

#### State Space Search

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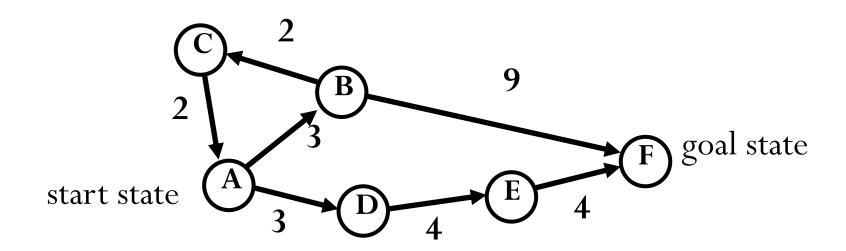


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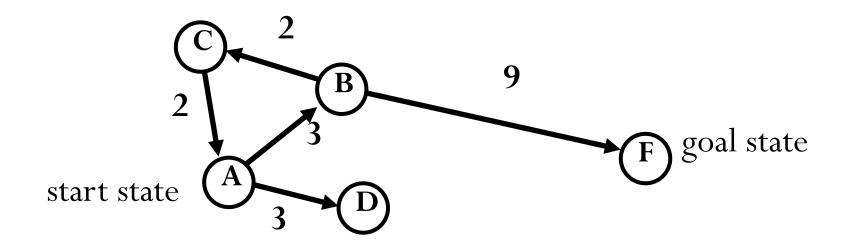
#### Search

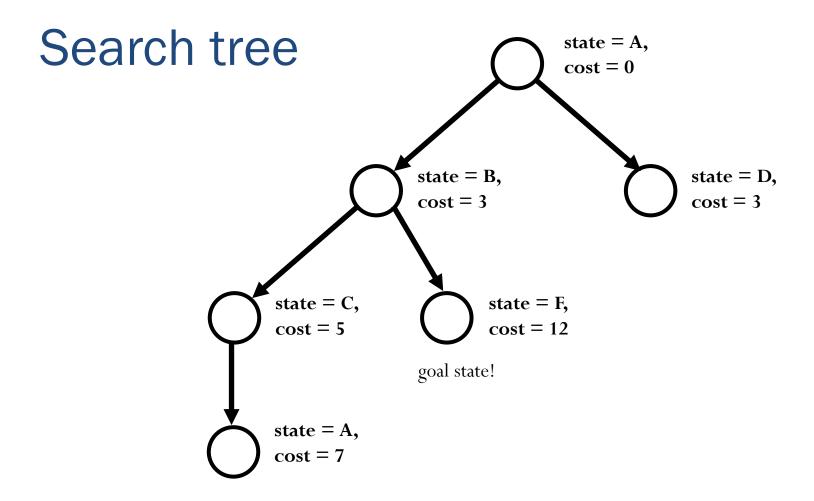
- We have some actions that can change the state of the world
  - Change induced by an action perfectly predictable
- Try to come up with a sequence of actions that will lead us to a goal state
  - May want to minimize number of actions
  - More generally, may want to minimize total cost of actions
- Do not need to execute actions in real life while searching for solution!
  - Everything perfectly predictable anyway

## A simple example: traveling on a graph

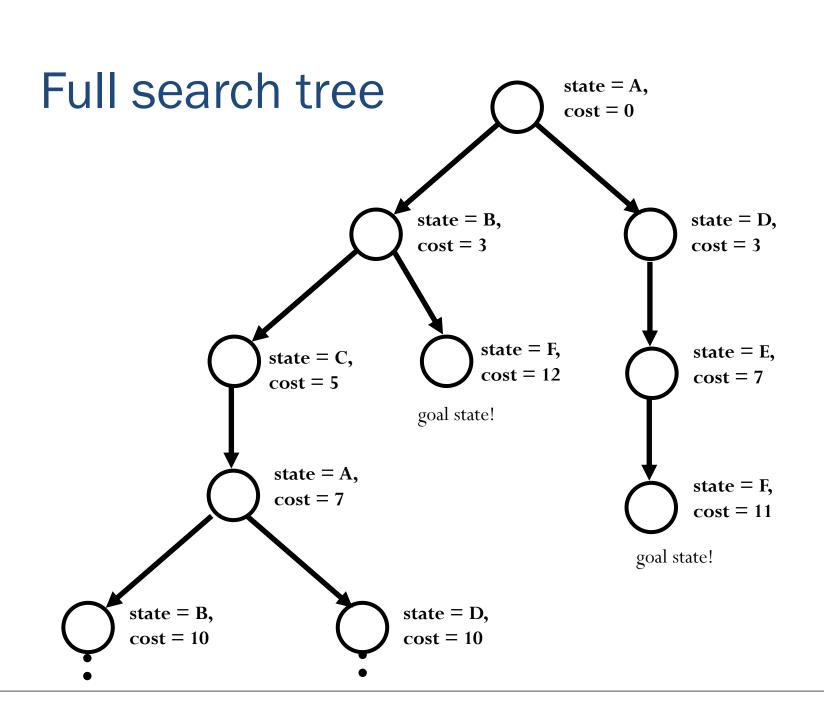


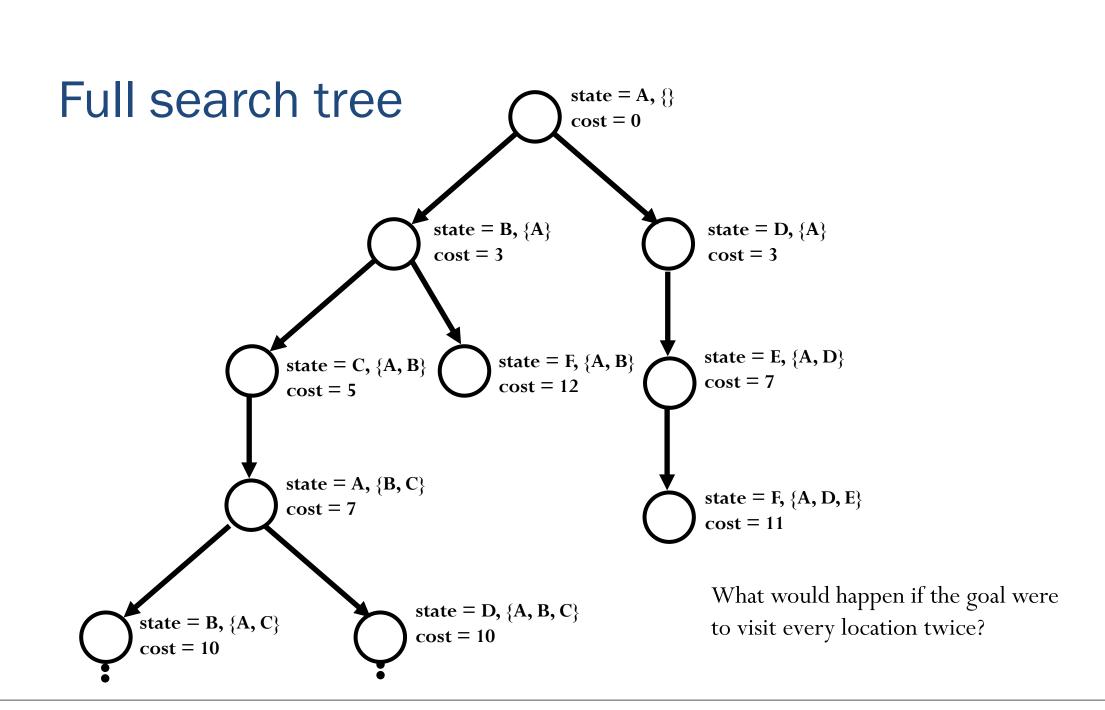
# Searching for a solution





search tree nodes and states are not the same thing!





## Key concepts in search

- Set of states that we can be in
  - Including an initial state...
  - ... and goal states (equivalently, a goal test)
- For every state, a set of actions that we can take
  - Each action results in a new state
  - Typically defined by successor function
    - Given a state, produces all states that can be reached from it
- Cost function that determines the cost of each action (or path = sequence of actions)
- Solution: path from initial state to a goal state
  - Optimal solution: solution with minimal cost

# Uninformed search

#### Uninformed search

- Given a state, we only know whether it is a goal state or not
- Cannot say one nongoal state looks better than another nongoal state
- Can only traverse state space blindly in hope of somehow hitting a goal state at some point
  - Also called blind search
  - Blind does **not** imply unsystematic!

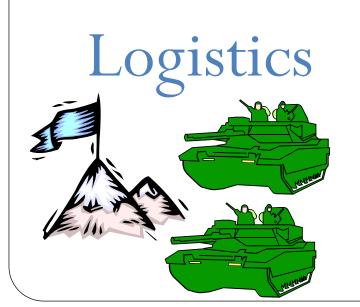
## Searching Examples

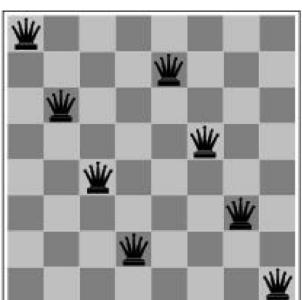


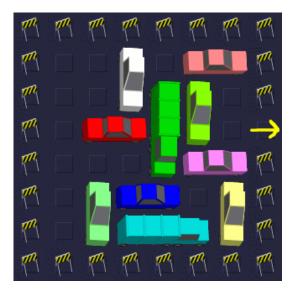


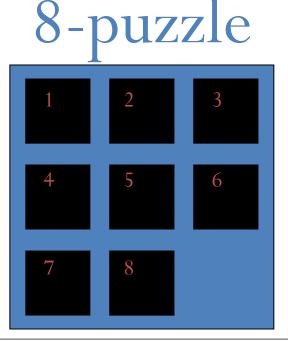
Rush Hour: Move cars forward and backward to "escape"











## Generic search algorithm

- Fringe = set of nodes generated but not expanded
- fringe := {initial state}
- loop:
  - if fringe empty, declare failure
  - choose and remove a node v from fringe
  - check if v's state s is a goal state; if so, declare success
  - if not, expand v, insert resulting nodes into fringe
- Key question in search: Which of the generated nodes do we expand next?

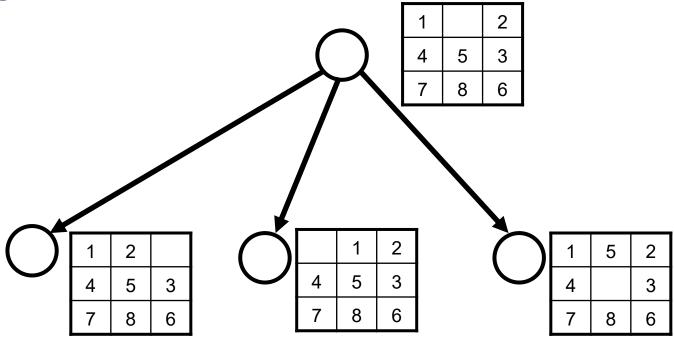
# 8-puzzle

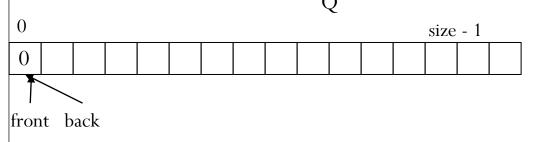
1		2
4	5	3
7	8	6

1	2	3
4	5	6
7	8	

goal state

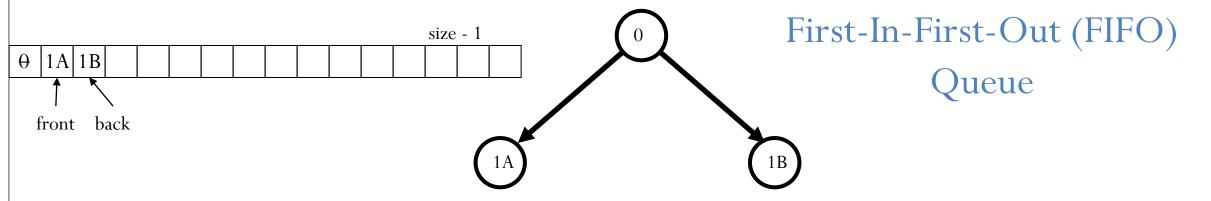
# 8-puzzle

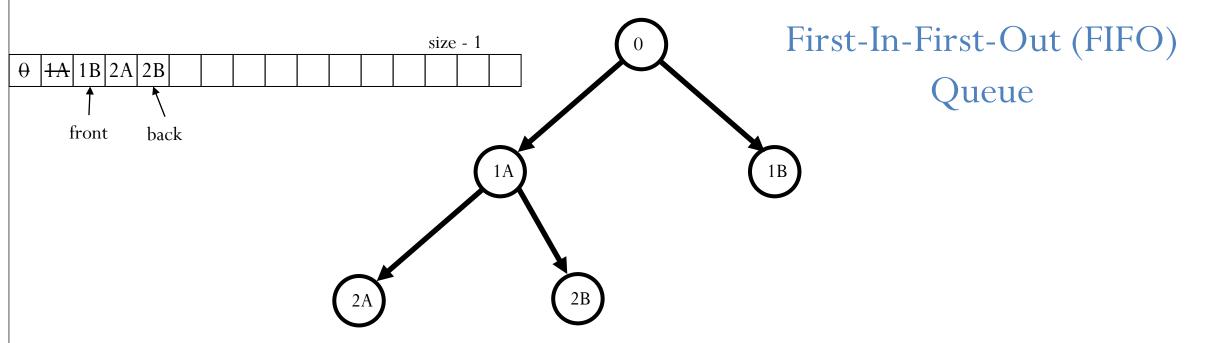


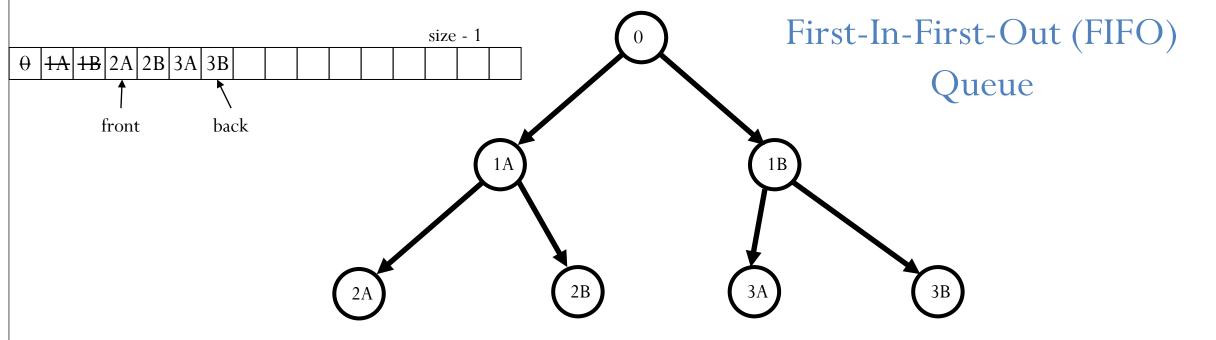


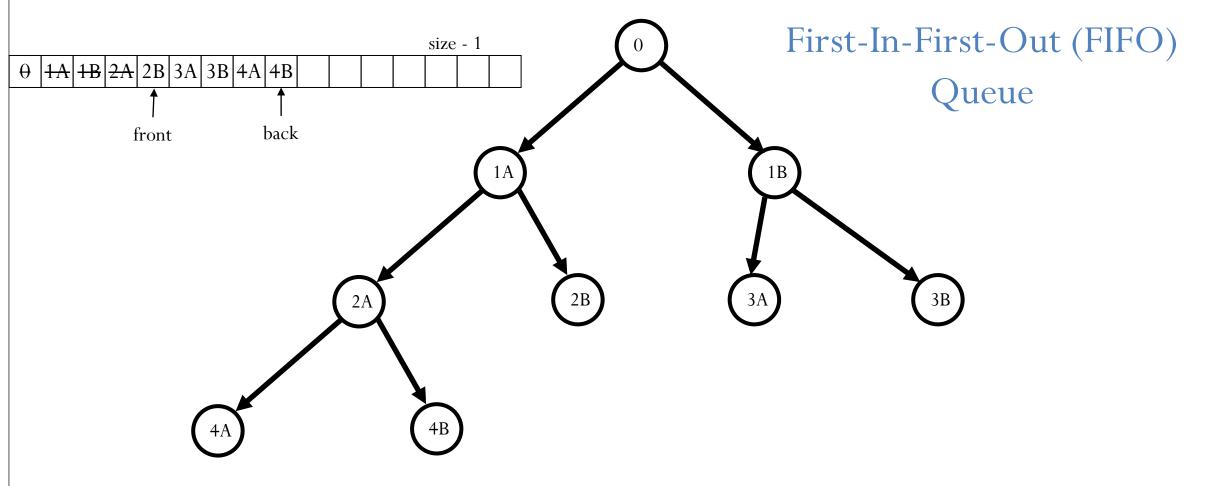


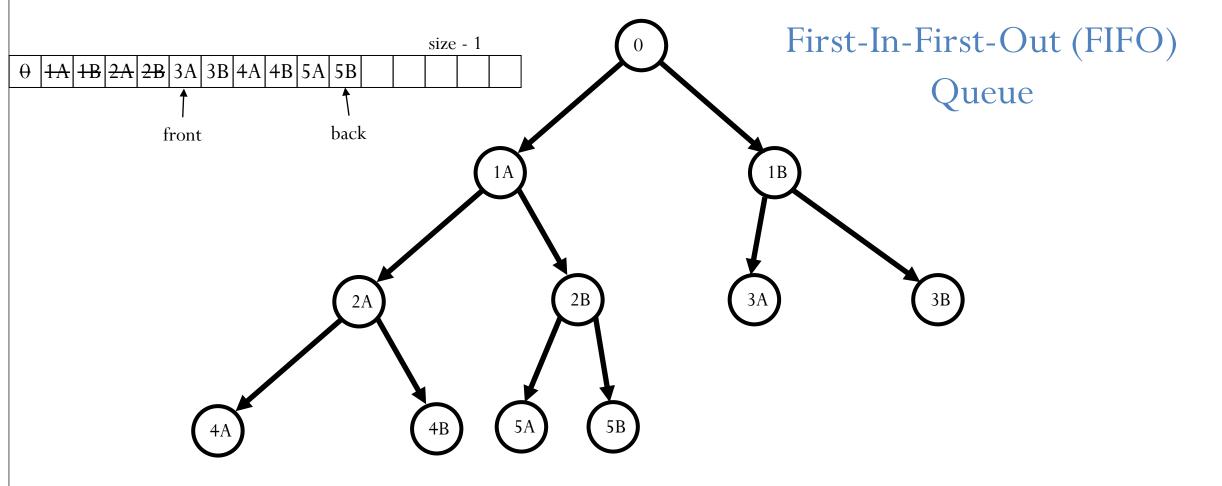
First-In-First-Out (FIFO)
Queue

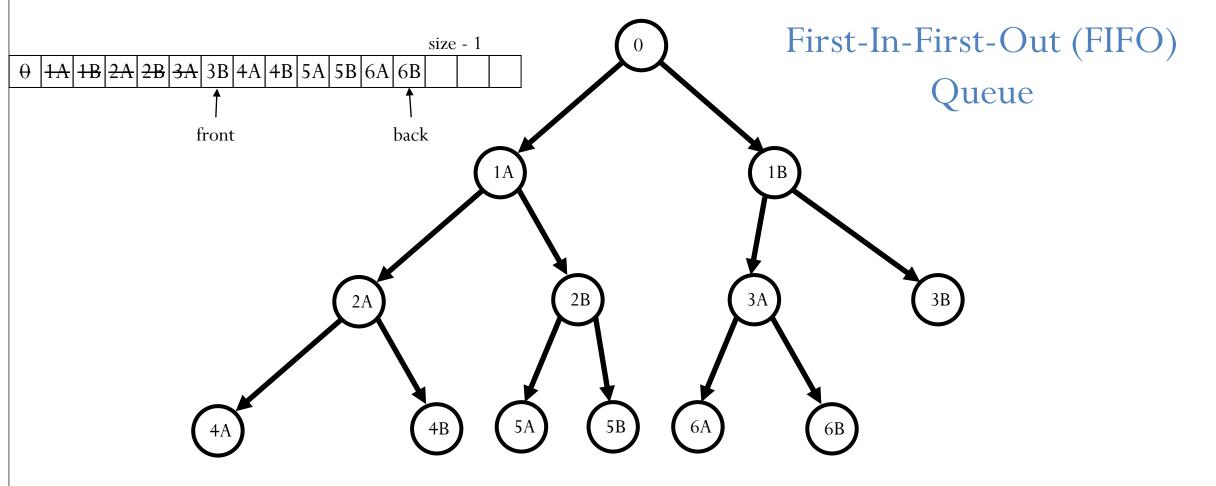


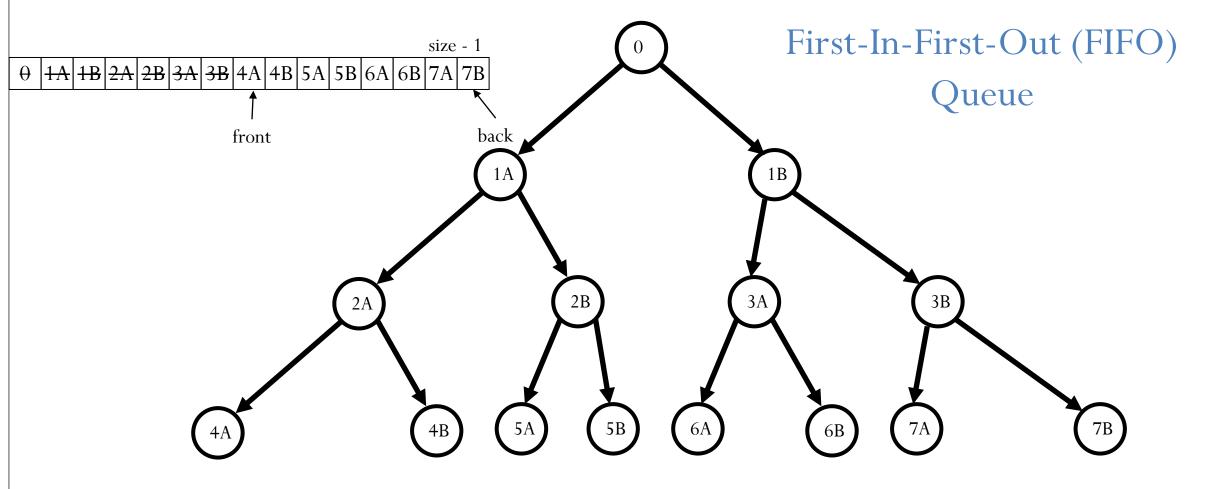


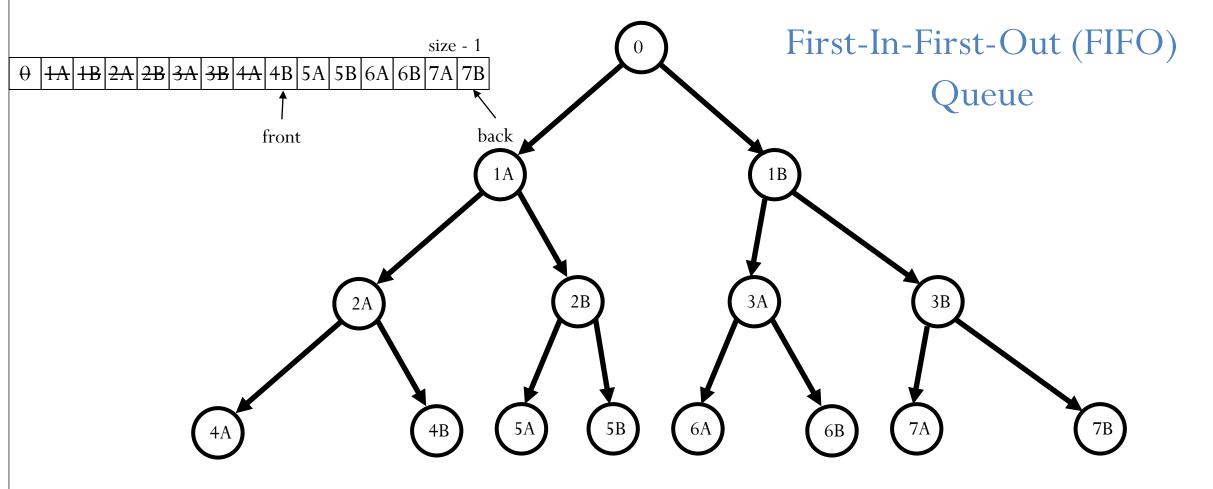


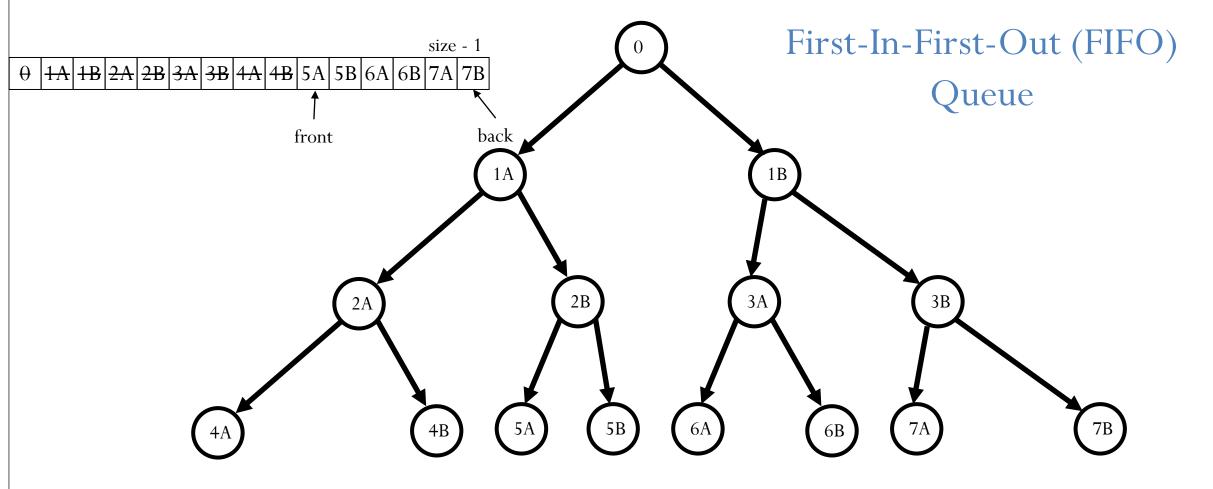


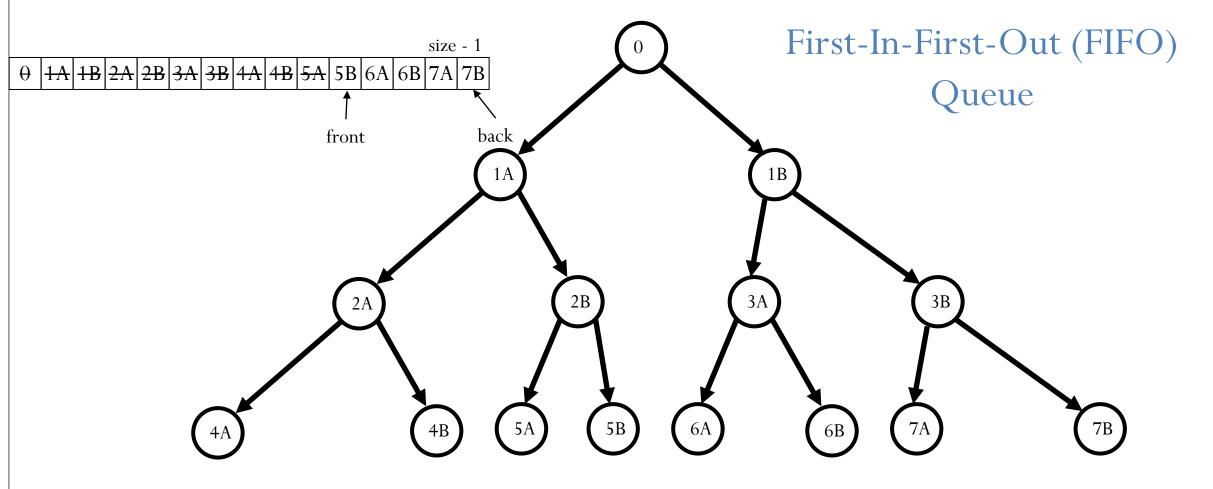


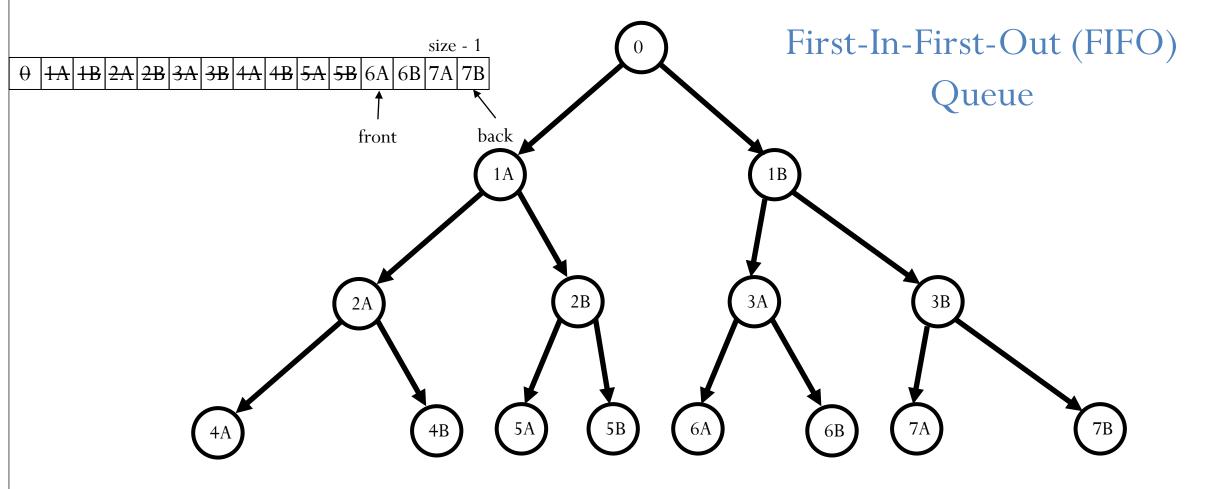


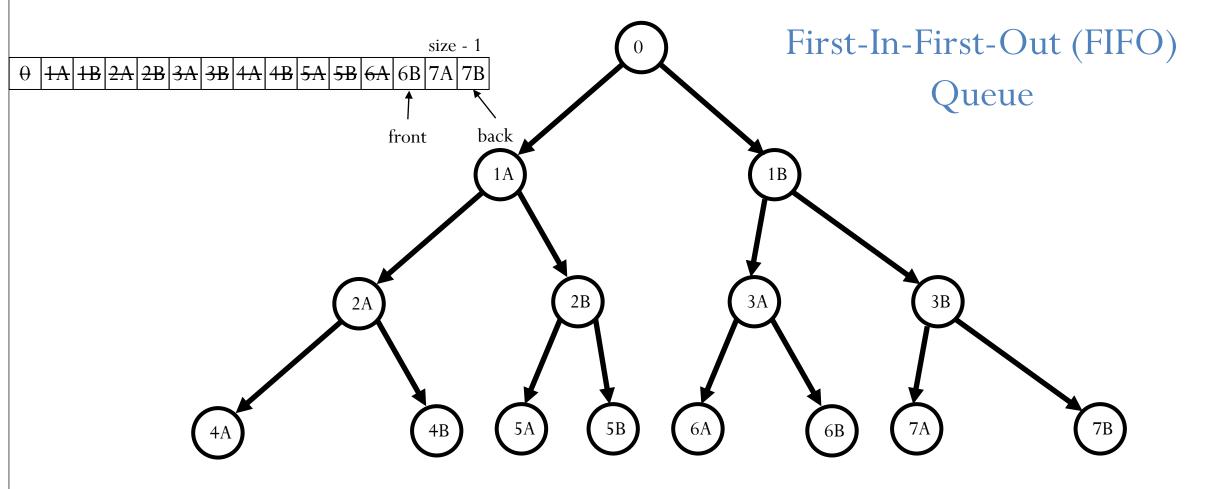


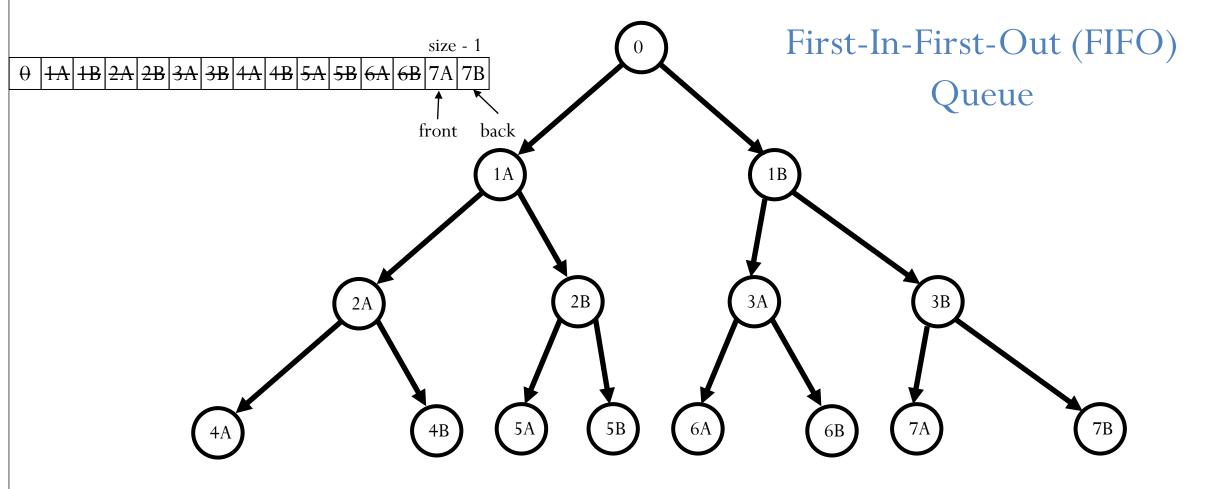


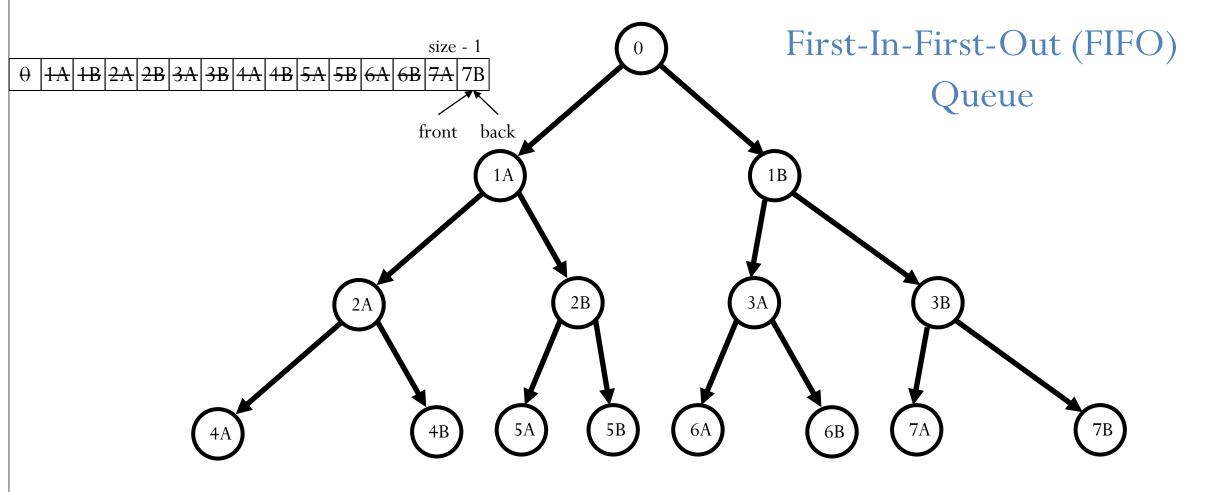


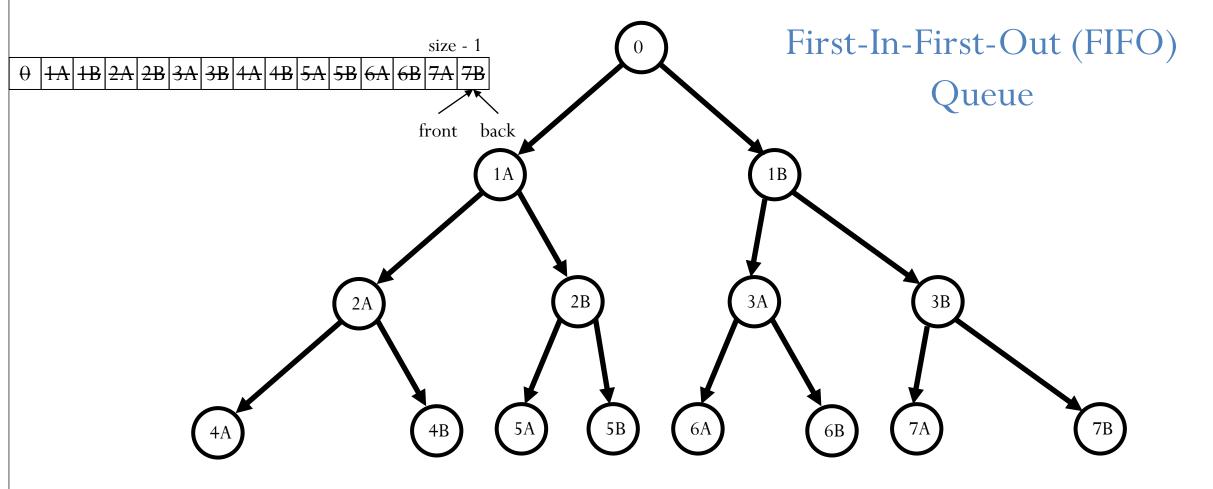


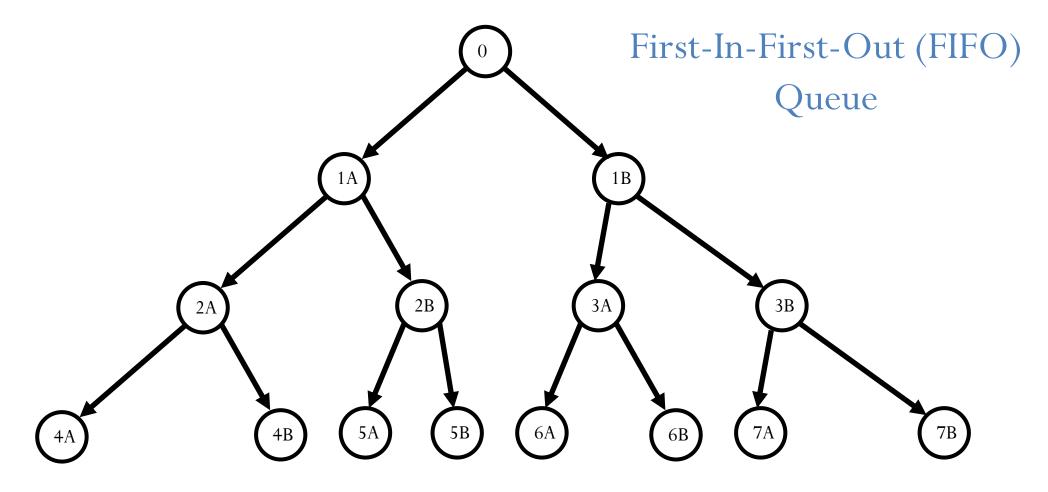






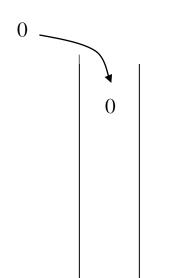






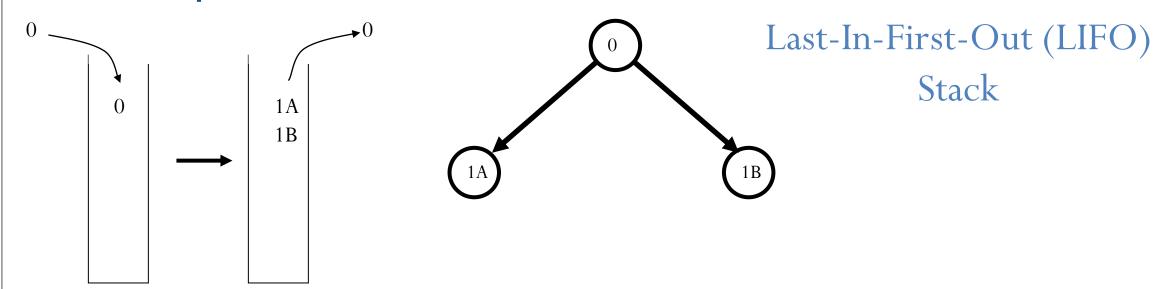
### Properties of Breadth-First Search

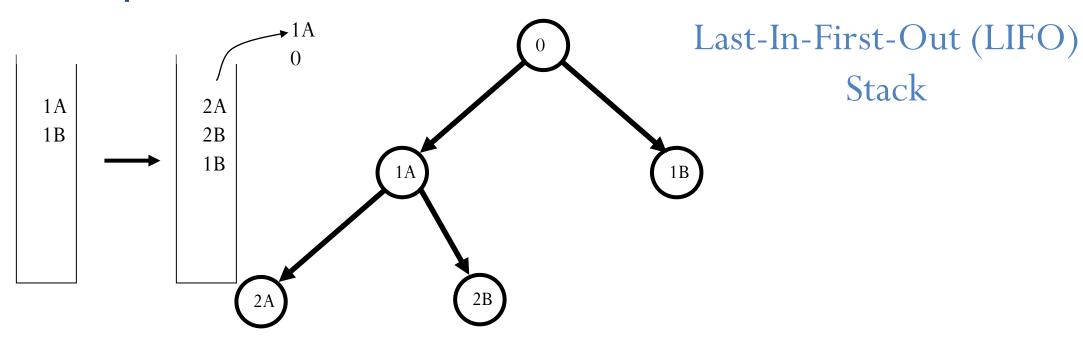
- Nodes are expanded in the same order in which they are generated
  - Fringe can be maintained as a First-In-First-Out (FIFO) queue
- BFS is complete: if a solution exists, one will be found
- BFS finds a shallowest solution
  - Not necessarily an optimal solution
- If every node has b successors (the branching factor), first solution is at depth d, then fringe size will be at least b<sup>d</sup> at some point
  - This much space (and time) required 😊

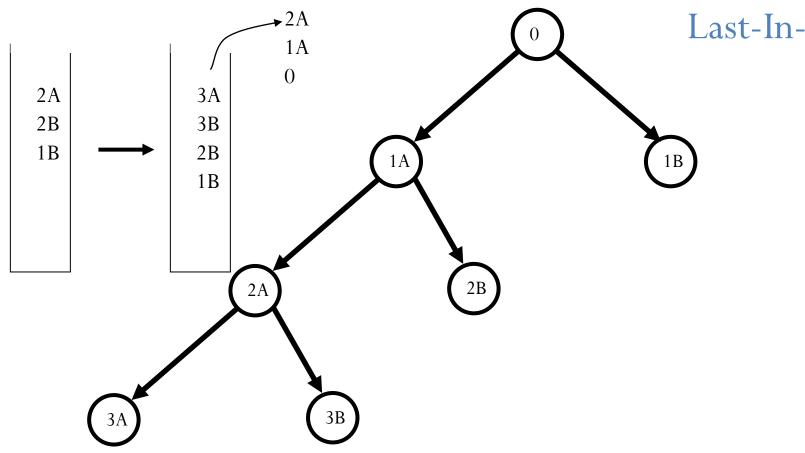




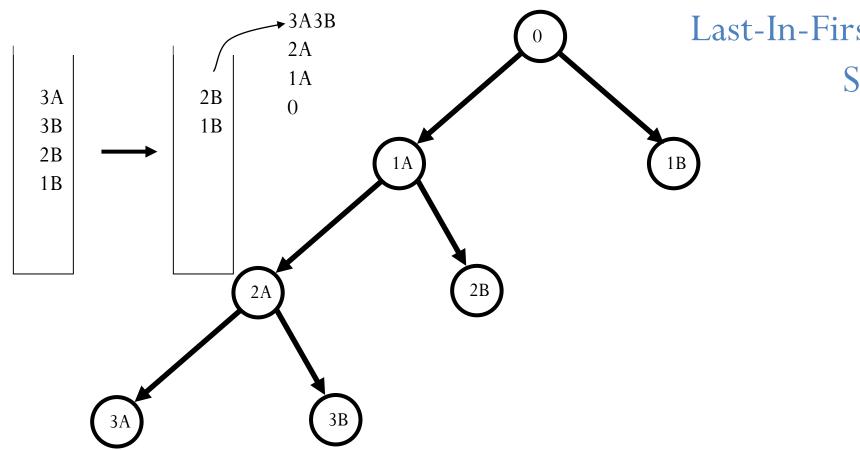
Last-In-First-Out (LIFO)
Stack



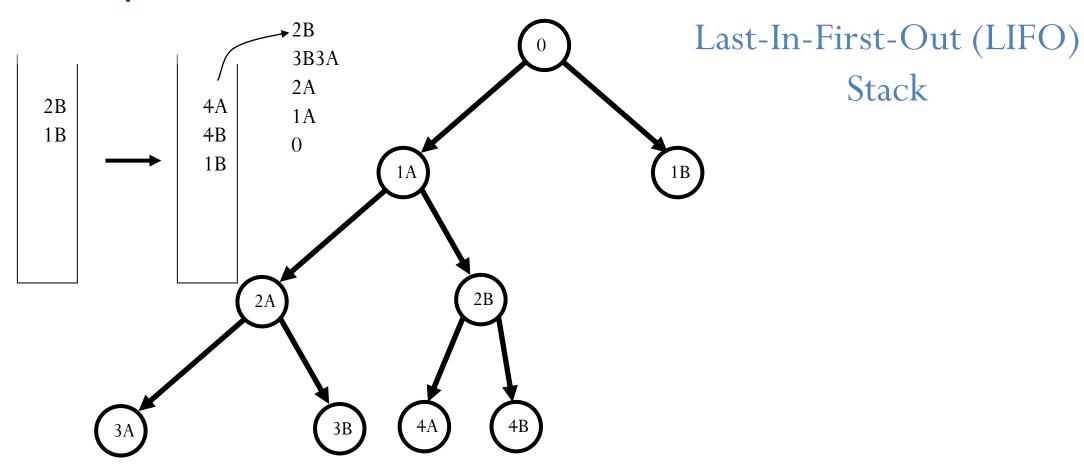




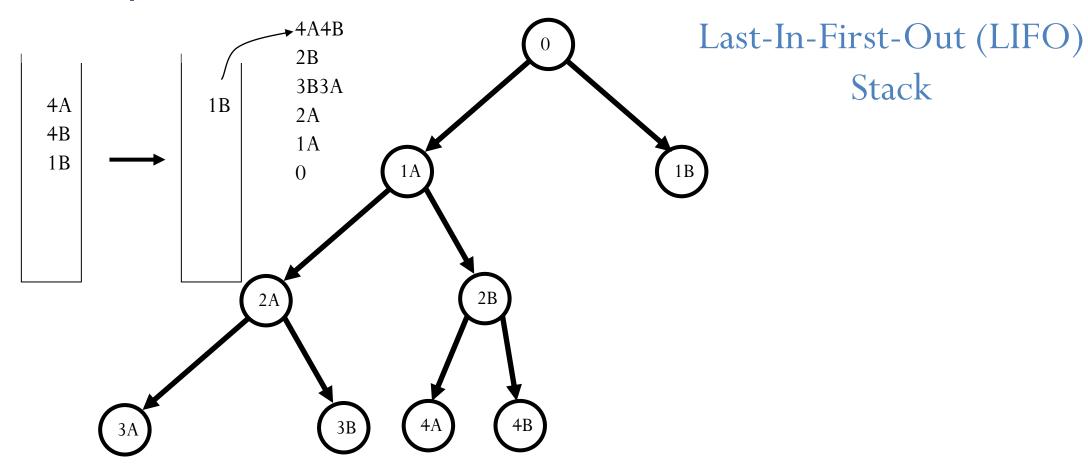
Last-In-First-Out (LIFO)
Stack



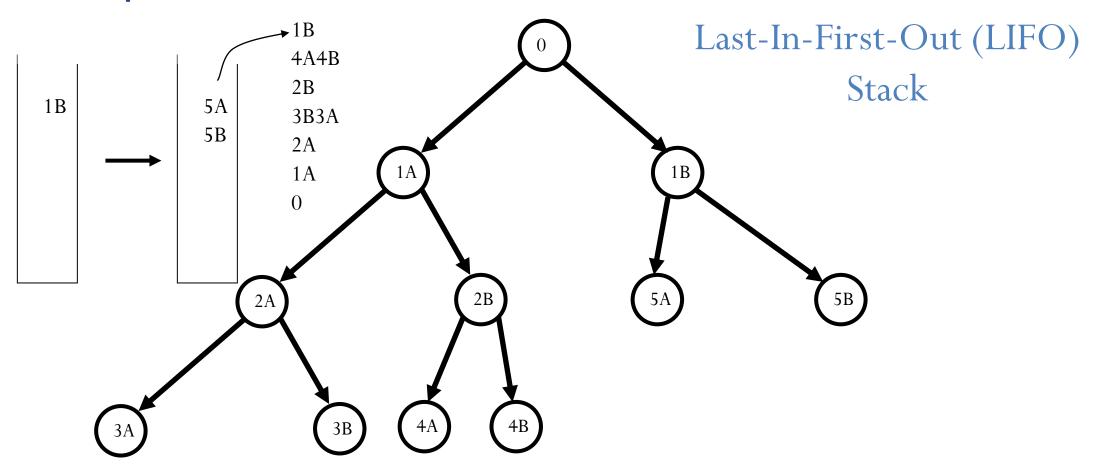
Last-In-First-Out (LIFO)
Stack

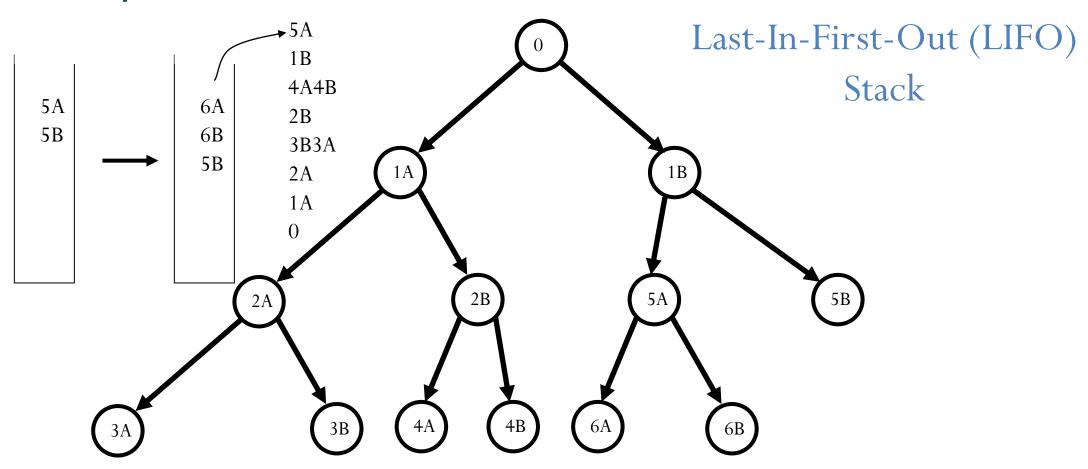


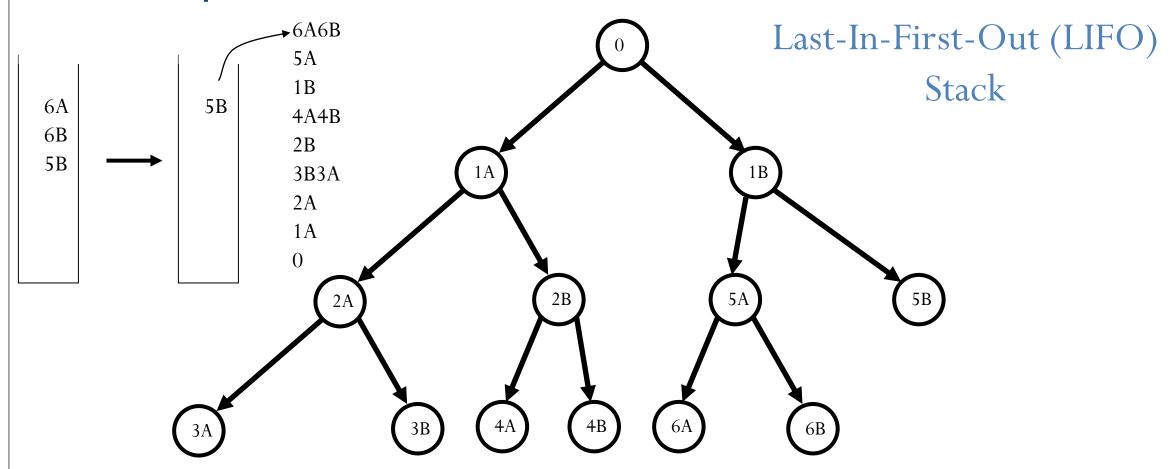
Animated PPT

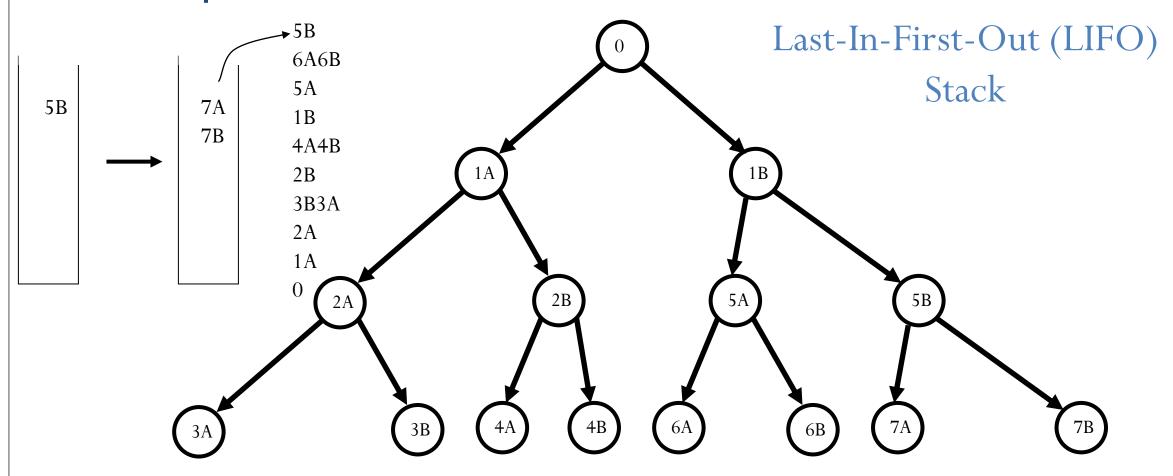


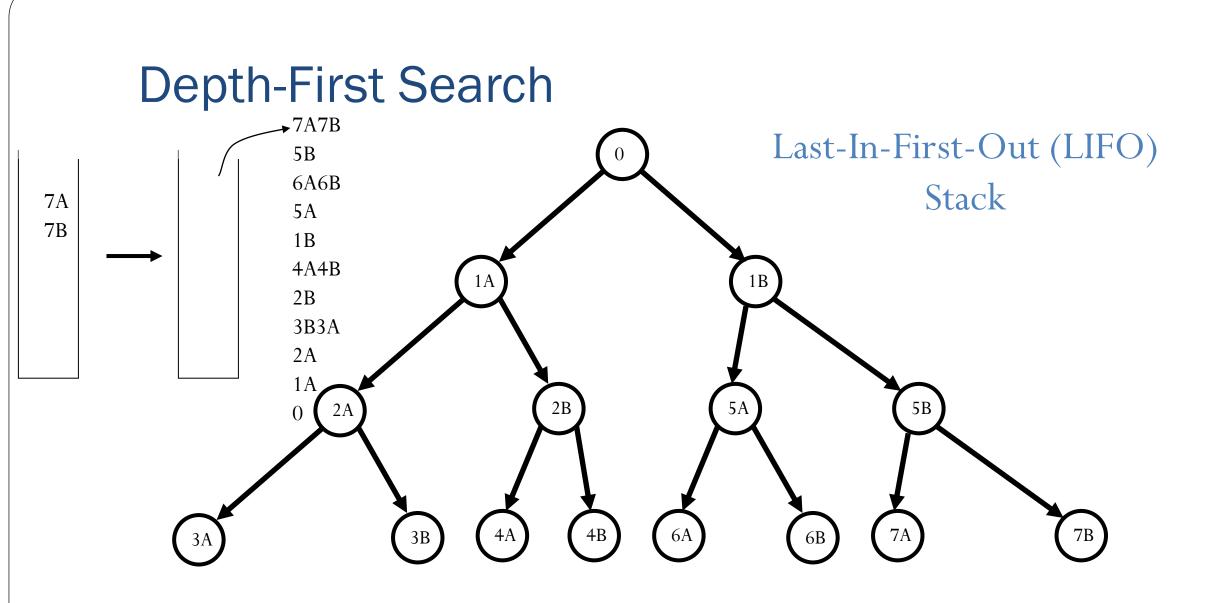
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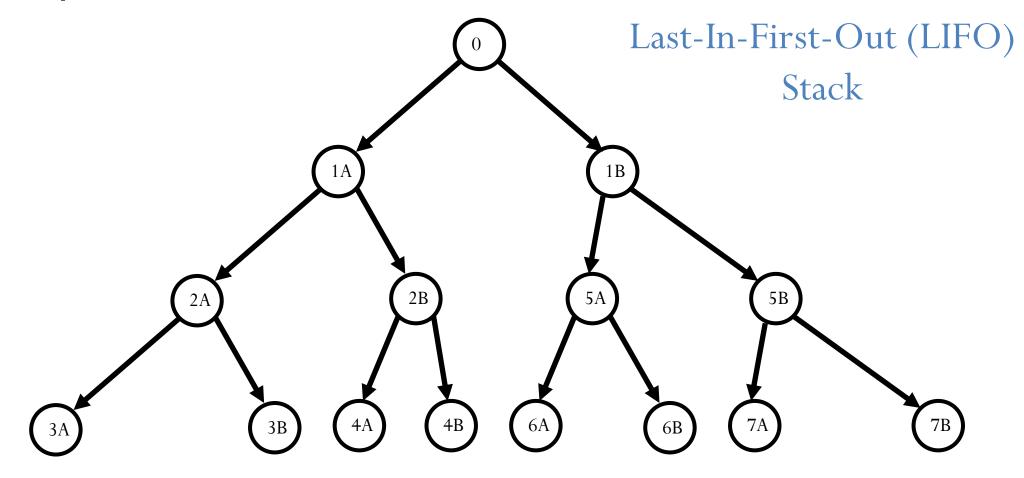












# Implementing Depth-First Search

- Fringe can be maintained as a Last-In-First-Out (LIFO) queue (aka. a stack)
- Also easy to implement recursively:
- DFS(node)
  - If goal(node) return solution(node);
  - For each successor of node
    - Return DFS(successor) unless it is *failure*;
  - Return *failure*;

# Properties of depth-first search

- Not complete (might cycle through nongoal states)
- If solution found, generally not optimal/shallowest
- If every node has b successors (the branching factor), and we search to at most depth m, fringe is at most bm
  - Much better space requirement ©
  - Actually, generally don't even need to store all of fringe
- Time: still need to look at every node
  - $b^m + b^{m-1} + ... + 1$  (for b > 1,  $O(b^m)$ )
  - Inevitable for uninformed search methods...

# Combining good properties of BFS and DFS

- Limited depth DFS: just like DFS, except never go deeper than some depth d
- Iterative deepening DFS:
  - Call limited depth DFS with depth 0;
  - If unsuccessful, call with depth 1;
  - If unsuccessful, call with depth 2;
  - Etc.
- Complete, finds shallowest solution
- Space requirements of DFS
- May seem wasteful timewise because replicating effort
  - Really not that wasteful because **almost all effort at deepest level**
  - $db + (d-1)b^2 + (d-2)b^3 + ... + 1b^d$  is  $O(b^d)$  for b > 1

# Searching solution evaluation

- Comparing multiple searching algorithm based on
  - Completeness: does it always find a solution if one exist?
  - Time complexity: How long depends on number of nodes
  - Space complexity: Memory depends on number of nodes
  - Optimality: Find shortest path (or least cost solution)?
  - Systematicity: does it visit each state at most once?

# Depth vs. Breadth-first

Let  $|T(s)| \le b$  (branching factor), goal at depth d

- How implement priority queue?
- Completeness?
- Time complexity?
- Space complexity?
- Optimality?

# **Breath First Search**

- Completeness?
  - Yes
- Time complexity?
  - O(b<sup>d</sup>)
- Space complexity?
  - O(b<sup>d</sup>) 🙁
- Optimality?
  - yes

# Depth First Search

- Completeness?
  - Yes, assuming state space finite
- Time complexity?
  - O(|V+E|), can do well if lots of goals
- Space complexity?
  - O(n), n deepest point of search
- Optimality?
  - No 😸

Let b as branching factor with goal at depth d

# Depth-limited Search

DFS, only expand nodes depth  $\leq 1$ .

- Completeness?
  - No, if  $l \leq d$ .  $\otimes$
- Time complexity?
  - O(b<sup>l</sup>)
- Space complexity?
  - O(l)
- Optimality?
  - No 🕃

# Iterative Deepening

Depth limited, increasing l.

- Completeness?
  - Yes. 🙂
- Time complexity?
  - O(b<sup>d</sup>), even with repeated work! ©
- Space complexity?
  - O(d) 🙂
- Optimality?
  - Yes 🙂

## Bidirectional search

- Even better: search from both the start and the goal, in parallel!
- If the shallowest solution has depth d and branching factor is b on both sides, requires only  $O(b^{d/2})$  nodes to be explored!

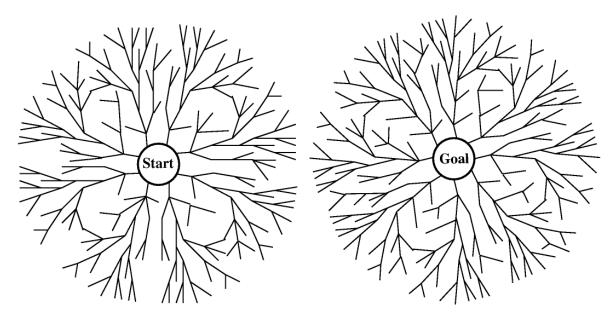


image from cs-alb-pc3.massey.ac.nz/notes/59302/fig03.17.gif

## **Bidirectional Search**

BFS in both directions

Need N<sup>-1</sup>

How could this help?

• bl vs 2bl/2

What makes this hard to implement?

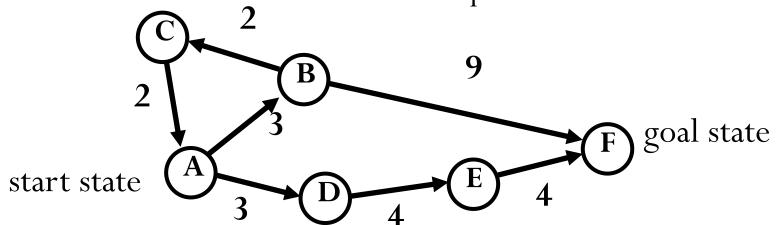
# Informed Search

## Informed search

- So far, have assumed that no nongoal state looks better than another
- Unrealistic
  - Even without knowing the road structure, some locations seem closer to the goal than others
  - Some states of the 8s puzzle seem closer to the goal than others
- Makes sense to expand closer-seeming nodes first

## Heuristics

- ullet Key notion: heuristic function h(n) gives an estimate of the distance from n to the goal
  - h(n)=0 for goal nodes
- E.g. straight-line distance for traveling problem
- Say: h(A) = 9, h(B) = 8, h(C) = 9, h(D) = 6, h(E) = 3, h(F) = 0
- We're adding something new to the problem!
- Can use heuristic to decide which nodes to expand first

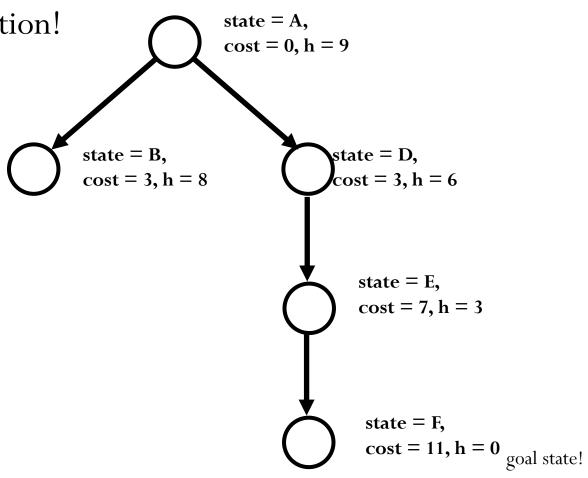


# Greedy best-first search

• Greedy best-first search: expand nodes with lowest h values first

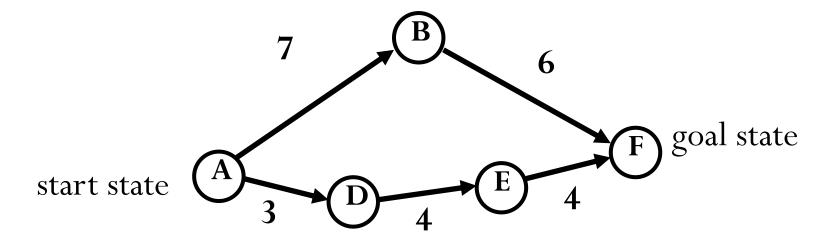
Rapidly finds the optimal solution!

• Does it always?



# A bad example for greedy

- Say: h(A) = 9, h(B) = 5, h(D) = 6, h(E) = 3, h(F) = 0
- Problem: greedy evaluates the promise of a node only by how far is left to go, does not take cost occurred already into account



## IDA\*

### **Memory Bounded**

Just as iterative deepening gives a more memory efficient version of BFS, can define IDA\* as a more memory efficient version of A\*.

Just use DFS with a cutoff on f values. Repeat with larger cutoff until solution found.

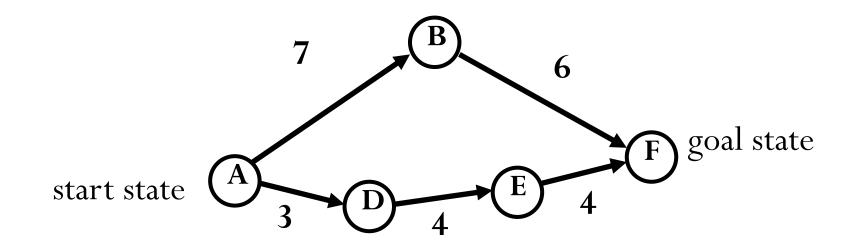
### What to Learn?

The A\* algorithm: its definition and behavior (finds optimal).

How to create admissible heuristics via relaxation.

## **A**\*

- Let g(n) be cost incurred already on path to n
- Expand nodes with lowest g(n) + h(n) first
- Say: h(A) = 9, h(B) = 5, h(D) = 6, h(E) = 3, h(F) = 0
- Note: if h=0 everywhere, then just uniform cost search



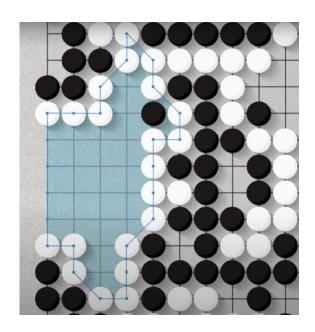
# Admissibility

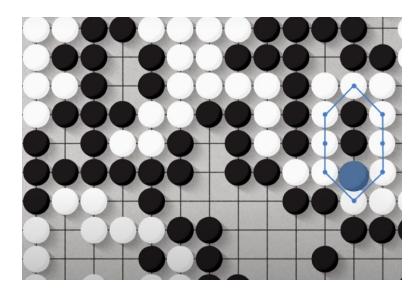
- A heuristic is admissible
  - if it never overestimates the distance to get the goal
  - If n is the optimal solution reachable from n', then  $g(n) \ge g(n') + h(n')$
- Straight-line distance is admissible: can't hope for anything better than a straight road to the goal
- Admissible heuristic means that A\* is always optimistic
- A\* is guaranteed to return a least-cost path from start to goal.

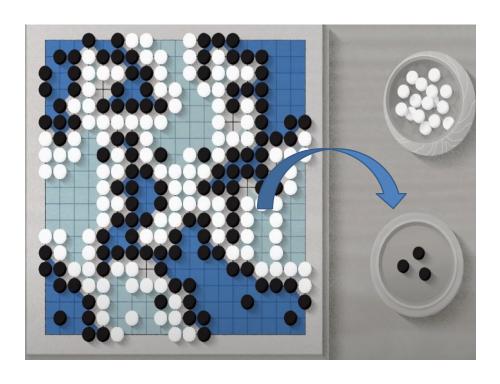
# Alpha Go Searching Example

# 2016: Alpha Go

- Make territories
- Capture opponent pieces
- Largest territory

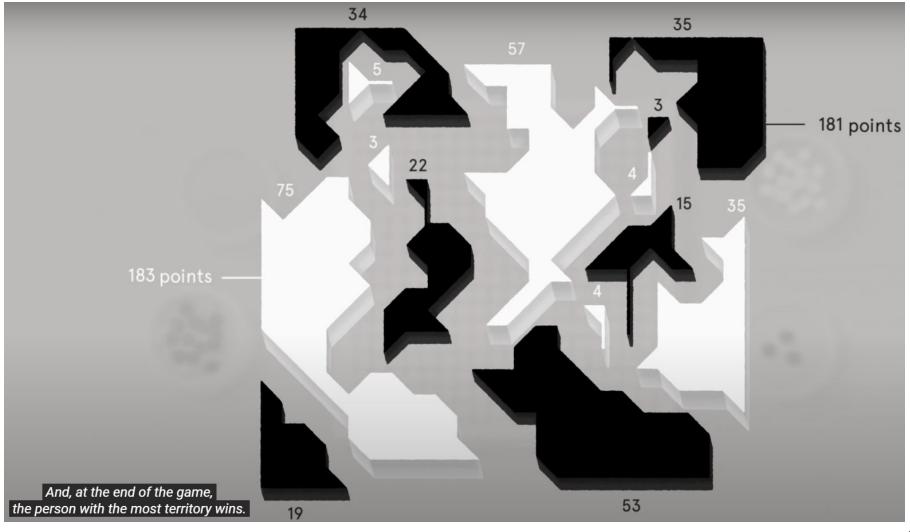






# 2016: Alpha Go





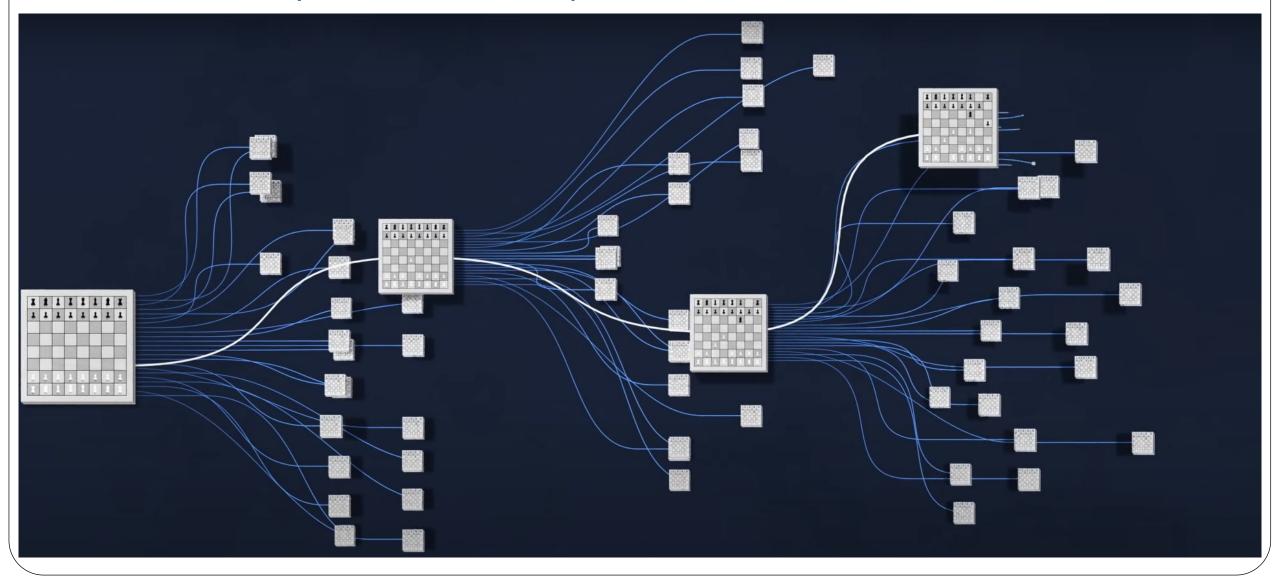
# 2016: Alpha Go

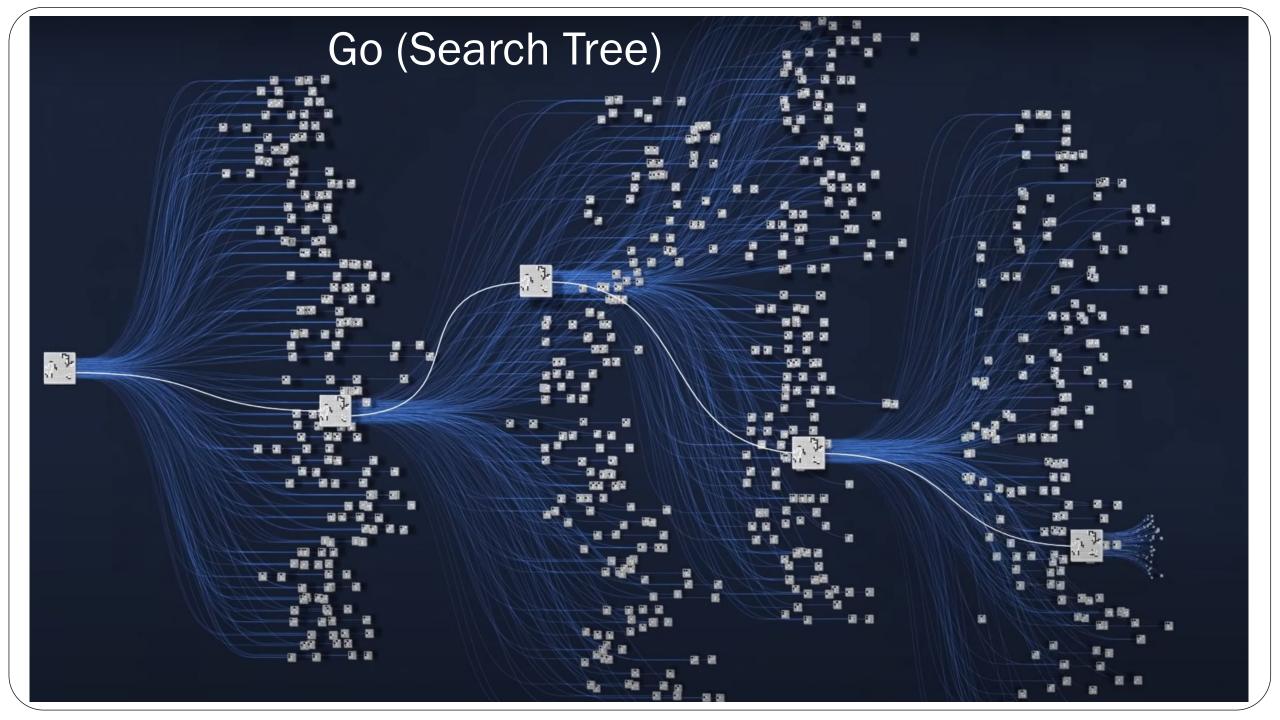
• https://www.buzzfeednews.com/article/alexkantrowitz/were-in-an-artificial-intelligence-hype-cycle





# Chess (Search Tree)





# Chess v/s Go

- At the opening move in Chess there are 20 possible moves.
- Go is simpler than Chess and yet more complex.
- In large games  $O(b^d)$ , such as
  - chess (**b≈35**, **d≈80**)
  - Go (**b≈250**, **d≈150**),
- Exhaustive search is infeasible, but the effective search space can be reduced by two general principles.
  - the depth of the search may be reduced by position evaluation: truncating (cut) the search tree at state s and replacing the subtree below s by an approximate value function  $\mathbf{v(s)} \approx \mathbf{v*(s)}$  that predicts the outcome from state s.
  - the breadth of the search may be reduced by sampling actions from a policy  $p(a \mid s)$  that is a probability distribution over possible moves a in position s.

## References

- Stuart Russel, and Peter Norvig. "Artificial intelligence: A modern approach. third edit." Upper Saddle River, New Jersey 7458 (2015).
- Introduction to Artificial Intelligence, Michael L. Littman, Fall 2001 mlittman@cs.brown.edu https://courses.cs.duke.edu/fall08/cps270/
- Vincent Conitzer, Artificial Intelligence <a href="http://www.cs.duke.edu/courses/fall08/">http://www.cs.duke.edu/courses/fall08/</a>
- Silver, David, et al. "Mastering the game of Go with deep neural networks and tree search." Nature 529.7587 (2016): 484-489.
- AlphaGo The Movie | Full award-winning documentary "DeepMind" <a href="https://www.youtube.com/watch?v=WXuK6gekU1Y">https://www.youtube.com/watch?v=WXuK6gekU1Y</a>

ขอบคุณ

תודה רבה Grazie Italian

Hebrew

Thai धन्यवादः

ಧನ್ಯವಾದಗಳು

Kannada

Ευχαριστώ

Sanskrit

Greek

Thank You English

Gracias

Spanish

Спасибо

Russian

Obrigado

Portuguese

شكراً

https://sites.google.com/site/animeshchaturvedi07

Merci

French

Arabic

多謝

**Traditional** 

Chinese

धन्यवाद

Hindi

Danke

German



Simplified

Chinese

நன்றி

Tamil

**Tamil** 

ありがとうございました 감사합니다

Japanese

Korean