



Budapest University of Technology and Economics  
Department of Artificial Intelligence and Systems Engineering

# Artificial intelligence – VIMIAC16-EN, VIMIAC10

## Informed Search

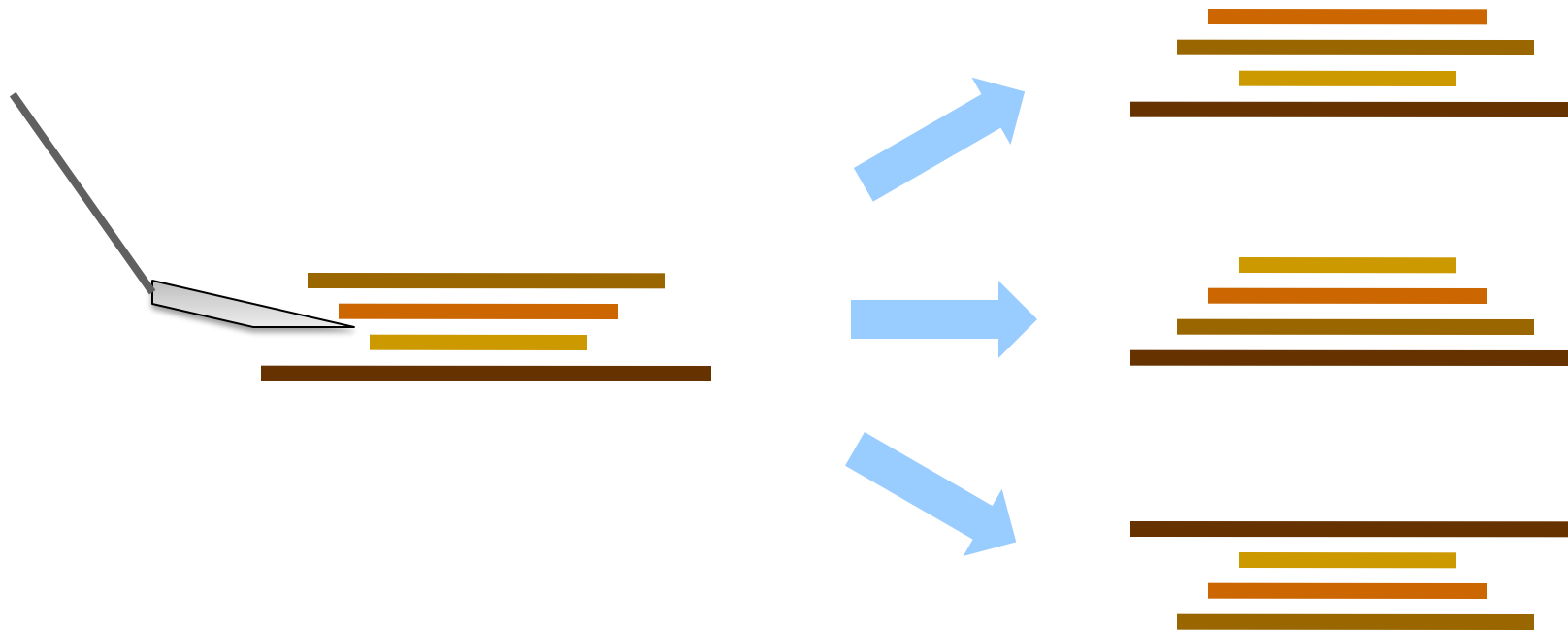
These slides are based on the AIMA book (<http://aima.cs.berkeley.edu>) and were adapted from the AI course material of University of California, Berkeley (<http://ai.berkeley.edu>).  
Original slides were created by Dan Klein and Pieter Abbeel for CS188 Intro to AI at UC Berkeley.

Lecturer: Dr. Gabor Hullam



# Example: Pancake Problem

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Cost: Number of pancakes flipped

# Example: Pancake Problem

## **BOUNDS FOR SORTING BY PREFIX REVERSAL**

William H. GATES

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*Department of Electrical Engineering, University of California, Berkeley, CA 94720, U.S.A.*

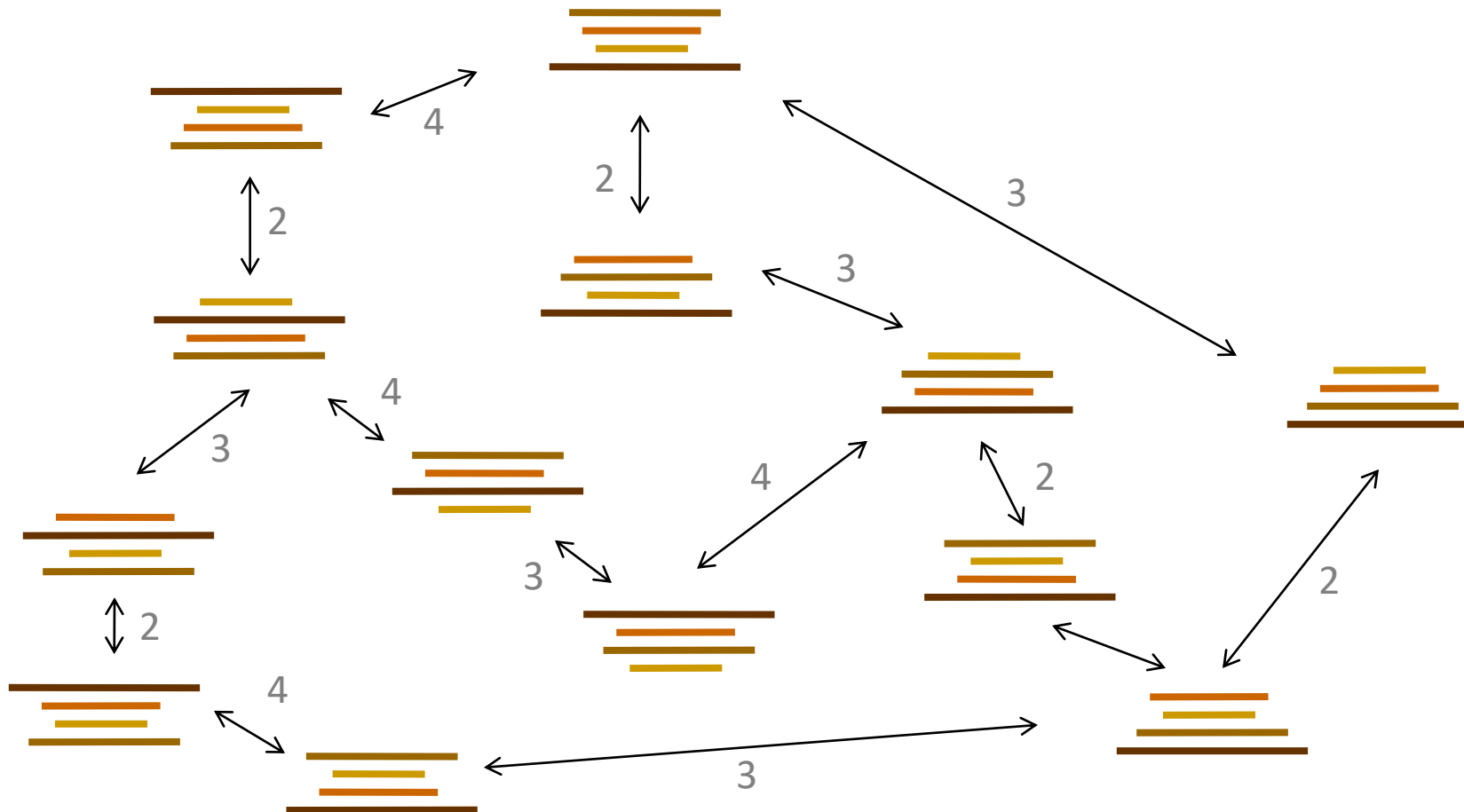
Received 18 January 1978

Revised 28 August 1978

For a permutation  $\sigma$  of the integers from 1 to  $n$ , let  $f(\sigma)$  be the smallest number of prefix reversals that will transform  $\sigma$  to the identity permutation, and let  $f(n)$  be the largest such  $f(\sigma)$  for all  $\sigma$  in (the symmetric group)  $S_n$ . We show that  $f(n) \leq (5n+5)/3$ , and that  $f(n) \geq 17n/16$  for  $n$  a multiple of 16. If, furthermore, each integer is required to participate in an even number of reversed prefixes, the corresponding function  $g(n)$  is shown to obey  $3n/2 - 1 \leq g(n) \leq 2n + 3$ .

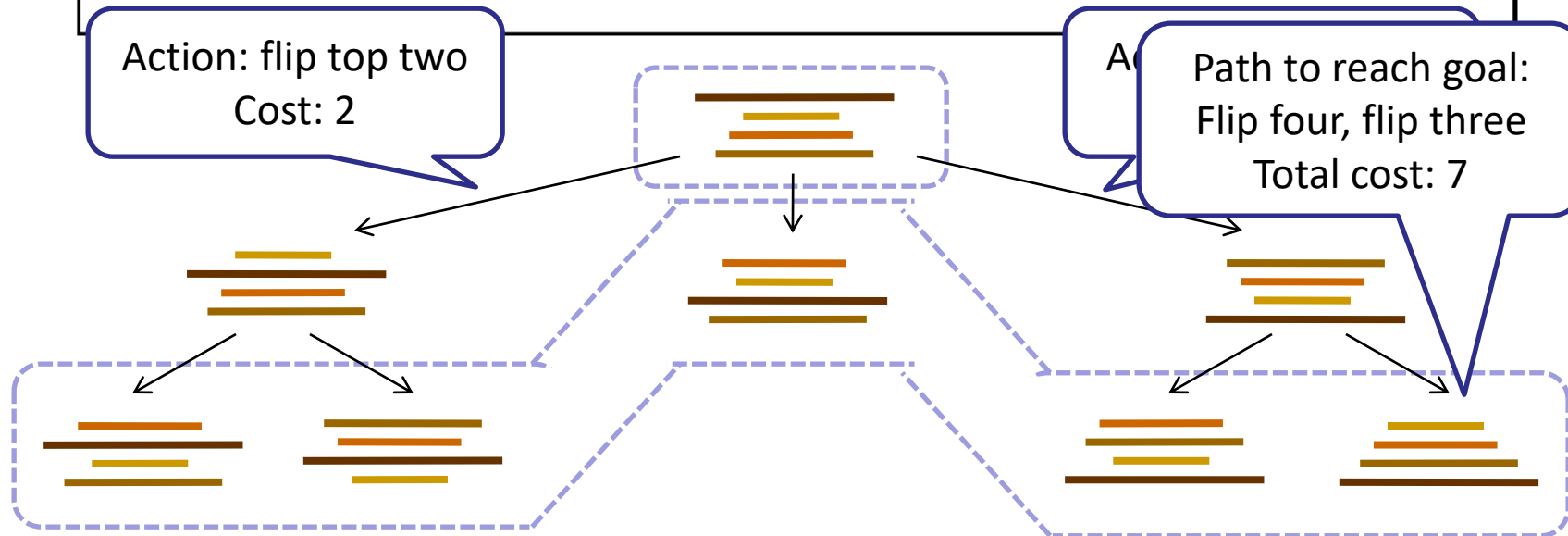
# Example: Pancake Problem

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
```



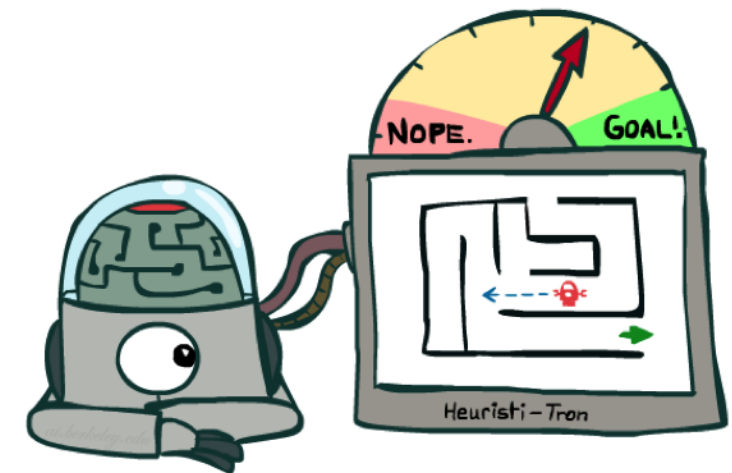
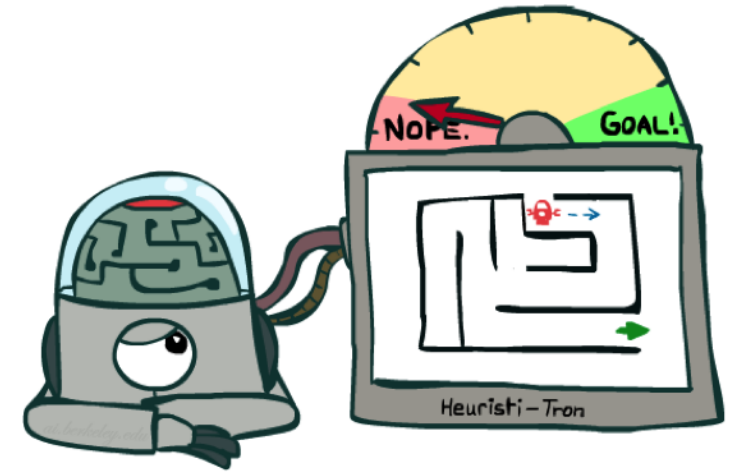
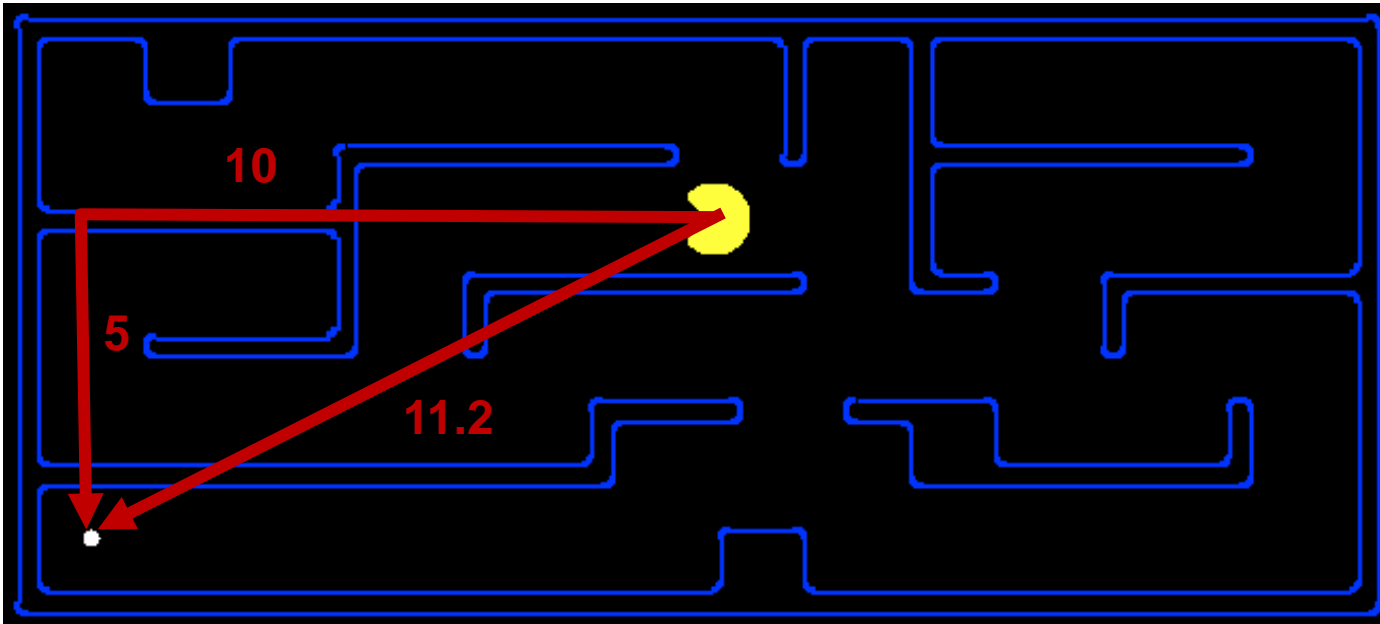
# Informed Search

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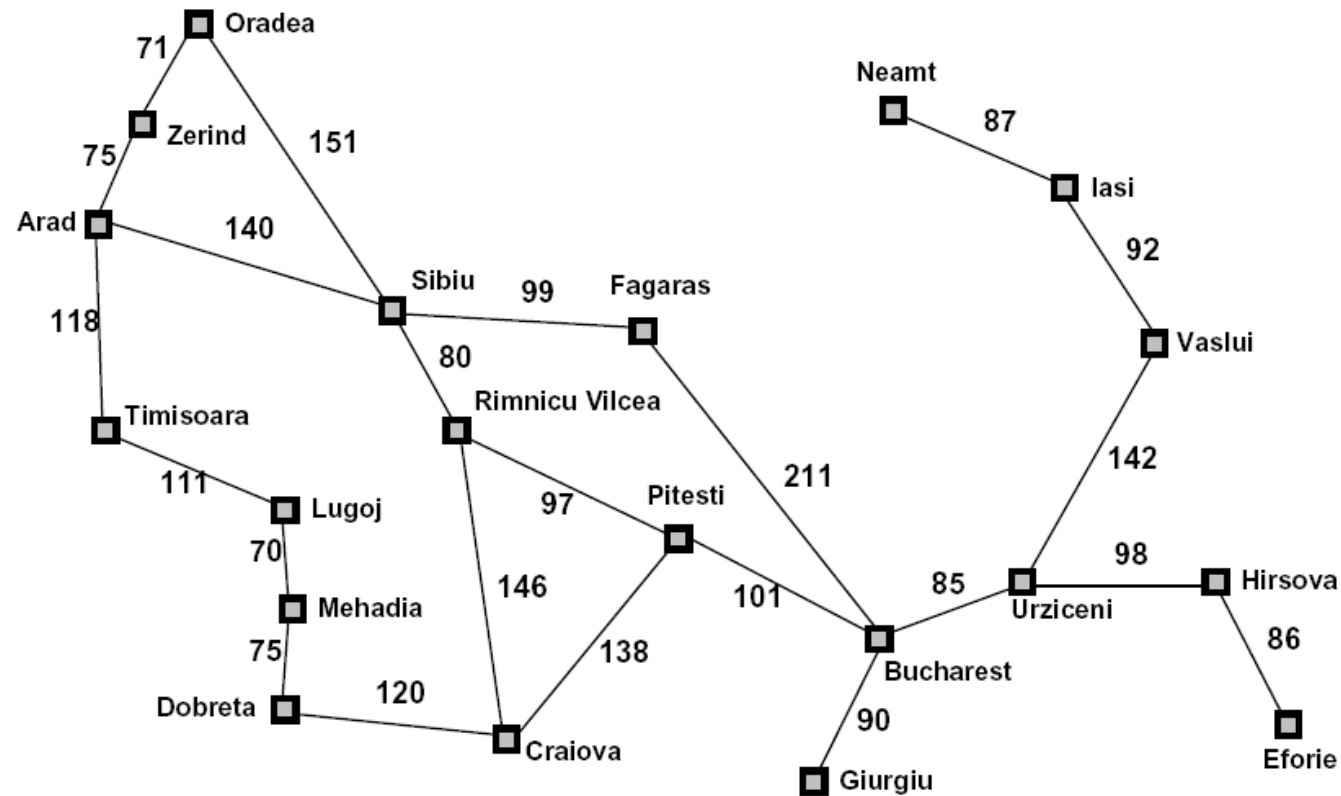


# Search Heuristics

- 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



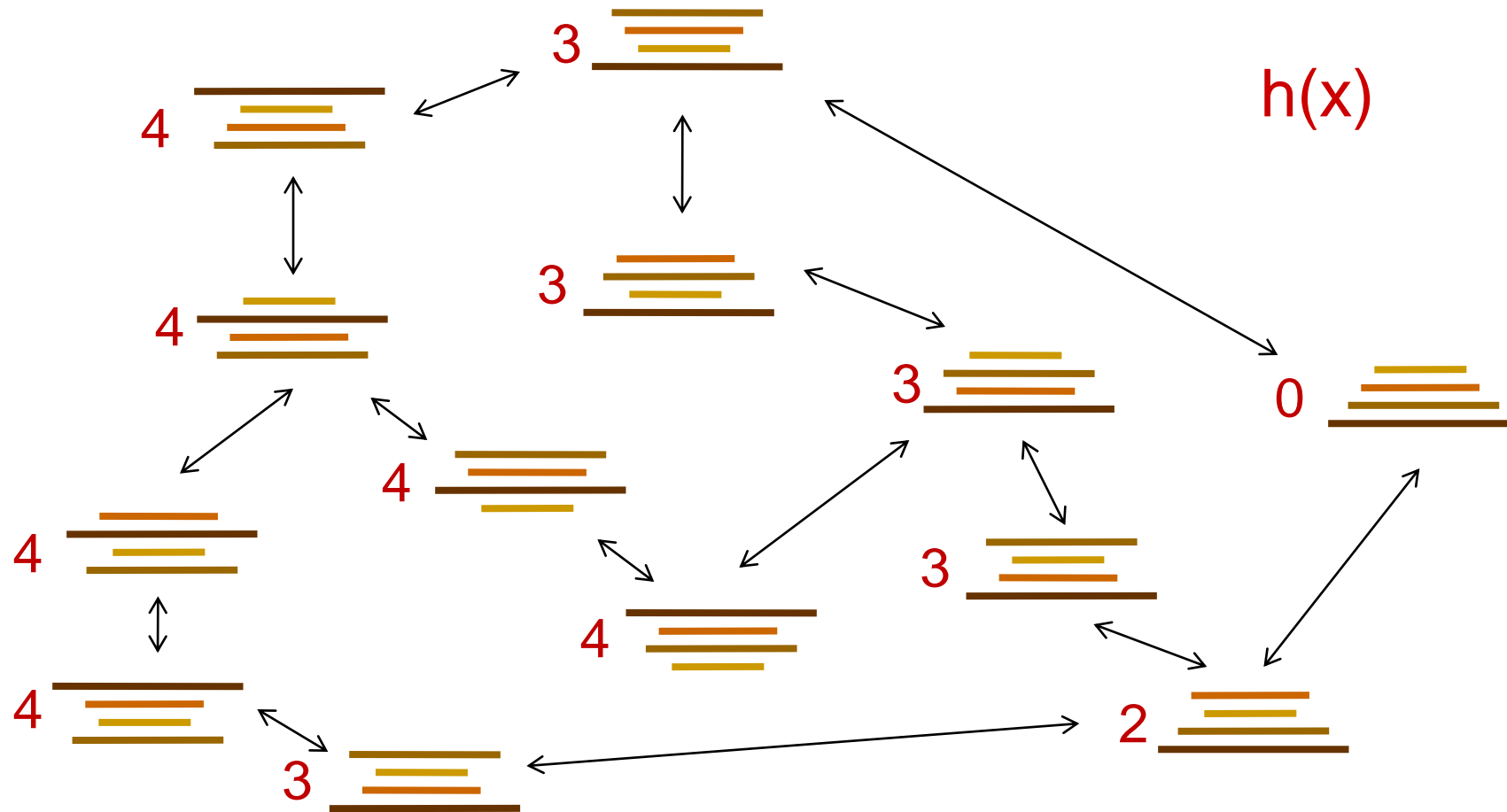
Straight-line distance to Bucharest	
Arad	366
Bucharest	0
Craiova	160
Dobreta	242
Eforie	161
Fagaras	178
Giurgiu	77
Hirsova	151
Iasi	226
Lugoj	244
Mehadia	241
Neamt	234
Oradea	380
Pitesti	98
Rimnicu Vilcea	193
Sibiu	253
Timisoara	329
Urziceni	80
Vaslui	199
Zerind	374

$h(x)$



# Example: Heuristic Function

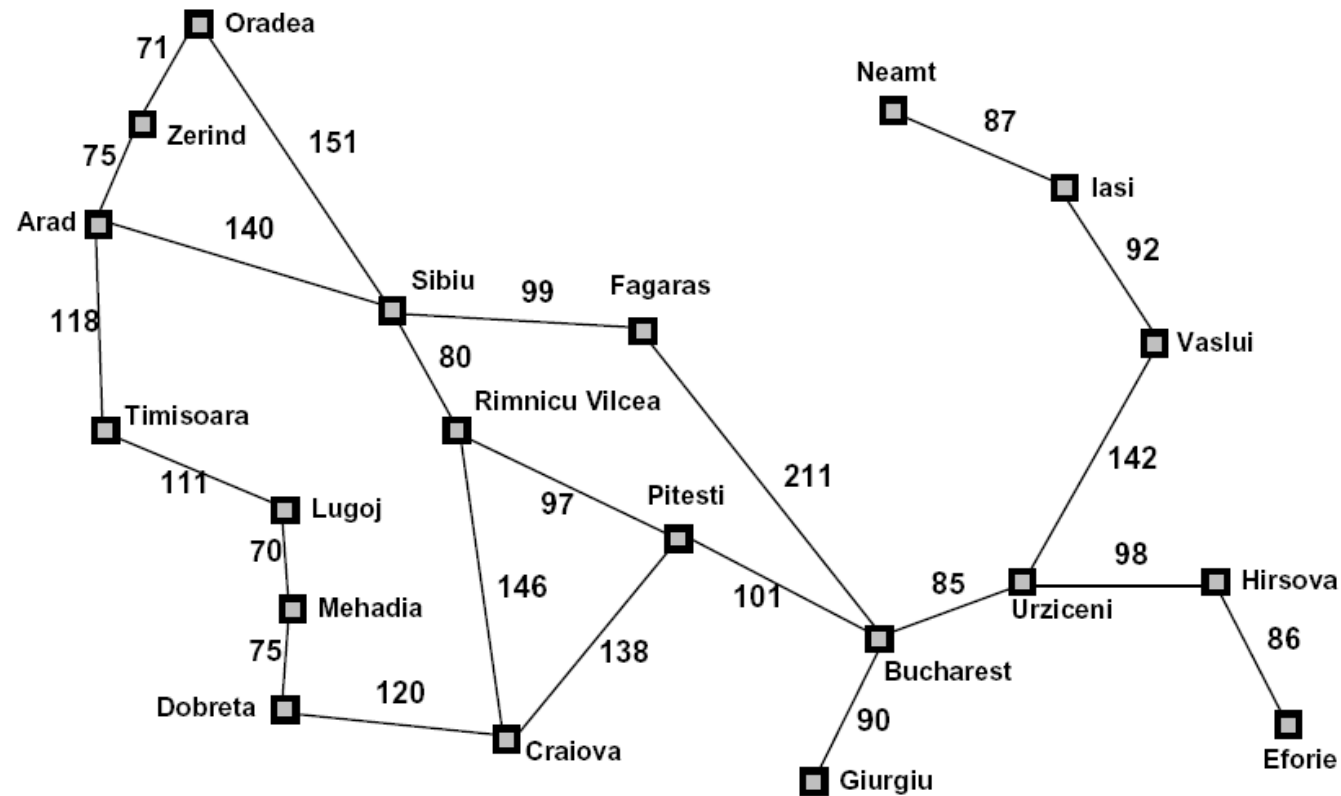
Heuristic: the number of the largest pancake that is still out of place



# Greedy Search



# Example: Heuristic Function



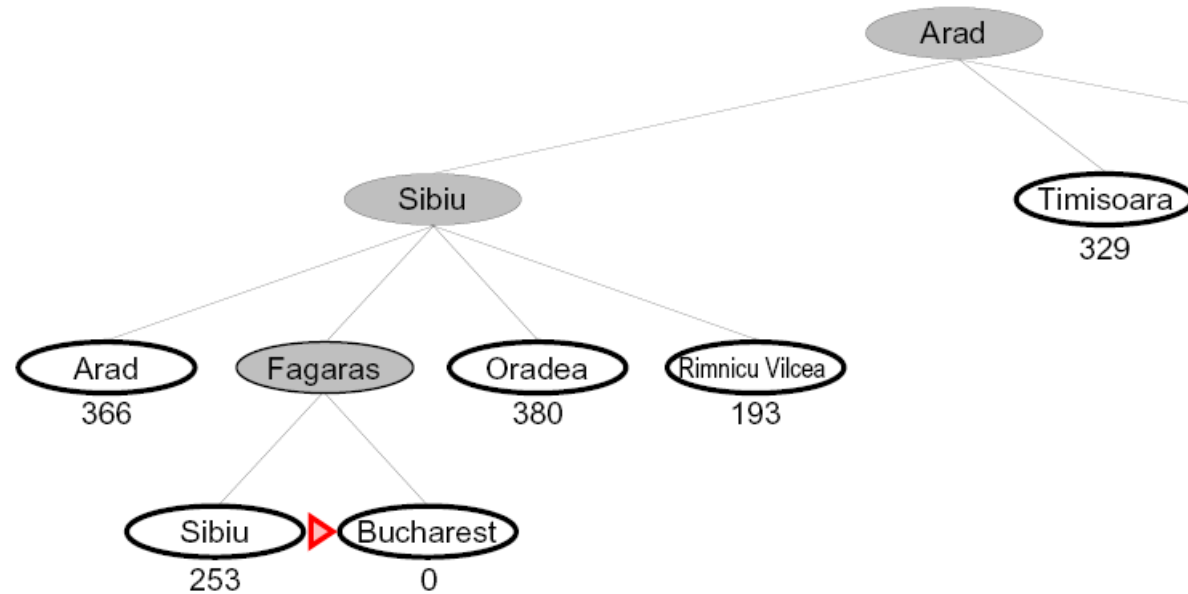
Straight-line distance  
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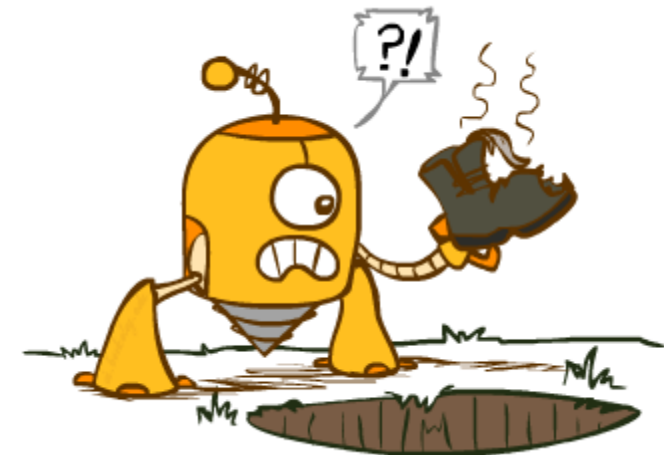
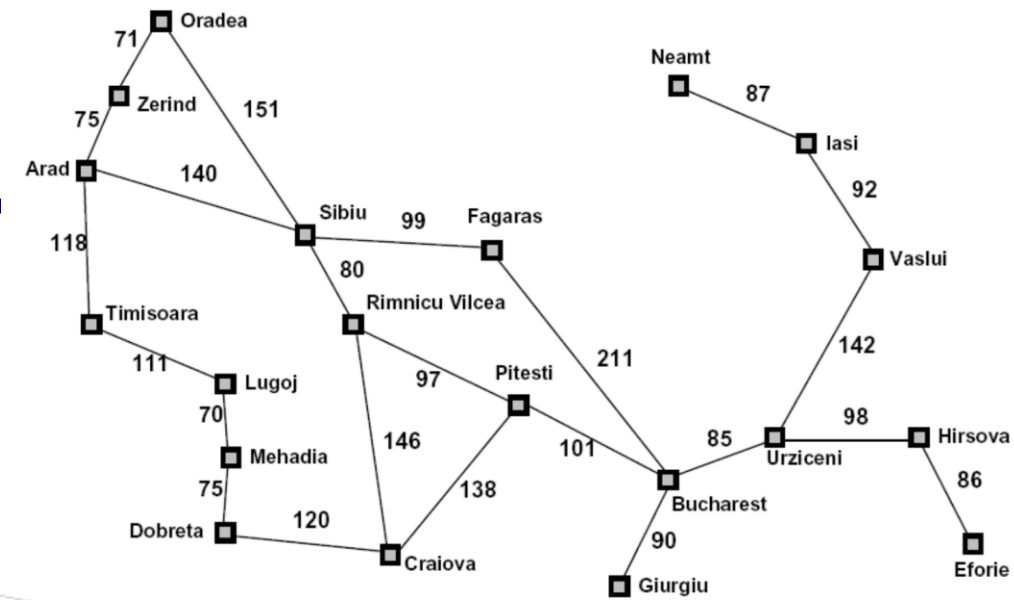
$h(x)$

# Greedy Search

- Expand the node that seems closest...

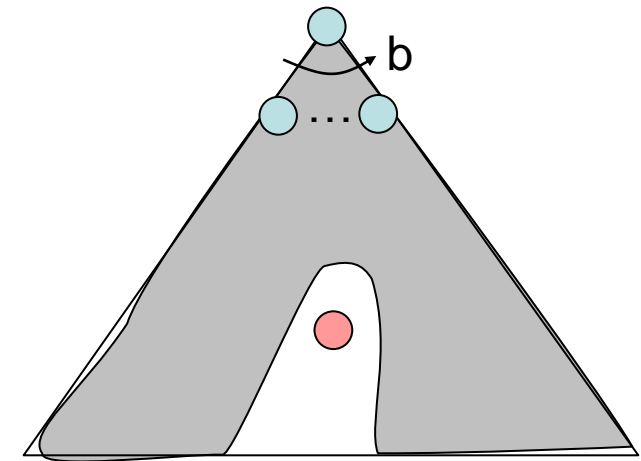
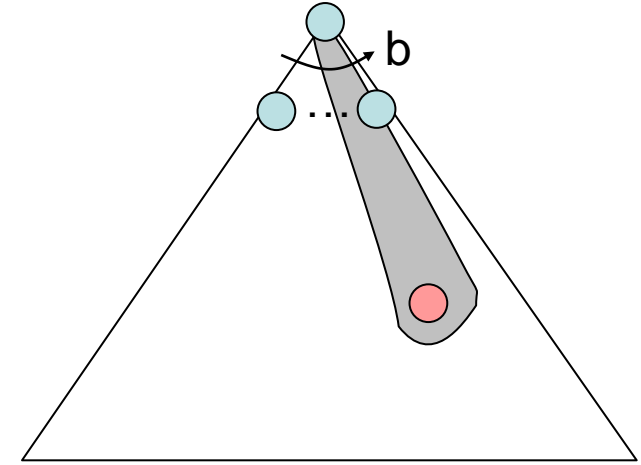


- What can go wrong?



# 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



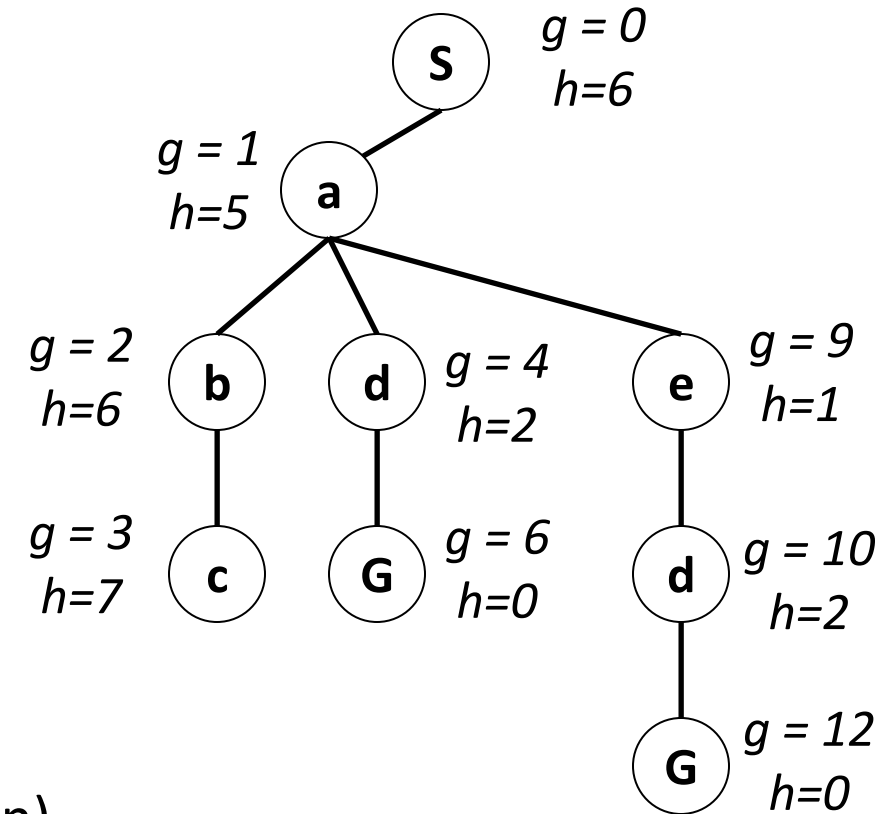
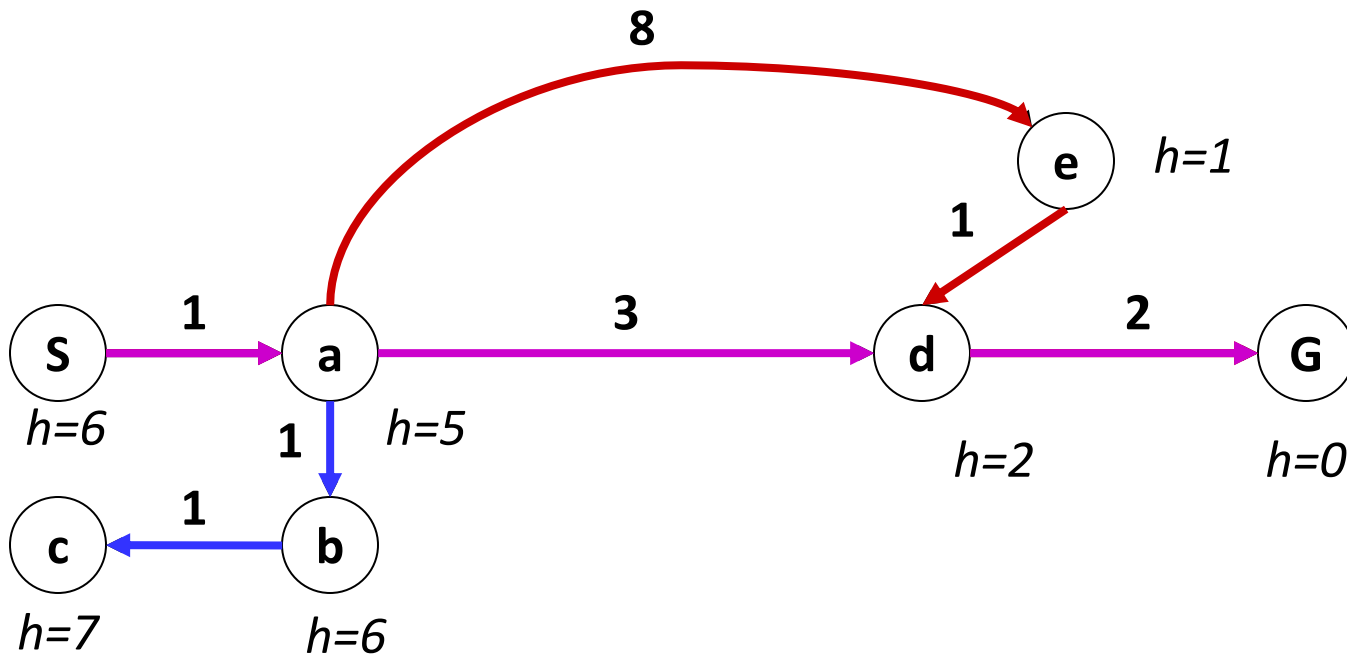
# A\* Search

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# Combining UCS and Greedy

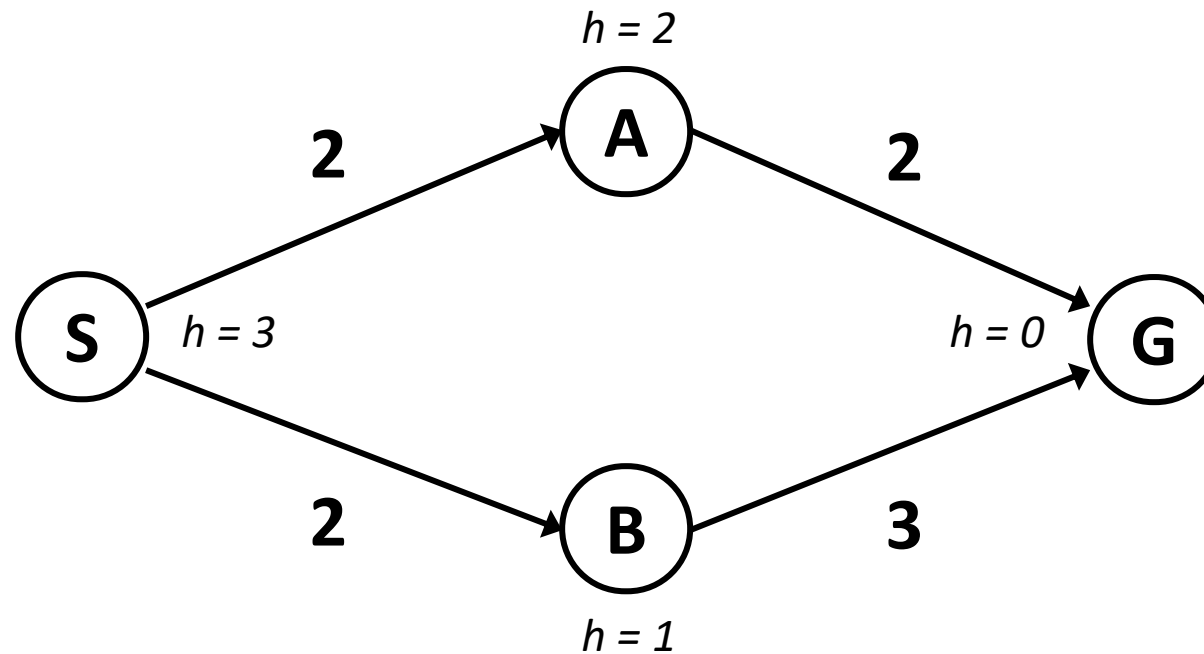
- **Uniform-cost** orders by path cost, or *backward cost*  $g(n)$
- **Greedy** orders by goal proximity, or *forward cost*  $h(n)$



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

# When should A\* terminate?

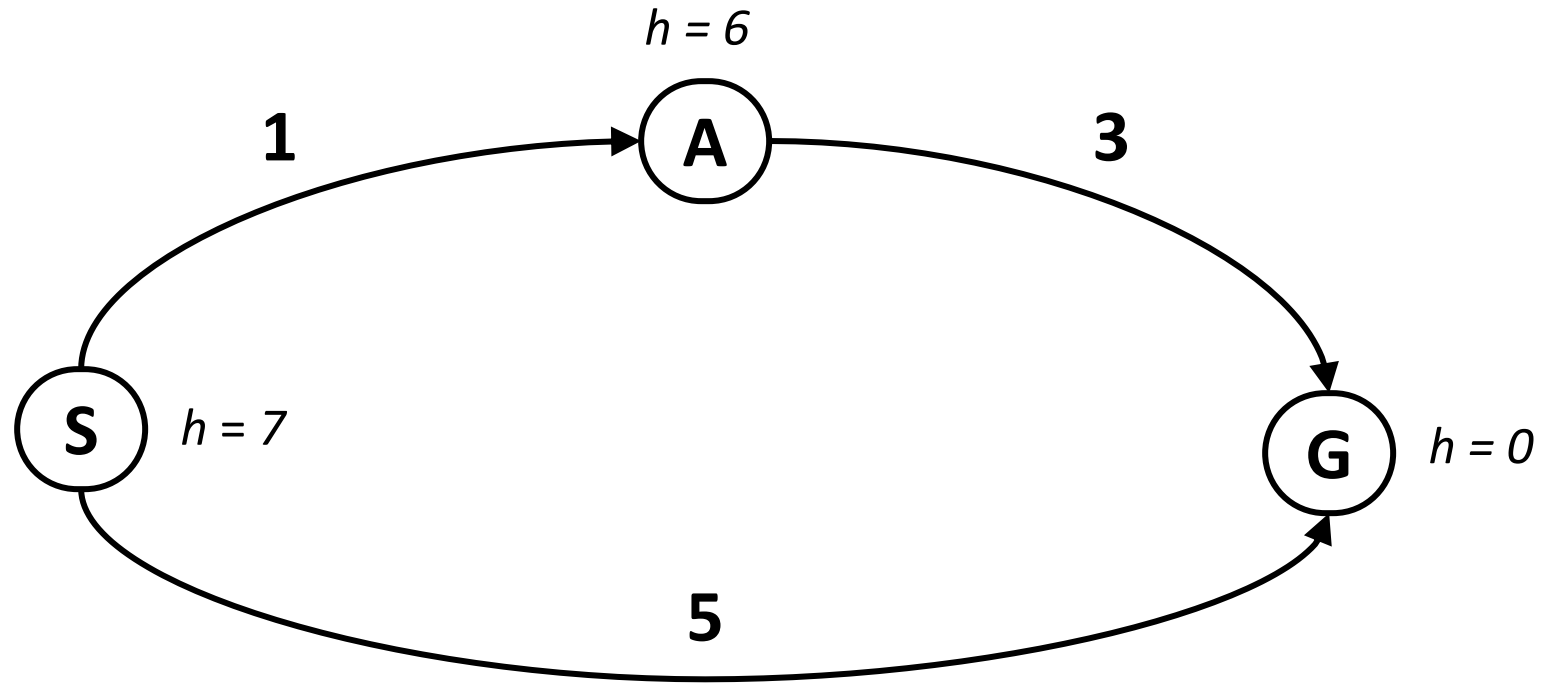
- Should we stop when we enqueue a goal?



- No: only stop when we dequeue a goal

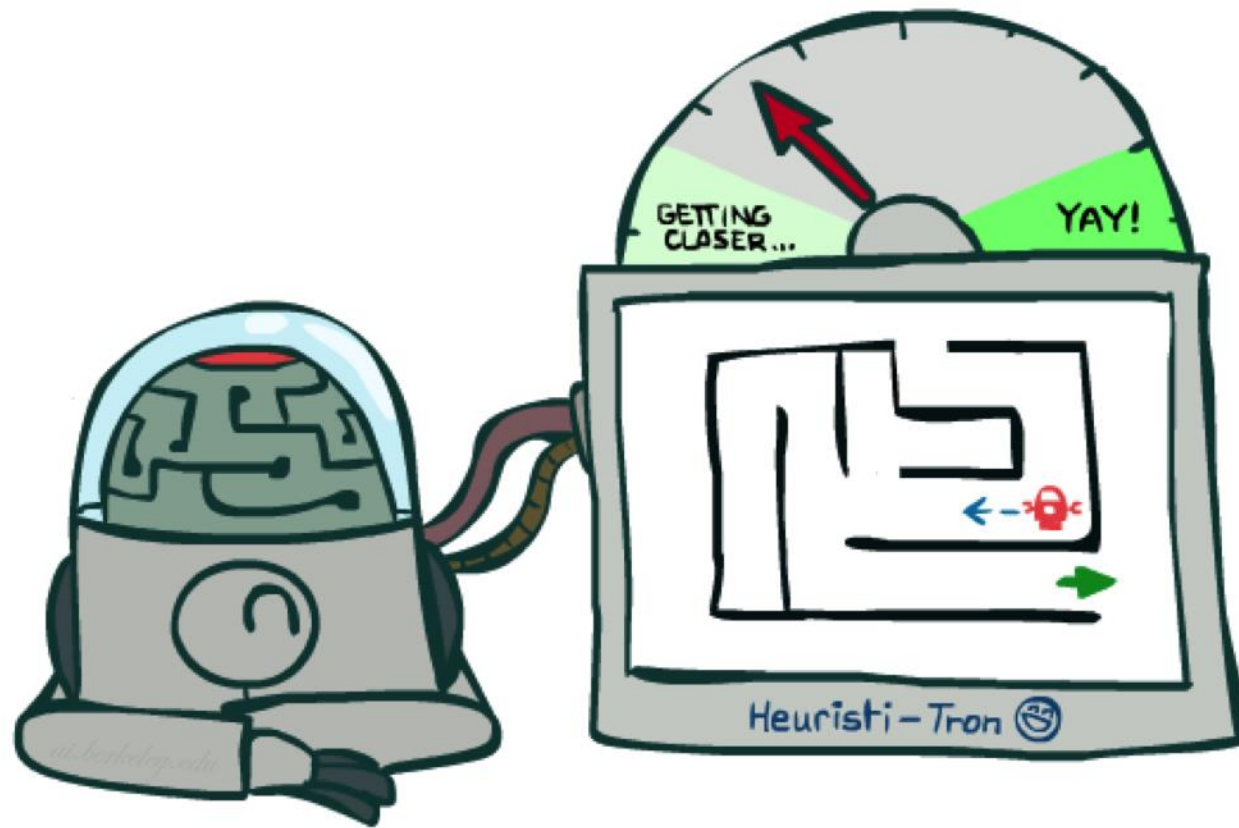


# Is A\* Optimal?

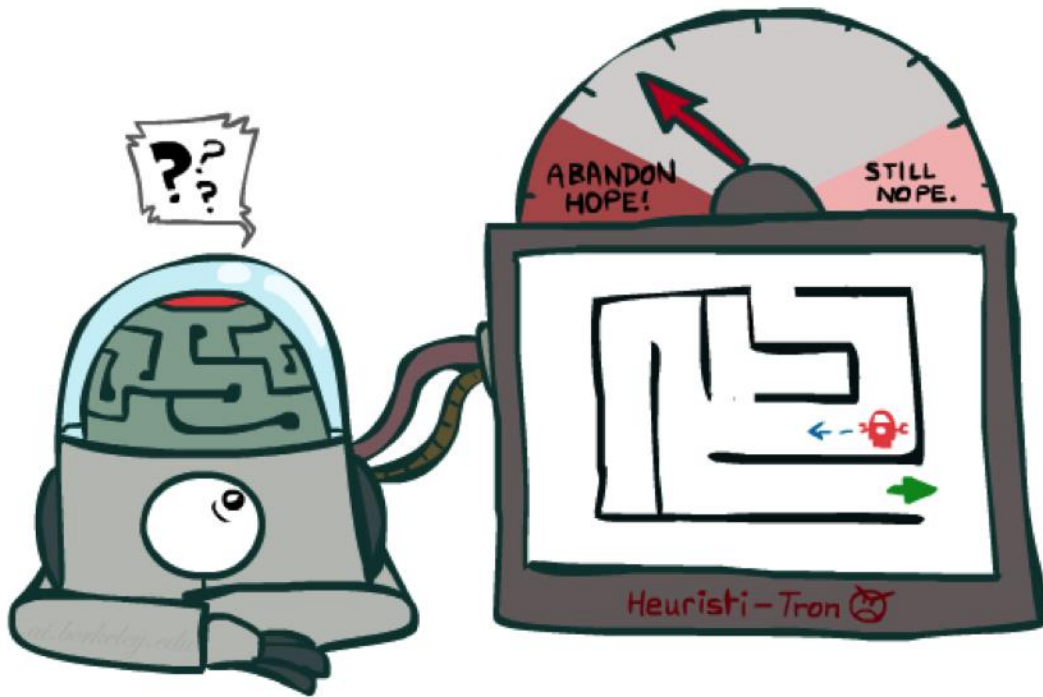


- What went wrong?
- Actual bad goal cost < estimated good goal cost
- We need estimates to be less than actual costs!

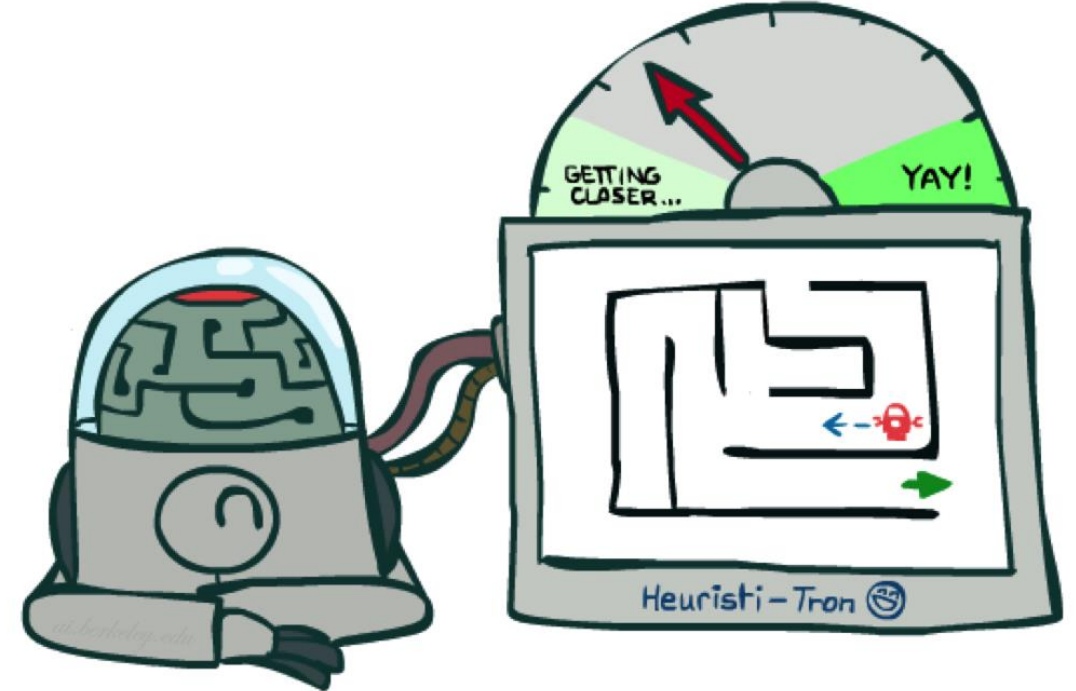
# Admissible Heuristics



# 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

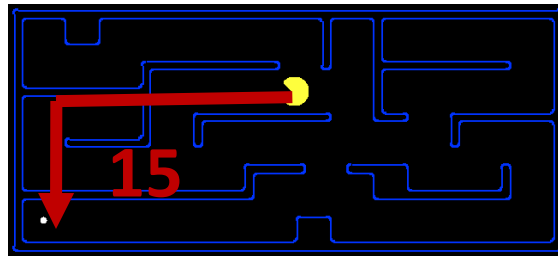
# Admissible Heuristics

- 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:



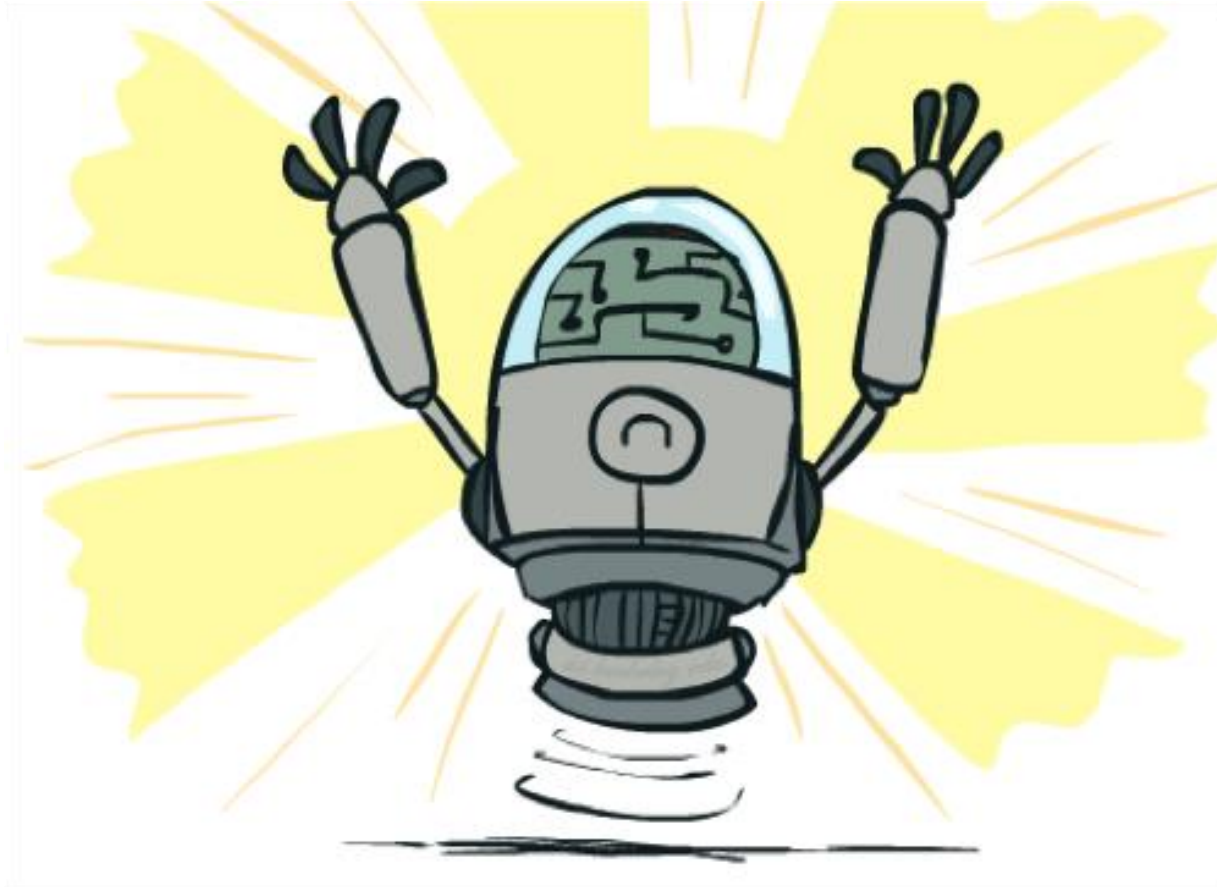
4



- 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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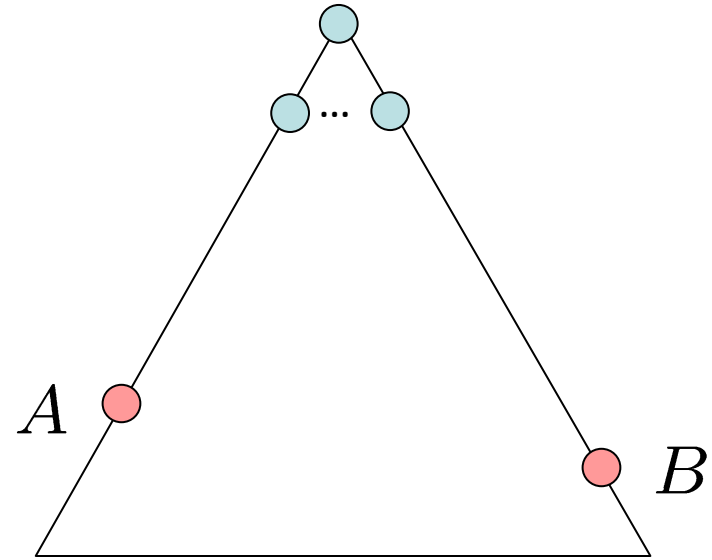
# Optimality of A\* Tree Search

Assume:

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

Claim:

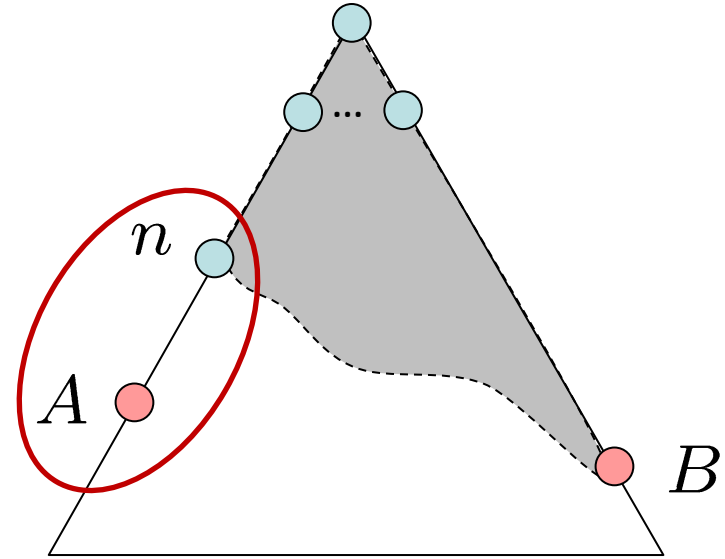
- A will exit the fringe before B



# 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

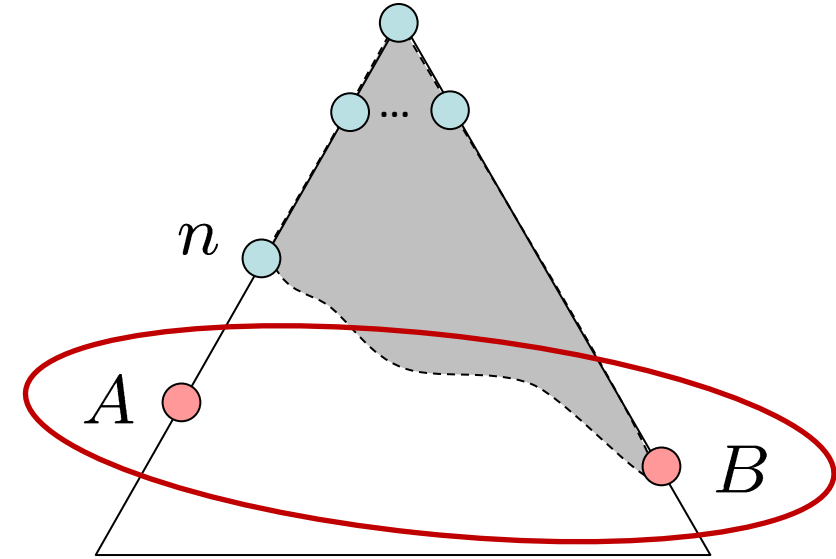
Admissibility of h

$h = 0$  at a goal

# Optimality of A\* Tree Search: Blocking

## 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  $f(B)$



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

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

B is suboptimal

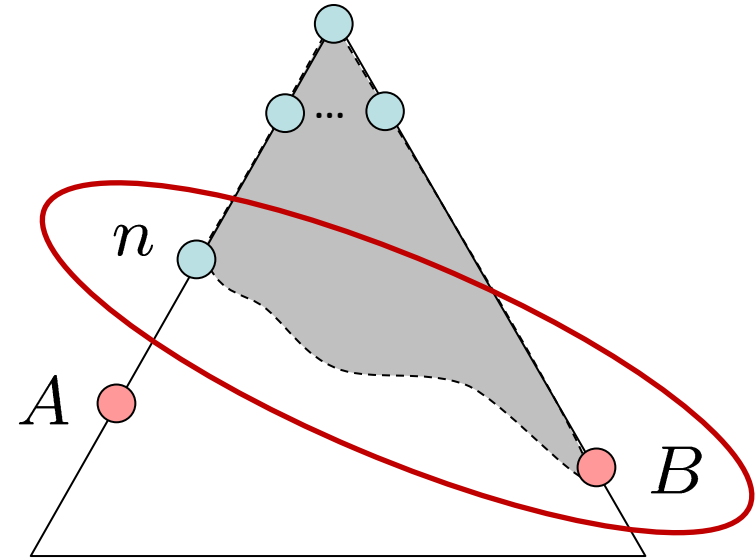
## h = 0 at a goal



# 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

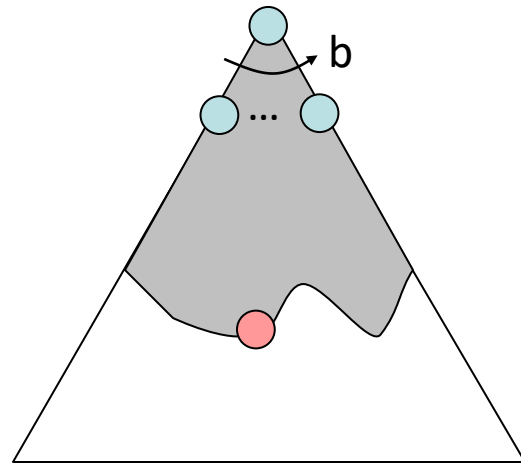


$$f(n) \leq f(A) < f(B)$$

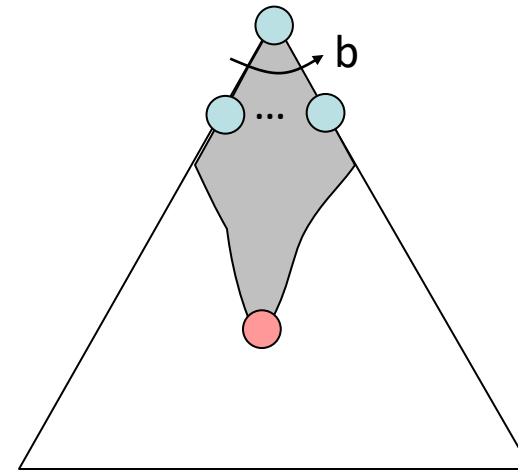
# Properties of $A^*$

# Properties of $A^*$

Uniform-Cost

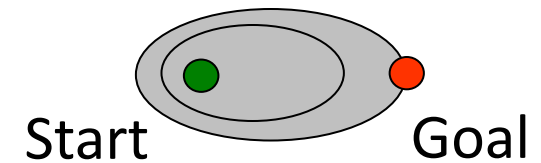
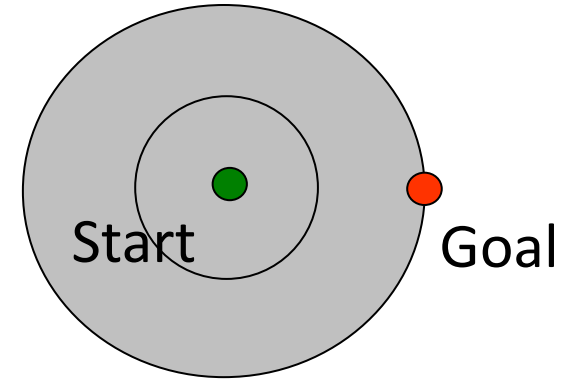


$A^*$



# 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



# Comparison



Greedy



Uniform Cost



A\*

# A\* Applications





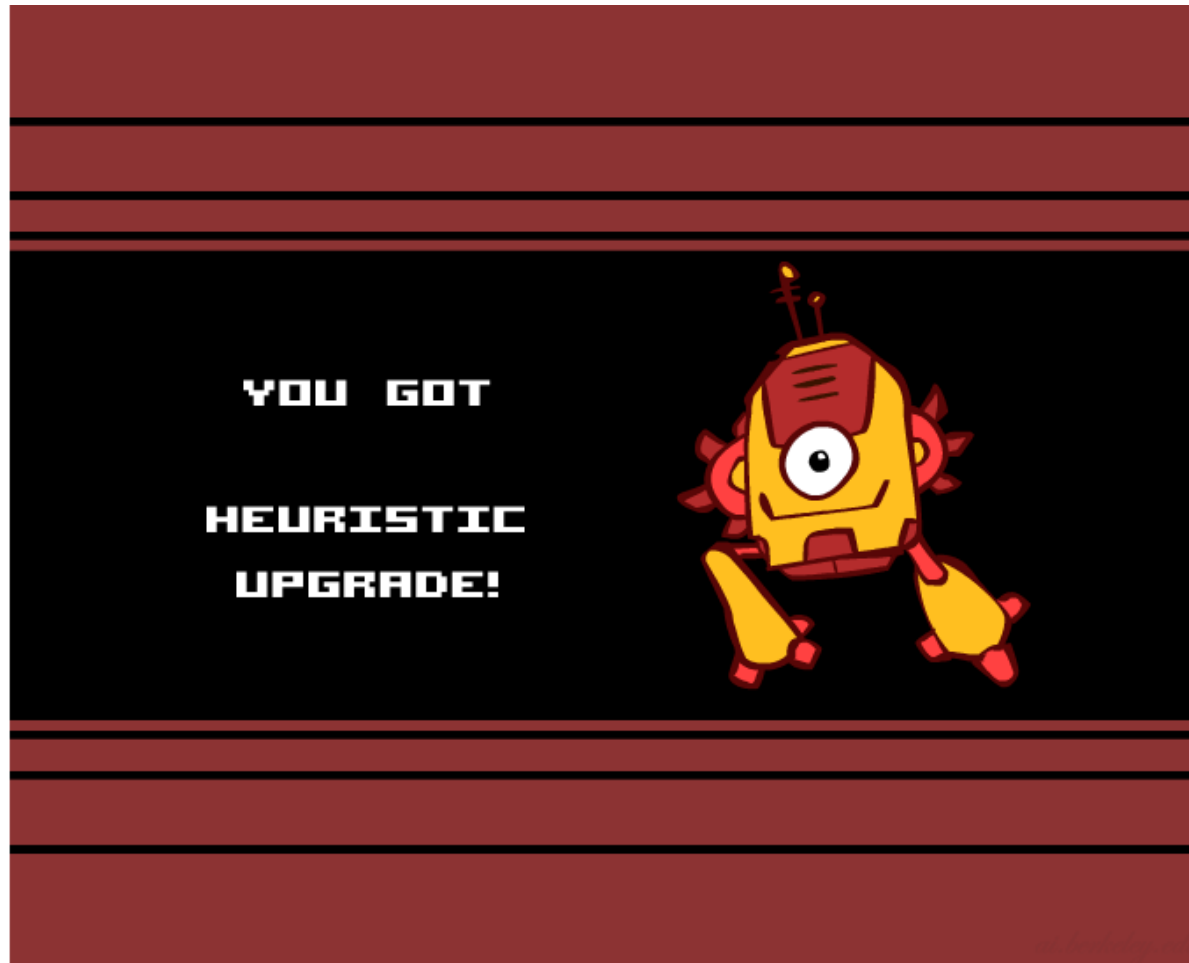
# A\* Applications

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



# Creating Heuristics

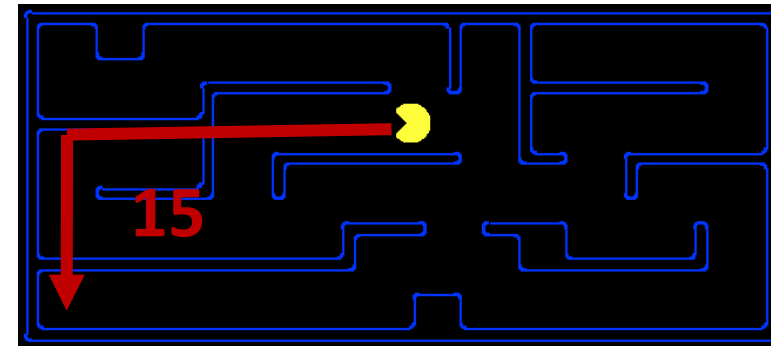
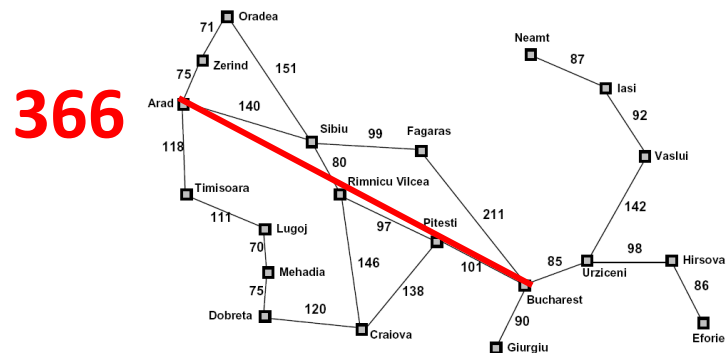
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# Creating Admissible Heuristics

- 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

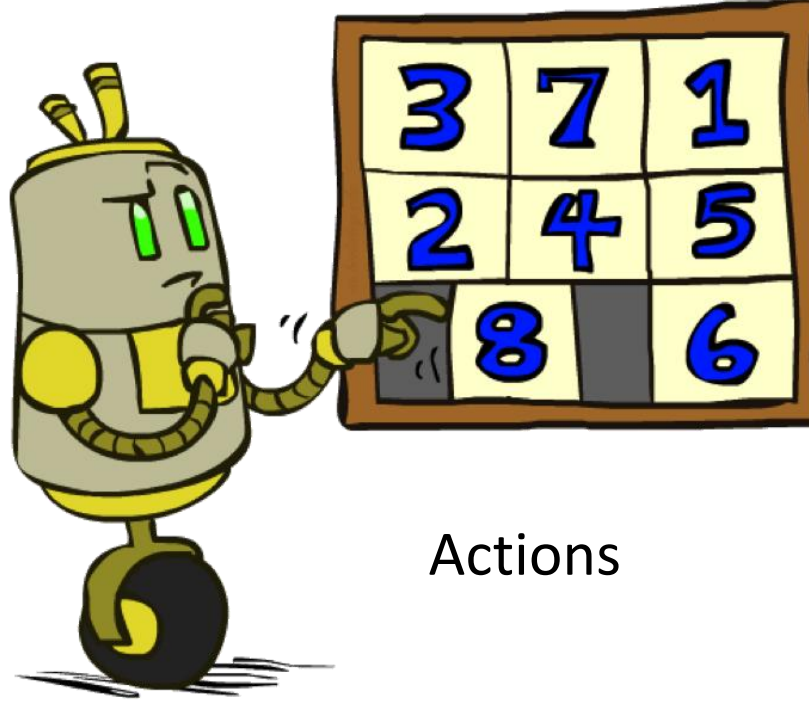


- Inadmissible heuristics are often useful too

# Example: 8 Puzzle

7	2	4
5		6
8	3	1

Start State



Actions

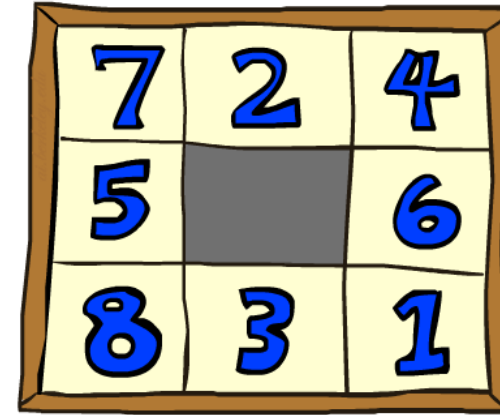
	1	2
3	4	5
6	7	8

Goal State

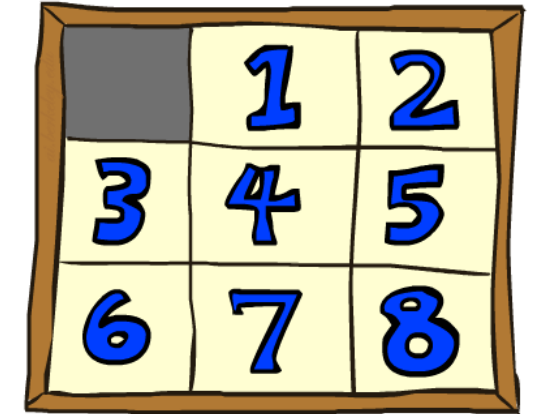
- What are the states?
- How many states?
- What are the actions?
- How many successors from the start state?
- What should the costs be?

# 8 Puzzle I

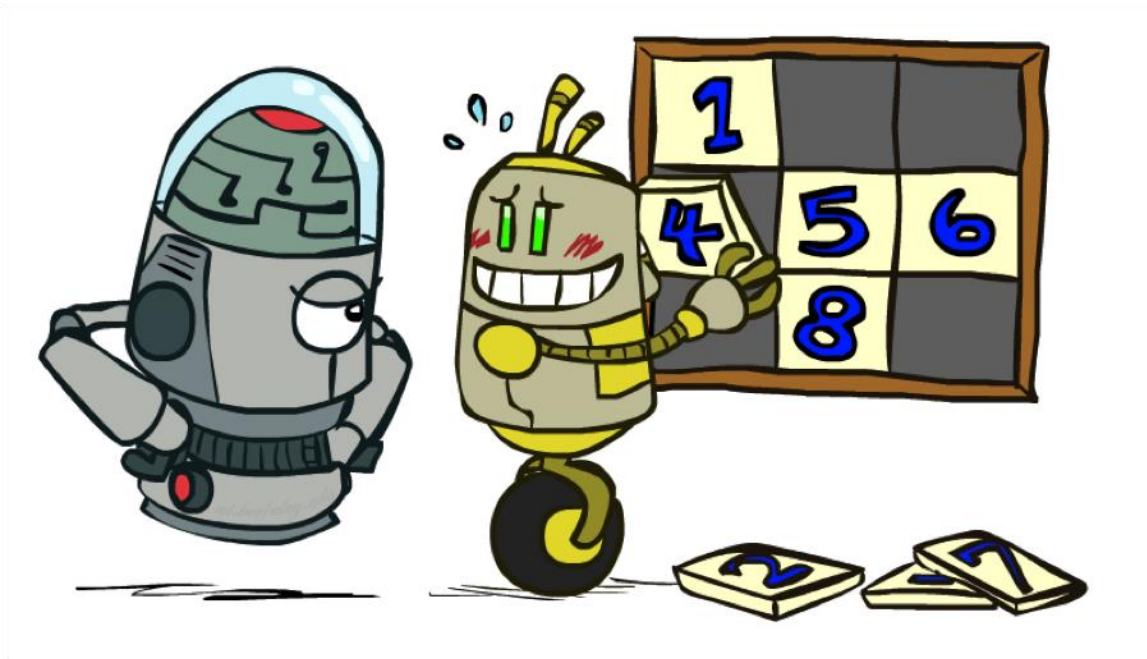
- Heuristic: Number of tiles misplaced
- Why is it admissible?
- $h(\text{start}) = 8$
- This is a *relaxed-problem* heuristic



Start State



Goal State

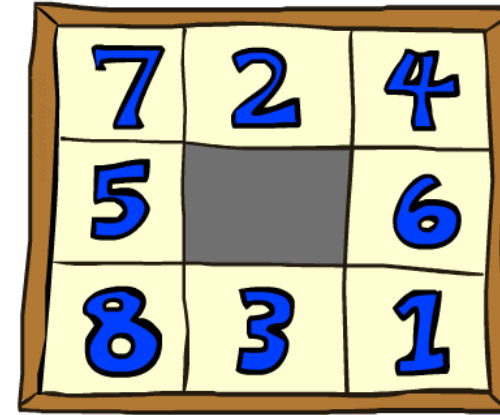


Average nodes expanded  
when the optimal path has...

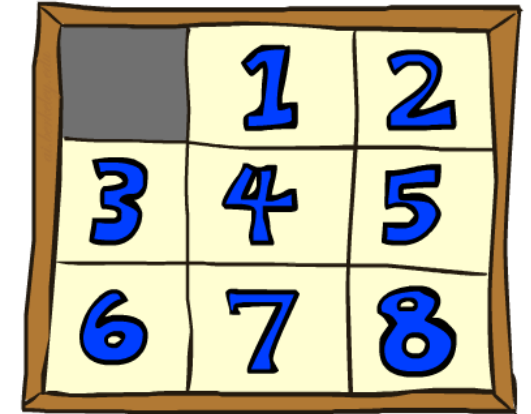
	...4 steps	...8 steps	...12 steps
UCS	112	6,300	$3.6 \times 10^6$
TILES	13	39	227

# 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



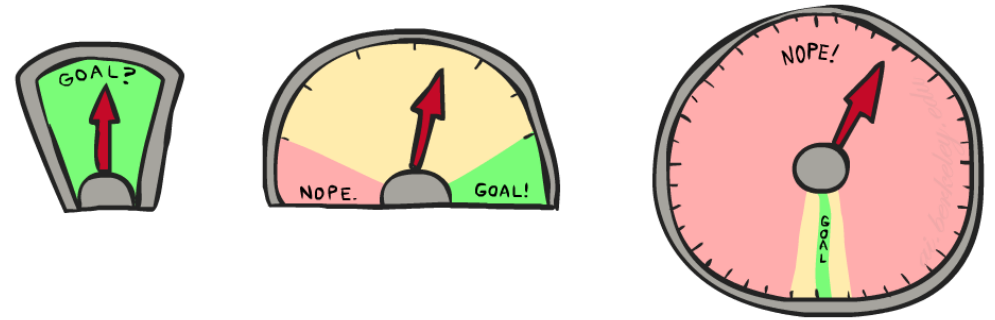
Goal State

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

# Trivial Heuristics, Dominance

- Dominance:  $h_a \geq h_c$  if

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

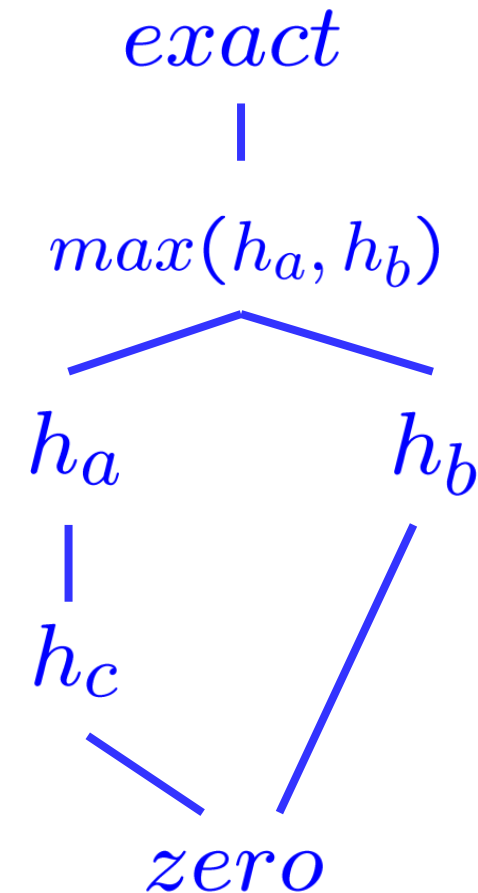
- Heuristics form a semi-lattice:

- 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



# Semi-Lattice of Heuristics

## Definition [\[ edit \]](#)

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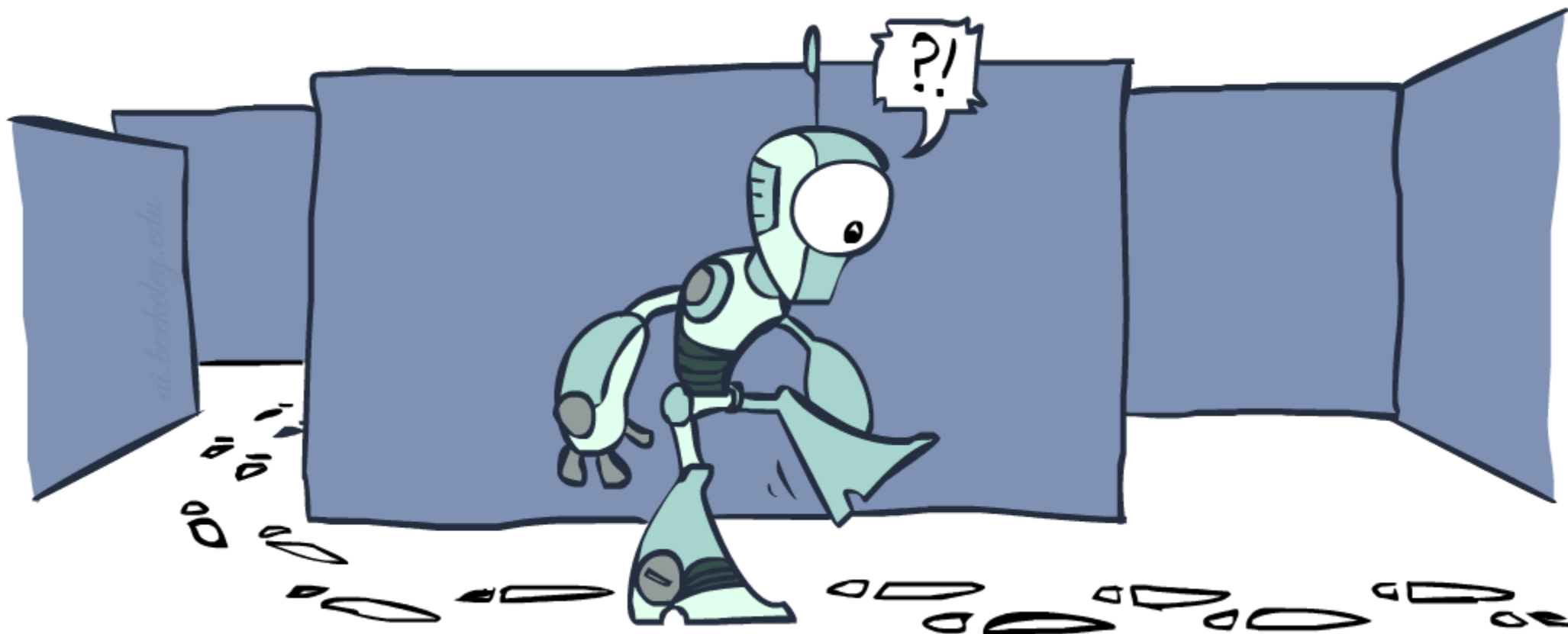
A lattice can be defined either order-theoretically as a partially ordered set, or as an algebraic structure.

### As partially ordered set [\[ edit \]](#)

A [partially ordered set](#) (poset)  $(L, \leq)$  is called a **lattice** if it is both a join- and a meet-[semilattice](#), i.e. each two-element subset  $\{a, b\} \subseteq L$  has a [join](#) (i.e. least upper bound, denoted by  $a \vee b$ ) and [dually](#) a [meet](#) (i.e. greatest lower bound, denoted by  $a \wedge b$ ). This definition makes  $\wedge$  and  $\vee$  [binary operations](#). Both operations are monotone with respect to the given order:  $a_1 \leq a_2$  and  $b_1 \leq b_2$  implies that  $a_1 \vee b_1 \leq a_2 \vee b_2$  and  $a_1 \wedge b_1 \leq a_2 \wedge b_2$ .

[https://en.wikipedia.org/wiki/Lattice\\_\(order\)](https://en.wikipedia.org/wiki/Lattice_(order))

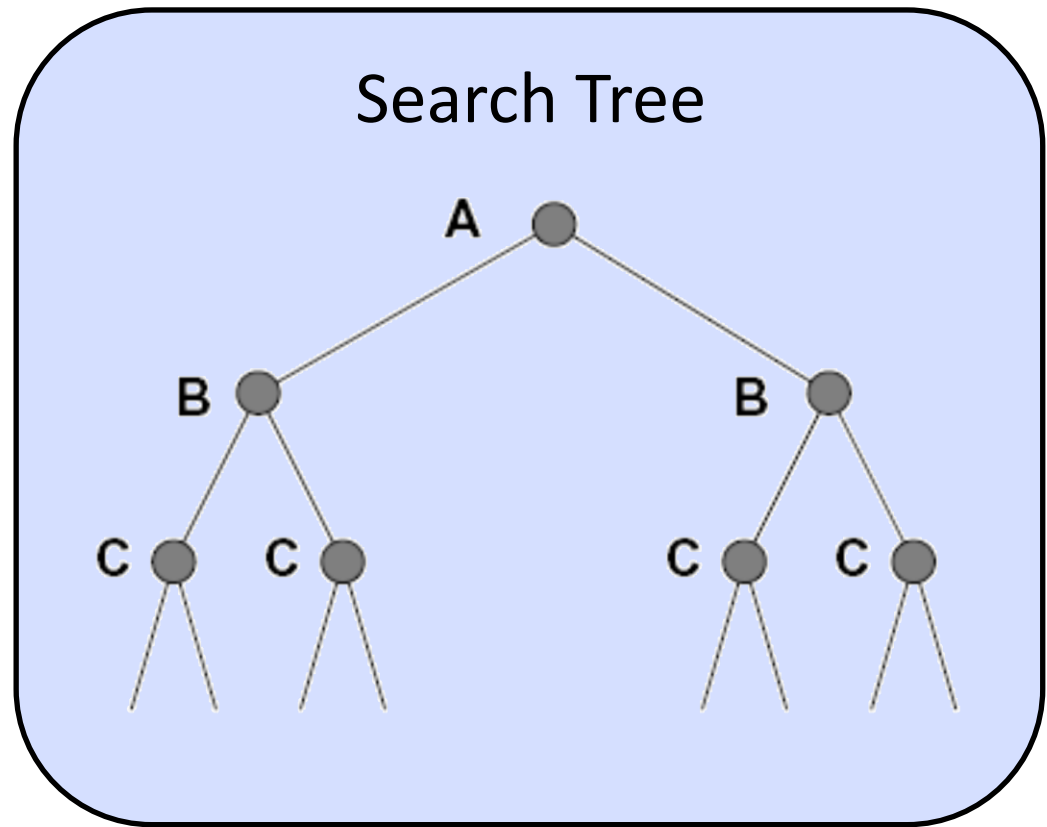
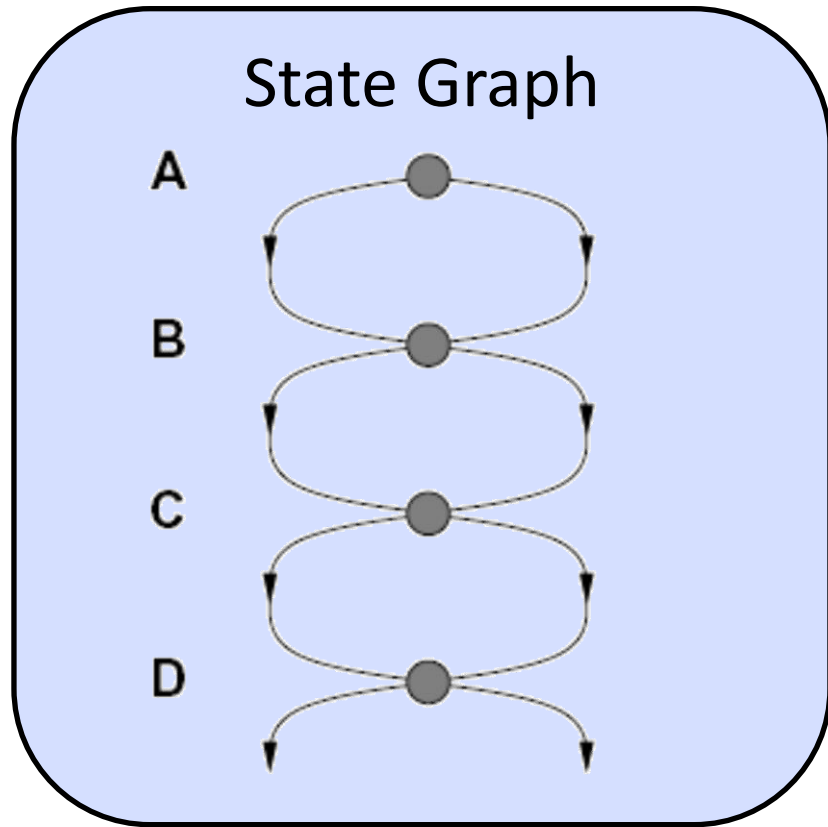
# Graph Search





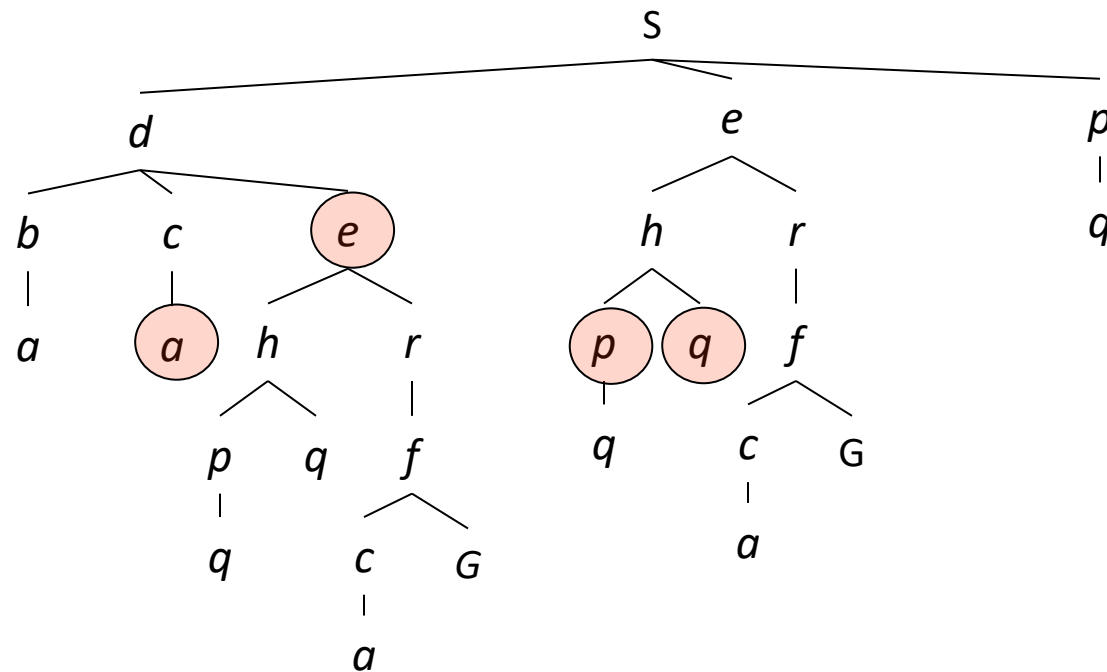
# Tree Search: Extra Work!

- 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?)



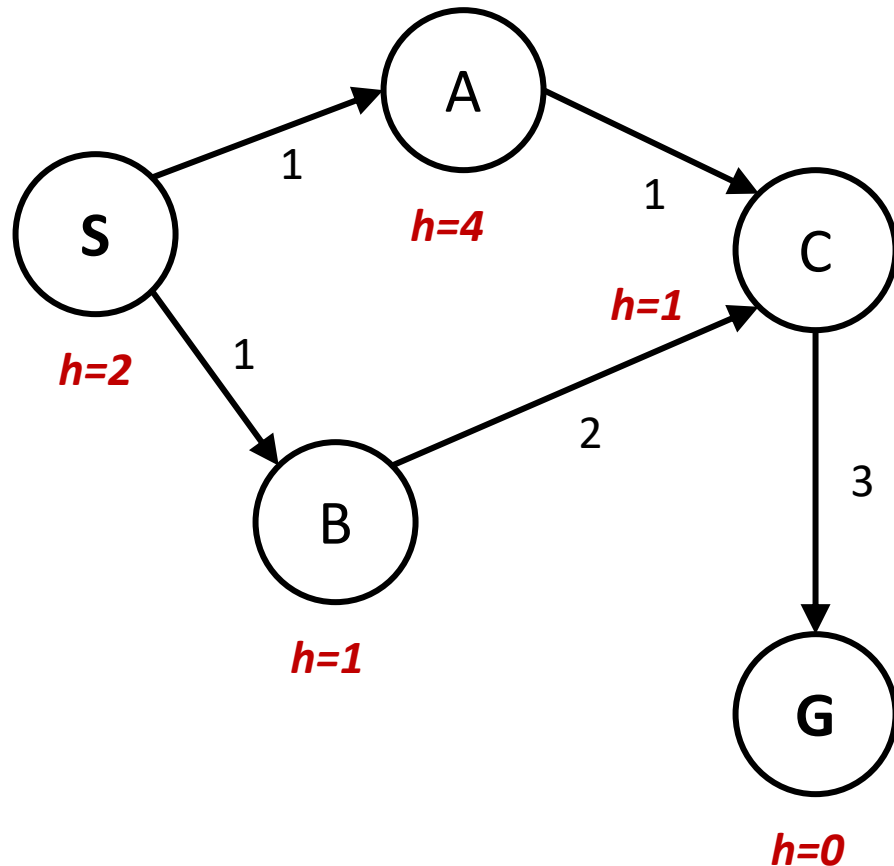
# Graph Search

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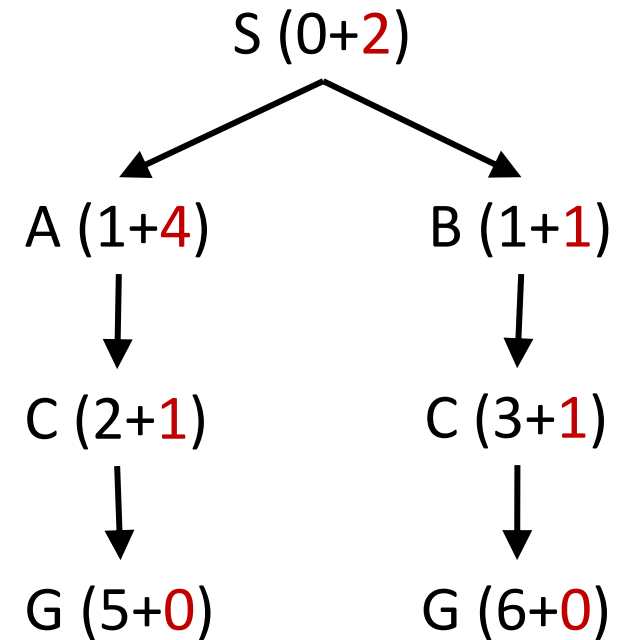
- Idea: never **expand** a state twice
- How to implement:
  - Tree search + set of expanded states (“closed set”)
  - Expand the search tree node-by-node, but...
  - Before expanding a node, check to make sure its state has never been expanded before
  - If not new, skip it, if new add to closed set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

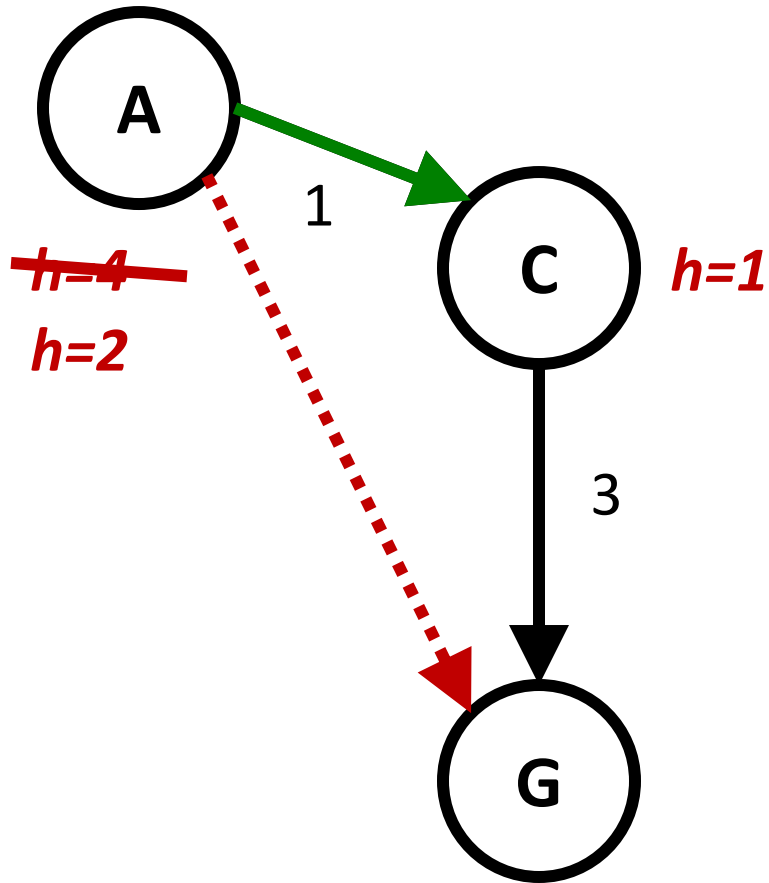
State space graph



Search tree

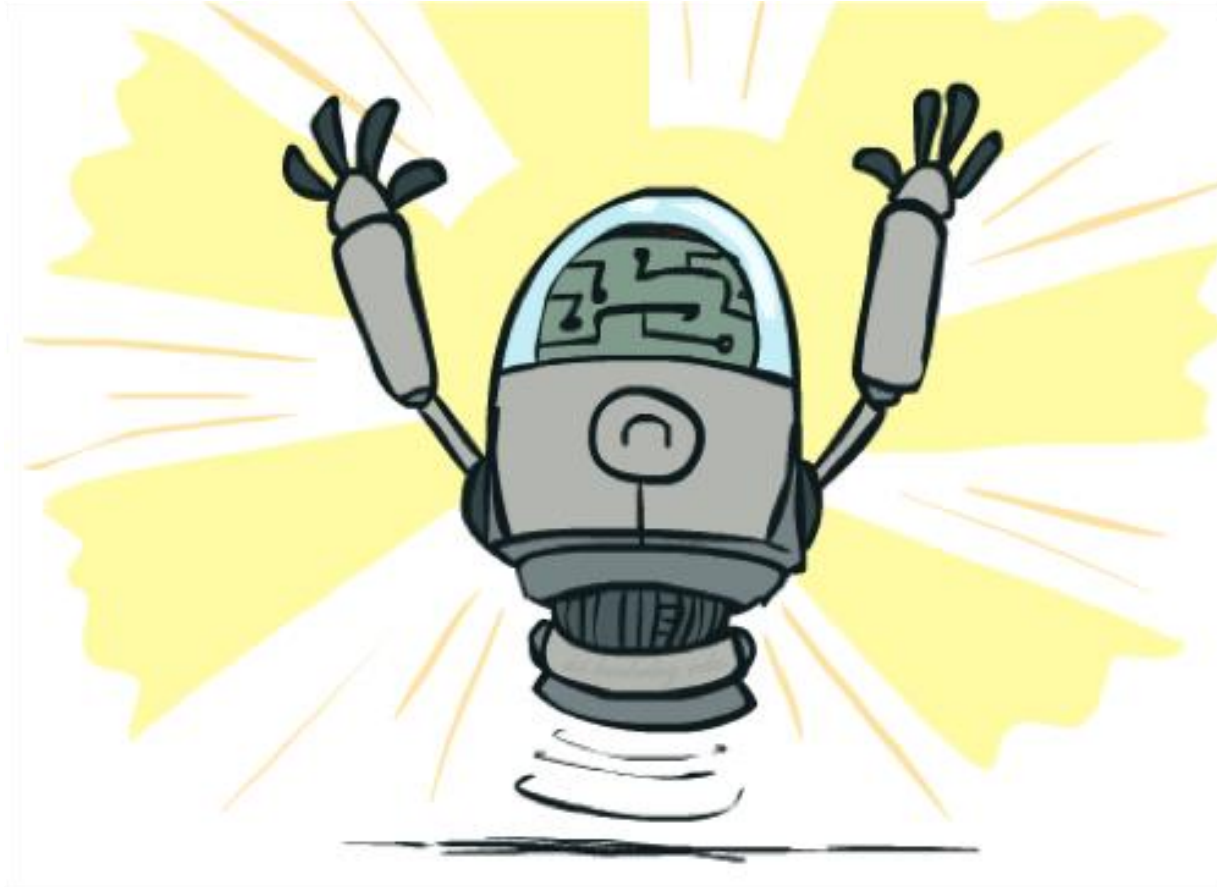


# Consistency of Heuristics



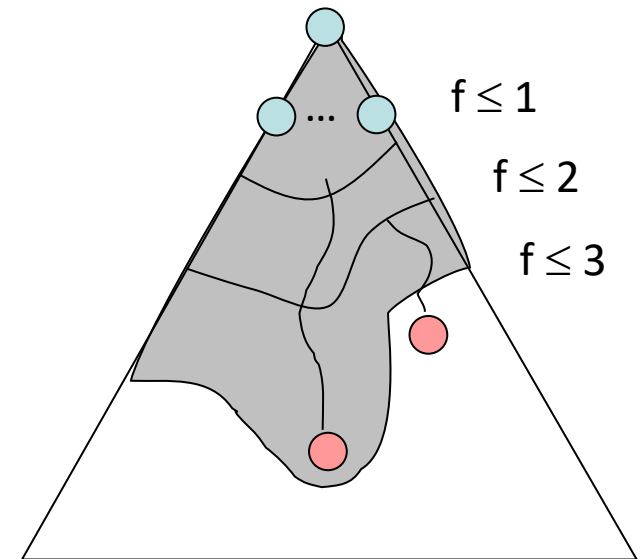
- Main idea: estimated heuristic costs  $\leq$  actual costs
  - Admissibility: heuristic cost  $\leq$  actual cost to goal
$$h(A) \leq \text{actual cost from A to G}$$
  - Consistency: heuristic “arc” cost  $\leq$  actual cost for each arc
$$h(A) - h(C) \leq \text{cost(A to C)}$$
- Consequences of consistency: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

# Optimality of A\* Graph Search



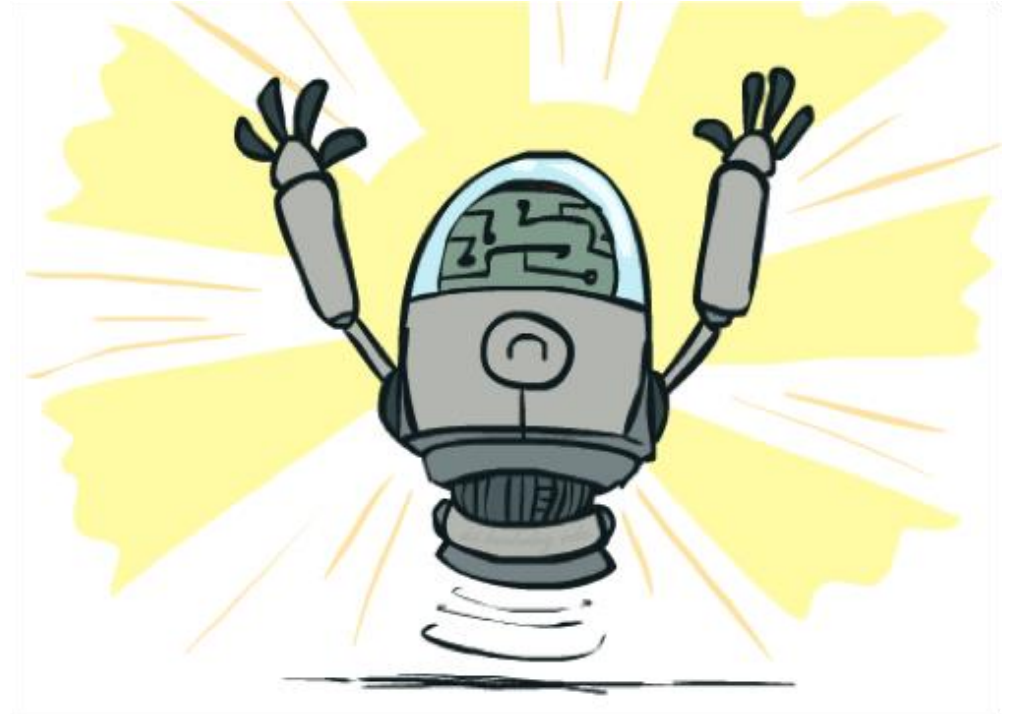
# Optimality of A\* Graph Search

- Sketch: consider what A\* does with a consistent heuristic:
  - Fact 1: In tree search, A\* expands nodes in increasing total f value (f-contours)
  - Fact 2: For every state s, nodes that reach s optimally are expanded before nodes that reach s suboptimally
  - Result: 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





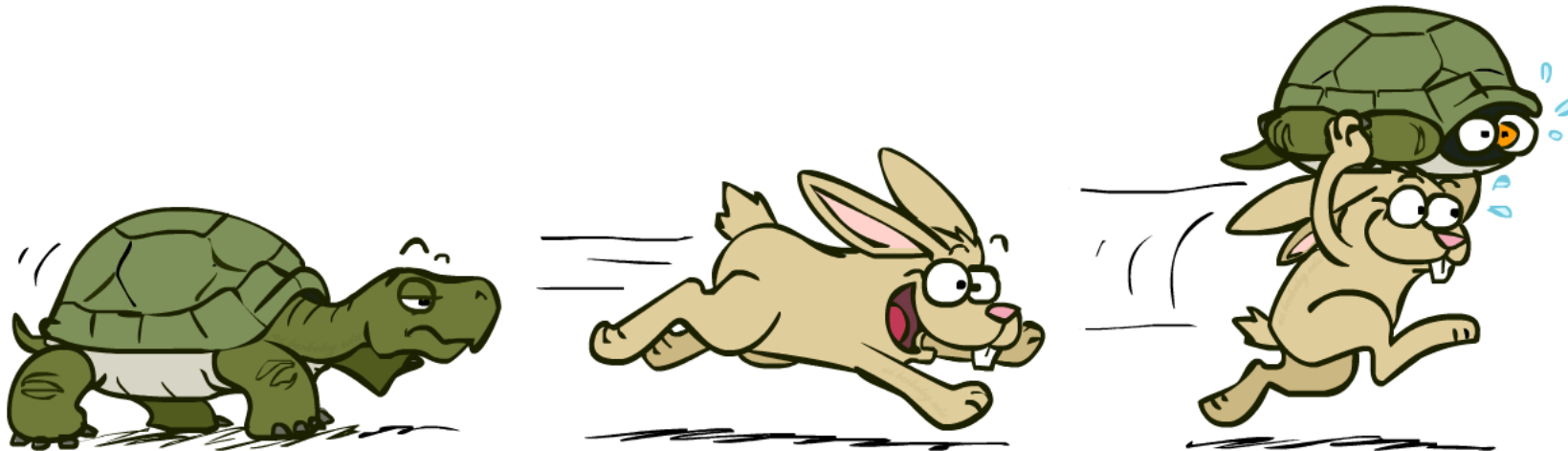
# A\*: Summary

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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



# Tree Search Pseudo-Code

```
function TREE-SEARCH(problem, fringe) return a solution, or failure
  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
    for child-node in EXPAND(STATE[node], problem) do
      fringe ← INSERT(child-node, fringe)
    end
  end
```

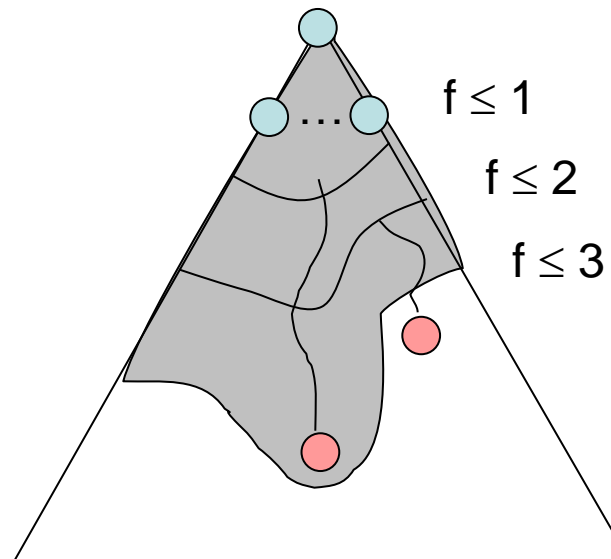
# Graph Search Pseudo-Code

```
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
  end
```

# Optimality of A\* Graph Search

- Consider what A\* does:
  - Expands nodes in increasing total f value (f-contours)  
Reminder:  $f(n) = g(n) + h(n) = \text{cost to } n + \text{heuristic}$
  - Proof idea: the optimal goal(s) have the lowest f value, so it must get expanded first

There's a problem with this argument. What are we assuming is true?



# Optimality of A\* Graph Search

Proof:

- New possible problem: some  $n$  on path to  $G^*$  isn't in queue when we need it, because some worse  $n'$  for the same state dequeued and expanded first (disaster!)
- Take the highest such  $n$  in tree
- Let  $p$  be the ancestor of  $n$  that was on the queue when  $n'$  was popped
- $f(p) < f(n)$  because of consistency
- $f(n) < f(n')$  because  $n'$  is suboptimal
- $p$  would have been expanded before  $n'$
- Contradiction!

