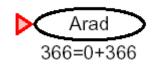
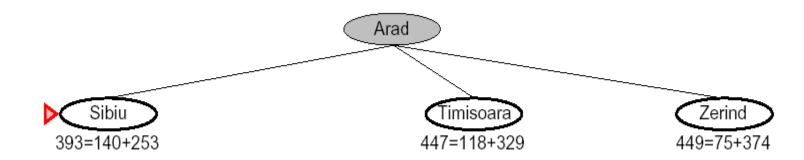
A* search

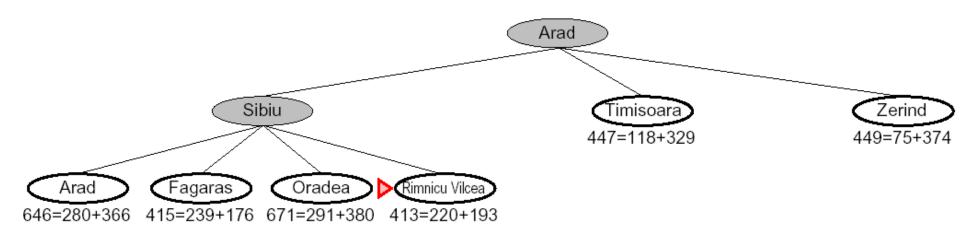
- Idea: avoid expanding paths that are already expensive
- Evaluation function f(n) = g(n) + h(n)

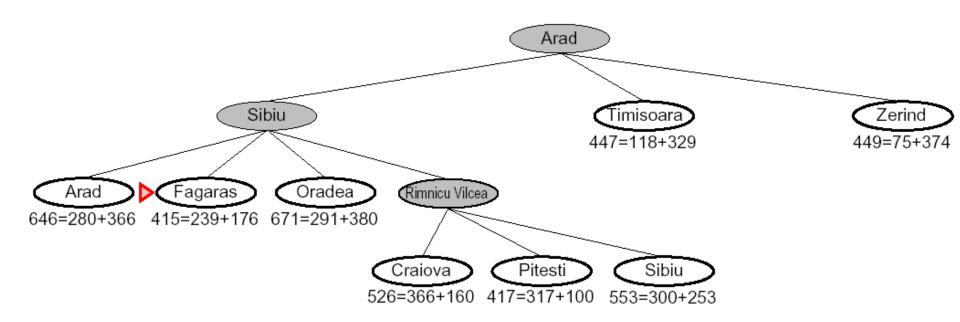
- $g(n) = \frac{\cos t}{\cos a} r$ to reach n
- h(n) = estimated cost from n to goal
- f(n) = estimated total cost of path through n to goal

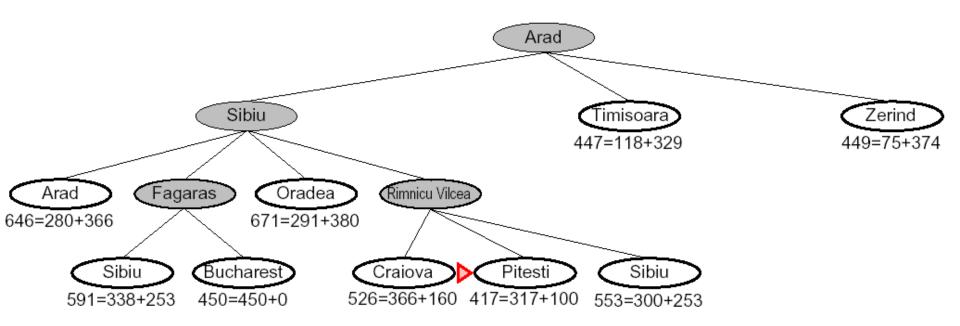
A* for Romanian Shortest Path

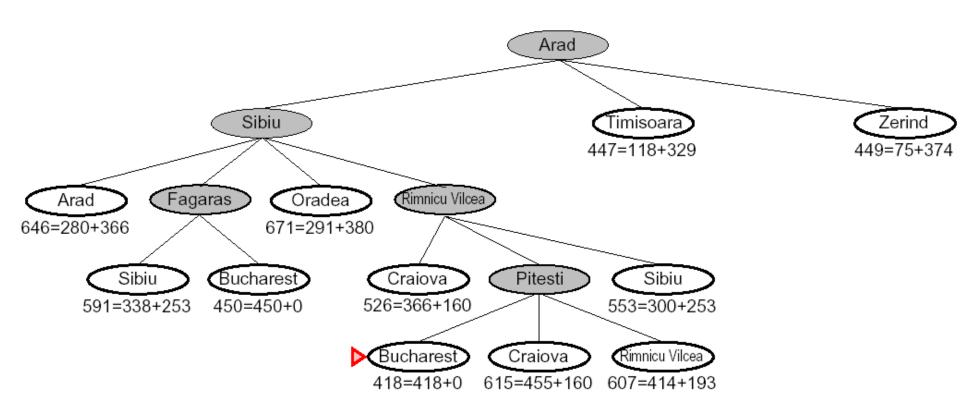










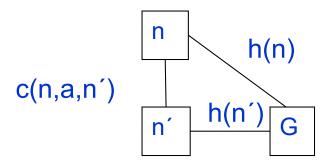


Admissible heuristics

- A heuristic function h(n) is admissible if for every node n, h(n) ≤ 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

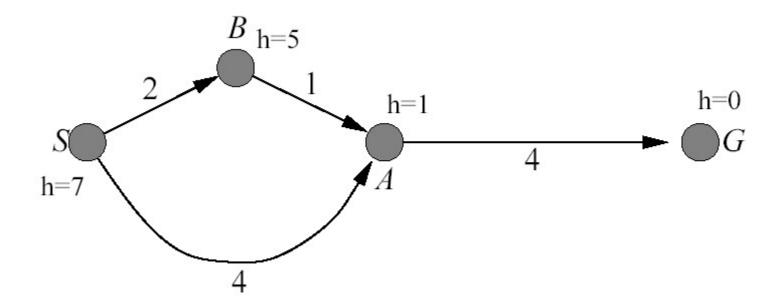
Consistent Heuristics

- h(n) is consistent if
 - for every node n
 - for every successor n´ due to legal action a
 - $-\frac{h(n)}{=c(n,a,n')+h(n')}$



- Every consistent heuristic is also admissible.
- Theorem: If h(n) is consistent, A* using GRAPH-SEARCH is optimal

Example



Source: http://stackoverflow.com/questions/25823391/suboptimal-solution-given-by-a-search

Proof of Optimality of (Tree) A*

• Assume h() is admissible. Say some sub-optimal goal state G_2 has been generated and is on the frontier. Let n be an unexpanded state such that n is on an optimal path to the optimal goal G.

G

Focus on G_2 :

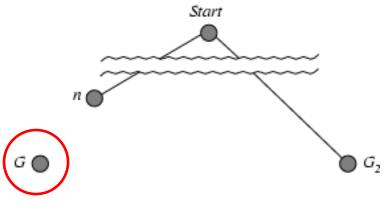
$$f(G_2) = g(G_2)$$
 since $h(G_2) = 0$
 $g(G_2) > g(G)$ since G_2 is suboptimal

Proof of Optimality of (Tree) A*

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goal G.



$$f(G_2) = g(G_2)$$
 since $h(G_2) = 0$

$$g(G_2) > g(G)$$
 since G_2 is suboptimal

Focus on G:

$$f(G) = g(G)$$
 since $h(G) = 0$

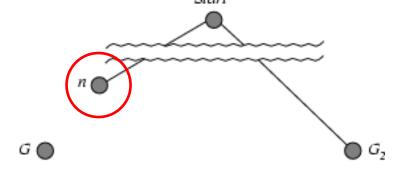
$$f(G_2) > f(G)$$
 substitution

Proof of Optimality of (Tree)A*

• Assume *h*() is admissible.

Say some sub-optimal goal state G_2 has been generated and is on the frontier. Let n be an unexpanded state such that n is on an optimal path to the optimal

goal G.



$$f(G_2) = g(G_2)$$
 since $h(G_2) = 0$
 $g(G_2) > g(G)$ since G_2 is suboptimal

$$f(G) = g(G)$$
 since $h(G) = 0$
 $f(G_2) > f(G)$ substitution

Now focus on n:

$$h(n) \le h^*(n)$$
 since h is admissible $g(n) + h(n) \le g(n) + h^*(n)$ algebra $f(n) = g(n) + h(n)$ definition $f(G) = g(n) + h^*(n)$ by assumption $f(n) \le f(G)$ substitution

Hence $f(G_2) > f(n)$, and A* will never select G_2 for expansion.

Properties of A*

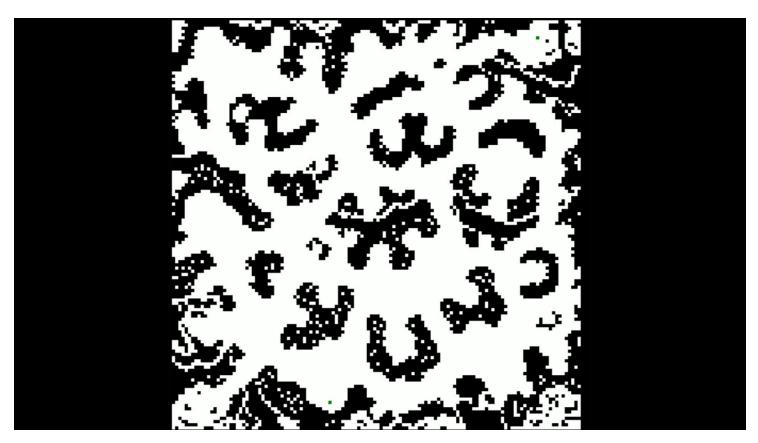
Complete?

Yes (unless there are infinitely many nodes with $f \le f(G)$)

- <u>Time?</u> Exponential (worst case all nodes are added)
- Space? Keeps all nodes in memory
- Optimal?

Yes (depending upon search algo and heuristic property)

A*



http://www.youtube.com/watch?v=huJEgJ82360

Memory Problem?

- Iterative deepening A*
 - Similar to ID search

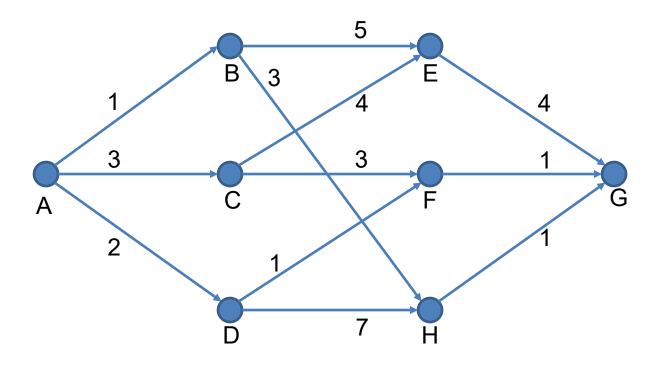
- While (solution not found)
 - Do DFS but prune when cost (f) > current bound
 - Increase bound

Depth First Branch and Bound

2 mechanisms:

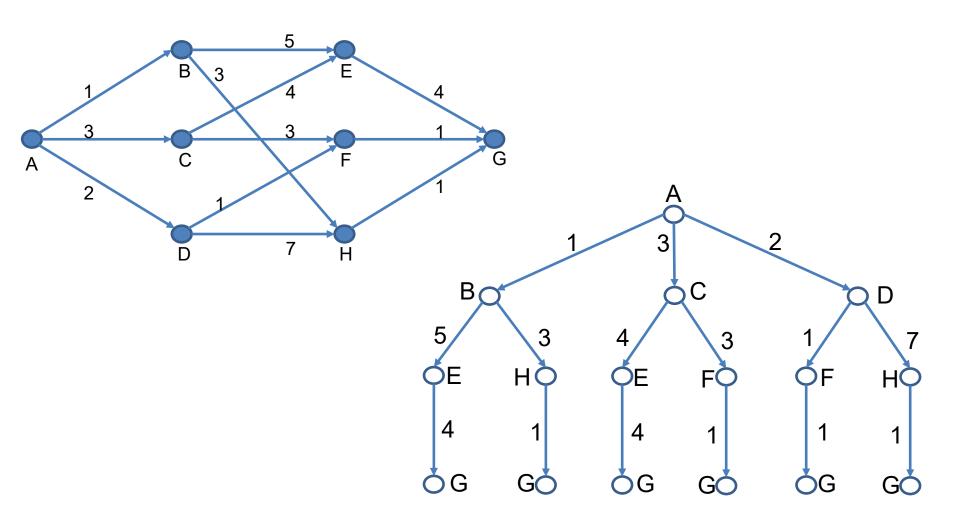
- BRANCH: A mechanism to generate branches when searching the solution space
 - Heuristic strategy for picking which one to try first.
- BOUND: A mechanism to generate a bound so that many branches can be terminated

Example



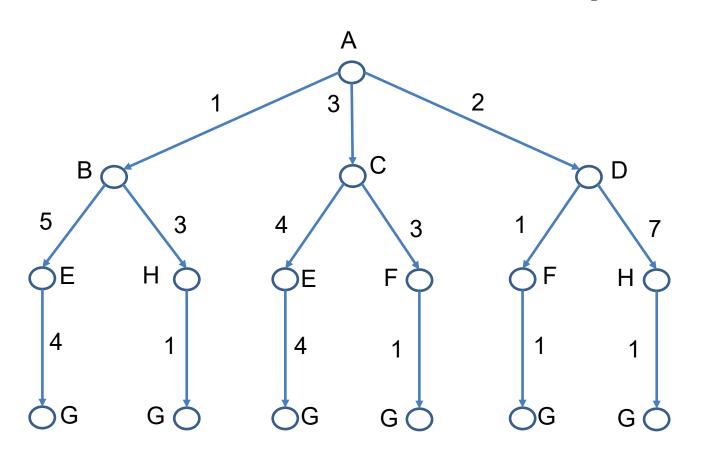
Find optimal path from A to G

Search Tree

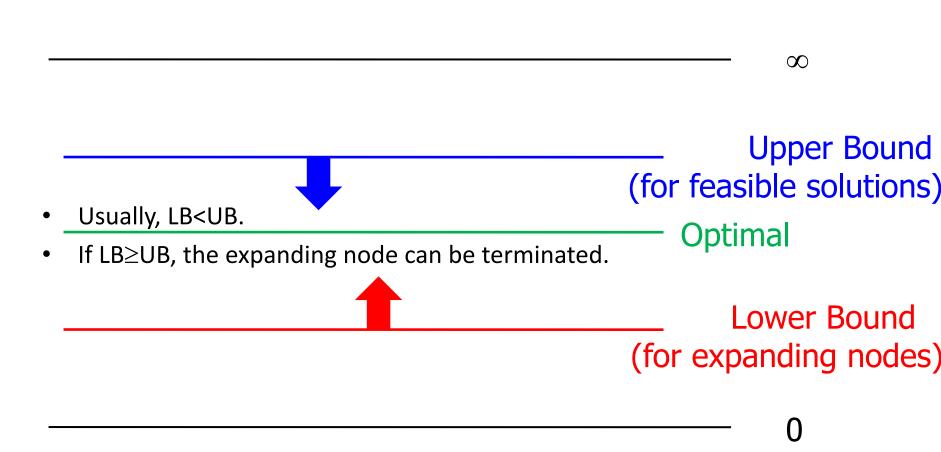


DFS B&B

E.g., Branch policy: take lowest cost edge first



For Minimization Problems



DFS B&B vs. IDA*

- Both optimal
- IDA* never expands a node with f > optimal cost
 - But not systematic
- DFb&b systematic never expands a node twice
 - But expands suboptimal nodes also
- Search tree of bounded depth?
- Easy to find suboptimal solution?
- Infinite search trees?
- Difficult to construct a single solution?

Non-optimal variations

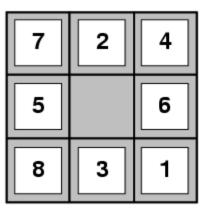
Use more informative, but inadmissible heuristics

- Weighted A*
 - -f(n) = g(n) + w.h(n) where w>1
 - Typically w=5.
 - Solution quality bounded by w for admissible h

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)



Start State

Goal State

•
$$h_1(S) = ?$$

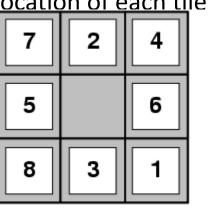
• $h_2(S) = ?$

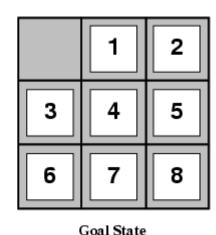
Admissible heuristics

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)





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

Dominance

- If $h_2(n) \ge h_1(n)$ for all n (both admissible) then h_2 dominates h_1
- h₂ is better for search
- Typical search costs (average number of node 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

Hamiltonian Cycle Problem

What can be relaxed?

Solution =

- 1) Each node degree 2
- 2) Visit all nodes
- 3) Visit nodes exactly once

What is a good admissible heuristic for $(a1 \rightarrow a2 \rightarrow ... \rightarrow ak)$

- length of the cheapest edge leaving ak +
 length of cheapest edge entering a1
- length of shortest path from ak to a1
- length of minimum spanning tree of rest of the nodes