

Heuristics and A* Search

CS 4300 — Fall 2025

Uniform-Cost Search (UCS): Reintroduction

- ▶ **UCS** expands the node with lowest path cost $g(n)$.
- ▶ Frontier is a **priority queue** ordered by $g(n)$.
- ▶ Goal test occurs when a node is *popped*, ensuring optimality.
- ▶ Appropriate when step costs are **non-uniform** and **positive**.

UCS (Graph Search)

Algorithm 1 *

Uniform-Cost Graph Search (UCS)

Require: initial state s_0 ; $A(s)$; $T(s, a)$; GOAL-TEST(s); step cost $c(s, a, s') > 0$

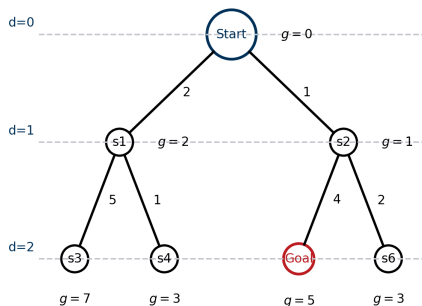
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1: Initialize the frontier as an empty min-priority queue (keyed by  $g$ )
2:  $g(s_0) \leftarrow 0$ ; PUSH(frontier,  $s_0$ , key =  $g(s_0)$ )
3: best_g  $\leftarrow$  empty map from state  $\rightarrow$  best known path cost; best_g[ $s_0$ ]  $\leftarrow 0$ 
4: while frontier is not empty do
5:    $n \leftarrow$  POP-MIN(frontier) ▷ state with lowest  $g(n)$ 
6:   if GOAL-TEST( $n.state$ ) then
7:     return solution path from  $s_0$  to  $n.state$ 
8:   end if
9:   for each  $a \in A(n.state)$  do
10:     $s' \leftarrow T(n.state, a)$ 
11:     $g' \leftarrow g(n) + c(n.state, a)$ 
12:    if  $s' \notin \text{best\_g}$  or  $g' < \text{best\_g}[s']$  then
13:      best_g[ $s'$ ]  $\leftarrow g'$ 
14:      PUSH(frontier,  $s'$ , key =  $g'$ )
15:    end if
16:  end for
17: end while
18: return failure

```

UCS Walkthrough (0/6): Init

UCS: Tree State

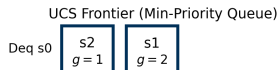
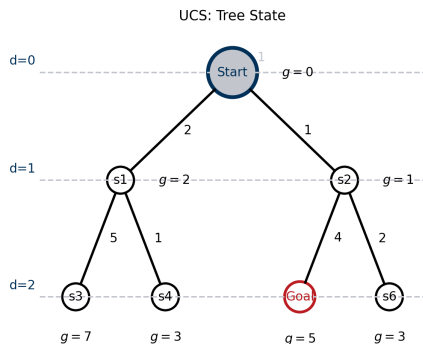


UCS Frontier (Min-Priority Queue)

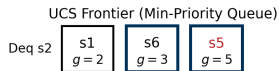
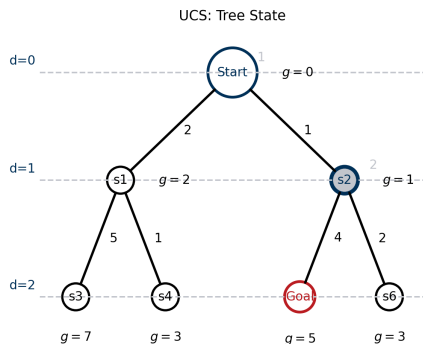
Init



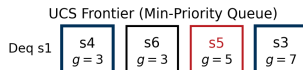
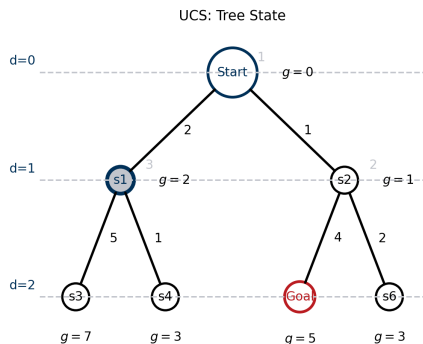
UCS Walkthrough (1/6): Dequeue Start



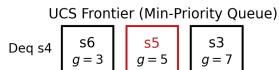
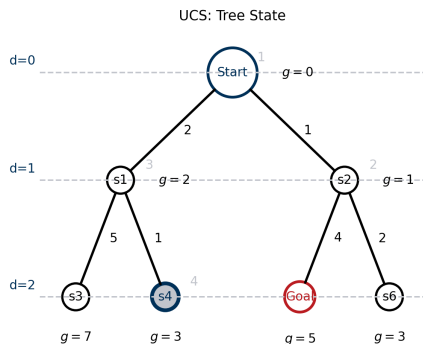
UCS Walkthrough (2/6): Dequeue s2



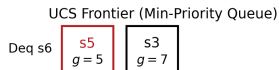
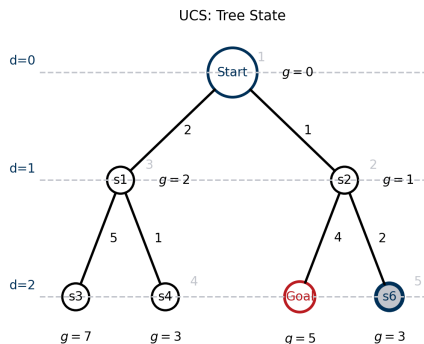
UCS Walkthrough (3/6): Dequeue s1



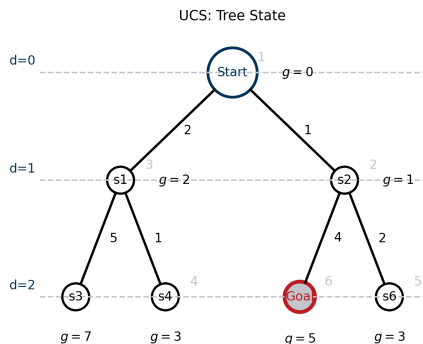
UCS Walkthrough (4/6): Dequeue s4



UCS Walkthrough (5/6): Dequeue s6



UCS Walkthrough (6/6): Dequeue s5 = Goal



UCS Frontier (Min-Priority Queue)

Deq s5 = GOAL

s3
g = 7

Motivation for Heuristics

- ▶ UCS only considers **cost so far**, $g(n)$.
- ▶ This can cause many unnecessary expansions if the goal is deep or far.
- ▶ Idea: add an estimate of the **remaining cost**.
- ▶ Define a **heuristic function** $h(n)$:
 - ▶ $h(n) \approx$ estimated cost from n to a goal.
 - ▶ Example: Manhattan distance in a grid world.

From UCS to A*

- ▶ Define the evaluation function:

$$f(n) = g(n) + h(n).$$

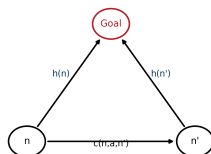
- ▶ $g(n)$ = cost so far, $h(n)$ = estimated cost-to-go.
- ▶ With a good heuristic, search focuses on promising areas.
- ▶ Guarantees:
 - ▶ **Admissibility:** $h(n)$ never overestimates true cost.
 - ▶ **Consistency:** heuristic obeys triangle inequality.

Consistent Heuristics

- ▶ A heuristic h is **consistent** (or monotone) if for every node n , successor n' by action a :

$$h(n) \leq c(n, a, n') + h(n')$$

- ▶ This is the *triangle inequality*: estimated cost at n is never more than the step cost plus estimate from n' .
- ▶ Consistency implies admissibility.
- ▶ With a consistent heuristic:
 - ▶ $f(n) = g(n) + h(n)$ is non-decreasing along a path.
 - ▶ Once a node is expanded, the best path to it has been found (no re-expansions needed).



A* (Tree Search)

Algorithm 2 A* (Tree Search)

Require: Problem with initial state s_0 , actions $A(s)$, transition $T(s, a)$,
 GoalTest(s, a), step cost $c(s, a, s') > 0$, heuristic $h(s) \geq 0$

```

1: frontier  $\leftarrow$  min-priority queue by  $f(n) = g(n) + h(n)$ 
2: push node( $s_0$ ) with  $g(s_0) = 0, f(s_0) = g(s_0) + h(s_0)$ 
3: while frontier not empty do
4:    $n \leftarrow \text{pop\_min}(\text{frontier})$  ▷ lowest  $f$ 
5:   if GoalTest( $n.\text{state}$ ) then
6:     return solution by following  $n$ 's parents
7:   end if
8:   for all  $a \in A(n.\text{state})$  do
9:      $s' \leftarrow T(n.\text{state}, a)$ 
10:     $g' \leftarrow g(n) + c(n.\text{state}, a, s')$ 
11:    push node( $s'$ ) with parent  $n$  and key  $f' = g' + h(s')$ 
12:   end for
13: end while
14: return failure
  
```

A* (Graph Search): with best-known g -costs

Algorithm 3 A* (Graph Search)

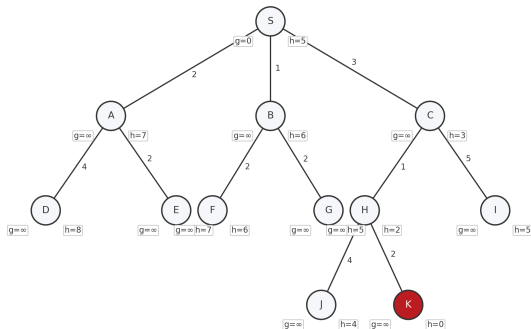
Require: $s_0, A(s), T(s, a), \text{GoalTest}(s, a), c(s, a, s') > 0, h(s)$

```

1: frontier  $\leftarrow$  min-PQ by  $f = g + h$ ; push node( $s_0$ ) with  $g = 0, f = h(s_0)$ 
2: best_g  $\leftarrow$  map (state  $\rightarrow$  best known  $g$ ); best_g[ $s_0$ ]  $\leftarrow$  0
3: while frontier not empty do
4:    $n \leftarrow$  pop_min(frontier)
5:   if GoalTest( $n$ .state) then return solution by following  $n$ 's parents
6:   end if
7:   for all  $a \in A(n$ .state) do
8:      $s' \leftarrow T(n$ .state,  $a$ )
9:      $g' \leftarrow g(n) + c(n$ .state,  $a, s')$ 
10:    if  $s' \notin \text{best\_g}$  or  $g' < \text{best\_g}[s']$  then
11:      best_g[ $s'$ ]  $\leftarrow g'$ 
12:      push/DecreaseKey node( $s'$ ) with parent  $n$  and  $f' = g' + h(s')$ 
13:    end if
14:  end for
15: end while
16: return failure

```

A* Search (Tree) — Intuition



Key ideas

- ▶ Score nodes with $f(n) = g(n) + h(n)$.
- ▶ Pop the lowest f from a min-PQ.
- ▶ g : path cost so far.
 h : est. cost to goal.
- ▶ Goal test on *pop*
⇒ optimal if h is admissible & consistent.

A* Search — Step 0

A* step 0 — initial frontier

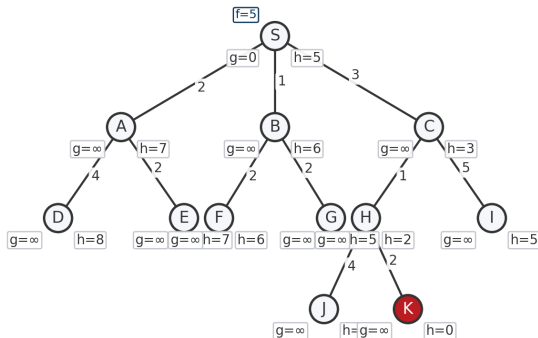
Frontier after step 0

S

$g=0$

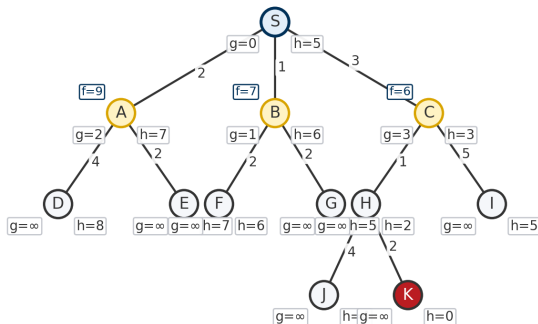
$h=5$

$f=5$



A* Search — Step 1

A* step 1 — popped S

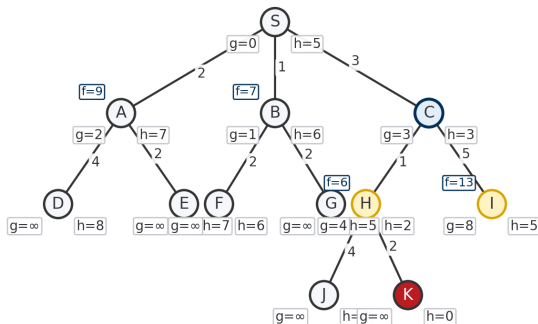


Frontier after expansion

C	g=3	h=3	f=6
B	g=1	h=6	f=7
A	g=2	h=7	f=9

A* Search — Step 2

A* step 2 — popped C

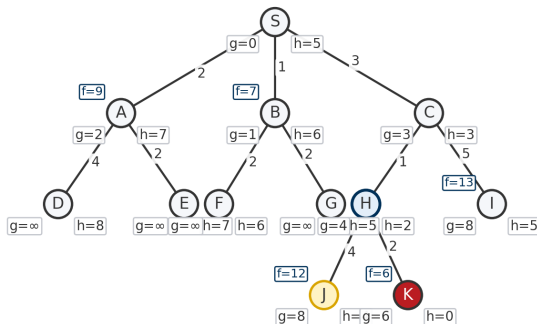


Frontier after expansion

H	g=4	h=2	f=6
B	g=1	h=6	f=7
A	g=2	h=7	f=9
I	g=8	h=5	f=13

A* Search — Step 3

A* step 3 — popped H

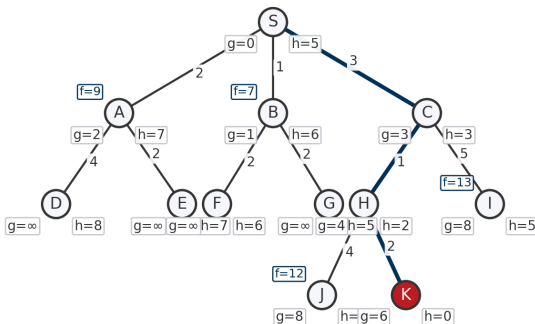


Frontier after expansion

K	g=6	h=0	f=6
B	g=1	h=6	f=7
A	g=2	h=7	f=9
J	g=8	h=4	f=12
I	g=8	h=5	f=13

A* Search — Step 4 (Goal Found)

A* step 4 — popped K (goal)



Frontier after expansion

B	g=1	h=6	f=7
A	g=2	h=7	f=9
J	g=8	h=4	f=12
I	g=8	h=5	f=13

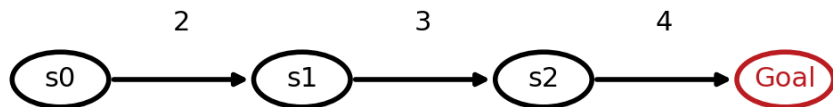
Properties of A*

- ▶ **Completeness:** Yes, if step costs $\geq \epsilon > 0$ and branching factor $b < \infty$.
- ▶ **Optimality:**
 - ▶ With **admissible** h , A* (tree search) is optimal.
 - ▶ With **consistent** h , A* (graph search) is optimal and never needs to reopen expanded nodes.
- ▶ **Time/Space Complexity:**
 - ▶ Worst case: $O(b^{C^*/\epsilon})$, exponential in the solution depth bound.
 - ▶ C^* = cost of the optimal solution.
 - ▶ ϵ = minimum positive step cost.
 - ▶ Effective branching factor b^* is reduced with a good heuristic:

$$O\left((b^*)^{C^*/\epsilon}\right)$$

Effective Depth of A*

Total optimal cost $C^* = 9$



Minimum step cost $\epsilon = 2$

Effective depth $C^* / \epsilon = 9/2$

Designing Heuristics

- ▶ **Problem relaxations:** remove constraints to get $h(n)$ from an easier subproblem.
- ▶ **Abstractions / pattern databases:** precompute exact distances in abstracted state spaces.
- ▶ **Additive heuristics:** when subproblems are independent ($h = h_1 + h_2$ is still admissible).
- ▶ **8-puzzle:** h_1 =#misplaced tiles; h_2 =sum of Manhattan distances; h_2 dominates h_1 .
- ▶ **Practical tip:** Start with a cheap admissible h , measure node expansions, iterate.

Summary of A*

- ▶ **UCS**: expands node with lowest cost so far $g(n)$.
- ▶ **A***: expands node with lowest estimated total cost $f(n) = g(n) + h(n)$.
- ▶ With admissible, consistent heuristics:
 - ▶ A* is **optimal**.
 - ▶ A* is often far more **efficient** than UCS.