21 Disjoint Set Data Structure

Used, for example, to represent multiple strongly-connected components.

Since a strongly-connected component of a graph is the maximal set of vertices satisfying a property, a vertex/edge may only belong to one SCC.

Each object in a set needs to be able to identify if other elements belong to the same set. this is easy to do if each set has a representative object that all objects in the set point to.

1:	procedure MakeSet(Object o)	$\triangleright O(1)$
2:	o.size $\leftarrow 1$	
3:	o.parent $\leftarrow 1$	
4:	end procedure	
1:	procedure FINDSET(Object o)	$\triangleright O(lg^* n)$
2:	if $o.parent = 0$ then return 0	
3:	end if	
4:	$o.parent \leftarrow FINDSET(o.parent)$	\triangleright path compression
5:	return o.parent	
6:	end procedure	
1:	procedure UNION(Object o, Object p)	$\triangleright O(lg^* n)$
2:	$\mathbf{x} \leftarrow \mathrm{FindSet}(\mathbf{o})$	
3:	$y \leftarrow FINDSET(p)$	
4:	if $x.size \ge y.size$ then	
5:	y.parent $\leftarrow x$	
6:	$x.size \leftarrow x.size + y.size$	
7:	else	
0	x parent ← v	
8:	x.parent (y	
8: 9:	y.size \leftarrow y.size + x.size	
8: 9: 10:	y.size \leftarrow y.size + x.size end if	

22 Graphs

BFS: O(V+E). Use a queue. Add every vertex to the queue as it is discovered for the first time.

DFS: Use recursive calls to DFS. (note: many applications of DFS require keeping track of the discovery/finish times from calling DFS)

1:	1: procedure DFS(Vertex v)	
2:	if v has been discovered then	
3:	return	
4:	end if	
5:	discover v	
6:	for all vertices \mathbf{u} such that \mathbf{v} has an edge to \mathbf{u} do	
7:	DFS(u)	
8:	end for	
9:	finish v	
10:	end procedure	

In DFS(u):

- (u, v) edge is a back edge $\iff v$ is discovered but not finished.
- (u, v) edge is a forward edge \iff v is discovered and finished and u is not finished.

 $\triangleright \Theta(V+E)$

• (u, v) edge is a cross edge $\iff v$ is finished before u was discovered.

Example: With these discovery/finish times $\binom{1}{A}\binom{2}{B}\binom{3}{C}A^{4}_{C}\binom{5}{D}\binom{7}{E}D^{8}_{B}\binom{9}{B}D^{10}_{A}$ (where '(' indicates discovery and ')' indicates finishing), we have:

- (C, A) is a back edge because it occurs after ($_A$ and ($_C$
- (E, D) is a cross edge because it occurs after $(_D,)_D$, and $(_E$
- (A, D) is a forward edge because it occurs after $(A, (D, and)_D)$

Topological Sort: $\Theta(V+E)$. Call DFS(G). As each vertex finishes, add it to the beginning of a linked list. Return this list.

A strongly-connected component of G is a maximal set of vertices $C \subseteq V$ such that for every $u, v \in C$, $u \rightsquigarrow v$ and $v \rightsquigarrow u$.

To find strongly-connected components of graph G

procedure StronglyConnectedComponents	$\triangleright O(\Theta(V+E))$
DFS(any vertex of G)	
for all vertices v in decreasing order of finish time do	
G^T .DFS(v) \triangleright All nodes discovered in this call to D	FS belong to the
same strongly-connected component	
	procedure STRONGLYCONNECTEDCOMPONENTS DFS(any vertex of G) for all vertices v in decreasing order of finish time do G^T .DFS(v) \triangleright All nodes discovered in this call to D same strongly-connected component

^{5:} end for

^{6:} end procedure

An alternate form of topological sort exists, which is also $\Theta(V+E)$. In the case it is called on a graph with cycles, it produces a flawed ordering and has poorer failure modes.

1.	procedure ALTTOPOLOGICAL SOBT(Graph G)	$\triangleright \Theta(V+E)$
1. 9.	Create a queue Topo	
2. 2.	Create a queue 1000	
J. ⊿.	for all vertices $\mathbf{y} \in \mathbf{C}$ do	
4. 5.	if u indegree $= 0$ then	
0: C	Ω ENQUELLE(x)	
0: -	Q.ENQUEUE(V)	
7:		
8:	end for	
9:	while Q nonempty do	
10:	vertex $\mathbf{u} \leftarrow \mathbf{Q}$.DEQUEUE	
11:	TOPO.ENQUEUE(u)	
12:	for all vertices v such that $(u, v) \in G$ do	
13:	v.indegree \leftarrow v.indegree - 1	
14:	if v.indegree $= 0$ then	
15:	$\mathrm{Q.enqueue}(\mathrm{v})$	
16:	end if	
17:	end for	
18:	end while	
19:	for all vertices $v \in G do$	
20:	if v.indegree $\neq 0$ then	\triangleright Found a cycle. Uh-oh!
21:	end if	
22:	end for	
23:	return Topo	
24:	end procedure	

23 Minimum Spanning Trees

Kruskal's Algorithm makes use of the disjoint set data structure.

Prim's Algorithm makes use of a min-Priority Queue to retrieve vertices in non-descending order of weight; and also so that their weights can be decreased.

24 Single-source Shortest Paths

It's often useful to figure out the shortest paths within a graph G, from vertex v to every other vertex in G. This general problem has several variants.

1:	procedure Kruskals $MST(Graph G)$ \triangleright	O(E lg V)
2:	for all vertices $v \in G do$	
3:	MAKESET(v)	
4:	end for	
5:	sort the edges of G in non-descending order by edge-weight	
6:	for all edges (u, v) in non-descending order by weight do	
7:	if $FINDSET(u) \neq FINDSET(v)$ then	
8:	add edge (u, v) to MST	
9:	UNION(u, v)	
10:	end if	
11:	end for	
12:	end procedure	

1:	procedure PrimsMST(Graph G)	$\triangleright O(E lg V)$
2:	for all vertices $v \in G$ do	\triangleright initialize all vertices
3:	$\mathrm{key}[\mathrm{v}] \leftarrow \infty$	
4:	$\pi[\mathrm{v}] \leftarrow null$	
5:	end for	
6:	$\text{key}[\text{some initial vertex}] \leftarrow 0$	
7:	PriorityQueue $\mathbf{Q} \leftarrow \text{all vertices}$	
8:	while Q not empty do	
9:	vertex $\mathbf{u} \leftarrow \text{ExtractMin}(\mathbf{Q})$	
10:	for all vertices v such that (u, v) is	s an edge in G do
11:	if $v \in Q$ and weight (u, v) ; key	[v] then
12:	$\pi[v] \leftarrow u$	
13:	$\text{key}[v] \leftarrow \text{weight}(u, v)$	
14:	end if	
15:	end for	
16:	add edge $(\pi[u], u)$ to MST	
17:	end while	
18:	end procedure	

- Single-destination shortest paths: This variant reduces to a SSSP problem if you reverse the direction of every edge in G.
- Single-pair shortest paths: If you need to find the shortest path between vertices u and v in G, solving the SSSP general problem will give you an answer. While it may seem like overkill, no algorithm is known that will solve this problem better than a SSSP algorithm.

Shortest paths have an interesting property: If $a \rightsquigarrow c$ is the shortest path from a to c, and passes through vertex b, then $a \rightsquigarrow b$ is the shortest path from a to b and $b \rightsquigarrow c$ is the shortest path from b to c.

Some gotchas:

- Some SSSP algorithms don't produce correct results (or even halt) if the graph contains negative edge-weights. In particular, cycles of negative weight can create a shortest path with weight $-\infty$.
- Cycles of weight 0 contribute no savings to overall path weight, yet add edge traversals. So no SSSP should contain a 0-weight cycle.
- Positive weight cycles have higher weight than the same path without the cycles, so no SSSP will contain one.

For Graph G and starting vertex s, SSSP algorithms use these common functions:

1: procedure INITIALIZESINGLESOURCE(Graph G, Vertex v) $\triangleright $	$\Theta(V)$
2: for all vertices $v \in G$ do	
3: distance[v] $\leftarrow \infty$	
4: $parent[v] \leftarrow null$	
5: end for	
6: distance[s] $\leftarrow 0$	
7: end procedure	

1: procedure RELAX(Source Vertex u, Destination Vertex v, Weight Function w) $\triangleright O(1)$ 2: if distance[v] > distance[u] + w(u, v) then 3: distance[v] \leftarrow distance[u] + w(u, v) 4: parent[v] \leftarrow u 5: end if 6: end procedure

Here's the first SSSP algorithm:

1:	procedure BellmanFord(G	Graph G, Weight Function w, Starting Vertex
	s)	$\triangleright O(VE)$
2:	InitializeSingleSource((G, s)
3:	for $i \leftarrow 1$ to $-V(G)$ - 1	do
4:	for all edge (u, v) in G	do
5:	Relax(u, v, w)	
6:	end for	
7:	end for	
8:	for all edge $(u, v) \in G$ do	
9:	$\mathbf{if} \operatorname{distance}[\mathbf{v}] > \operatorname{distance}$	ce[u] + w(u, v) then
10:	return false	\triangleright found a negative-weight cycle
11:	end if	
12:	end for	
13:	return true	\triangleright found no negative-weight cycles
14:	end procedure	

Though Bellman-Ford is slow, one benefit is that it can determine if there are negative-weight cycles in G, which are detectable if the shortest path keeps getting smaller past a fixed number of relaxation attempts.

DagShortestPaths only works on a DAG (directed acyclic graph), but is faster than Bellman-Ford.

1: procedure DAGSHORTESTPATHS(Graph G, Weight Function	w, Starting
Vertex s)	$\triangleright \Theta(V+E)$
2: $T \leftarrow a$ list of the vertices of G, sorted topologically	
3: INITIALIZESINGLESOURCE (G, s)	
4: for all vertices $u \in T$ do	
5: for all vertices v such that (u, v) is an edge in G do	
6: $RELAX(u, v, w)$	
7: end for	
8: end for	
9: end procedure	

Dijkstra's/Dantzig's algorithm finds SSSPs in much the same way as Prim's algorithm finds MSTs. Whereas Prim's uses a Min-Priority Queue to keep track of minimum edge weights to a vertex, Dijkstra's associates with each vertex the minimum path weight to reach that vertex.

Dijkstra's algorithm will give the wrong answer if the graph it's used on has negative weights.

1. procedure DIJKSTRA(Graph G Weight Function w Starting Vertex s)
o (D L L)
$O(E \ lg \ V)$
2: INITIALIZESINGLESOURCE (G, s)
3: MinPriorityQueue $\mathbf{Q} \leftarrow \text{all vertices} \in \mathbf{G}$
4: while Q is not empty do
5: Vertex $\mathbf{u} \leftarrow \text{EXTRACTMIN}(\mathbf{Q})$
6: for all vertices v such that $(u, v) \in G$ do
7: $\operatorname{RELAX}(u, v, w)$
8: end for
9: end while
10: end procedure

25 All-Pairs Shortest Paths

The Floyd-Warshall algorithm is similar to the Bellman-Ford SSSP algorithm, but with more work and storage. Whereas B-F stored, for each destination vertex, what the parent and path-cost is on a path originating at some source vertex, F-W must store those two facts for each source vertex \times destination vertex pair.

Basically, you start with an adjacency matrix. Then, for each vertex, { v_1 , v_2 , ..., v_n } you derive a matrix from it that indicates the shortest paths from each vertex to each other vertex by storing only information about vertices that precede it on the path.

```
\triangleright \Theta(V^3) time, O(V^2)
 1: procedure FLOYDWARSHALL(n \times n \text{ Matrix } W)
       memory
             n \leftarrow rows(W)
 2:
             \mathbf{D}^0 \leftarrow \mathbf{W}
 3:
             for k \leftarrow 1 to n do
 4:
                   for i \leftarrow 1 to n do
 5:
                         \begin{array}{l} \textbf{for } \mathbf{j} \leftarrow 1 \text{ to n } \mathbf{do} \\ d_{i,j}^k \leftarrow \min(d_{i,j}^{k-1}, \, d_{i,k}^{k-1} + d_{k,j}^{k-1}) \end{array}
 6:
 7:
                         end for
 8:
                   end for
 9:
                   Destroy \mathbf{D}^{k-1}
10:
             end for
11:
             return \mathbf{D}^n
12:
13: end procedure
```

 $i \rightsquigarrow k \rightsquigarrow j$ implies that $i \rightsquigarrow k$ and $k \rightsquigarrow j$. So if you're running Floyd-Warshall, you can save a lot of arithmetic by applying these rules:

1. if a row has ∞ in column k, then nothing in this row will change during

this iteration of the outer loop. i.e., $i \rightsquigarrow j$ does not pass through k if i has no path to k.

2. if a column has ∞ in row k, then nothing in that column will change during this k. This is because $i \rightsquigarrow j \rightsquigarrow k$ only if $j \rightsquigarrow k$.