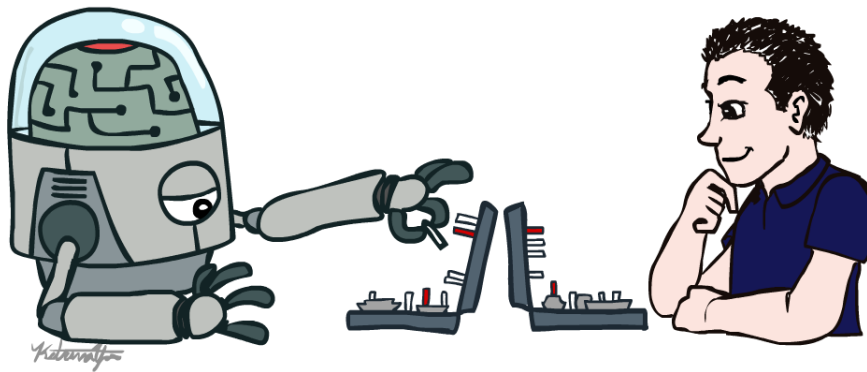


# CSE 3521: Introduction to Artificial Intelligence



[These slides are partially adapted from the [UC Berkeley. CS188 Intro to AI](#) at UC Berkeley]

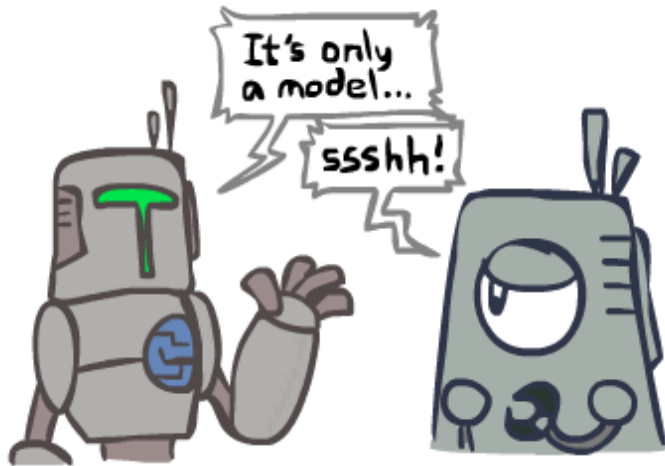


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# Search and Models

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- 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...



# Uninformed vs. Informed Search

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- Uninformed search

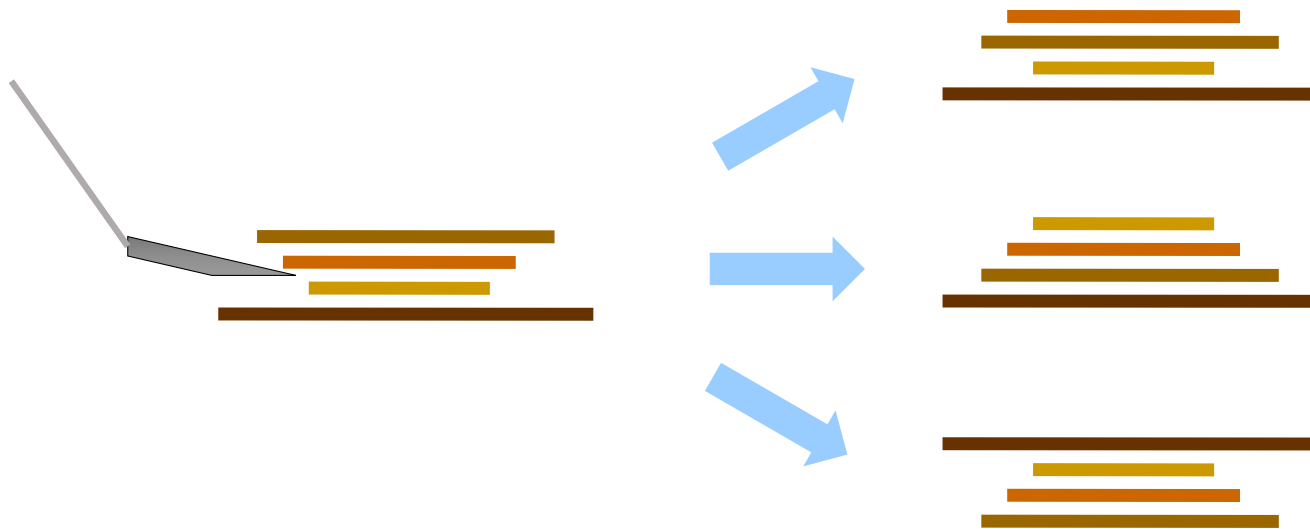
- Given no information about problem (other than its definition)
- Find solutions to problems by systematically generating new states and testing for goal

- Informed search

- Given some ideas of where to look for solutions
- Use problem-specific knowledge

# Example: Pancake Problem

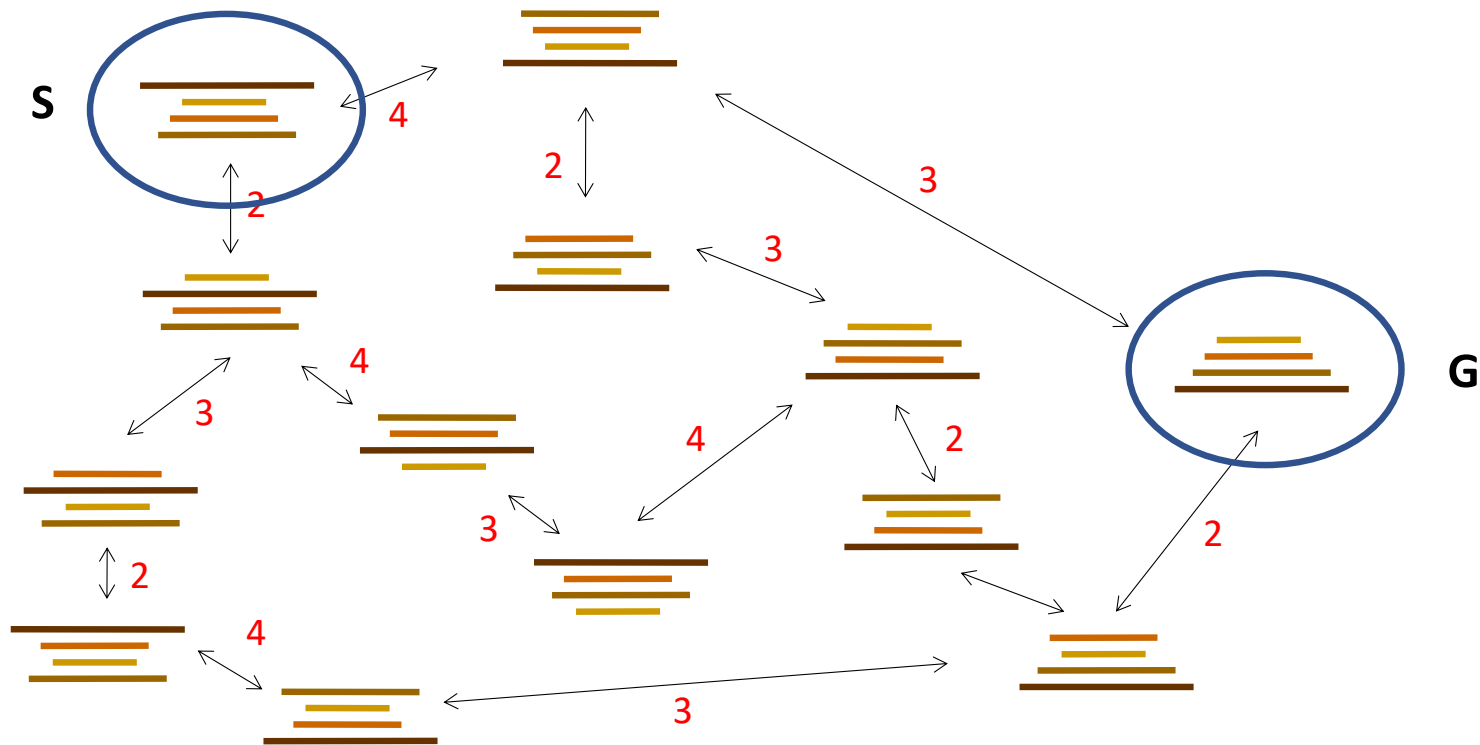
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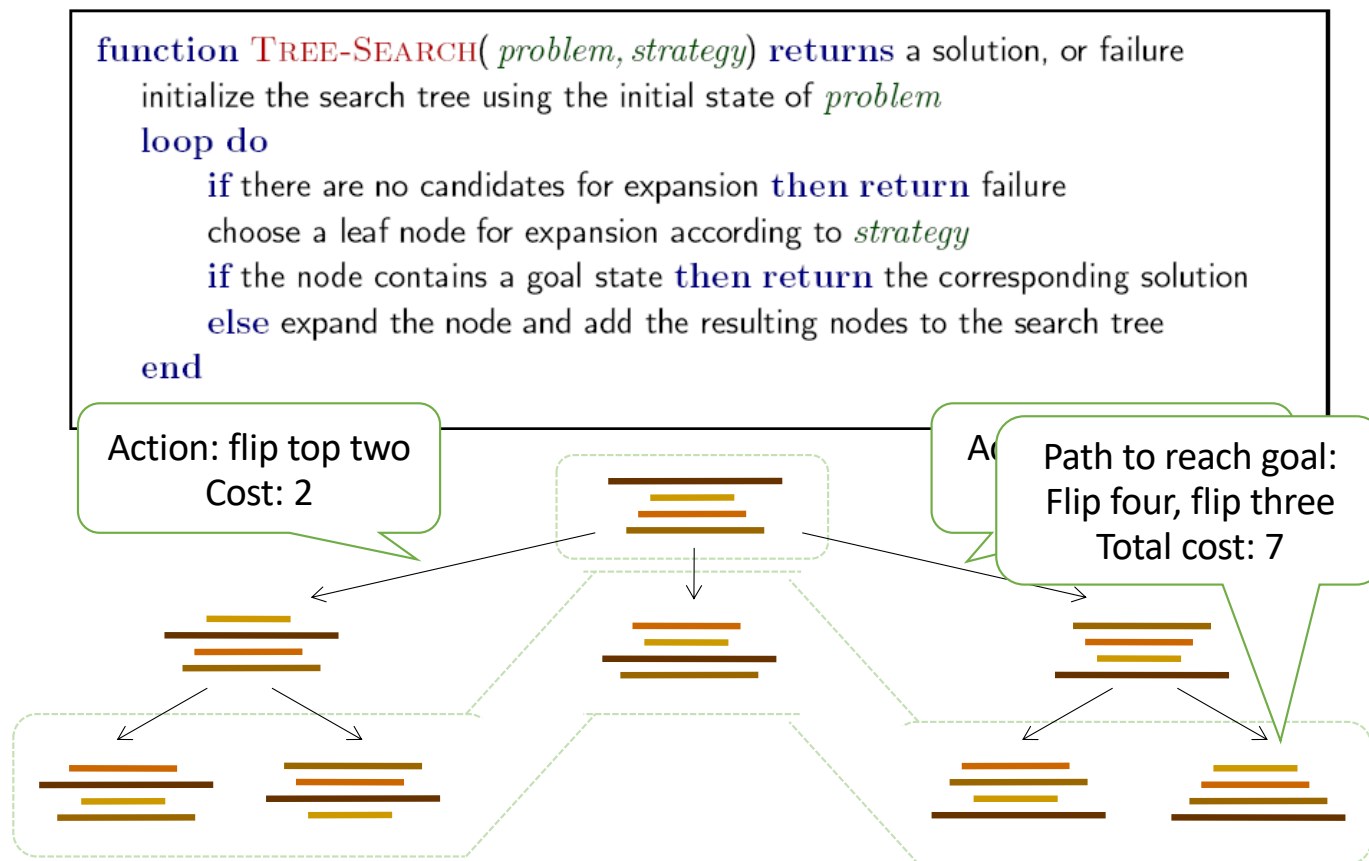
Cost: Number of pancakes flipped

## Example: Pancake Problem

## State space graph with costs as weights



# General Tree Search



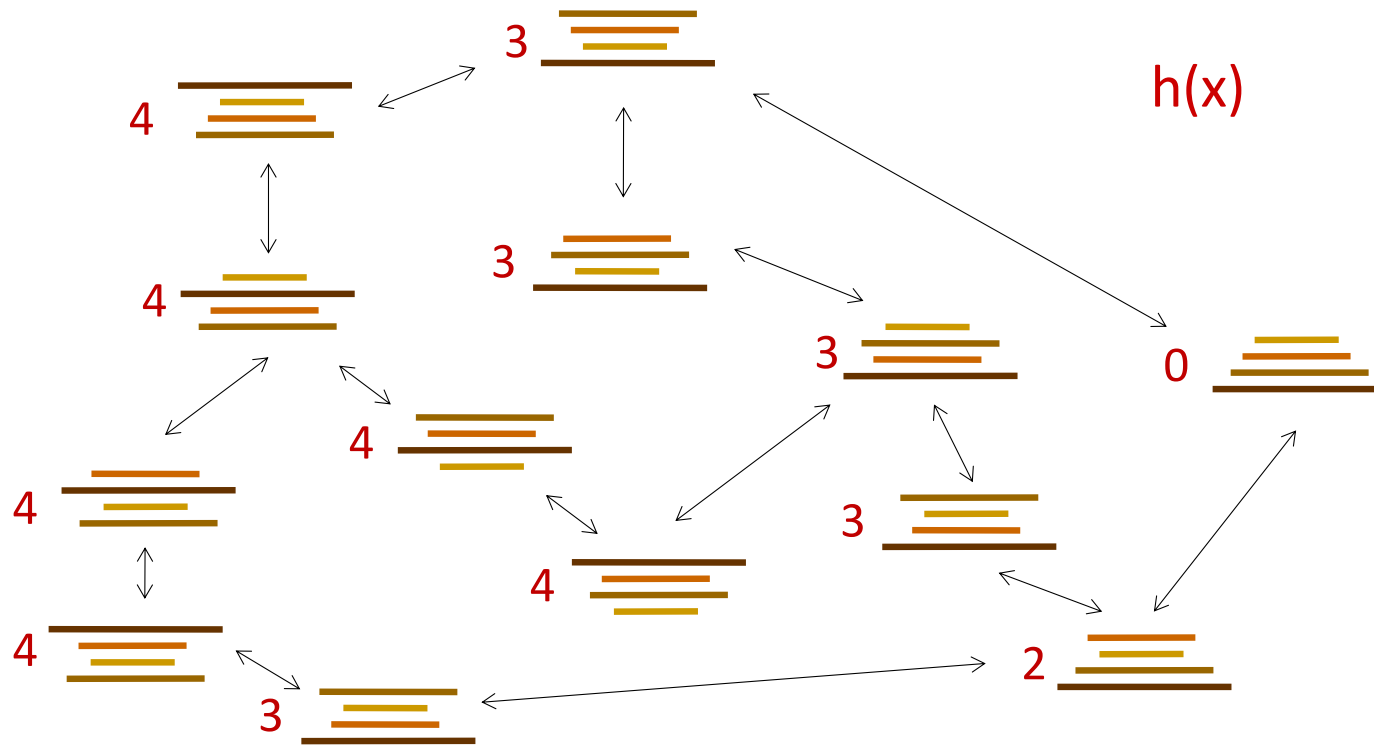
# Search Heuristics

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- 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
    - not the exact “path” distance

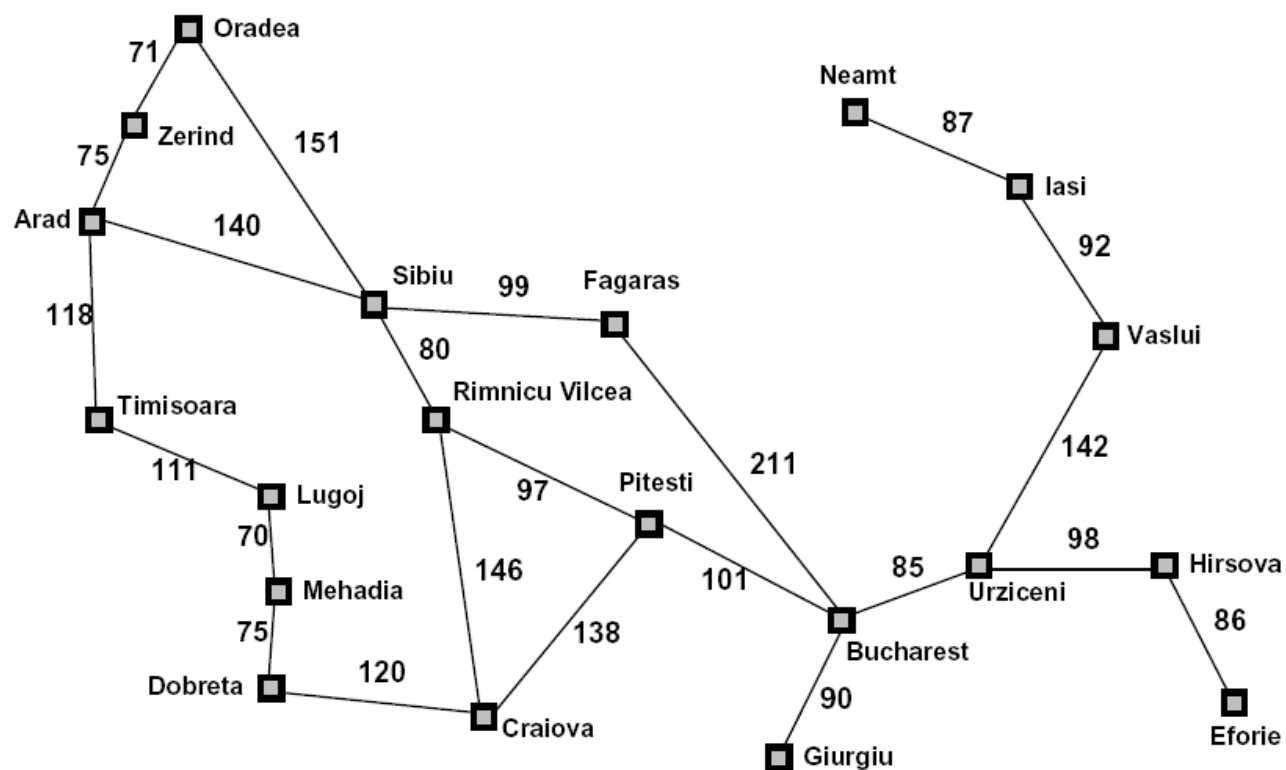
# Example: Heuristic Function

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





# Example: Heuristic Function

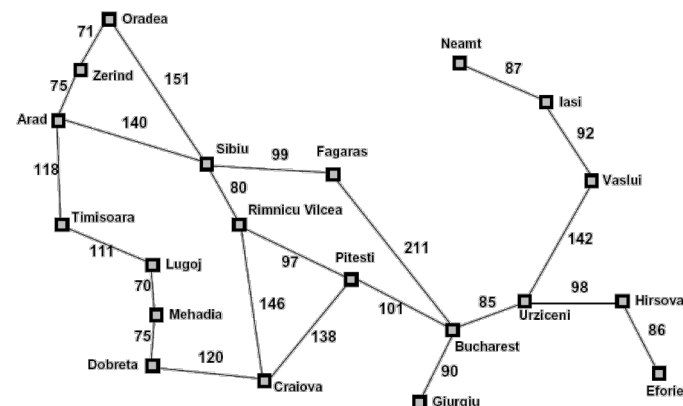
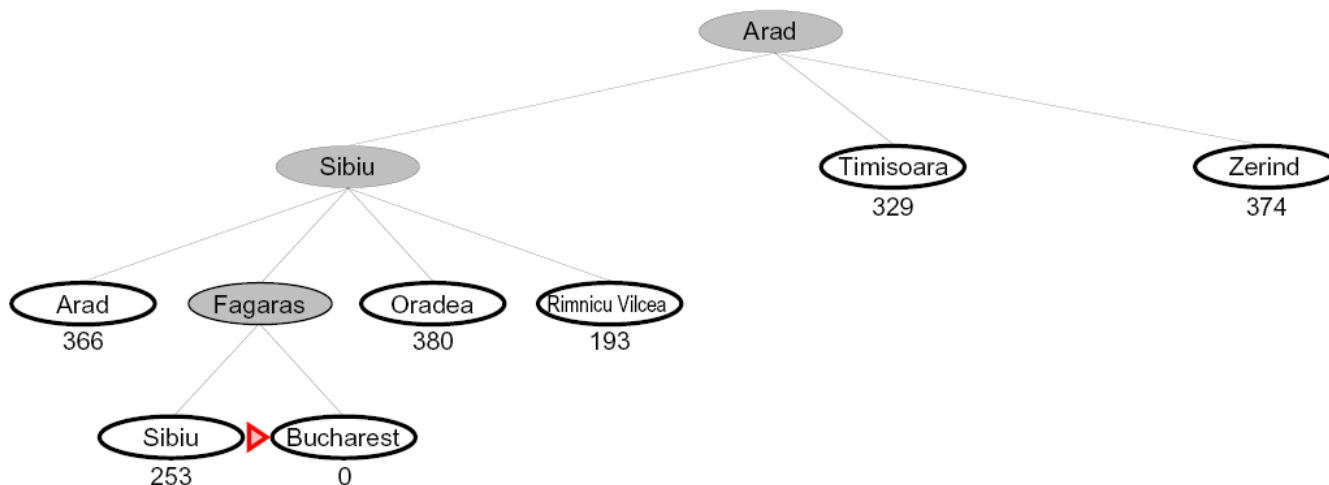


Straight-line distance to Bucharest	
Arad	366
Bucharest	0
Craiova	160
Dobreta	242
Eforie	161
Fagaras	178
Giurgiu	77
Hirsova	151
Iasi	226
Lugoj	244
Mehadia	241
Neamt	234
Oradea	380
Pitesti	98
Rimnicu Vilcea	193
Sibiu	253
Timisoara	329
Urziceni	80
Vaslui	199
Zerind	374

$h(x)$

# Greedy Search

- Expand the node that seems closest...

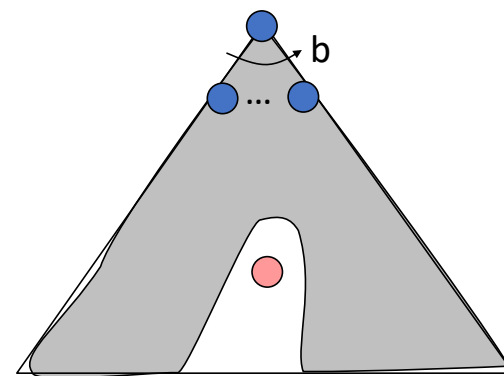
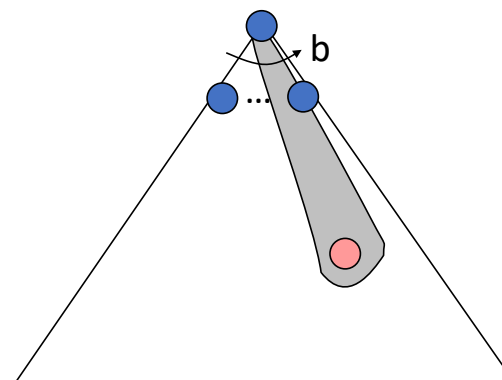


- What can go wrong?
  - Does not guarantee the optimal solution

# Greedy Search

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- 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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UCS



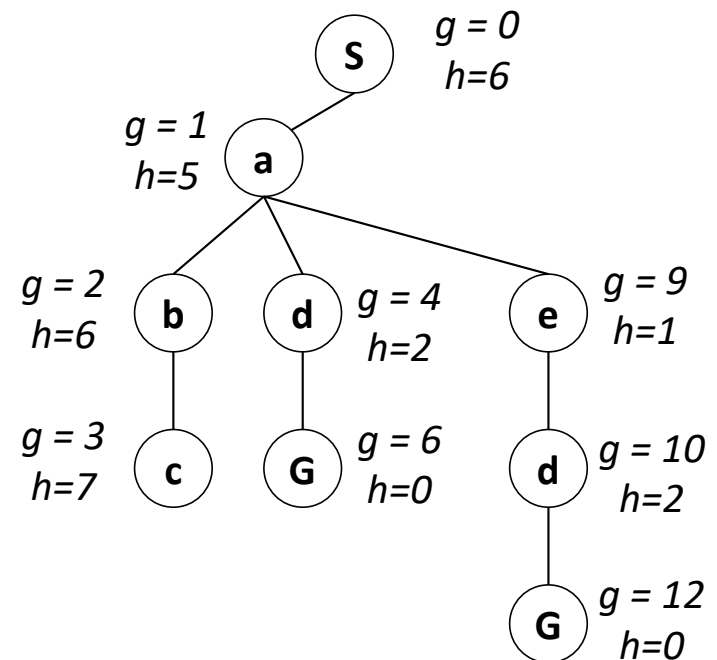
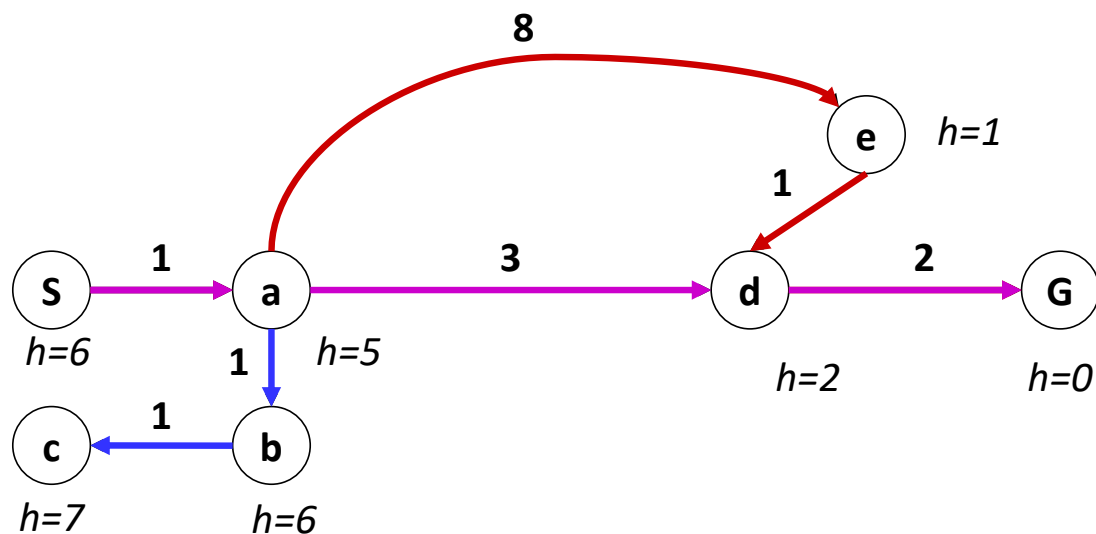
Greedy



A\*

# Combining UCS and Greedy

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

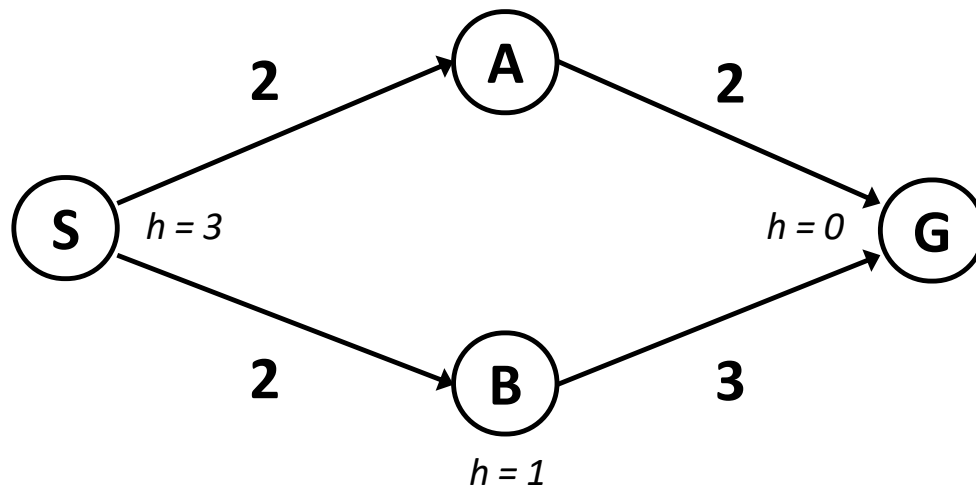


- **A\* Search** orders by the sum:  $f(n) = g(n) + h(n)$

# When Should we terminate A\*

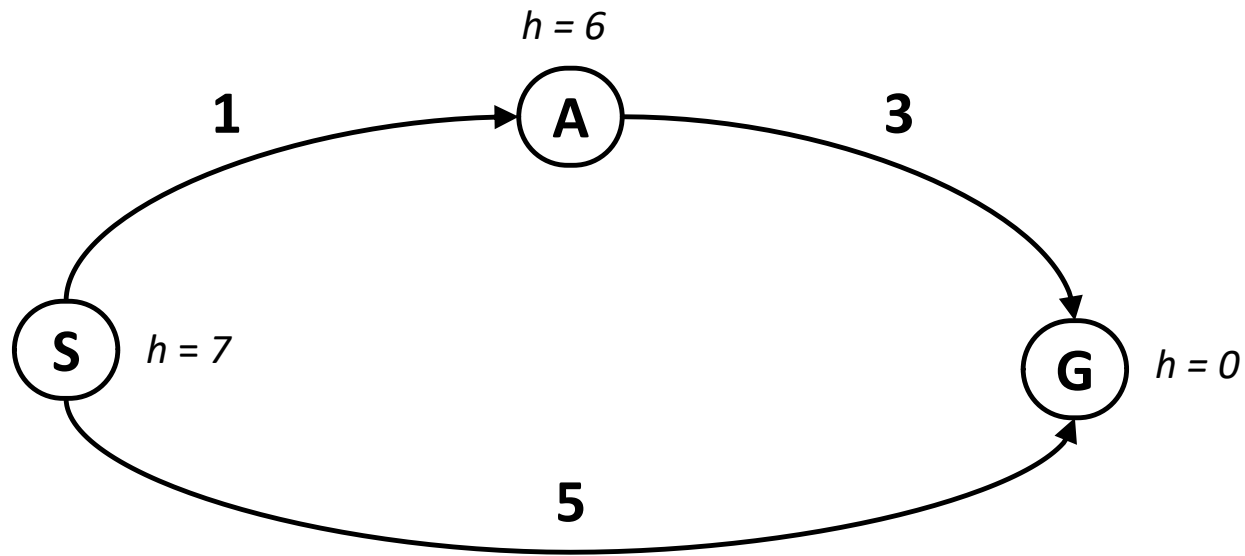
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- Should we stop when we enqueue a goal?
  - No: only stop when we dequeue a goal



## Is A\* Optimal?

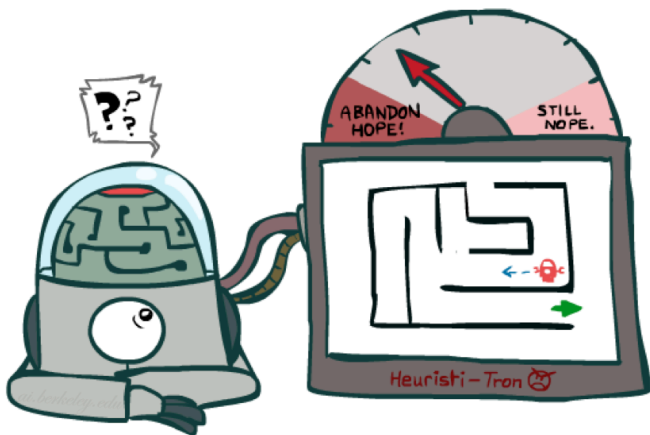
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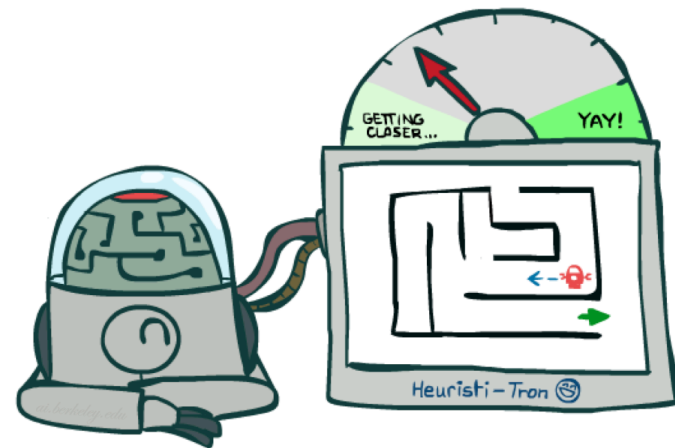
- What went wrong?
- Actual bad goal cost < estimated good goal cost
- We need estimates to be less than actual costs!

# Idea: Admissibility

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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

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

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

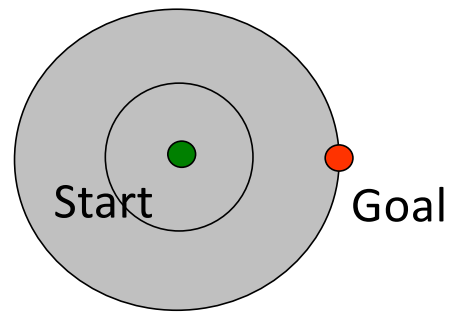
where  $h^*(n)$  is the true cost to a nearest goal

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

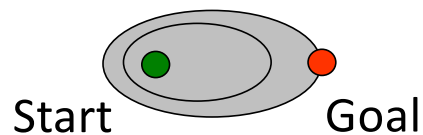
# UCS vs. A\* Contours

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- Uniform-cost expands equally in all “directions”



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



# A\* Applications

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

# 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

