

9 Union Find

Union Find Data Structure \mathcal{P} : Maintains a partition of **disjoint** sets over elements.

- ▶ \mathcal{P} . **makeset**(x): Given an element x , adds x to the data-structure and creates a singleton set that contains only this element. Returns a locator/handle for x in the data-structure.
- ▶ \mathcal{P} . **find**(x): Given a handle for an element x ; find the set that contains x . Returns a representative/identifier for this set.
- ▶ \mathcal{P} . **union**(x, y): Given two elements x , and y that are currently in sets S_x and S_y , respectively, the function replaces S_x and S_y by $S_x \cup S_y$ and returns an identifier for the new set.

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Applications:

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Algorithm 16 Kruskal-MST($G = (V, E), w$)

```
1:  $A \leftarrow \emptyset$ ;  
2: for all  $v \in V$  do  
3:    $v.\text{set} \leftarrow \mathcal{P}.\text{makeset}(v.\text{label})$   
4: sort edges in non-decreasing order of weight  $w$   
5: for all  $(u, v) \in E$  in non-decreasing order do  
6:   if  $\mathcal{P}.\text{find}(u.\text{set}) \neq \mathcal{P}.\text{find}(v.\text{set})$  then  
7:      $A \leftarrow A \cup \{(u, v)\}$   
8:      $\mathcal{P}.\text{union}(u.\text{set}, v.\text{set})$ 
```

List Implementation

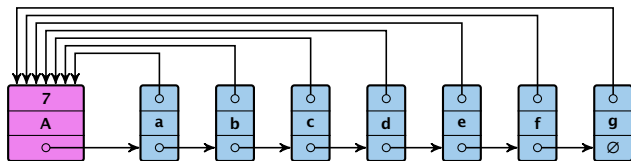
- ▶ The elements of a set are stored in a list; each node has a backward pointer to the head.
- ▶ The head of the list contains the identifier for the set and a field that stores the **size** of the set.



- ▶ `makeset(x)` can be performed in constant time.
- ▶ `find(x)` can be performed in constant time.

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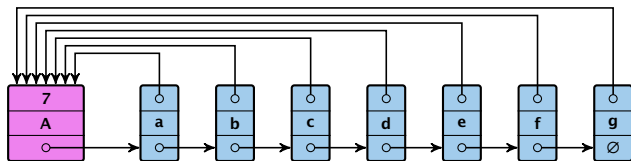
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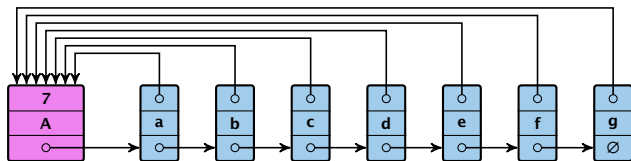
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union(x, y)

- ▶ Determine sets S_x and S_y .
- ▶ Traverse the smaller list (say S_y), and change all backward pointers to the head of list S_x .
- ▶ Insert list S_y at the head of S_x .
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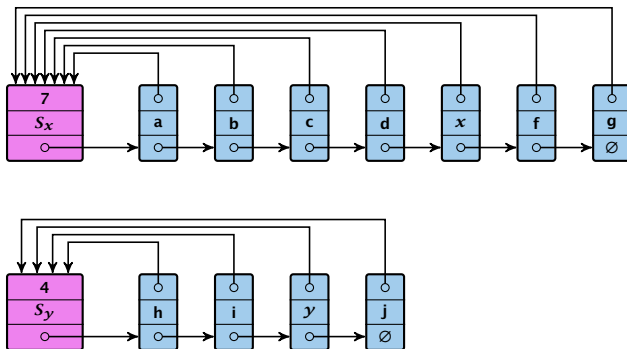
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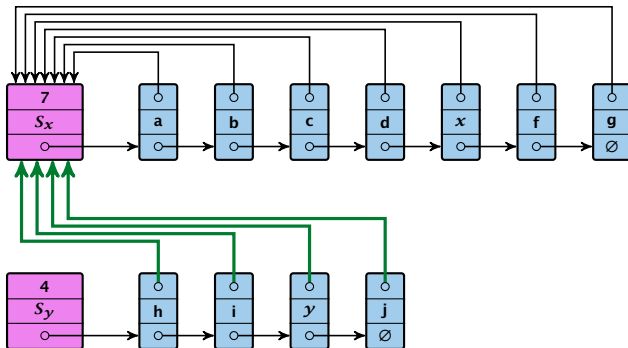
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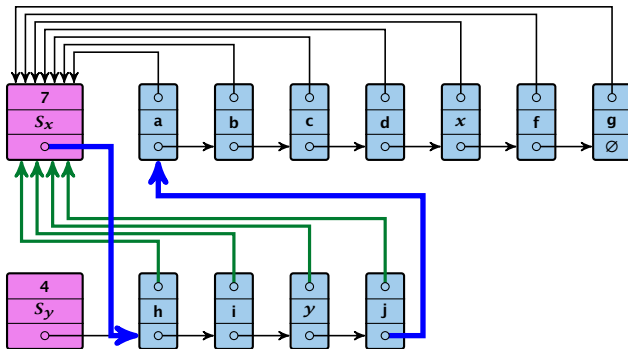
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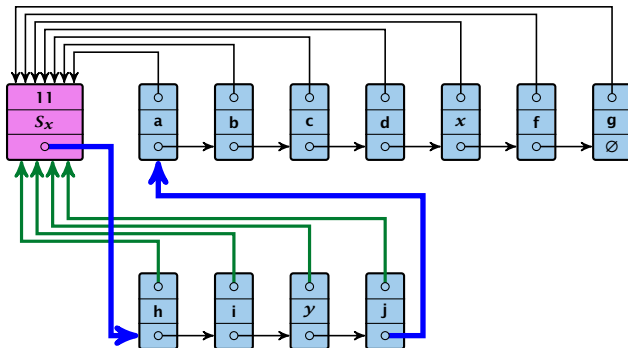
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Running times:

- ▶ $\text{find}(x)$: constant
- ▶ $\text{makeset}(x)$: constant
- ▶ $\text{union}(x, y)$: $\mathcal{O}(n)$, where n denotes the number of elements contained in the set system.

List Implementation

Lemma 1

The list implementation for the ADT union find fulfills the following amortized time bounds:

- ▶ $\text{find}(x): \mathcal{O}(1)$.
- ▶ $\text{makeset}(x): \mathcal{O}(\log n)$.
- ▶ $\text{union}(x, y): \mathcal{O}(1)$.

The Accounting Method for Amortized Time Bounds

- ▶ There is a bank account for every element in the data structure.
- ▶ Initially the balance on all accounts is zero.
- ▶ Whenever for an operation the amortized time bound exceeds the actual cost, the difference is credited to some bank accounts of elements involved.
- ▶ Whenever for an operation the actual cost exceeds the amortized time bound, the difference is charged to bank accounts of some of the elements involved.
- ▶ If we can find a charging scheme that guarantees that balances always stay positive the amortized time bounds are proven.

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List Implementation

- ▶ For an operation whose actual cost exceeds the amortized cost we charge the **excess** to the elements involved.
- ▶ In total we will charge at most $\mathcal{O}(\log n)$ to an element (regardless of the request sequence).
- ▶ For each element a makeset operation occurs as the first operation involving this element.
- ▶ We inflate the amortized cost of the makeset-operation to $\Theta(\log n)$, i.e., at this point we fill the bank account of the element to $\Theta(\log n)$.
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makeiset(x): The actual cost is $\mathcal{O}(1)$. Due to the cost inflation the amortized cost is $\mathcal{O}(\log n)$.

find(x): For this operation we define the amortized cost and the actual cost to be the same. Hence, this operation does not change any accounts. Cost: $\mathcal{O}(1)$.

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Lemma 2

An element is charged at most $\lfloor \log_2 n \rfloor$ times, where n is the total number of elements in the set system.

Proof.

Whenever an element x is charged the number of elements in x 's set doubles. This can happen at most $\lfloor \log n \rfloor$ times. \square

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Implementation via Trees

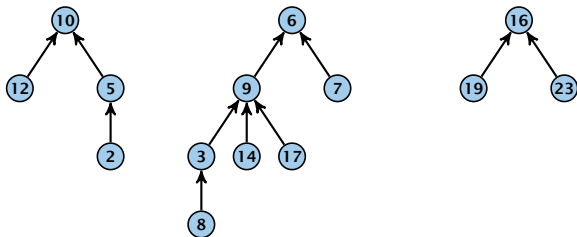
- ▶ Maintain nodes of a set in a tree.
- ▶ The root of the tree is the label of the set.
- ▶ Only pointer to parent exists; we cannot list all elements of a given set.
- ▶ Example:



Set system $\{2, 5, 10, 12\}$, $\{3, 6, 7, 8, 9, 14, 17\}$, $\{16, 19, 23\}$.

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- ▶ Create a singleton tree. Return pointer to the root.
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find(x)

Start at element x in the tree, and repeatedly update x to be its parent until it reaches the root.

Time complexity: $\mathcal{O}(h)$, where h is the height of the tree.

Improvement: The root of the tree is the same for all elements in the same tree. We can store the root of the tree in an array, and update it when we find a new root.

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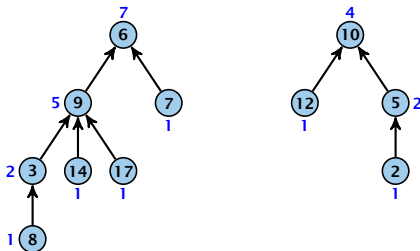
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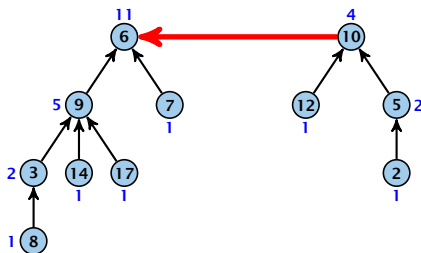


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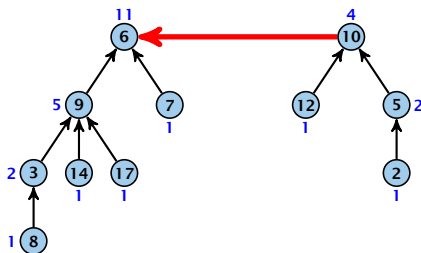


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- ▶ Time: constant for $\text{link}(a, b)$ plus two find-operations.

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Path Compression

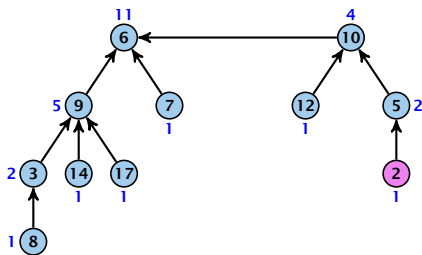
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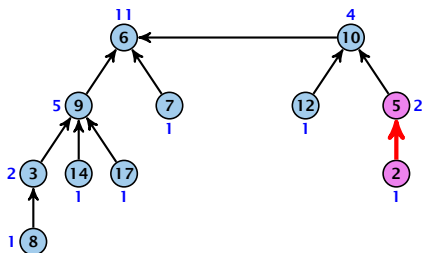


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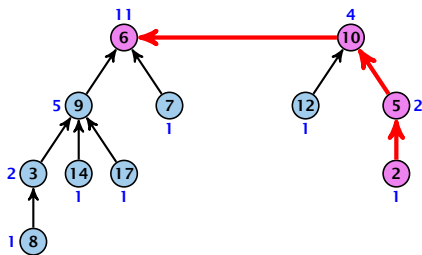


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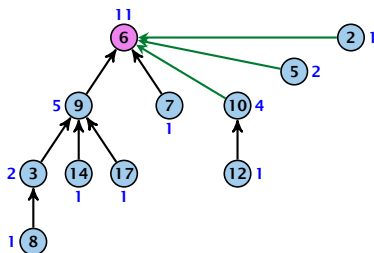


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Asymptotically the cost for a find-operation does not increase due to the path compression heuristic.

However, for a worst-case analysis there is no improvement on the running time. It can still happen that a find-operation takes time $\mathcal{O}(\log n)$.

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Amortized Analysis

Definitions:

$n(x)$ = the number of nodes that were in the splay tree started at x when x became the child of another node (i.e. the number of nodes if x is the root).

Note that this is the same as the size of x 's subtree in the case that there are no find-operations.

Lemma 4

The rank of a parent must be strictly larger than the rank of a child.

Amortized Analysis

Definitions:

- ▶ $\text{size}(v) :=$ the number of nodes that were in the sub-tree rooted at v when v became the child of another node (or the number of nodes if v is the root).

Note that this is the same as the size of v 's subtree in the case that there are no find-operations.

- ▶ $\text{rank}(v) = \lfloor \log(\text{size}(v)) \rfloor$.
- ▶ $\Rightarrow \text{size}(v) \geq 2^{\text{rank}(v)}$.

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Amortized Analysis

Lemma 5

There are at most $n/2^s$ nodes of rank s .

Proof.

Let's say a node x has rank s . Then it has at least 2^{s-1} children. The total number of nodes is n .

Each node has at most one node of rank s as child during the running time of the algorithm.

This being the case, the rank sequence of the roots of the trees is a decreasing sequence during the running time of the algorithm. In particular, there can be at most one node of rank s .

Therefore, there can be at most $n/2^s$ nodes of rank s . □

Amortized Analysis

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Proof.

- ▶ Let's say a node v sees node x if v is in x 's sub-tree at the time that x becomes a child.
- ▶ A node v sees at most one node of rank s during the running time of the algorithm.
- ▶ This holds because the rank-sequence of the roots of the different trees that contain v during the running time of the algorithm is a strictly increasing sequence.
- ▶ Hence, every node sees at most one rank s node, but every rank s node is seen by at least 2^s different nodes. □

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We define

$$\text{tow}(i) := \begin{cases} 1 & \text{if } i = 0 \\ 2^{\text{tow}(i-1)} & \text{otw.} \end{cases}$$

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Theorem 6

Union find with path compression fulfills the following amortized running times:

- ▶ $\text{makeset}(x) : \mathcal{O}(\log^*(n))$
- ▶ $\text{find}(x) : \mathcal{O}(\log^*(n))$
- ▶ $\text{union}(x, y) : \mathcal{O}(\log^*(n))$

Amortized Analysis

In the following we assume $n \geq 2$.

rank-group:

A node with rank r belongs to the rank-group r .

The rank-group r contains only nodes with rank $\geq r$.

rank

rank-group: \geq rank

The maximum number of rank-groups

is $\lceil \lg n \rceil$ (rank of root is $\lceil \lg n \rceil$)

The total number of rank-groups is at most

Amortized Analysis

In the following we assume $n \geq 2$.

rank-group:

- ▶ A node with rank $\text{rank}(v)$ is in **rank group** $\log^*(\text{rank}(v))$.
- ▶ The rank-group $g = 0$ contains only nodes with rank 0 or rank 1.
- ▶ A rank group $g \geq 1$ contains ranks $\text{tow}(g-1) + 1, \dots, \text{tow}(g)$.
- ▶ The maximum non-empty rank group is $\log^*(\lfloor \log n \rfloor) \leq \log^*(n) - 1$ (which holds for $n \geq 2$).
- ▶ Hence, the total number of rank-groups is at most $\log^* n$.

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Amortized Analysis

Accounting Scheme:

• Create an account for every find-operation

• Create an account for every node

The cost for a find-operation is equal to the length of the path traversed. We charge the cost for going from v to $\text{parent}[v]$ as follows:

• If v is the root we charge the cost to the account of v .

• Otherwise:

• If the credit-number of v is 0, then use as that of $\text{parent}[v]$.

• If v has a credit-number (before starting path compression) we

charge the cost to the node-account of v and decrease the credit-

number of v by 1. The cost is charged to the account of v .

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- ▶ if v is the root we charge the cost to the account of the root
- ▶ if v is not the root we charge the cost to the account of the root of the path from v to the root. (Before starting path compression we charge the cost to the node v and then we charge the cost to the root of the path.)

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Accounting Scheme:

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The cost for a find-operation is equal to the length of the path traversed. We charge the cost for going from v to $\text{parent}[v]$ as follows:

- ▶ if the node v has a credit, we charge the cost to the credit
- ▶ if the credit is not enough, we charge the cost to the account of the parent
- ▶ if we are working with path compression, we charge the cost to the account of the root

The cost of the find-operation is at most the number of nodes on the path.

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- ▶ If $\text{parent}[v]$ is the root we charge the cost to the find-account.
- ▶ If the group-number of $\text{rank}(v)$ is the same as that of $\text{rank}(\text{parent}[v])$ (before starting path compression) we charge the cost to the node-account of v .
- ▶ Otherwise we charge the cost to the find-account.

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Amortized Analysis

Observations:

- The number of changed elements is bounded from above by the number of elements in the array, which grows when increasing the size of the array.
- The number of changed elements is bounded from below by half of the current array size.
- The time charges to the parent will be in a lower rank group, and will never be charged again.
- Any time charge made to a node in rank group r is at most

Amortized Analysis

Observations:

- ▶ A find-account is charged at most $\log^*(n)$ times (once for the root and at most $\log^*(n) - 1$ times when increasing the rank-group).
- ▶ After a node v is charged its parent-edge is re-assigned. The rank of the parent strictly increases.
- ▶ After some charges to v the parent will be in a larger rank-group. $\Rightarrow v$ will **never** be charged again.
- ▶ The total charge made to a node in rank-group g is at most $\text{tow}(g) - \text{tow}(g - 1) - 1 \leq \text{tow}(g)$.

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What is the total charge made to nodes?

- ▶ The total charge is at most

$$\sum_g n(g) \cdot \text{tow}(g),$$

where $n(g)$ is the number of nodes in group g .

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Without loss of generality we can assume that all **makeset**-operations occur at the start.

This means if we inflate the cost of **makeset** to $\log^* n$ and add this to the node account of v then the balances of all node accounts will sum up to a positive value (this is sufficient to obtain an amortized bound).

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The analysis is not tight. In fact it has been shown that the amortized time for the union-find data structure with path compression is $\mathcal{O}(\alpha(m, n))$, where $\alpha(m, n)$ is the inverse Ackermann function which grows a lot lot slower than $\log^* n$. (Here, we consider the average running time of m operations on at most n elements).

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$$A(x, y) = \begin{cases} y + 1 & \text{if } x = 0 \\ A(x - 1, 1) & \text{if } y = 0 \\ A(x - 1, A(x, y - 1)) & \text{otw.} \end{cases}$$

$$\alpha(m, n) = \min\{i \geq 1 : A(i, \lfloor m/n \rfloor) \geq \log n\}$$

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- ▶ $A(1, y) = y + 2$
- ▶ $A(2, y) = 2y + 3$
- ▶ $A(3, y) = 2^{y+3} - 3$
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