CSE 373: Disjoint sets

Michael Lee Wednesday, Feb 28, 2018 Warn-yo:
Remind your neightor:
How does's Knotal's
algorithm work?

Review

Last time...

► Prim's algorithm:

Nearly identical to Dijkstra's, except we use the distance to any already-visited node as the cost.

Review

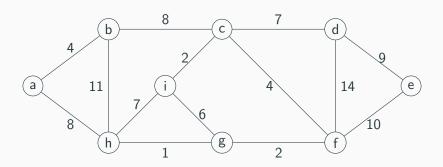
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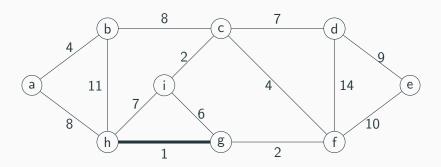
► Prim's algorithm:

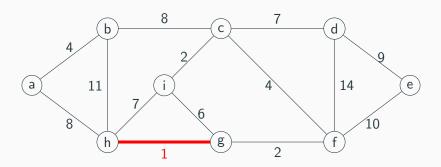
Nearly identical to Dijkstra's, except we use the distance to any already-visited node as the cost.

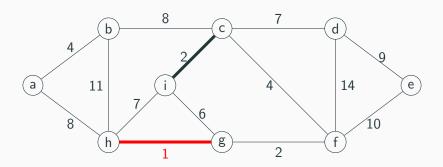
► Kruskal's algorithm:

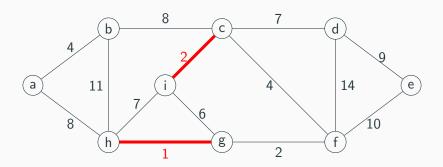
Loop over edges, from smallest to largest. Use the edge only if it doesn't introduce a cycle.

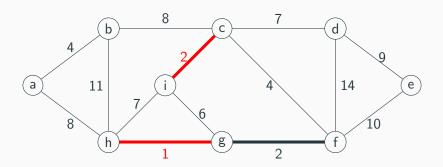


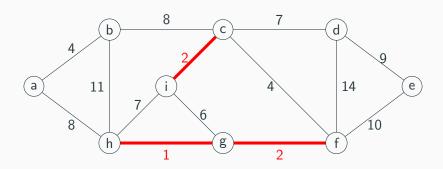


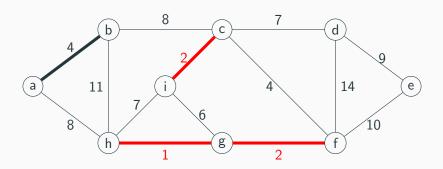


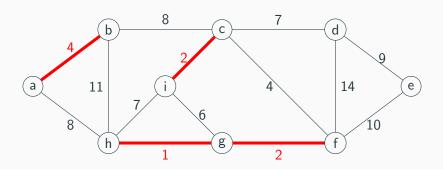


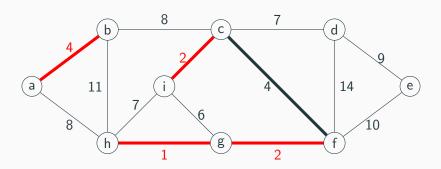


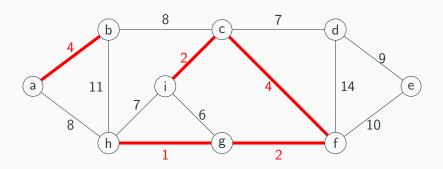


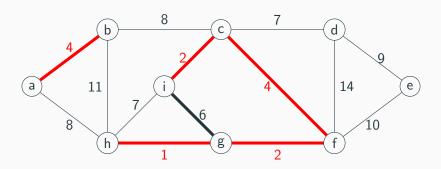


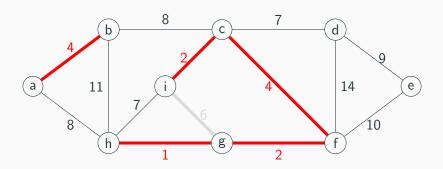


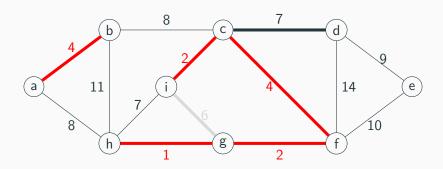


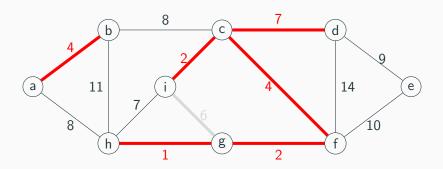


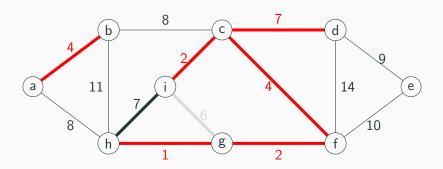


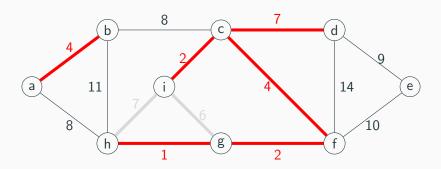


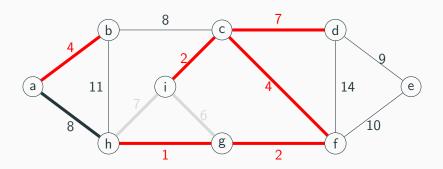


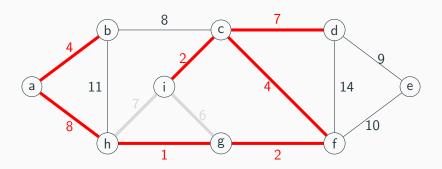


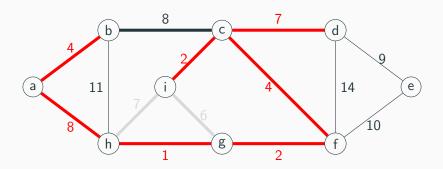


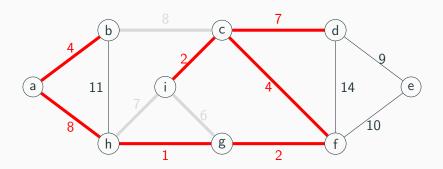


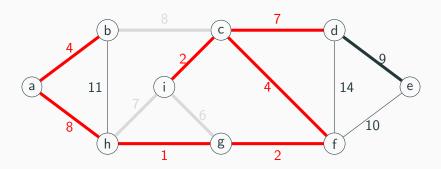


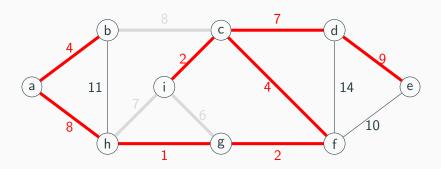


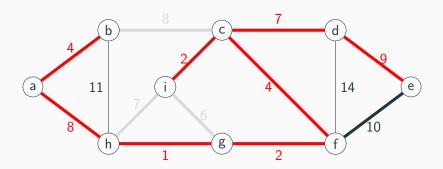


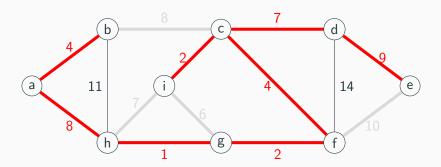


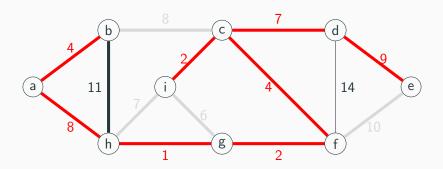


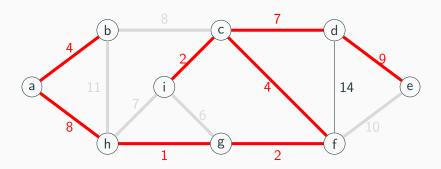


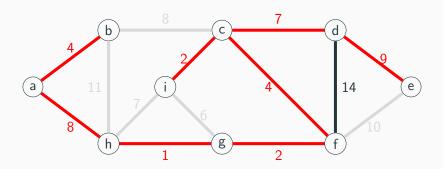


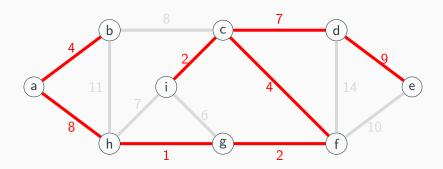












Kruskal's algorithm: analysis

Runtime analysis:

```
def kruskal():
    for (v : vertices):
        makeMST(v)

    sort edges in ascending order by their weight

mst = new SomeSet<Edge>()
    for (edge : edges):
        if findMST(edge.src) != findMST(edge.dst):
            union(edge.src, edge.dst)
        mst.add(edge)

return mst
```

Note: assume that...

- ightharpoonup makeMST(v) takes $\mathcal{O}\left(t_{m}
 ight)$ time
- ▶ findMST(v): takes $\mathcal{O}(t_f)$ time
- ▶ union(u, v): takes $\mathcal{O}(t_u)$ time

Kruskal's algorithm: analysis

- ▶ Making the |V| MSTs takes $\mathcal{O}(|V| \cdot t_m)$ time
- ▶ Sorting the edges takes $\mathcal{O}(|E| \cdot \log(|E|))$ time, assuming we use a general-purpose comparison sort
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Putting it all together:

$$O(|V| \cdot t_m + |E| \cdot \log(|E|) + |E| \cdot t_f + |V| \cdot t_u)$$
int sort core loop

The DisjointSet ADT

But wait, what exactly is t_m , t_f , and t_u ? How exactly do we implement makeMST(v), findMST(v), and union(u, v)?

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We can do so using a new ADT called the DisjointSet ADT!

Review: what is a set?

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We implemented a set in project 2: ChainedHashSet

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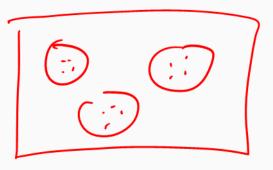
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Interesting note: sets come up all the time in math.

Properties of a disjoint-set data structure:

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- ► Each set is associated with some *representative*. What is a representative? Any sort of unique "identifier". Examples:
 - ► We could pick some arbitrary element in the set to be the "representative"
 - ► We could assign each set some unique integer id.

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Example:

- makeSet(a)
- makeSet(b)
- makeSet(c)
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Rep: 4

e

Rep: 2

Rep: 3

С

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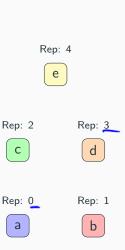
Rep: 0

Rep: 1

а

b

Example: makeSet(a) makeSet(b) makeSet(c) makeSet(d) makeSet(e) print(findSet(a)) print(findSet(d))



```
Example:
makeSet(a)
makeSet(b)
                                                   Rep: 4
makeSet(c)
makeSet(d)
makeSet(e)
print(findSet(a))
                                             Rep: 2
                                                         Rep: 3
print(findSet(d))
union(a, c)
union(b, d)
print(findSet(a) == findSet(c))
                                             Rep: 0
                                                         Rep: 1
print(findSet(a) == findSet(d))
```

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                                              C
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                                              a
union(c, b)
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```

```
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                                              C
union(a, c)
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                                                          b
                                              a
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```

What operations does a disjoint-set **NOT** support?

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Answer: The ability to actually get the entire set.

We can *make* a set, *check* if an item is in a set, and *combine* two sets, but we don't have a built-in way of *getting* the entire set itself.

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Insight: The few operations we need to support, the more creative our implementation can be.

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Insight: The few operations we need to support, the more creative our implementation can be.

(If the client really wants the sets, they can get it themselves in $\mathcal{O}\left(n\right)$ time – how?)

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Core idea:

- ► We represent each set as a tree
- ► The disjoint-set keeps track of a "forest" of trees

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We want union-ing to be cheap.
Combining two trees is cheap; we just manipulate pointers.

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Core idea:

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- ► The disjoint-set keeps track of a "forest" of trees

Intuitions:

- We want union-ing to be cheap.
 Combining two trees is cheap; we just manipulate pointers.
- ▶ We want a single "representative" per set. A tree has a single root!

High-level overview:

- ► makeSet(x): Adds a new tree (of size 1) to our "forest"
- ▶ findSet(x): Looks up the node, then finds root of tree
- ▶ union(x, y): Combines two trees into one

Suppose we call make Set(...) on 0 through 5.

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- 0
- 1
- 2
- (3)

4

(5)

Each makeSet(...) adds a new tree to our "forest".

Note that right now, each tree has only one element.

Suppose we call union(3, 5).

0

1

(2)

3

4

(5)

Suppose we call union(3, 5).

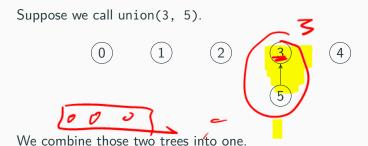
0 1 2 3 4 5

We combine those two trees into one.

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Assumption: we have an $\mathcal{O}\left(1\right)$ way of getting each node. (E.g. maintain a hashmap of numbers to node objects.)

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Question: how do we implement findSet(...)?

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We combine those two trees into one.

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Question: how do we implement findSet(5.)?

Once we find a node, move upwards until we're looking at root.

Then, return the root's data field.

Suppose we call union(5, 4).











Suppose we call union(5, 4).



(1)

(2)



Suppose we call union(5, 4).



Algorithm: Find the roots of both trees and add one tree as a subchild of the other.

Which tree becomes the new root? For now, pick randomly.

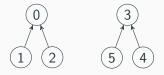
Suppose we call union(0, 1), then union(2, 0).

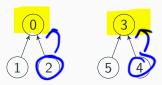


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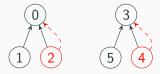
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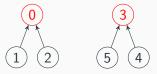




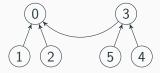
Step 1: We look up 2 and 3



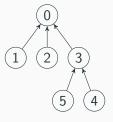
Step 2: We find the roots of 2 and 3



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Better question: are our trees guaranted to be balanced?

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Hint: When union-ing, we pick which tree is nested randomly.

Does that guarantee we'll get a balanced tree?

The worst-case scenario:

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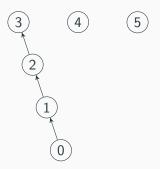
Possible outcome of calling union(0, 1)

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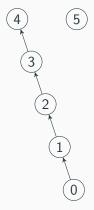
Possible outcome of calling union(0, 2)

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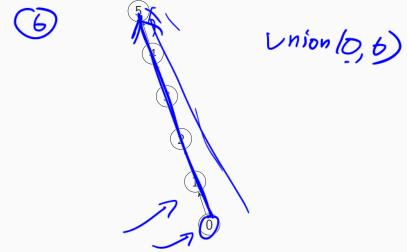
Possible outcome of calling union(0, 3)

The worst-case scenario:



Possible outcome of calling union(0, 4)

The worst-case scenario:



So, what are the worst-case runtimes?

- ► makeSet(x):
- b union(x, y): ○()

So, what are the worst-case runtimes?

- ▶ makeSet(x):
 - $\mathcal{O}\left(1\right)$ creating the tree takes constant time
- ► findSet(x):
 - $\mathcal{O}(n)$ if it's a linked list, we need to traverse n elements!
- ▶ union(x, y):
 - $\mathcal{O}(n)$ union calls findSet(...) on both elements

...where n is the total number of items added to the disjoint-set.

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Strategy to make sure trees are balanced

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Hijack findSet(x) and make it do a little extra work to improve overall performance.

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1. Union-by-rank:

Strategy to make sure trees are balanced

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Hijack findSet(x) and make it do a little extra work to improve overall performance.

3. Array representation:

Takes advantage of cache locality, simplifies implementation, etc.

Problem: Our trees could be unbalanced

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Solution:

Let $\operatorname{rank}(x)$ be a number representing the upper-bound of the height of x. So, $\operatorname{rank}(x) \geq \operatorname{height}(x)$.

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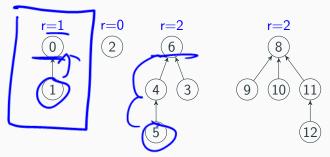
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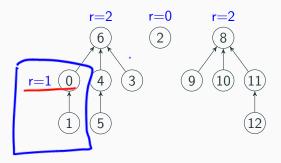
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(Why not keep track of the height? When we look at path compression, keeping track of the height becomes more challenging.)

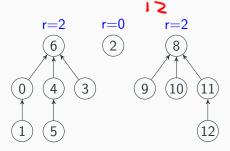
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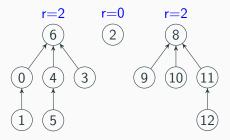
Example: Suppose we call union(1, **\$**)?



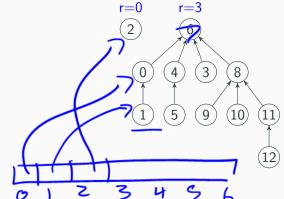
The tree with the root of "6" has the larger rank, so we make it the root.

Note: we're not really "removing" the rank from node 0-it's just irrelevant, so we're ignoring it and omitting it from the diagram to save space. We only care about the ranks at the roots.

Example: Suppose we call union(5, 11)?



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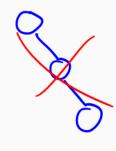


Here, there's a tie. We break the tie arbitrarily, and increment the rank of the new tree by one.

Net effect? Our trees stay relatively balanced.

So, what are the worst-case runtimes now?

- ▶ makeSet(x):
- O(log(n))
 O(log(n)) ► findSet(x):
- ▶ union(x, y):



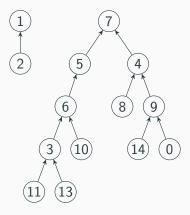


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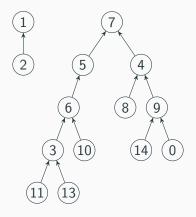
So, what are the worst-case runtimes now?

- ▶ makeSet(x):
 - $\mathcal{O}(1)$ still the same
- ► findSet(x):
 - $\mathcal{O}\left(\log(n)\right)$ since the tree is balanced
- ▶ union(x, y):
 - $\mathcal{O}(\log(n))$ since union calls findSet

Consider the following forest:

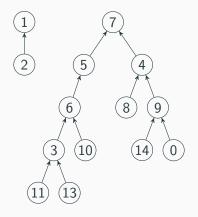


Consider the following forest:



Suppose we call findSet(3) a few hundred times.

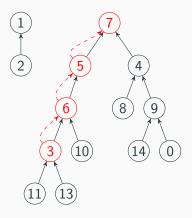
Consider the following forest:



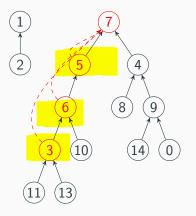
Suppose we call findSet(3) a few hundred times.

Why do we have to keep finding the root again and again?

Observation: To find root, we must also traverse these nodes:

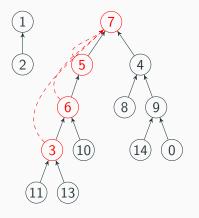


Observation: To find root, we must also traverse these nodes:



What if, next time, we could just jump straight to the root?

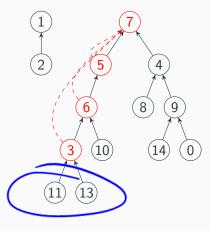
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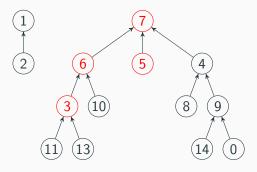
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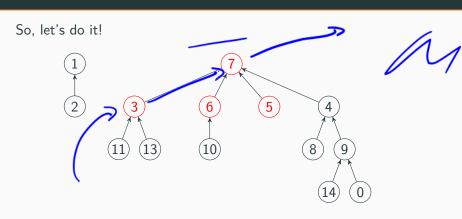
Same for the other nodes we visited

So, let's do it!

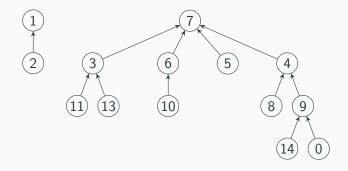


So, let's do it!

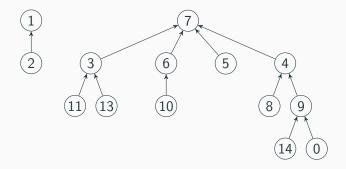




So, let's do it!



So, let's do it!



Now what happens if we try calling findSet(3)?

One additional note: path compression changes the heights of our trees.

This means it could be the case that rank \neq height.

Is this a problem?

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Is this a problem?

Answer: No; proof is beyond the scope of this class

Path compression: runtime

Now, what are the worst-case and best-case runtime of the following?

- ► makeSet(x):
- ► findSet(x):
- ► union(x, y):

Path compression: runtime

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- ▶ makeSet(x): $\mathcal{O}(1)$ still the same
- ▶ findSet(x): In the best case, $\mathcal{O}(1)$, in the worst case $\mathcal{O}(\log(n))$
- ▶ union(x, y): In the best case, $\mathcal{O}(1)$, in the worst case $\mathcal{O}(\log(n))$

Why are we doing this? To help us implement Kruskal's algorithm:

```
def kruskal():
    for (v : vertices):
        makeMST(v)

    sort edges in ascending order by their weight

    mst = new SomeSet<Edge>()
    for (edge : edges):
        if findMST(edge.src) != findMST(edge.dst):
            union(edge.src, edge.dst)
            mst.add(edge)

    return mst
```

- lacktriangledown makeMST(v) takes $\mathcal{O}\left(t_{m}
 ight)$ time
- ▶ findMST(v): takes $\mathcal{O}(t_f)$ time
- ▶ union(u, v): takes $\mathcal{O}\left(t_{u}\right)$ time

We concluded that the runtime is:

$$\mathcal{O}\left(\underbrace{|V| \cdot t_m}_{\text{setup}} + \underbrace{|E| \cdot \log(|E|)}_{\text{sorting edges}} + \underbrace{|E| \cdot t_f + |V| \cdot t_u}_{\text{core loop}}\right)$$

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Well, we just said that in the worst case:

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So the worst-case overall runtime of Kruskal's is:

$$\mathcal{O}\left(|V| + |E| \cdot \log(|E|) + (|E| + |V|) \cdot \log(|V|)\right)$$

Our worst-case runtime:

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One minor improvement: since our edge weights are numbers, we can likely use a *linear sort* and improve the runtime to:

$$\mathcal{O}(|V| + |E| + (|E| + |V|) \cdot \log(|V|))$$

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$$\mathcal{O}\left(|V| + |E| + \left(|E| + |V|\right) \cdot \log(|V|\right)\right)$$

We can drop the |V| + |E|, since they're dominated by the last term:

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...and we're left with something that's basically the same as Prim's algorithm.

...or are we?

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Observation: each call to findSet(x) improves all future calls. How much of a difference does that make?

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Observation: each call to findSet(x) improves all future calls.

How much of a difference does that make?

Interesting result:

It turns out union and find are amortized $\log^*(n)$.

Iterated log

The expression $\log^*(n)$ is equivalent to the number of times you need to compute $\log(x)$ to bring the value down to at most 1

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Example:

- $ightharpoonup \log^*(2^{65536}) = \dots = 5$

What is 2^{65536} ?

```
2^{65536} =
2003529930406846464979072351560255750447825475569751419
2650169737108940595563114530895061308809333481010382343429072
6318182294938211881266886950636476154702916504187191635158796
6347219442930927982084309104855990570159318959639524863372367
2030029169695921561087649488892540908059114570376752085002066
7156370236612635974714480711177481588091413574272096719015183
6282560618091458852699826141425030123391108273603843767876449
0432059603791244909057075603140350761625624760318637931264847
0374378295497561377098160461441330869211810248595915238019533
1030292162800160568670105651646750568038741529463842244845292
5373614425336143737290883037946012747249584148649159306472520
1515569392262818069165079638106413227530726714399815850881129
2628901134237782705567421080070065283963322155077831214288551
```

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Punchline? $\log^*(n) \le 5$, for basically any reasonable value of n.

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Runtime of Kruskal? $\mathcal{O}\left((|E|+|V|)\log^*(|V|)\right) \approx \mathcal{O}\left(|E|+|V|\right)$

Inverse of the Ackerman function

But wait!

Somebody then came along and proved that find and union are amortized $\mathcal{O}\left(\alpha(n)\right)$ – the inverse of the Ackermann function.

This grows even more slowly then $\log^*(n)!$