Lecture 15

Minimum Spanning Trees

Announcements

- Next week is fall break!
  - No class!
  - Happy impending Thanksgiving!

- HW6 due Friday
- HW7 out now/soon
  - It's the last one!!!!! Woohoo!!!!!!
  - Not due until 12/5 (the Friday after the break)

Last time

- Greedy algorithms
  - Make a series of choices.
    - Choose this activity, then that one, ..
    - Never backtrack.
  - Show that, at each step, your choice does not rule out success.
    - At every step, there exists an optimal solution consistent with the choices we've made so far.
  - At the end of the day:
    - you've built only one solution,
    - never having ruled out success,
    - **so your solution must be correct.**

Today

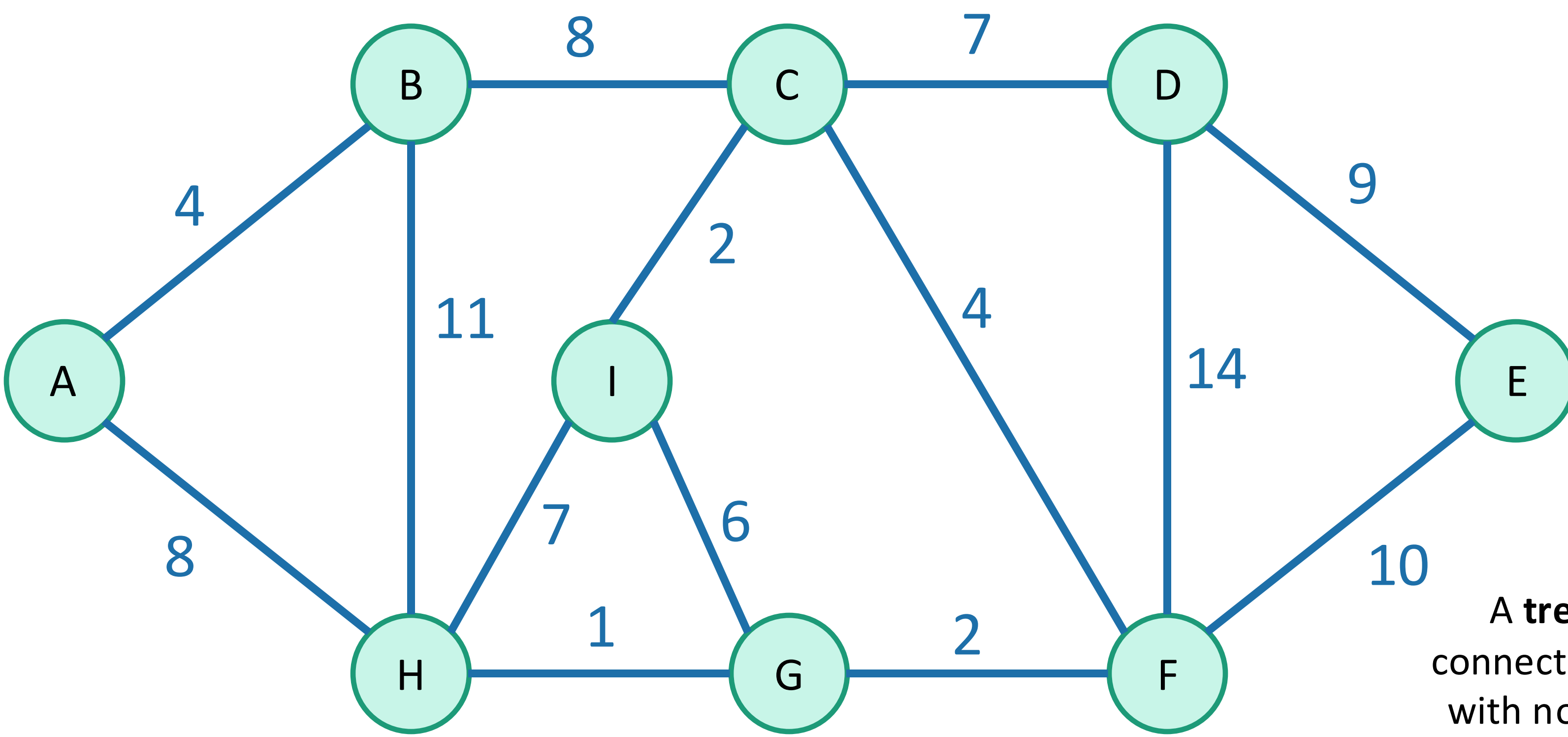
- Greedy algorithms for Minimum Spanning Tree.

- Agenda:
  1. What is a Minimum Spanning Tree?
  2. Short break to introduce some graph theory tools
  3. Prim's algorithm
  4. Kruskal's algorithm

Minimum Spanning Tree

For today, we will focus on connected graphs!

Say we have an undirected weighted graph



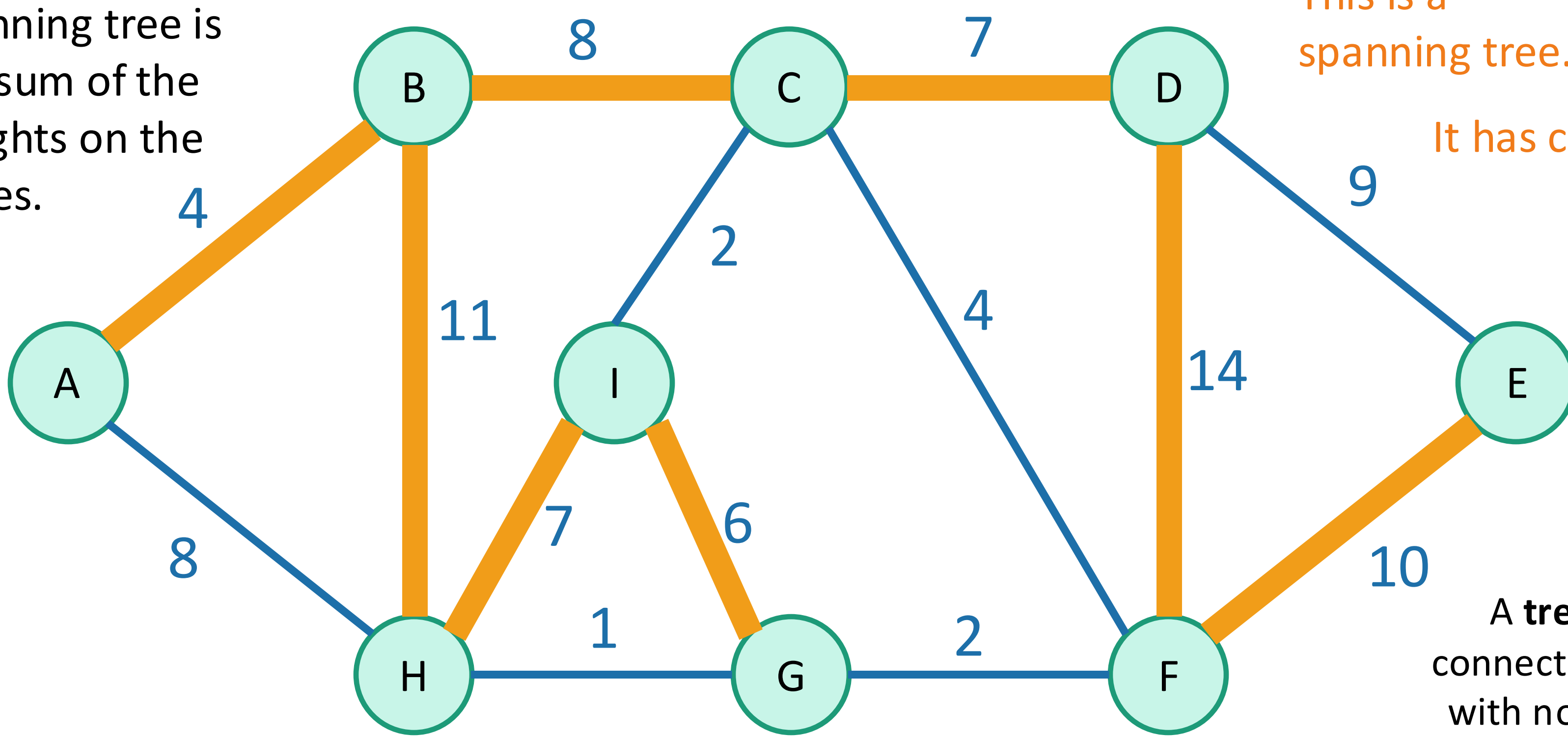
A **tree** is a connected graph with no cycles!

A **spanning tree** is a **tree** that connects all of the vertices.

Minimum Spanning Tree

Say we have an undirected weighted graph

The **cost** of a spanning tree is the sum of the weights on the edges.



This is a spanning tree.

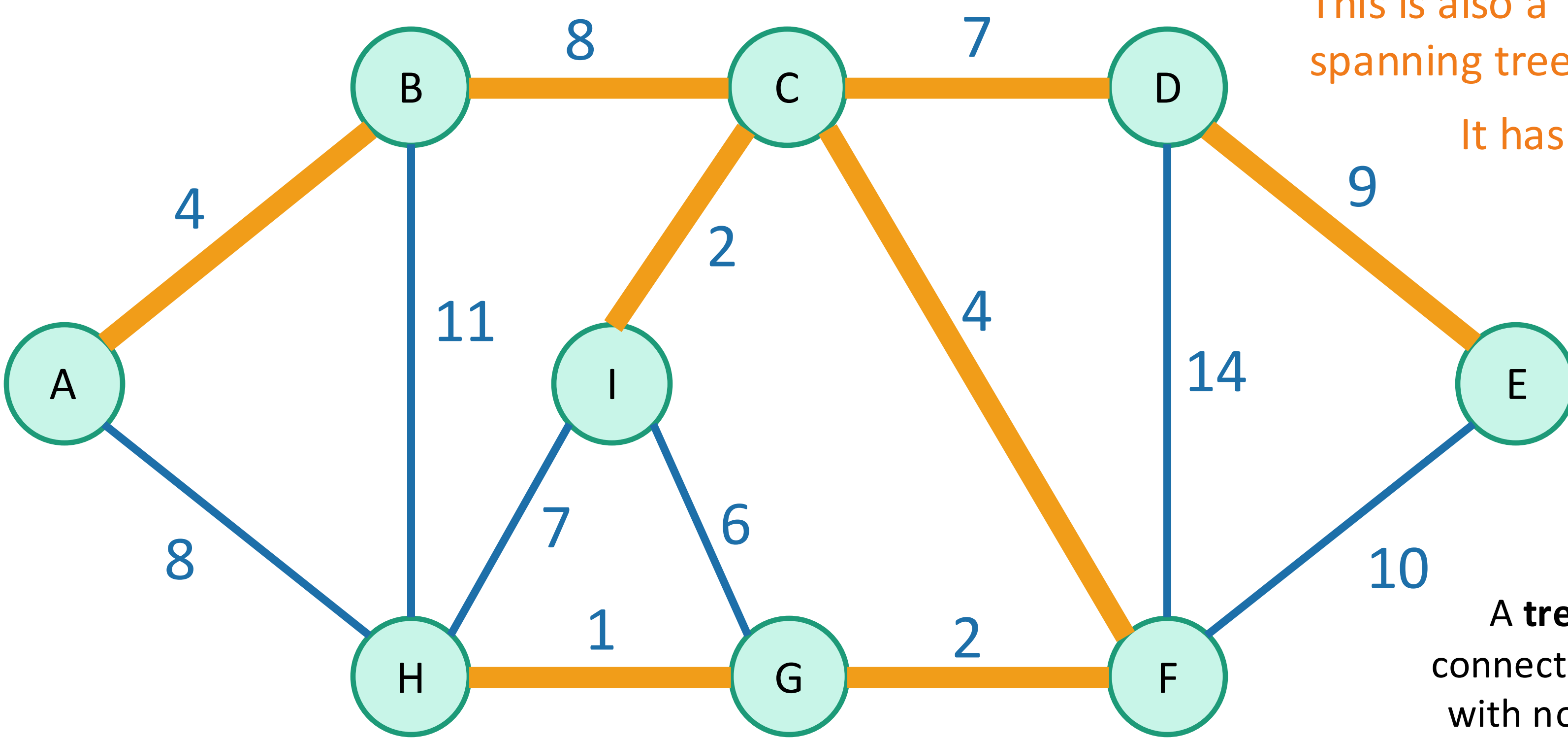
It has cost 67

A **tree** is a connected graph with no cycles!

A **spanning tree** is a **tree** that connects all of the vertices.

Minimum Spanning Tree

Say we have an undirected weighted graph



This is also a spanning tree.

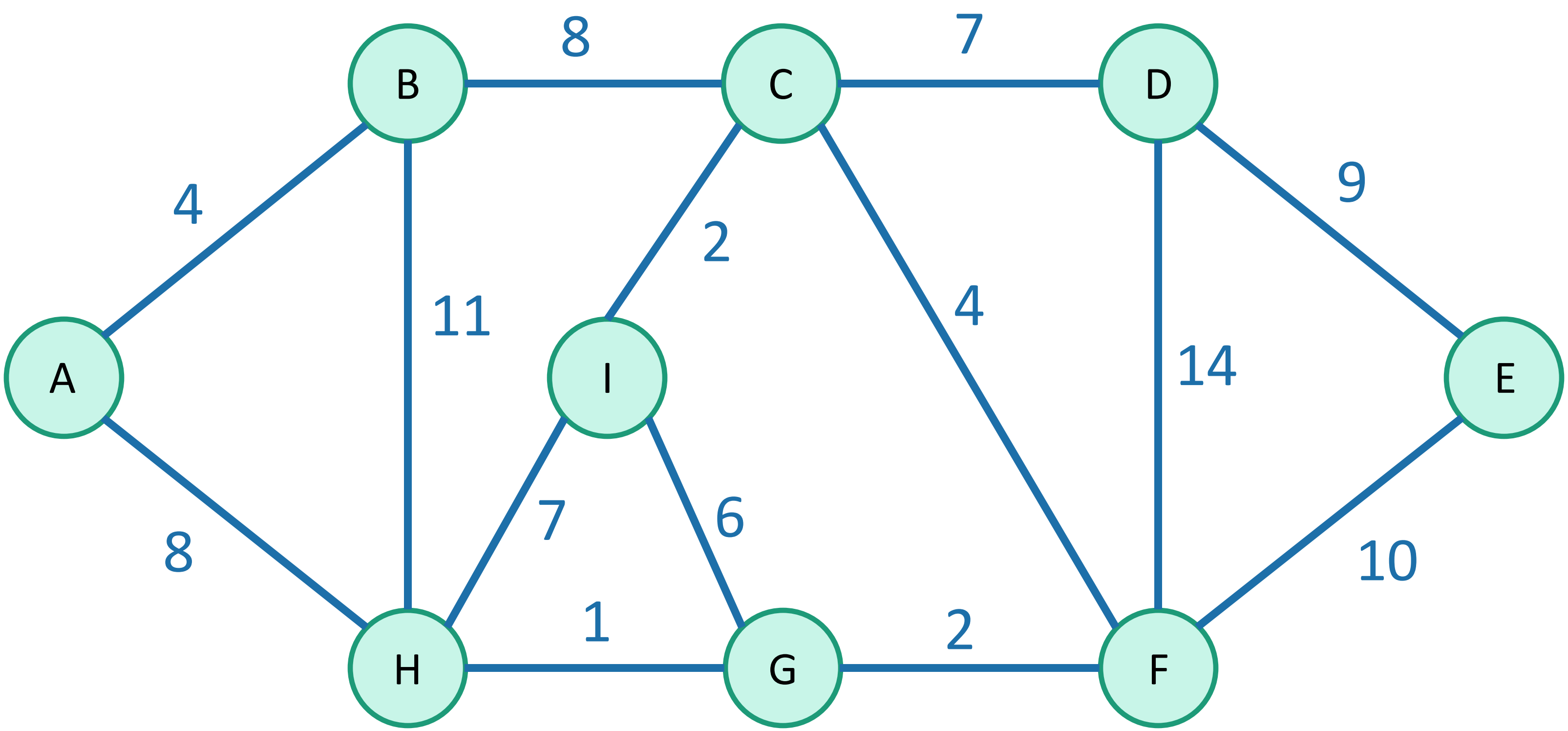
It has cost 37

A **tree** is a connected graph with no cycles!

A **spanning tree** is a **tree** that connects all of the vertices.

Minimum Spanning Tree

Say we have an undirected weighted graph



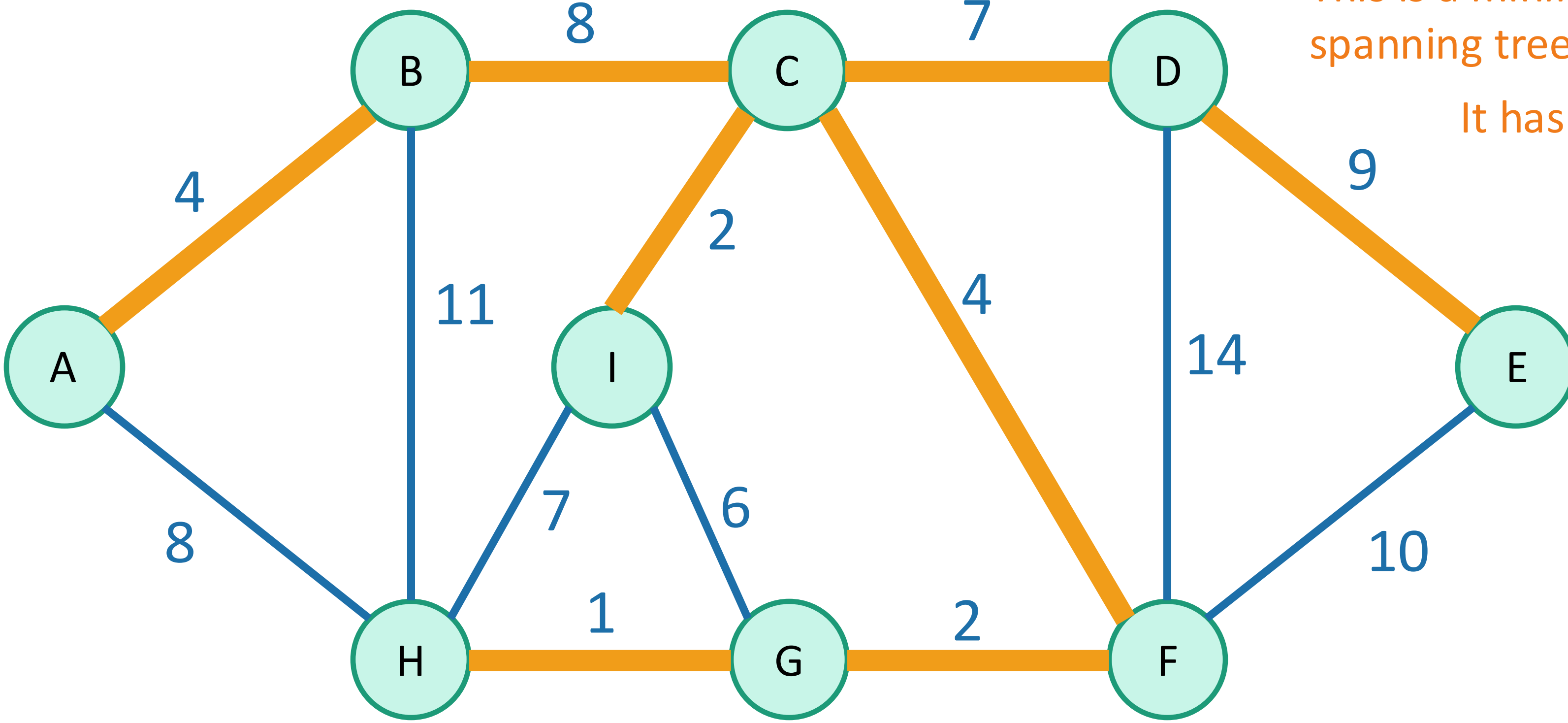
minimum

of minimum cost

A **spanning tree** is a **tree** that connects all of the vertices.

Minimum Spanning Tree

Say we have an undirected weighted graph



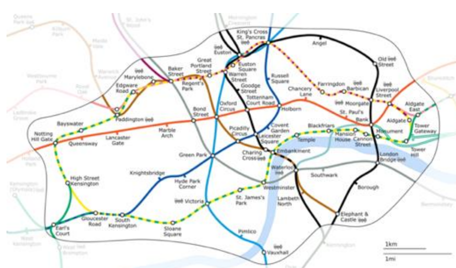
minimum

of minimal cost

A **spanning tree** is a **tree** that connects all of the vertices.

Why MSTs?

- Network design
  - Connecting cities with roads/electricity/telephone/…
- cluster analysis
  - eg, genetic distance
- image processing
  - eg, image segmentation
- Useful primitive
  - for other graph algs



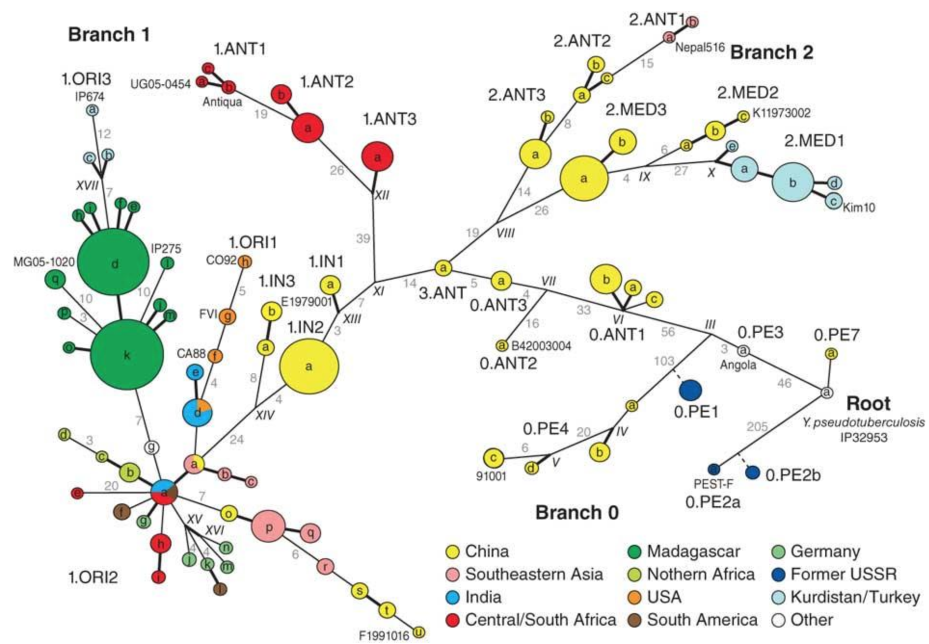
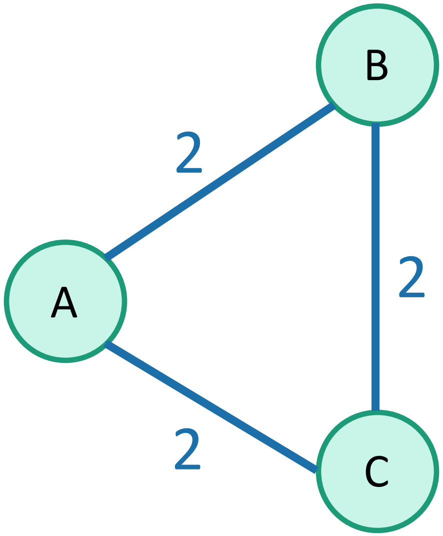


Figure 2: Fully parsimonious minimal spanning tree of 933 SNPs for 282 isolates of *Y. pestis* colored by location.

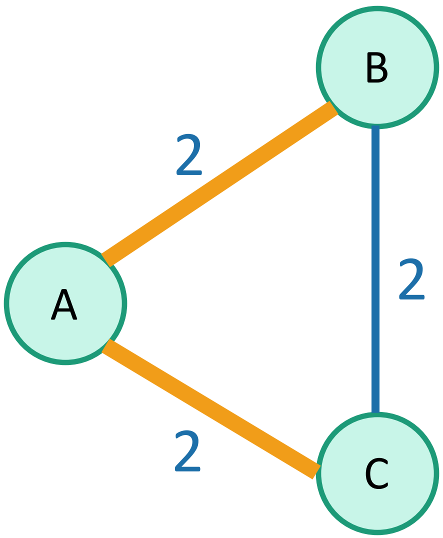
Morelli et al. Nature genetics 2010

Are MSTs Unique?



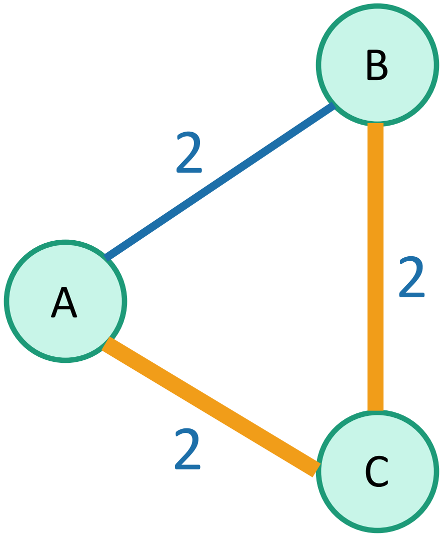
Not here!

Are MSTs Unique?



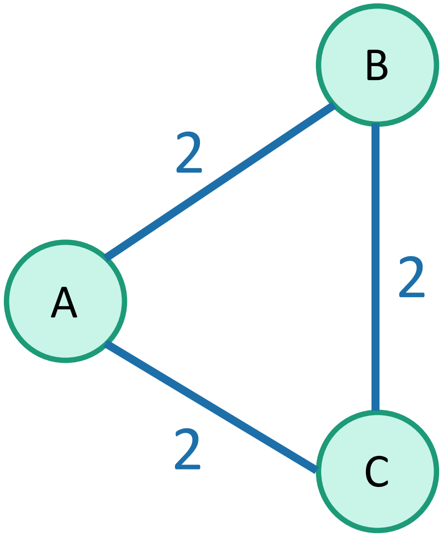
Not here!

Are MSTs Unique?

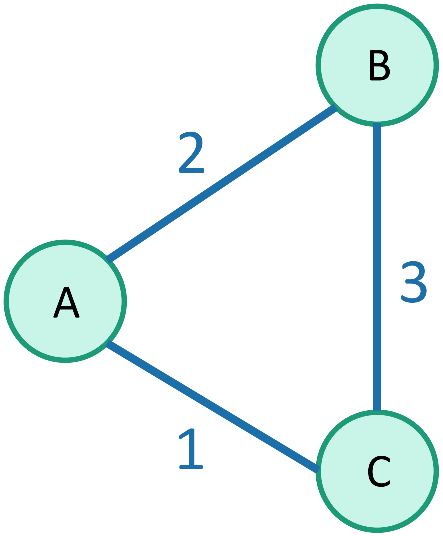


Not here!

Are MSTs Unique?

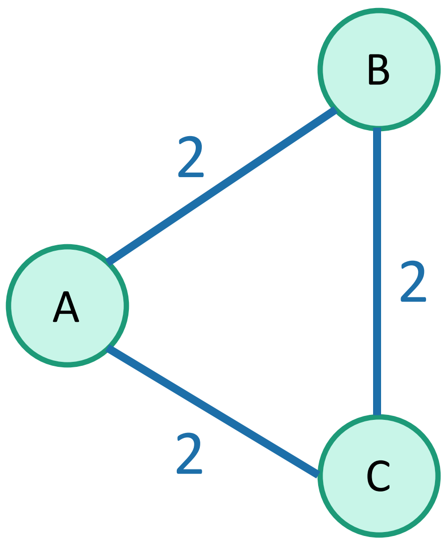


Not here!

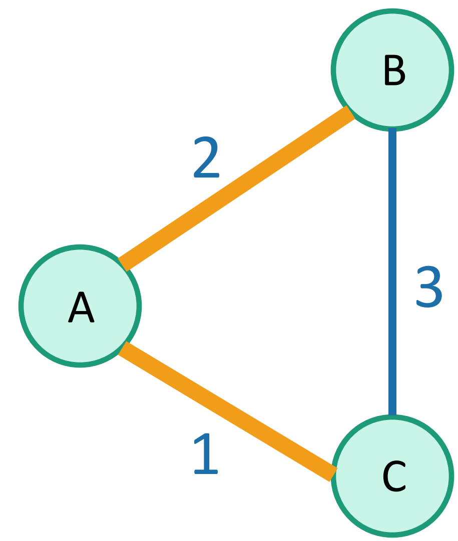


But this one has a unique MST!

Are MSTs Unique?

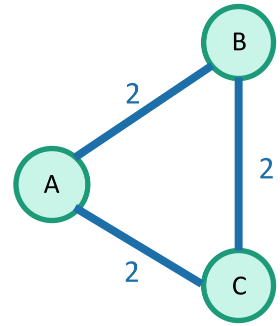


Not here!

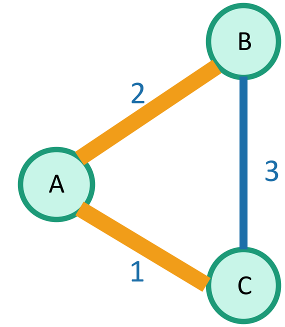


But this one has a unique MST!

Are MSTs Unique?



Not here!



But this one has a unique MST!

- **Lemma:** Let G be a connected, weighted, undirected graph, so that all of the edge weights are distinct. Then G has a unique MST.

You'll prove this on your HW!

How to find an MST?

- Today we'll see two greedy algorithms.
- In order to prove that these greedy algorithms work, we'll show something like:

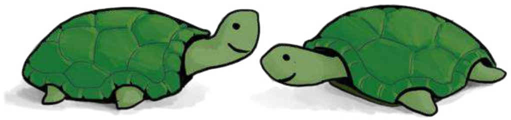
Suppose that our choices so far are consistent with an MST.

Then the next greedy choice that we make is still consistent with an MST.

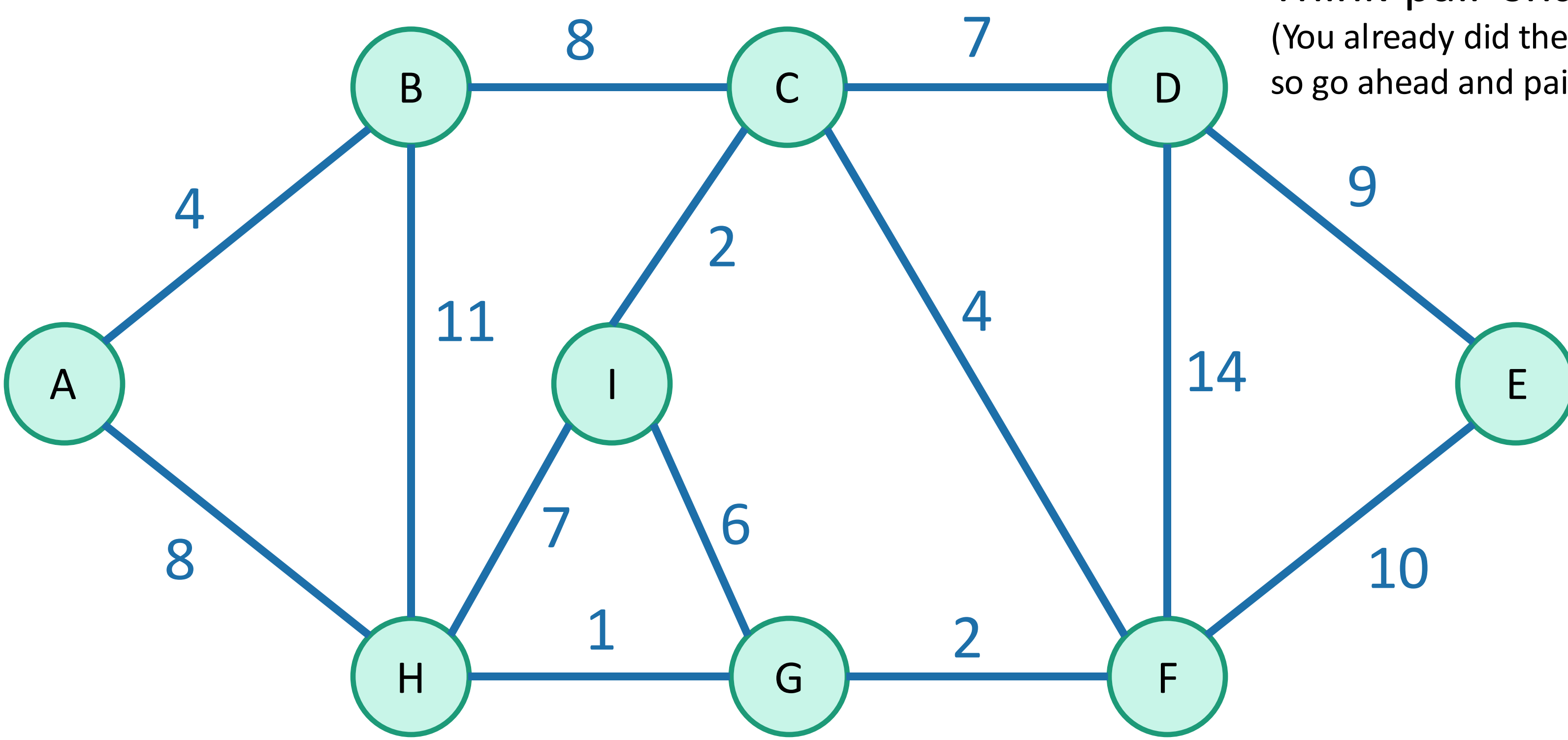
- This is not the only way to prove that these algorithms work!
  - See a different way in the Algorithms Illuminated reading.

Following your pre-lecture exercise…

Let’s brainstorm some greedy algorithms!



Think-pair-share!
(You already did the thinking, so go ahead and pair+share).

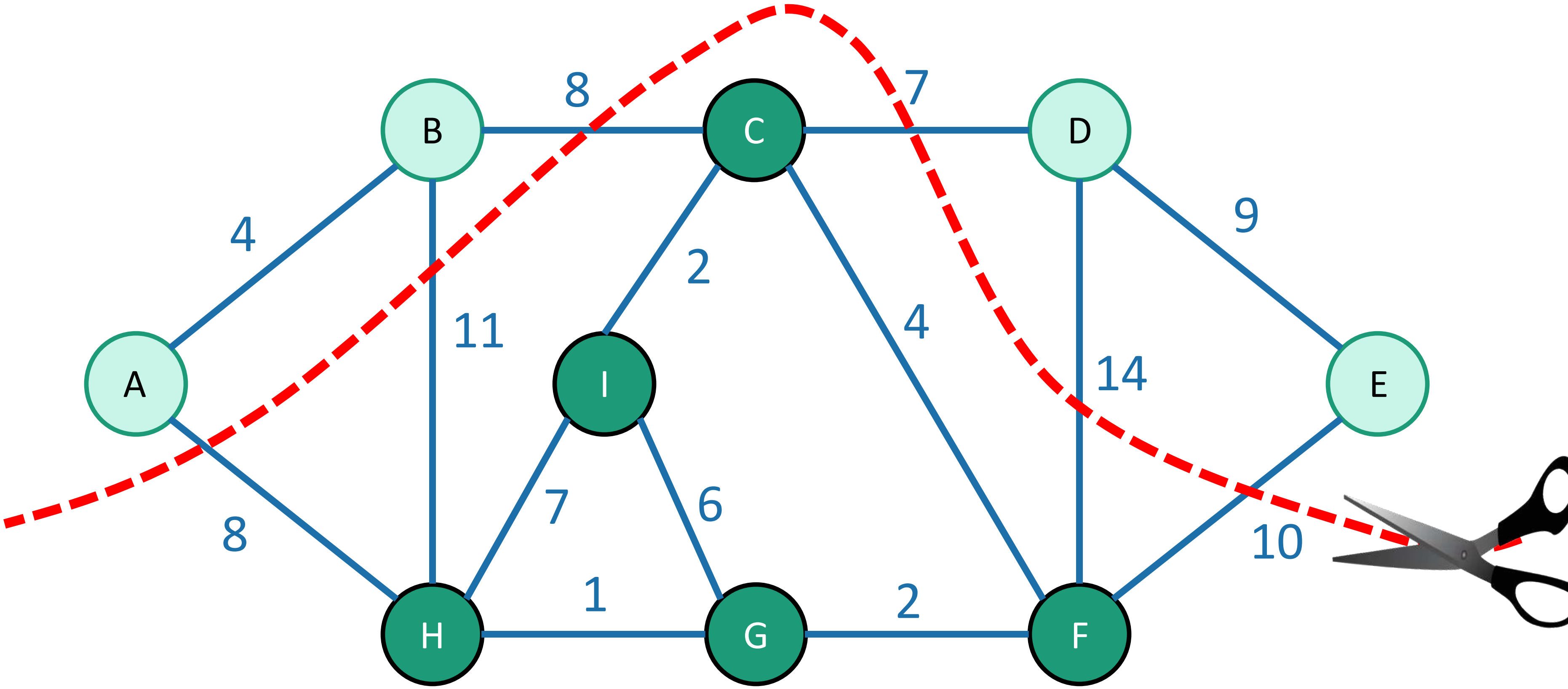


Brief aside

for a discussion of cuts in graphs!

Cuts in graphs

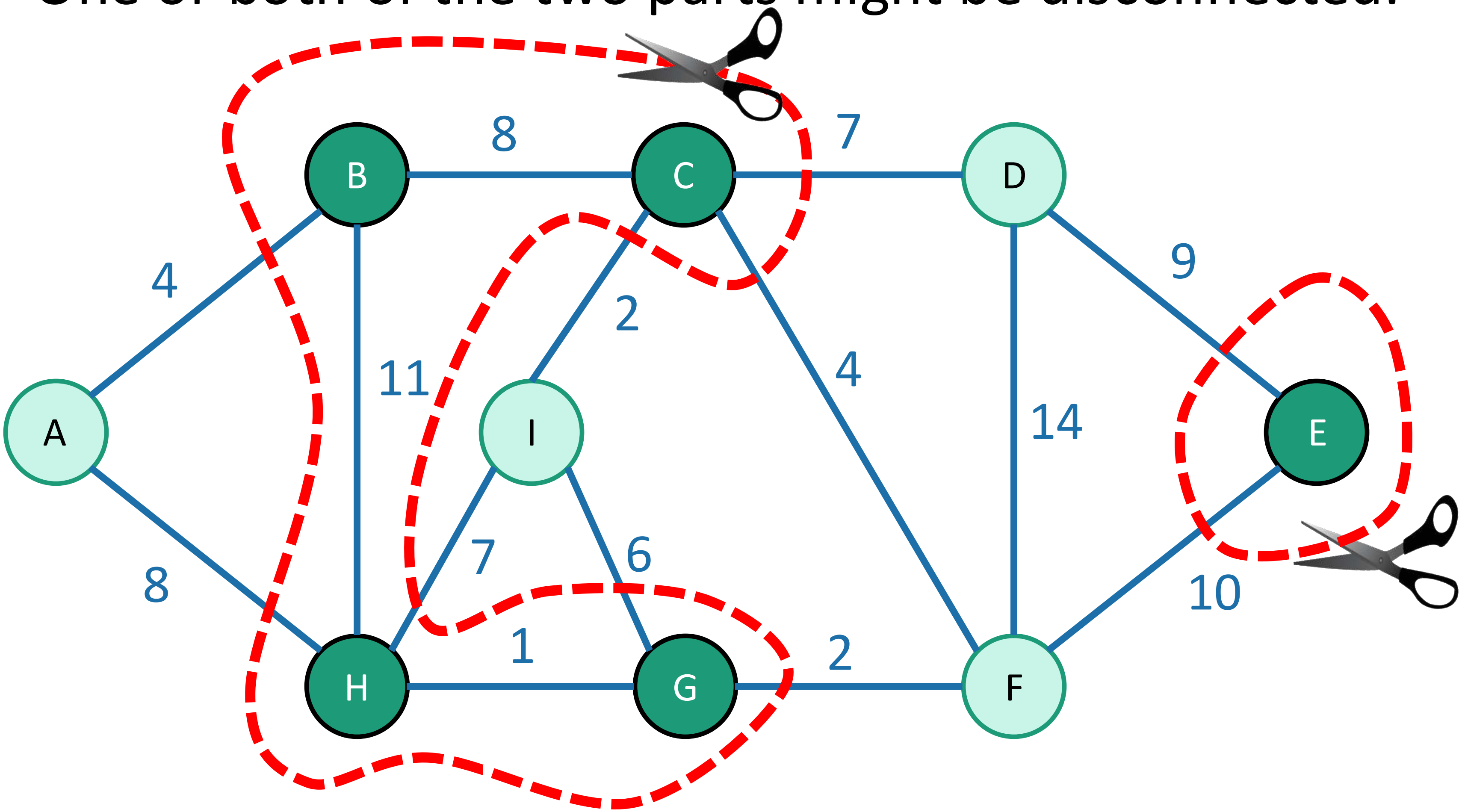
- A cut is a partition of the vertices into two parts:



This is the cut **"{A,B,D,E} and {C,I,H,G,F}"**

Cuts in graphs

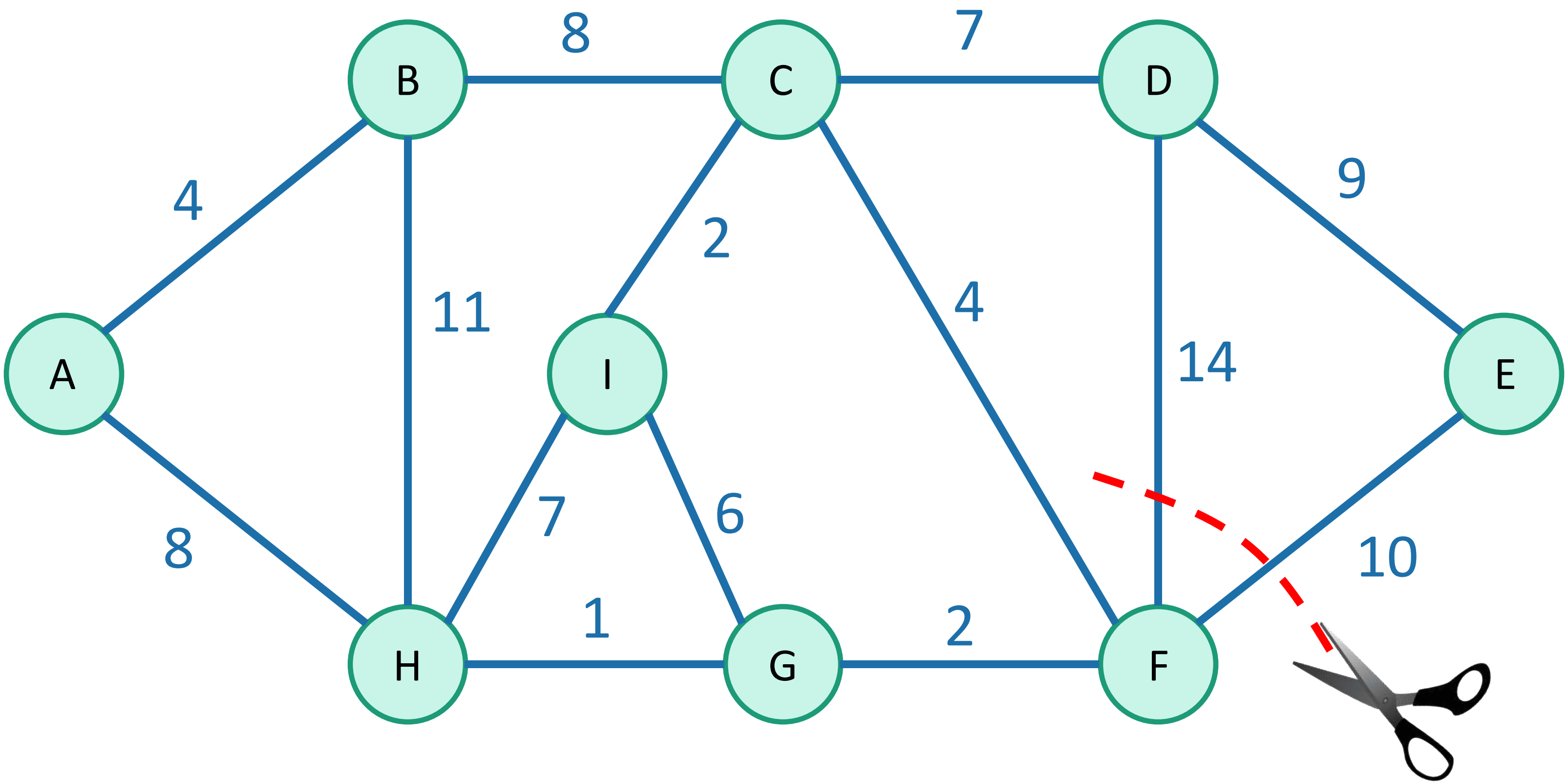
- One or both of the two parts might be disconnected.



This is the cut **"{B,C,E,G,H} and {A,D,I,F}"**

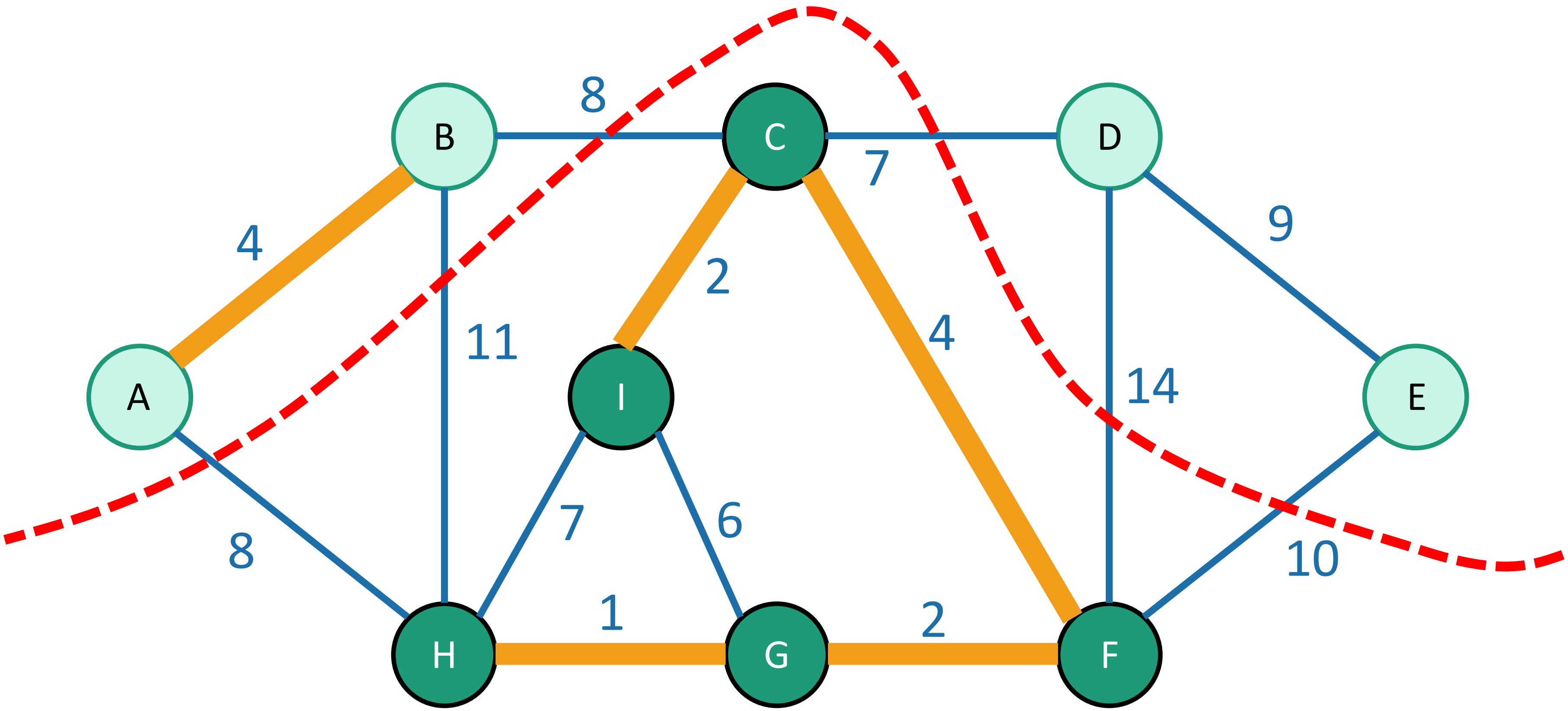
Cuts in graphs

- This is ***not*** a cut. Cuts are partitions of vertices.



Let S be a set of edges in G

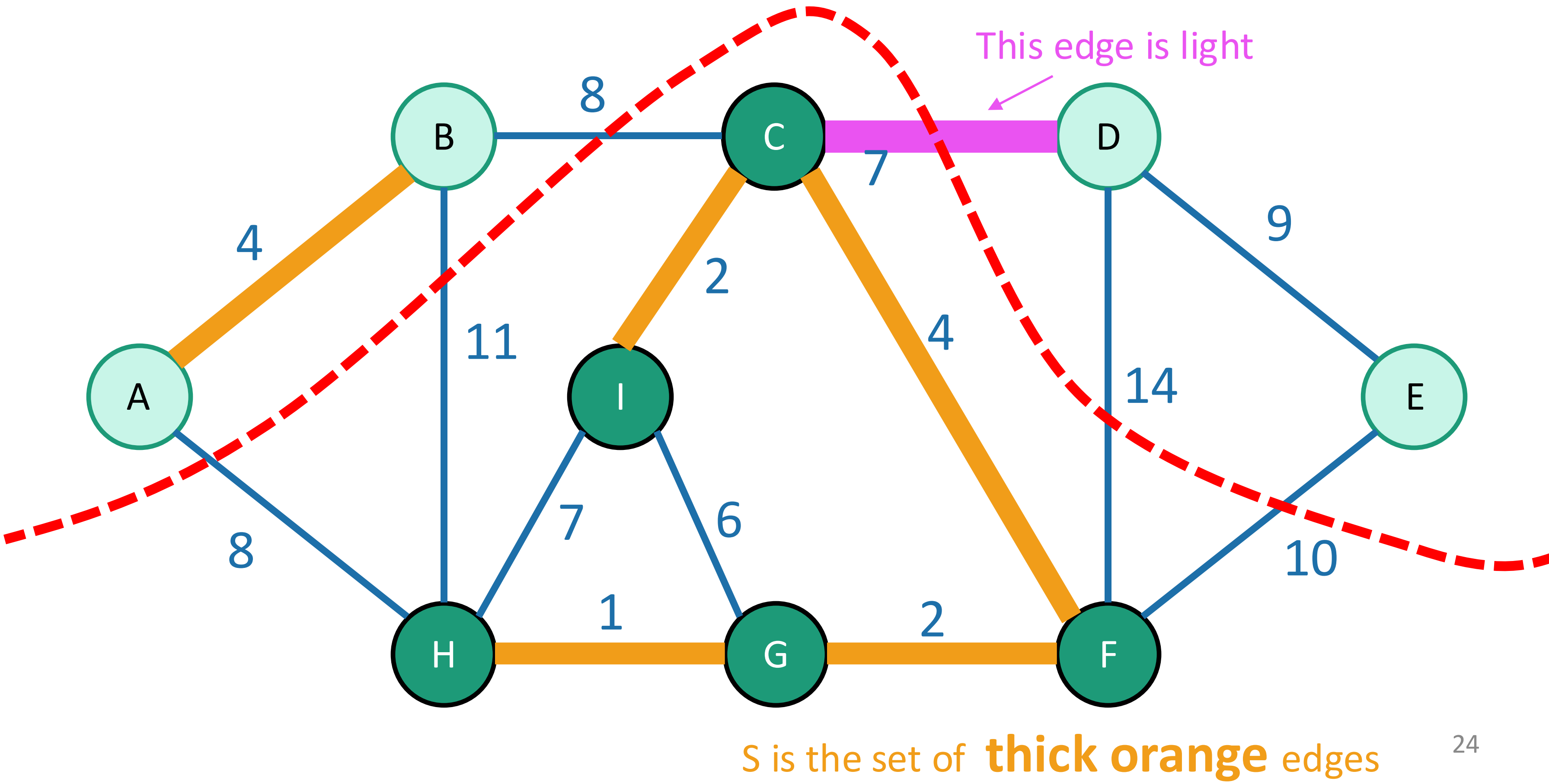
- We say a cut **respects** S if no edges in S cross the cut.
- An edge crossing a cut is called **light** if it has the smallest weight of any edge crossing the cut.



S is the set of **thick orange** edges

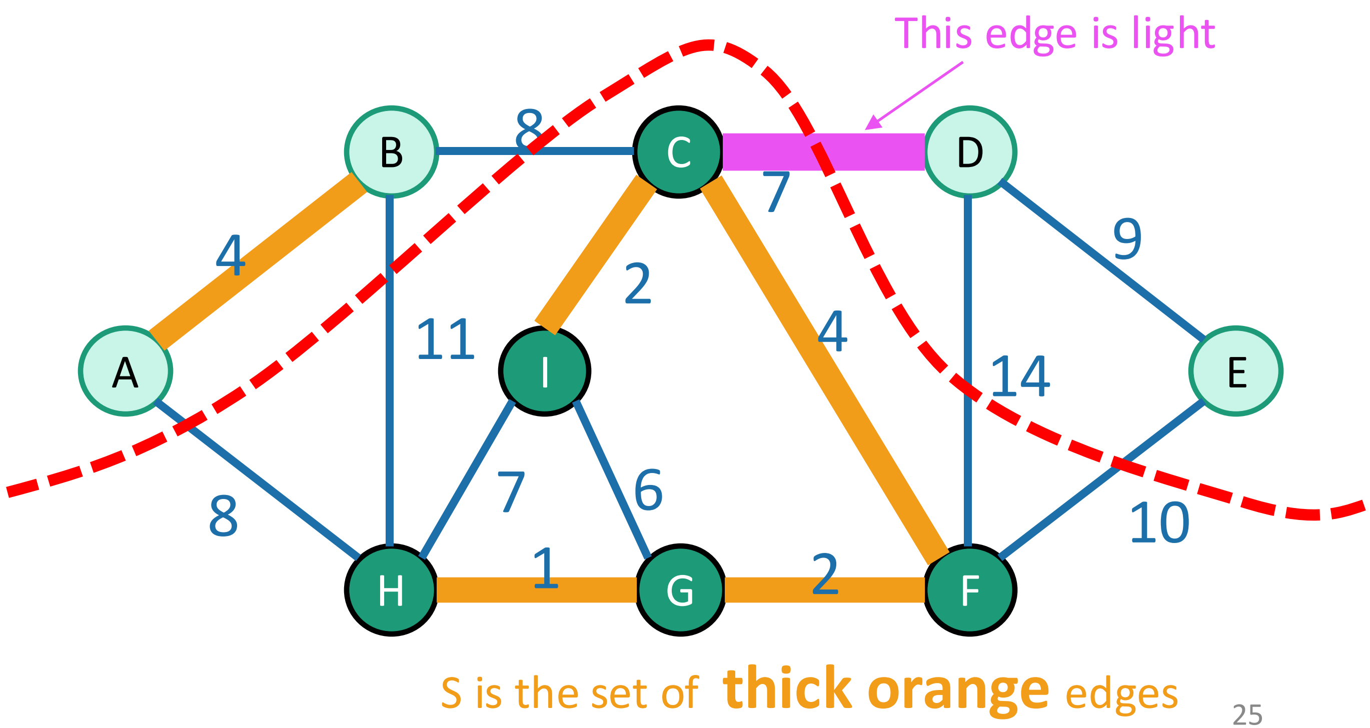
Let S be a set of edges in G

- We say a cut **respects** S if no edges in S cross the cut.
- An edge crossing a cut is called **light** if it has the smallest weight of any edge crossing the cut.



Lemma

- Let S be a set of edges, and consider a cut that respects S.
- Suppose there is an MST containing S.
- Let {u,v} be a light edge.
- Then there is an MST containing S ∪ {{u,v}}

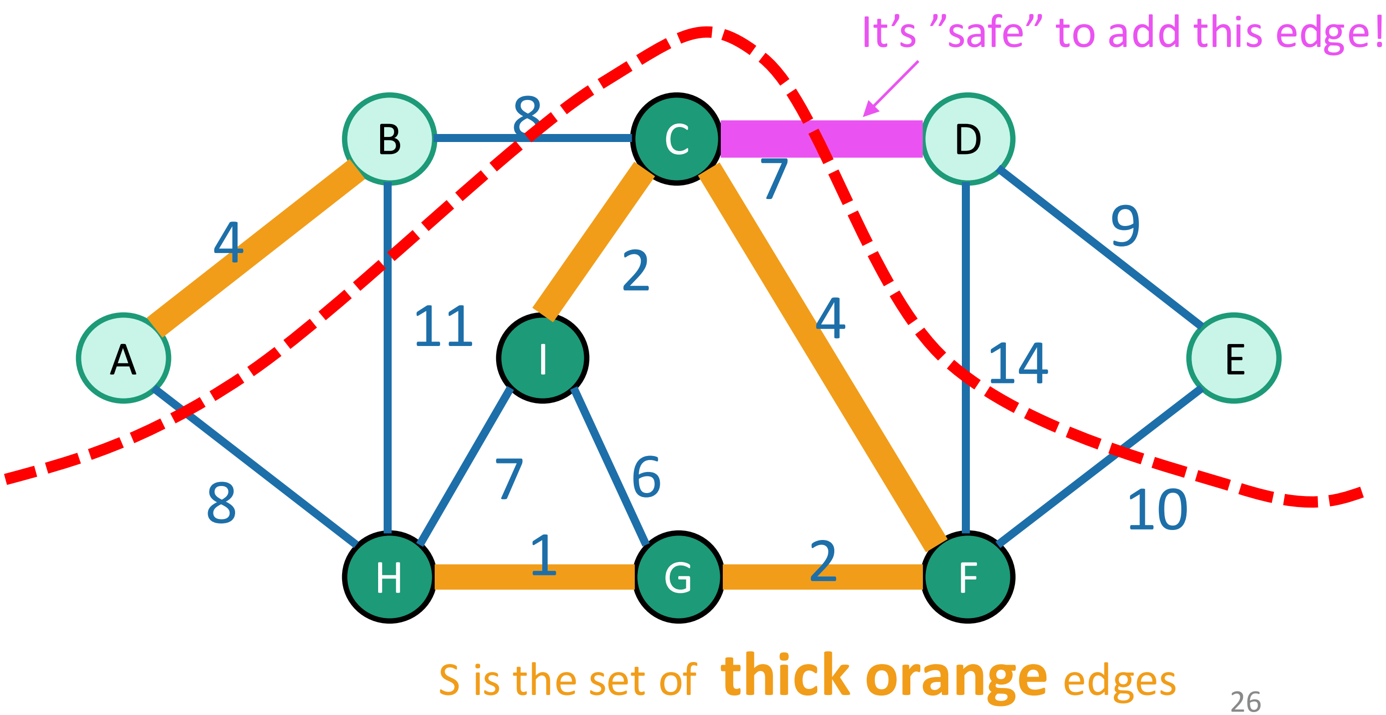


Lemma

- Let S be a set of edges, and consider a cut that respects S.
- Suppose there is an MST containing S.
- Let {u,v} be a light edge.
- Then there is an MST containing S U {{u,v}}

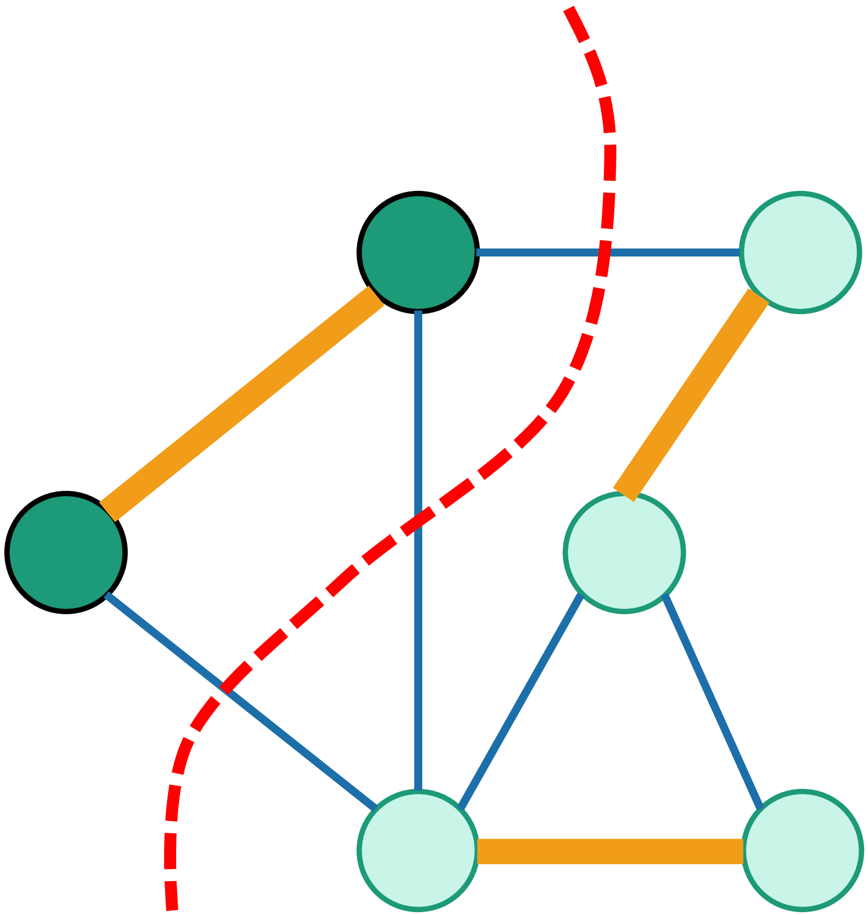
Aka:

If we haven't ruled out the possibility of success so far, then adding a light edge still won't rule it out.



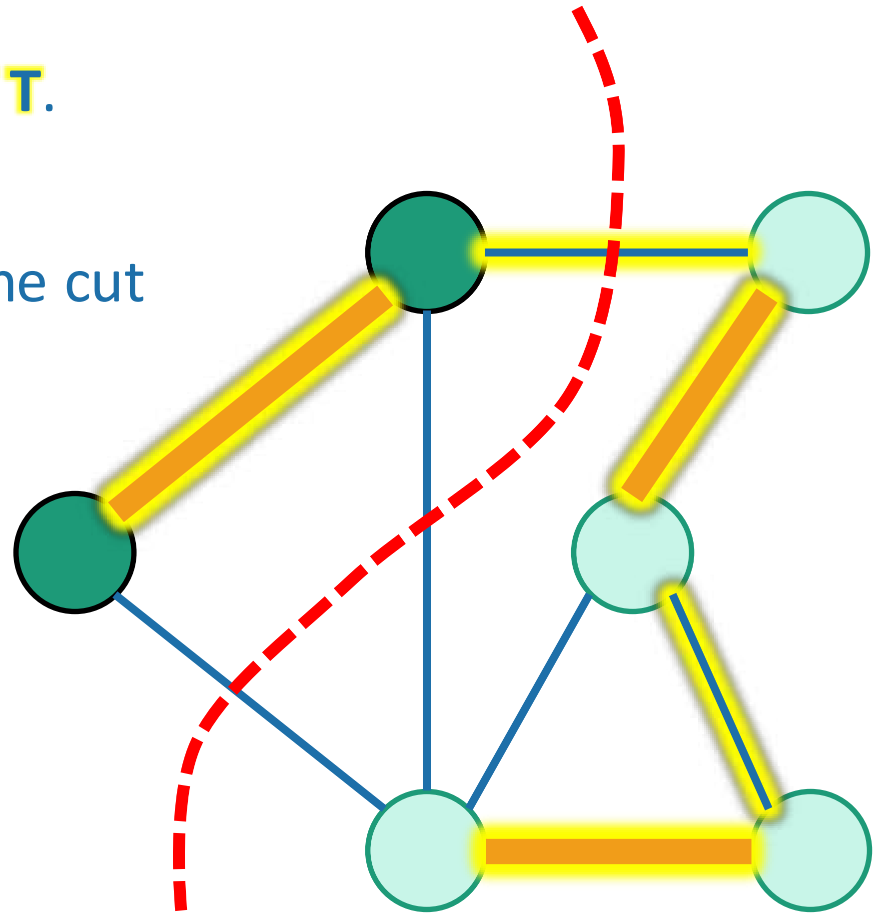
Proof of Lemma

- Assume that we have:
  - a **cut** that respects **S**



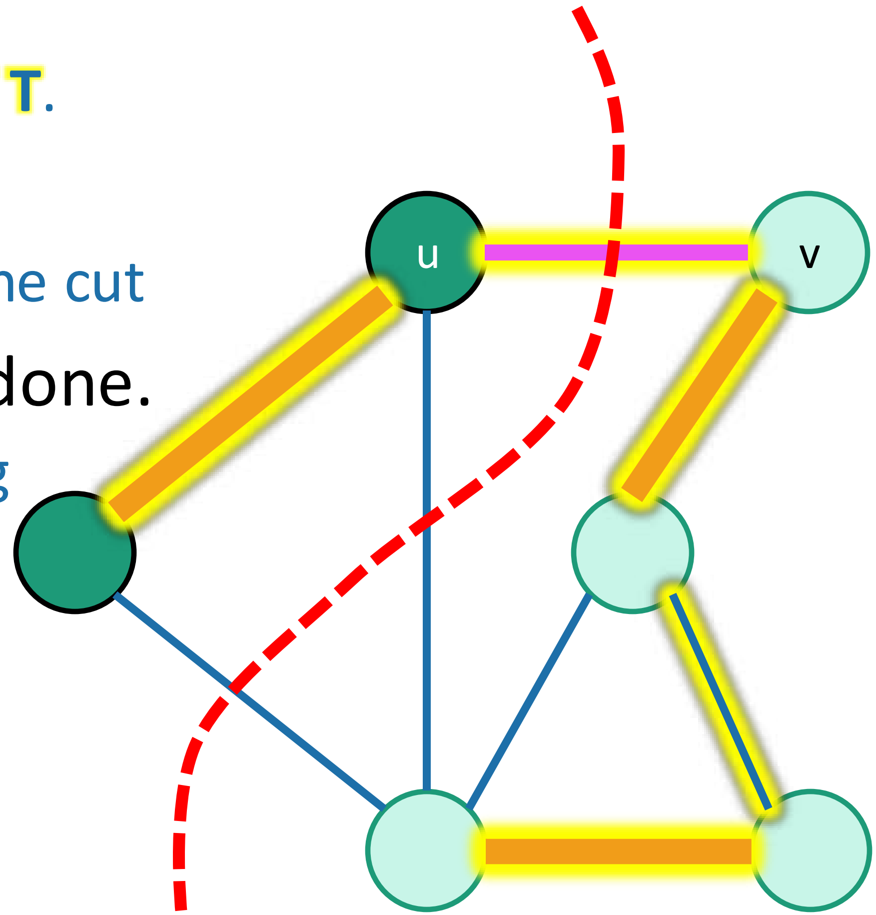
Proof of Lemma

- Assume that we have:
  - a **cut** that respects **S**
  - **S** is part of some **MST T**.
- Say that **{u,v}** is light.
  - lowest cost crossing the cut



Proof of Lemma

- Assume that we have:
  - a **cut** that respects **S**
  - **S** is part of some **MST T**.
- Say that **{u,v}** is light.
  - lowest cost crossing the cut
- If **{u,v}** is in T, we are done.
  - T is an MST containing both {u,v} and S.

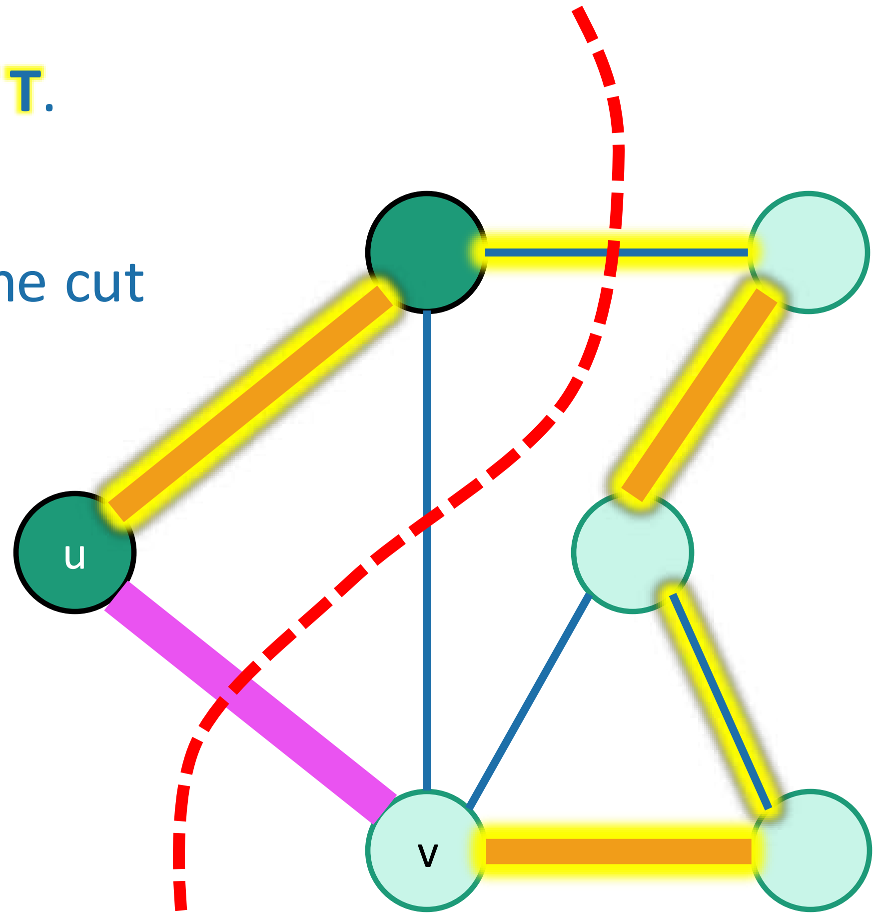


Proof of Lemma

Claim: Adding any additional edge to a spanning tree will create a cycle.

Proof: Both endpoints are already in the tree and connected to each other via the tree, so adding an edge makes a cycle.

- Assume that we have:
  - a **cut** that respects **S**
  - **S** is part of some **MST T**.
- Say that **{u,v}** is light.
  - lowest cost crossing the cut
- Say **{u,v}** is not in **T**.
- Note that adding **{u,v}** to **T** will make a cycle.

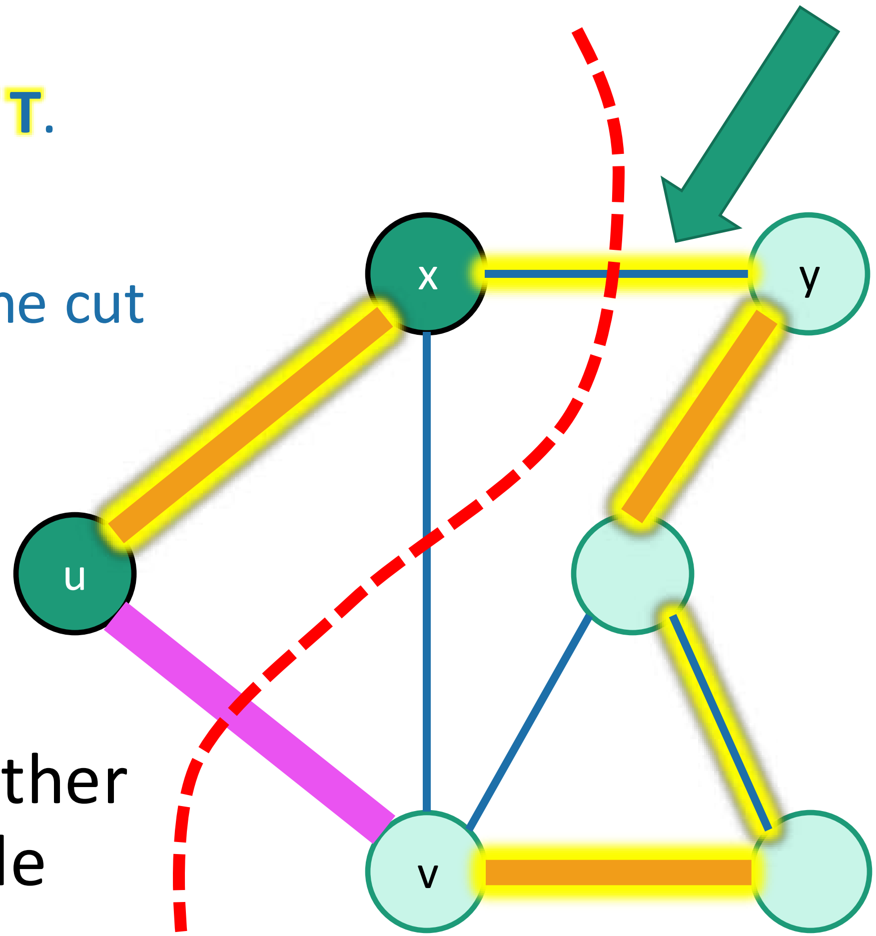


Proof of Lemma

Claim: Adding any additional edge to a spanning tree will create a cycle.

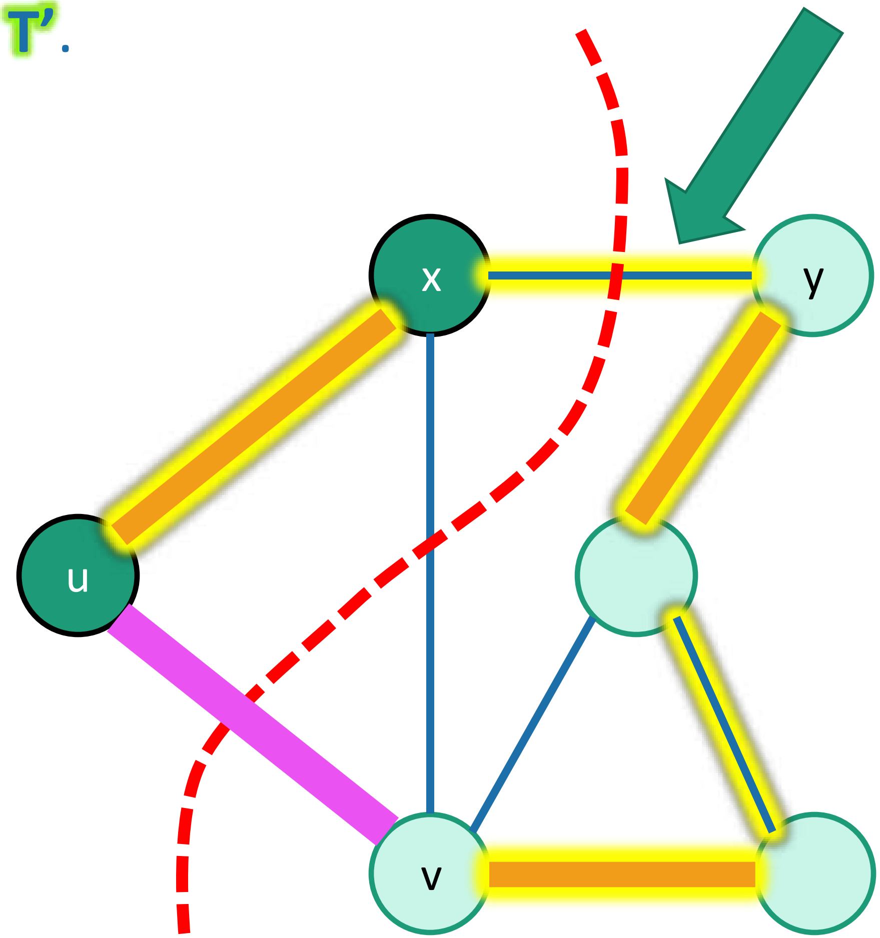
Proof: Both endpoints are already in the tree and connected to each other via the tree, so adding an edge makes a cycle.

- Assume that we have:
  - a **cut** that respects **S**
  - **S** is part of some **MST T**.
- Say that **{u,v}** is light.
  - lowest cost crossing the cut
- Say **{u,v}** is not in **T**.
- Note that adding **{u,v}** to **T** will make a cycle.
- There is at least one other edge, **{x,y}**, in this cycle crossing the cut.



Proof of Lemma ctd.

- Consider swapping {u,v} for {x,y} in **T**.
  - Call the resulting tree **T'**.

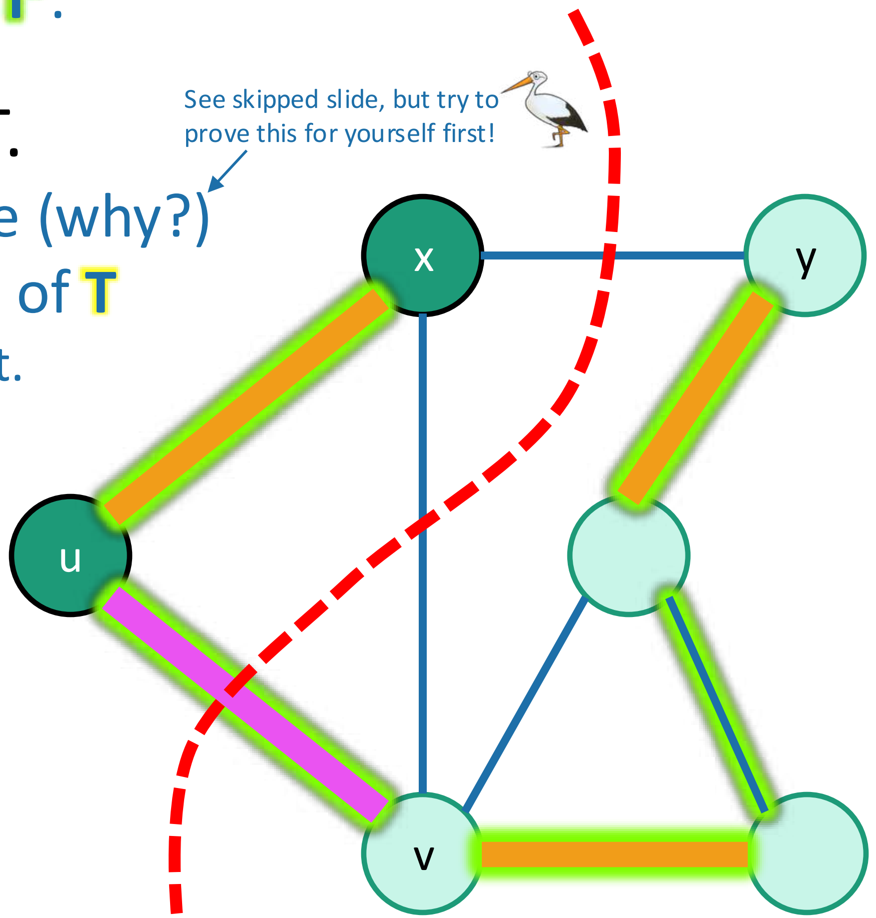


Proof of Lemma ctd.

- Consider swapping {u,v} for {x,y} in **T**.
  - Call the resulting tree **T'**.

- **Claim**: **T'** is still an MST.
  - It is still a spanning tree (why?)
  - It has cost at most that of **T**
    - because {u,v} was light.
  - **T** had minimal cost.
  - So **T'** does too.

See skipped slide, but try to prove this for yourself first!



- So **T'** is an MST containing S and {u,v}.
  - This is what we wanted.

SLIDE SKIPPED IN CLASS

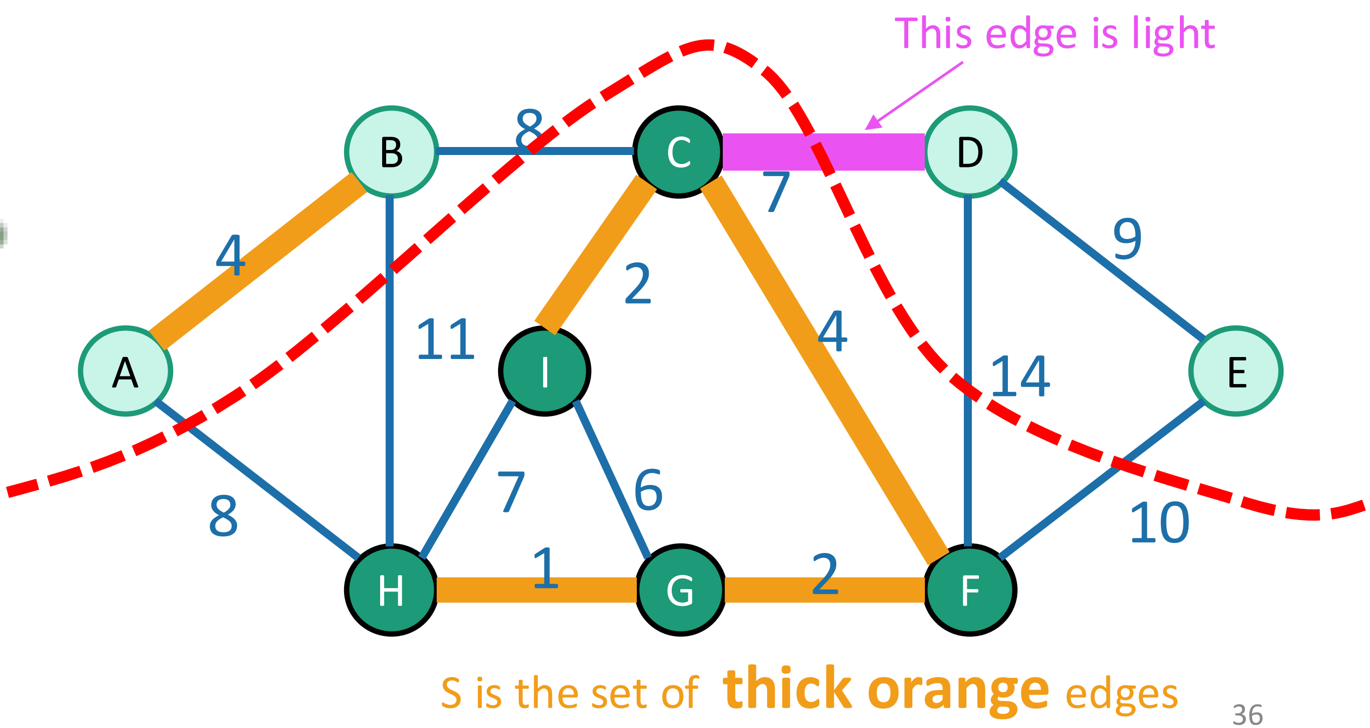
Why is T’ still a spanning tree?

- It spans because we didn’t change which vertices it touches.
- **Fact:** A undirected graph on n vertices is a tree if and only if it is connected and contains n-1 edges. (You can take this Fact as given, for example, on any HW problems…)
- G is a tree:
  - G is connected (why?)
  - G has n-1 edges (why?)
  - G touches n vertices, since we just said it spanned all of them.
- So G is a tree, and hence a spanning tree.

Still a few steps for you to fill in here!

Lemma

- Let S be a set of edges, and consider a cut that respects S.
- Suppose there is an MST containing S.
- Let {u,v} be a light edge.
- Then there is an MST containing S ∪ {{u,v}}



End aside

Back to finding MSTs!

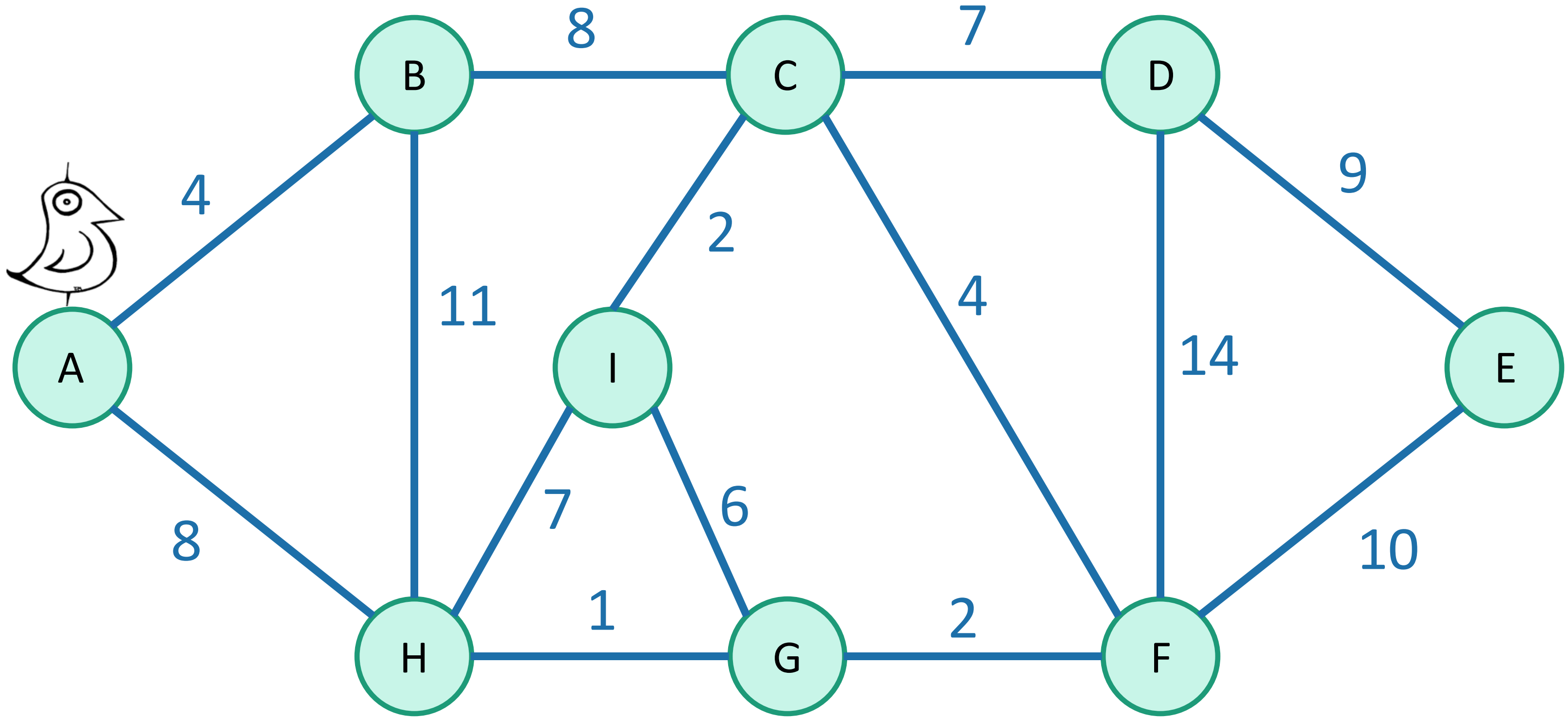
Back to MSTs

- How do we find one?
- Today we'll see **two greedy algorithms**.

- The strategy:
  - Make a **series of choices,** adding edges to the tree.
  - Show that each edge we add is **safe to add**:
    - we do not rule out the possibility of success
    - we will choose **light edges** crossing **cuts** and **use the Lemma**.
  - **Keep going** until we have an MST.

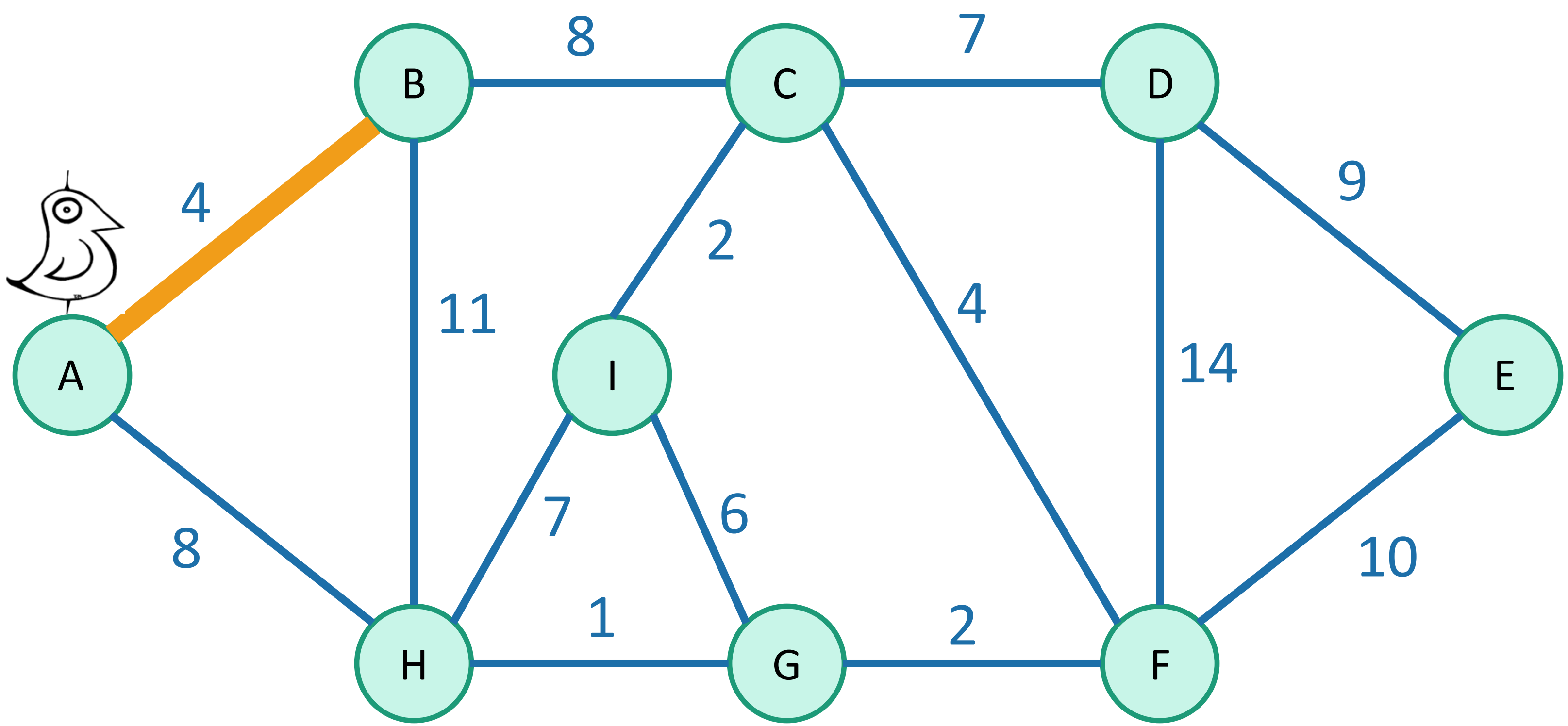
Idea 1

Start growing a tree, greedily add the shortest edge we can to grow the tree.



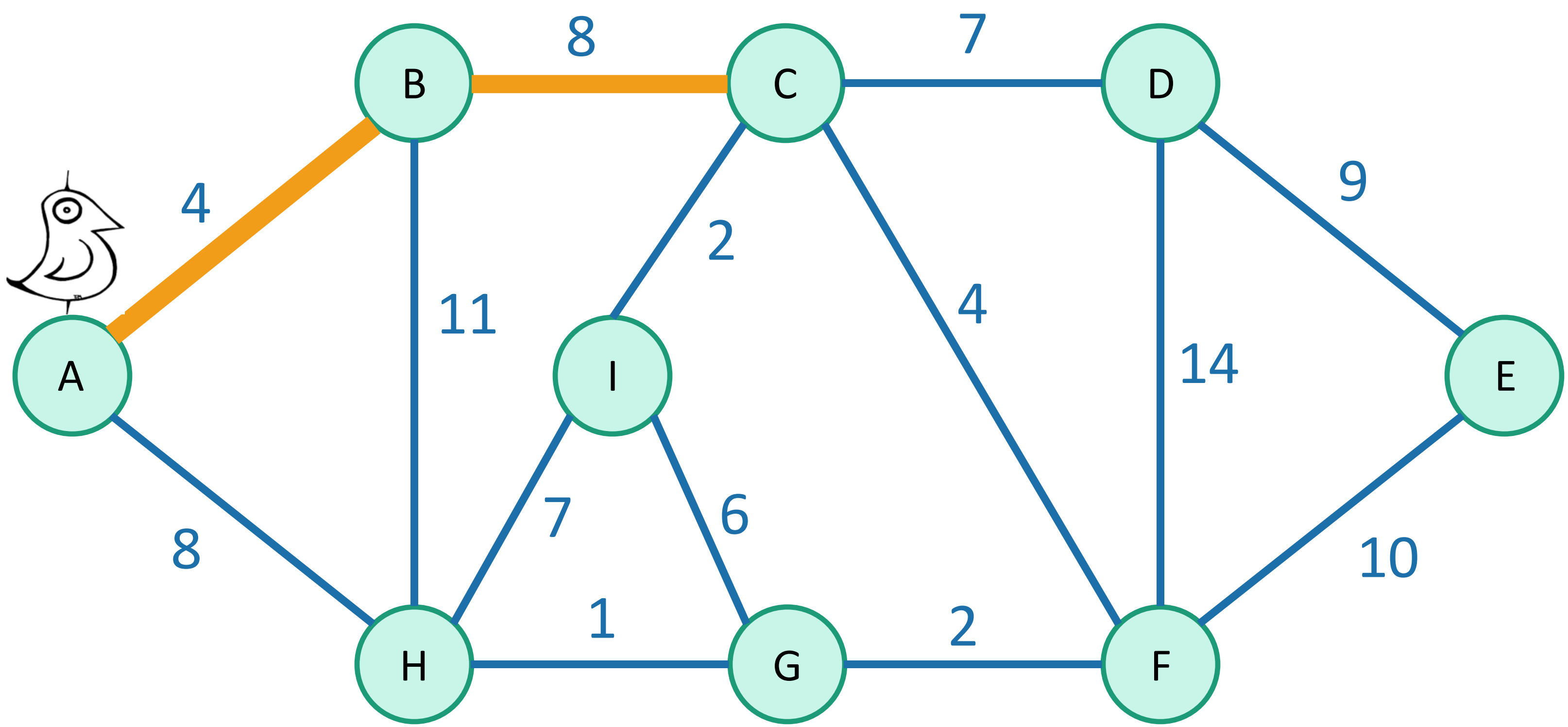
Idea 1

Start growing a tree, greedily add the shortest edge we can to grow the tree.



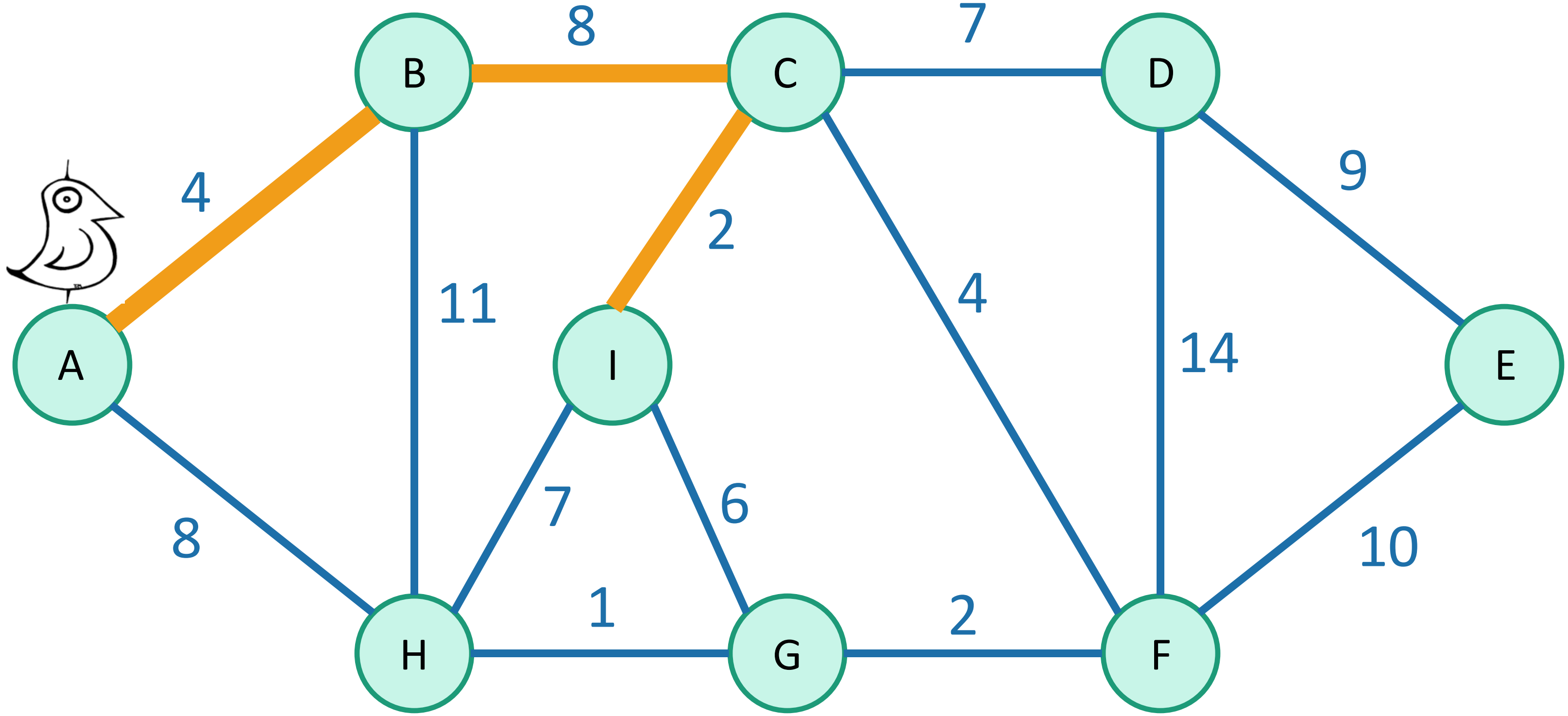
Idea 1

Start growing a tree, greedily add the shortest edge we can to grow the tree.



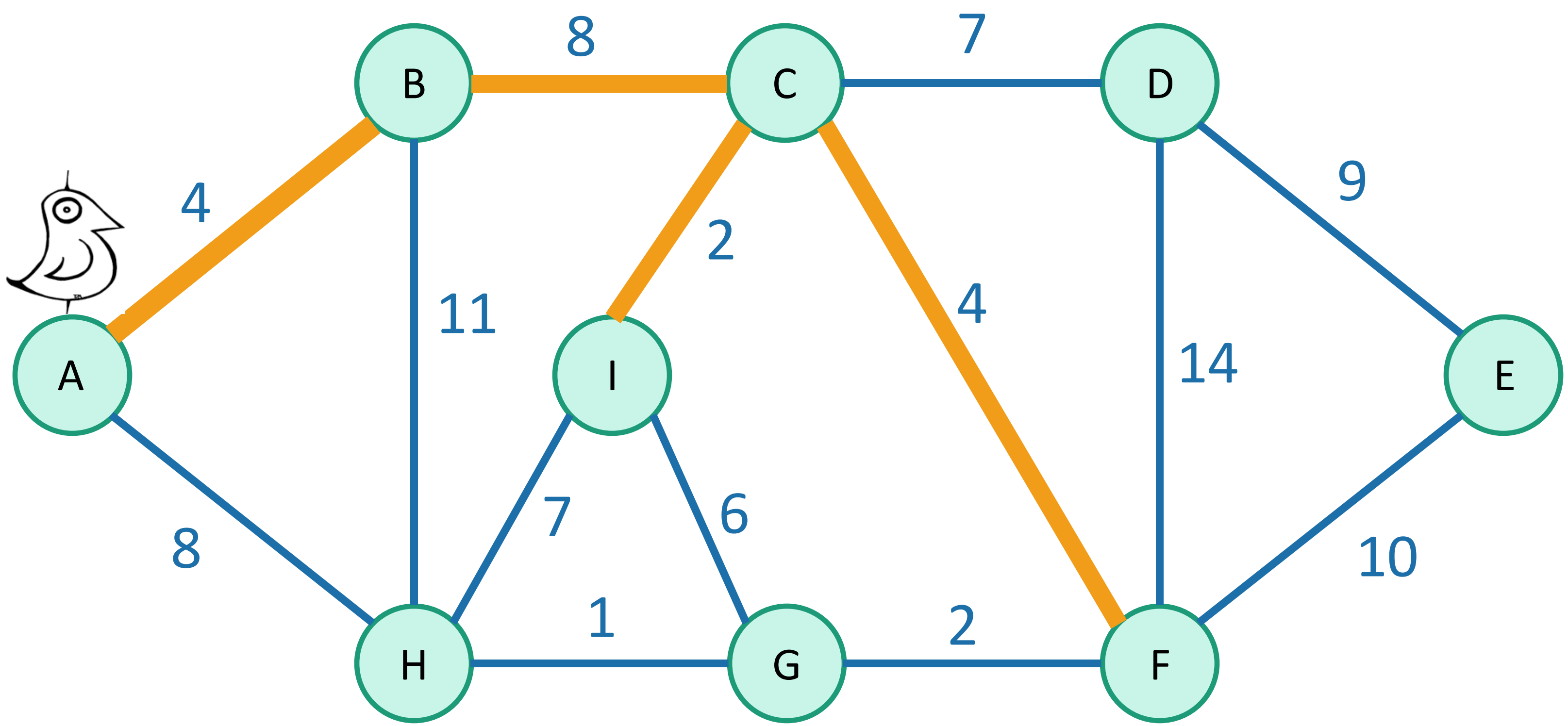
Idea 1

Start growing a tree, greedily add the shortest edge we can to grow the tree.



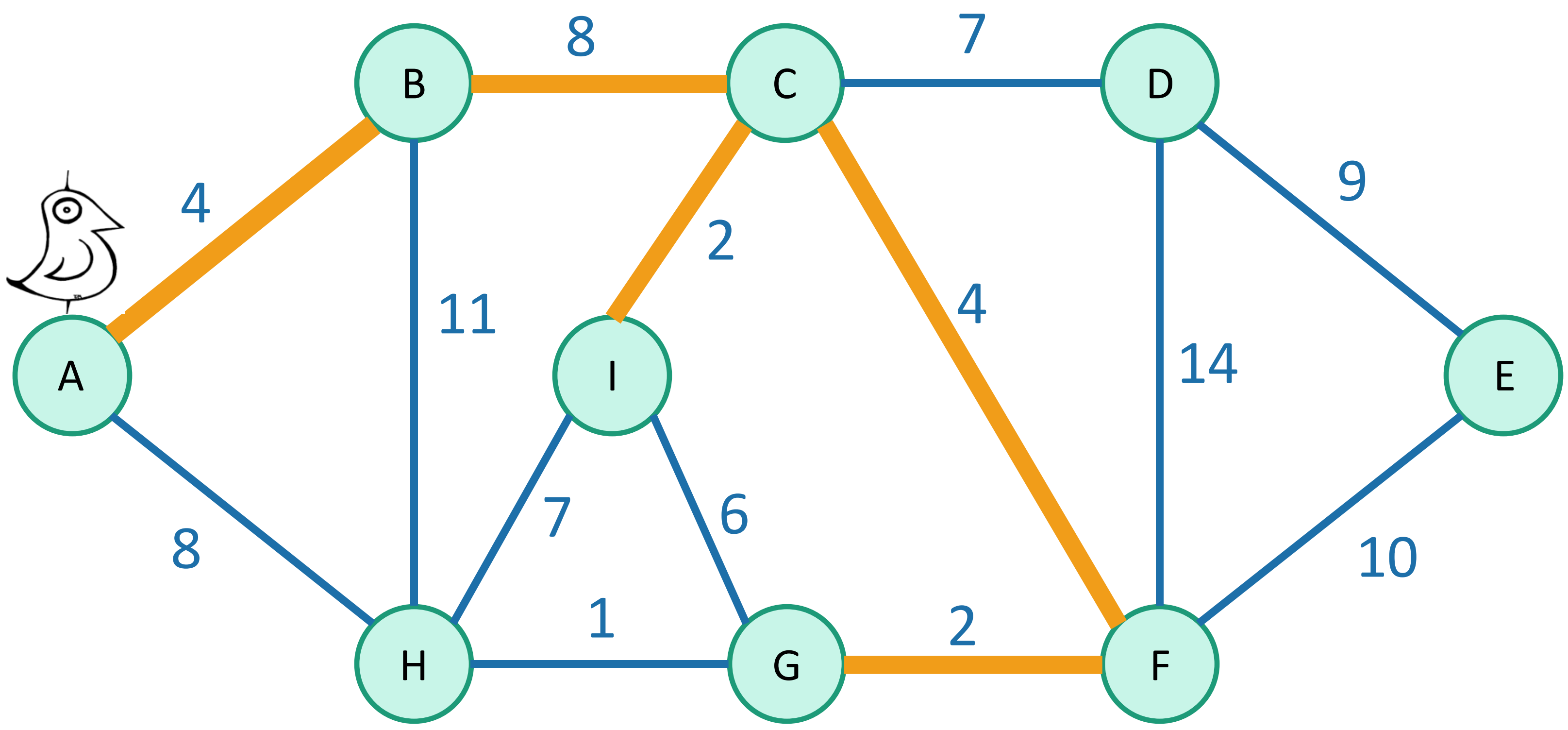
Idea 1

Start growing a tree, greedily add the shortest edge we can to grow the tree.



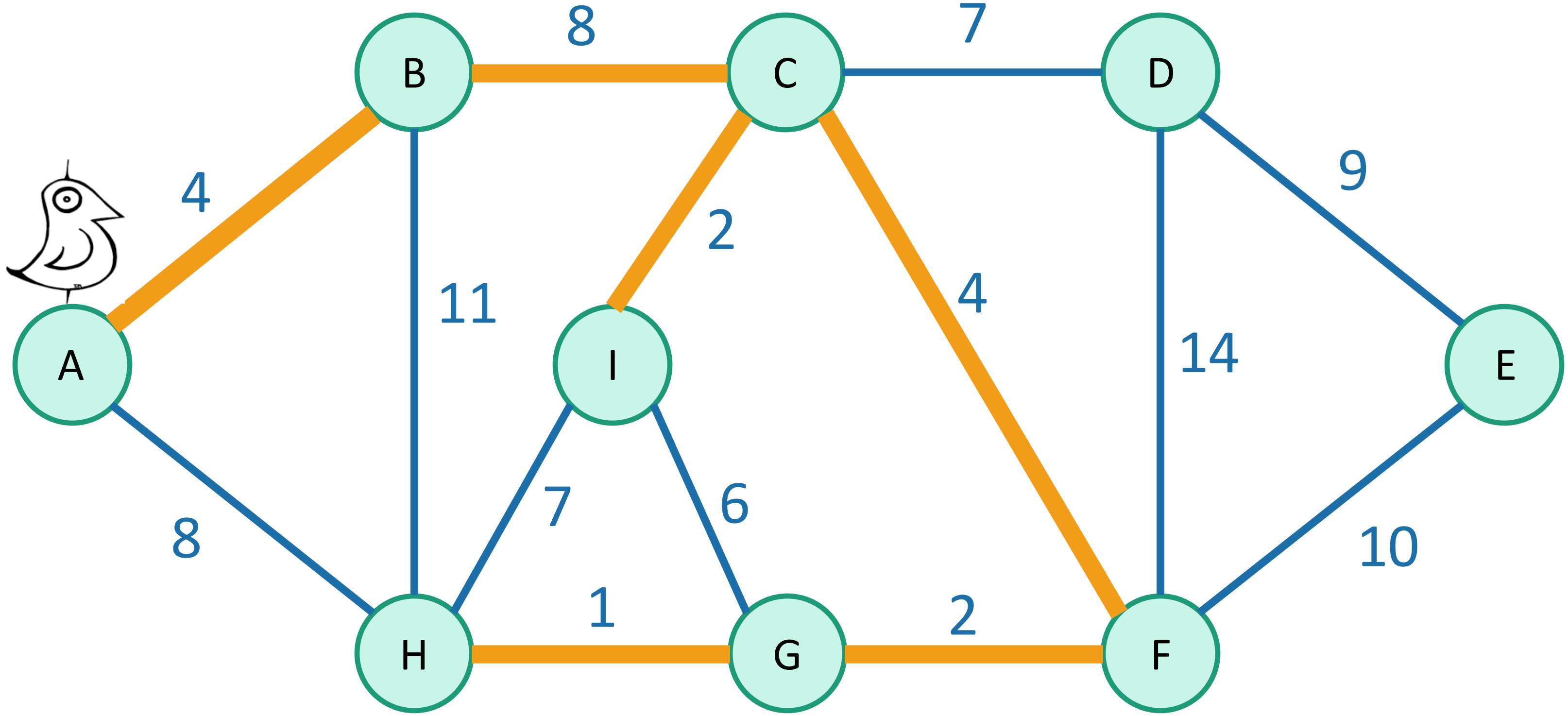
Idea 1

Start growing a tree, greedily add the shortest edge we can to grow the tree.



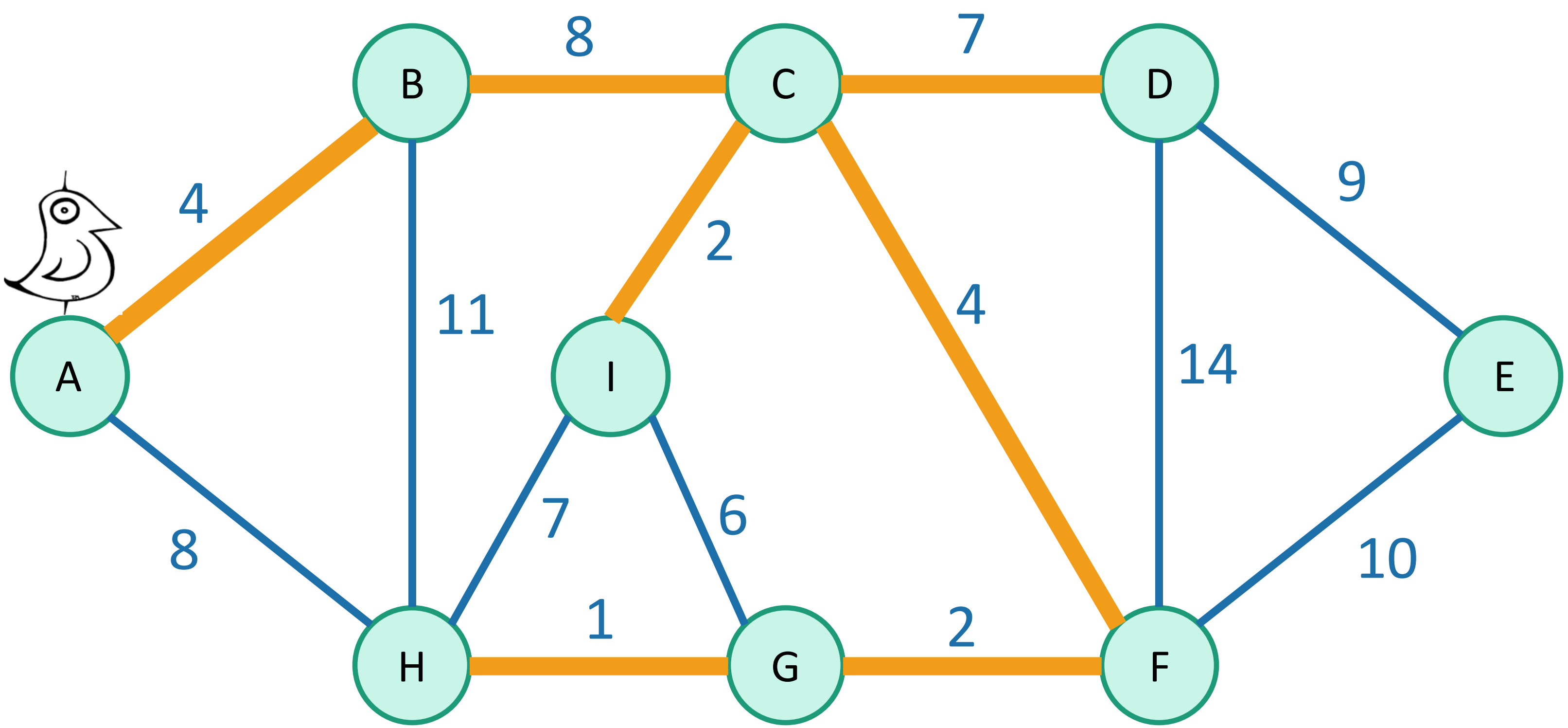
Idea 1

Start growing a tree, greedily add the shortest edge we can to grow the tree.



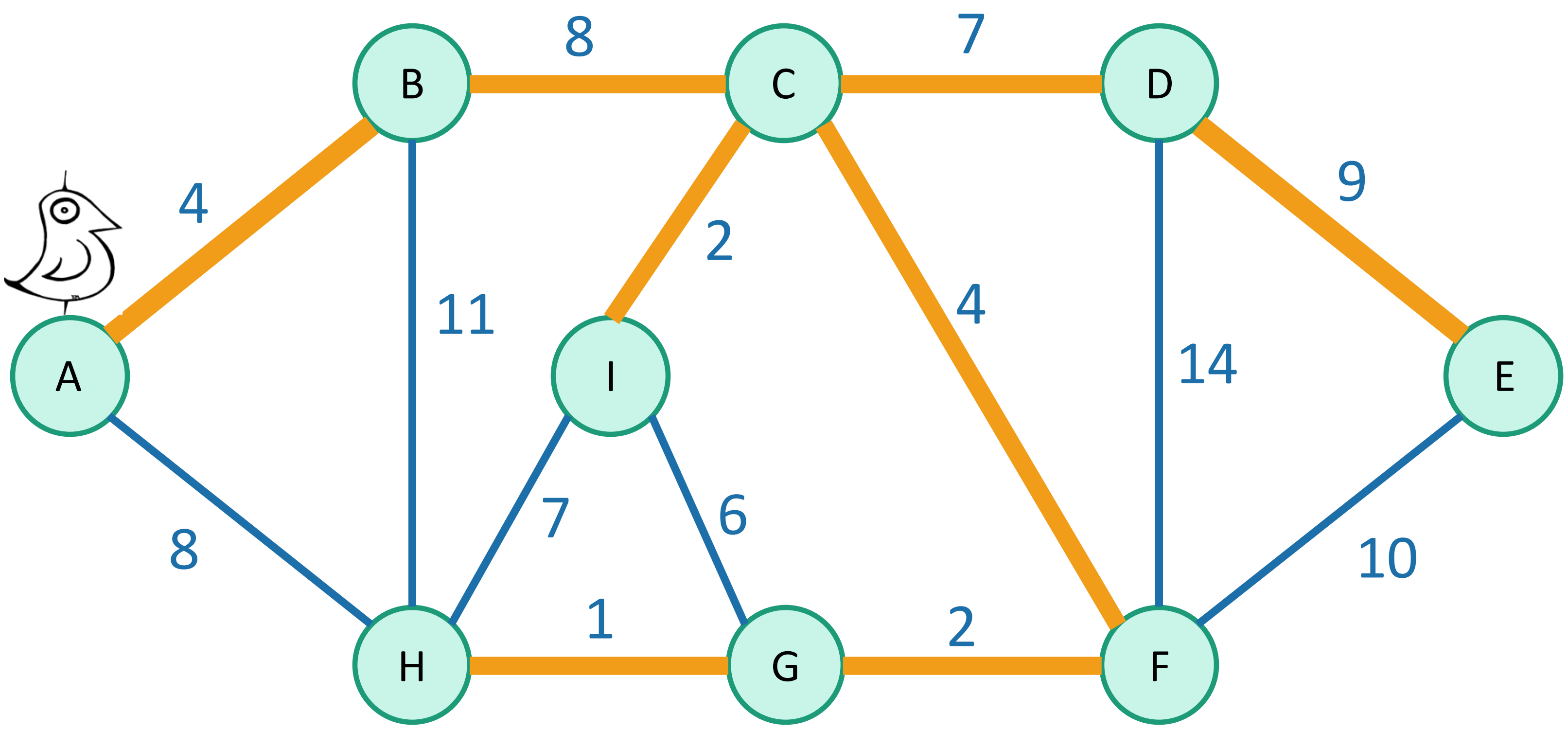
Idea 1

Start growing a tree, greedily add the shortest edge we can to grow the tree.



Idea 1

Start growing a tree, greedily add the shortest edge we can to grow the tree.



We've discovered

Prim's algorithm!

- slowPrim(G = (V,E), starting vertex s):
  - Let {s,u} be the lightest edge coming out of s.
  - MST = { {s,u} }
  - verticesVisited = { s, u }
  - **while** |verticesVisited| < |V|:
    - find the lightest edge {x,v} in E so that:
      - x is in verticesVisited
      - v is not in verticesVisited
    - add {x,v} to MST
    - add v to verticesVisited
  - **return** MST

At most n iterations of this while loop.

Time at most m to go through all the edges and find the lightest.

Naively, the running time is O(nm):

- For each of $\leq$n iterations of the while loop:
  - Go through all the edges.

Two questions

1. Does it work?
    - That is, does it actually return a MST?

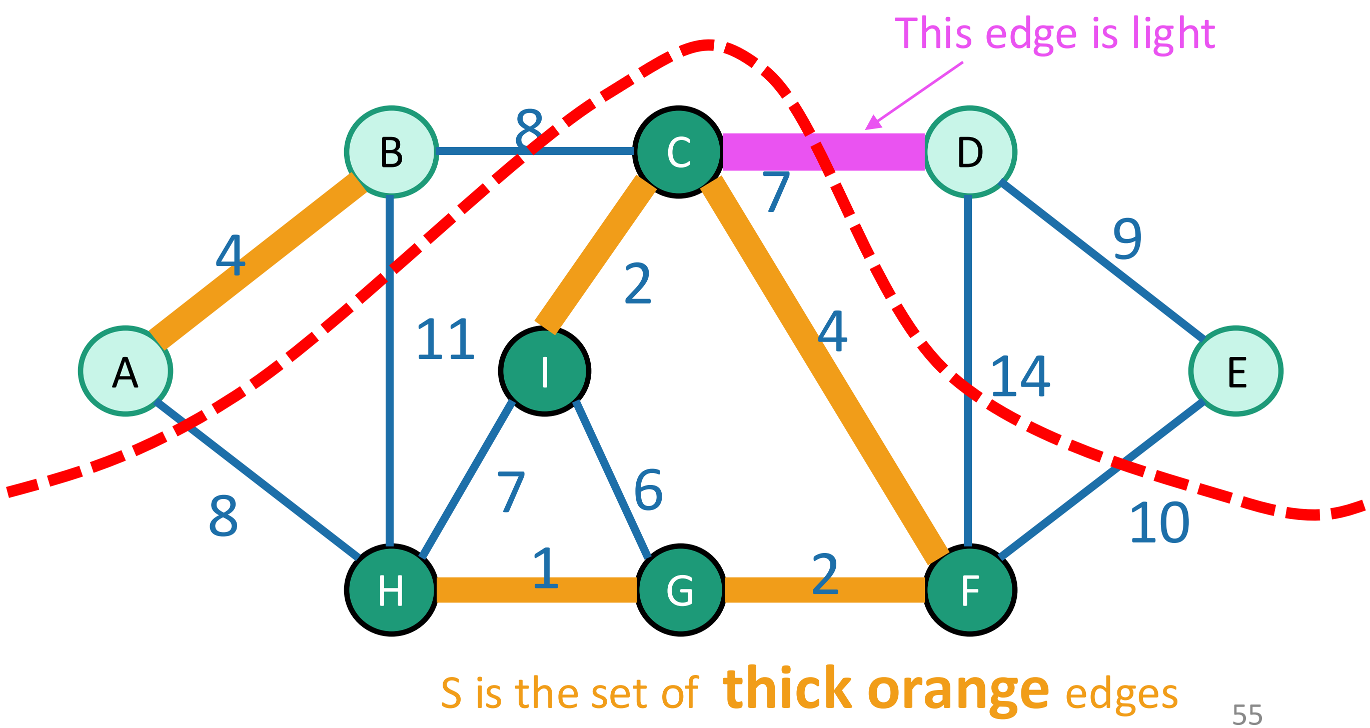
2. ~~Is it fast?~~ How do we make it fast?
    - the pseudocode above says “slowPrim”…

Does it work?

- We need to show that our greedy choices **don't rule out success.**
- That is, at every step:
  - If there exists an MST that contains all of the edges S we have added so far…
  - …then when we make our next choice {u,v}, there is still an MST containing S and {u,v}.
- Now it is time to use our lemma!

Lemma

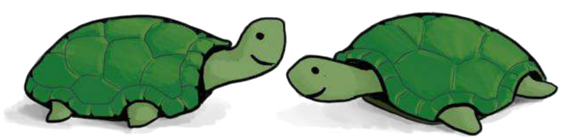
- Let S be a set of edges, and consider a cut that respects S.
- Suppose there is an MST containing S.
- Let {u,v} be a light edge.
- Then there is an MST containing S ∪ {{u,v}}



Partway through Prim

- Assume that our choices **S** so far don't rule out success
  - There is an MST consistent with those choices

How can we use our lemma to show that our next choice also does not rule out success?

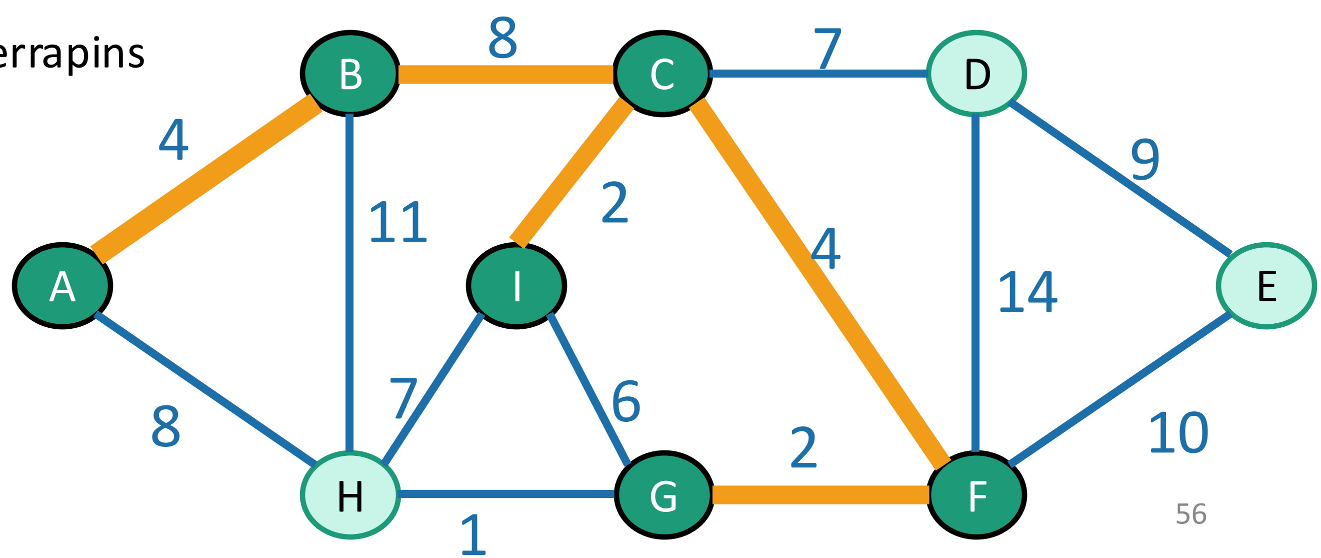


Think-Pair-Share Terrapins

Lemma

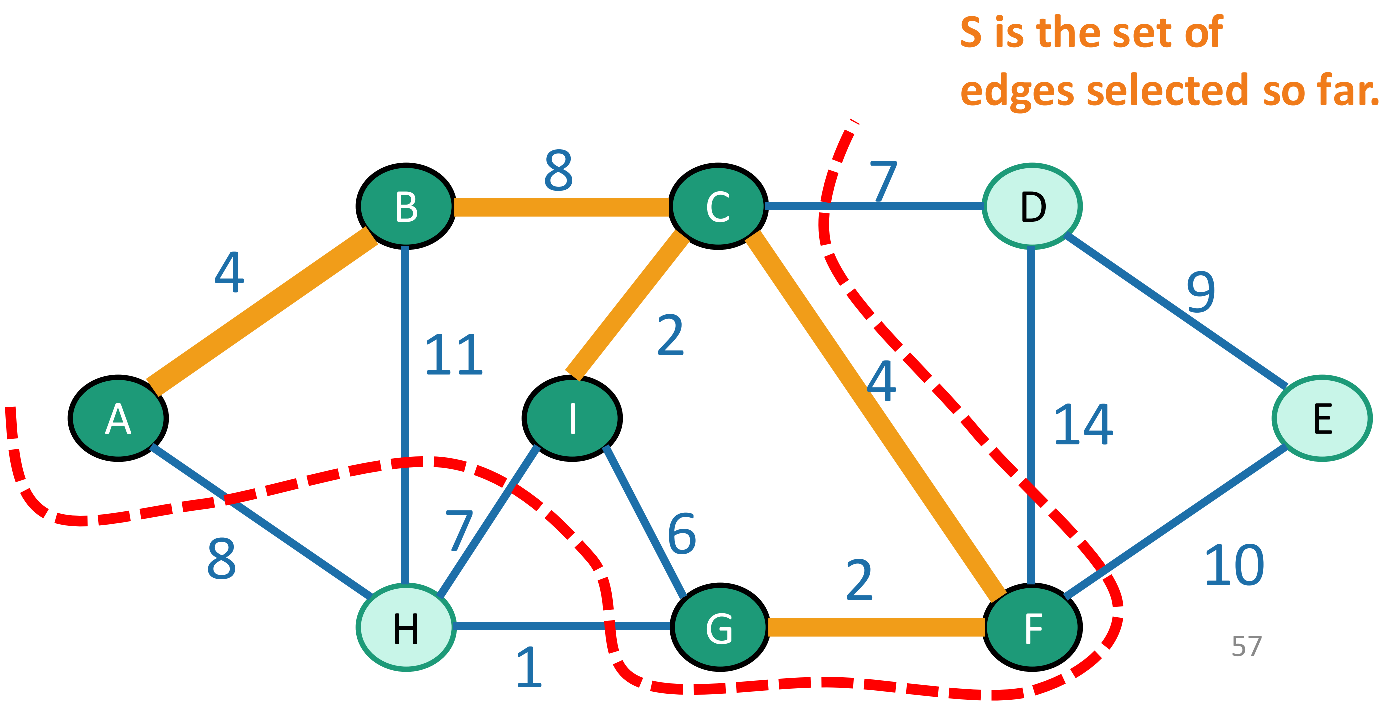
- Let S be a set of edges, and consider a cut that respects S.
- Suppose there is an MST containing S.
- Let {u,v} be a light edge.
- Then there is an MST containing S U {{u,v}}

S is the set of edges selected so far.



Partway through Prim

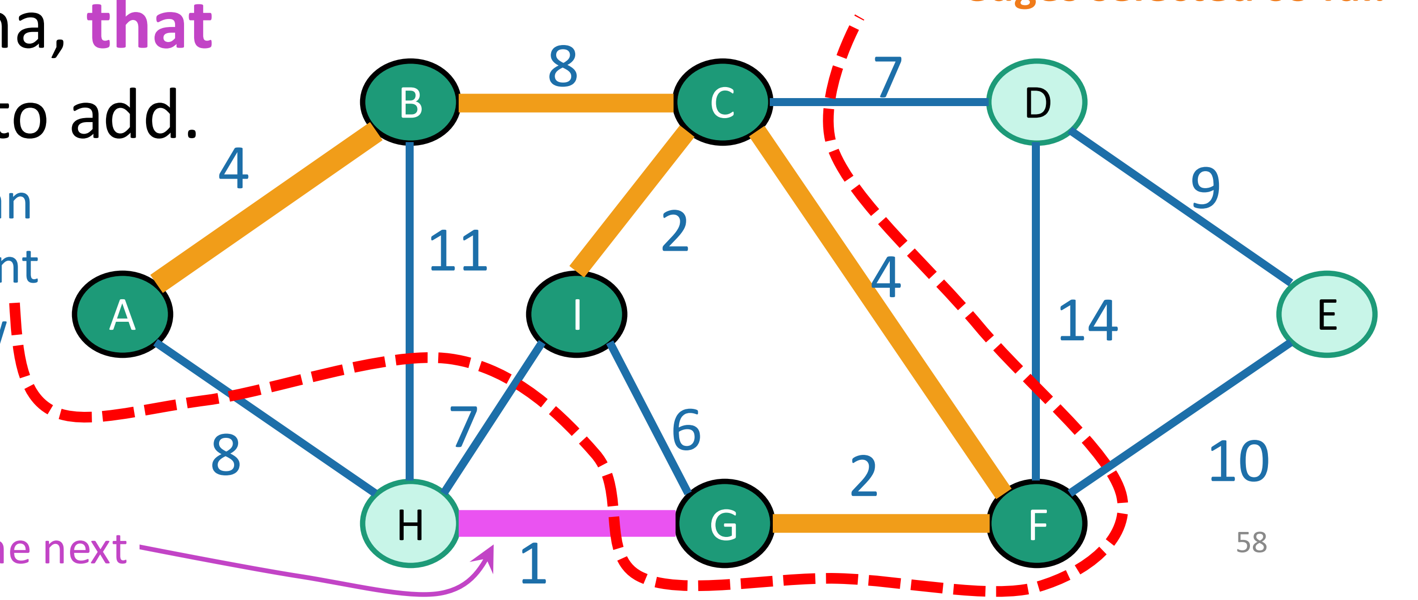
- Assume that our choices **S** so far don't rule out success
  - There is an MST consistent with those choices
- Consider the cut {**visited**, **unvisited**}
  - This cut respects S.



Partway through Prim

- Assume that our choices **S** so far don't rule out success
  - There is an MST consistent with these choices
- Consider the cut {**visited**, **unvisited**}
  - This cut respects S.
- The edge we add next is a **light edge**.
  - Least weight of any edge crossing the cut.

- By the Lemma, **that edge** is safe to add.
  - There is still an MST consistent with the new set of edges.



Hooray!

- Our greedy choices **don't rule out success**.
- This is enough (along with an argument by induction) to guarantee correctness of Prim's algorithm.

(See skipped next slide for a few more details)

Formally(ish)

SLIDE SKIPPED IN CLASS

- Inductive hypothesis:
  - After adding the t'th edge, there exists an MST with the edges added so far.
- Base case:
  - After adding the 0'th edge, there exists an MST with the edges added so far. **YEP.**
- Inductive step:
  - If the inductive hypothesis holds for t (aka, the choices so far are safe), then it holds for t+1 (aka, the next edge we add is safe).
  - **That's what we just showed.**
- Conclusion:
  - After adding the n-1'st edge, there exists an MST with the edges added so far.
  - At this point we have a spanning tree, so it better be minimal.

Two questions

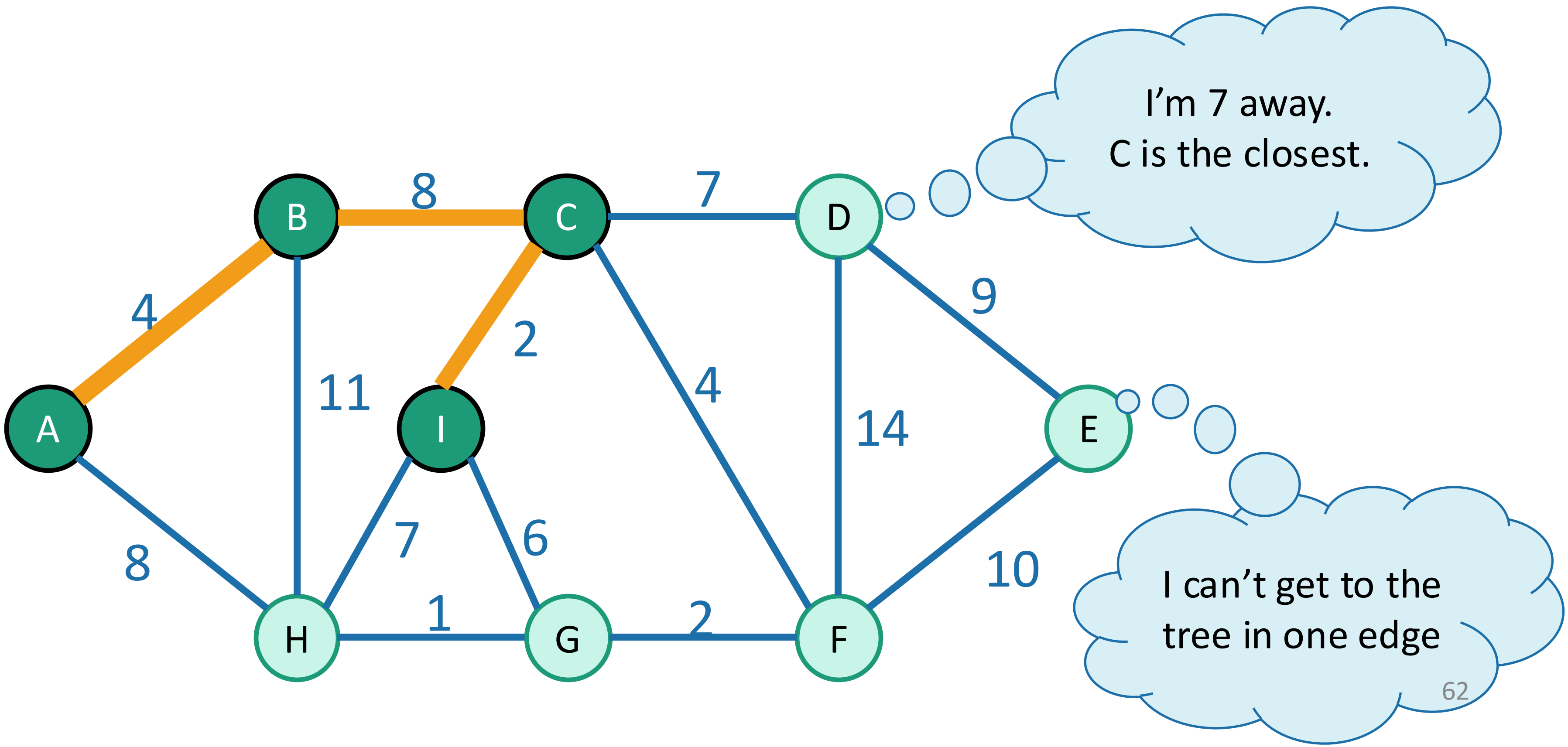
1. Does it work?
   - That is, does it actually return a MST?
     - **Yes!**

2. How do we actually implement this?
   - the pseudocode above says "slowPrim"…

How do we actually implement this?

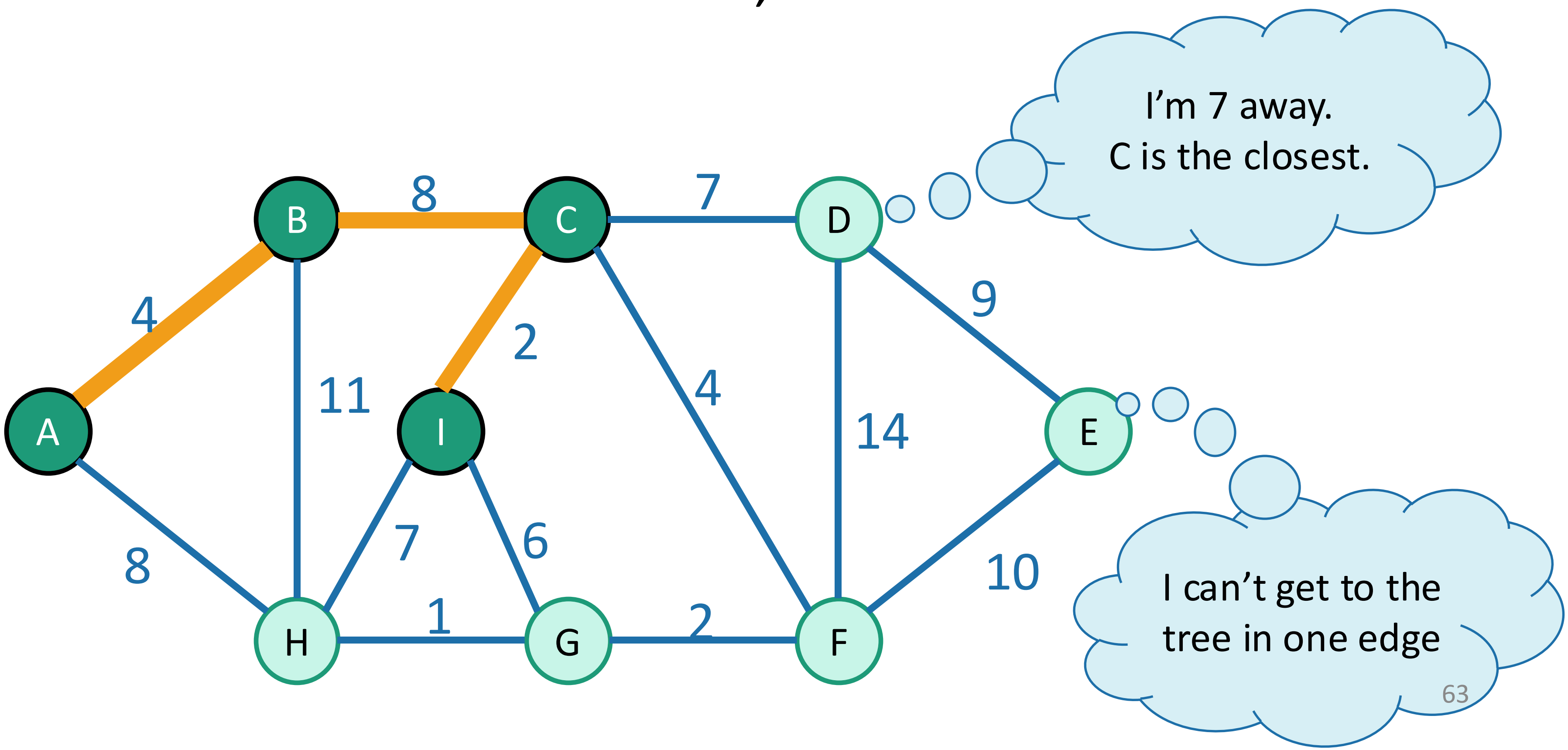
- Each vertex keeps:
  - the **distance** from itself to the **growing spanning tree**
  - **how to get there**.

if you can get there in one edge.



How do we actually implement this?

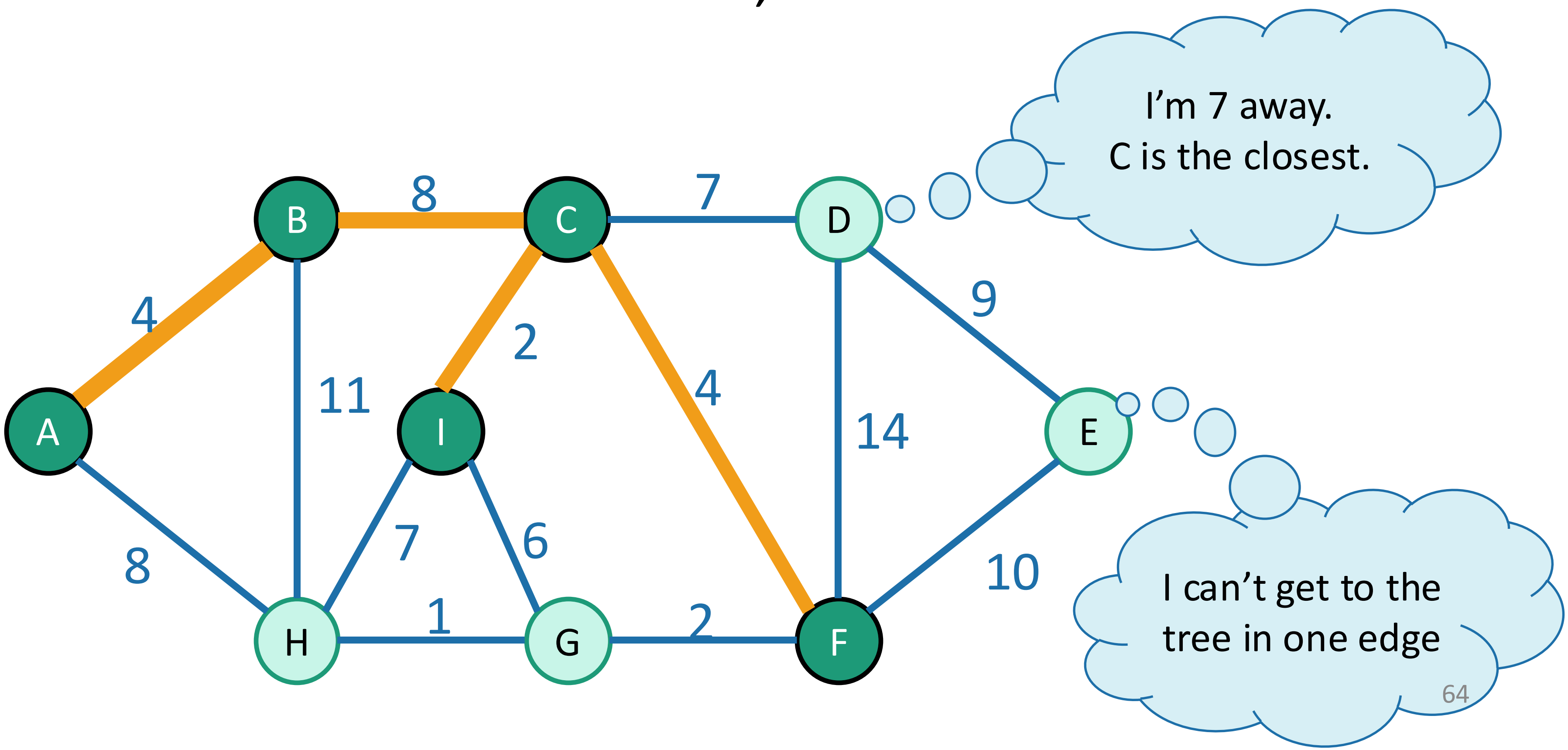
- Each vertex keeps:
  - the **distance** from itself to the **growing spanning tree** if you can get there in one edge.
  - **how to get there**.
- Choose the closest vertex, add it.



How do we actually implement this?

- Each vertex keeps:
  - the **distance** from itself to the **growing spanning tree**
  - **how to get there**.

  if you can get there in one edge.
- Choose the closest vertex, add it.

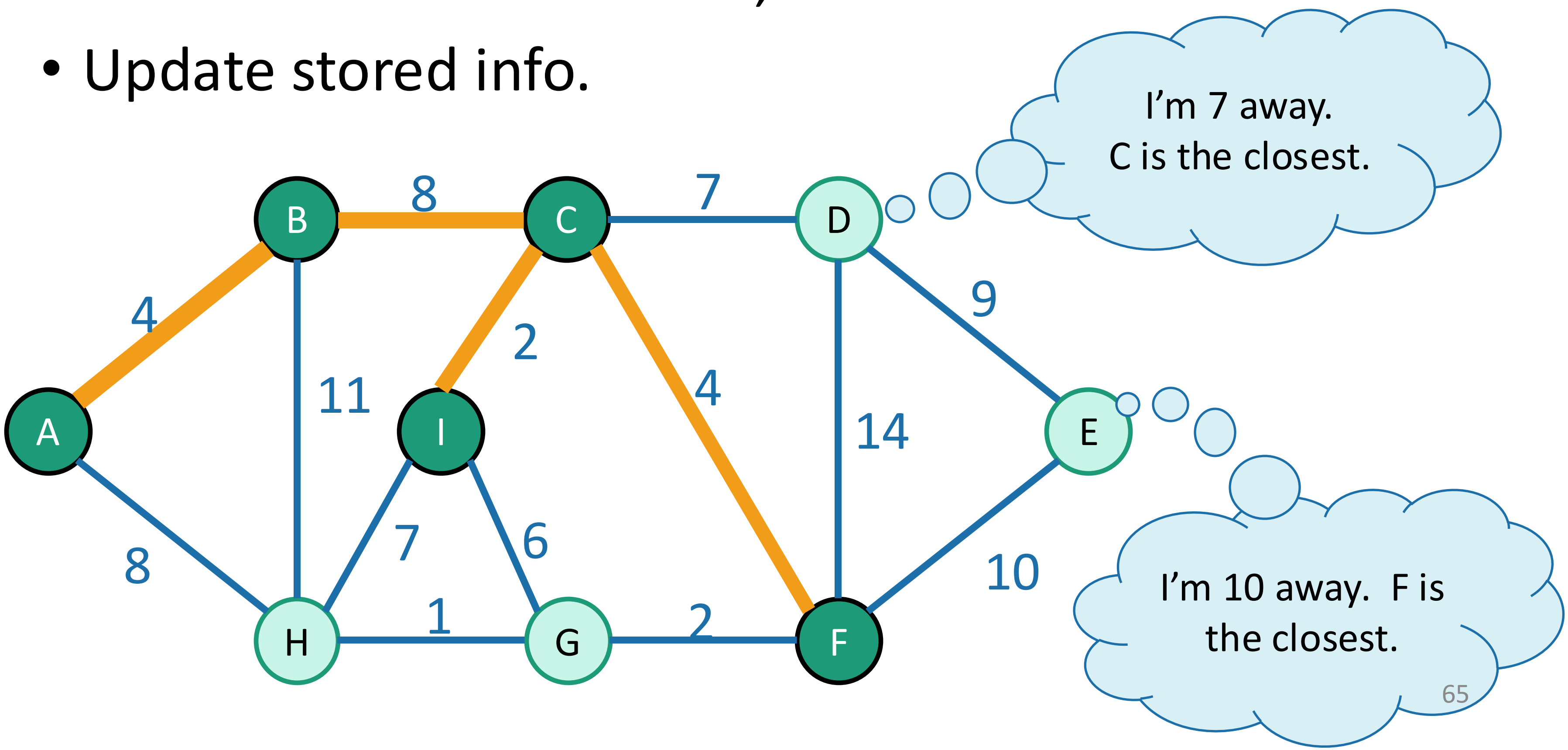


How do we actually implement this?

- Each vertex keeps:
  - the **distance** from itself to the **growing spanning tree**
  - **how to get there**.

if you can get there in one edge.

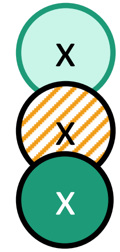
- Choose the closest vertex, add it.
- Update stored info.



Efficient implementation

Every vertex has a key and a parent

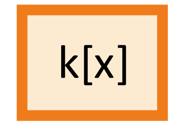
Until all the vertices are **reached:**



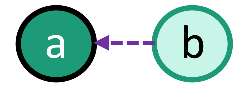
Can't reach x yet

x is "active"

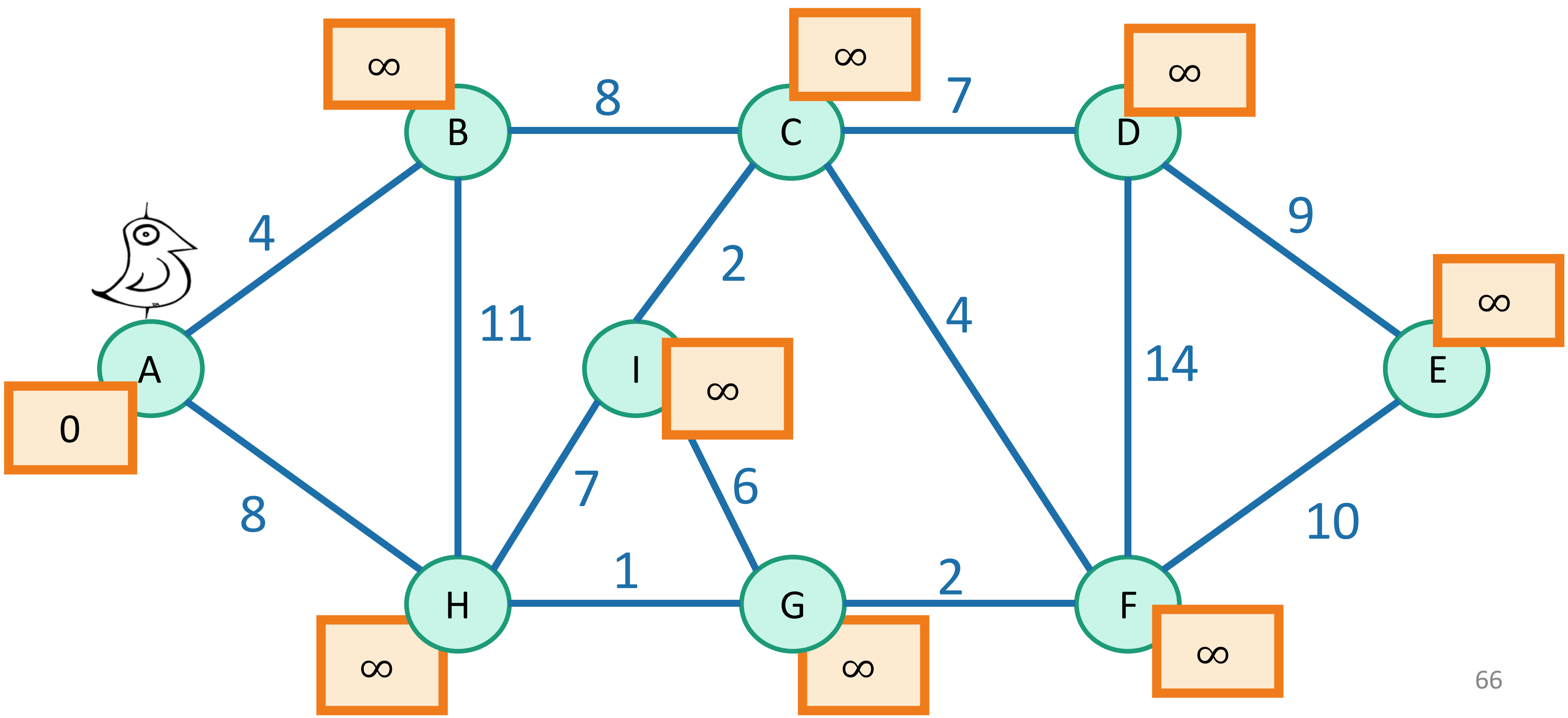
Can reach x



k[x] is the distance of x from the growing tree



p[b] = a, meaning that a was the vertex that k[b] comes from.



Efficient implementation

Every vertex has a key and a parent

Until all the vertices are **reached:**

- Activate the **unreached** vertex u with the smallest key.

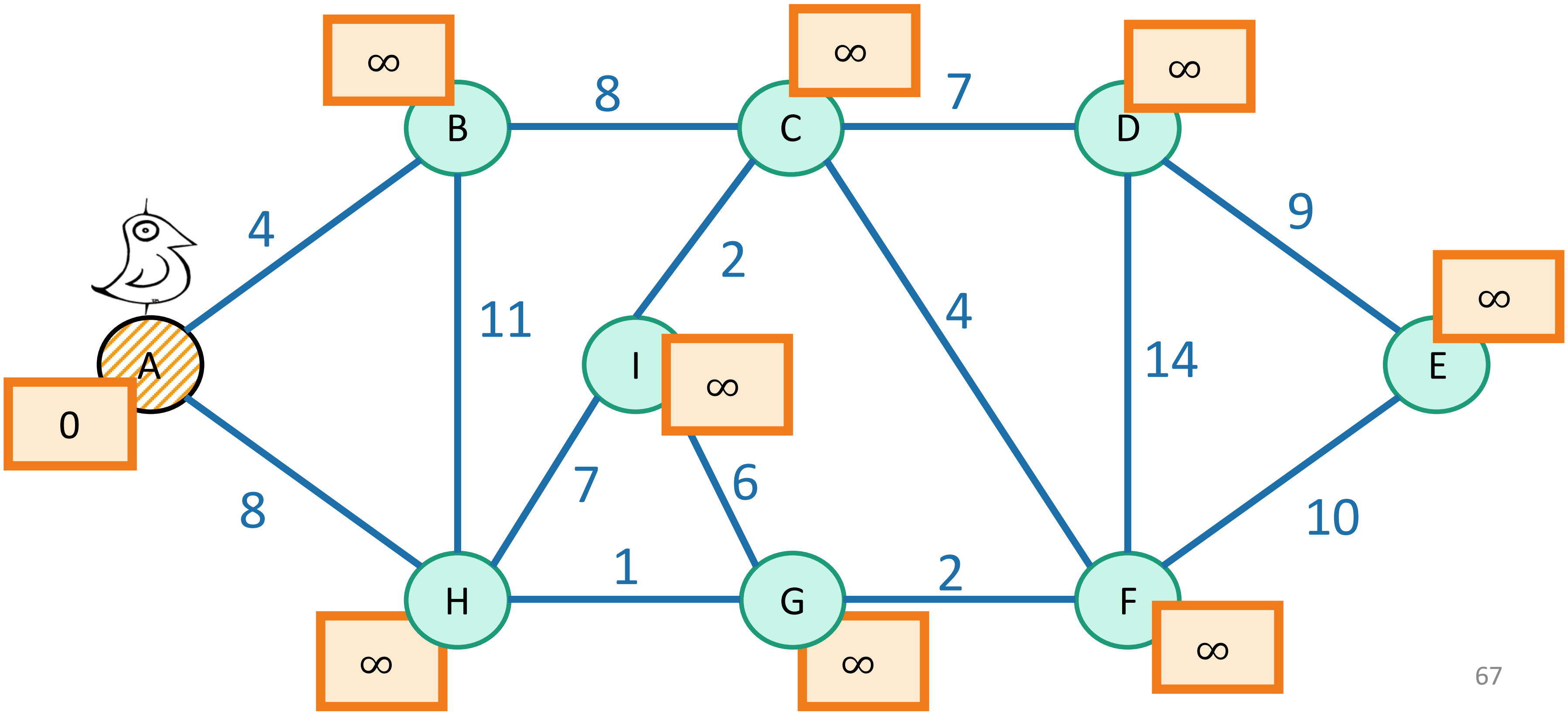
x Can't reach x yet

x x is "active"

x Can reach x

k[x] k[x] is the distance of x from the growing tree

a b p[b] = a, meaning that a was the vertex that k[b] comes from.

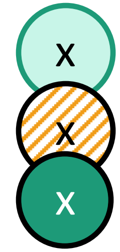


Efficient implementation

Every vertex has a key and a parent

Until all the vertices are **reached:**

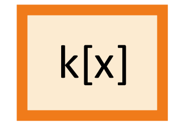
- Activate the **unreached** vertex u with the smallest key.
- **for each** of u’s unreached neighbors v:
  - k[v] = min(k[v], weight(u,v))
  - if k[v] updated, p[v] = u



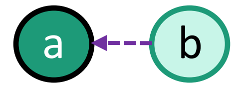
Can’t reach x yet

x is “active”

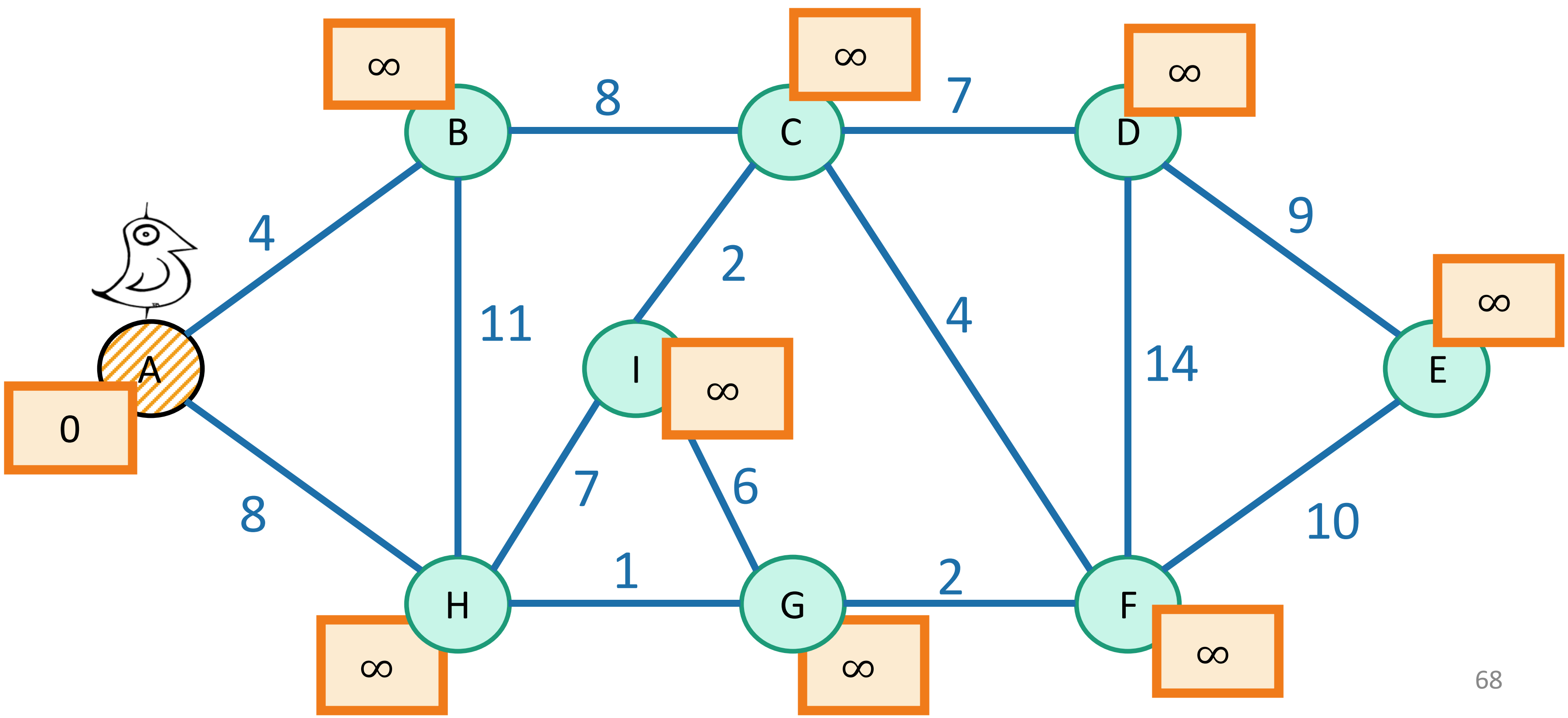
Can reach x



k[x] is the distance of x from the growing tree



p[b] = a, meaning that a was the vertex that k[b] comes from.



Efficient implementation

Every vertex has a key and a parent

Can't reach x yet

x is "active"

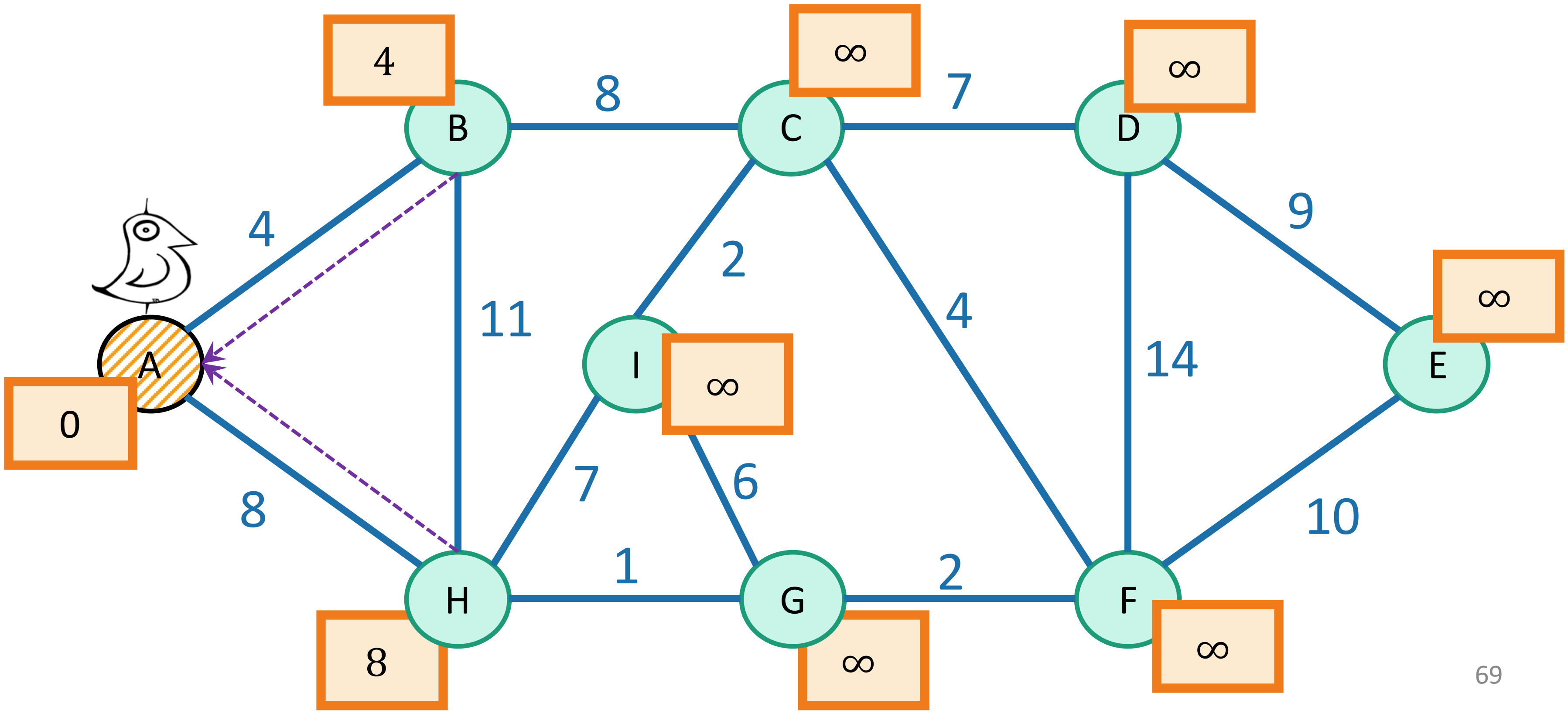
Can reach x

k[x] is the distance of x from the growing tree

p[b] = a, meaning that a was the vertex that k[b] comes from.

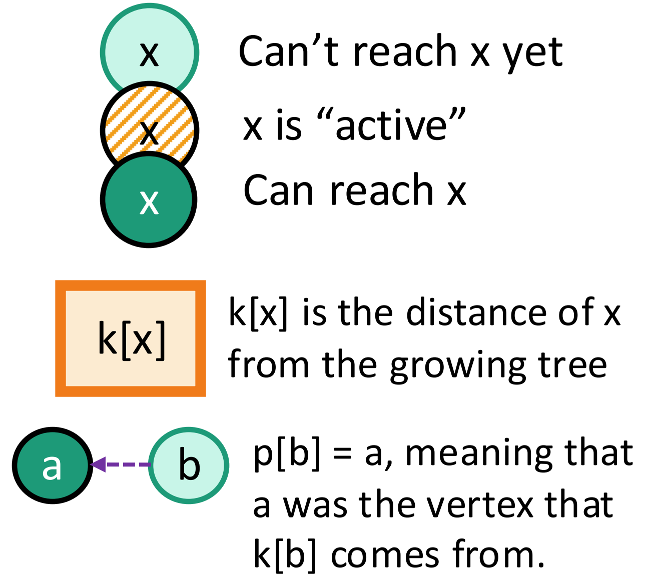
Until all the vertices are **reached:**

- Activate the **unreached** vertex u with the smallest key.
- **for each** of u's unreached neighbors v:
  - k[v] = min(k[v], weight(u,v))
  - if k[v] updated, p[v] = u



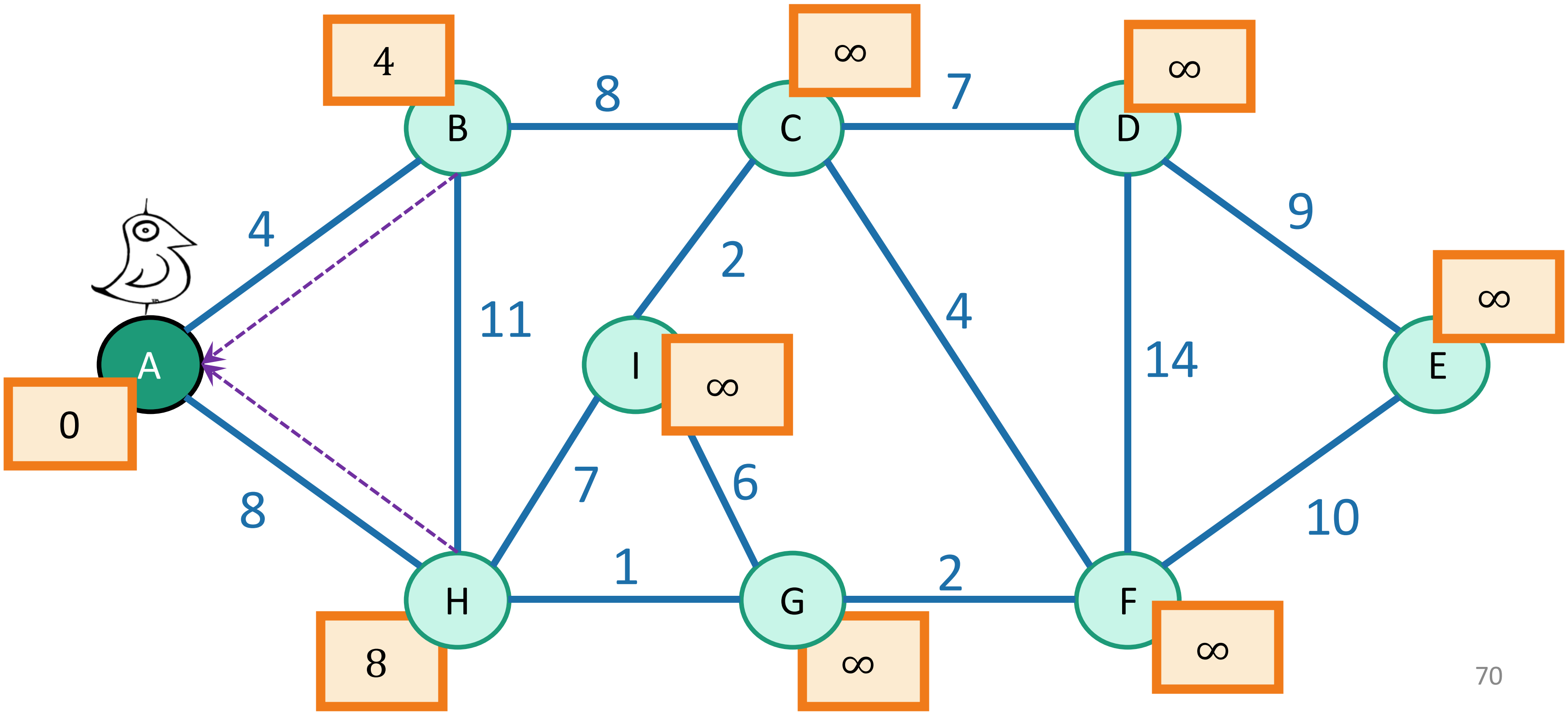
Efficient implementation

Every vertex has a key and a parent



Until all the vertices are **reached:**

- Activate the **unreached** vertex u with the smallest key.
- **for each** of u's unreached neighbors v:
  - k[v] = min(k[v], weight(u,v))
  - if k[v] updated, p[v] = u
- Mark u as **reached,** and **add {p[u],u} to MST.**

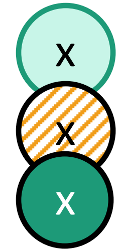


Efficient implementation

Every vertex has a key and a parent

Until all the vertices are **reached:**

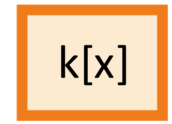
- Activate the **unreached** vertex u with the smallest key.
- **for each** of u's unreached neighbors v:
    - k[v] = min(k[v], weight(u,v))
    - if k[v] updated, p[v] = u
- Mark u as **reached,** and **add {p[u],u} to MST.**



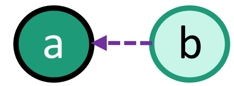
Can't reach x yet

x is "active"

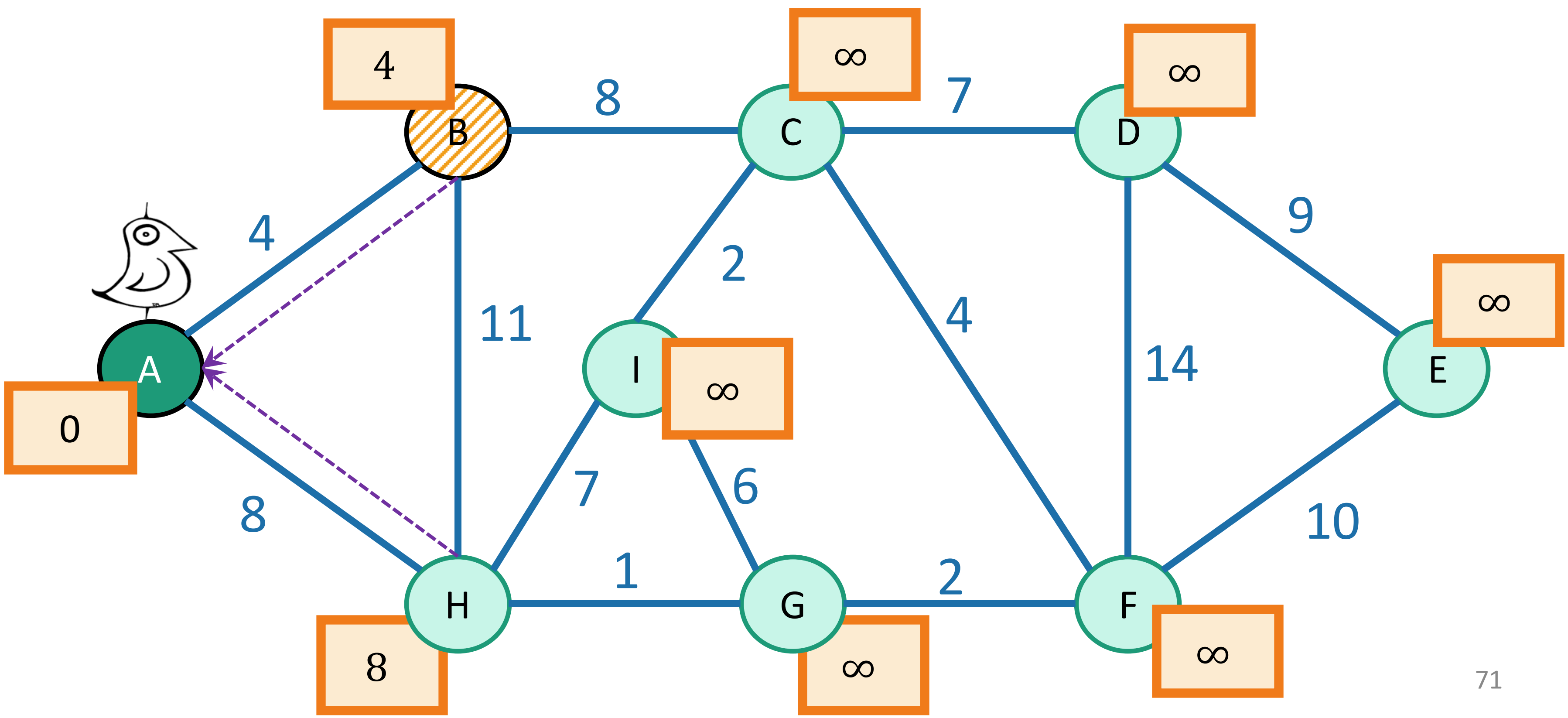
Can reach x



k[x] is the distance of x from the growing tree

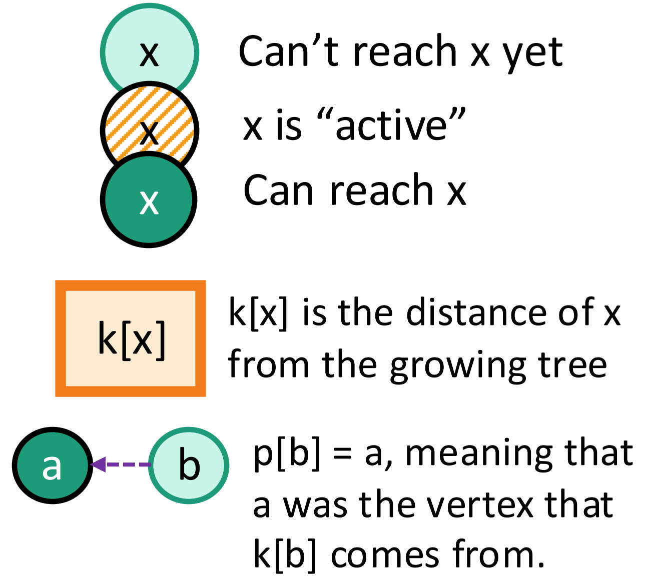


p[b] = a, meaning that a was the vertex that k[b] comes from.



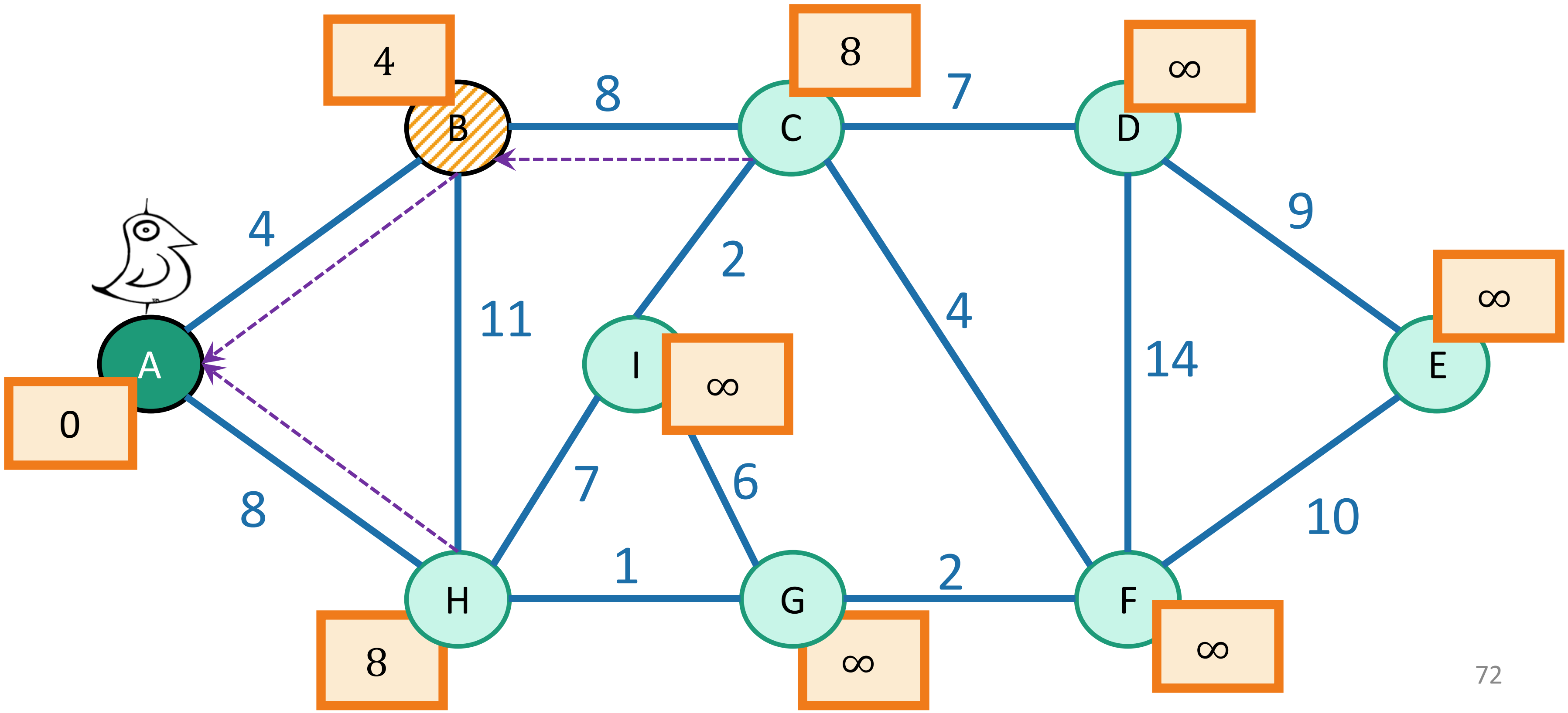
Efficient implementation

Every vertex has a key and a parent



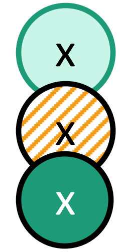
Until all the vertices are **reached:**

- Activate the **unreached** vertex u with the smallest key.
- **for each** of u's unreached neighbors v:
  - k[v] = min(k[v], weight(u,v))
  - if k[v] updated, p[v] = u
- Mark u as **reached,** and **add {p[u],u} to MST.**



Efficient implementation

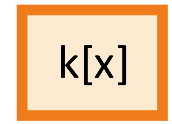
Every vertex has a key and a parent



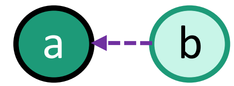
Can't reach x yet

x is "active"

Can reach x



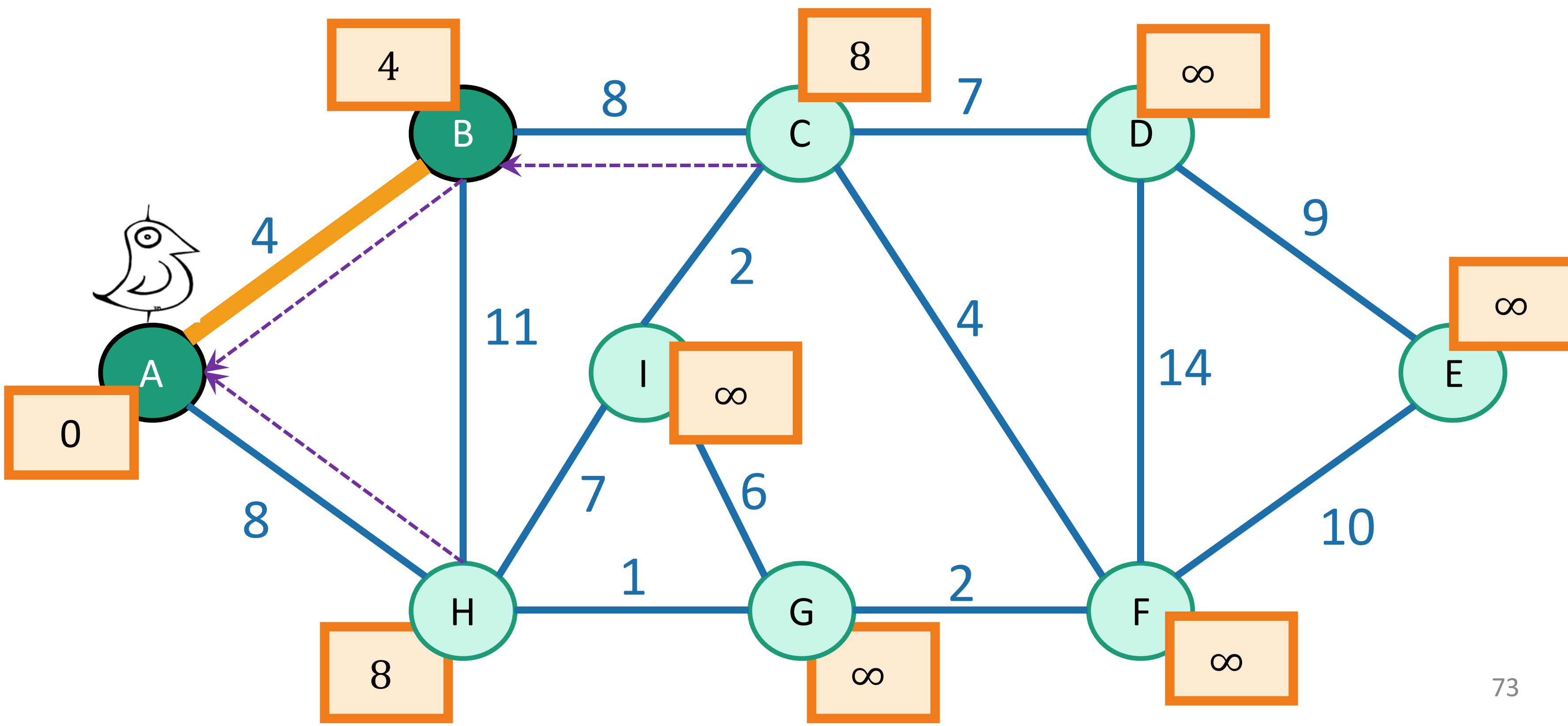
k[x] is the distance of x from the growing tree



p[b] = a, meaning that a was the vertex that k[b] comes from.

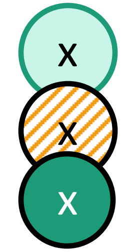
Until all the vertices are **reached:**

- Activate the **unreached** vertex u with the smallest key.
- **for each** of u's unreached neighbors v:
  - k[v] = min(k[v], weight(u,v))
  - if k[v] updated, p[v] = u
- Mark u as **reached,** and **add {p[u],u} to MST.**



Efficient implementation

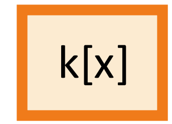
Every vertex has a key and a parent



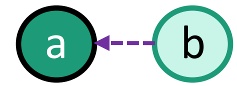
Can't reach x yet

x is "active"

Can reach x



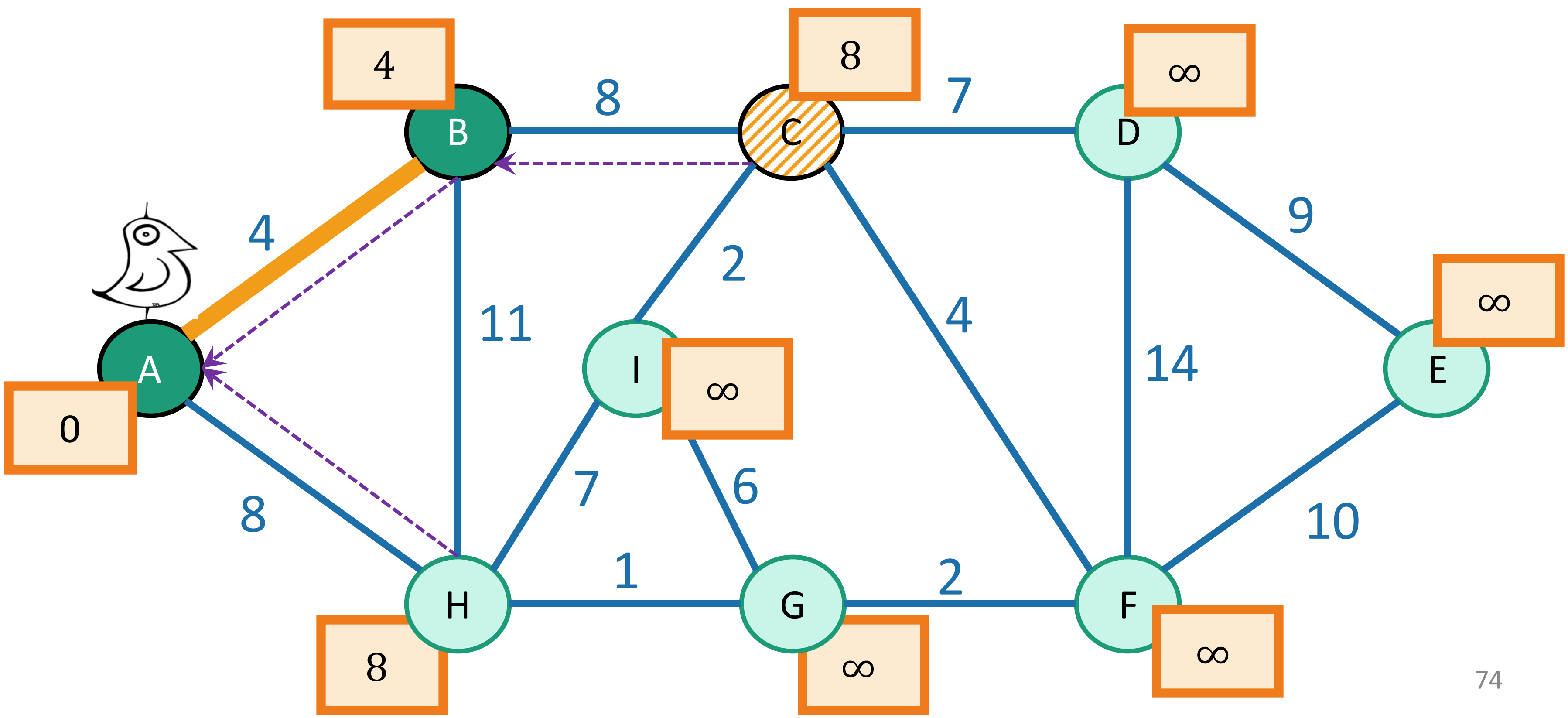
k[x] is the distance of x from the growing tree



p[b] = a, meaning that a was the vertex that k[b] comes from.

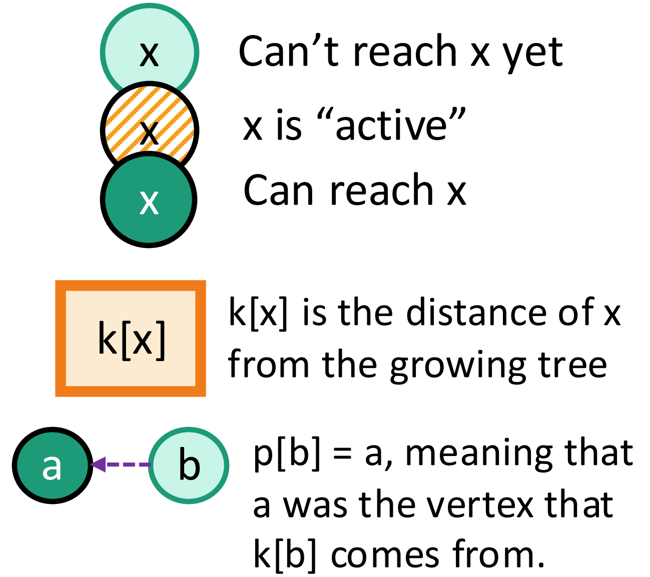
Until all the vertices are **reached:**

- Activate the **unreached** vertex u with the smallest key.
- **for each** of u's unreached neighbors v:
  - k[v] = min(k[v], weight(u,v))
  - if k[v] updated, p[v] = u
- Mark u as **reached,** and **add {p[u],u} to MST.**



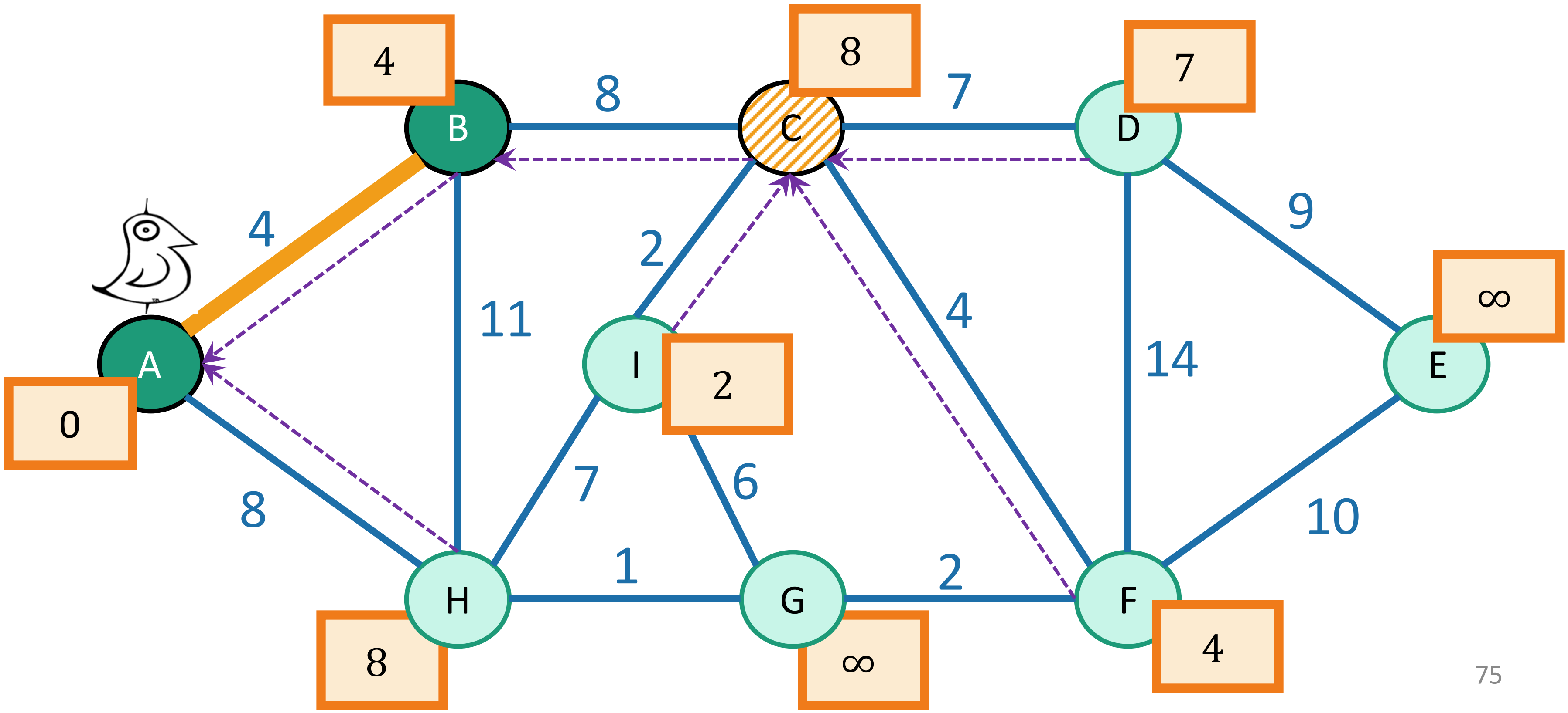
Efficient implementation

Every vertex has a key and a parent



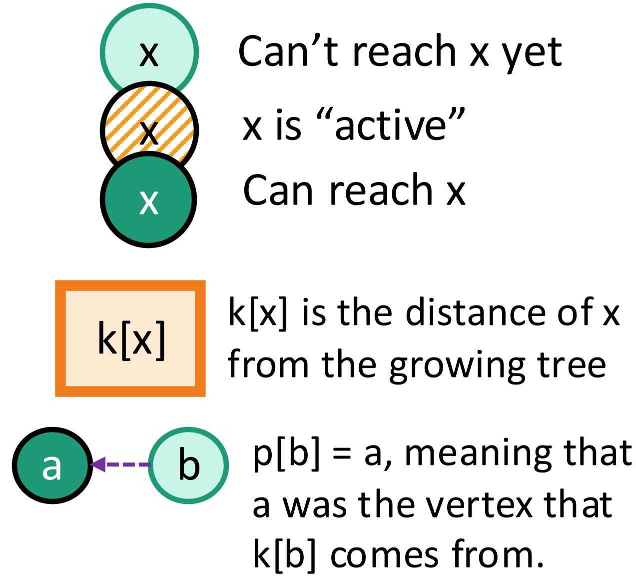
Until all the vertices are **reached:**

- Activate the **unreached** vertex u with the smallest key.
- **for each** of u's unreached neighbors v:
  - k[v] = min(k[v], weight(u,v))
  - if k[v] updated, p[v] = u
- Mark u as **reached,** and **add {p[u],u} to MST.**



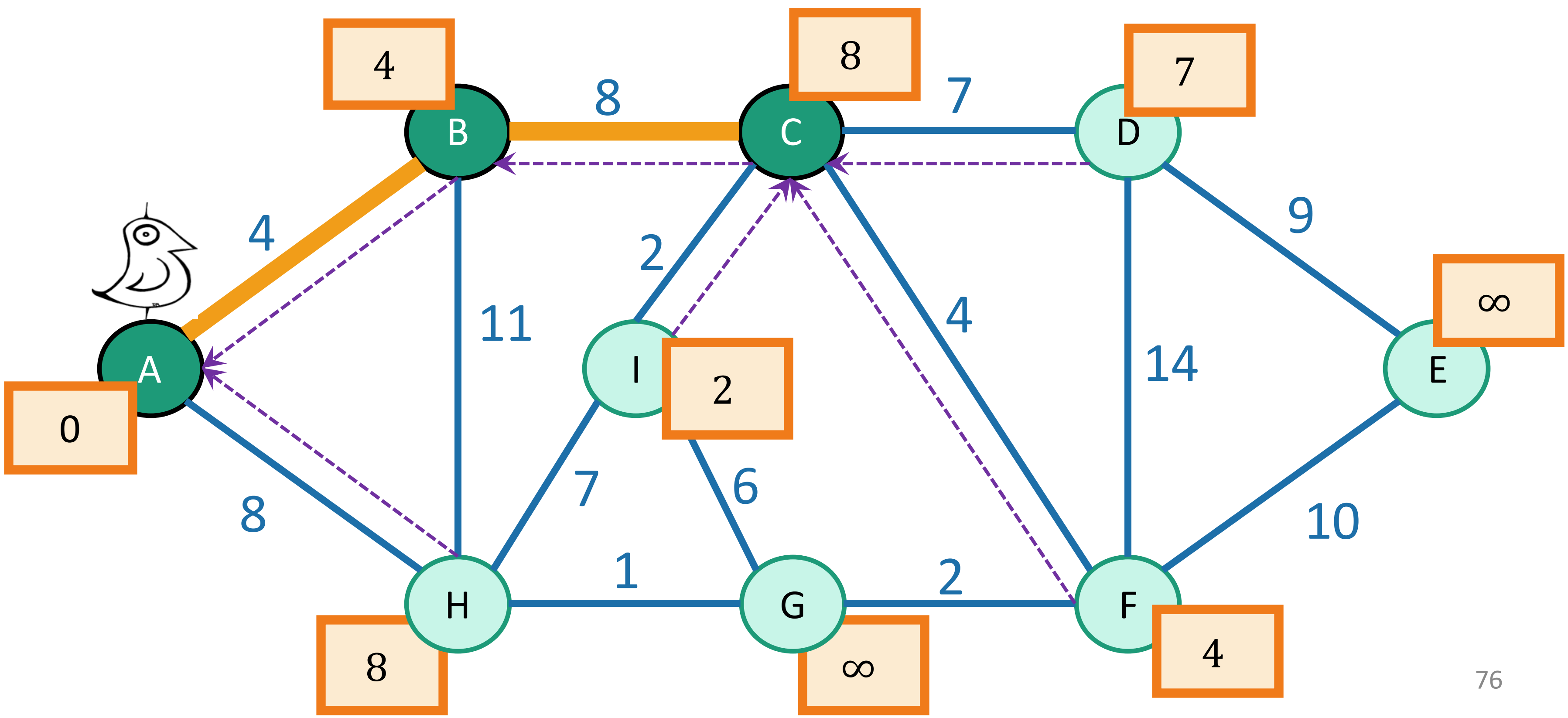
Efficient implementation

Every vertex has a key and a parent



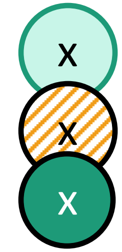
Until all the vertices are **reached:**

- Activate the **unreached** vertex u with the smallest key.
- **for each** of u's unreached neighbors v:
  - k[v] = min(k[v], weight(u,v))
  - if k[v] updated, p[v] = u
- Mark u as **reached,** and **add {p[u],u} to MST.**



Efficient implementation

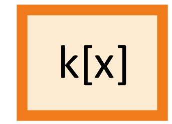
Every vertex has a key and a parent



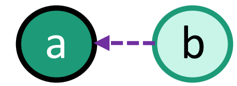
Can't reach x yet

x is "active"

Can reach x



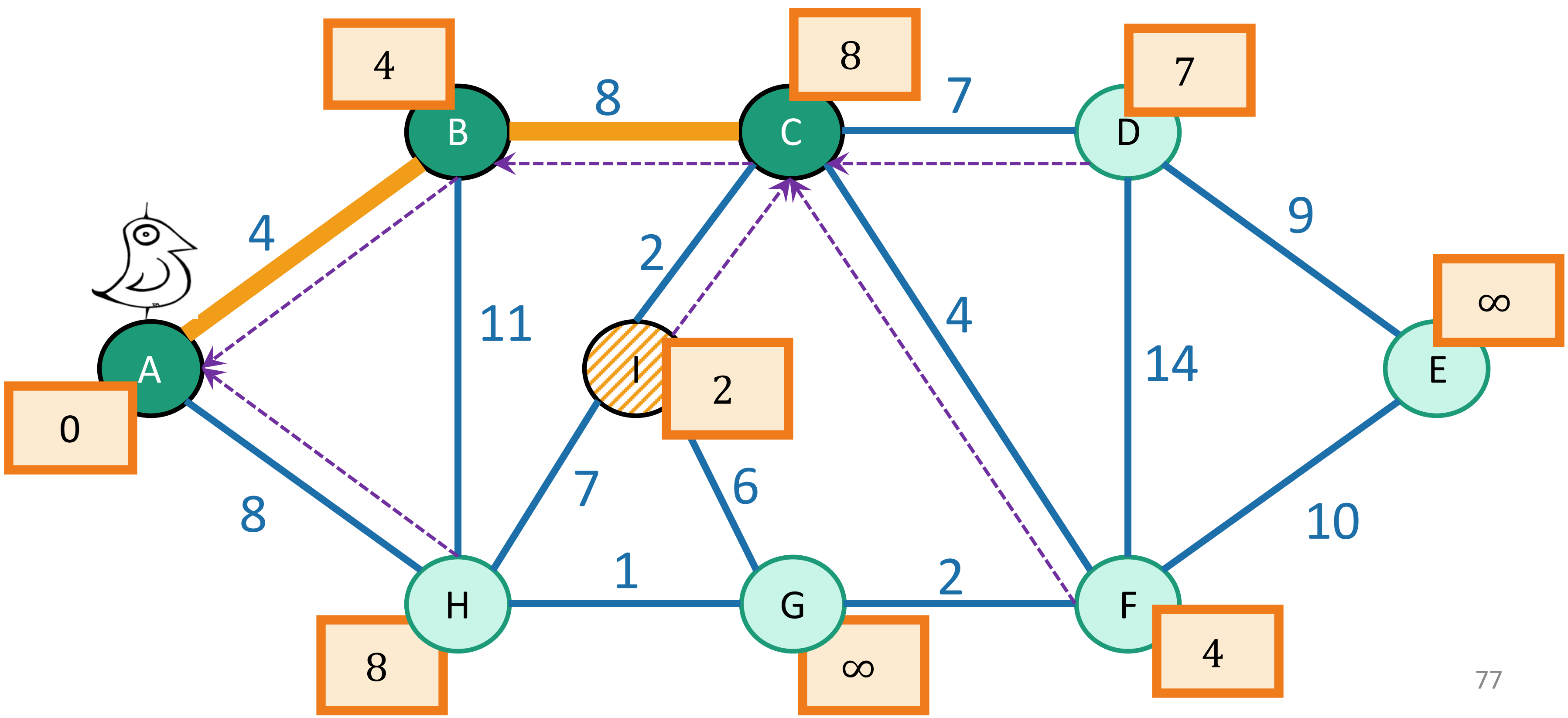
k[x] is the distance of x from the growing tree



p[b] = a, meaning that a was the vertex that k[b] comes from.

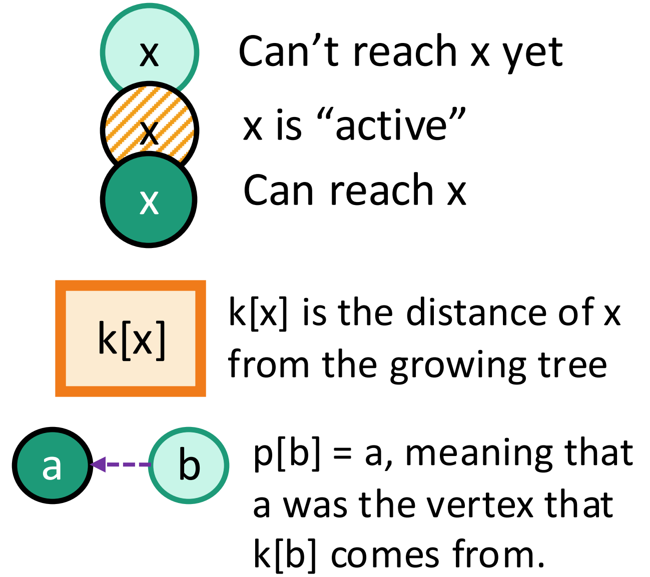
Until all the vertices are **reached:**

- Activate the **unreached** vertex u with the smallest key.
- **for each** of u's unreached neighbors v:
  - k[v] = min(k[v], weight(u,v))
  - if k[v] updated, p[v] = u
- Mark u as **reached,** and **add {p[u],u} to MST.**



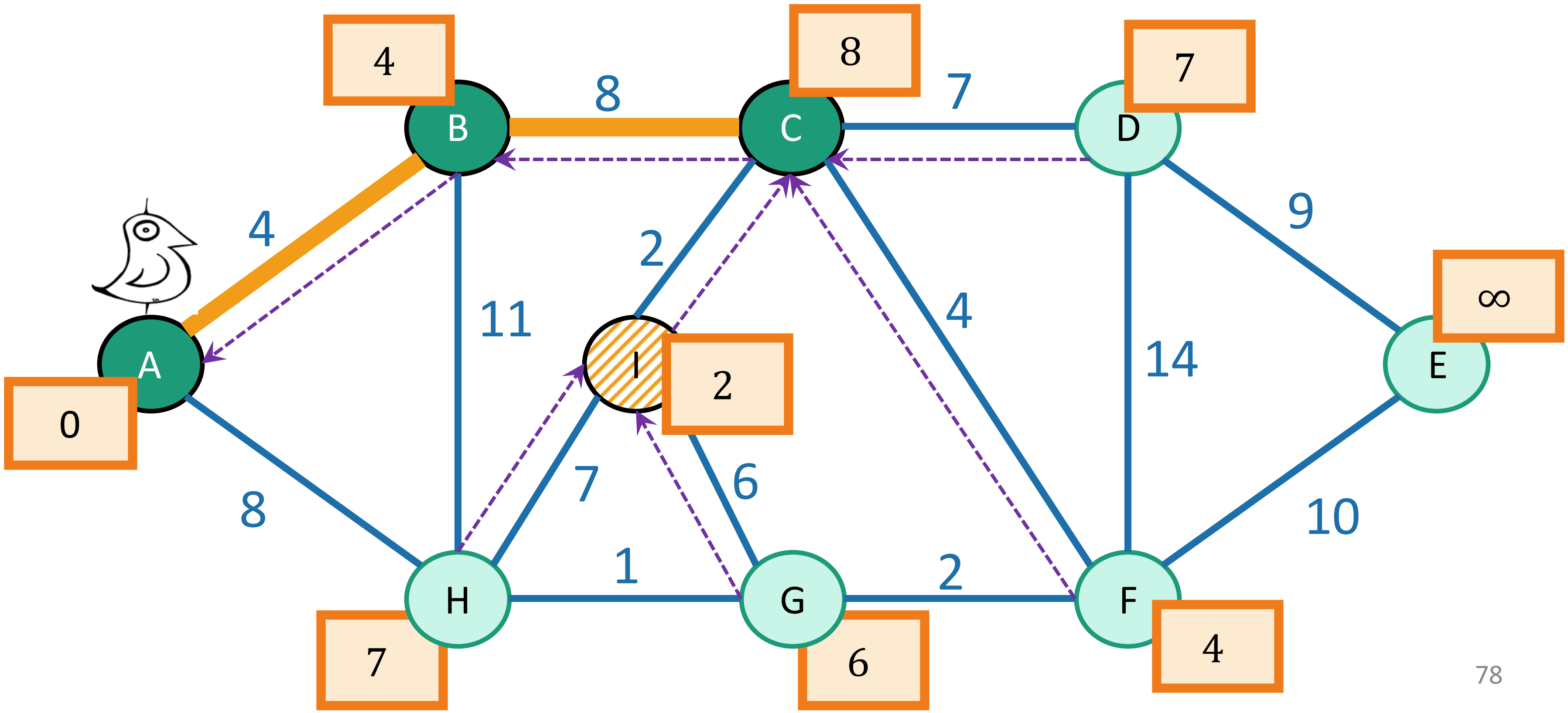
Efficient implementation

Every vertex has a key and a parent



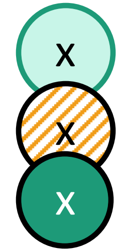
Until all the vertices are **reached:**

- Activate the **unreached** vertex u with the smallest key.
- **for each** of u's unreached neighbors v:
  - k[v] = min(k[v], weight(u,v))
  - if k[v] updated, p[v] = u
- Mark u as **reached,** and **add {p[u],u} to MST.**



Efficient implementation

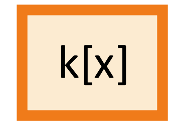
Every vertex has a key and a parent



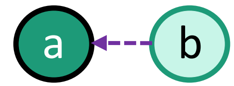
Can't reach x yet

x is "active"

Can reach x



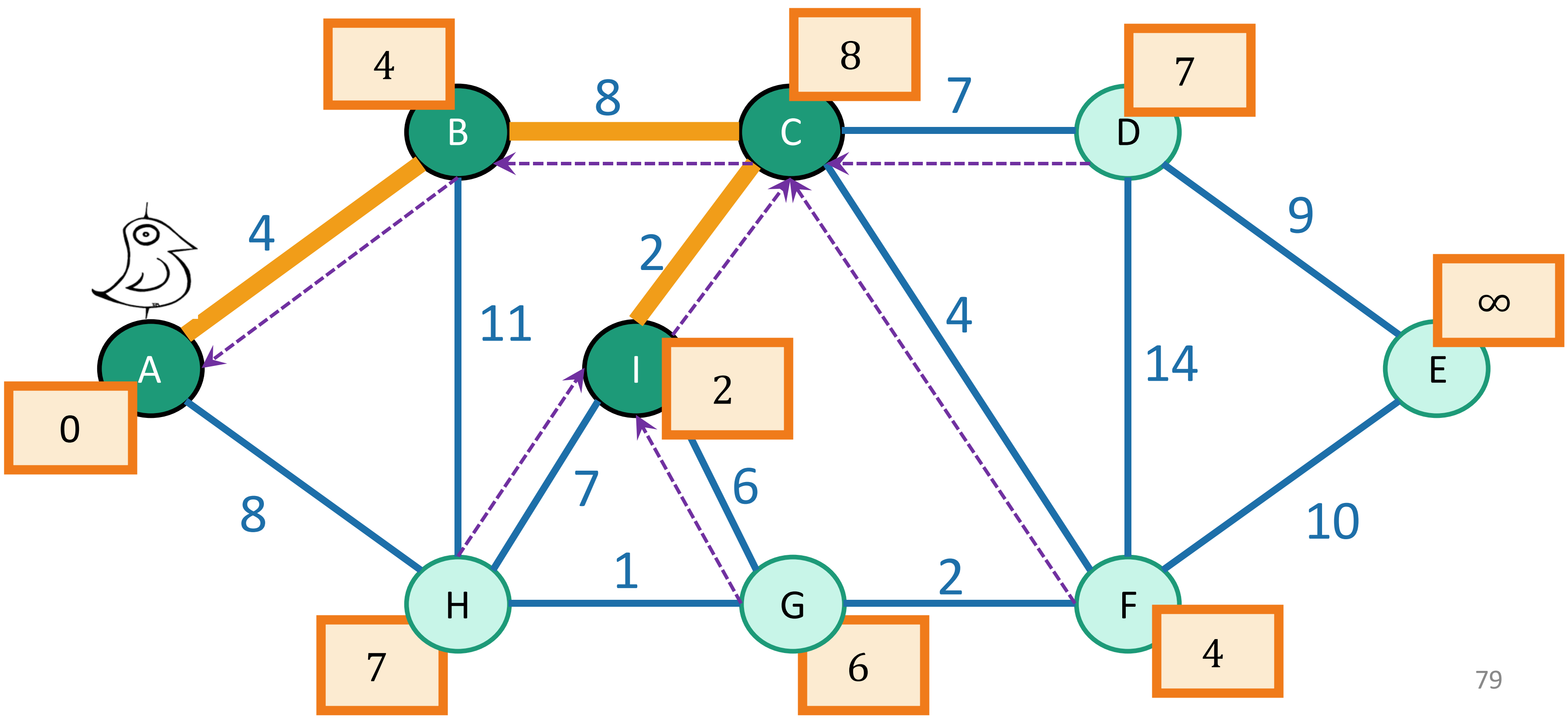
k[x] is the distance of x from the growing tree



p[b] = a, meaning that a was the vertex that k[b] comes from.

Until all the vertices are **reached:**

- Activate the **unreached** vertex u with the smallest key.
- **for each** of u's unreached neighbors v:
  - k[v] = min(k[v], weight(u,v))
  - if k[v] updated, p[v] = u
- Mark u as **reached,** and **add {p[u],u} to MST.**

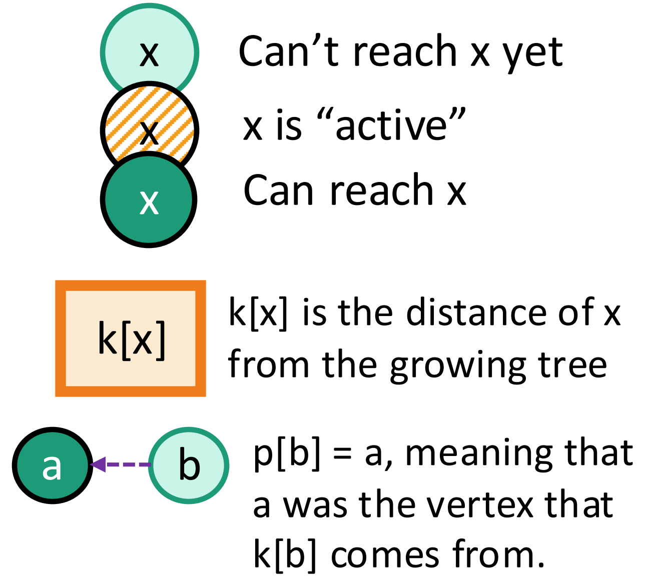


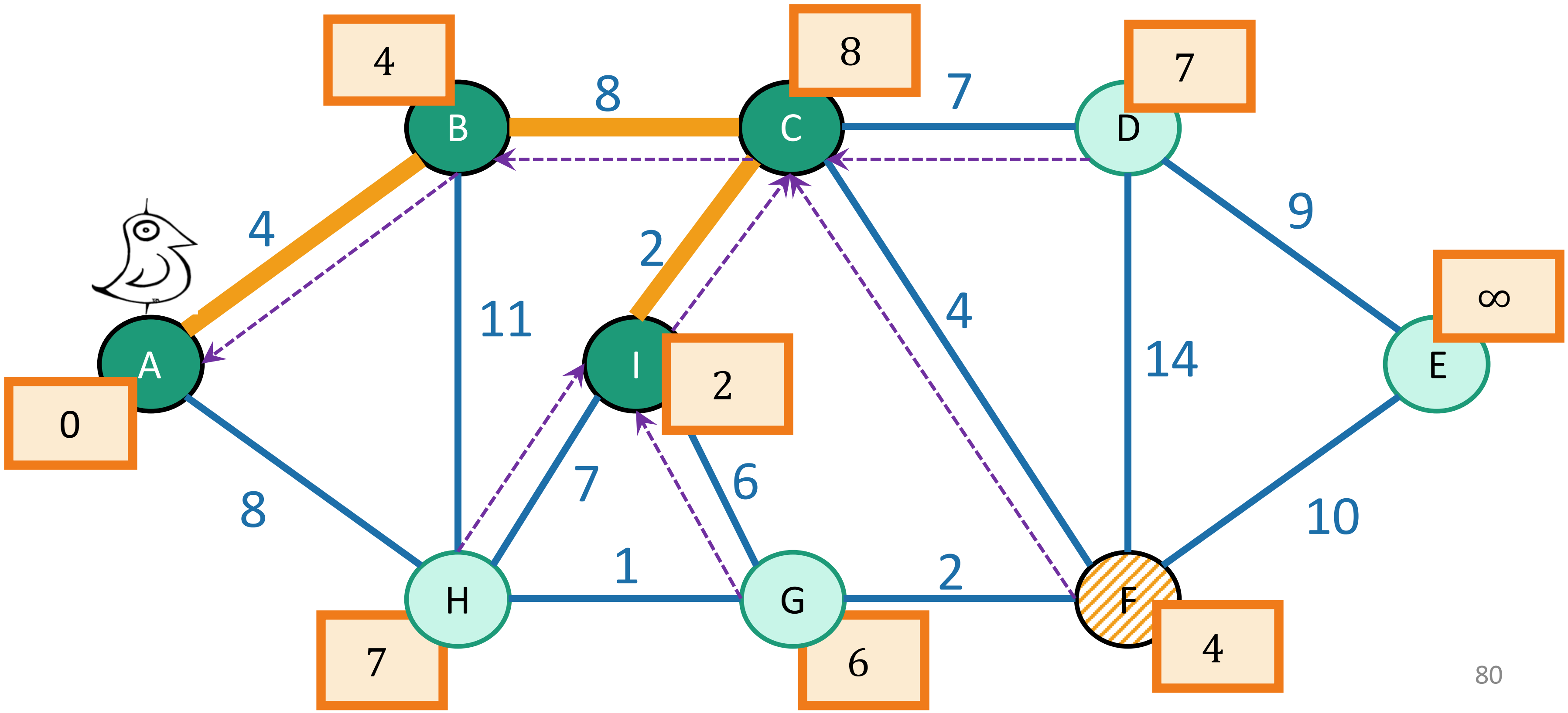
Efficient implementation

Every vertex has a key and a parent

Until all the vertices are **reached:**

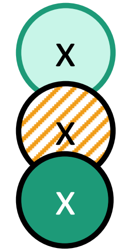
- Activate the **unreached** vertex u with the smallest key.
- **for each** of u's unreached neighbors v:
  - k[v] = min(k[v], weight(u,v))
  - if k[v] updated, p[v] = u
- Mark u as **reached,** and **add {p[u],u} to MST.**





Efficient implementation

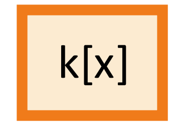
Every vertex has a key and a parent



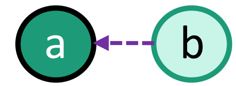
Can't reach x yet

x is "active"

Can reach x



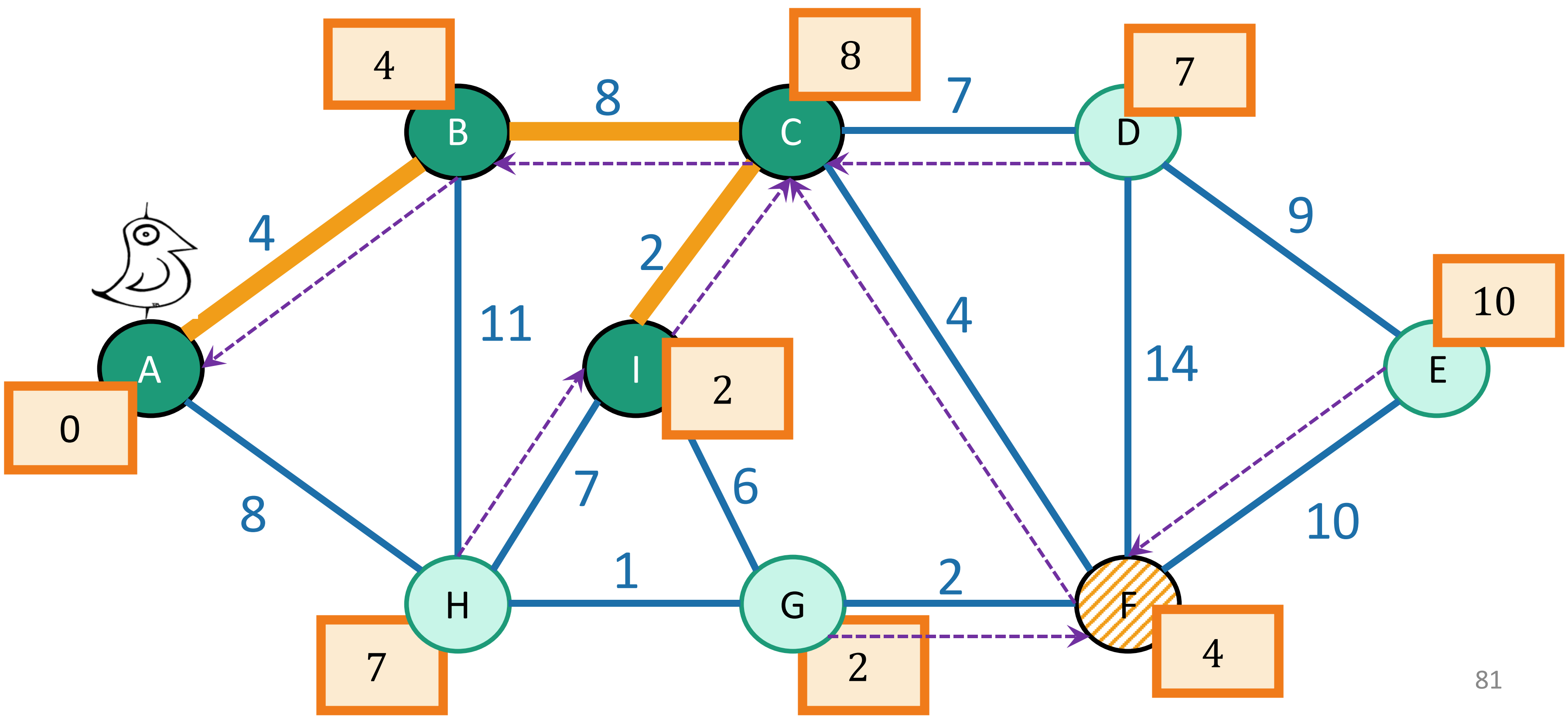
k[x] is the distance of x from the growing tree



p[b] = a, meaning that a was the vertex that k[b] comes from.

Until all the vertices are **reached:**

- Activate the **unreached** vertex u with the smallest key.
- **for each** of u's unreached neighbors v:
  - k[v] = min(k[v], weight(u,v))
  - if k[v] updated, p[v] = u
- Mark u as **reached,** and **add {p[u],u} to MST.**

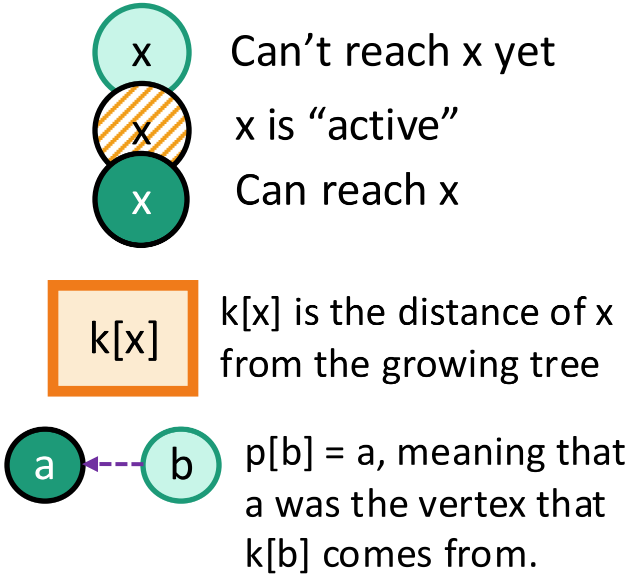


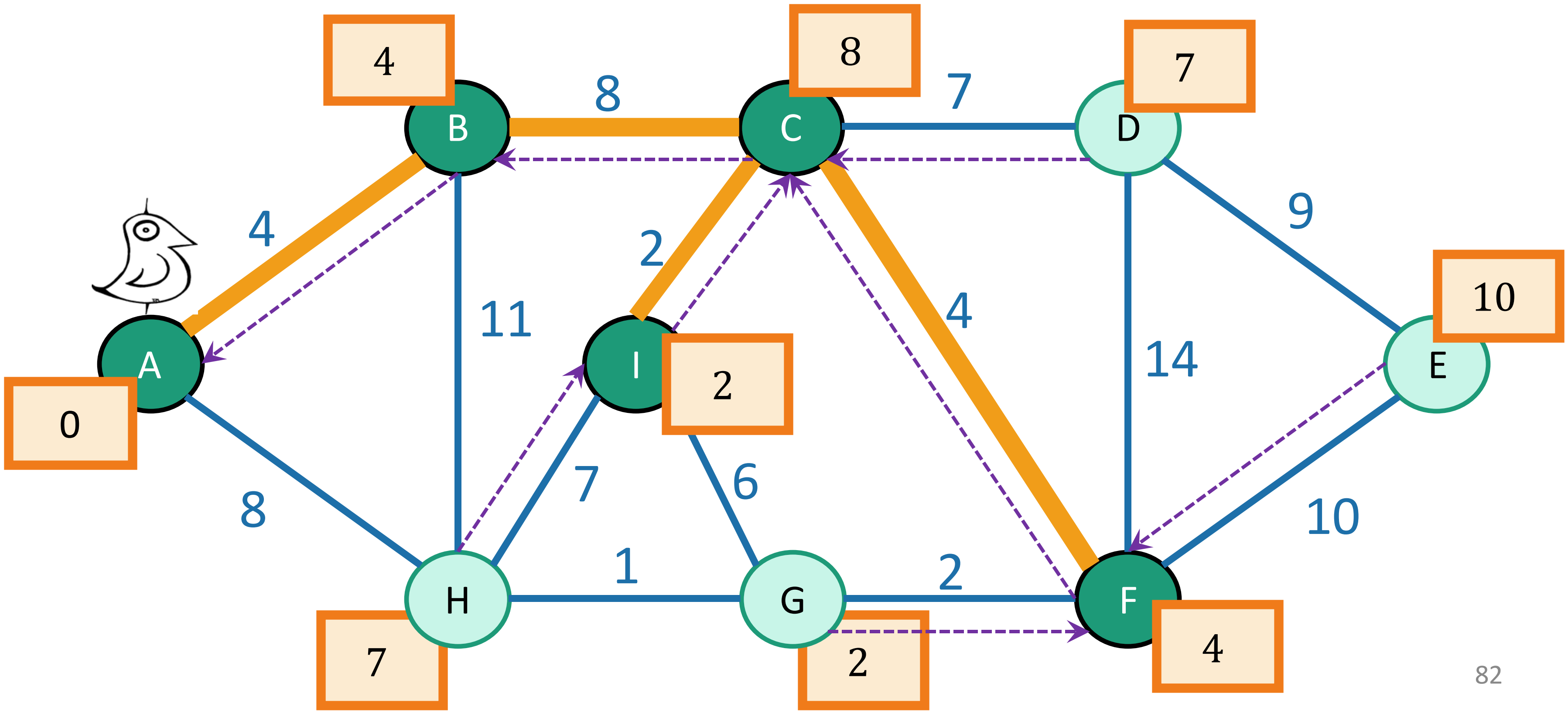
Efficient implementation

Every vertex has a key and a parent

Until all the vertices are **reached:**

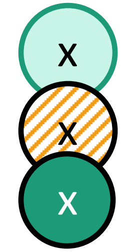
- Activate the **unreached** vertex u with the smallest key.
- **for each** of u's unreached neighbors v:
  - k[v] = min(k[v], weight(u,v))
  - if k[v] updated, p[v] = u
- Mark u as **reached,** and **add {p[u],u} to MST.**





Efficient implementation

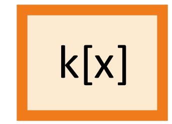
Every vertex has a key and a parent



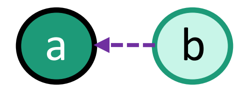
Can't reach x yet

x is "active"

Can reach x



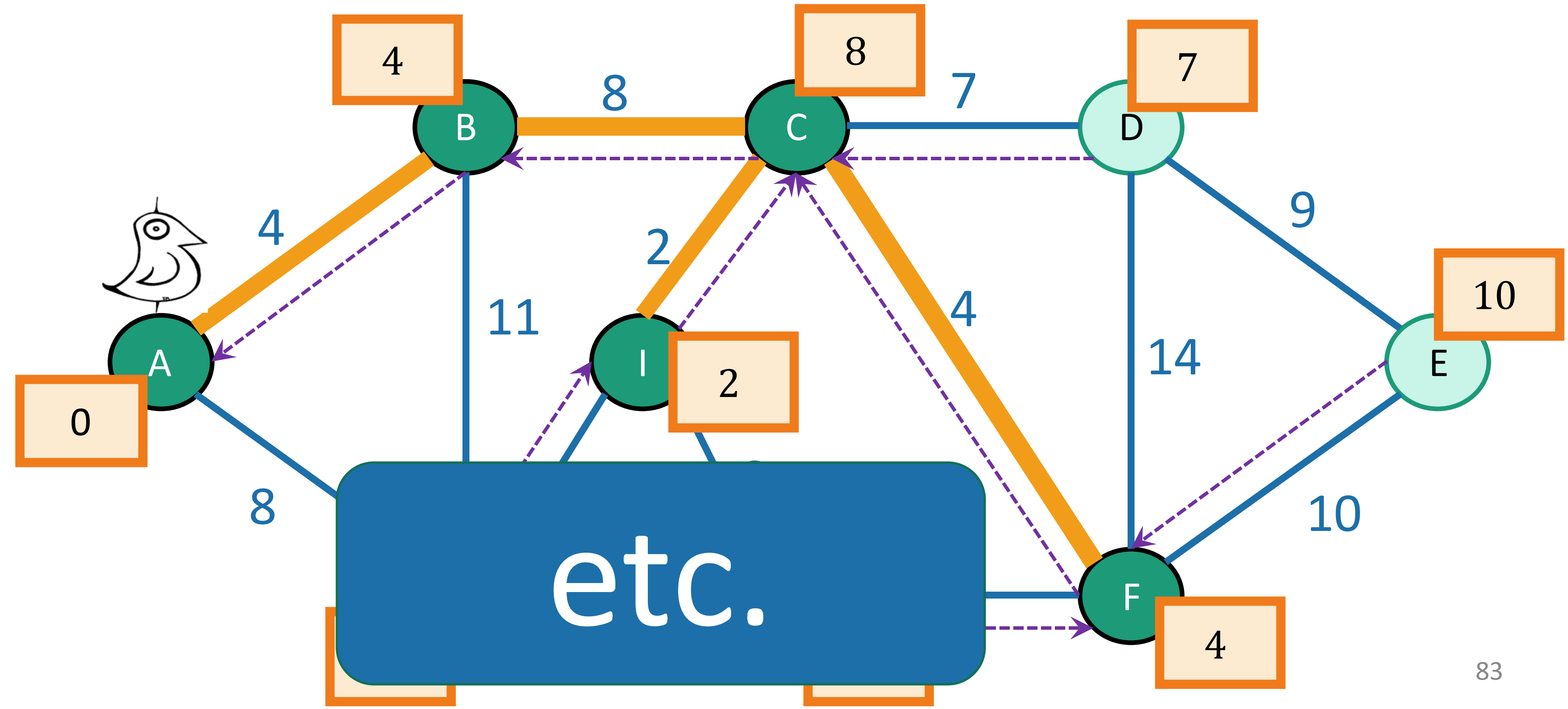
k[x] is the distance of x from the growing tree



p[b] = a, meaning that a was the vertex that k[b] comes from.

Until all the vertices are **reached:**

- Activate the **unreached** vertex u with the smallest key.
- **for each** of u's unreached neighbors v:
  - k[v] = min(k[v], weight(u,v))
  - if k[v] updated, p[v] = u
- Mark u as **reached,** and **add {p[u],u} to MST.**



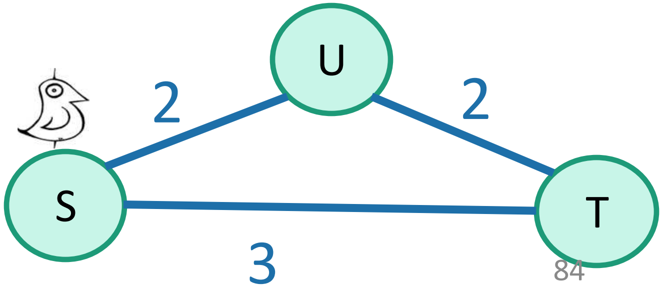
This should look pretty familiar

- Very similar to Dijkstra's algorithm!
- **Differences:**
  1. Keep track of p[v] in order to return a tree at the end
     - But Dijkstra's can do that too, that's not a big difference.
  2. Instead of d[v] which we update by
     - d[v] = min(d[v], d[u] + w(u,v))

     we keep k[v] which we update by
     - k[v] = min(k[v], w(u,v))

Thing 2 is the big difference.

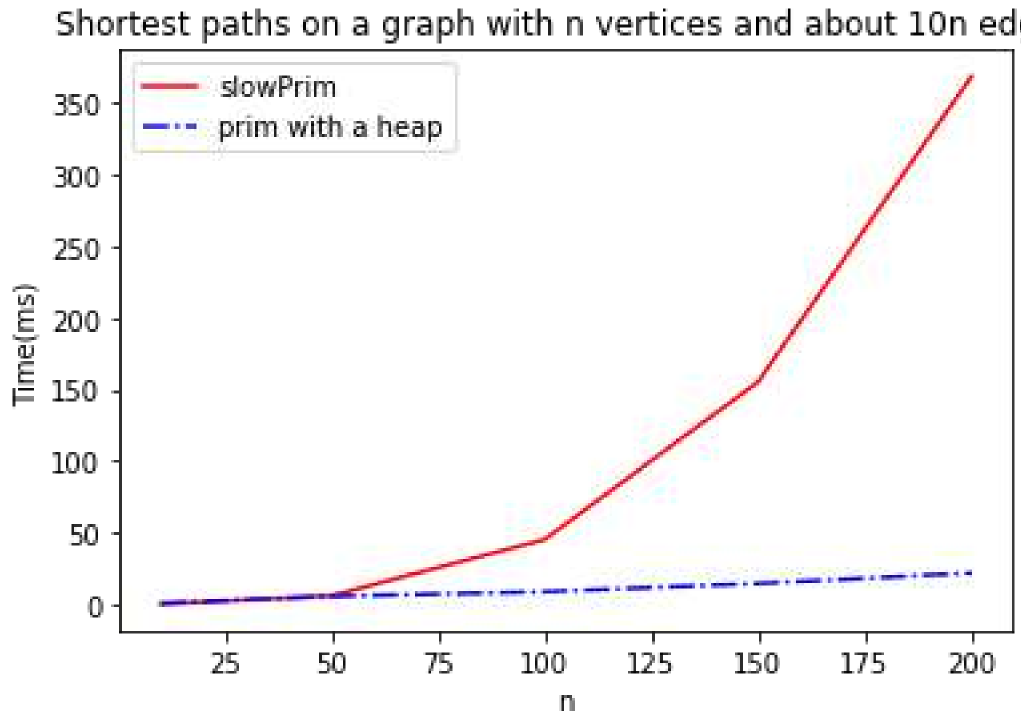
- To see the difference, consider:



*Note: Dijkstra's running time with an RBTree was $O((n+m)\log n)$. Since we are assuming that our graph is connected, this is the same as $O(m \log n)$

One thing that is similar:
Running time

- Exactly the same* as Dijkstra:
  - O(mlog(n)) using a Red-Black tree.
  - O(m + nlog(n)) time if we use a Fibonacci Heap.



Two questions

1. Does it work?
   - That is, does it actually return a MST?
     - **Yes!**

2. How do we actually implement this?
   - the pseudocode above says “slowPrim”…
     - **Implement it basically the same way we’d implement Dijkstra!**
     - See IPython notebook for an implementation.

What have we learned?

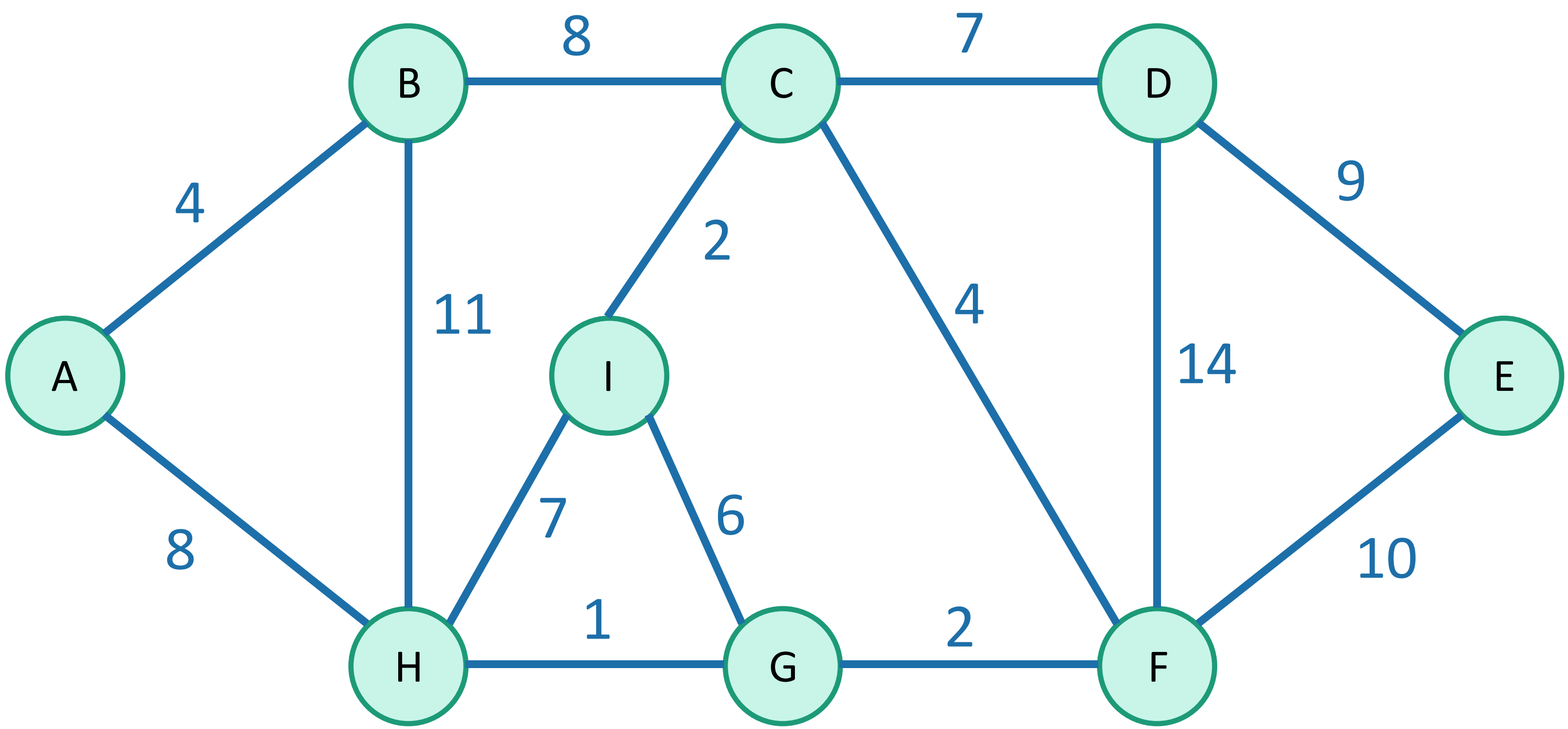
- Prim’s algorithm greedily grows a tree
  - smells a lot like Dijkstra’s algorithm
- It finds a Minimum Spanning Tree!
  - in time **O(mlog(n))** if we implement it with a Red-Black Tree.
  - In time **O(m + nlog(n))** with a Fibonacci heap.
- To prove it worked, we followed the same recipe for greedy algorithms we saw last time.
  - Show that, at every step, we **don’t rule out success.**

That’s not the only greedy algorithm for MST!

That's not the only greedy algorithm

what if we just always take the cheapest edge?

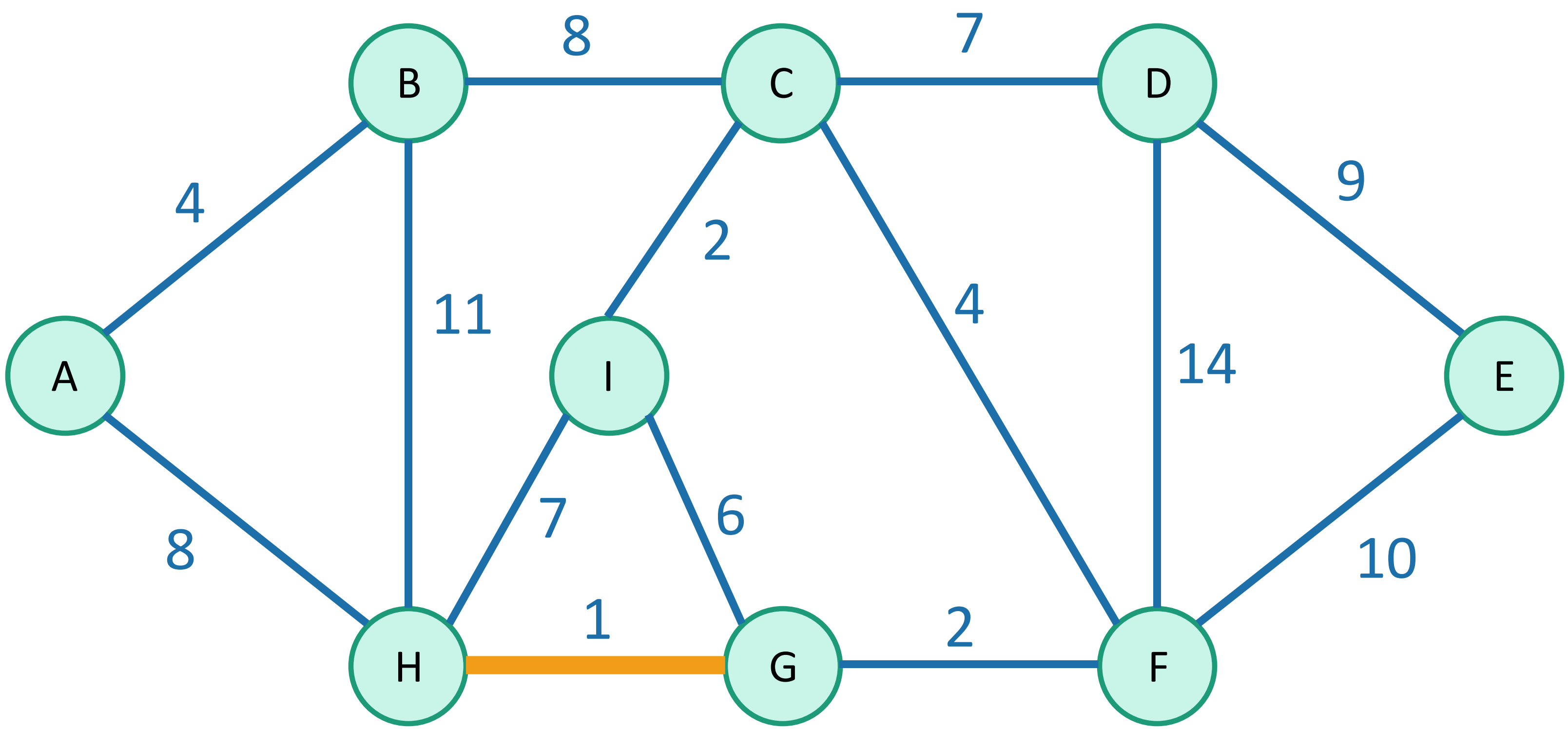
whether or not it's connected to what we have so far?



That’s not the only greedy algorithm

what if we just always take the cheapest edge?

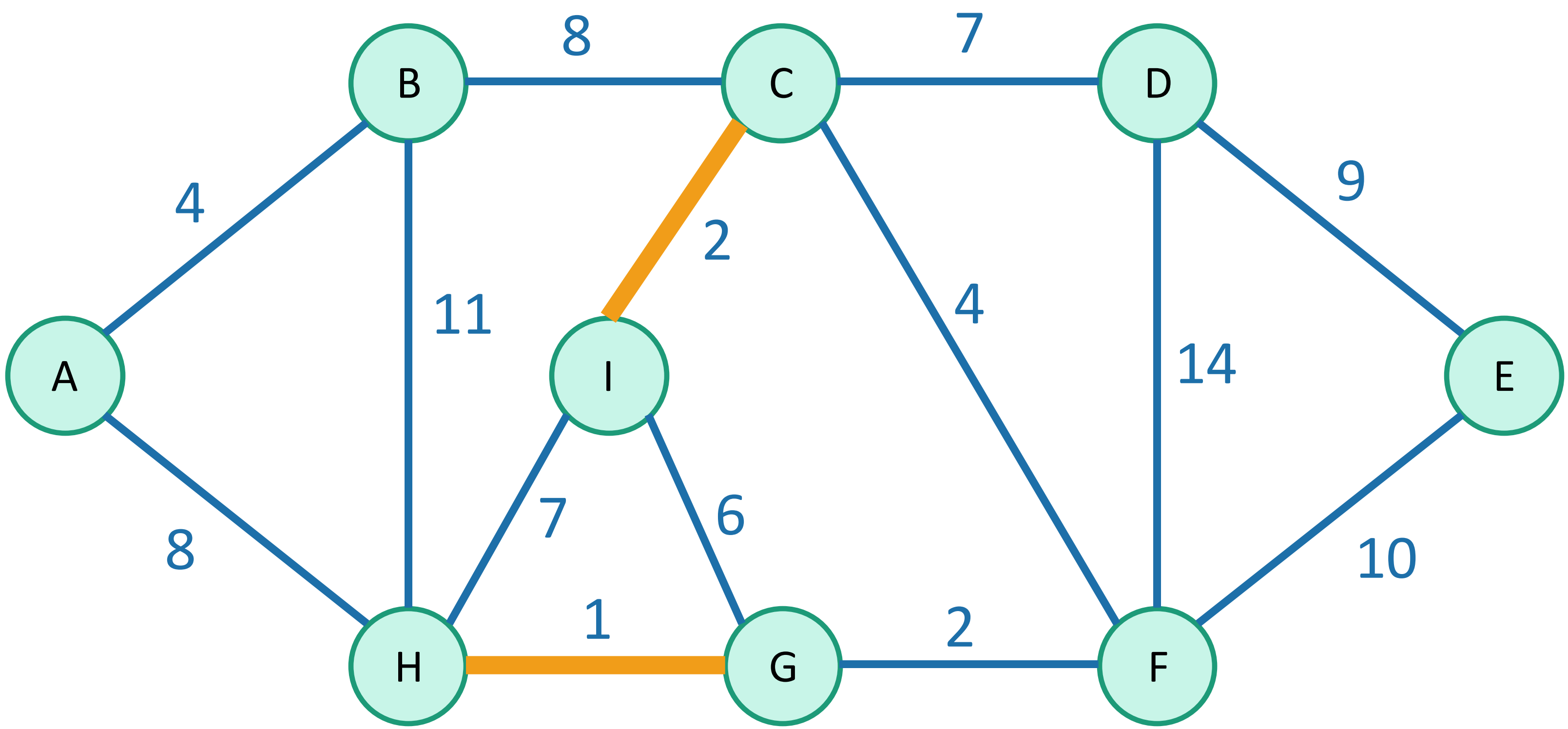
whether or not it’s connected to what we have so far?



That's not the only greedy algorithm

what if we just always take the cheapest edge?

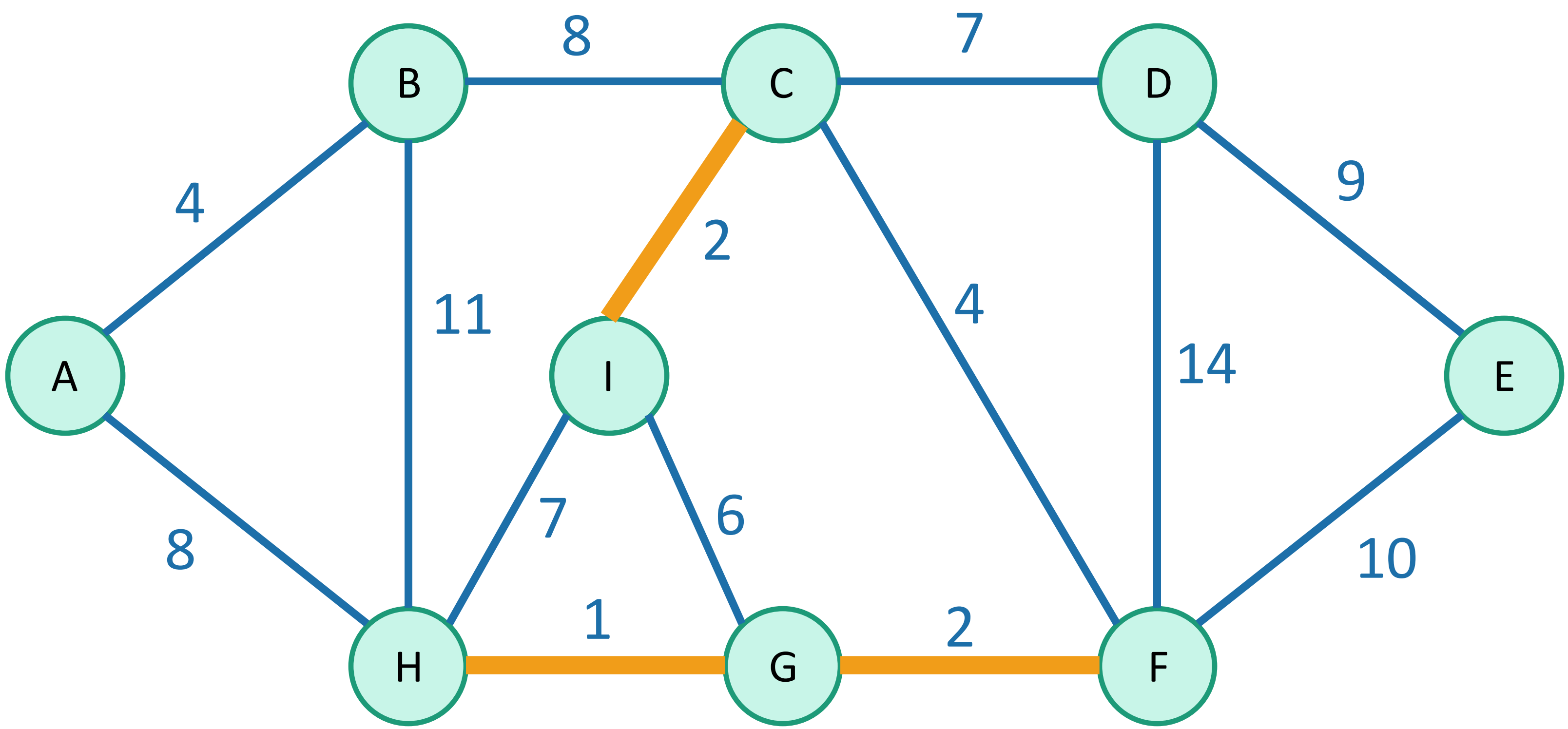
whether or not it's connected to what we have so far?



That’s not the only greedy algorithm

what if we just always take the cheapest edge?

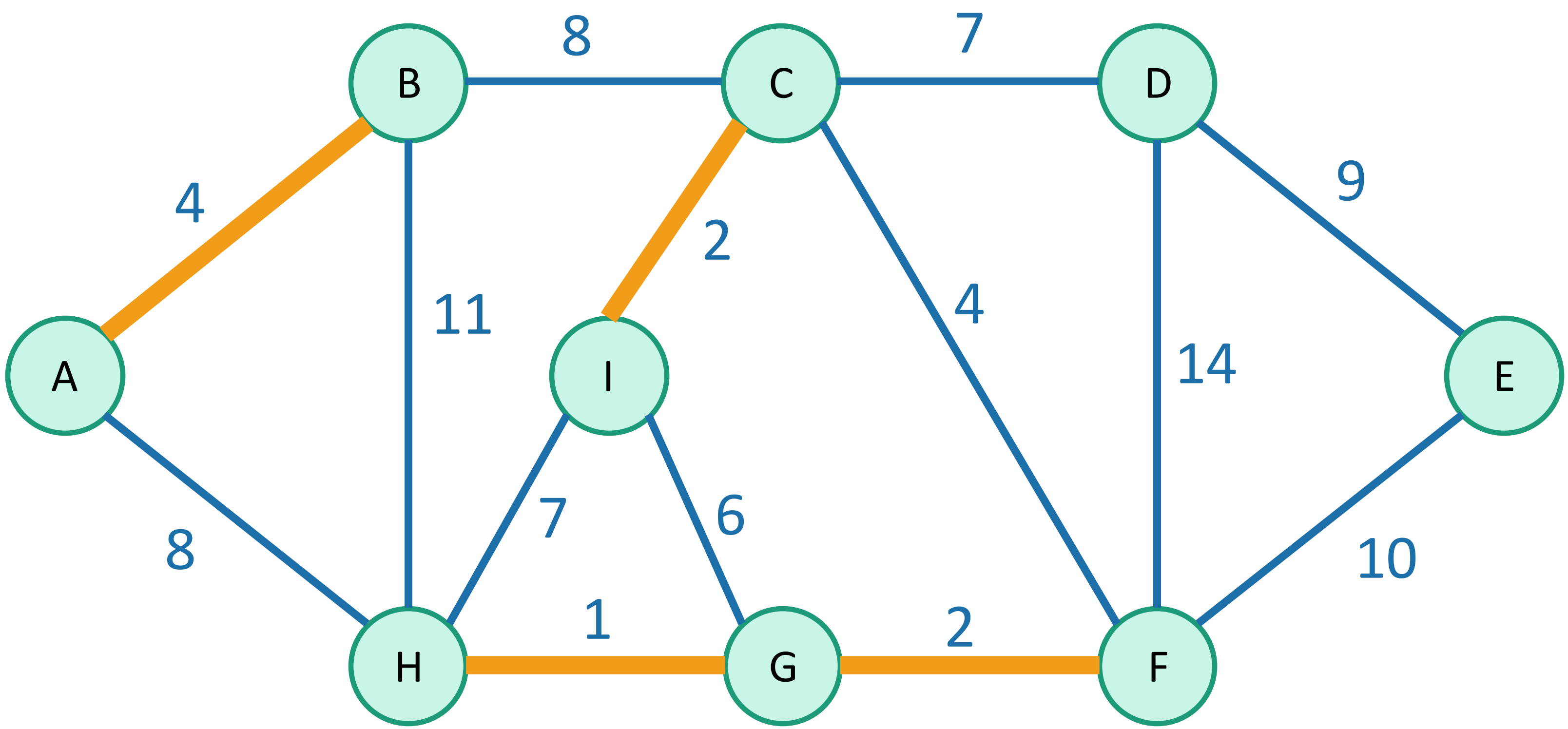
whether or not it’s connected to what we have so far?



That’s not the only greedy algorithm

what if we just always take the cheapest edge?

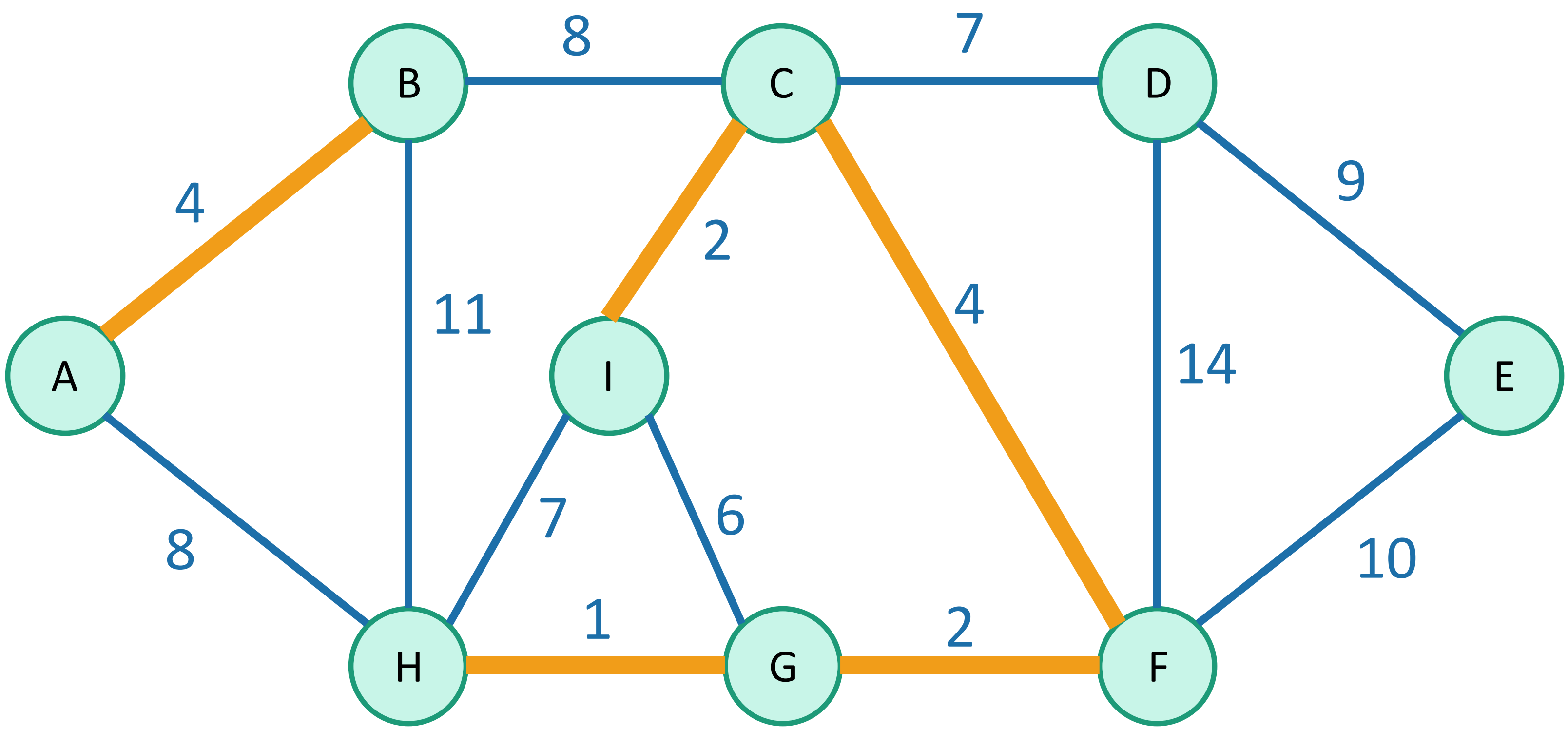
whether or not it’s connected to what we have so far?



That’s not the only greedy algorithm

what if we just always take the cheapest edge?

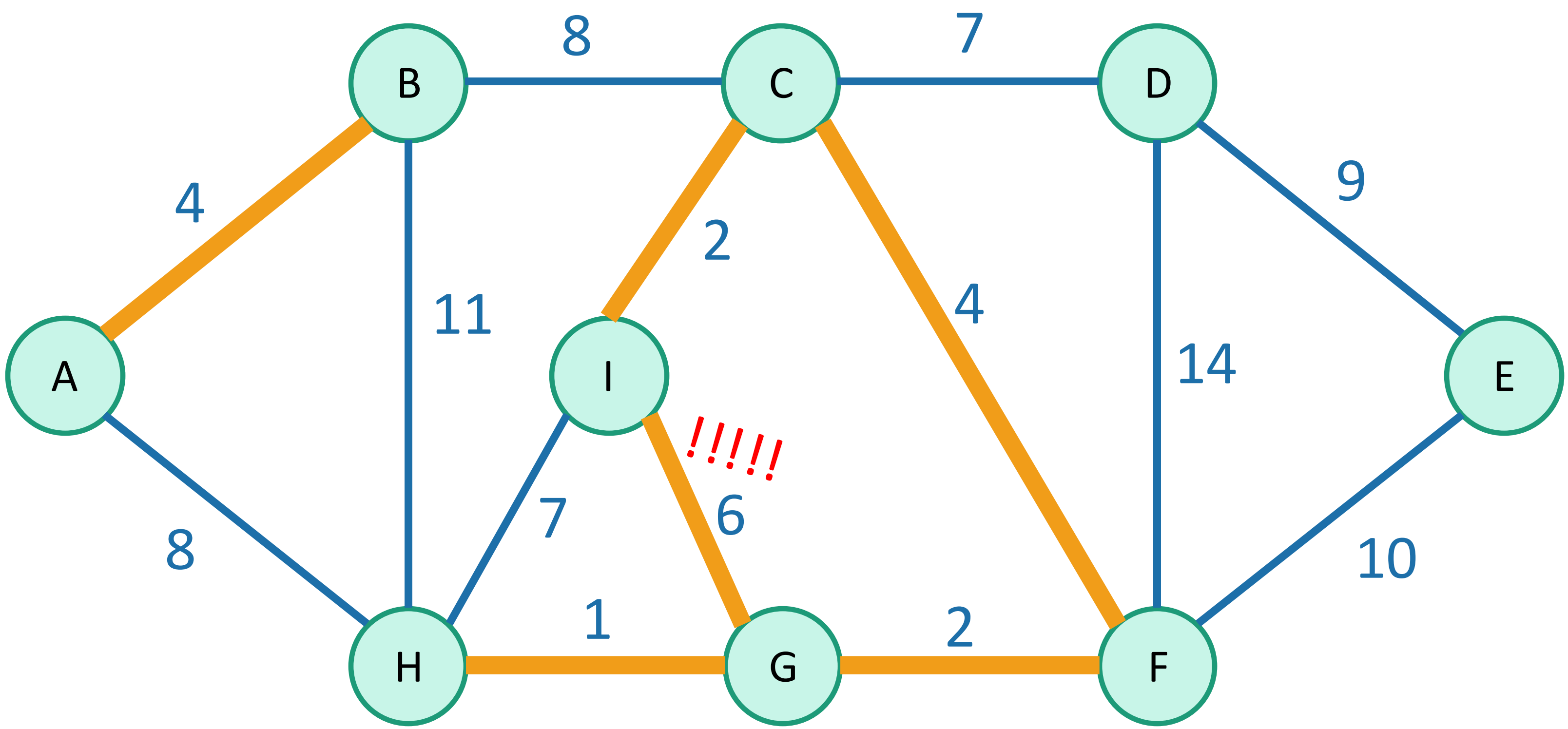
whether or not it’s connected to what we have so far?



That’s not the only greedy algorithm

what if we just always take the cheapest edge?
whether or not it’s connected to what we have so far?

That won’t cause a cycle

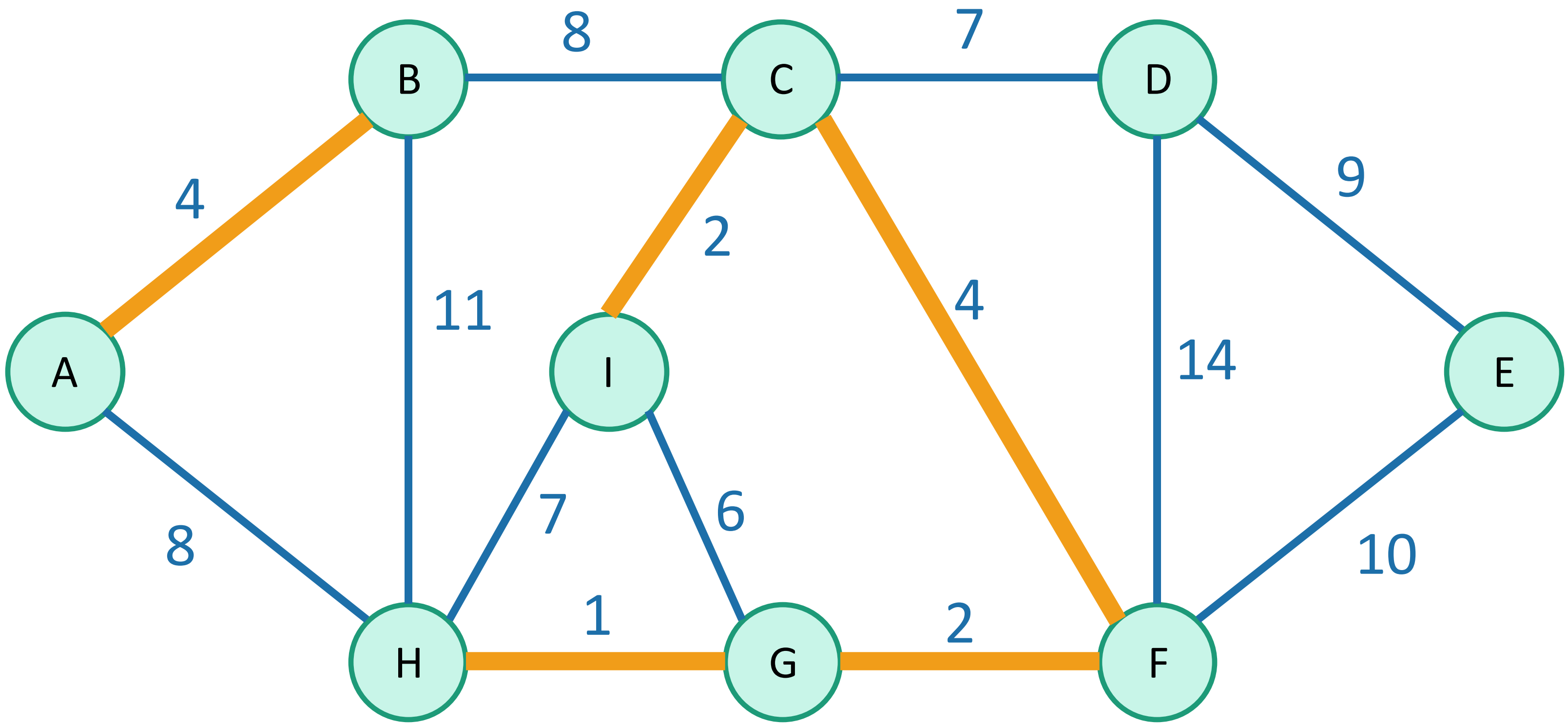


That’s not the only greedy algorithm

what if we just always take the cheapest edge?

whether or not it’s connected to what we have so far?

That won’t cause a cycle

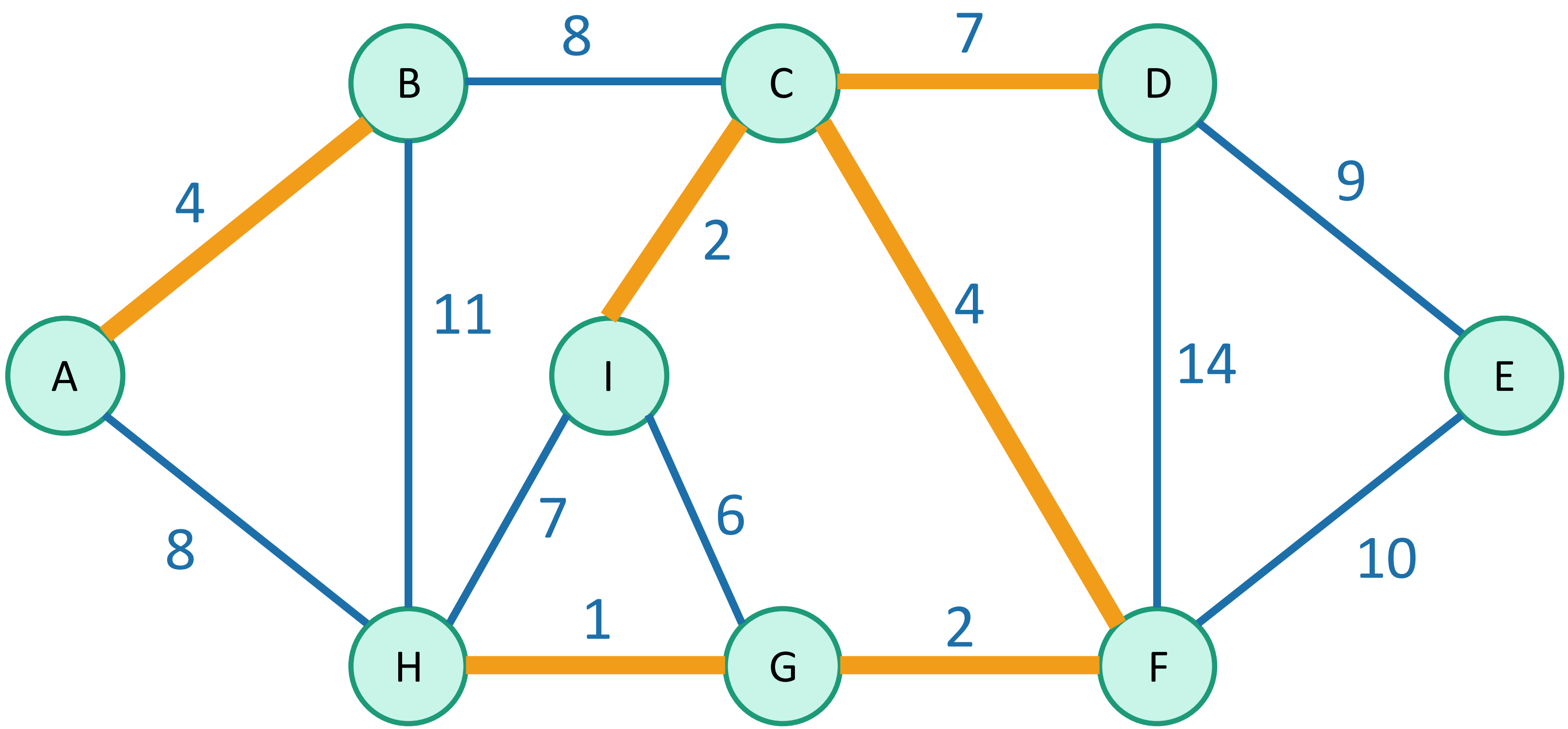


That’s not the only greedy algorithm

what if we just always take the cheapest edge?

whether or not it’s connected to what we have so far?

That won’t cause a cycle

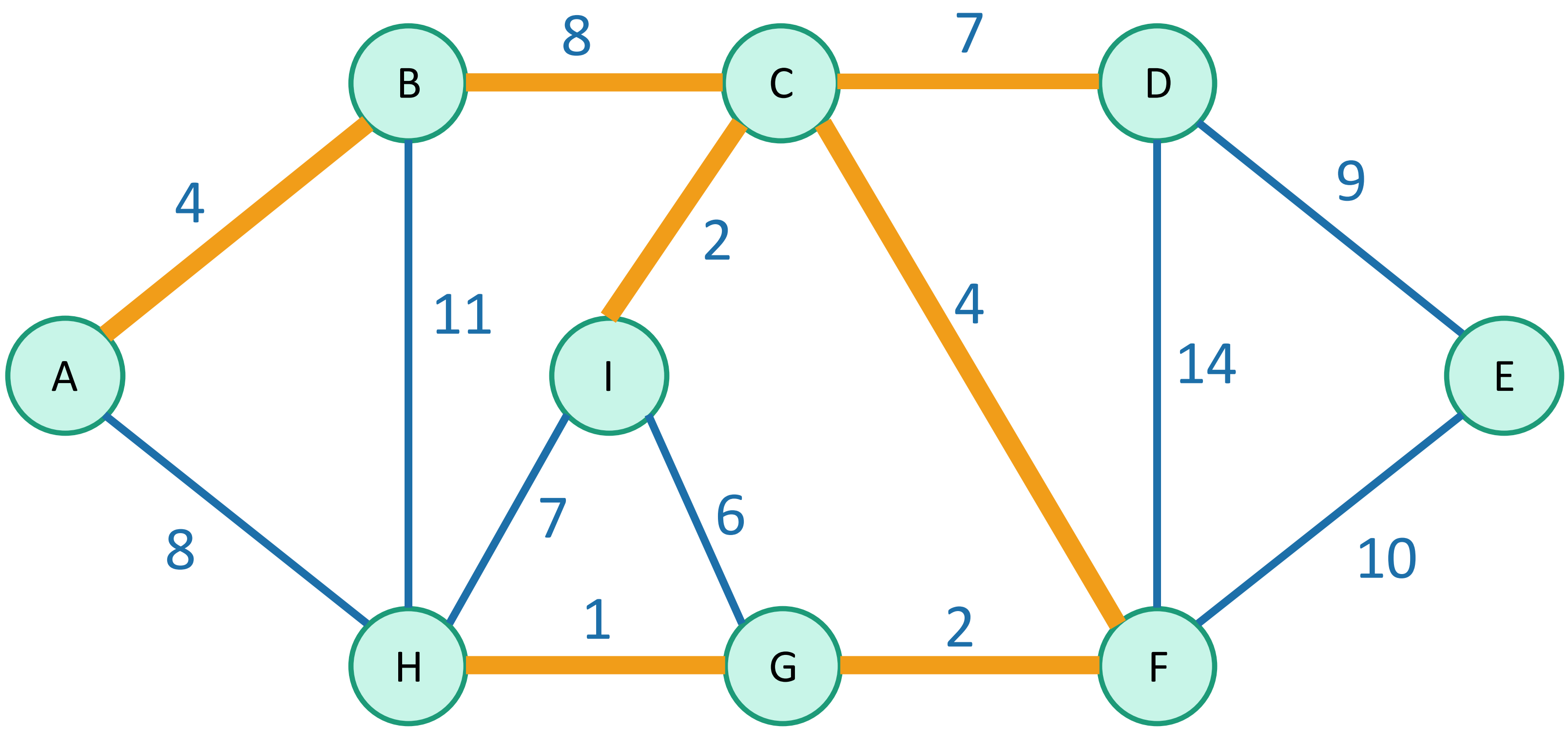


That's not the only greedy algorithm

what if we just always take the cheapest edge?

whether or not it's connected to what we have so far?

That won't cause a cycle

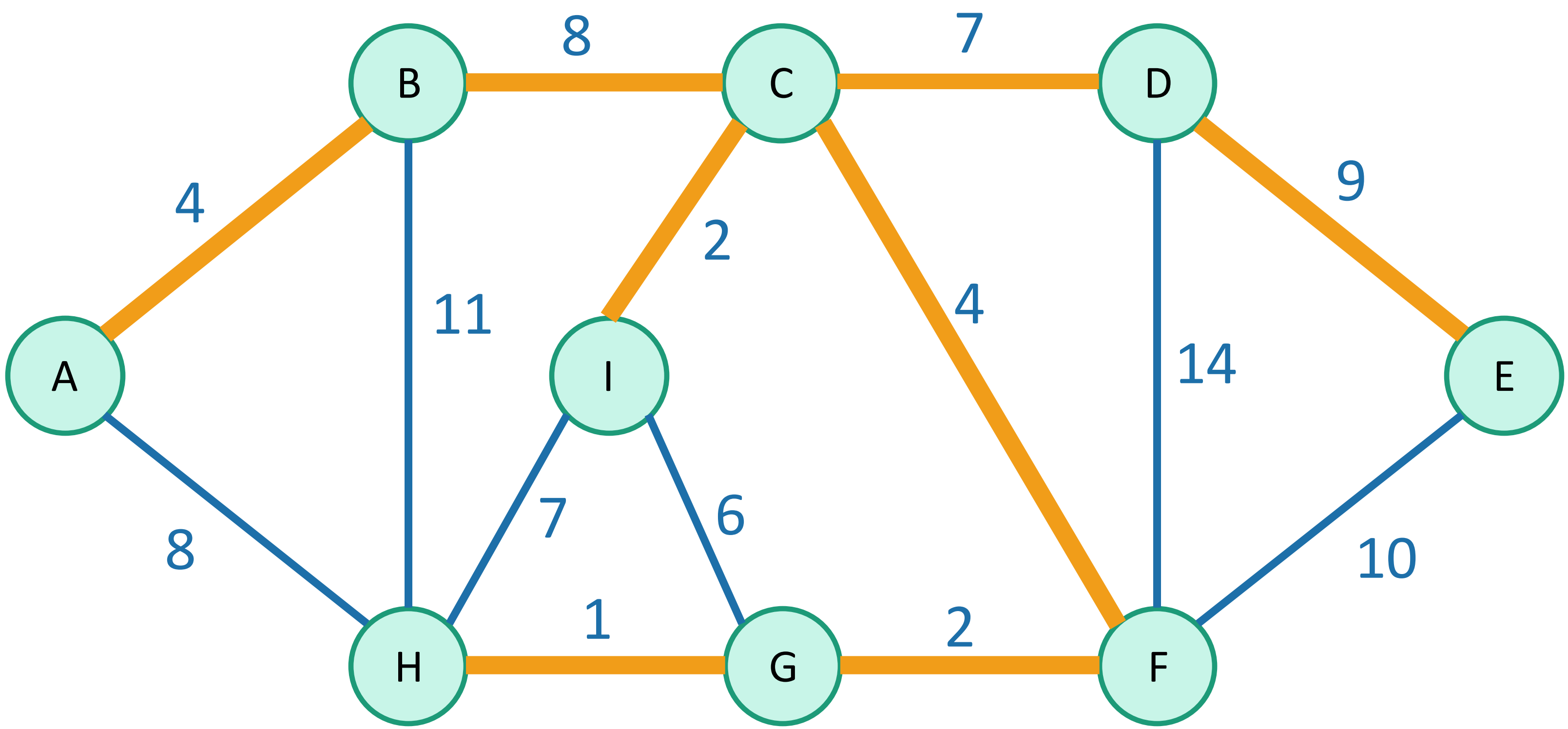


That's not the only greedy algorithm

what if we just always take the cheapest edge?

whether or not it's connected to what we have so far?

That won't cause a cycle

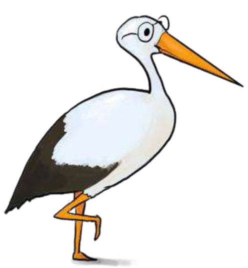


We've discovered Kruskal's algorithm!

- **slowKruskal**(G = (V,E)):
  - Sort the edges in E by non-decreasing weight.
  - MST = {}
  - **for** e in E (in sorted order):
    - **if** adding e to MST won't cause a cycle:
      - add e to MST.
  - **return** MST

m iterations through this loop

How do we check this?



How **would** you figure out if added e would make a cycle in this algorithm?

<u>Naively, the running time is ???:</u>

- For each of m iterations of the for loop:
  - Check if adding e would cause a cycle…

Two questions

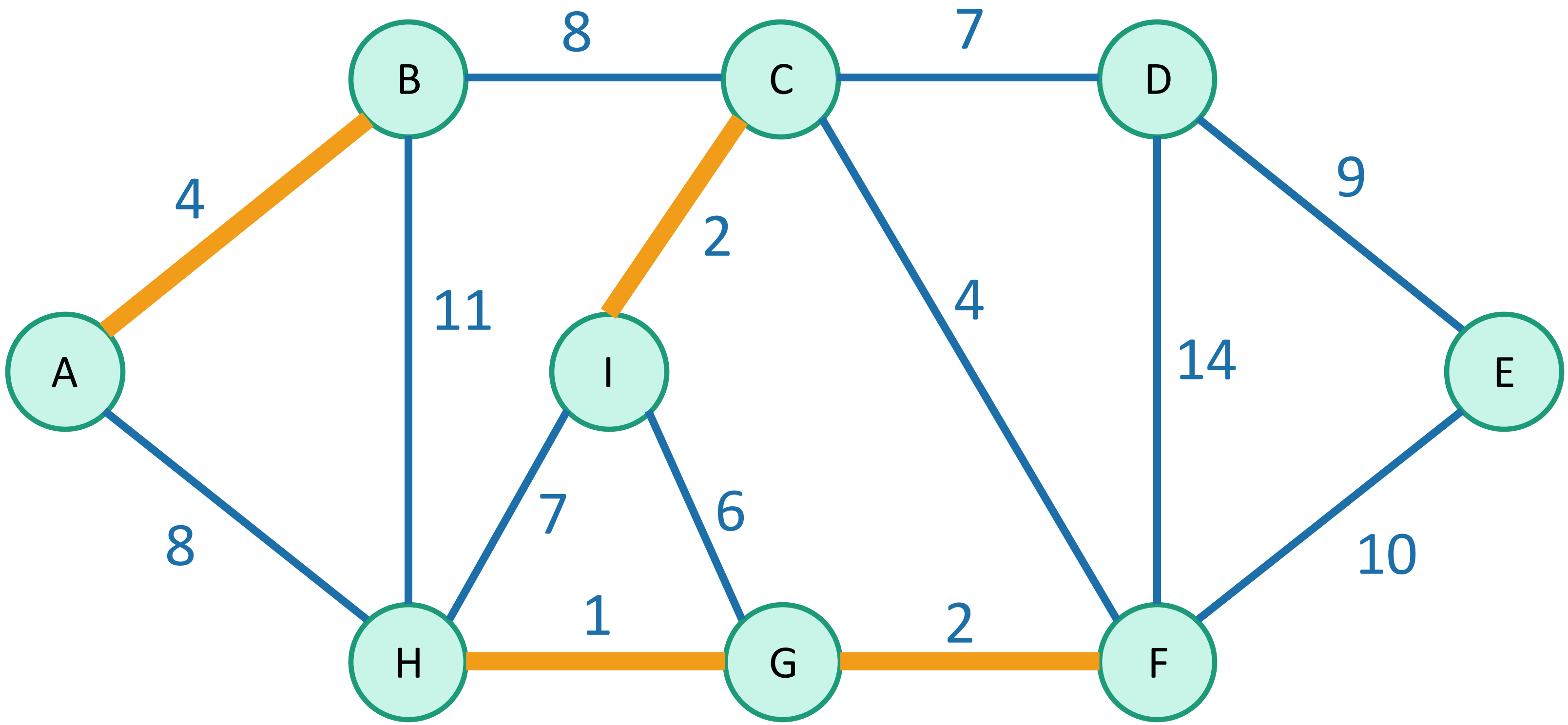
1. Does it work?
   - That is, does it actually return a MST?

2. ~~Is it fast?~~ How do we make it fast?
   - the pseudocode above says “slowKruskal”…

Let’s do this one first

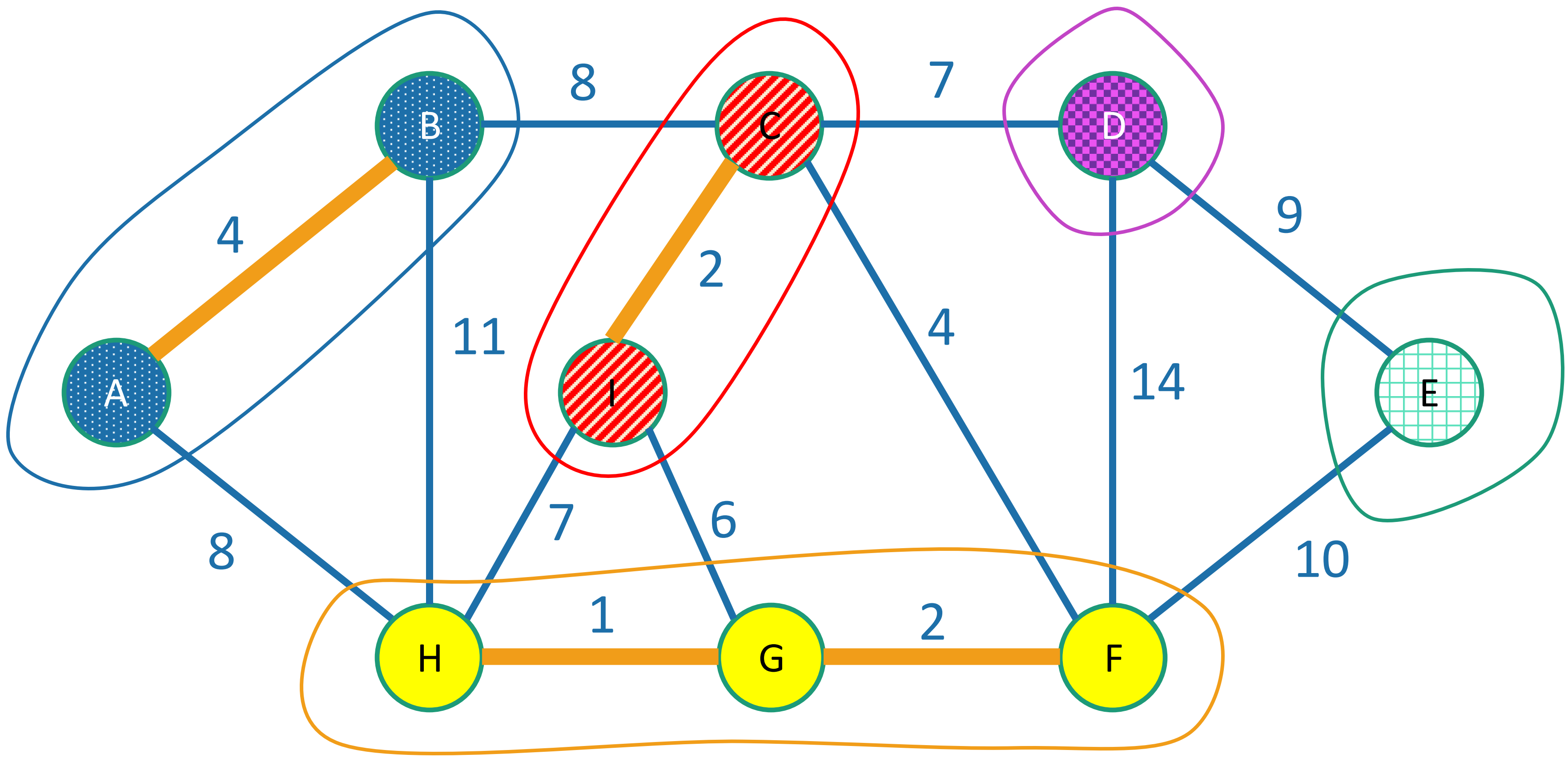
At each step of Kruskal's, we are maintaining a forest.

A **forest** is a collection of disjoint trees



At each step of Kruskal's, we are maintaining a forest.

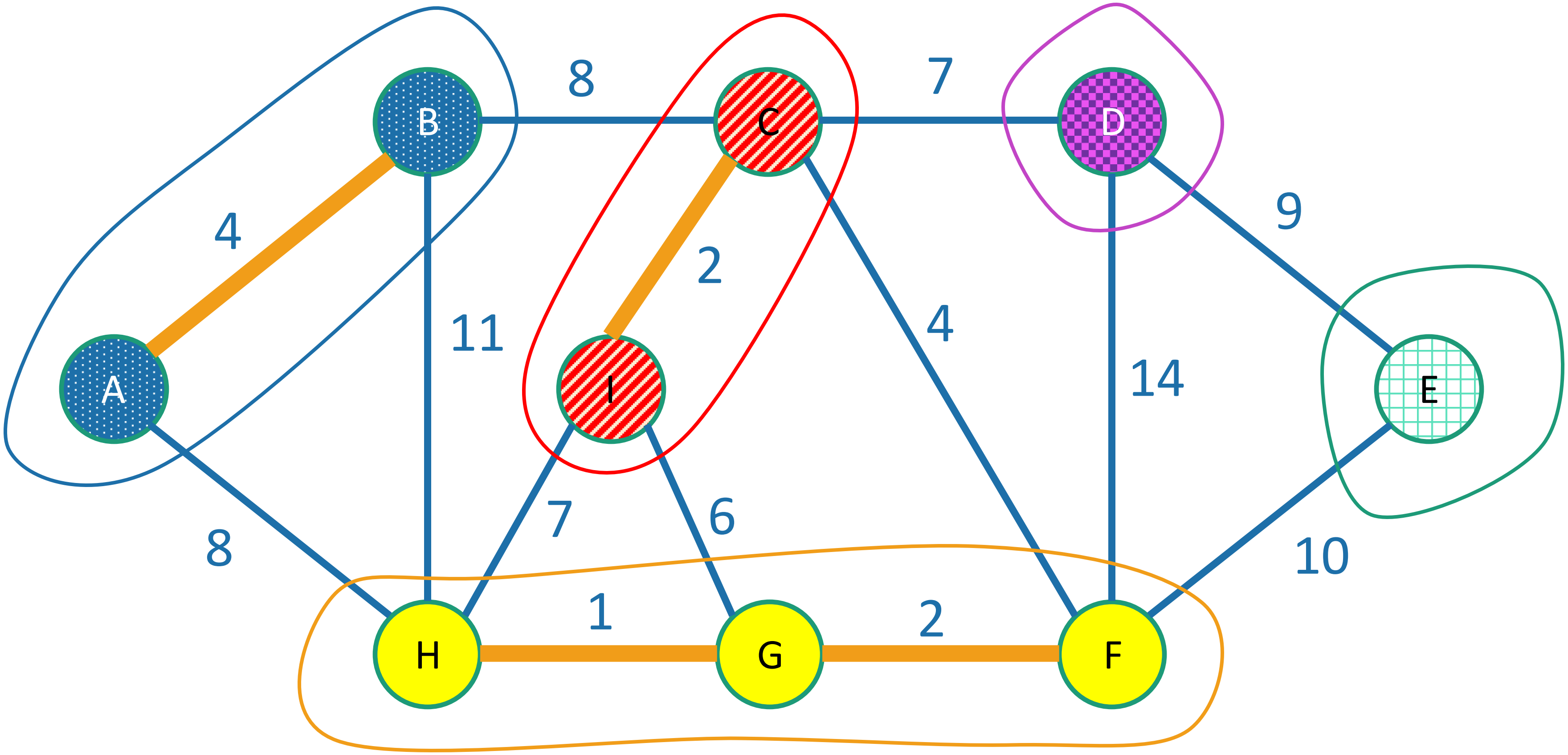
A **forest** is a collection of disjoint trees



At each step of Kruskal's, we are maintaining a forest.

A **forest** is a collection of disjoint trees

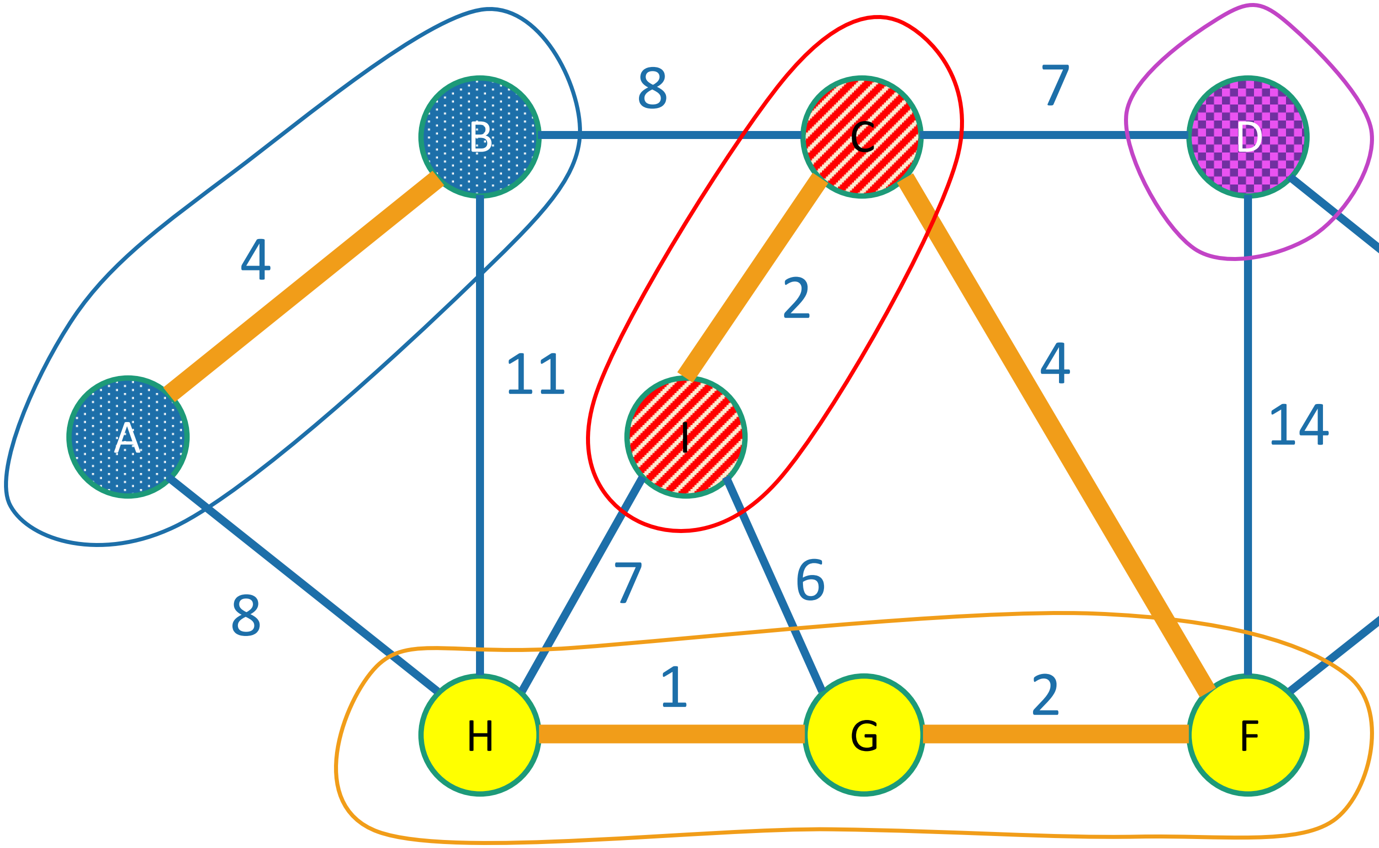
When we add an edge, we merge two trees:



At each step of Kruskal's, we are maintaining a forest.

A **forest** is a collection of disjoint trees

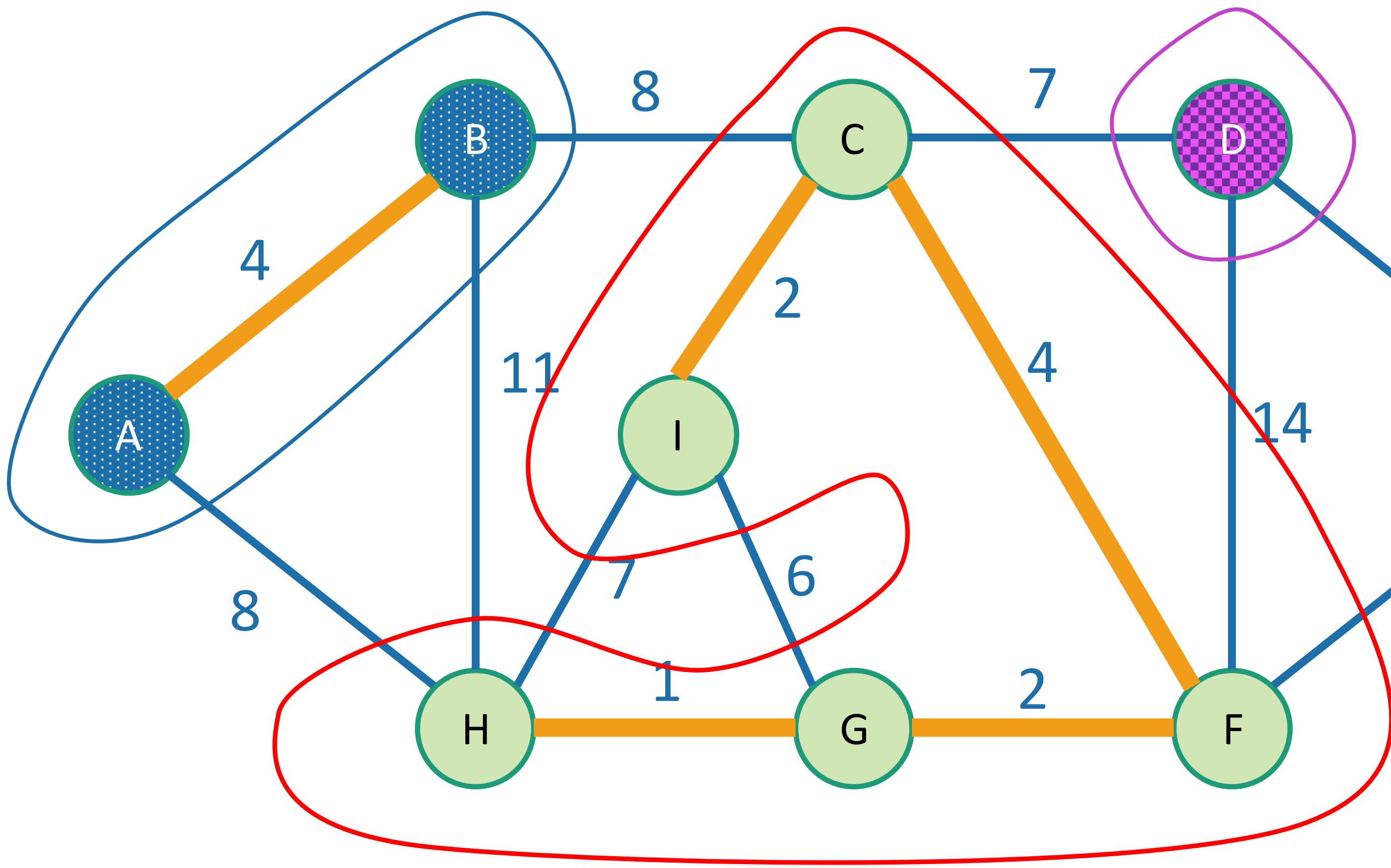
When we add an edge, we merge two trees:



At each step of Kruskal's, we are maintaining a forest.

A **forest** is a collection of disjoint trees

When we add an edge, we merge two trees:



We never add an edge within a tree since that would create a cycle.

Keep the trees in a special data structure

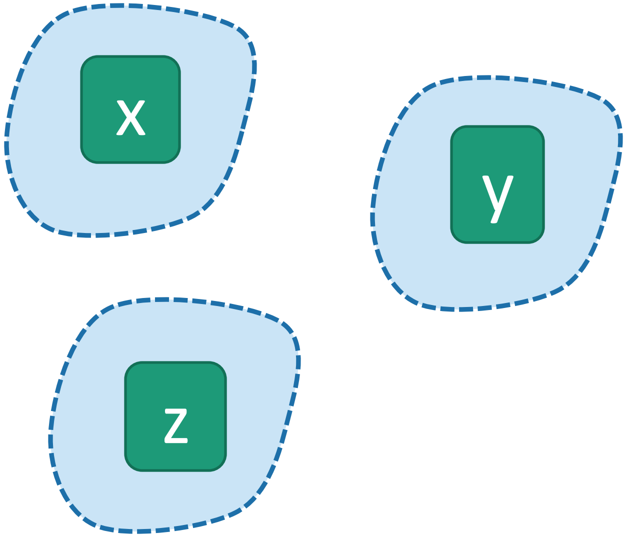
"treehouse"?

Union-find data structure
also called disjoint-set data structure

- Used for storing collections of sets
- Supports:
  - **makeSet(u):** create a set {u}
  - **find(u):** return the set that u is in
  - **union(u,v):** merge the set that u is in with the set that v is in.

```
makeSet(x)
makeSet(y)
makeSet(z)

union(x,y)
```

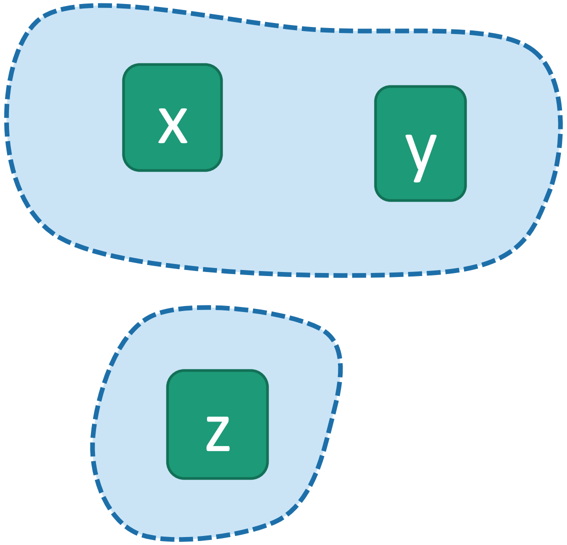


Union-find data structure
also called disjoint-set data structure

- Used for storing collections of sets
- Supports:
  - **makeSet(u):** create a set {u}
  - **find(u):** return the set that u is in
  - **union(u,v):** merge the set that u is in with the set that v is in.

```
makeSet(x)
makeSet(y)
makeSet(z)

union(x,y)
```



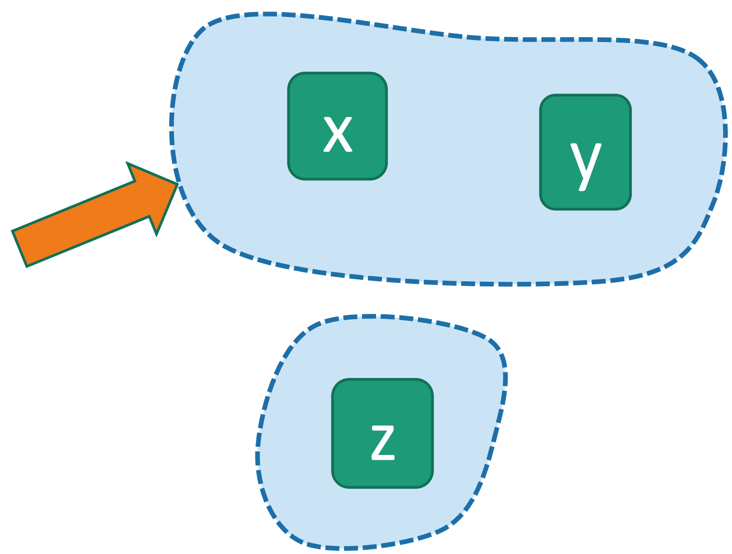
Union-find data structure
also called disjoint-set data structure

- Used for storing collections of sets
- Supports:
  - **makeSet(u):** create a set {u}
  - **find(u):** return the set that u is in
  - **union(u,v):** merge the set that u is in with the set that v is in.

```
makeSet(x)
makeSet(y)
makeSet(z)

union(x,y)

find(x)
```

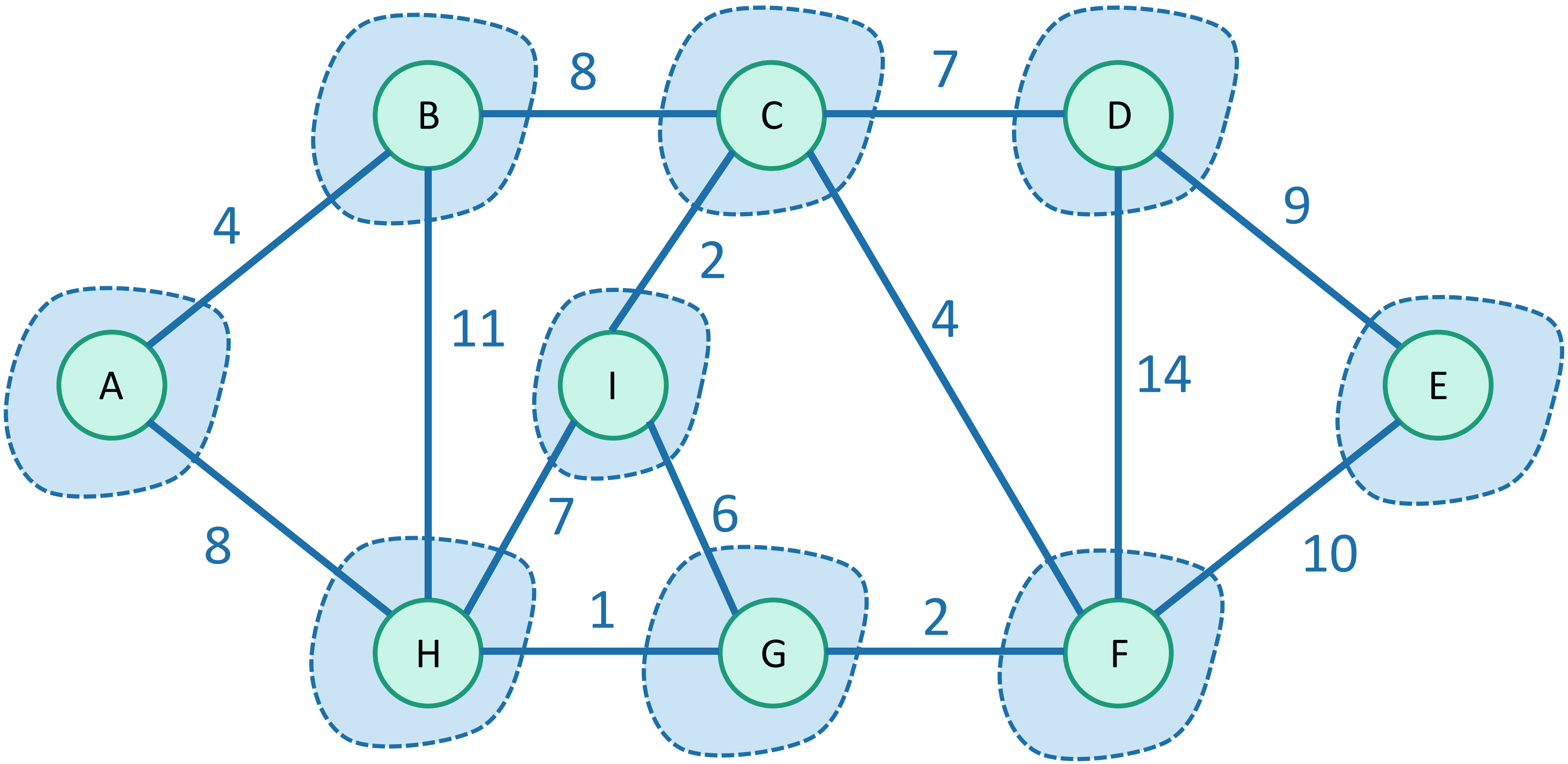


Kruskal pseudo-code

- **kruskal**(G = (V,E)):
  - Sort E by weight in non-decreasing order
  - MST = {} // initialize an empty tree
  - **for** v in V:
    - **makeSet**(v) // put each vertex in its own tree in the forest
  - **for** {u,v} in E: // go through the edges in sorted order
    - **if find**(u) != **find**(v): // if u and v are not in the same tree
      - add {u,v} to MST
      - **union**(u,v) // merge u's tree with v's tree
  - **return** MST

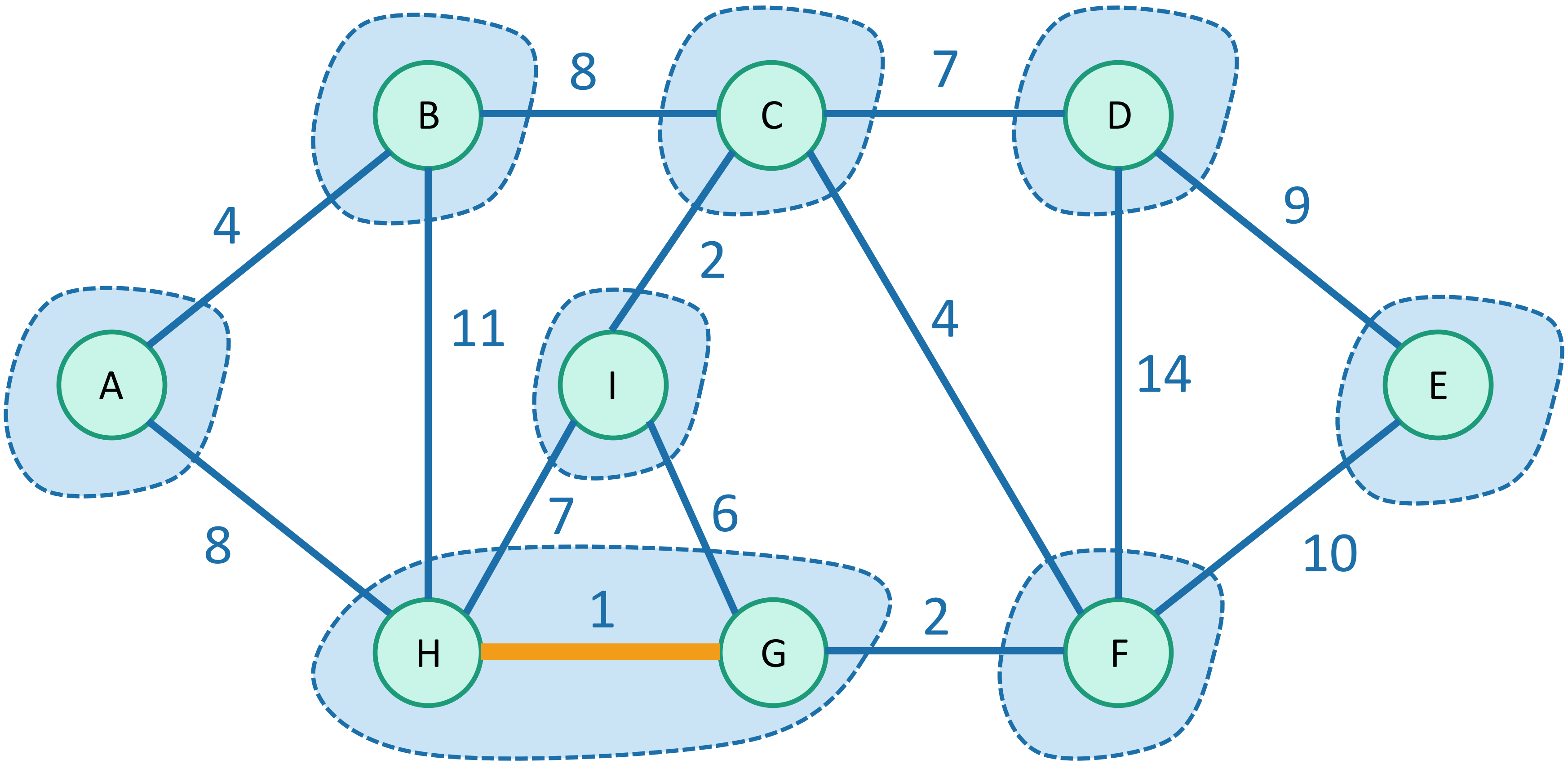
Once more…

To start, every vertex is in its own tree.



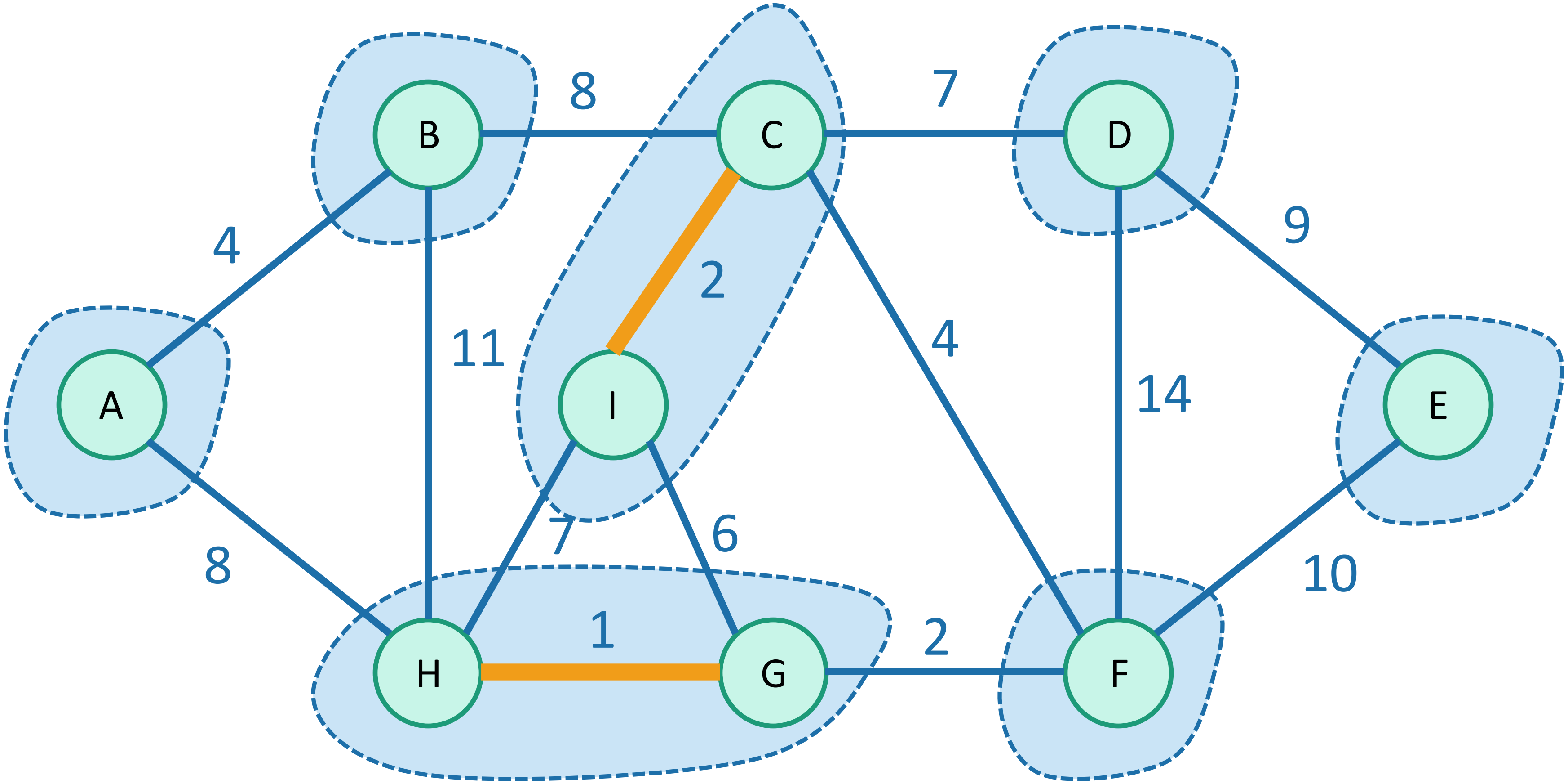
Once more…

Then start merging.



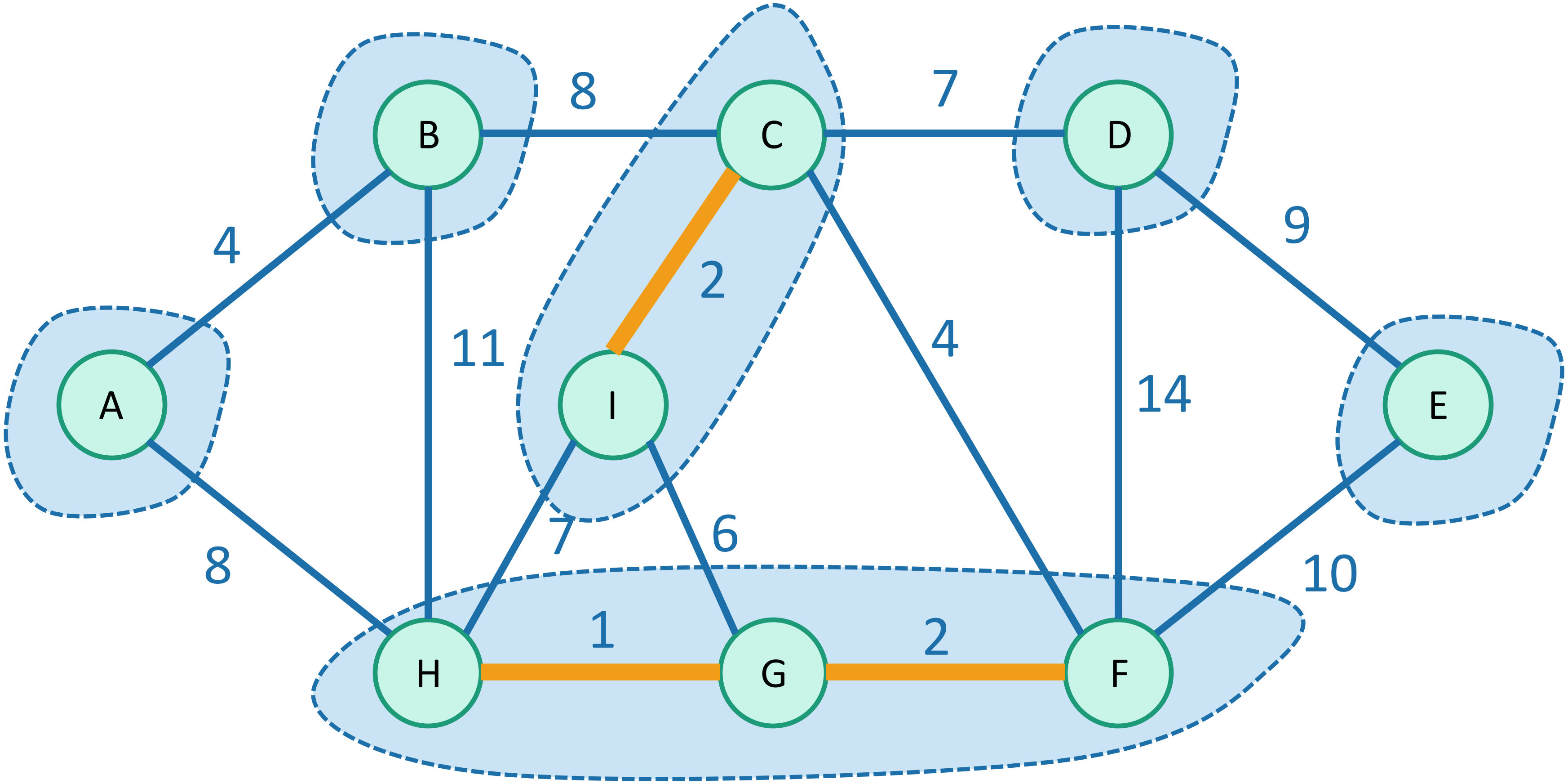
Once more…

Then start merging.



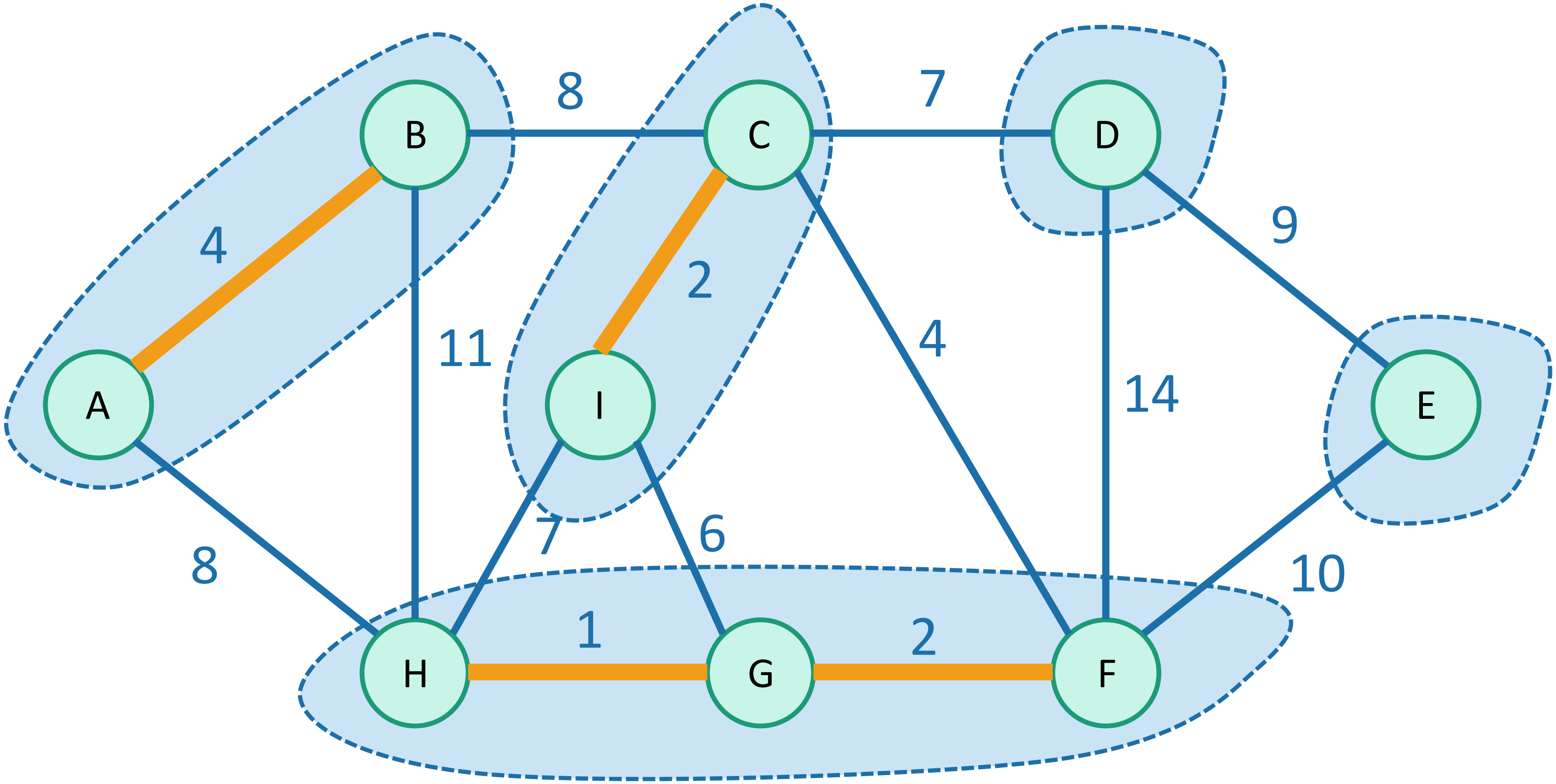
Once more…

Then start merging.



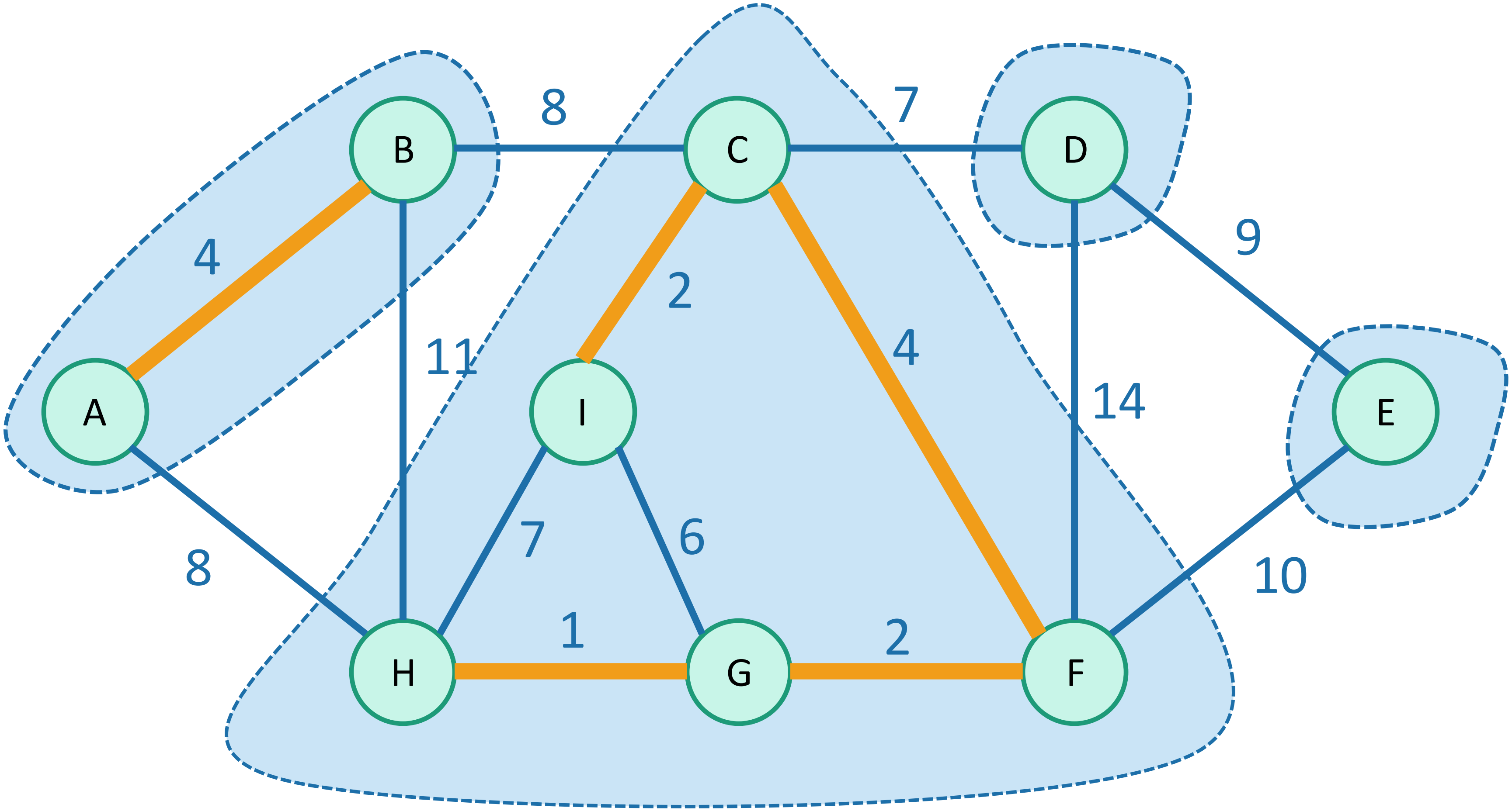
Once more…

Then start merging.



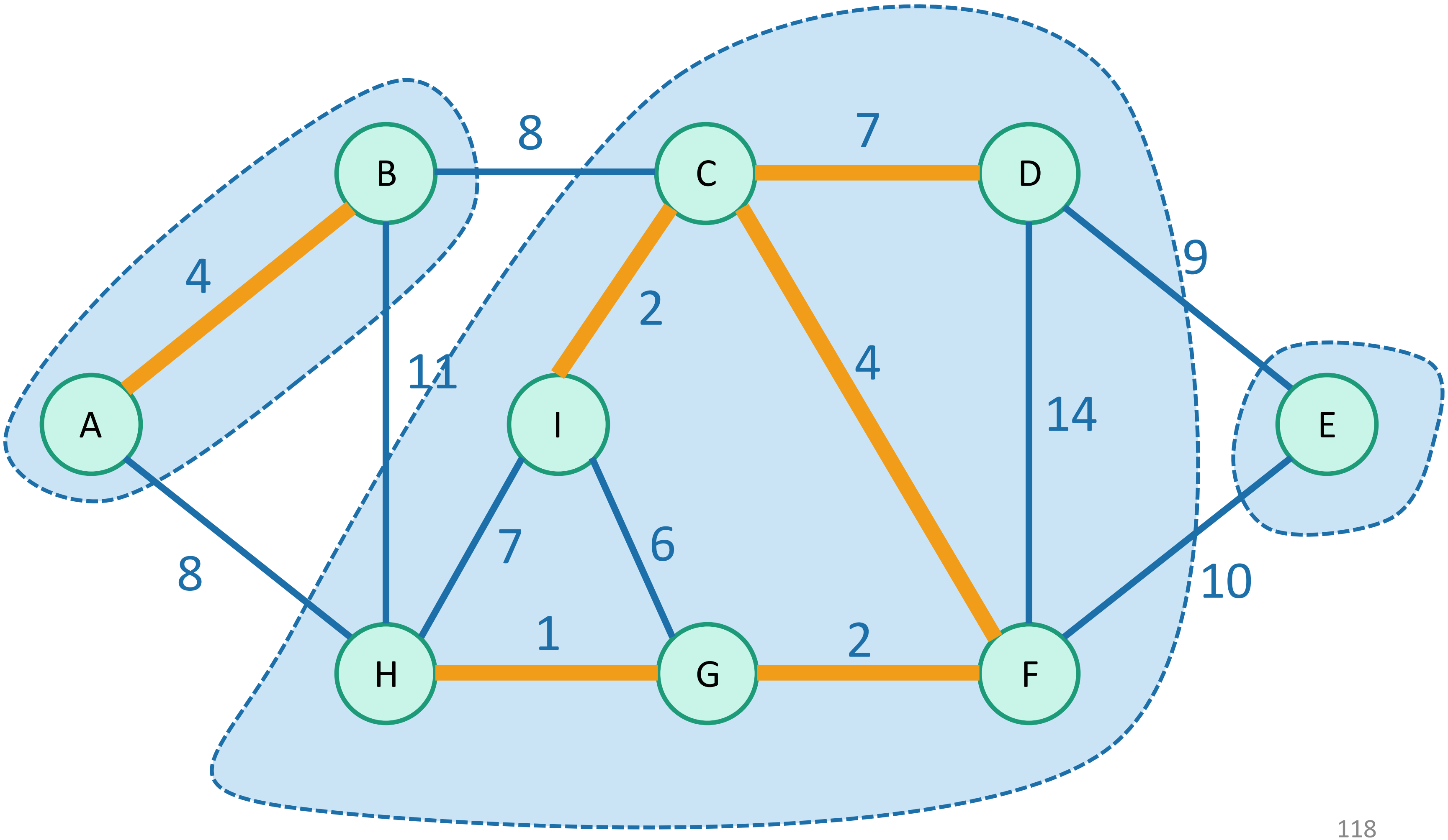
Once more…

Then start merging.



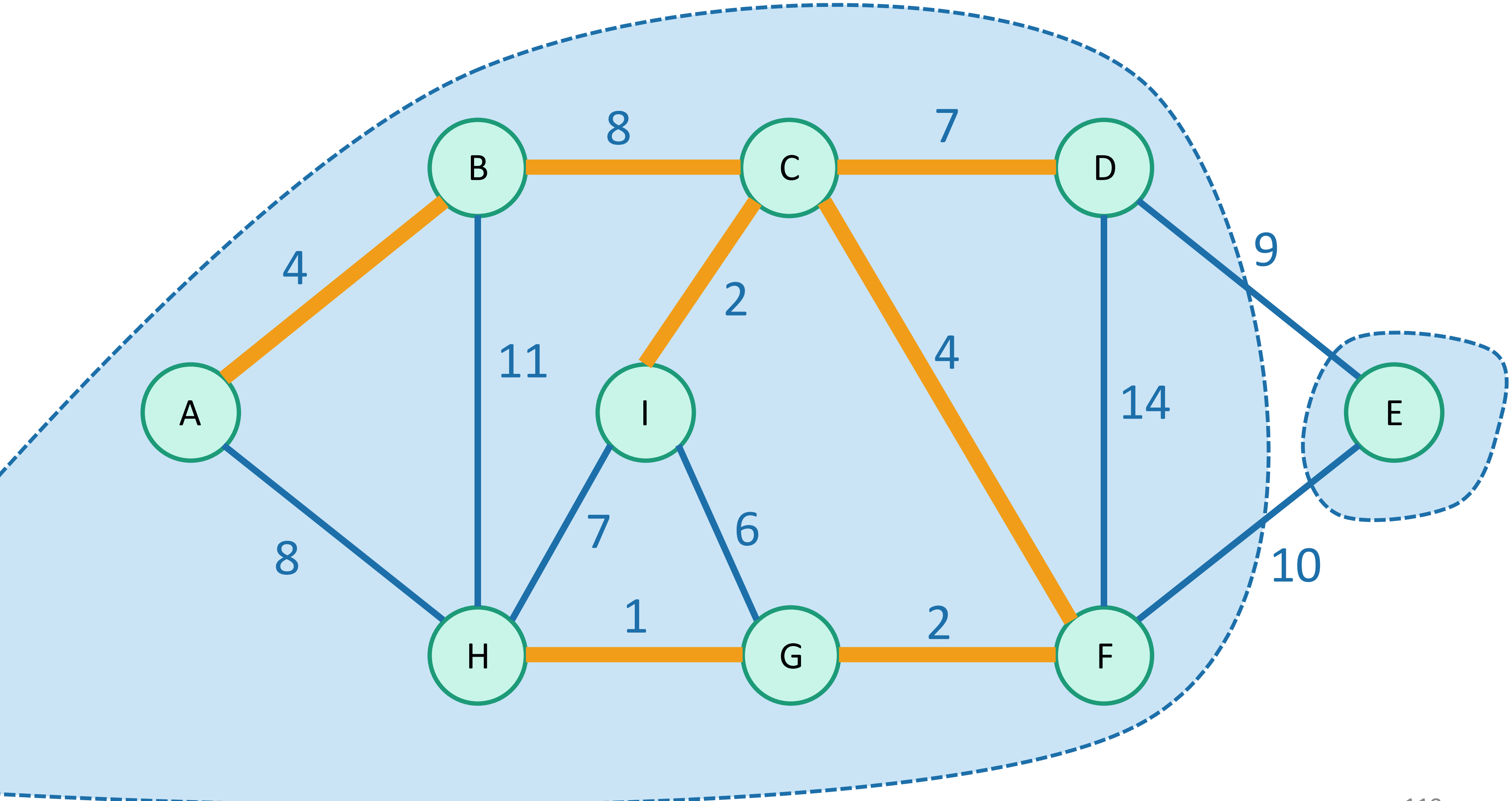
Once more…

Then start merging.



Once more…

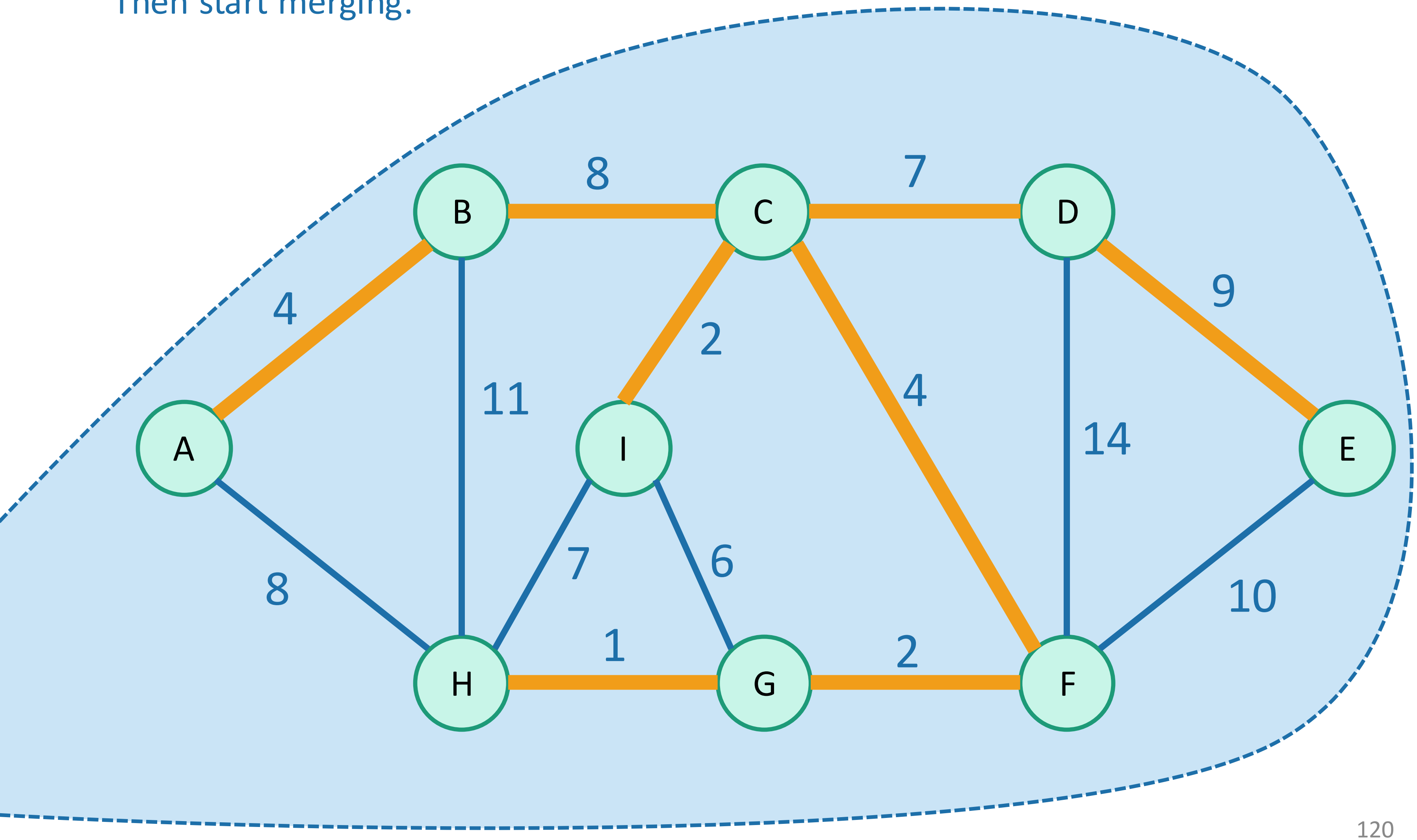
Then start merging.



Stop when we have one big tree!

Once more…

Then start merging.



Running time

- Sorting the edges takes O(m log(n))
  - In practice, if the weights are small integers we can use radixSort and take time O(m)
- For the rest:
  - n calls to **makeSet**
    - put each vertex in its own set
  - 2m calls to **find**
    - for each edge, **find** its endpoints
  - n-1 calls to **union**
    - we will never add more than n-1 edges to the tree,
    - so we will never call **union** more than n-1 times.
- Total running time:
  - Worst-case O(mlog(n)), just like Prim with an RBtree.
  - Closer to O(m) if you can do radixSort

In practice, each of makeSet, find, and union run in constant time*

(See Algs. Illuminated, Section 15.6.4, for a simpler way which does find and union in time O(log n)).

*technically, they run in *amortized time* O($\alpha(n)$), where $\alpha(n)$ is the *inverse Ackerman function*. $\alpha(n) \leq 4$ provided that n is smaller than the number of atoms in the universe.

Two questions

1. Does it work?
   - That is, does it actually return a MST?

Now that we understand this “tree-merging” view, let’s do this one.

2. How do we actually implement this?
   - the pseudocode above says “slowKruskal”…
     - **Worst-case running time O(mlog(n)) using a union-find data structure.**

Does it work?

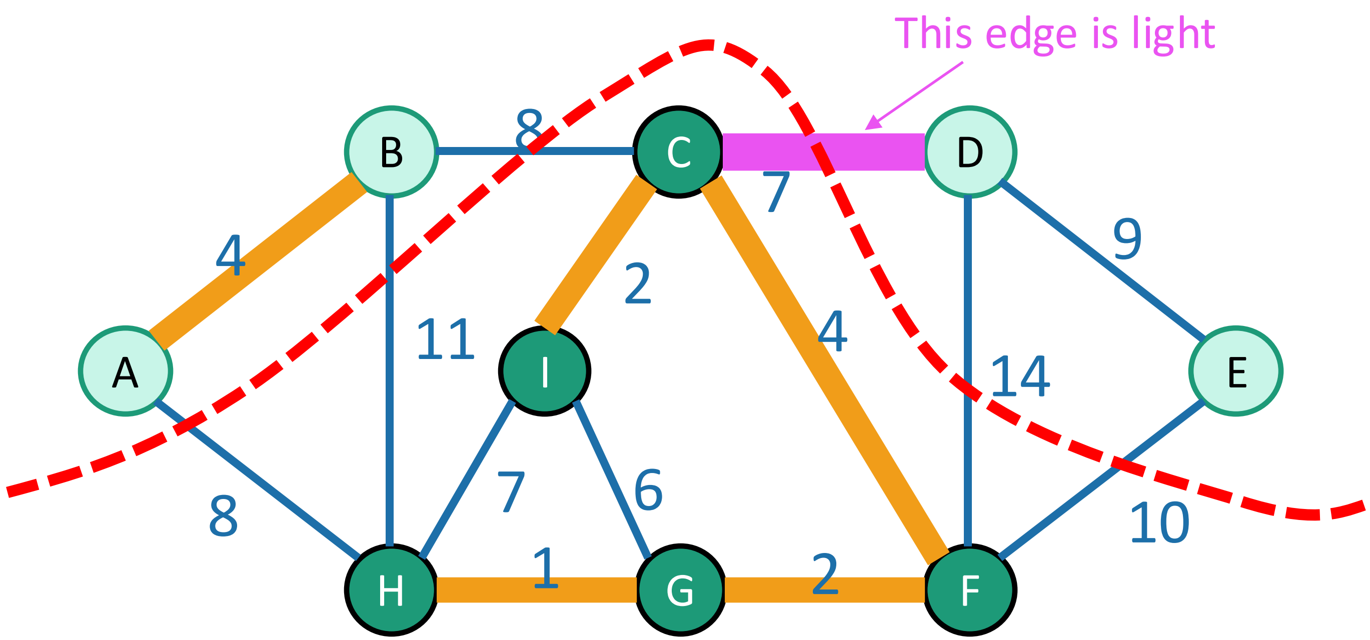
- We need to show that our greedy choices **don't rule out success.**
- That is, at every step:
  - There exists an MST that contains all of the edges we have added so far.

- Now it is time to use our lemma!

again!

Lemma

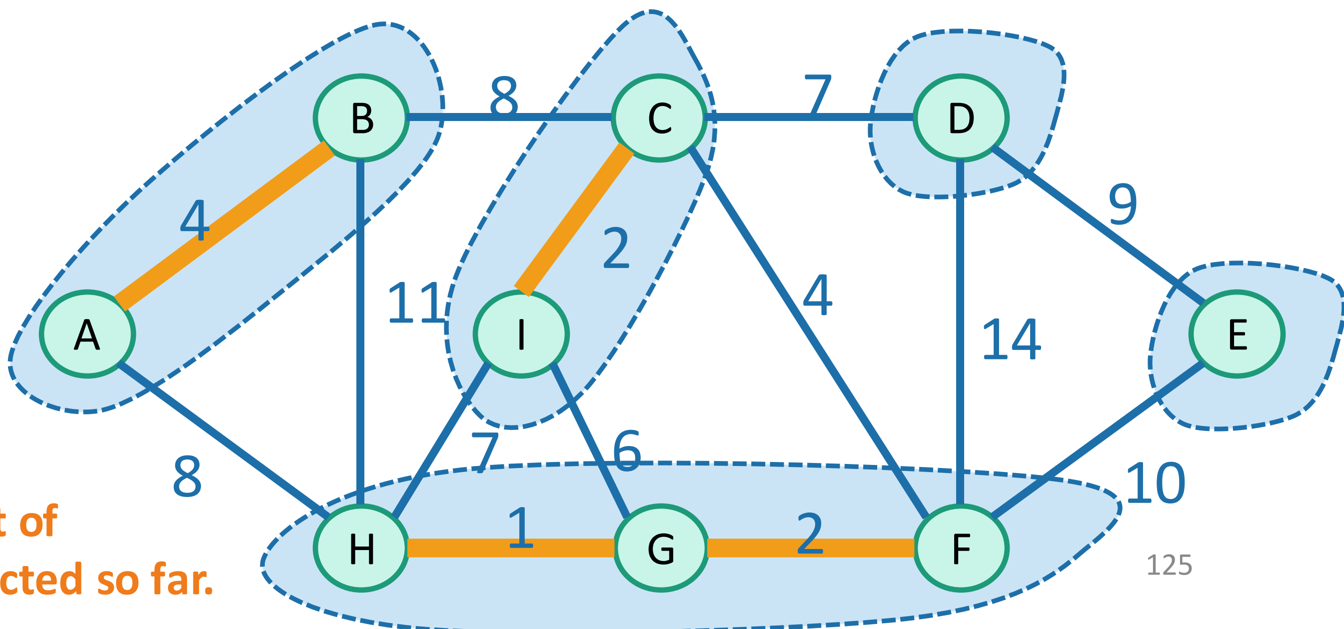
- Let S be a set of edges, and consider a cut that respects S.
- Suppose there is an MST containing S.
- Let {u,v} be a light edge.
- Then there is an MST containing S ∪ {{u,v}}



S is the set of **thick orange** edges

Partway through Kruskal

- Assume that our choices **S** so far don't rule out success.
  - There is an MST extending them
- The **next edge** we add will merge two trees, **T1, T2**



S is the set of edges selected so far.

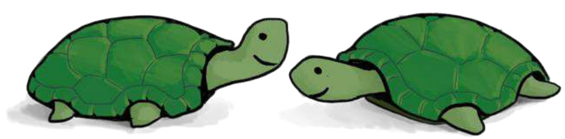
Partway through Kruskal

- Assume that our choices **S** so far don't rule out success.
  - There is an MST extending them
- The **next edge** we add will merge two trees, **T1, T2**

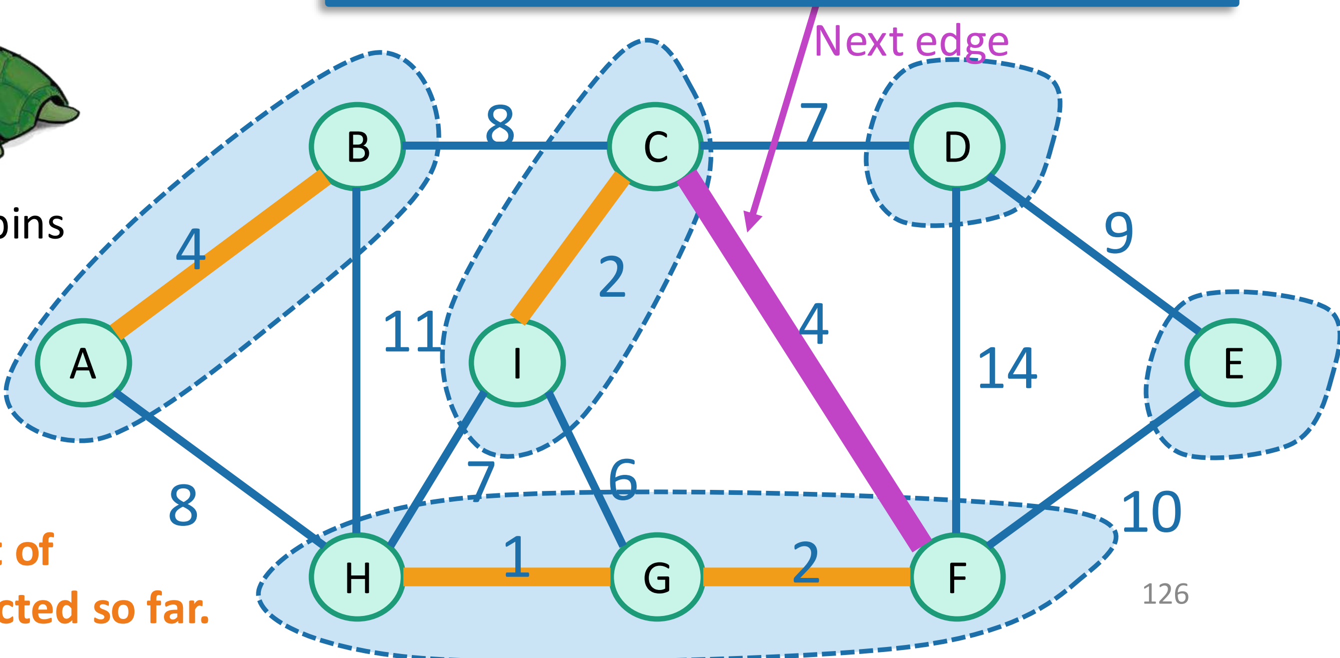
Lemma

- Let S be a set of edges, and consider a cut that respects S.
- Suppose there is an MST containing S.
- Let {u,v} be a light edge.
- Then there is an MST containing S ∪ {{u,v}}

How can we use our lemma to show that our next choice also does not rule out success?



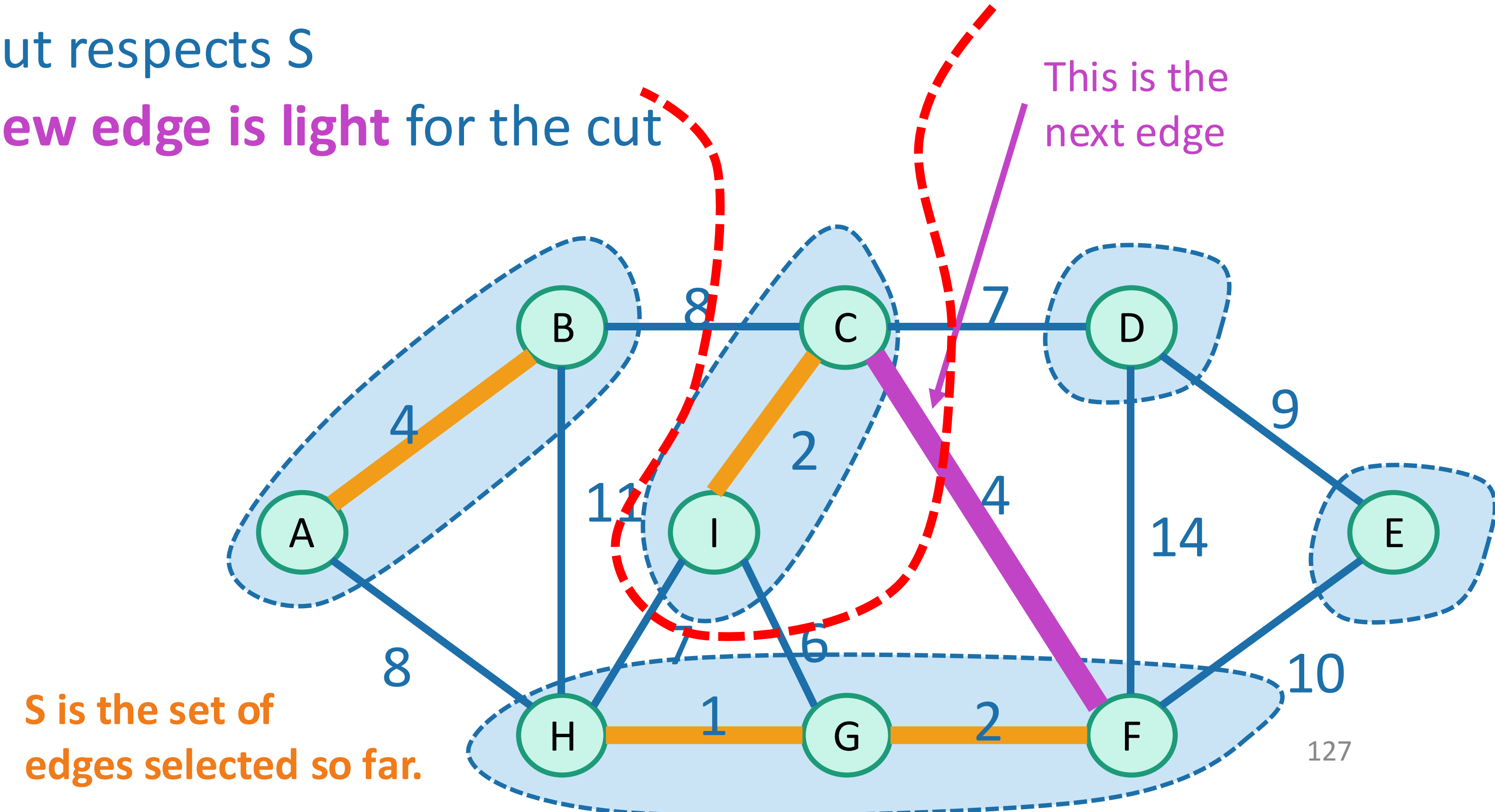
Think-Pair-Share Terrapins



S is the set of edges selected so far.

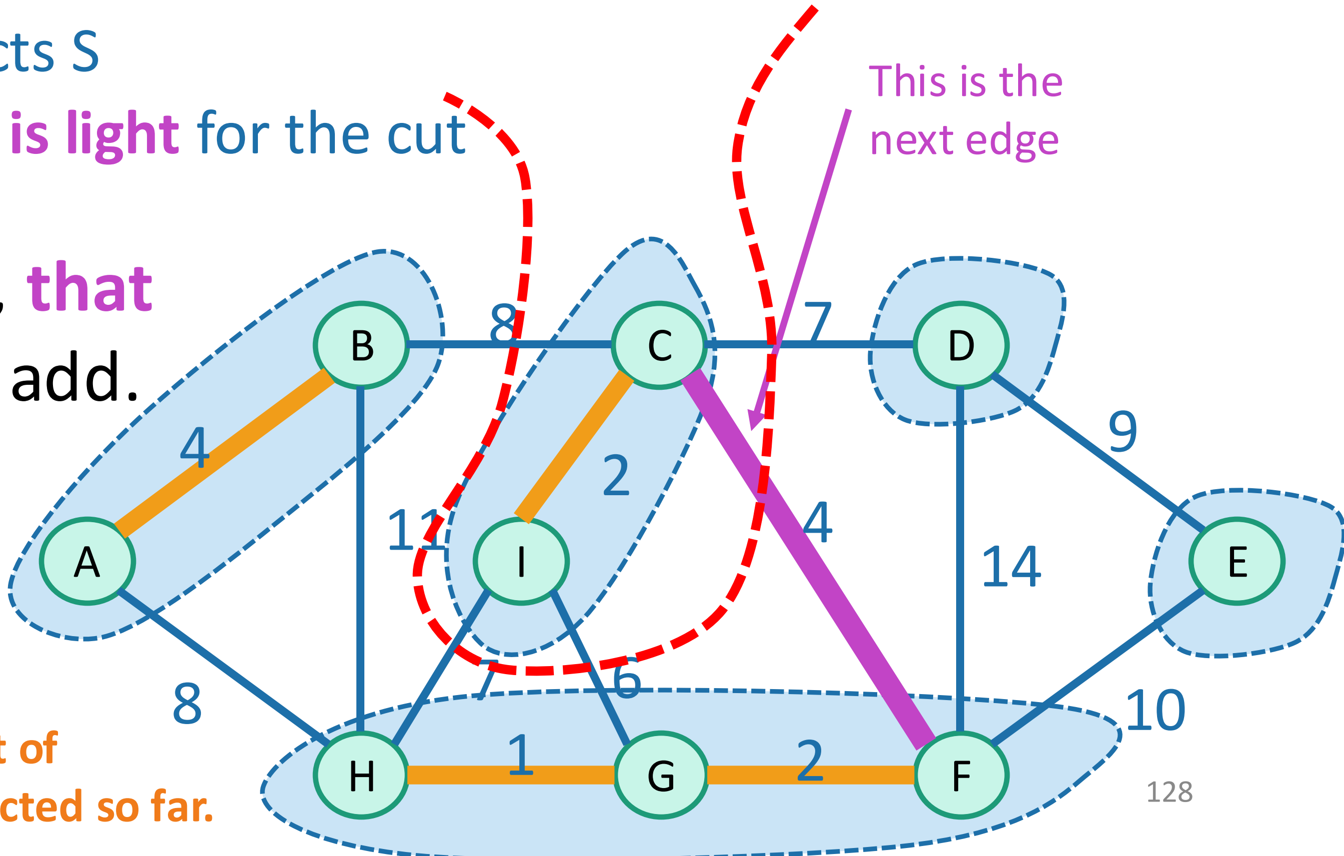
Partway through Kruskal

- Assume that our choices **S** so far don't rule out success.
  - There is an MST extending them
- The **next edge** we add will merge two trees, **T1, T2**
- Consider the cut **{T1, V – T1}.**
  - This cut respects S
  - Our **new edge is light** for the cut



Partway through Kruskal

- Assume that our choices **S** so far don’t rule out success.
  - There is an MST extending them
- The **next edge** we add will merge two trees, **T1, T2**
- Consider the cut **{T1, V – T1}.**
  - This cut respects S
  - Our **new edge is light** for the cut
- By the Lemma, **that edge** is safe to add.
  - There is still an MST extending the new set



Hooray!

- Our greedy choices **don’t rule out success**.
- This is enough (along with an argument by induction) to guarantee correctness of Kruskal’s algorithm.

Two questions

1. Does it work?
    - That is, does it actually return a MST?
        - **Yes**
2. How do we actually implement this?
    - the pseudocode above says “slowKruskal”…
        - **Using a union-find data structure!**

What have we learned?

- Kruskal's algorithm greedily grows a forest
- It finds a Minimum Spanning Tree in time O(mlog(n))
  - if we implement it with a Union-Find data structure
  - if the edge weights are reasonably-sized integers and we ignore the inverse Ackerman function, basically O(m) in practice.
- To prove it worked, we followed the same recipe for greedy algorithms we saw last time.
  - Show that, at every step, we **don't rule out success.**

Compare and contrast

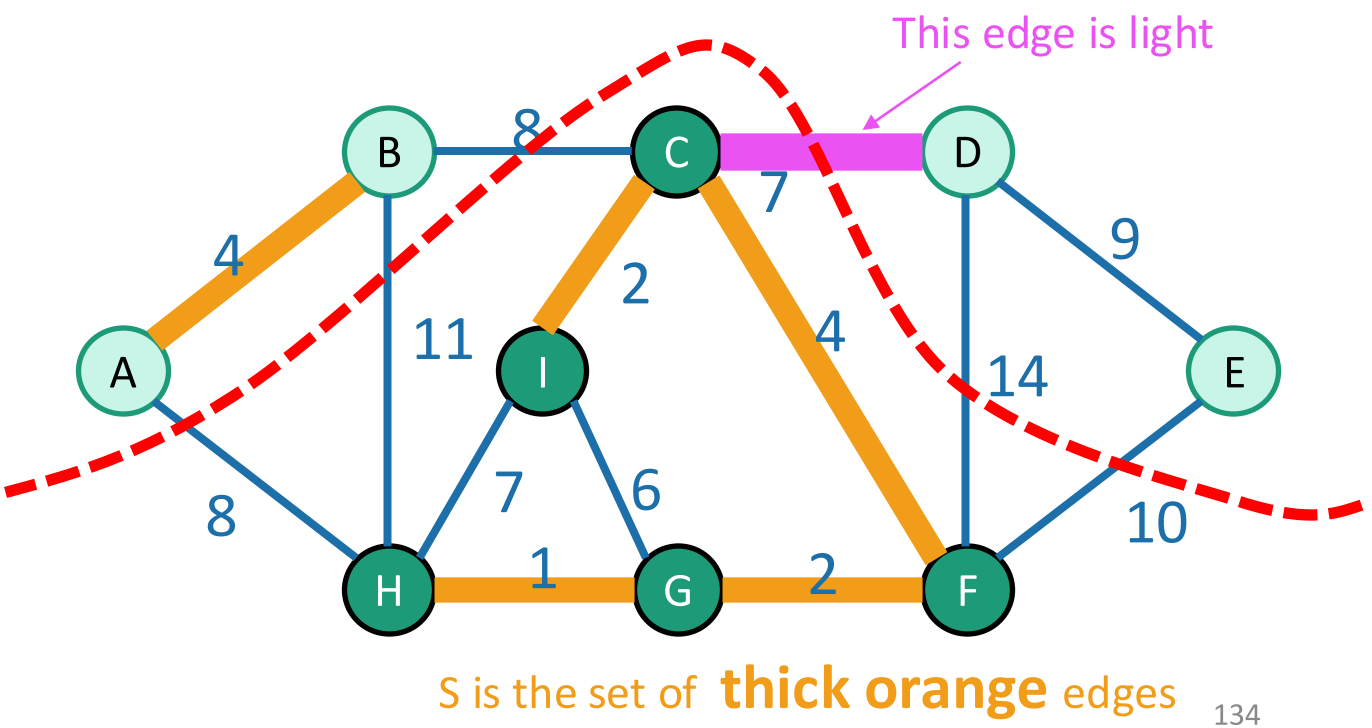
- Prim:
  - Grows a tree.
  - Time O(mlog(n)) with a red-black tree
  - Time O(m + nlog(n)) with a Fibonacci heap
- Kruskal:
  - Grows a forest.
  - Time O(mlog(n)) with a union-find data structure
  - If you can do radixSort on the edge weights, morally O(m)

Prim might be a better idea on dense graphs if you can't radixSort edge weights

Kruskal might be a better idea on sparse graphs if you can radixSort edge weights

Both Prim and Kruskal

- Greedy algorithms for MST.
- Similar reasoning:
  - Optimal substructure: subgraphs generated by cuts.
  - The way to make safe choices is to choose light edges crossing the cut.



Can we do better?

State-of-the-art MST on connected undirected graphs

- Karger-Klein-Tarjan 1995:
  - O(m) time randomized algorithm
- Chazelle 2000:
  - O(m$\cdot$ $\alpha(n)$) time deterministic algorithm
- Pettie-Ramachandran 2002:
  - O$\left(\begin{array}{c}\text{The optimal number of comparisons} \\ \text{you need to solve the problem,} \\ \text{whatever that is...}\end{array}\right)$ time deterministic algorithm

What is this number?
Do we need that silly $\alpha(n)$?
Open questions!

Recap

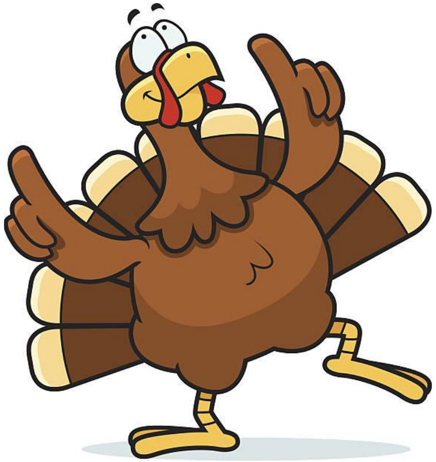
- Two algorithms for Minimum Spanning Tree
  - Prim's algorithm
  - Kruskal's algorithm

- Both are (more) examples of greedy algorithms!
  - Make a **series of choices**.
  - Show that at each step, your choice **does not rule out success.**
  - At the end of the day, you haven't ruled out success, so **you must be successful**.

Next time (after fall break)

- Min cuts and max flow!

Before next time



- Have a great fall break!
- Pre-lecture exercise: routing people across rickety bridges…