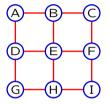
6.01

Lecture 13: Uniform-Cost Search

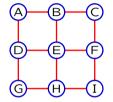
Last Time: Graph Search

Find path between 2 points in an arbitrary graph.

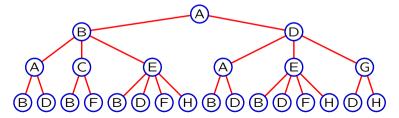


Last Time: Graph Search

Find path between 2 points in an arbitrary graph.



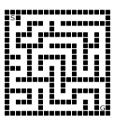
Represent all possible paths from A with a tree:



Labs

Last Week: Robots in Mazes

This Week: Uniform Cost Search, MapQuest

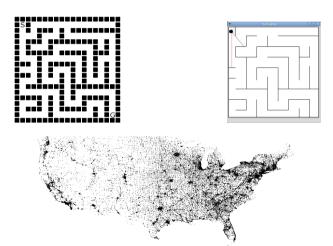




Labs

Last Week: Robots in Mazes

This Week: Uniform Cost Search, MapQuest



Graph Search Algorithm

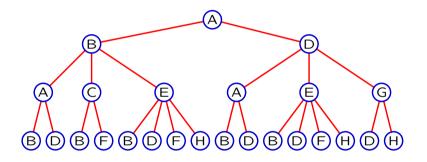
Basic Algorithm:

- Initialize agenda (list of nodes to consider)
- Repeat the following:
 - Remove one node from the agenda
 - Add its children to the agenda

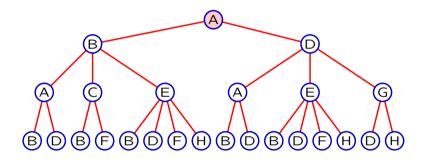
until goal is found or agenda is empty

Return resulting path

Strategy: Replace last node in agenda by its successors

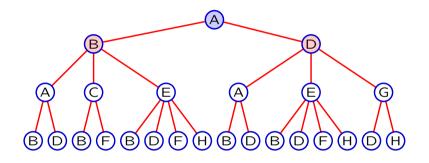


Strategy: Replace last node in agenda by its successors



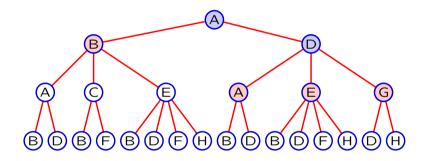
Agenda: A

Strategy: Replace last node in agenda by its successors



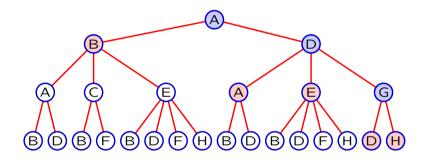
Agenda: A AB AD

Strategy: Replace last node in agenda by its successors



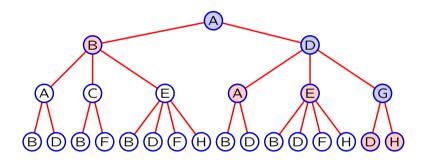
Agenda: A AB AD ADA ADE ADG

Strategy: Replace last node in agenda by its successors



Agenda: A AB AD ADA ADE ADG ADGD ADGH

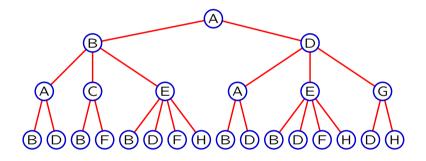
Strategy: Replace last node in agenda by its successors



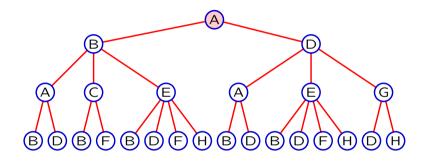
Agenda: A AB AD ADA ADE ADG ADGD ADGH

Depth-first Search

Strategy: Remove first node and add its successors to end

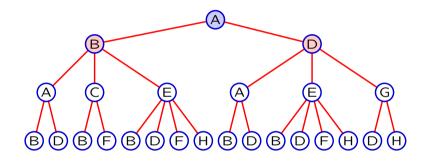


Strategy: Remove first node and add its successors to end



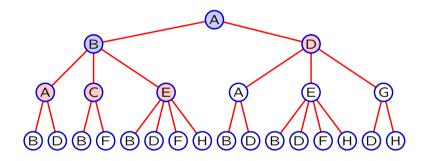
Agenda: A

Strategy: Remove first node and add its successors to end



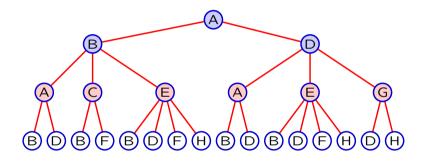
Agenda: A AB AD

Strategy: Remove first node and add its successors to end



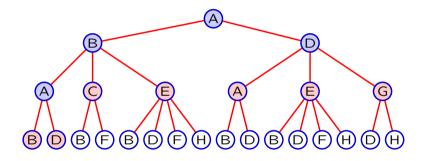
Agenda: A AB AD ABA ABC ABE

Strategy: Remove first node and add its successors to end



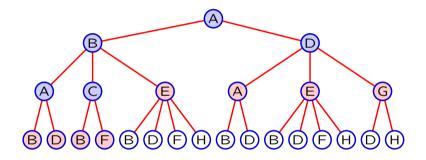
Agenda: A AB AD ABA ABC ABE ADA ADE ADG

Strategy: Remove first node and add its successors to end



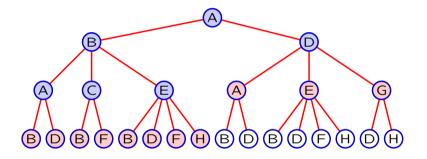
Agenda: A AB AD ABA ABC ABE ADA ADE ADG ABAB ABAD

Strategy: Remove first node and add its successors to end



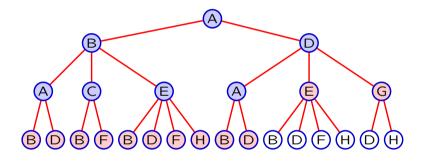
Agenda: A AB AD ABA ABC ABE ADA ADE ADG ABAB ABAD ABCB ABCF

Strategy: Remove first node and add its successors to end



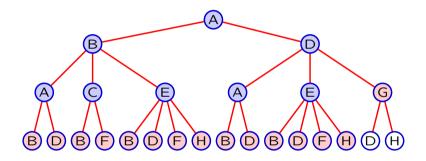
Agenda: A AB AD ABA ABC ABE ADA ADE ADG ABAB ABAD ABCB ABCF ABEB ABED ABEF ABEH

Strategy: Remove first node and add its successors to end



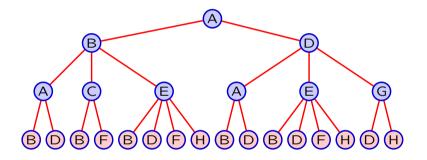
Agenda: A AB AD ABA ABC ABE ADA ADE ADG ABAB ABAD ABCB ABCF ABEB ABED ABEF ABEH ADAB ADAD

Strategy: Remove first node and add its successors to end



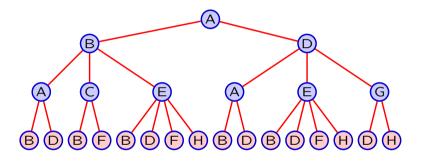
Agenda: A AB AD ABA ABC ABE ADA ADE ADG ABAB ABAD ABCB ABCF ABEB ABED ABEF ABEH ADAB ADAD ADEB ADED ADEF ADEH

Strategy: Remove first node and add its successors to end



Agenda: A AB AD ABA ABC ABE ADA ADE ADG ABAB ABAD ABCB ABCF ABEB ABED ABEF ABEH ADAB ADAD ADEB ADED ADEF ADEH ADGD ADGH

Strategy: Remove first node and add its successors to end



Agenda: A AB AD ABA ABC ABE ADA ADE ADG ABAB ABAD ABCB ABCF ABEB ABED ABEF ABEH ADAB ADAD ADEB ADED ADEF ADEH ADGD ADGH

Breadth-first Search

Dynamic Programming

As applies to search:

(Depends slightly on which algorithm we're using)

BFS: The shortest path $S \to X \to G$ is made up of the shortest path $S \to X$ and the shortest path $X \to G$.

DFS: A path $S \to X \to G$ is made up of a path $S \to X$ and a path $X \to G$.

The moral: once we have found a path $S \to X$, we don't need to spend time looking for other paths through X.

Dynamic Programming

Algorithm (including dynamic programming):

- Initialize **agenda** (list of nodes to consider)
- Intialize visited set (set of states visited)
- Repeat the following:
 - Remove one node from the agenda
 - For each of that node's children:
 - If its state is in the visited list, skip it
 - Otherwise, add it to agenda and add its state to visited list

until goal is found or agenda is empty

Return resulting path

Python Framework

- SearchNode class:
 - Attributes:
 - state (arbitrary)
 - parent (instance of SearchNode, Or None)
 - Methods:
 - path (returns list of states representing path from root)
- search function:
 - Arguments:
 - successor function (function state→list of states)
 - starting state
 - goal test (function state→bool)
 - dfs (True for DFS, False for BFS)

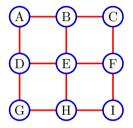
```
def search(successors, start_state, goal_test, dfs = False):
 if goal_test(start_state):
     return [start state]
 else:
     agenda = [SearchNode(start_state, None)]
     visited = {start_state}
     while len(agenda) > 0:
         parent = agenda.pop(-1 if dfs else 0)
         for child_state in successors(parent.state):
             child = SearchNode(child_state, parent)
             if goal_test(child_state):
                 return child.path()
             if child state not in visited:
                 agenda.append(child)
                 visited.add(child state)
     return None
```

```
def search(successors, start_state, goal_test, dfs = False):
 if goal_test(start_state):
     return [start state]
 else:
     agenda = [SearchNode(start_state, None)]
     visited = {start_state}
     while len(agenda) > 0:
         parent = agenda.pop(-1 \text{ if dfs else } 0)
         for child_state in successors(parent.state):
             child = SearchNode(child_state, parent)
              if goal_test(child_state):
                 return child.path()
              if child state not in visited:
                  agenda.append(child)
                  visited.add(child state)
     return None
```

```
def search(successors, start_state, goal_test, dfs = False):
 if goal_test(start_state):
     return [start state]
 else:
     agenda = [SearchNode(start_state, None)]
     visited = {start_state}
     while len(agenda) > 0:
         parent = agenda.pop(-1 \text{ if dfs else } 0)
         for child_state in successors(parent.state):
             child = SearchNode(child_state, parent)
              if goal_test(child_state):
                 return child.path()
              if child state not in visited:
                  agenda.append(child)
                  visited.add(child state)
     return None
```

Example

Find path $A \rightarrow I$, BFS w/ DP

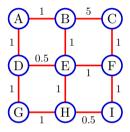


What is a Graph?

Set V of vertices Set E of edges connecting vertices Set W of edge costs (or "weights")

Example

Find path $A \rightarrow I$, minimizing total cost



Uniform-Cost Search

Consider searching for **least-cost** paths instead of *shortest* paths. Instead of popping from agenda based on when nodes were added, pop based on of the cost of the paths they represent.

Slight change to framework:

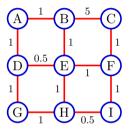
- SearchNode class:
 - Attributes:
 - state (arbitrary)
 - parent (instance of SearchNode, or None)
 - cost of whole path from start
 - Methods:
 - path (returns list of states representing path from root)
- uniform_cost_search function:
 - Arguments:
 - successor function (state→list of (state,cost) tuples)
 - starting state
 - goal test (function state→bool)

```
def uniform_cost_search(successors. start_state. goal_test):
 if goal_test(start_state):
     return [start_state]
 agenda = [(0. SearchNode(start_state, None, cost=0))]
 expanded = set()
 while len(agenda) > 0:
     agenda.sort()
     priority, parent = agenda.pop(0)
     if parent.state not in expanded:
         expanded.add(parent.state)
         if goal_test(parent.state):
             return parent.path()
         for child_state, cost in successors(parent.state):
             child = SearchNode(child_state, parent, parent.cost+cost)
             if child_state not in expanded:
                 agenda.append((child.cost.child))
return None
```

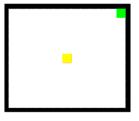
Testing for goal condition must be done at **expansion** time, not at visit time. Similarly for dynamic programming.

Example

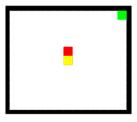
Find path $A \rightarrow I$, Uniform Cost Search



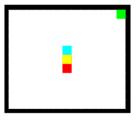
So far, searches have radiated outward from the starting point.



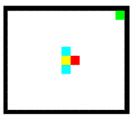
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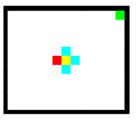
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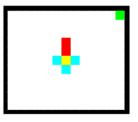
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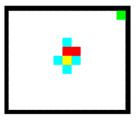
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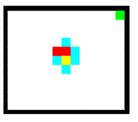
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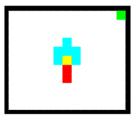
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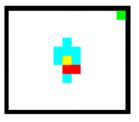
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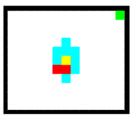
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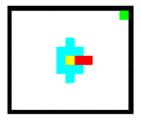
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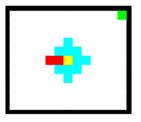
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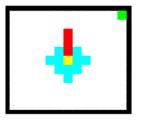
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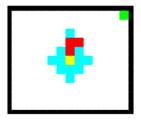
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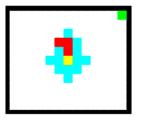
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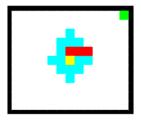
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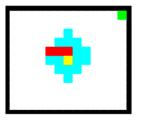
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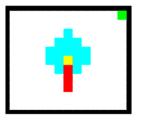
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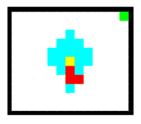
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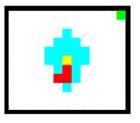
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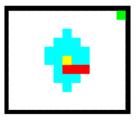
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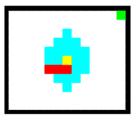
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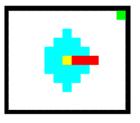
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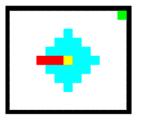
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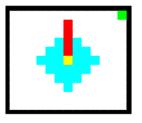
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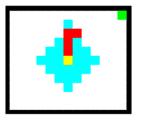
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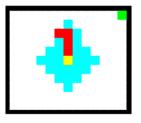
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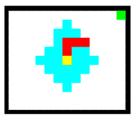
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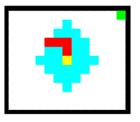
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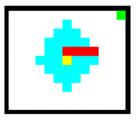
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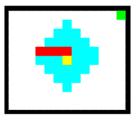
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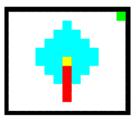
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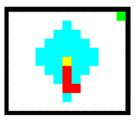
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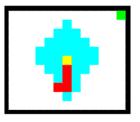
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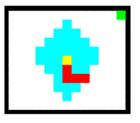
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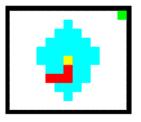
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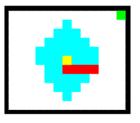
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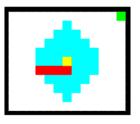
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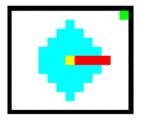
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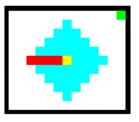
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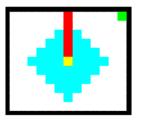
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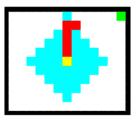
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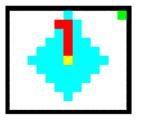
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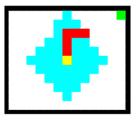
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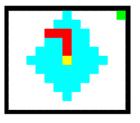
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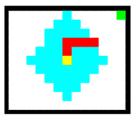
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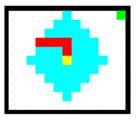
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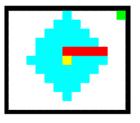
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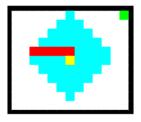
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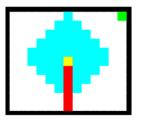
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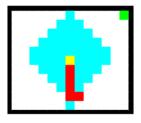
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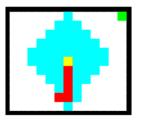
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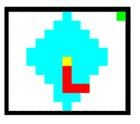
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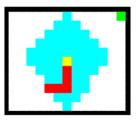
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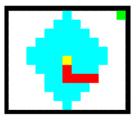
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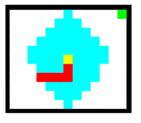
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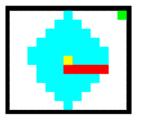
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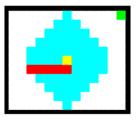
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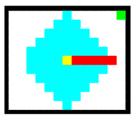
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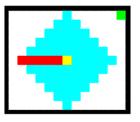
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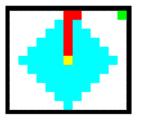
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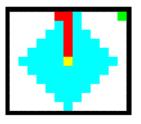
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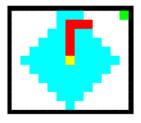
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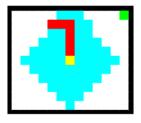
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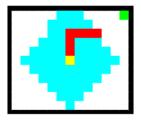
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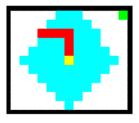
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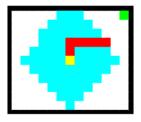
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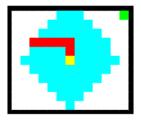
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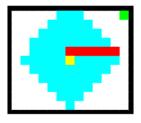
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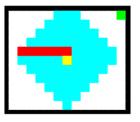
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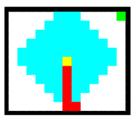
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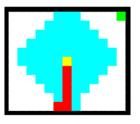
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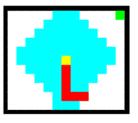
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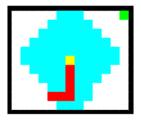
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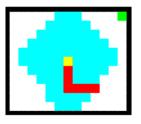
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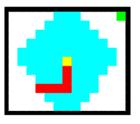
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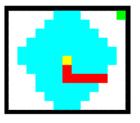
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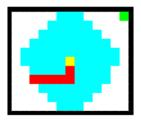
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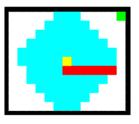
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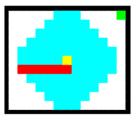
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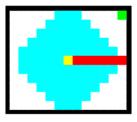
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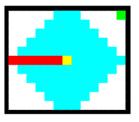
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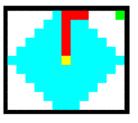
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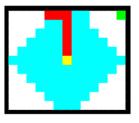
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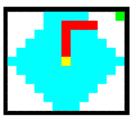
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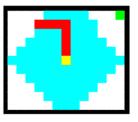
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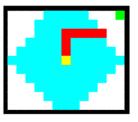
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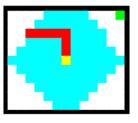
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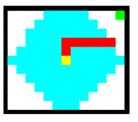
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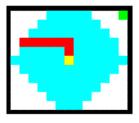
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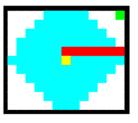
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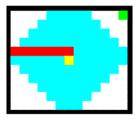
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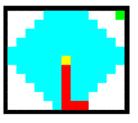
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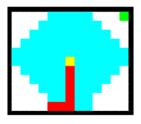
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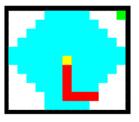
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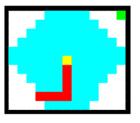
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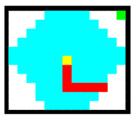
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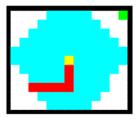
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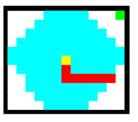
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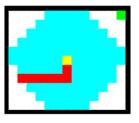
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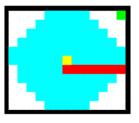
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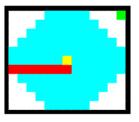
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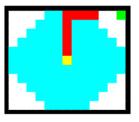
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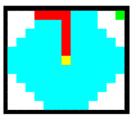
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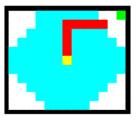
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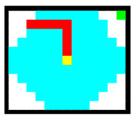
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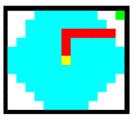
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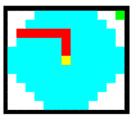
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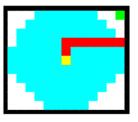
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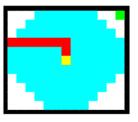
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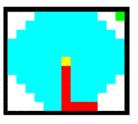
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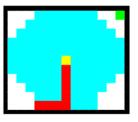
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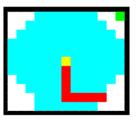
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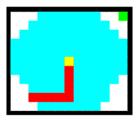
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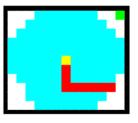
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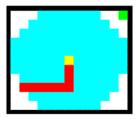
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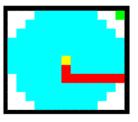
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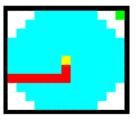
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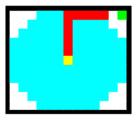
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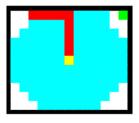
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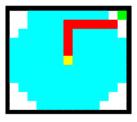
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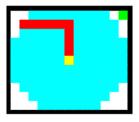
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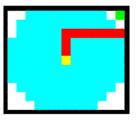
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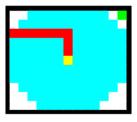
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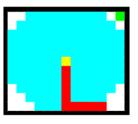
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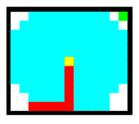
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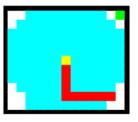
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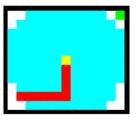
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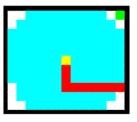
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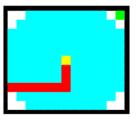
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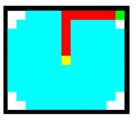
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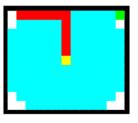
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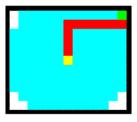
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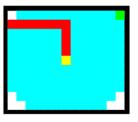
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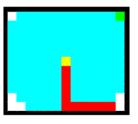
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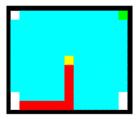
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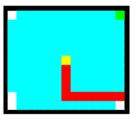
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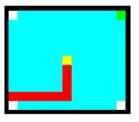
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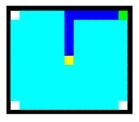
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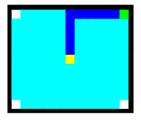


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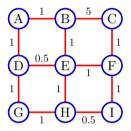
We only notice the goal when we stumble upon it.



Too much time spent searching on the **wrong side of the goal**.

Example

Find path $E \rightarrow I$, Uniform Cost Search



Heuristics

So far, our searches only consider **start-to-current**. We can add **heuristics** to consider an estimate of **current-to-goal** as well.

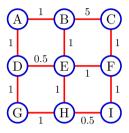
h(x) estimate of cost of lowest-cost path $X \to goal$

- SearchNode class:
 - Attributes:
 - state (arbitrary)
 - parent (instance of SearchNode, or None)
 - cost of whole path from start
 - Methods:
 - path (returns list of states representing path from root)
- uniform_cost_search function:
 - Arguments:
 - successor function (state→list of (state,cost) tuples)
 - starting state
 - goal test (function state→bool)
 - heuristic (function state→estimated cost)

```
def uniform_cost_search(successors, start_state, goal_test, heuristic=lambda s: 0):
 if goal_test(start_state):
     return [start_state]
 agenda = [(heuristic(start_state), SearchNode(start_state, None, cost=0))]
 expanded = set()
 while len(agenda) > 0:
     agenda.sort()
     priority, parent = agenda.pop(0)
     if parent.state not in expanded:
         expanded.add(parent.state)
         if goal_test(parent.state):
             return parent.path()
         for child_state, cost in successors(parent.state):
             child = SearchNode(child_state, parent, parent.cost+cost)
             if child state not in expanded:
                 agenda.append((child.cost+heuristic(child_state).child))
return None
```

Example

Find path $E \to I$, A*, heuristic: h(s) = M(s, I)/2



Admissible Heuristics

An admissible heuristic does not overestimate the actual cost of the shortest cost path.

If the heuristic h(s) is larger than the actual cost from s to goal, then the "best" solution may be missed!

If the heuristic is an underestimate, the search space will be larger than necessary, but we are guaranteed the shortest path.

The ideal heuristic should be:

- as close as possible to actual cost (without overestimating)
- easy to calculate

A* (without DP) is guaranteed to find least-cost path if heuristic is admissible.

With DP, heuristic must also be consistent.

Consider searching in a four-action grid (up, down, left, right), where all actions have cost 1. Let (r0, c0) represent the current location, and (r1, c1) represent the goal.

Which of the following heuristics are admissible?

- 1. abs(r0-r1) + abs(c0-c1)
- 2. min(abs(r0-r1), abs(c0-c1))
- 3. $\max(abs(r0-r1), abs(c0-c1))$
- 4. 2*min(abs(r0-r1), abs(c0-c1))
- 5. 2*max(abs(r0-r1), abs(c0-c1))

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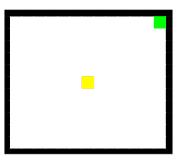
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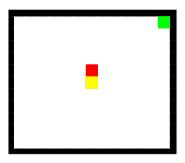
Which of the admissible heuristics minimizes the number of nodes expanded?

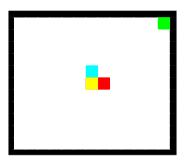
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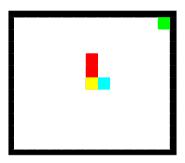
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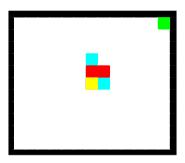
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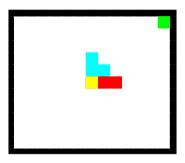


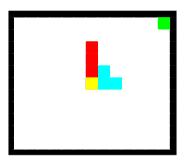


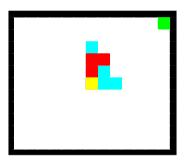


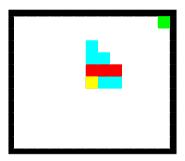


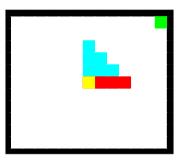


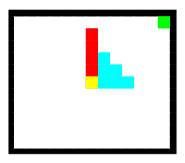


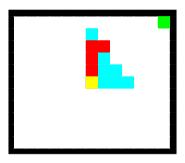


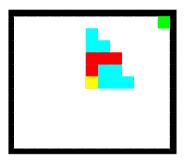


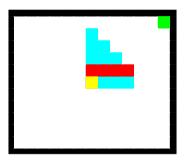


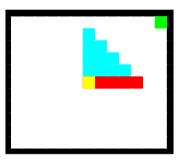


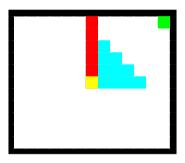


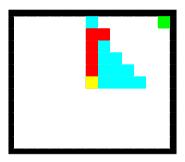


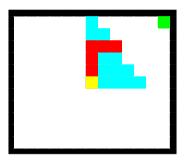


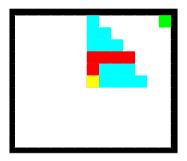


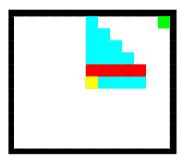


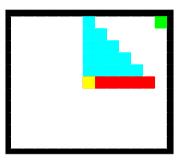


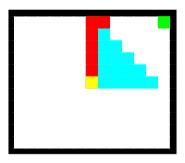


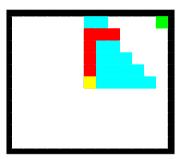


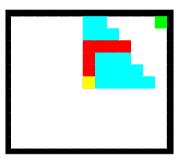


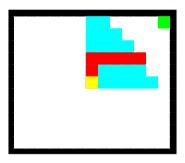


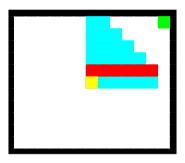


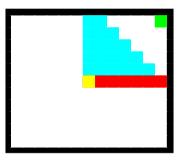


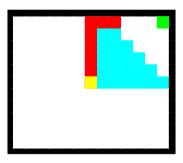


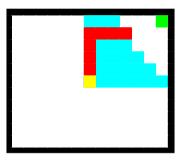


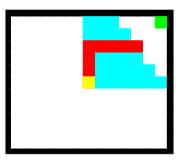


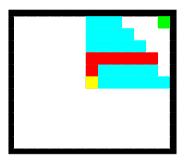


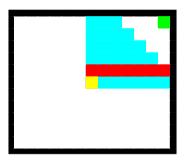


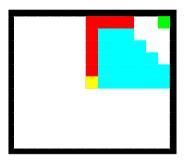


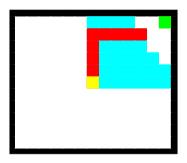


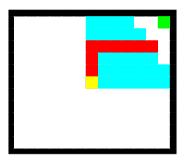


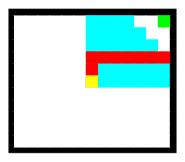


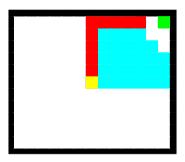


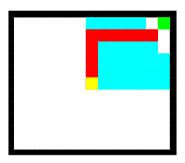


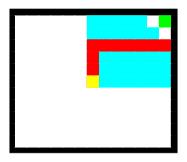


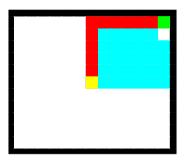


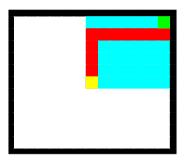


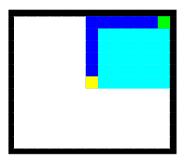


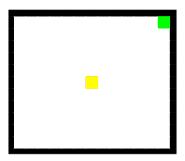


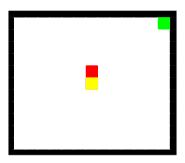


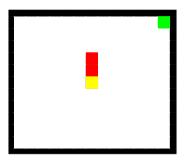


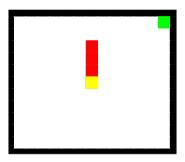


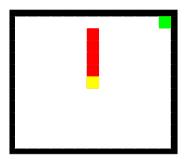


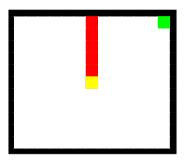


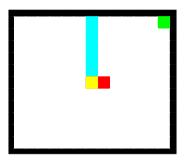


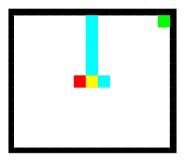


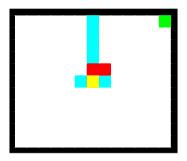


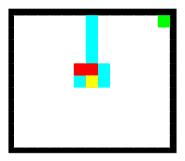


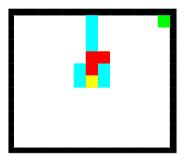


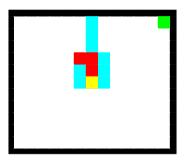


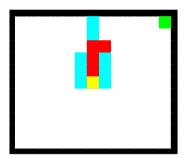


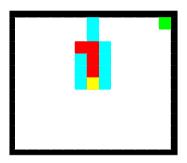


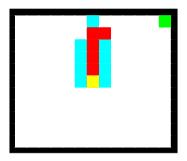


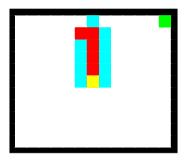


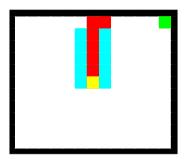


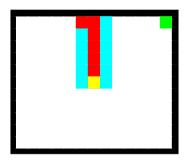


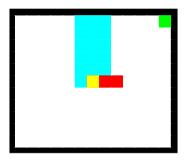


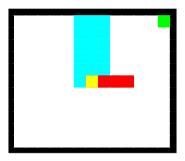


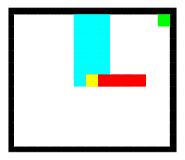


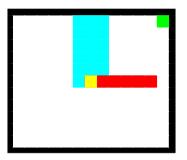


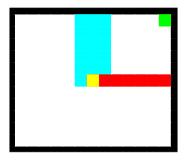


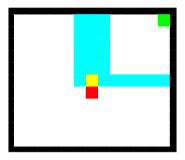


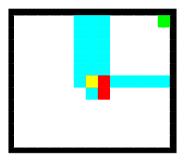


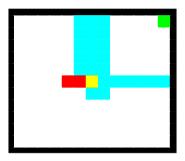


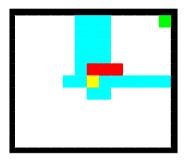


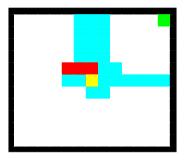


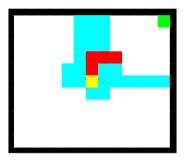


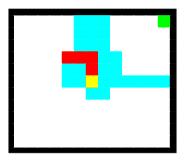


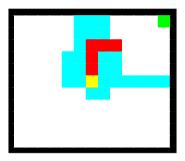


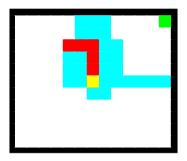


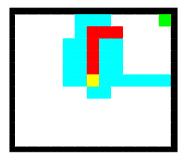


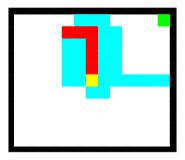


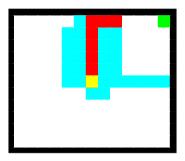


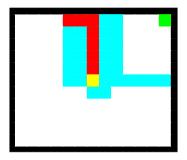


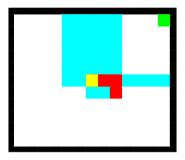


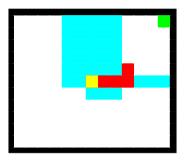


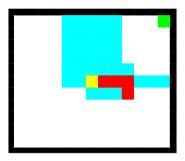


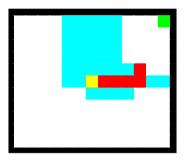


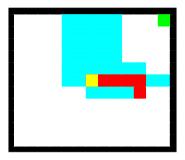


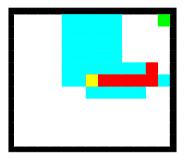


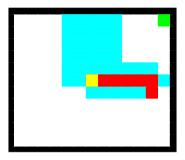


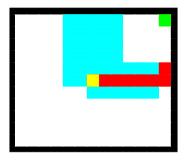


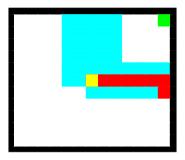


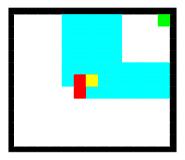


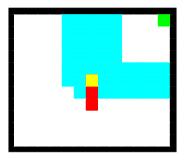


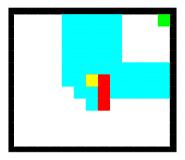


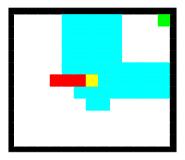


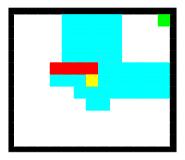


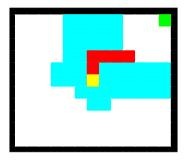


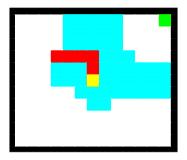


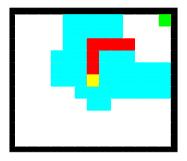


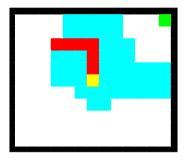


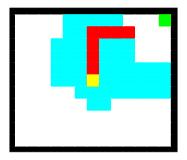


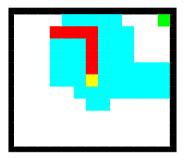


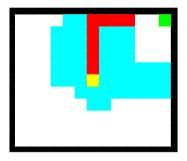


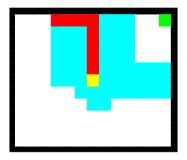


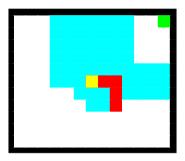


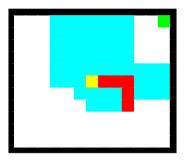


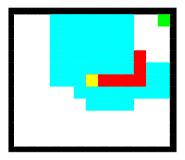


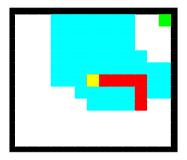


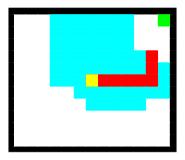


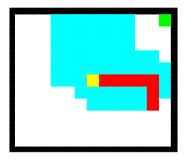


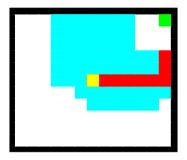


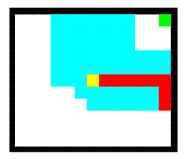


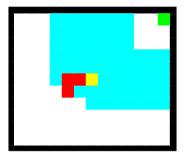


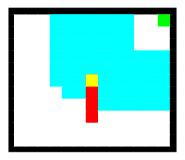


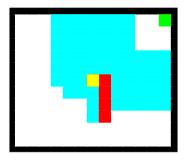


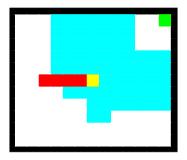


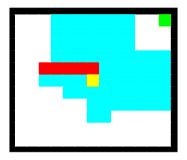


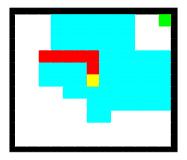


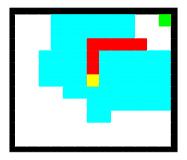


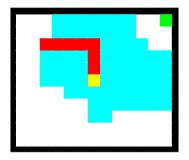


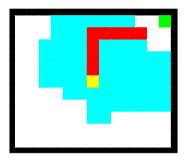


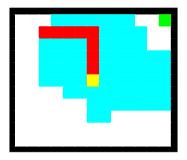


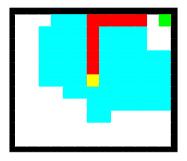


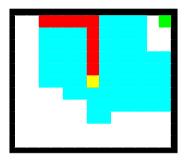


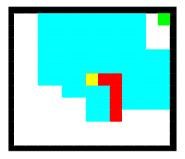


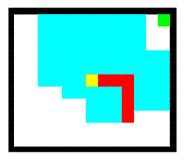


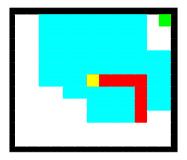


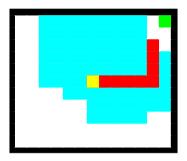


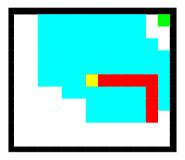


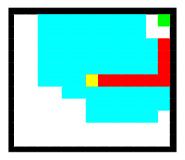


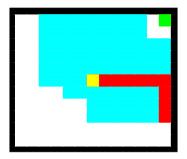


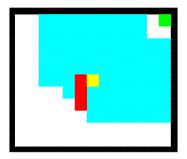


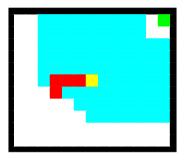


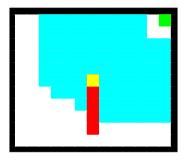


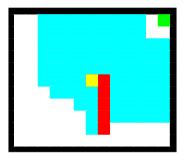


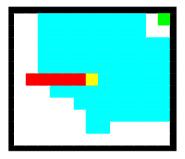


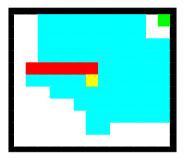


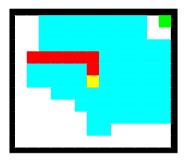


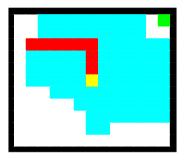


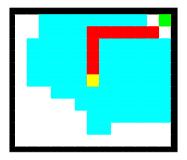


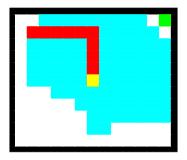


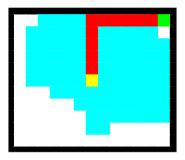


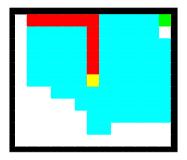


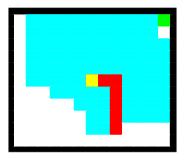


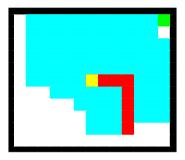


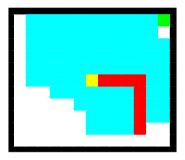


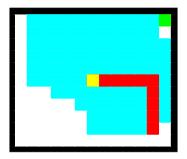


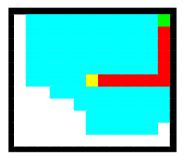


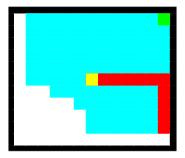


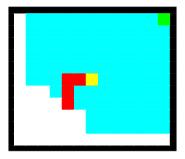


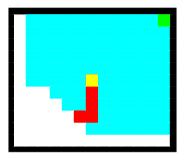


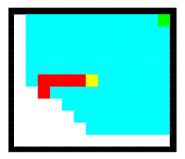


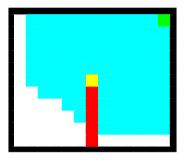


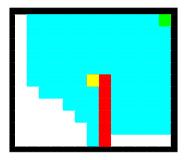


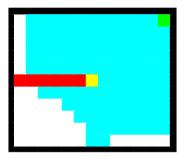


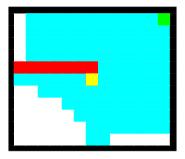


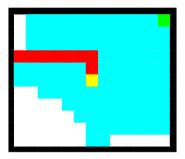


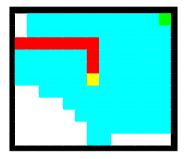


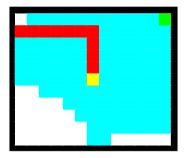


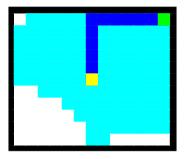


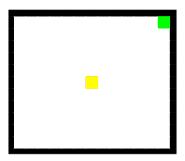


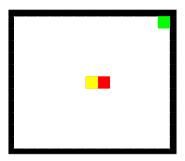


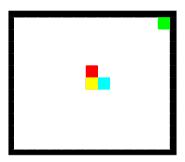


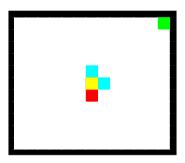


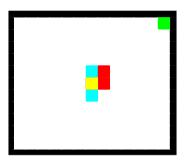


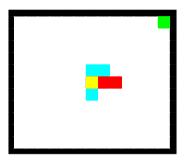


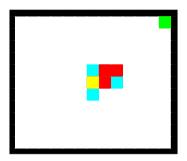


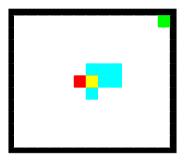


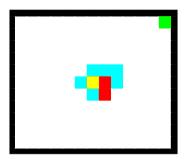


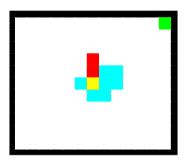


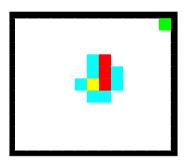


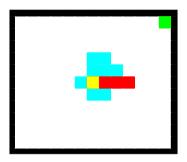


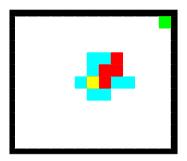


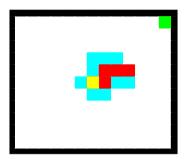


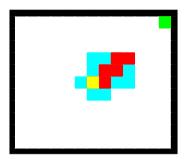


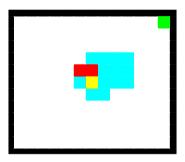


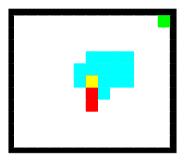


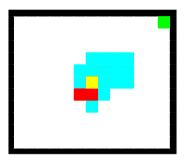


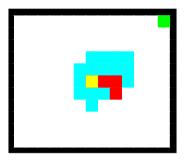


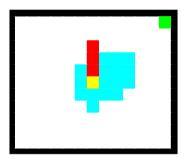


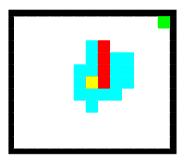


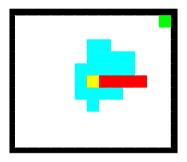


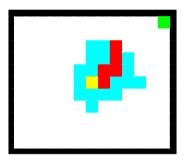


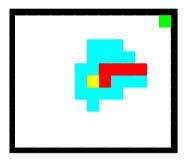


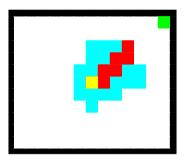


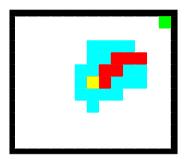


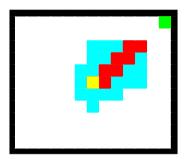


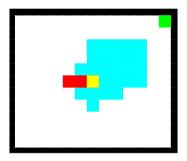


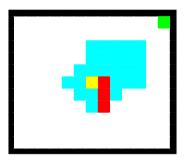


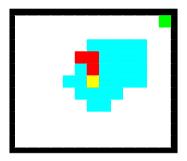


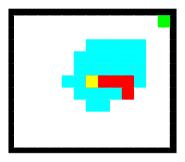


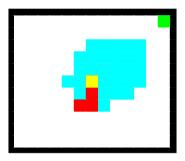


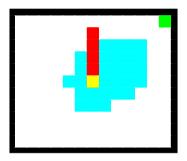


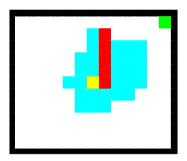


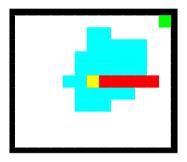


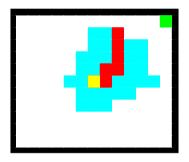


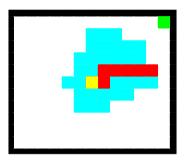


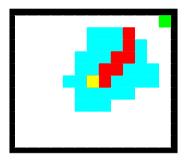


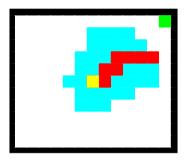


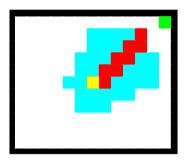


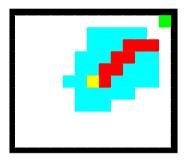


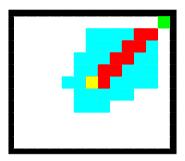


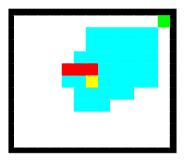


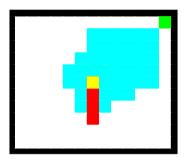


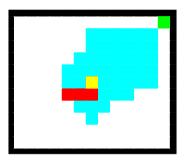


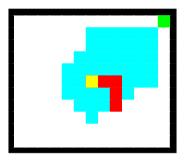


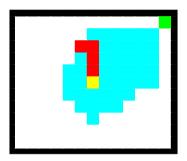


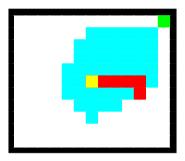


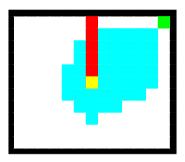


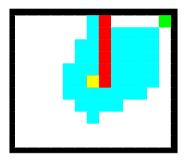


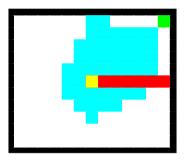


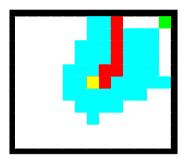


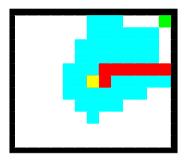


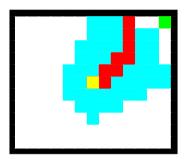


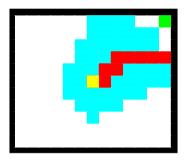


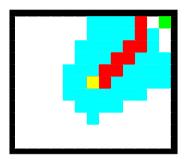


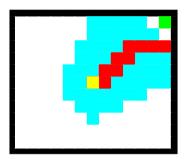


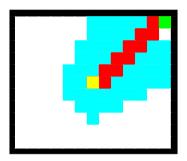


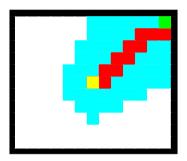


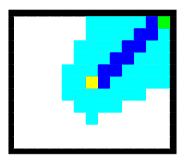


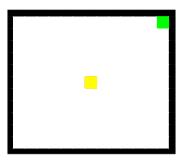


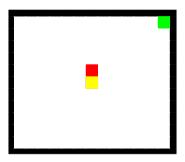


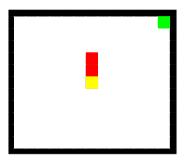


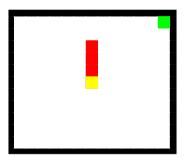


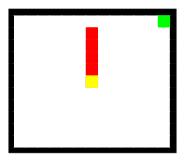


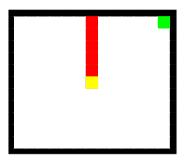


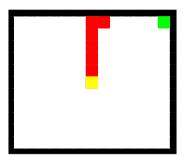


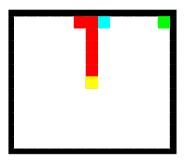


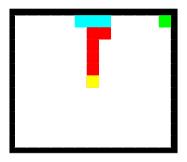


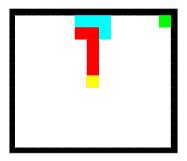


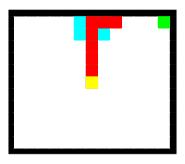


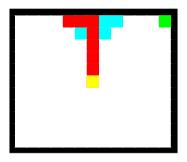


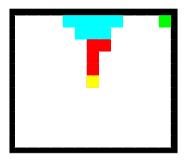


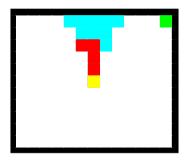


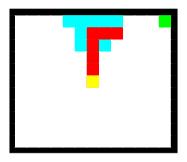


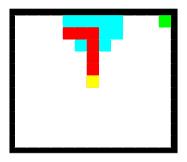


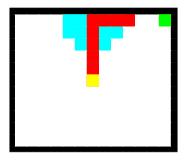


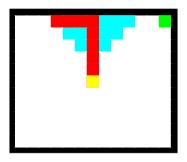


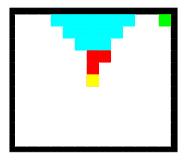


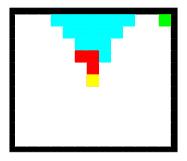


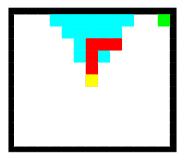


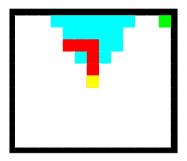


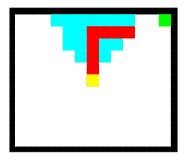


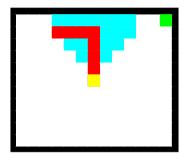


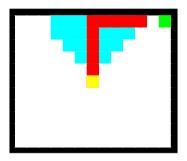


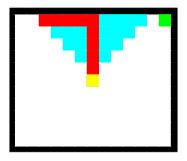


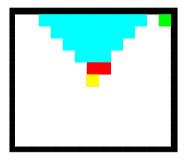


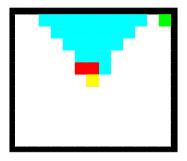


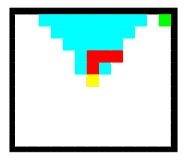


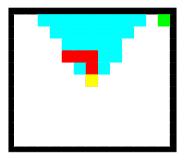


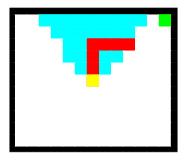


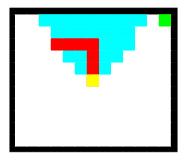


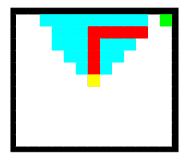


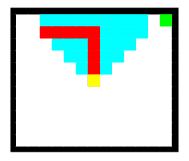


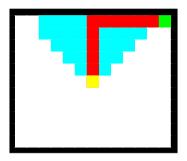


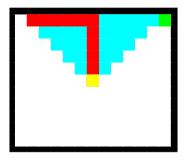


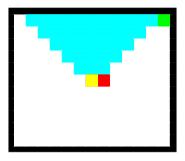


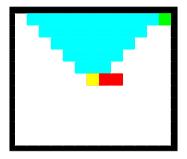


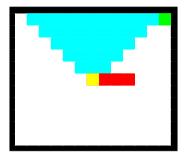


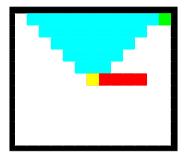


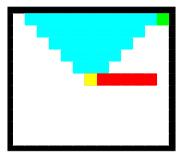


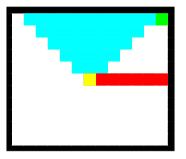


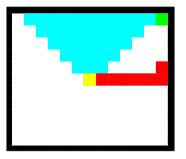


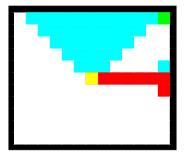


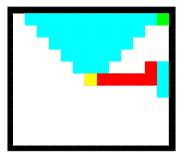


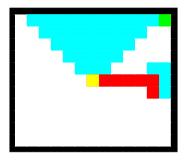


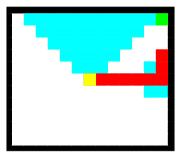


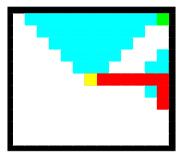


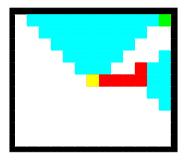


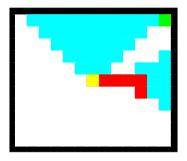


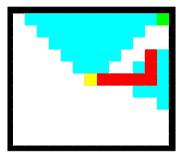


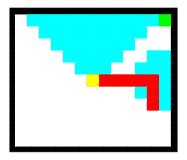


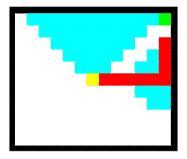


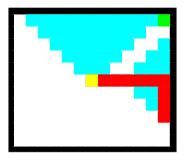


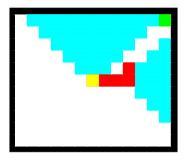


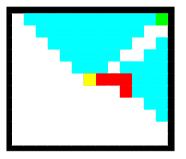


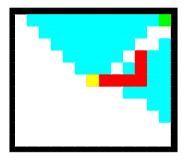




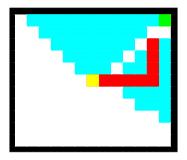


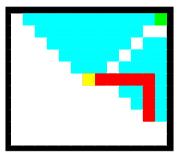


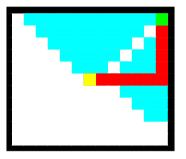


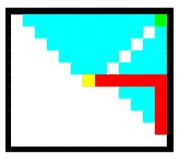


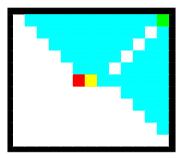


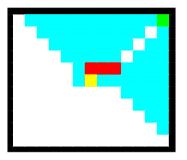


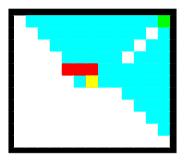


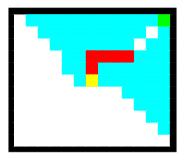


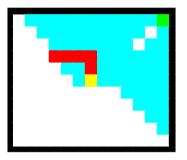


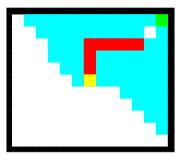


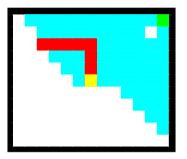


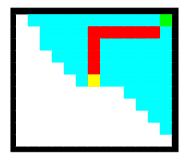


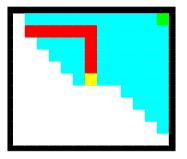


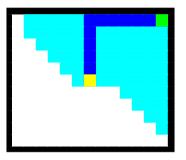












| Heuristic | States Expanded |
|-------------------------------|-----------------|
| abs(r0-r1) + abs(c0-c1) | 42 |
| min(abs(r0-r1), abs(c0-c1)) | 114 |
| max(abs(r0-r1), abs(c0-c1)) | 60 |
| 2*min(abs(r0-r1), abs(c0-c1)) | 72 |

Heuristics in Other Domains

Consider the "word ladder" problem from EX12 (and last lecture). Searching from "quiz" to "best".

quiz

quid

quip

quit

quad

suit

quay

skit

slit

snit

spit

suet

skid

skim

skin

skip

skis

alit

flit

slat

slot

slid

slim

slip

knit

unit

snip

spat

spot

spin

duet

stet

sued

sues

said

shim

swim

akin

shin

ship

alia

flat

flip

plat

scat

seat

swat

slab

slag

slam

slap

slav

slaw

slay

blot

clot

plot

scot

shot

soot

sloe

slog

slop

slow

sled

slum

blip

clip

knot

snap

span

spar

spas

spay

spun

diet

duct

dust

duel

dues

stem

step

stew

cued

hued

rued

seed

shed

sped

surd

cues

hues

rues

sees

subs

suds

sums

suns

sups

laid

maid

paid

raid

sand

sail

whim

sham

swam

swum

swig

chin

thin

shun

chip

whip

shop

ilia

aria

asia

alga

alma

feat

fiat

flab

flag

flak

flap

flaw

flax

flay

flop

peat

plan

play

scab

scan

scar

beat

heat

meat

neat

teat

sect

sent

seal

seam

sear

seas

swab

swag

swan

swap

sway

blab

stab

shag

snag

stag

slug

clam

siam

clap

soap

claw

slew

clay

shay

stay

boot

blob

bloc

blow

coot

clod

clog

clop

cloy

plod

plop

plow

ploy

SCOW

shut

shod

shoe

shoo

show

foot

hoot

loot

moot

root

toot

soft

sort

soon

aloe

floe

slue

flog

smog

stop

flow

glow

snow

stow

bled

fled

pled

alum

glum

plum

scum

slur

knob

know

soar

star

spur

spry

stun

spud

dint

dirt

died

diem

dies

duck

bust

gust

just

lust

must

oust

rust

dusk

fuel

dual

dull

does

dyes

dubs

duds

duns

duos

item

seem

seep

skew

spew

curd

heed

hied

hoed

reed

deed

feed

meed

need

teed

weed

send

seek

seen

seer

shad

aped

sure

surf

cubs

cuds

cups

curs

cuss

cuts

hies

hoes

hubs

hugs

hums

huns

huts

ryes

rubs

rugs

rums

runs

ruts

bees

fees

lees

tees

sets

sews

nubs

pubs

tubs

sibs

sobs

buds

muds

sods

bums

gums

mums

sump

buns

funs

guns

nuns

puns

tuns

sins

sons

sung

sunk

pups

saps

sips

sops

land

lard

laud

laic

lain

lair

mail

maim

main

pard

pail

pain

pair

rail

rain

band

hand

wand

sane

sang

sank

bail

fail

hail

jail

nail

tail

wail

soil

wham

whom

whig

whir

whit

whiz

shah

twig

cain

coin

chic

twin

than

then

this

chap

chop

ilea

area

arid

aril

alms

feet

felt

fear

fist

flew

flex

flux

fray

pelt

pert

pest

peak

peal

pear

peas

clan

elan

klan

pray

boat

brat

beet

belt

bent

best

quiz

quit

quid

quip

suit

quad

skit

slit

snit

spit

suet

quay

alit

flit

slat

slot

knit

unit

spat

spot

duet

stet

seat

blot

dust

beat

bust

best

Heuristics in other domains

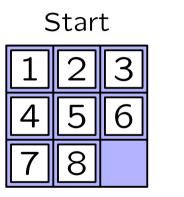
Consider the "word ladder" problem from EX12 (and last lecture). Searching from "quiz" to "best".

UC

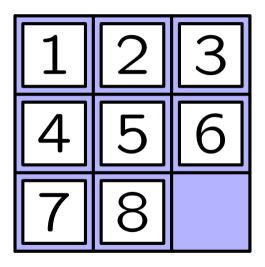
```
States expanded: 396 ['quiz', 'quit', 'suit', 'slit', 'slat', 'seat', 'beat', 'best']
```

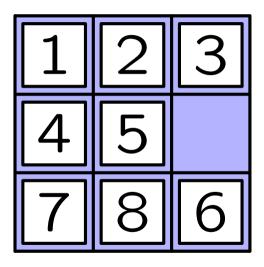
Δ*

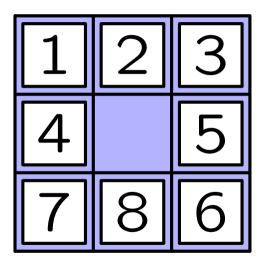
```
States expanded: 28 ['quiz', 'quit', 'suit', 'slit', 'slat', 'seat', 'beat', 'best']
```

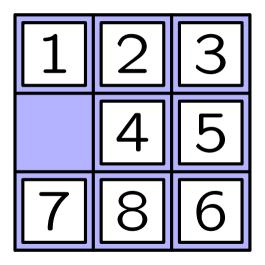


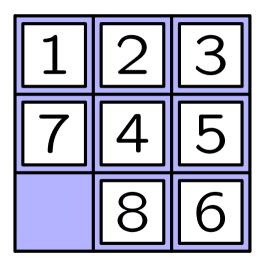




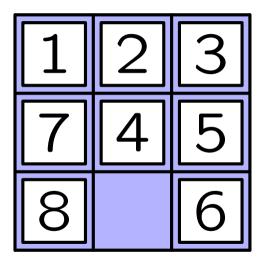


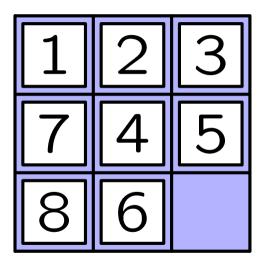


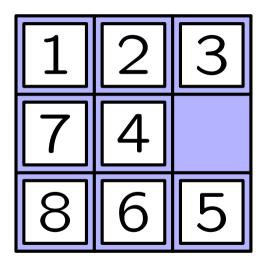


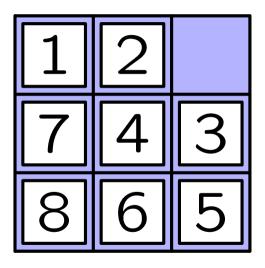


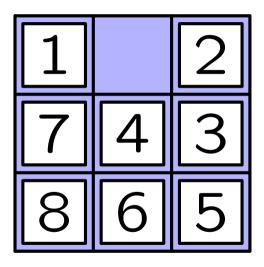
Example: 8-Puzzle

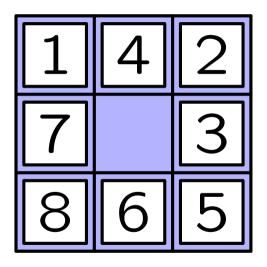


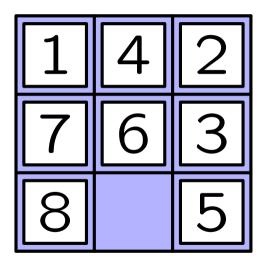


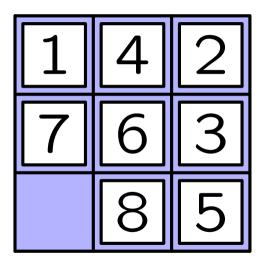


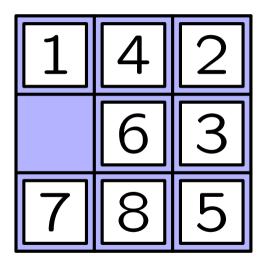


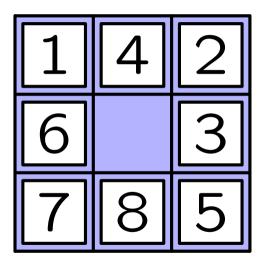


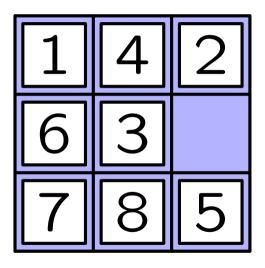


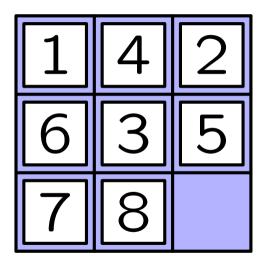


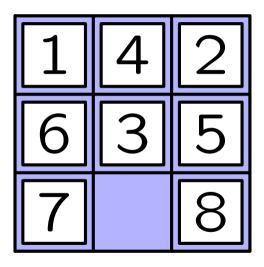


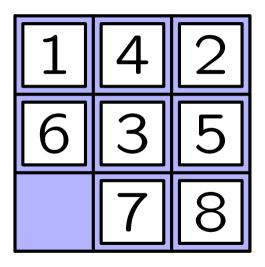


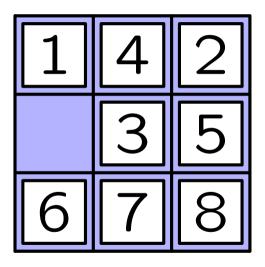


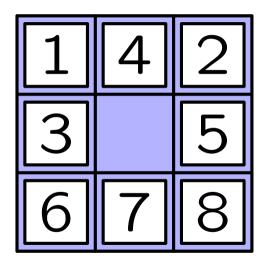


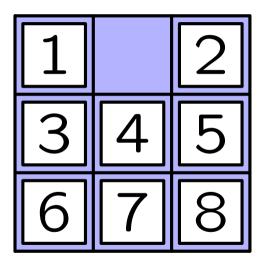


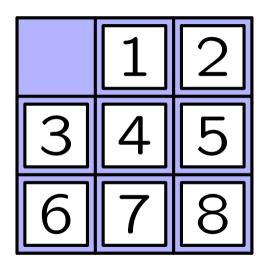




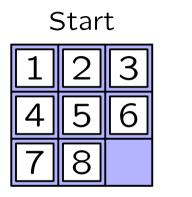


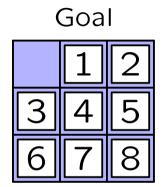






Example: 8-Puzzle





Large number of board configurations (states):

- -9! = 362,880 (if you count all)
- 9!/2 = 181,440 accessible from start state

Almost half of accessible states (84,516) are expanded by UC.

Consider three heuristics for the "eight puzzle":

- 1. 0
- 2. number of tiles out of place
- 3. sum over tiles of Manhattan distances to their goals

Let $M_i = \text{num}$. moves in the best solution using heuristic i. Let $E_i = \text{num}$. states expanded using heuristic i.

Which of the following are true?

- 1. $M_1 = M_2 = M_3$
- 2. $M_1 > M_2 > M_3$
- 3. $E_1 = E_2 = E_3$
- **4**. $E_1 \geq E_2 \geq E_3$
- 5. the same "best" solution results from all three heuristics

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- 5. the same "best" solution results from all three heuristics

Check Yourself!

Results.

Heuristics:

- 1. 0
- 2. number of tiles out of place
- 3. sum over tiles of Manhattan distances to their goals

| Heuristic | Expanded | Moves |
|-----------|----------|-------|
| 1 | 84,516 | 22 |
| 2 | 8,329 | 22 |
| 3 | 1,348 | 22 |

Developed a new class of search algorithms: uniform cost Developed a new class of optimizations: heuristics

| Algorithm | Agenda | Goal Test | DP | Guarantees [†] |
|-----------|--------|-----------|----|-------------------------|
| DFS | | | | |
| BFS | | | | |
| UC | | | | |

[†] Provided a path exists

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| DFS | Stack (LIFO) | Visit | Visited Set | Some Path* |
| BFS | | | | |
| UC | | | | |

[†] Provided a path exists

^{*} In a finite search domain

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|-----------|--------------|-----------|-------------|-------------------------|
| DFS | Stack (LIFO) | Visit | Visited Set | Some Path* |
| BFS | Queue (FIFO) | Visit | Visited Set | Shortest Path |
| UC | | | | |

[†] Provided a path exists

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| Algorithm | Agenda | Goal Test | DP | Guarantees [†] |
|-----------|----------------|-----------|--------------|-------------------------|
| DFS | Stack (LIFO) | Visit | Visited Set | Some Path* |
| BFS | Queue (FIFO) | Visit | Visited Set | Shortest Path |
| UC | Priority Queue | Expand | Expanded Set | Least-cost Path |

[†] Provided a path exists

^{*} In a finite search domain