CS 188: Artificial Intelligence

Lectures 2 and 3: Search

Pieter Abbeel – UC Berkeley
Many slides from Dan Klein

Reminder

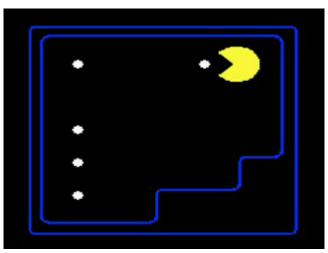
- Only a very small fraction of AI is about making computers play games intelligently
- Recall: computer vision, natural language, robotics, machine learning, computational biology, etc.

- That being said: games tend to provide relatively simple example settings which are great to illustrate concepts and learn about algorithms which underlie many areas of AI

Reflex Agent

- Choose action based on current percept (and maybe memory)
- May have memory or a model of the world's current state
- Do not consider the future consequences of their actions
- Act on how the world IS
- Can a reflex agent be rational?

A reflex agent for pacman

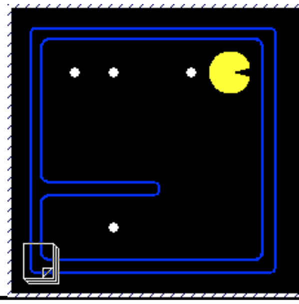


4 actions: move North, East, South or West

Reflex agent

- While(food left)
  - Sort the possible directions to move according to the amount of food in each direction
  - Go in the direction with the largest amount of food

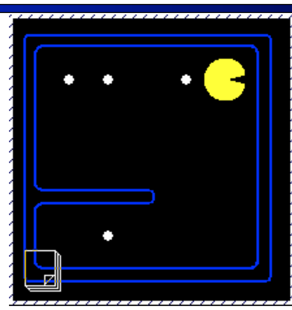
A reflex agent for pacman (2)



Reflex agent

- While(food left)
  - Sort the possible directions to move according to the amount of food in each direction
  - Go in the direction with the largest amount of food

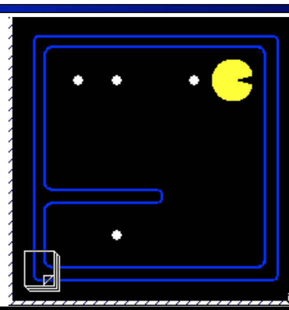
A reflex agent for pacman (3)



Reflex agent

- While(food left)
  - Sort the possible directions to move according to the amount of food in each direction
  - Go in the direction with the largest amount of food
    - But, if other options are available, exclude the direction we just came from

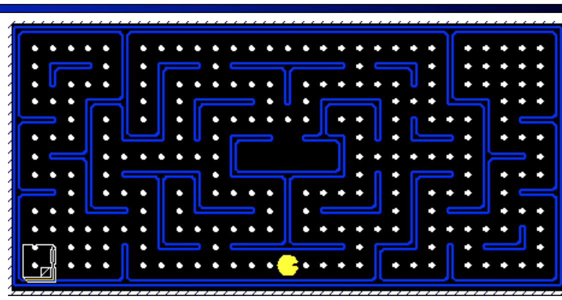
A reflex agent for pacman (4)



Reflex agent

- While(food left)
  - If can keep going in the current direction, do so
  - Otherwise:
    - Sort directions according to the amount of food
    - Go in the direction with the largest amount of food
    - But, if other options are available, exclude the direction we just came from

A reflex agent for pacman (5)



Reflex agent

- While(food left)
  - If can keep going in the current direction, do so
  - Otherwise:
    - Sort directions according to the amount of food
    - Go in the direction with the largest amount of food
    - But, if other options are available, exclude the direction we just came from

Reflex Agent

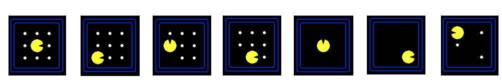
- Choose action based on current percept (and maybe memory)
- May have memory or a model of the world’s current state
- Do not consider the future consequences of their actions
- Act on how the world IS
- Can a reflex agent be rational?

Goal-based Agents

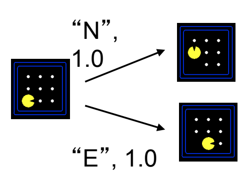
- Plan ahead
- Ask “what if”
- Decisions based on (hypothesized) consequences of actions
- Must have a model of how the world evolves in response to actions
- Act on how the world WOULD BE

Search Problems

- A search problem consists of:
  - A state space

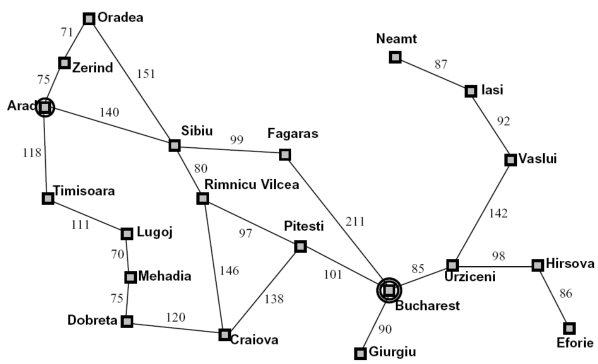


  - A successor function



  - A start state and a goal test
- A solution is a sequence of actions (a plan) which transforms the start state to a goal state

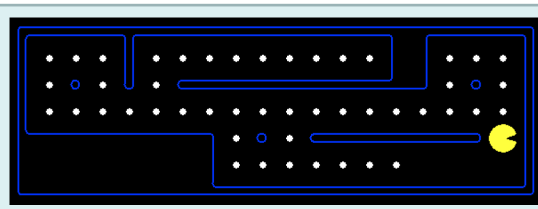
Example: Romania



- State space:
  - Cities
- Successor function:
  - Go to adj city with cost = dist
- Start state:
  - Arad
- Goal test:
  - Is state == Bucharest?
- Solution?

What's in a State Space?

The world state specifies every last detail of the environment

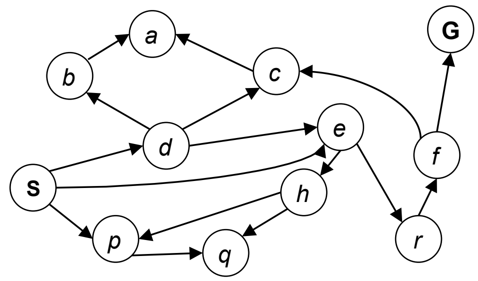


A search state keeps only the details needed (abstraction)

- Problem: Pathing
  - States: (x,y) location
  - Actions: NSEW
  - Successor: update location only
  - Goal test: is (x,y)=END
- Problem: Eat-All-Dots
  - States: {(x,y), dot booleans}
  - Actions: NSEW
  - Successor: update location and possibly a dot boolean
  - Goal test: dots all false

State Space Graphs

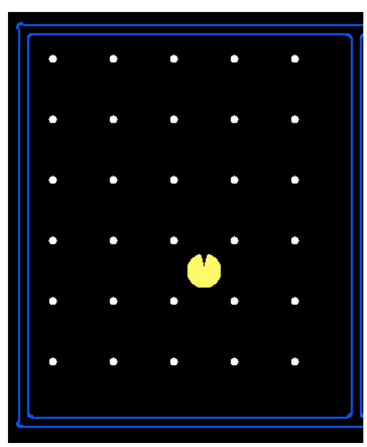
- State space graph: A mathematical representation of a search problem
  - For every search problem, there’s a corresponding state space graph
  - The successor function is represented by arcs
- We can rarely build this graph in memory (so we don’t)



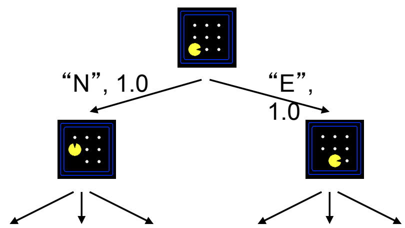
Ridiculously tiny state space graph for a tiny search problem

State Space Sizes?

- Search Problem:
  Eat all of the food
- Pacman positions:
  10 x 12 = 120
- Food count: 30

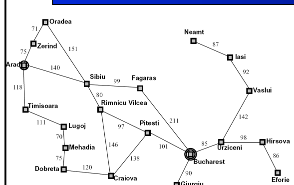


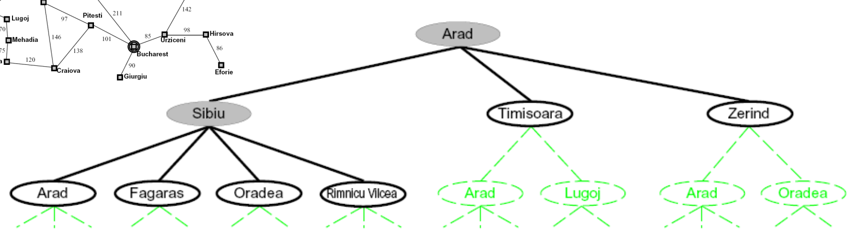
Search Trees



- A search tree:
  - This is a "what if" tree of plans and outcomes
  - Start state at the root node
  - Children correspond to successors
  - Nodes contain states, correspond to PLANS to those states
  - For most problems, we can never actually build the whole tree

Another Search Tree





- Search:
  - Expand out possible plans
  - Maintain a fringe of unexpanded plans
  - Try to expand as few tree nodes as possible

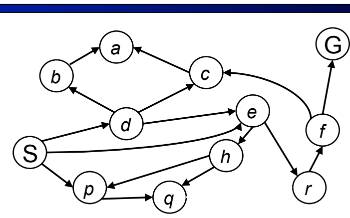
General Tree Search

```
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
```

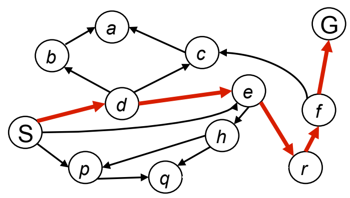
Detailed pseudocode is in the book!

- Important ideas:
  - Fringe
  - Expansion
  - Exploration strategy
- Main question: which fringe nodes to explore?

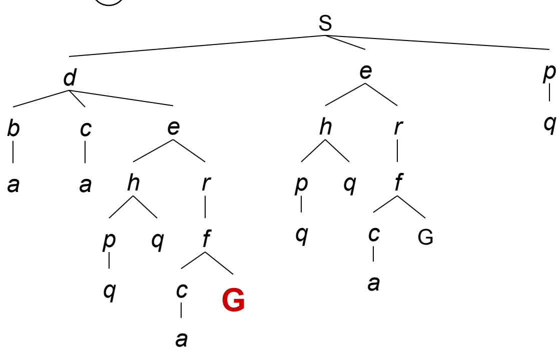
Example: Tree Search



State Graphs vs. Search Trees



Each NODE in in the search tree is an entire PATH in the problem graph.

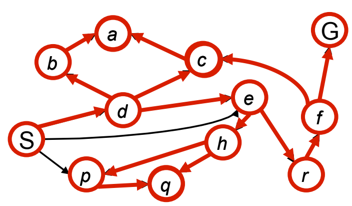


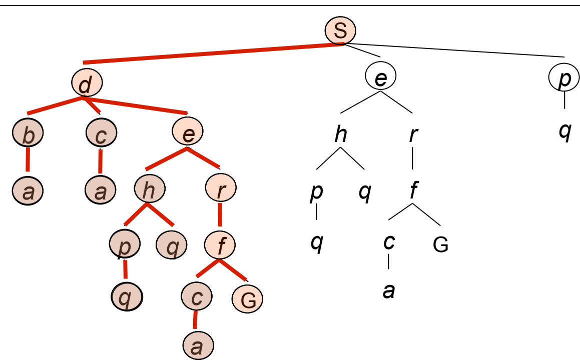
We construct both on demand – and we construct as little as possible.

Review: Depth First (Tree) Search

Strategy: expand deepest node first

Implementation: Fringe is a LIFO stack

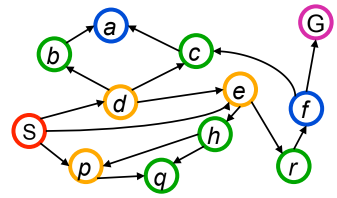


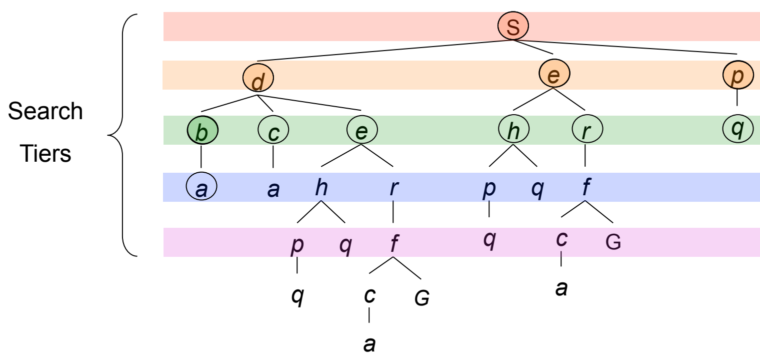


Review: Breadth First (Tree) Search

Strategy: expand shallowest node first

Implementation: Fringe is a FIFO queue





Search Algorithm Properties

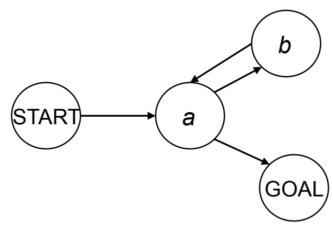
- Complete? Guaranteed to find a solution if one exists?
- Optimal? Guaranteed to find the least cost path?
- Time complexity?
- Space complexity?

Variables:

n	Number of states in the problem
b	The average branching factor *B* (the average number of successors)
C^*	Cost of least cost solution
s	Depth of the shallowest solution
m	Max depth of the search tree

DFS

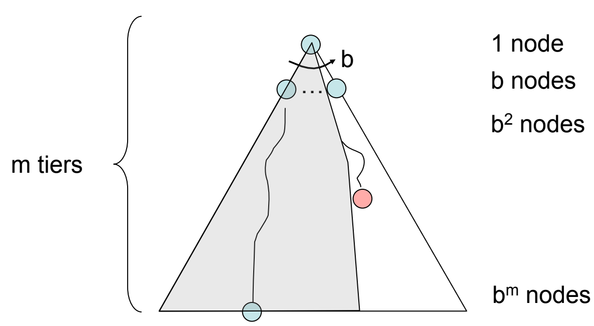
Algorithm		Complete	Optimal	Time	Space
DFS	Depth First Search	N	N	Infinite	Infinite



- Infinite paths make DFS incomplete…
- How can we fix this?

DFS

- With cycle checking, DFS is complete.*



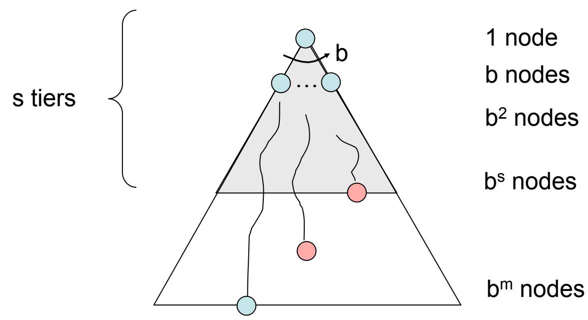
Algorithm		Complete	Optimal	Time	Space
DFS	w/ Path Checking	Y	N	$O(b^m)$	$O(bm)$

- When is DFS optimal?

* Or graph search – next lecture.

BFS

Algorithm		Complete	Optimal	Time	Space
DFS	w/ Path Checking	Y	N	$O(b^m)$	$O(bm)$
BFS		Y	N*	$O(b^{s+1})$	$O(b^{s+1})$



- When is BFS optimal?

Comparisons

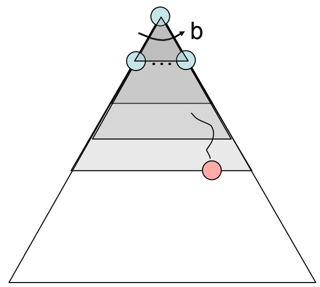
- When will BFS outperform DFS?
- When will DFS outperform BFS?

Iterative Deepening

Iterative deepening uses DFS as a subroutine:

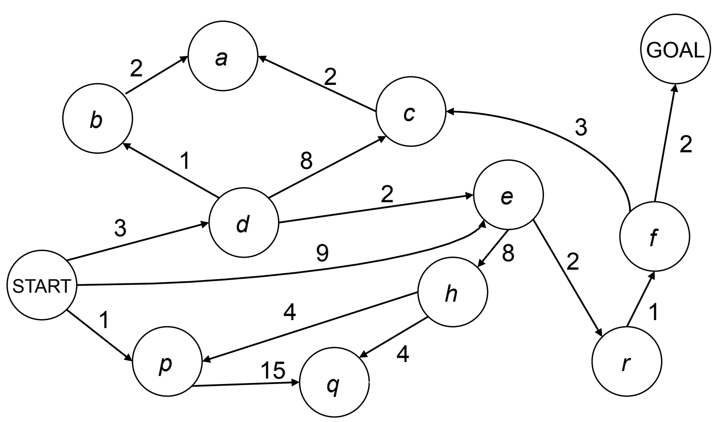
1. Do a DFS which only searches for paths of length 1 or less.
2. If "1" failed, do a DFS which only searches paths of length 2 or less.
3. If "2" failed, do a DFS which only searches paths of length 3 or less.

….and so on.



Algorithm		Complete	Optimal	Time	Space
DFS	w/ Path Checking	Y	N	$O(b^m)$	$O(bm)$
BFS		Y	N*	$O(b^{s+1})$	$O(b^{s+1})$
ID		Y	N*	$O(b^{s+1})$	$O(bs)$

Costs on Actions



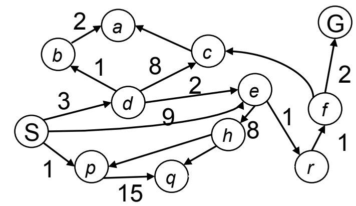
Notice that BFS finds the shortest path in terms of number of transitions. It does not find the least-cost path.

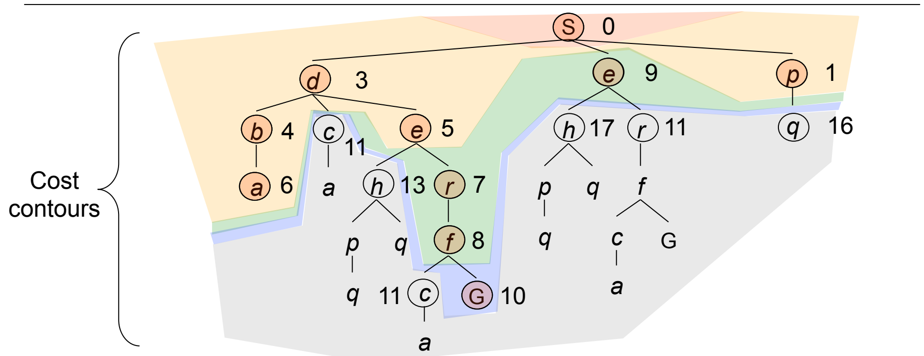
We will quickly cover an algorithm which does find the least-cost path.

Uniform Cost (Tree) Search

Expand cheapest node first:

Fringe is a priority queue





Priority Queue Refresher

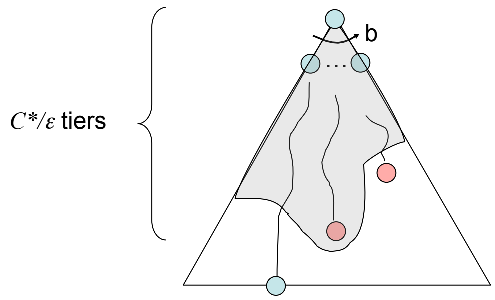
- A priority queue is a data structure in which you can insert and retrieve (key, value) pairs with the following operations:

pq.push(key, value)	inserts *(key, value)* into the queue.
pq.pop()	returns the key with the lowest value, and removes it from the queue.

- You can decrease a key's priority by pushing it again
- Unlike a regular queue, insertions aren't constant time, usually O(log *n*)
- We'll need priority queues for cost-sensitive search methods

Uniform Cost (Tree) Search

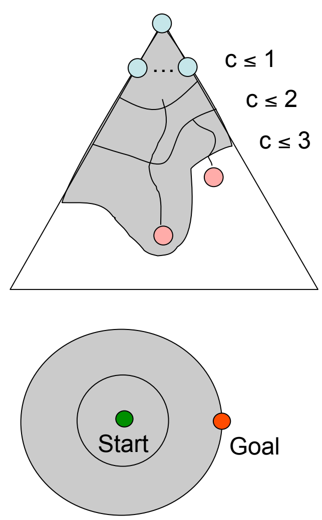
Algorithm		Complete	Optimal	Time (in nodes)	Space
DFS	w/ Path Checking	Y	N	$O(b^m)$	$O(bm)$
BFS		Y	N	$O(b^{s+1})$	$O(b^{s+1})$
UCS		Y*	Y	$O(b^{C^*/\varepsilon})$	$O(b^{C^*/\varepsilon})$



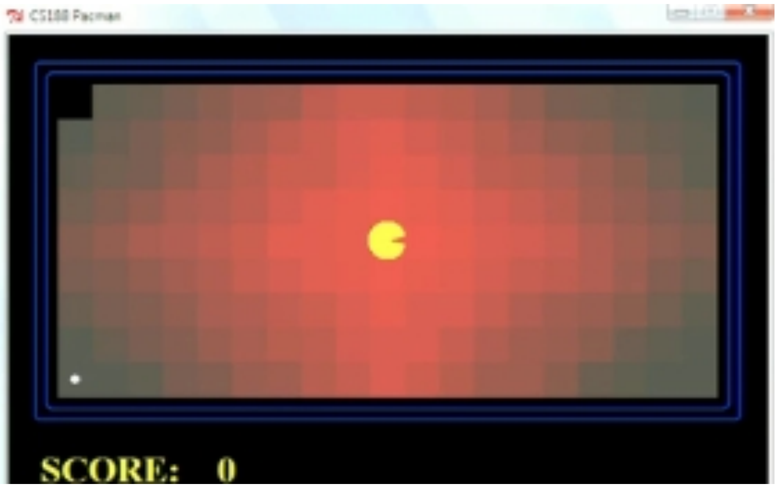
** UCS can fail if actions can get arbitrarily cheap*

Uniform Cost Issues

- Remember: explores increasing cost contours
- The good: UCS is complete and optimal!
- The bad:
  - Explores options in every "direction"
  - No information about goal location

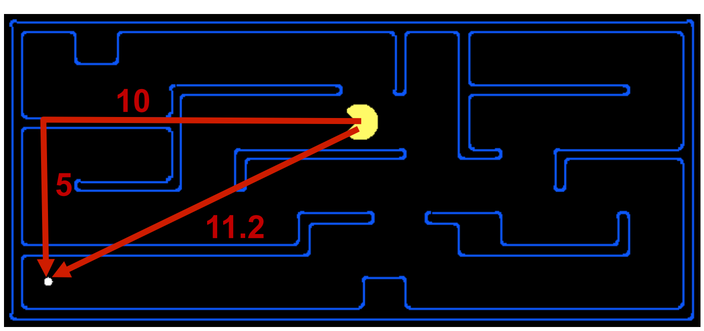


Uniform Cost Search Example

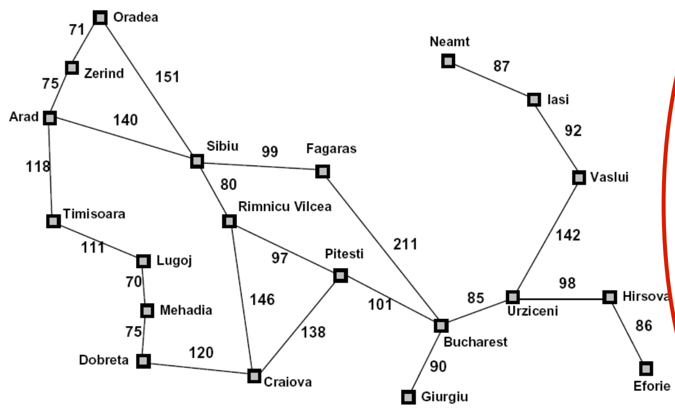


Search Heuristics

- Any *estimate* of how close a state is to a goal
- Designed for a particular search problem
- Examples: Manhattan distance, Euclidean distance



Example: Heuristic Function

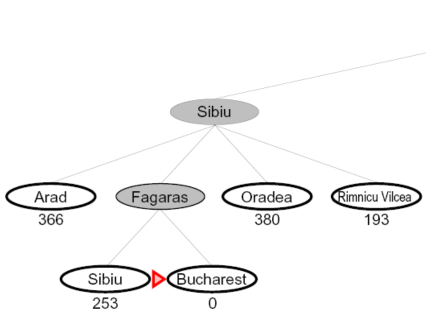


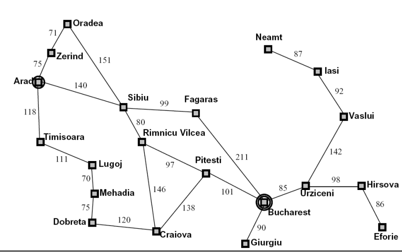
Straight–line distance to Bucharest	
Arad	366
Bucharest	0
Craiova	160
Dobreta	242
Eforie	161
Fagaras	178
Giurgiu	77
Hirsova	151
Iasi	226
Lugoj	244
Mehadia	241
Neamt	234
Oradea	380
Pitesti	98
Rimnicu Vilcea	193
Sibiu	253
Timisoara	329
Urziceni	80
Vaslui	199
Zerind	374

h(x)

Best First / Greedy Search

- Expand the node that seems closest…

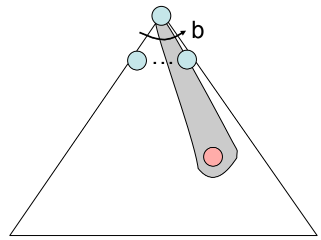


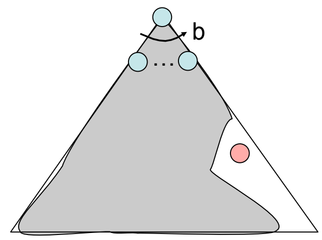


- What can go wrong?

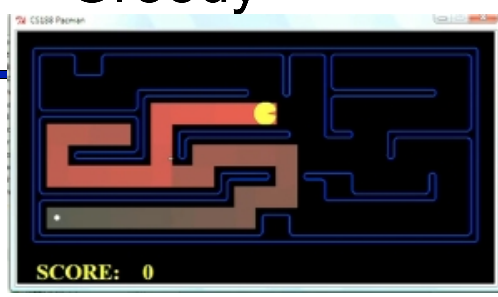
Best First / Greedy Search

- A common case:
  - Best-first takes you straight to the (wrong) goal
- Worst-case: like a badly-guided DFS in the worst case
  - Can explore everything
  - Can get stuck in loops if no cycle checking
- Like DFS in completeness (finite states w/ cycle checking)





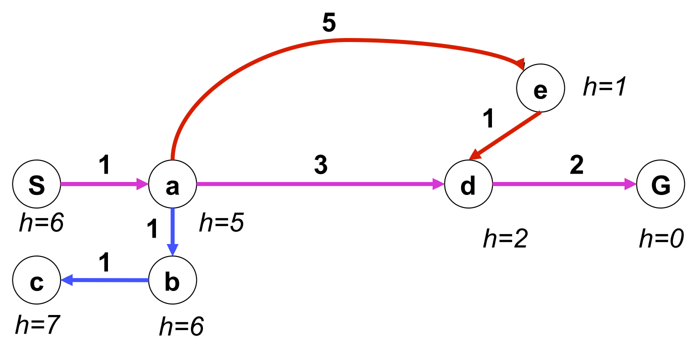
Greedy



Uniform Cost

Combining UCS and Greedy

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

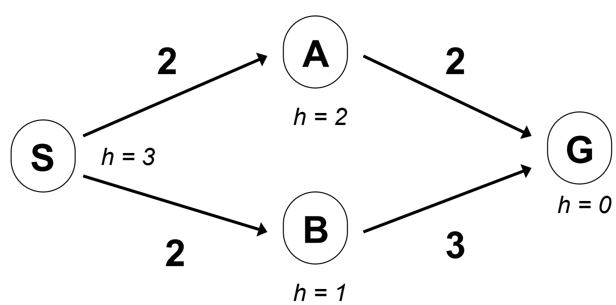


- A* Search orders by the sum: f(n) = g(n) + h(n)

Example: Teg Grenager

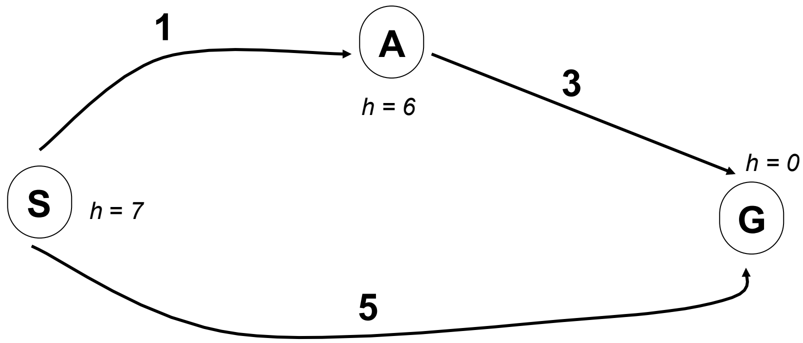
When should A* terminate?

- 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

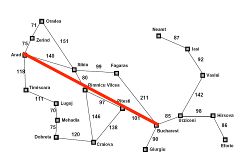
- A heuristic h is *admissible* (optimistic) if:

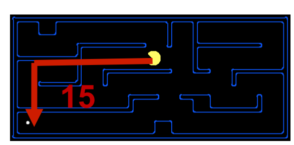
$$h(n) \leq h^*(n)$$

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

- Examples:

366



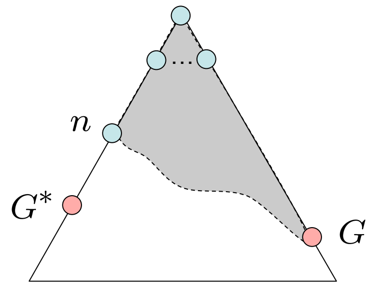


- Coming up with admissible heuristics is most of what's involved in using A* in practice.

Optimality of A*: Blocking

Proof:

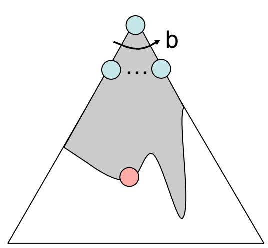
- What could go wrong?
- We'd have to have to pop a suboptimal goal G off the fringe before G*
- This can't happen:
  - Imagine a suboptimal goal G is on the queue
  - Some node *n* which is a subpath of G* must also be on the fringe (why?)
  - *n* will be popped before G



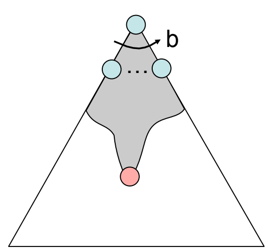
$$f(n) = g(n) + h(n)$$
$$g(n) + h(n) \leq g(G^*)$$
$$g(G^*) < g(G)$$
$$g(G) = f(G)$$
$$f(n) < f(G)$$

Properties of A*

Uniform-Cost

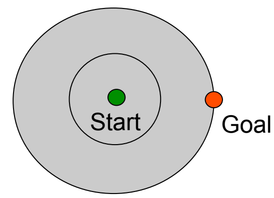


A*

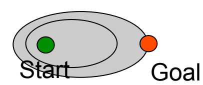


UCS vs A* Contours

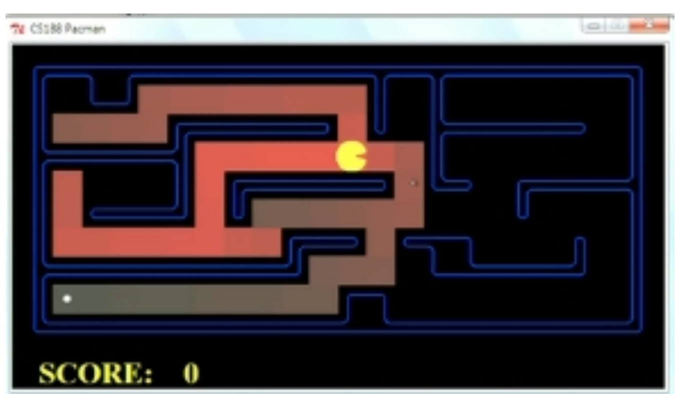
- Uniform-cost expanded in all directions



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



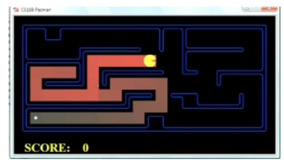
Example: Explored States with A*



Heuristic: manhattan distance ignoring walls

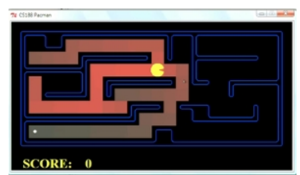
Comparison

Greedy



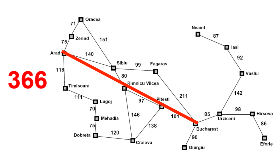
Uniform Cost

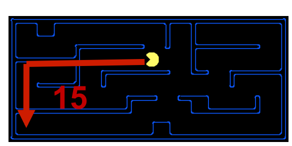
A star



Creating Admissible Heuristics

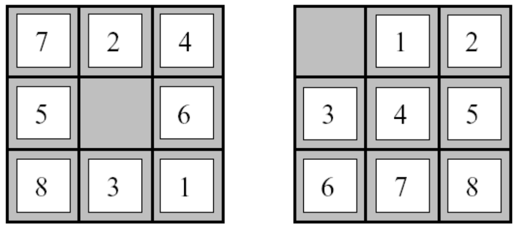
- Most of the work in solving hard search problems optimally is in coming up with admissible heuristics
- Often, admissible heuristics are solutions to *relaxed problems,* with new actions ("some cheating") available





- Inadmissible heuristics are often useful too (why?)

Example: 8 Puzzle

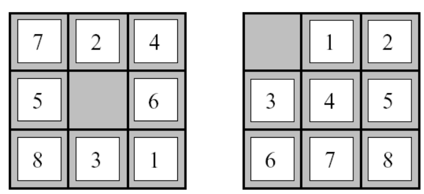


Start State Goal State

- What are the states?
- How many states?
- What are the actions?
- What states can I reach from the start state?
- What should the 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

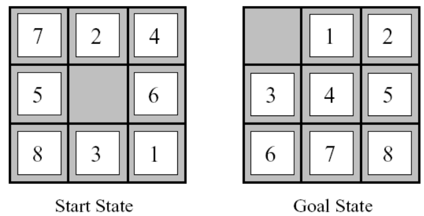
	Average nodes expanded when optimal path has length…		
	…4 steps	…8 steps	…12 steps
UCS	112	6,300	3.6×10^6
TILES	13	39	227

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 admissible?
- h(start) =

  3 + 1 + 2 + …

  = 18



	Average nodes expanded when optimal path has length…		
	…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!

Trivial Heuristics, Dominance

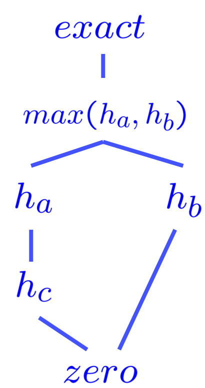
- Dominance: $h_a \geq h_c$ if

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

- 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

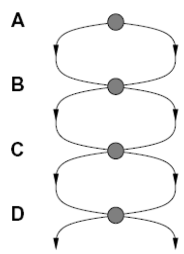


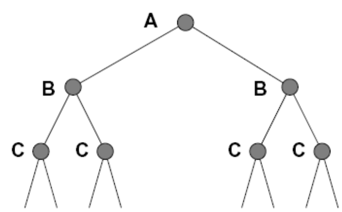
Other A* Applications

- Pathing / routing problems
- Resource planning problems
- Robot motion planning
- Language analysis
- Machine translation
- Speech recognition
- …

Tree Search: Extra Work!

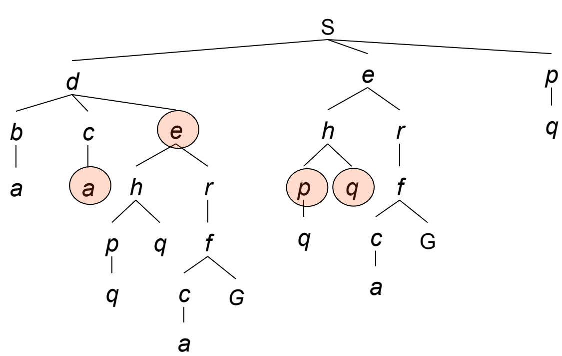
- Failure to detect repeated states can cause exponentially more work. Why?





Graph Search

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



Graph Search

- Idea: never expand a state twice
- How to implement:
  - Tree search + list of expanded states (closed list)
  - Expand the search tree node-by-node, but…
  - Before expanding a node, check to make sure its state is new
- Python trick: store the closed list as a set, not a list
- Can graph search wreck completeness? Why/why not?
- How about optimality?

Graph Search

- Very simple fix: never expand a state twice

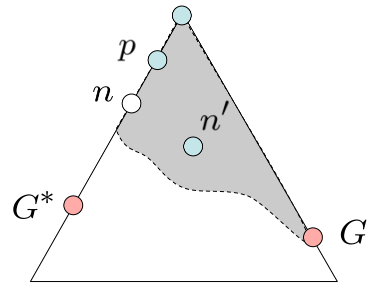
```
function GRAPH-SEARCH(problem, fringe) returns a solution, or failure
    closed ← an empty set
    fringe ← INSERT(MAKE-NODE(INITIAL-STATE[problem]), fringe)
    loop do
        if fringe is empty then return failure
        node ← REMOVE-FRONT(fringe)
        if GOAL-TEST(problem, STATE[node])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

- Can this wreck completeness? Optimality?

Optimality of A* Graph Search

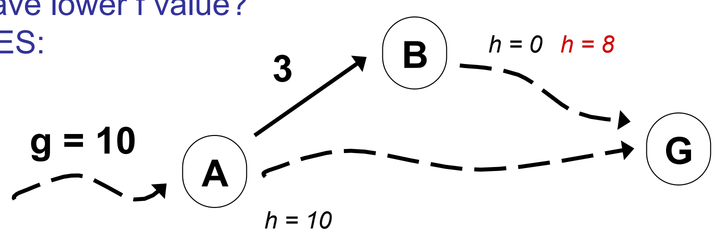
Proof:

- New possible problem: nodes on path to G* that would have been in queue aren't, because some worse *n'* for the same state as some *n* was dequeued and expanded first (disaster!)
- Take the highest such *n* in tree
- Let *p* be the ancestor which was on the queue when *n'* was expanded
- Assume *f(p) < f(n)*
- *f(n) < f(n')* because *n'* is suboptimal
- *p* would have been expanded before *n'*
- So *n* would have been expanded before *n'*, too
- Contradiction!



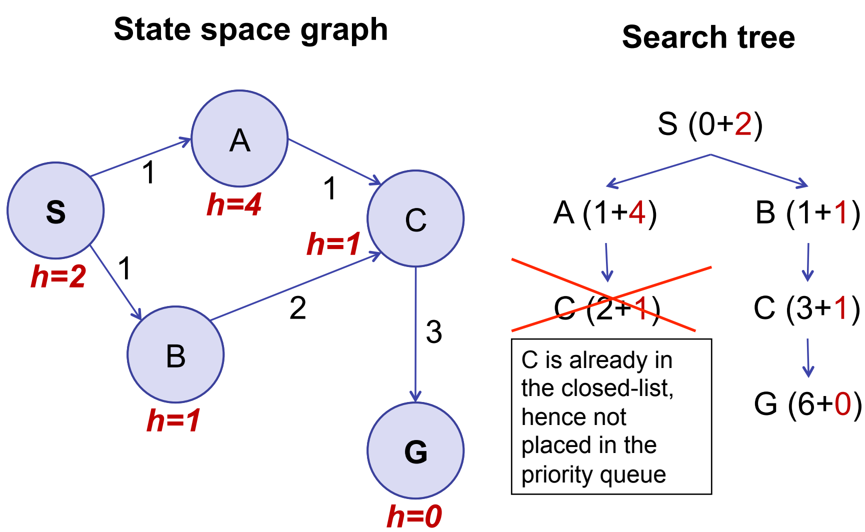
Consistency

- Wait, how do we know parents have better f-values than their successors?
- Couldn't we pop some node *n*, and find its child *n'* to have lower f value?
- YES:

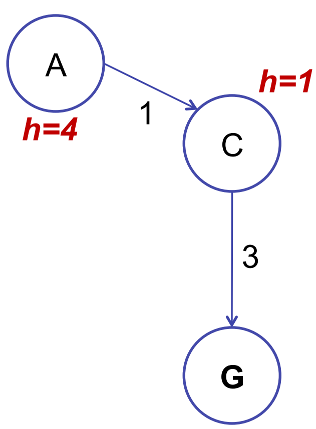


- What can we require to prevent these inversions?
- Consistency: $c(n, a, n') \geq h(n) - h(n')$
- Real cost must always exceed reduction in heuristic

A* Graph Search Gone Wrong



Consistency



The story on Consistency:

- Definition:
  cost(A to C) + h(C) ≥ h(A)
- Consequence in search tree:
  Two nodes along a path: $N_{A,}$ N_C
  $g(N_C) = g(N_A) + cost(A\ to\ C)$
  $g(N_C) + h(C) \geq g(N_A) + h(A)$
- The f value along a path never decreases
- Non-decreasing f means you're optimal to every state (not just goals)

Optimality Summary

- Tree search:
  - A* optimal if heuristic is admissible (and non-negative)
  - Uniform Cost Search is a special case (h = 0)
- Graph search:
  - A* optimal if heuristic is consistent
  - UCS optimal (h = 0 is consistent)
- Consistency implies admissibility
  - Challenge:Try to prove this.
  - Hint: try to prove the equivalent statement *not admissible implies not consistent*
- In general, natural admissible heuristics tend to be consistent
- Remember, costs are always positive in search!

Summary: A*

- A* uses both backward costs and (estimates of) forward costs
- A* is optimal with admissible heuristics
- Heuristic design is key: often use relaxed problems

A* Memory Issues → IDA*

- IDA* (Iterative Deepening A*)

  1. set $f_{max} = 1$ (or some other small value)
  2. Execute DFS that does not expand states with $f>f_{max}$
  3. If DFS returns a path to the goal, return it
  4. Otherwise $f_{max}=f_{max}+1$ (or larger increment) and go to step 2

- Complete and optimal
- Memory: $O(bs)$, where b – max. branching factor, s – search depth of optimal path
- Complexity: $O(kb^s)$, where k is the number of times DFS is called

69

Recap Search I

- Agents that plan ahead → formalization: Search
- Search problem:
  - States (configurations of the world)
  - Successor function: a function from states to lists of (state, action, cost) triples; drawn as a graph
  - 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)

Recap Search II

- Tree Search vs. Graph Search
- Priority queue to store fringe: different priority functions → different search method
  - Uninformed Search Methods
    - Depth-First Search
    - Breadth-First Search
    - Uniform-Cost Search
  - Heuristic Search Methods
    - Greedy Search
    - A* Search --- heuristic design!
      - Admissibility: h(n) <= cost of cheapest path to a goal state. Ensures when goal node is expanded, no other partial plans on fringe could be extended into a cheaper path to a goal state
      - Consistency: c(n->n') >= h(n) – h(n'). Ensures when any node n is expanded during graph search the partial plan that ended in n is the cheapest way to reach n.
- Time and space complexity, completeness, optimality
- Iterative Deepening: enables to retain optimality with little computational overhead and better space complexity