Chapter 5
Data Structures

Algorithm Theory
WS 2018/19

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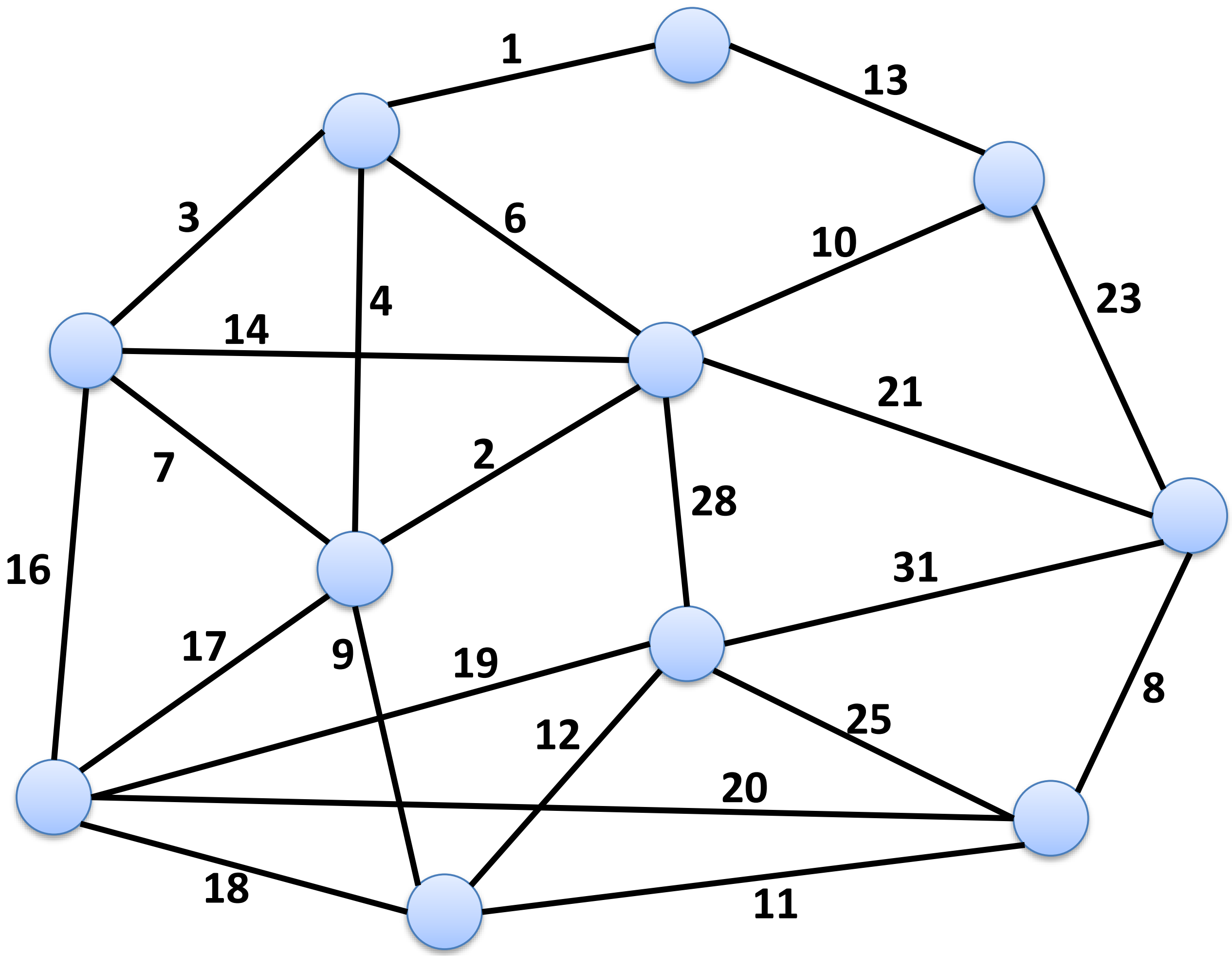
Kruskal Algorithm



1. Start with an empty edge set

2. In each step: Add minimum weight edge e such that e does *not* close a cycle

Implementation of Kruskal Algorithm

1. Go through edges in order of increasing weights

2. For each edge e:

   if ***e* does not close a cycle** **then**

   add *e* to the current solution

Union-Find Data Structure

Also known as **Disjoint-Set Data Structure**…

Manages partition of a set of elements

- set of disjoint sets

Operations:

- $\mathbf{make\_set}(\boldsymbol{x})$**:** create a new set that only contains element x

- $\mathbf{find}(\boldsymbol{x})$**:** return the set containing x

- $\mathbf{union}(\boldsymbol{x}, \boldsymbol{y})$**:** merge the two sets containing x and y

Implementation of Kruskal Algorithm

1. Initialization:
   For each node v: $\text{make\_set}(v)$

2. Go through edges in order of increasing weights:
   Sort edges by edge weight

3. For each edge $e = \{u, v\}$:

   if $\mathbf{find}(\boldsymbol{u}) \neq \mathbf{find}(\boldsymbol{v})$ **then**

   add e to the current solution

   $\mathbf{union}(\boldsymbol{u}, \boldsymbol{v})$

Managing Connected Components

- Union-find data structure can be used more generally to manage the connected components of a graph

  … if edges are added incrementally

- $\mathrm{make\_set}(v)$ for every node v
- $\mathrm{find}(v)$ returns component containing v
- $\mathrm{union}(u, v)$ merges the components of u and v
  (when an edge is added between the components)

- Can also be used to manage biconnected components

Basic Implementation Properties

Representation of sets:

- Every set S of the partition is identified with a representative, by one of its members $x \in S$

Operations:

- $\text{make\_set}(x)$: x is the representative of the new set $\{x\}$

- $\text{find}(x)$: return representative of set S_x containing x

- $\text{union}(x, y)$: unites the sets S_x and S_y containing x and y and returns the new representative of $S_x \cup S_y$

Observations

Throughout the discussion of union-find:

- n: total number of make_set operations
- m: total number of operations (make_set, find, and union)

Clearly:

- $m \geq n$
- There are at most $n - 1$ union operations

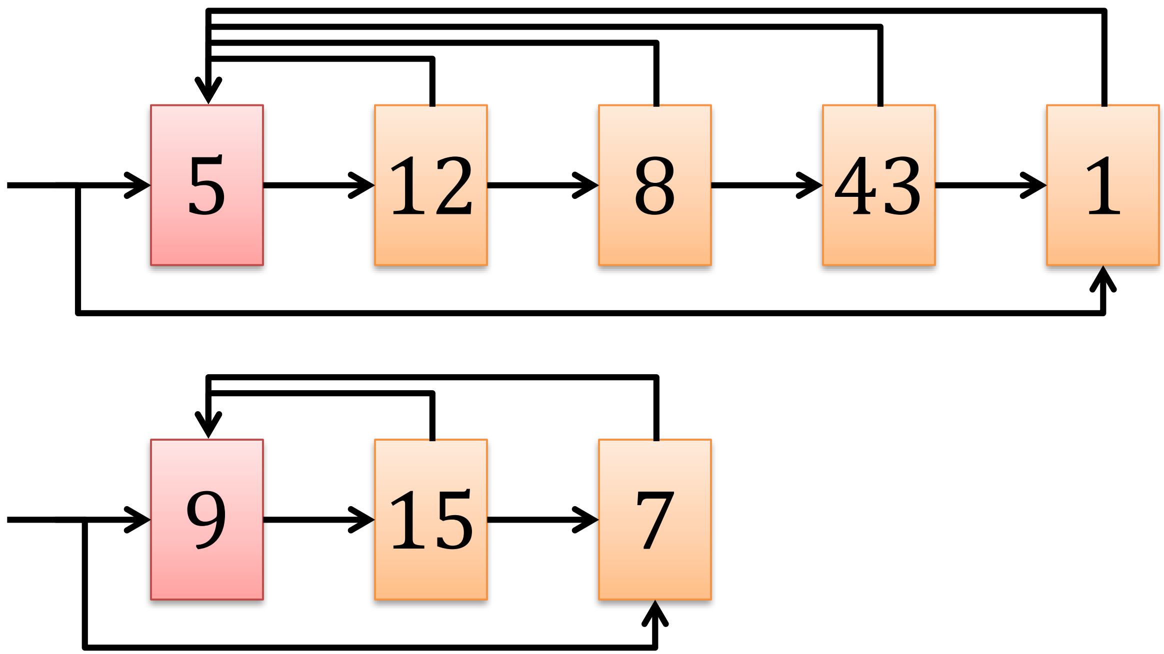
Remark:

- We assume that the n make_set operations are the first n operations
  - Does not really matter…

Linked List Implementation

Each set is implemented as a linked list:

- representative: first list element (all nodes point to first elem.)
  in addition: pointer to first and last element



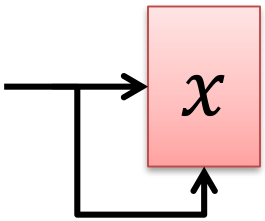
- sets: $\{1,5,8,12,43\}, \{7,9,15\}$; representatives: $5, 9$

Linked List Implementation

make_set(x):

- Create list with one element:

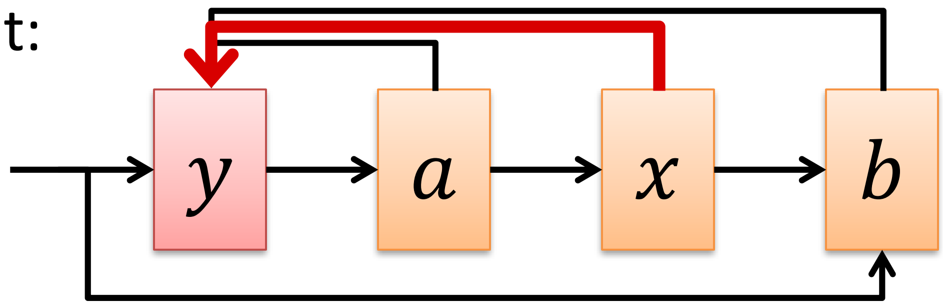
time: $O(1)$



find(x):

- Return first list element:

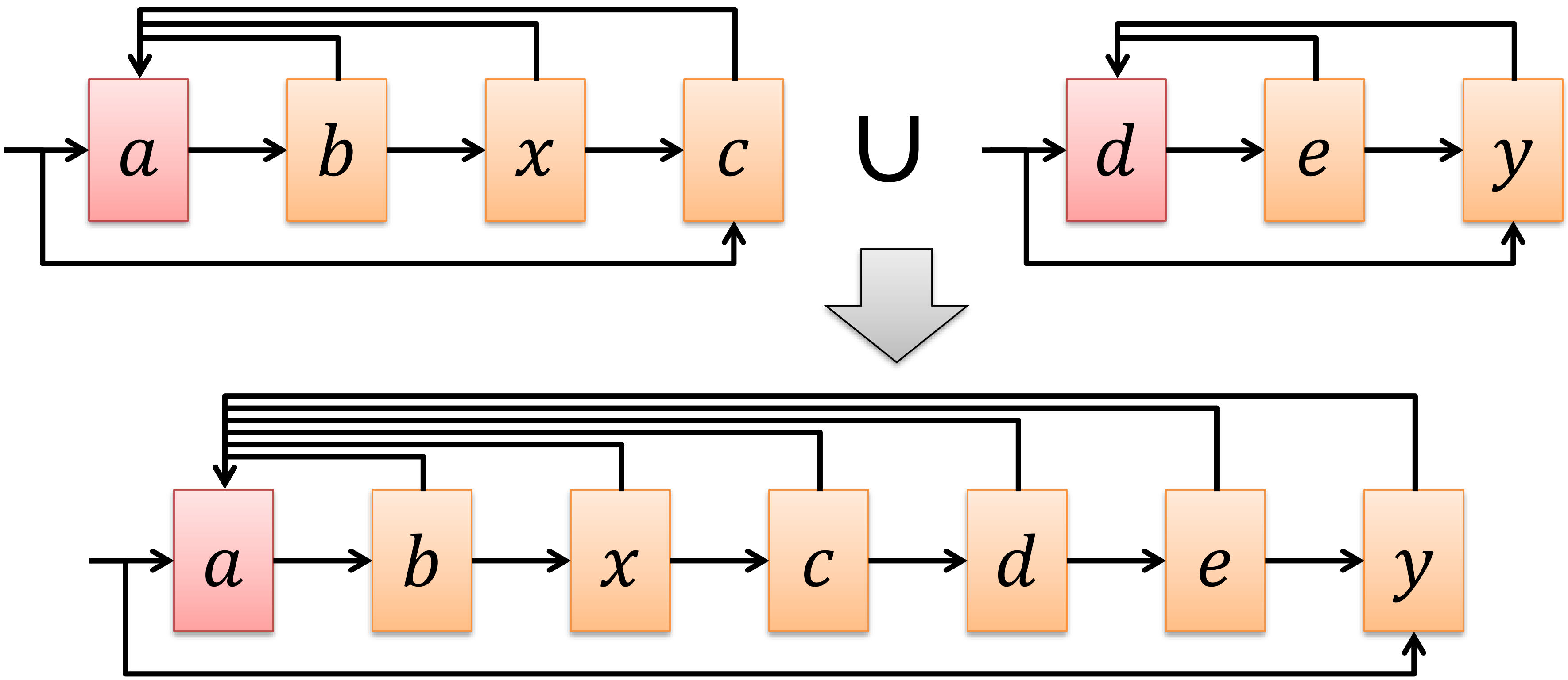
time: $O(1)$



Linked List Implementation

union(x, y):

- Append list of y to list of x:



Time: O(length of list of y)

Cost of Union (Linked List Implementation)

Total cost for $n-1$ union operations can be $\Theta(n^2)$:

- $\text{make\_set}(x_1), \text{make\_set}(x_2), \dots, \text{make\_set}(x_n)$, $\text{union}(x_{n-1}, x_n), \text{union}(x_{n-2}, x_{n-1}), \dots, \text{union}(x_1, x_2)$

Weighted-Union Heuristic

- In a bad execution, average cost per union can be $\Theta(n)$
- Problem: The longer list is always appended to the shorter one

Idea:

- In each union operation, append shorter list to longer one!

Cost for union of sets S_x and S_y: $O\left(\min\{|S_x|, |S_y|\}\right)$

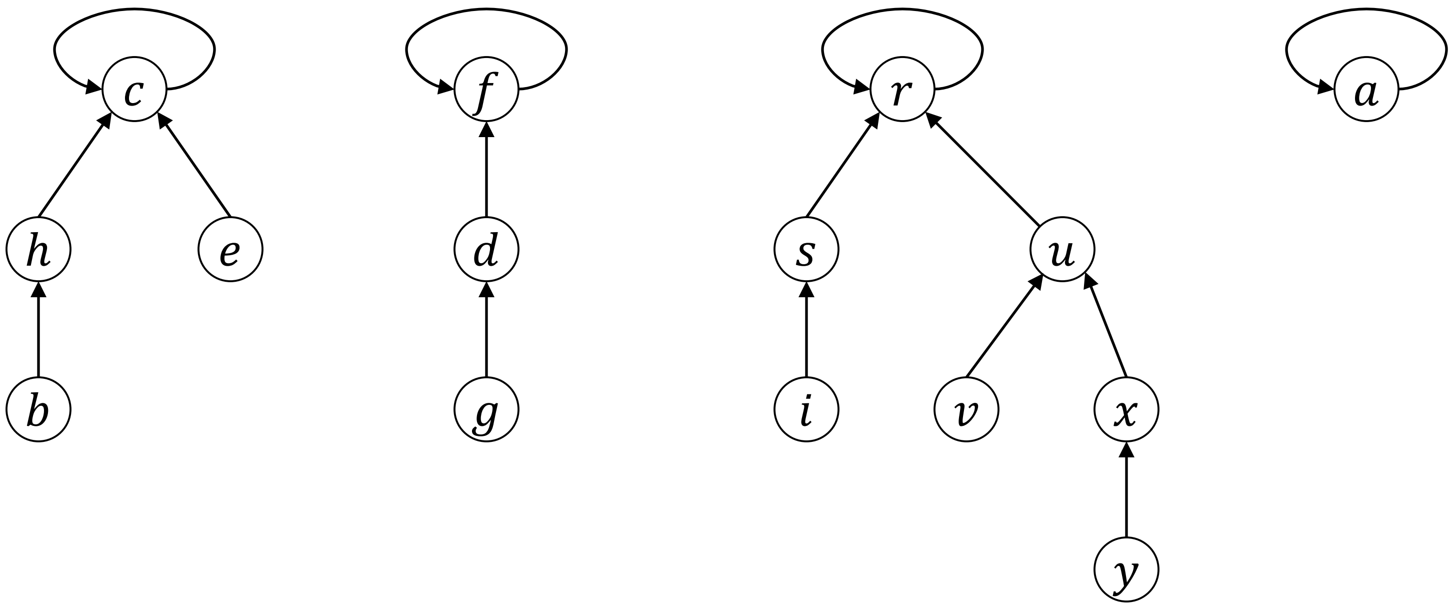
Theorem: The overall cost of m operations of which at most n are $\mathrm{make\_set}$ operations is $\boldsymbol{O(m + n \log n)}$.

Weighted-Union Heuristic

Theorem: The overall cost of m operations of which at most n are $\mathrm{make\_set}$ operations is $\boldsymbol{O(m + n \log n)}$.

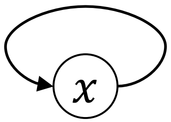
Proof:

Disjoint-Set Forests

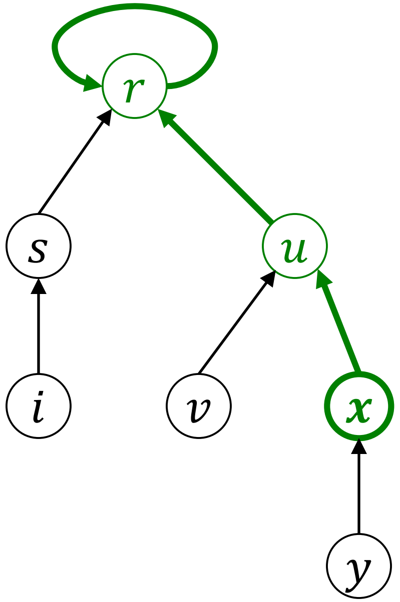


- Represent each set by a tree
- Representative of a set is the root of the tree

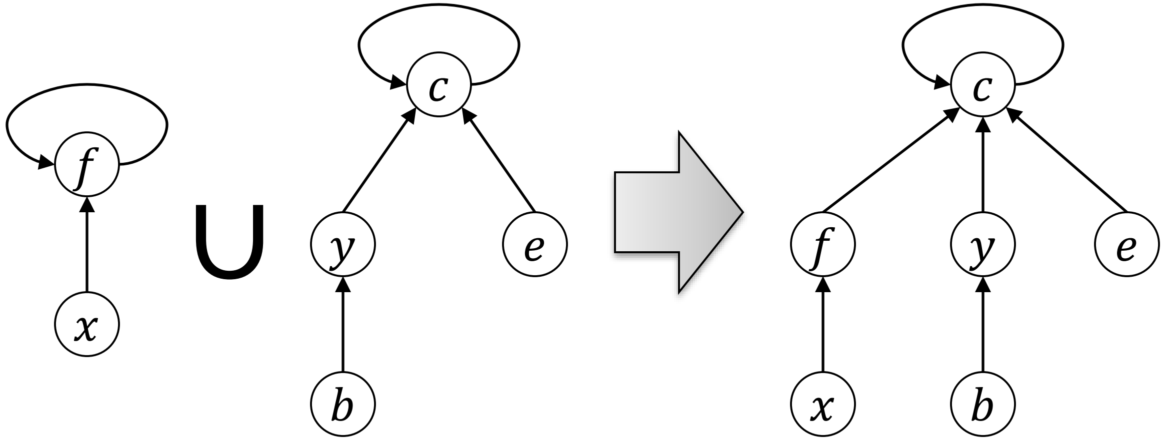
make_set(x): create new one-node tree



find(x): follow parent point to root
(parent pointer to itself)



union(x, y): attach tree of x to tree of y



Bad Sequence

Bad sequence leads to tree(s) of depth $\Theta(n)$

- $\text{make\_set}(x_1), \text{make\_set}(x_2), \dots, \text{make\_set}(x_n),$
  $\text{union}(x_1, x_2), \text{union}(x_1, x_3), \dots, \text{union}(x_1, x_n)$

Union-By-Size Heuristic

Union of sets $\boldsymbol{S_1}$ and $\boldsymbol{S_2}$:

- Root of trees representing S_1 and S_2: r_1 and r_2
- W.l.o.g., assume that $|S_1| \geq |S_2|$
- Root of $S_1 \cup S_2$: r_1 (r_2 is attached to r_1 as a new child)

Theorem: If the union-by-size heuristic is used, the **worst-case cost of a $\mathbf{find}$-operation is $\boldsymbol{O(\log n)}$**

Proof:

Similar Strategy: union-by-rank

- rank: essentially the depth of a tree

Union-Find Algorithms

Recall: m operations, n of the operations are make_set-operations

Linked List with Weighted Union Heuristic:

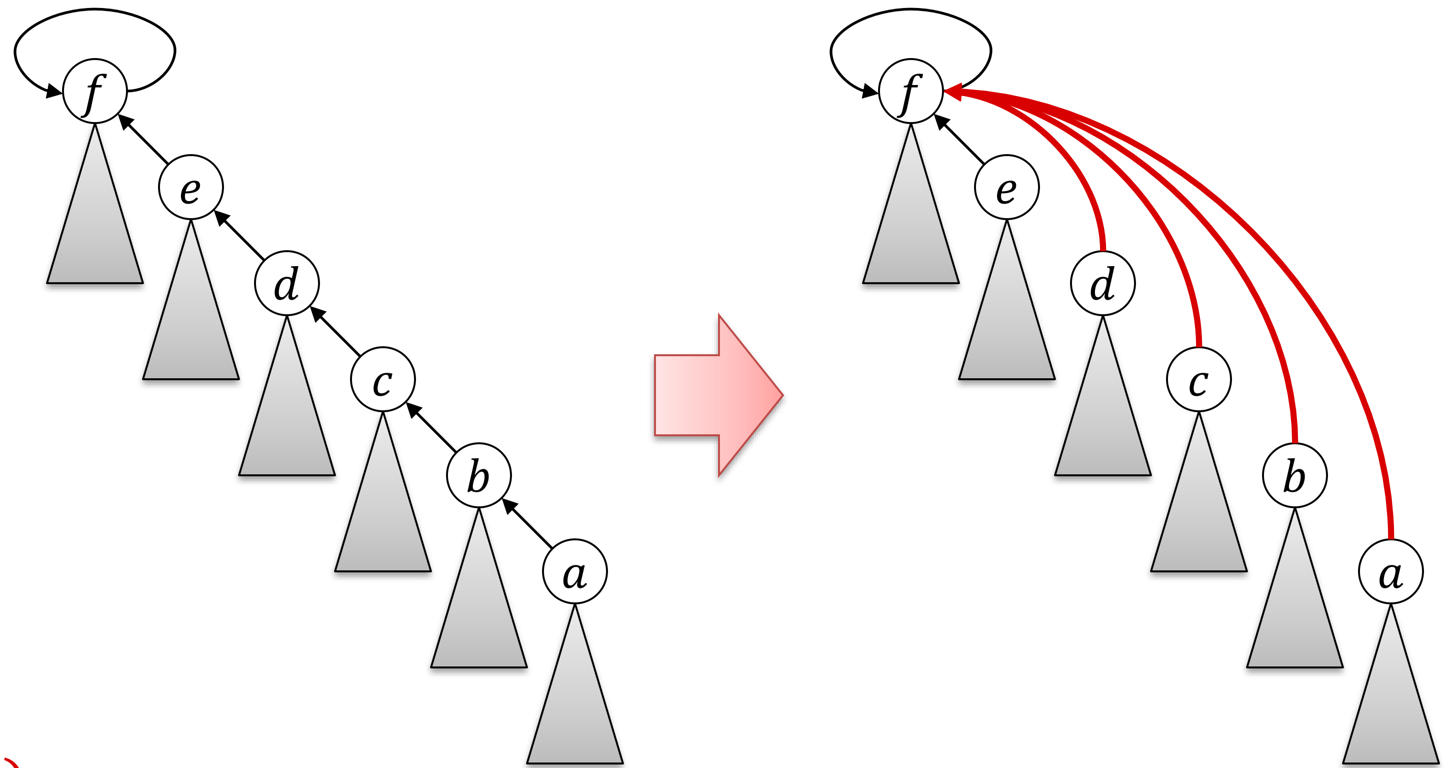
- make_set: worst-case cost $O(1)$
- find : worst-case cost $O(1)$
- union : amortized worst-case cost $O(\log n)$

Disjoint-Set Forest with Union-By-Size Heuristic:

- make_set: worst-case cost $O(1)$
- find : worst-case cost $O(\log n)$
- union : worst-case cost $O(\log n)$

Can we make this faster?

Path Compression During Find Operation



find(a):

1. **if** $a \neq a.parent$ **then**
2. $\quad a.parent := \text{find}(a.parent)$
3. **return** $a.parent$

Complexity With Path Compression

When using only path compression (without union-by-rank):

m: total number of operations

- f of which are find-operations
- n of which are make_set-operations
  → at most $n - 1$ are union-operations

Total cost: $\boldsymbol{O\left(m + f \cdot \left\lceil \log_{2+f/n} n \right\rceil\right) = O\left(m + f \cdot \log_{2+m/n} n\right)}$

Union-By-Size and Path Compression

Theorem:

Using the combined union-by-rank and path compression heuristic, the running time of m disjoint-set (union-find) operations on n elements (at most n $\mathrm{make\_set}$-operations) is

$$\boldsymbol{\Theta}\big(\boldsymbol{m} \cdot \boldsymbol{\alpha}(\boldsymbol{m}, \boldsymbol{n})\big),$$

Where $\alpha(m, n)$ is the inverse of the Ackermann function.

Ackermann Function and its Inverse

Ackermann Function:

For $k, \ell \geq 1$,

$$A(k,\ell) := \begin{cases} 2^{\ell}, & \text{if } k = 1, \ell \geq 1 \\ A(k-1, 2), & \text{if } k > 1, \ell = 1 \\ A\big(k-1, A(k, \ell-1)\big), & \text{if } k > 1, \ell > 1 \end{cases}$$

Inverse of Ackermann Function:

$$\alpha(m,n) := \min\{k \geq 1 \mid A(k, \lfloor {}^{m}/_{n} \rfloor) > \log_2 n\}$$

Inverse of Ackermann Function

- $\alpha(m,n) := \min\{k \geq 1 \mid A(k, \lfloor m/n \rfloor) > \log_2 n\}$

  $m \geq n \Longrightarrow A(k, \lfloor m/n \rfloor) \geq A(k,1) \Longrightarrow \alpha(m,n) \leq \min\{k \geq 1 | A(k,1) > \log n\}$

- $A(1,\ell) = 2^\ell, \quad A(k,1) = A(k-1,2),$
  $A(k,\ell) = A\big(k-1, A(k,\ell-1)\big)$