



# CSE373: Data Structures & Algorithms Lecture 10: Implementing Union-Find

Dan Grossman Fall 2013

### The plan

#### Last lecture:

- · What are disjoint sets
  - And how are they "the same thing" as equivalence relations
- · The union-find ADT for disjoint sets
- · Applications of union-find

#### Now:

- · Basic implementation of the ADT with "up trees"
- Optimizations that make the implementation much faster

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Our goal

- Start with an initial partition of n subsets
  - Often 1-element sets, e.g., {1}, {2}, {3}, ..., {n}
- May have m find operations and up to n-1 union operations in any order
  - After *n*-1 union operations, every find returns same 1 set
- If total for all these operations is O(m+n), then amortized O(1)
  - We will get very, very close to this
  - O(1) worst-case is impossible for find and union
    - Trivial for one or the other

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Up-tree data structure

- · Tree with:
  - No limit on branching factor
  - References from children to parent
- · Start with forest of 1-node trees





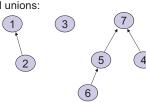








- · Possible forest after several unions:
  - Will use roots for set names



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**Find** 

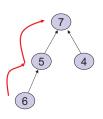
#### find(x):

- Assume we have O(1) access to each node
  - Will use an array where index i holds node i
- Start at x and follow parent pointers to root
- Return the root

**find**(6) = 7



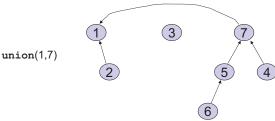




#### Union

#### union(x,y):

- Assume x and y are roots
  - · Else find the roots of their trees
- Assume distinct trees (else do nothing)
- Change root of one to have parent be the root of the other
  - Notice no limit on branching factor



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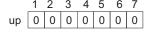
### Simple implementation

- If set elements are contiguous numbers (e.g., 1,2,...,n), use an array of length n called up
  - Starting at index 1 on slides
  - Put in array index of parent, with 0 (or -1, etc.) for a root

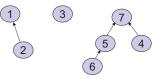
• Example:











1 2 3 4 5 6 7 up 0 1 0 7 7 5 0

 If set elements are not contiguous numbers, could have a separate dictionary to map elements (keys) to numbers (values)
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### Implement operations

```
// assumes x in range 1,n
int find(int x) {
   while(up[x] != 0) {
      x = up[x];
   }
   return x;
}
```

// assumes x,y are roots
void union(int x, int y) {
 up[y] = x;
}

- Worst-case run-time for union?
- · Worst-case run-time for find?
- Worst-case run-time for m finds and n-1 unions?

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#### Implement operations

```
// assumes x in range 1,n
int find(int x) {
   while(up[x] != 0) {
      x = up[x];
   }
   return x;
}
```

// assumes x,y are roots
void union(int x, int y) {
 up[y] = x;
}

- Worst-case run-time for union? O(1)
- Worst-case run-time for find? O(n)
- Worst-case run-time for m finds and n-1 unions?  $O(n^*m)$

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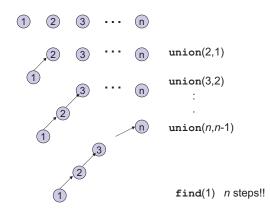
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### Two key optimizations

- 1. Improve union so it stays O(1) but makes find  $O(\log n)$ 
  - So m finds and n-1 unions is  $O(m \log n + n)$
  - Union-by-size: connect smaller tree to larger tree
- 2. Improve find so it becomes even faster
  - Make m finds and n-1 unions almost O(m + n)
  - Path-compression: connect directly to root during finds

#### The bad case to avoid



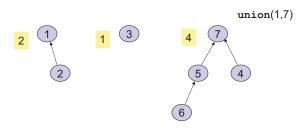
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### Weighted union

#### Weighted union:

 Always point the smaller (total # of nodes) tree to the root of the larger tree

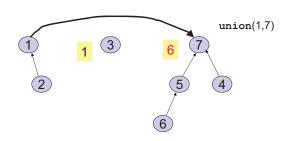


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### Weighted union

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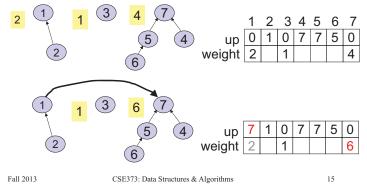


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### Array implementation

Keep the weight (number of nodes in a second array)

- Or have one array of objects with two fields

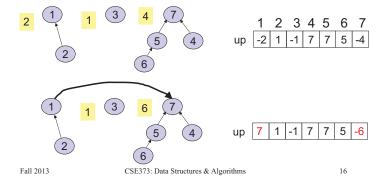


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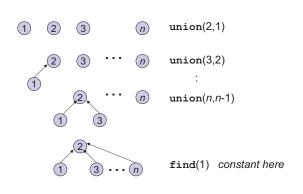
### Nifty trick

Actually we do not need a second array...

- Instead of storing 0 for a root, store negation of weight
- So up value < 0 means a root



### Bad example? Great example...



## General analysis

- Showing one worst-case example is now good is not a proof that the worst-case has improved
- · So let's prove:
  - union is still O(1) this is "obvious"
  - find is now O(log n)
- Claim: If we use weighted-union, an up-tree of height h has at least 2<sup>h</sup> nodes
  - Proof by induction on h...

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#### Exponential number of nodes

P(h)= With weighted-union, up-tree of height h has at least  $2^h$  nodes

Proof by induction on h...

- Base case: h = 0: The up-tree has 1 node and  $2^0 = 1$
- Inductive case: Assume P(h) and show P(h+1)
  - A height h+1 tree T has at least one height h child T1
  - T1 has at least 2<sup>h</sup> nodes by induction
  - And T has at least as many nodes not in T1 than in T1
    - · Else weighted-union would have had T point to T1, not T1 point to T (!!)
  - So total number of nodes is at least  $2^h + 2^h = 2^{h+1}$



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then height is logarithmic in number of nodes

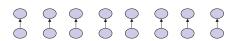
The key idea

So find is  $O(\log n)$ 

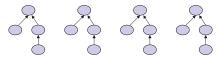
nodes

#### The new worst case

n/2 Weighted Unions



n/4 Weighted Unions



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### What about union-by-height

We could store the height of each root rather than number of descendants (weight)

- Still guarantees logarithmic worst-case find
  - Proof left as an exercise if interested
- But does not work well with our next optimization
  - Maintaining height becomes inefficient, but maintaining weight still easy

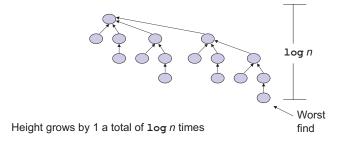
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So, as usual, if number of nodes is exponential in height,

Intuition behind the proof: No one child can have more than half the

### The new worst case (continued)

After n/2 + n/4 + ...+ 1 Weighted Unions:



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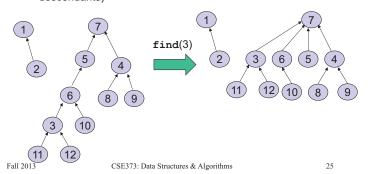
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#### Path compression

- Simple idea: As part of a find, change each encountered node's parent to point directly to root
  - Faster future finds for everything on the path (and their descendants)



#### Pseudocode

```
// performs path compression
int find(i) {
    // find root
    int r = i
    while(up[r] > 0)
        r = up[r]
    // compress path
    if i==r
        return r;
    int old parent = up[i]
    while(old parent != r) {
        up[i] = r
        i = old parent;
        old parent = up[i]
    }
    return r;
}
```

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#### So, how fast is it?

A single worst-case find could be  $O(\log n)$ 

- But only if we did a lot of worst-case unions beforehand
- And path compression will make future finds faster

Turns out the amortized worst-case bound is much better than  $O(\log n)$ 

- We won't prove it see text if curious
- But we will understand it:
  - How it is almost O(1)
  - Because total for m finds and n-1 unions is almost O(m+n)

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## A really slow-growing function

log\* x is the minimum number of times you need to apply "log of log of log of" to go from x to a number <= 1</pre>

```
For just about every number we care about, log* x is 5 (!) If x \le 2^{65536} then log* x \le 5

- log* 2 = 1

- log* 4 = log* 2^2 = 2

- log* 16 = log* 2^{(2^2)} = 3 (log log log log* 16 = 1)

- log* 65536 = log* 2^{((2^2)^2)} = 4 (log log log log log* 65536 = 1)

- log* 2^{65536} = \dots = 5
```

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#### Almost linear

- Turns out total time for m finds and n-1 unions is O((m+n)\*(log\* (m+n))
  - Remember, if  $m+n < 2^{65536}$  then log\* (m+n) < 5
- At this point, it feels almost silly to mention it, but even that bound is not tight...
  - "Inverse Ackerman's function" grows even more slowly than log\*
    - · Inverse because Ackerman's function grows really fast
    - · Function also appears in combinatorics and geometry
    - For any number you can possibly imagine, it is < 4
  - Can replace log\* with "Inverse Ackerman's" in bound

### Theory and terminology

- Because log\* or Inverse Ackerman's grows soooo slowly
  - For all practical purposes, amortized bound is constant, i.e., total cost is linear
  - We say "near linear" or "effectively linear"
- Need weighted-union and path-compression for this bound
  - Path-compression changes height but not weight, so they interact well
- · As always, asymptotic analysis is separate from "coding it up"

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