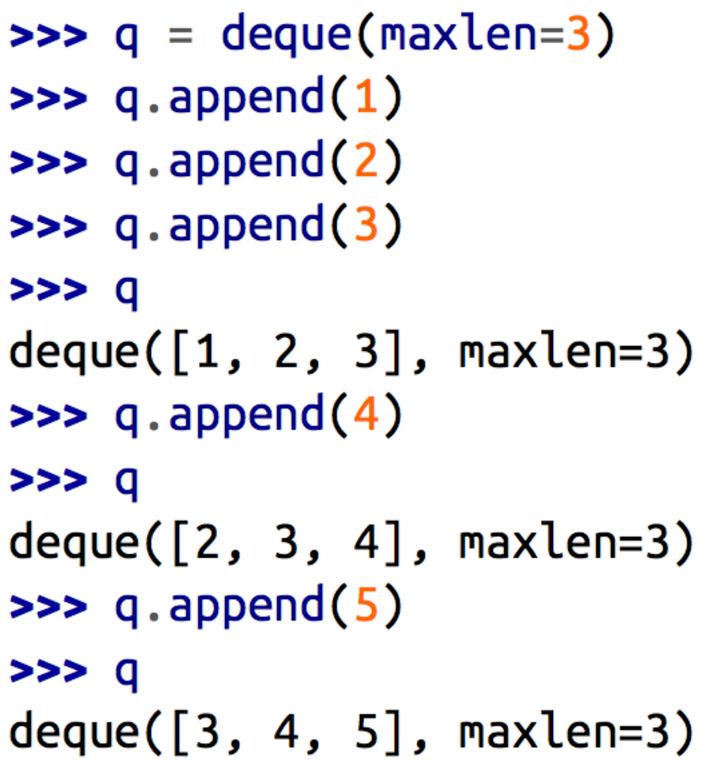
Python Programming

```python
from collections import deque

def search(lines, pattern, history=5):
    previous_lines = deque(maxlen=history)
    for line in lines:
        if pattern in line:
            yield line, previous_lines
        previous_lines.append(line)

# Example use on a file
if __name__ == '__main__':
    with open('somefile.txt') as f:
        for line, prevlines in search(f, 'python', 5):
            for pline in prevlines:
                print(pline, end='')
            print(line, end='')
            print('-'*20)
```

Source: Beazley, David; Jones, Brian K. (2013). *Python Cookbook* (3rd ed.).

Python Programming



```
>>> q = deque(maxlen=3)
>>> q.append(1)
>>> q.append(2)
>>> q.append(3)
>>> q
deque([1, 2, 3], maxlen=3)
>>> q.append(4)
>>> q
deque([2, 3, 4], maxlen=3)
>>> q.append(5)
>>> q
deque([3, 4, 5], maxlen=3)
```

Source: Beazley, David; Jones, Brian K. (2013). *Python Cookbook* (3rd ed.).

Python Programming

```
>>> q = deque()
>>> q.append(1)
>>> q.append(2)
>>> q.append(3)
>>> q
deque([1, 2, 3])
>>> q.appendleft(4)
>>> q
deque([4, 1, 2, 3])
>>> q.pop()
3
>>> q
deque([4, 1, 2])
>>> q.popleft()
4
```

Source: Beazley, David; Jones, Brian K. (2013). *Python Cookbook* (3rd ed.).

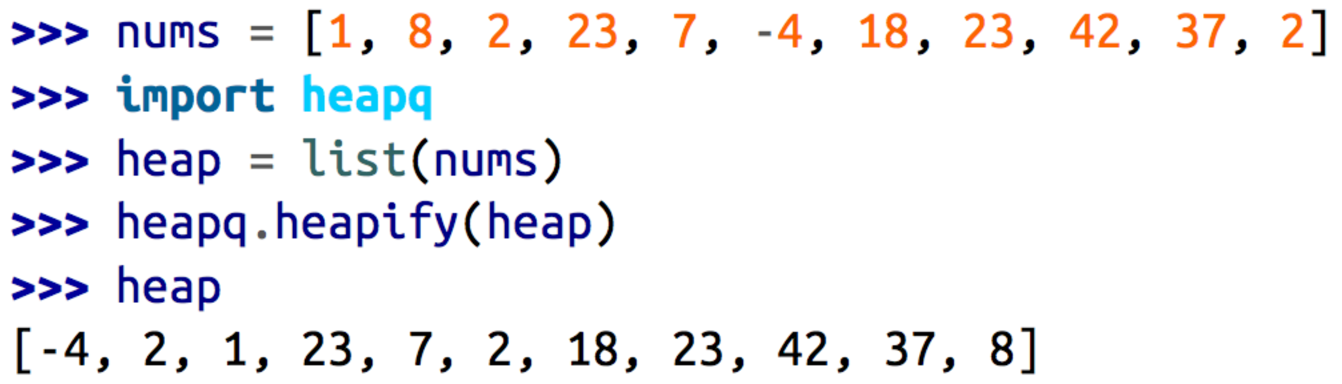
Python Programming

```python
import heapq

nums = [1, 8, 2, 23, 7, -4, 18, 23, 42, 37, 2]
print(heapq.nlargest(3, nums))  # Prints [42, 37, 23]
print(heapq.nsmallest(3, nums)) # Prints [-4, 1, 2]
```

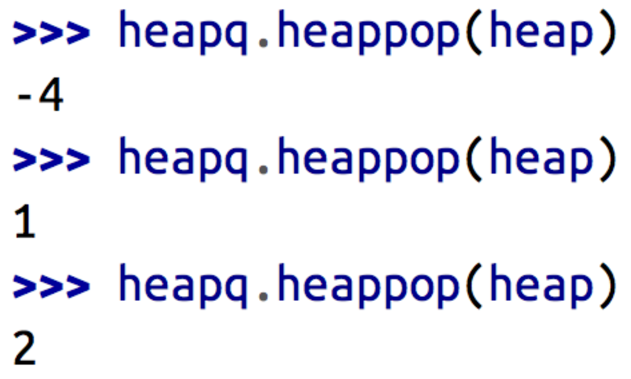
```python
portfolio = [
   {'name': 'IBM', 'shares': 100, 'price': 91.1},
   {'name': 'AAPL', 'shares': 50, 'price': 543.22},
   {'name': 'FB', 'shares': 200, 'price': 21.09},
   {'name': 'HPQ', 'shares': 35, 'price': 31.75},
   {'name': 'YHOO', 'shares': 45, 'price': 16.35},
   {'name': 'ACME', 'shares': 75, 'price': 115.65}
]

cheap = heapq.nsmallest(3, portfolio, key=lambda s: s['price'])
expensive = heapq.nlargest(3, portfolio, key=lambda s: s['price'])
```

Source: Beazley, David; Jones, Brian K. (2013). *Python Cookbook* (3rd ed.).

Python Programming



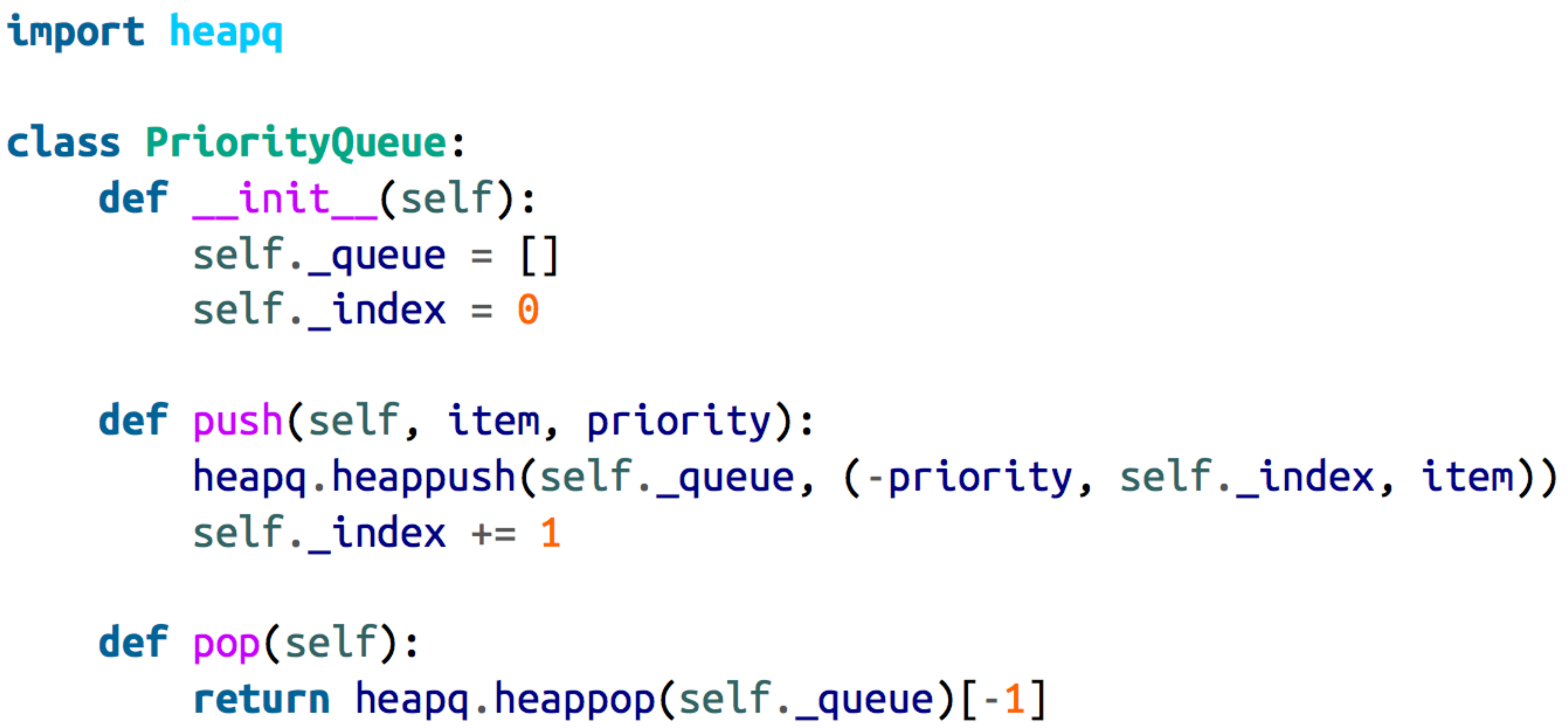
```
>>> nums = [1, 8, 2, 23, 7, -4, 18, 23, 42, 37, 2]
>>> import heapq
>>> heap = list(nums)
>>> heapq.heapify(heap)
>>> heap
[-4, 2, 1, 23, 7, 2, 18, 23, 42, 37, 8]
```



```
>>> heapq.heappop(heap)
-4
>>> heapq.heappop(heap)
1
>>> heapq.heappop(heap)
2
```

Source: Beazley, David; Jones, Brian K. (2013). *Python Cookbook* (3rd ed.).

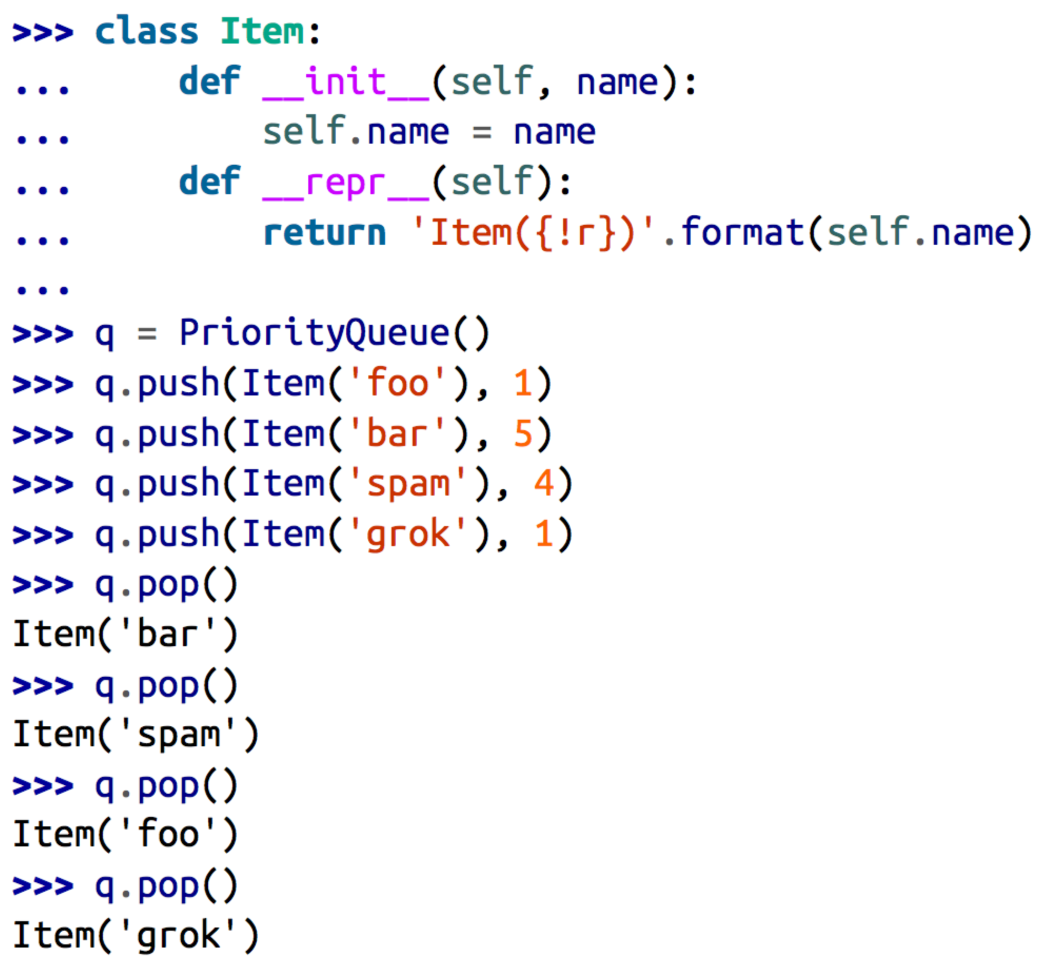
Python Programming



```python
import heapq

class PriorityQueue:
    def __init__(self):
        self._queue = []
        self._index = 0

    def push(self, item, priority):
        heapq.heappush(self._queue, (-priority, self._index, item))
        self._index += 1

    def pop(self):
        return heapq.heappop(self._queue)[-1]
```

Source: Beazley, David; Jones, Brian K. (2013). *Python Cookbook* (3rd ed.).

Python Programming



```
>>> class Item:
...     def __init__(self, name):
...         self.name = name
...     def __repr__(self):
...         return 'Item({!r})'.format(self.name)
...
>>> q = PriorityQueue()
>>> q.push(Item('foo'), 1)
>>> q.push(Item('bar'), 5)
>>> q.push(Item('spam'), 4)
>>> q.push(Item('grok'), 1)
>>> q.pop()
Item('bar')
>>> q.pop()
Item('spam')
>>> q.pop()
Item('foo')
>>> q.pop()
Item('grok')
```

Source: Beazley, David; Jones, Brian K. (2013). *Python Cookbook* (3rd ed.).

Python Programming

```
>>> a = Item('foo')
>>> b = Item('bar')
>>> a < b
Traceback (most recent call last):
  File "<stdin>", line 1, in <module>
TypeError: unorderable types: Item() < Item()
```

```
>>> a = (1, Item('foo'))
>>> b = (5, Item('bar'))
>>> a < b
True
>>> c = (1, Item('grok'))
>>> a < c
Traceback (most recent call last):
  File "<stdin>", line 1, in <module>
TypeError: unorderable types: Item() < Item()
>>>
```

```
>>> a = (1, 0, Item('foo'))
>>> b = (5, 1, Item('bar'))
>>> c = (1, 2, Item('grok'))
>>> a < b
True
```

Source: Beazley, David; Jones, Brian K. (2013). *Python Cookbook* (3rd ed.).

Python Programming

```python
d = {
    'a' : [1, 2, 3],
    'b' : [4, 5]
}

e = {
    'a' : {1, 2, 3},
    'b' : {4, 5}
}
```

```python
from collections import defaultdict

d = defaultdict(list)
d['a'].append(1)
d['a'].append(2)
d['b'].append(4)
...

d = defaultdict(set)

 d['a'].add(1)
 d['a'].add(2)
 d['b'].add(4)
 ...
```

Source: Beazley, David; Jones, Brian K. (2013). *Python Cookbook* (3rd ed.).

Python Programming

```python
d = {}
for key, value in pairs:
    if key not in d:
        d[key] = []
    d[key].append(value)
```

```python
d = defaultdict(list)
for key, value in pairs:
    d[key].append(value)
```

Source: Beazley, David; Jones, Brian K. (2013). *Python Cookbook* (3rd ed.).

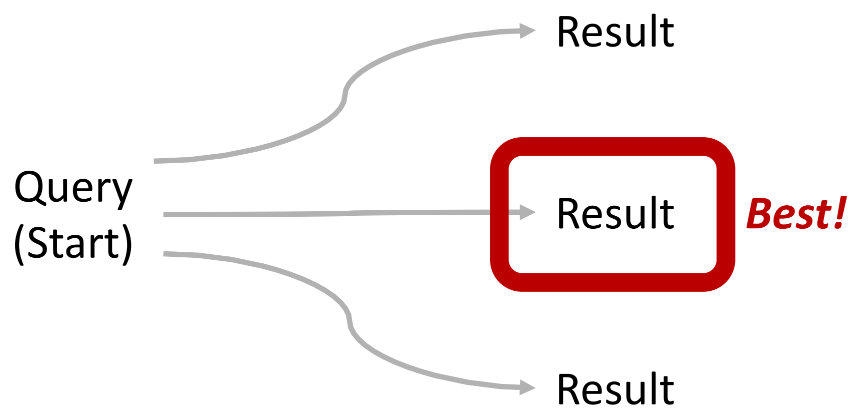
Search Problems

Search?

Information Retrieval vs Search

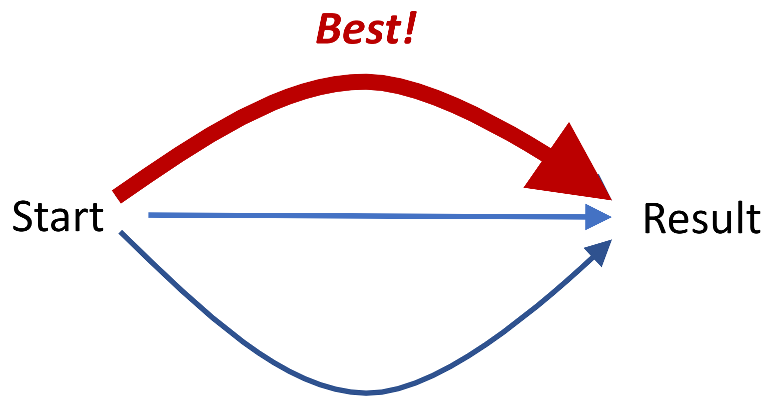
Google

(Information Retrieval)



Search

(Problem-Solving)



Definition of Search

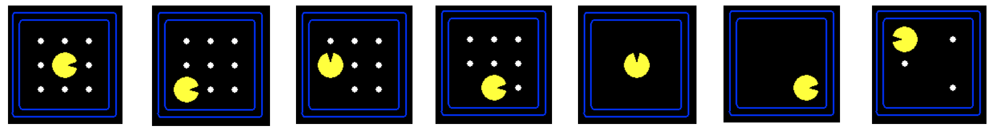
Finding a (best) sequence of actions to solve a problem

For now, assume the problem is

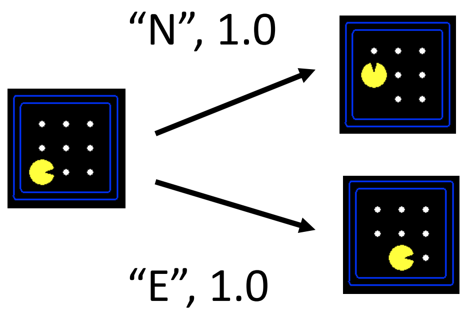
- Deterministic
- Fully observable
- Known

Search Problem Mechanics

- A search problem consists of:
  - A state space



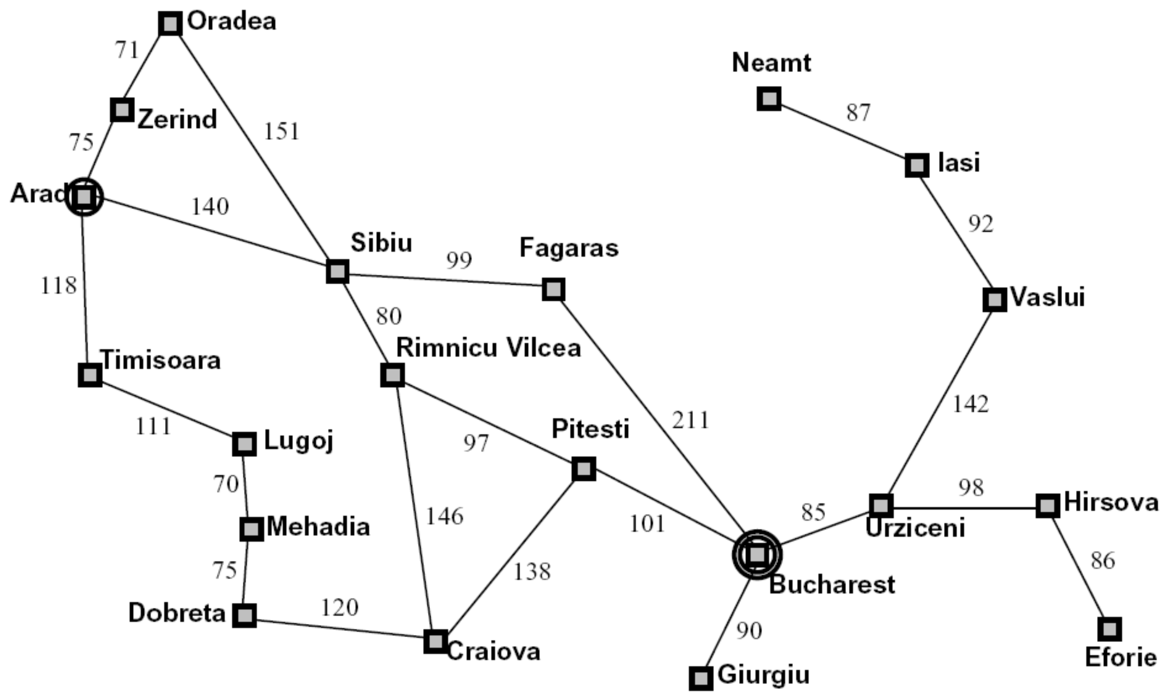
  - A successor function (with actions, costs)



  - 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

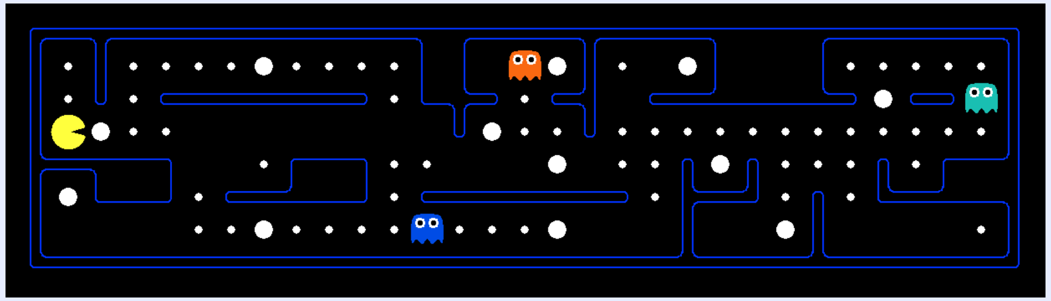
Example: Traveling in Romania



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

What's in a State Space?

The world state includes every last detail of the environment



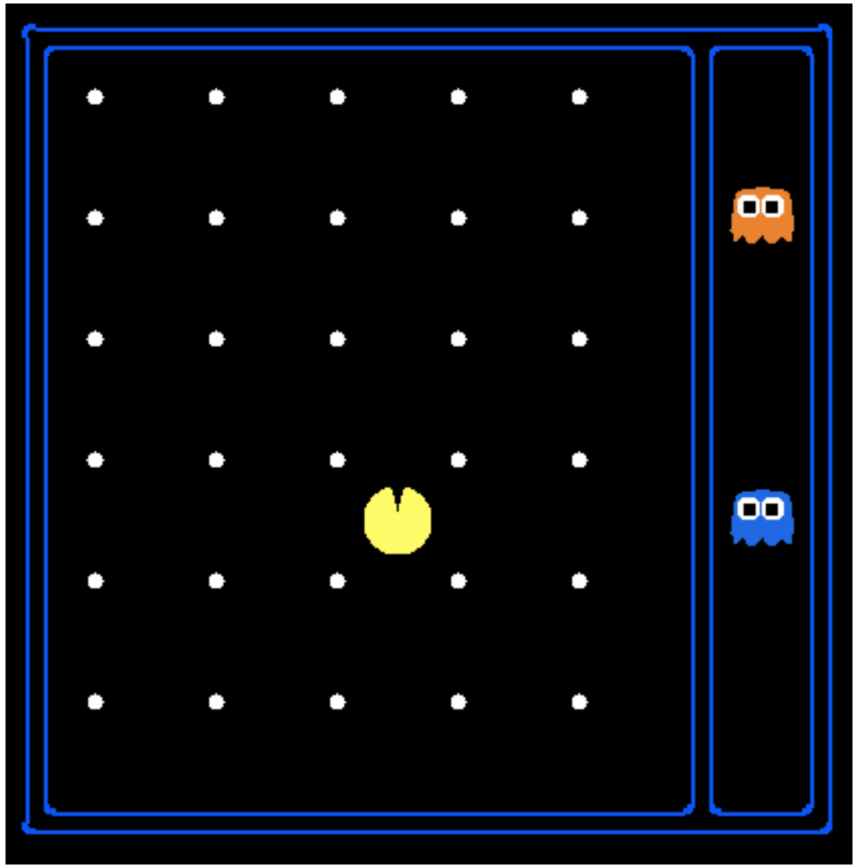
A search state keeps only the details needed for planning (abstraction)

- 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

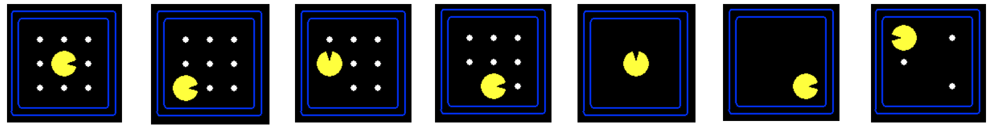
State Space Sizes?

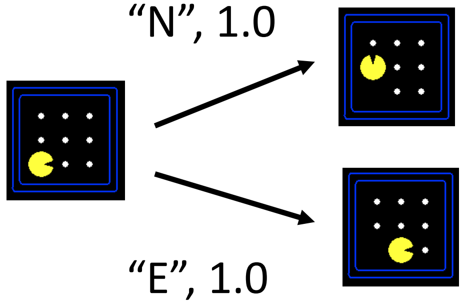
- World state:
  - Agent positions: 120
  - Food count: 30
  - Ghost positions: 12
  - Agent facing: NSEW
- How many
  - World states?
    120x(2^{30})x(12^2)x4
  - States for pathing?
    120
  - States for eat-all-dots?
    120x(2^{30})



Search Problem Mechanics

- A search problem consists of:
  - A state space
  - A successor function (with actions, costs)
  - A start state and a goal test

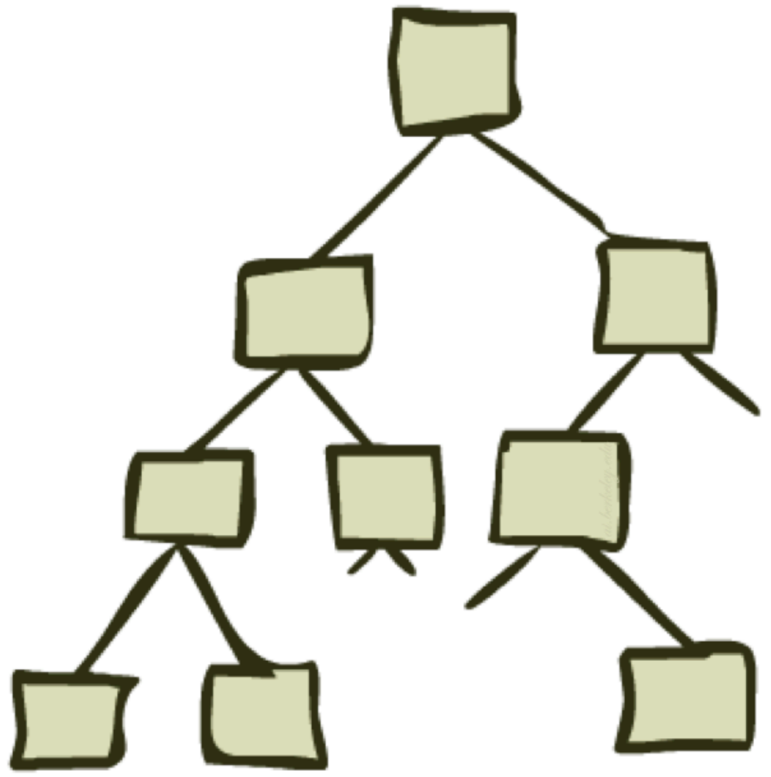




- A solution is a sequence of actions (a plan) which transforms the start state to a goal state

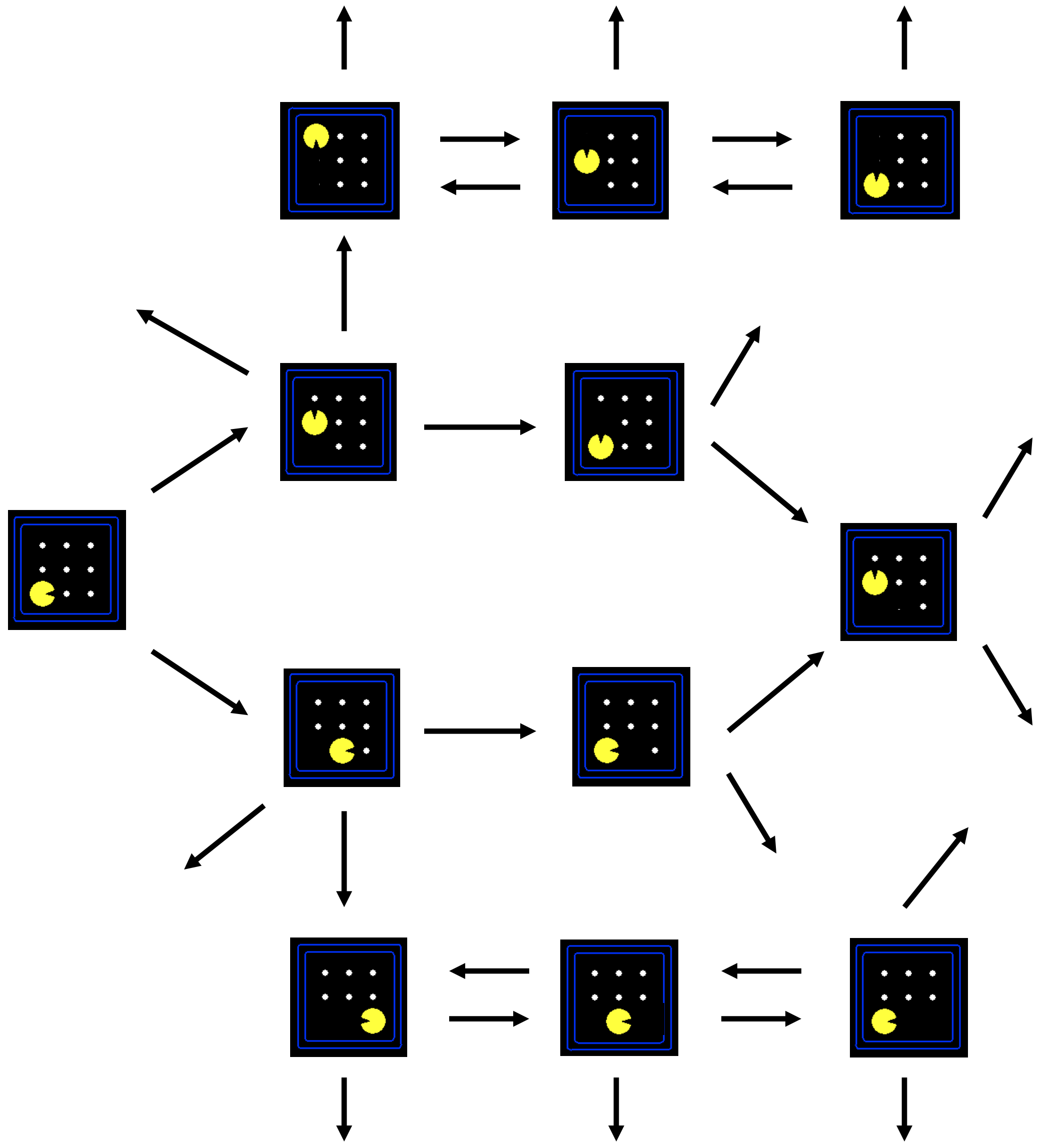
What are some problems that <u>can't</u> be formulated as search?

State Space Graphs and Search Trees



State Space Graphs

- State space graph: A mathematical representation of a search problem
  - Nodes are (abstracted) world configurations
  - Arcs represent successors (action results)
  - The goal test is a set of goal nodes (maybe only one)
- In a state space graph, each state occurs only once!
- We can rarely build this full graph in memory (it's too big), but it's a useful idea



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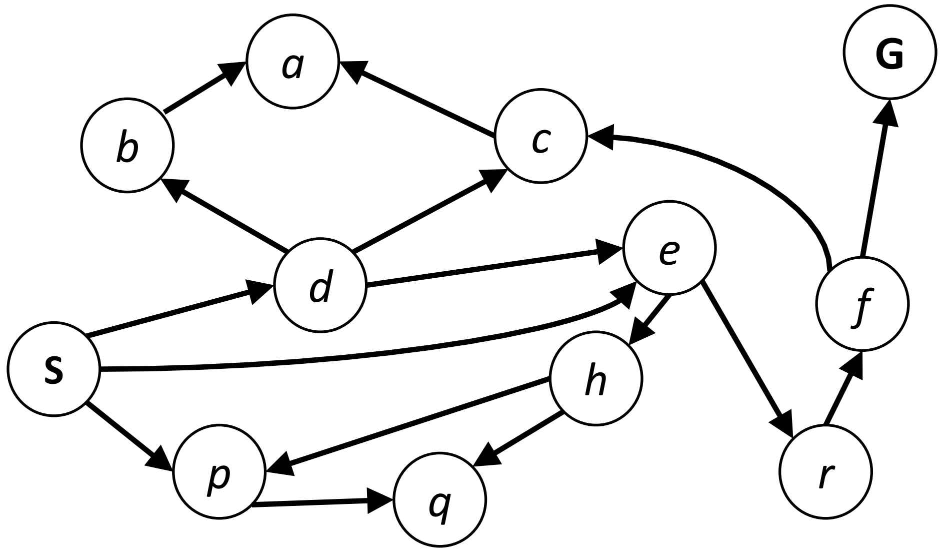
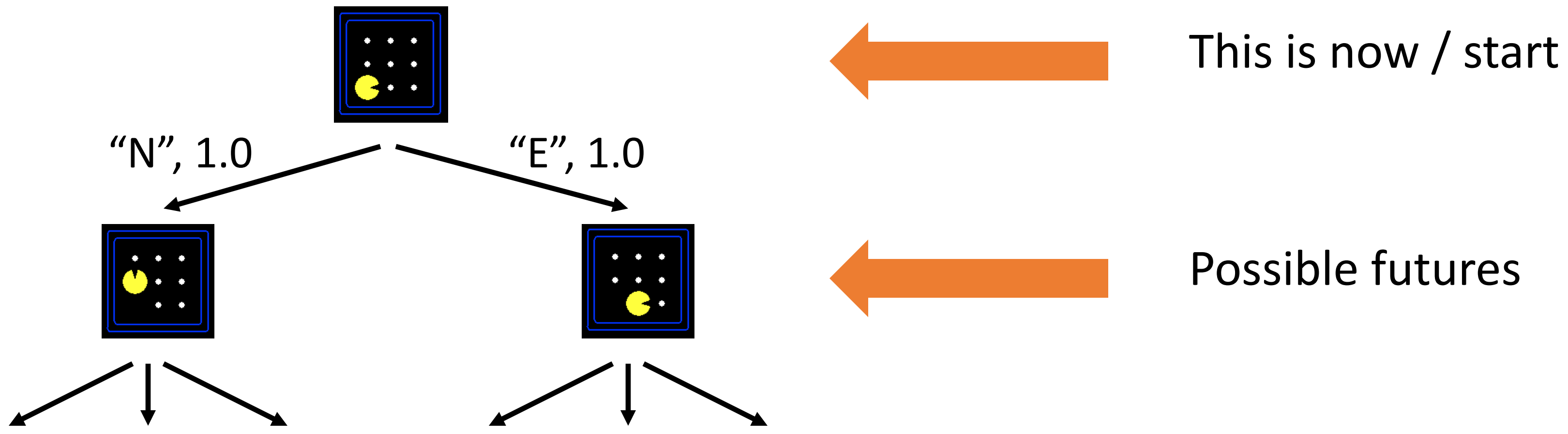


Tiny search graph for a tiny search problem

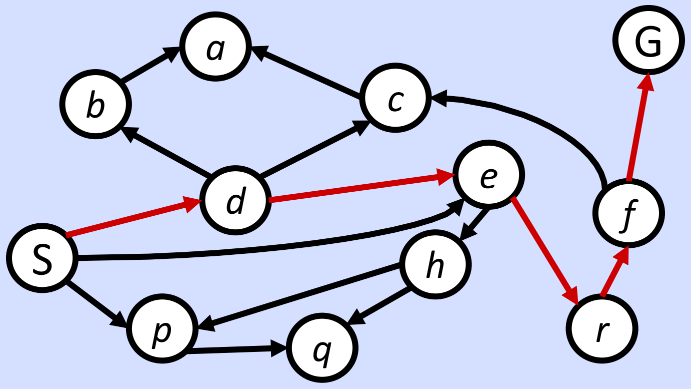
Search Trees



- A search tree:
  - A "what if" tree of plans and their outcomes
  - The start state is the root node
  - Children correspond to successors
  - Nodes show states, but correspond to ACTION SEQUENCES that achieve those states
  - For most problems, we can never actually build the whole tree

State Space Graphs vs. Search Trees

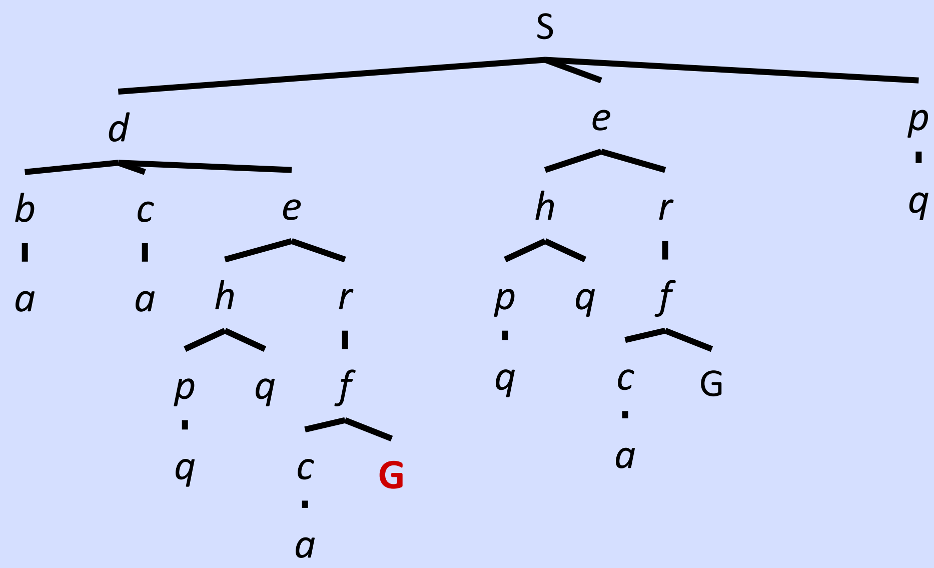
State Space Graph



Each NODE in in the search tree corresponds to an entire PATH in the state space graph.

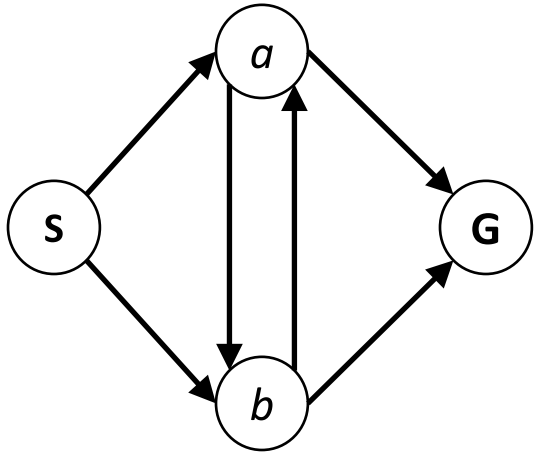
We construct both on demand – and we construct as little as possible.

Search Tree



Quiz: State Space Graphs vs. Search Trees

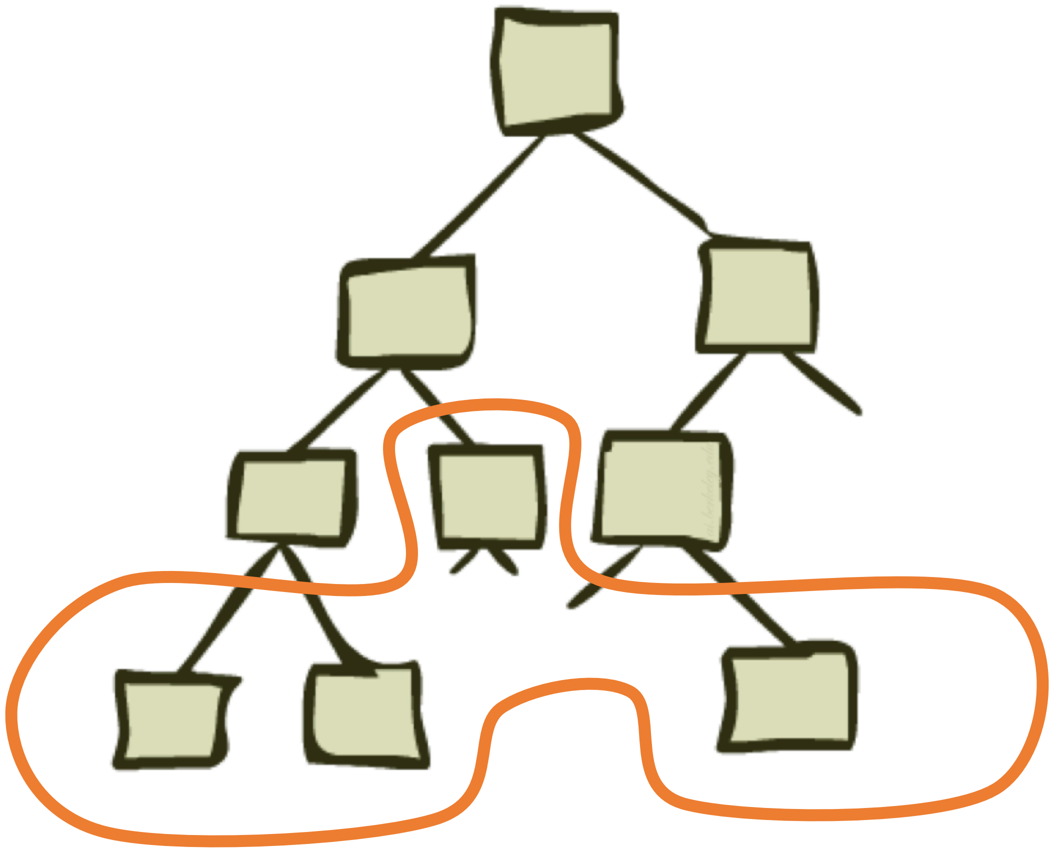
Consider this 4-state graph:



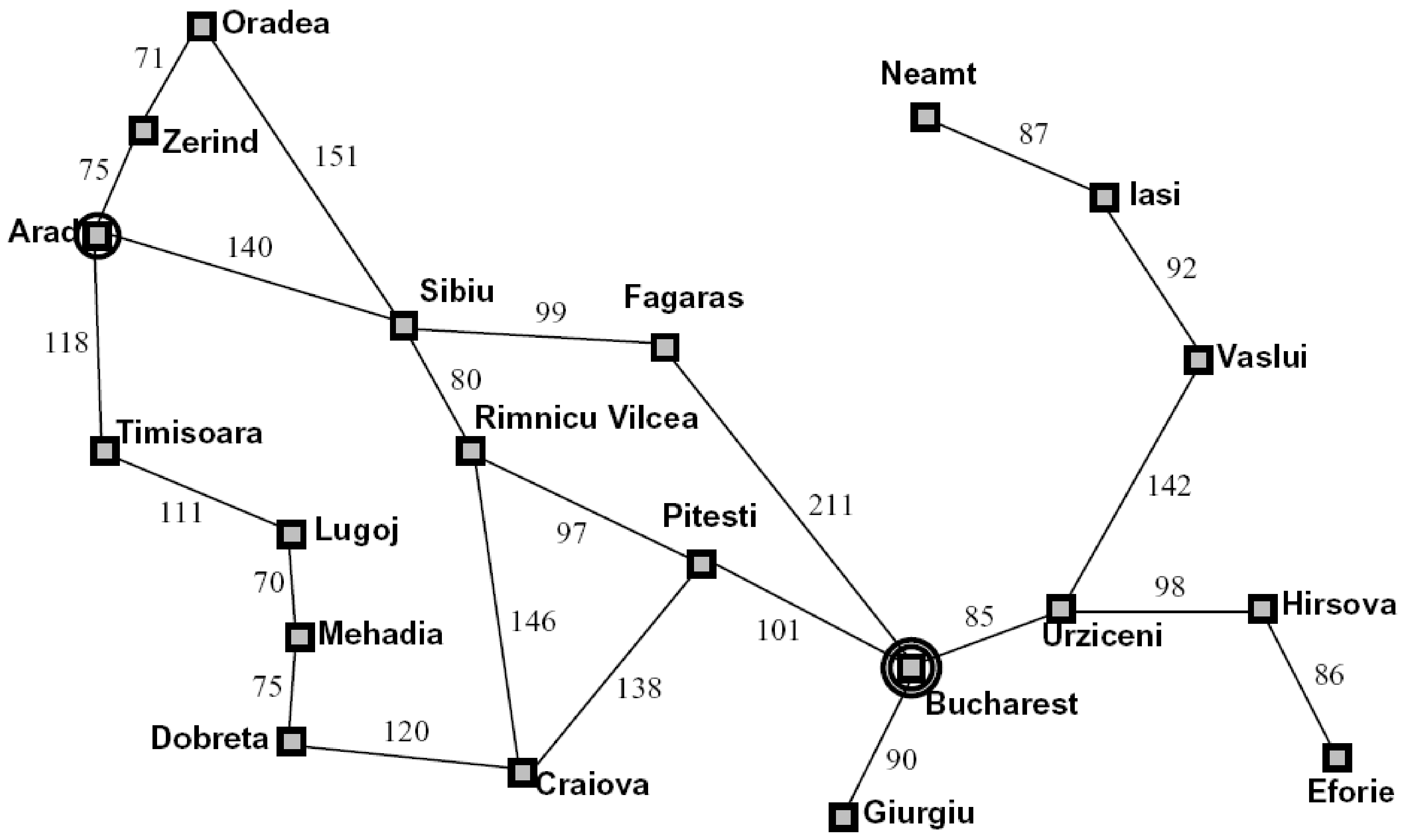
How big is its search tree (from S)?

Important: Lots of repeated structure in the search tree!

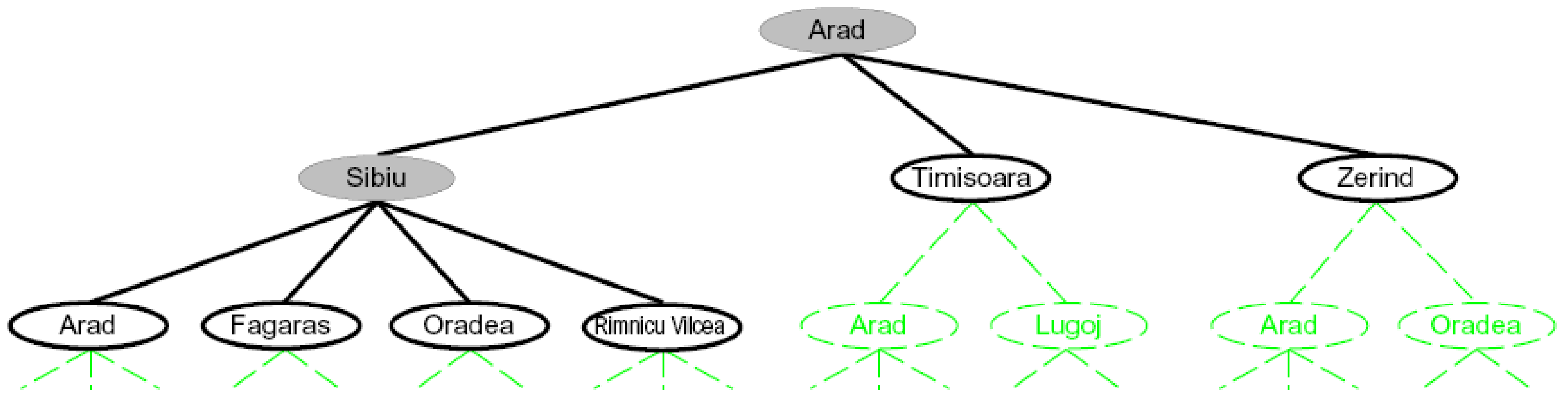
Tree Search



Search Example: Romania



Searching with a Search Tree



- Search:
  - Expand out potential plans (tree nodes)
  - Maintain a fringe of partial plans under consideration
  - Try to expand as few tree nodes as possible

General Tree Search

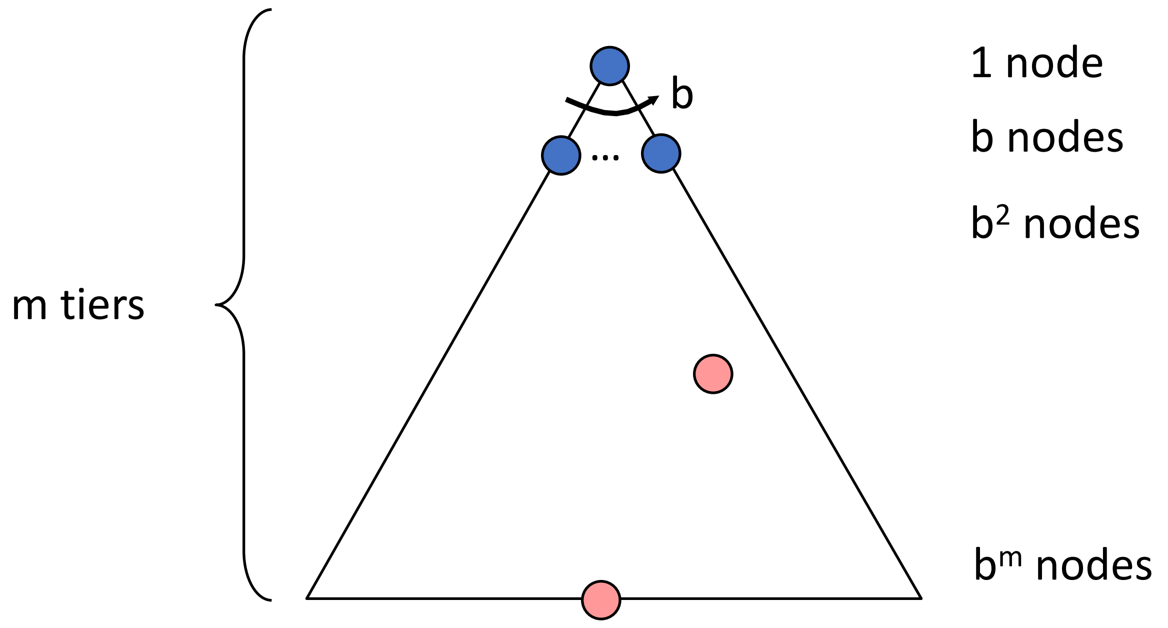
```
function TREE-SEARCH( problem, strategy) returns a solution, or failure
    initialize the search tree using the initial state of problem
    loop do
        if there are no candidates for expansion then return failure
        choose a leaf node for expansion according to strategy
        if the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

Search Algorithm Properties

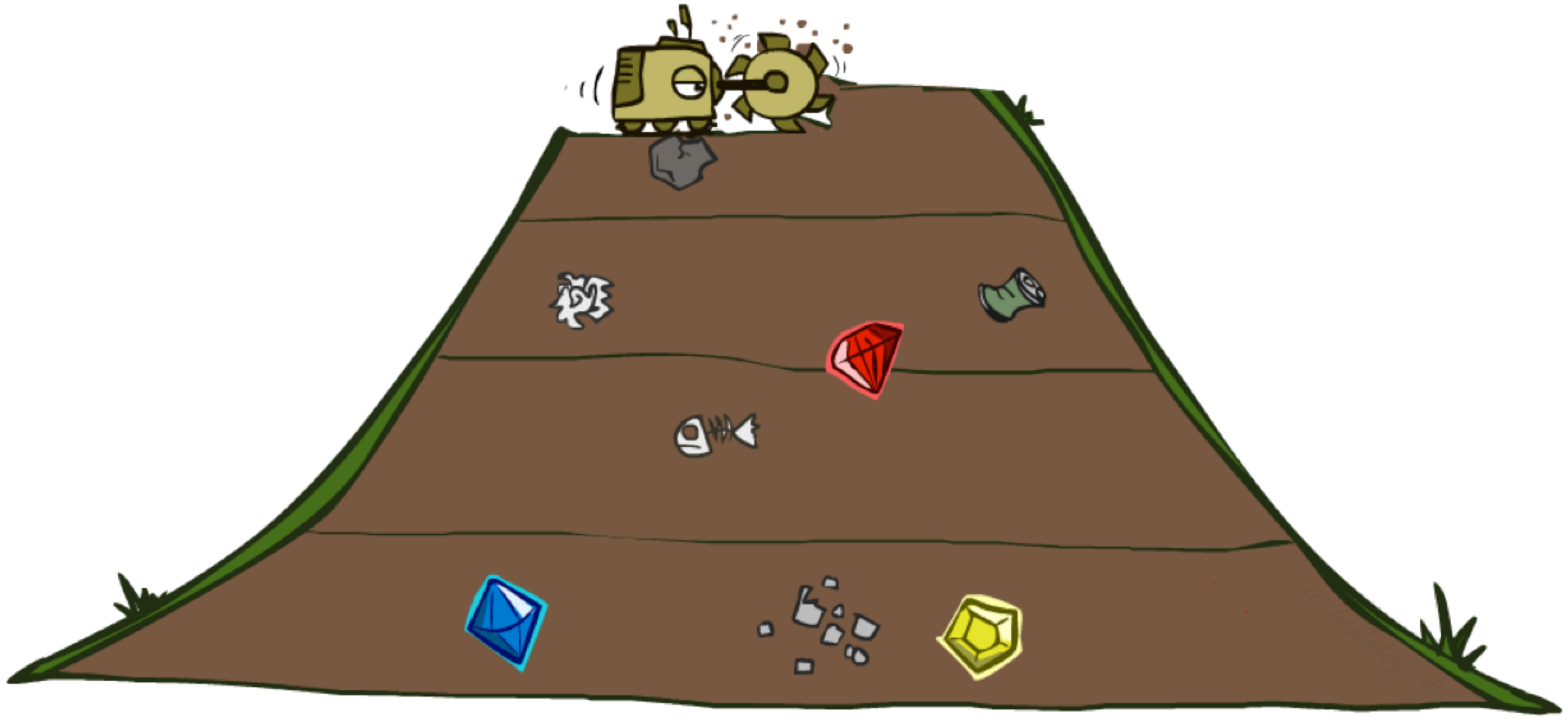
- Complete: Guaranteed to find a solution if one exists?
- Optimal: Guaranteed to find the least cost path?
- Time complexity?
- Space complexity?

- Cartoon of search tree:
  - b is the branching factor
  - m is the maximum depth
  - solutions at various depths

- Number of nodes in entire tree?
  - $1 + b + b^2 + \ldots. b^m = O(b^m)$



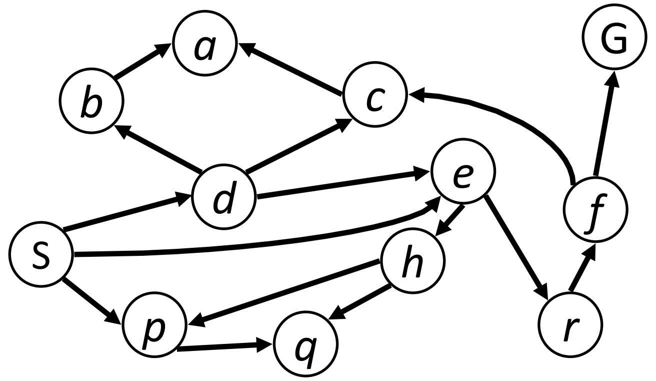
Breadth-First Search

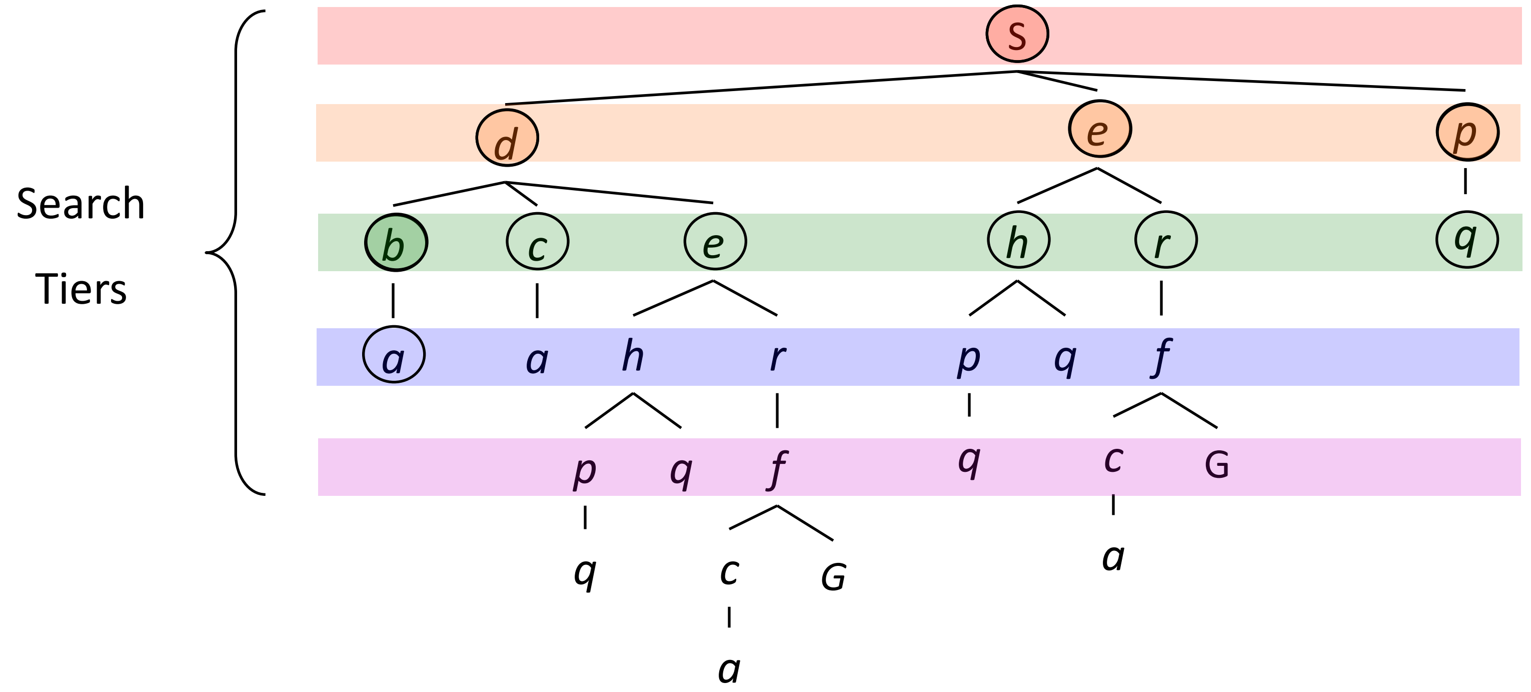


Breadth-First Search

Strategy: expand a shallowest node first

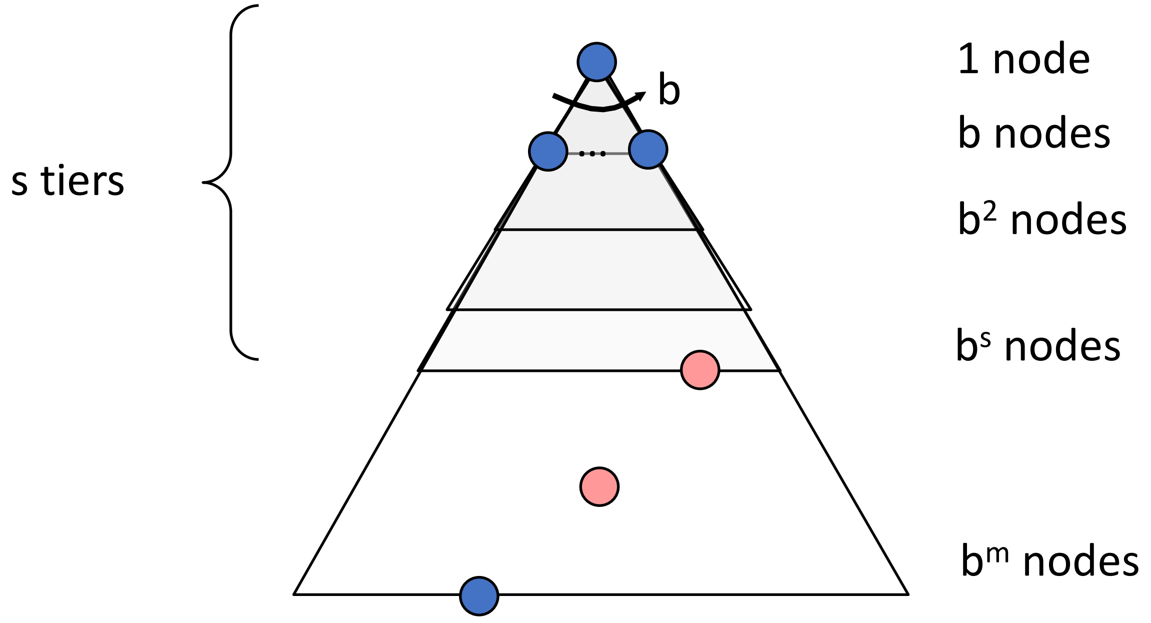
Implementation: Fringe is a FIFO queue



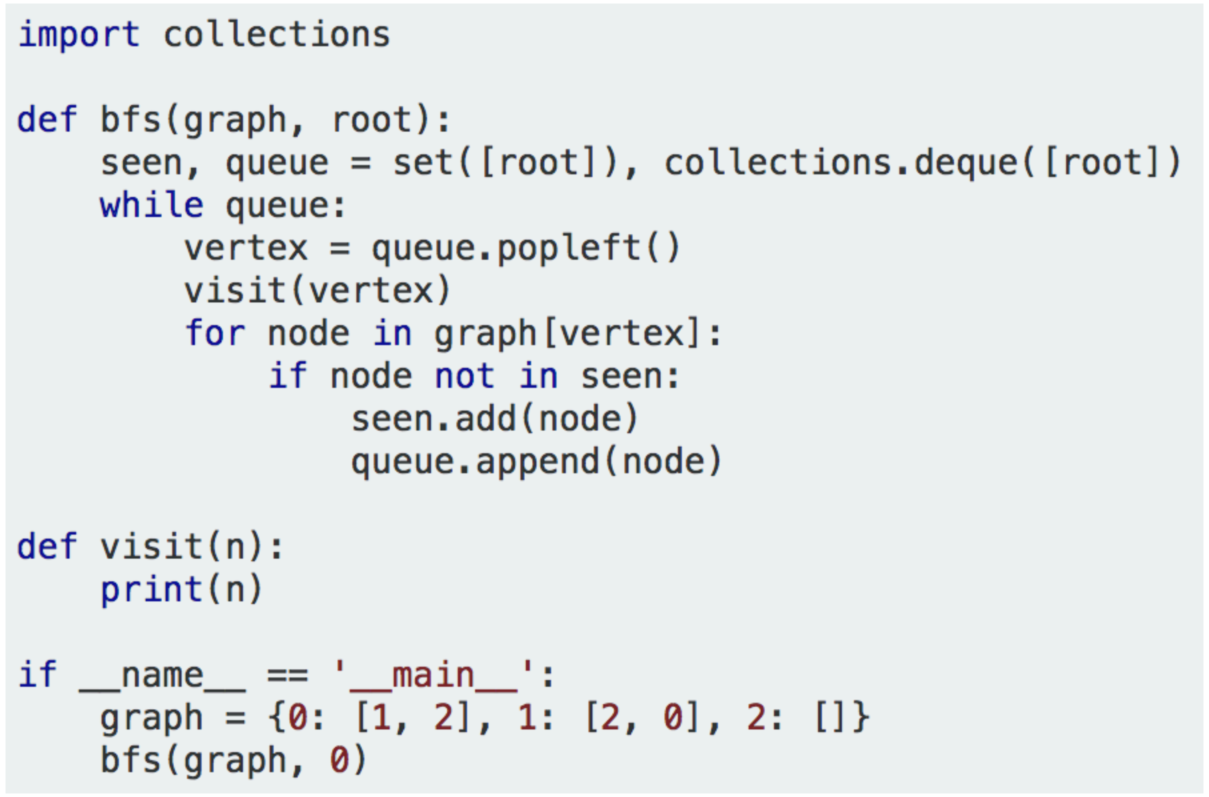


Breadth-First Search (BFS) Properties

- 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 fringe 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 1 (more on costs later)

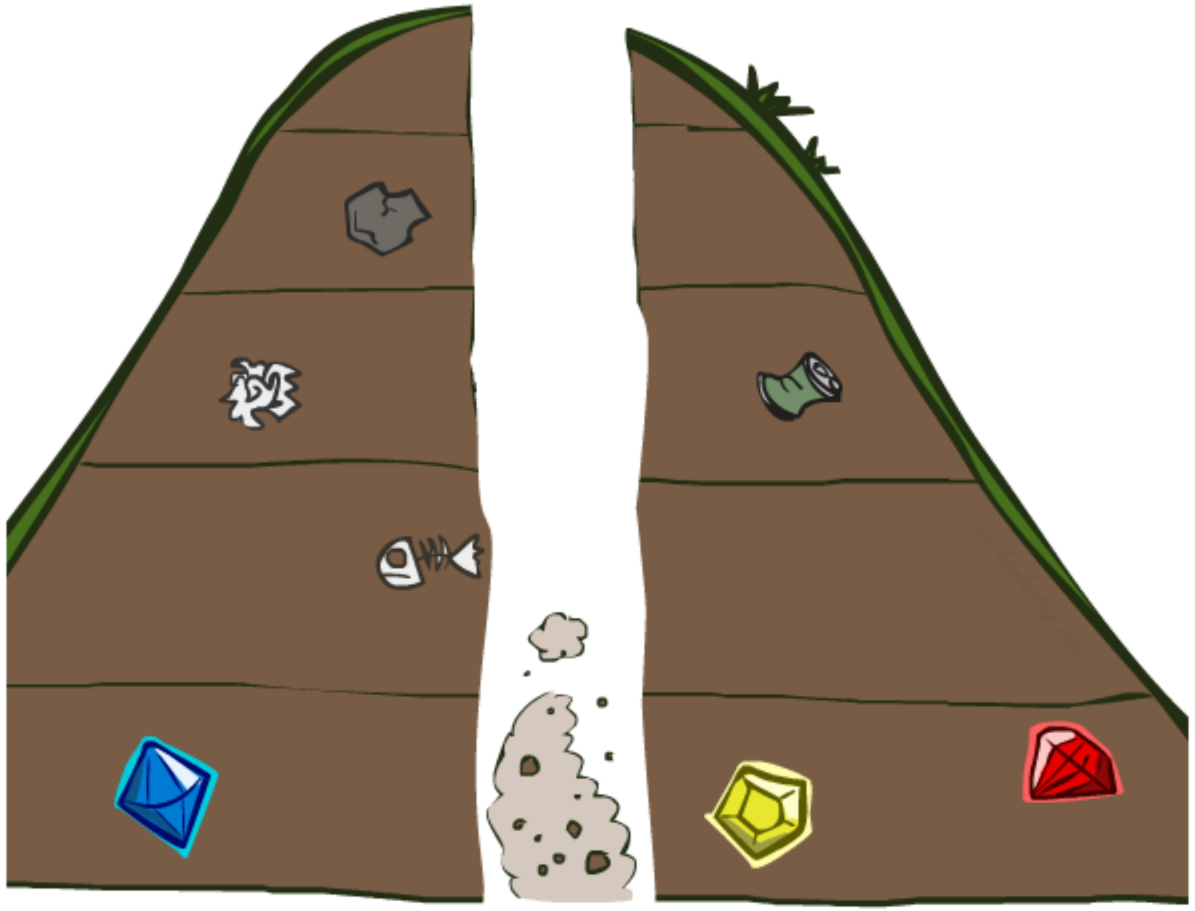


Python code for BFS



```python
import collections

def bfs(graph, root):
    seen, queue = set([root]), collections.deque([root])
    while queue:
        vertex = queue.popleft()
        visit(vertex)
        for node in graph[vertex]:
            if node not in seen:
                seen.add(node)
                queue.append(node)

def visit(n):
    print(n)

if __name__ == '__main__':
    graph = {0: [1, 2], 1: [2, 0], 2: []}
    bfs(graph, 0)
```

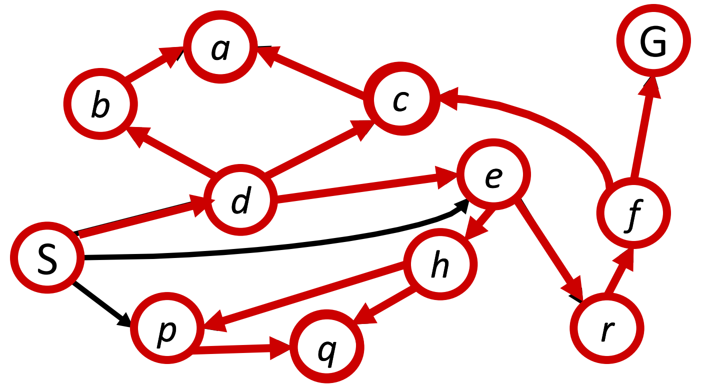
Depth-First Search

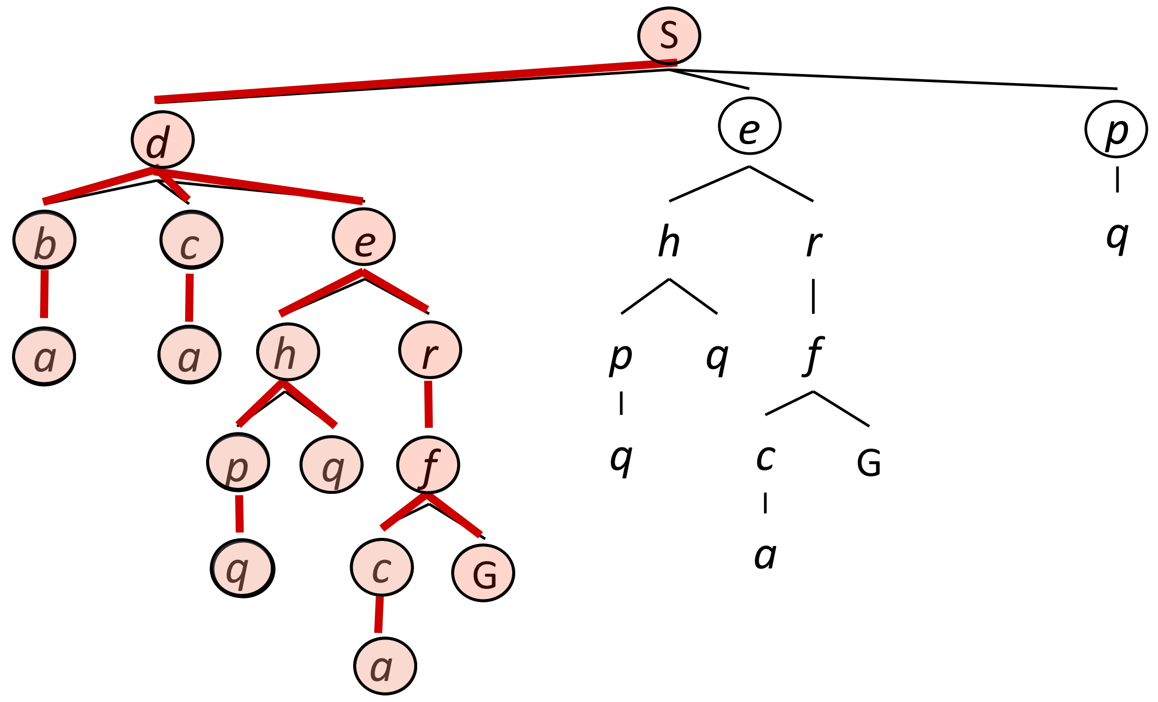


Depth-First Search

Strategy: expand a deepest node first

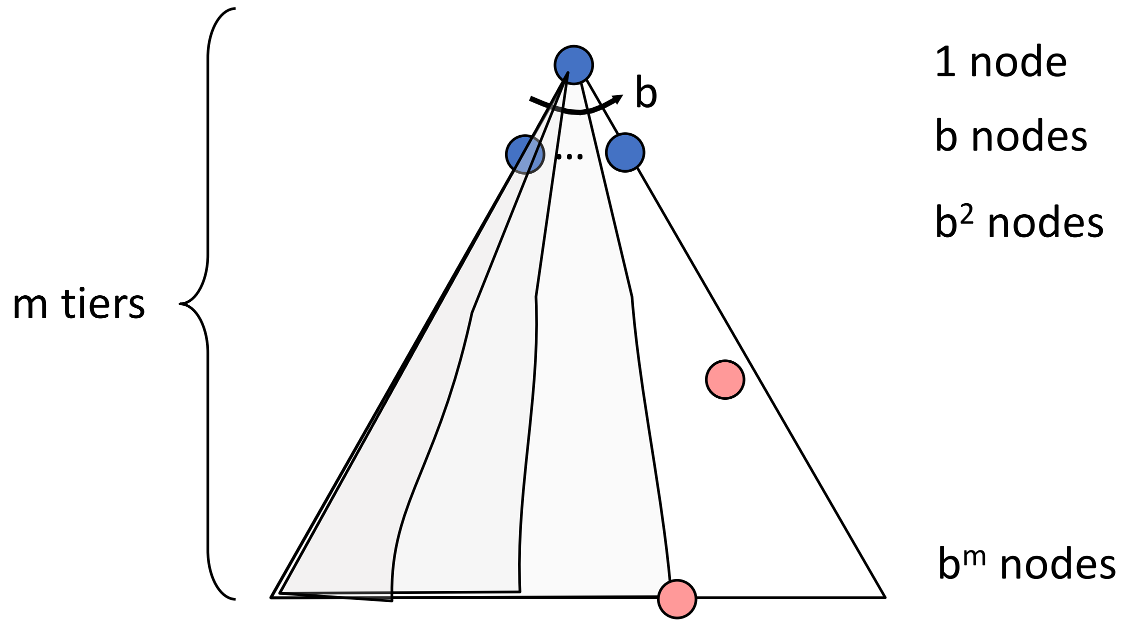
Implementation: Fringe is a LIFO stack



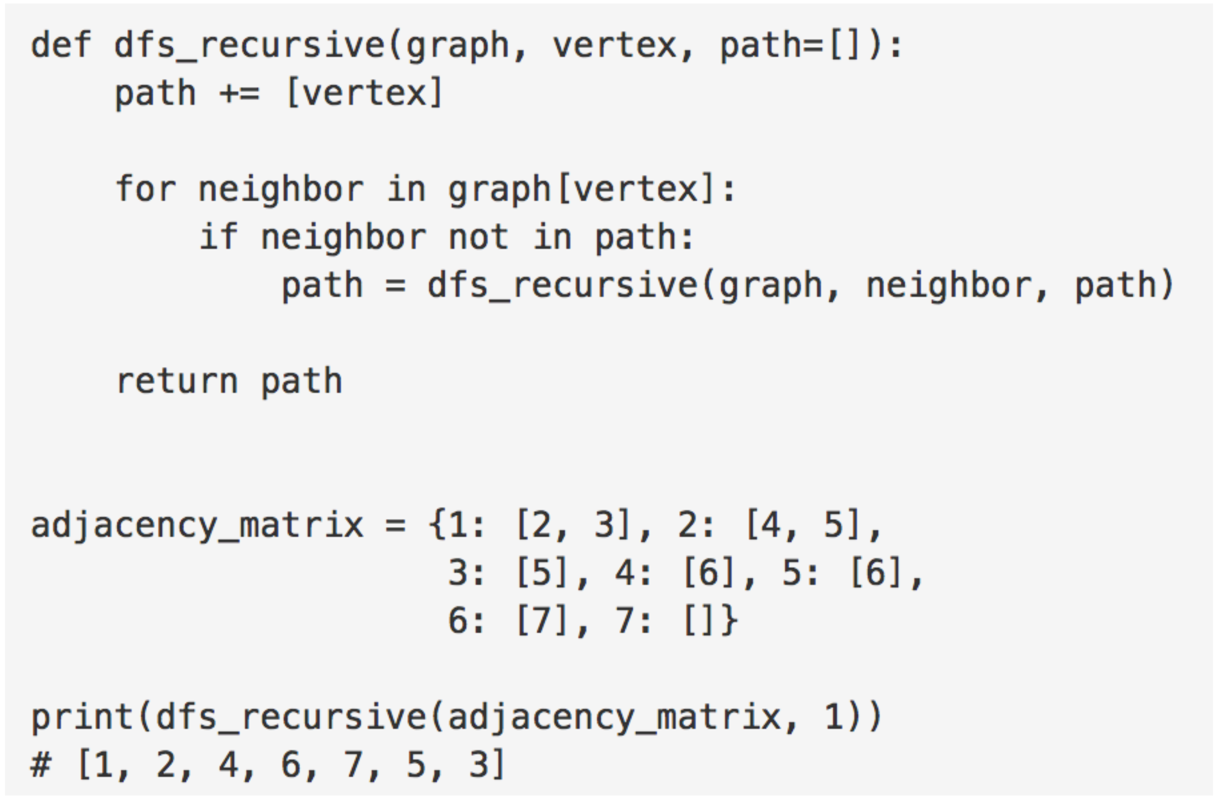


Depth-First Search (DFS) Properties

- What nodes 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 fringe take?
  - Only has siblings on path to root, so $O(bm)$
- Is it complete?
  - m could be infinite, so only if we prevent cycles (more later)
- Is it optimal?
  - No, it finds the “leftmost” solution, regardless of depth or cost



Python code for DFS



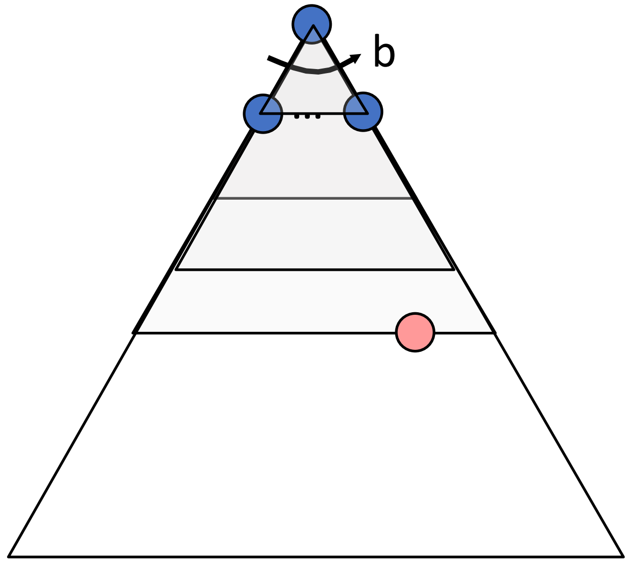
```python
def dfs_recursive(graph, vertex, path=[]):
    path += [vertex]

    for neighbor in graph[vertex]:
        if neighbor not in path:
            path = dfs_recursive(graph, neighbor, path)

    return path


adjacency_matrix = {1: [2, 3], 2: [4, 5],
                    3: [5], 4: [6], 5: [6],
                    6: [7], 7: []}

print(dfs_recursive(adjacency_matrix, 1))
# [1, 2, 4, 6, 7, 5, 3]
```

DFS vs BFS

- If you know a solution is not far from the root of the tree, a breadth first search (BFS) might be better.
- If the tree is very deep and solutions are rare, depth first search (DFS) might take an extremely long time, but BFS could be faster.
- If the tree is very wide, a BFS might need too much memory, so it might be completely impractical.
- If solutions are frequent but located deep in the tree, BFS could be impractical.
- If the search tree is very deep you will need to restrict the search depth for depth first search (DFS), anyway (for example with iterative deepening).

Iterative Deepening

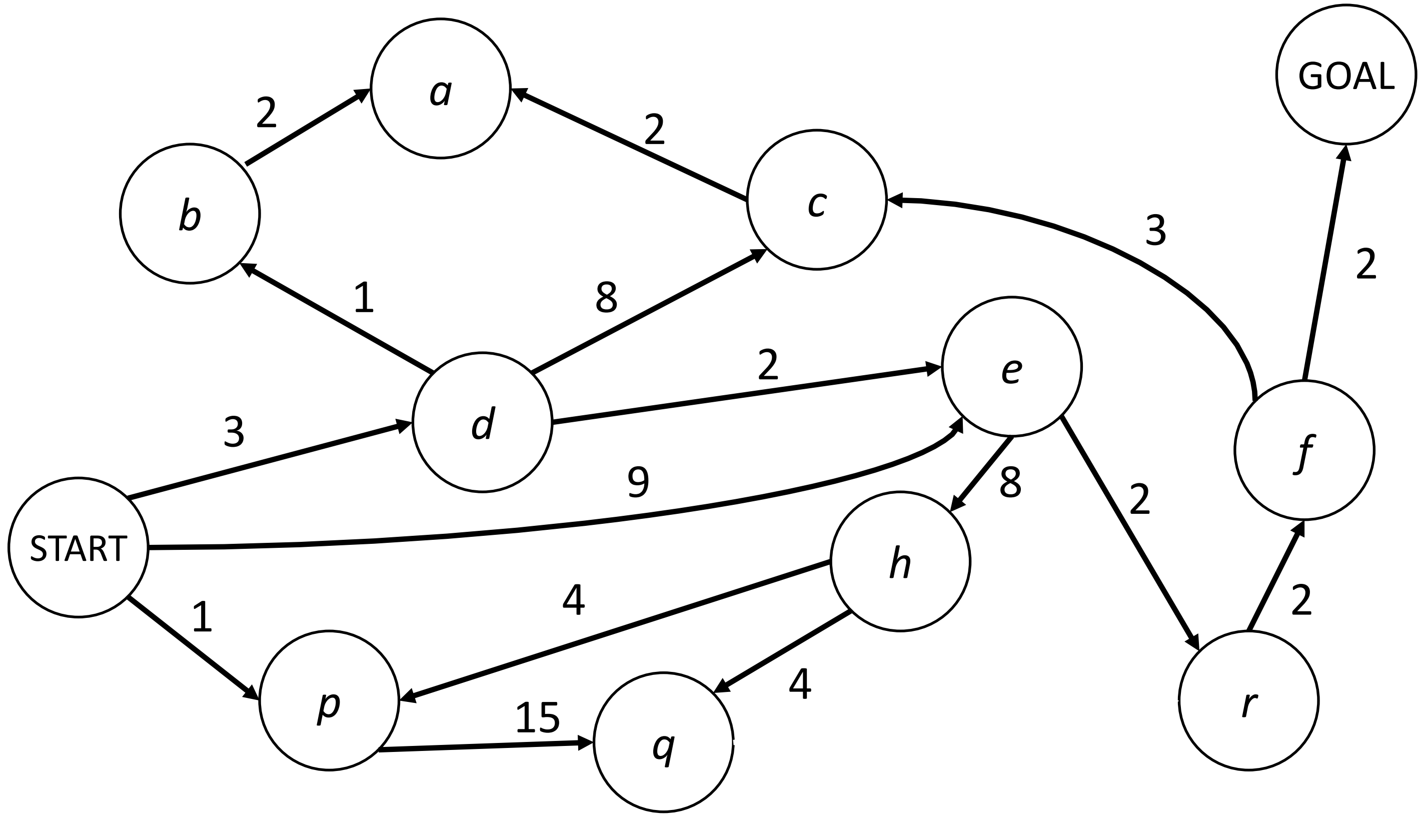
- Idea: get DFS's space advantage with BFS's time / shallow-solution advantages
  - Run a DFS with depth limit 1. If no solution…
  - Run a DFS with depth limit 2. If no solution…
  - Run a DFS with depth limit 3. …..
- Isn't that wastefully redundant?
  - Generally most work happens in the lowest level searched, so not so bad!



Python Code for Iterative Deepening

```python
# A function to perform a Depth-Limited search
# from given source 'src'
def DLS(src,target,maxDepth):

    if src == target : return True

    # If reached the maximum depth, stop recursing.
    if maxDepth <= 0 : return False

    # Recur for all the vertices adjacent to this vertex
    for i in graph[src]:
            if(DLS(i,target,maxDepth-1)):
                return True
    return False

# IDDFS to search if target is reachable from v.
# It uses recursive DLS()
def IDDFS(src,target, maxDepth):

    # Repeatedly depth-limit search till the
    # maximum depth
    for i in range(maxDepth):
        if (DLS(src, target, i)):
            return True
    return False
```

Cost-Sensitive Search

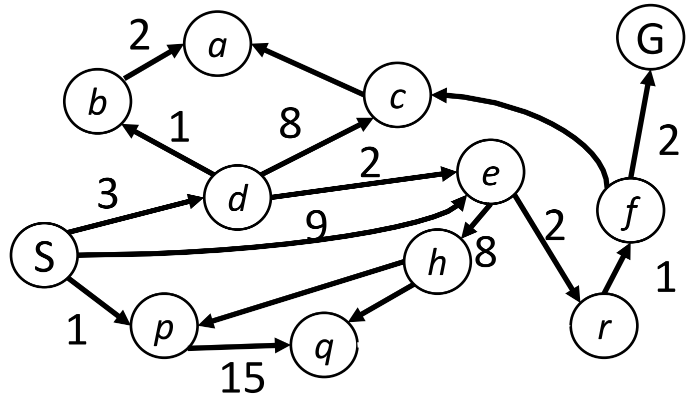


BFS finds the shortest path in terms of number of actions.
It does not find the least-cost path. We will now cover
a similar algorithm which does find the least-cost path.

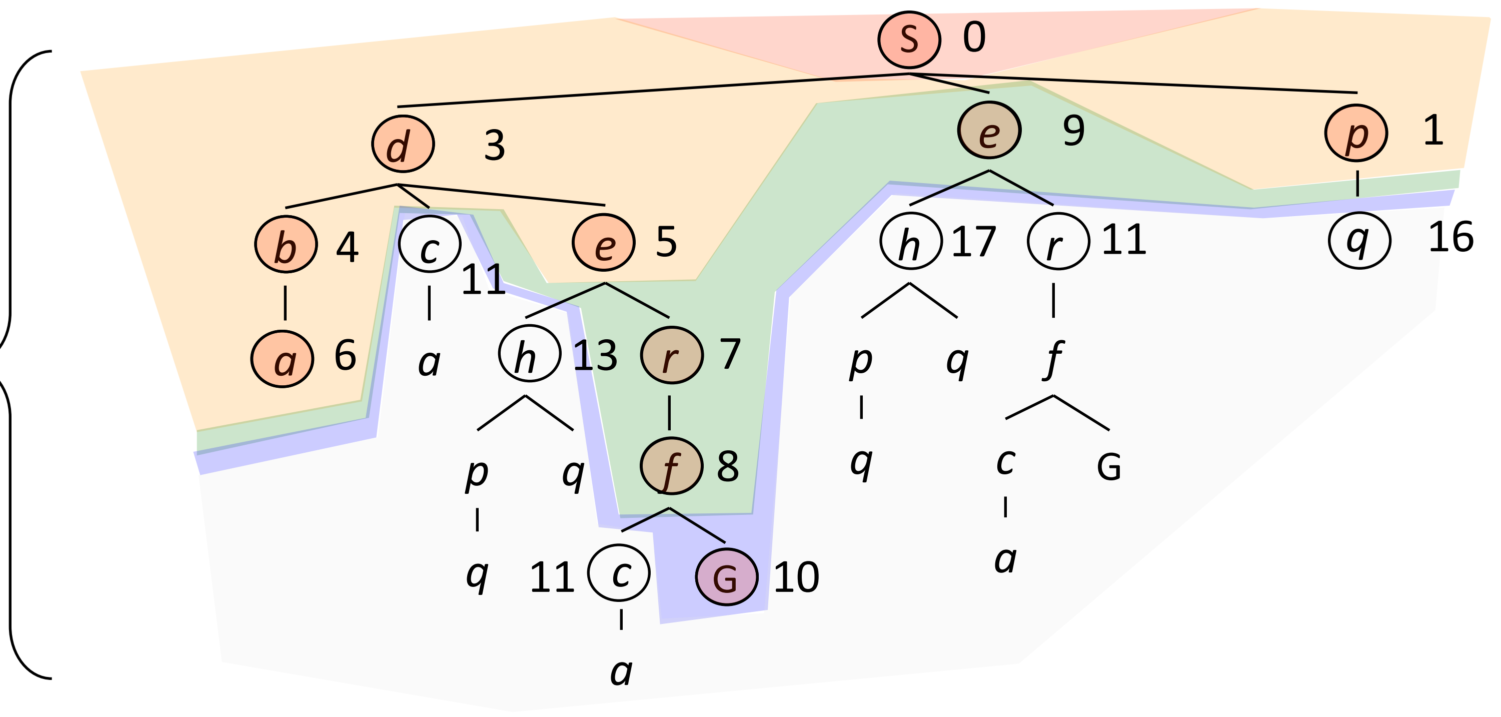
Uniform Cost Search

Strategy: expand a cheapest node first:

Fringe is a priority queue (priority: cumulative cost)

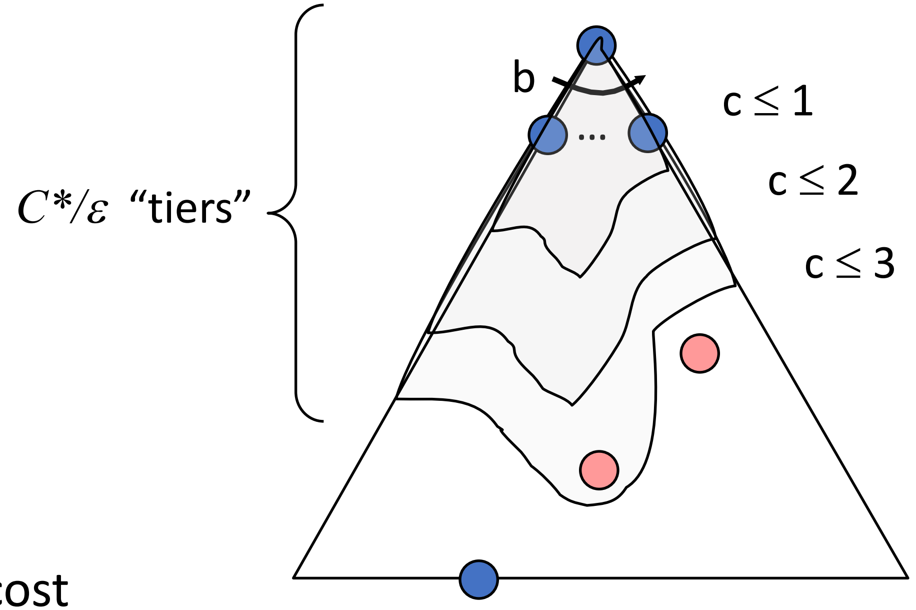


Cost contours



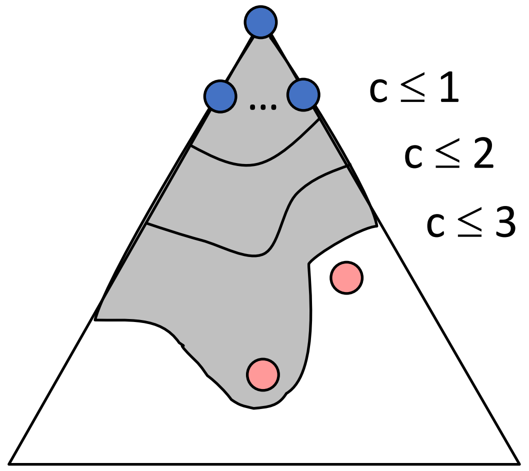
Uniform Cost Search (UCS) Properties

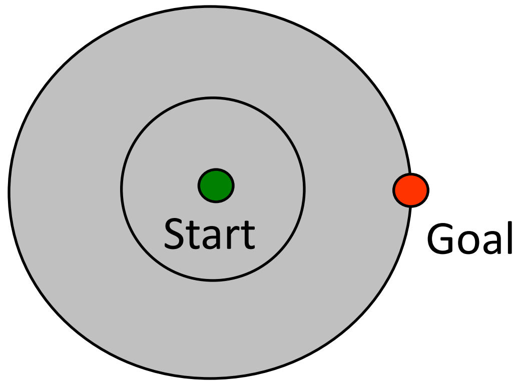
- What nodes does UCS expand?
  - Processes all nodes with cost less than cheapest solution!
  - If that solution costs C^* and arcs cost at least ε, then the "effective depth" is roughly C^*/ε
  - Takes time O($b^{C^*/\varepsilon}$) (exponential in effective depth)
- How much space does the fringe take?
  - Has roughly the last tier, so O($b^{C^*/\varepsilon}$)
- Is it complete?
  - Assuming best solution has a finite cost and minimum arc cost is positive, yes!
- Is it optimal?
  - Yes! (skipping the proof for now)



Uniform Cost Issues

- Remember: UCS explores increasing cost contours
- The good: UCS is complete and optimal!
- The bad:
  - Explores options in every “direction”
  - No information about goal location
- We’ll fix that soon!





Next time

Informed search methods