

# Branch & Bound

or, How I Learned to Stop Worrying and Love Depth First Search

CMPUT 366: Intelligent Systems

P&M §3.7-3.8

# Logistics

- **Assignment #1 released**
  - Available on eClass
  - Due: Monday **February 8, 2021**
- TA office hours discussion
  - Some students have expressed preference for later times
  - Depends on TA availability

# Recap: Heuristics

## Definition:

A **heuristic function** is a function  $h(n)$  that returns a non-negative estimate of the cost of the cheapest path from  $n$  to a goal node.

- e.g., Euclidean distance instead of travelled distance

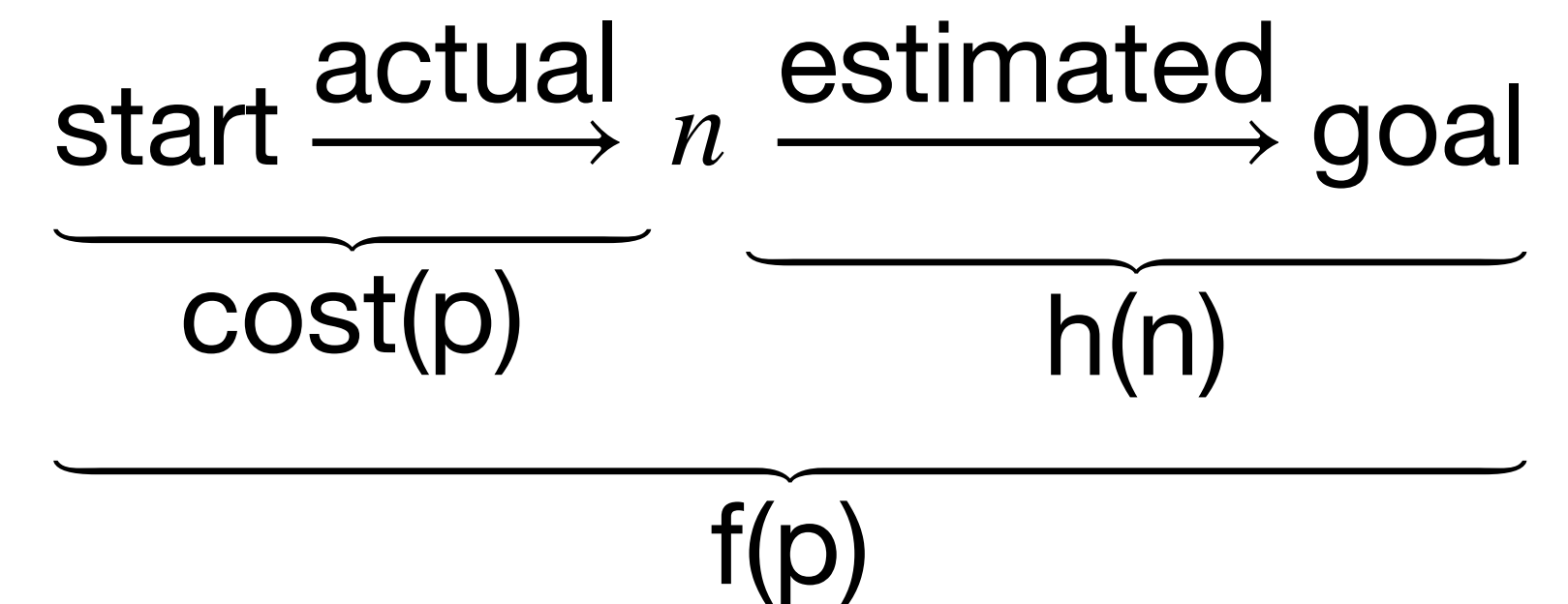
## Definition:

A heuristic function is **admissible** if  $h(n)$  is always less than or equal to the cost of the cheapest path from  $n$  to a goal node.

- i.e.,  $h(n)$  is a **lower bound** on  $\text{cost}(\langle n, \dots, g \rangle)$  for any **goal node**  $g$

# Recap: A\* Search

- A\* search uses **both** path cost information and heuristic information to select paths from the frontier
- Let  $f(p) = \text{cost}(p) + h(p)$ 
  - $f(p)$  **estimates** the total cost to the nearest goal node **starting from  $p$**
- A\* removes paths from the frontier with **smallest  $f(p)$**
- When  $h$  is **admissible**,  
 $p^* = \langle s, \dots, n, \dots, g \rangle$  is a **solution**, and  
 $p = \langle s, \dots, n \rangle$  is a **prefix** of  $p^*$ :
  - $f(p) \leq \text{cost}(p^*)$



# Recap: A\* Search Algorithm

**Input:** a *graph*; a set of *start nodes*; a *goal* function

*frontier* := {  $\langle s \rangle$  |  $s$  is a start node }

**while** *frontier* is not empty:

**select** *f*-minimizing path  $\langle n_1, n_2, \dots, n_k \rangle$  from *frontier*

**remove**  $\langle n_1, n_2, \dots, n_k \rangle$  from *frontier*

if *goal*( $n_k$ ):

**return**  $\langle n_1, n_2, \dots, n_k \rangle$

**for each** neighbour  $n$  of  $n_k$ :

**add**  $\langle n_1, n_2, \dots, n_k, n \rangle$  to *frontier*

**end while**

i.e.,  $f(\langle n_1, n_2, \dots, n_k \rangle) \leq f(p)$   
for all other paths  $p \in \textit{frontier}$

# Recap: $A^*$ Theorem

## Theorem:

If there is a solution,  $A^*$  using heuristic function  $h$  always returns an **optimal** solution (in **finite time**), if

1. The branching factor is **finite**,
2. All **arc costs** are greater than some  $\epsilon > 0$ , and
3.  $h$  is an **admissible** heuristic.

## Proof:

1. The **optimal solution** is guaranteed to be **removed from the frontier** eventually
2. **No suboptimal solution** will be removed from the frontier whenever the frontier contains a **prefix of the optimal solution**

# Lecture Outline

1. Recap & Logistics
2. Cycle Pruning
3. Branch & Bound
4. Exploiting Search Direction

# Cycle Pruning

- Even on **finite graphs**, depth-first search may not be complete, because it can get trapped in a **cycle**.
- A search algorithm can **prune** any path that ends in a node already on the path **without missing an optimal solution** (**Why?**)

## Questions:

1. Is depth-first search on with cycle pruning **complete** for finite graphs?
2. What is the **time complexity** for cycle checking in **depth-first search**?
3. What is the **time complexity** for cycle checking in **breadth-first search**?



# Cycle Pruning Depth First Search

**Input:** a graph; a set of start nodes; a goal function

*frontier* := {  $\langle s \rangle$  |  $s$  is a start node }

**while** *frontier* is not empty:

**select** the newest path  $\langle n_1, n_2, \dots, n_k \rangle$  from *frontier*

**remove**  $\langle n_1, n_2, \dots, n_k \rangle$  from *frontier*

**if**  $n_k \neq n_j$  for all  $1 \leq j < k$ :

**if**  $goal(n_k)$ :

**return**  $\langle n_1, n_2, \dots, n_k \rangle$

**for each** neighbour  $n$  of  $n_k$ :

**add**  $\langle n_1, n_2, \dots, n_k, n \rangle$  to *frontier*

**end while**

# Heuristic Depth First Search

	Heuristic Depth First	A*	Branch & Bound
Space complexity	$O(mb)$	$O(b^m)$	$O(mb)$
Heuristic Usage	Limited	Optimal	Optimal (if bound low enough)
Optimal?	No	Yes	Yes (if bound high enough)

# Branch & Bound

- The  $f(p)$  function provides a **path-specific lower bound** on solution cost starting from  $p$
- **Idea:** Maintain a **global upper bound** on solution cost also
  - Then prune any path whose lower bound **exceeds** the upper bound
- **Question:** Where does the upper bound come from?
  - **Cheapest** solution found so far
  - Before solutions found, specified on entry
  - Can increase the global upper bound **iteratively** (as in iterative deepening search)

# Branch & Bound Algorithm

**Input:** a graph; a set of start nodes; a goal function; heuristic  $h(n)$ ;  $bound_0$

$frontier := \{ \langle s \rangle \mid s \text{ is a start node} \}$

$bound := bound_0$

$best := \emptyset$

**while**  $frontier$  is not empty:

**select** the newest path  $\langle n_1, n_2, \dots, n_k \rangle$  from  $frontier$

**remove**  $\langle n_1, n_2, \dots, n_k \rangle$  from  $frontier$

**if**  $cost(\langle n_1, n_2, \dots, n_k \rangle) + h(n_k) \leq bound$ :

**if**  $goal(n_k)$ :

$bound := cost(\langle n_1, n_2, \dots, n_k \rangle)$

$best := \langle n_1, n_2, \dots, n_k \rangle$

**else:**

**for each** neighbour  $n$  of  $n_k$ :

**add**  $\langle n_1, n_2, \dots, n_k, n \rangle$  to  $frontier$

**end while**

**return**  $best$

# Branch & Bound Analysis

- If  $bound_0$  is set to just above the optimal cost, branch & bound will explore no more paths than  $A^*$   
(**Why?**)
- With **iterative increasing** of  $bound_0$ , will re-explore some lower-cost paths, but still similar time-complexity to  $A^*$

**Question:** How *much* should the bound get increased by?

- Iteratively increase bound to the **lowest-f-value** node that was **pruned**
- Worse than  $A^*$  by no more than a **linear** factor of  $m$ ,  
by the same argument as for iterative deepening search
- Choosing next  $f$ -limit is an active area of research

# Exploiting Search Direction

- When we care about finding the path to a known goal node, we can search forward, but we can often search **backward**
- Given a search graph  $G=(N,A)$ , **known** goal node  $g$ , and set of start nodes  $S$ , can construct a **reverse search problem**  $G=(N, A^r)$ :
  1. Designate  $g$  as the start node
  2.  $A^r = \{ \langle n_2, n_1 \rangle \mid \langle n_1, n_2 \rangle \in A \}$
  3.  $\text{goal}^r(n) = \text{True}$  if  $n \in S$   
(i.e., if  $n$  is a start node of the original problem)

## Questions:

1. When is this **useful**?
2. When is this **infeasible**?

# Reverse Search

## Definitions:

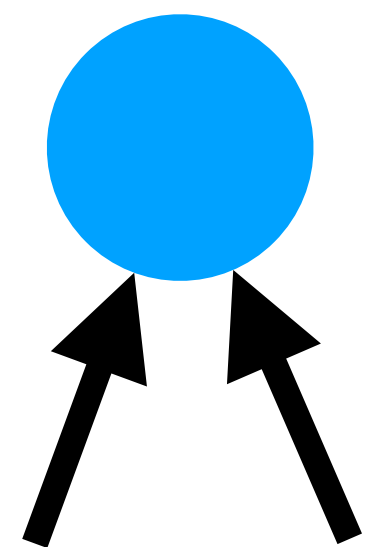
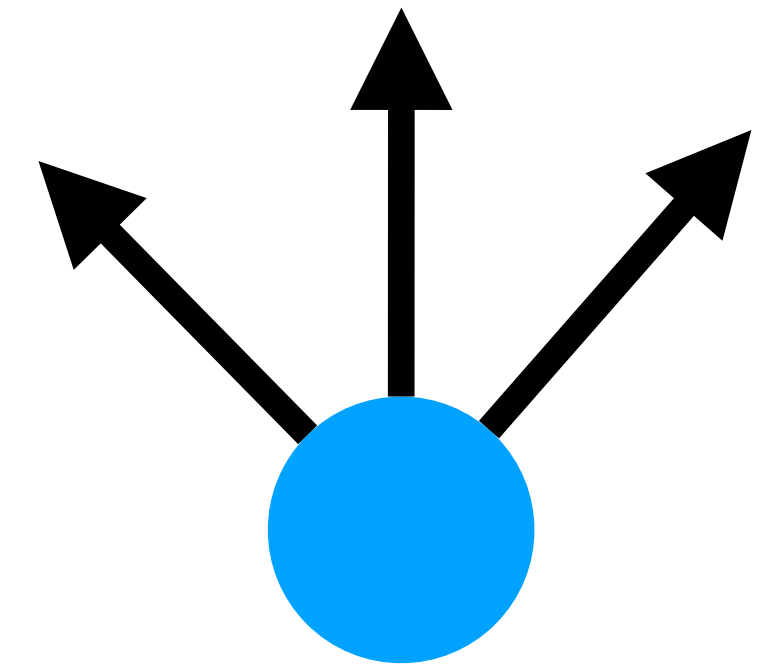
1. **Forward branch factor**: Maximum number of **outgoing** neighbours  
Notation:  $b$

- Time complexity of forward search:  $O(b^m)$

2. **Reverse branch factor**: Maximum number of **incoming** neighbours  
Notation:  $r$

- Time complexity of reverse search:  $O(r^m)$

When the reverse branch factor is **smaller** than the forward branch factor, reverse search is more **time-efficient**.



# Bidirectional Search

- **Idea:** Search backward from goal and forward from start **simultaneously**
- Time complexity is **exponential in path length**, so exploring half the path length is an exponential improvement
  - Even though must explore half the path length **twice**
- Main problems:
  - **Ensuring** that the frontiers meet
  - **Checking** that the frontiers have met

## Questions:

What bidirectional **combinations** of search algorithm make sense?

- Breadth first + Breadth first?
- Depth first + Depth first?
- Breadth first + Depth first?



# Summary

- A\* considers both **path cost** and **heuristic cost** when selecting paths:

$$f(p) = \text{cost}(p) + h(p)$$

- **Admissible** heuristics guarantee that A\* will be **optimal**
- Admissible heuristics can be built from **relaxations** of the original problem
- The more **accurate** the heuristic is, the **fewer** the paths A\* will explore
- **Branch & bound** combines the **optimality** guarantee and **heuristic efficiency** of A\* with the space efficiency of depth-first search
- Tweaking the **direction of search** can yield efficiency gains