

Get To Know Your Trees

David Pritchard

Canadian Computing Competition, 2006 Stage 2

Outline

- 1 Preliminaries
- 2 Spanning Trees of Graphs
- 3 A General Framework
 - Depth-First Search
 - Breath-First Search
 - Minimum Spanning Tree
 - Dijkstra's Shortest Paths Algorithm
- 4 Advanced Tactics
 - A-Star, Meet in the Middle
 - Preorder, Postorder, Topological Sort
 - Biconnectivity, Strong Connectivity

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 - ▶ *A connected graph with no cycles*
 - ▶ *A graph where there is each pair of vertices is joined by a single path*
- ...but we won't talk about this here.

Basic Botany

- In this talk we mainly deal with *rooted, labelled* trees.

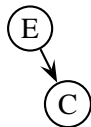
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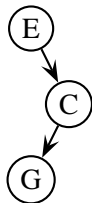
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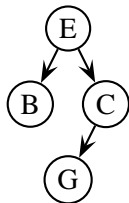
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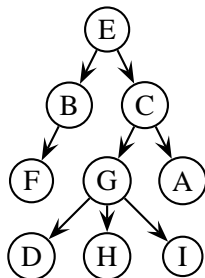
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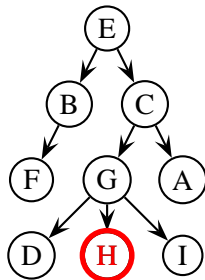
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- If node x is a child of node y then we say that y is the parent of x . Each non-root node has exactly one parent.



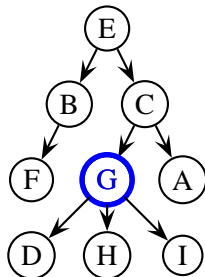
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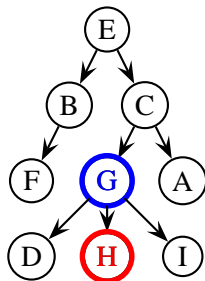
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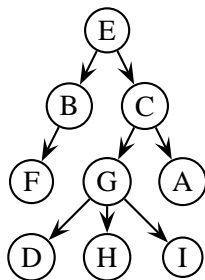
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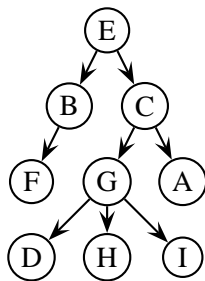
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- In this tree the leaves are F, D, H, I, A.



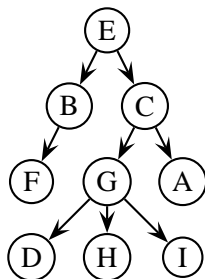
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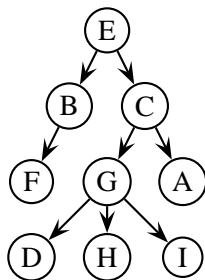
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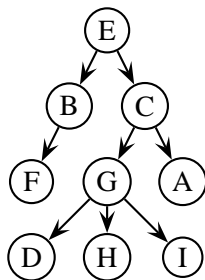
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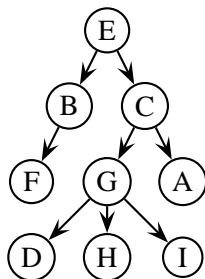
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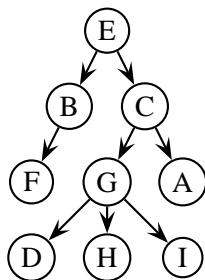
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 - an expression (leaves = values, internal nodes = functions)
 - states of a game (nodes = board positions, root = initial board, edges = valid moves, leaves = ending positions)
 - occasionally, a tree (leaves = leaves, root = root)



Basic Botany

- Straightforward representation: keep an array P of the nodes' parents and an array C of child-lists.

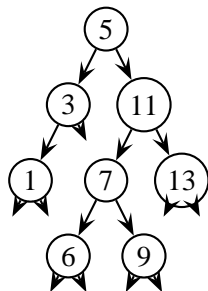
x	$P[x]$	$C[x]$
A	C	()
B	E	(F)
C	E	(G,A)
D	G	()
E	nil	(B,C)
F	B	()
G	C	(D,H,I)
H	G	()
I	G	()



- If we don't care about (or don't know) the order of each node's children then we may only need to keep track of P .
- Alternatively, we can just keep track of C .

Aside: Binary Trees

- Another form of tree is a *binary tree*.
- Each node may or may not have a left child, and may or may not have a right child.
- Each node is a record with fields (value, left, right), where left and right are pointers to nodes. A null pointer means that that child doesn't exist.
- If we stick values in the nodes the right way, we can make a *binary search tree* which is useful for some applications.
- Different generalization: k child positions is a *k-ary tree*.

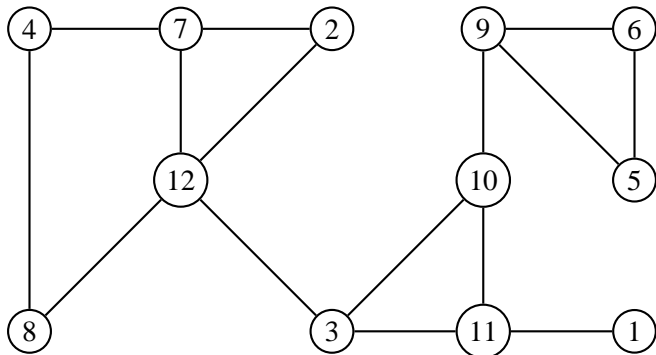


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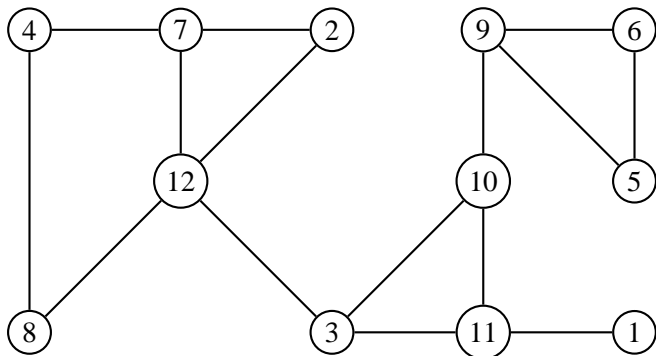
Definitions

- A graph $G = (V, E)$ is a set V of n nodes (which we call $1, \dots, n$) together with a collection E of *edges*. Each edge is just a pair of nodes.
- E.g., nodes/edges = cities/roads or computers/links.



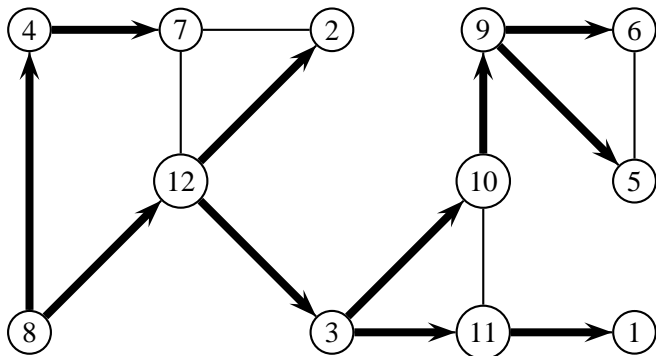
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- A *spanning tree* is a tree that contains every node.
- Here's a spanning tree with root 8:



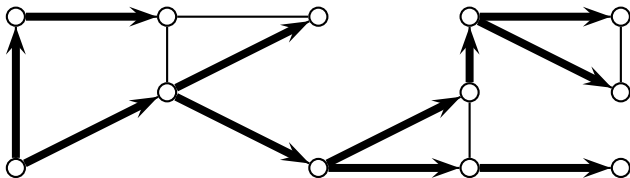
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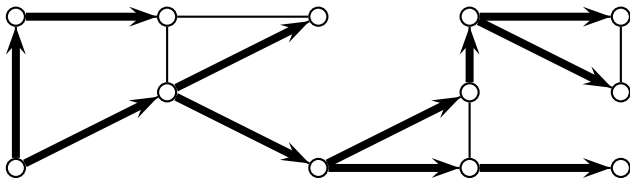
Spanning Tree \Rightarrow Check Bipartite

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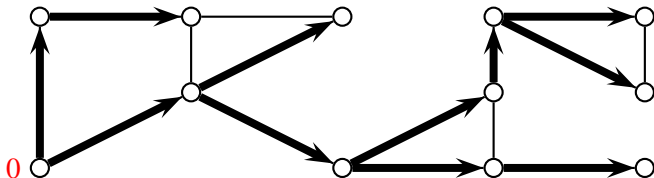
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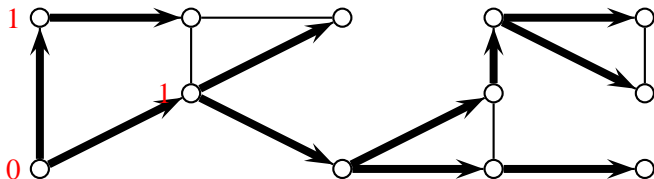
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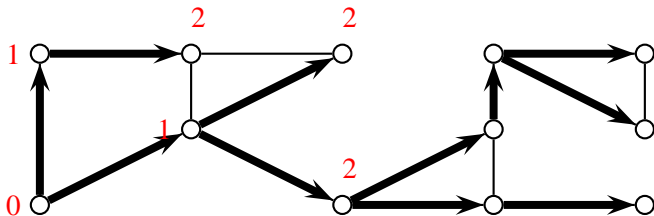
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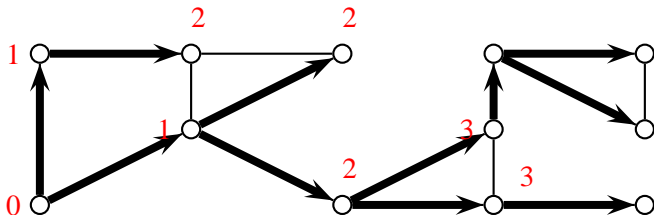
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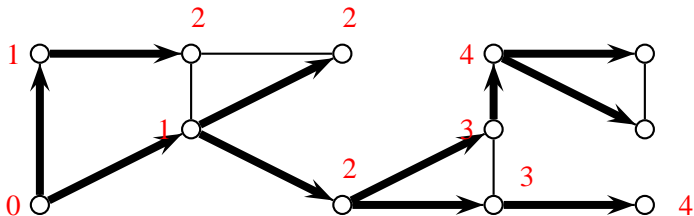
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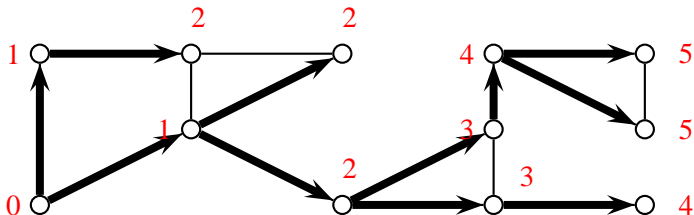
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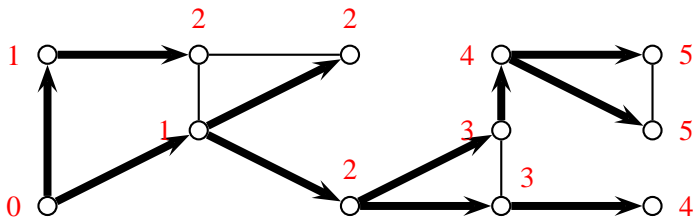
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- Definition: a graph is *bipartite* if the nodes can be colored green and blue so that each there are no green-green or blue-blue edges.



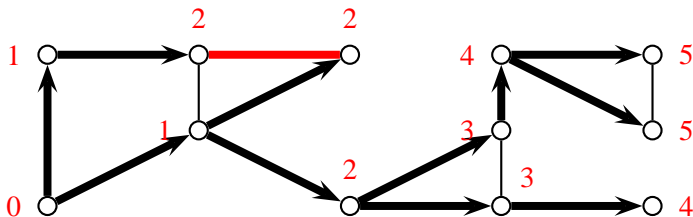
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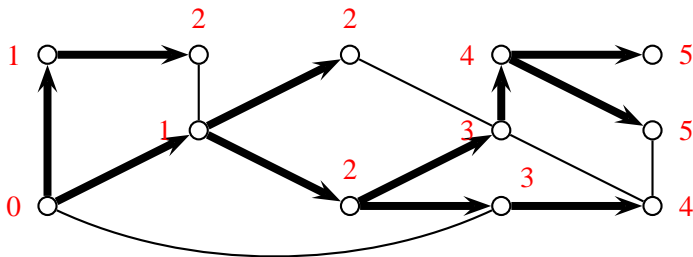
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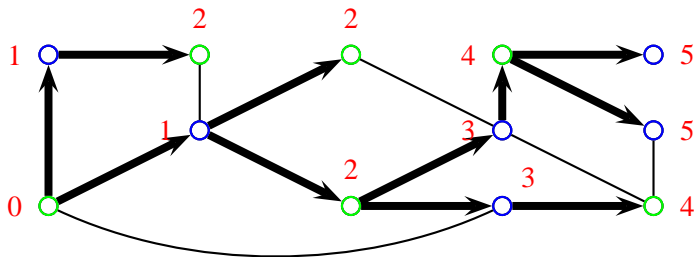
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- We color the even-level nodes green and the odd-level nodes blue.



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- A *priority queue* is a cheapest-out structure.
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- Implement priority queue with a *heap* or *balanced binary tree*.

Exploring a Graph

- Here is an abstract algorithm for exploring a graph.

```
1: procedure SEARCH-GRAPH( $G$ , root)
2:   isExplored := boolean[vertices of  $G$ ], initially false
3:   waitingEdges := struct⟨ pair⟨ vertex ⟩ ⟩
4:   waitingEdges.add((nil, root))
5:   while waitingEdges is not empty do
6:     ( $p, v$ ) := waitingEdges.remove()
7:     if (!isExplored[ $v$ ]) then
8:       isExplored[ $v$ ] := true
9:       parent[ $v$ ] :=  $p$ 
10:      for all neighbours  $w$  of  $v$  such that !isExplored[ $w$ ] do
11:        waitingEdges.add(( $v, w$ ))
```

- Basically we try to explore every edge that we learn about.
- No matter what order edges are removed from waitingEdges, we get a spanning tree.

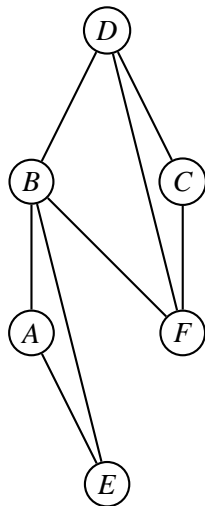
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- Stack is LIFO (last in, first out).

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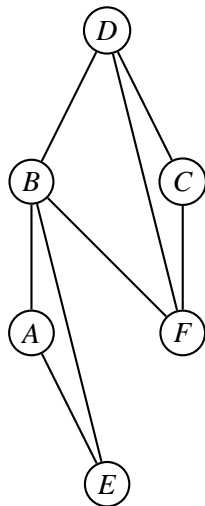


[Top] [Bot]

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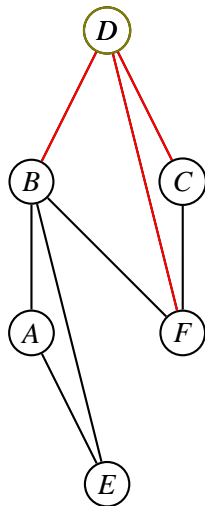


[Top] (**nil**, D)[Bot]

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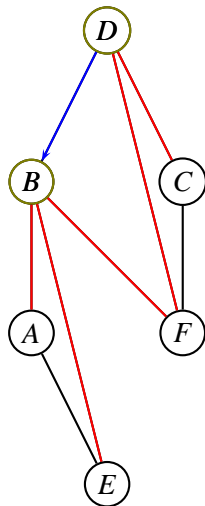


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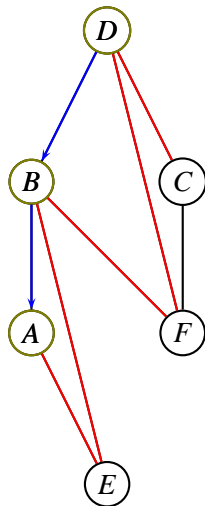


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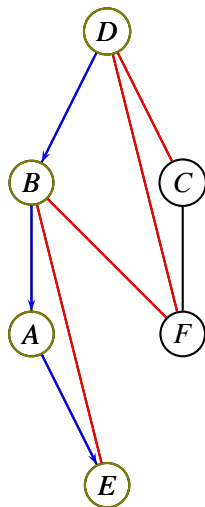


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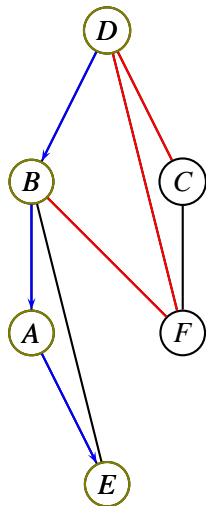


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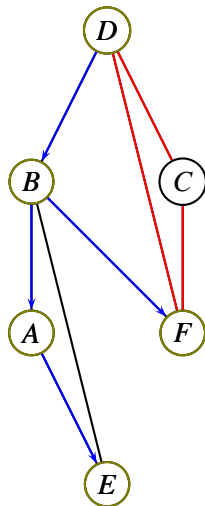


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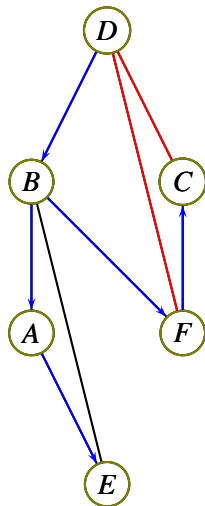


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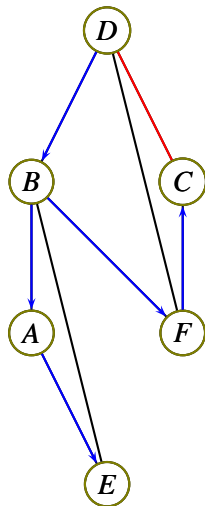


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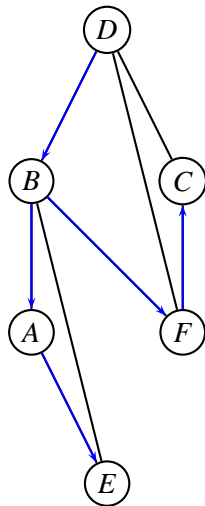
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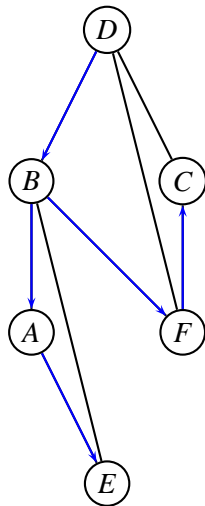
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- So $O(m + n)$ time complexity where $m = |E|, n = |V|$



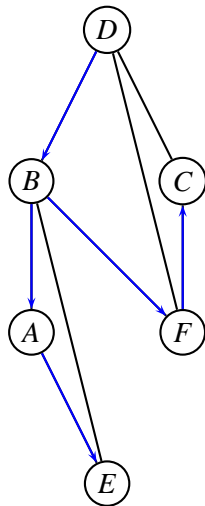
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- *Applications*
- We will see later that using DFS and some other ideas (preorder, postorder) we can get efficient algorithms for biconnectivity and strong connectivity.



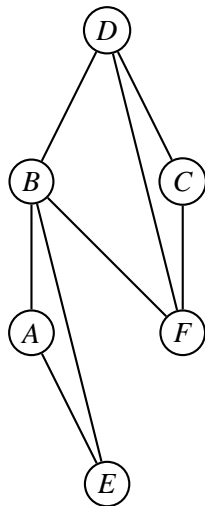
Outline

- 1 Preliminaries
- 2 Spanning Trees of Graphs
- 3 A General Framework**
 - Depth-First Search
 - Breath-First Search**
 - Minimum Spanning Tree
 - Dijkstra's Shortest Paths Algorithm
- 4 Advanced Tactics
 - A-Star, Meet in the Middle
 - Preorder, Postorder, Topological Sort
 - Biconnectivity, Strong Connectivity

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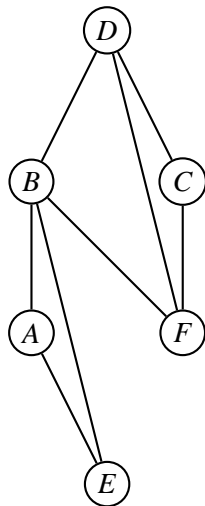


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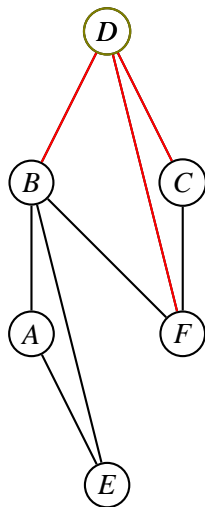


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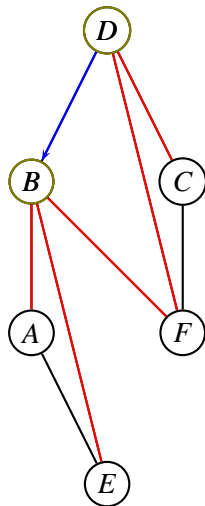


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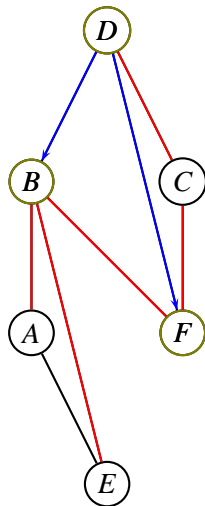


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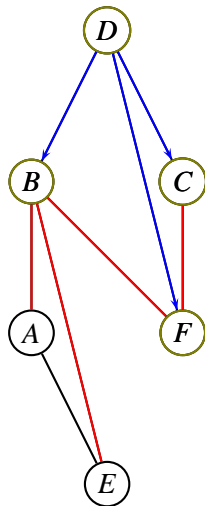


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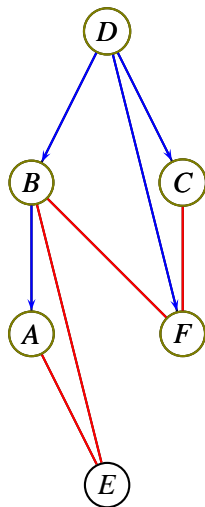


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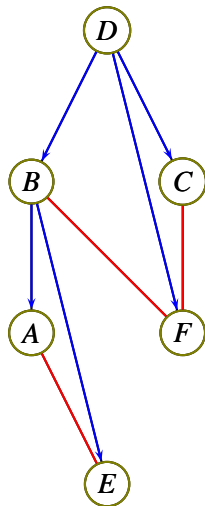


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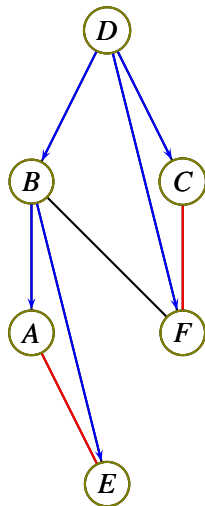


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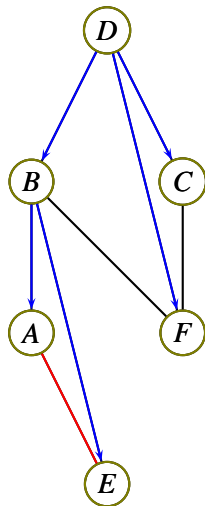


[Head] (F, C)(A, E) [Tail]

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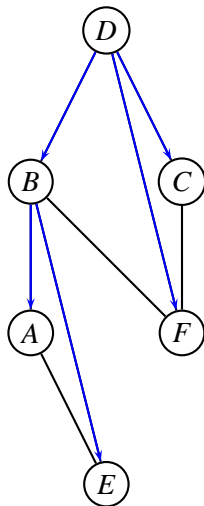
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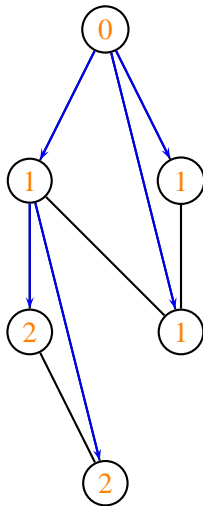
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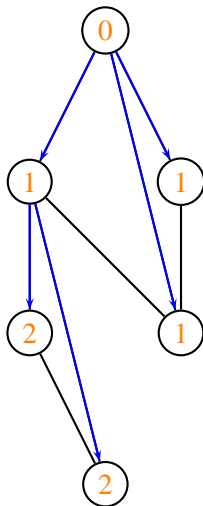
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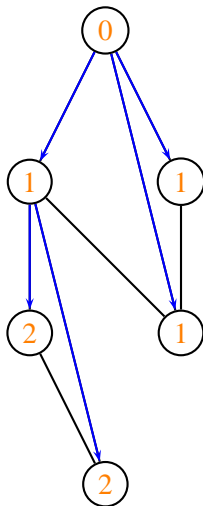
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- No known fast algorithm for determining the *longest* cycle.



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- Here's pseudocode for connected components. $\text{Search-and-Label}(G, \text{root})$ is any kind of search routine, but when it explores a node w it sets $\text{connected-component-label}[w] := \text{root}$.
 - 1: **procedure** CONNECTED-COMPONENTS(G)
 - 2: $\text{isExplored} := \text{boolean}[v]$ ▷ Assume vertices are $0, \dots, v - 1$
 - 3: **for** $i := 1$ to $v - 1$ **do**
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 - 5: $\text{Search-and-Label}(G, i)$

Interlude

- What if the graph we are given is not connected?
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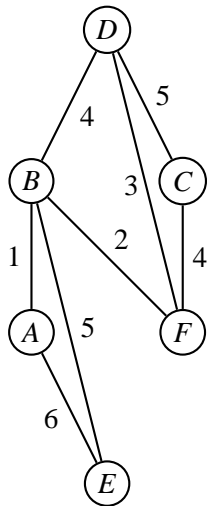
- Computes a *spanning forest* of G .

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Minimum Spanning Tree

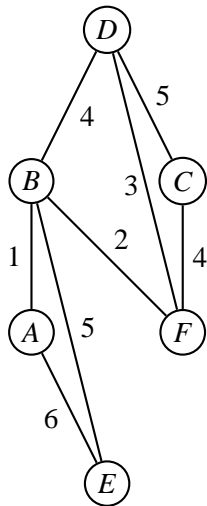
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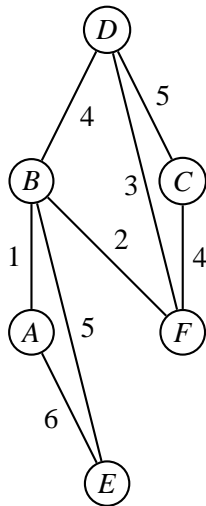
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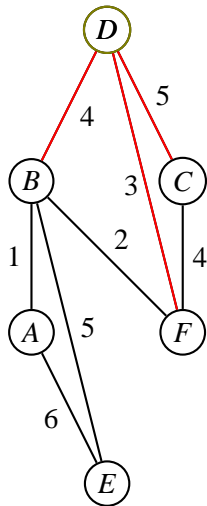
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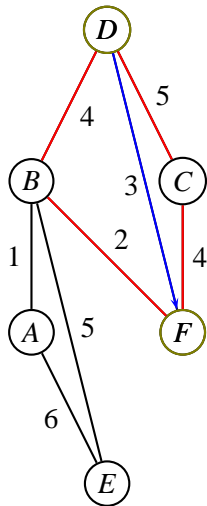
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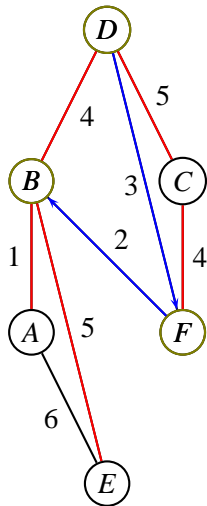
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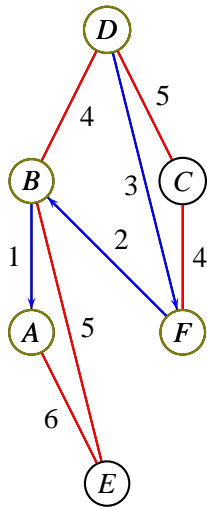
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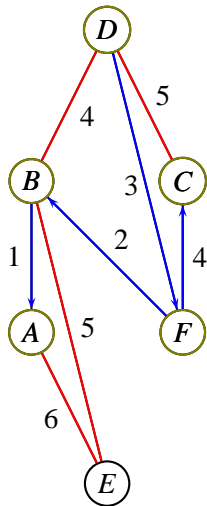
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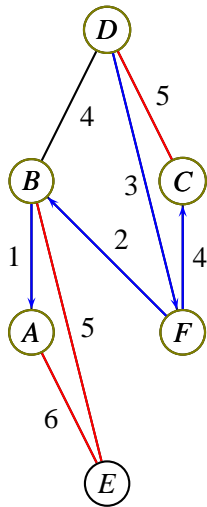
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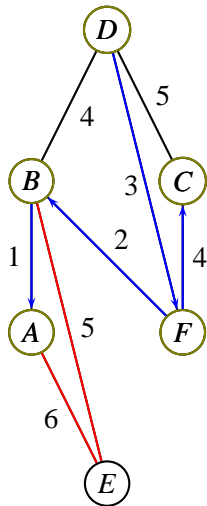
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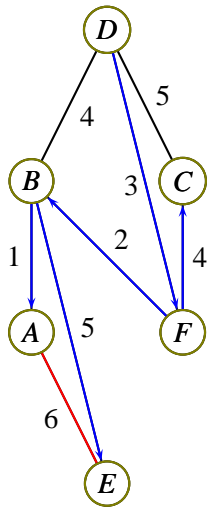
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- Intuitively, we are “growing” a spanning tree starting from the specified root.
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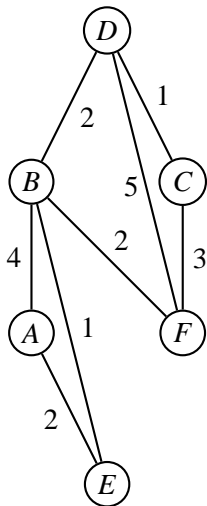
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- Also known as Prim’s algorithm.
- Can be implemented somewhat faster, in $O(m + n \log n)$ time.

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Single-Source Weighted Shortest Paths

- Find the shortest distance $d[x]$ from root to each vertex x in a *weighted* graph.

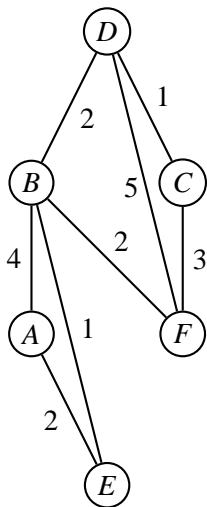


[Top]

Single-Source Weighted Shortest Paths

- Find the shortest distance $d[x]$ from root to each vertex x in a *weighted* graph.
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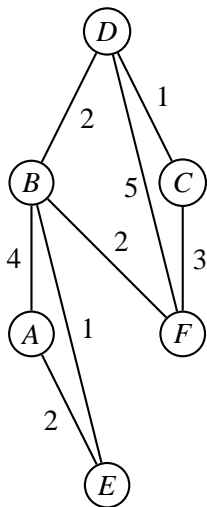


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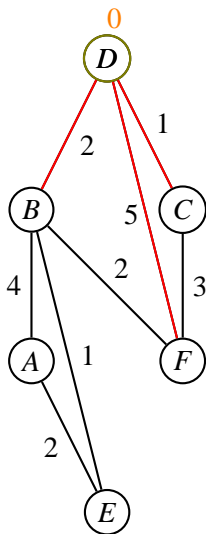


[Top] (nil, D)⁰

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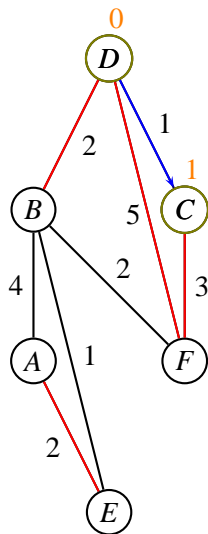


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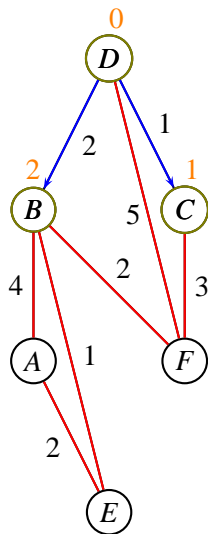


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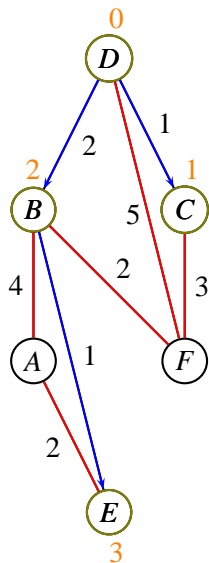


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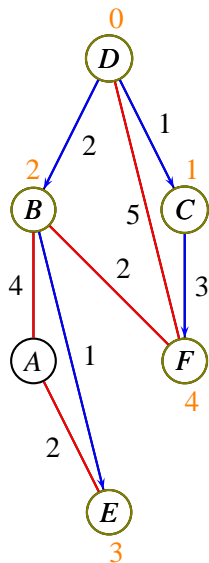


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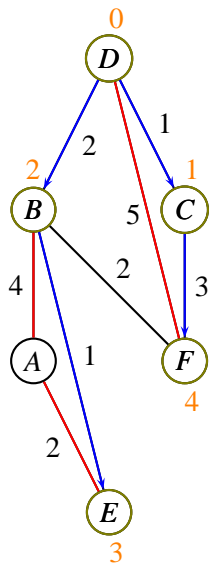


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5:     ( $p, v$ ) := waitingEdges.remove()
6:     if (!isExplored[ $v$ ]) then
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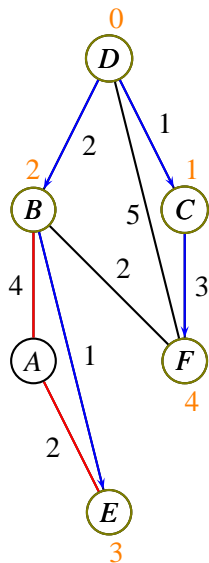


[Top] (D, F)⁵(E, A)⁵(B, A)⁶

Single-Source Weighted Shortest Paths

- Find the shortest distance $d[x]$ from root to each vertex x in a *weighted* graph.
- Use a **priority queue**, $\text{priority}(uv) = d[u] + c[u, v]$.

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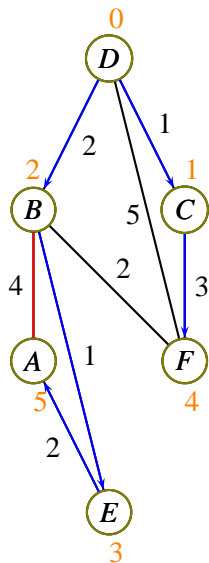


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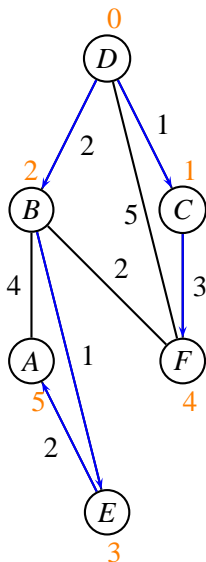
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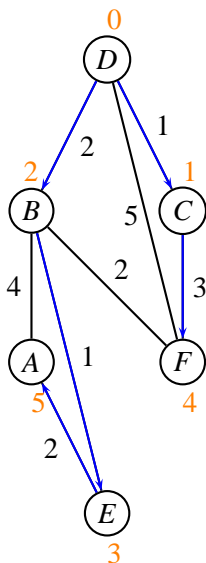
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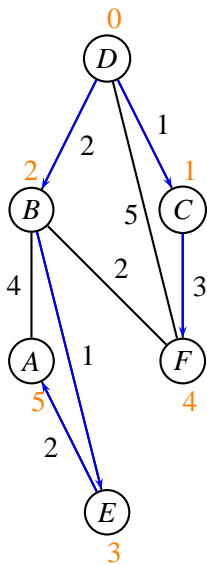
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- Is it somewhat surprising that the shortest paths can be even be *represented* by a tree?
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- Nodes are discovered in increasing order of distance from root.



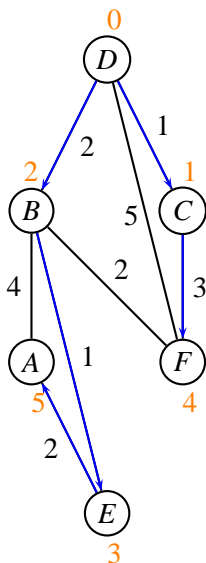
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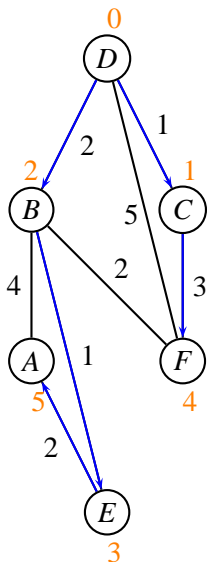
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- Works for directed graphs. *Doesn't work* if there are negative edge weights.



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- 2 Spanning Trees of Graphs
- 3 A General Framework
 - Depth-First Search
 - Breath-First Search
 - Minimum Spanning Tree
 - Dijkstra's Shortest Paths Algorithm
- 4 Advanced Tactics
 - A-Star, Meet in the Middle
 - Preorder, Postorder, Topological Sort
 - Biconnectivity, Strong Connectivity

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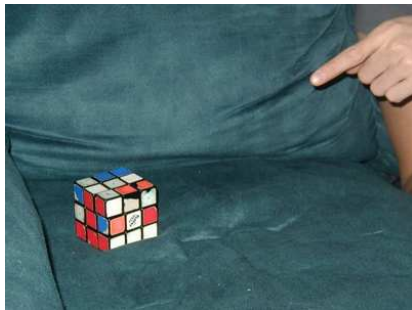
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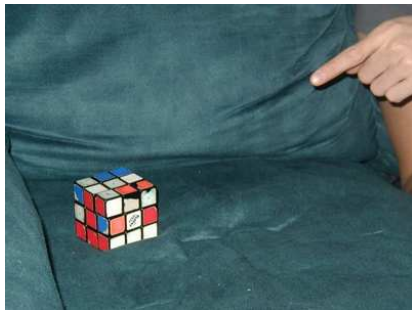
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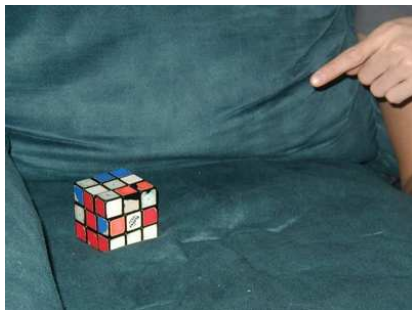
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- Can we use BFS without actually constructing the whole graph?
- Sure. It is trickier to keep track of isExplored; you can use a Set class like a *hash set* or a *sorted set / balanced binary tree*.

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- Summary of last slide: to find path from x to y do a BFS from x , stopping when we hit y .
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- 43,252,003,274,489,856,000 positions for a Rubik’s cube.
- Actually, if x and y are diametrically opposite then the given strategy still would explore (nearly) the entire graph just to find the x - y path.
- But now I will explain 2 ways to improve performance even in this “worst” case: Meet-in-the-Middle and A^* (“A-star”) search.

Meet in the Middle

- Suppose that each node of our graph has k neighbours, and we are applying the previous BFS technique to find a shortest path between x and y who are at distance d .
- Roughly speaking, each level of the search will expand the universe of “explored” nodes by a factor of d , so about d^k total time is needed.
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- What’s a simple way to improve? (Hint: look at the title)
- Conduct a BFS simultaneously from x and y .
- Think of the BFS from y as going backwards.
- Do a level of x ’s BFS, then y ’s BFS, then x ’s, etc.
- Let P be a shortest path between x and y , and z be a middle point of that path; hence it is distance $k/2$ from both x and y .
- We can detect that two trees will hit after $k/2$ rounds — total time complexity $O(d^{k/2})$.

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- If y is the unscrambled state, then we may take

$$h(v) = \text{number of out-of-position elements in } v.$$

- In route planning, h can be the Euclidean distance to y .

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- Unfortunately, this doesn't exactly work as we had hoped. In order to get the right answer we may have to explore some nodes many times.
- Essentially, inconsistent local overestimates can deter us from short paths.
- We must add the following two *consistency* conditions to h :
 - ▶ $h(y) = 0$,
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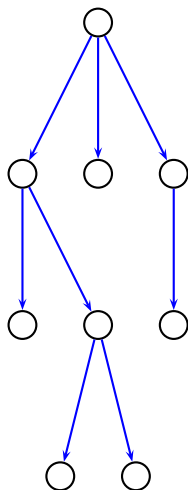
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- This *always* performs at least as quickly as Dijkstra's algorithm.
- As $h(v)$ increases towards a better underapproximation of $dist[v, y]$, the number of iterations required by A^* search decreases.

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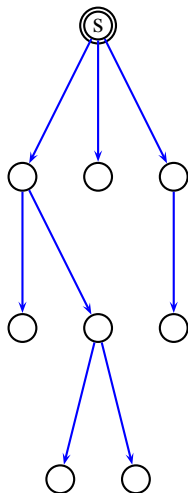
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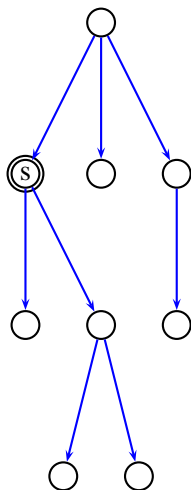
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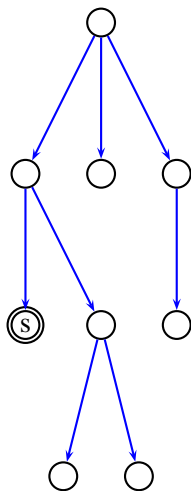
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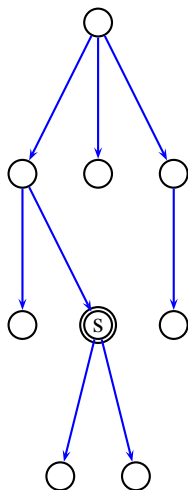
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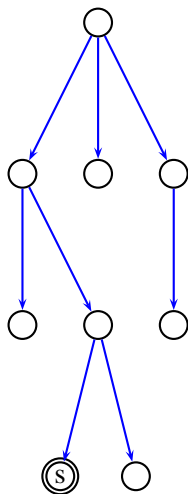
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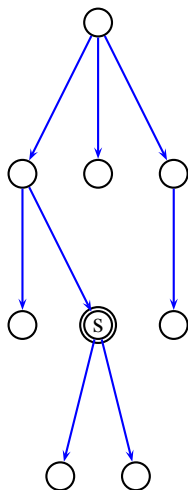
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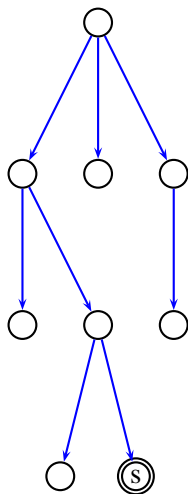
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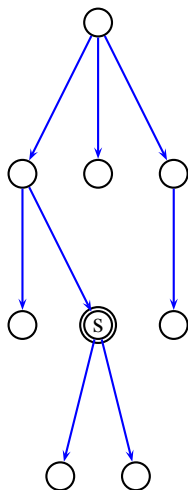
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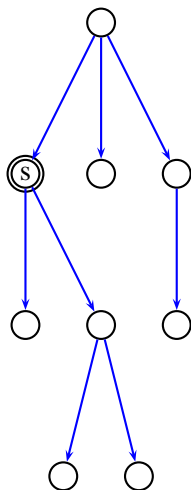
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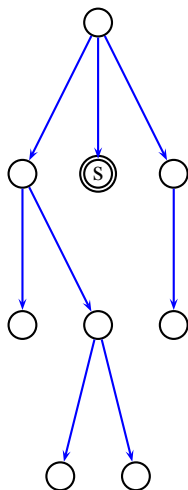
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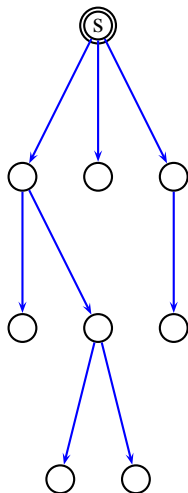
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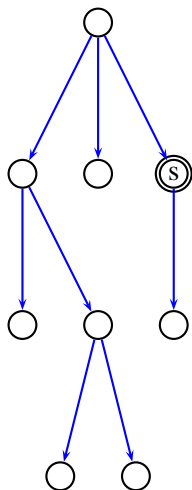
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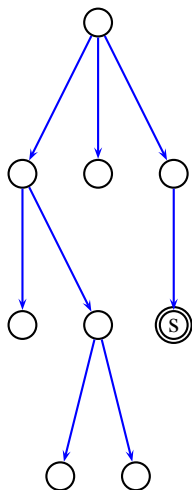
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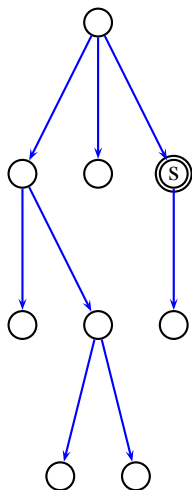
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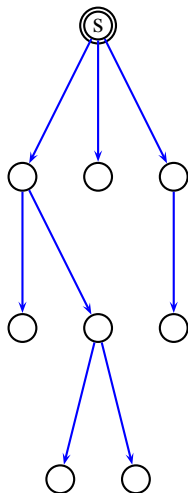
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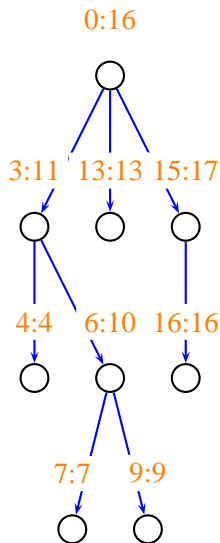
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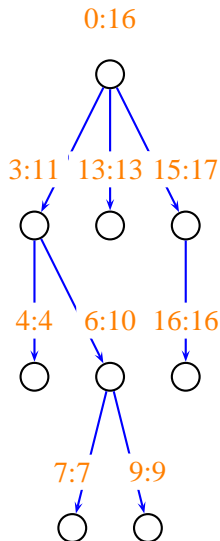
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- For each node record the first and last time the squirrel visited the node.



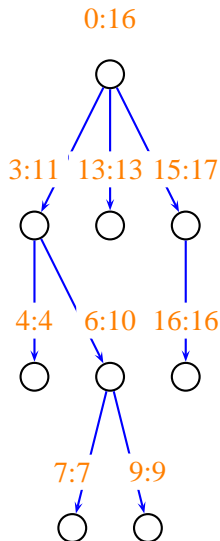
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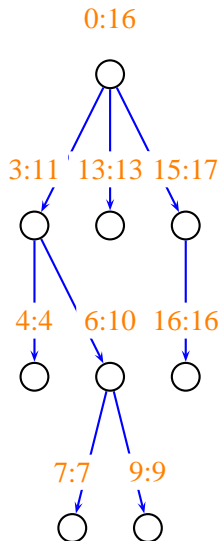
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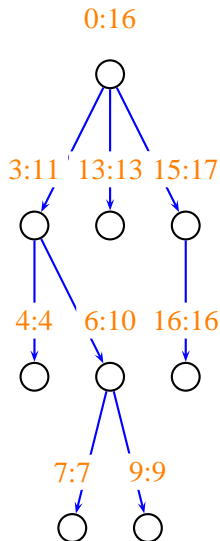
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- *Aside*: for binary trees there is also *inorder* where you first visit the left child, then the root, then the right child.



Topological Sort

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- How can we determine an order to get dressed?
- Basic idea: make any¹ (directed) search tree and use postorder.
- Complication: may need to pick multiple trees.

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DFS Lite & Topological Sort

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DFS Lite & Topological Sort

- DFS is often implemented without an *explicit* stack.
- Here's a short implementation of topological sort:

```
1: isExplored := boolean[v]
2: postList := list< int >
3: procedure DFS-ORDER( $G, v$ )
4:   isExplored[v] := true
5:   //preList.add(v)
6:   for all outneighbours  $w$  of  $v$  do
7:     if (!isExplored[ $w$ ]) then DFS-Order( $G, w$ )
8:   postList.add(v)
9: procedure TOPOLOGICALSORT( $G, v$ )
10:  for  $i := 0$  to  $v - 1$  do
11:    DFS-Order( $G, i$ )
12:  return postList
```

- ▷ Initialized to false.
- ▷ Initially empty.

Outline

- 1 Preliminaries
- 2 Spanning Trees of Graphs
- 3 A General Framework
 - Depth-First Search
 - Breath-First Search
 - Minimum Spanning Tree
 - Dijkstra's Shortest Paths Algorithm
- 4 **Advanced Tactics**
 - A-Star, Meet in the Middle
 - Preorder, Postorder, Topological Sort
 - **Biconnectivity, Strong Connectivity**

Bridge-Finding

- An edge of a connected graph is a *bridge* if, when it is deleted, the graph is no longer connected.
- Equivalently uv is a bridge if every path from u to v uses the edge uv .
- How can we determine the bridges of a graph?

Bridge-Finding

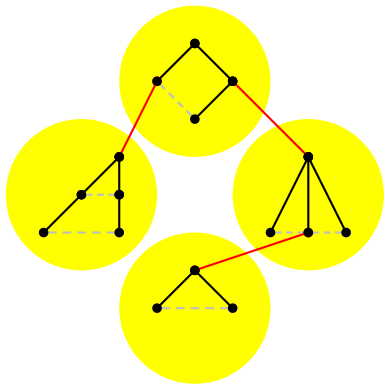
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- How can we compute this “out of” property precisely? Use the squirrel.

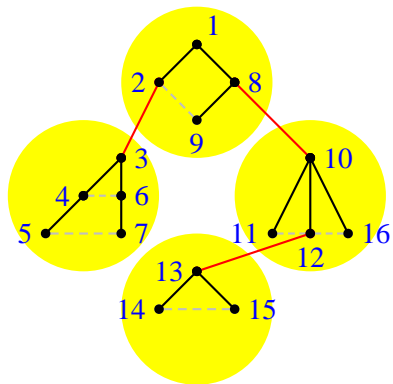
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- What does “out of the subtree” mean?

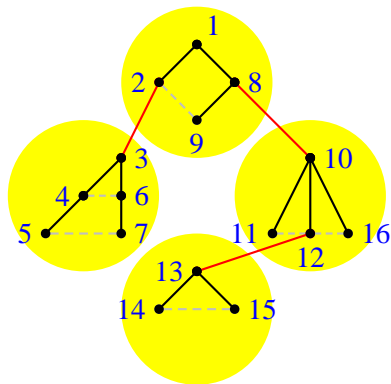


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Bridge-Finding



- What does “out of the subtree” mean?
- For each node let $low(v)$ be the minimum of its **prelabel**, its non-tree neighbours’ **prelabels**, and its children’s low values.
- For each node let $high(v)$ be the maximum of its **prelabel**, its non-tree neighbours’ **prelabels**, and its children’s $high$ values.
- Can show that $(P[v], v)$ is a **bridge** if and only if $low(v) = pre(v)$ and $high(v) = pre(v) + subtreeSize(v) - 1$.

Bridge-Finding

- An *articulation point*, analogous to a bridge, is a *vertex* whose deletion causes a graph to be disconnected.
- By refining the ideas above we can get a $O(n + m)$ time algorithm for articulation points. The formulation is cleanest using DFS because then there are no *cross edges* (edges uv such that neither u nor v is an ancestor of the other).
- Note that the naive algorithm for articulation points — delete each point in turn and see if the graph is connected — takes $O(n(m + n))$ time.
- You can also compute some other things called *biconnected components* and *blocks*. Roughly speaking, you can cut the graph into parts such that each part can tolerate any single node or vertex failure.

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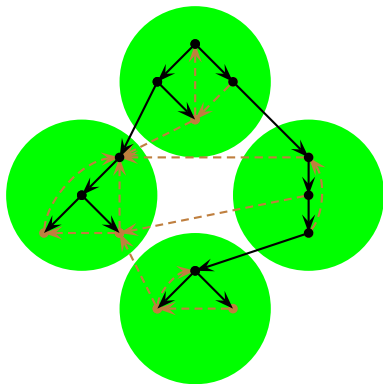
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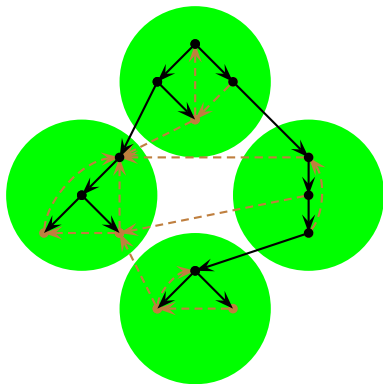
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2: postList := list< int >                                  ▷ Initially empty.
3: procedure STRONGCOMPONENTS( $G, v$ )
4:   for  $i := 0$  to  $v - 1$  do
5:     DFS-Order( $G, i$ )
6:   newOrder := postList.copy().reverse()
7:   fill(isExplore, false)
8:   for  $i$  in newOrder do
9:     if !isExplored[ $i$ ] then
10:       DFS-Label( $G^T, i$ )                                ▷ When  $j$  is explored, label[ $j$ ] :=  $i$ .
11:   return labels
```

Strong Components

- Why does this DFS witchcraft work?

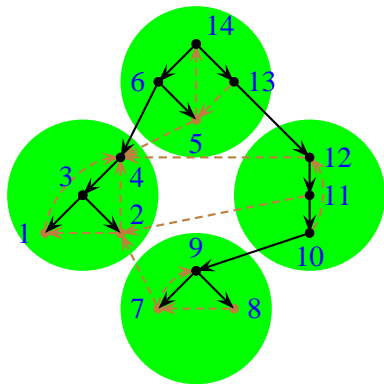


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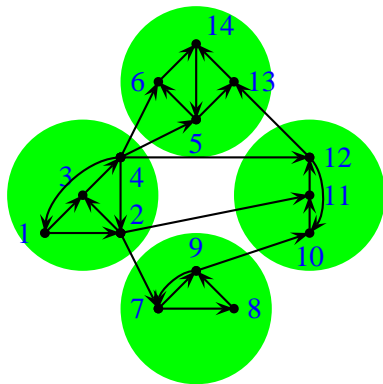
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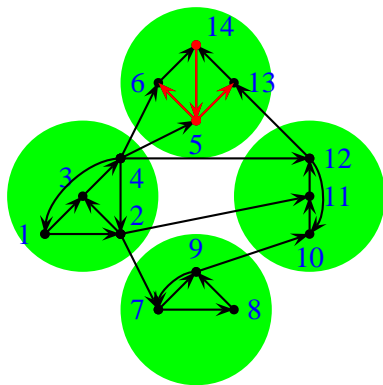
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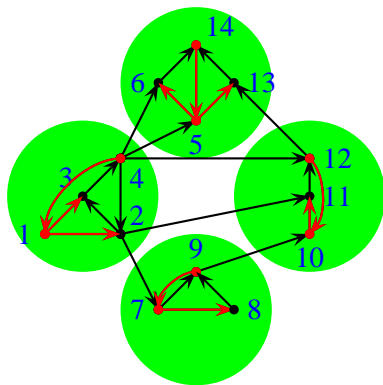
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- Explore other blobs in turn.

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