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

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## 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


## Our goal

- Start with an initial partition of $n$ subsets
- Often 1-element sets, e.g., $\{1\},\{2\},\{3\}, \ldots,\{n\}$
- 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


## 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



## Find

find(x):

- Assume we have $O(1)$ access to each node
- Will use an array where index i holds node i
- Start at $\mathbf{x}$ and follow parent pointers to root
- Return the root
find(6) $=7$



## Union

union( $\mathbf{x}, \mathrm{y}$ ):

- Assume $\mathbf{x}$ and y are roots
- If they are not, just 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
union(1,7)



## Simple implementation

- If set elements are contiguous numbers (e.g., $1,2, \ldots, n$ ), 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:


- Example:


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


## Implement operations

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

- Worst-case run-time for union?
- Worst-case run-time for $f$ ind?
- Worst-case run-time for $m$ finds and $n-1$ unions?


## 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 $y$ ) \{
// $y=$ find $(y)$
// x = find (x)
$\operatorname{up}[y]=x ;$
\}

- Worst-case run-time for union?
$O(1)$ (with our assumption...)
- Worst-case run-time for find?

O(n)

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


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


## 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

(1) (2) (3) $\cdots$ (n) union $(2,1)$


## Weighted union

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



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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



## 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...

(1) (2) (3) union $(2,1)$

find(1) constant here

## General analysis

- Showing that 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 fairly easy to show
- find is now $O(\log n)$
- Claim: If we use weighted-union, an up-tree of height $h$ has at least $2^{h}$ nodes
- Proof by induction on $h . .$.


## Exponential number of nodes

$\mathrm{P}(h)=$ With weighted-union, up-tree of height $h$ has at least $2^{h}$ nodes
Proof by induction on $h \ldots$

- 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 $2^{h}$ 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 $2^{h}+2^{h}=2^{h+1}$



## The key idea

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


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

So find is $O(\log n)$

## The new worst case

n/2 Weighted Unions

n/4 Weighted Unions





## The new worst case (continued)

After $\mathrm{n} / 2+\mathrm{n} / 4+\ldots+1$ Weighted Unions:


## 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


## 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 $O(m \log n+n)$
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2. Improve find so it becomes even faster

- Make $m$ finds and $n-1$ unions almost $O(m+n)$
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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)

Solution
(good exampleof psuedocode!)

```
// performs path compression
find(i)
    // find root
    r = i
    while up[r] > 0
        r = up [r]
    // compress path
    if i == r
    return r
    old_parent = up[i]
    while (old_parent != r)
        up[i] = r
        i = old_parent
        old_parent = up[i]
    return r
```


## 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 $O(m+n)$


## A really slow-growing function

$\log *(x)$ is the minimum number of times you need to apply " $10 g$ of $\log$ of $\log$ of" to go from $x$ to a number <= 1

For just about every number we care about, $\log \boldsymbol{*}(x)$ is 5 (!) If $x<=2^{65536}$ then log* $x<=5$
$-\log ^{*} 2=1$
$-\log ^{*} 4=\log ^{*} 2^{2}=2$
$-\log ^{*} 16=\log ^{*} 2^{\left(2^{2}\right)}=3 \quad(\log (\log (\log (16)))=1)$
$-\log ^{*} 65536=\log ^{*} 2^{\left(\left(2^{2}\right)^{2}\right)}=4 \quad(\log (\log (\log (\log (65536))))=1)$
$-\log ^{*} 2^{65536}=\ldots \ldots \ldots \ldots . .=5$

## Wait.... how big?

Just how big is $2^{65536}$

$$
\begin{aligned}
& \text { Well } 2^{10}=1024 \\
& \qquad \begin{array}{l}
2^{20}=1048576 \\
2^{30}=1073741824 \\
2^{100}=1.125 \times 10^{15} \\
2^{65536}=\ldots \text { pretty big }
\end{array}
\end{aligned}
$$

## But its still not technically constant

## Almost linear

- Turns out total time for $m$ finds and $n-1$ unions is:
$O\left((m+n)^{\star}(\log *(m+n))\right.$
- 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 so incredibly 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"

