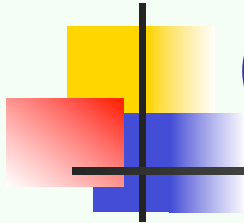




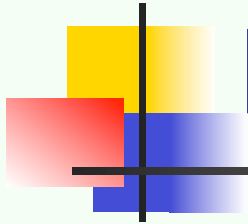
Informed search algorithms

Chapter 4



Outline

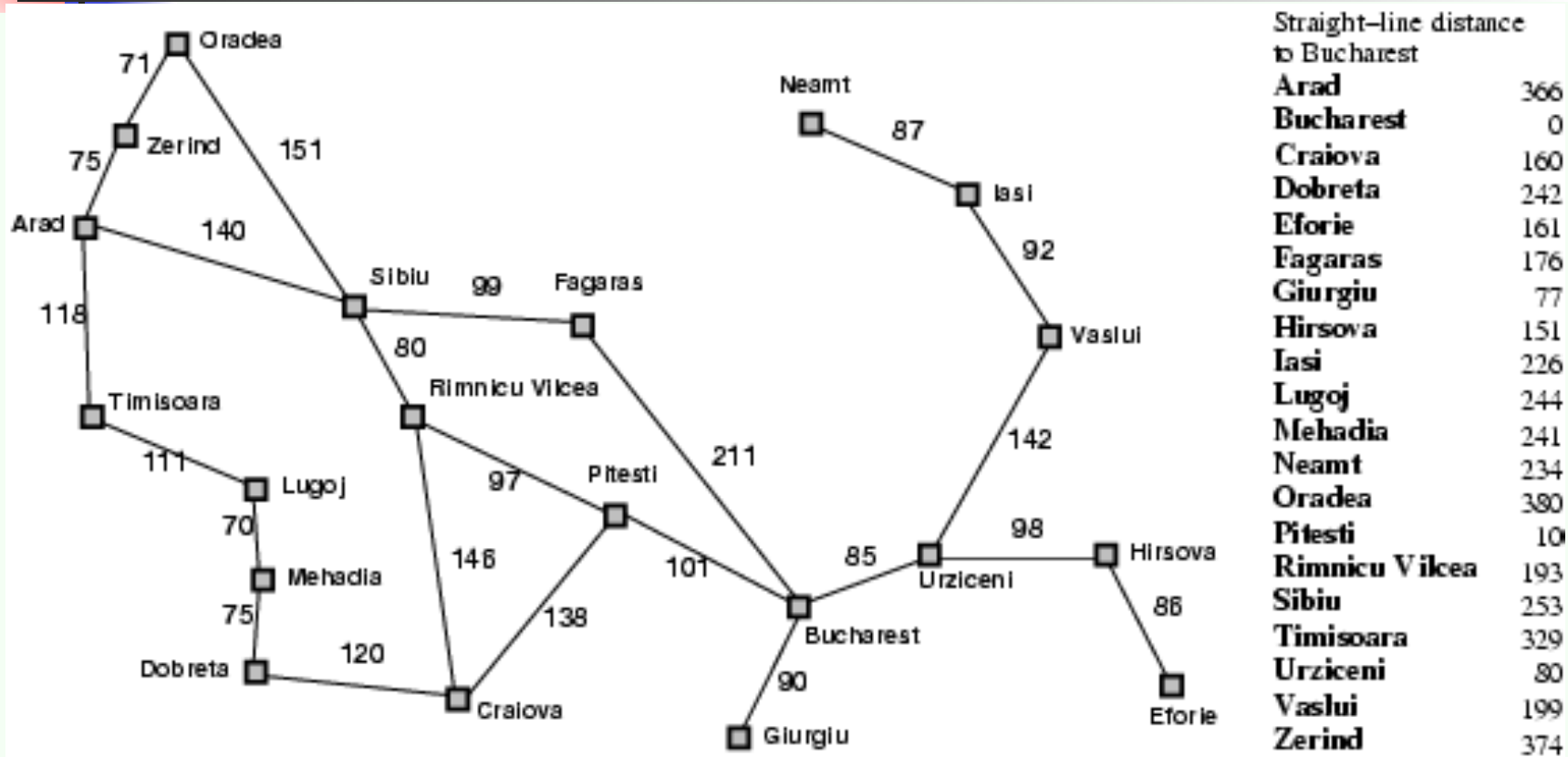
- Best-first search
- Greedy best-first search
- A^* search
- Heuristics
- Memory Bounded A^* Search

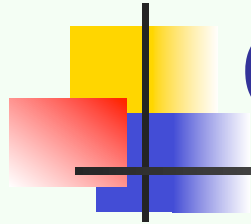


Best-first search

- Idea: use an **evaluation function** $f(n)$ for each node
 - $f(n)$ provides an estimate for the total cost.
 - Expand the node n with smallest $f(n)$.
- Implementation:
Order the nodes in fringe in increasing order of cost.
- Special cases:
 - greedy best-first search
 - A^* search

Romania with straight-line dist.



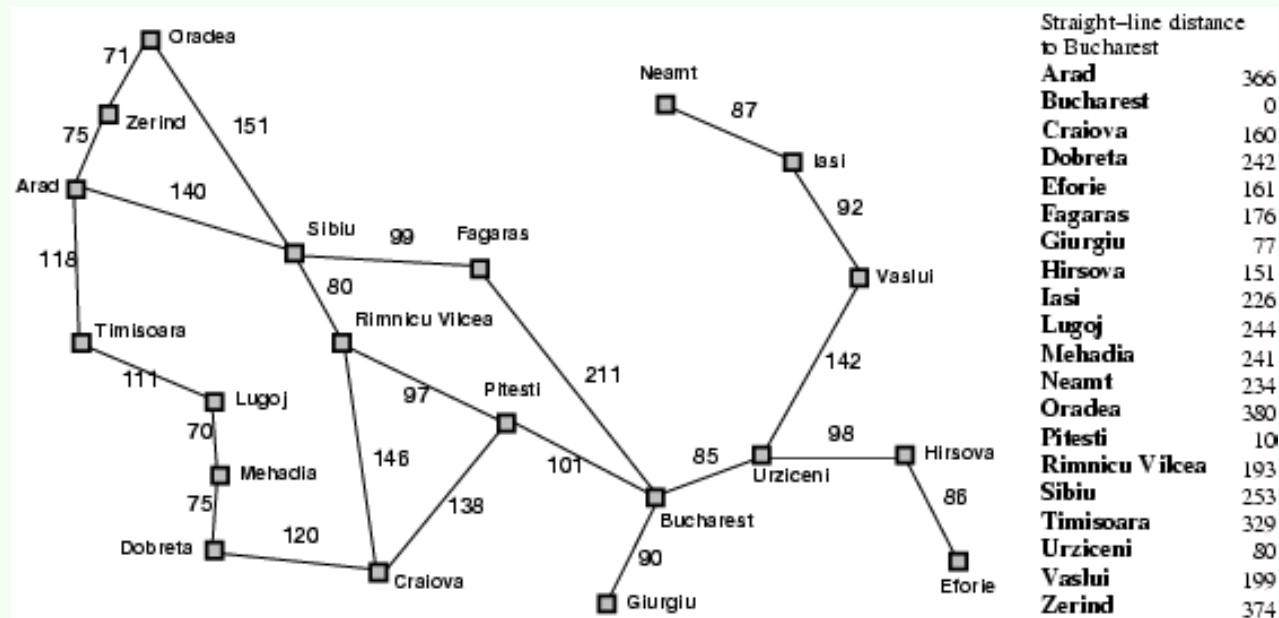


Greedy best-first search

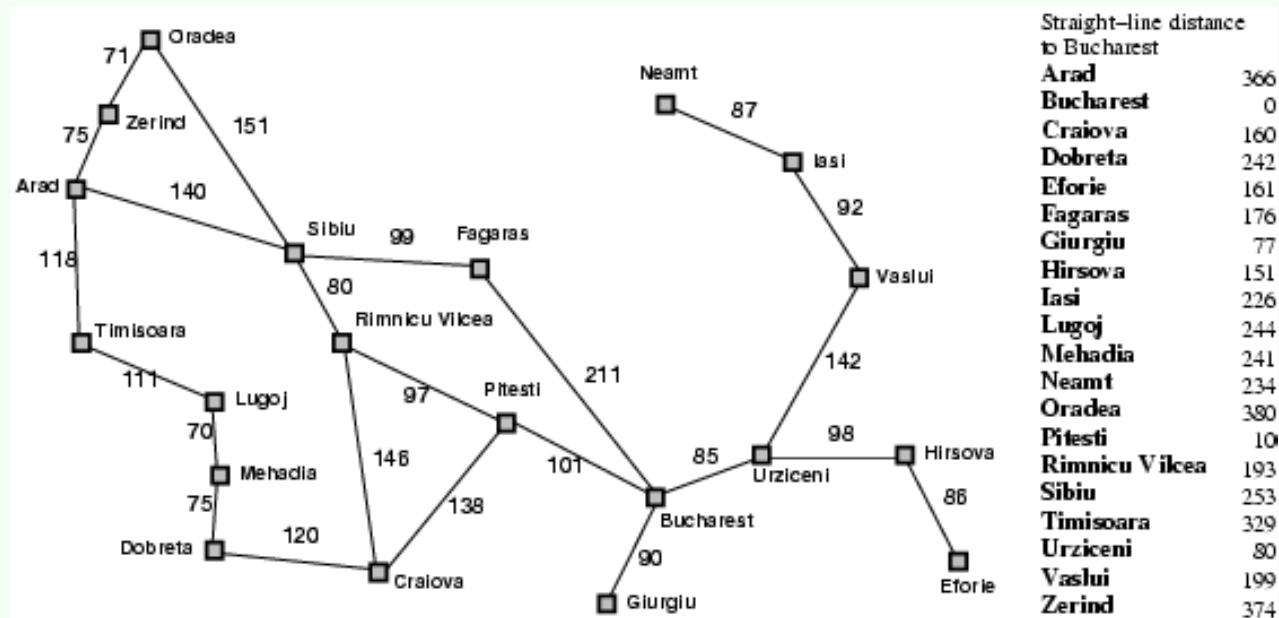
- $f(n)$ = estimate of cost from n to *goal*
- e.g., $f(n)$ = straight-line distance from n to Bucharest
- Greedy best-first search expands the node that **appears** to be closest to goal.

Greedy best-first search example

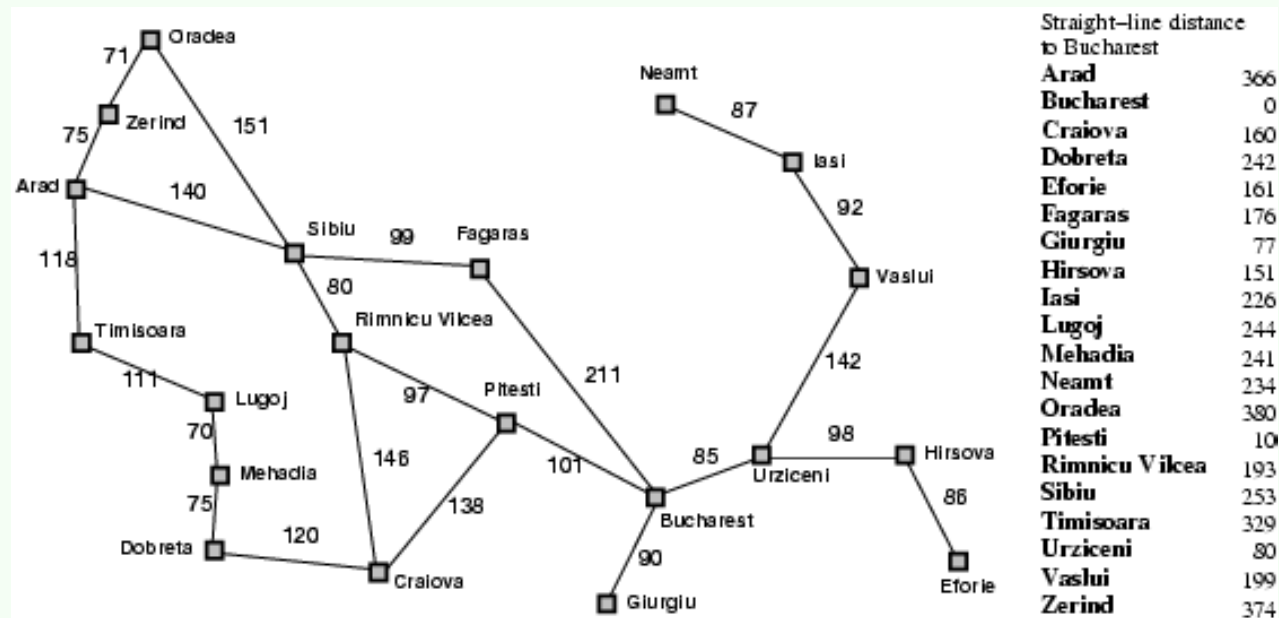
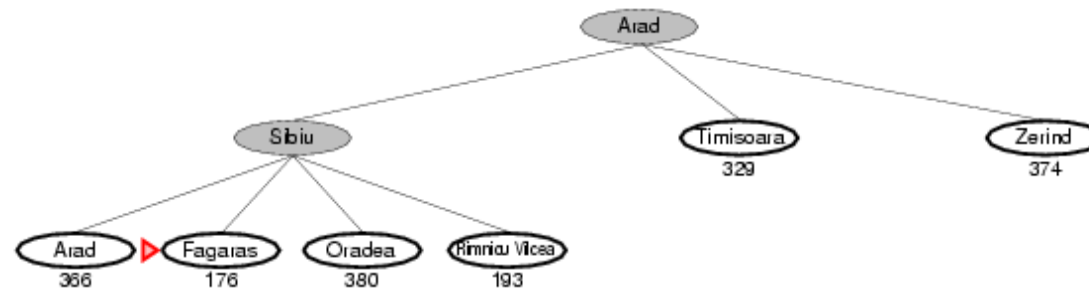
Arad
366



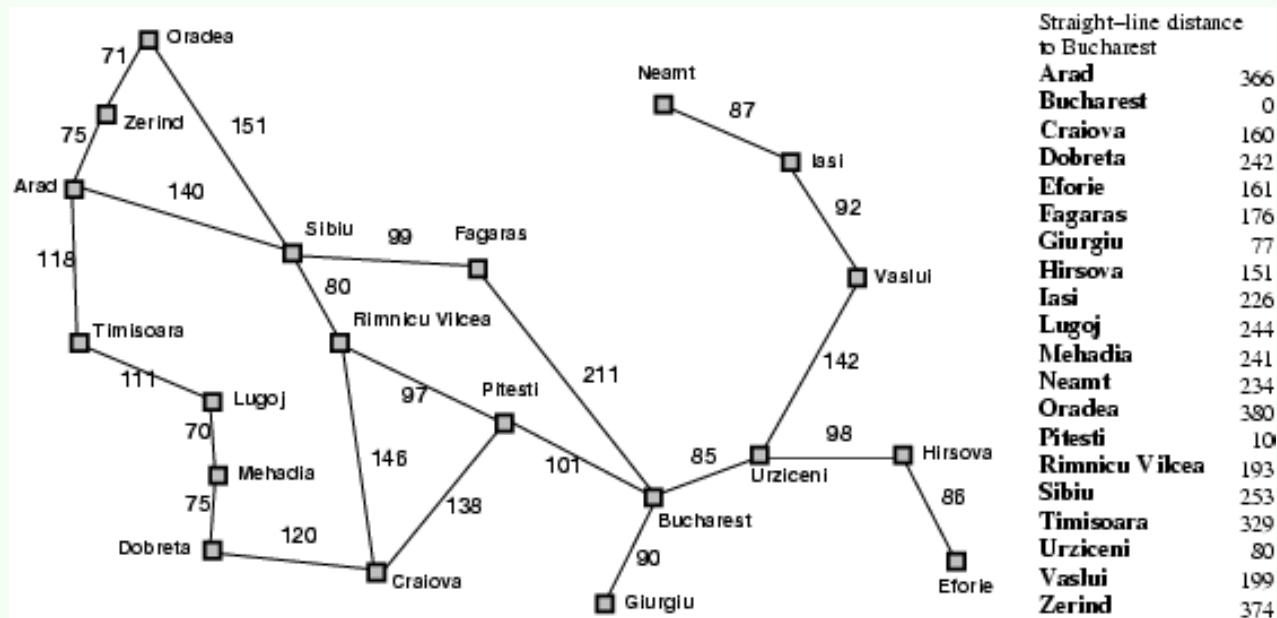
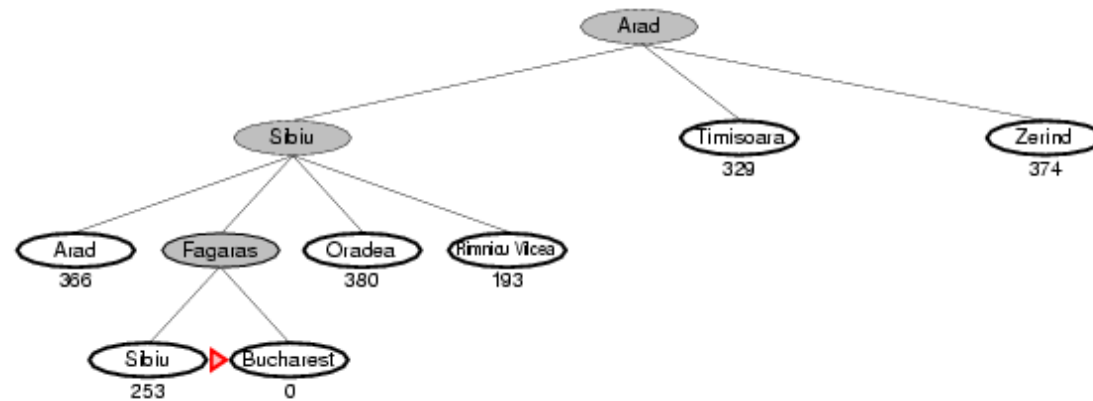
Greedy best-first search example



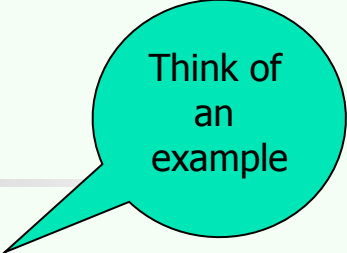
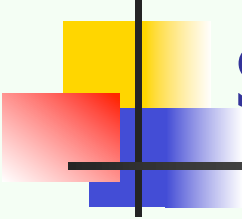
Greedy best-first search example



Greedy best-first search example



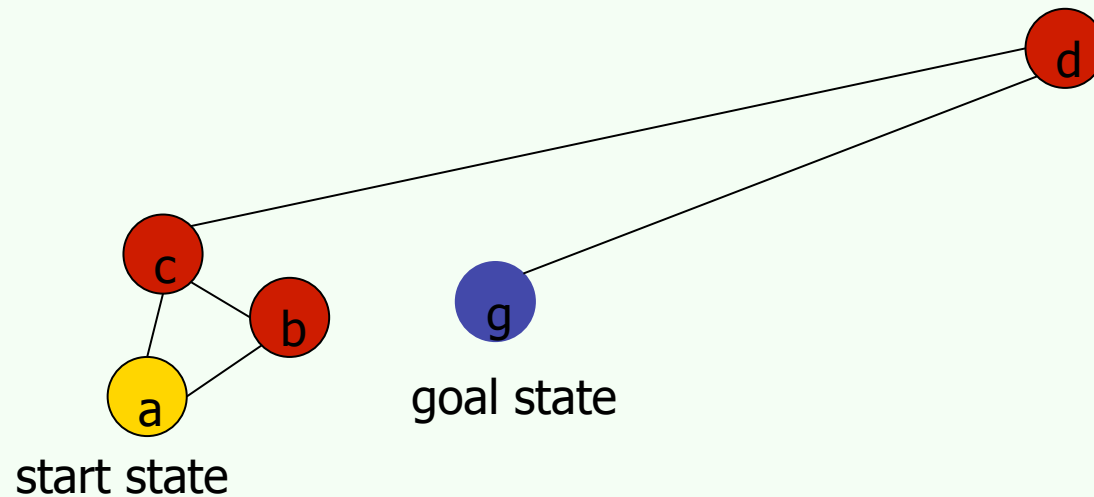
Properties of greedy best-first search



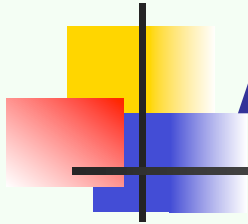
Think of
an
example

- Complete? No – can get stuck in loops.
- Time? $O(b^m)$, but a good heuristic can give dramatic improvement
- Space? $O(b^m)$ - keeps all nodes in memory
- Optimal? No
e.g. Arad→Sibiu→Rimnicu
Virea→Pitesti→Bucharest is shorter!

Properties of greedy best-first search



$f(n)$ = straightline distance



A* 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
- $f(n)$ = estimated total cost of path through n to goal
- Best First search has $f(n)=h(n)$
- Uniform Cost search has $f(n)=g(n)$



Admissible heuristics

- A heuristic $h(n)$ is **admissible** if for every node n , $h(n) \leq h^*(n)$, where $h^*(n)$ is the **true** cost to reach the goal state from n .
- An admissible heuristic **never overestimates** the cost to reach the goal, i.e., it is **optimistic**
- Example: $h_{SLD}(n)$ (never overestimates the actual road distance)
- **Theorem**: If $h(n)$ is admissible, A^* using TREE-SEARCH is optimal



Admissible heuristics

E.g., for the 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)

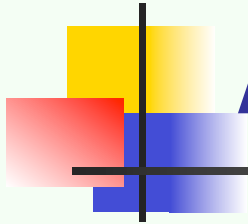
7	2	4
5		6
8	3	1

Start State

	1	2
3	4	5
6	7	8

Goal State

- $h_1(S) = ?$
- $h_2(S) = ?$



Admissible heuristics

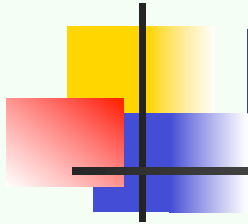
E.g., for the 8-puzzle:

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

7	2	4							
5									
8	3	1							
Start State									

	1	2							
3	4	5							
6	7	8							
Goal State									

- $h_1(S)$ = ? 8
- $h_2(S)$ = ? $3+1+2+2+2+3+3+2 = 18$



Dominance

- If $h_2(n) \geq h_1(n)$ for all n (both admissible)
- then h_2 **dominates** h_1
- h_2 is better for search: it is guaranteed to expand less or equal nr of nodes.
- Typical search costs (average number of nodes expanded):
 - $d=12$ IDS = 3,644,035 nodes
 $A^*(h_1)$ = 227 nodes
 $A^*(h_2)$ = 73 nodes
 - $d=24$ IDS = too many nodes
 $A^*(h_1)$ = 39,135 nodes
 $A^*(h_2)$ = 1,641 nodes



Relaxed problems

- 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
- If the rules of the 8-puzzle are relaxed so that a tile can move **anywhere**, then $h_1(n)$ gives the shortest solution
- If the rules are relaxed so that a tile can move to **any adjacent square**, then $h_2(n)$ gives the shortest solution

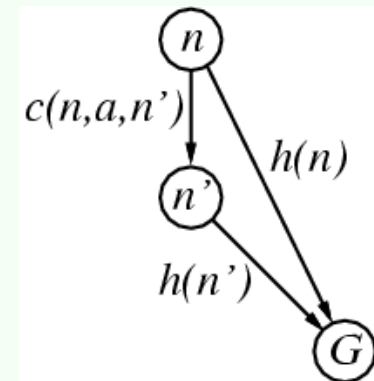
Consistent heuristics

- A heuristic is **consistent** if for every node n , every successor n' of n generated by any action a ,

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

- If h is consistent, we have

$$\begin{aligned} f(n') &= g(n') + h(n') && \text{(by def.)} \\ &= g(n) + c(n,a,n') + h(n') && (g(n')=g(n)+c(n.a.n')) \\ &\geq g(n) + h(n) = f(n) && \text{(consistency)} \\ f(n') &\geq f(n) \end{aligned}$$



It's the triangle inequality !

- i.e., $f(n)$ is non-decreasing along any path.

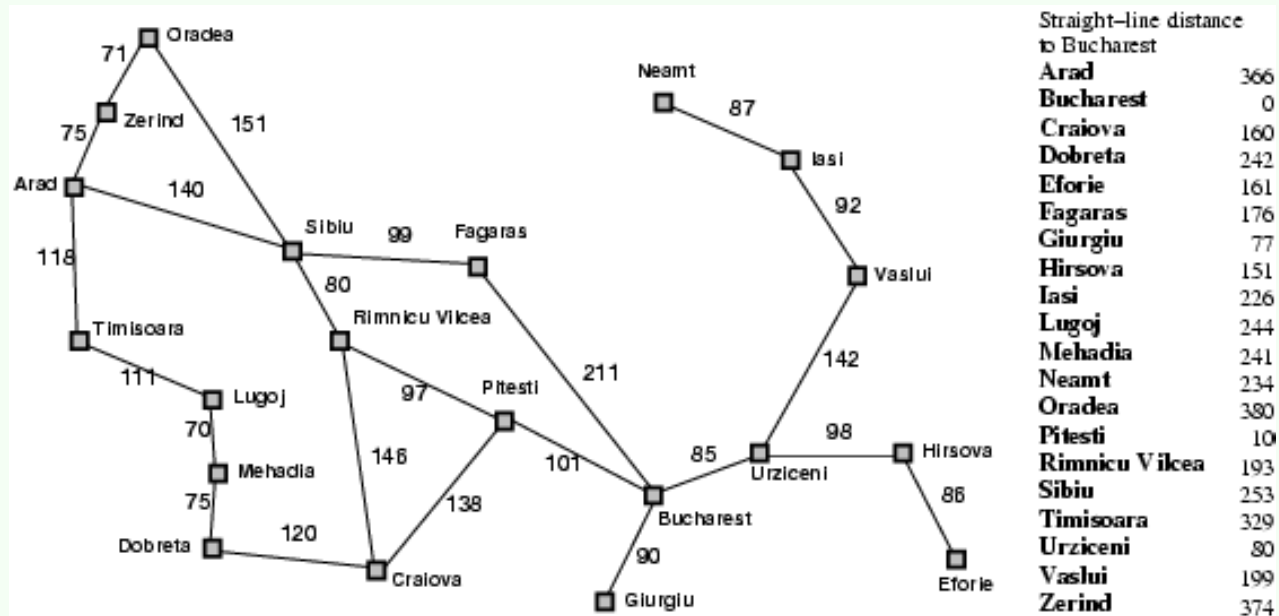
- Theorem:**

If $h(n)$ is consistent, A^* using GRAPH-SEARCH is optimal

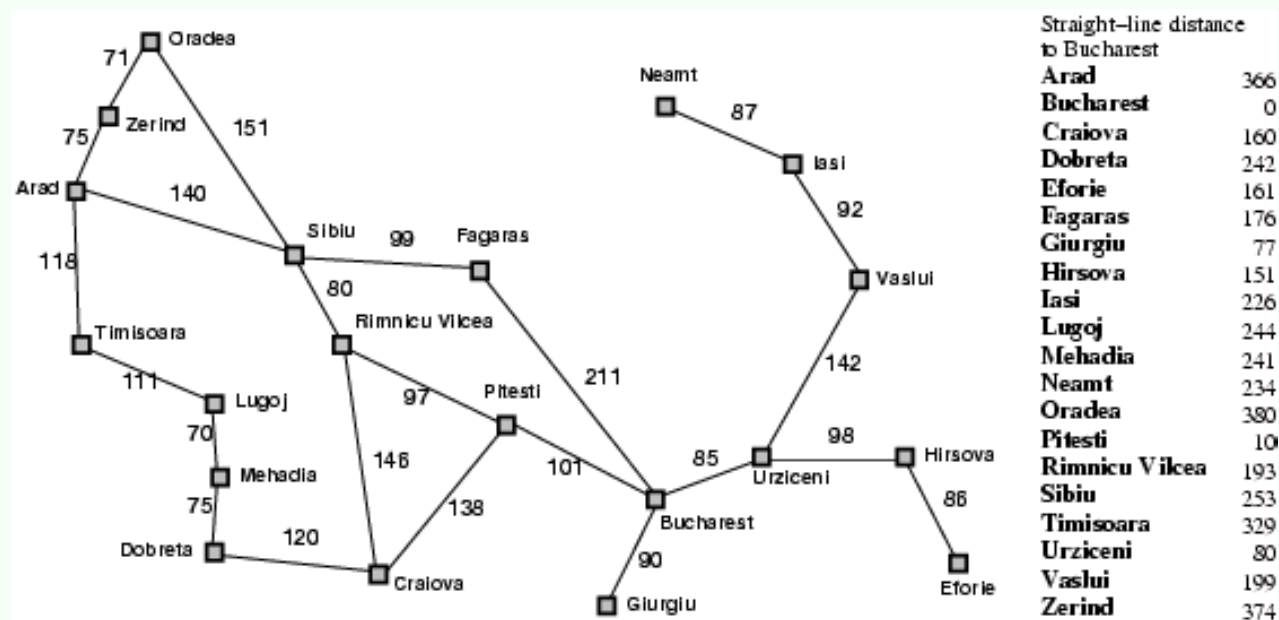
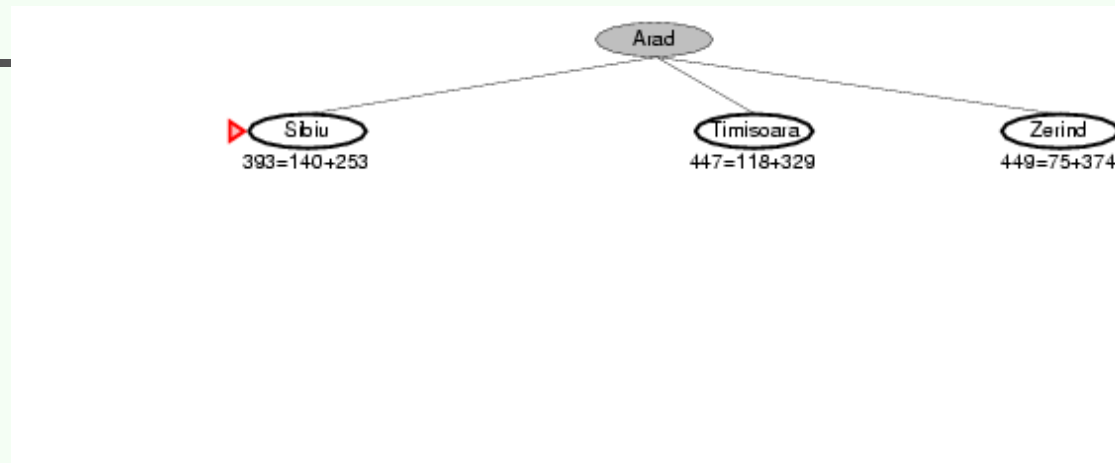
keeps all checked nodes
in memory to avoid repeated
states

A* search example

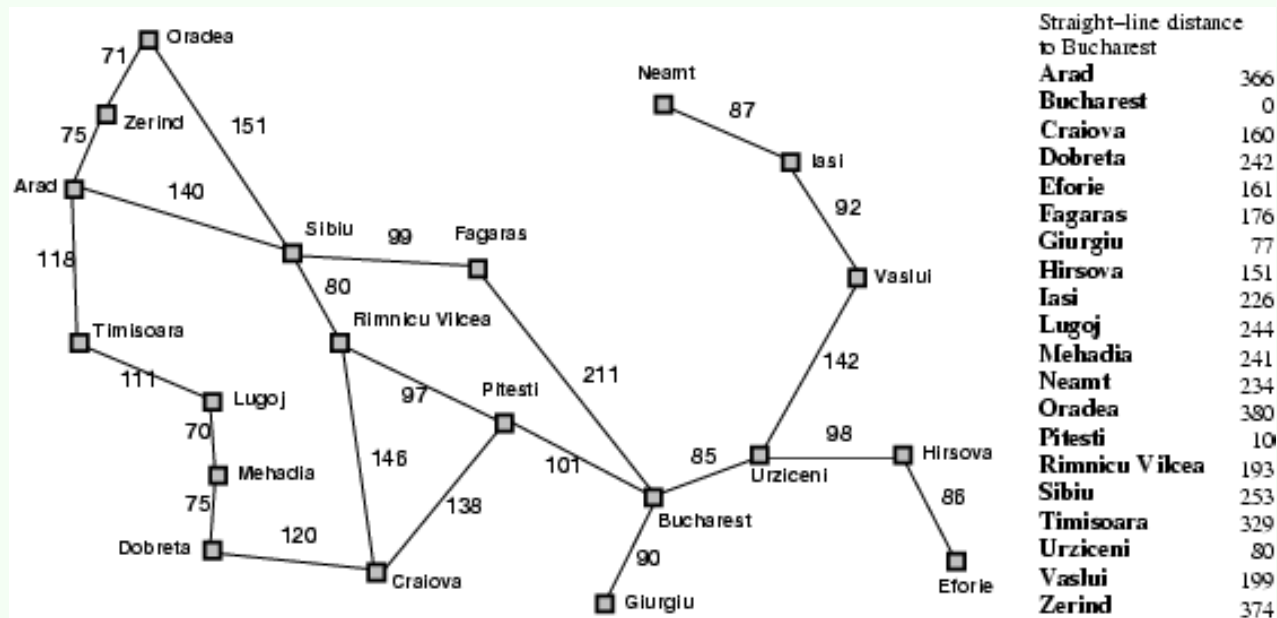
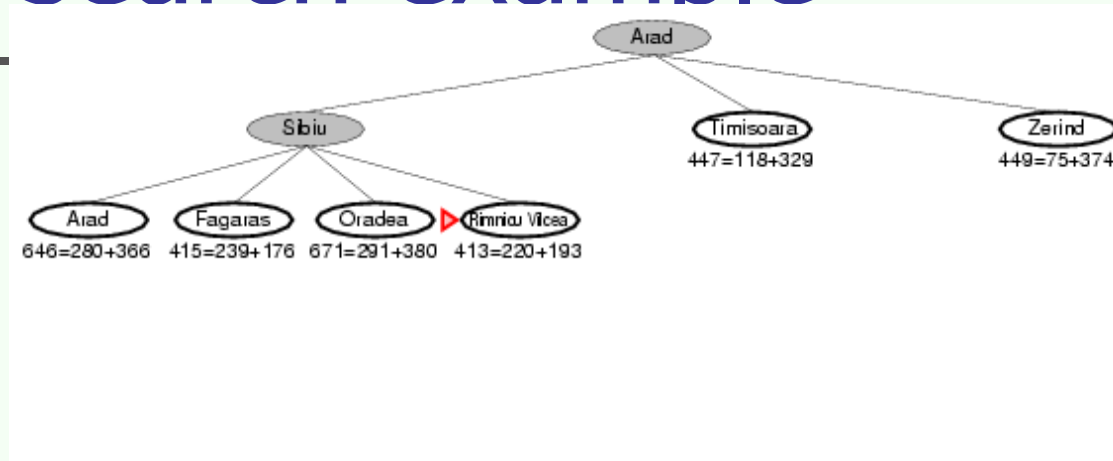
Arad
366=0+366

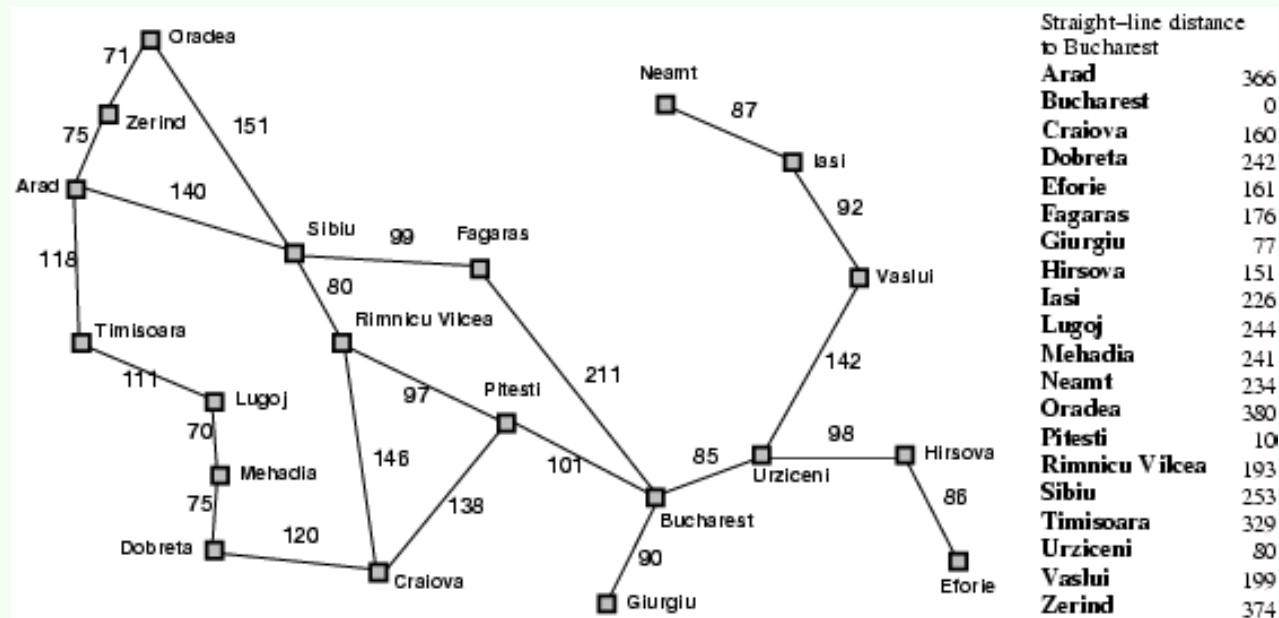
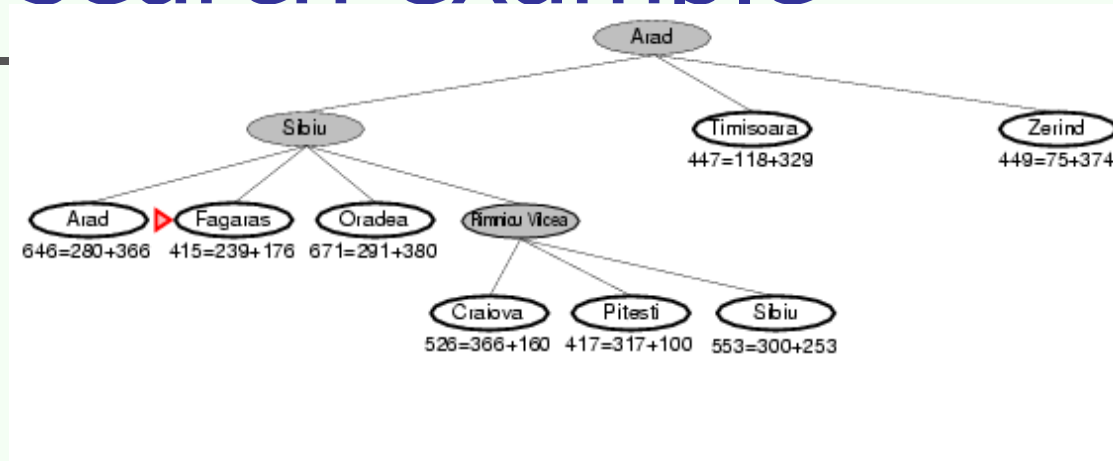


A* search example

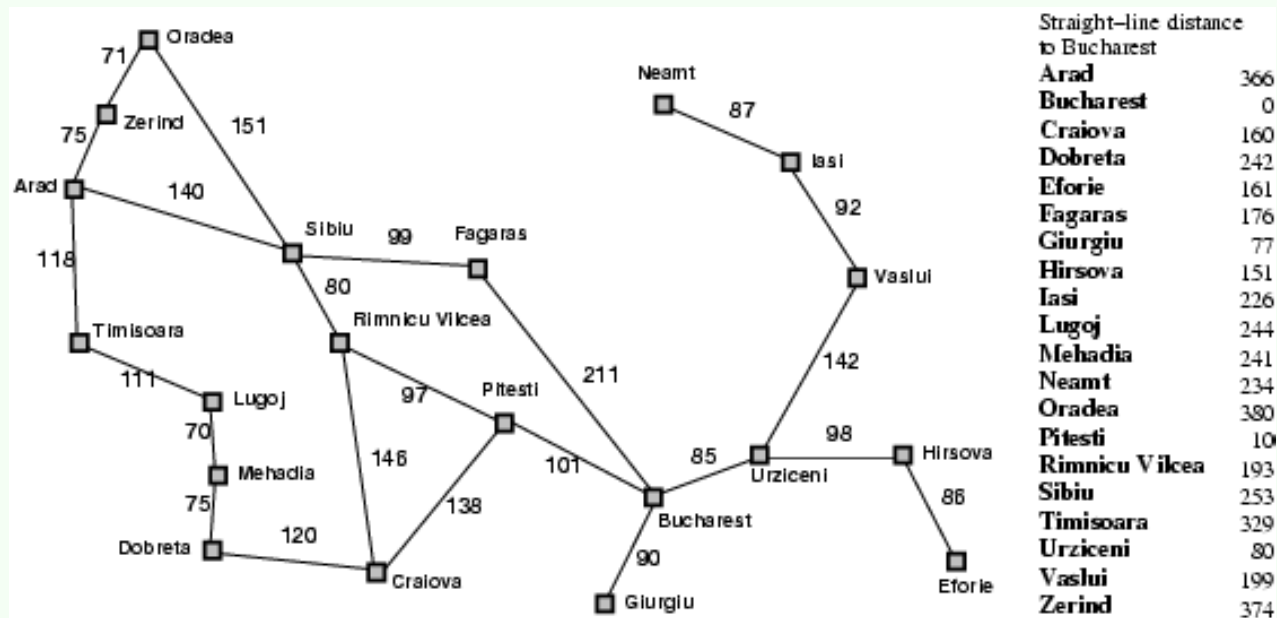
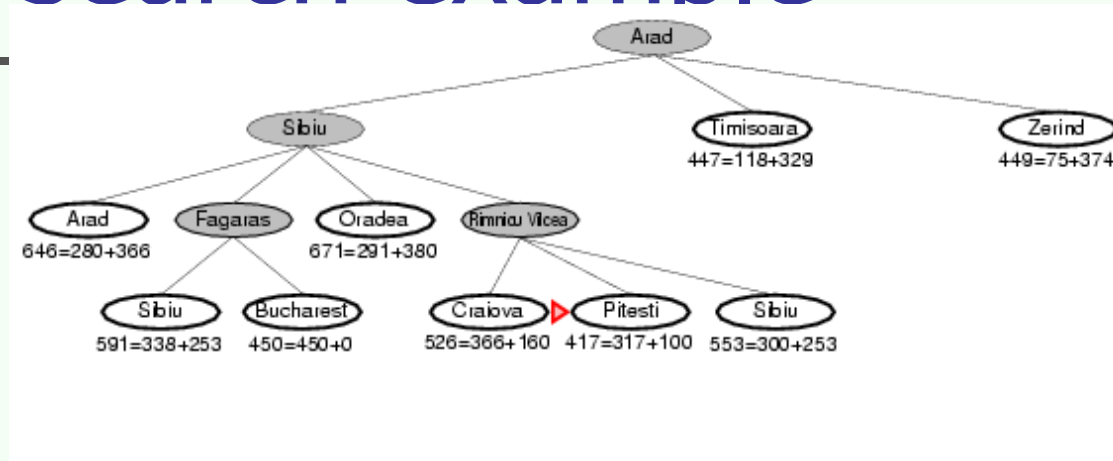


A* search example

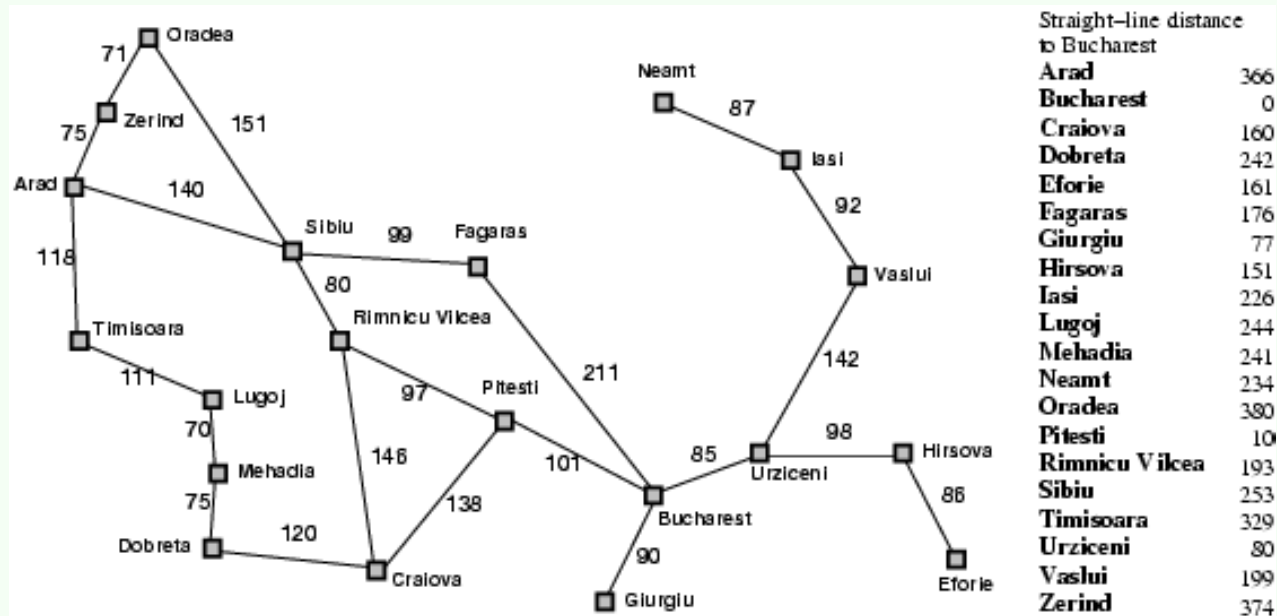
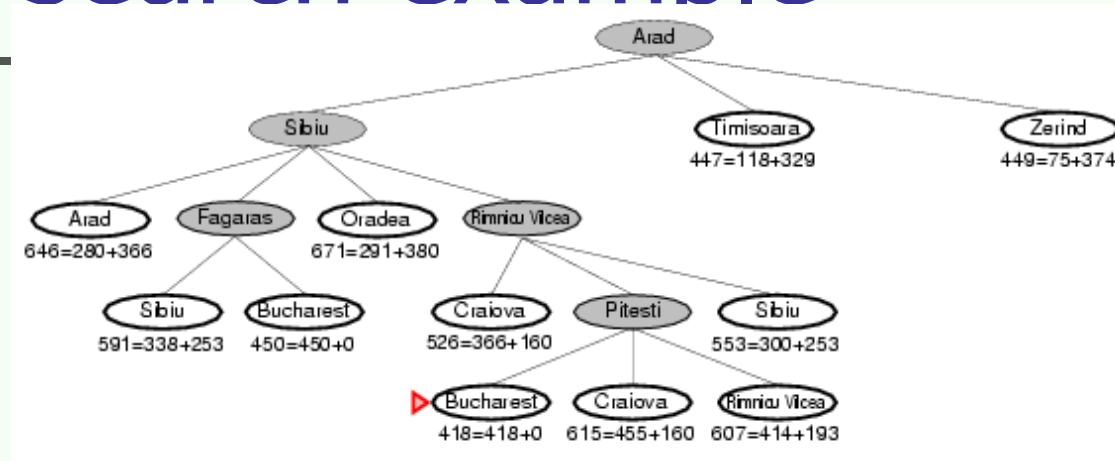




A* search example



A* search example





Properties of A*

- Complete? Yes (unless there are infinitely many nodes with $f \leq f(G)$, i.e. step-cost $> \varepsilon$)
- Time/Space? Exponential b^d
except if: $|h(n) - h^*(n)| \leq O(\log h^*(n))$
- Optimal? Yes
- Optimally Efficient: Yes (no algorithm with the same heuristic is guaranteed to expand fewer nodes)

Optimality of A^* (proof)

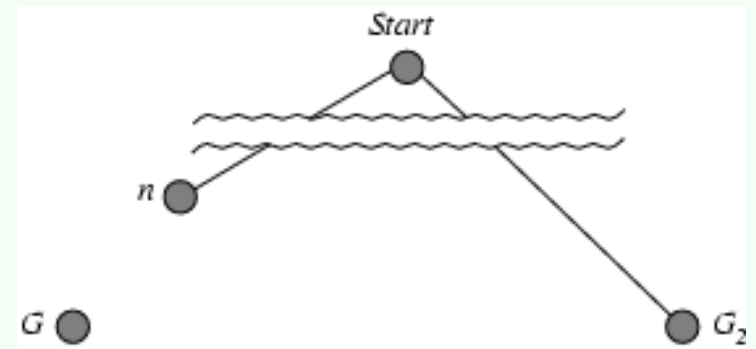
- Suppose some suboptimal goal G_2 has been generated and is in the fringe. Let n be an unexpanded node in the fringe such that n is on a shortest path to an optimal goal G .

We want to prove:

$f(n) < f(G_2)$

(then A^* will prefer n over G_2)

- $f(G_2) = g(G_2)$ since $h(G_2) = 0$
- $f(G) = g(G)$ since $h(G) = 0$
- $g(G_2) > g(G)$ since G_2 is suboptimal
- $f(G_2) > f(G)$ from above
- $h(n) \leq h^*(n)$
- $g(n) + h(n) \leq g(n) + h^*(n)$
- $f(n) \leq f(G)$
- $f(n) < f(G_2)$



since h is admissible (*under-estimate*)
 from above
 since $g(n) + h(n) = f(n)$ & $g(n) + h^*(n) = f(G)$
 from

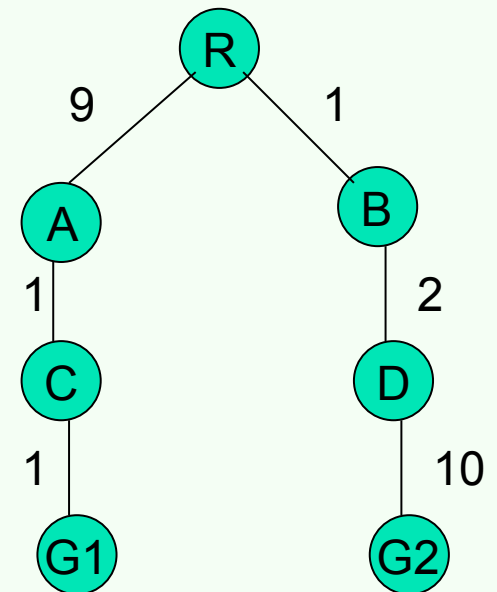


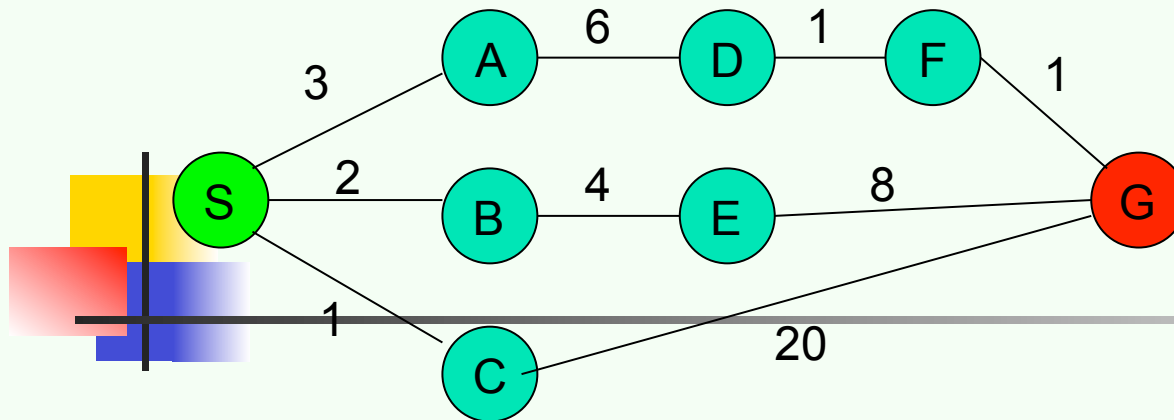
Exercise

1) Consider the search tree to the right.
There are 2 goal states, G1 and G2.
The numbers on the edges represent step-costs.
You also know the following heuristic estimates:
 $h(B \rightarrow G2) = 9$, $h(D \rightarrow G2) = 10$, $h(A \rightarrow G1) = 2$, $h(C \rightarrow G1) = 1$

a) *In what order will A* search visit the nodes? Explain your answer by indicating the value of the evaluation function for those nodes that the algorithm considers.*

SEARCH TREE





straight-line distances

$$h(S-G)=10$$

$$h(A-G)=7$$

$$h(D-G)=1$$

$$h(F-G)=1$$

$$h(B-G)=10$$

$$h(E-G)=8$$

$$h(C-G)=20$$

try yourself

The graph above shows the step-costs for different paths going from the start (S) to the goal (G). On the right you find the straight-line distances.

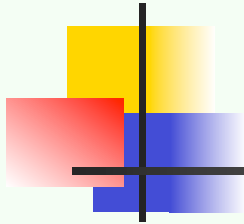
1. Draw the search tree for this problem. *Avoid repeated states.*
2. Give the order in which the tree is searched (e.g. S-C-B...-G) for A* search. Use the straight-line dist. as a heuristic function, i.e. $h=SLD$, and indicate for each node visited what the value for the evaluation function, f , is.



Memory Bounded Heuristic Search: Recursive BFS

- How can we solve the memory problem for A* search?
- Idea: Try something like depth first search, but let's not forget everything about the branches we have partially explored.
- *We remember the best f -value we have found so far in the branch we are deleting.*

RBFS:

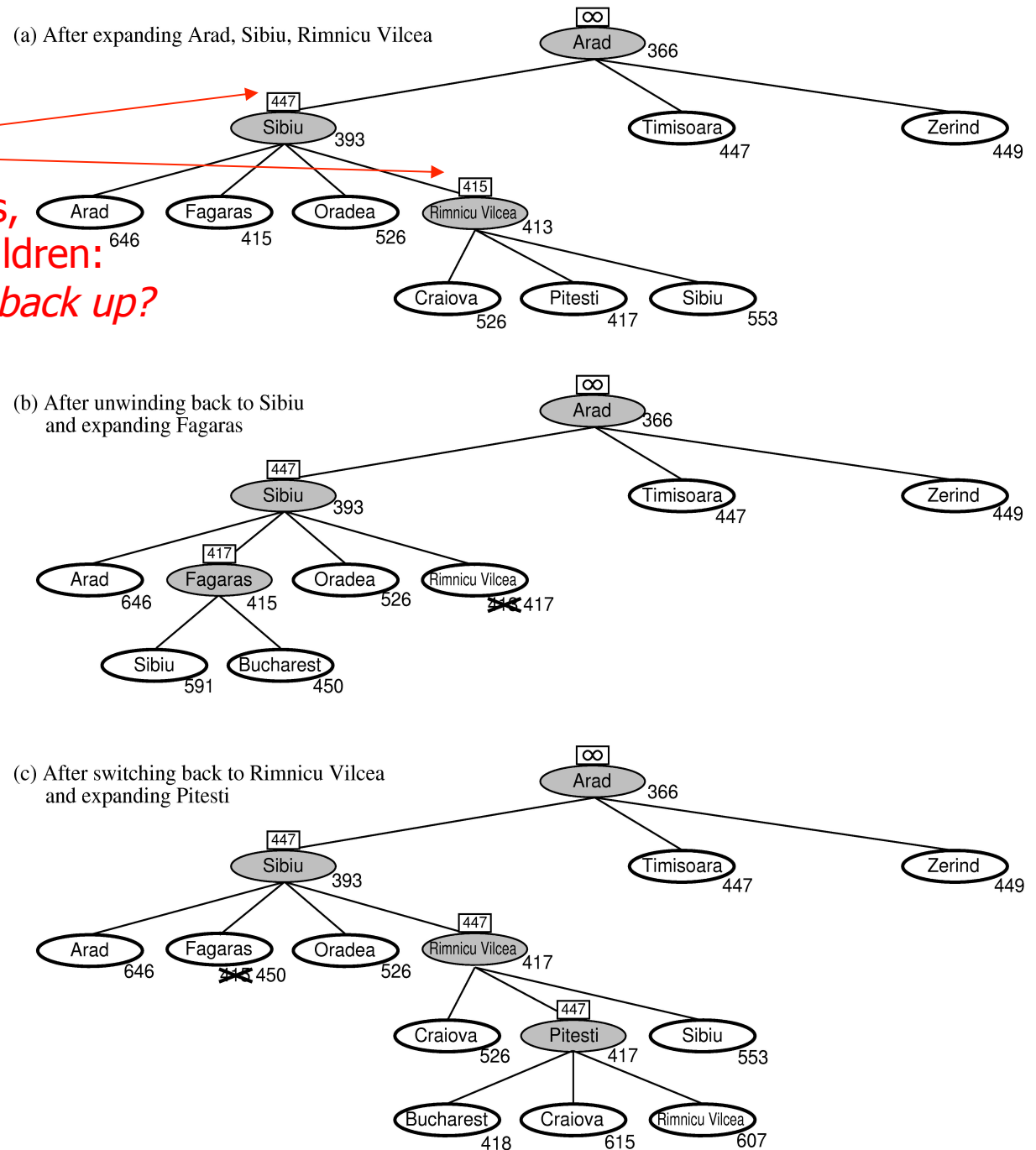


best alternative
over fringe nodes,
which are not children:
i.e. do I want to back up?

RBFS changes its mind
very often in practice.

This is because the
 $f=g+h$ become more
accurate (less optimistic)
as we approach the goal.
Hence, higher level nodes
have smaller f -values and
will be explored first.

Problem: We should keep
in memory whatever we can.



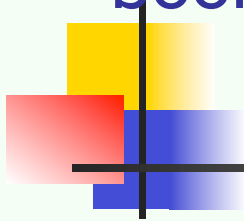


Simple Memory Bounded A*

- This is like A*, but when memory is full we delete the worst node (largest f-value).
- Like RBFS, we remember the best descendent in the branch we delete.
- If there is a tie (equal f-values) we delete the oldest nodes first.
- simple-MBA* finds the optimal *reachable* solution given the memory constraint.
- Time can still be exponential.

A Solution is not reachable
if a single path from root to goal
does not fit into memory

SMA* pseudocode (not in 2nd edition 2 of book)



function SMA*(*problem*) **returns** a solution sequence

inputs: *problem*, a problem

static: *Queue*, a queue of nodes ordered by *f*-cost

Queue \leftarrow MAKE-QUEUE({MAKE-NODE(INITIAL-STATE[*problem*])})

loop do

if *Queue* is empty **then return** failure

n \leftarrow deepest least-*f*-cost node in *Queue*

if GOAL-TEST(*n*) **then return** success

s \leftarrow NEXT-SUCCESSOR(*n*)

if *s* is not a goal and is at maximum depth **then**

f(*s*) $\leftarrow \infty$

else

f(*s*) \leftarrow MAX(*f*(*n*), *g*(*s*)+*h*(*s*))

if all of *n*'s successors have been generated **then**

 update *n*'s *f*-cost and those of its ancestors if necessary

if SUCCESSORS(*n*) all in memory **then** remove *n* from *Queue*

if memory is full **then**

 delete shallowest, highest-*f*-cost node in *Queue*

 remove it from its parent's successor list

 insert its parent on *Queue* if necessary

 insert *s* in *Queue*

end

Simple Memory-bounded A* (SMA*)

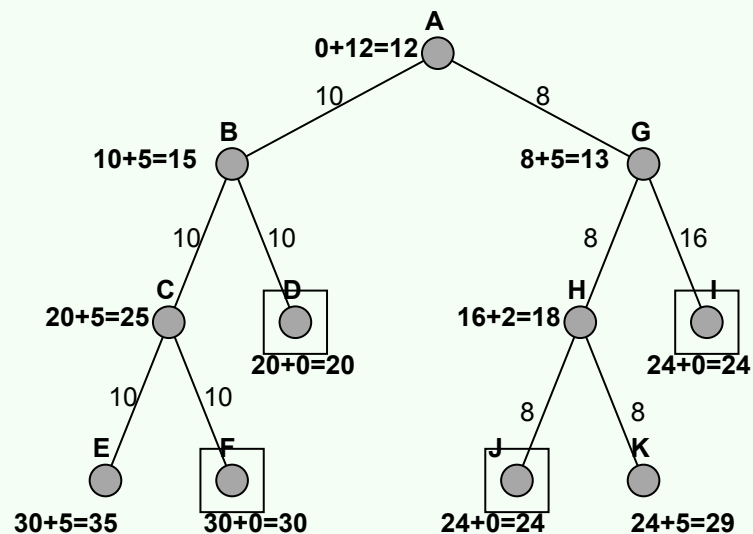
(Example with 3-node memory)

maximal depth is 3, since memory limit is 3. This branch is now useless.

Progress of SMA*. Each node is labeled with its *current* f -cost. Values in parentheses show the value of the best forgotten descendant.

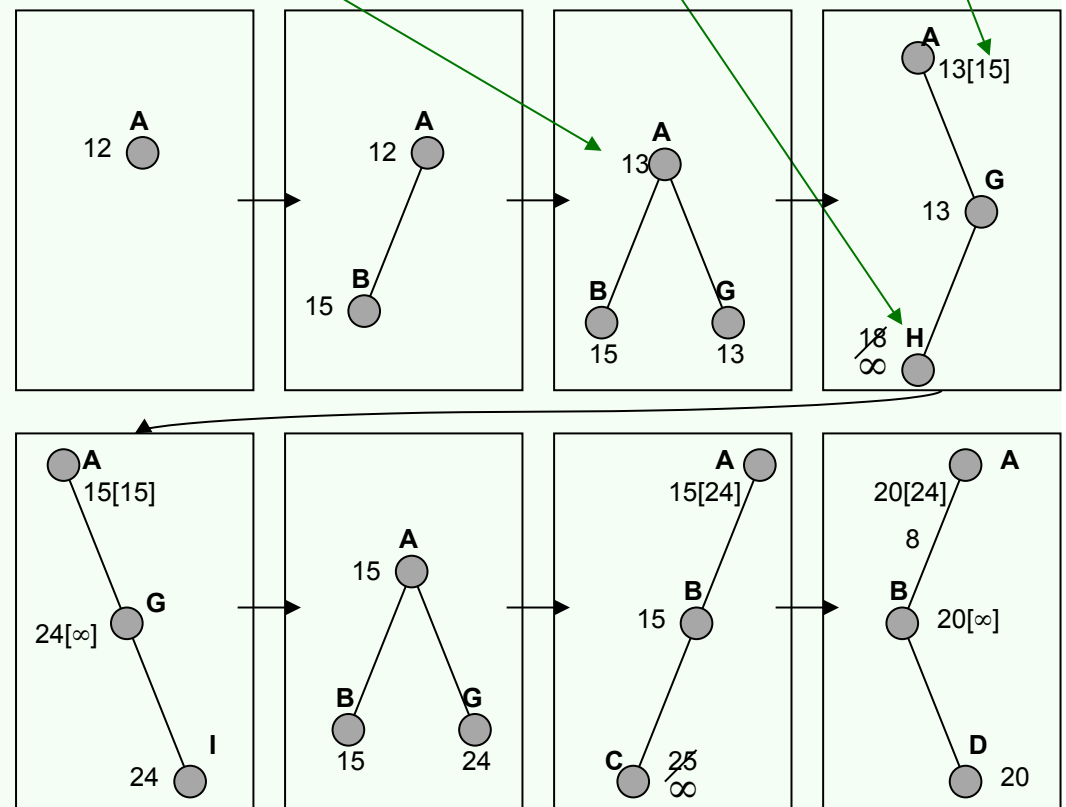
Search space

$f = g + h$ $\square = \text{goal}$

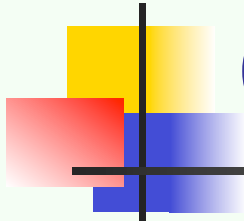


best estimated solution so far for that node

best forgotten node



Algorithm can tell you when best solution found within memory constraint is optimal or not.



Conclusions

- The Memory Bounded A* Search is the best of the search algorithms we have seen so far. It uses all its memory to avoid double work and uses smart heuristics to first descend into promising branches of the search-tree.