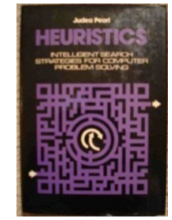
# Set 3: Informed Heuristic Search

ICS 271 Fall 2012

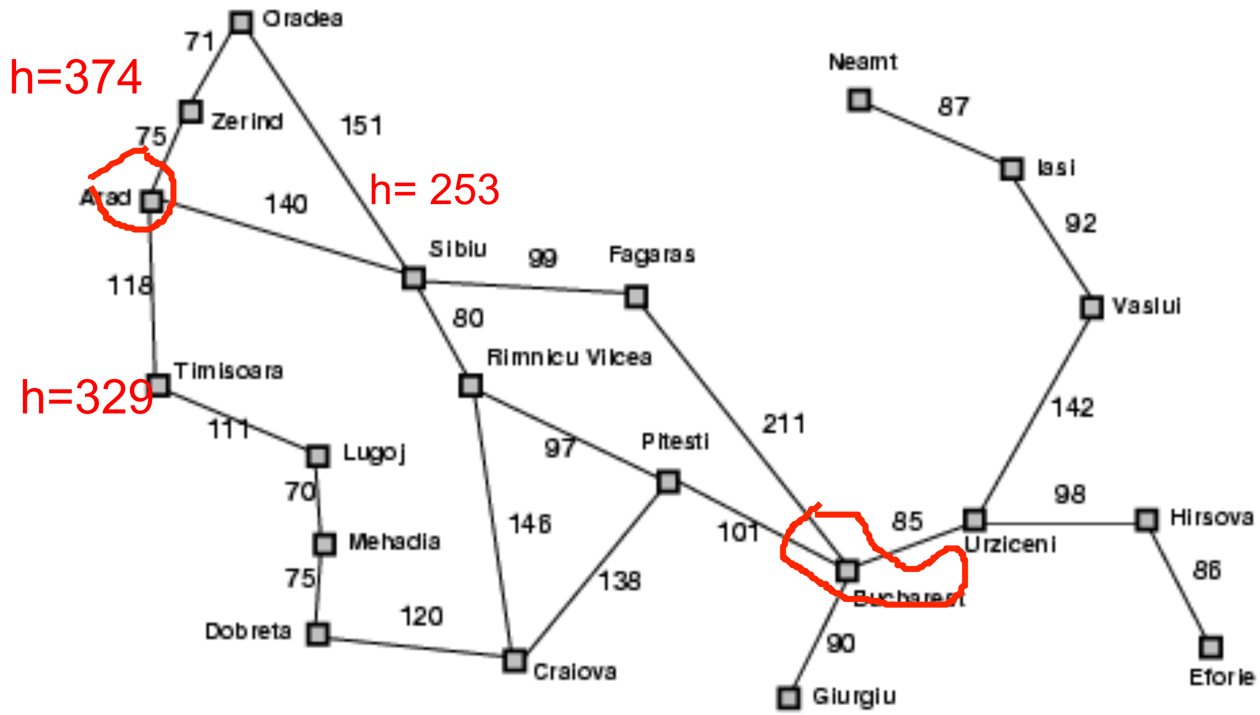
# Overview

- Heuristics and Optimal search strategies
  - heuristics
  - hill-climbing algorithms
  - Best-First search
  - A*: optimal search using heuristics
  - Properties of A*
    - admissibility,
    - consistency,
    - accuracy and dominance
    - Optimal efficiency of A*
  - Branch and Bound
  - Iterative deepening A*
  - Automatic generation of heuristics

# Heuristic Search




- State-Space Search: every problem is like search of a map
- A problem solving robot finds a path in a state-space graph from start state to goal state, using heuristics




Straight–line distance to Bucharest

| | |
|---|---|
| **Arad** | 366 |
| **Bucharest** | 0 |
| **Craiova** | 160 |
| **Dobreta** | 242 |
| **Eforie** | 161 |
| **Fagaras** | 176 |
| **Giurgiu** | 77 |
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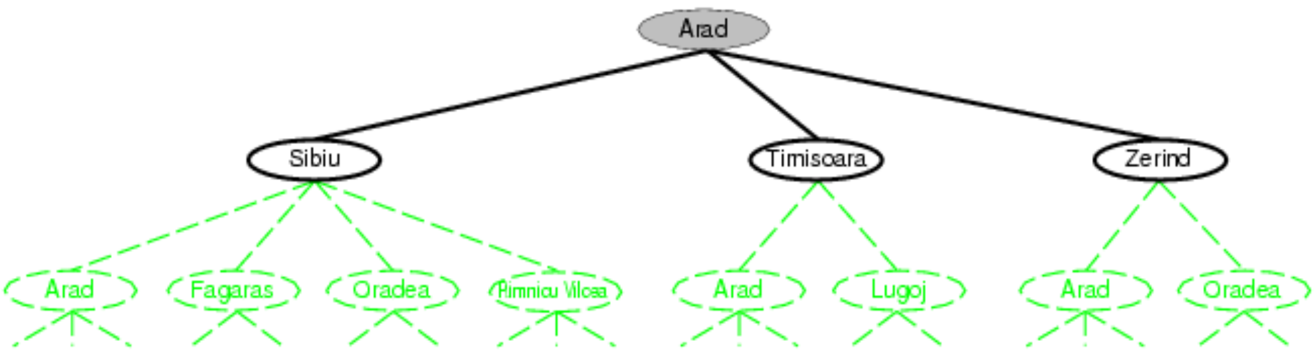
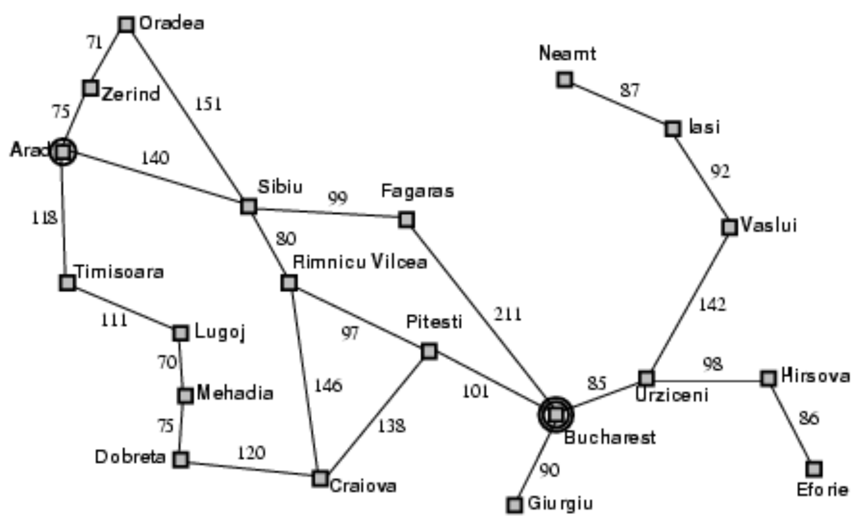
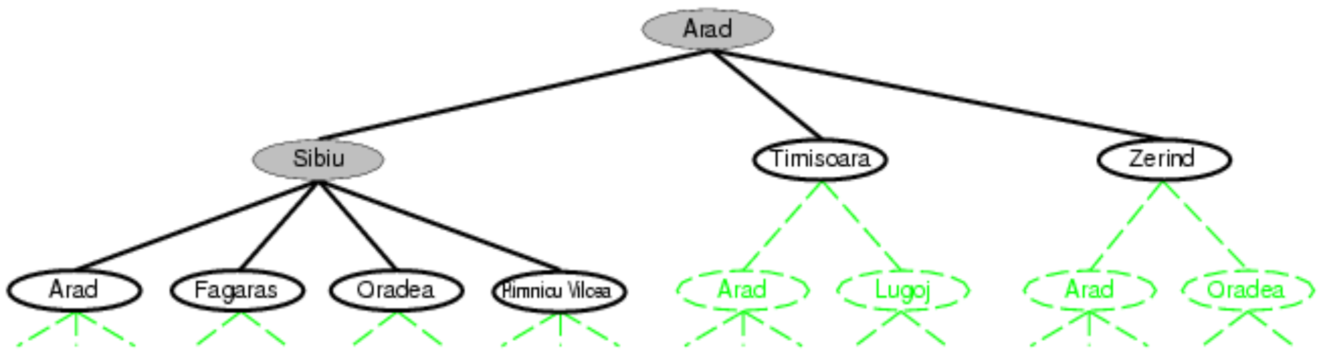
Heuristic = air distance

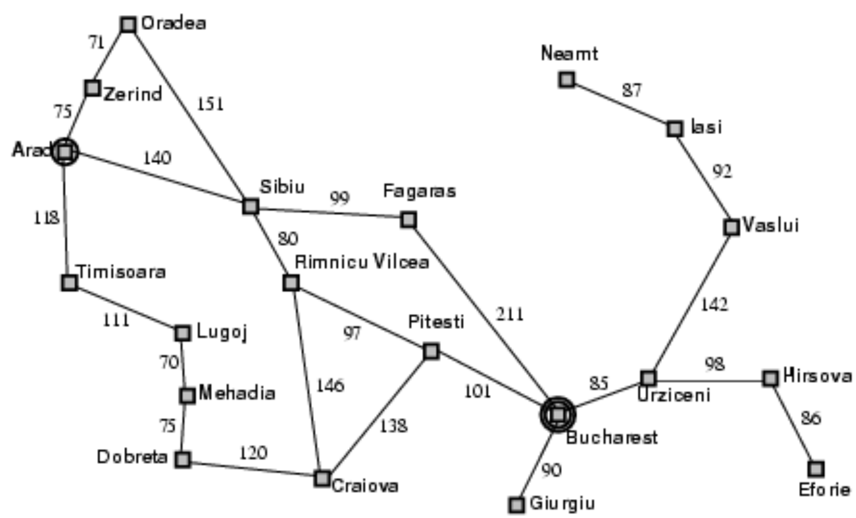
# State Space for Path Finding in a Map



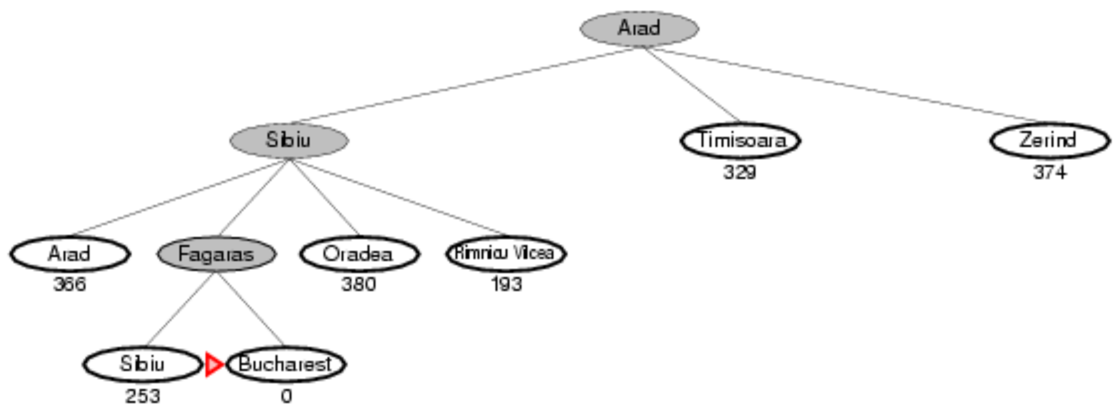



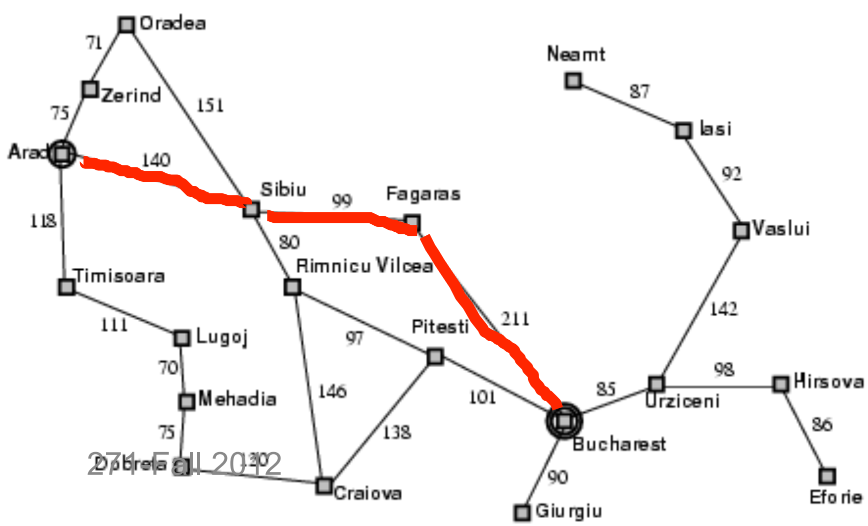
# State Space for Path Finding in a Map



# Greedy Search Example



# State Space of the 8 Puzzle Problem

Initial state

goal

| | | |
|---|---|---|
| 1 | 2 | 3 |
| 4 | 5 | 6 |
| 7 | 8 | |

**8-puzzle: 181,440 states**
**15-puzzle: 1.3 trilion**
**24-puzzle: 10^25**

**Search space exponential**

**Use Heuristics as people do**

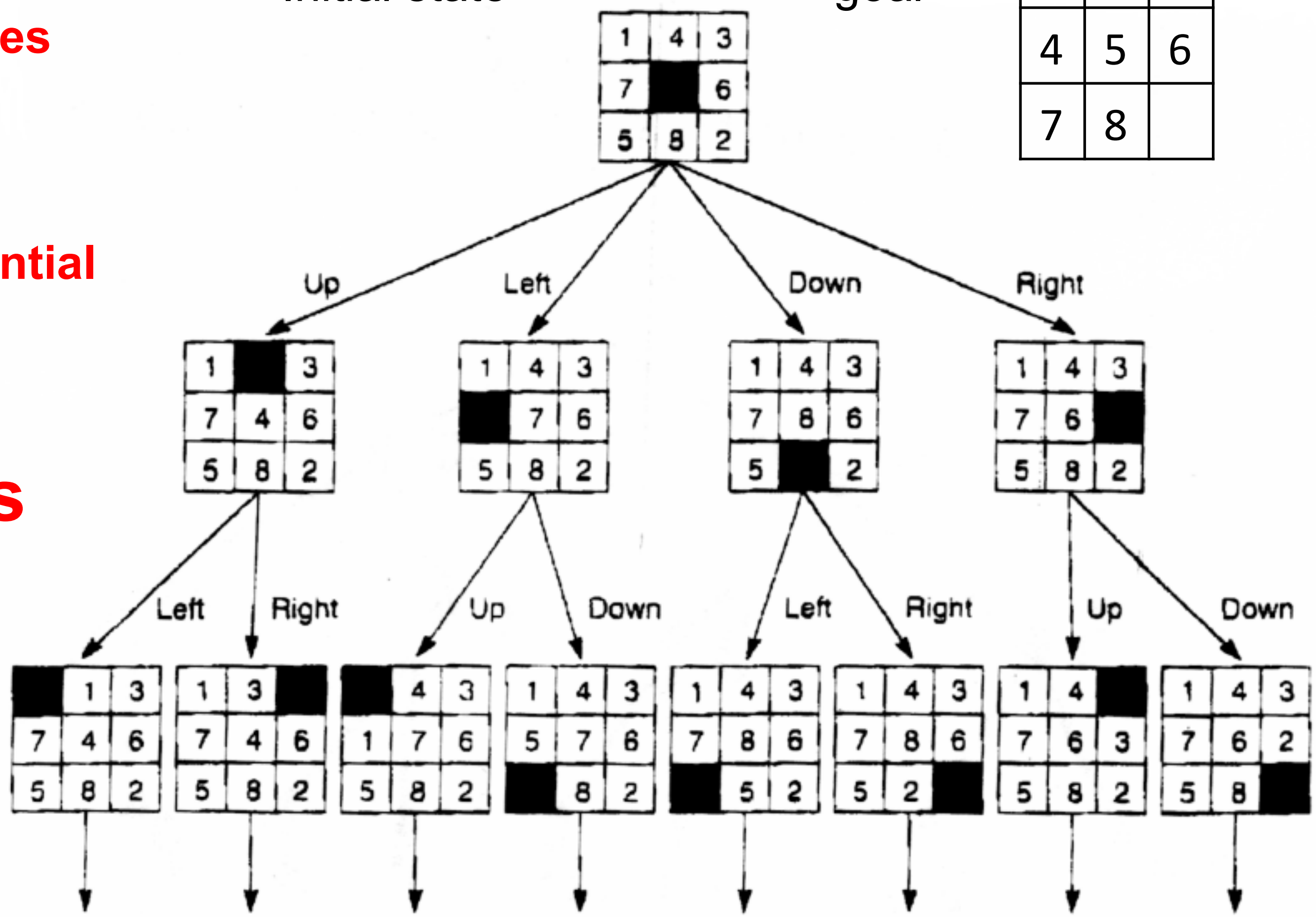



**Figure 3.6** State space of the 8-puzzle generated by "move blank" operations.

# State Space of the 8 Puzzle Problem

| | | |
|---|---|---|
| 1 | 2 | 3 |
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**h1 = number of misplaced tiles**

**h2 = Manhattan distance**

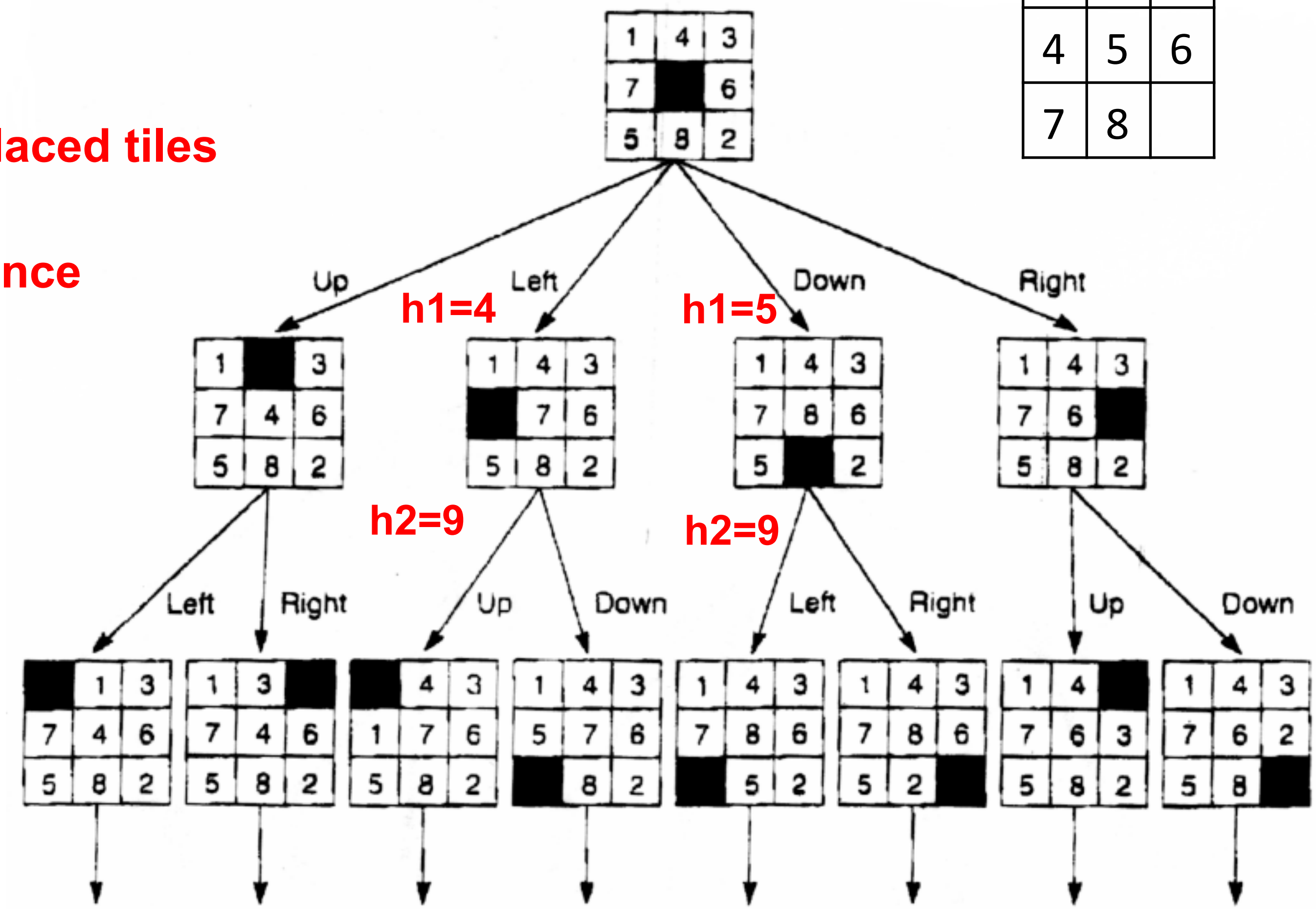
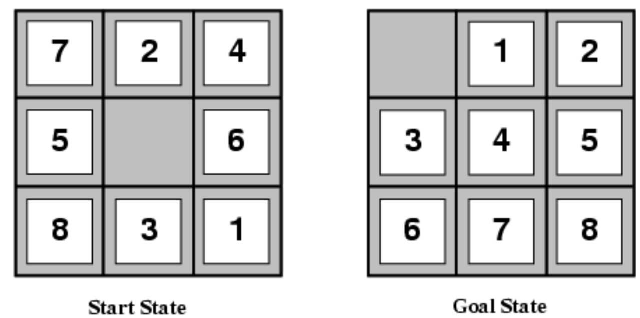



**Figure 3.6** State space of the 8-puzzle generated by "move blank" operations.

# What are Heuristics

- **Rule of thumb, intuition**
- **A quick way to estimate how close we are to the goal. How close is a state to the goal..**
- Pearl: "the ever-amazing observation of how much people can accomplish with that simplistic, unreliable information source known as *intuition*."



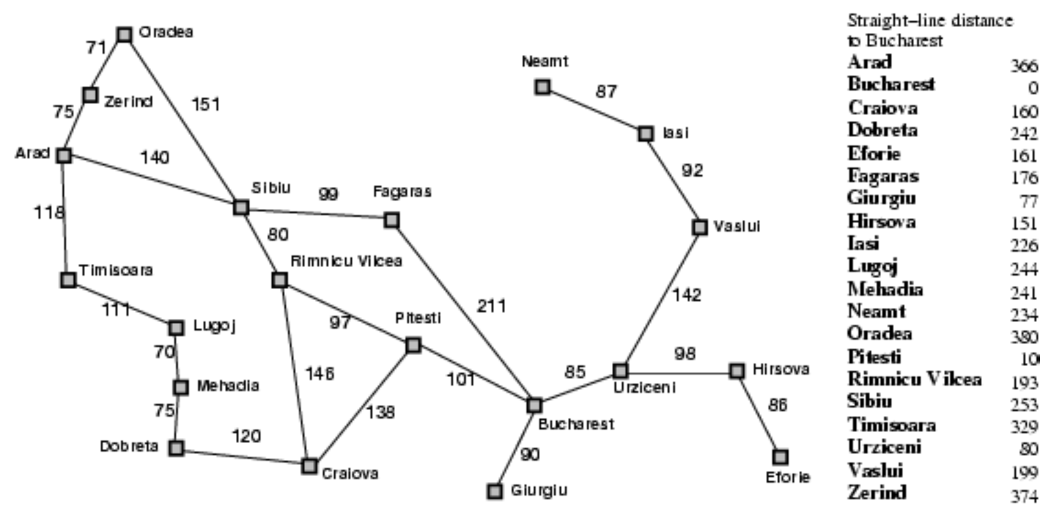

8-puzzle

- **h1(n): number of misplaced tiles**
- **h2(n): Manhattan distance**

$h_1(S) = ?$ 8

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

- Path-finding on a map
  - Euclidean distance

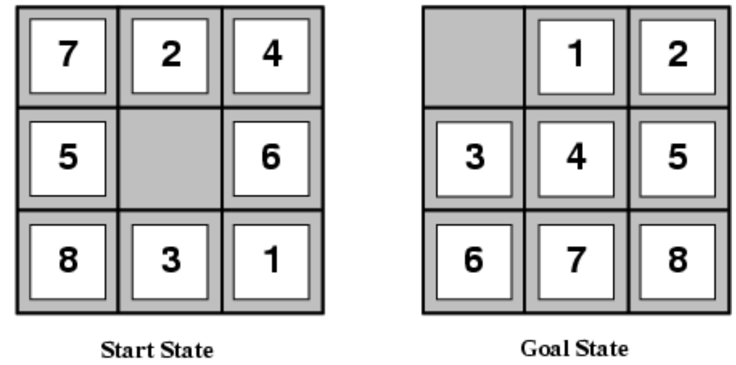


# Problem: Finding a Minimum Cost Path

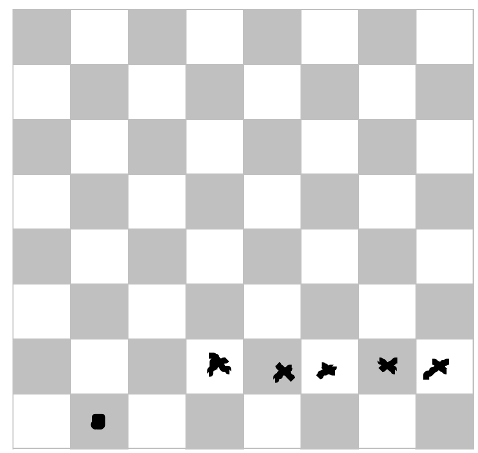
- Previously we wanted an arbitrary path to a goal or best cost. Now, we want the minimum cost path to a goal G
  - Cost of a path = sum of individual transitions along path
- Examples of path-cost:
  - Navigation
    - path-cost = distance to node in miles
      - minimum => minimum time, least fuel
  - VLSI Design
    - path-cost = length of wires between chips
      - minimum => least clock/signal delay
  - 8-Puzzle
    - path-cost = number of pieces moved
      - minimum => least time to solve the puzzle
- Algorithm: Uniform-cost search… still somewhat blind

# Heuristic Functions

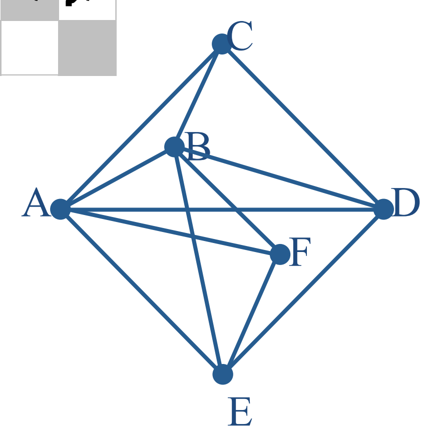
- 8-puzzle
  - Number of misplaced tiles
  - Manhatten distance
  - Gaschnig’s




- 8-queen
  - Number of future feasible slots
  - Min number of feasible slots in a row
  - Min number of conflicts (in complete assignments states)



- Travelling salesperson
  - Minimum spanning tree
  - Minimum assignment problem



# Best-First (Greedy) Search:
# f(n) = number of misplaced tiles

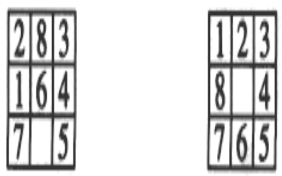
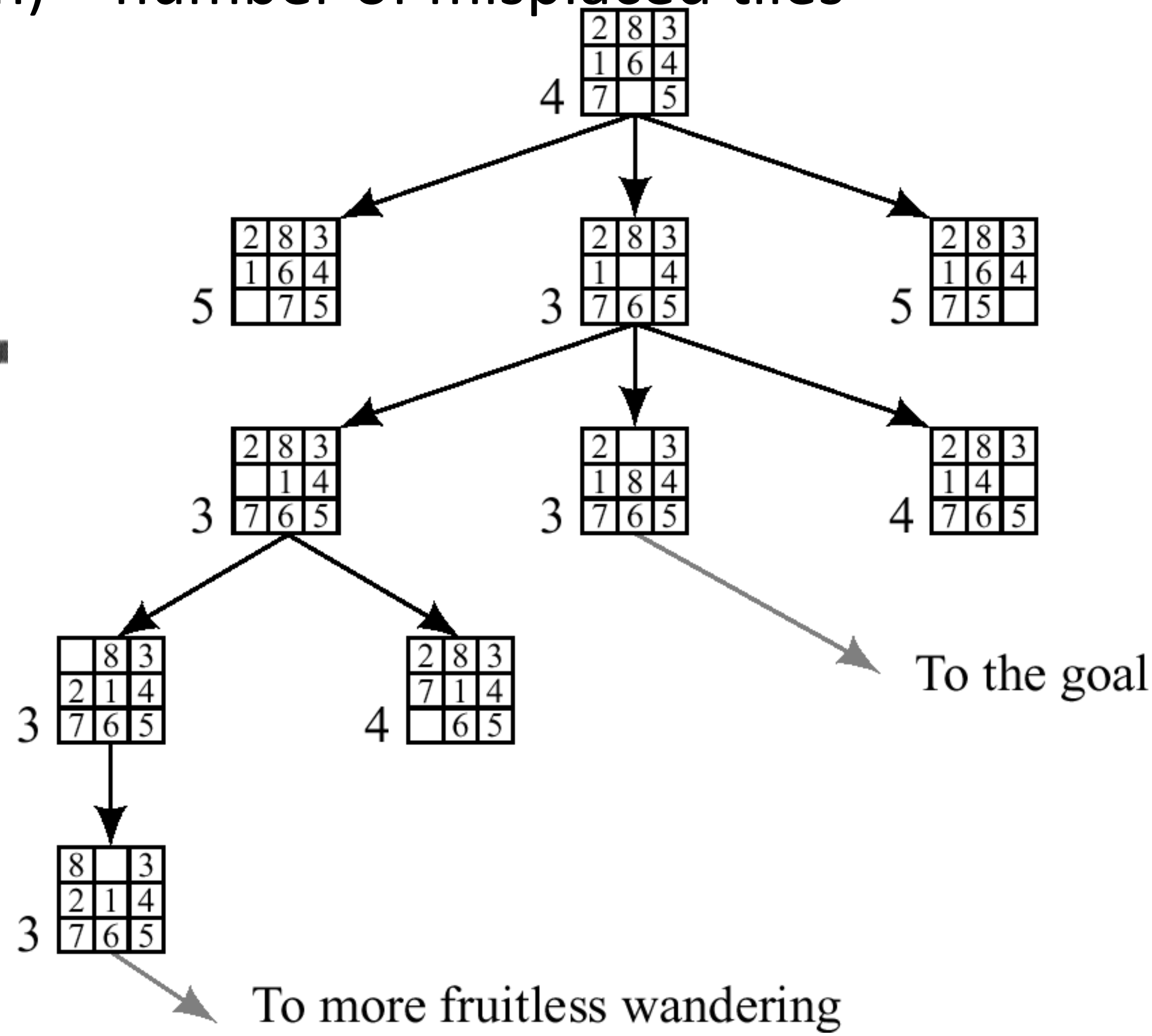
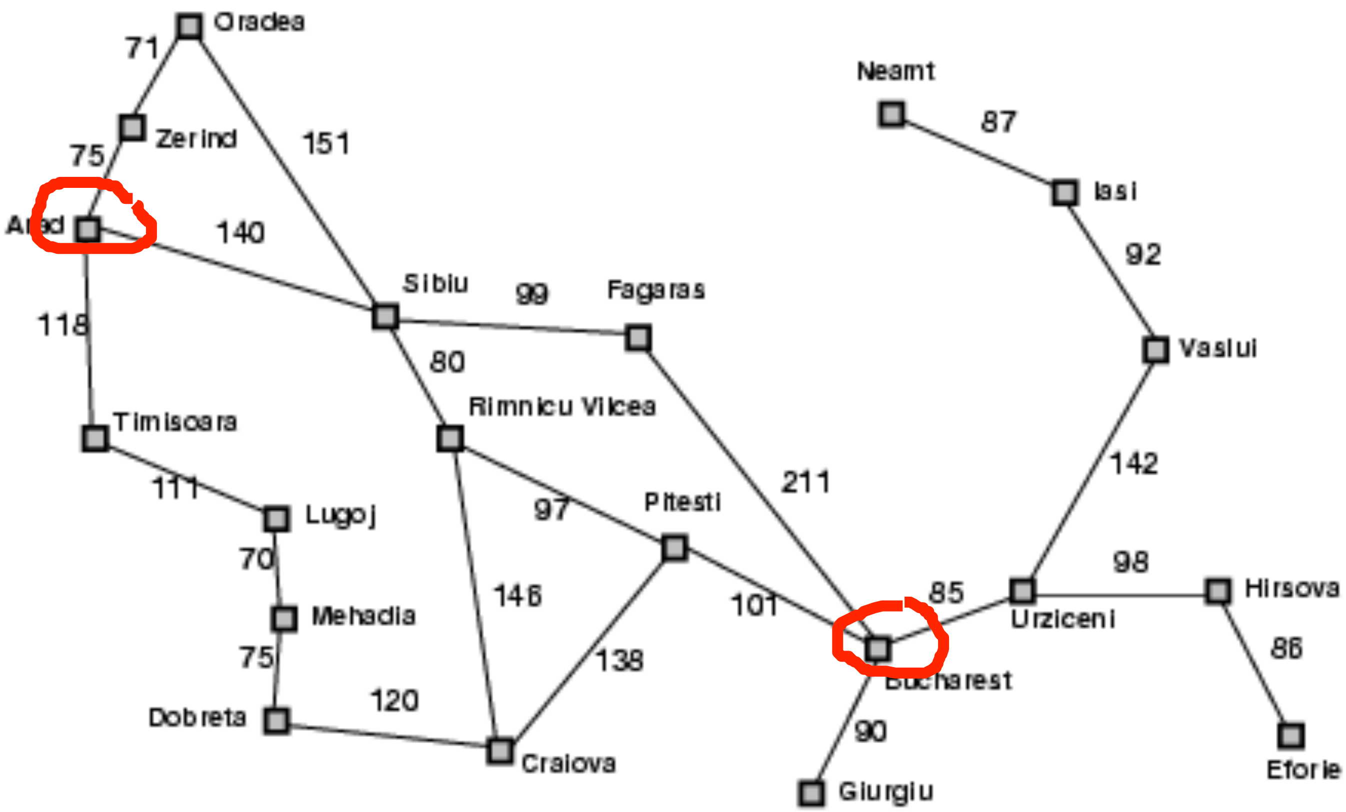


Figure 8.1

Start and Goal Configurations for the Eight-Puzzle



# Romania with Step Costs in km

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# Greedy Best-First Search

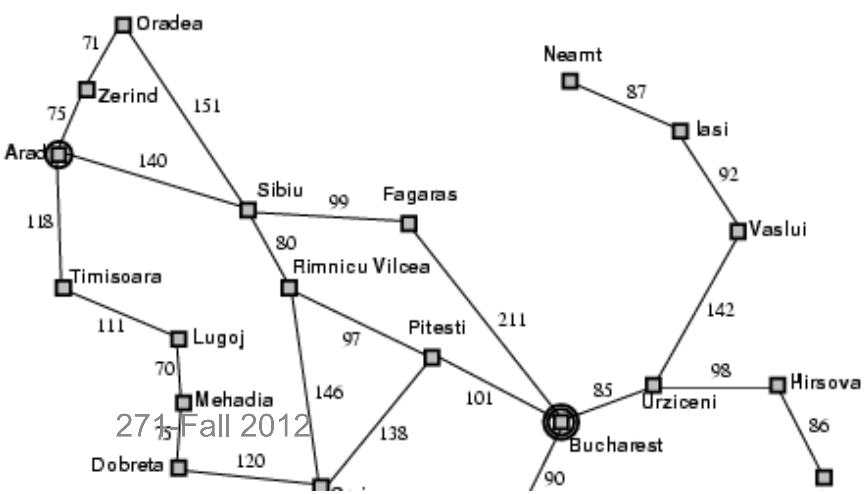
- Evaluation function $f(n) = h(n)$ (heuristic)
- = estimate of cost from *n* to *goal*

- e.g., $h_{SLD}(n)$ = 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

# Greedy Best-First Search Example

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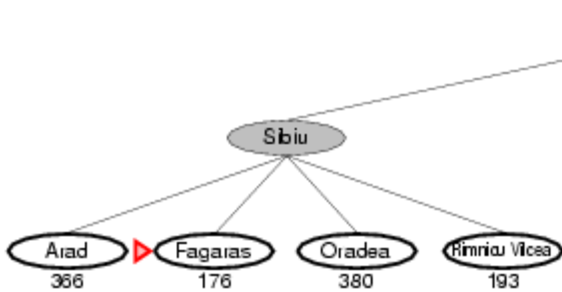


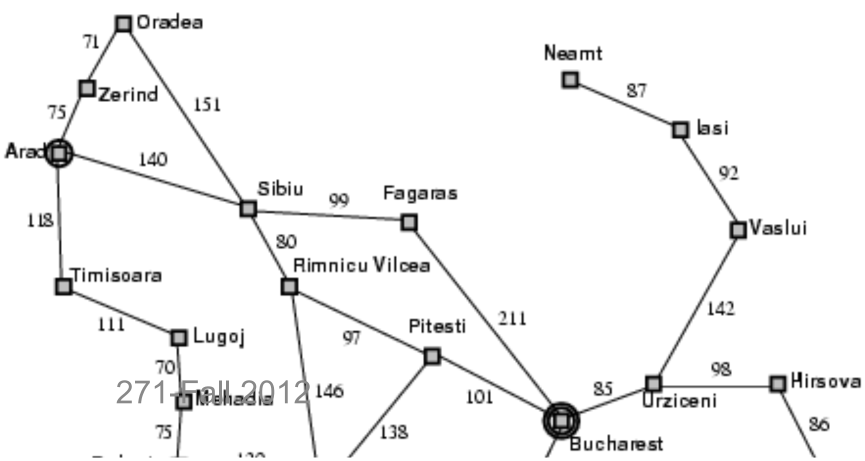

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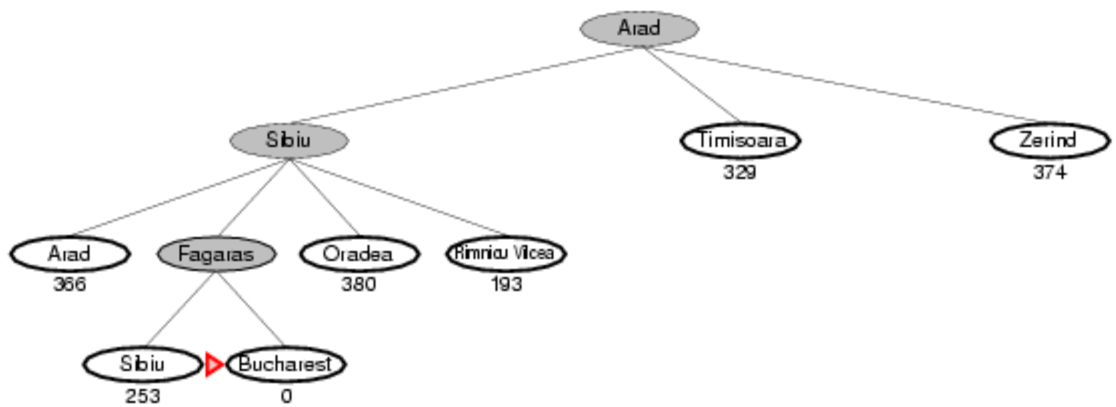
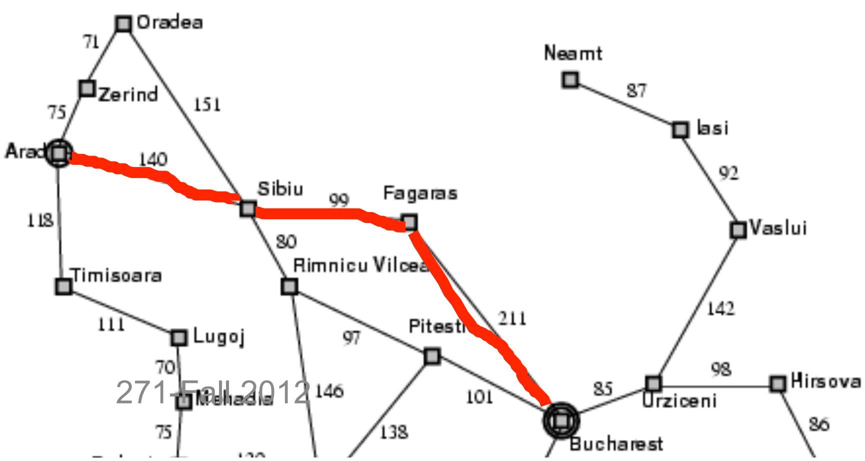


# Problems with Greedy Search

- Not complete
- Get stuck on local minimas and plateaus,
- Irrevocable,
- Infinite loops
- Can we incorporate heuristics in systematic search?

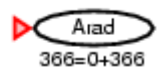
# Informed Search - Heuristic Search

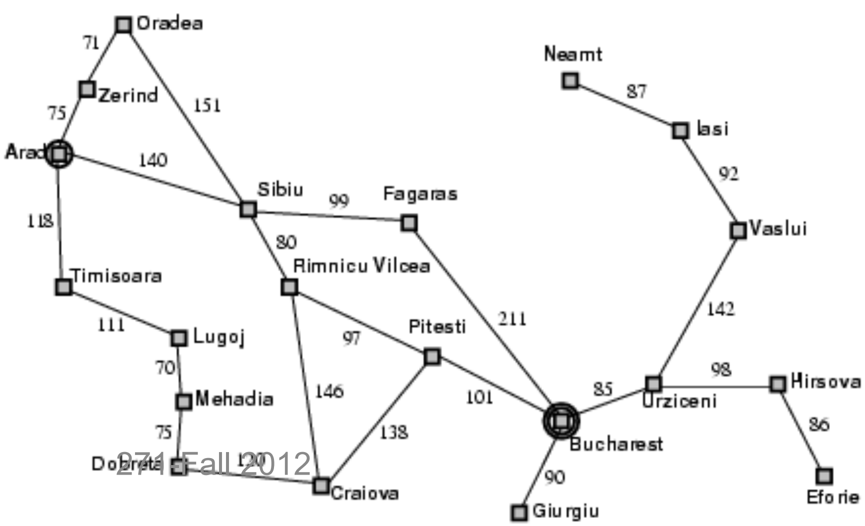
- How to use heuristic knowledge in systematic search?
- Where ? (in node expansion? hill-climbing ?)
- Best-first:
  - select the best from **all** the nodes encountered so far in OPEN.
  - "good" use heuristics
- Heuristic estimates value of a node
  - promise of a node
  - difficulty of solving the subproblem
  - quality of solution represented by node
  - the amount of information gained.
- f(n)- heuristic evaluation function.
  - depends on n, goal, search so far, domain

# $A^*$ 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

# A* Search Example



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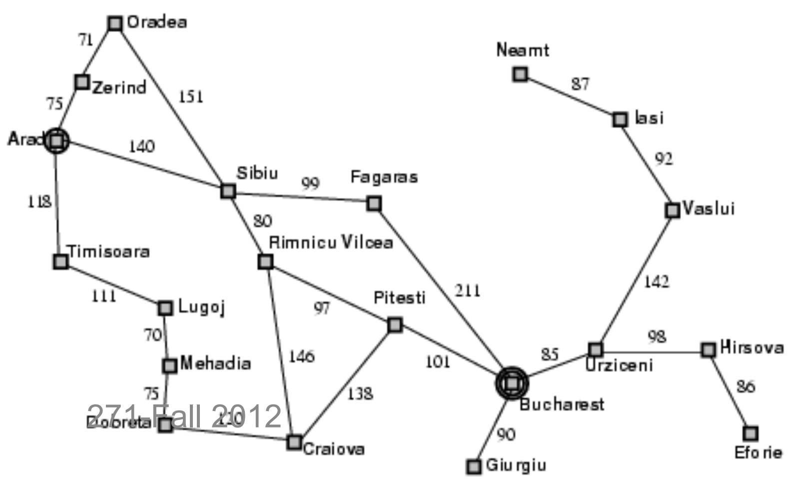

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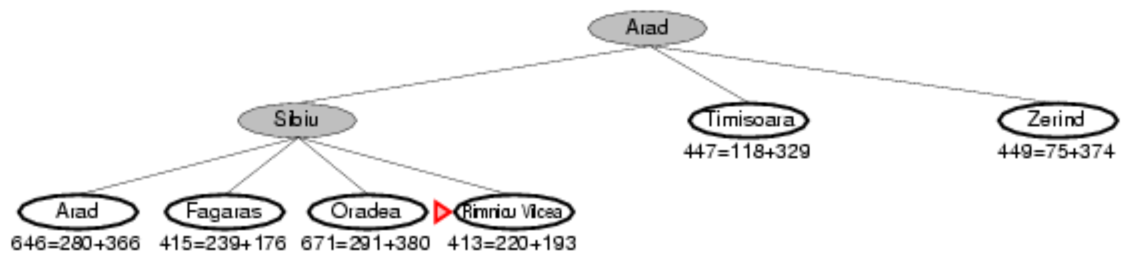
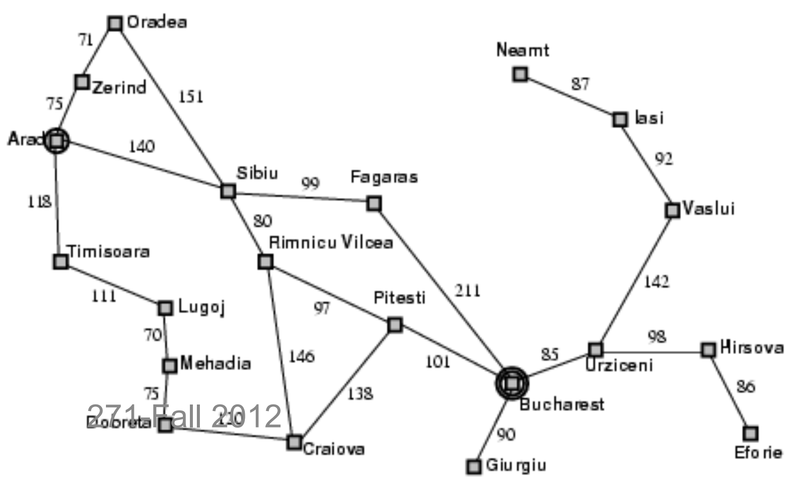
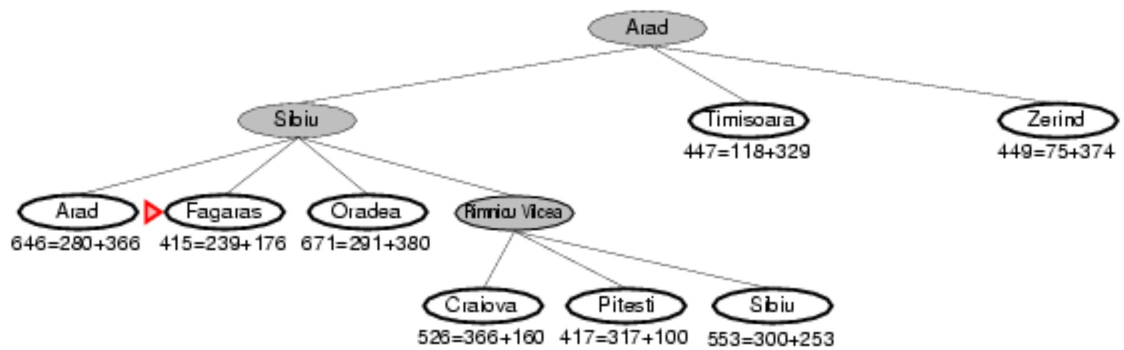
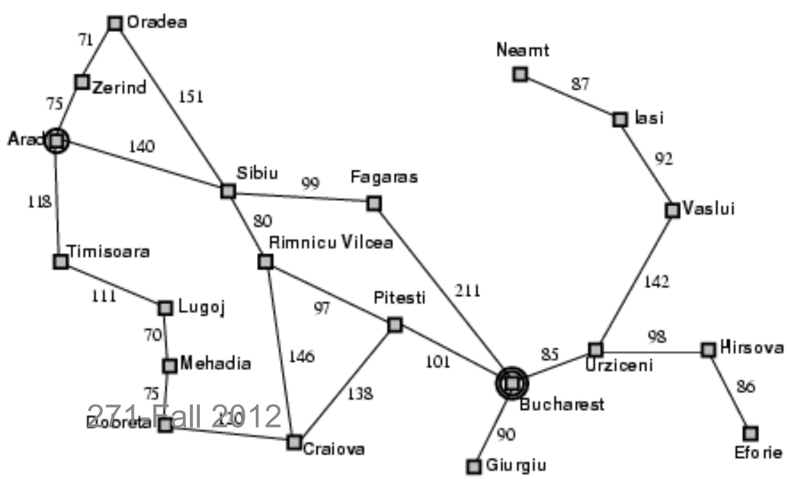


# A* Search Example



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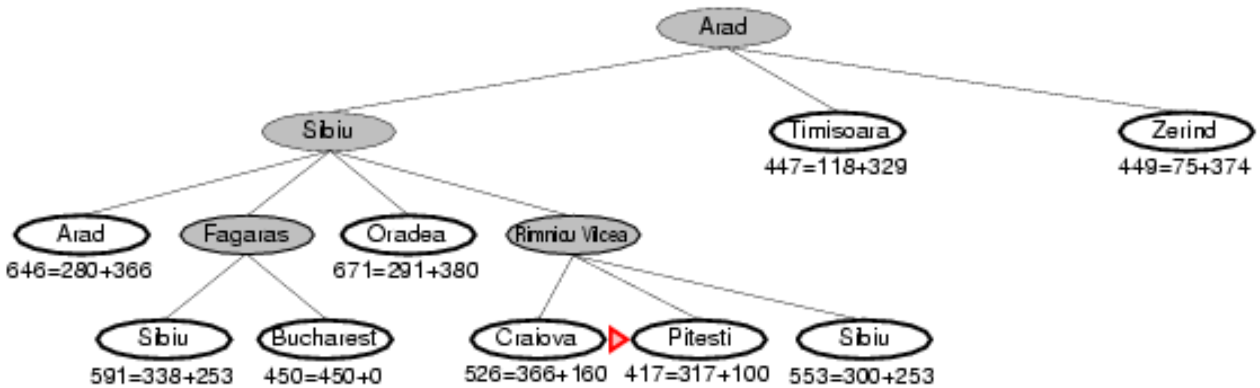


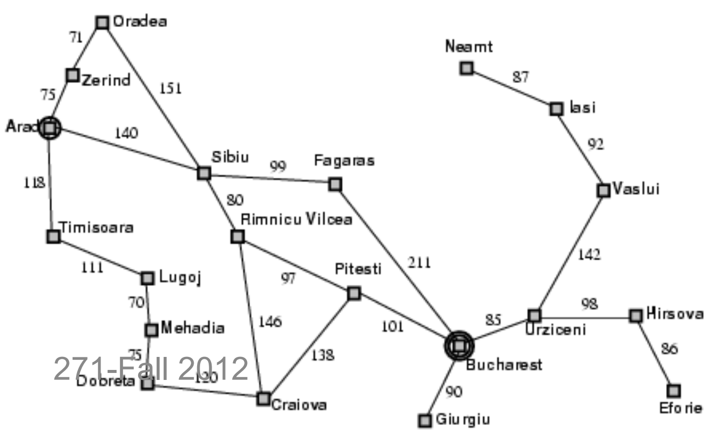

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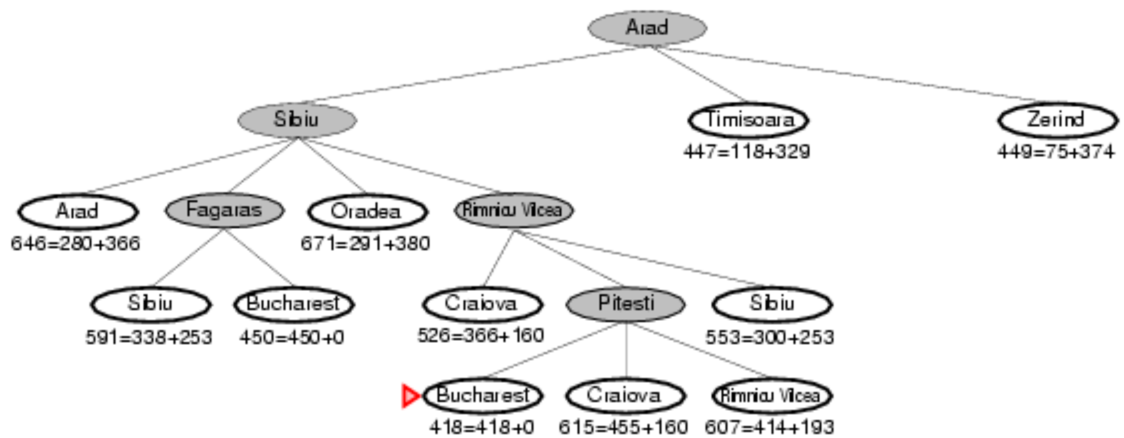
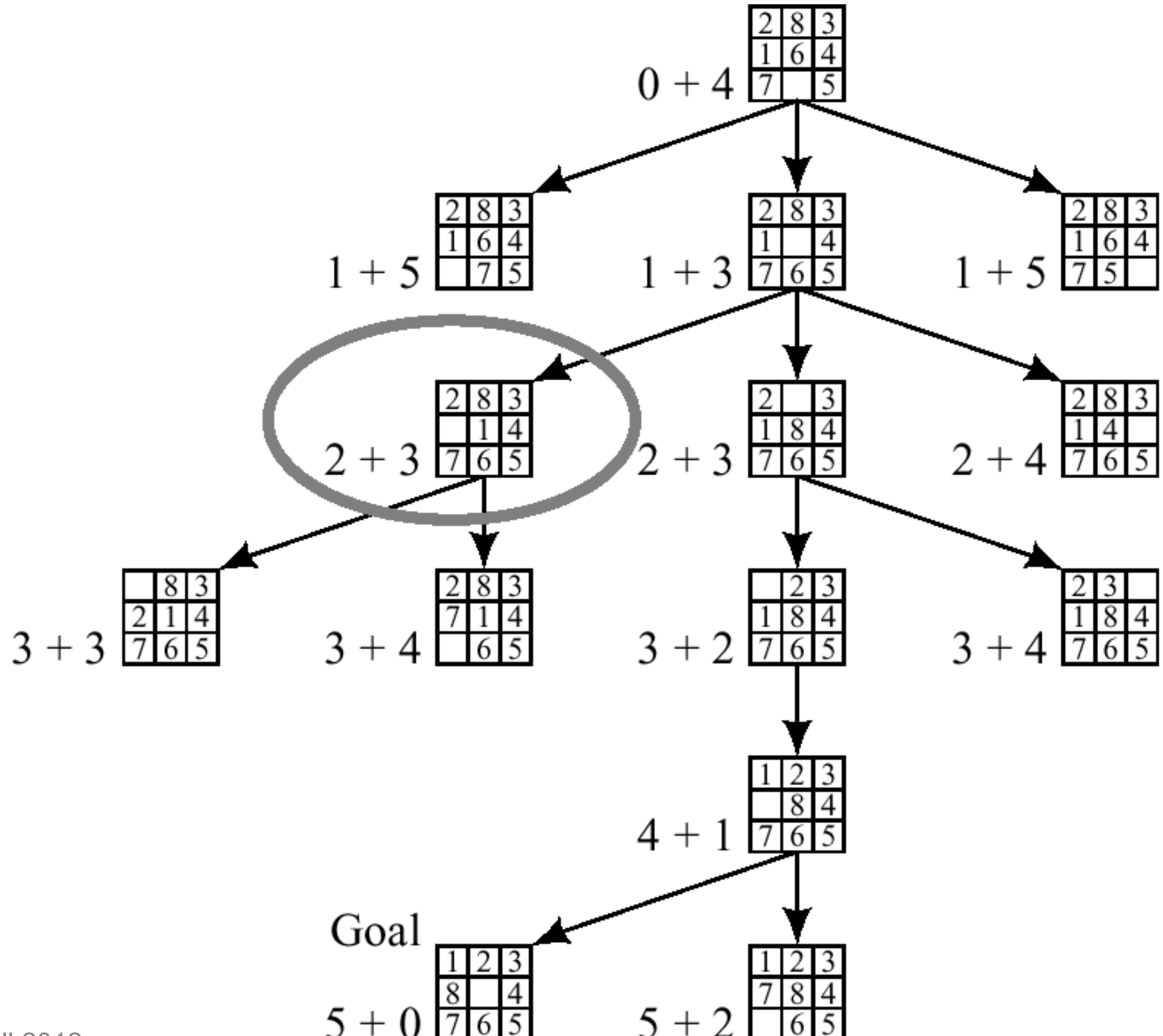


# A*- a Special Best-First Search

- Goal: find a minimum sum-cost path
- Notation:
  - c(n,n') - cost of arc (n,n')
  - g(n) = cost of current path from start to node n in the search tree.
  - h(n) = estimate of the cheapest cost of a path from n to a goal.
  - Special evaluation function: f = g+h
- f(n) estimates the cheapest cost solution path that goes through n.
  - h*(n) is the true cheapest cost from n to a goal.
  - g*(n) is the true shortest path from the start s, to n.

- If the heuristic function, h always underestimate the true cost (h(n) is smaller than h*(n)), then A* is guaranteed to find an optimal solution.

# A* on 8-Puzzle with h(n) = w(n)



# Algorithm A* (with any h on search Graph)

- Input: an implicit search graph problem with cost on the arcs
- Output: the minimal cost path from start node to a goal node.
  - 1. Put the start node s on OPEN.
  - 2. If OPEN is empty, exit with failure
  - 3. Remove from OPEN and place on CLOSED a node n having minimum f.
  - 4. If n is a goal node exit successfully with a solution path obtained by tracing back the pointers from n to s.
  - 5. Otherwise, expand n generating its children and directing pointers from each child node to n.
    - For every child node n' do
      - evaluate h(n') and compute f(n') = g(n') +h(n')= g(n)+c(n,n')+h(n)
      - If n' is already on OPEN or CLOSED compare its new f with the old f. If th enew value is higher, discard the node.
      - Else, put n' with its f value in the right order in OPEN
  - 6. Go to step 2.

In the book: Uniform search with queue ranked by g+h instead of just g
Simpler… but not exactly the same.

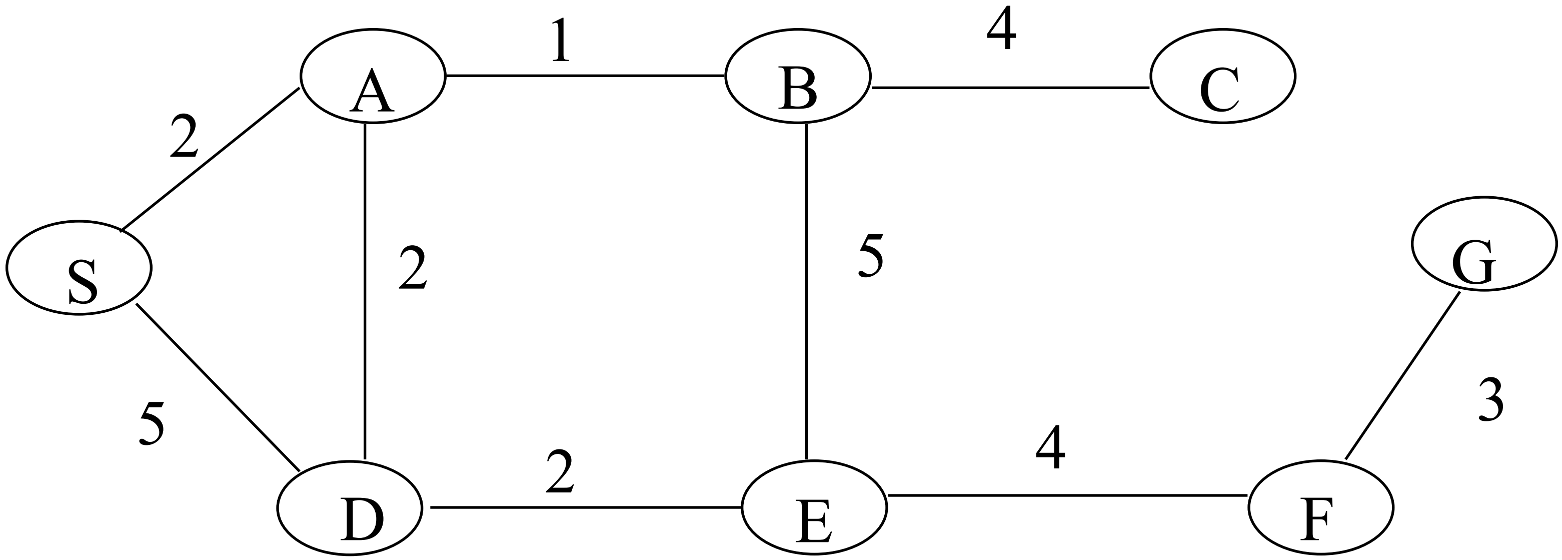
# Best-First Algorithm *BF (*)*

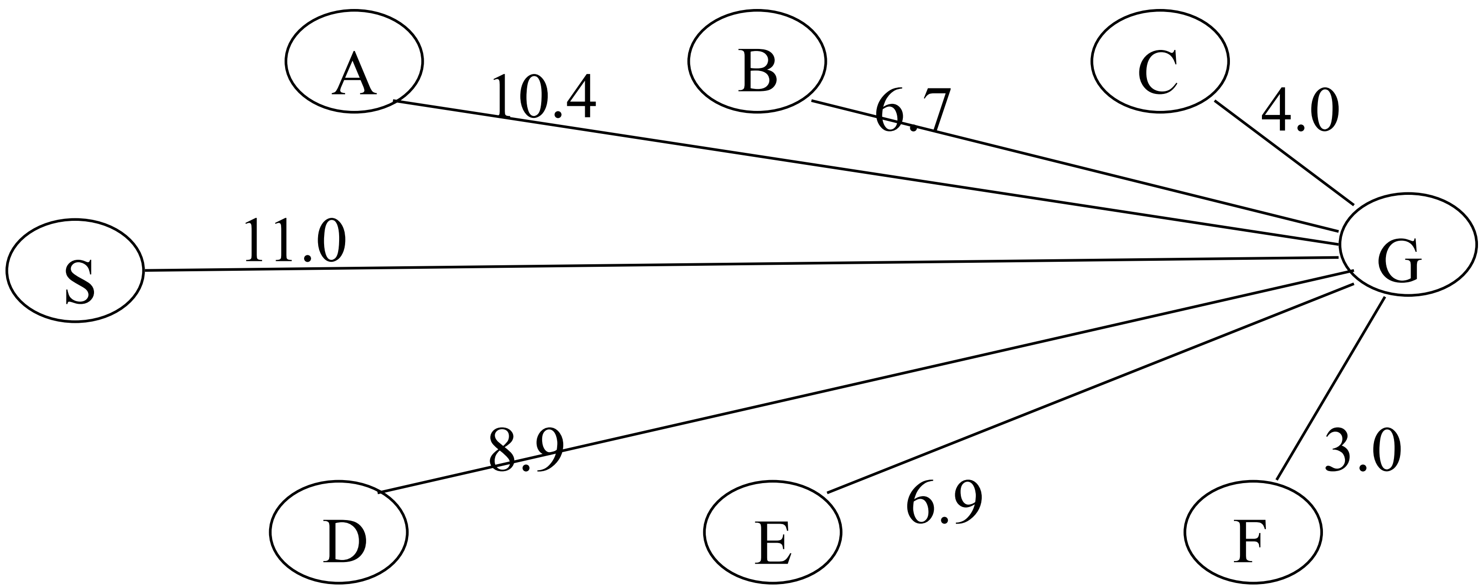
1. Put the start node *s* on a list called *OPEN* of unexpanded nodes.
2. If *OPEN* is empty exit with failure; no solutions exists.
3. Remove the first *OPEN* node *n* at which f is minimum (break ties arbitrarily), and place it on a list called *CLOSED* to be used for expanded nodes.
4. Expand node *n*, generating all it's successors with pointers back to *n*.
5. If any of *n*'s successors is a goal node, exit successfully with the solution obtained by tracing the path along the pointers from the goal back to *s*.

6. For every successor *n'* on *n*:
   a. Calculate *f* (*n'*).
   b. if *n'* was neither on *OPEN* nor on *CLOSED*, add it to *OPEN*. Attach a pointer from *n'* back to *n*. Assign the newly computed *f(n')* to node *n'*.
   c. if *n'* already resided on *OPEN* or *CLOSED*, compare the newly computed *f(n')* with the value previously assigned to *n'*. If the old value is lower, discard the newly generated node. If the new value is lower, substitute it for the old (*n'* now points back to *n* instead of to its previous predecessor). If the matching node *n'* resided on *CLOSED*, move it back to *OPEN*.

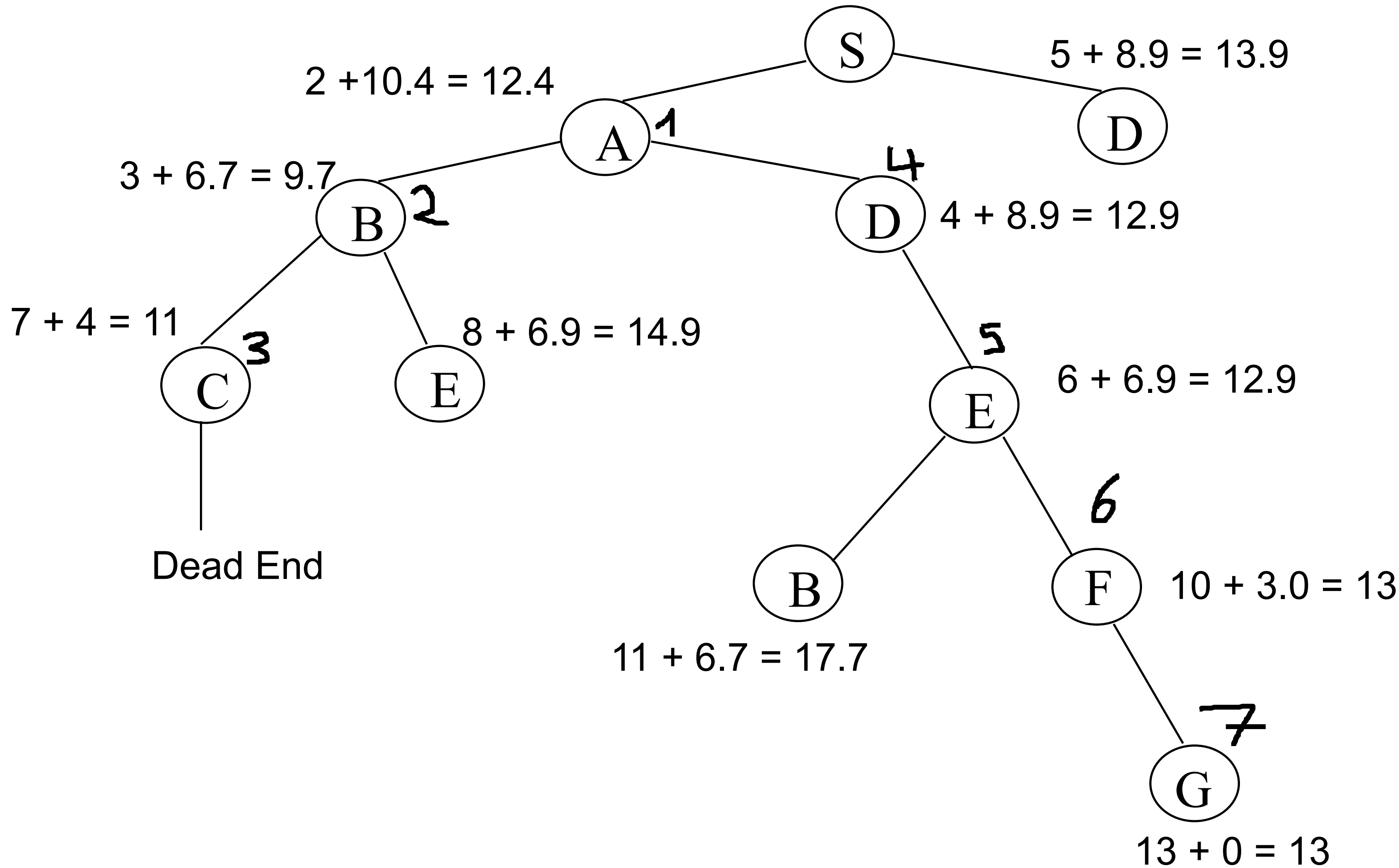
7. Go to step 2.

* With tests for duplicate nodes.


1
4
A
B
C
2
2
5
S
G
3
5
2
4
D
E
F


A
B
C
10.4
6.7
4.0
11.0
S
G
8.9
3.0
6.9
D
E
F

# Example of A* Algorithm in Action



# Behavior of A - Termination

- The heuristic function h(n) is called admissible if h(n) is never larger than h*(n), namely h(n) is always less or equal to true cheapest cost from n to the goal.

- A* is admissible if it uses an admissible heuristic, and h(goal) = 0.

- Theorem (completeness) (Hart, Nillson and Raphael, 1968)
  - A* always terminates with a solution path (h is not necessarily admissible) if
    - costs on arcs are positive, above epsilon
    - branching degree is finite.
- Proof: The evaluation function f of nodes expanded must increase eventually (since paths are longer and more costly) until all the nodes on an optimal path are expanded .

# Behavior of A* - Completeness

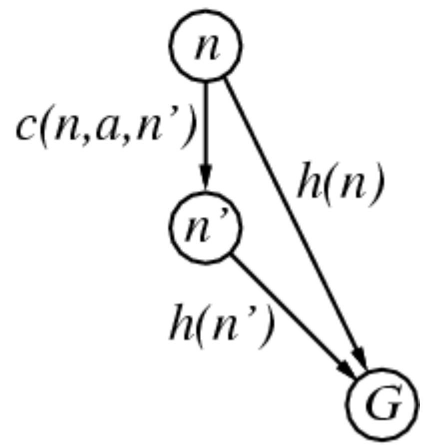
- Theorem (completeness for optimal solution) (HNL, 1968):
  - If the heuristic function is admissible than A* finds an optimal solution.

- Proof:
  - 1. A* will expand only nodes whose f-values are less (or equal) to the optimal cost path C* (f(n) is less-or-equal C*).
  - 2. The evaluation function of a goal node along an optimal path equals C*.
- Lemma:
  - Anytime before A* terminates there exists and OPEN node n' on an optimal path with f(n') <= C*.

# Consistent (monotone) 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

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

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

- Theorem: If *h(n)* is consistent, f along any path is non-decreasing.
- Corollary: the f values seen by A* are non-decreasing.

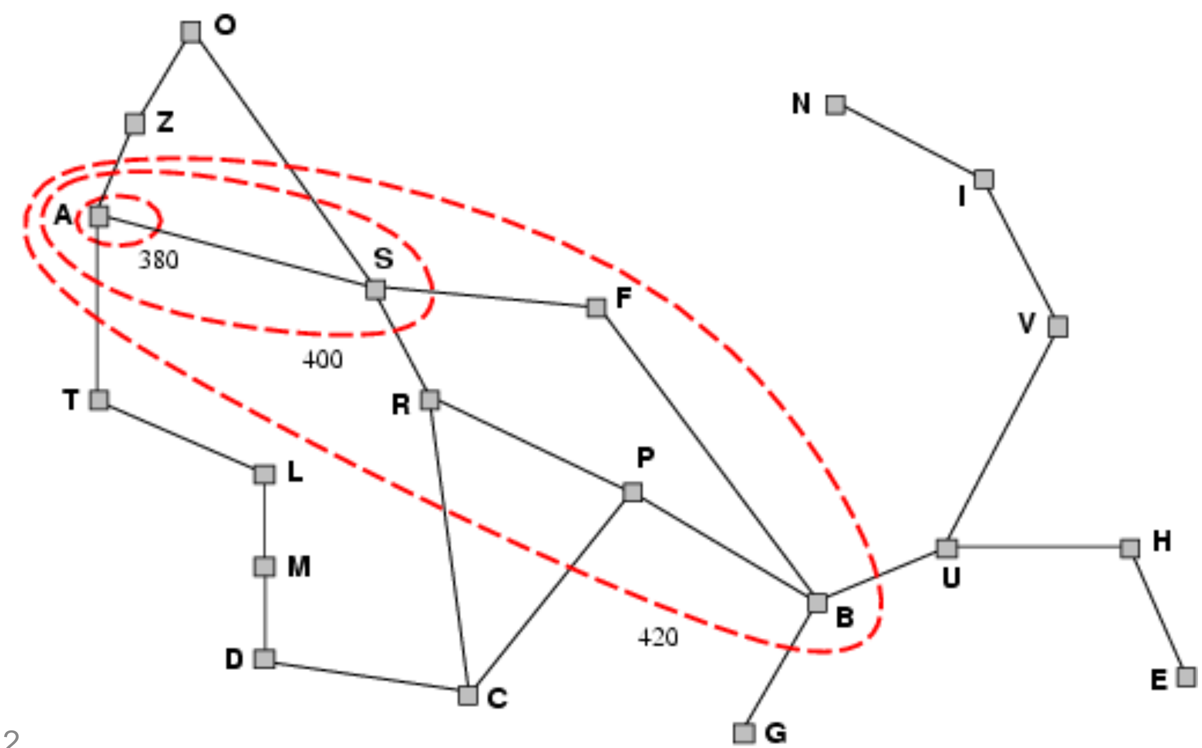
# Consistent Heuristics

- If h is consistent) and h(goal)=0 then h is admissible
  - Proof: (by induction of distance from the goal)

- An A* guided by consistent heuristic finds an optimal paths to all expanded nodes, namely g(n) = g*(n) for any closed n.
  - Proof: Assume g(n) > g*(n) and n expanded along a non-optimal path.
  - Let n' be the shallowest OPEN node on optimal path p to n →
  - g(n') = g*(n') and therfore f(n')=g*(n')+h(n')
  - Due to consistency we get f(n') <=g*(n')+k(n',n)+h(n)
  - Since g*(n) = g*(n')+k(n',n) along the optimal path, we get that
  - f(n') <= g*(n) + h(n)
  - And since g(n) > g*(n) then f(n') < g(n)+h(n) = f(n), contradiction

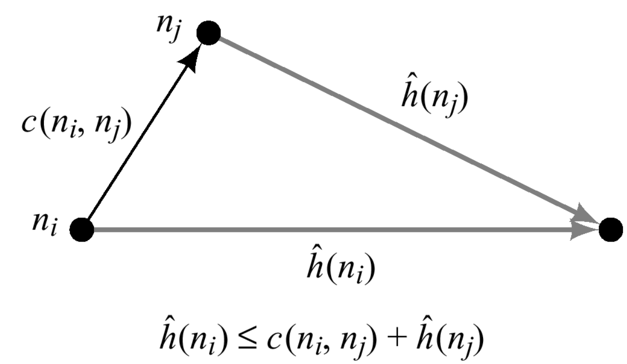
# A* with Consistent Heuristics

- A* expands nodes in order of increasing *f* value
- Gradually adds "*f*-contours" of nodes
- Contour *i* has all nodes with $f=f_i$, where $f_i < f_{i+1}$



# Summary of Consistent Heuristics

- h is consistent if the heuristic function satisfies triangle inequality for every n and its child node n’ : h(ni) <= h(nj) + c(ni,nj)



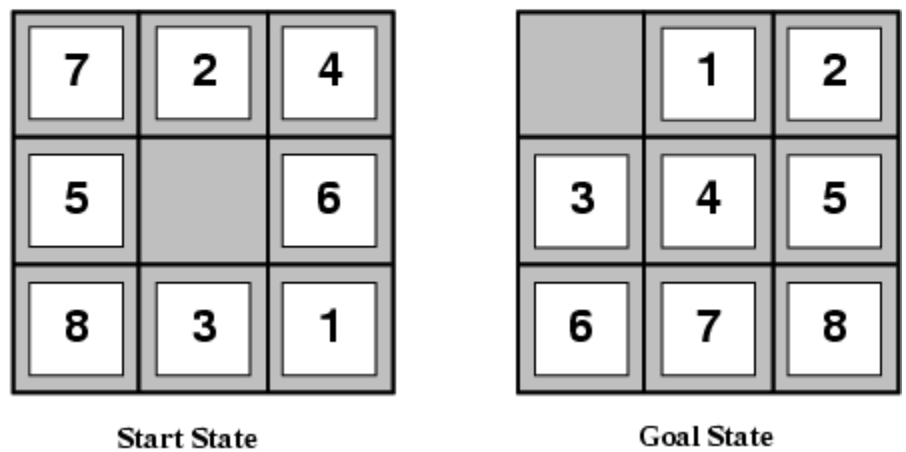

- When h is consistent, the f values of nodes expanded by A* are never decreasing.
- When A* selected n for expansion it already found the shortest path to it.
- When h is consistent every node is expanded once (if check for duplicates).
- Normally the heuristics we encounter are consistent
  - –the number of misplaced tiles
  - –Manhattan distance
  - –air-line distance

# Admissible and Consistent 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)
The true cost is 26.
Average cost for 8-puzzle is 22. Branching degree 3.




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

# Effectiveness of A* search

- How quality of heuristic impact search?
- What is the time and space complexity?
- Is any algorithm better? Worse?
- Case study: the 8-puzzle

# Effectiveness of A* Search Algorithm

Average number of nodes expanded

| d | IDS | A*(h1) | A*(h2) |
|---|---|---|---|
| 2 | 10 | 6 | 6 |
| 4 | 112 | 13 | 12 |
| 8 | 6384 | 39 | 25 |
| 12 | 364404 | 227 | 73 |
| 14 | 3473941 | 539 | 113 |
| 20 | ------------ | 7276 | 676 |

Average over 100 randomly generated 8-puzzle problems
h1 = number of tiles in the wrong position
h2 = sum of Manhattan distances

# Dominance

- Definition: If $h_2(n) \geq h_1(n)$ for all $n$ (both admissible) then $h_2$ dominates $h_1$
- *Is* $h_2$ better for search?

- 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

# Heuristic's Dominance and Pruning Power

- Definition:
  - A heuristic function h (strictly) dominates h' if both are admissible and for every node n, h(n) is (strictly) greater than h'(n).
- Theorem (Hart, Nillson and Raphale, 1968):
  - An A* search with a dominating heuristic function h has the property that any node it expands is also expanded by A* with h'.
- Question: Does manhattan distance dominate the number of misplaced tiles?
- Extreme cases
  - h = 0
  - h = h*

# Summary of A* properties

- A* expands every path along which f(n) < C*
- A* will never expand any node s.t. f(n) > C*
- If h is consistent A* will expand any node such that f(n) <C*
- Therefore, A* expands all the nodes for which f(n) < C* and a subset of the nodes for which f(n) = C*.
- Therefore, if $h_1(n) < h_2(n)$ clearly the subset of nodes expanded by h_2 is smaller.

# Non-admissible heuristics: Adjust weights of g and h

$$f_w(n) = (1 - w)g(n) + w \cdot h(n)$$

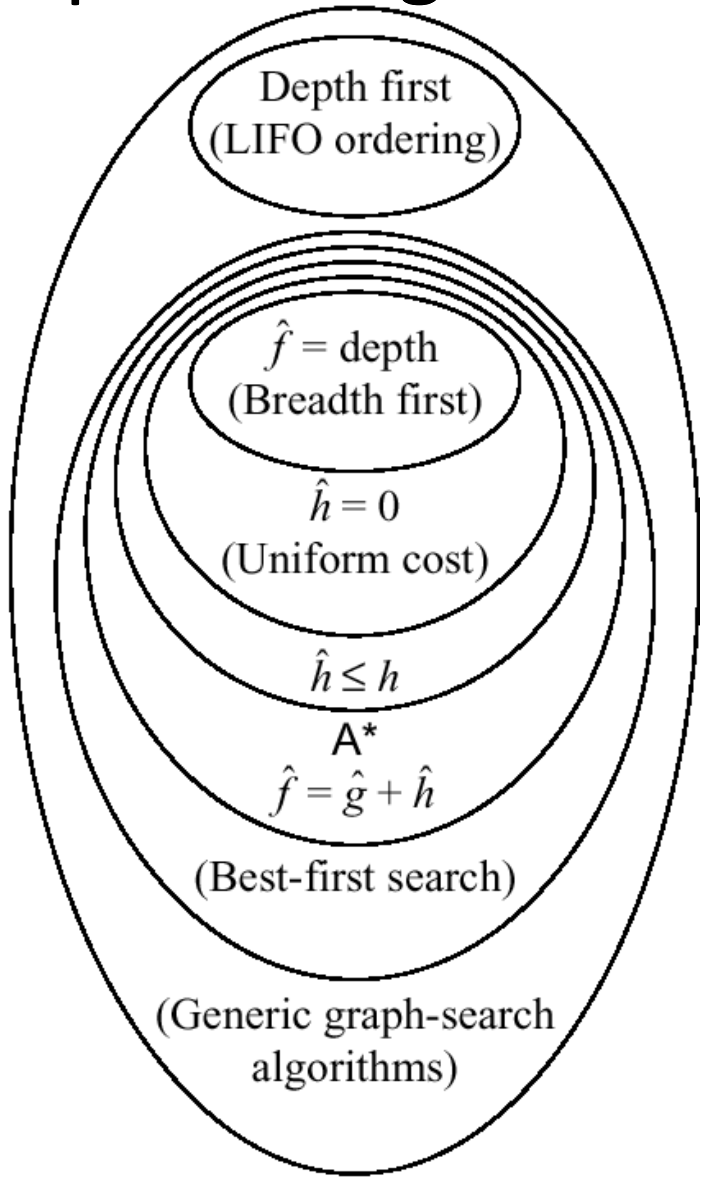
- W = 0  (uniform cost)
- W=1/2  (A*)
- W=1  (DFS greedy)

- If h is admissible then f_w is admissible for 0 <=w<=1/2

# Complexity of A*

- A* is optimally efficient (Dechter and Pearl 1985):
  - It can be shown that all algorithms that do not expand a node which A* did expand (inside the contours) may miss an optimal solution
- A* worst-case time complexity:
  - is exponential unless the heuristic function is very accurate
- If h is exact (h = h*)
  - search focus only on optimal paths
- Main problem: space complexity is exponential
- Effective branching factor:
  - logarithm of base (d+1) of average number of nodes expanded.

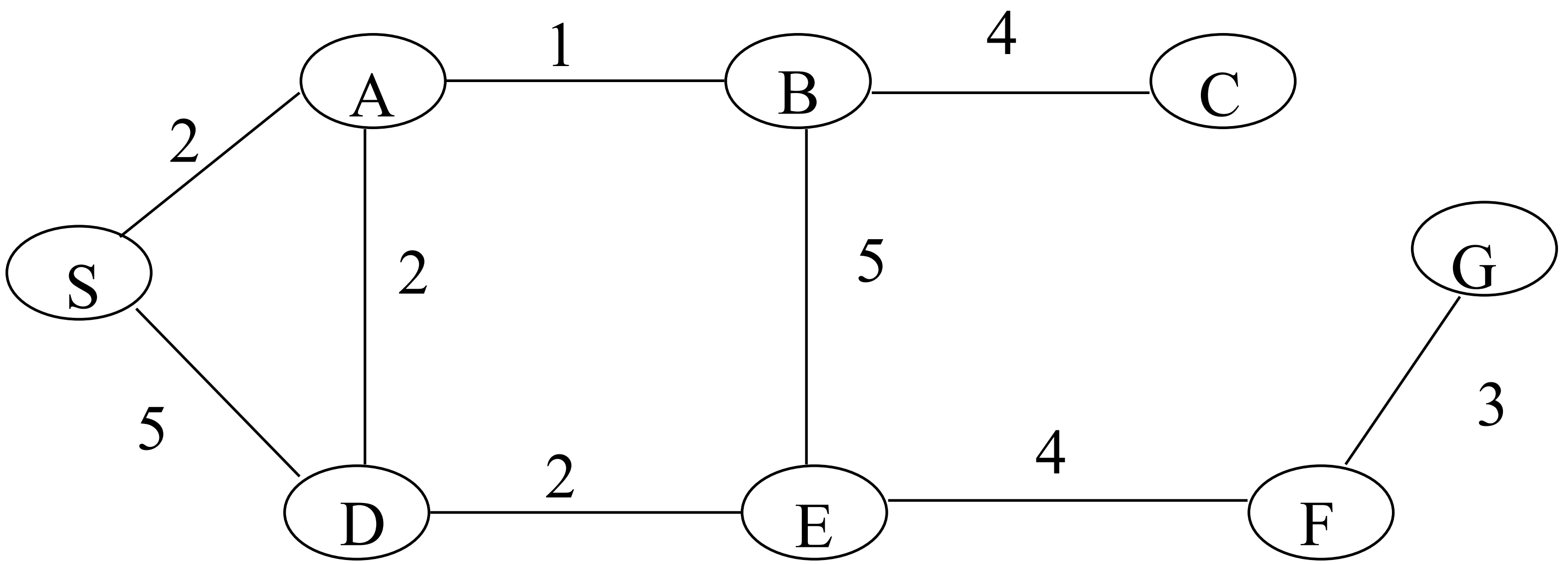
# Relationships among Search Algorithms

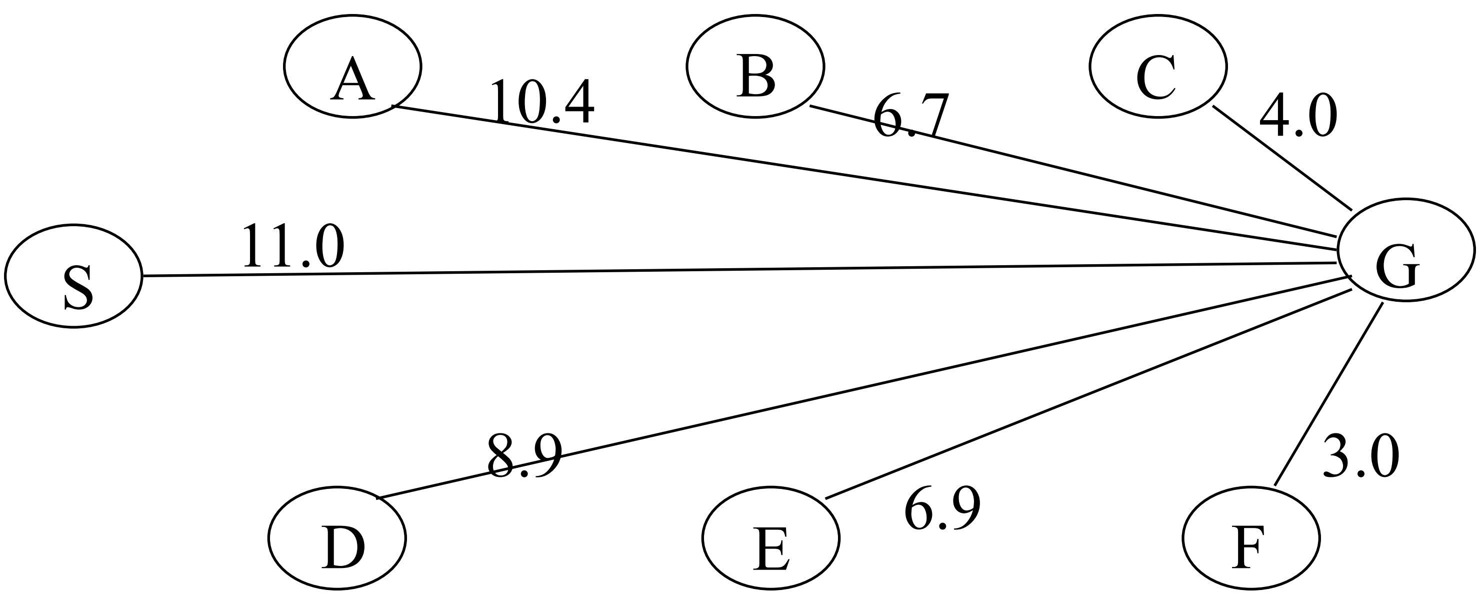


# Pseudocode for Branch and Bound Search (An informed depth-first search)

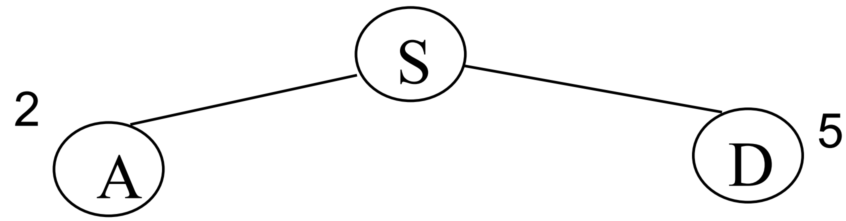
```
Initialize: Let Q = {S}
While Q is not empty
        pull Q1, the first element in Q
        if Q1 is a goal compute the cost of the solution and update
          L <-- minimum between new cost and old cost
        else
                child_nodes = expand(Q1),
               <eliminate child_nodes which represent simple
                loops>,
                For each child node n do:
                        evaluate f(n).  If f(n) is greater than L
                        discard n.
                end-for
                Put remaining child_nodes on top of queue
                in the order of their evaluation function, f.

        end
Continue
```


A
B
C
S
G
D
E
F
2
1
4
2
5
5
2
4
3


A
B
C
S
G
D
E
F
10.4
6.7
4.0
11.0
8.9
6.9
3.0

# Example of Branch and Bound in action



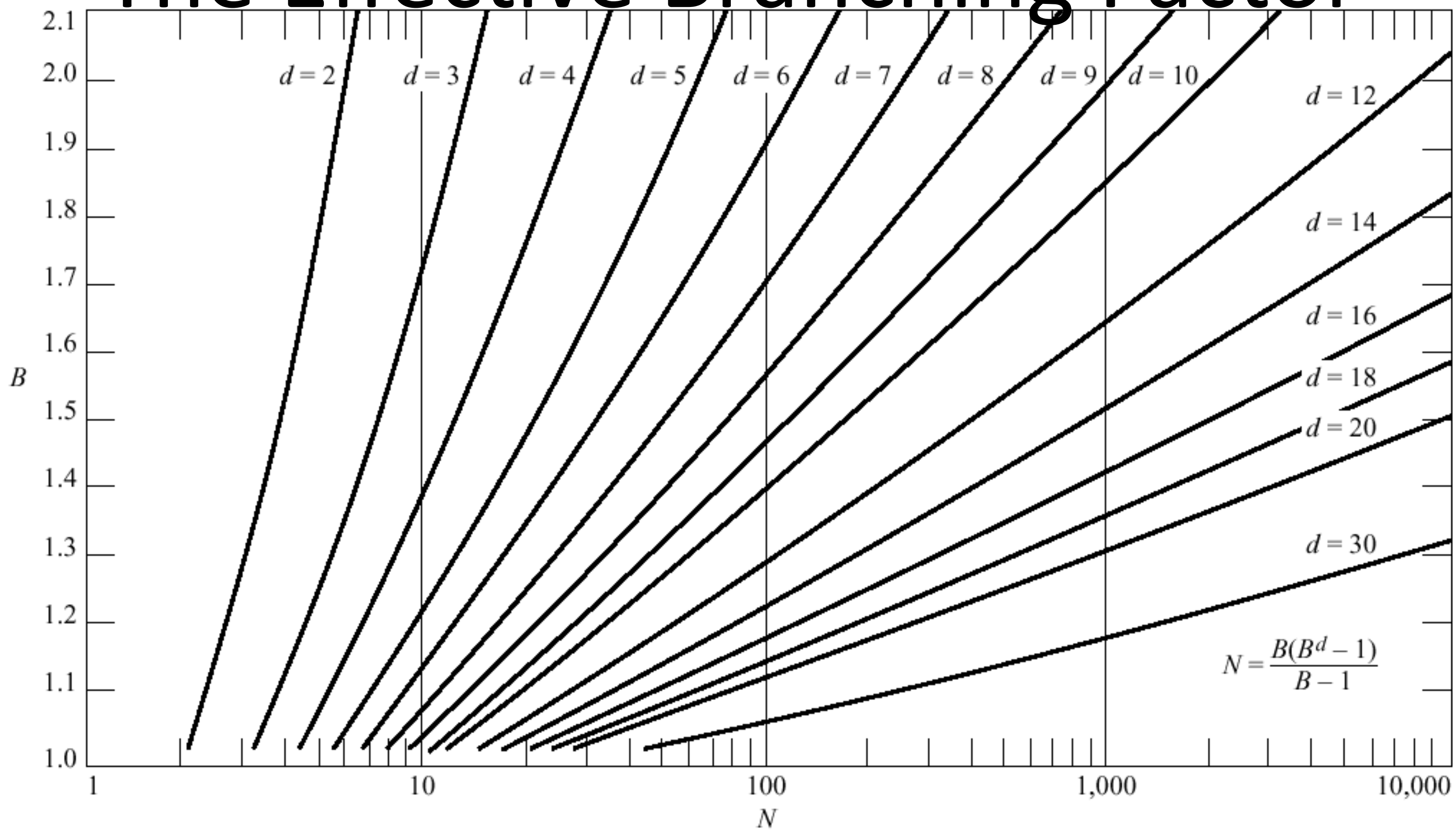
# Properties of Branch-and-Bound

- Not guaranteed to terminate unless has depth-bound
- Optimal:
  - finds an optimal solution
- Time complexity: exponential
- Space complexity: can be linear

# Iterative Deepening A* (IDA*) (combining Branch-and-Bound and A*)

- Initialize: f <-- the evaluation function of the start node
- until goal node is found
  - Loop:
    - Do Branch-and-bound with upper-bound L equal current evaluation function f.
    - Increment evaluation function to next contour level
  - end
- continue
- Properties:
  - Guarantee to find an optimal solution
  - time: exponential, like A*
  - space: linear, like B&B.
  - Problems: The number of iterations may be large.

# The Effective Branching Factor



# Inventing Heuristics automatically

- Examples of Heuristic Functions for A*
  - the 8-puzzle problem
    - the number of tiles in the wrong position
      - is this admissible?
    - Manhattan distance
      - is this admissible?

  - How can we invent admissible heuristics in general?
    - look at "relaxed" problem where constraints are removed
      - e.g.., we can move in straight lines between cities
      - e.g.., we can move tiles independently of each other

# Inventing Heuristics Automatically (continued)

- How did we
  - find h1 and h2 for the 8-puzzle?
  - verify admissibility?
  - prove that air-distance is admissible? MST admissible?
- Hypothetical answer:
  - Heuristic are generated from relaxed problems
  - Hypothesis: relaxed problems are easier to solve
- In relaxed models the search space has more operators, or more directed arcs
- Example: 8 puzzle:
  - A tile can be moved from A to B if A is adjacent to B and B is clear
  - We can generate relaxed problems by removing one or more of the conditions
    - A tile can be moved from A to B if A is adjacent to B
    - ...if B is blank
    - A tile can be moved from A to B.

# Relaxed Problems

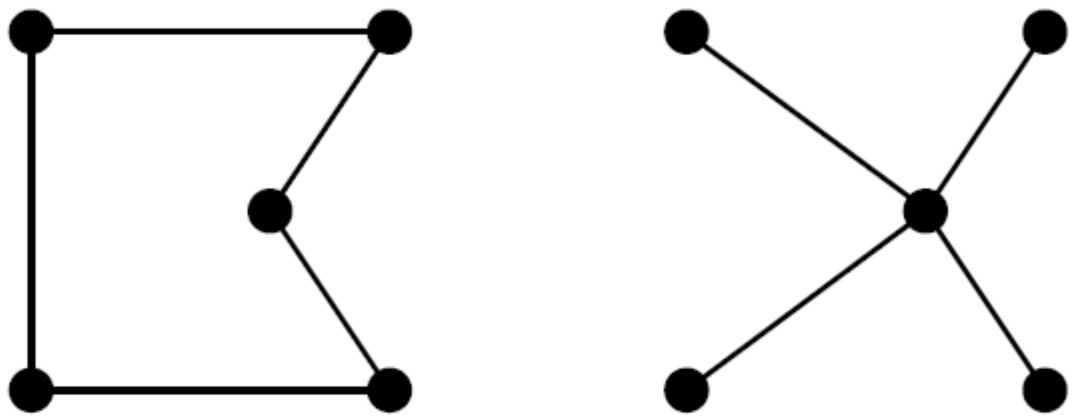
- A problem with fewer restrictions on the actions is called a relaxed problem
- The cost of an optimal solution to a relaxed problem is an admissible heuristic for the original problem
- If the rules of the 8-puzzle are relaxed so that a tile can move anywhere, then $h_1(n)$ *(number of misplaced tiles)* gives the shortest solution
- If the rules are relaxed so that a tile can move to any adjacent square, then $h_2(n)$ *(Manhatten distance)* gives the shortest solution

# Generating heuristics (continued)

- Example: TSP
- Find a tour. A tour is:
  - 1. A graph
  - 2. Connected
  - 3. Each node has degree 2.
- Eliminating 3 yields MST.

# Relaxed problems contd.

Well-known example: travelling salesperson problem (TSP)
Find the shortest tour visiting all cities exactly once



Minimum spanning tree can be computed in $O(n^2)$
and is a lower bound on the shortest (open) tour

# Automating Heuristic generation

- Use STRIPs language representation:
- Operators:
  - pre-conditions, add-list, delete list
- 8-puzzle example:
  - on(x,y), clear(y) adj(y,z) ,tiles x1,…,x8
- States: conjunction of predicates:
  - on(x1,c1),on(x2,c2)….on(x8,c8),clear(c9)
- move(x,c1,c2) (move tile x from location c1 to location c2)
  - pre-cond: on(x1,c1), clear(c2), adj(c1,c2)
  - add-list: on(x1,c2), clear(c1)
  - delete-list: on(x1,c1), clear(c2)
- Relaxation:
- 1. Remove from prec-cond: clear(c2), adj(c2,c3) → #misplaced tiles
- 2. Remove clear(c2) → manhatten distance
- 3. Remove adj(c2,c3) → h3, a new procedure that transfer to the empty location a tile appearing there in the goal

# Heuristic generation

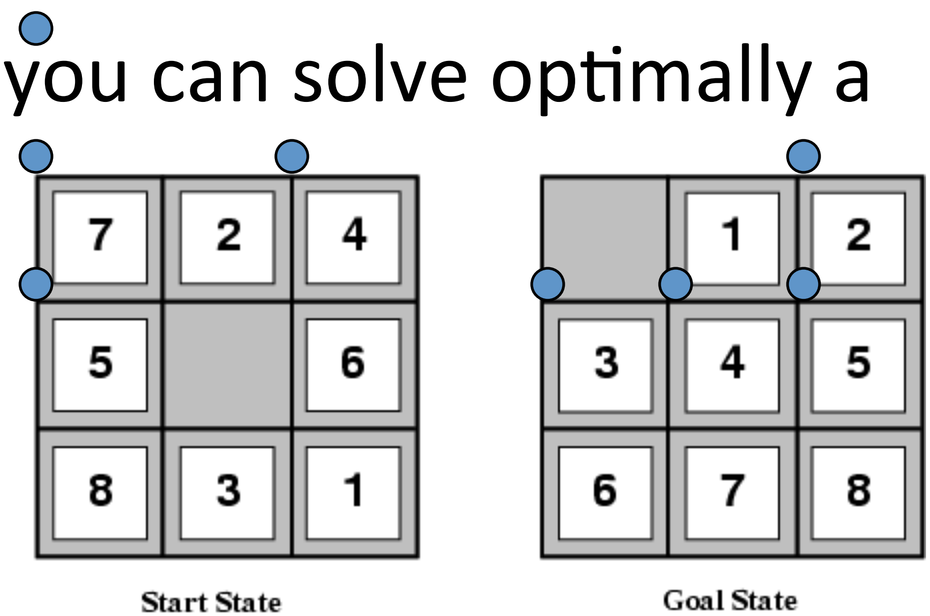
- The space of relaxations can be enriched by predicate refinements
- adj(y,z) iff neigbour(y,z) and same-line(y,z)

- Theorem: Heuristics that are generated from relaxed models are consistent.

- Proof: h is true shortest path in a relaxed model
  - h(n) <=c’ (n,n’ )+h(n’ ) (c’ are shortest distances in relaxed graph)
  - c’ (n,n’ ) <=c(n,n’ )
  - → h(n) <= c(n,n’ )+h(n’ )
- Problem: not every relaxed problem is easy, often, a simpler problem which is more constrained will provide a good upper-bound.
- The main question: how to recognize a relaxed easy problem.
- A proposal: a problem is easy if it can be solved optimally by a greedy algorithm

# Improving Heuristics

- If we have several heuristics which are non dominating we can select the max value.
- Reinforcement learning.
- Pattern Databases: you can solve optimally a sub-problem



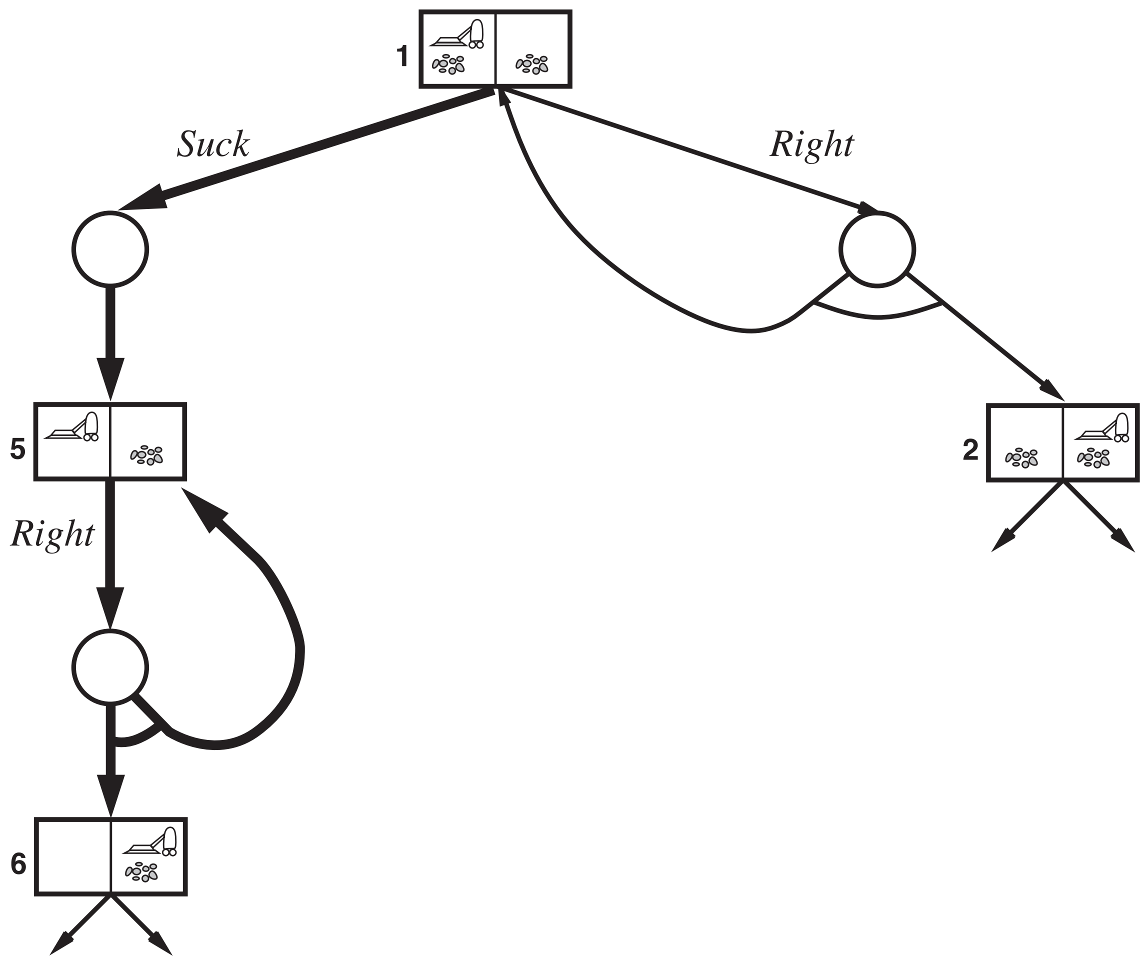
# Pattern Databases

- For sliding tiles and Rubic's cube
- For a subset of the tiles compute shortest path to the goal using breadth-first search
- For 15 puzzles, if we have 7 fringe tiles and one blank, the number of patterns to store are 16!/(16-8)! = 518,918,400.
- For each table entry we store the shortest number of moves to the goal from the current location.
- Use different subsets of tiles and take the max heuristic during IDA* search. The number of nodes to solve 15 puzzles was reduced by a factor of 346 (Culberson and Schaeffer)
- How can this be genaralized? (a possible project)

## Problem-reduction representations
## AND/OR search spaces

- Decomposable production systems (Natural language parsing)
  Initial database: (C,B,Z)
  Rules: R1: C → (D,L)
  R2: C → (B,M)
  R3: B → (M,M)
  R4: Z → (B,B,M)
  Find a path generating a string with M's only.
- The erratic vacuum world (actions are non-deterministic)
- The tower of Hanoi
  To move n disks from peg 1 to peg 3 using peg 2
  Move n-1 pegs to peg 2 via peg 3,
  move the nth disk to peg 3,
  move n-1 disks from peg 2 to peg 3 via peg 1.

# Erratic Vacuum



# AND/OR Graphs

- Nodes represent subproblems
  - And links represent subproblem decompositions
  - OR links represent alternative solutions
  - Start node is initial problem
  - Terminal nodes are solved subproblems
- Solution graph
  - It is an AND/OR subgraph such that:
  - 1. It contains the start node
  - 2. All it terminal nodes (nodes with no successors) are solved primitive problems
  - 3. If it contains an AND node L, it must contain the entire group of AND links that leads to children of L.

# Algorithms searching AND/OR graphs

- All algorithms generalize using hyper-arc suscessors rather than simple arcs.
- AO*: is A* that searches AND/OR graphs for a solution subgraph.
- The cost of a solution graph is the sum cost of it arcs. It can be defined recursively as: $k(n,N) = c\_n+k(n1,N)+\dots k(n\_k,N)$
- h*(n) is the cost of an optimal solution graph from n to a set of goal nodes
- h(n) is an admissible heuristic for h*(n)
- Monotonicity:
- $h(n) \le c+h(n1)+\dots h(nk)$ where n1,…nk are successors of n
- AO* is guaranteed to find an optimal solution when it terminates if the heuristic function is admissiblels h is

# Summary

- In practice we often want the goal with the minimum cost path
- Exhaustive search is impractical except on small problems
- Heuristic estimates of the path cost from a node to the goal can be efficient in reducing the search space.
- The A* algorithm combines all of these ideas with admissible heuristics (which underestimate) , guaranteeing optimality.
- Properties of heuristics:
  - admissibility, consistency, dominance, accuracy
- Reading
  - R&N Chapter 3-4

# Beyond Classical Search (chapter 4 3rd eddition)

- Local search for optimization
  - Greedy, hill-climbing search, simulated annealing, local beem search, genetic algorithms
  - Local search in continuous spaces
- Searching with non-deterministic actions
  - The erratic vaccum cleaner example
  - Using and/or search spaces.
- Searching with partial observations
  - Using belief states
- Online search agents and unknown environments
  - Actions, costs, goal-tests are revealed in state only
  - Exploration problems. Safely explorable