

# Heuristic Search and A\*

CPSC 322 Lecture 7

September 19, 2007  
Textbook §3.5

# Lecture Overview

- 1 Recap
- 2 Heuristic Search
- 3 Best-First Search
- 4  $A^*$  Search
- 5 Optimality of  $A^*$

# Breadth-first Search

- **Breadth-first search** treats the frontier as a queue
  - It always selects one of the first elements added to the frontier.
  
- **Complete** even when the graph has cycles or is infinite
- **Time complexity** is  $O(b^m)$
- **Space complexity** is  $O(b^m)$

# Search with Costs

- Sometimes there are **costs** associated with arcs.
  - The cost of a path is the sum of the costs of its arcs.
- In this setting we often don't just want to find just any solution
  - Instead, we usually want to find the solution that **minimizes cost**
- We call a search algorithm which always finds such a solution **optimal**
- **Lowest-Cost-First Search**: expand paths from the frontier in order of their costs.

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# Past knowledge and search

- Some people believe that they are good at solving hard problems without search
  - However, consider e.g., public key encryption codes (or combination locks): the search problem is clear, but people can't solve it
  - When people do perform well on hard problems, it is usually because they have **useful knowledge** about the structure of the problem domain
- Computers can also improve their performance when given this sort of knowledge
  - in search, they can estimate the distance from a given node to the goal through a **search heuristic**
  - in this way, they can take the goal into account when selecting path

# Heuristic Search

## Definition (search heuristic)

A **search heuristic**  $h(n)$  is an estimate of the cost of the shortest path from node  $n$  to a goal node.

- $h$  can be extended to paths:  $h(\langle n_0, \dots, n_k \rangle) = h(n_k)$
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## Definition (admissible heuristic)

A search heuristic  $h(n)$  is **admissible** if it is never an overestimate of the cost from  $n$  to a goal.

- there is never a path from  $n$  to a goal that has path length less than  $h(n)$ .
- another way of saying this:  $h(n)$  is a **lower bound** on the cost of getting from  $n$  to the nearest goal.



# Example Heuristic Functions

- If the nodes are **points on a Euclidean plane** and the cost is the distance, we can use the straight-line distance from  $n$  to the closest goal as the value of  $h(n)$ .
  - this makes sense if there are obstacles, or for other reasons not all adjacent nodes share an arc

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- Likewise, if nodes are **cells in a grid** and the cost is the number of steps, we can use “Manhattan distance”
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- In the **8-puzzle**, we can use the number of moves between each tile’s current position and its position in the solution

# How to Construct a Heuristic

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- It's usually possible to identify constraints which, when dropped, make the problem extremely easy to solve
  - this is important because heuristics are not useful if they're as hard to solve as the original problem!
- Another **trick for constructing heuristics**: if  $h_1(n)$  is an admissible heuristic, and  $h_2(n)$  is also an admissible heuristic, then  $\max(h_1(n), h_2(n))$  is also admissible.

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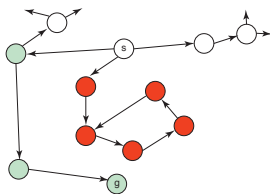


# Best-First Search

- **Idea:** select the path whose end is closest to a goal according to the heuristic function.
- Best-First search selects a path on the frontier with minimal  $h$ -value.
- It treats the frontier as a priority queue ordered by  $h$ .
- This is a **greedy** approach: it always takes the path which appears locally best

# Complexity of Best-First Search

- **Complete:** no: a low heuristic value can mean that a cycle gets followed forever.



- **Time complexity** is  $O(b^m)$
- **Space complexity** is  $O(b^m)$
- **Optimal:** no (why not?)

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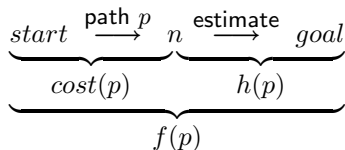
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# $A^*$ Search

- $A^*$  search uses both **path costs** and **heuristic values**
  - $cost(p)$  is the cost of the path  $p$ .
  - $h(p)$  estimates the cost from the end of  $p$  to a goal.

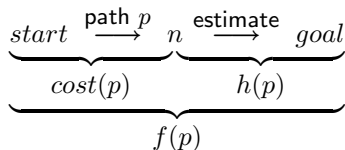
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- Let  $f(p) = cost(p) + h(p)$ .
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- A\* treats the frontier as a **priority queue ordered by  $f(p)$** .
  - It always selects the node on the frontier with the lowest estimated **total** distance.
  - It's a mix of lowest-cost-first and best-first search.

# Analysis of A\*

Let's assume that arc costs are strictly positive.

- **Completeness:** yes.
- **Time complexity:**  $O(b^m)$ 
  - the heuristic could be completely uninformative and the edge costs could all be the same, meaning that A\* does the same thing as BFS
- **Space complexity:**  $O(b^m)$ 
  - like BFS, A\* maintains a frontier which grows with the size of the tree
- **Optimality:** yes.

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# Optimality<sup>1</sup> of $A^*$

If  $A^*$  returns a solution, that solution is guaranteed to be optimal, as long as

- the branching factor is finite
- arc costs are strictly positive
- $h(n)$  is an underestimate of the length of the shortest path from  $n$  to a goal node, and is non-negative

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<sup>1</sup>Some literature, and the textbook, uses the word “admissibility” here. ▶

# Why is $A^*$ optimal?

## Theorem

*If  $A^*$  selects a path  $p$ ,  $p$  is the shortest (i.e., lowest-cost) path.*

- Assume for contradiction that some other path  $p'$  is actually the shortest path to a goal
- Consider the moment just before  $p$  is chosen from the frontier. Some part of path  $p'$  will also be on the frontier; let's call this partial path  $p''$ .
- Because  $p$  was expanded before  $p''$ ,  $f(p) \leq f(p'')$ .
- Because  $p$  is a goal,  $h(p) = 0$ . Thus  $cost(p) \leq cost(p'') + h(p'')$ .
- Because  $h$  is admissible,  $cost(p'') + h(p'') \leq cost(p')$  for any path  $p'$  to a goal that extends  $p''$
- Thus  $cost(p) \leq cost(p')$  for any other path  $p'$  to a goal. This contradicts our assumption that  $p'$  is the shortest path.