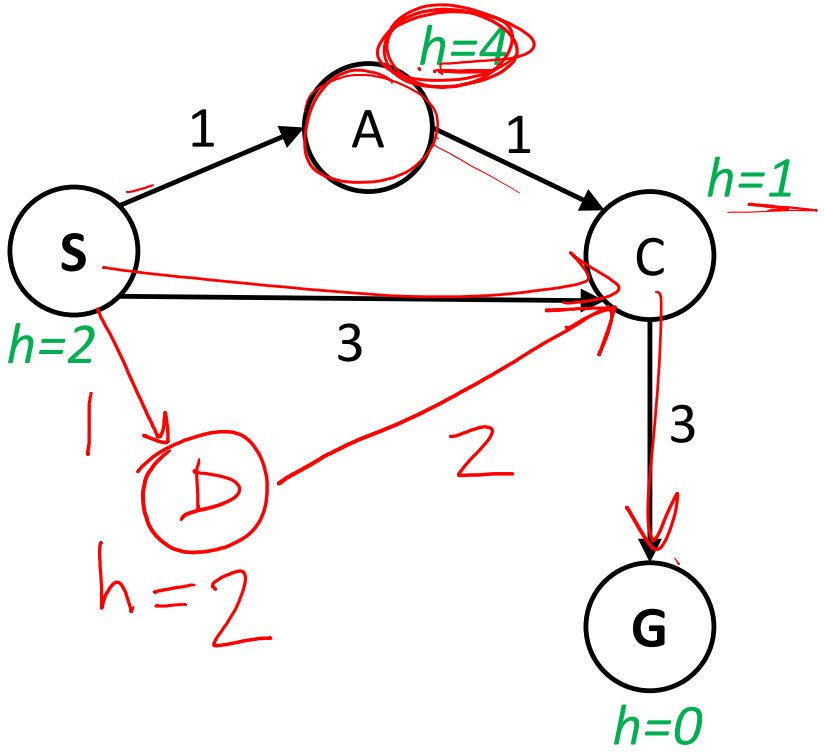


Search tree



Piazza Poll: A* Graph Search

What paths does A* graph search consider during its search?



A) S, S-A, S-C, S-C-G

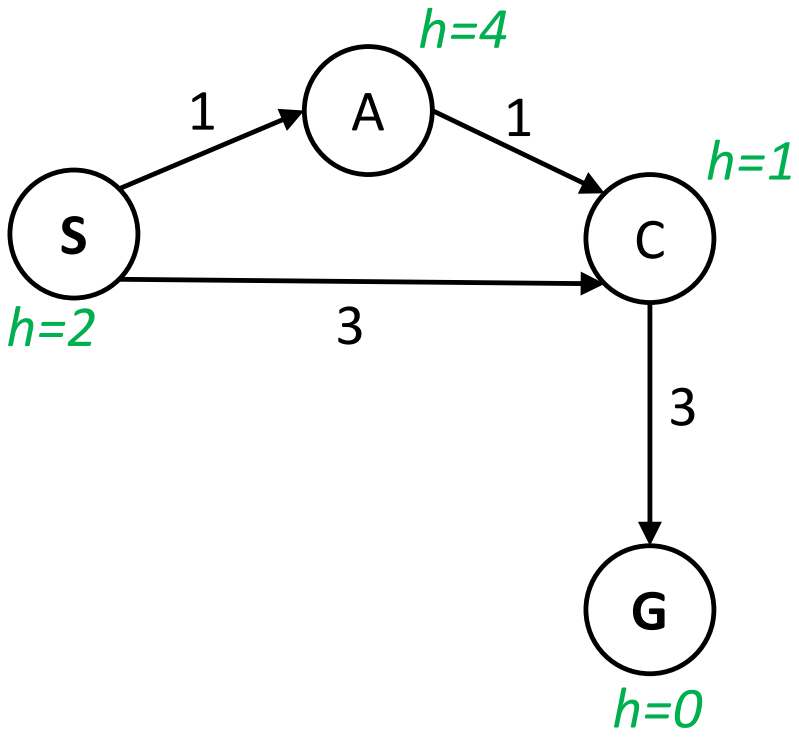
B) S, S-A, S-C, S-A-C, S-C-G

C) S, S-A, S-A-C, S-A-C-G

D) S, S-A, S-C, S-A-C, S-A-C-G

Piazza Poll: A* Graph Search

What paths does A* graph search consider during its search?



A) ~~*S*~~, ~~S-A~~, ~~S-C~~, S-C-G

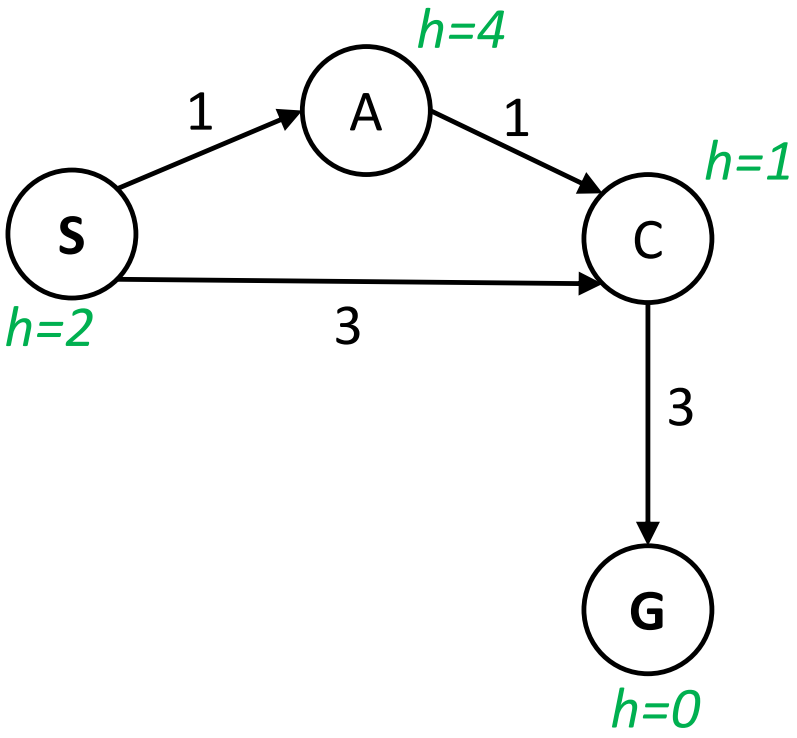
B) ~~*S*~~, ~~S-A~~, S-C, ~~S-A-C~~, S-C-G

C) ~~*S*~~, ~~S-A~~, ~~S-A-C~~, S-A-C-G

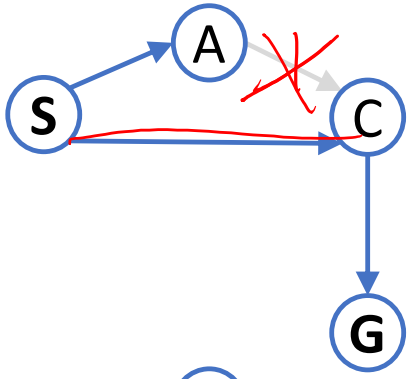
D) ~~*S*~~, ~~S-A~~, ~~S-C~~, ~~S-A-C~~, S-A-C-G

A* Graph Search

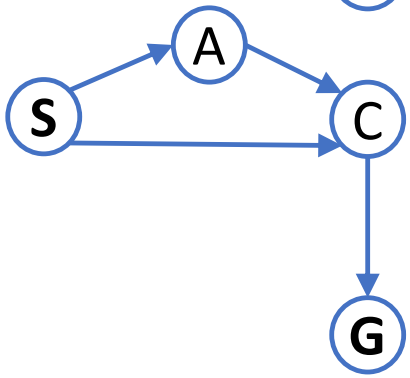
What does the resulting graph tree look like?



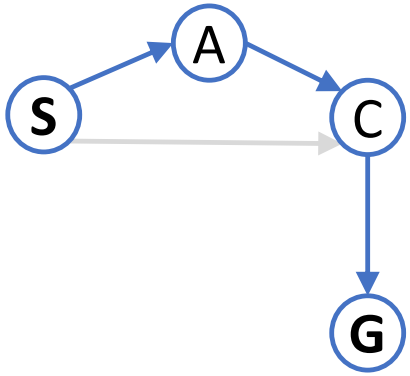
A)



B)

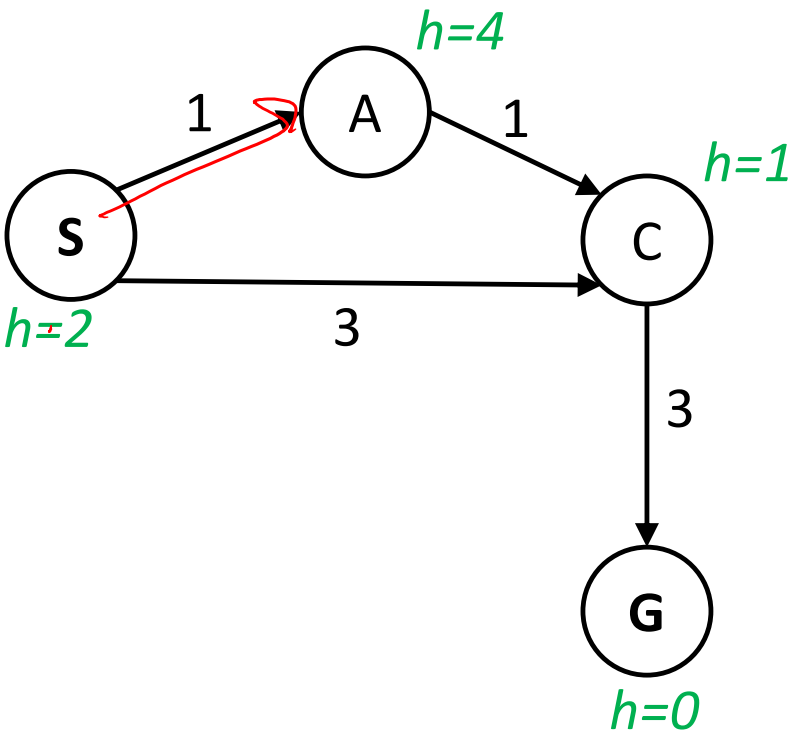


C & D)

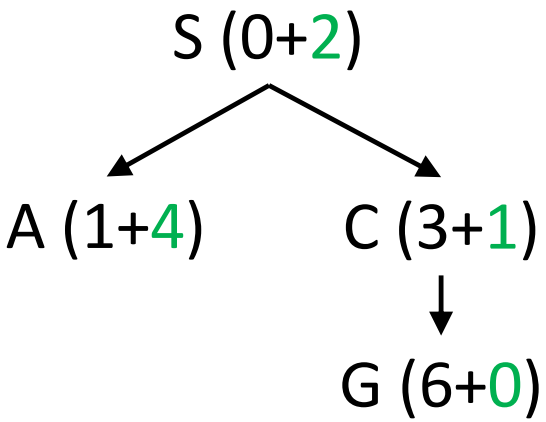


A* Graph Search Gone Wrong?

State space graph



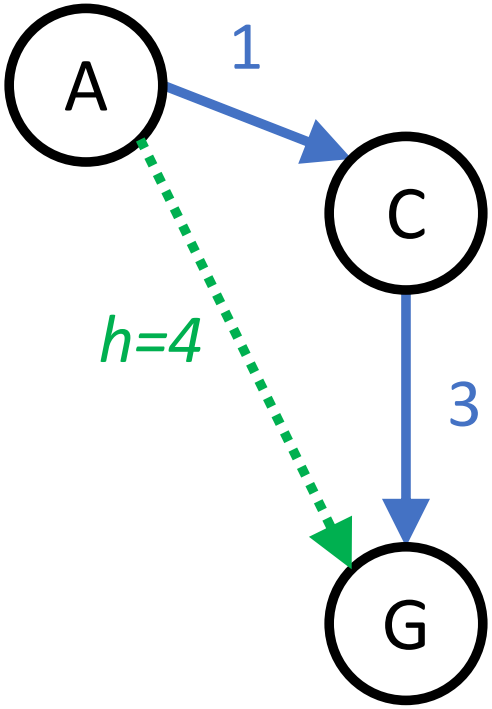
Search tree



Simple check against explored set blocks C

Fancy check allows new C if cheaper than old but requires recalculating C's descendants

Admissibility of Heuristics



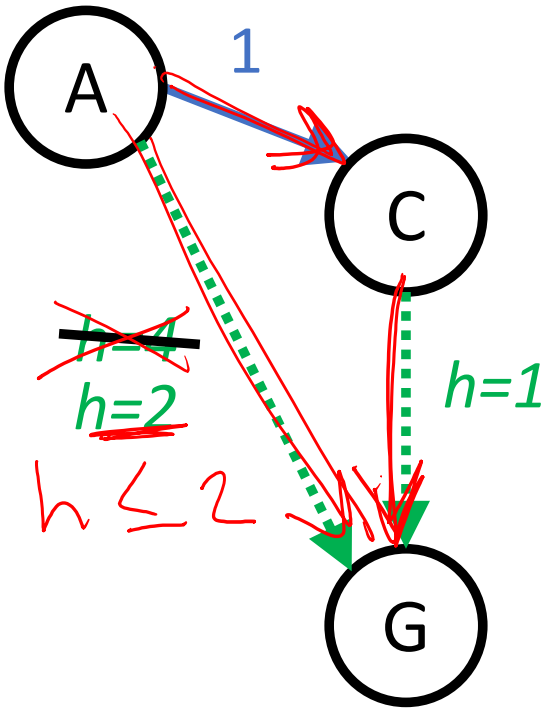
Main idea: Estimated heuristic values ≤ actual costs

- Admissibility:

  heuristic value ≤ actual cost to goal

  h(A) ≤ actual cost c(A-…-G)

Consistency of Heuristics



Main idea: Estimated heuristic costs ≤ actual costs

- Admissibility:

  heuristic cost ≤ actual cost to goal

  $h(A) \leq c(A\text{-}\ldots\text{-}G)$

- Consistency:

  "heuristic step cost" ≤ actual cost for each step

  $h(A) - h(C) \leq c(A\text{-}C)$

  triangle inequality

  $h(A) \leq c(A\text{-}C) + h(C)$

Consequences of consistency:

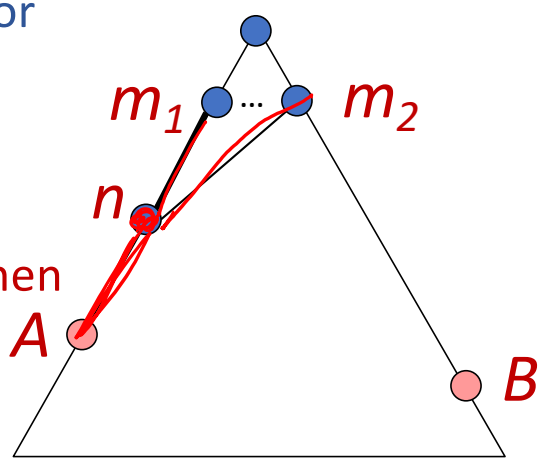
- The f value along a path never decreases
- A* graph search is optimal

Proof Optimality of A* Graph Search

Where does our A* tree search optimality proof break down for graph search?

The explored set! We need to know that all ancestors of A are explored before B.

If f(A) < f(B) but A is not on the frontier before B is explored, then there exists some node n that was explored before its optimal ancestor m_1 was added to the frontier.



Can $f(m_2) \leq f(n) < f(m_1)$ and A* explore n before m_1?

$h(m_1) \leq c(m_1\text{-}n) + h(n)$ Consistency

$f(m_1) \leq g(m_1) + c(m_1\text{-}n) + h(n)$ Substitution

$f(n) = g(m_1) + c(m_1\text{-}n) + h(n)$ definition of g

$f(m_1) \leq f(n)$ **m1 must be on the frontier before n**

A* graph search is optimal

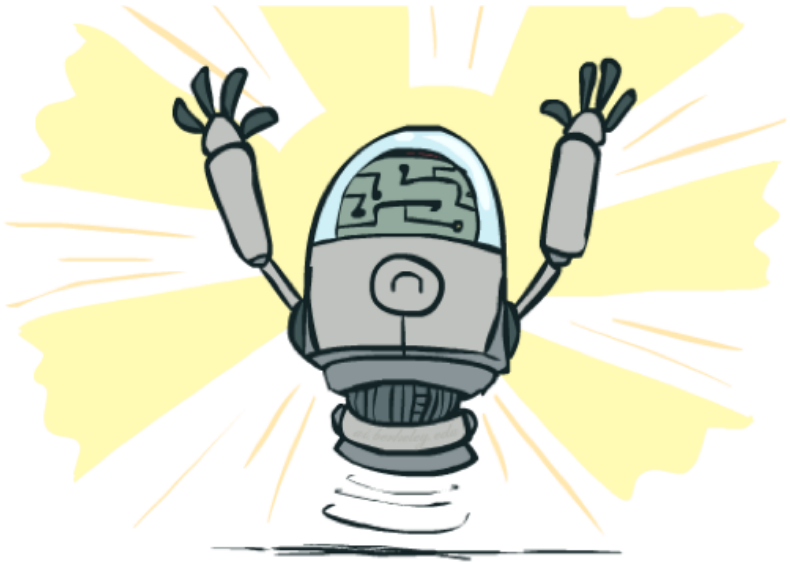
Optimality

Tree search:

- A* is optimal if heuristic is admissible
- UCS is a special case (h = 0)

Graph search:

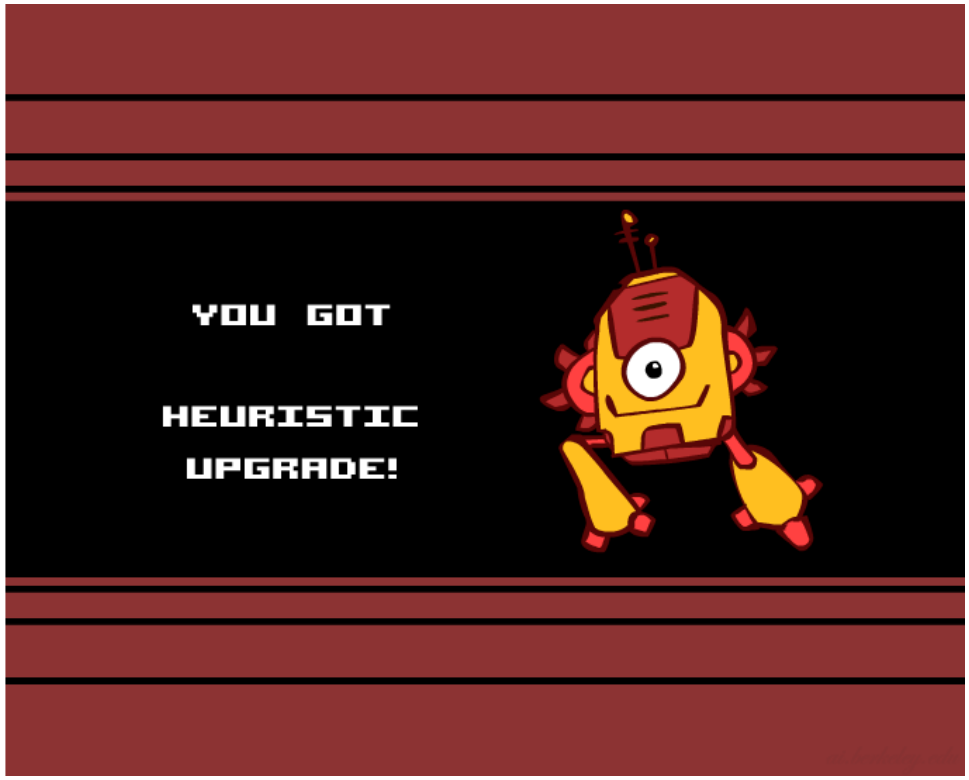
- A* optimal if heuristic is consistent
- UCS optimal (h = 0 is consistent)



Consistency implies admissibility

In general, most natural admissible heuristics tend to be consistent, especially if from relaxed problems

Creating Heuristics



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

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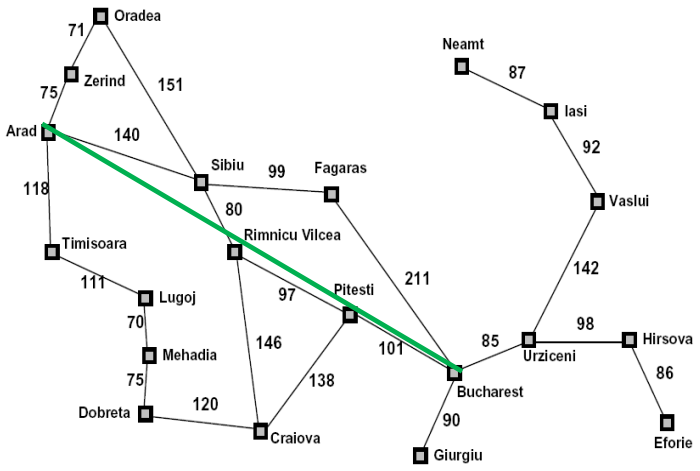
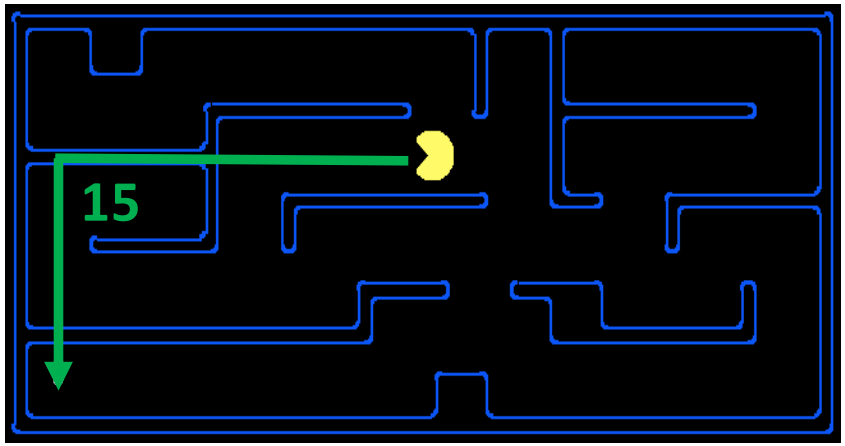
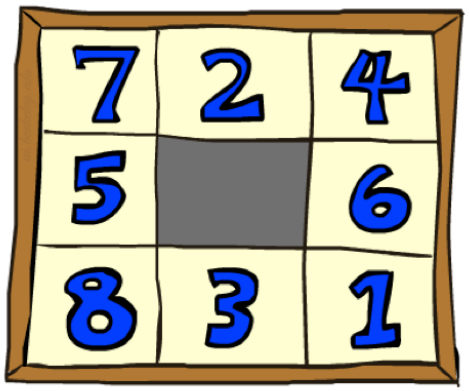
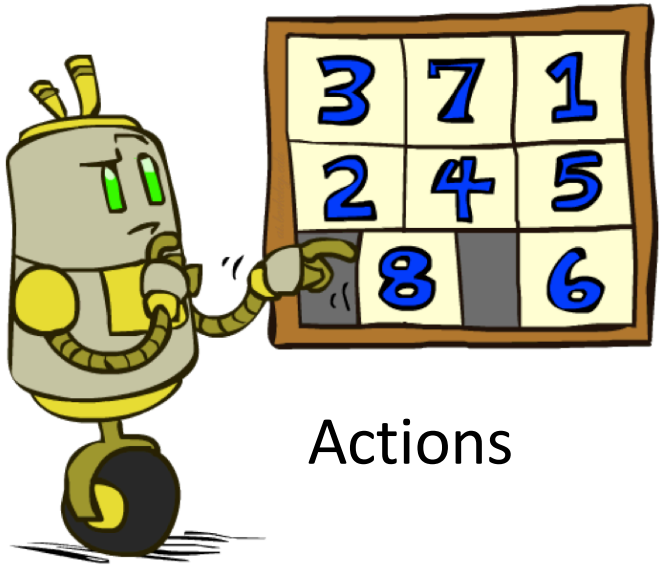




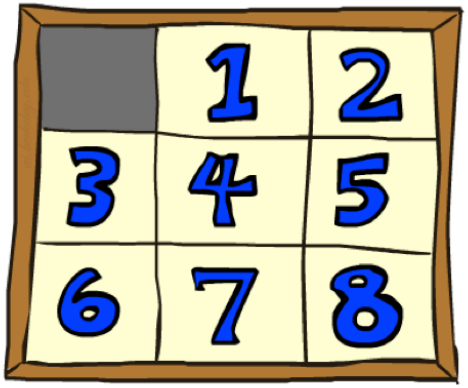
Example: 8 Puzzle



Start State



Actions



Goal State

What are the states?

How many states?

What are the actions?

How many actions from the start state?

What should the step costs be?

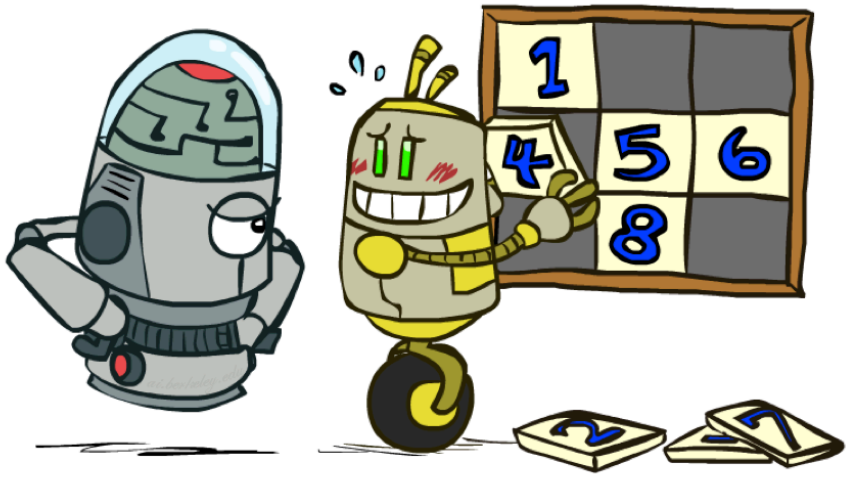
8 Puzzle I

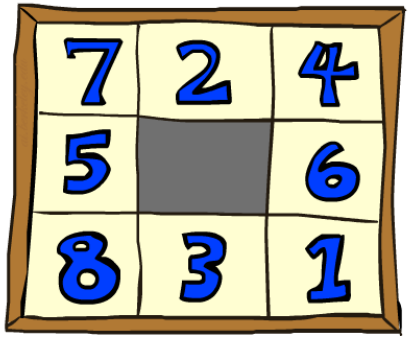
Heuristic: Number of tiles misplaced

Why is it admissible?

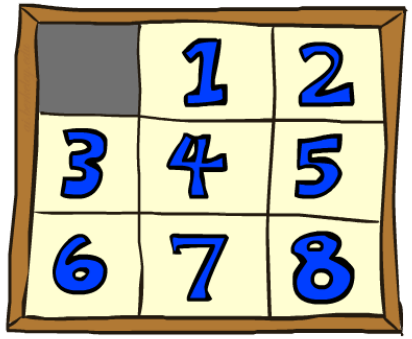
h(start) = 8

This is a *relaxed-problem* heuristic





Start State



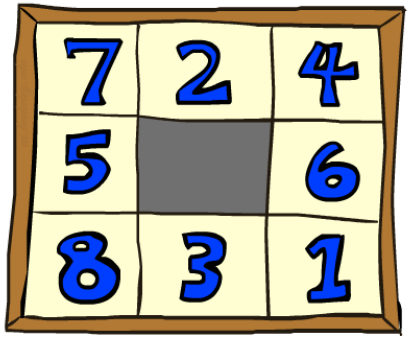
Goal State

	Average nodes expanded when the optimal path has…		
	…4 steps	…8 steps	…12 steps
UCS	112	6,300	3.6×10^6
A*TILES	13	39	227

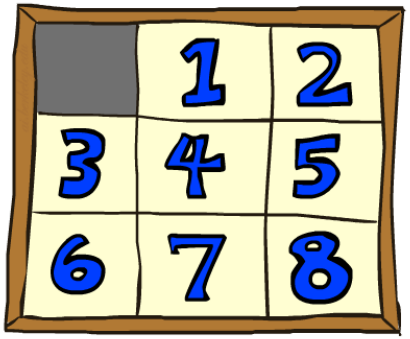
Statistics from Andrew Moore

8 Puzzle II

What if we had an easier 8-puzzle where any tile could slide any direction at any time, ignoring other tiles?



Start State



Goal State

Total *Manhattan* distance

Why is it admissible?

h(start) = 3 + 1 + 2 + … = 18

	Average nodes expanded when the optimal path has…		
	…4 steps	…8 steps	…12 steps
A*TILES	13	39	227
A*MANHATTAN	12	25	73

Combining heuristics

Dominance: $h_a \geq h_c$ if

$$\forall n \;\; h_a(n) \geq h_c(n)$$

- Roughly speaking, larger is better as long as both are admissible
- The zero heuristic is pretty bad (what does A* do with h=0?)
- The exact heuristic is pretty good, but usually too expensive!

What if we have two heuristics, neither dominates the other?

- Form a new heuristic by taking the max of both:

$$h(n) = \max(h_a(n), h_b(n))$$

- Max of admissible heuristics is admissible and dominates both!

A*: Summary

A*: Summary

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