### Lecture 11

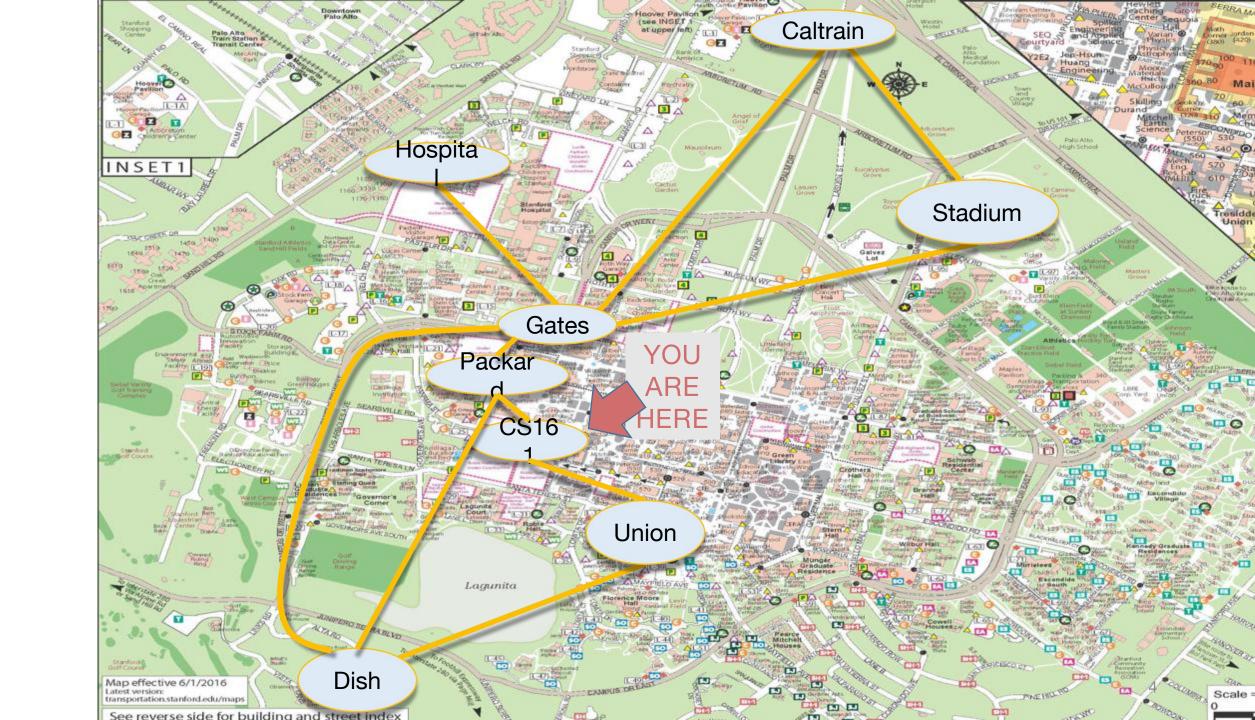
Weighted Graphs: Dijkstra and Bellman-Ford

#### Previous two lectures

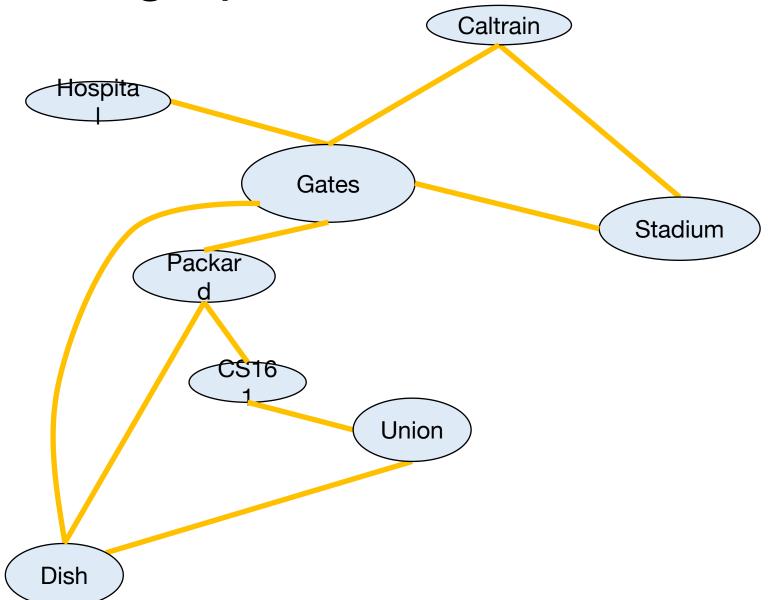
- Graphs!
- DFS
  - Topological Sorting
  - Strongly Connected Components
- BFS
  - Shortest Paths in unweighted graphs

### Today

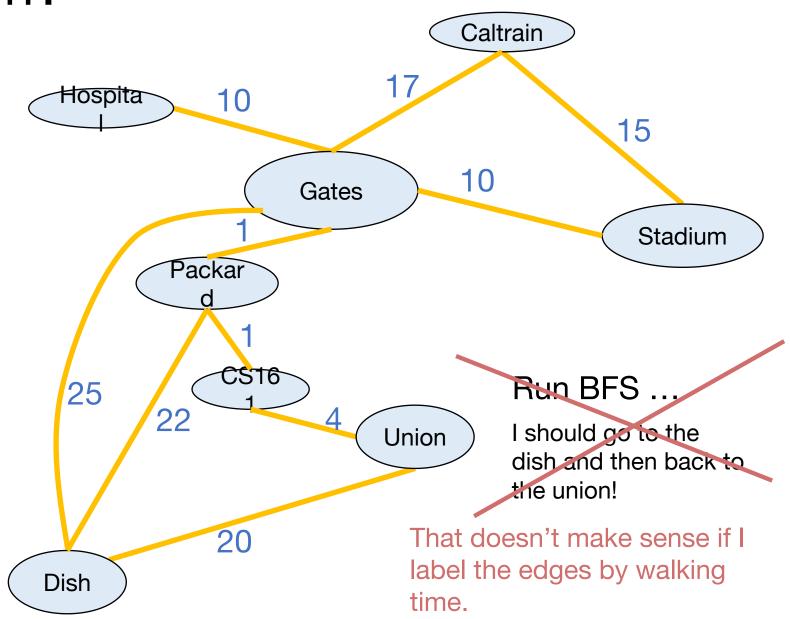
- What if the graphs are weighted?
- Part 1: Dijkstra!
  - This will take most of today's class
- Part 2: Bellman-Ford!
  - Real quick at the end if we have time!
  - We'll come back to Bellman-Ford in more detail, so today is just a taste.



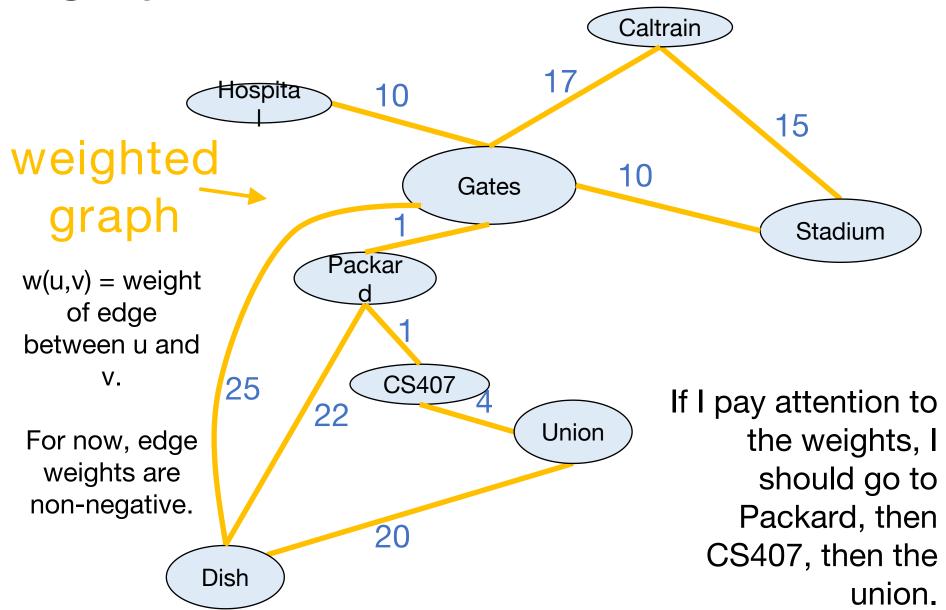
Just the graph



### Shortest path from Gates to the Union?

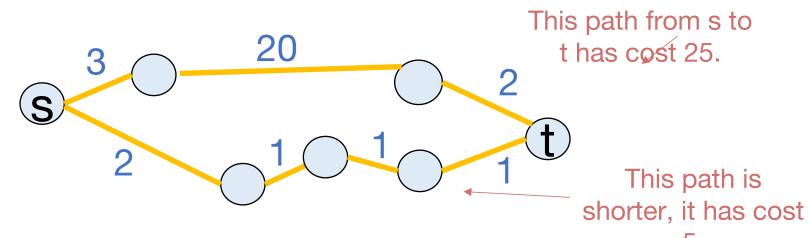


### Shortest path from Gates to the Union?

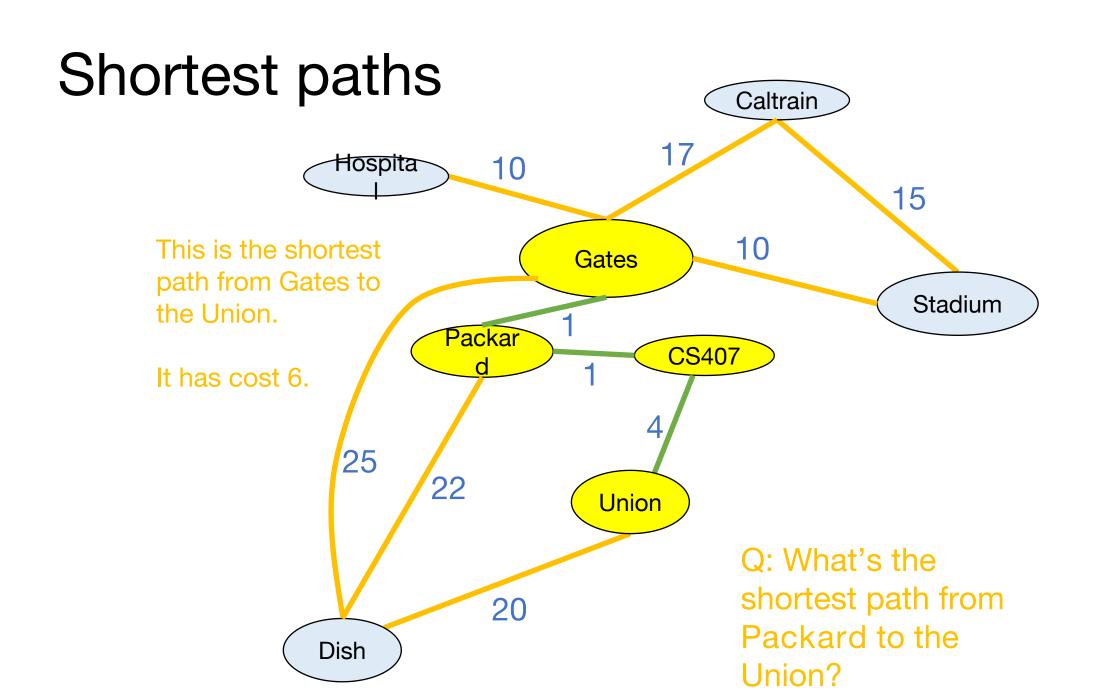


### Shortest path problem

- What is the shortest path between u and v in a weighted graph?
  - the cost of a path is the sum of the weights along that path
  - The shortest path is the one with the minimum cost.



- The distance d(u,v) between two vertices u and  $v^2$  is the cost of the the shortest path between u and v.
- For this lecture all graphs are directed, but to save on notation I'm just going to draw undirected egge



#### Warm-up

 A sub-path of a shortest path is also a shortest path.

- Say this is a shortest path from s to t.
  Claim: this is a shortest path from s to x.
  Suppose not, this one is a shorter path from s to But them that gives an even shorter path from s
- s (x)

#### Single-source shortest-path problem

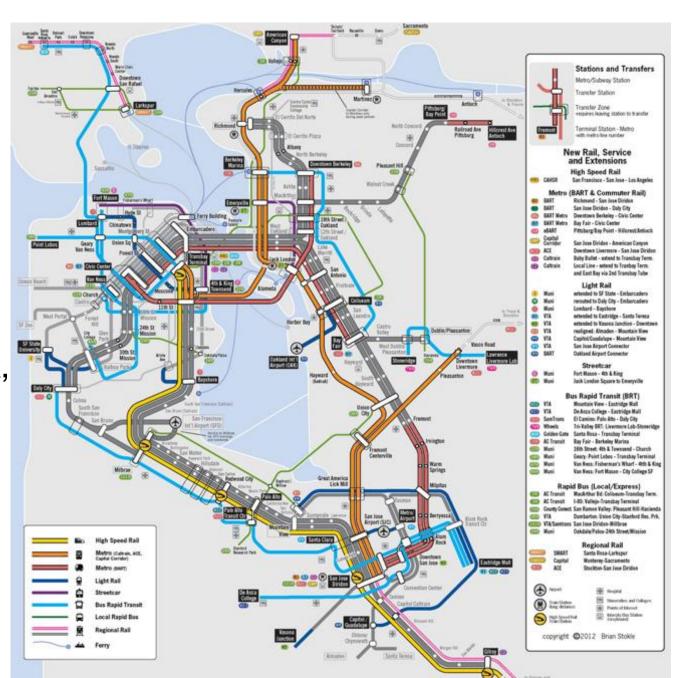
 I want to know the shortest path from one vertex (Gates) to all other vertices.

Destination	Cost	To get there
Packard	1	Packard
CS407	2	Packard-CS407
Hospital	10	Hospital
Caltrain	17	Caltrain
Union	6	Packard-CS407- Union
Stadium	10	Stadium
Dish	23	Packard-Dish

(Not necessarily stored as a table – how this information is represented will depend on the

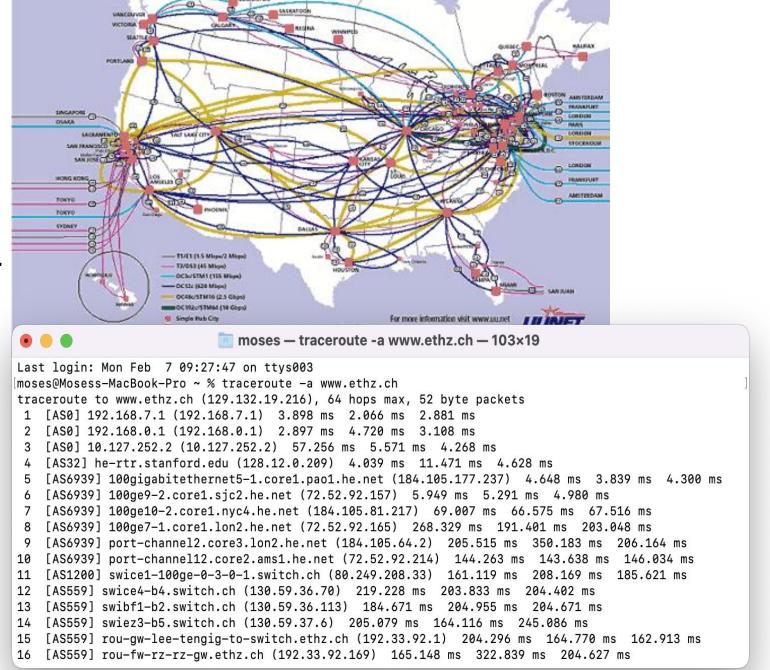
### Example

- "what is the shortest path from Palo Alto to [anywhere else]" using BART, Caltrain, lightrail, MUNI, bus, Amtrak, bike, walking, uber/lyft.
- Edge weights have something to do with time, money, hassle.



#### Example

- Network routing
- I send information over the internet, from my computer to to all over the world.
- Each path has a cost which depends on link length, traffic, other costs, etc..
- How should we send packets?

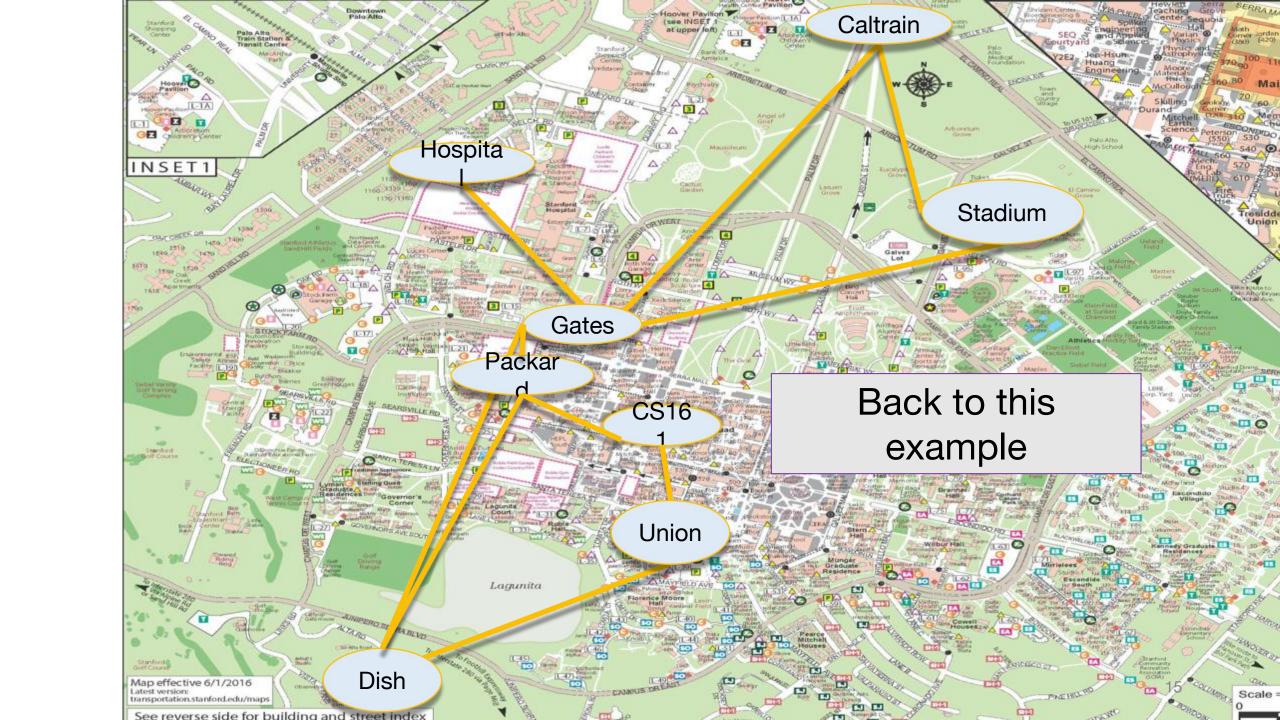


UUNET's North America Internet network

#### Aside: These are difficult problems

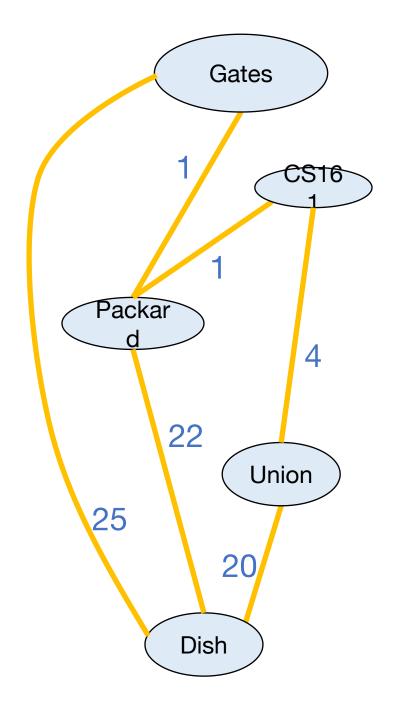
- Costs may change
  - If it's raining the cost of biking is higher
  - If a link is congested, the cost of routing a packet along it is higher
- The network might not be known
  - My computer doesn't store a map of the internet
- We want to do these tasks really quickly
  - I have time to bike to Berkeley, but not to think about whether I should bike to Berkeley...
  - More seriously, the internet.

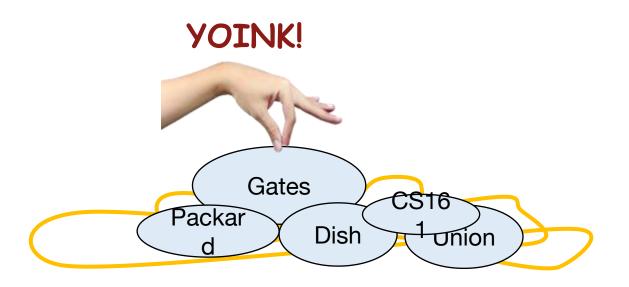
This is a joke.



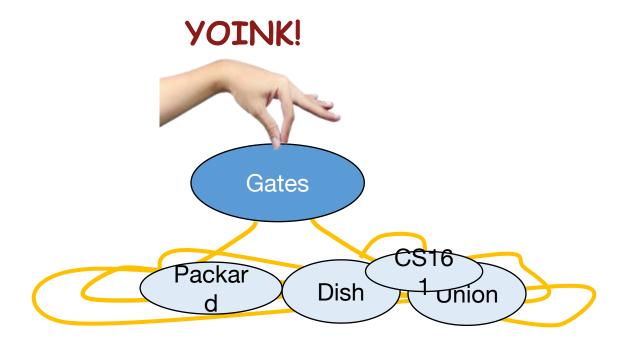
### Dijkstra's algorithm

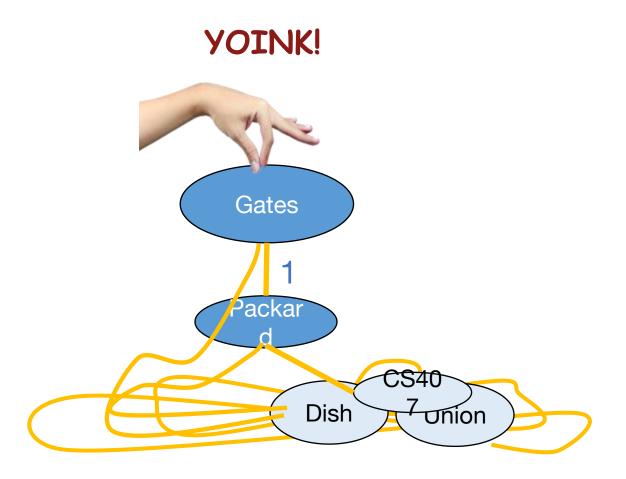
• Finds shortest paths from Gates to everywhere else.



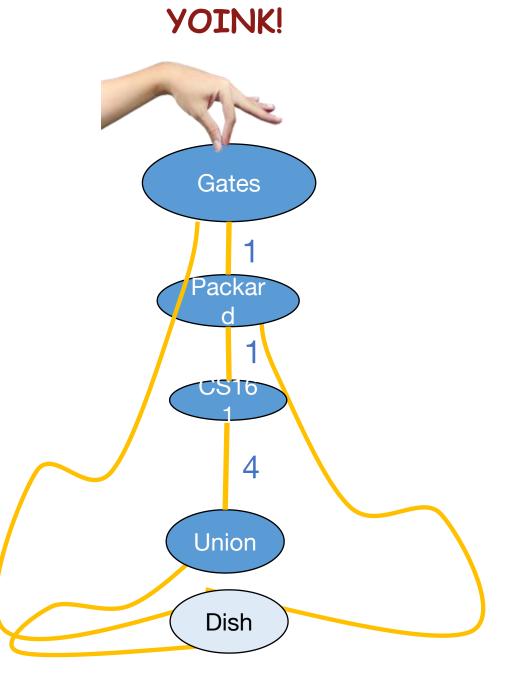


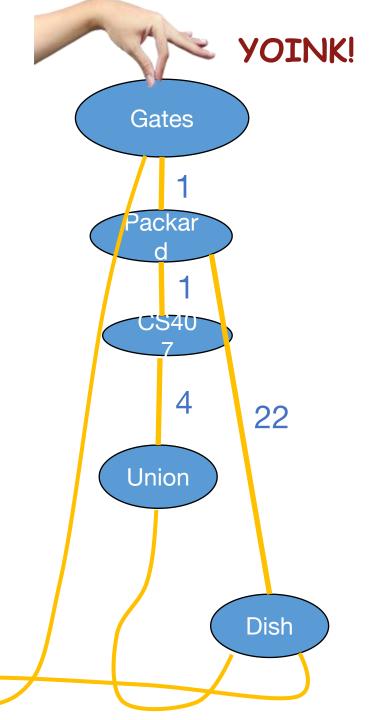
A vertex is done when it's not on the ground anymore.





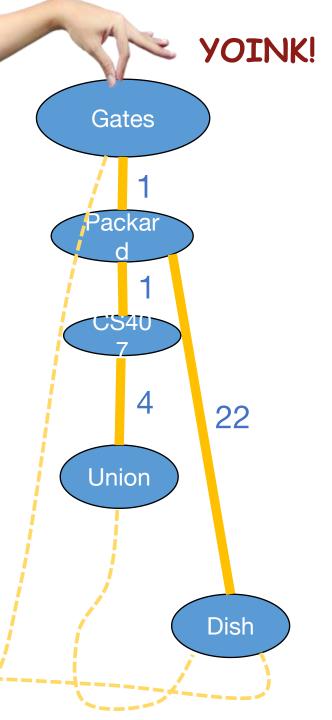
### YOINK! Gates ackar CS16 Dish Union





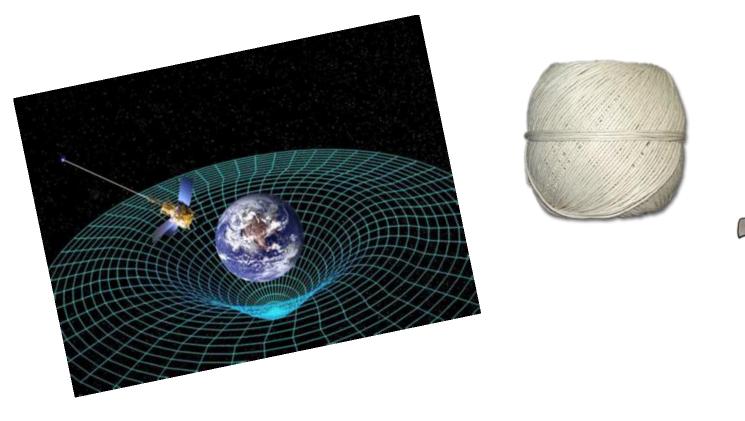
This creates a tree!

The shortest paths are the lengths along this tree.



#### How do we actually implement this?

Without string and gravity?





How far is a node from Gates?

ales

I'm not sure yet



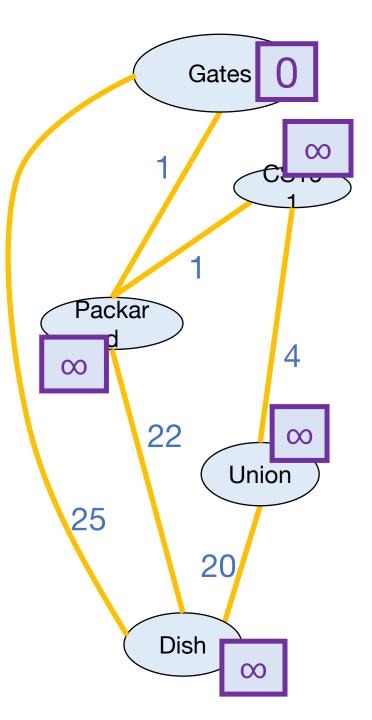
I'm sure



x = d[v] is my best overestimate for dist(Gates,v).

Initialize  $d[v] = \infty$  for all non-starting vertices

• Pick the **not-sure** node u with the smallest estimate d[u].



How far is a node from Gates?



I'm not sure yet



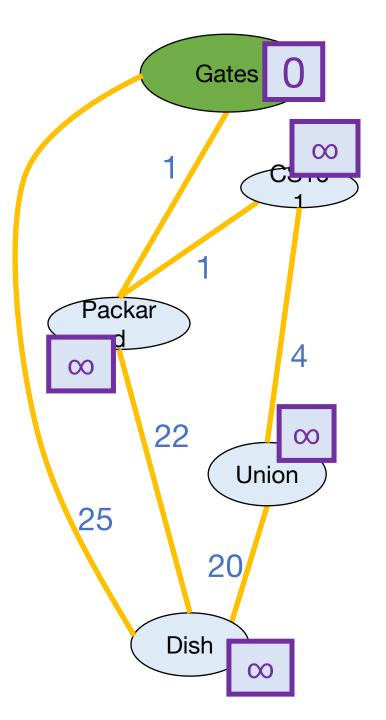
I'm sure



x = d[v] is my best overestimate for dist(Gates,v).



- Pick the not-sure node u with the smallest estimate d[u].
- Update all u's neighbors v:
  - d[v] = min(d[v], d[u] + edgeWeight(u,v))



How far is a node from



I'm not sure yet



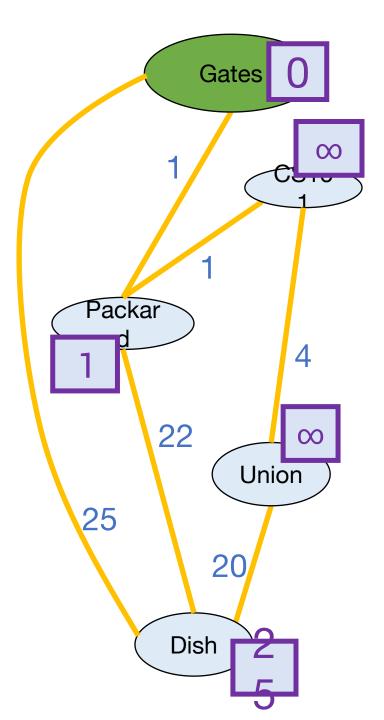
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- Pick the not-sure node u with the smallest estimate d[u].
- Update all u's neighbors v:
  - d[v] = min(d[v], d[u] + edgeWeight(u,v))
- Mark u as Sure.



How far is a node from



I'm not sure yet



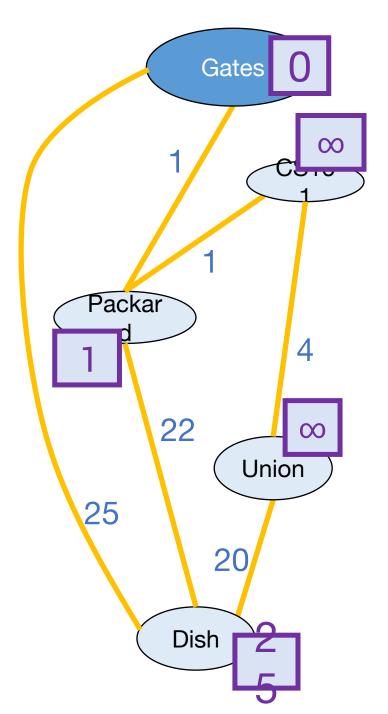
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- Pick the not-sure node u with the smallest estimate d[u].
- Update all u's neighbors v:
  - d[v] = min(d[v], d[u] + edgeWeight(u,v))
- Mark u as Sure.
- Reneat



neighbors. What

update them?

How far is a node from Gates?

I'm not sure yet



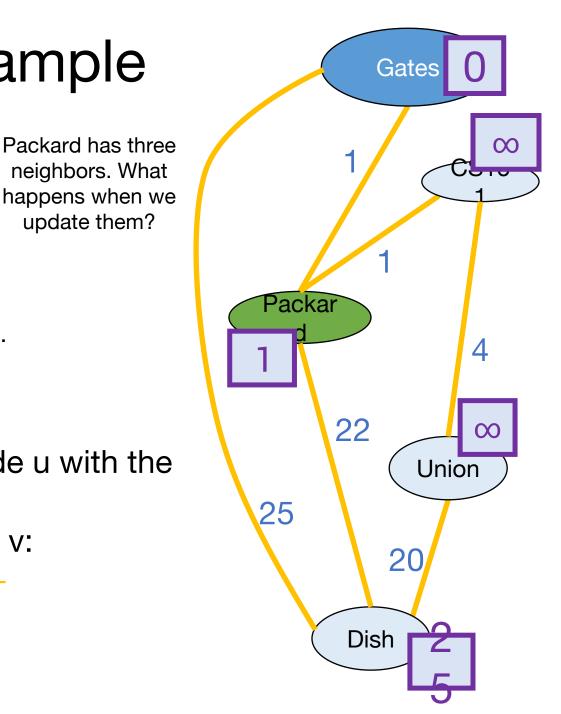
I'm sure



x = d[v] is my best overestimate for dist(Gates,v).



- Pick the not-sure node u with the smallest estimate d[u].
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  - d[v] = min(d[v], d[u] +edgeWeight(u,v))
- Mark u as SUre.
- Reneat



neighbors. What

update them?

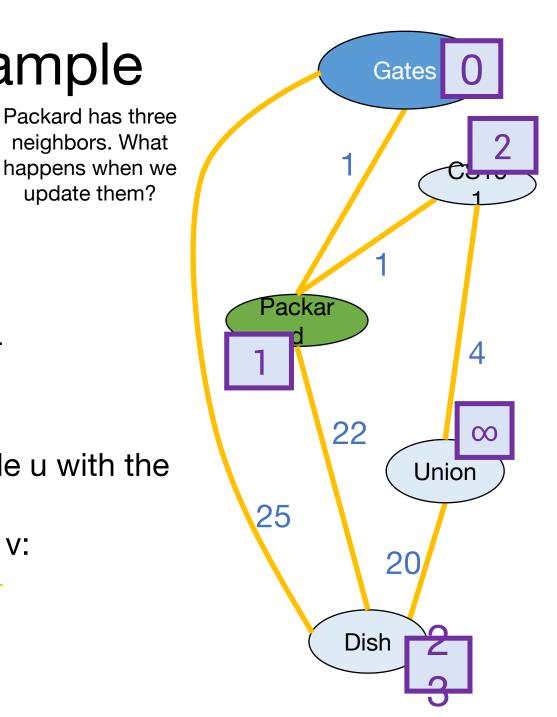
How far is a node from Gates?

I'm not sure yet

I'm sure

x = d[v] is my best overestimate for dist(Gates,v).

- Pick the not-sure node u with the smallest estimate d[u].
- Update all u's neighbors v:
  - d[v] = min(d[v], d[u] +edgeWeight(u,v))
- Mark u as SUre.
- Reneat



How far is a node from



I'm not sure yet



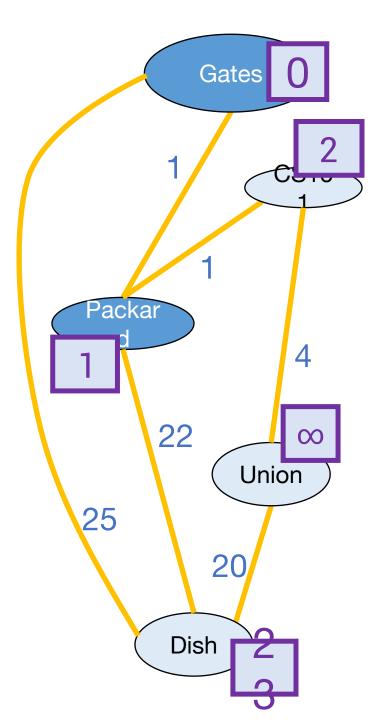
I'm sure



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- Reneat



How far is a node from



I'm not sure yet



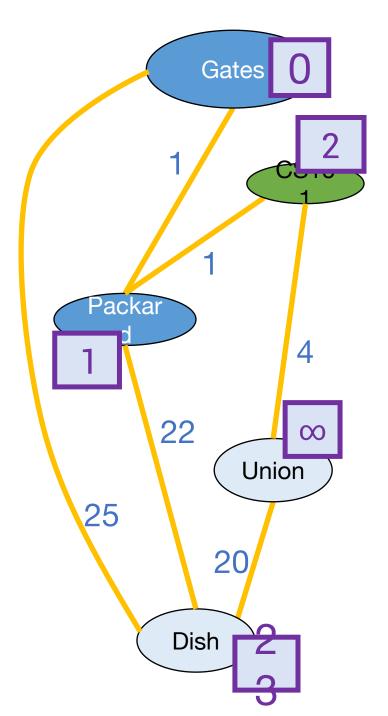
I'm sure



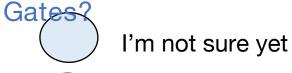
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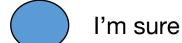


- Pick the not-sure node u with the smallest estimate d[u].
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- Mark u as Sure.
- Reneat



How far is a node from

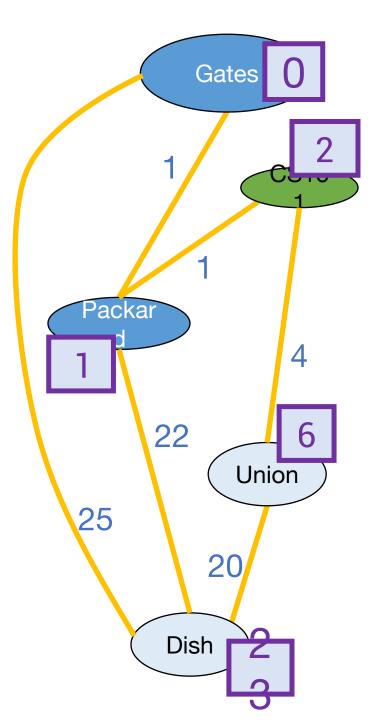








- Pick the not-sure node u with the smallest estimate d[u].
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How far is a node from



I'm not sure yet



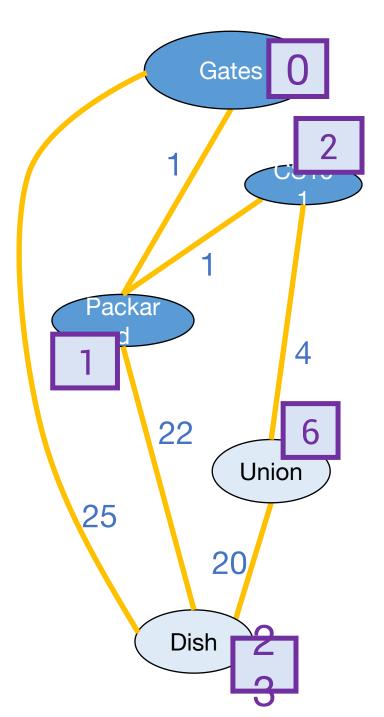
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How far is a node from



I'm not sure yet



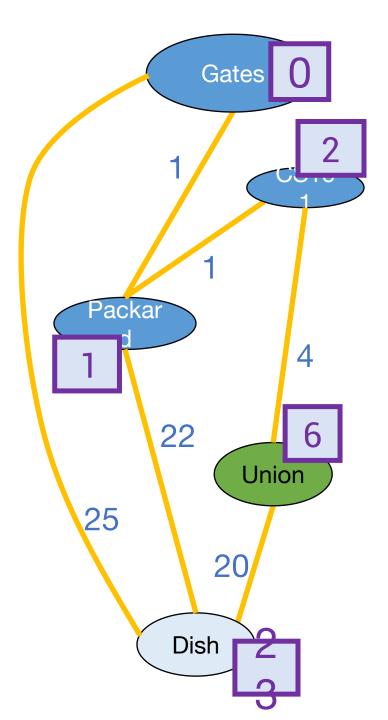
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- Mark u as Sure.
- Repeat



How far is a node from



I'm not sure yet



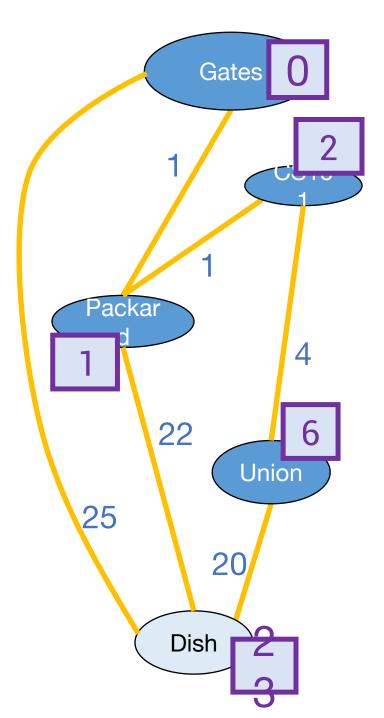
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- Mark u as Sure.
- Reneat



## Dijkstra by example

How far is a node from

Gates?

I'm not sure yet



I'm sure

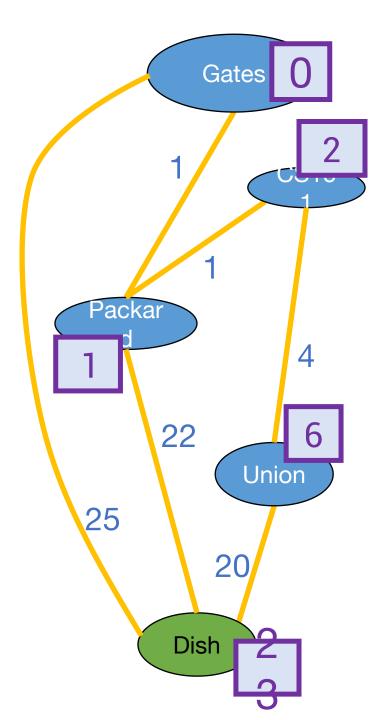


x = d[v] is my best overestimate for dist(Gates, v).



Current node u

- Pick the not-sure node u with the smallest estimate d[u].
- Update all u's neighbors v:
  - d[v] = min(d[v], d[u] + edgeWeight(u,v))
- Mark u as Sure.
- Repeat



## Dijkstra by example

How far is a node from



I'm not sure yet



I'm sure

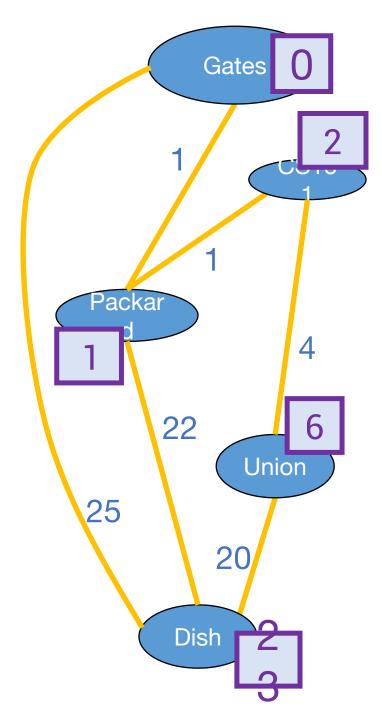


x = d[v] is my best overestimate for dist(Gates, v).



Current node u

- Pick the not-sure node u with the smallest estimate d[u].
- Update all u's neighbors v:
  - d[v] = min(d[v], d[u] + edgeWeight(u,v))
- Mark u as Sure.
- Reneat



Dijkstra by example

How far is a node from

Gates?

I'm not sure yet



I'm sure

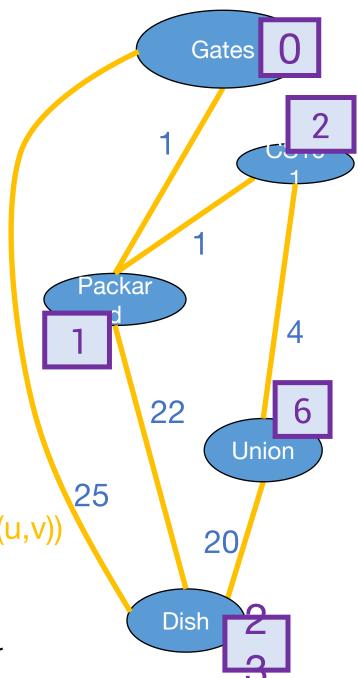


x = d[v] is my best overestimate for dist(Gates, v).



Current node u

- Pick the not-sure node u with the smallest estimate d[u].
- Update all u's neighbors v:
  - d[v] = min(d[v], d[u] + edgeWeight(u,v))
- Mark u as Sure.
- Repeat
- After all nodes are sure, say that d(Gates, v) = d[v] for all v



## Dijkstra's algorithm

#### Dijkstra(G,s):

- Set all vertices to not-sure
- $d[v] = \infty$  for all v in V
- d[s] = 0
- While there are not-sure nodes:
  - Pick the not-sure node u with the smallest estimate d[u].
  - For v in u.neighbors:
    - d[v] ← min(d[v], d[u] + edgeWeight(u,v))
  - Mark u as sure.
- Now d(s, v) = d[v]

Lots of implementation details left unexplained. We'll get to that!

## As usual

- Does it work?
  - Yes.

- Is it fast?
  - Depends on how you implement it.

## Why does this work?

#### • Theorem:

- Suppose we run Dijkstra on G = (V,E), starting from s.
- At the end of the algorithm, the estimate d[v] is the actual distance d(s,v).

#### Proof outline:

Let's rename "Gates" to "s", our starting vertex.

- Claim 1: For all  $v, d[v] \ge d(s,v)$ .
- Claim 2: When a vertex v is marked sure, d[v] = d(s,v).
- Claims 1 and 2 imply the theorem. Claim 2
  - When v is marked sure, d[v] = d(s,v).
  - d[v] ≥ d(s,v) and never increases, so after v is sime, d[v] stops changing.
  - This implies that at any time after v is marked sure, d[v] = d(s,v).
  - All vertices are sure at the end, so all vertices end up with d[v] = d(s,v).

## Claim 1

 $d[v] \ge d(s,v)$  for all v.

#### Informally:

• Every time we update d[v], we have a path in mind:

 $d[v] \leftarrow min(d[v], d[u] + edgeWeight(u,v))$ 

Whatever path we had in mind before

The shortest path to u, and then the edge from u to v.

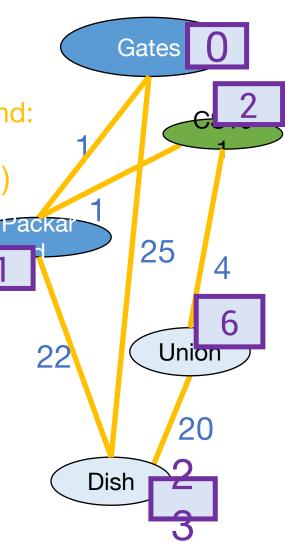
d[v] = length of the path we have in mind

≥ length of shortest path

= d(s,v)

#### Formally:

- We should prove this by induction.
  - (See skipped slide or do it yourself)



Intuition!

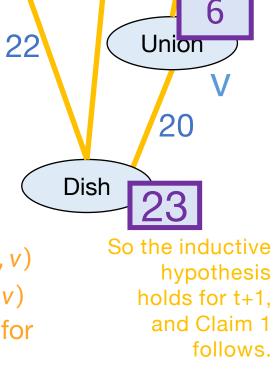
## Claim 1

 $d[v] \ge d(s,v)$  for all v.

- Inductive hypothesis.
  - After t iterations of Dijkstra,
     d[v] ≥ d(s,v) for all v.
- Base case:
  - At step 0, d(s,s) = 0, and  $d(s,v) \le \infty$
- Inductive step: say hypothesis holds for t.
  - At step t+1:
    - Pick u; for each neighbor v:
    - $d[v] \leftarrow min(d[v], d[u] + w(u,v) \stackrel{>}{>} d(s,v)$

By induction,  $d(s, v) \leq d[v]$ 

 $d(s, v) \le d(s, u) + d(u, v)$   $\le d[u] + w(u, v)$ using induction again for d[u]



Gates

25

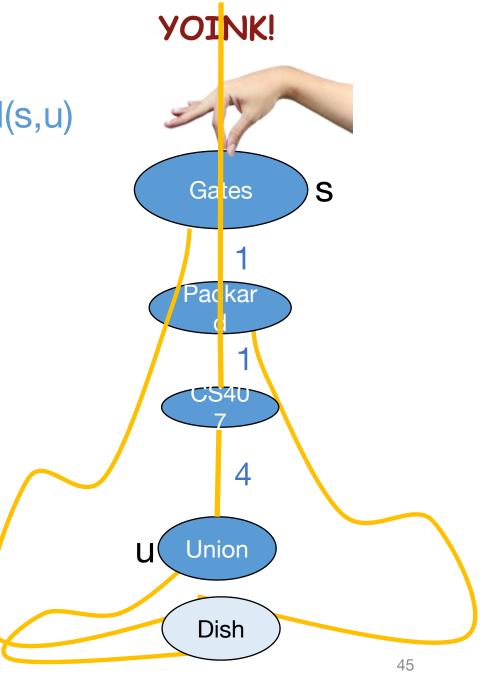
**Packard** 

## Intuition for Claim 2

When a vertex u is marked sure, d[u] = d(s,u)

 The first path that lifts u off the ground is the shortest one.

- Let's prove it!
  - Or at least see a proof outline.



### Claim 2

## When a vertex u is marked sure, d[u] = d(s,u)

- Inductive Hypothesis:
  - When we mark the t'th vertex v as sure, d[v] = dist(s,v).
- Base case (t=1):
- Inductive step:
  - Assume by induction that every v already marked sure has d[v] = d(s,v).
  - Suppose that we are about to add u to the sure list.
  - That is, we picked u in the first line here:
    - Pick the not-sure node u with the smallest estimate d[u].
    - Update all u's neighbors v:
      - d[v] ← min(d[v], d[u] + edgeWeight(u,v))
    - Mark u as sure.
    - Repeat
  - Want to show that d[u] = d(s,u).

because they may or

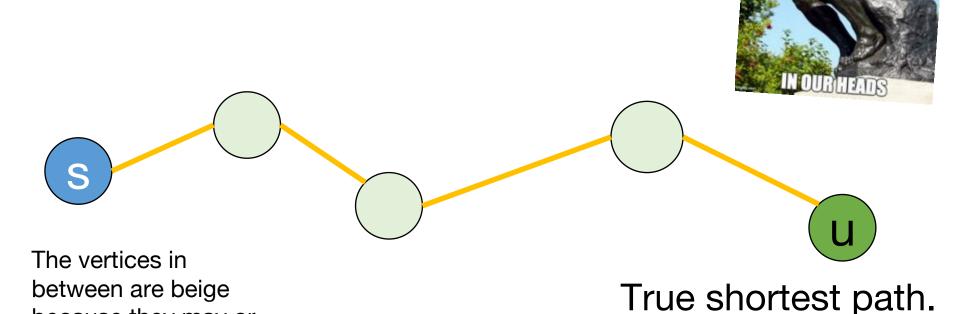
may not be sure.

Temporary definition: v is "good" means that d[v] = d(s,v)

THOUGHT EXPERIMENT

Want to show that u is good.

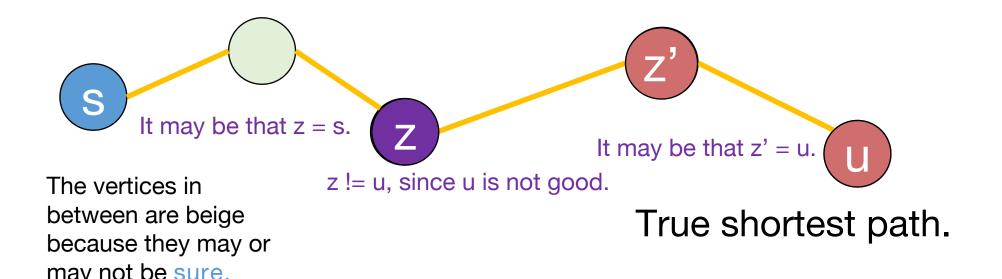
Consider a true shortest path from s to



47

#### Temporary definition: v is "good" means that d[v] =

- means not good good "by way of contradiction"
- Want to show that u is goodWOC, suppose u isn't good.
- Say z is the last good vertex before u (on shortest path to u).
- z' is the vertex after z.

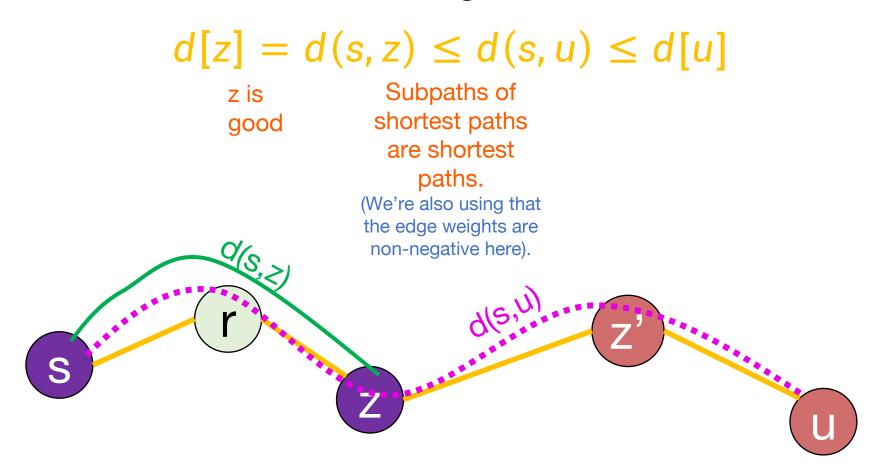


## Temporary definition: v is "good" means that d[v] = """ means not

good

• Want to show that u is goodWOC, suppose u isn't good.

good

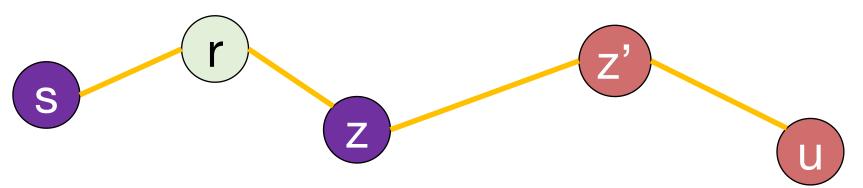


# Temporary definition: v is "good" means that d[v] = """ means not good """ good

• Want to show that u is goodWOC, suppose u isn't good.

$$d[z] = d(s, z) \le d(s, u) \le d[u]$$
z is
good
Subpaths of
shortest paths
are shortest

- Since u is not good,  $paths[z] \neq d[u]$ .
- So d[z] < d[u], so z is sur  $e^{\text{We chose u so that d[u] was}}$

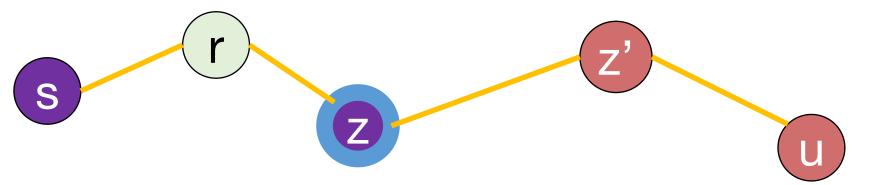


# Temporary definition: v is "good" means that d[v] = """ means not good """ good

• Want to show that u is goodWOC, suppose u isn't good.

$$d[z] = d(s, z) \le d(s, u) \le d[u]$$
z is
good
Subpaths of Claim 1
shortest paths
are shortest

- If d[z] = d[u], then u is not good!
- So d[z] < d[u], so z is sure. We chose u so that d[u] was smallest of the unsure vertices.



#### Temporary definition: v is "good" means that d[v] =

good

- means not good
- Want to show that u is goodWOC, suppose u isn't good.
- If z is sure then we've already updated z';
- $d[z'] \leftarrow \min\{d[z'], d[z] + w(z, z')\}$ •  $d[z'] \leq d[z] + w(z,z')$  def of update

= d(s,z) + w(z,z) By induction when z was added to the sure list it had d(s,z) = d[z]

That is, the value of d[z] when z was marked sure...

Claim 1

= d(s, z') sub-paths of shortest paths are shortest paths

So d(s,z') = d[z'] and so z' is good.



CONTRADICTIO

## Claim 2

## Back to this slide

## When a vertex u is marked sure, d[u] = d(s,u)

- Inductive Hypothesis:
  - When we mark the t'th vertex v as sure, d[v] = dist(s,v).
- Base case:
  - The first vertex marked sure is s, and d[s] = d(s,s) = 0.
- Inductive step:
  - Suppose that we are about to add u to the sure list.
  - That is, we picked u in the first line here:
    - Pick the not-sure node u with the smallest estimate d[u].
    - Update all u's neighbors v:
      - d[v] ← min( d[v] , d[u] + edgeWeight(u,v))
    - Mark u as sure.
    - Repeat
  - Assume by induction that every v already marked sur has d[v] = d(s,v).
- Want to show that d[u] = d(s,u). Conclusion: Claim 2 holds!

## Why does this work?



#### Theorem:

- Run Dijkstra on G = (V,E) starting from s.
- At the end of the algorithm, the estimate d[v] is the actual distance d(s,v).

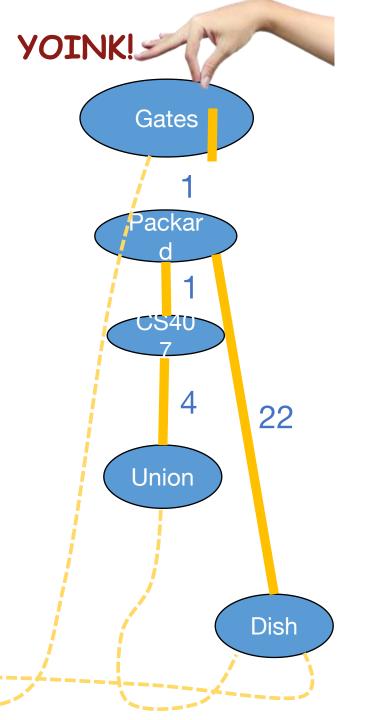
#### Proof outline:

- Claim 1: For all  $v, d[v] \ge d(s,v)$ .
- Claim 2: When a vertex is marked sure, d[v] = d(s,v).
- Claims 1 and 2 imply the theorem.

### What have we learned?

 Dijkstra's algorithm finds shortest paths in weighted graphs with non-negative edge weights.

- Along the way, it constructs a nice tree.
  - We could post this tree in Gates!
  - Then people would know how to get places quickly.



## As usual

- Does it work?
  - Yes.



- Is it fast?
  - Depends on how you implement it.

## Running time?

#### Dijkstra(G,s):

- Set all vertices to not-sure
- $d[v] = \infty$  for all v in V
- d[s] = 0
- While there are not-sure nodes:
  - Pick the not-sure node u with the smallest estimate d[u].
  - For v in u.neighbors:
    - d[v] ← min(d[v], d[u] + edgeWeight(u,v))
  - Mark u as sure.
- Now dist(s, v) = d[v]
   n iterations (one per vertex)
  - How long does one iteration take?

### We need a data structure that:

- Stores unsure vertices v
- Keeps track of d[v]
- Can find u with minimum d[u]
  - findMin()
- Can remove that u
  - removeMin(u)
- Can update (decrease) d[v]
  - updateKey(v,d)

#### Just the inner

Pick the not-sure node u with the smallest estimate d[u].

- Update all u's neighbors v:
  - d[v] ← min( d[v], d[u] + edgeWeight(u,v))
- Mark u as sure.

Total running time is big-oh of:

$$\sum_{u \in V} (T(\text{findMin}) + (\sum_{v \in u.neighbors} T(\text{updateKey})) + T(\text{removeMin}))$$

= n( T(findMin) + T(removeMin) ) + m T(updateKey)

## If we use an array

- T(findMin) = O(n)
- T(removeMin) = O(n)
- T(updateKey) = O(1)

Running time of Dijkstra

```
= O(n(T(findMin) + T(removeMin)) + m T(updateKey))
= O(n^2) + O(m)
= O(n^2)
```

### If we use a red-black tree

- T(findMin) = O(log(n))
- T(removeMin) = O(log(n))
- T(updateKey) = O(log(n))
- Running time of Dijkstra

```
= O(n( T(findMin) + T(removeMin) ) + m T(updateKey))
```

```
= O(nlog(n)) + O(mlog(n))
```

```
= O((n + m)log(n))
```

Better than an array if the graph is sparse!

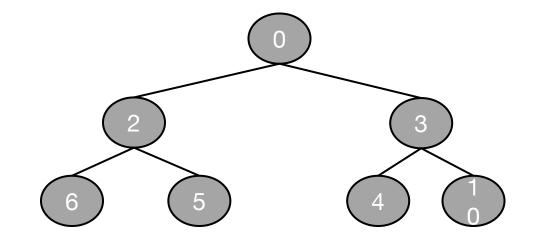
aka if m is much smaller than n<sup>2</sup>

## Is a hash table a good idea here?

- Not really:
  - Search(v) is fast (in expectation)
  - But findMin() will still take time O(n) without more structure.

## Heaps support these operations

- findMin
- removeMin
- updateKey



- A heap is a tree-based data structure that has the property that every node has a smaller key than its children.
- Not covered in this class
- But! We will use them.

## Many heap implementations

#### Nice chart on

Wikipedia: Operation	Binary <sup>[7]</sup>	Leftist	Binomial <sup>[7]</sup>	Fibonacci <sup>[7][8]</sup>	Pairing <sup>[9]</sup>	Brodal <sup>[10][b]</sup>	Rank-pairing <sup>[12]</sup>	Strict Fibonacci <sup>[13]</sup>
find-min	Θ(1)	Θ(1)	Θ(log n)	Θ(1)	Θ(1)	Θ(1)	Θ(1)	Θ(1)
delete-min	$\Theta(\log n)$	Θ(log n)	Θ(log n)	O(log n)[c]	O(log n)[c]	O(log n)	O(log n)[c]	O(log n)
insert	O(log n)	Θ(log n)	Θ(1) <sup>[c]</sup>	Θ(1)	Θ(1)	Θ(1)	Θ(1)	Θ(1)
decrease-key	$\Theta(\log n)$	$\Theta(n)$	$\Theta(\log n)$	Θ(1) <sup>[c]</sup>	o(log n)[c][d]	Θ(1)	Θ(1) <sup>[c]</sup>	Θ(1)
merge	Θ(n)	Θ(log n)	O(log n)[e]	Θ(1)	Θ(1)	Θ(1)	Θ(1)	Θ(1)

## Say we use a Fibonacci Heap

```
    T(findMin) = O(1) (amortized time*)
    T(removeMin) = O(log(n)) (amortized time*)
    T(updateKey) = O(1) (amortized time*)
```

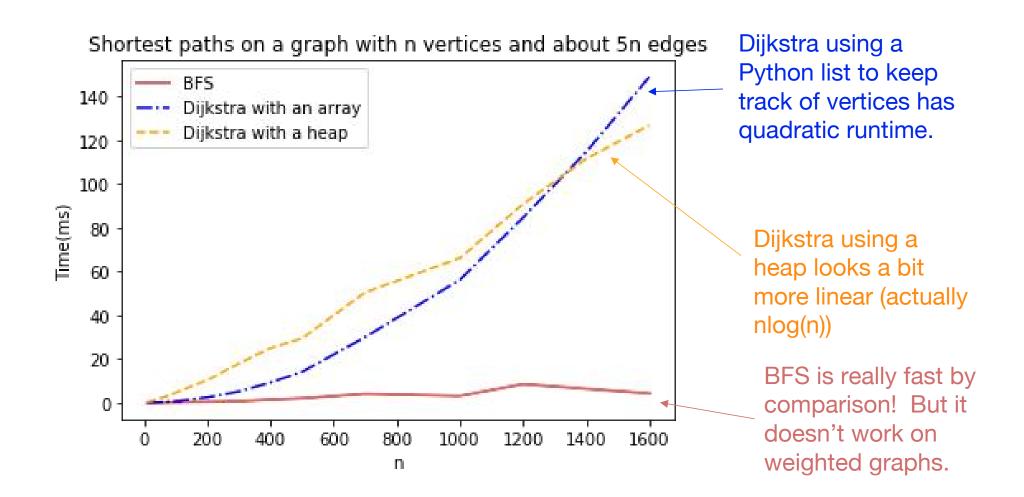
- See Data Sturcture for more!
- Running time of Dijkstra

```
= O(n(T(findMin) + T(removeMin)) + m T(updateKey))
```

= O(nlog(n) + m) (amortized time)

\*This means that any sequence of d removeMin calls takes time at most O(dlog(n)). But a few of the d may take longer than O(log(n)) and some may take less time...

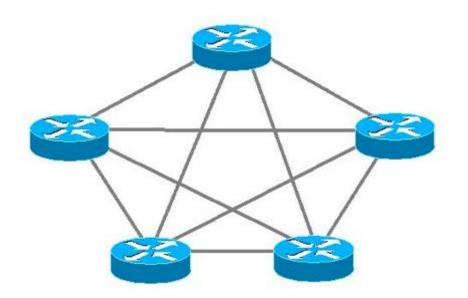
## In practice



## Dijkstra is used in practice

 eg, OSPF (Open Shortest Path First), a routing protocol for IP networks, uses Dijkstra.

But there are some things it's not so good at.



## Dijkstra Drawbacks

- Needs non-negative edge weights.
- If the weights change, we need to re-run the whole thing.
  - in OSPF, a vertex broadcasts any changes to the network, and then every vertex reruns Dijkstra's algorithm from scratch.

## Bellman-Ford algorithm

- (-) Slower than Dijkstra's algorithm
- (+) Can handle negative edge weights.
  - Can be useful if you want to say that some edges are actively good to take, rather than costly.
  - Can be useful as a building block in other algorithms.
- (+) Allows for some flexibility if the weights change.
  - We'll see what this means later

## Today: intro to Bellman-Ford

- We'll see a definition by example.
- We'll come back to it next lecture with more rigor.
  - Don't worry if it goes by quickly today.
  - There are some skipped slides with pseudocode, but we'll see them again next lecture.

- Basic idea:
  - Instead of picking the u with the smallest d[u] to update, just update all
    of the u's simultaneously.

## Bellman-Ford algorithm

#### Bellman-Ford(G,s):

- $d[v] = \infty$  for all v in V
- d[s] = 0
- For i=0,...,n-1:

Instead of picking u cleverly, just update for all of the u's.

- For u in V:
  - For v in u.neighbors:
    - d[v] ← min(d[v], d[u] + edgeWeight(u,v))

#### Compare to Dijkstra:

- While there are not-sure nodes:
  - Pick the not-sure node u with the smallest estimate d[u].
  - For v in u.neighbors:
    - d[v] ← min(d[v], d[u] + edgeWeight(u,v))
  - · Mark u as sure.

## For pedagogical reasons

#### which we will see next lecture

- We are actually going to change this to be less smart.
- Keep n arrays: d<sup>(0)</sup>, d<sup>(1)</sup>, ..., d<sup>(n-1)</sup>

#### Bellman-Ford\*(G,s):

- $d^{(i)}[v] = \infty$  for all v in V, for all i=0,...,n-1
- $d^{(0)}[s] = 0$
- For i=0,...,n-2:
  - For u in V:
    - For v in u.neighbors:
      - $d^{(i+1)}[v] \leftarrow \min(d^{(i)}[v], d^{(i+1)}[v], d^{(i)}[u] + edgeWeight(u,v))$
- Then dist(s,v) =  $d^{(n-1)}[v]$

Slightly different than the original Bellman-Ford algorithm, but the analysis is basically the same.

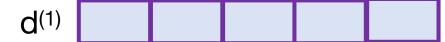
Bellman-Ford no negative weights.

Start with the same graph,

How far is a node from

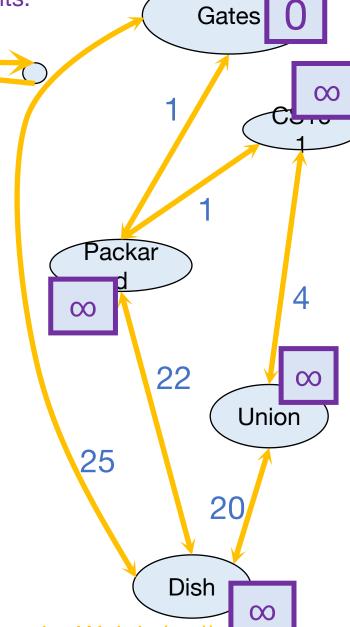
Gates? Gates Packard CS407 Union Dish

$Q_{(0)}$ 0 $\infty$ $\infty$ $\infty$ $\infty$
---





- For i=0,...,n-2:
  - For u in V:
    - For v in u.neighbors:
      - $d^{(i+1)}[v] \leftarrow \min(d^{(i)}[v], d^{(i+1)}[v], d^{(i)}[u] + edgeWeight(u,v))$



How far is a node from

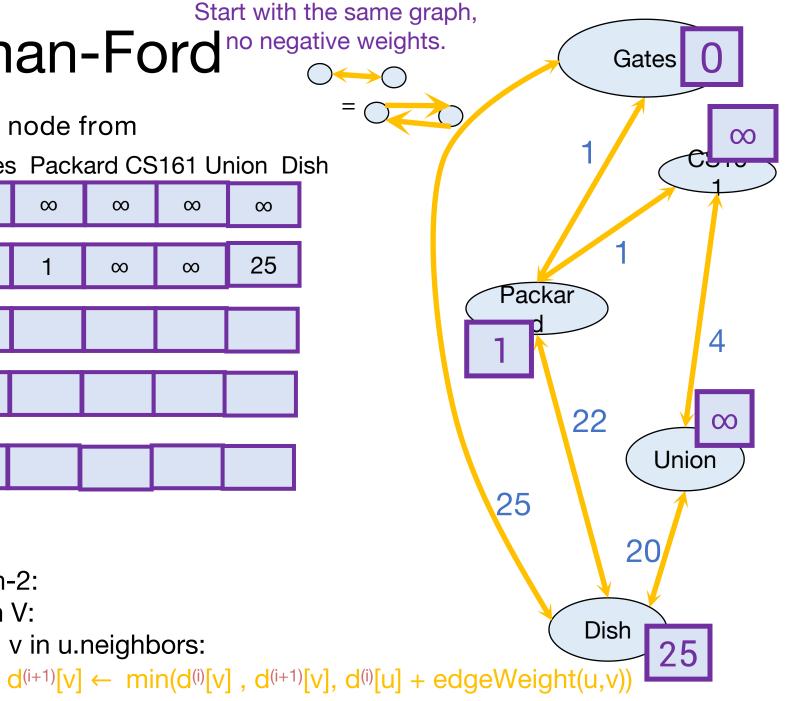
Gates? Gates Packard CS161 Union Dish

d <sup>(0)</sup>	0	∞	∞	∞	$\infty$
------------------	---	---	---	---	----------

$$d^{(1)}$$
 0 1  $\infty$   $\infty$  25



- For i=0,...,n-2:
  - For u in V:
    - For v in u.neighbors:



Start with the same graph,

How far is a node from

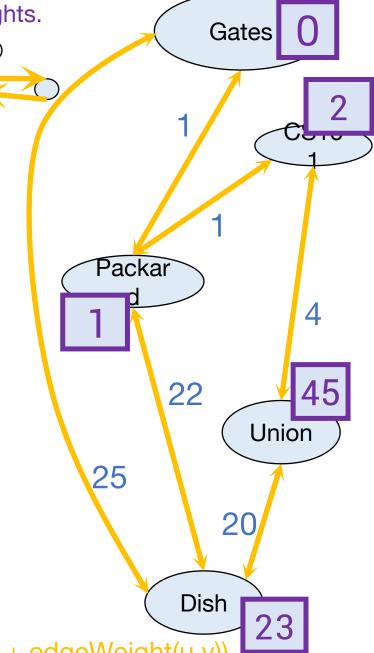
Gates? Gates Packard CS161 Union Dish

$Q_{(0)}$ 0 $\infty$ $\infty$ $\infty$ $\infty$
---





- For i=0,...,n-2:
  - For u in V:
    - For v in u.neighbors:
      - $d^{(i+1)}[v] \leftarrow \min(d^{(i)}[v], d^{(i+1)}[v], d^{(i)}[u] + edgeWeight(u,v))$



Start with the same graph,

How far is a node from

Gates? Gates Packard CS161 Union Dish

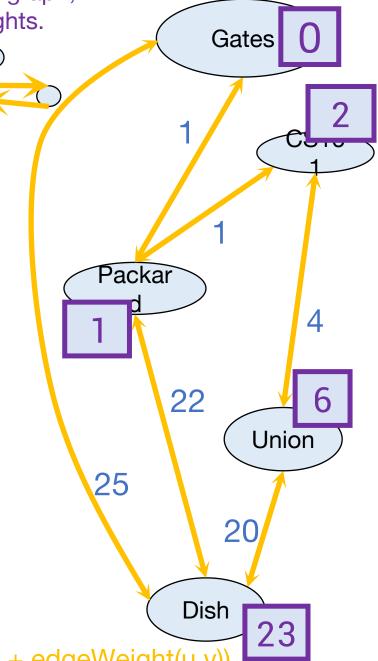
$Q_{(0)}$ 0 $\infty$ $\infty$ $\infty$ $\infty$
---

$$d^{(1)} = 0 = 1 = \infty = \infty = 25$$



- For i=0,...,n-2:
  - For u in V:
    - For v in u.neighbors:

 $d^{(i+1)}[v] \leftarrow \min(d^{(i)}[v], d^{(i+1)}[v], d^{(i)}[u] + edgeWeight(u,v))$ 



Start with the same graph,

How far is a node from

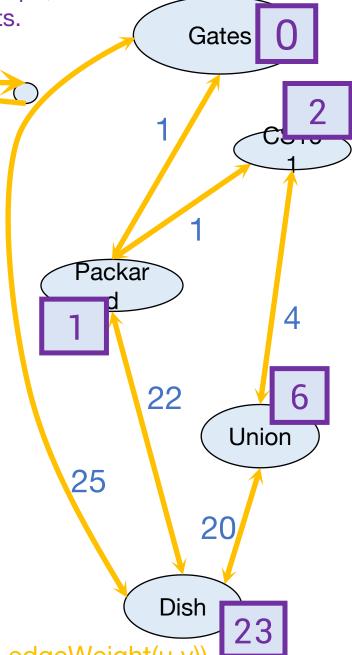
Gates? Gates Packard CS161 Union Dish

$Q_{(0)}$ 0 $\infty$ $\infty$ $\infty$ $\infty$
---

$$d^{(1)}$$
 0 1  $\infty$   $\infty$  25

These are the final distances!

- For i=0,...,n-2:
  - For u in V:
    - For v in u.neighbors:
      - $d^{(i+1)}[v] \leftarrow \min(d^{(i)}[v], d^{(i+1)}[v], d^{(i)}[u] + edgeWeight(u,v))$



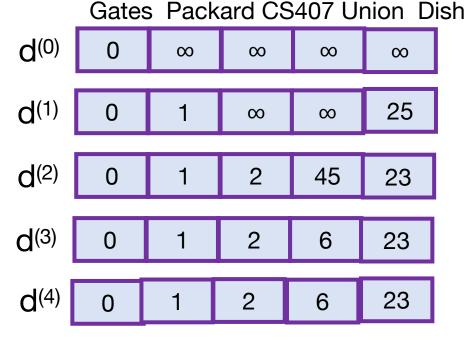
### As usual

- Does it work?
  - Yes
  - Idea to the right.
  - (See hidden slides for details)

• Is it fast?

Not really...

A simple path is a path with no cycles.



Idea: proof by induction.
Inductive Hypothesis:
d(i)[v] is equal to the cost of the shortest path between s and v with at most i edges.

Conclusion:

d<sup>(n-1)</sup>[v] is equal to the cost of the shortest simple path between s and v. (Since all simple paths have at most n-1 edges).

## Proof by induction

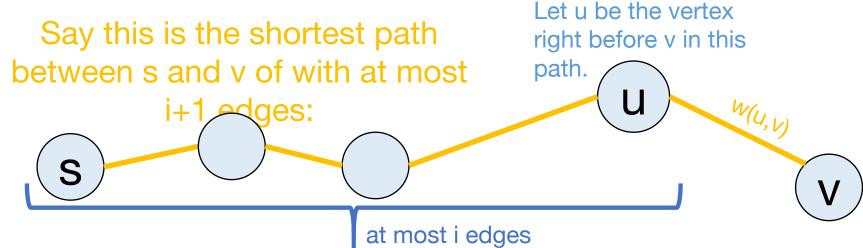
- Inductive Hypothesis:
  - After iteration i, for each v, d(i)[v] is equal to the cost of the shortest path between s and v with at most i edges.
- Base case:
  - After iteration 0...



Inductive step:

Hypothesis: After iteration i, for each v, d(i) [v] Inductive step is equal to the cost of the shortest path between s and v with at most i edges.

- Suppose the inductive hypothesis holds for i.
- We want to establish it for i+1.



- By induction, d<sup>(i)</sup>[u] is the cost of a shortest path between s and u of i edges.
- By setup,  $d^{(i)}[u] + w(u,v)$  is the cost of a shortest path between s and v of i+1 edges.
- In the i+1'st iteration, we ensure  $d^{(i+1)}[v] \le d^{(i)}[u] + w(u,v)$ .
- So  $d^{(i+1)}[v] \le cost$  of shortest path between s and v with i+1 edges.
- But  $d^{(i+1)}[v] = cost$  of a particular path of at most i+1 edges >= cost of shortest path.
- So d[v] = cost of shortest path with at most i+1 edges.

## Proof by induction

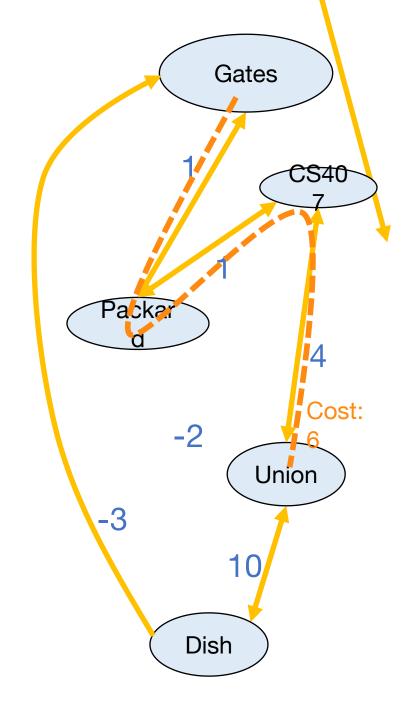
- Inductive Hypothesis:
  - After iteration i, for each v, d<sup>(i)</sup>[v] is equal to the cost of the shortest path between s and v of length at most i edges.
- Base case:
  - After iteration 0...
- Inductive step:
- Conclusion:
  - After iteration n-1, for each v, d[v] is equal to the cost of the shortest path between s and v of length at most n-1 edges.
  - Aka, d[v] = d(s,v) for all v as long as there are no negative cycles!

### Pros and cons of Bellman-Ford

- Running time: O(mn) running time
  - For each of n steps we update m edges
  - Slower than Dijkstra
- However, it's also more flexible in a few ways.
  - Can handle negative edges
  - If we constantly do these iterations, any changes in the network will eventually propagate through.

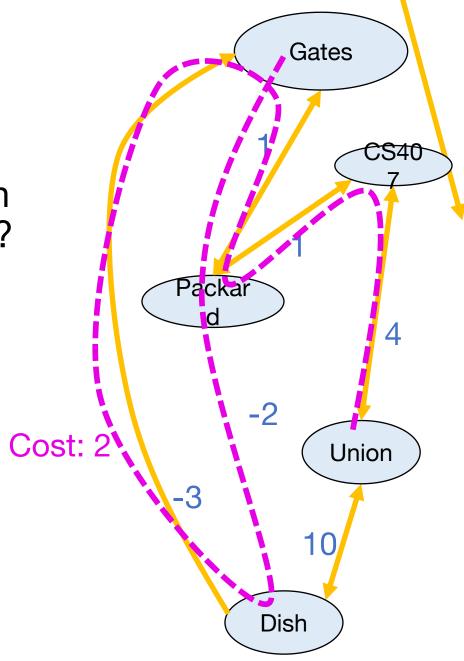
### Wait a second...

 What is the shortest path from Gates to the Union?



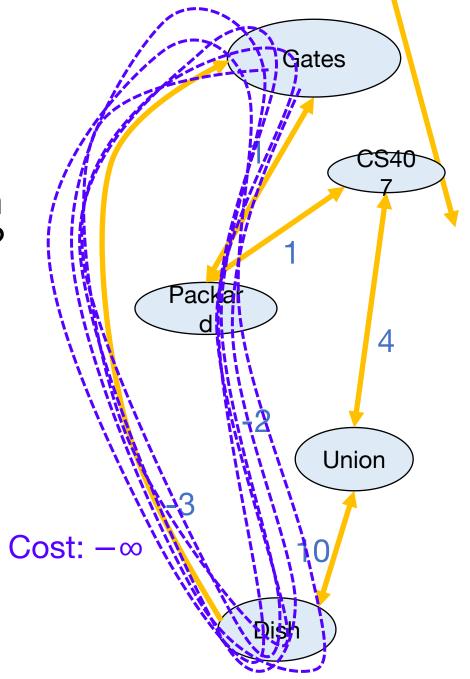
### Wait a second...

 What is the shortest path from Gates to the Union?



### Negative edge weights?

- What is the shortest path from Gates to the Union?
- Shortest paths aren't defined if there are negative cycles!



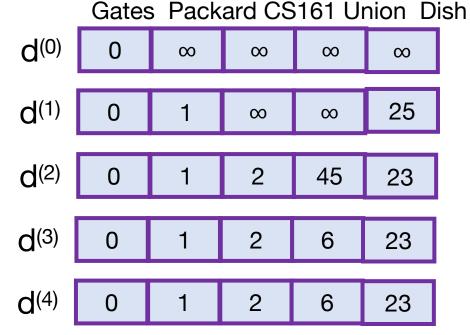
# Bellman-Ford and negative edge weights

- B-F works with negative edge weights...as long as there are no negative cycles.
  - A negative cycle is a path with the same start and end vertex whose cost is negative.
- However, B-F can detect negative cycles.

## Back to the correctness

- Does it work?
  - Yes
  - Idea to the right.

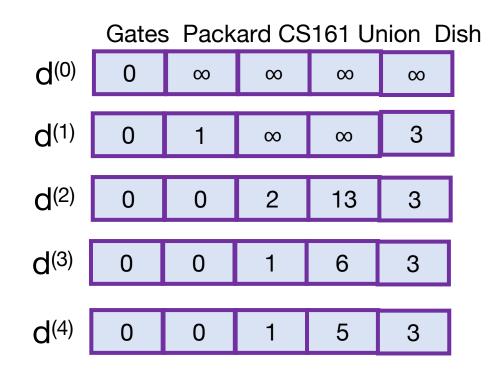
If there are negative cycles, then non-simple paths matter! So the proof breaks for negative cycles.

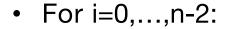


Idea: proof by induction.
Inductive Hypothesis:
d(i)[v] is equal to the cost of the shortest path between s and v with at most i edges.

Conclusion:

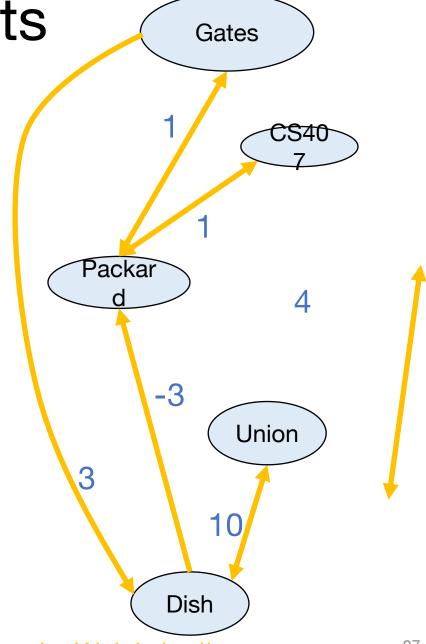
d<sup>(n-1)</sup>[v] is equal to the cost of the shortest simple path between s and v. (Since all simple paths have at most n-1 edges). Negative edge weights





- For u in V:
  - For v in u.neighbors:

•  $d^{(i+1)}[v] \leftarrow \min(d^{(i)}[v], d^{(i+1)}[v], d^{(i)}[u] + edgeWeight(u,v))$ 

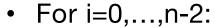


B-F with negative cycles



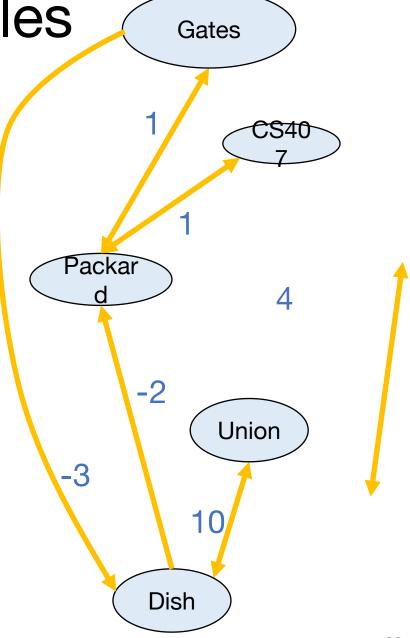


This is not looking good!

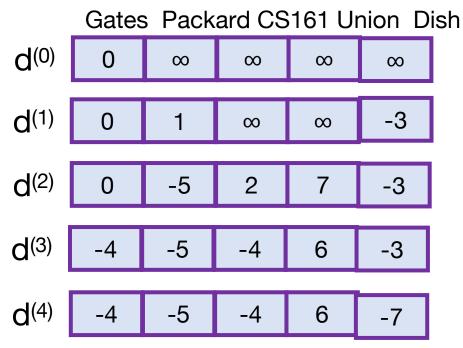


- For u in V:
  - For v in u.neighbors:

•  $d^{(i+1)}[v] \leftarrow \min(d^{(i)}[v], d^{(i+1)}[v], d^{(i)}[u] + edgeWeight(u,v))$ 



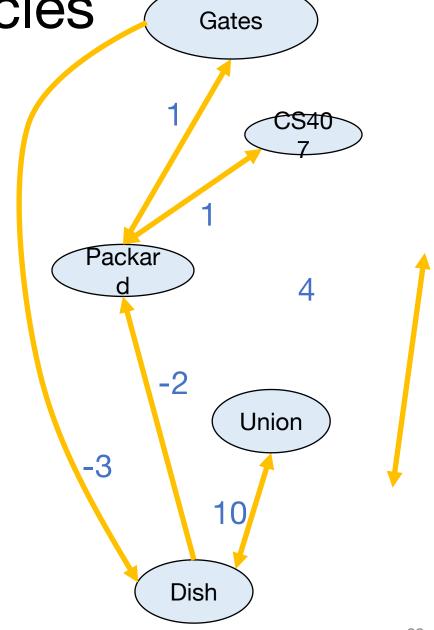
B-F with negative cycles



But we can tell that it's not looking

good: d<sup>(5)</sup>

- For i=0,...,n-1:
  - For u in V:
    - For v in u.neighbors:



Some stuff

changed!

## How Bellman-Ford deals with negative cycles

- If there are no negative cycles:
  - Everything works as it should.
  - The algorithm stabilizes after n-1 rounds.
  - Note: Negative edges are okay!!
- If there are negative cycles:
  - Not everything works as it should...
    - it couldn't possibly work, since shortest paths aren't well-defined if there are negative cycles.
  - The d[v] values will keep changing.
- Solution:
  - Go one round more and see if things change.
    - If so, return NEGATIVE CYCLE ⊗
  - (Pseudocode on skipped slide)

## Bellman-Ford algorithm

#### Bellman-Ford\*(G,s):

- $d^{(0)}[v] = \infty$  for all v in V
- $d^{(0)}[s] = 0$
- For i=0,...,n-1:
  - For u in V:
    - For v in u.neighbors:
      - $d^{(i+1)}[v] \leftarrow \min(d^{(i)}[v], d^{(i+1)}[v], d^{(i)}[u] + edgeWeight(u,v))$
- If  $d^{(n-1)} != d^{(n)}$ :
  - Return NEGATIVE CYCLE (8)
- Otherwise,  $dist(s,v) = d^{(n-1)}[v]$

### Summary

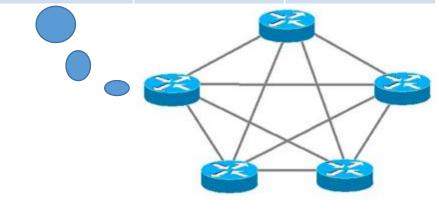
It's okay if that went by fast, we'll come back to Bellman-Ford

- The Bellman-Ford algorithm:
  - Finds shortest paths in weighted graphs with negative edge weights
  - runs in time O(nm) on a graph G with n vertices and m edges.
- If there are no negative cycles in G:
  - the BF algorithm terminates with  $d^{(n-1)}[v] = d(s,v)$ .
- If there are negative cycles in G:
  - the BF algorithm returns negative cycle.

## Bellman-Ford is also used in practice.

- eg, Routing Information Protocol (RIP) uses something like Bellman-Ford.
  - Older protocol, not used as much anymore.
- Each router keeps a table of distances to every other router.
- Periodically we do a Bellman-Ford update.
- This means that if there are changes in the network, this will propagate. (maybe slowly...)

Destination	Cost to get there	Send to whom?
172.16.1.0	34	172.16.1.1
10.20.40.1	10	192.168.1.2
10.155.120. 1	9	10.13.50.0



## Recap: shortest paths

#### BFS:

- (+) O(n+m)
- (-) only unweighted graphs

#### Dijkstra's algorithm:

- (+) weighted graphs
- (+) O(nlog(n) + m) if you implement it right.
- (-) no negative edge weights
- (-) very "centralized" (need to keep track of all the vertices to know which to update).

### The Bellman-Ford algorithm:

- (+) weighted graphs, even with negative weights
- (+) can be done in a distributed fashion, every vertex using only information from its neighbors.
- (-) O(nm)

### **Next Time**

• Dynamic Programming!!!