

Disjoint Sets and Union-Find Operations

Consider a finite set $S = \{x_1, x_2, \dots, x_n\}$, $n \geq 1$.

Observations:

1. A trivial partition P of S can be obtained by simply defining $S_i = \{x_i\}$, for all i , $1 \leq i \leq n$.
2. Given a partition P of S with k sets, $k \geq 2$, a new partition of S can be formed by taking some unions of the sets in P .
3. One can perform at most $n-1$ union operations on the sets in P before S is re-generated.

Questions:

For any given partition P of S ,

1. How do we represent/naming a set?
2. What kind of data structure should we use to implement a set so as to support the following two basic operations:
 - (i) $\text{find}(x)$, $x \in S$: Return the (unique) set containing x .
 - (ii) $\text{union}(x,y)$: Return the union of the two sets containing with representative x , and y , respectively.

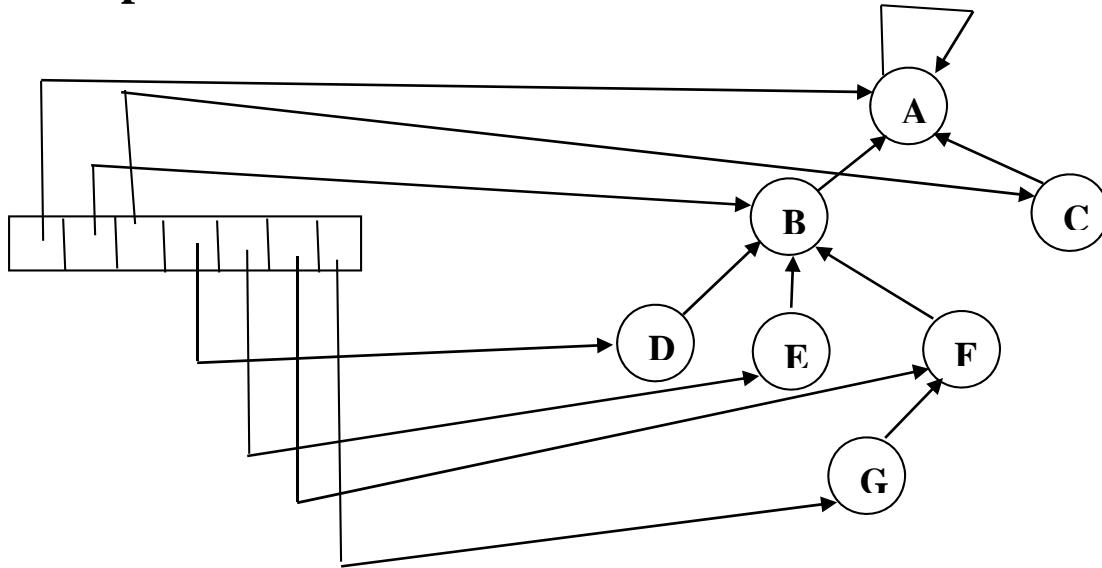
A Simple Approach:

- Given any set S_i . Use an element $x \in S_i$ as the representative/name of the set.
- Use a tree to implement a set with the root of the tree being the representative of the set.

Implementing a Set using a Tree Structure:

Each set S_i will be implemented as a (rooted) tree T_i such that each element $x \in S_i$ will be represented by a node with a parent pointer pointing to its parent in T_i .

Example:



Remark: The array of pointers will be used to access the nodes of the tree.

Set Union and Trees Merging:

Given two sets S_i and S_j with representatives x_i and x_j , the operation $\text{union}(x_i, x_j)$ is equivalent to merging two trees with roots x_i and x_j together. To merge two trees together, one can simply set the parent pointer of x_i to point at x_j with x_j being the representative of the new set. Observe that, independent of the sizes of the two sets, $\text{union}(x_i, x_j)$ can now be executed in $O(1)$ time.

Union and Find Operations in Disjoint Sets:

If each element $x \in S$ is being used to represent a data object, then one of the most important and relevant operations in a partition of S will be the *find* operation, $\text{find}(x)$, which will return the representative of the unique set that contains x .

Basic find Operation:

Approach:

- Using the array of pointers to locate the element x , and the tree containing x , among the trees in a partition.
- Follow the parent pointer of x to the root of the tree that contains x .
- Return the root of the tree that contains x .

Complexity of find Operations:

Recall that if one performs $O(n)$ union operations on the sets of a given partition using the above tree structures and trees merging algorithm, a tree with height $O(n)$ can be formed. Hence, in order to find the root of the tree that contains x , one may have to follow the parent pointers of a leaf to the root, resulting in $T(n) = O(n)$.

Amortized Analysis of Disjoint Set Operations:

Given a sequence of $O(n)$ union operations intermixed with a sequence of $O(m)$ find operations, where $m \gg n$, what is a good data structure and its complexity $T(m,n)$ in performing these $O(n)$ union and $O(m)$ find operations?

Simple Approach:

Using the above implementation, we have $T(m,n) = O(mn)$.

Questions:

Can we do it better?

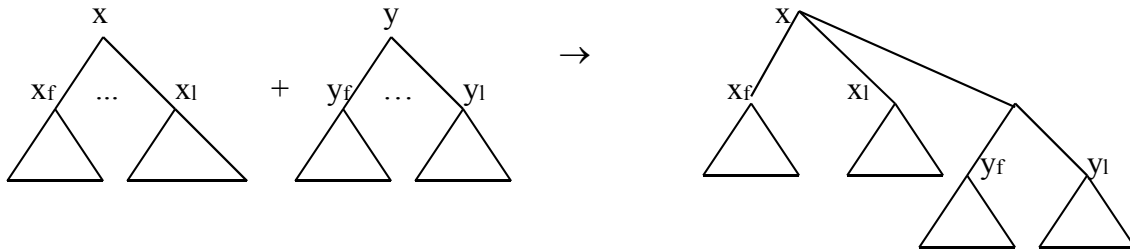
Two Possible Approaches:

1. Minimize the height of the resulting tree during union operation.
2. Modify the structure of a tree during find operations so that subsequent find operations performed on the same tree can be speeded up.

Union-by-Height Heuristic:

For each node x in a tree T , recall that the height of x , $h(x)$, is the length of a longest path from x to a leaf node in T . In performing $\text{union}(x_i, x_j)$ operation, the parent pointer of x_i is set to point at x_j iff $h(x_i) \leq h(x_j)$. Otherwise, we will set the parent pointer of x_j to point at x_i instead. Observe that, by using this union-by-height heuristic, the height of the resulting tree will increase by 1 iff both trees have the same height.

Example: Performing $\text{union}(x,y)$ using union-by-height with $h(x) \geq h(y)$.



Other Union Heuristics:

1. Union-by-Rank Heuristic:

For each node x in S , define $\text{rank}(x)$ as followed:

Initially, when x is in a tree by itself, $\text{rank}(x) = 0$.

When performing $\text{union}(x_i, x_j)$ operation, the parent pointer of x_i is set to point at x_j iff $\text{rank}(x_i) \leq \text{rank}(x_j)$.

And if $\text{rank}(x_i) = \text{rank}(x_j)$, then $\text{rank}(x_j) = \text{rank}(x_j) + 1$. If $\text{rank}(x_i) > \text{rank}(x_j)$, then we will set the parent pointer of x_j to point at x_i instead. Observe that, by using this union-by-rank heuristic, the rank of the resulting tree will increase by 1 iff both trees have the same rank.

Also, the rank of a root can only be changed during union operation. Hence, the $\text{rank}(x) \geq h(x)$, $\forall x \in S$.

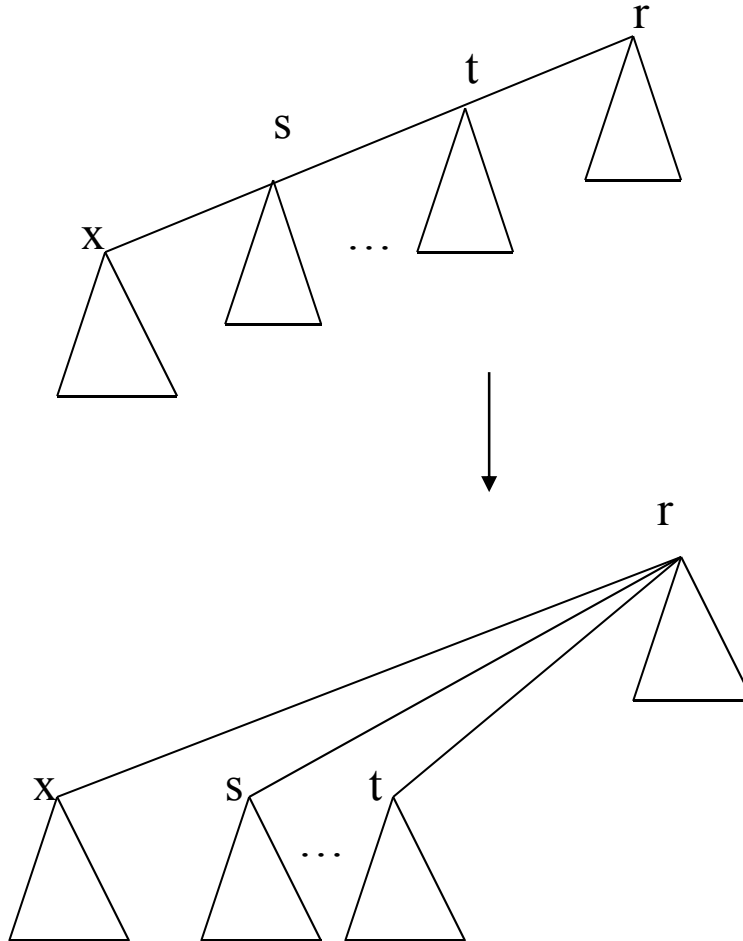
2. Union-by-Weight/Size Heuristic:

For each node x in S , define $w(x)$ be the number of nodes, including x , in the tree rooted at x . When performing $\text{union}(x_i, x_j)$ operation, the parent pointer of x_i is set to point at x_j iff $w(x_i) \leq w(x_j)$. Otherwise, we will set the parent pointer of x_j to point at x_i instead. Observe that, by using this union-by-weight heuristic, the weight of the resulting tree will always be increased by the size of the additional tree.

Path Compression Heuristic:

In performing $\text{find}(x)$ operation, after the tree T that contains x and the root r of T is identified, every node on the path from x to r will be made a new child of r .

Example: Performing $\text{find}(x)$ using path compression.



Theorem (Tarjan): By using union-by-rank and path compression heuristics, $T(m,n) = O(m\alpha(m,n))$, where $\alpha(m,n)$ is the inverse Ackerman's function $A(m,n)$.

Review: Ackermann's Function

Define the **Ackermann's function** $A : \mathbb{N} \times \mathbb{N} \rightarrow \mathbb{N}$ by

$$\begin{aligned} A(0, n) &= n + 1, \\ A(m, 0) &= A(m-1, 1), \text{ if } m > 0, \\ A(m, n) &= A(m-1, A(m, n-1)), \text{ if } m, n > 0. \end{aligned}$$

Example:

$$\begin{aligned} A(0, 0) &= 1, \\ A(0, 1) &= 2, \\ A(0, 2) &= 3, \\ A(0, 3) &= 4, \\ &\dots \end{aligned}$$

$$\begin{aligned} A(1, 0) &= A(0, 1) = 2, \\ A(1, 1) &= A(0, A(1, 0)) = A(0, 2) = 3, \\ A(1, 2) &= A(0, A(1, 1)) = A(0, 3) = 4, \\ A(1, 3) &= 5, \\ &\dots \end{aligned}$$

$$\begin{aligned} A(2, 0) &= A(1, 1) = 3, \\ A(2, 1) &= A(1, A(2, 0)) = A(1, 3) = 5, \\ A(2, 2) &= A(1, A(2, 1)) = A(1, 5) = 7, \\ A(2, 3) &= 9, \\ &\dots \end{aligned}$$

$$\begin{aligned}
A(3,0) &= A(2, 1) = 5, \\
A(3, 1) &= A(2, A(3,0)) = A(2, 5) = 13, \\
A(3, 2) &= A(2, A(3, 1)) = A(2, 13) = 29, \\
A(3, 3) &= A(2, A(3, 2)) = A(2, 29) = 61, \\
&\dots
\end{aligned}$$

$$\begin{aligned}
A(4,0) &= A(3,1) = 13, \\
A(4,1) &= A(3, A(4,0)) = A(3, 13), \\
A(4,2) &= ?
\end{aligned}$$

Remark: $A(m,n)$ is an extremely fast growing function and, hence, its inverse function $\alpha(m,n)$, which often appears in data structures analyses and counting, grows extremely slow. For all practical purpose, $\alpha(m,n)$ can be treated as a constant.