

Data Structures and Algorithms

8. Search Algorithms

Basic Stuff You're Gonna Need to Search over a Graph
Where To Search Next?

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Path-finding in graphs

Search algorithms over directed graphs:

- The **search nodes** (vertex) of the graph represent some information
- The edges (v, v') capture transitions

One way to understand search algorithms is to think about **path-finding** over **graphs**.

Classification of Search Algorithms

Blind search vs. heuristic (or informed) search:

- **Blind search algorithms:** Only use the basic ingredients for general search algorithms.
 - *e.g., Depth First Search (DFS), Breadth-first search (BrFS), Uniform Cost (Dijkstra), Iterative Deepening (ID)*
- **Heuristic search algorithms:** Additionally use **heuristic functions** which estimate the distance (or remaining cost) to reach an target vertex.
 - *e.g., A*, IDA*, Hill Climbing, Best First, WA*, DFS B&B, LRTA*, ...*

Systematic search vs. local search:

- **Systematic search algorithms:** Consider a large number of search nodes simultaneously.
- **Local search algorithms:** Work with one (or a few) candidate solutions (search nodes) at a time.
 - This is not a black-and-white distinction; there are *crossbreeds* (e.g., **enforced hill-climbing**).

Blind Search

Blind search:

→ Here, we cover the subset of search algorithms. Only some Blind search algorithms are covered. Some Algorithms do not appear in Skiena's book.

Agenda

1 Basics

2 Blind Systematic Search Algorithms

Search Terminology

Search node n : Contains a *vertex* reached by the search, plus information about how it was reached.

Path cost $g(n)$: The cost of the path reaching n .

Optimal cost g^* : The cost of an optimal solution path. For a state s , $g^*(s)$ is the cost of a cheapest path reaching s .

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Search strategy: Method for deciding which node is expanded next.

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Open list: Set of all *nodes* that currently are candidates for expansion. Also called **frontier**.

Closed list: Set of all *nodes/vertexes* that were already expanded. Used only in **graph search**, not in **tree search** (up next). Also called **explored set**.

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Search Nodes

- **Search nodes σ** : Search vertexes, plus information on where/when/how they are encountered during search.

What is in a search node?

Different search algorithms store different information in a search node σ , but typical information includes:

- $Vertex(\sigma)$: Associated search vertex.
- $parent(\sigma)$: Pointer to search node from which σ is reached.
- $g(\sigma)$: Cost of σ (cost of path from the root node to σ).

For the root node, $parent(\sigma)$ and $action(\sigma)$ are undefined.

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Criteria for Evaluating Search Strategies

Guarantees:

Completeness: Is the strategy guaranteed to find a solution when there is one?

Optimality: Are the returned solutions guaranteed to be optimal?

Complexity:

Time Complexity: How long does it take to find a solution? (Measured in **generated nodes**.)

Space Complexity: How much memory does the search require? (Measured in **nodes**.)

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Branching factor b : How many successors does each node have?

Goal depth d : The number of actions required to reach the shallowest goal vertex.

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Blind search vs. informed search:

- **Blind search** does not require any input beyond the graph.

→ **Pros and Cons?** Pro: No additional work for the programmer. Con: It's not called "blind" for nothing ... same expansion order regardless what the problem actually is.

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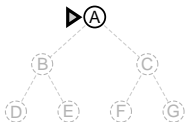
Blind search strategies we'll discuss:

- **Breadth-first search**. Advantage: time complexity.
Variant: **Uniform cost search**.
- **Depth-first search**. Advantage: space complexity.
- **Iterative deepening search**. Combines advantages of breadth-first search and depth-first search. Uses **depth-limited search** as a sub-procedure.

Breadth-First Search: Illustration and Guarantees

Strategy: Expand nodes in the order they were produced (FIFO frontier).

Illustration:



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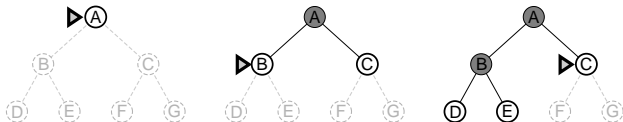
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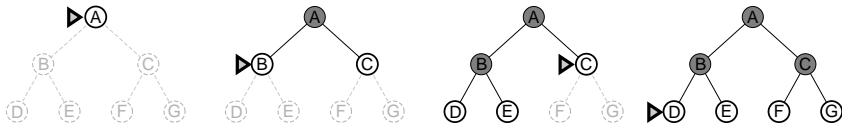
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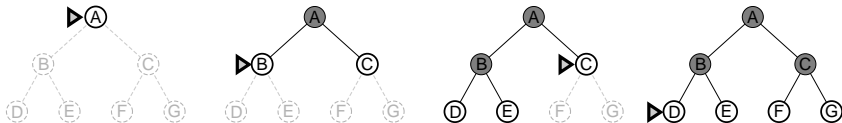
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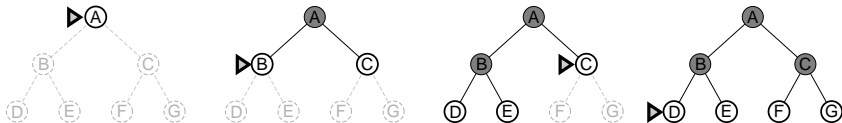
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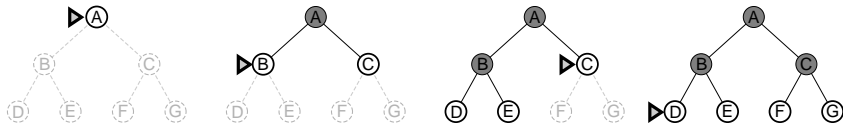
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- **Completeness?** Yes.
- **Optimality?** Yes, for uniform action costs. Breadth-first search always finds a shallowest goal vertex. If costs are not uniform, this is not necessarily optimal.

Breadth-First Search: Complexity

Time Complexity: Say that b is the maximal branching factor, and d is the depth of goal vertex.

- **Upper bound on the number of generated nodes?** $b + b^2 + b^3 + \dots + b^d$: In the worst case, the algorithm generates all nodes in the first d layers.
- So the time complexity is $O(b^d)$.
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Setting: $b = 10$; 10000 nodes/second; 1000 bytes/node.

Yields data: (inserting values into previous equations)

Depth	Nodes	Time		Memory	
2	110	.11	milliseconds	107	kilobytes
4	11110	11	milliseconds	10.6	megabytes
6	10^6	1.1	seconds	1	gigabyte
8	10^8	2	minutes	103	gigabytes
10	10^{10}	3	hours	10	terabytes
12	10^{12}	13	days	1	petabyte
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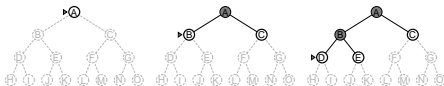
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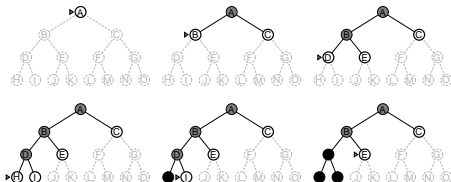
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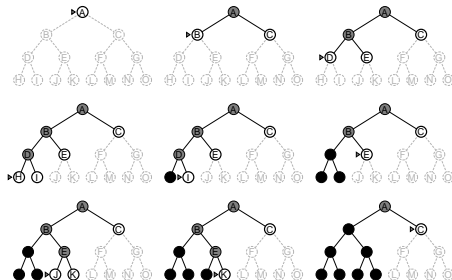
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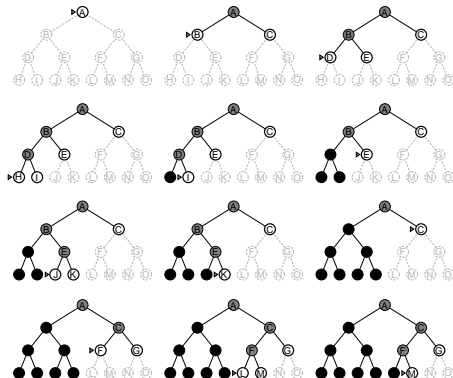
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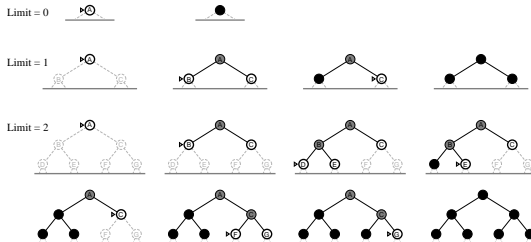
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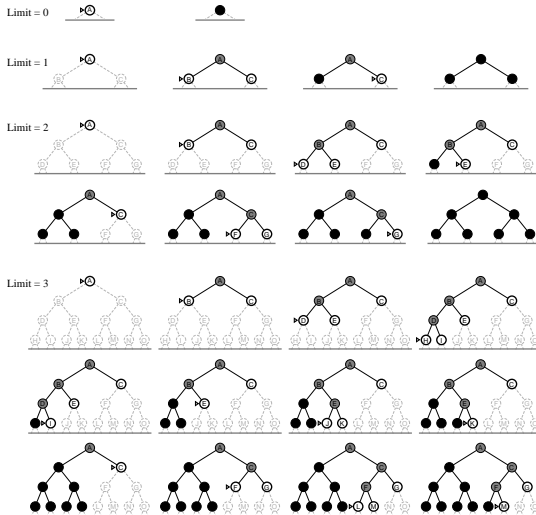
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Time complexity:

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Iterative Deepening Search	$(d)b + (d-1)b^2 + \dots + 3b^{d-2} + 2b^{d-1} + 1b^d \in O(b^d)$

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Example: $b = 10, d = 5$

Breadth-First Search	$10 + 100 + 1,000 + 10,000 + 100,000 = 111,110$
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