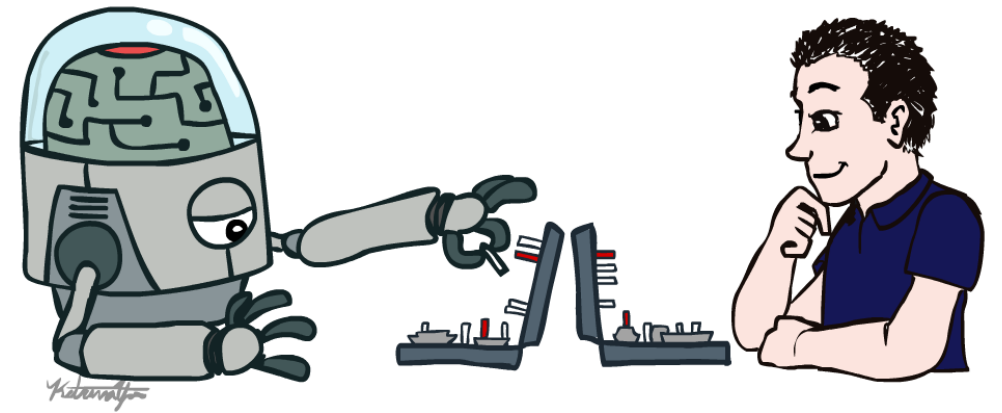


Lecture 03

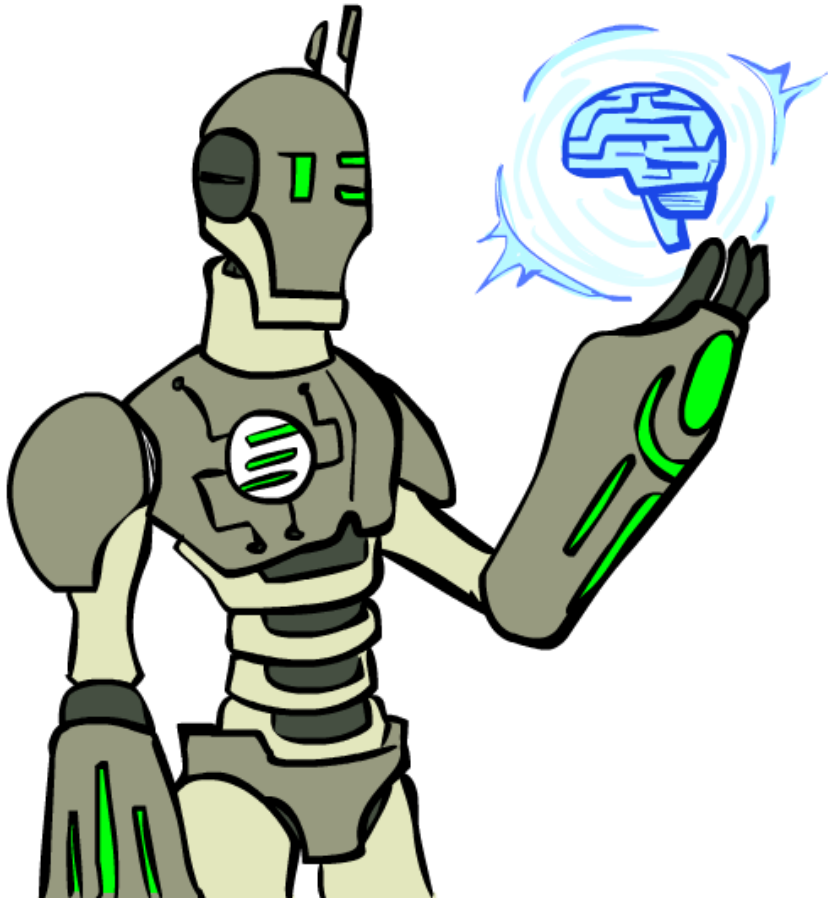
Ashis Kumar Chanda
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Search Algorithms

- Blind search – BFS, DFS, uniform cost
 - No concept of the “right direction”
 - can only recognize goal once it’s achieved
- Heuristic search – we have rough idea of how good various states are, and use this knowledge to guide our search

Today

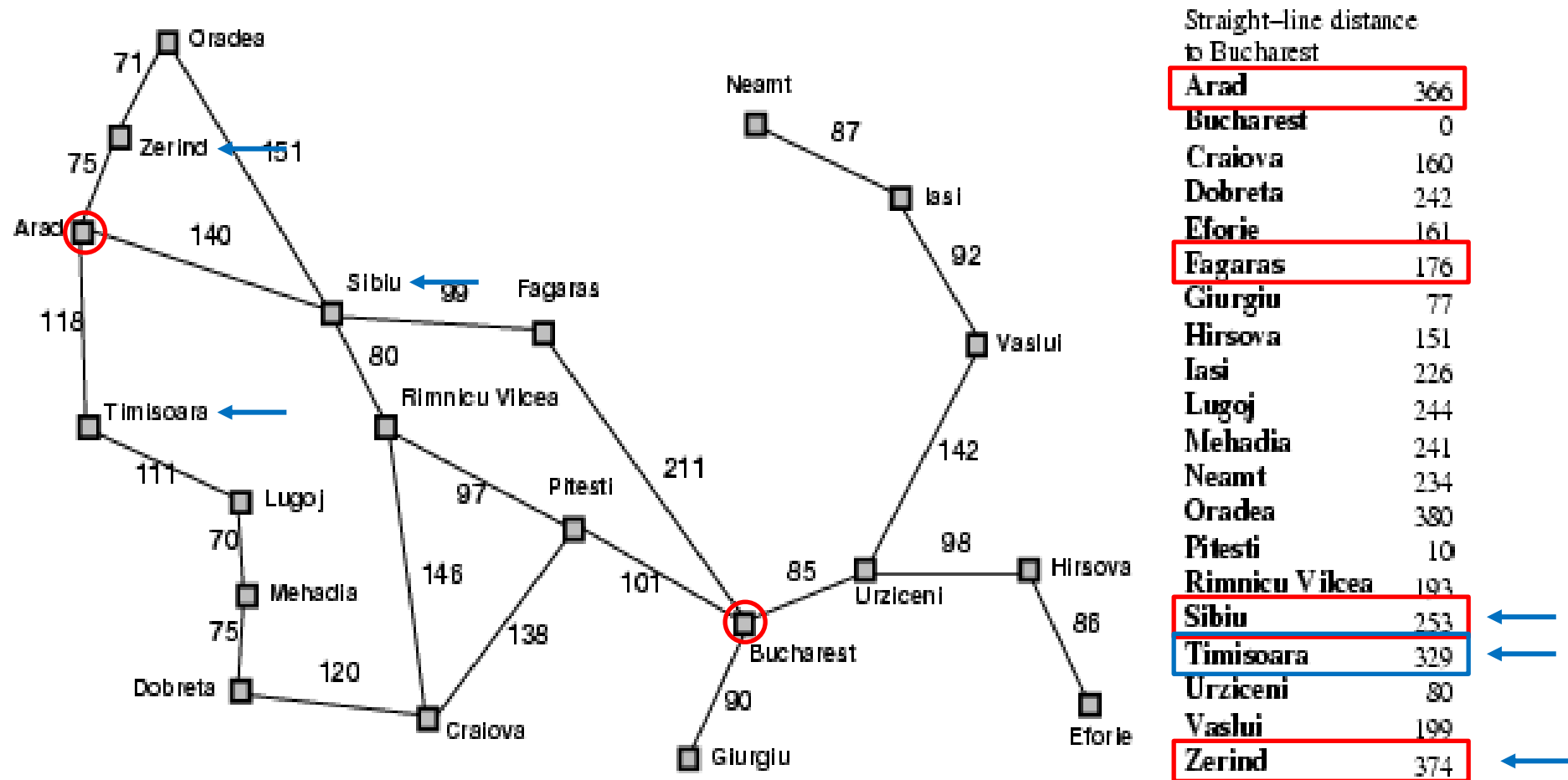


- Best-first search
- Greedy best-first search
- A^* search

Best-first search

- Idea: use an evaluation function $f(n)$ for each node
 - Estimate of "desirability"
 - Expand most desirable unexpanded node
 - Use domain-specific hints about the location of goals
- Implementation:
 - Order the nodes in fringe in decreasing order of desirability

Romania with step costs in km



Showing straight line distances to Bucharest

Greedy best-first search

- Greedy best first search is a form of best-first search that expands first the node with the lowest $h(n)$ value (node that appears to be closest to the goal).
- Evaluation function $f(n) = h(n)$ (heuristic)
= estimate of cost from n to *goal*

Example:

$h_{SLD}(n)$ = straight-line distance from n to Bucharest

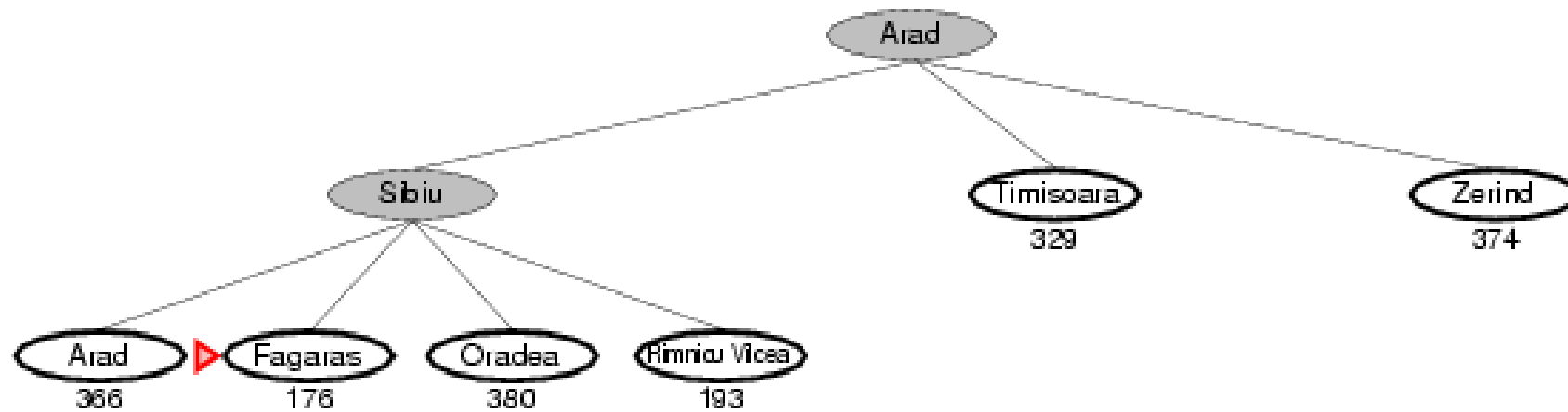
Greedy best-first search example



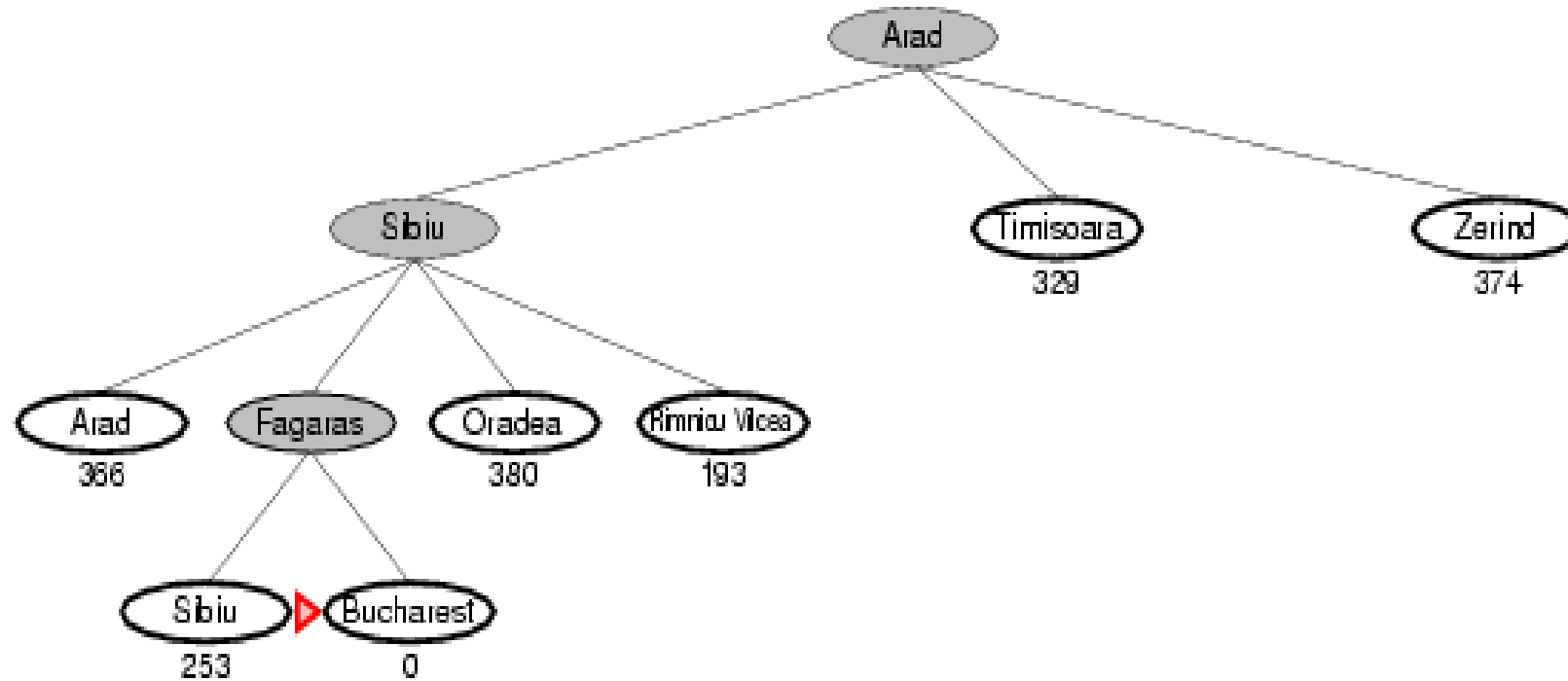
Greedy best-first search example



Greedy best-first search example

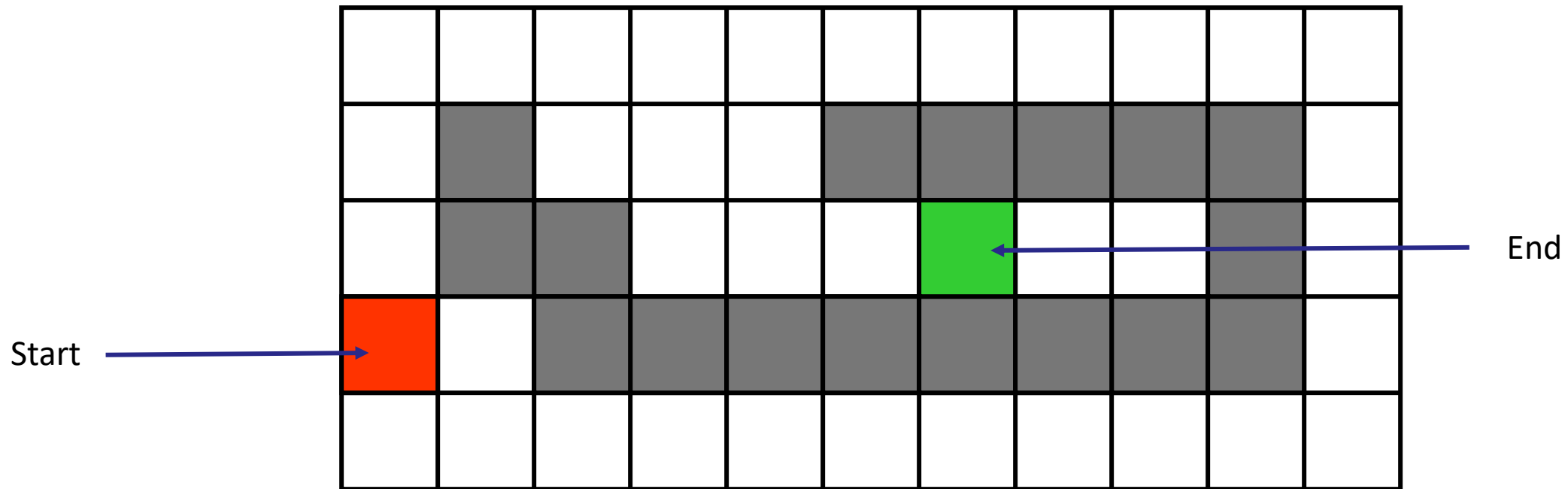


Greedy best-first search example



Robot Navigation

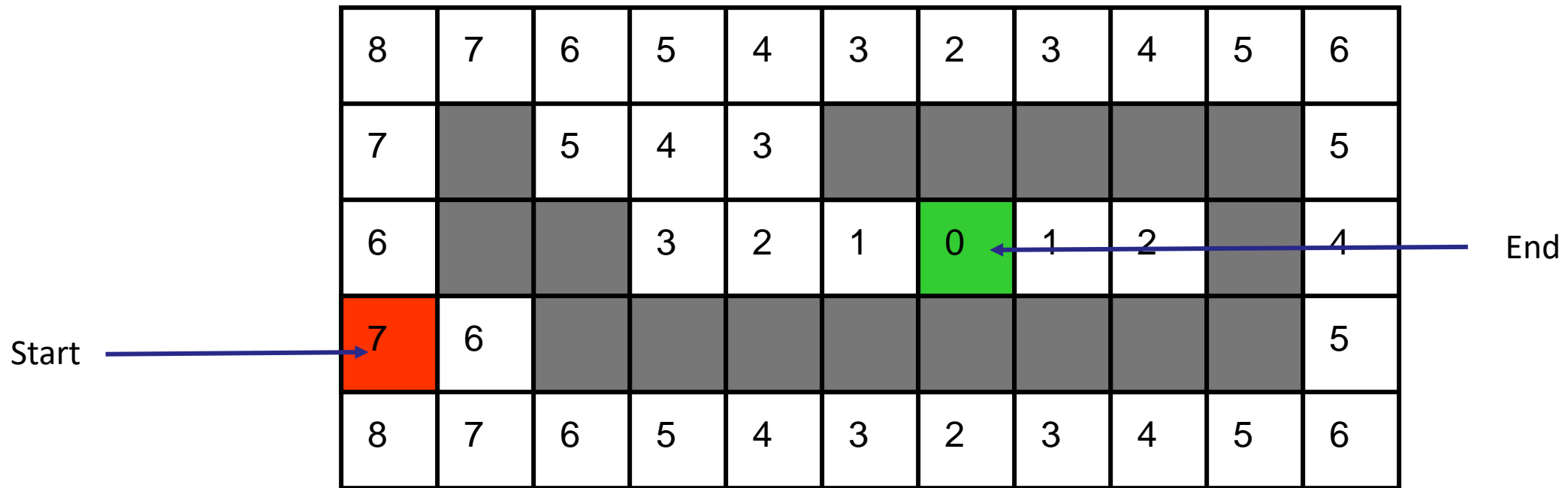
We can consider a 2D Grid having several obstacles and we start from a source cell (colored red below) to reach towards a goal cell (colored green below).



Robot Navigation

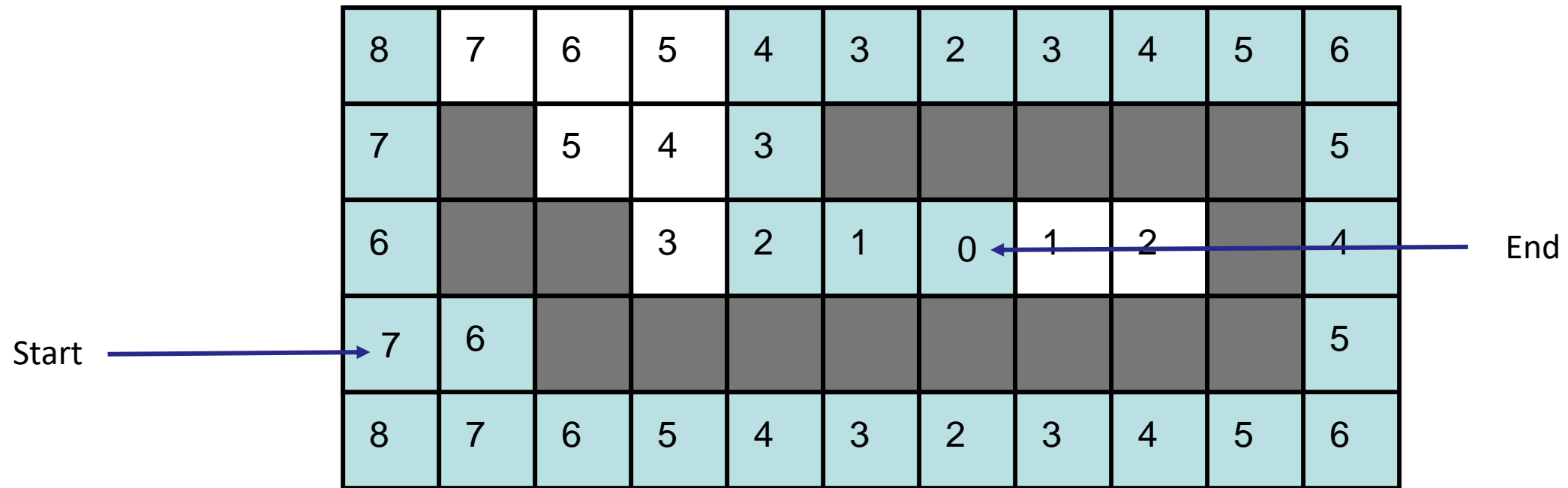
	5	4	3	4	5	
5	4	3	2	3	4	5
4	3	2	1	2	3	4
3	2	1	0	1	2	3
4	3	2	1	2	3	4
5	4	3	2	3	4	5
	5	4	3	4	5	

$f(N) = h(N)$, with $h(N)$ = Manhattan distance to the goal



Robot Navigation

$f(N) = h(N)$, with $h(N)$ = Manhattan distance to the goal



Properties of greedy best-first search

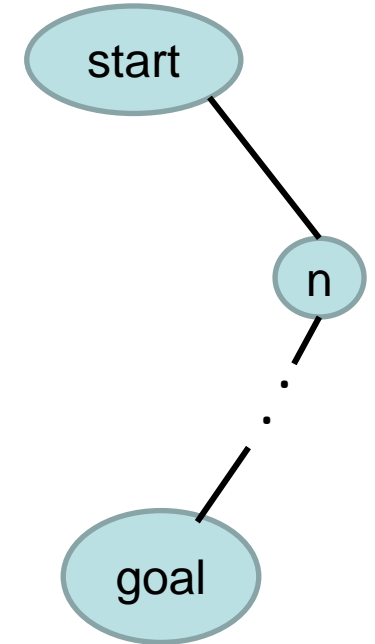
- **Complete?** If we eliminate endless loops, yes
- **Time?** $O(b^m)$, but a good heuristic can give dramatic improvement
- **Space?** $O(b^m)$ - keeps all nodes in memory
- **Optimal?** No
 - b : maximum branching factor of the search tree
 - m : maximum depth of the state space (may be ∞)

More informed search

- We kept looking at nodes **closer and closer to the goal**, but were accumulating costs as we got further from the initial state.
- Our goal is not to **minimize the distance from the current head of our path to the goal**, we want to minimize the *overall* length of the path to the goal!
- Let **$g(n)$** be the cost of the best path found so far between the initial node and n
- $f(n) = g(n) + h(n)$

A* search (Or, A star search)

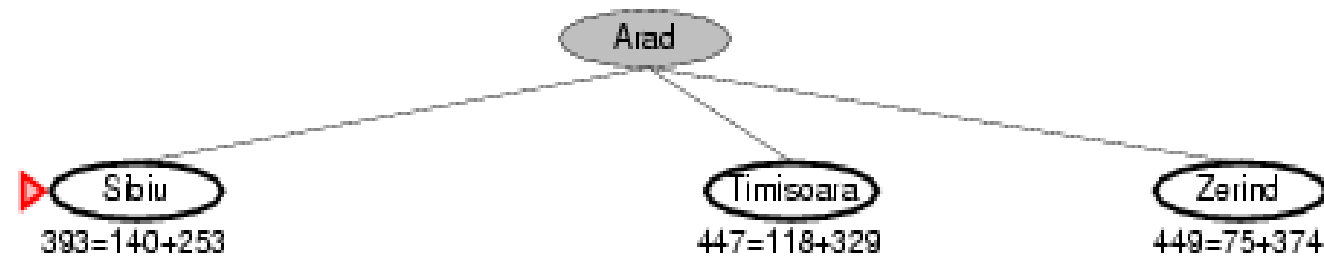
- Idea: avoid expanding paths that are already expensive.
- Evaluation function $f(n) = g(n) + h(n)$
 - $g(n)$ = cost so far to reach n
 - $h(n)$ = estimated cost from n to goal (admissible heuristic)
 - $f(n)$ = estimated total cost of path through n to goal
- Then, best-first search with this evaluation function is called A* search



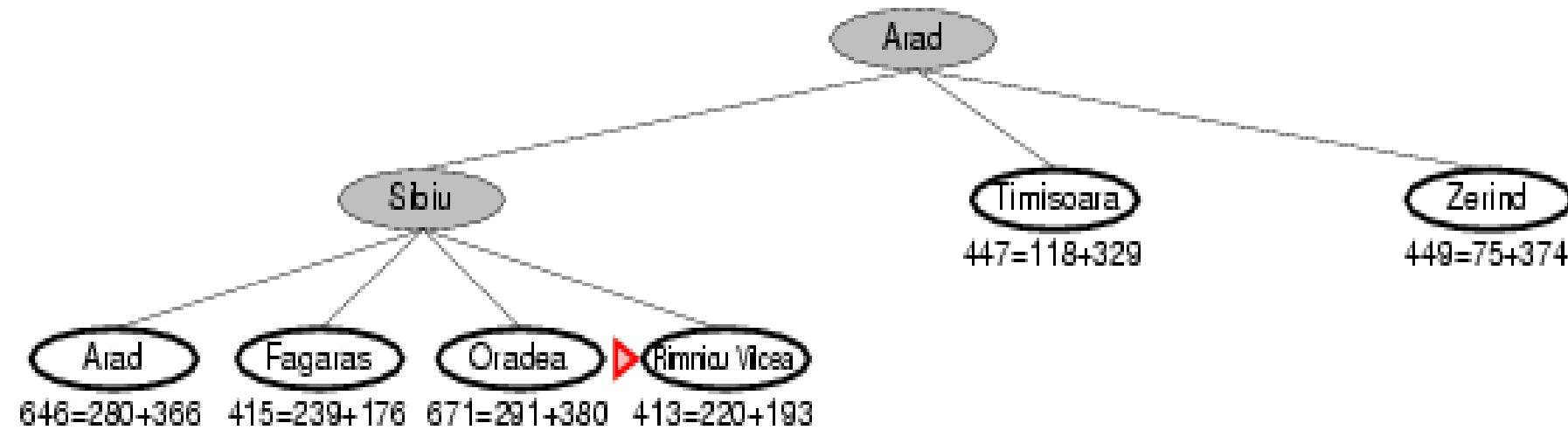
A* search example

▶ Arad
366=0+366

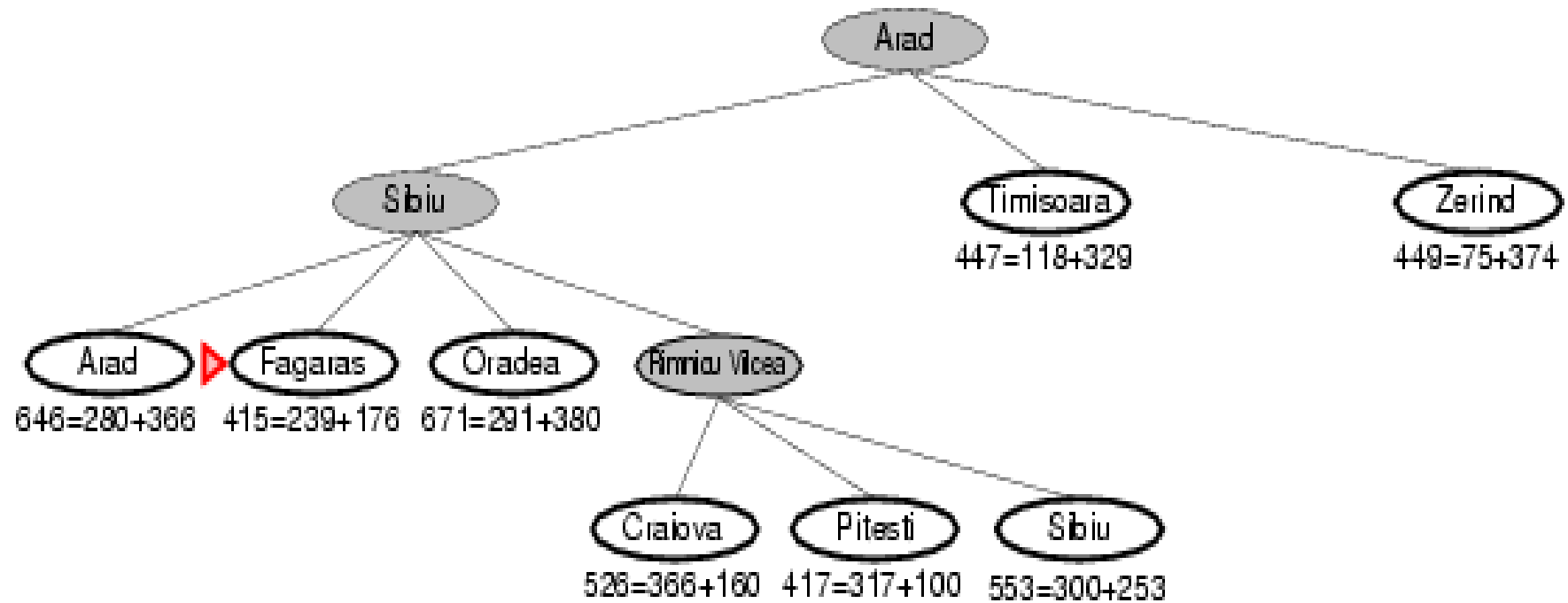
A* search example



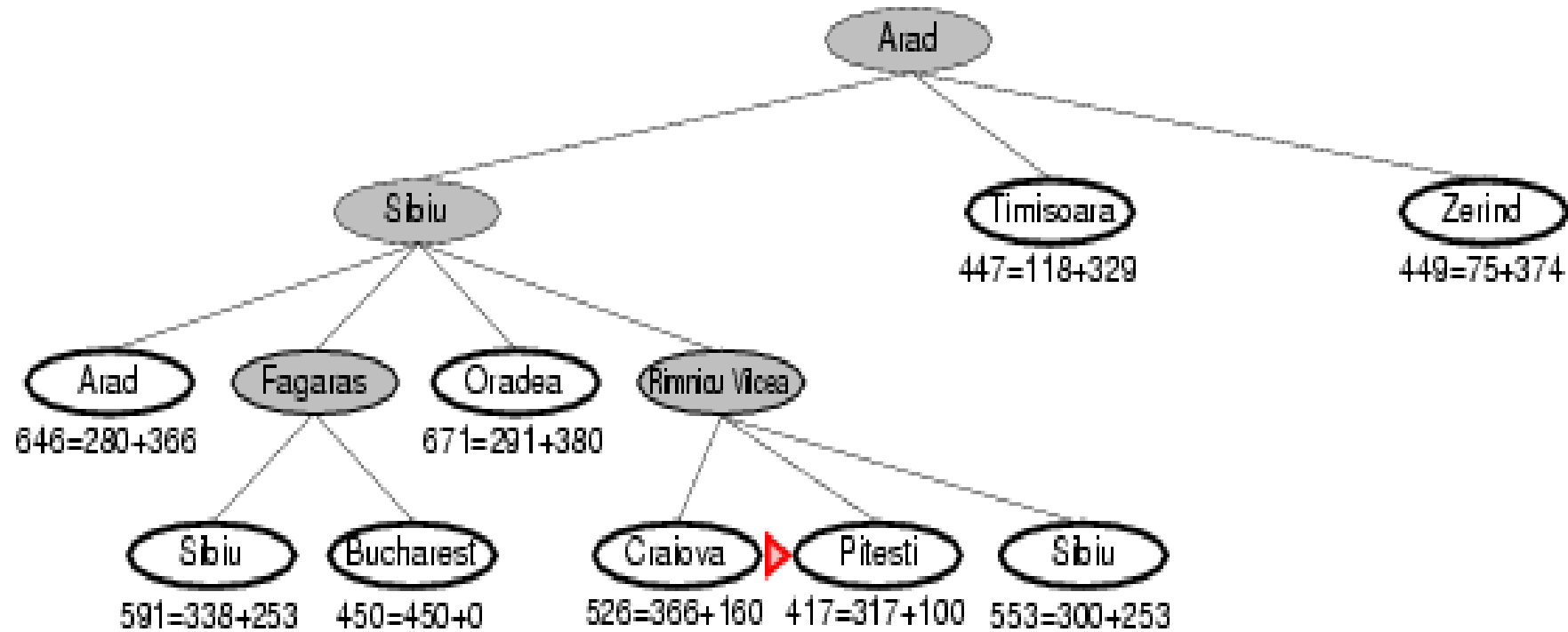
A* search example



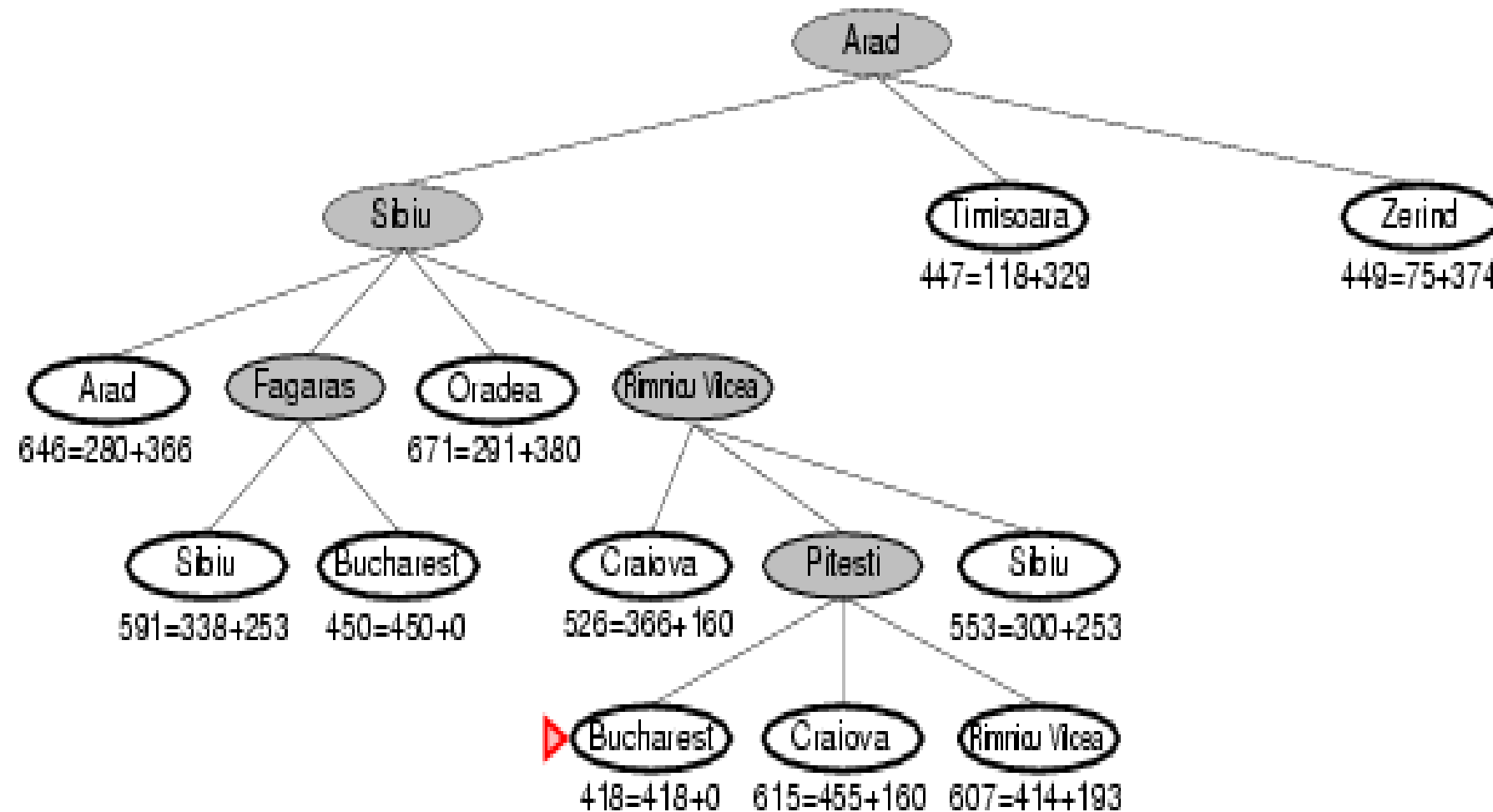
A* search example



A* search example



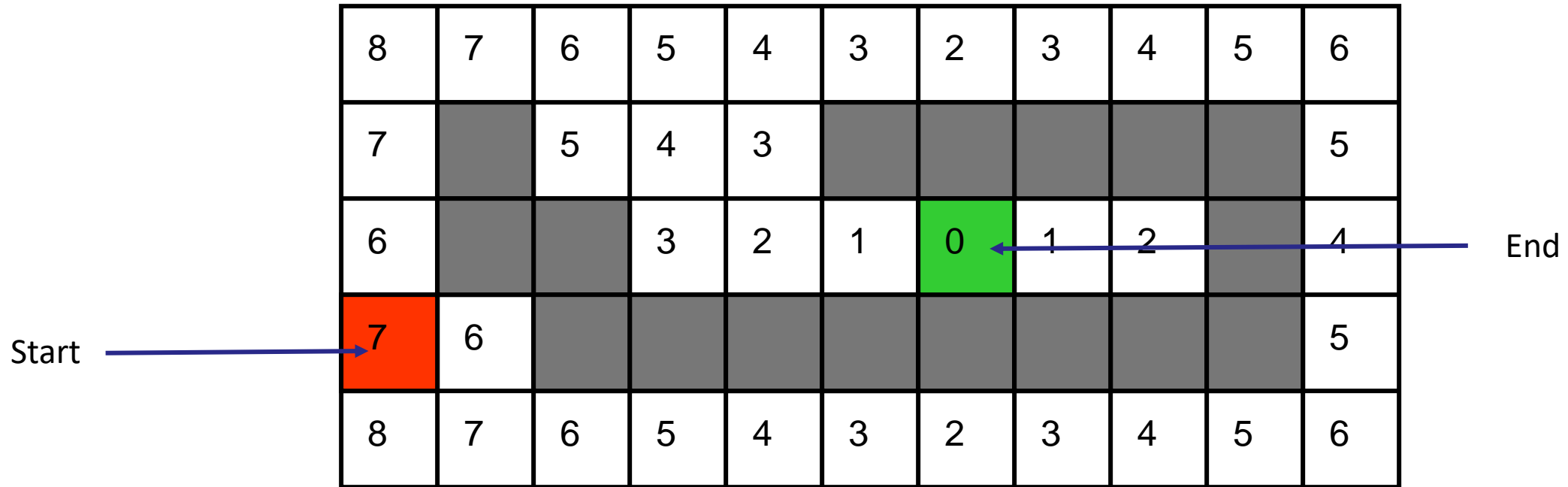
A* search example



Robot Navigation

	5	4	3	4	5	
5	4	3	2	3	4	5
4	3	2	1	2	3	4
3	2	1	0	1	2	3
4	3	2	1	2	3	4
5	4	3	2	3	4	5
	5	4	3	4	5	

What should be $f(n)$ for the robot navigation problem?



Robot Navigation

$f(N) = g(N) + h(N)$, with $h(N)$ = Manhattan distance to goal

8+3	7+4	6+3	5+6	4+7	3+8	2+9	3+10	4	5	6
7+2		5+6	4+7	3+8						5
6+1			3	2+9	1+10	0+11	1	2		4
7+0	6+1									5
8+1	7+2	6+3	5+4	4+5	3+6	2+7	3+8	4	5	6

Completeness and Optimality of A^*

- **Claim 1:** If there is a path from the initial to a goal node, A^* (with no removal of repeated states) terminates by finding the best path, hence is:
 - complete
 - optimal
- requirements:
 - Each node has a finite number of successors

Completeness of A^*

- Theorem: If there is a finite path from the initial state to a goal node, A^* will find it.

Optimality of A^*

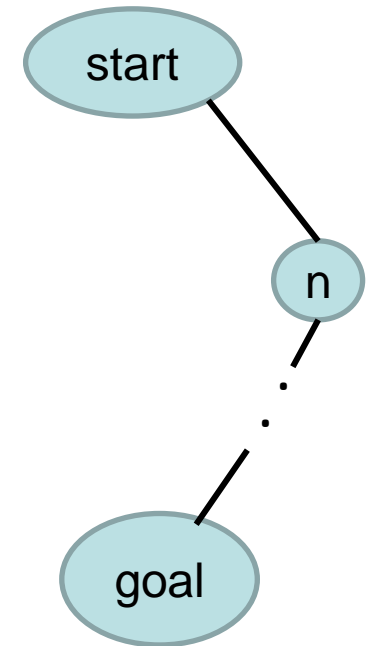
- Theorem: If $h(n)$ is admissible, then A^* is optimal.
- Admissible: An admissible heuristic is one that never overestimates the cost to reach a goal.

Admissible Heuristic

- Let $h^*(n)$ be the true cost of the optimal path from n to a goal node
- Heuristic $h(n)$ is admissible if:
$$0 \leq h(n) \leq h^*(n)$$
- An admissible heuristic is always optimistic.

Proof of Optimality of A^*

- Suppose, the optimal path has cost C^*
- But the algorithm returns a path with cost C , and $C > C^*$
- $g^*(n)$: the cost of optimal path from start to n
- $h^*(n)$: the cost of optimal path from n to goal
 - $C > C^*$
 - $f(n) > C^*$
 - We know that $f(n) = g(n) + h(n) = g^*(n) + h(n)$ [because, n is optimal path]
 - $f(n) \leq g^*(n) + h^*(n)$ [because, $h(n) \leq h^*(n)$]
 - $f(n) \leq C^*$, but it is a contradiction



Heuristic Function

- Function $h(N)$ that estimates the cost of the cheapest path from node N to goal node.
- Example: 8-puzzle

5		8
4	2	1
7	3	6

N

1	2	3
4	5	6
7	8	

goal

$h(N)$ = number of misplaced tiles
= 6

Heuristic Function

- Function $h(N)$ that estimates the cost of the cheapest path from node N to goal node.
- Example: 8-puzzle

5		8
4	2	1
7	3	6

N

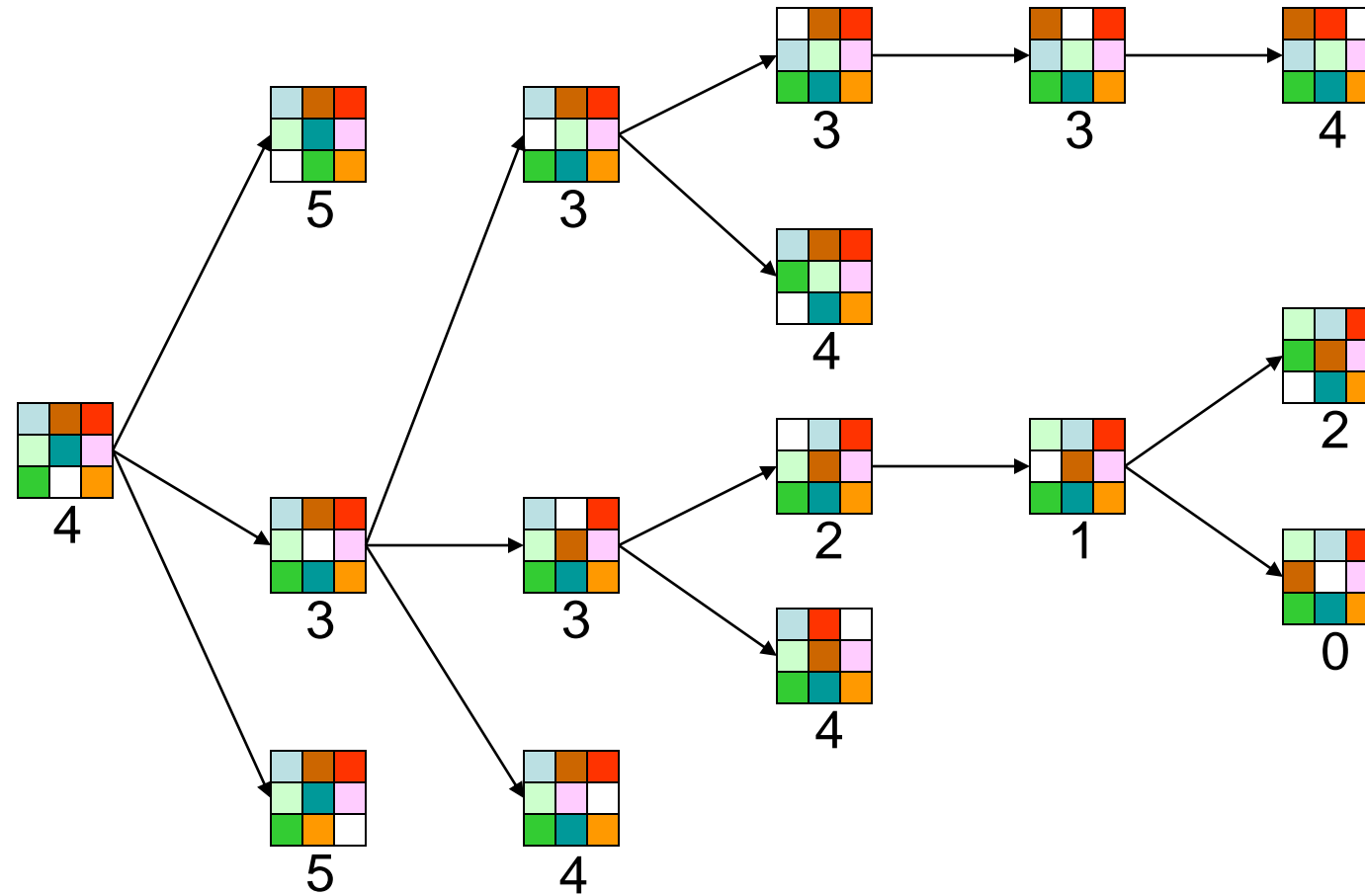
1	2	3
4	5	6
7	8	

goal

$h(N)$ = sum of the distances of every tile to its goal position
= $3 + 1 + 3 + 0 + 2 + 1 + 0 + 3$
[Here, four and seven are in right place]
= 13

8-puzzle

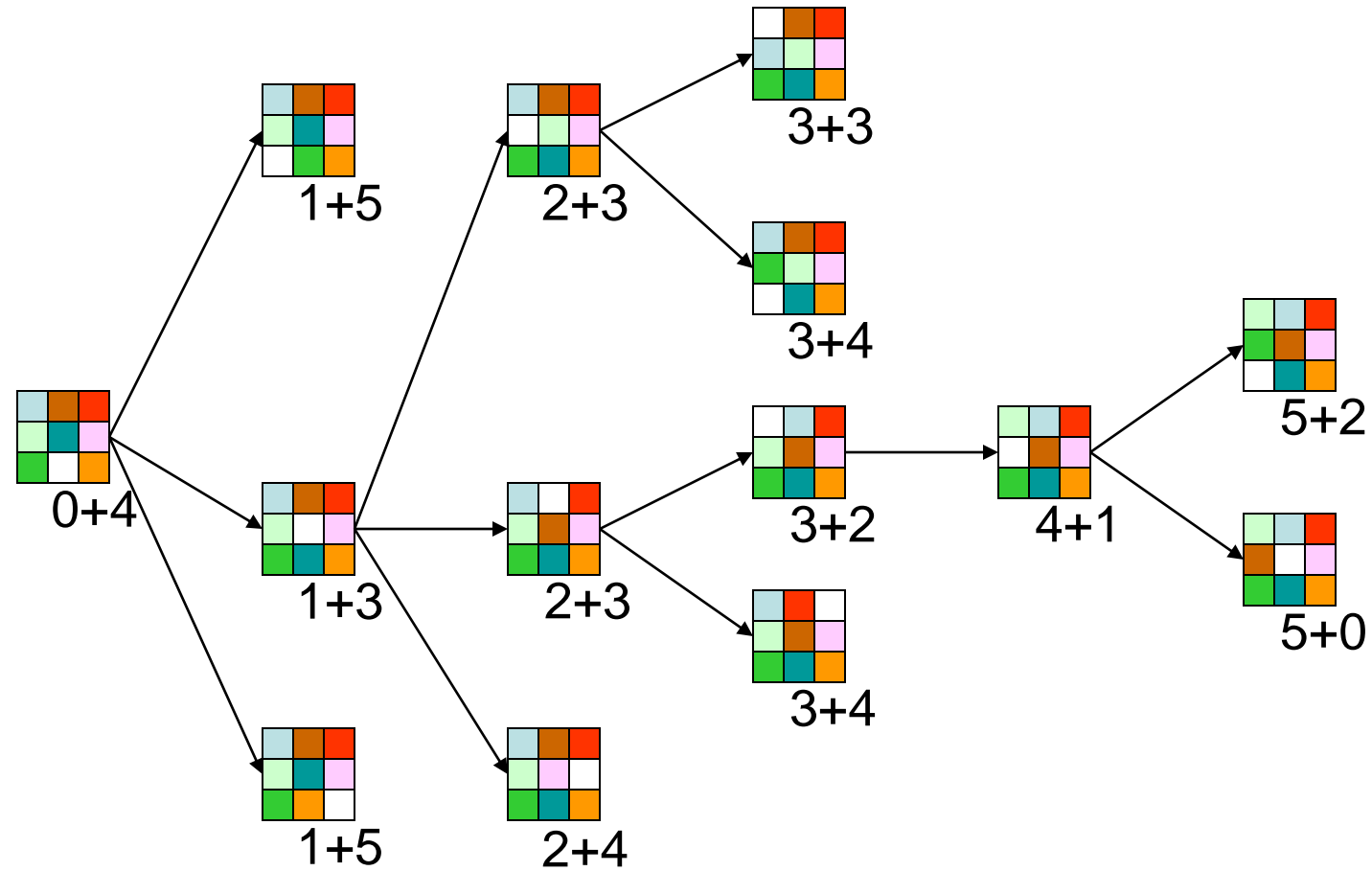
$f(N) = h(N) = \text{number of misplaced tiles}$



8-puzzle

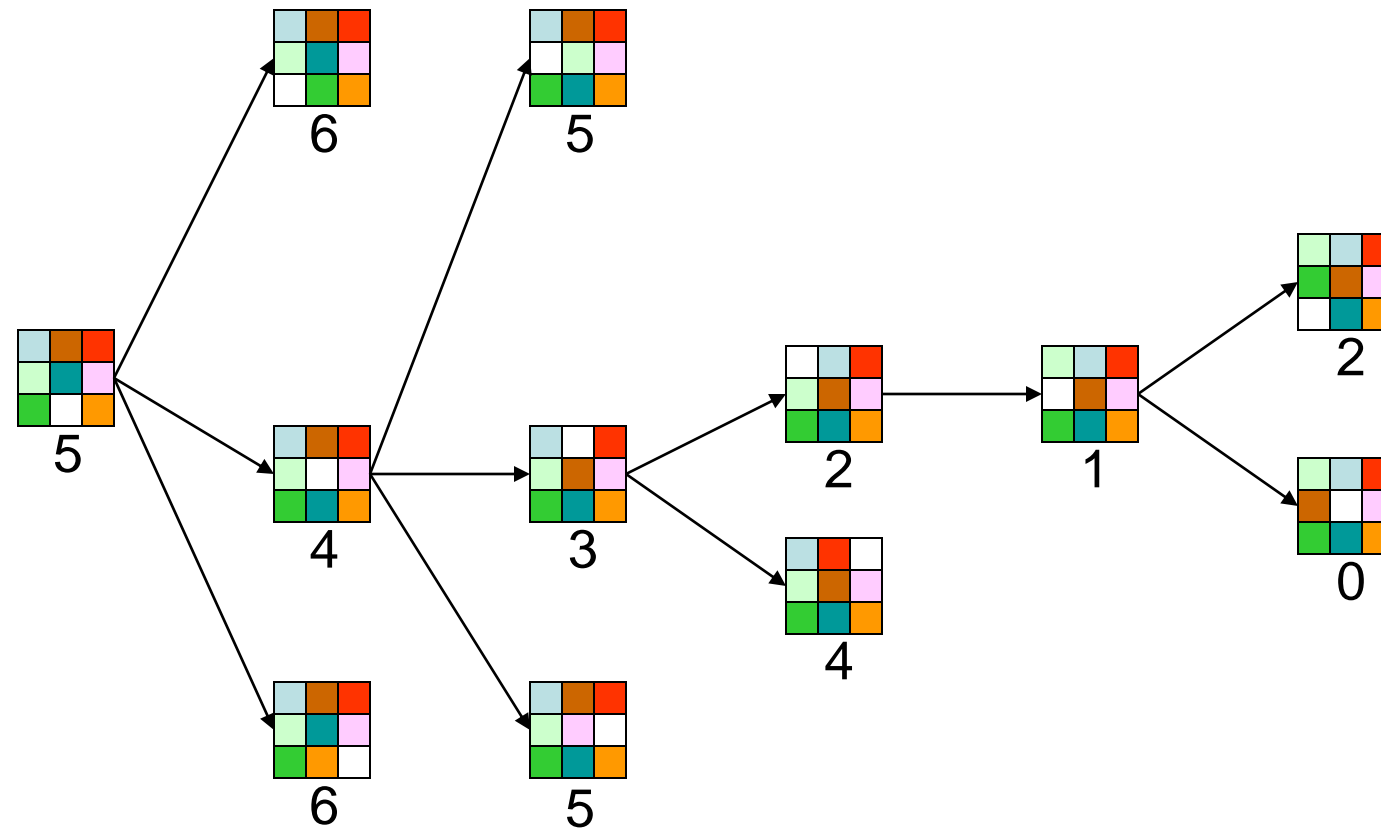
$$f(N) = g(N) + h(N)$$

with $h(N)$ = number of misplaced tiles



8-puzzle

$$f(N) = h(N) = \sum \text{distances of tiles to goal}$$



8-puzzle

5		8
4	2	1
7	3	6

N

1	2	3
4	5	6
7	8	

goal

- $h1(N)$ = number of misplaced tiles = 6 is admissible
- $h2(N)$ = sum of distances of each tile to goal = 13 is admissible

8-puzzle

5		8
4	2	1
7	3	6

N

1	2	3
4	5	6
7	8	

goal

- $h1(N)$ = number of misplaced tiles
- $h2(N)$ = sum of distances of each tile to goal

are both consistent

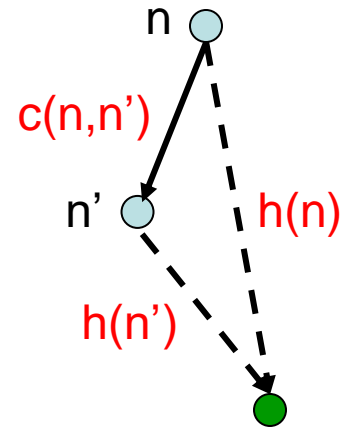
Consistent Heuristic

- The admissible heuristic h is **consistent** (or satisfies the **monotone restriction**) if for every node n and every successor n' of n :

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

This is a form of triangular inequality.

- A side of a triangle cannot be longer than the sum of the other two sides.

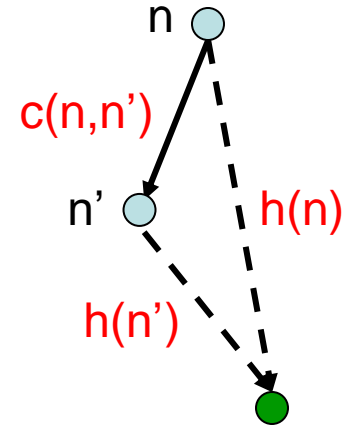


Claims

- If h is consistent, then the function f along any path is **non-decreasing**:

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

$$f(n') = g(n) + c(n, n') + h(n')$$



Claims

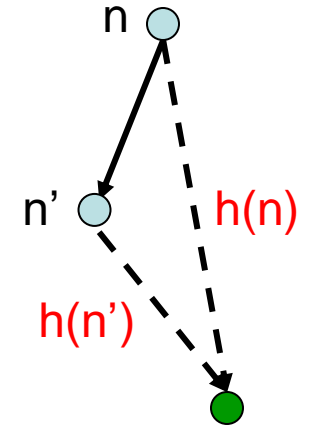
- If h is consistent, then the function f along any path is non-decreasing:

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

$$f(n') = g(n) + c(n, n') + h(n')$$

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

$$f(n) \leq f(n')$$



Claims

- If h is consistent, then the function f along any path is non-decreasing:

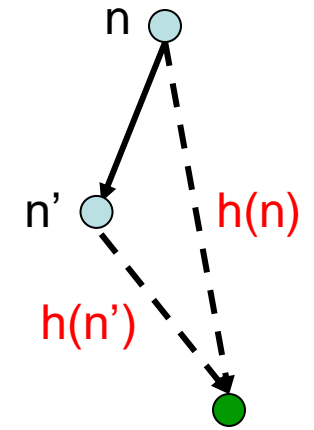
$$f(n) = g(n) + h(n)$$

$$f(n') = g(n) + c(n, n') + h(n')$$

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

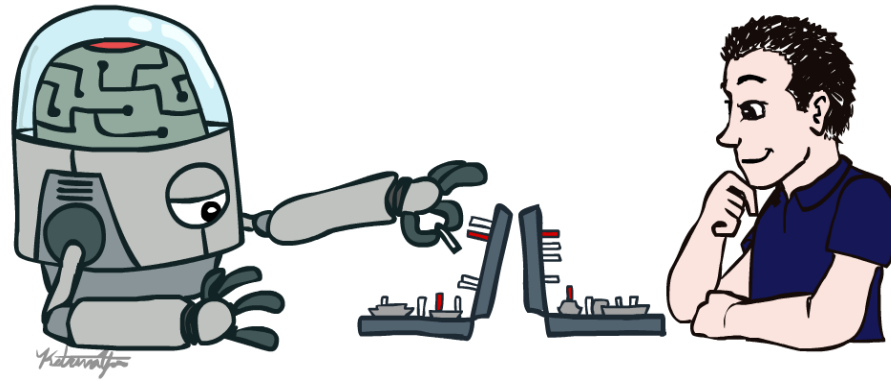
$$f(n) \leq f(n')$$

- If h is consistent, then whenever A^* expands a node it has already found an optimal path to the state associated with this node



Next class?

- Local search algorithm
- Hill climbing problem



Thanks!