

CS 440

Introduction to Artificial Intelligence

Lecture 3:

Search & Genetic Algorithms

28 January 2020

SPN numbers have been issued

Review Hill climbing

Genetic Algorithms

Heuristic Search

Hill climbing

Always select action that leads to state with best heuristic

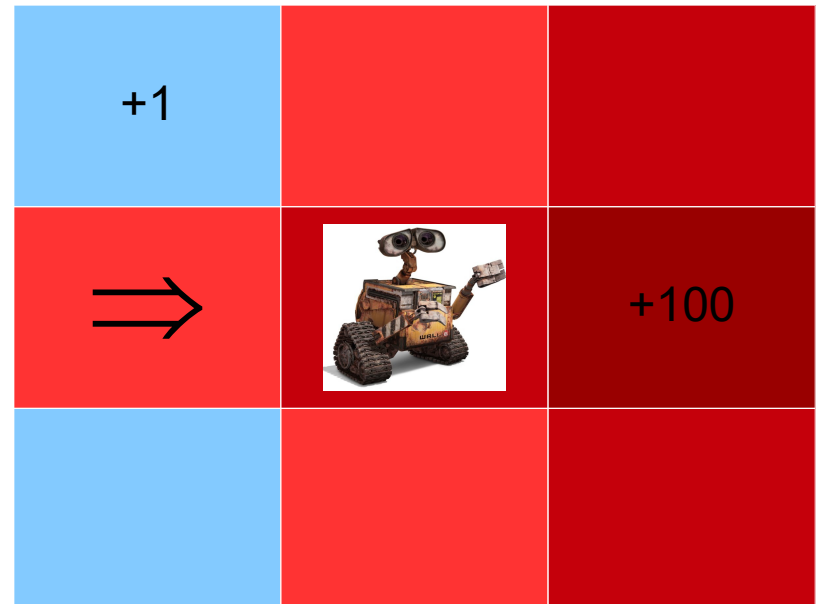
Let s = current state

For all $a \in A$

$$s' = \tau(s, a)$$

$$h_a = h(s')$$

Select a with largest reward h_a



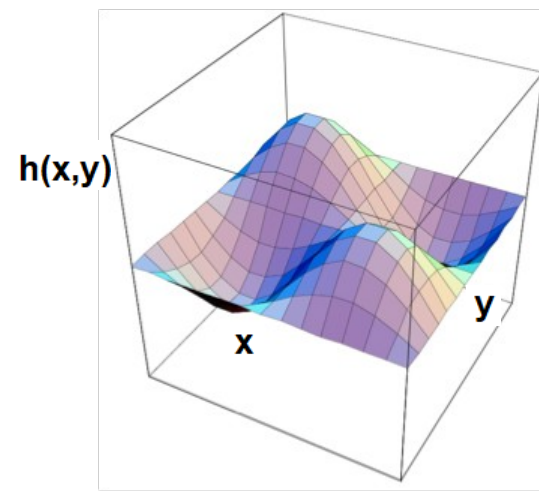
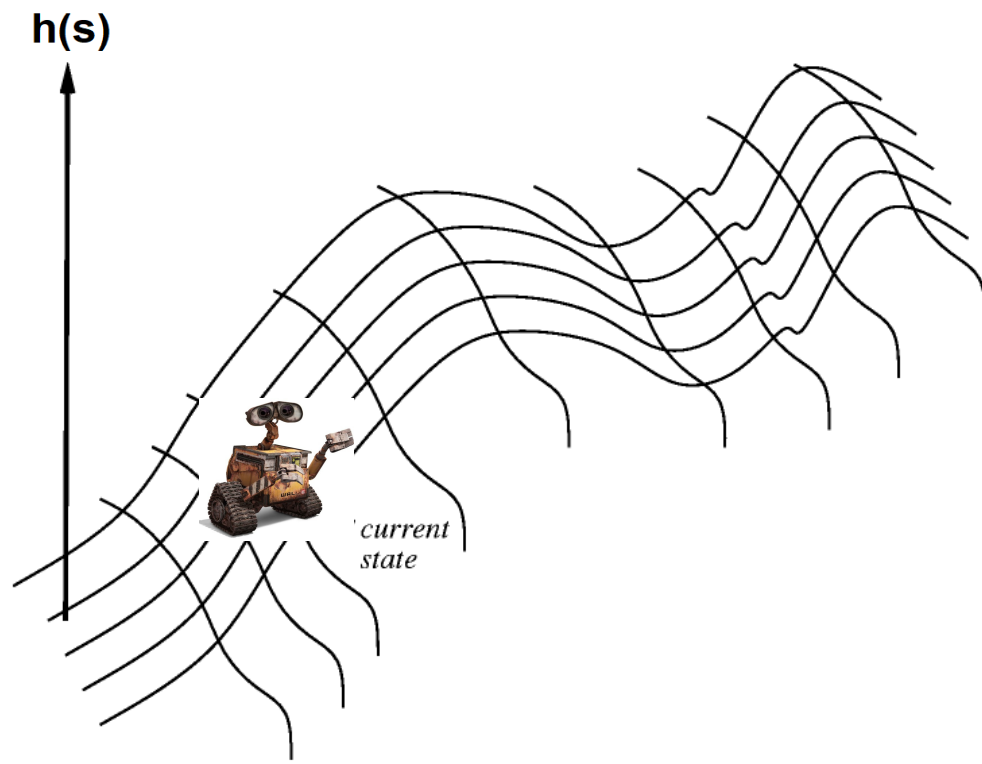
Can we apply hill climbing to continuous state spaces?

Example 2D Euclidean space

Gradient ascent / descent

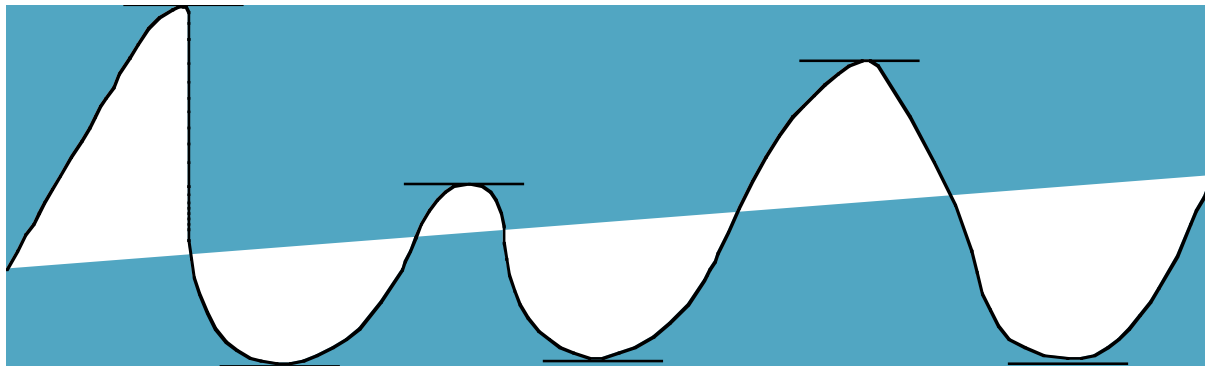
Move in direction of gradient

$\nabla h(s)$



Discussion

- How does GD algorithm know it has reached min/max?
 - Hint GD computes direction by computing $\nabla h(s)$
- What are some methods for escaping local minimums?
- What are some methods for approximating gradient descent if gradient can't be computed?



- Genetic algorithms are a randomized local search strategy.
- Basic idea: Simulate natural selection, where the population is composed of
 - *an evolving population of candidate solutions.*
- Focus is on evolving a population from which strong and diverse candidates can emerge via:
 - survival of the fittest,
 - crossover (mating),
 - and mutation.

Create an initial population, either random or “blank”.

While the best candidate so far is not a solution:

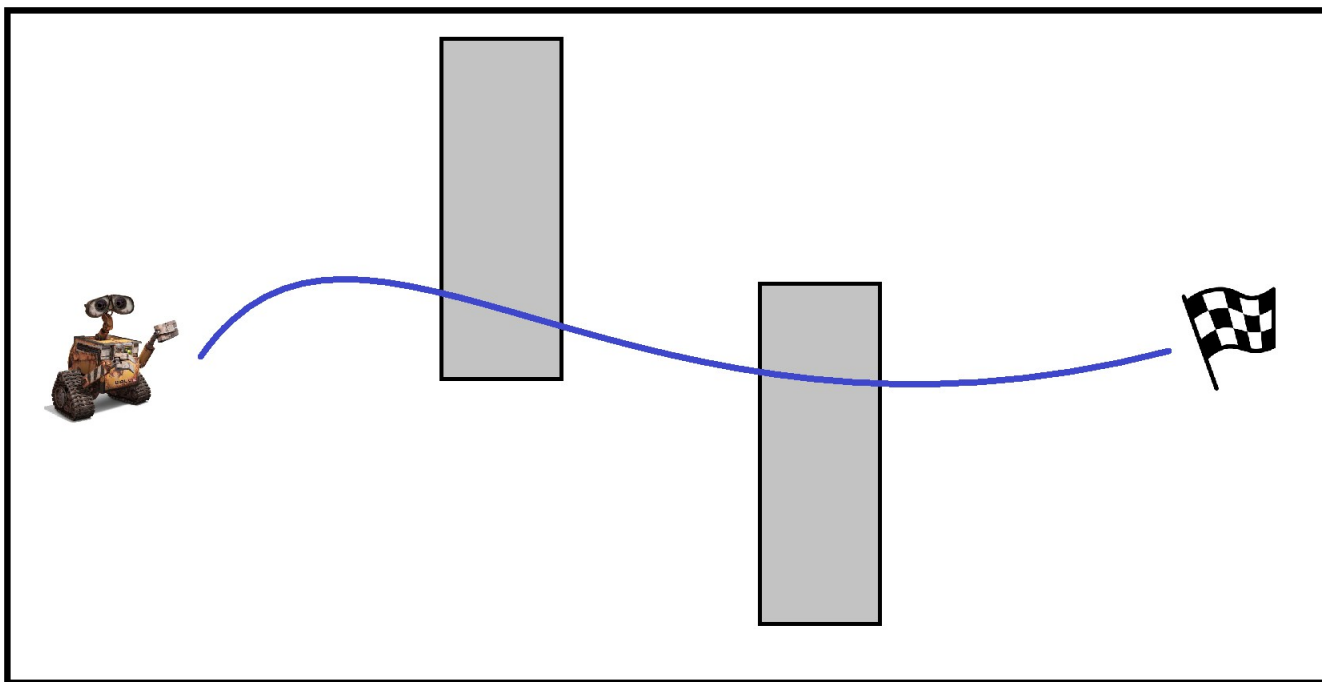
- Create new population using successor functions.

- Evaluate the fitness of each candidate in the population.

Return the best candidate found.

- Let's try to evolve a length 4 alternating string
 - Fitness function - number of consecutive occurrences
 - Evolve by flipping 1 bit
- Initial population: C1=0011
- We roll the dice and end up creating C1' = 1011 and C2' = 0001.
 - C1' = 1011 \Rightarrow score of -1
 - C2' = 0001 \Rightarrow score of -2
 - Keep C1'
- Roll the dice again and end up creating C1'' = 1001 and C2'' = 1010.
 - We run our solution test on each. C2'' is a solution, so we return it and are done.

Genetic algorithm example: Robot path planning



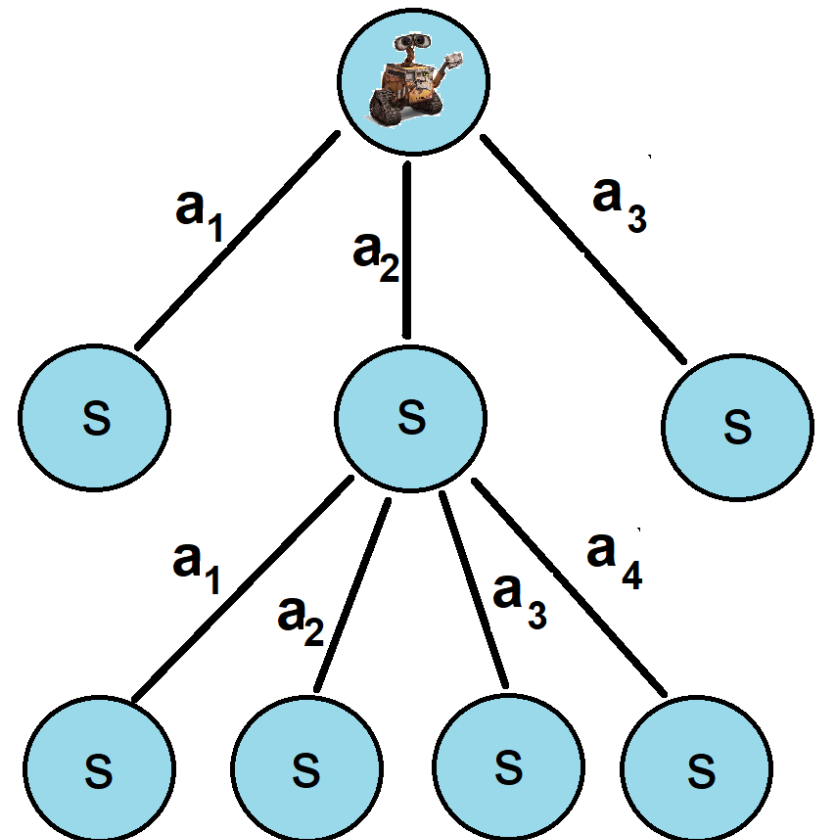
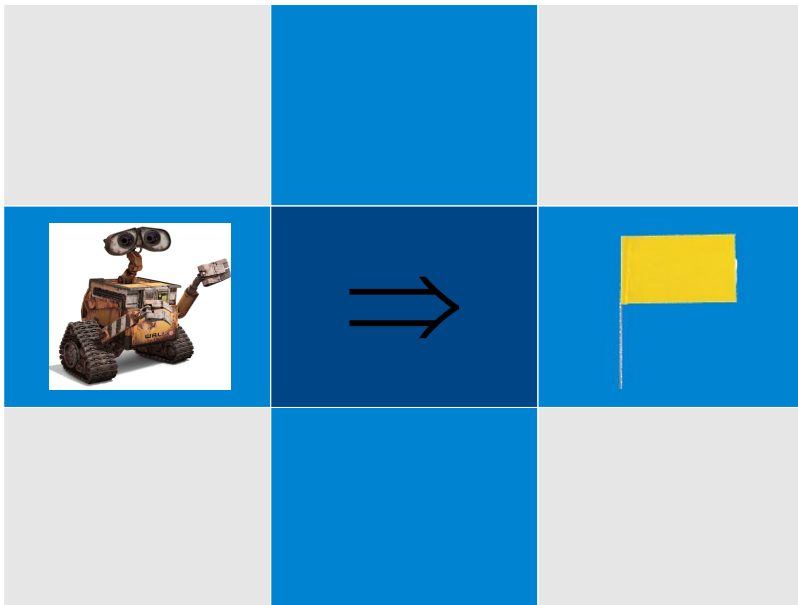
- Let's try to evolve a length 4 alternating string
 - Fitness function - number of consecutive occurrences
- Initial population: $C1=1000$, $C2=0011$
- We roll the dice and end up creating $C1' = \text{cross}(C1, C2) = 1011$ and $C2' = \text{cross}(C1, C1) = 1000$.
 - $C1' \Rightarrow$ score of -1
 - $C2' \Rightarrow$ score of -3
 - Keep $C1'$
- We mutate $C1'$ and the fourth bit flips, giving 1010. We mutate $C2'$ and get 1000.
 - We run our solution test on each. $C1'$ is a solution, so we return it and are done.

- What are some possible variations of genetic algorithms?
 - When would these variations be advantageous
- What are some limitations of genetic algorithms?

- Initial population: $C1=0011$, $C2=1000$
- We roll the dice and end up creating $C1' = \text{cross}(C1, C2) = 1011$, $C2' = \text{cross}(C2, C2) = 1000$, $C3' = \text{cross}(C1, C1) = 0011$ and $C4' = \text{cross}(C1, C2) = 0110$
 - $C1' = 1011 \Rightarrow$ score of -1
 - $C2' = 1000 \Rightarrow$ score of -2
 - $C3' = 0011 \Rightarrow$ score of -2
 - $C4' = 0110 \Rightarrow$ score of -1
 - Keep $C1'$ and $C4'$
- Roll the dice again and end up creating $C1'' = \text{cross}(C1, C1) = 1011$ and $C2'' = \text{cross}(C1, C4) = 1010$.
 - We run our solution test on each. $C2''$ is a solution, so we return it and are done.

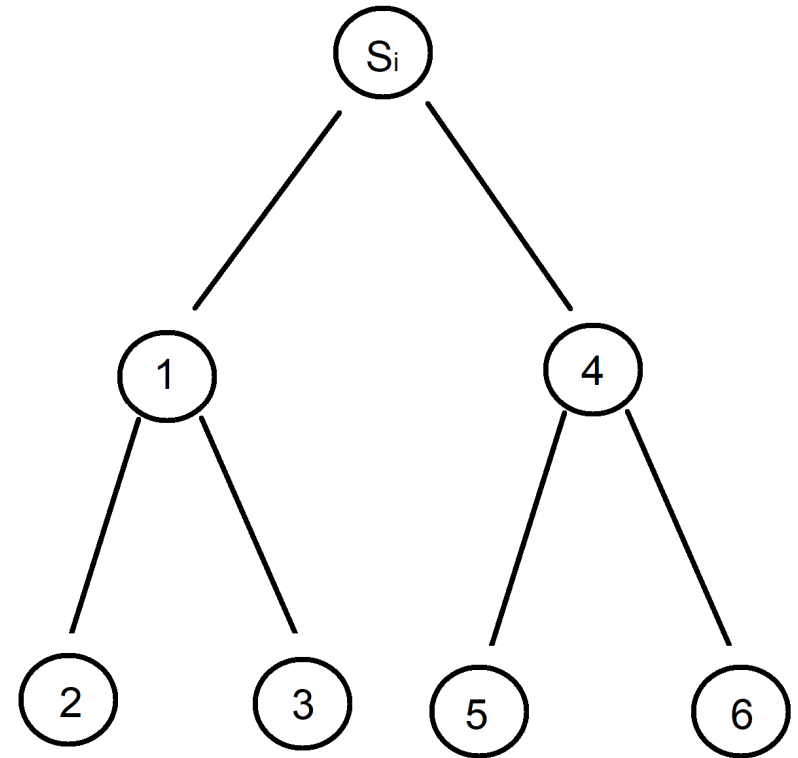
Represent as a tree

- Nodes represent states
- Edges represent actions
- Root is current state
- Children - states you get by taking each action



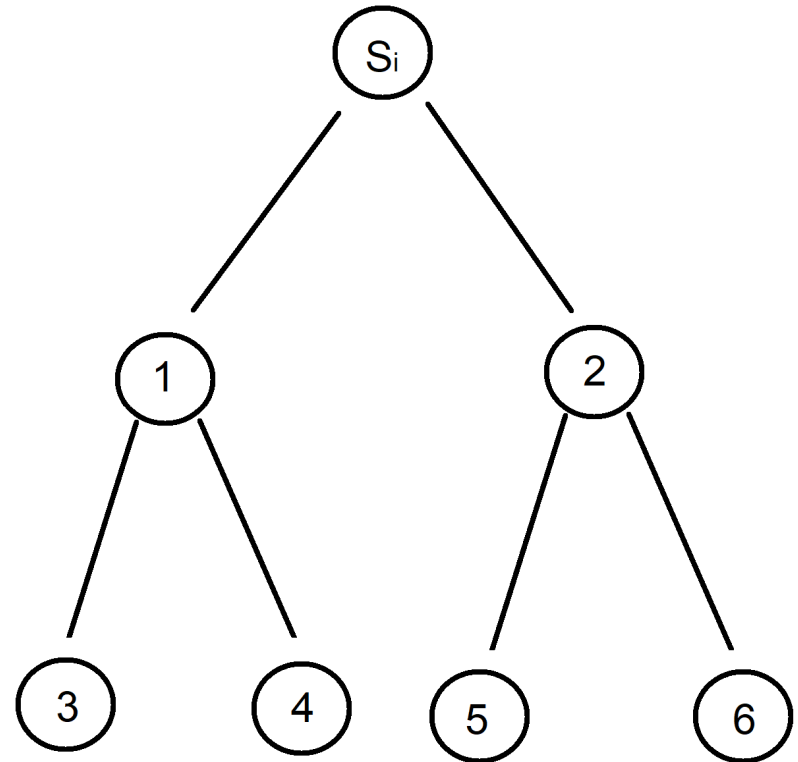
Depth first search

```
stack.push(initial state)
While(!stack.empty())
  s = stack.pop
  if(s == goal)
    return
  if (!s.visited)
    s.visited=true
    for all actions  $a \in A$ 
       $s' = \tau(s, a)$ 
      stack.push( $s'$ )
```



Breath first search

```
queue.push(initial state)
While(!queue.empty())
    s = queue.pop
    if(s == goal)
        return
    if (!s.visited)
        s.visited=true
        for all actions  $a \in A$ 
             $s' = \tau(s, a)$ 
            queue.push_back(s')
```



Weighted actions

- Each action has a cost associated with it
- $c(a)$ = Cost of performing action a in state s

Variations

- Cost of going through state
- Cost of performing action while in state
 - $c(a,s)$

How would we adapt BFS to accommodate weighted actions

- Find shortest path to goal

- Priority queue ordered by path length

```
priority_queue.push(initial state, 0)
```

```
While(!priority_queue.empty())
```

```
    s = priority_queue.pop()
```

```
    if(s == goal)
```

```
        return
```

```
    if (!s.visited)
```

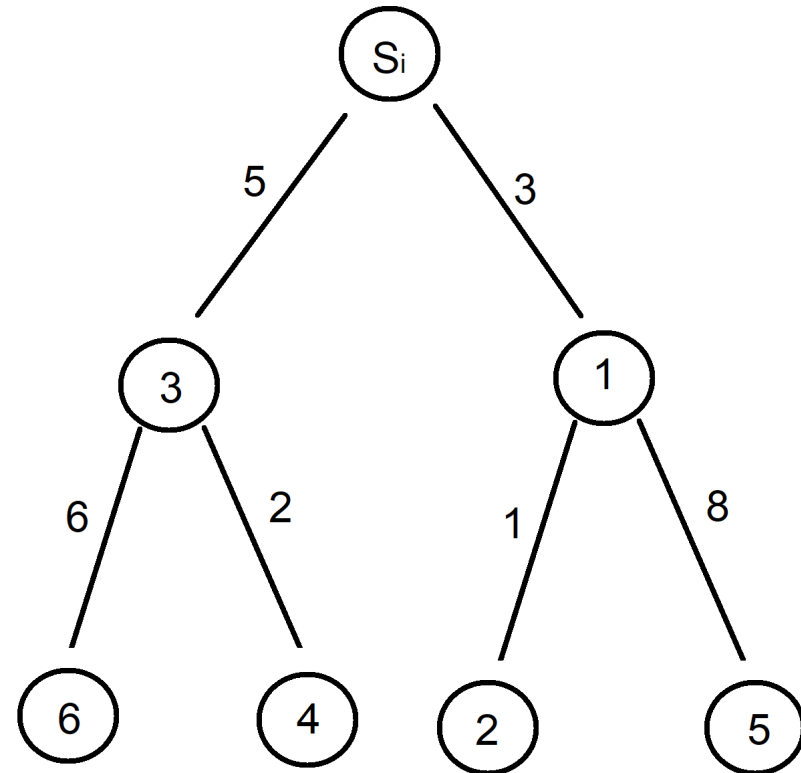
- s.visited=true

```
    for all actions  $a \in A$ 
```

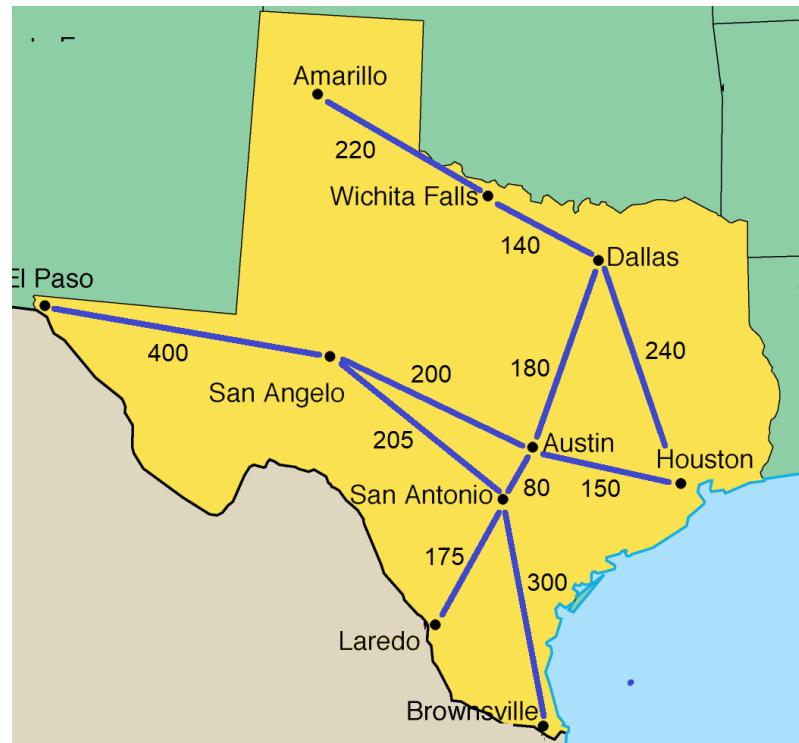
```
         $s' = \tau(s, a)$ 
```

```
         $s'_{\text{path\_length}} = s_{\text{path\_length}} + \text{length}(a)$ 
```

```
        priority_queue.push(s',  $s'_{\text{path\_length}}$ )
```



- Map of driving routs
 - Find shortest rout
- Find shortest path first algorithm also called Dijkstra's Algorithm



Heuristic

- Estimate of utility of state
- Real value indicating utility of state
- Must be defined for all states in S

Convention

- $h(s) \Rightarrow \mathcal{R}$

Examples

- Chess: Value of pieces captured/lost
- Robotics: Euclidean distance from goal
- Sudoku: Numbers placed, rows/columns/blocks filled in.

Always select open state with best heuristic value

```
priority_queue.push(initial state, 0)
While(!priority_queue.empty())
    s = priority_queue.pop()
    if(s == goal)
        return
    if (!s.visited)
        • s.visited=true
    for all actions  $a \in A$ 
         $s' = \tau(s, a)$ 
        priority_queue.push(s', h(s'))
```

Not guaranteed to find optimal path

- Order nodes by sum of path length and heuristic
- Priority queue order by $\text{path}(s) + h(s)$
- Will find optimal path if using admissible heuristic

```
priority_queue.push(initial state, 0)
```

```
While(!priority_queue.empty())
```

```
    s = priority_queue.pop()
```

```
    if(s == goal)
```

```
        return
```

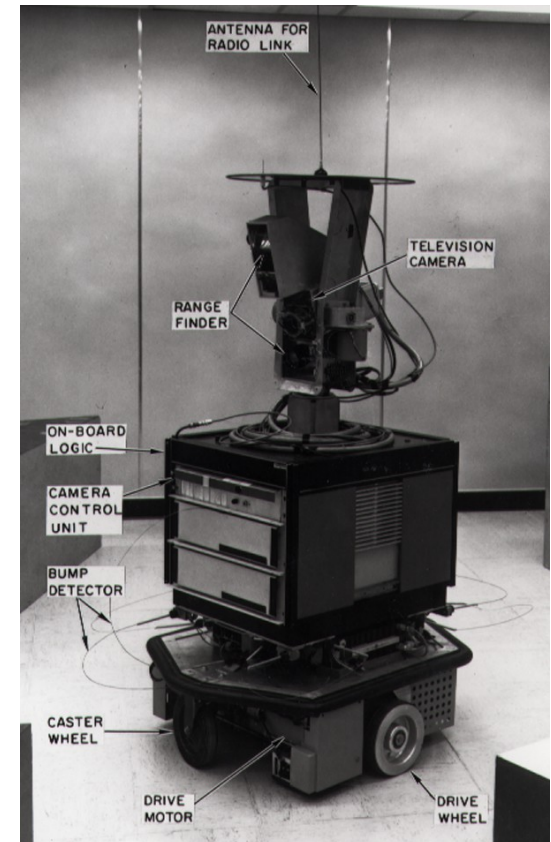
```
    if (!s.visited)
```

- $s.\text{visited} = \text{true}$
- for all actions $a \in A$

```
     $s' = \tau(s, a)$ 
```

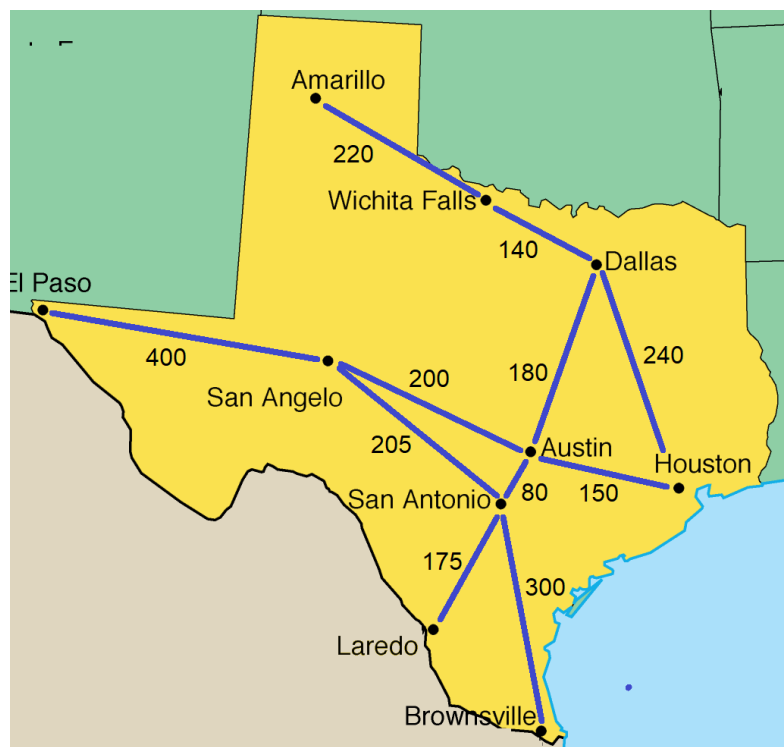
```
     $s'_{\text{path\_length}} = s_{\text{path\_length}} + \text{length}(a)$ 
```

```
    priority_queue.push( $s'$ ,  $s'_{\text{path\_length}} + h(s')$ )
```

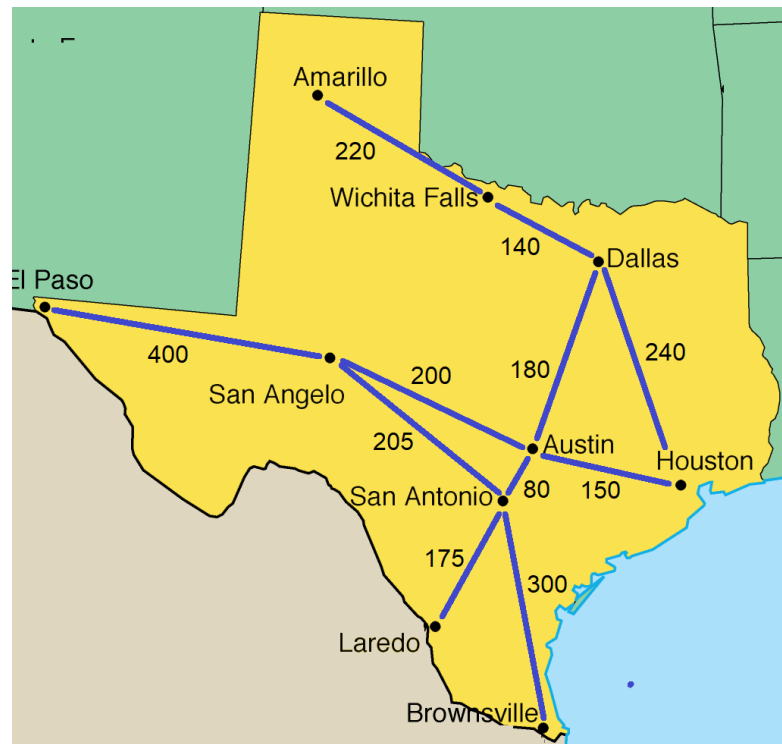


- Never overestimates cost to goal
 - $h(s) < \text{optimal_path}(s, \text{goal})$
- What can we say about A* search with admissible heuristic
- Examples of admissible heuristics for
 - Robot
 - Sudoku
 - Chess
 - Not trivial

- Map of driving routes
 - Find shortest rout
 - What are some good heuristics?



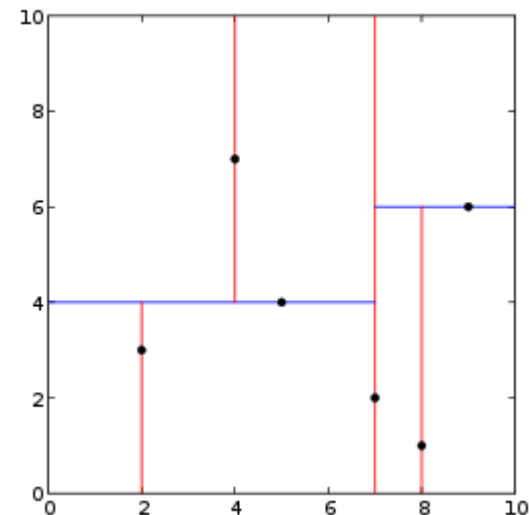
- Map of driving routes
 - Find shortest route
 - Heuristic = Euclidean distance to goal



How can we apply A* to problems with continuous state spaces?

- Robot in XY-plane

- Generate graph in space of problem
- Grid up state space
 - What resolution to use
 - More cells \Rightarrow higher computation cost
 - Complexity exponential with respect to dimension of state space
 - $O(x^d)$
 - Curse of dimensionality
- Generate graph in space of problem
 - Example robotics
- Adaptive grid
 - Recursively subdivide cells that are interesting
 - Example: Robotics - use higher resolution cells in difficult regions



Can we apply A^* to chess?

- Apply to adversarial/strategic problems
- Select best move during your turn and worst move (opponent's best move) during opponent's turn
 - Move you would make if you were opponent