

Property	BFS	UCS	DFS	DLS	IDS
Complete	Yes¹	Yes²	No	No	Yes¹
Optimal	No <sup>3</sup>	Yes	No	No	No <sup>3</sup>
Time	$\mathcal{O}ig(b^dig)$	$O\left(b^{1+\left\lfloor \frac{C^*}{\varepsilon}\right\rfloor}\right)$	$\mathcal{O}(b^m)$	$\mathcal{O}ig(b^\ellig)$	$\mathcal{O}(b^d)$
Space		$O\left(b^{1+\left\lfloor \frac{C^*}{\varepsilon}\right\rfloor}\right)$		$\mathcal{O}(b\ell)$	O(bd)
<ol> <li>BFS and IDS are complete if b is finite.</li> <li>UCS is complete if b is finite and step cost ≥ ε</li> </ol>					
BFS and IDS are optimal if step costs are identical.					

# Previously...

- Uninformed search strategies use only the information available in the problem definition
  - Breadth-first search
  - Uniform-cost search
  - Depth-first search
  - Depth-limited search
  - Iterative deepening search
- This class –exploit additional information!

Q1. Consider the following parameters b=3, d=3, what is the overhead of IDS as compared to DLS?

Q2. Consider the following parameters b=3, d=3, what is the number of nodes to keep track in DFS?

# Choosing a Search Strategy

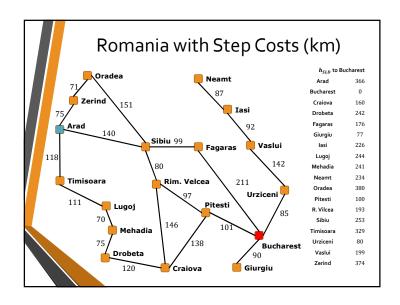
- Depends on the problem:
  - Finite/infinite depth of search tree
  - Known/unknown solution depth
  - Repeated states
  - Identical/non-identical step costs
  - Completeness and optimality needed?
  - Resource constraints (e.g., time, space)

# Can We Do Better?

- Yes! Exploit problem-specific knowledge; obtain heuristics to guide search
- Today:
  - Informed (heuristic) search
  - Expand "more promising" nodes.







### Best-First Search

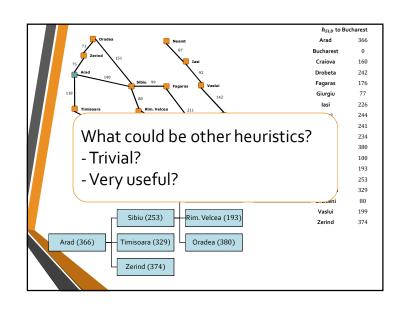
- Idea: use an evaluation function f(n) for each node n
  - Cost estimate → Expand node with lowest evaluation/cost first
- Implementation:

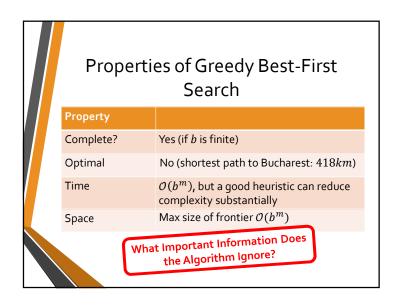
Frontier = priority queue ordered by nondecreasing cost f

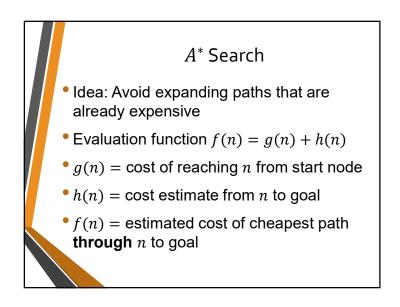
- Special cases (different choices of *f* ):
  - Greedy best-first search
  - A\* search

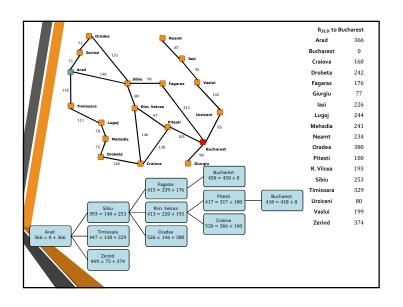
# **Greedy Best-First Search**

- Evaluation function f(n) = h(n) (heuristic function) = estimated cost of cheapest path from n to goal
  - Restriction: h(goal) = 0
- e.g.,  $h_{SLD}(n) = \text{straight-line distance from } n$  to Bucharest
- Greedy best-first search expands the node that appears to be closest to goal









# Admissible Heuristics

- h(n) is admissible if,  $\forall n, h(n) \leq h^*(n)$
- $h^*(n) = \text{true cost to reach the goal state from } n$ .
- Never overestimates cost to reach goal
- Example: h<sub>SLD</sub>(n) never overestimates the actual road distance (roads are at best straight!)

# Admissible Heuristics

Theorem: If h(n) is admissible, then  $A^*$  using TREE-SEARCH is optimal

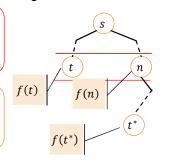
# Optimality of A\* using TREE-SEARCH

t - a suboptimal goal in the frontier.

n - an unexpanded node in the frontier; n is on a shortest path to an optimal goal  $t^*$ .

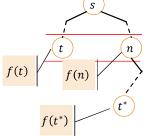
It would be **very** bad if suboptimal goal node *t* gets checked before *n* !!

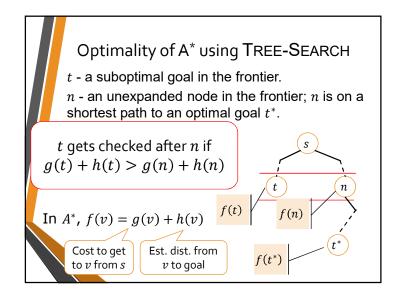
 $\Rightarrow$  f(t) is lower than f(n)

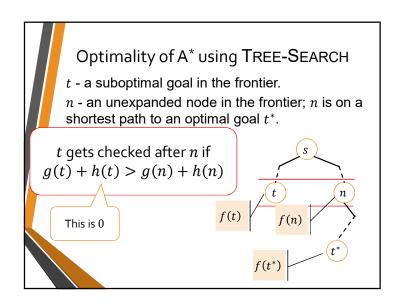


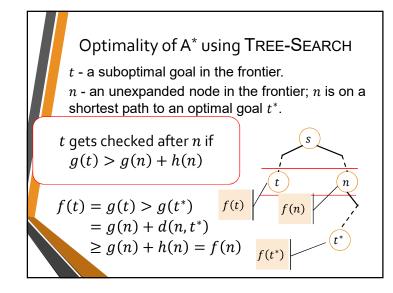
# Optimality of A\* using TREE-SEARCH t - a suboptimal goal in the frontier. n - an unexpanded node in the frontier; n is on a shortest path to an optimal goal $t^*$ . t gets checked after n if f(t) > f(n)

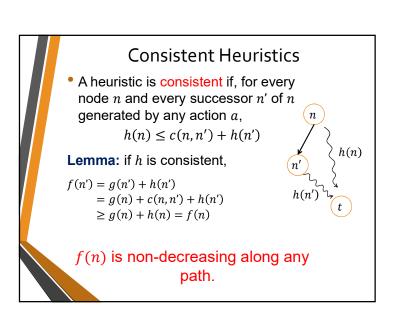
We need to show that t gets checked after n



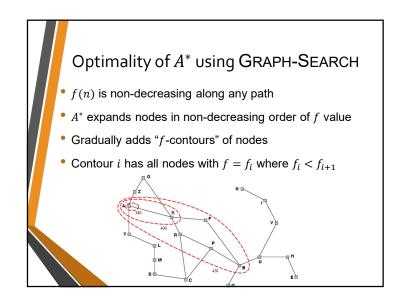


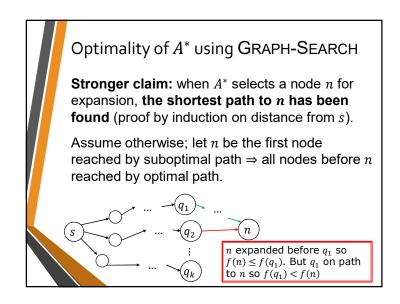


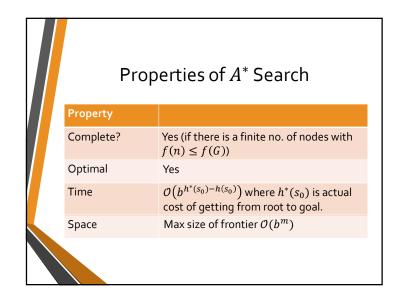




# Consistent Heuristics Theorem: If h(n) is consistent, then $A^*$ using GRAPH-SEARCH is optimal







# Admissible vs. Consistent Heuristics

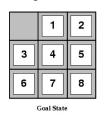
- Why is consistency a stronger sufficient condition than admissibility?
  - Consistent ⇒ admissible
  - Admissible ⇒ consistent
- k(n) be the cost of cheapest path from n to goal
- To prove,  $h(n) \le k(n)$ 
  - If n is the goal,  $h(n) = 0 \le k(n)$
  - Induction hypothesis:  $h(n') \le k(n')$
  - Let, path from n to goal has i steps, n' is the successor of n
  - $n' \sim goal, i-1$  steps
- h is consistent  $\Rightarrow$  we have:  $h(n) \le c(n, n') + h(n')$ 
  - $\leq c(n,n') + k(n') = k(n)$

# Admissible vs. Consistent Heuristics • An admissible but inconsistent heuristic cannot guarantee optimality of A\* using GRAPH-SEARCH • GRAPH-SEARCH discards new paths to a repeated state. May discard the optimal path. • Consistent heuristic: always follows optimal path (that lemma was important!)

### Admissible Heuristics

- Let's revisit the 8-puzzle
  - Branching factor is about 3
  - Average solution depth is about 22 steps
  - Exhaustive tree search examines 3<sup>22</sup> states
- How do we come up with good heuristics?

7	2	4
5		6
8	3	1



### Admissible Heuristics

E.g., 8-puzzle:

- $h_1(n)$  = number of misplaced tiles
- $h_2(n)$  = total Manhattan distance (i.e., no. of squares from desired location of each tile)

7	2	4
5		6
8	3	1



•  $h_1(s) = 8$ 

$$h_2(s) = 3 + 1 + 2 + 2 + 2 + 3 + 3 + 2 = 18$$

#### **Dominance**

• If  $h_2(n) \ge h_1(n)$  for all n (both admissible), then  $h_2$  dominates  $h_1$ . It follows that  $h_2$  incurs lower search cost than  $h_1$ .

Average search costs (nodes generated):

d = 12

d = 24

Algorithm	# Nodes
IDS	3,644,035
$A^*(h_1)$	227
$A^*(h_2)$	73

Algorithm	# Nodes
IDS	Galactic Number
$A^*(h_1)$	39,135
$A^*(h_2)$	1,641

# Deriving Admissible Heuristics

• Rules of 8-puzzle:

A tile can move from square *A* to square *B* if *A* is horizontally or vertically adjacent to *B* and *B* is blank

- We can generate three relaxed problems
  - 1. A tile can move from square A to square B if A is adjacent to B
  - 2. A tile can move from square A to square B if B is blank
  - 3. A tile can move from square A to square B

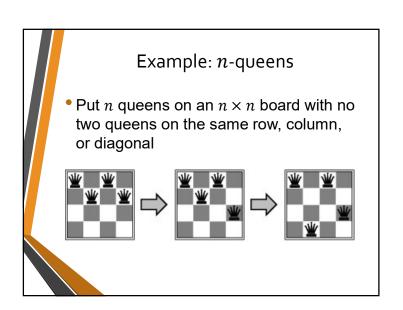
# **Deriving Admissible Heuristics**

- A problem with fewer restrictions on the actions is called a relaxed problem
- The cost of an optimal solution to a relaxed problem is an admissible heuristic for the original problem

# **Deriving Admissible Heuristics**

- If the rules of the 8-puzzle are relaxed so that a tile can move anywhere, then  $h_1(n)$  is the resulting heuristic.
- If the rules are relaxed so that a tile can move to any adjacent square, then  $h_2(n)$  (Manhattan Dist.) is the resulting heuristic





# Local Search Algorithms

- The path to goal is irrelevant; the goal state itself is the solution
- State space = set of "complete" configurations
- Find final configuration satisfying constraints, e.g., n-queens
- Local search algorithms: maintain single "current best" state and try to improve it
- Advantages:
  - very little/constant memory
  - find reasonable solutions in large state space

# Hill-Climbing Search

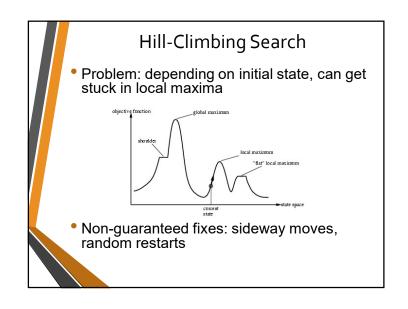
**function** HILL-CLIMBING(problem) **returns** a state that is a local maximum

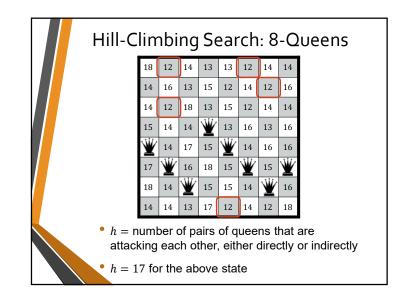
 $current \leftarrow \texttt{Make-Node}(problem.\texttt{Initial-State}) \\ \textbf{loop do}$ 

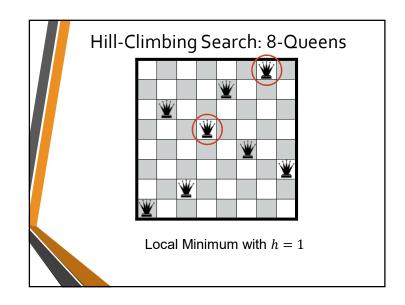
 $neighbor \leftarrow$  a highest-valued successor of current

if neighbor. Value  $\leq$  current. Value then return current.State  $current \leftarrow neighbor$ 

"Like climbing Mt. Everest in thick fog with amnesia"









# Local search strategies

• Hill-climbing search: use of heuristic function to improve "current" state