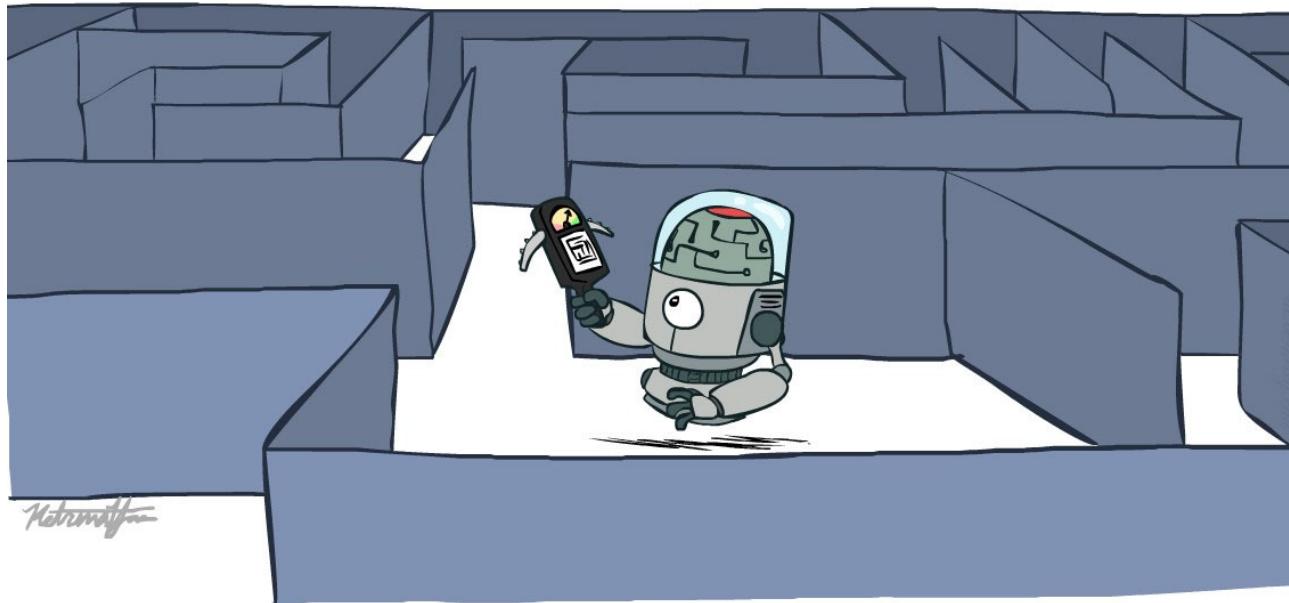


# CS 188: Artificial Intelligence

## Informed Search



Spring 403

University of Isfahan

[These slides were created by Dan Klein and Pieter Abbeel for CS188 Intro to AI at UC Berkeley. All CS188 materials are available at <http://ai.berkeley.edu>.]

# Today

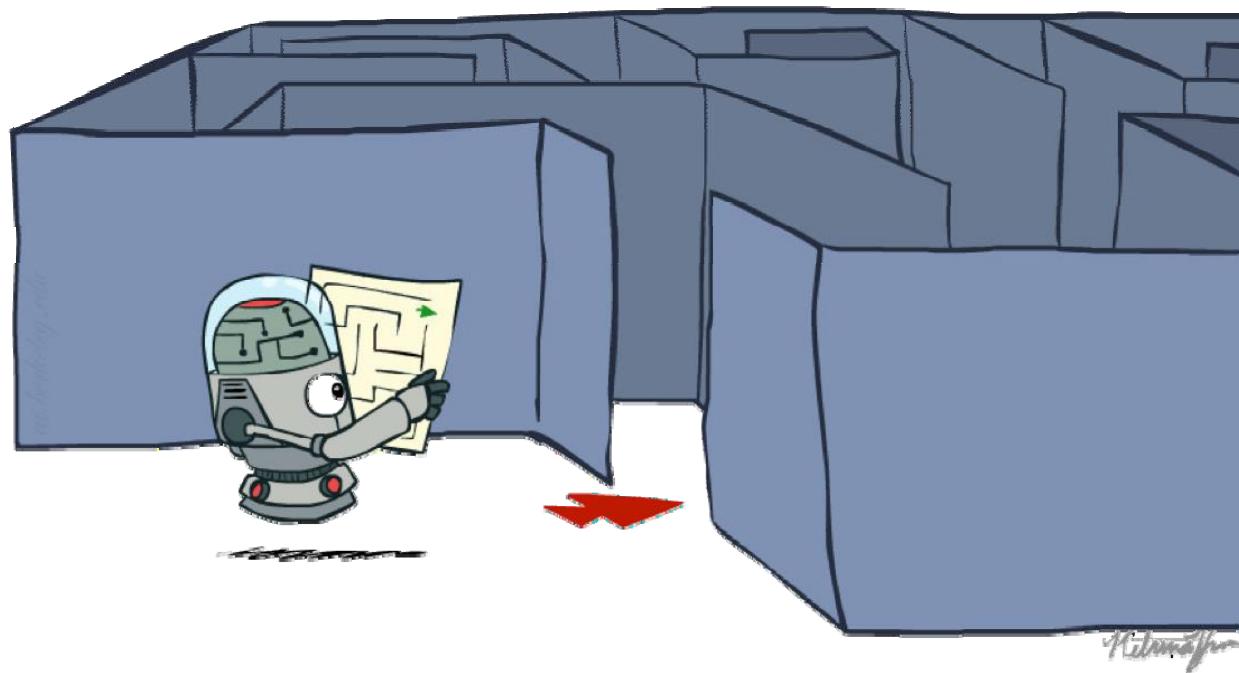
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- Informed Search
  - Heuristics
  - Greedy Search
  - A\* Search
  
- Graph Search



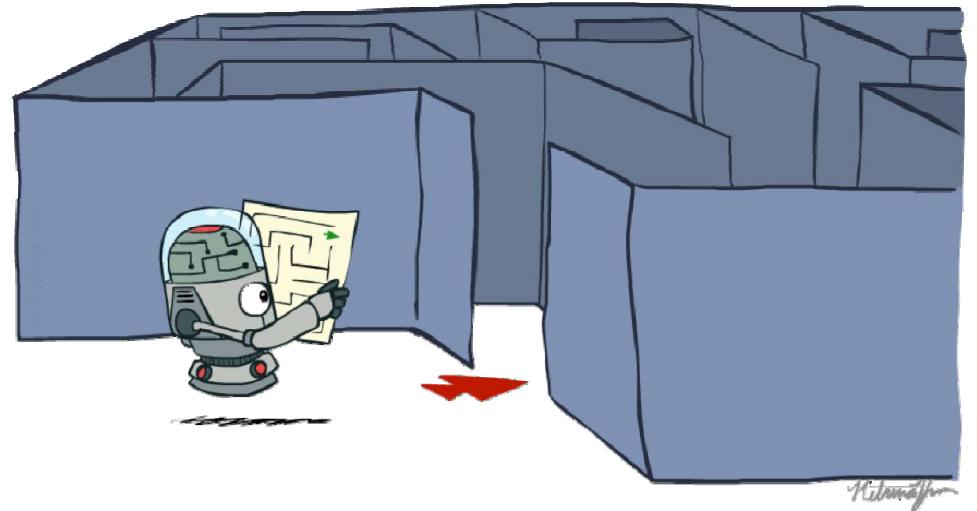
# Recap: Search

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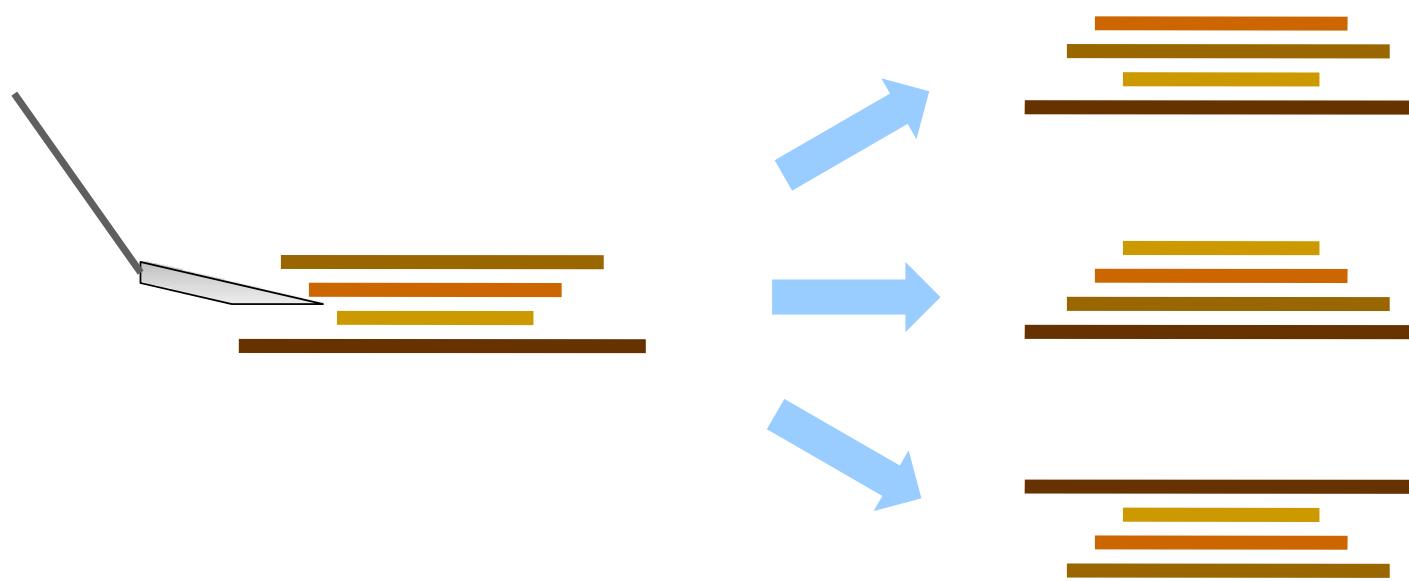


# Recap: Search

- **Search problem:**
  - States (configurations of the world)
  - Actions and costs
  - Successor function (world dynamics)
  - 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)
  - Optimal: finds least-cost plans



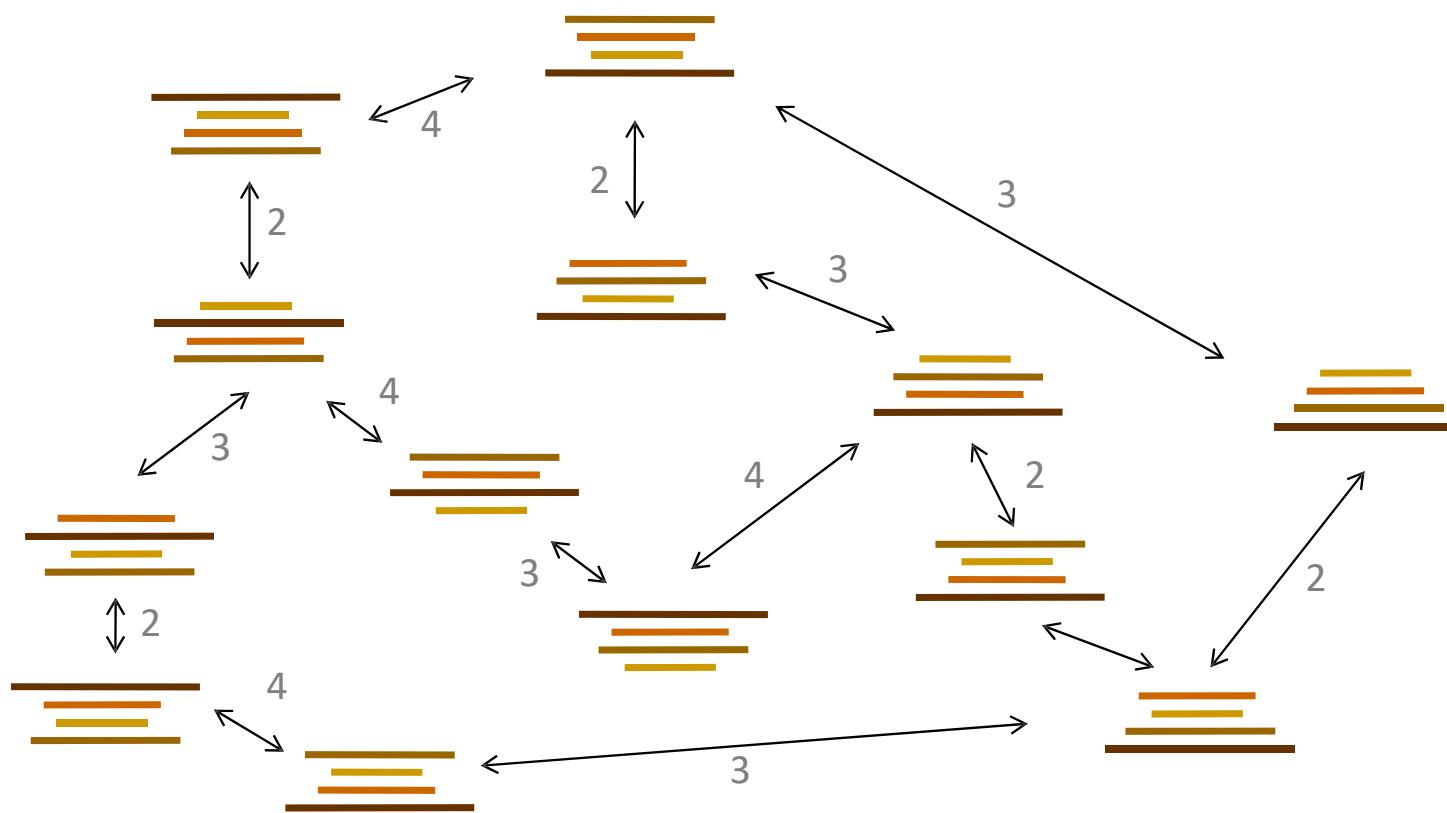
# Example: Pancake Problem



Cost: Number of pancakes flipped

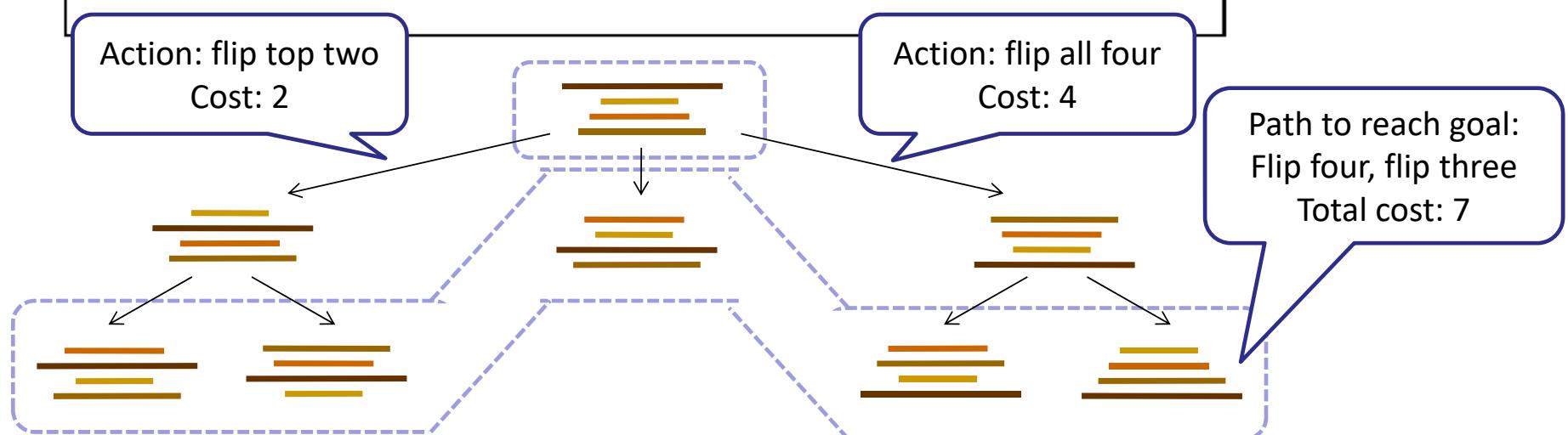
# Example: Pancake Problem

State space graph with costs as weights



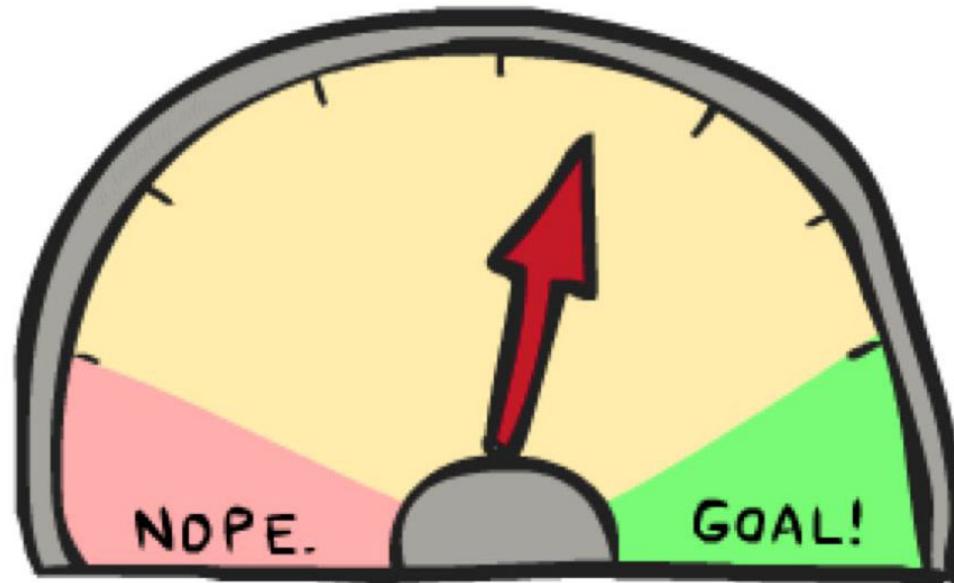
# General Tree Search

```
function TREE-SEARCH( problem, strategy) returns a solution, or failure
    initialize the search tree using the initial state of problem
    loop do
        if there are no candidates for expansion then return failure
        choose a leaf node for expansion according to strategy
        if the node contains a goal state then return the corresponding solution
        else expand the node and add the resulting nodes to the search tree
    end
```



# Informed Search

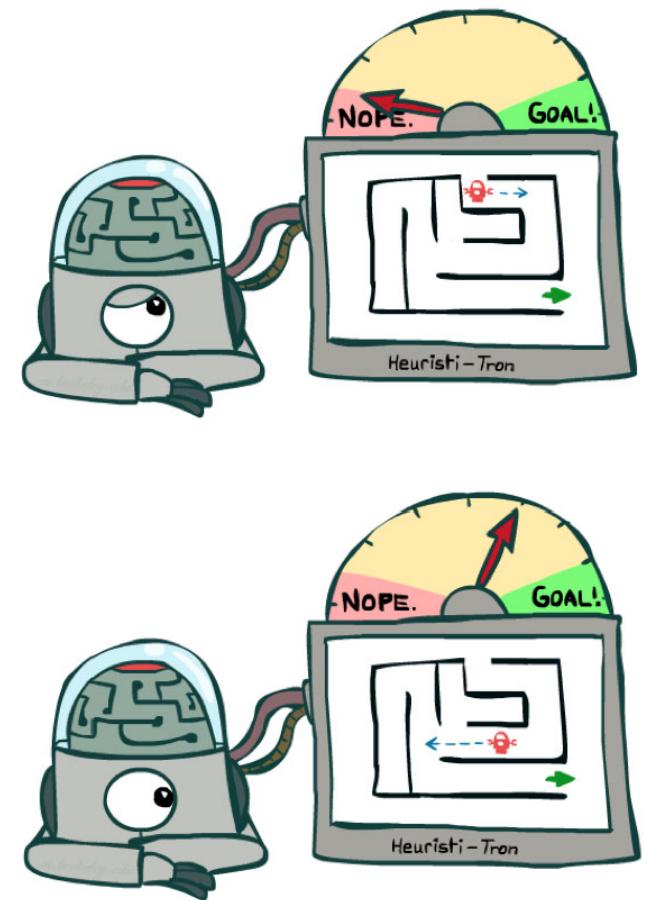
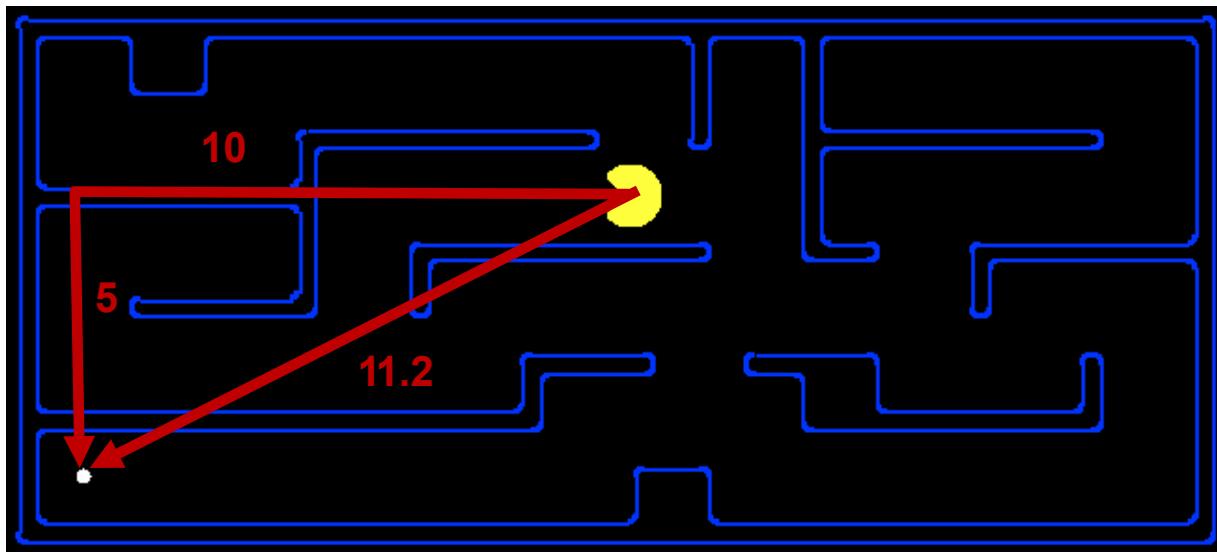
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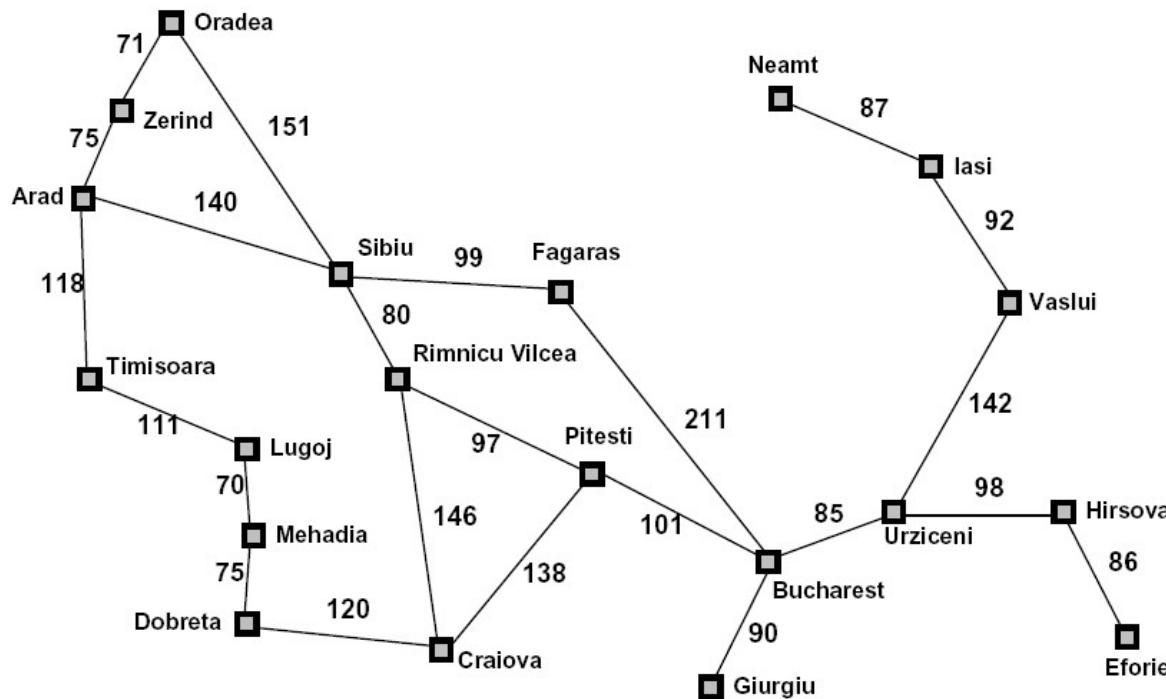
# Search Heuristics

- 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: Heuristic Function

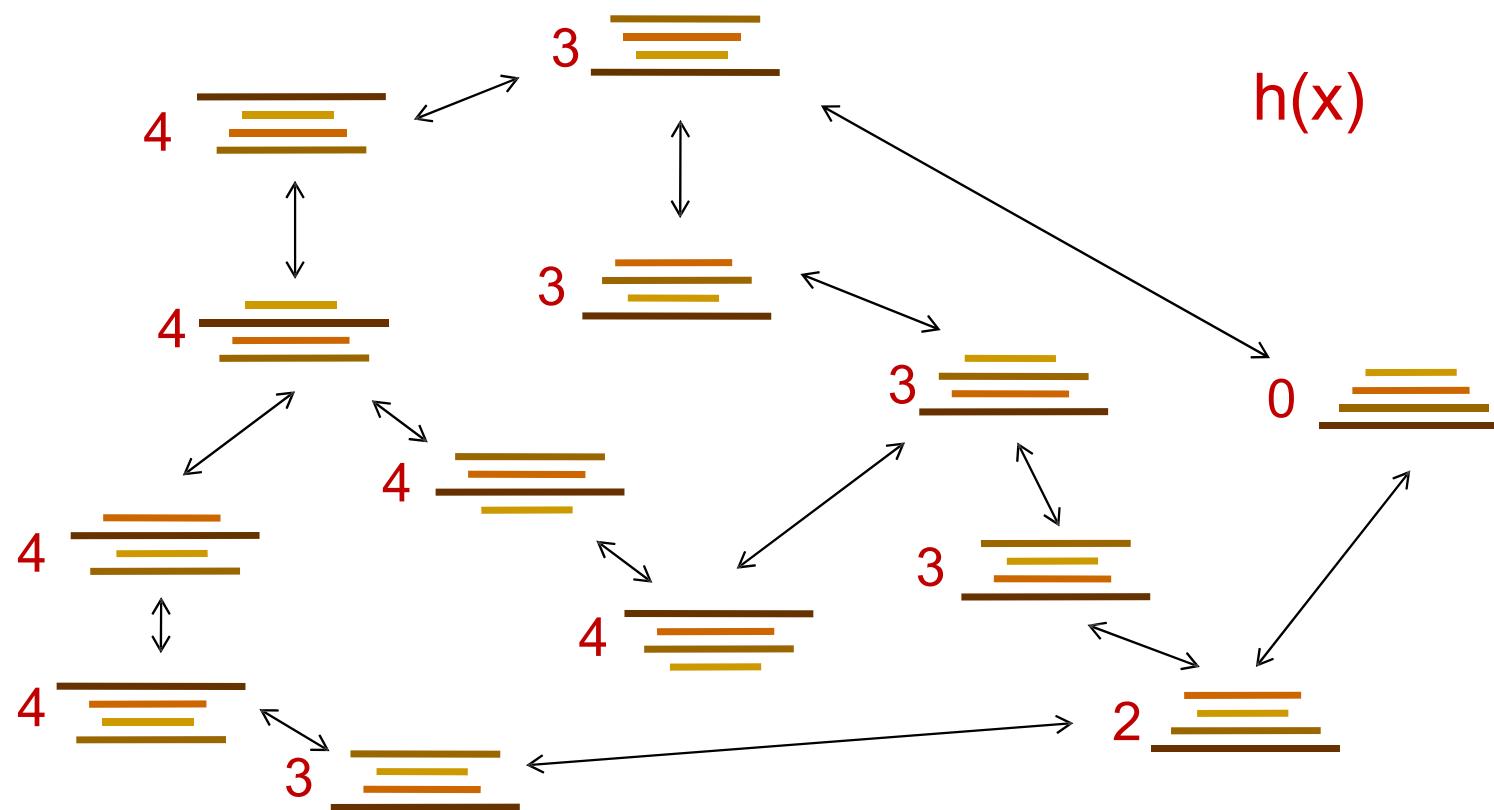


Straight-line distance to Bucharest	
Arad	366
Bucharest	0
Craiova	160
Dobrete	242
Eforie	161
Fagaras	178
Giurgiu	77
Hirsova	151
Iasi	226
Lugoj	244
Mehadia	241
Neamt	234
Oradea	380
Pitesti	98
Rimnicu Vilcea	193
Sibiu	253
Timisoara	329
Urziceni	80
Vaslui	199
Zerind	374

$h(x)$

# Example: Heuristic Function

Heuristic: the number of the largest pancake that is still out of place



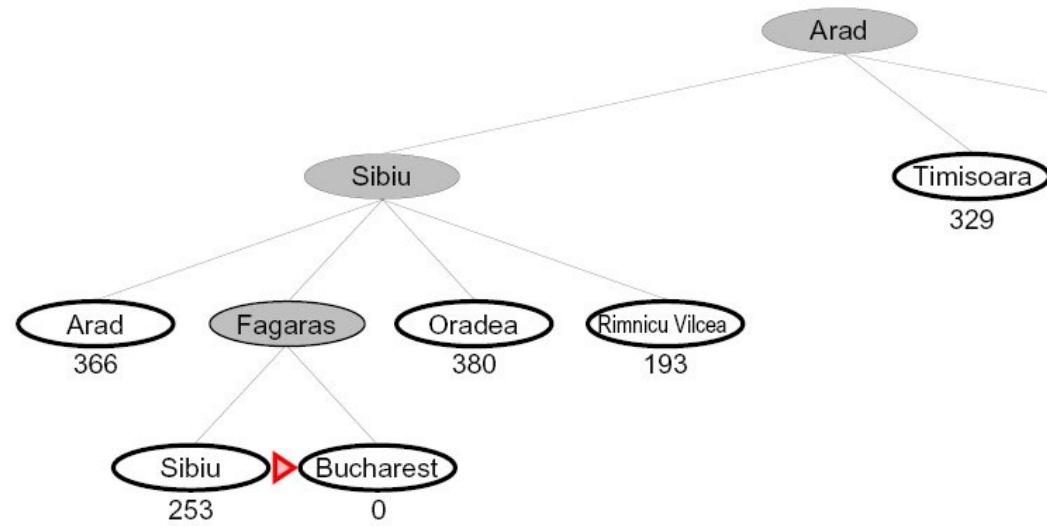
# Greedy Search

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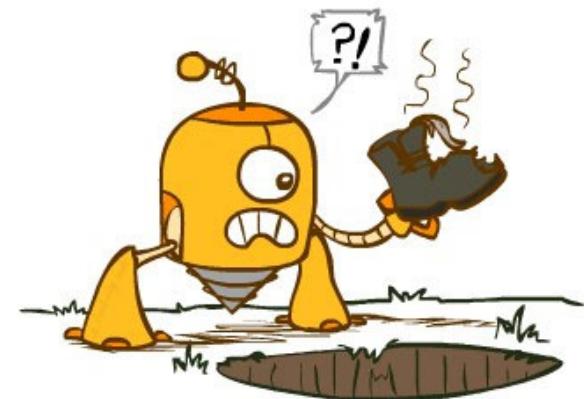
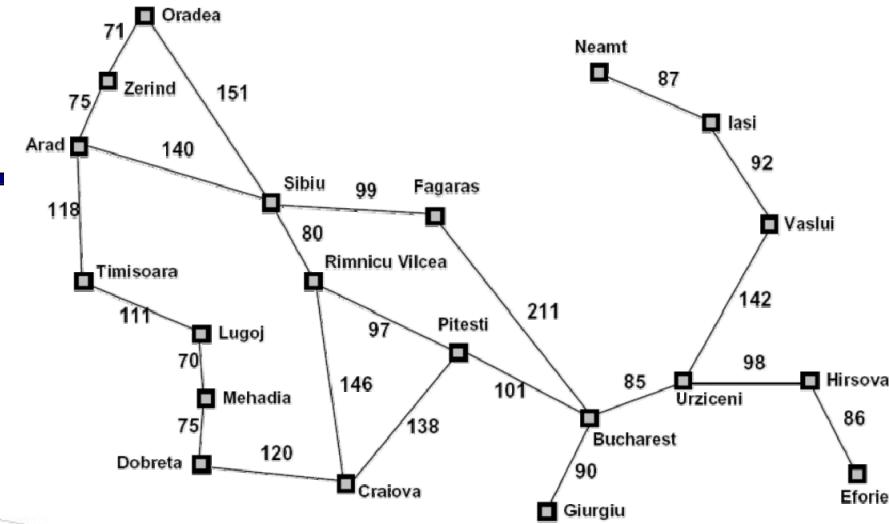


# Greedy Search

- Expand the node that seems closest...

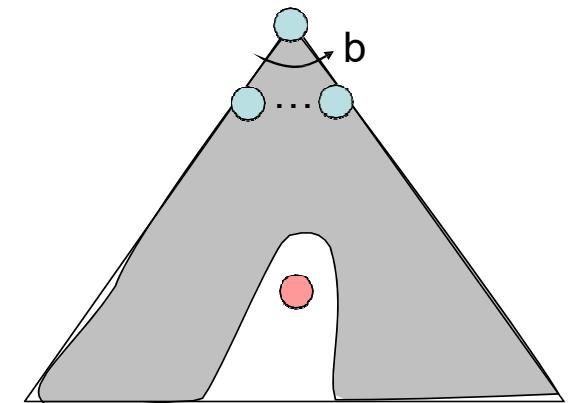
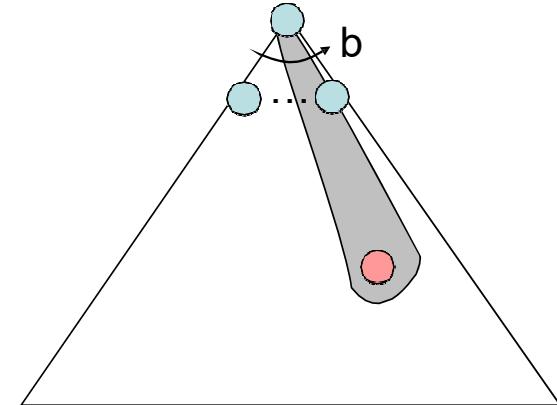


- What can go wrong?



# 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



[Demo: contours greedy empty (L3D1)]

[Demo: contours greedy pacman small maze (L3D4)]

# A\* Search

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# A\* Search

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UCS



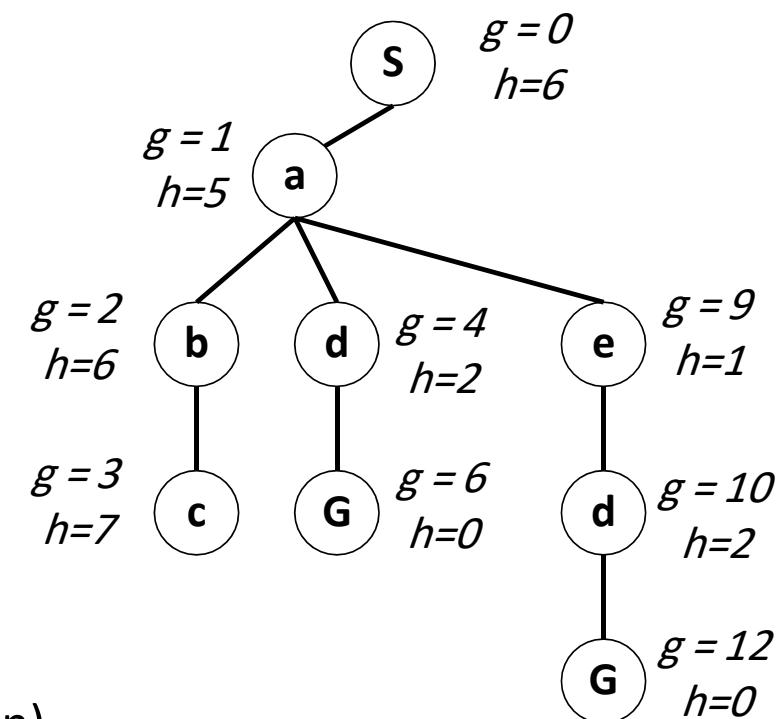
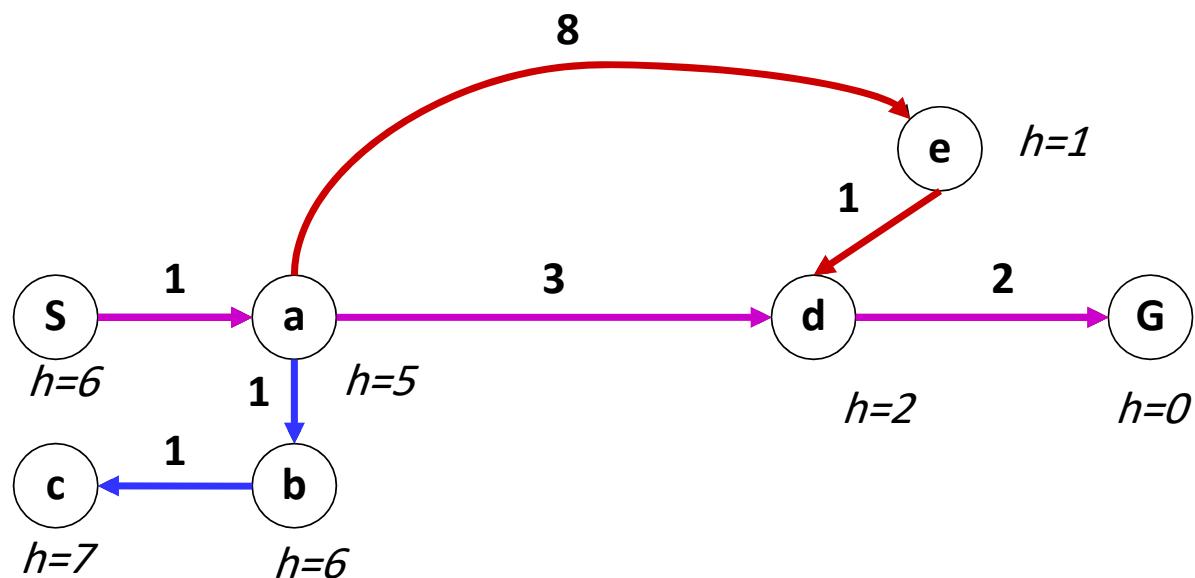
Greedy



A\*

# Combining UCS and Greedy

- Uniform-cost orders by path cost, or *backward cost*  $g(n)$
- Greedy orders by goal proximity, or *forward cost*  $h(n)$

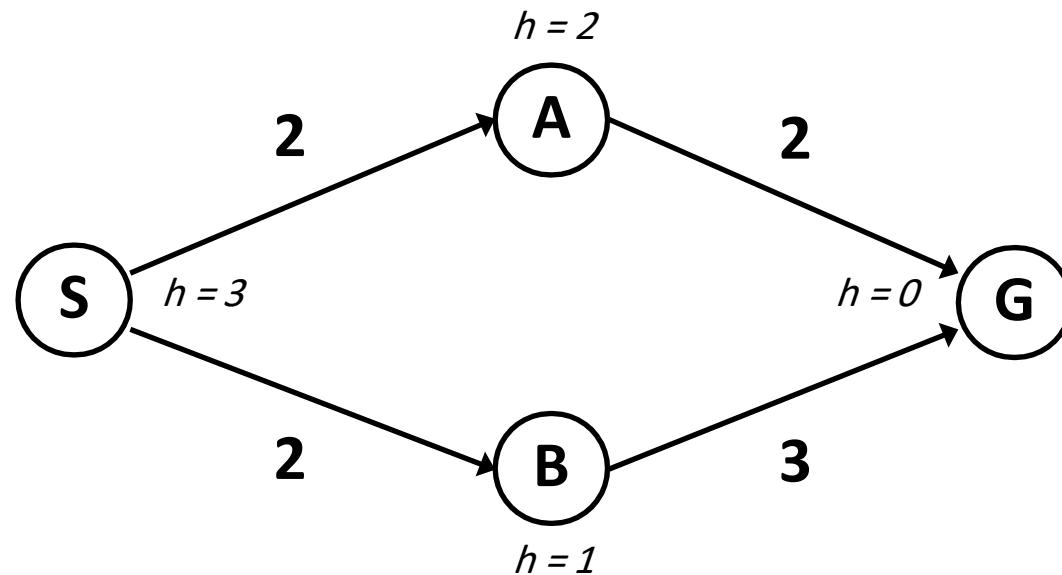


- A\* Search orders by the sum:  $f(n) = g(n) + h(n)$

Example: Teg Grenager

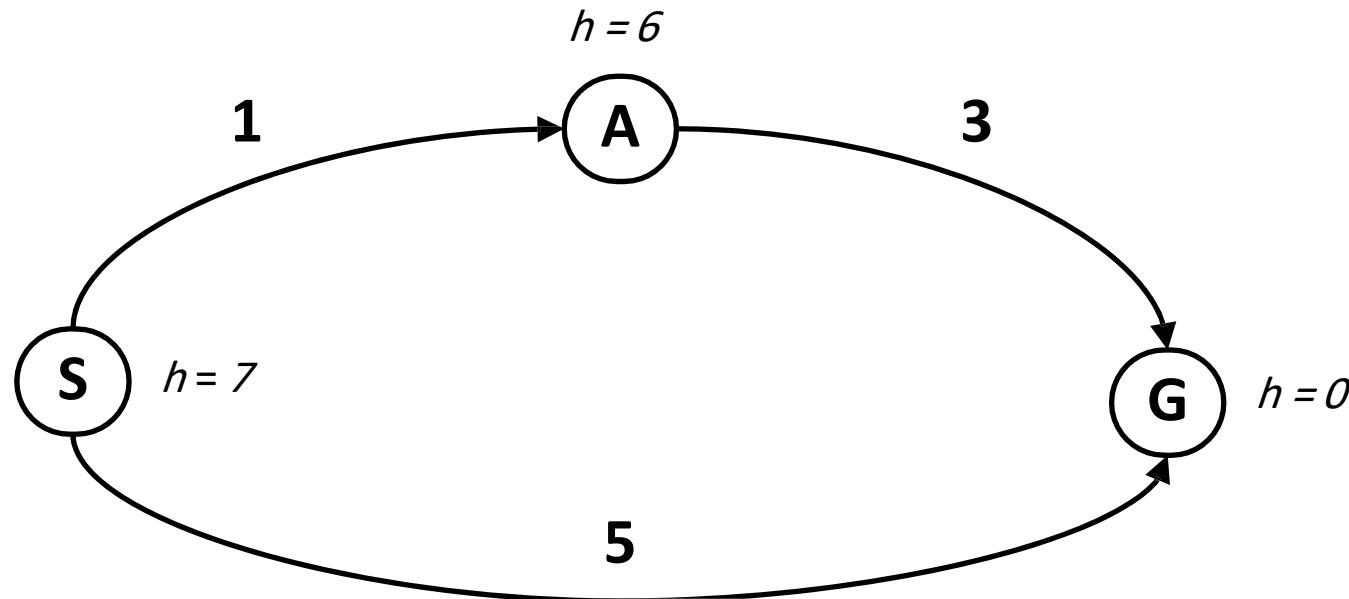
# When should A\* terminate?

- Should we stop when we enqueue a goal?



- No: only stop when we dequeue a goal

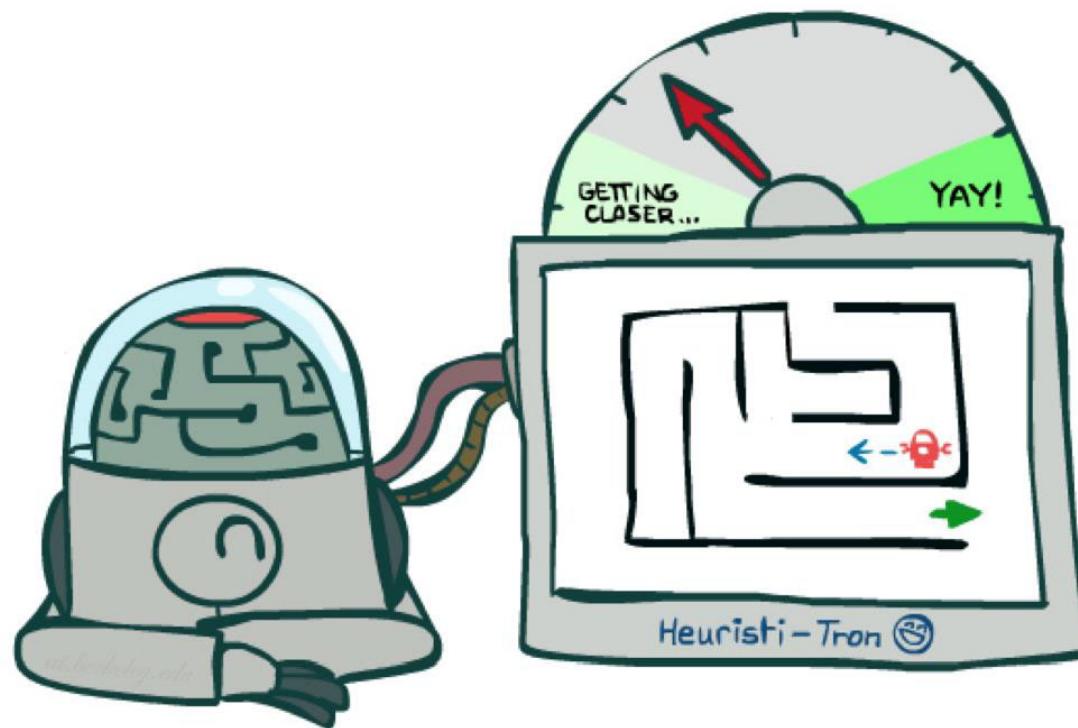
# Is A\* Optimal?



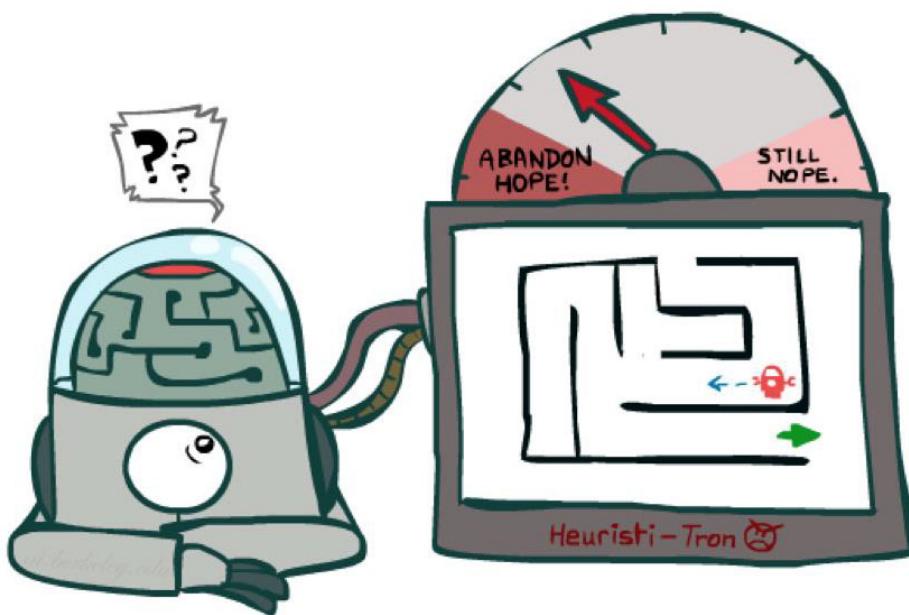
- What went wrong?
- Actual bad goal cost < estimated good goal cost
- We need estimates to be less than actual costs!

# Admissible Heuristics

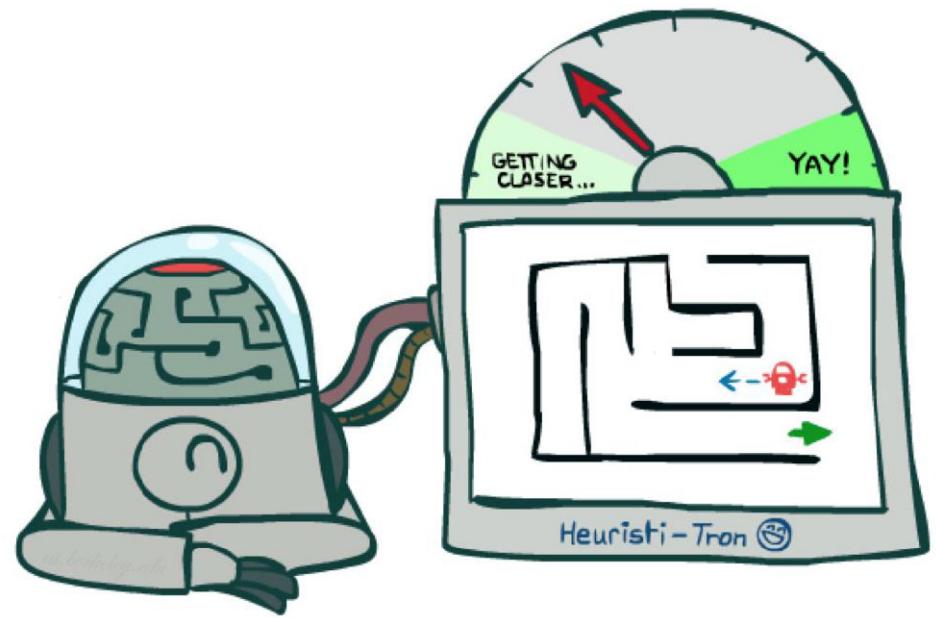
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# Idea: Admissibility



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



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

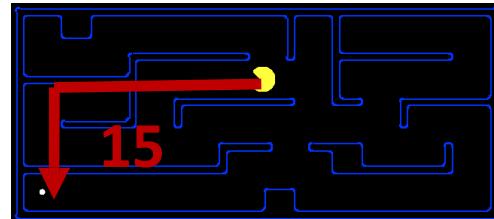
# Admissible Heuristics

- 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

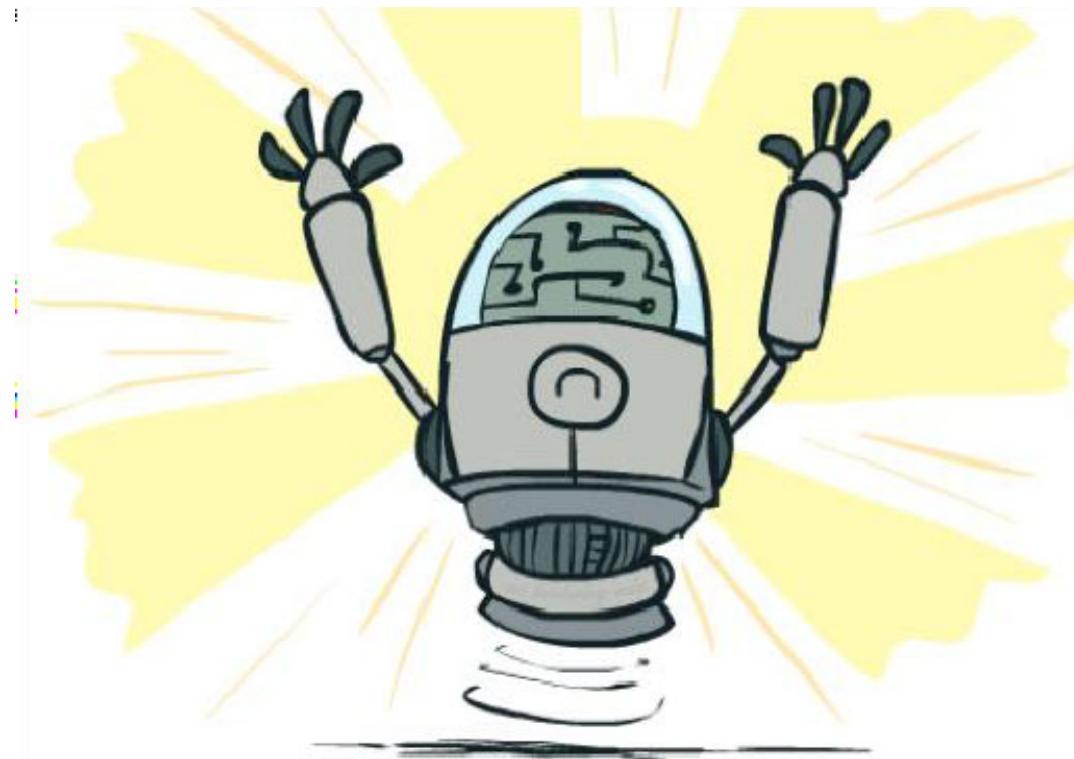
- Examples:



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

# Optimality of A\* Tree Search

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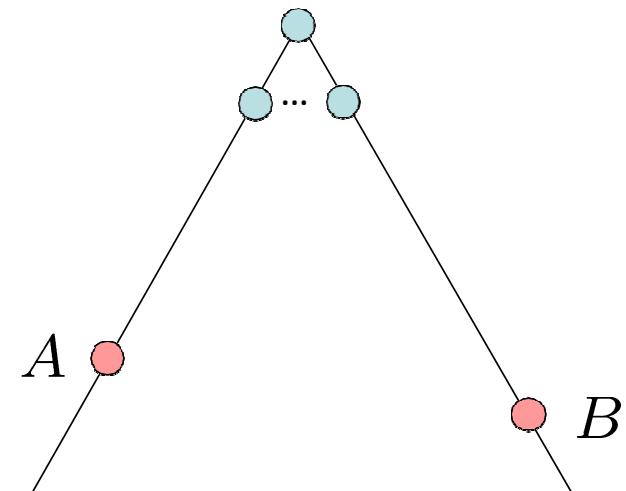
# Optimality of A\* Tree Search

Assume:

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

Claim:

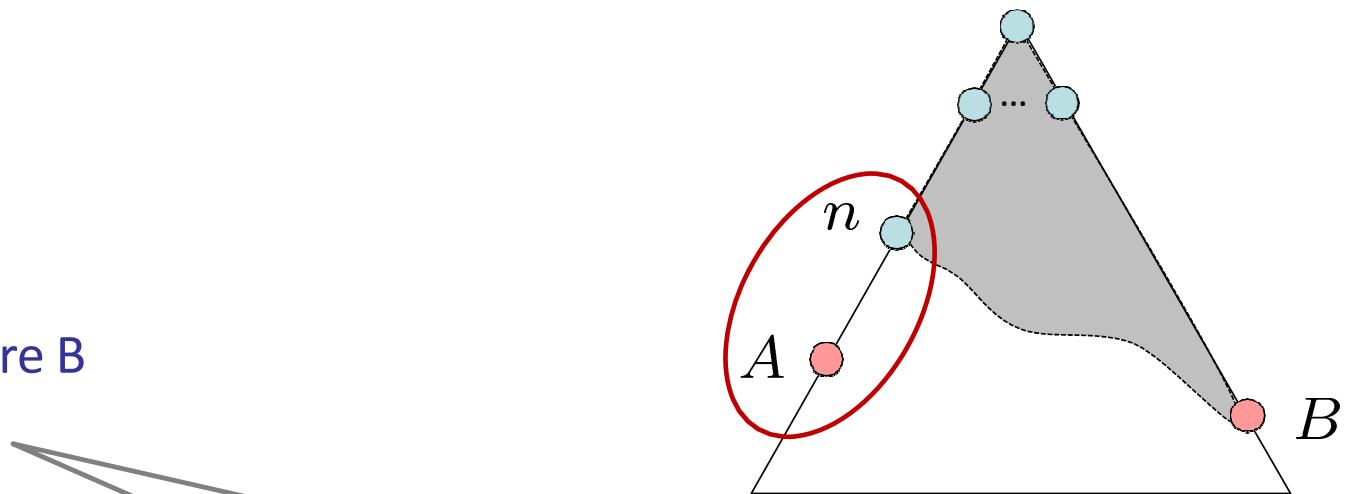
- A will exit the fringe before B



# 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  $f(A)$



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

$$f(n) \leq g(A)$$

$$g(A) = f(A)$$

Definition of f-cost

Admissibility of  $h$

$h = 0$  at a goal

# Optimality of A\* Tree Search: Blocking

## 1. $f(n)$ is less than or equal to $f(A)$

- Definition of  $f$ -cost says:

$$f(n) = g(n) + h(n) = (\text{path cost to } n) + (\text{est. cost of } n \text{ to } A)$$

$$f(A) = g(A) + h(A) = (\text{path cost to } A) + (\text{est. cost of } A \text{ to } A)$$

- The admissible heuristic must underestimate the true cost

$$h(A) = (\text{est. cost of } A \text{ to } A) = 0$$

- So now, we have to compare:

$$f(n) = g(n) + h(n) = (\text{path cost to } n) + (\text{est. cost of } n \text{ to } A)$$

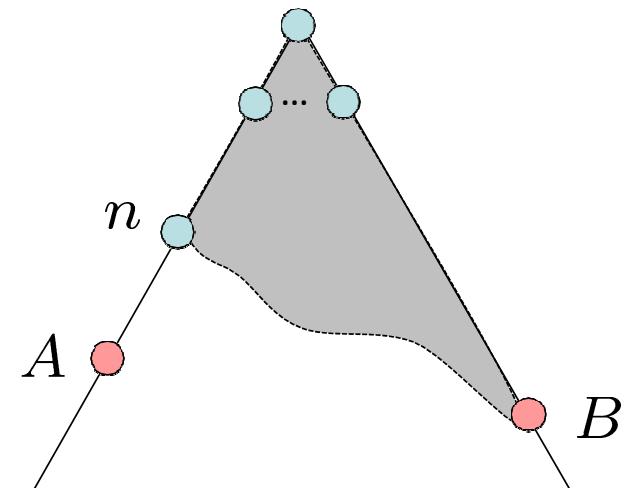
$$f(A) = g(A) = (\text{path cost to } A)$$

- $h(n)$  must be an underestimate of the true cost from  $n$  to  $A$

$$(\text{path cost to } n) + (\text{est. cost of } n \text{ to } A) \leq (\text{path cost to } A)$$

$$g(n) + h(n) \leq g(A)$$

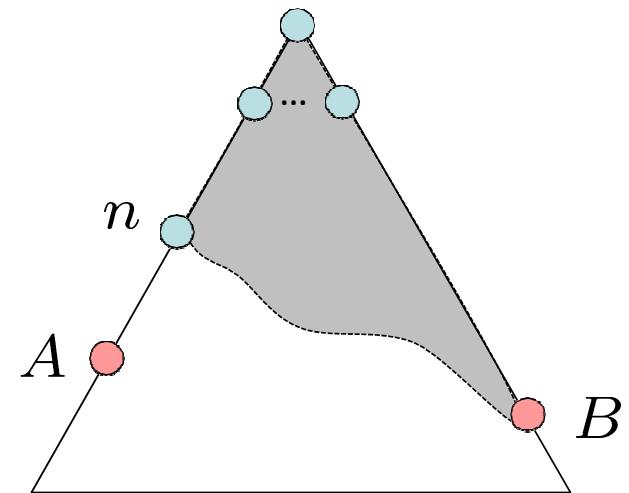
$$f(n) \leq f(A)$$



# 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  $f(B)$



$$\begin{aligned}g(A) &< g(B) \\ f(A) &< f(B)\end{aligned}$$

B is suboptimal  
 $h = 0$  at a goal

# Optimality of A\* Tree Search: Blocking

## 2. $f(A)$ is less than $f(B)$

- We know that:

$$f(A) = g(A) + h(A) = (\text{path cost to } A) + (\text{est. cost of } A \text{ to } A)$$

$$f(B) = g(B) + h(B) = (\text{path cost to } B) + (\text{est. cost of } B \text{ to } B)$$

- The heuristic must underestimate the true cost:

$$h(A) = h(B) = 0$$

- So now, we have to compare:

$$f(A) = g(A) = (\text{path cost to } A)$$

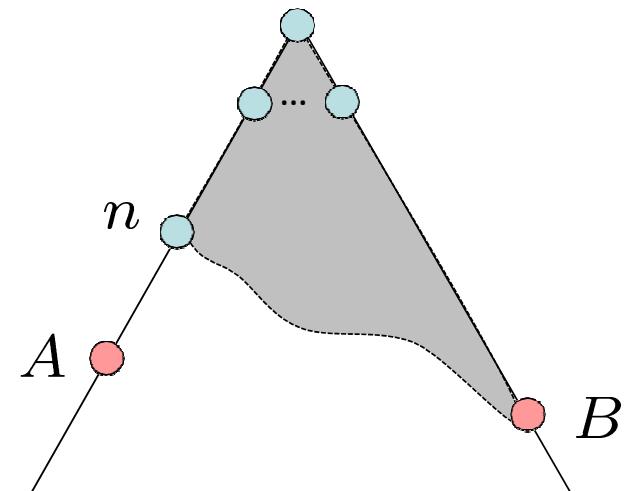
$$f(B) = g(B) = (\text{path cost to } B)$$

- We assumed that B is suboptimal! So

$$(\text{path cost to } A) < (\text{path cost to } B)$$

$$g(A) < g(B)$$

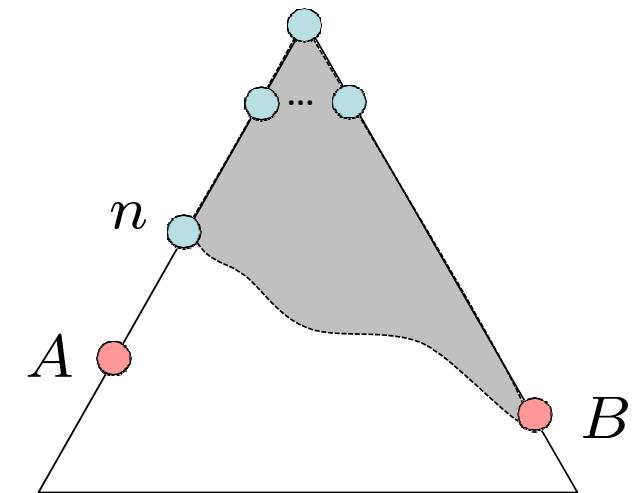
$$f(A) < f(B)$$



# 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  $f(A)$
  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

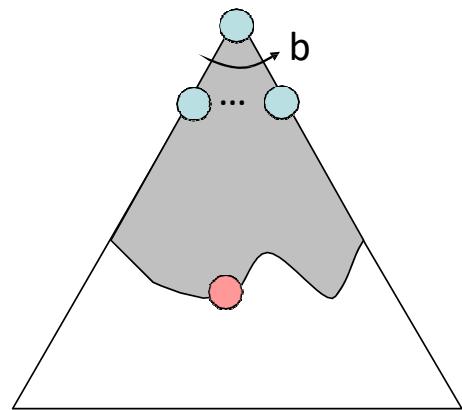


$$f(n) \leq f(A) < f(B)$$

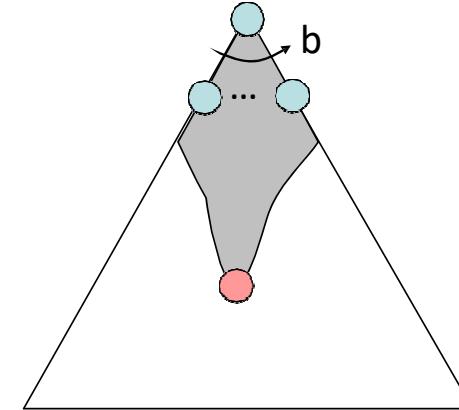
# Properties of A\*

# Properties of A\*

Uniform-Cost

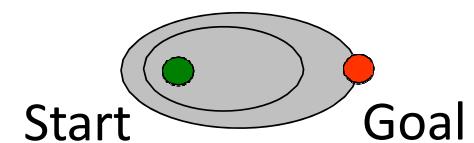
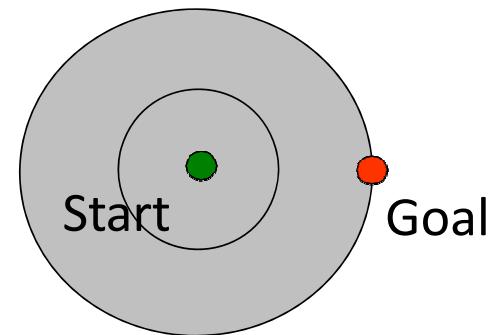


A\*



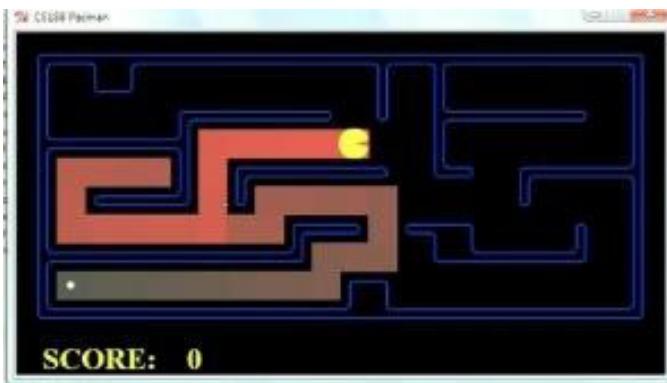
# UCS vs A\* Contours

- Uniform-cost expands equally in all “directions”
- A\* expands mainly toward the goal, but does hedge its bets to ensure optimality

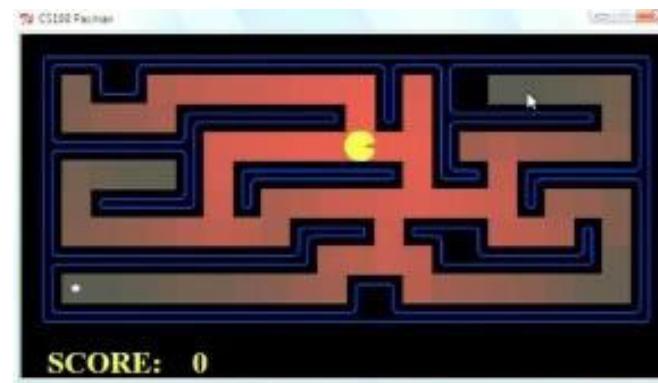


[Demo: contours UCS / greedy / A\* empty (L3D1)]  
[Demo: contours A\* pacman small maze (L3D5)]

# Comparison



Greedy



Uniform Cost



A\*

# A\* Applications

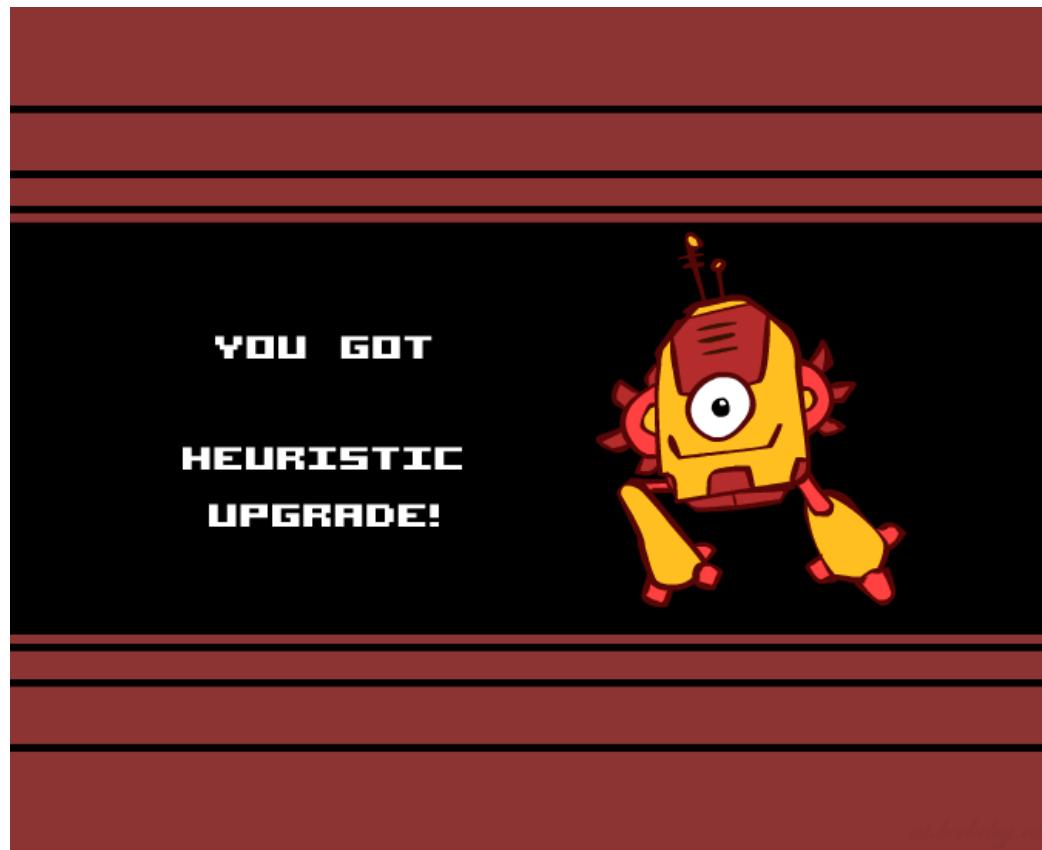
- Video games
- Pathing / routing problems
- Resource planning problems
- Robot motion planning
- Language analysis
- Machine translation
- Speech recognition
- ...



[Demo: UCS / A\* pacman tiny maze (L3D6,L3D7)]  
[Demo: guess algorithm Empty Shallow/Deep (L3D8)]

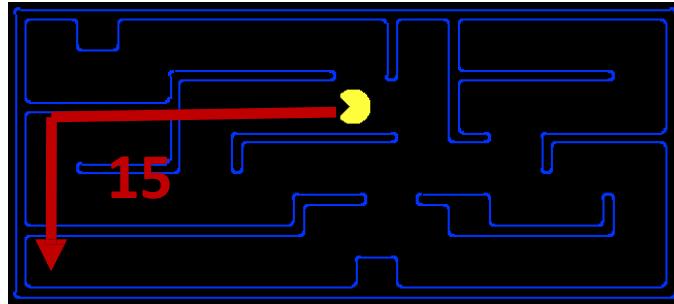
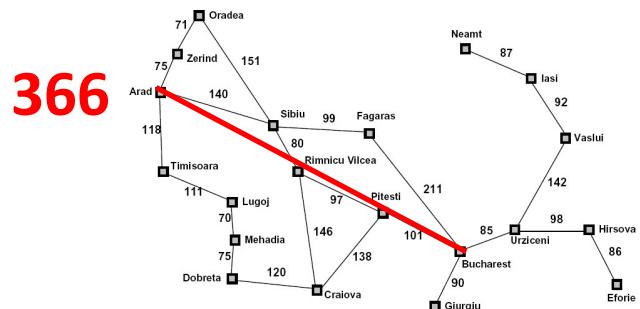
# Creating Heuristics

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# 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

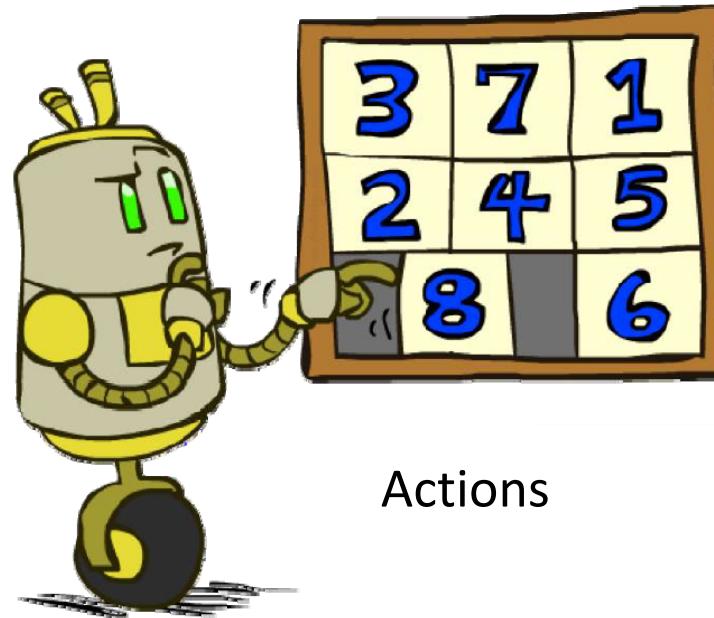


- Inadmissible heuristics are often useful too

# Example: 8 Puzzle

7	2	4
5		6
8	3	1

Start State



Actions

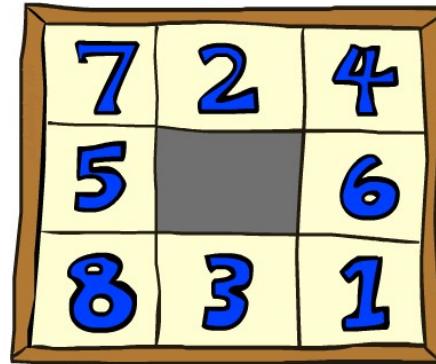
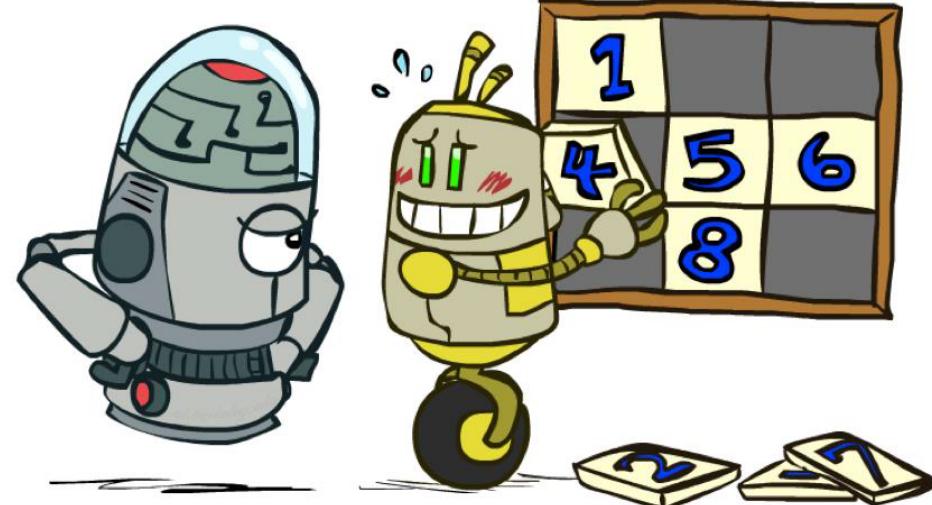
	1	2
3	4	5
6	7	8

Goal State

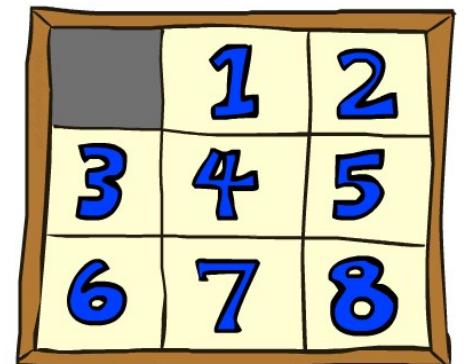
- What are the states?
- How many states?
- What are the actions?
- How many successors from the start state?
- What should the costs be?

# 8 Puzzle I

- Heuristic: Number of tiles misplaced
- Why is it admissible?
- $h(\text{start}) = 8$
- This is a *relaxed-problem* heuristic



Start State



Goal State

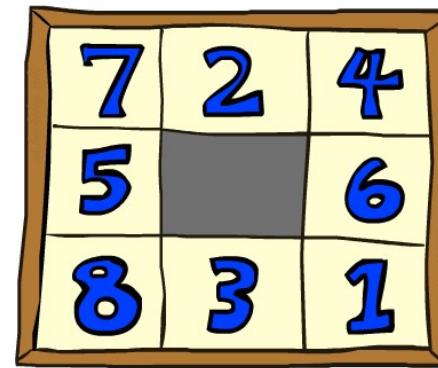
Average nodes expanded  
when the optimal path has...

	...4 steps	...8 steps	...12 steps
UCS	112	6,300	$3.6 \times 10^6$
TILES	13	39	227

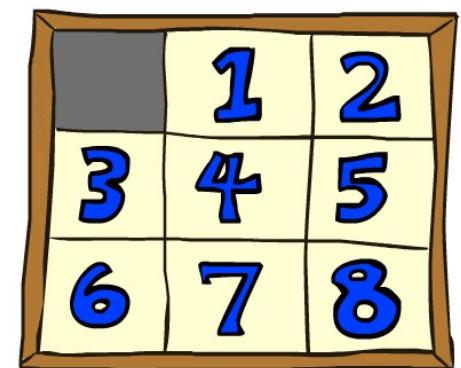
Statistics from Andrew Moore

# 8 Puzzle II

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



Start State



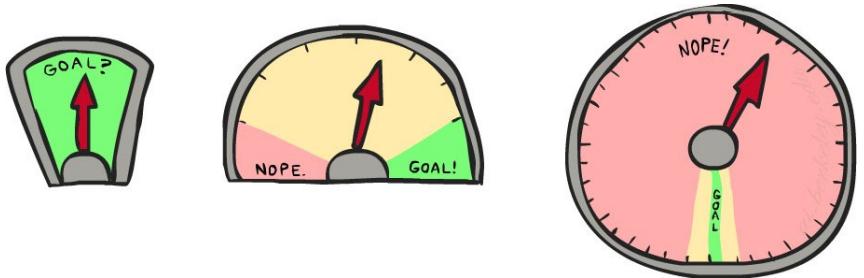
Goal State

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

# 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

- As heuristics get closer to the true cost, you will expand fewer nodes but usually do more work per node to compute the heuristic itself

# Semi-Lattice of Heuristics

# Trivial Heuristics, Dominance

- Dominance:  $h_a \geq h_c$  if

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

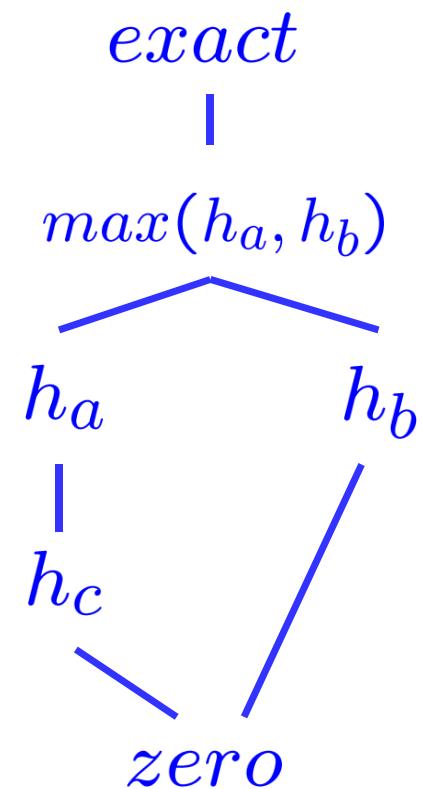
- Heuristics form a semi-lattice:

- Max of admissible heuristics is admissible

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

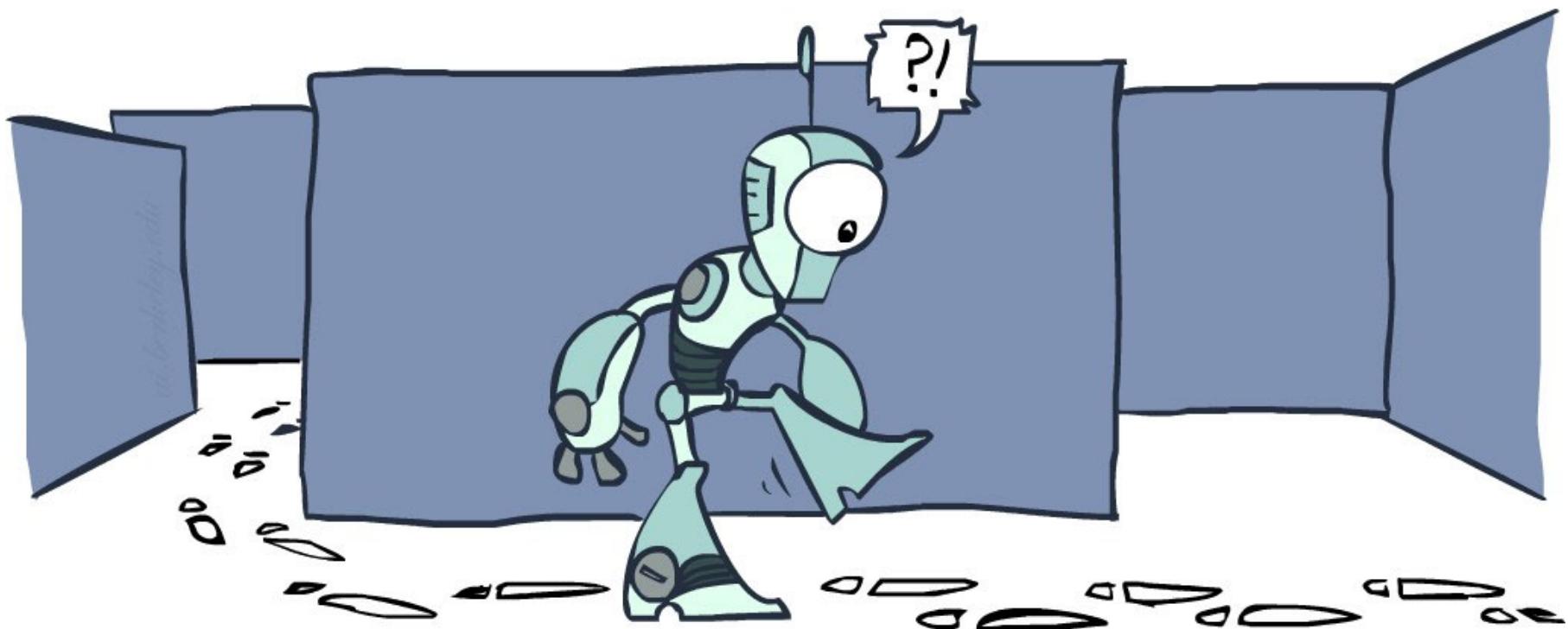
- Trivial heuristics

- Bottom of lattice is the zero heuristic (what does this give us?)
  - Top of lattice is the exact heuristic



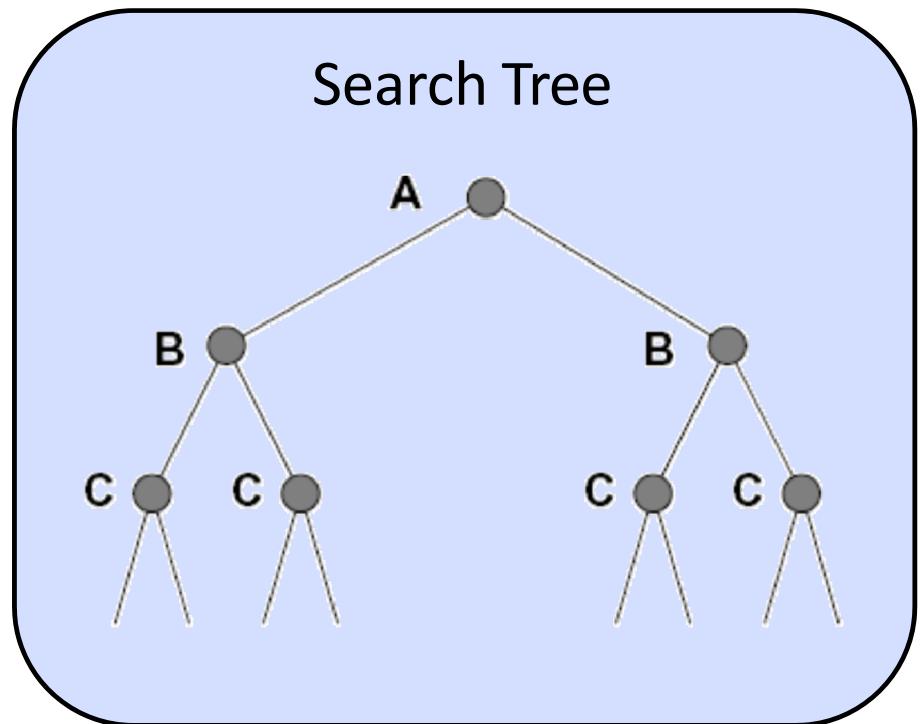
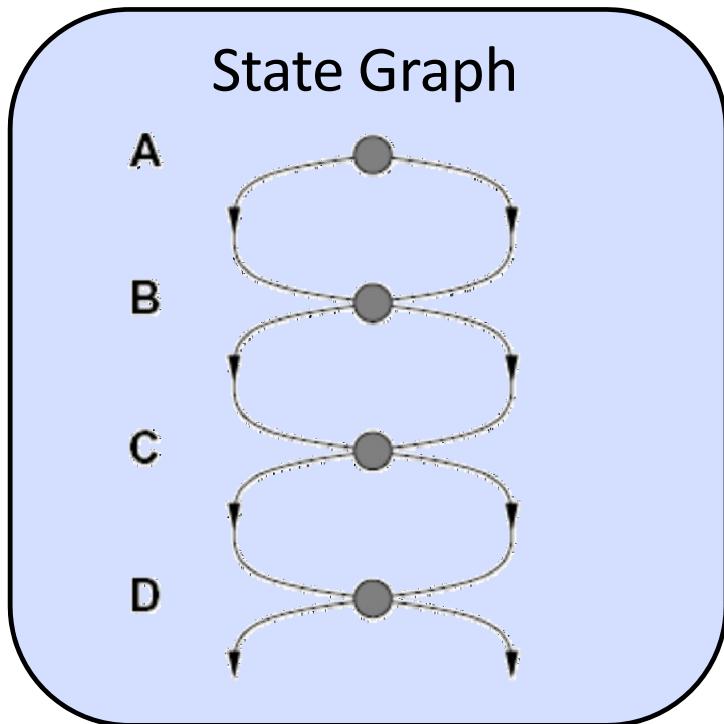
# Graph Search

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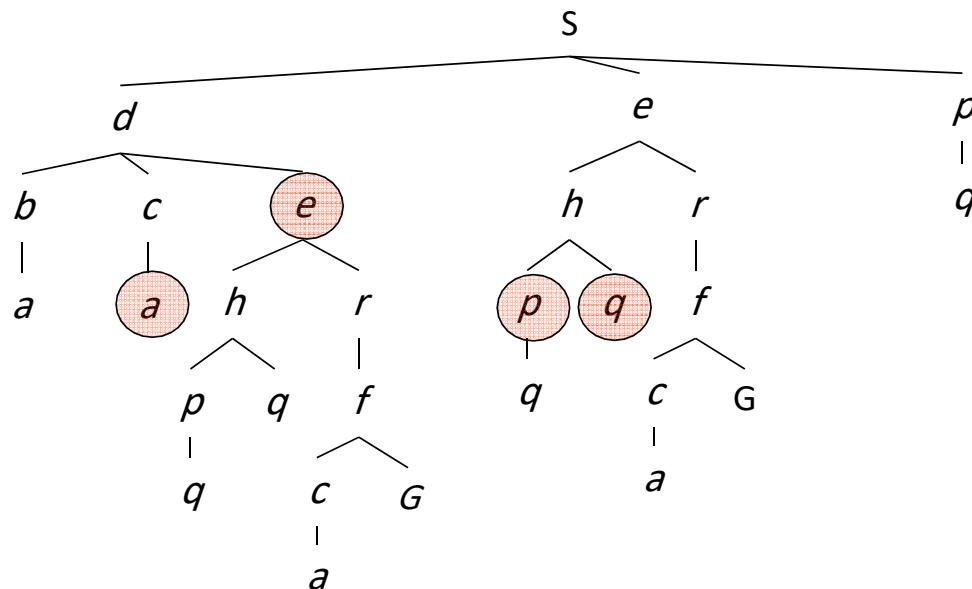
# Tree Search: Extra Work!

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



# Graph Search

- In BFS, for example, we shouldn't bother expanding the circled nodes (why?)



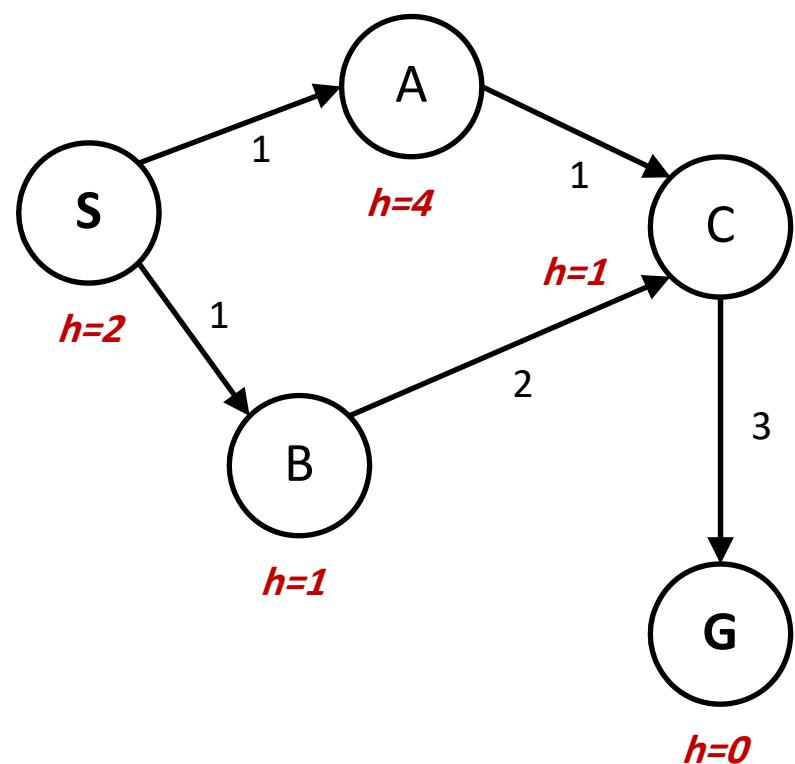
# Graph Search

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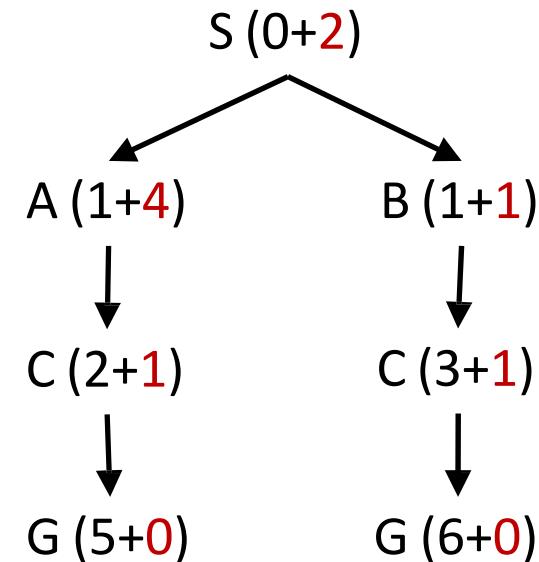
- Idea: never **expand** a state twice
- How to implement:
  - Tree search + set of expanded states (“closed set”)
  - Expand the search tree node-by-node, but...
  - Before expanding a node, check to make sure its state has never been expanded before
  - If not new, skip it, if new add to closed set
- Important: **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?

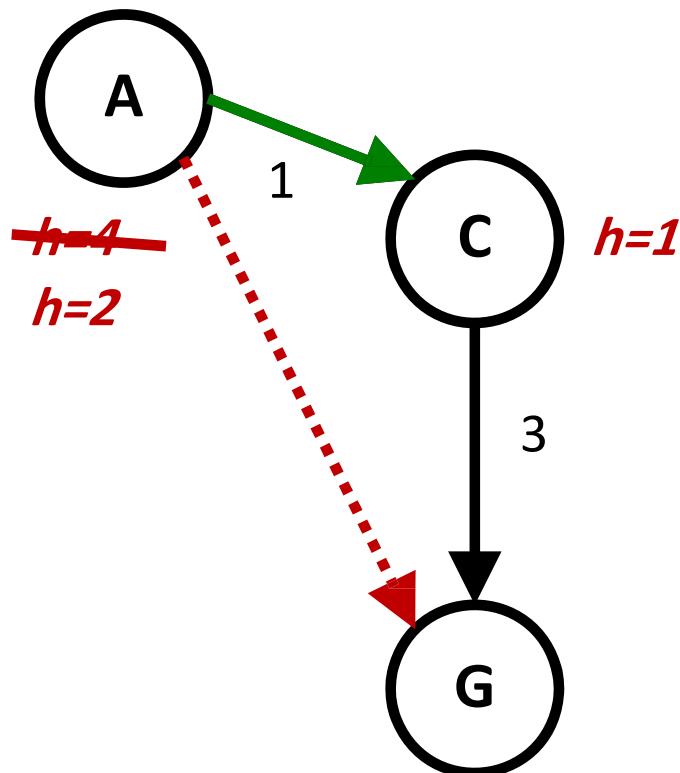
State space graph



Search tree



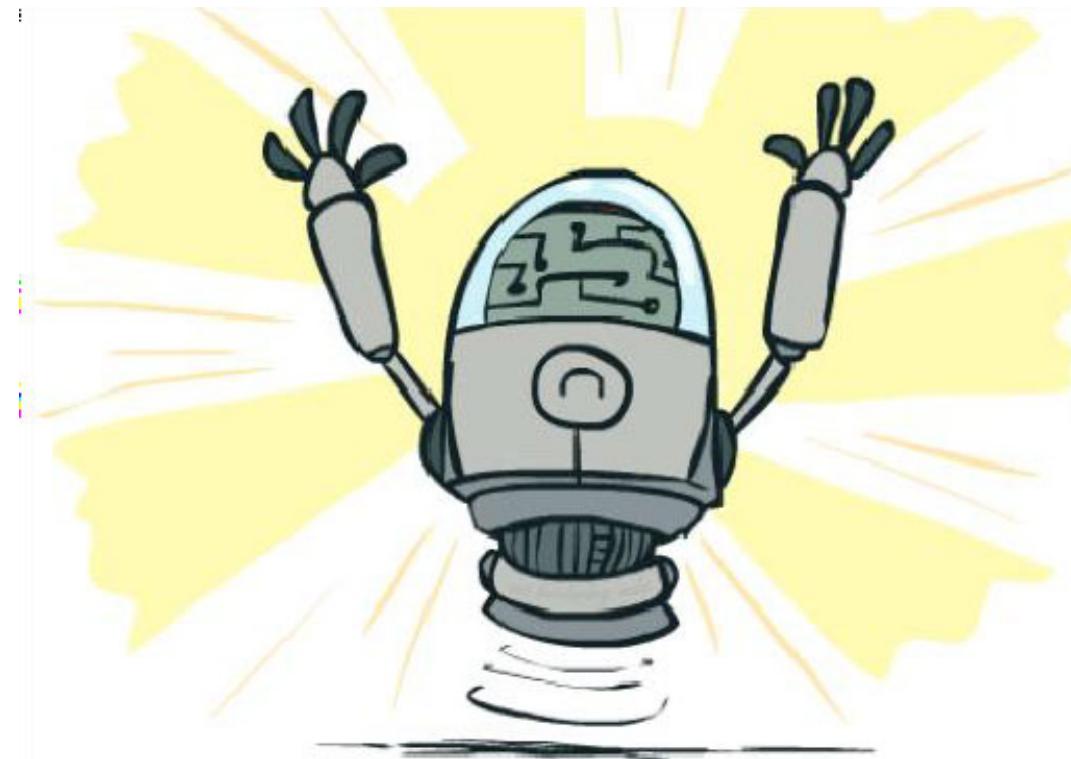
# Consistency of Heuristics



- Main idea: estimated heuristic costs  $\leq$  actual costs
  - Admissibility: heuristic cost  $\leq$  actual cost to goal
$$h(A) \leq \text{actual cost from } A \text{ to } G$$
  - Consistency: heuristic “arc” cost  $\leq$  actual cost for each arc
$$h(A) - h(C) \leq \text{cost}(A \text{ to } C)$$
- Consequences of consistency:
  - The f value along a path never decreases
$$h(A) \leq \text{cost}(A \text{ to } C) + h(C)$$
  - A\* graph search is optimal

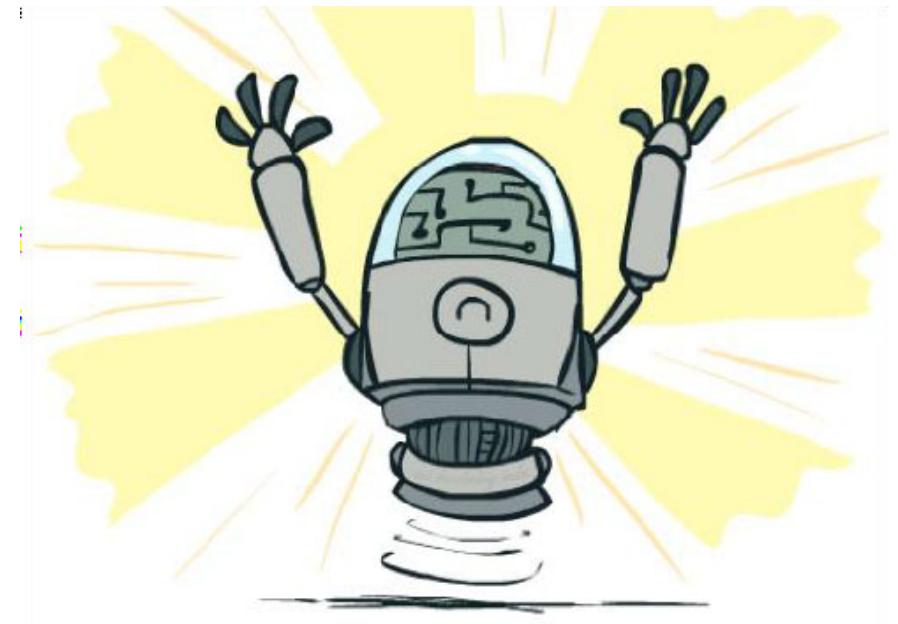
# Optimality of A\* Graph Search

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# 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



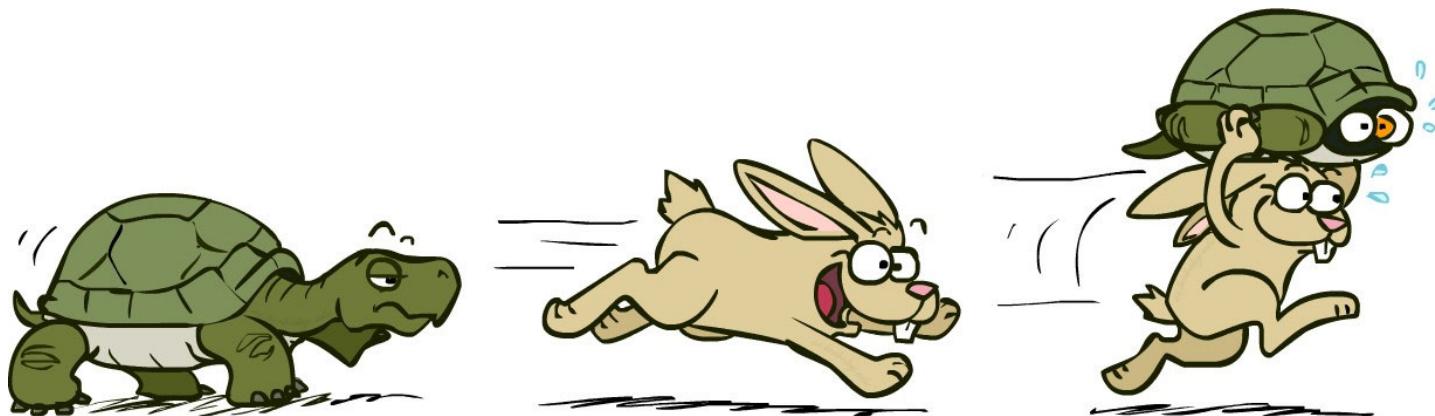
# A\*: Summary

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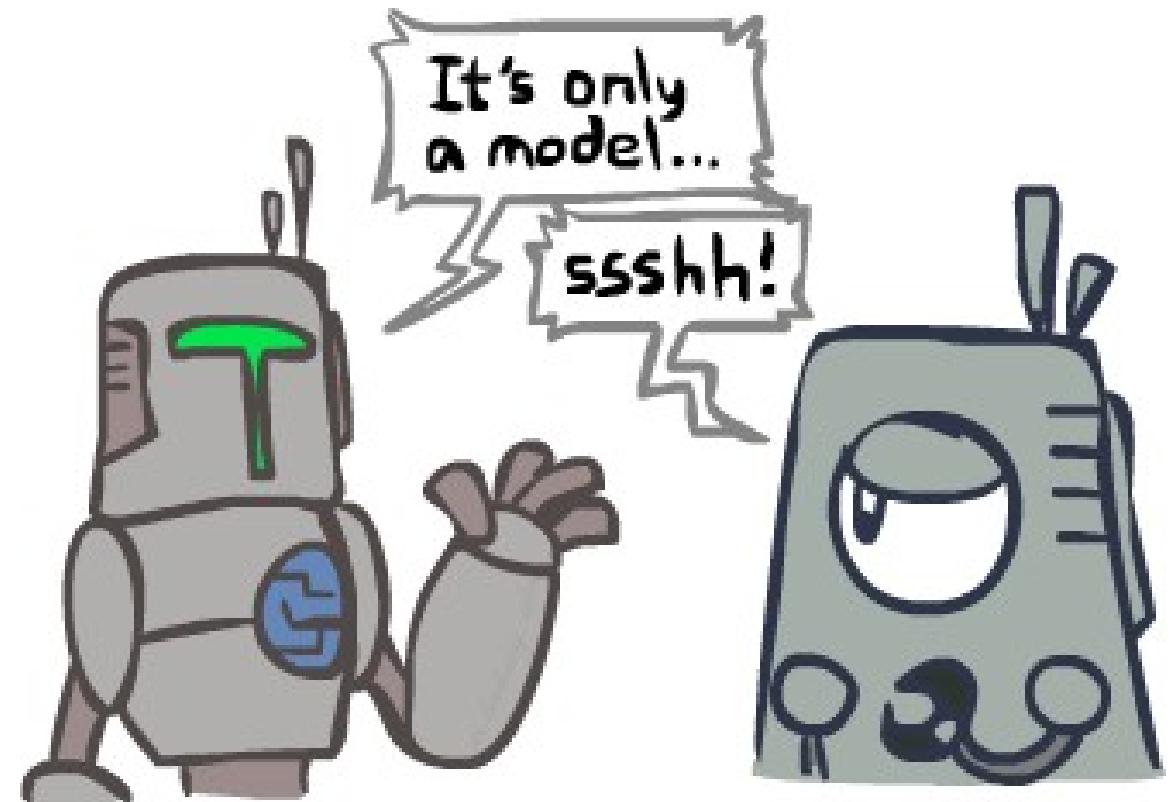
# A\*: Summary

- 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



# Search and Models

- Search operates over models of the world
  - The agent doesn't actually try all the plans out in the real world!
  - Planning is all “in simulation”
  - Your search is only as good as your models...



# Appendix: Search Pseudo-Code

# Tree Search Pseudo-Code

```
function TREE-SEARCH(problem, fringe) return a solution, or failure
  fringe  $\leftarrow$  INSERT(MAKE-NODE(INITIAL-STATE[problem]), fringe)
  loop do
    if fringe is empty then return failure
    node  $\leftarrow$  REMOVE-FRONT(fringe)
    if GOAL-TEST(problem, STATE[node]) then return node
    for child-node in EXPAND(STATE[node], problem) do
      fringe  $\leftarrow$  INSERT(child-node, fringe)
    end
  end
```

# Graph Search Pseudo-Code

```
function GRAPH-SEARCH(problem, fringe) return a solution, or failure
  closed ← an empty set
  fringe ← INSERT(MAKE-NODE(INITIAL-STATE[problem]), fringe)
  loop do
    if fringe is empty then return failure
    node ← REMOVE-FRONT(fringe)
    if GOAL-TEST(problem, STATE[node]) then return node
    if STATE[node] is not in closed then
      add STATE[node] to closed
      for child-node in EXPAND(STATE[node], problem) do
        fringe ← INSERT(child-node, fringe)
    end
  end
```