

CS 520: Introduction to Artificial Intelligence

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Lecture 3:

uninformed search

uninformed search

Lectures on Search



- **Formulation of search problems.**
 - State Spaces
- **Uninformed (blind) search algorithms.**
- **Informed (heuristic) search algorithms.**
- **Constraint Satisfaction Problems.**
- **Game Playing Problems.**

Review

State spaces: formulating problems as graph search

- **States**
- **Operators**
- **Start and goal states**
- **Costs**
 - **Cost of search**
 - **Cost of path from start to goal**
 - **Cost of goal**


Review

- **Some classical problems**
 - **As examples of formulation**
 - **Because they are often referred to**
- **Problems**
 - **8 puzzle (also 15 puzzle)**
 - **N-queens**
 - **Water jugs**
 - **Towers of Hanoi**

Review

- **The same problem can be formalized in different ways.**
 - Better if fewer nodes in space
 - Better if fewer paths to same node
- **A non-classical problem: vacuum cleaner**
 - An example of a non-observable environment

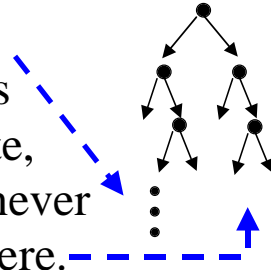
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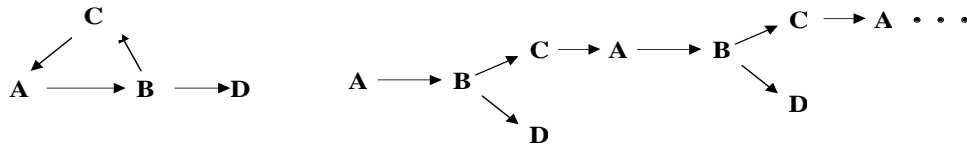
Searching a Graph

- **Simple tree search**
 - **Depth first, breadth first, constant cost**
- **Problem: infinite trees**

If this path is infinite, DFS never gets here.



- **Problem: cycles look like infinite trees**

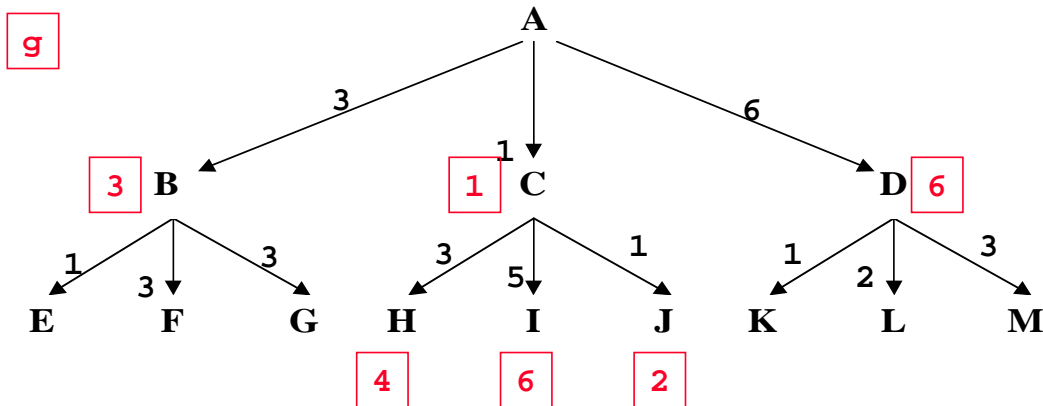


Iterative Deepening

- **Completeness and shortest-first order of BFS**
- **Space cost of DFS**
- **Time cost not much more than B/DFS**

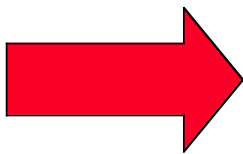
Uniform Cost

- Keep a list of open nodes (aka frontier)
- $g(n)$ = distance from root
- Loop expanding node with minimal g



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Informed Search

- Incorporate problem-specific knowledge into the search strategy.
- Only useful if extra knowledge exists.
- One common form:
 $f(n)$ = estimate of distance to goal

Best-First Search

- Expand the nodes in order of their f value.
- Also known as “Greedy” search

Initialize open to contain root

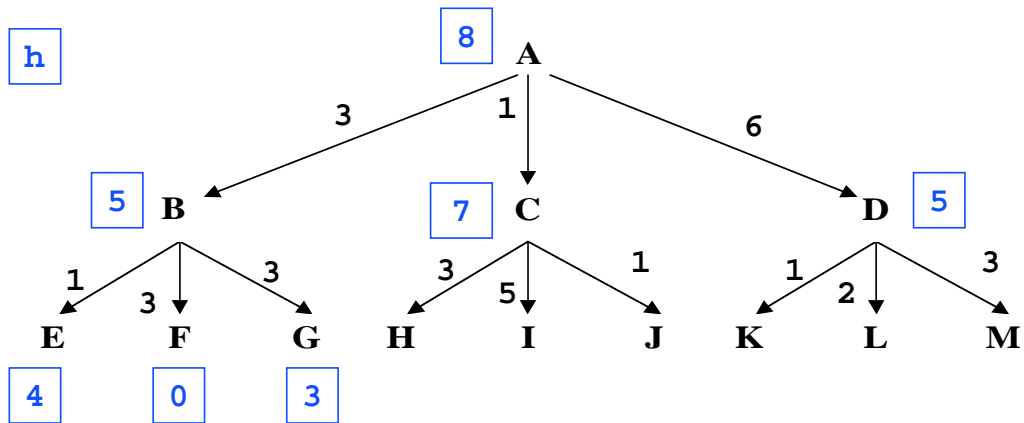
Loop while not(found or empty(open))

 new = expand(head (open))

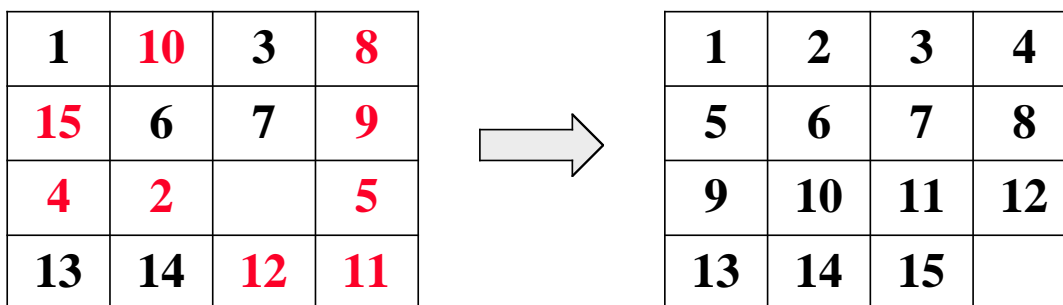
 open =

 sort-by-value(append(rest(open), new))

Example

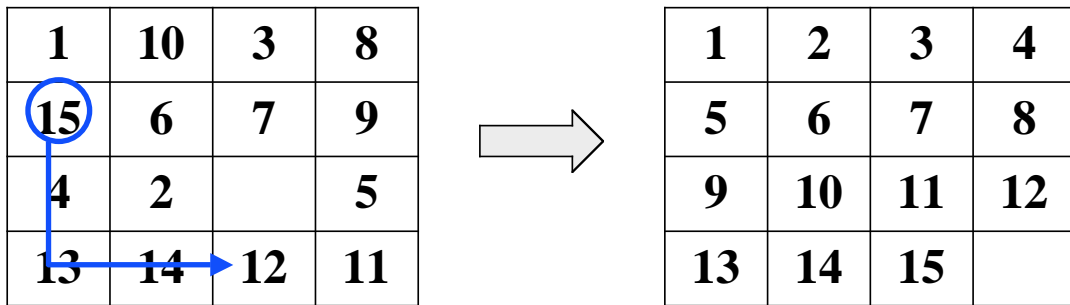


The Sixteen Puzzle



- **Number of misplaced tiles: $h(n) = 9$**

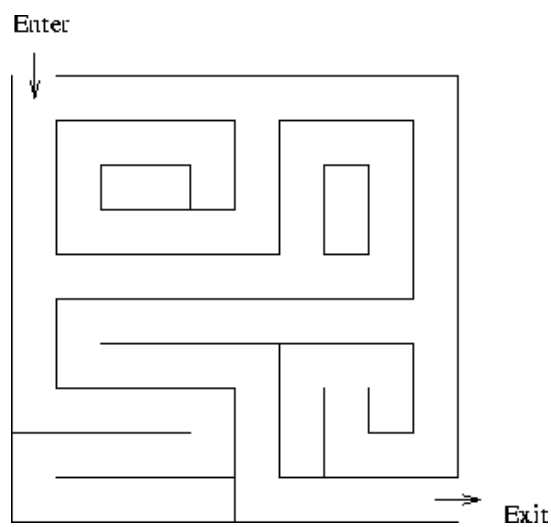
The Sixteen Puzzle



5 steps

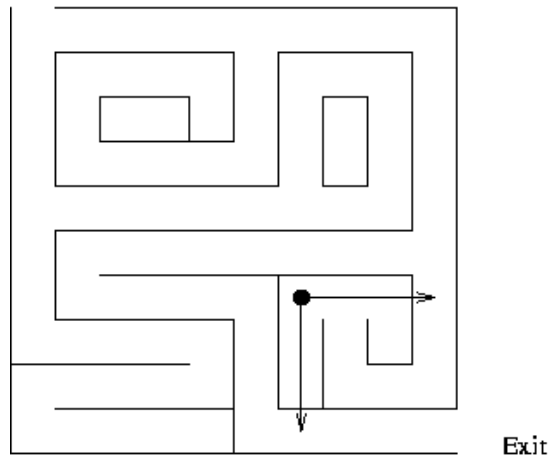
- Sum of Manhattan distances to correct place, $h(n)=26$

A Maze Problem



Heuristic for a Maze Problem

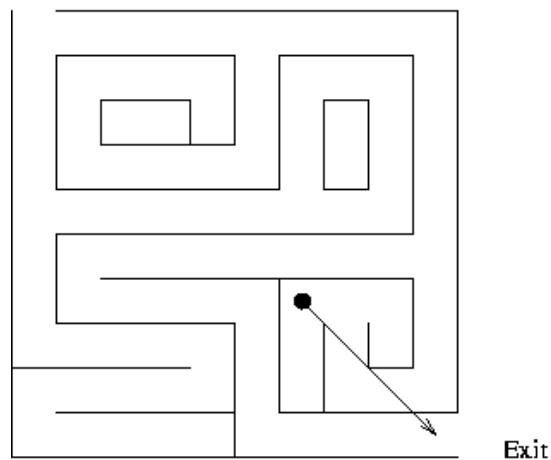
Enter



Manhattan Distance: $h(s) = \text{North/South distance to exit}$
+ East/West distance to exit.

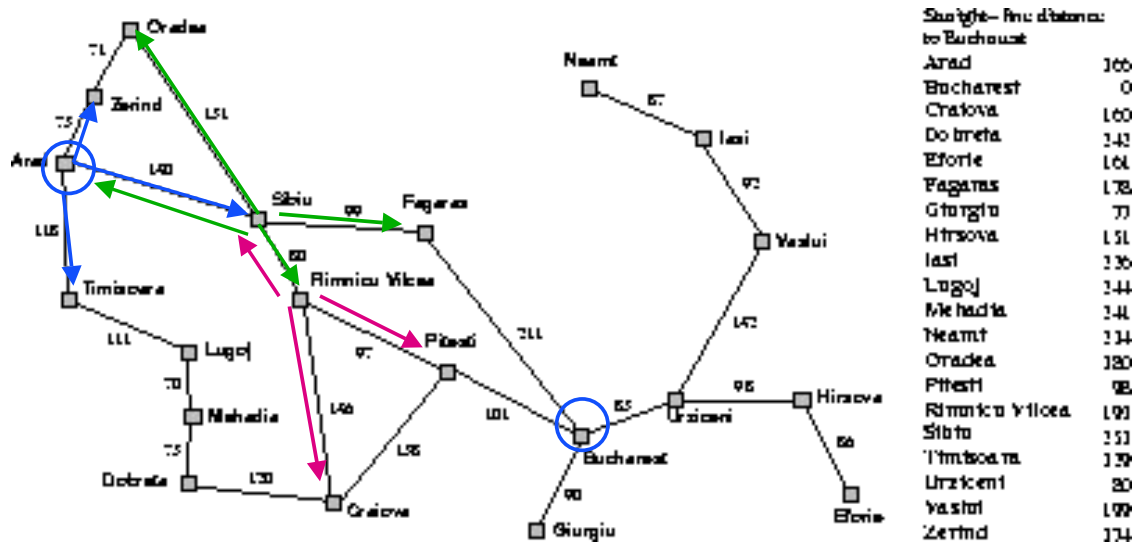
Heuristic for a Maze Problem

Enter



Euclidean Distance: $h(s) = \text{Straight line distance to exit "as the crow flies"}$.

Greedy Search example

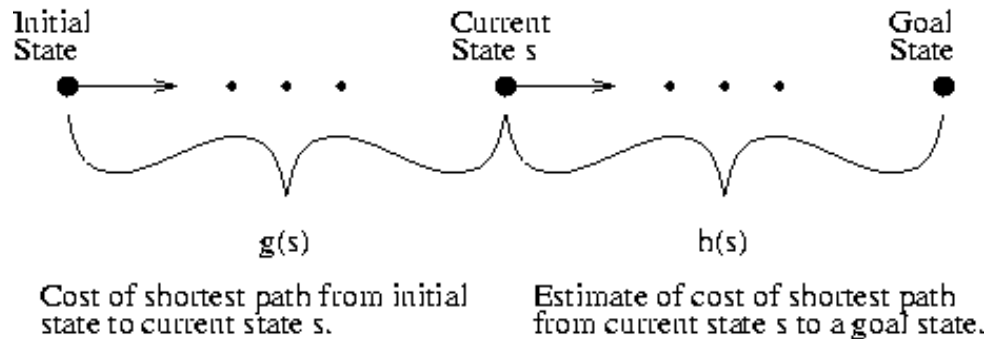


Greedy Search example

- **Notes:**
 - not optimal (best path through R.V. and Pitesti)
 - prone to false starts (consider Iasi to Fagaras)
 - not complete (if repeated states are not checked)

A* idea

Heuristic Evaluation Functions



$f(s)$ = Estimate of cost of shortest solution path going through state s.

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

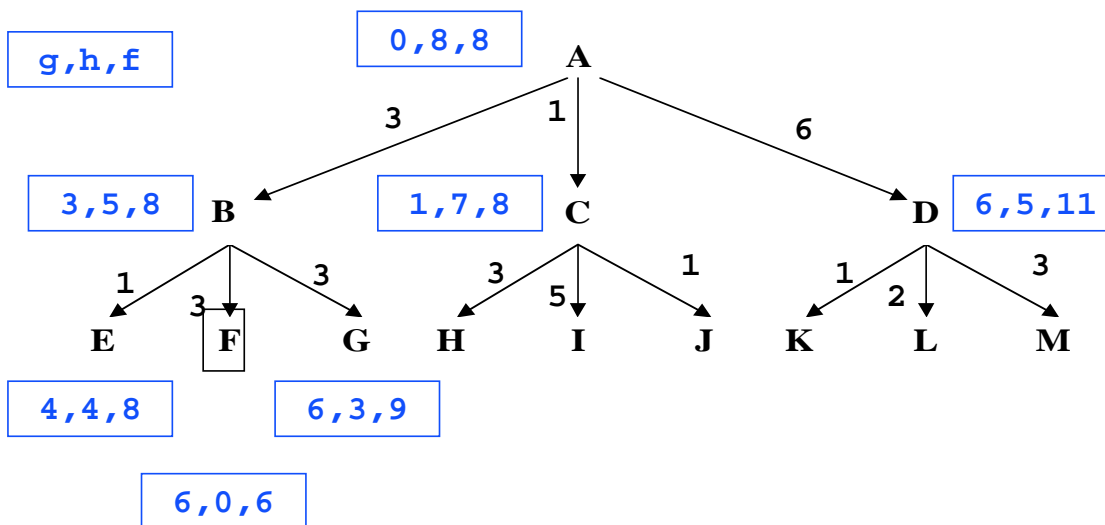
Monotonic Heuristic Function

- A heuristic evaluation function $h(s)$ is said to be "monotonic" if $f(s)=g(s)+h(s)$ does not go down along any path in the state space.

Monotone f

- $f(s_{i+1}) \geq f(s_i)$
 - $g(s_{i+1}) + h(s_{i+1}) \geq g(s_i) + h(s_i)$
 - $g(s_i) + \text{cost}(O(s_i)) + h(s_{i+1}) \geq g(s_i) + h(s_i)$
 - $\text{cost}(O(s_i)) + h(s_{i+1}) \geq h(s_i)$
 - $h(s_{i+1}) \geq h(s_i) - \text{cost}(O(s_i))$
- **How to define a monotonic heuristic evaluation function?**
 - $h_{\text{monotonic}}(s_{i+1}) = \max[h(s_{i+1}), h(s_i) - \text{cost}(O(s_i))]$

A* example

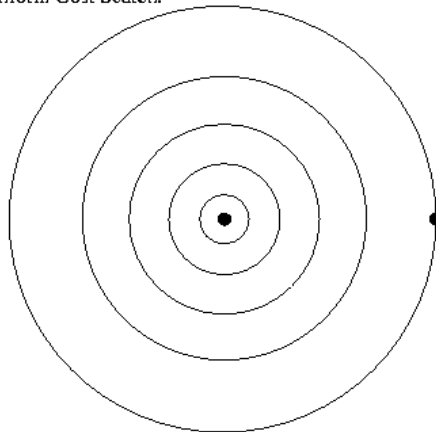


A* search contours

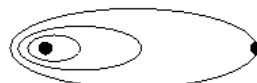
- If f^* is the cost of the optimal solution path, then:
 - A* expands all nodes with $f(n) < f^*$.
 - A* may expand some of the nodes on the “goal contour” for which $f(n) = f^*$ before selecting a goal node.
 - A* is optimally efficient for a give heuristic (no other algorithm is guaranteed to expand fewer nodes).

Topographical Interpretation of A* Algorithm

Uniform Cost Search:



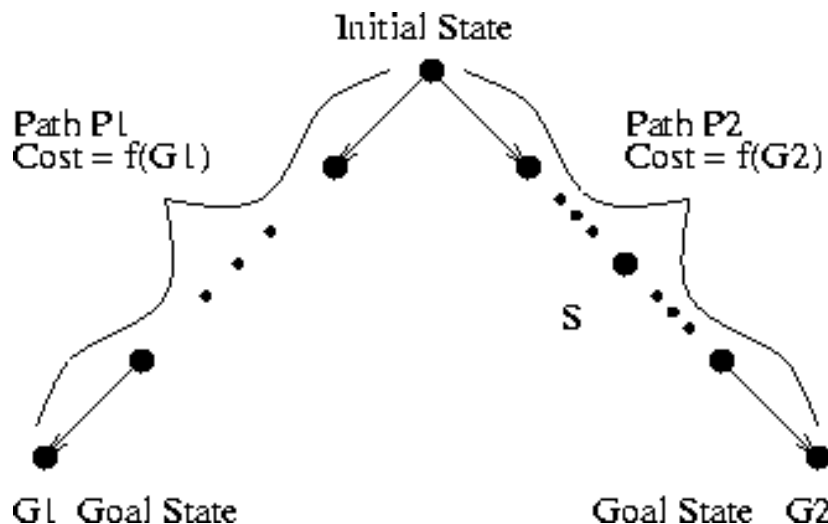
A* Search:



Admissible Heuristic Function

- A heuristic evaluation function $h(s)$ is said to be "admissible" if $h(s)$ is always less than or equal to the cost of the shortest path
- from s to a goal state, i.e., $h(s)$ underestimates the cost of reaching a solution from state s .
- Therefore:
 - The value of $h(\text{GoalState})$ is zero.
 - The value of $f(\text{GoalState})$ is the exact cost of a shortest path
 - from the initial state to a goal state.

A* Finds Optimal Solutions if $h(s)$ is Admissible



How complete is A*

- A* will expand nodes in order of increasing f and thus it will eventually reach a goal state with cost f^*
- Unless there is an infinite number of states with $f(n) \leq f^*$.

Heuristic Performance

- If N nodes are expanded and the solution depth is d , then the **effective branching** factor, b^* , is the branching factor that a uniform tree of depth d would need to contain N nodes.
- $N = 1 + b^* + (b^*)^2 + \dots + (b^*)^d$
- h_2 **dominates** h_1 if, for every node n ,
 $h_2(n) \geq h_1(n)$
- Larger heuristics have smaller branching factors.
- If several heuristics exist for a problem, the best way is to use a composite heuristic:
- $h(n) = \max(h_1(n), \dots, h_m(n))$

Comparison of performance for 8-puzzle

| d | Search Cost | | | Effective Branching Factor | | |
|-----|-------------|------------|------------|----------------------------|------------|------------|
| | IDS | $A^*(h_1)$ | $A^*(h_2)$ | IDS | $A^*(h_1)$ | $A^*(h_2)$ |
| 2 | 10 | 6 | 6 | 2.45 | 1.79 | 1.79 |
| 4 | 112 | 13 | 12 | 2.87 | 1.48 | 1.45 |
| 6 | 680 | 20 | 18 | 2.73 | 1.34 | 1.30 |
| 8 | 6384 | 39 | 25 | 2.80 | 1.33 | 1.24 |
| 10 | 47127 | 93 | 39 | 2.79 | 1.38 | 1.22 |
| 12 | 364404 | 227 | 73 | 2.78 | 1.42 | 1.24 |
| 14 | 3473941 | 539 | 113 | 2.83 | 1.44 | 1.23 |
| 16 | – | 1301 | 211 | – | 1.45 | 1.25 |
| 18 | – | 3056 | 363 | – | 1.46 | 1.26 |
| 20 | – | 7276 | 676 | – | 1.47 | 1.27 |
| 22 | – | 18094 | 1219 | – | 1.48 | 1.28 |
| 24 | – | 39135 | 1641 | – | 1.48 | 1.26 |

Where do Heuristics Come From?

- **Convert the original problem into a simpler one.**
 - E.g., A decomposable problem.
- **Solve the simple problem using a specialized method.**
 - E.g., By decomposition/recomposition.
- **Use the solution of the simple problem as a guide to solving the original problem.**
 - E.g., Let heuristic evaluation function $h(s)$ compute the length of the solution to the simple problem.