

Advance Discrete Planning (1)

A* variants

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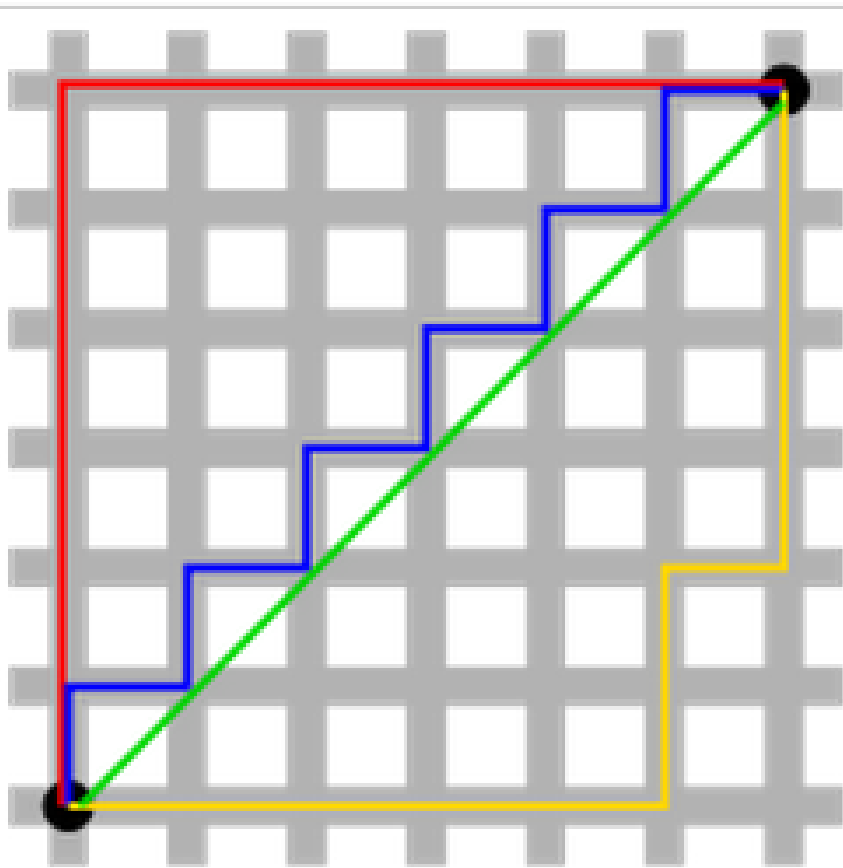
Worcester Polytechnic Institute




Quiz (10 pts)

- (2 pts) How to measure distance in Cspace? List at least two metrics.
- (2 pts) Why do we need anytime search algorithm?
- (2 pts) Describe an example of abstract goal?
- (4 pts) What are the pros and cons of inflating the heuristic of a best-first search algorithm (like A*)?

Distance in C-space



	a	b	c	d	e	f	g	h	
8	5	4	3	2	2	2	2	2	8
7	5	4	3	2	1	1	1	2	7
6	5	4	3	2	1		1	2	6
5	5	4	3	2	1	1	1	2	5
4	5	4	3	2	2	2	2	2	4
3	5	4	3	3	3	3	3	3	3
2	5	4	4	4	4	4	4	4	2
1	5	5	5	5	5	5	5	5	1
	a	b	c	d	e	f	g	h	

Distance metrics

- L₁-norm (Manhattan distance)

$$d_1(\mathbf{p}, \mathbf{q}) = \|\mathbf{p} - \mathbf{q}\|_1 = \sum_{i=1}^n |p_i - q_i|,$$

- L₂-norm (Euclidian distance)

$$d(\mathbf{p}, \mathbf{q}) = d(\mathbf{q}, \mathbf{p}) = \sqrt{(q_1 - p_1)^2 + (q_2 - p_2)^2 + \cdots + (q_n - p_n)^2}$$

- L_∞-norm (chessboard distance)

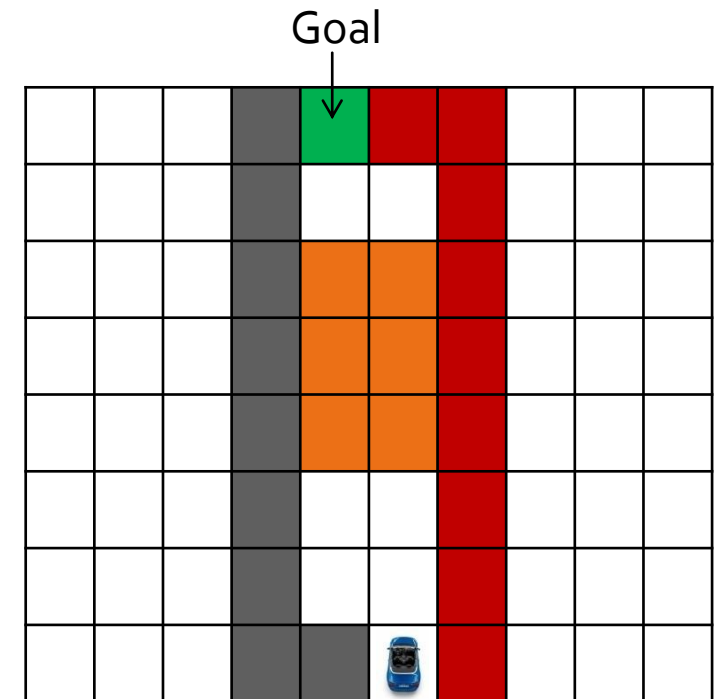
$$D_{\text{Chebyshev}}(p, q) := \max_i (|p_i - q_i|).$$

How to search

- More issues
 - Do you need to search again, and again?
 - What if you search within limited amount of time?
 - What if your search may terminate all of sudden?

Goal Test

- Goals are most commonly specific cells you want to get to
- But they can be more abstract, too!
- Example Goals?
 - A state where X is visible
 - A state where the robot is contacting X
 - Topological goals



Admissibility

- $h(x)$ must *never overestimate* the true cost-to-come
 - $h(x) < h^*(x)$, where $h^*(x)$ is the true cost
 - $h(x) > 0$ (so $h(G) = 0$ for goals G)
- If $h(x)$ is *admissible*, A^* will find the **least-cost path!**

- “Inflating” the heuristic
 - Faster search
 - Least-cost path is not guaranteed

Advanced Discrete Motion Planning

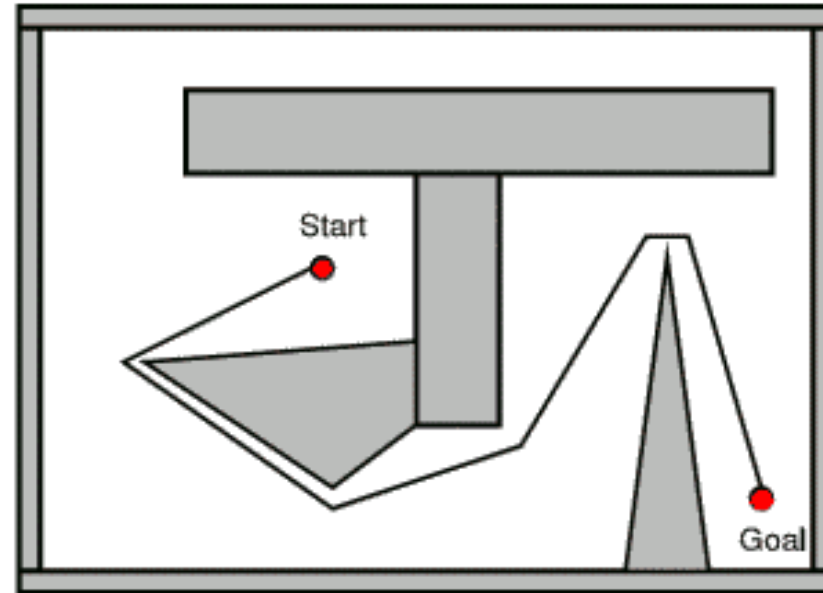
Overview of Advance Discrete Motion Planning

- **More on search algorithms**
 - Toward optimal and quicker solutions
 - Variants of A*
- Practical issues
 - Case study – Practical search techniques for autonomous driving
- Other advanced topics
 - Roadmaps for planning in dynamic environment
 - Learning search via imitation

A* Variants

Problem Statement

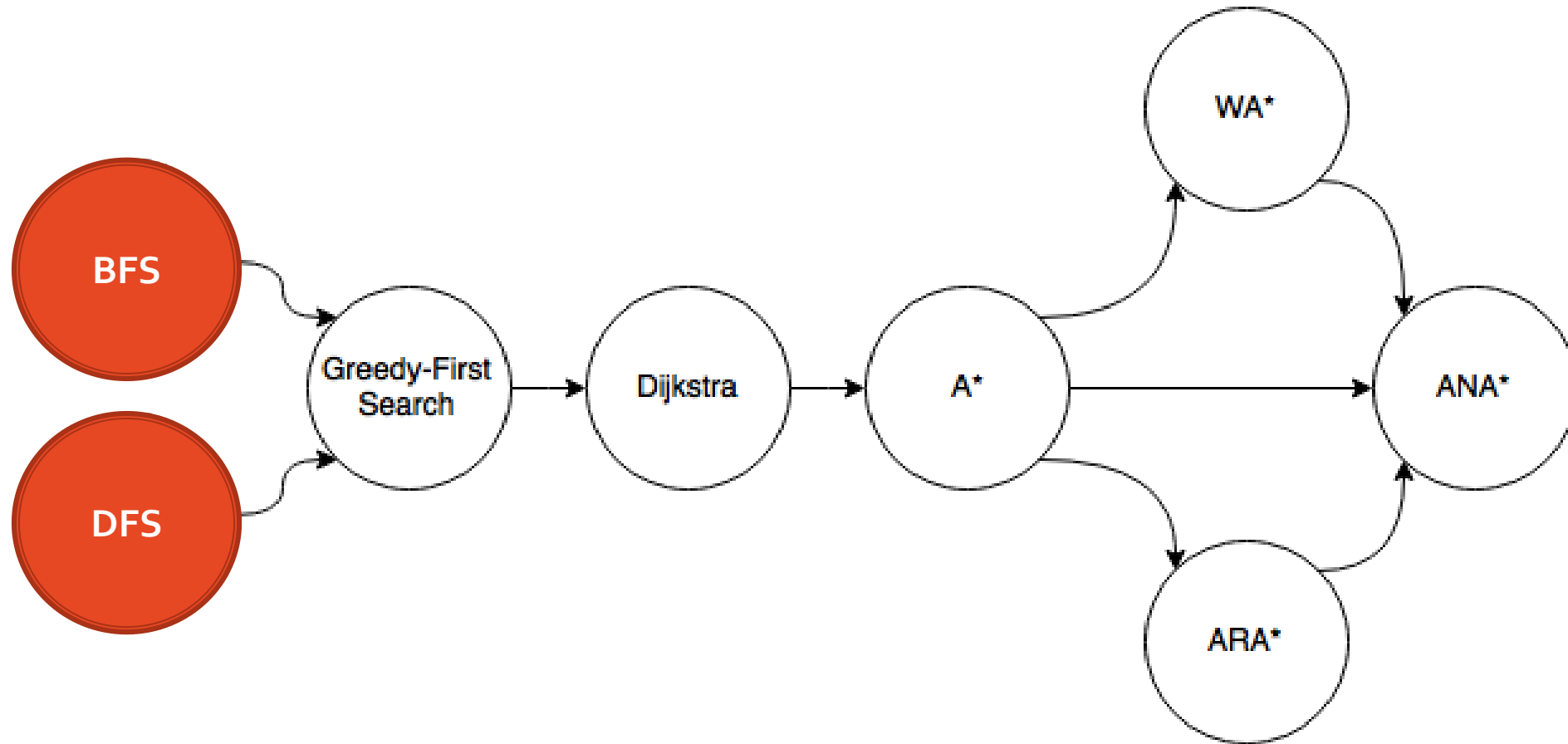
- Given a graph (G), find a path from start state to goal state.
- Parameters:
 - Optimal Path
 - Quicker Solution



Current state-of-the-arts: ANA*

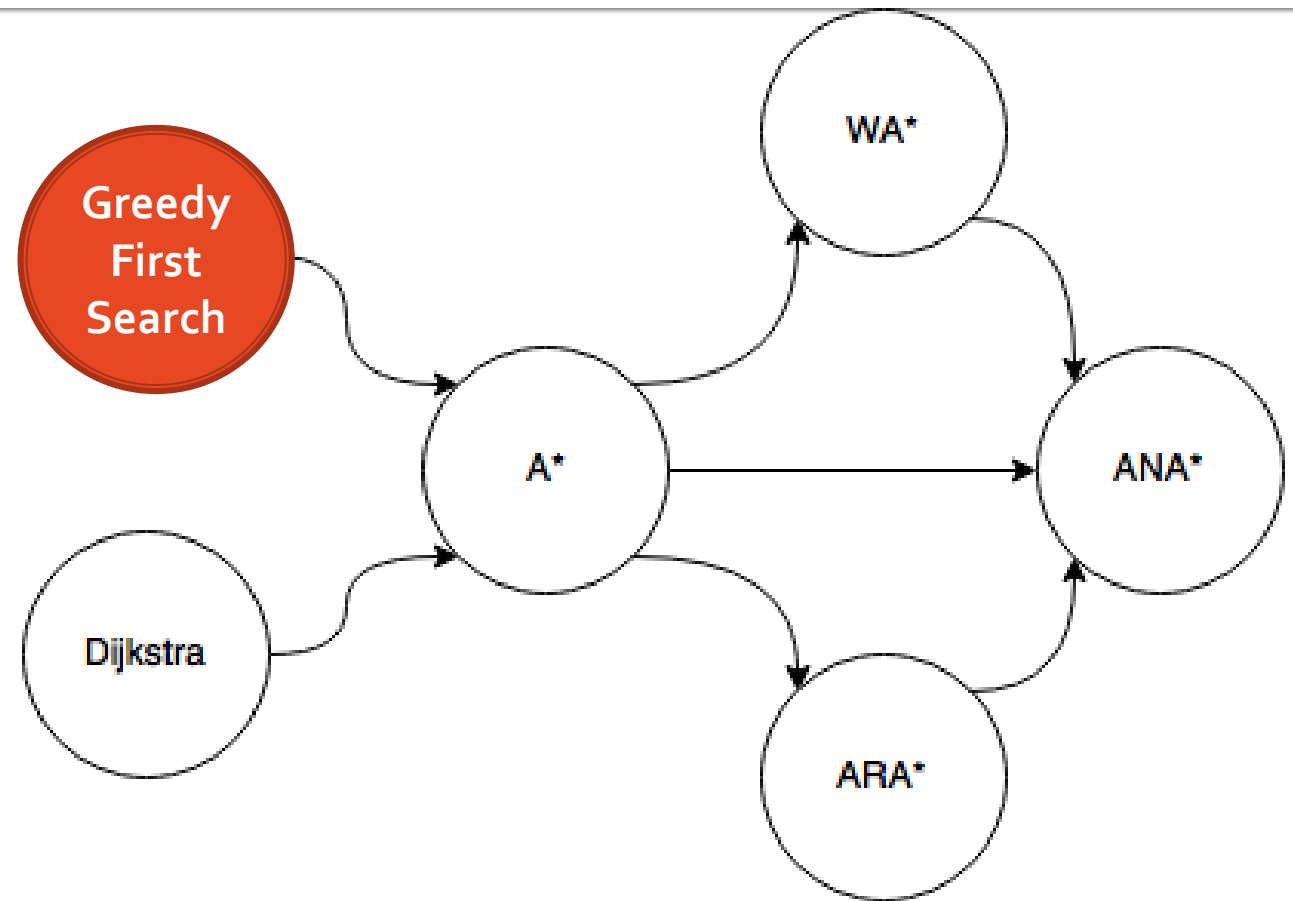
- Key idea:
 - Quickly find a sub-optimal solution
 - Improve it over time
- Features
 - Finds an initial solution faster
 - Spends less time in improving the solution
 - Improves solution sub-optimality bound in elegant way
 - Converges to optimal solution faster

Evolution of Search Algorithms



Greedy First

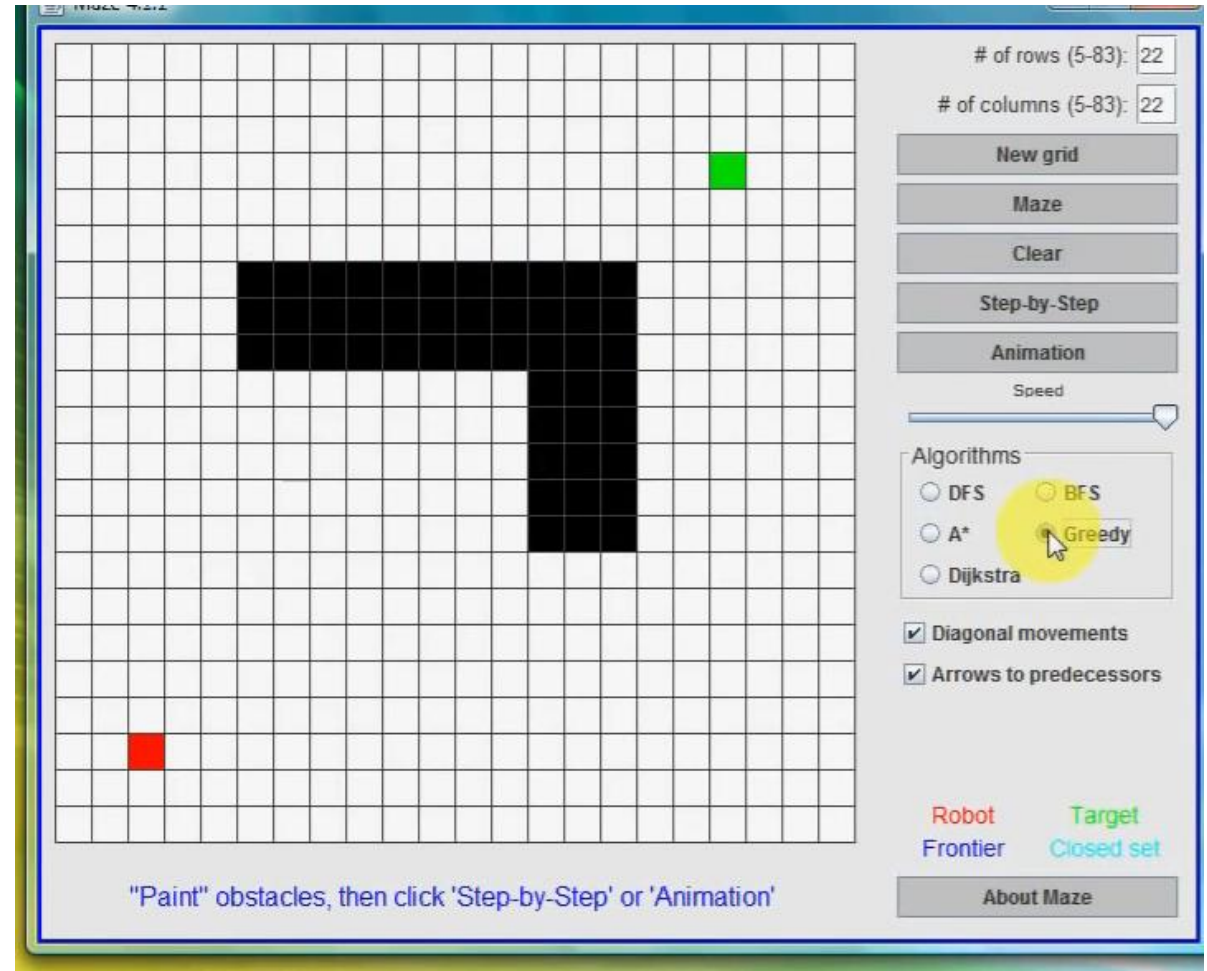
$$f(s) = h(s)$$



- Goal gets full attention
- Next expanded node has best estimate

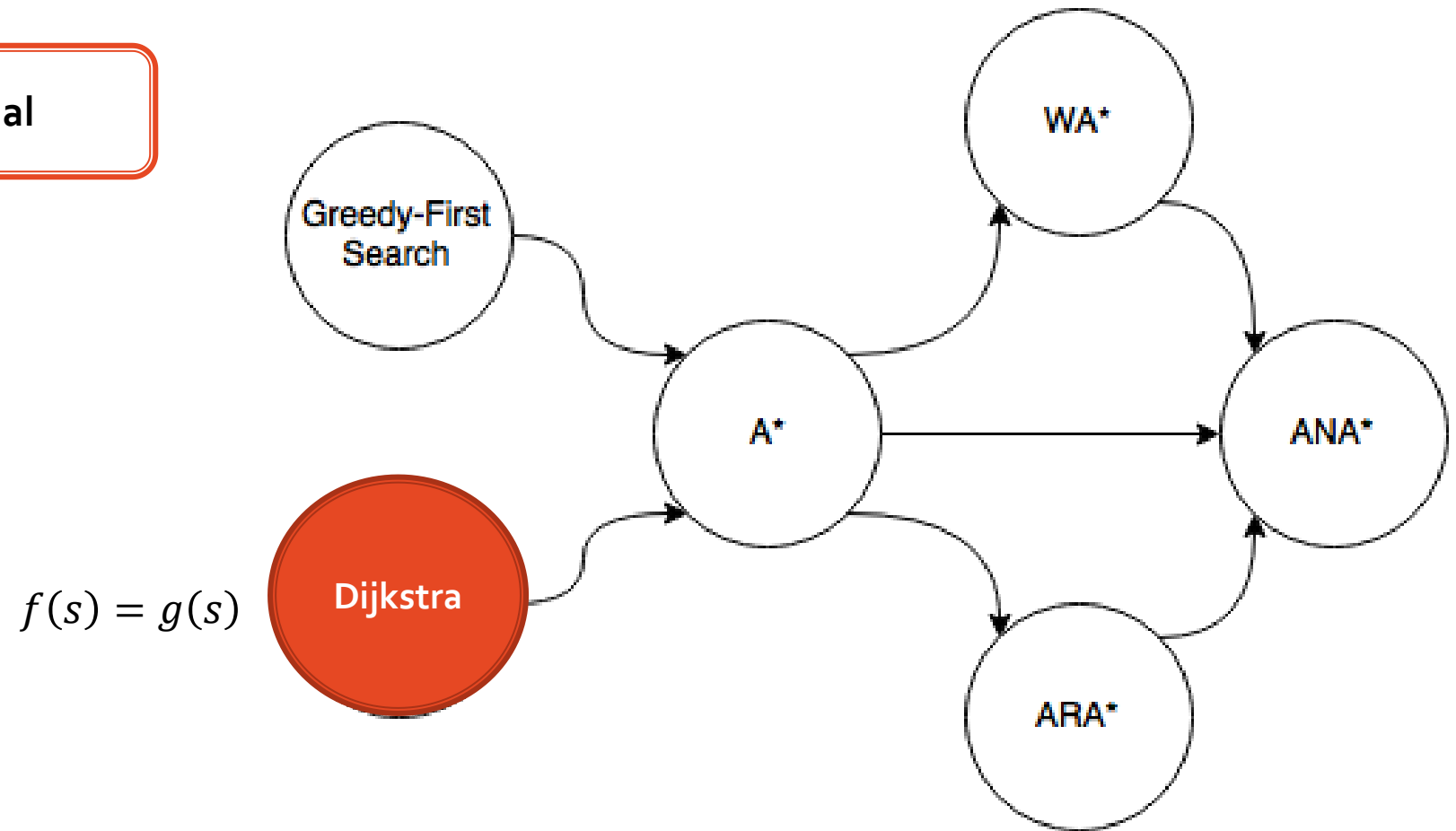
Greedy Search Algorithm

- Cost function
 - $f(s) = h(s)$



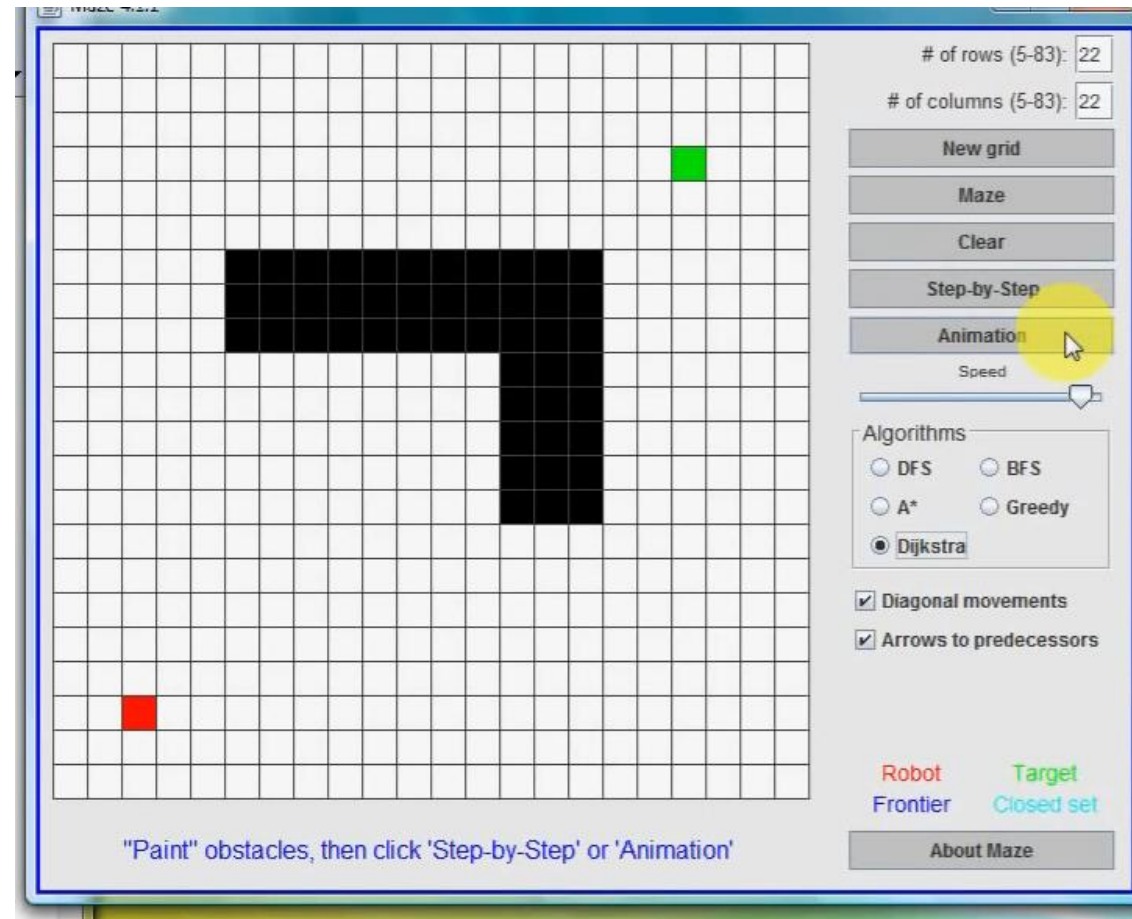
Dijkstra

Optimality of Path to Goal



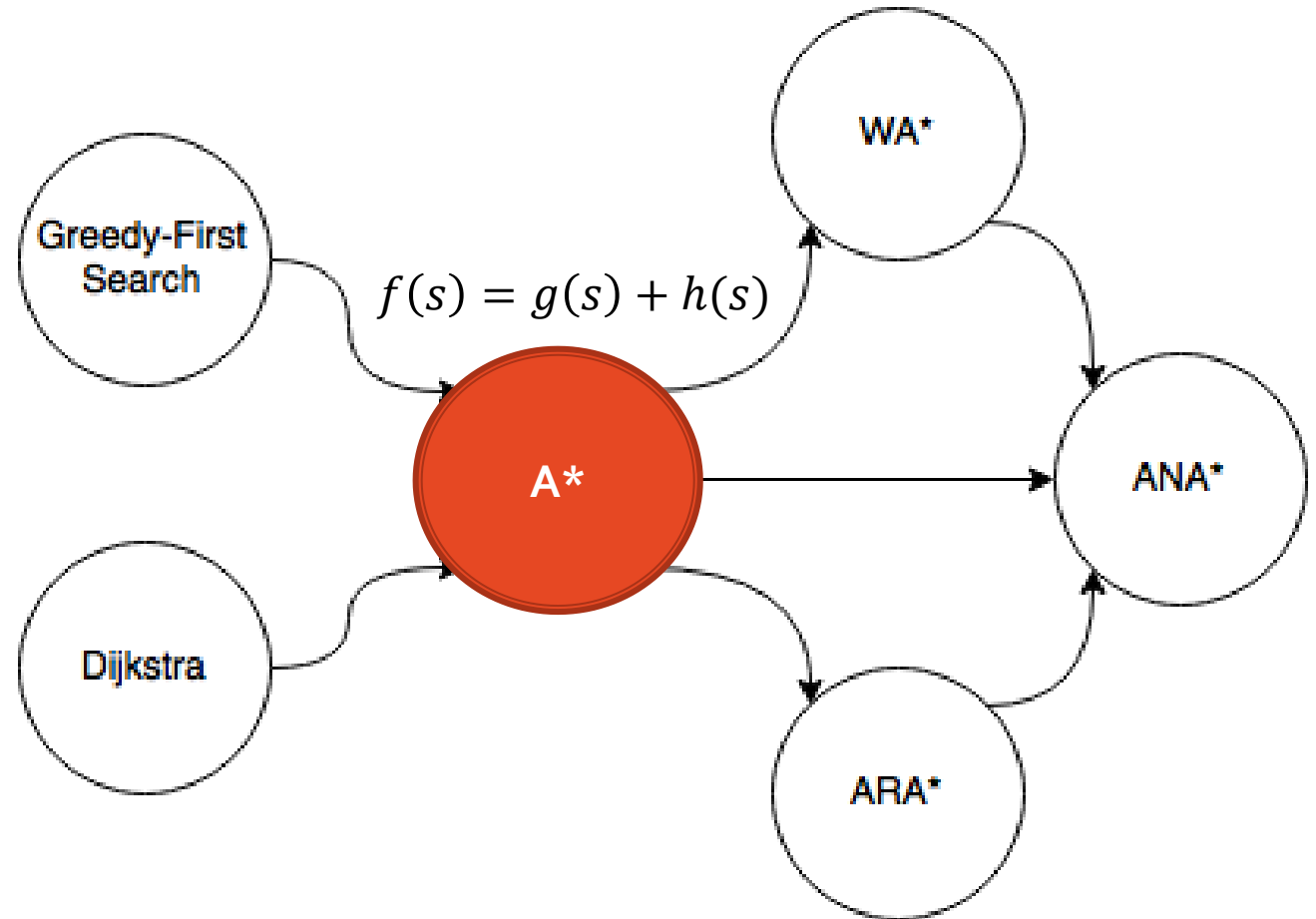
Dijkstra Algorithm

- Cost function
 - $f(s)=g(s)$



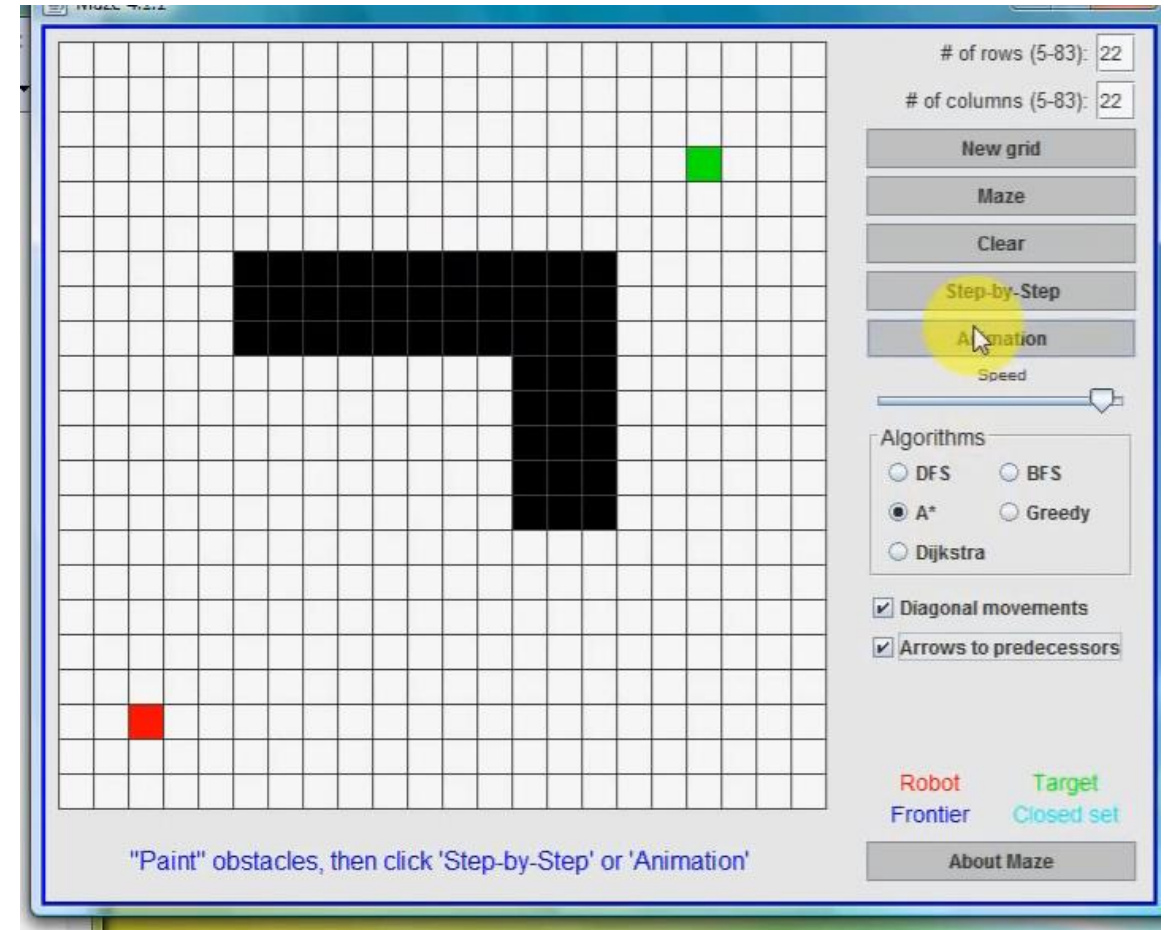
A*

- Converges Quickly to Optimal Path
- Heuristic Functions

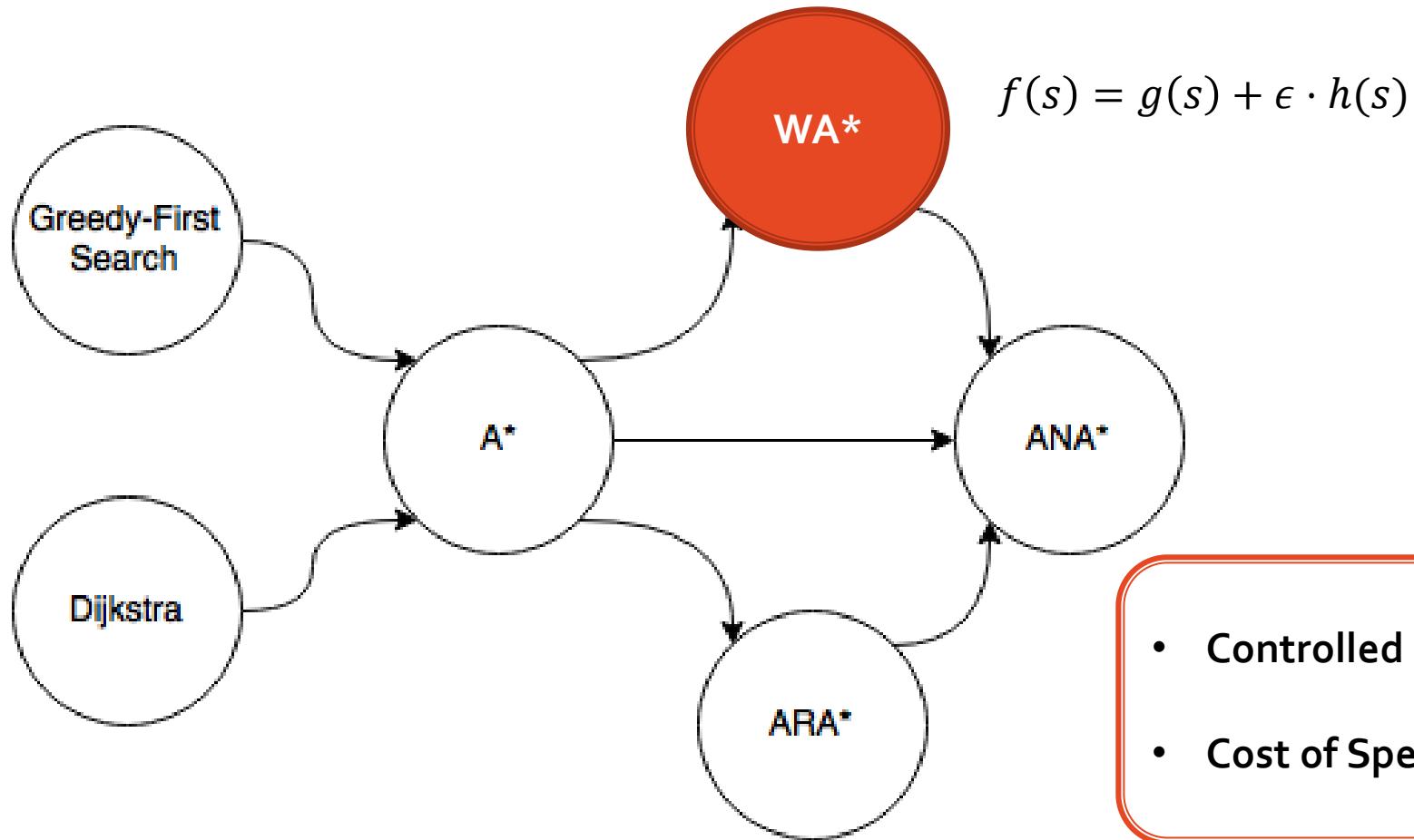


A* Algorithm

- A*: Cost function
 - $f(s)=g(s)+h(s)$
- A* is Optimal, if and only if heuristic is **Admissible!**



Weighted A*



- Controlled Speed of Convergence to Path
- Cost of Speed is Optimality!

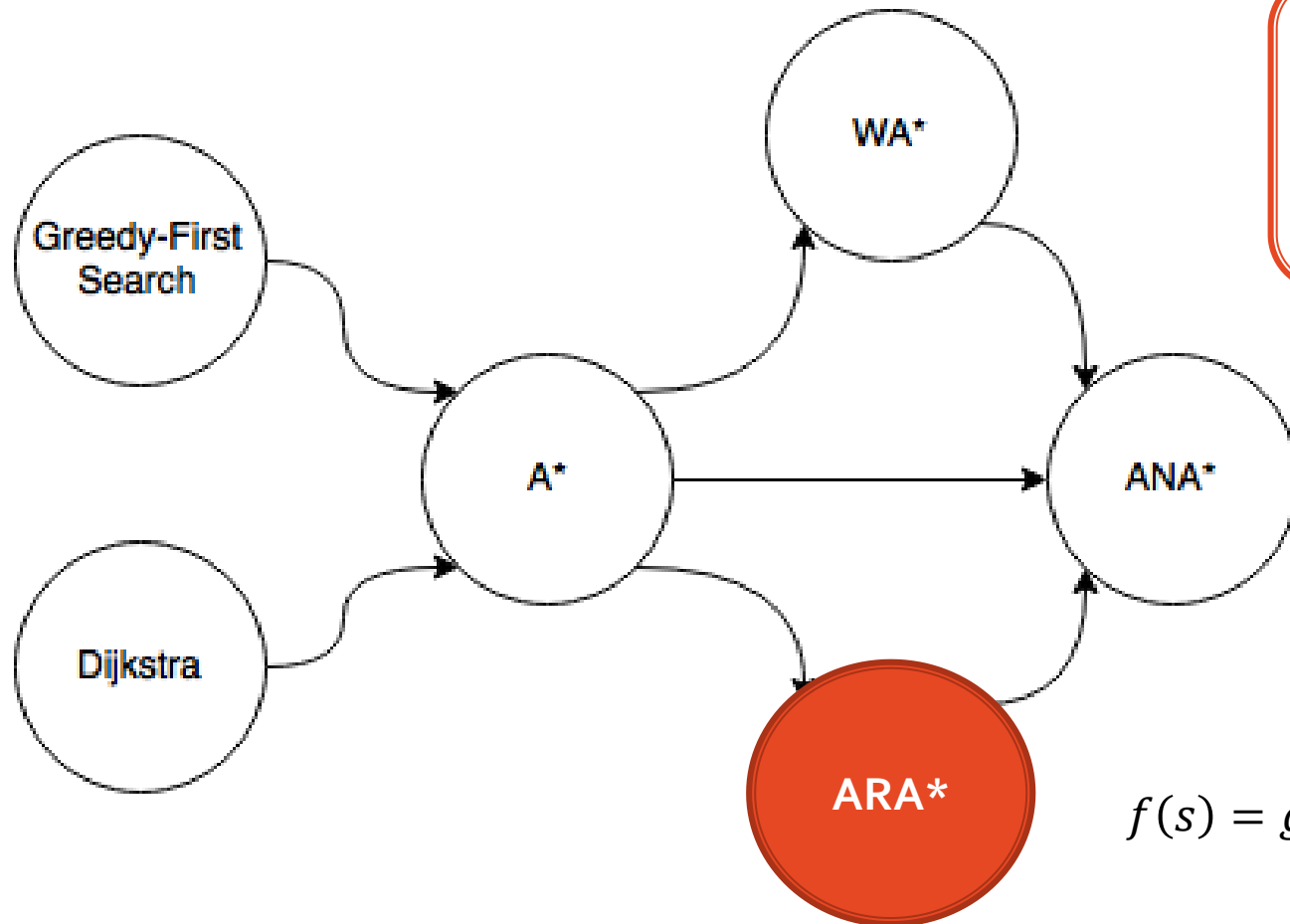
WA* Algorithm

- WA* cost function

$$f(s) = g(s) + \epsilon \cdot h(s)$$

- WA* is optimal, if and only if $\epsilon \cdot h(s)$ is Admissible.
 - $\epsilon > 1$ may lead to sub-optimal, but faster solution
- Note: We have a parameter to set ϵ !!

ARA*



- Issue WA*: Terminates with Sub-Optimal Solution
- ARA*: Iteratively **reduces ϵ** till Optimal Solution

$$f(s) = g(s) + \epsilon \cdot h(s)$$

ARA* Algorithm

- ARA*

$$f(s) = g(s) + \epsilon \cdot h(s)$$
$$\epsilon_{new} = \epsilon_{old} - \Delta\epsilon$$

- Benefit

- Can return anytime
- No need to wait for Optimal Solution!

- Guarantee

- ARA* Eventually Converges to Optimal Solution

Pseudo-Code Notation

- Start state = s_{start}
- Goal state = s_{goal}
- For each state s ,
 - $g(s)$ = minimal cost from start to s $g(s_{start}) = 0, g(s) = \infty$
 - $h(s)$ = heuristics
- Global variable \mathbf{G} = cost of the current best solution

Pseudo-Code Notation

- ***OPEN*** queue = the open list
- Initially, ***OPEN*** only contains s_{start}
- Expand the node in ***OPEN*** with the minimal [something]

ARA* Algorithm

ARA*($\epsilon_0, \Delta\epsilon$)

13: $G \leftarrow \infty; \epsilon \leftarrow \epsilon_0; OPEN \leftarrow \emptyset; \forall s: g(s) \leftarrow \infty; g(s_{\text{start}}) \leftarrow 0$
14: Insert s_{start} into $OPEN$ with key $f(s_{\text{start}})$
15: **while** $OPEN \neq \emptyset$ **do**
16: IMPROVESOLUTION()
17: Report current ϵ -suboptimal solution
18: $\epsilon \leftarrow \epsilon - \Delta\epsilon$
19: Update keys $f(s)$ in $OPEN$ and **prune if $g(s) + h(s) \geq G$**

IMPROVESOLUTION()

1: **while** $OPEN \neq \emptyset$ and $\min_{s \in OPEN} \{f(s)\} \leq G$ **do**
2: $s \leftarrow \arg \min_{s \in OPEN} \{f(s)\}$
3: $OPEN \leftarrow OPEN \setminus \{s\}$
4: **if** ISGOAL(s) **then**
5: $G \leftarrow g(s)$
6: **return**
7: **for each** successor s' of s **do**
8: **if** $g(s) + c(s, s') < g(s')$ **then**
9: $g(s') \leftarrow g(s) + c(s, s')$
10: $\text{pred}(s') \leftarrow s$
11: **if** $g(s') + h(s') < G$ **then**
12: Insert or update s' in $OPEN$ with key $f(s')$

Expand node s
with best $f(s)$

Update cost of
successors

- Note: We have another parameter to set $\Delta\epsilon$!!

Pruning

- Remove the node, if

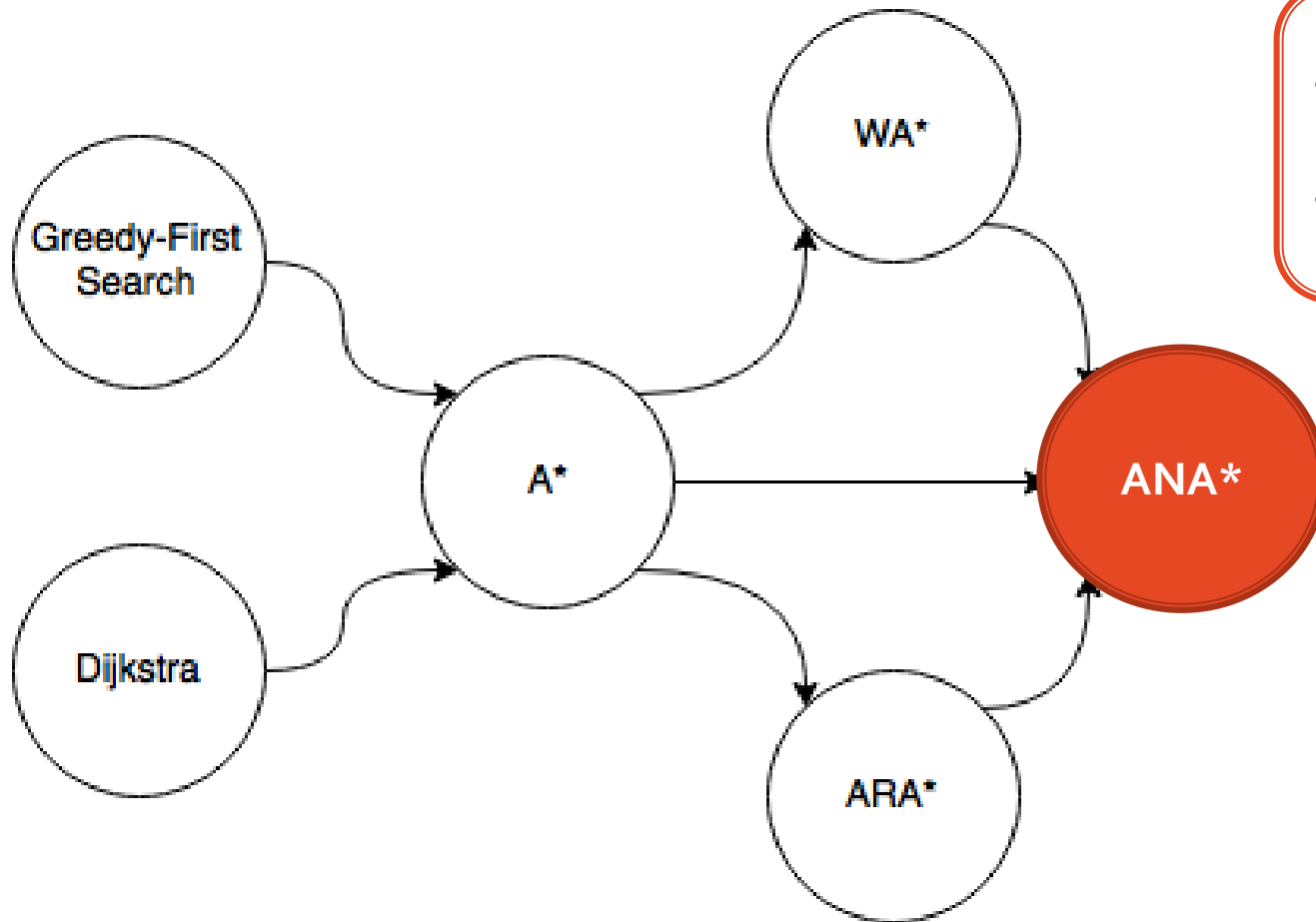
$$g(s) + h(s) > G$$

- This node can never be a part of optimal path!

Ad-hoc Parameters!!

- We must select 2 parameters - ϵ , $\Delta\epsilon$
- If ϵ is too large and $\Delta\epsilon$ is small enough?
 - Convergence is slow
- Example: $\epsilon = 1000$, $\Delta\epsilon=1$
 - $f(s)=g(s)+1000\cdot h(s)$
 - $f(s)=g(s)+999\cdot h(s)$
 - No change in path!
- Path is modified **iff** order relationship between $f(s)$ changes!

ANA*



- No Parameters
- Elegant choice of $\Delta\epsilon \Rightarrow$ Selected On-the-fly

$$f(s) = g(s) + \epsilon \cdot h(s)$$

ANA*

- Objective 1:
 - Converge quickly to initial solution
- Recall:
 - Greedy-First Search \Rightarrow Only heuristic counts!

$$f(s) = g(s) + \epsilon \cdot h(s)$$
$$\epsilon \rightarrow \infty$$

- This offers a quick initial solution

ANA* Algorithm

- Objective 2
 - Automate selection of $\Delta\epsilon$

- Define:
$$e(s) = \frac{G - g(s)}{h(s)}$$
$$\epsilon_{new} = \max_{\{s \in OPEN\}} e(s)$$

- G: is the best known cost of goal node.

ANA* Algorithm

- What does ϵ_{new} represent?

$$e(s) = \frac{G - g(s)}{h(s)}$$

- Intuitively – We explore the node with following properties
 - It has a large scope of optimality-improvement
 - It has a low heuristic value

ANA* Algorithm

ANA*()

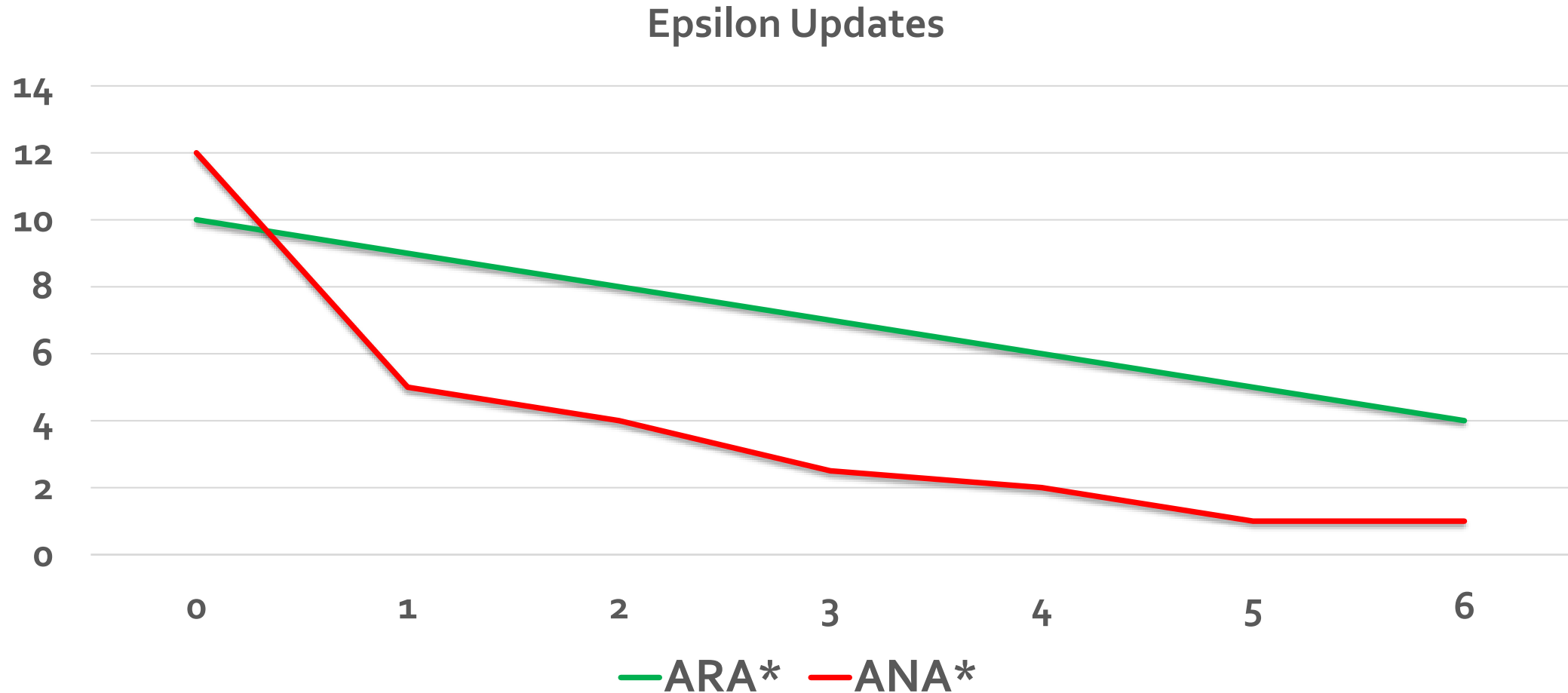
- 15: $G \leftarrow \infty; E \leftarrow \infty; OPEN \leftarrow \emptyset; \forall s : g(s) \leftarrow \infty; g(s_{\text{start}}) \leftarrow 0$
- 16: Insert s_{start} into $OPEN$ with key $e(s_{\text{start}})$
- 17: **while** $OPEN \neq \emptyset$ **do**
- 18: IMPROVESOLUTION()
- 19: Report current E -suboptimal solution
- 20: Update keys $e(s)$ in $OPEN$ and prune if $g(s) + h(s) \geq G$

Note: No parameters!

IMPROVESOLUTION()

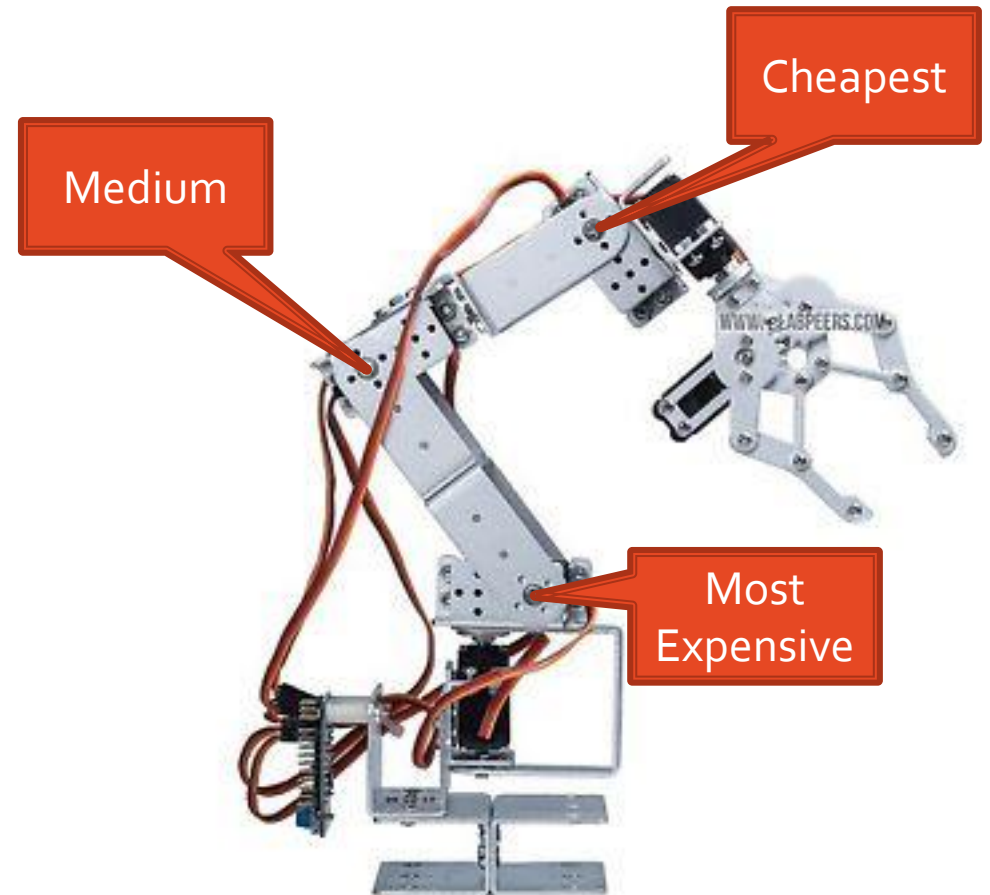
- 1: **while** $OPEN \neq \emptyset$ **do**
- 2: $s \leftarrow \arg \max_{s \in OPEN} \{e(s)\}$
- 3: $OPEN \leftarrow OPEN \setminus \{s\}$
- 4: **if** $e(s) < E$ **then**
- 5: $E \leftarrow e(s)$
- 6: **if** ISGOAL(s) **then**
- 7: $G \leftarrow g(s)$
- 8: **return**
- 9: **for each** successor s' of s **do**
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Epsilon-Convergence



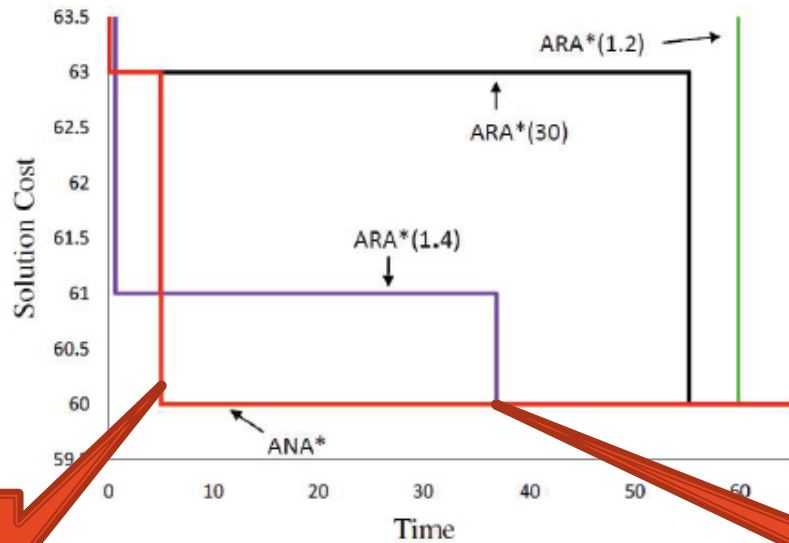
Benchmark Test 1: Robot Arm

- Experiment Setup
 - 6-DOF (and 20-DOF) Arms, fixed base
 - Changing Joint angle closer to base cost more energy
 - Heuristic = Euclidean 2-norm to goal



Benchmark Test 1: Robot Arm

$$\Delta\epsilon = 0.2$$

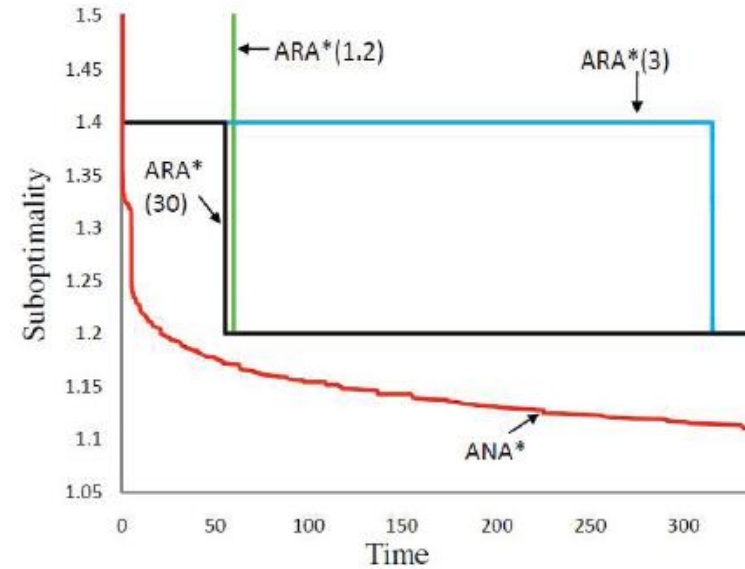


(a) 6DOF, Uniform

Solution Cost

5 sec!
ANA*

36.8 sec!
ARA*

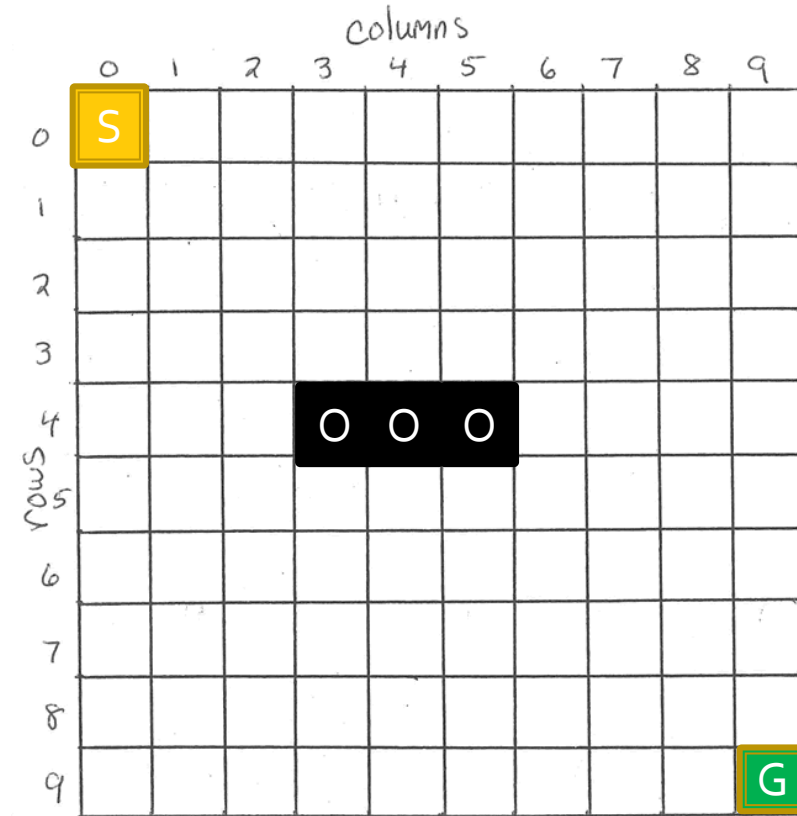


(b) 6DOF, Uniform

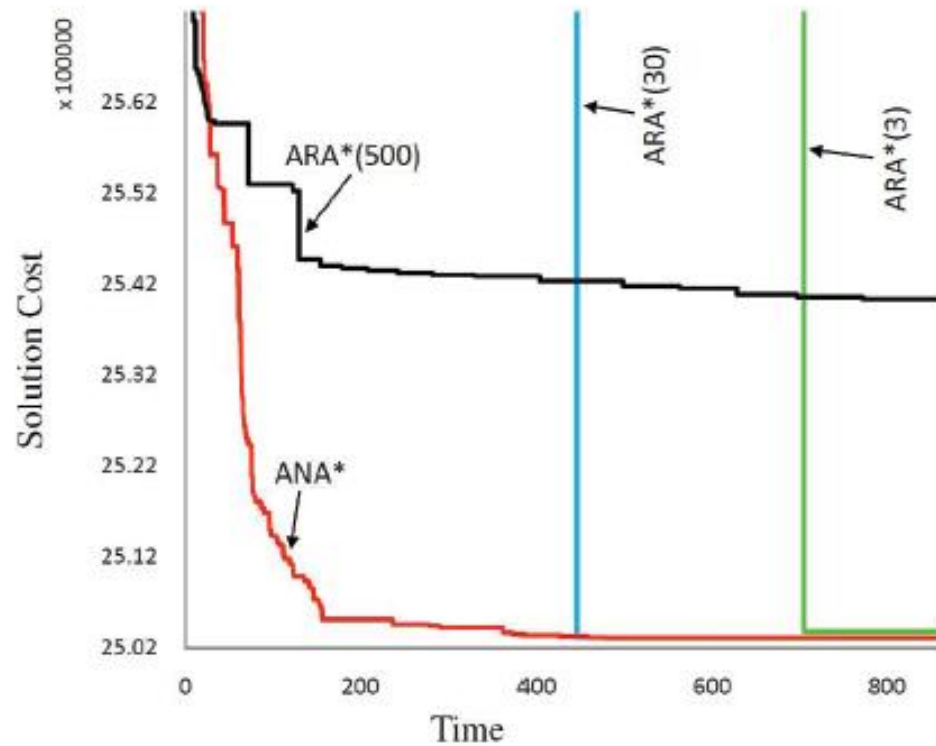
Sub-Optimality (ϵ)

Benchmark Test 2: Gridworld

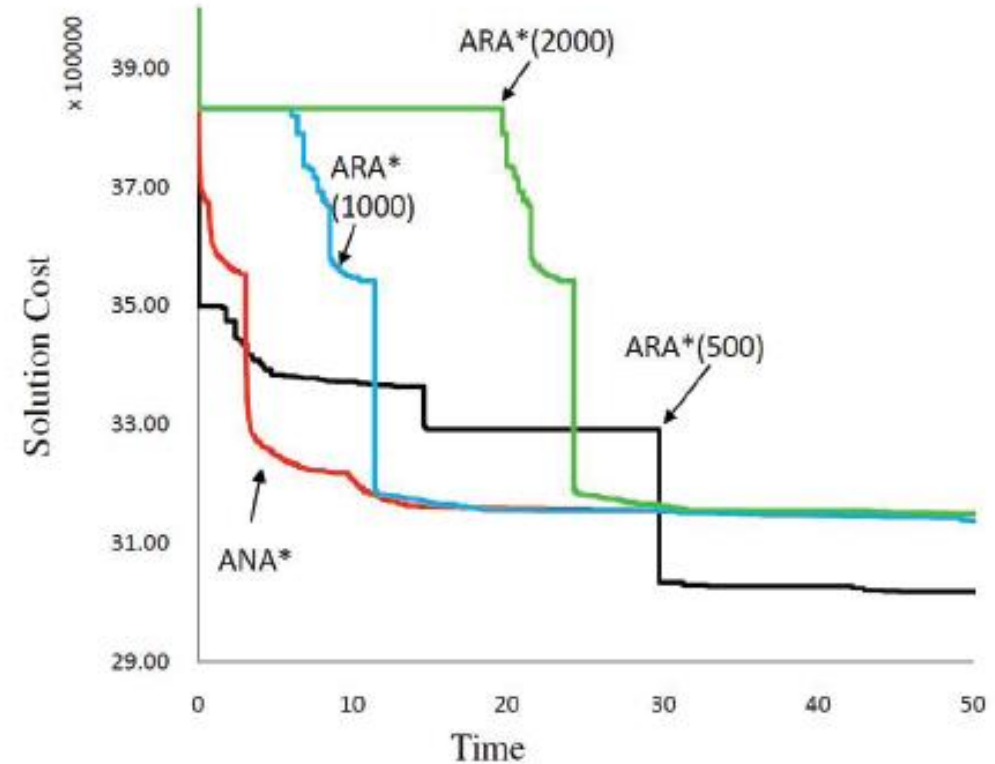
- Experiment Setup
 - 5000 x 5000 4-connected grid
 - Start at top-left corner
 - Goal at right-bottom
 - Obstacles are static



Benchmark Test 2: Gridworld



(a) Without obstacles



(b) With obstacles

Conclusion

- ANA* has **superior** properties among Anytime-Heuristic Search Algorithms
- ANA* uses **dynamic ϵ -choosing mechanism**, that removes need for ad-hoc parameter selection

Conclusion

- Advantages:
 - No parameters
 - Maximally greedy for Initial Solution
 - Maximally greedy to Improve Solution
 - Sub-optimality is reduced dynamically
- What ANA* can't do:
 - Not suitable for dynamic environments

Assignment Due Feb 16

- Implement ANA* and test on a grid search problem

ANA*()

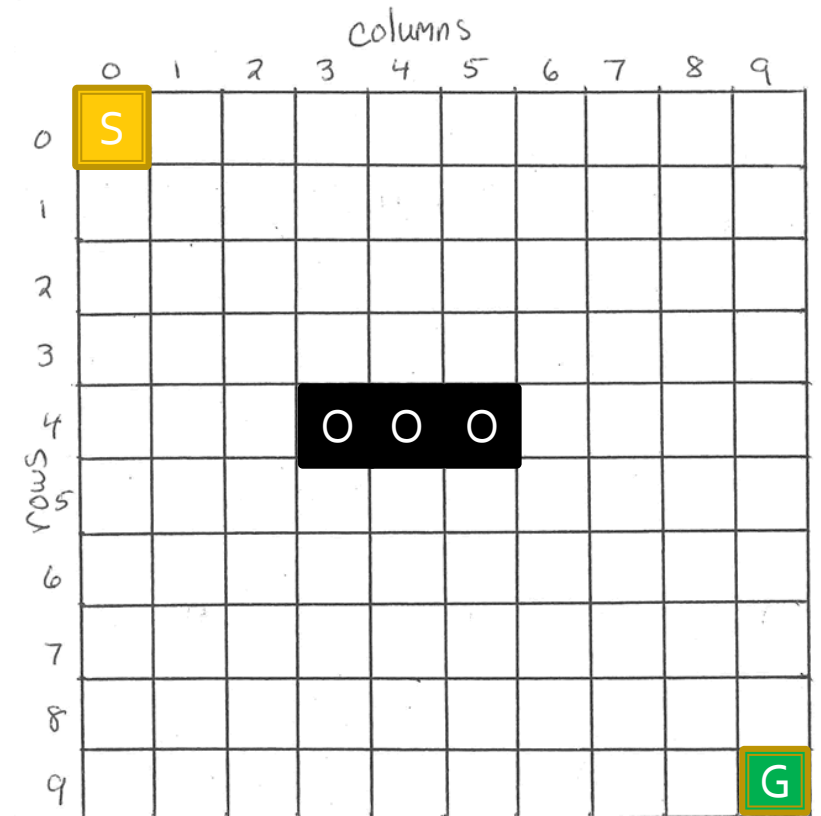
```
15:  $G \leftarrow \infty$ ;  $E \leftarrow \infty$ ;  $OPEN \leftarrow \emptyset$ ;  $\forall s : g(s) \leftarrow \infty$ ;  $g(s_{start}) \leftarrow 0$ 
16: Insert  $s_{start}$  into  $OPEN$  with key  $e(s_{start})$ 
17: while  $OPEN \neq \emptyset$  do
18:   IMPROVESOLUTION()
19:   Report current  $E$ -suboptimal solution
20:   Update keys  $e(s)$  in  $OPEN$  and prune if  $g(s) + h(s) \geq G$ 
```

IMPROVESOLUTION()

```
1: while  $OPEN \neq \emptyset$  do
2:    $s \leftarrow \arg \max_{s \in OPEN} \{e(s)\}$ 
3:    $OPEN \leftarrow OPEN \setminus \{s\}$ 
4:   if  $e(s) < E$  then
5:      $E \leftarrow e(s)$ 
6:   if ISGOAL( $s$ ) then
7:      $G \leftarrow g(s)$ 
8:     return
9:   for each successor  $s'$  of  $s$  do
10:    if  $g(s) + c(s, s') < g(s')$  then
11:       $g(s') \leftarrow g(s) + c(s, s')$ 
12:       $pred(s') \leftarrow s$ 
13:      if  $g(s') + h(s') < G$  then
14:        Insert or update  $s'$  in  $OPEN$  with key  $e(s')$ 
```

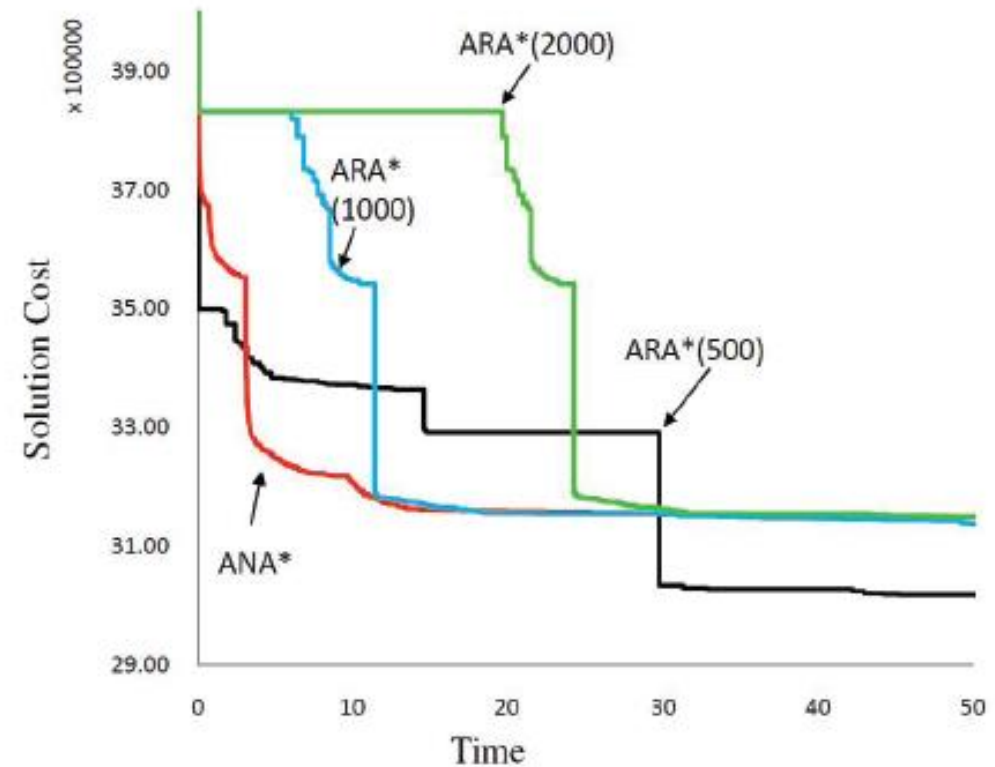
Assignment Due Feb 16

- Experiment Setup
 - 5000 x 5000, 4-connected grid
 - Start = top-left corner, Goal = right-bottom
 - Set your own static obstacles



Assignment Due Feb 16 by noon

- Submission include
 - Python code with problem setup and search using ANA*
 - Pdf report with the figure of solution cost vs Time



(b) With obstacles

Assignment Due Feb 16 by noon

- Refer to the paper on ANA* for more details
 - Van Den Berg, Jur, et al. "ANA*: anytime nonparametric A*." *Proceedings of Twenty-fifth AAAI Conference on Artificial Intelligence (AAAI-11)*. 2011.
- Acknowledgement to **Abhishek Kulkarni**
 - Current WPI graduate student
 - Best literature review presentation in RBE 550, 2017

Important!

- If the assignment description is not clear to you, **please** ask me and/or TA
 - After class
 - During office hour
 - On piazza
- We are willing to help as long as you ask!
 - If you don't ask, we could only assume everything is okay

Student talk

Spatiotemporal state lattice

End
