



Parallel Search Algorithms

CS121 Parallel Computing
Spring 2020

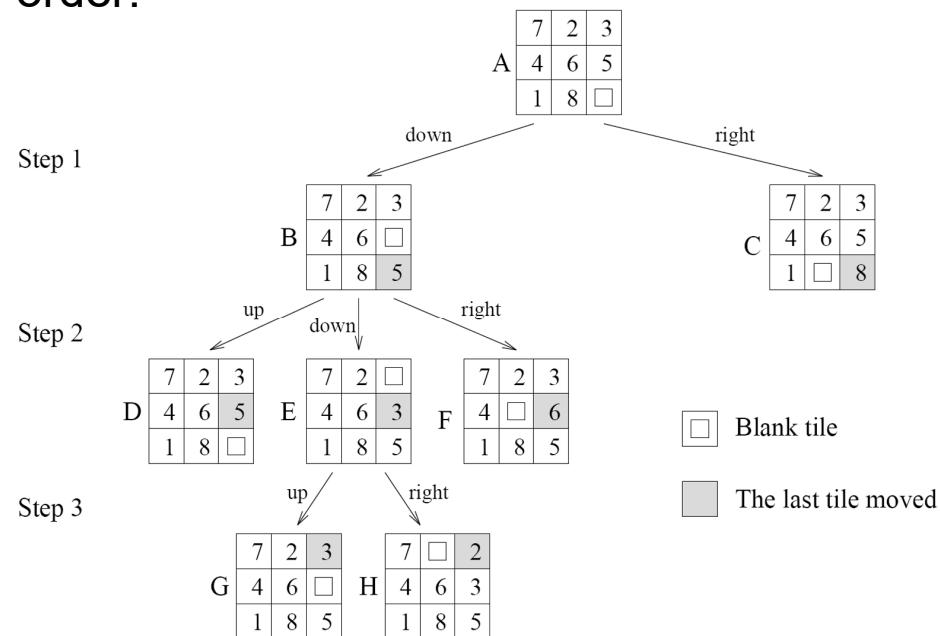


Discrete optimization problems

- A discrete optimization problem (DOP) consists of a tuple (S, f) , where S is a (finite or infinite) set of feasible solutions satisfying certain constraints, and f is a cost function for each solution, $f: S \rightarrow \mathbb{R}$.
- **Ex** Planning and scheduling, optimal layout in VLSI, logistics and control, satisfiability problems.
- We consider the minimization problem, i.e. find $x^* \in S$ s.t. $\forall x \in S: f(x^*) \leq f(x)$.

Searching for solutions

- Many interesting DOPs are NP-hard, so we either rely on heuristics or search algorithms.
- Searching a DOP can be modeled by a graph, with nodes (aka states) being (possibly infeasible) solutions and edges between states that are “close enough”.
 - Cost of states can be modeled using weights on nodes and edges.
 - Search process traverses states in some order to find min cost feasible state.
 - State with no successor in traversal called terminal state. Otherwise it's a nonterminal state.
- **Ex 8-puzzle.** From starting configuration, move blank tile to lower right so all tiles are in order.



Searching for solutions

- **Ex** A mixed integer program (MIP) consists of a linear objective function and a system of linear constraints, where some of the variables are required to be integers.

- States are assignments of values to the variables.
- MIPs can model many interesting DOPs, including NP-hard ones.

- **Ex** $\min 2x_1 + x_2 - x_3 - 2x_4 \quad \text{s.t.}$

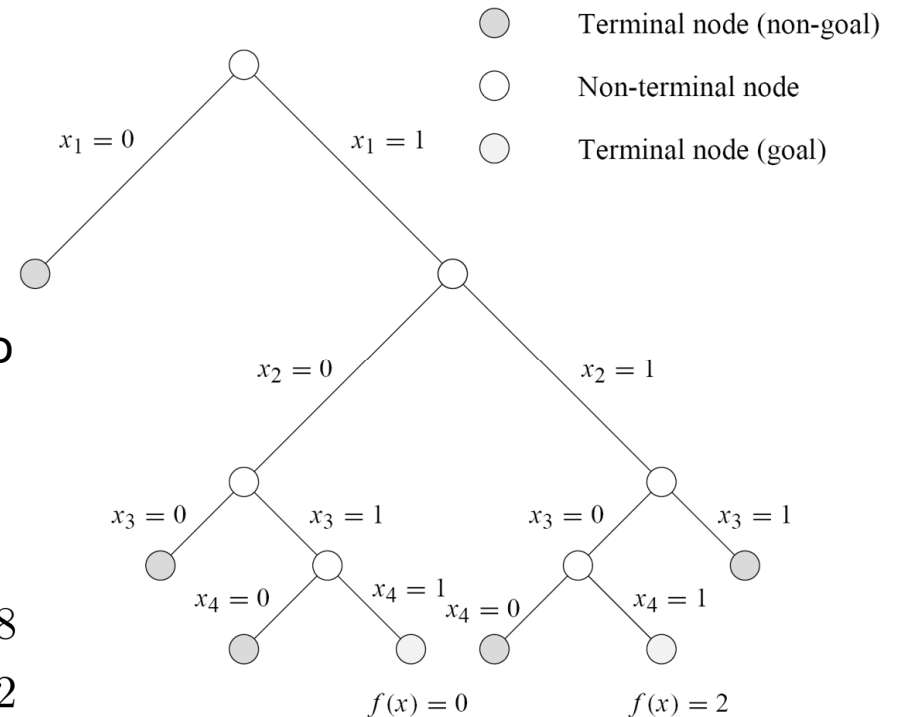
$$5x_1 + 2x_2 + x_3 + 2x_4 \geq 8$$

$$x_1 - x_2 - x_3 + 2x_4 \geq 2$$

$$3x_1 + x_2 + x_3 + 3x_4 \geq 5$$

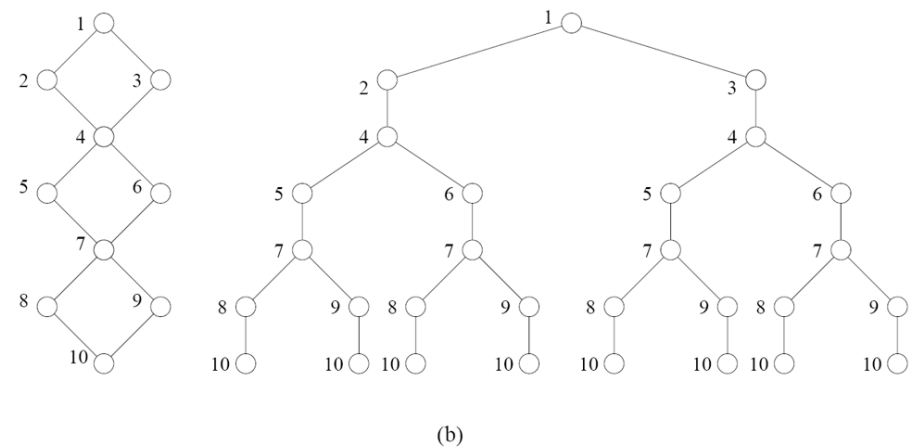
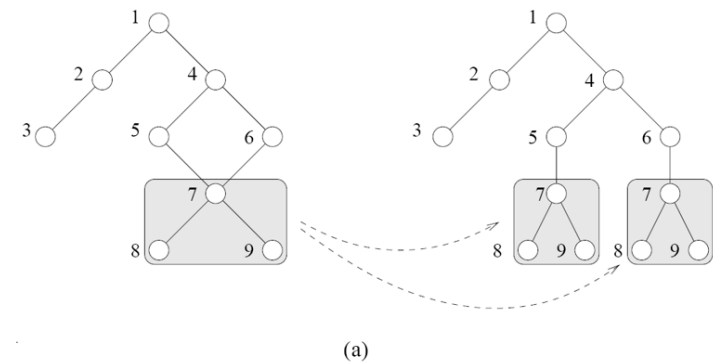
- Feasible solutions must satisfy

$$\sum_{x_j \text{ is free}} \max\{A[i, j], 0\} + \sum_{x_j \text{ is fixed}} A[i, j]x_j \geq b_i, i = 1, \dots, m$$



Structure of search graph

- When the search graph is a tree, there's only one way to arrive at each state, and the state has a unique cost determined by the root-state path.
- When the search graph is not a tree, there can be multiple paths to each state.
- Can unfold graph into a tree to use tree based search methods.
 - Sometimes unfolded tree much larger than original graph.
- Same state may be discovered multiple times.
 - Use duplicate detection to detect if node has already been explored.
 - Ex Store explored nodes in hash table.
 - Cost to the state is the minimum among all the paths.
 - Update the cost as different paths discovered.
 - Ex Hash table store both a state and its current min cost.



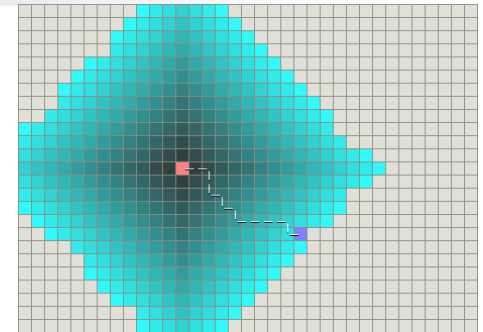


Branch and bound

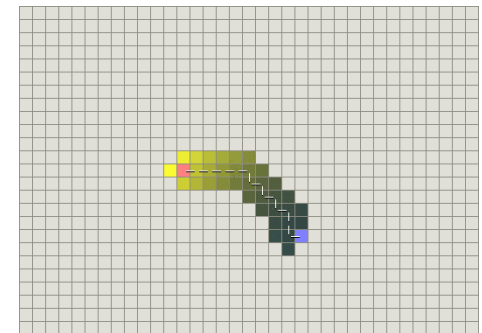
- Traverse the search graph in some order. At any time, we have a frontier of deepest nodes that have been explored.
- For each node p on the frontier, maintain a pair $(m(p), M(p))$, where $m(p) \leq \min$ possible value of any feasible descendant of p , and $M(p) \geq \max$ possible value of any feasible descendant of p .
 - m and M can be computed using a fast inexact heuristic.
 - **Ex** In knapsack, m can be the value of current knapsack, M can be the value if all remaining items are placed in knapsack.
- If $m(p) \geq M(q)$ for nodes p, q on the frontier, then don't need to explore any descendants of p .
 - The best (smallest) solution starting from p is worse (larger) than the worst possible solution starting from q , so we shouldn't explore p .

A* search

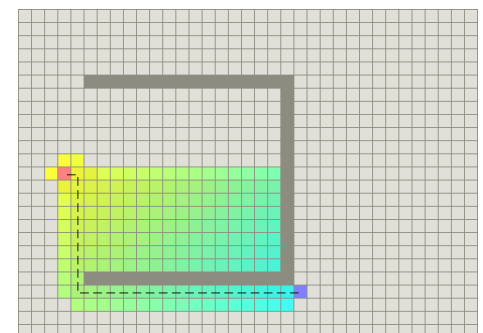
- An improvement of Dijkstra's shortest path (i.e. min cost) algorithm that searches "most promising" paths first.
- For each node n in search graph, let
 - $g(n)$ = cost from root to n .
 - $h(n)$ = a lower bound on the cost from n to a solution (aka admissible heuristic).
 - $f(n) = g(n) + h(n)$, i.e. a lower bound on a solution from n .
- A* search expands nodes in order of nondecreasing $f(n)$.
 - Dijkstra's expands nodes in nondecreasing order of $g(n)$.
- Can be implemented in a similar way to Dijkstra.
 - Keep a closed list of explored nodes. Their values are already minimal.
 - Keep an open list of nodes whose values are tentative and can still decrease.
 - Repeatedly explore min $f(n)$ node. Then update g , h and f functions.
- Guaranteed to find min cost solution.
- If $h(n)$ close to real cost from n to a solution, then A* searches few nodes and is fast.
 - Ex $h(n)$ for grid search can be Manhattan distance from n to goal.



Dijkstra's algorithm



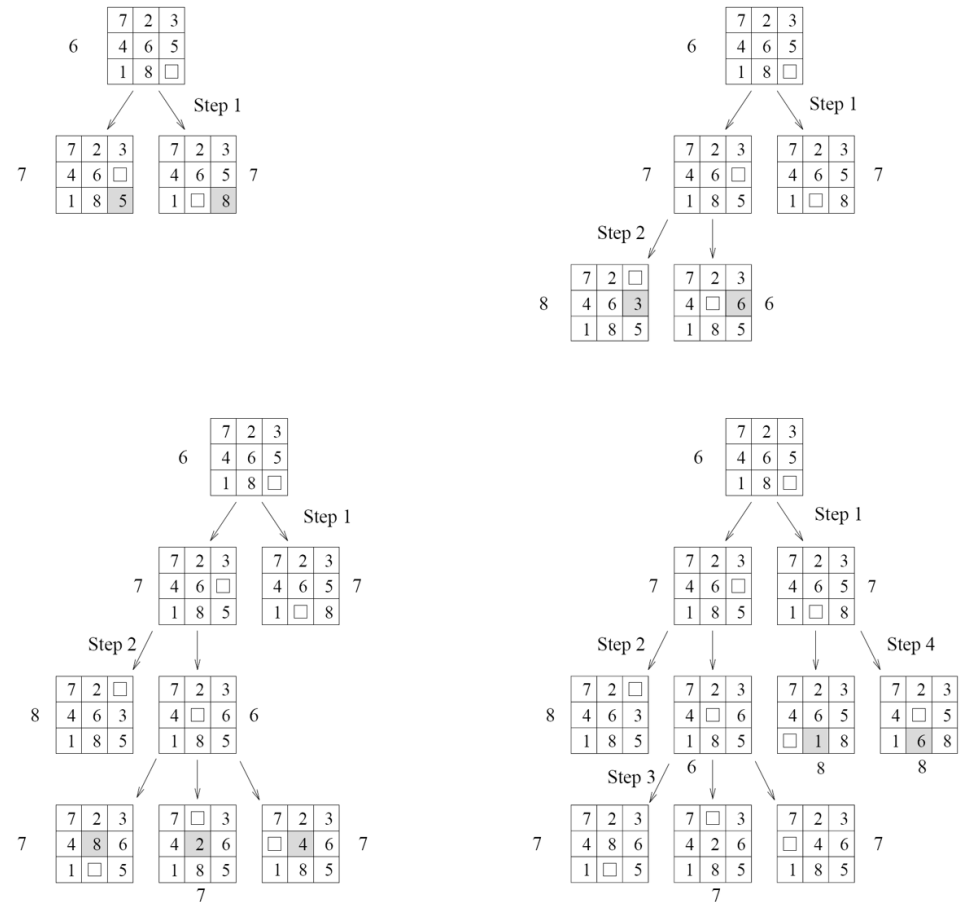
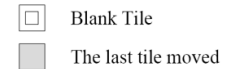
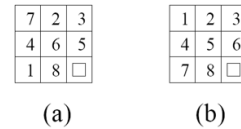
A* search with Manhattan distance heuristic



A* search with an obstacle

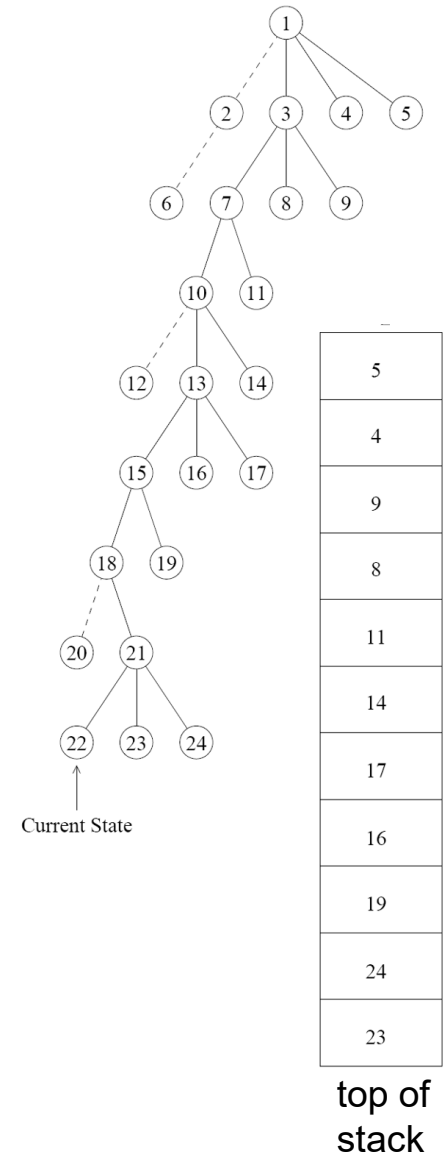
A* search

- **Ex** For 8 puzzle, one possible $h_1(n)$ is number of tiles in incorrect positions.
- **Ex** Another $h_2(n)$ is the sum of the Manhattan distances of each tile from its final position.
 - Each move of the blank tile moves one numbered tile one position.
- Decreases number of states searched by many orders of magnitude.
- Can also use $h(n)$ that's slightly larger than cost from n to goal.
 - Further reduces number of nodes searched.
 - Can produce somewhat suboptimal solution.



DFS and variants

- Depth first search
 - Do DFS on the search graph. Backtrack from infeasible terminal nodes.
 - Visit node at top of stack. Add new unvisited nodes to top of stack.
- Depth first branch and bound
 - Search in DFS order, but cut off branches using BB.
- Iterative deepening A*
 - DFS can search very deep in part of the tree, whereas a better solution exists higher up.
 - Instead, do multiple rounds of DFS, each round searching deeper.
 - For each search, set an upper bound B for cost. If current node n has $f(n) > B$, then backtrack.
 - On the next round, increase B to smallest non-explored $f(n)$ value from last round.
 - For first round, set $B = f(\text{root})$.
- Other more advanced algorithms used in practice include cutting plane methods and branch and cut.



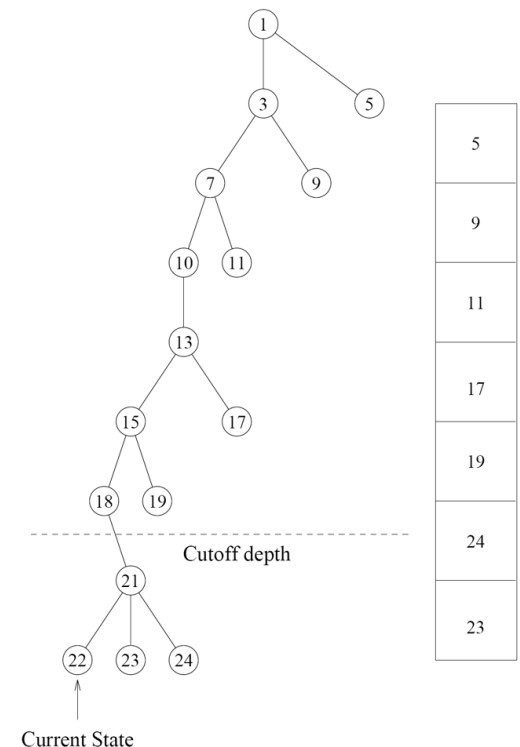
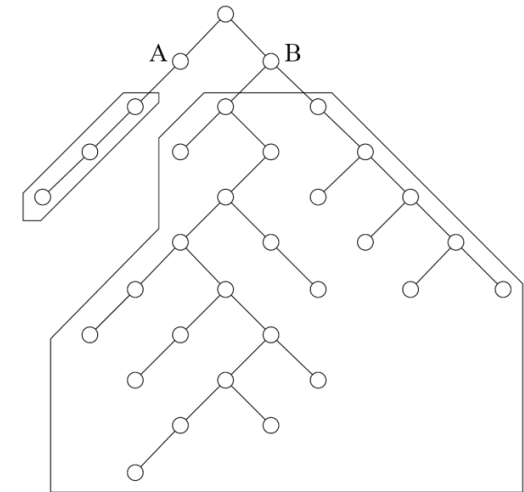


Parallel search

- Tree and graph searches can be very slow, so we can parallelize these algorithms.
- Parallel search algorithms have several sources of overhead, including communication, load imbalance and contention for shared data structures.
- Parallel algorithms can explore different part of search tree than the sequential algorithm, since the exploration order is different.
- Let W_s, W_p be the number of nodes explored by sequential and parallel algorithms, resp.
 - Search overhead factor is $\frac{W_p}{W_s}$.
 - Overhead may be $>$, $=$ or $<$ than 1.
 - As discussed later, when overhead < 1 , we have a speedup anomaly.

Parallel DFS

- To parallelize DFS, can assign different processors parts of the DFS stack to explore.
- Static assignments cause poor load balancing, since different branches have different sizes.
- Hard to estimate the sizes of branches. So instead, do dynamic load balancing.
 - Can use e.g. the work-stealing algorithm from previous lecture.
- Control how much to steal.
 - Stealing too little causes overhead from many steals.
 - Stealing too much can cause poor load balancing.
- Also choose who to steal from.
 - In asynchronous round robin, processors choose victims independently, and round robin through them.
 - In global round robin, processors maintain victim in a global variable, and round robin through them.
 - In randomized work stealing, nodes pick victim randomly.
- To avoid sending very small amounts of work, set a cutoff depth and don't send work past cutoff.

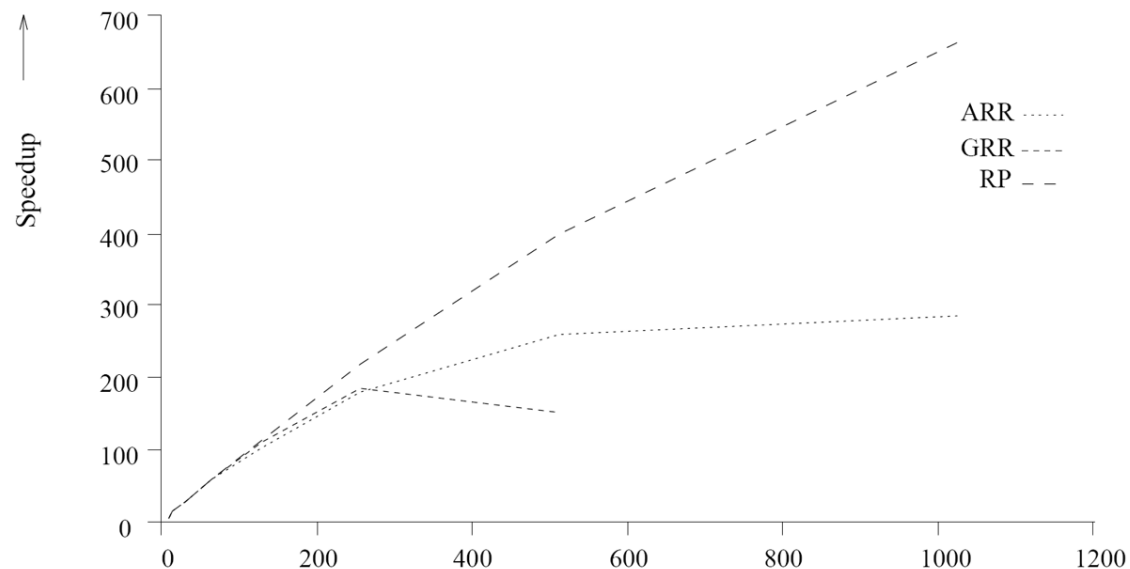


Load balancing overhead

- Since load is generated dynamically, it's hard to estimate the precise overhead. So we make the following simplifying assumptions.
 - If victim processor has W amount of work, after work stealing the victim and stealing processors each have $\geq \alpha W$ amount of work, for $\alpha > 0$.
 - I.e. the work stealing roughly balances the work between the thief and victim.
 - After load balancing, both processors have $\leq (1 - \alpha)W$ work.
 - If a processor has $\leq \epsilon$ work, for a small $\epsilon > 0$, it doesn't do load balancing.
- Suppose there are p processors, and let $V(p)$ be total number of steals before every processor receives one steal attempt.
 - $V(p)$ depends on the particular work stealing algorithm.
- Suppose the max amount of work at any processor is currently W . Then after $V(p)$ steals, the max amount is $\leq (1 - \alpha)W$, by assumption above.
 - After $2V(p)$ steals, max work at any processor is $\leq (1 - \alpha)^2 W$. In general, after $kV(p)$ steals, it's $\leq (1 - \alpha)^k W$.
 - So after $\log_{\frac{1}{1-\alpha}} \left(\frac{W}{\epsilon} \right) V(p)$ steals, each processor has $\leq \epsilon$ amount of work.
 - So total overhead from work stealing is $O(V(p) \log W)$.
 - Efficiency is $1 / \left(1 + \frac{t_{comm} V(p) \log W}{W} \right)$.

Load balancing overhead

- For asynchronous round robin, $p \leq V(p) \leq p^2$, because each processor round robs through victim processors.
 - For isoefficiency need $W = \Omega(V(p) \log W) = \Omega(p^2 \log p)$.
- For global round robin, $V(p) = p$.
 - So the victim variable is accessed $O(p \log W)$ times.
 - There is contention on shared victim variable. Total variable access time is $O(p \log W)$.
 - For isoefficiency, we want each process's execution time \geq variable access time.
 - So $\frac{W}{p} = \Omega(p \log W)$, and $W = \Omega(p^2 \log p)$.
- For randomized, can prove expected $V(p) = O(p \log p)$.
 - For isoefficiency need $W = \Omega(p \log^2 p)$.





Parallel DFBB and IDA*

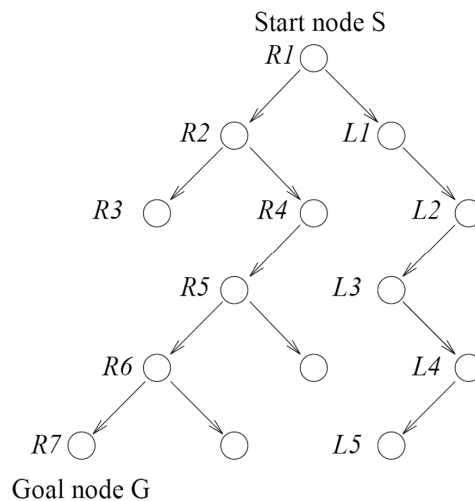
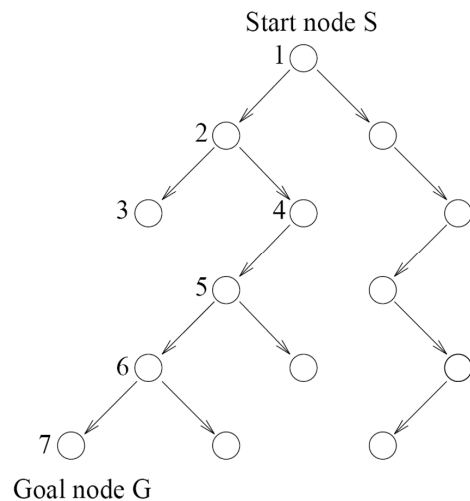
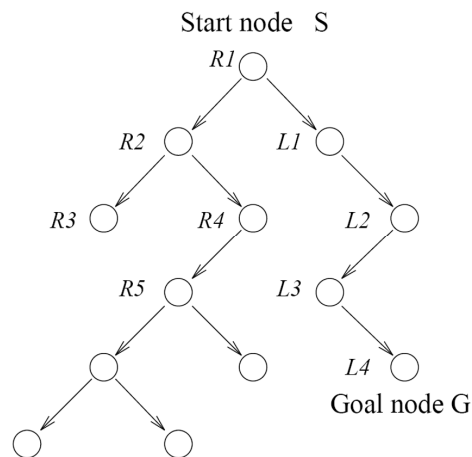
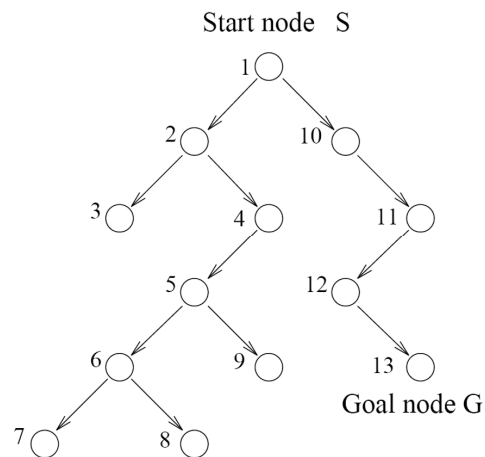
- To parallelize depth first branch and bound, processors store the globally best solution.
 - If a processor finds a better solution, it broadcasts it.
 - Since the best solution changes infrequently, there's not much overhead.
- For parallel IDA*, broadcast the bound for each round of DFS, then parallelize the DFS.



Parallel A*

- In A*, the cost of nodes are stored in a priority queue.
 - Parallelizing A* requires accessing the queue in parallel.
- With p processors, expand smallest p nodes in queue.
 - This expands some nodes that aren't expanded in the sequential algorithm, leading to redundant work.
- Another problem is contention when accessing the queue.
 - To decrease contention, can give each processor its own copy of the queue.
 - If a processor finds a good node (with small $f(n)$), it should update other nodes so they don't expand non-minimal nodes.
 - More updates reduces redundancy but increases communication, so need to find a tradeoff.
- If the search graph is not a tree, then can visit the same node multiple times, so need duplicate detection.
 - Can store visited nodes in a hash table and distribute hash table among processors.
 - Causes communication for each node visited.
 - Can be amortized if amount of computation per node is large.

Speedup anomalies



- Since parallel search explores nodes in a different order than sequential search, it can explore fewer or more nodes.
- Ex In the upper figures, the sequential search on the left explores 13 nodes before finding the goal. On the right, parallel search using two processors R and L explores 9 nodes.
 - There is a superlinear speedup of $13/5 > 2$.
 - This is called an acceleration anomaly.
- Ex In the lower figures, the left sequential search explores 7 nodes, but the right parallel search explores 12 nodes.
 - This is called a deceleration anomaly.



Average speedup in DFS

- In certain simple settings we can analyze the expected speedup using parallel DFS.
- Assume the following
 - The search graph is a tree with M leaves. All the solutions are at the leaves, and there is at least one solution.
 - The number of nodes explored is proportional to the number of leaves explored.
 - The parallel DFS partitions the tree into m (= number processor) equal parts. All processors run at the same speed.
 - The sequential DFS orders the partitions randomly and searches each completely before searching the next partition.
 - In the i 'th partition, each leaf has an independent probability ρ_i of being a solution.
 - Both sequential and parallel DFS stop after finding one solution.

Average speedup in DFS

- The expected number of leaves (and hence nodes) searched in the i 'th partition is $1/\rho_i$.
- The expected running time W_s of sequential DFS is proportional to $\frac{1}{m} \left(\frac{1}{\rho_1} + \frac{1}{\rho_2} + \dots + \frac{1}{\rho_m} \right)$, since it searches a random partition.
- In parallel DFS, in each parallel step one leaf from each partition is searched. The probability that at least one of them is a solution (and hence DFS stops) is $1 - \prod_{i=1}^m (1 - \rho_i) \approx \rho_1 + \rho_2 + \dots + \rho_m$ for small ρ 's.
 - The expected work W_m of parallel DFS is proportional to $\frac{m}{\rho_1 + \rho_2 + \dots + \rho_m}$.
- $W_m = O(1/(\text{arithmetic mean of } \rho_1, \dots, \rho_m))$, and $W_s = O(1/(\text{harmonic mean of } \rho_1, \dots, \rho_m))$.
 - Since arithmetic mean \geq harmonic mean, then $W_m \leq W_s$.
 - $W_m = W_s$ only if $\rho_1 = \rho_2 = \dots = \rho_m$.
 - If the ρ 's aren't equal, then $W_m < W_s$. So we can get superlinear speedup if the solutions aren't equally distributed in the search partitions.