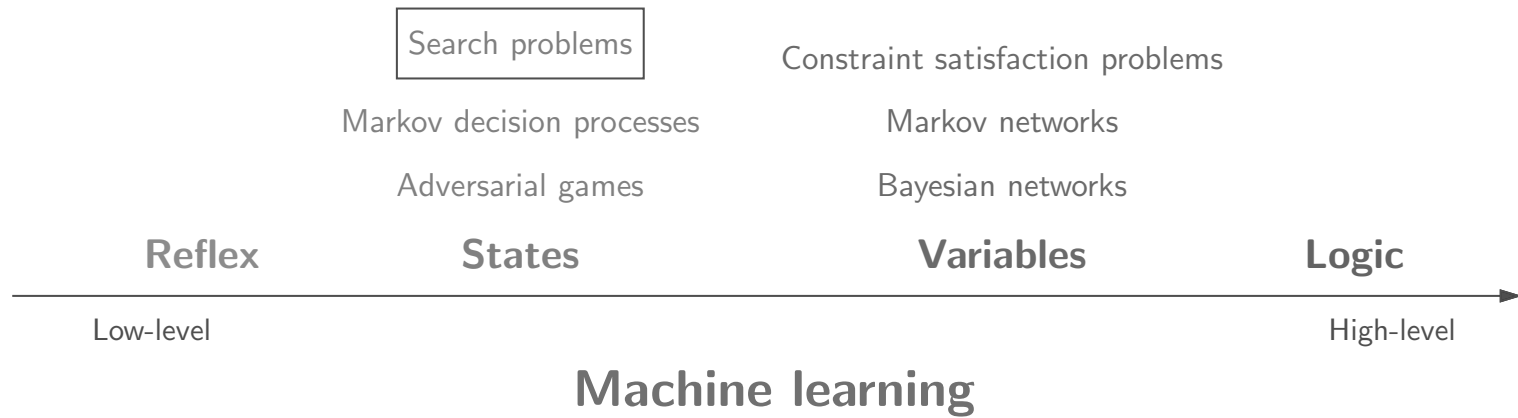


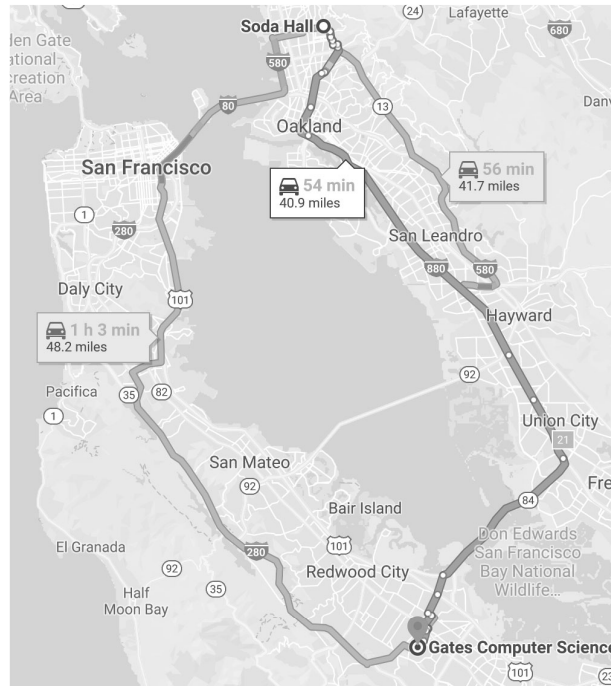
# Search: overview



# Course plan



# Application: route finding



Objective: shortest? fastest? most scenic?

Actions: go straight, turn left, turn right

# Application: robot motion planning



Objective: fastest path

Actions: acceleration and throttle

# Application: robot motion planning



Objective: fastest? most energy efficient? safest? most expressive?

Actions: translate and rotate joints

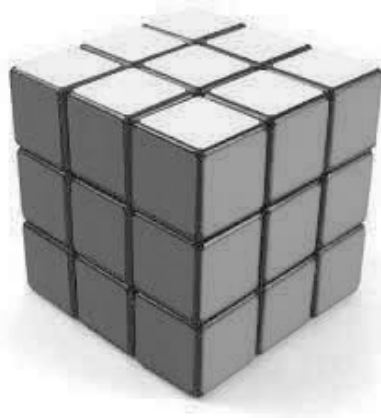
# Application: multi-robot systems



Objective: fastest? most energy efficient?

Actions: acceleration and steering of all robots

## Application: solving puzzles



Objective: reach a certain configuration

Actions: move pieces (e.g., Move12Down)

# Application: machine translation

*la maison bleue*



*the blue house*

Objective: use fluent English and preserve meaning

Actions: append single words (e.g., the)



# Beyond reflex

Classifier (reflex-based models):



Search problem (state-based models):



**Key: need to consider future consequences of an action!**

Paradigm

Modeling

Inference

Learning

# Roadmap

## Modeling

Modeling Search Problems

## Algorithms

Tree Search

Dynamic Programming

Uniform Cost Search

Programming and Correctness of UCS

A\*

A\* Relaxations

## Learning

Structured Perceptron



# Search: modeling

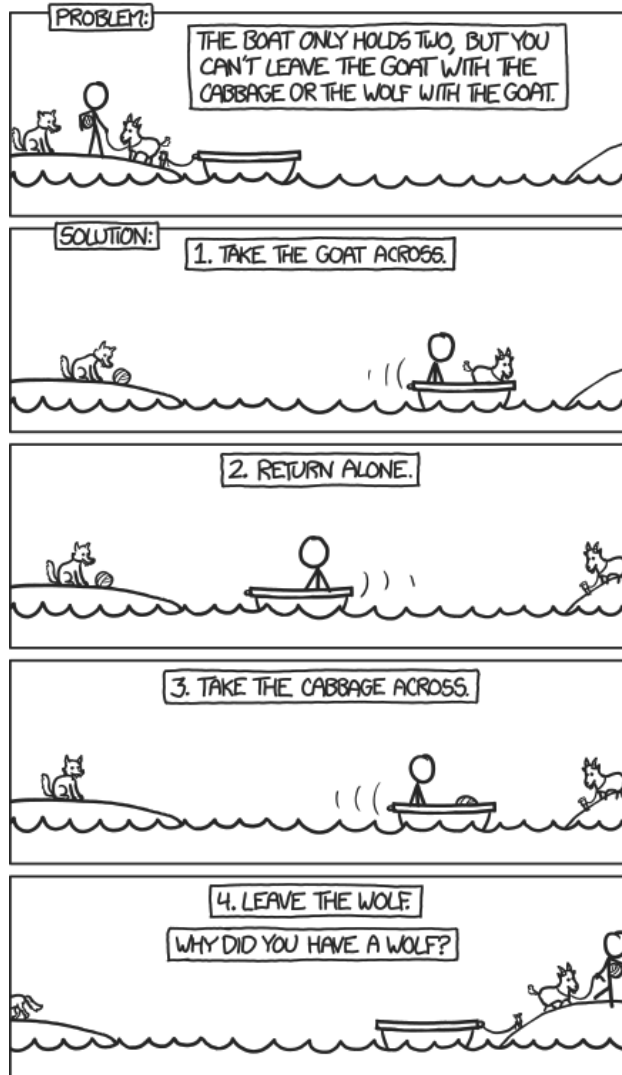


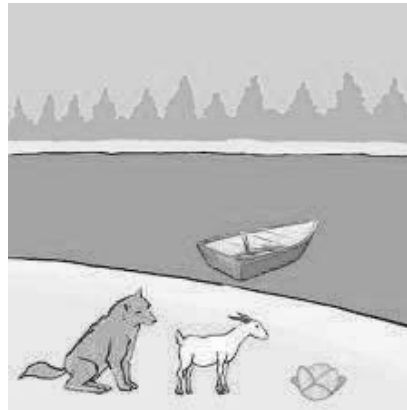


## Question

A **farmer** wants to get his **cabbage**, **goat**, and **wolf** across a river. He has a boat that only holds two. He cannot leave the cabbage and goat alone or the goat and wolf alone. How many river crossings does he need?

- 4
- 5
- 6
- 7
- no solution



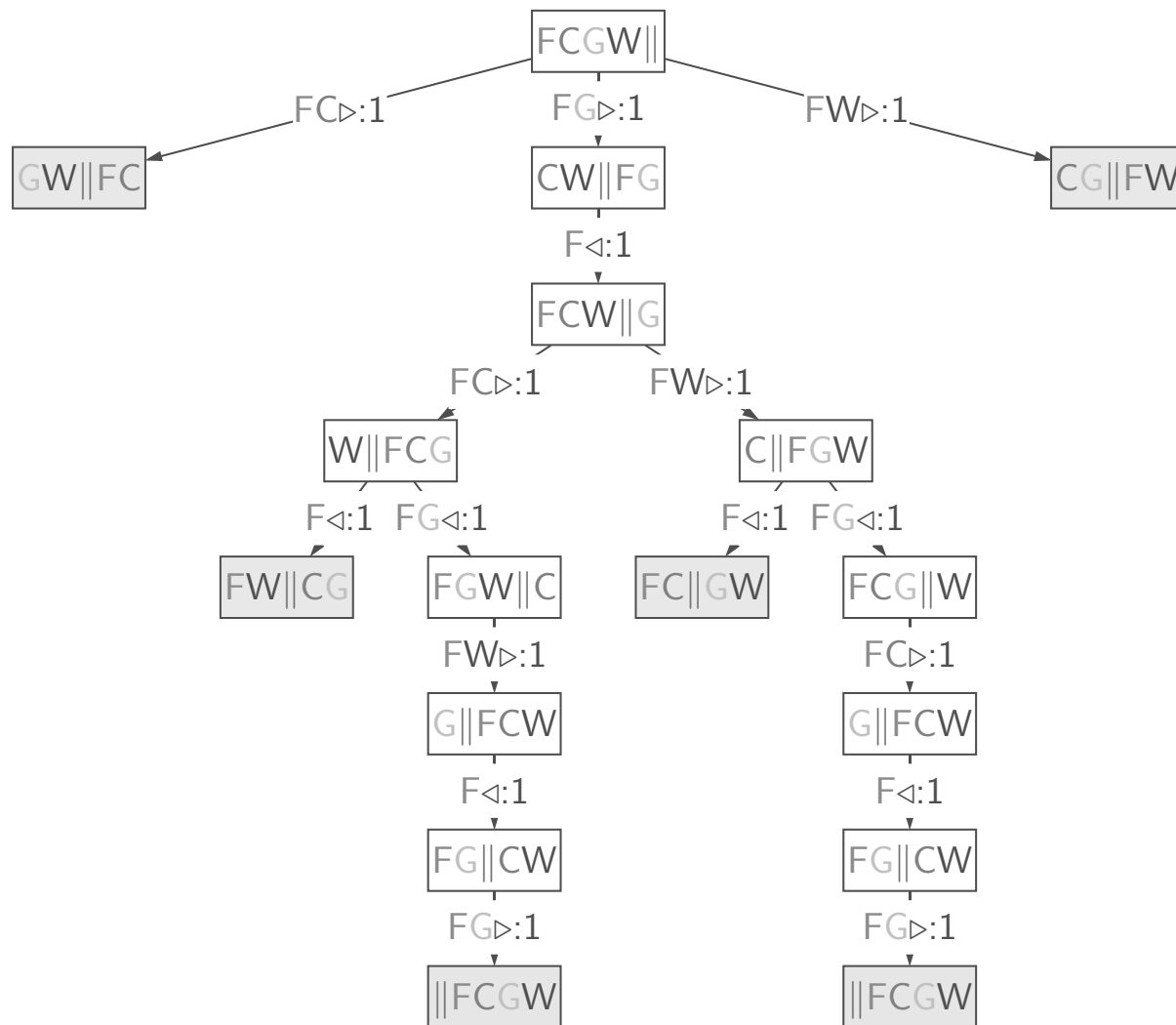


Farmer   Cabbage   Goat   Wolf

Actions:

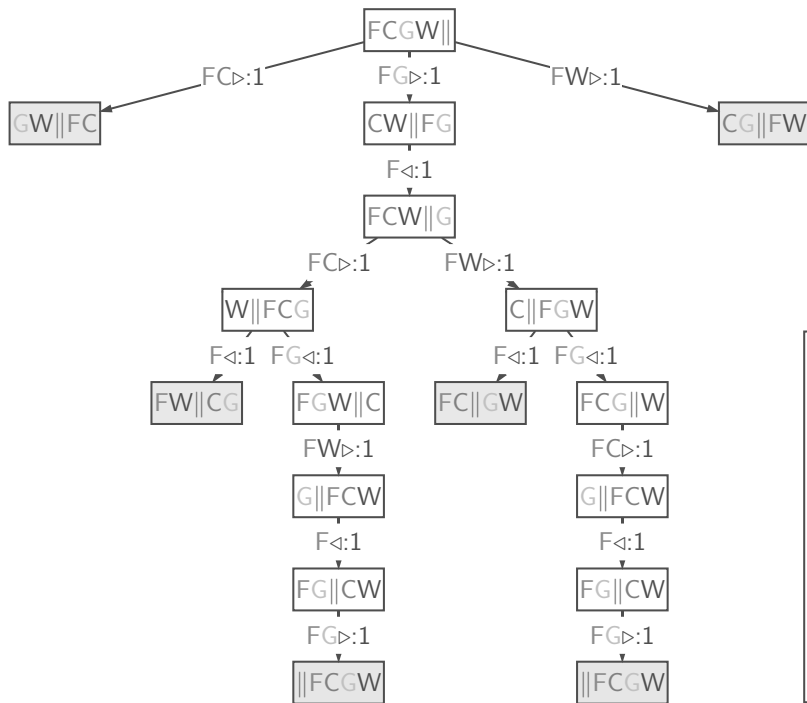
F▷	F◁
FC▷	FC◁
FG▷	FG◁
FW▷	FW◁

Approach: build a **search tree** ("what if?")



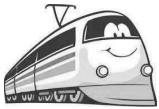


# Search problem



## Definition: search problem

- $s_{\text{start}}$ : starting state
- $\text{Actions}(s)$ : possible actions
- $\text{Cost}(s, a)$ : action cost
- $\text{Succ}(s, a)$ : successor
- $\text{IsEnd}(s)$ : reached end state?



# Transportation example



## Example: transportation

Street with blocks numbered 1 to  $n$ .

Walking from  $s$  to  $s + 1$  takes 1 minute.

Taking a magic tram from  $s$  to  $2s$  takes 2 minutes.

How to travel from 1 to  $n$  in the least time?

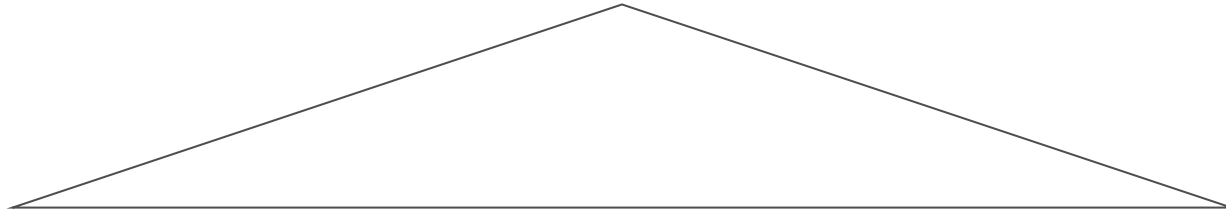
[live solution: `TransportationProblem`]



# Search: tree search



# Backtracking search



[whiteboard: search tree]

If  $b$  actions per state, maximum depth is  $D$  actions:

- Memory:  $O(D)$  (small)
- Time:  $O(b^D)$  (huge) [ $2^{50} = 1125899906842624$ ]

# Backtracking search



## Algorithm: backtracking search

```
def backtrackingSearch( $s$ , path):  
    If IsEnd( $s$ ): update minimum cost path  
    For each action  $a \in \text{Actions}(s)$ :  
        Extend path with Succ( $s, a$ ) and Cost( $s, a$ )  
        Call backtrackingSearch(Succ( $s, a$ ), path)  
    Return minimum cost path
```

[live solution: backtrackingSearch]

# Depth-first search



**Assumption: zero action costs**

Assume action costs  $\text{Cost}(s, a) = 0$ .

Idea: Backtracking search + stop when find the first end state.

If  $b$  actions per state, maximum depth is  $D$  actions:

- Space: still  $O(D)$
- Time: still  $O(b^D)$  worst case, but could be much better if solutions are easy to find

# Breadth-first search



**Assumption: constant action costs**

Assume action costs  $\text{Cost}(s, a) = c$  for some  $c \geq 0$ .

Idea: explore all nodes in order of increasing depth.

Legend:  $b$  actions per state, solution has  $d$  actions

- Space: now  $O(b^d)$  (a lot worse!)
- Time:  $O(b^d)$  (better, depends on  $d$ , not  $D$ )

# DFS with iterative deepening



**Assumption: constant action costs**

Assume action costs  $\text{Cost}(s, a) = c$  for some  $c \geq 0$ .

Idea:

- Modify DFS to stop at a maximum depth.
- Call DFS for maximum depths  $1, 2, \dots$

DFS on  $d$  asks: is there a solution with  $d$  actions?

Legend:  $b$  actions per state, solution size  $d$

- Space:  $O(d)$  (saved!)
- Time:  $O(b^d)$  (same as BFS)





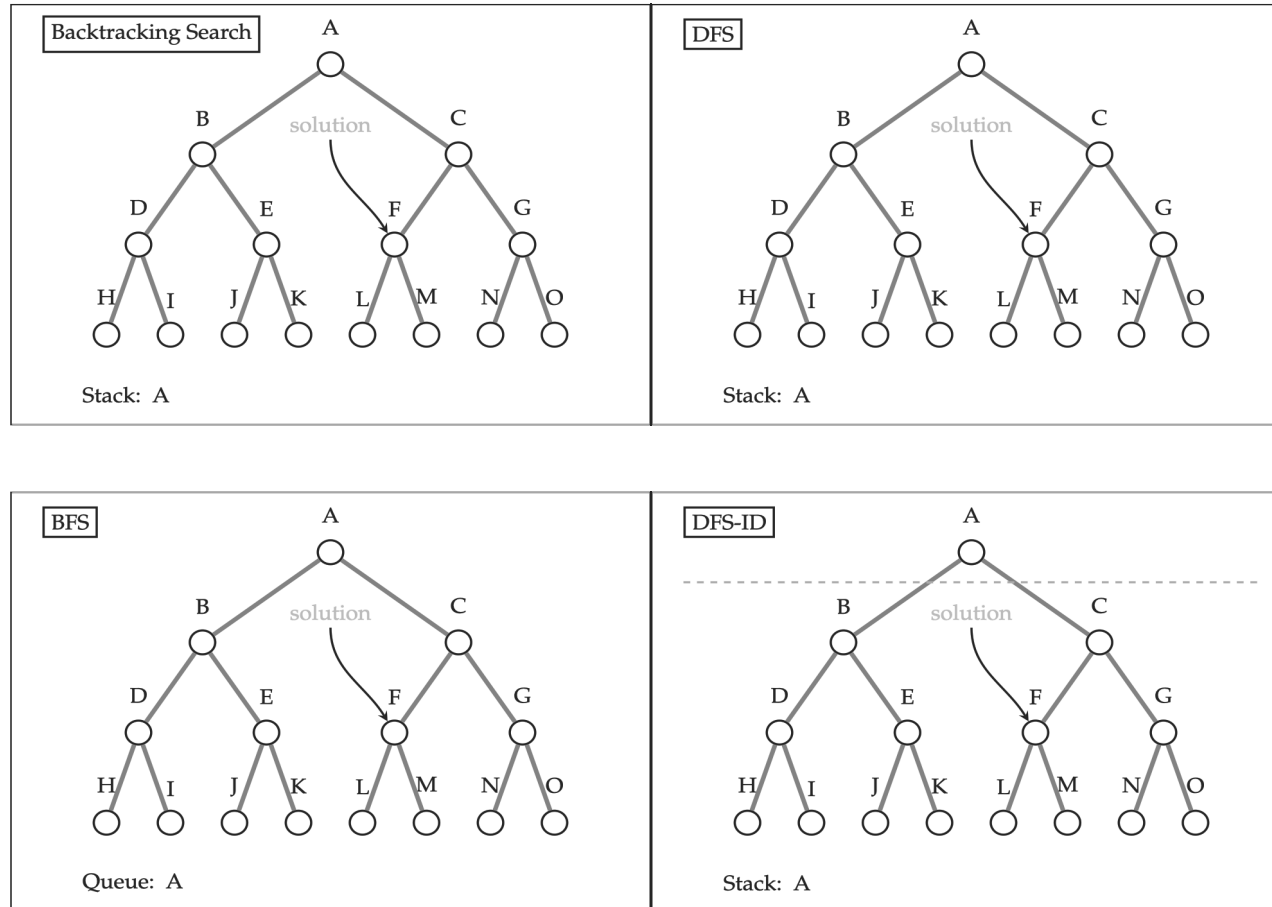
# Tree search algorithms

Legend:  $b$  actions/state, solution depth  $d$ , maximum depth  $D$

Algorithm	Action costs	Space	Time
Backtracking	any	$O(D)$	$O(b^D)$
DFS	zero	$O(D)$	$O(b^D)$
BFS	constant $\geq 0$	$O(b^d)$	$O(b^d)$
DFS-ID	constant $\geq 0$	$O(d)$	$O(b^d)$

- Always exponential time
- Avoid exponential space with DFS-ID

# Tree Search Review

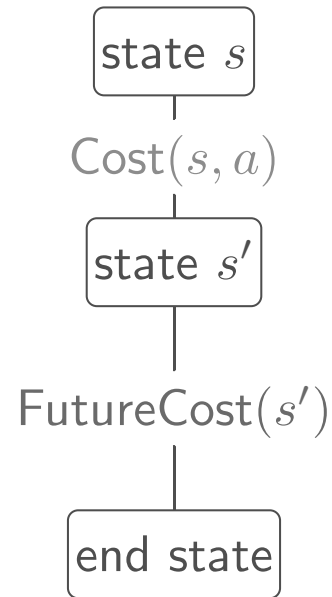




# Search: dynamic programming



# Dynamic programming



Minimum cost path from state  $s$  to a end state:

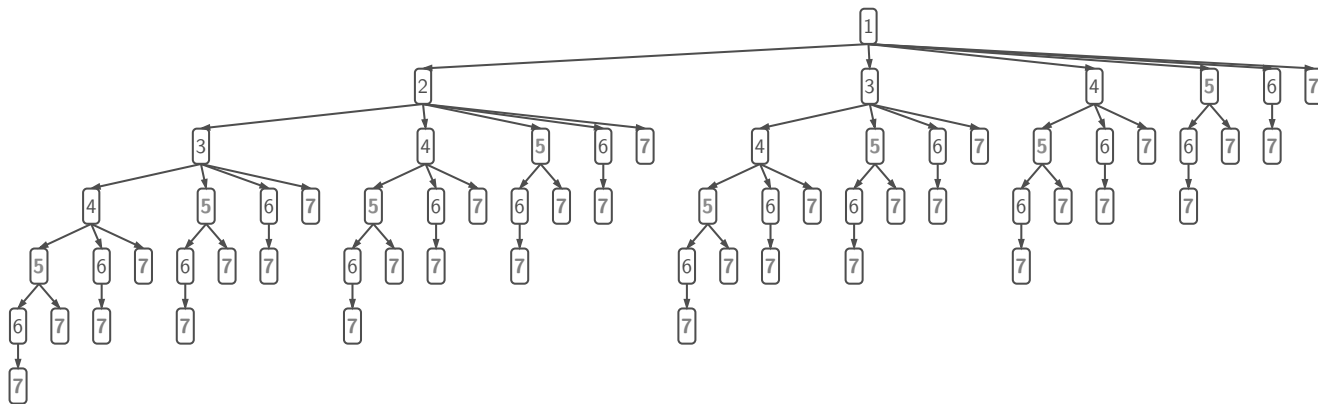
$$\text{FutureCost}(s) = \begin{cases} 0 & \text{if } \text{IsEnd}(s) \\ \min_{a \in \text{Actions}(s)} [\text{Cost}(s, a) + \text{FutureCost}(\text{Succ}(s, a))] & \text{otherwise} \end{cases}$$

# Motivating task



## Example: route finding

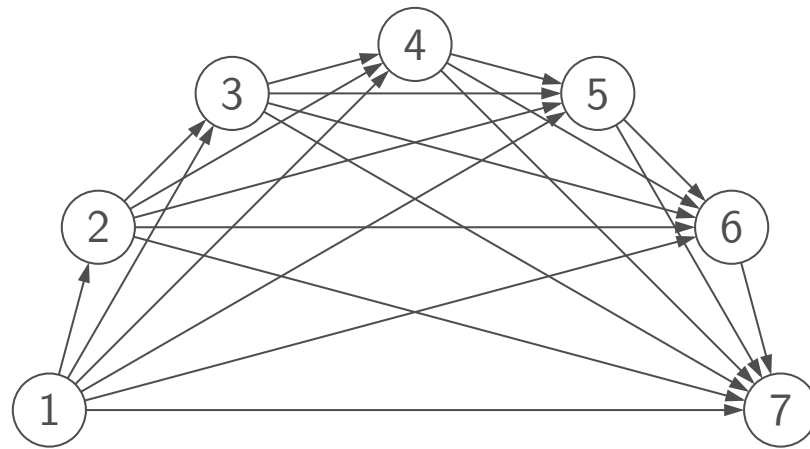
Find the minimum cost path from city 1 to city  $n$ , only moving forward. It costs  $c_{ij}$  to go from  $i$  to  $j$ .



Observation: future costs only depend on current city

# Dynamic programming

**State:** ~~past sequence of actions~~ current city



**Exponential saving in time and space!**

# Dynamic programming



## Algorithm: dynamic programming

```
def DynamicProgramming( $s$ ):  
    If already computed for  $s$ , return cached answer.  
    If IsEnd( $s$ ): return solution  
    For each action  $a \in \text{Actions}(s)$ : ...
```

[live solution: Dynamic Programming]



## Assumption: acyclicity

The state graph defined by  $\text{Actions}(s)$  and  $\text{Succ}(s, a)$  is acyclic.

# Dynamic programming



Key idea: state

A **state** is a summary of all the past actions sufficient to choose future actions **optimally**.

past actions (all cities)      1 3 4 6

state (current city)          1 3 4 6



# Handling additional constraints

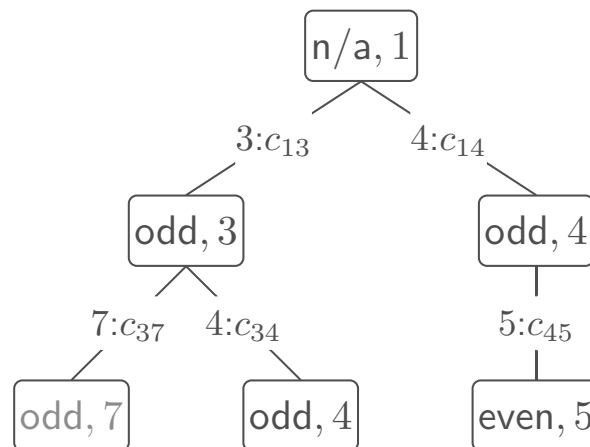


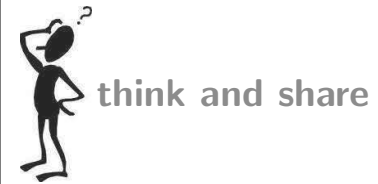
## Example: route finding

Find the minimum cost path from city 1 to city  $n$ , only moving forward. It costs  $c_{ij}$  to go from  $i$  to  $j$ .

**Constraint:** Can't visit three odd cities in a row.

**State:** (whether previous city was odd, current city)



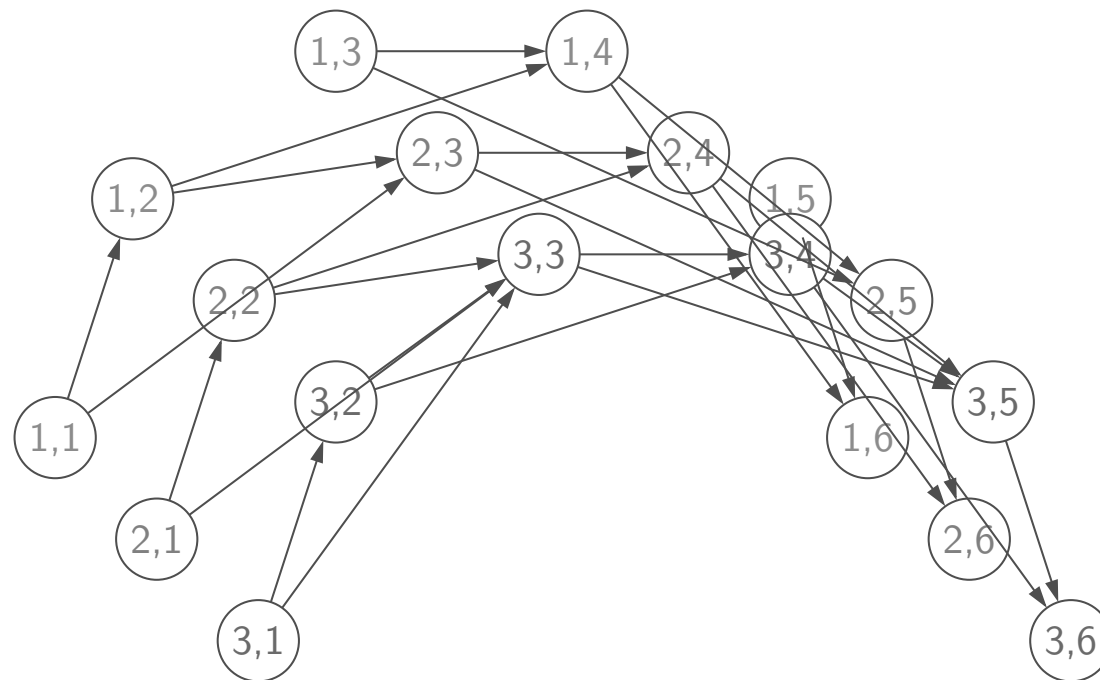


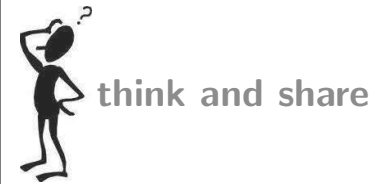
## Question

Objective: travel from city 1 to city  $n$ , visiting at least 3 odd cities. What is the minimal state?

# State graph

State:  $(\min(\text{number of odd cities visited}, 3), \text{current city})$





## Question

Objective: travel from city 1 to city  $n$ , visiting more odd than even cities. What is the minimal state?

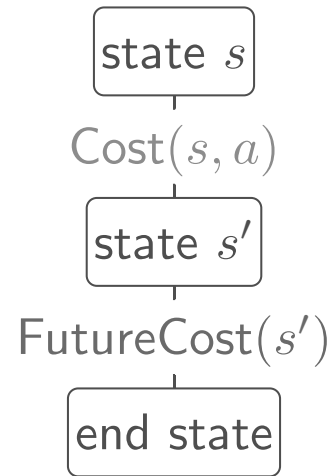


# Summary

- State: summary of past actions sufficient to choose future actions optimally
- Dynamic programming: backtracking search with **memoization** — potentially exponential savings

Dynamic programming only works for acyclic graphs...what if there are cycles?

# Dynamic Programming Review



$$\text{FutureCost}(s) = \begin{cases} 0 & \text{if IsEnd}(s) \\ \min_{a \in \text{Actions}(s)} [\text{Cost}(s, a) + \text{FutureCost}(\text{Succ}(s, a))] & \text{otherwise} \end{cases}$$



**Key idea: state**

A **state** is a summary of all the past actions sufficient to choose future actions **optimally**.

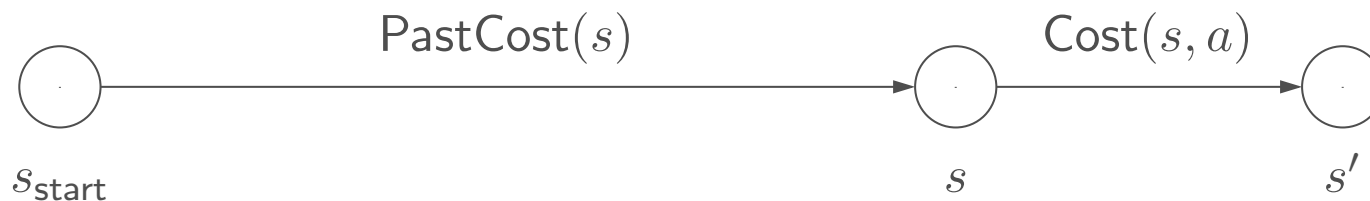


## Search: uniform cost search



# Ordering the states

Observation: prefixes of optimal path are optimal



Key: if graph is acyclic, dynamic programming makes sure we compute  $\text{PastCost}(s)$  before  $\text{PastCost}(s')$

If graph is cyclic, then we need another mechanism to order states...



# Uniform cost search (UCS)



**Key idea: state ordering**

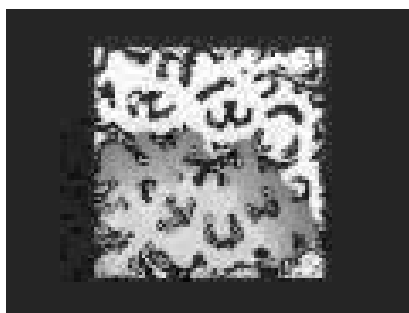
UCS enumerates states in order of increasing past cost.



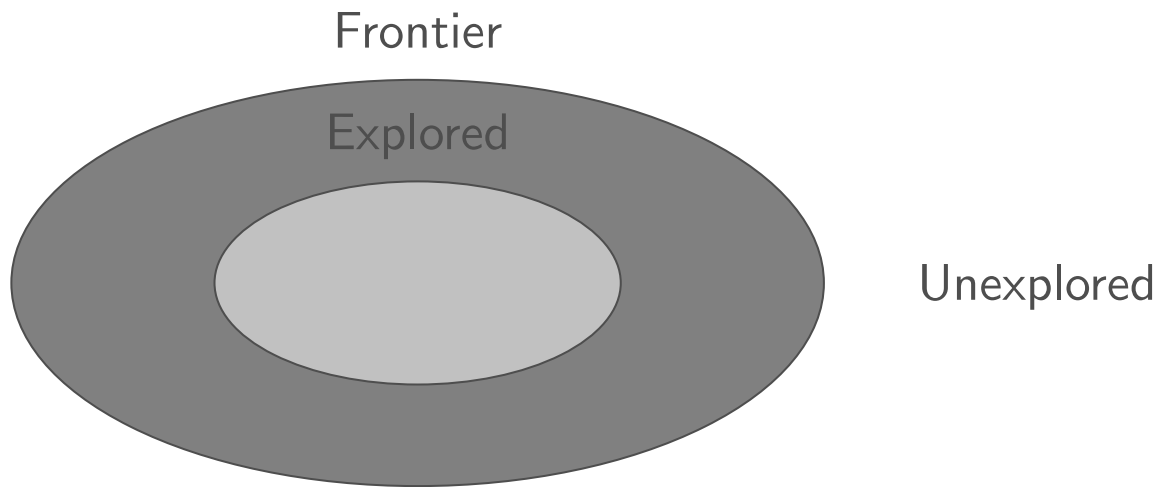
**Assumption: non-negativity**

All action costs are non-negative:  $\text{Cost}(s, a) \geq 0$ .

UCS in action:

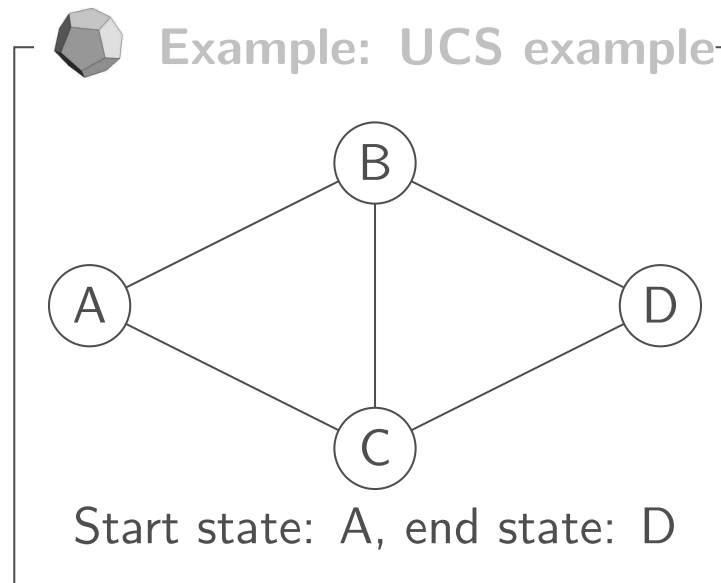


# High-level strategy



- Explored: states we've found the optimal path to
- Frontier: states we've seen, still figuring out how to get there cheaply
- Unexplored: states we haven't seen

# Uniform cost search example



[whiteboard]

Minimum cost path:

$A \rightarrow B \rightarrow C \rightarrow D$  with cost 3