

EC504 ALGORITHMS AND DATA STRUCTURES
FALL 2020 MONDAY & WEDNESDAY
2:30 PM - 4:15 PM

Prof: David Castañón, dac@bu.edu

GTF: Mert Toslali, toslali@bu.edu

Haoyang Wang: haoxyangw@bu.edu

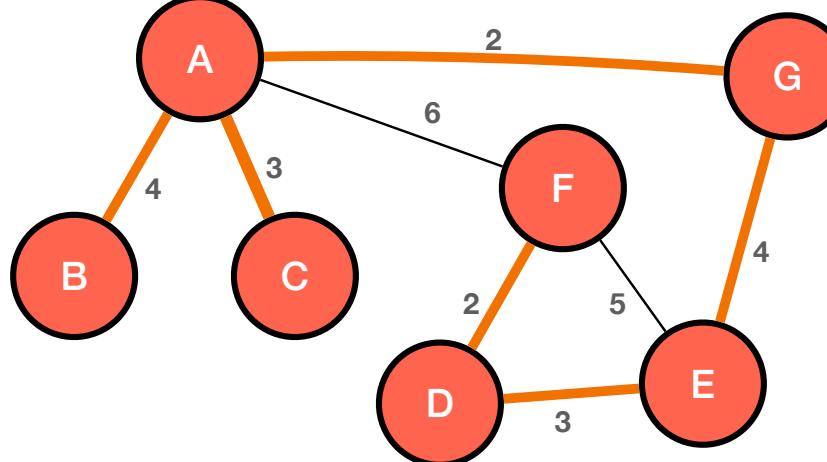
Christopher Liao: cliao25@bu.edu

Minimum Spanning Trees

- ▶ A **minimum spanning tree** (MST) of an undirected weighted graph (V, E) with weights $w(\cdot)$:

Connected subgraph (V, E') which is a tree and for which

$$\sum_{\{i,j\} \in E'} w(i, j) \text{ is minimized}$$



Kruskal's Algorithm

- ▶ Sort edges by weight in ascending order
- ▶ Start with empty set T (note: it is promising)
- ▶ For each edge e in sorted list
 - ▶ If adding edge e to T does not create cycle in $(V, T \cup e)$
 - ▶ ...add it to MST: $T = T \cup \{e\}$
 - ▶ Claim: T is now promising set with one more edge
- ▶ Stop when you have $\#V - 1$ edges in T

Kruskal Runtime

- $O(|V|)$ for iterating through vertices
- $O(|E|\log|E|)$ for sorting edges
- $O(|E| \times 1)$ for iterating through edges and merging clouds with path compression
- $O(|V| + |E|\log|E| + |E| \times 1)$
 - $= O(|V| + |E|\log|E|)$
- $O(|V| + |E|\log|E|)$
 - Better than simple $O(|V|^3)$ without disjoint sets

Example

Disjoint components:

1 2 3 4 5 6 7 8 9

1) Add {3,6}

Disjoint components:

3 1 2 4 5 7 8 9

|

6

2) Add {4,6}

3 1 2 5 7 8 9

/ \

6 4

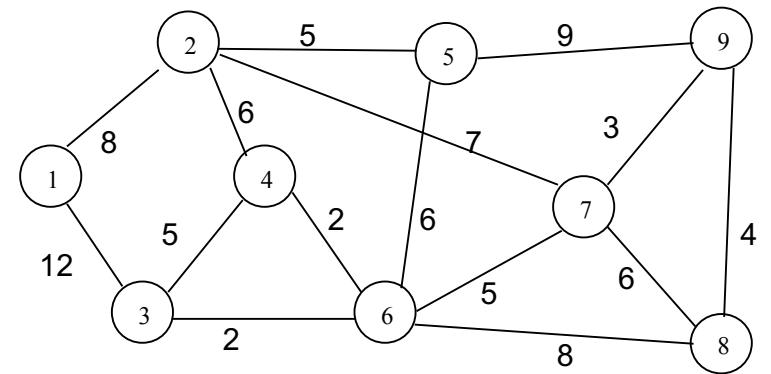
Minimum Spanning Tree

Empty

Minimum Spanning Tree

3--6

3--6--4



Sorted edges

{3,6}, {4,6}, {7,9}, {8,9}, {3,4}, {6,7},
{2,5}, {2,4}, {5,6}, {7,8}, {2,7}, {1,2},
{6,8}, {5,9}, {1,3}

Example

Disjoint components:

3) Add {7,9}

3 7 1 2 5 8

/ \ |

6 4 9

4) Add {8,9}

3 7 1 2 5

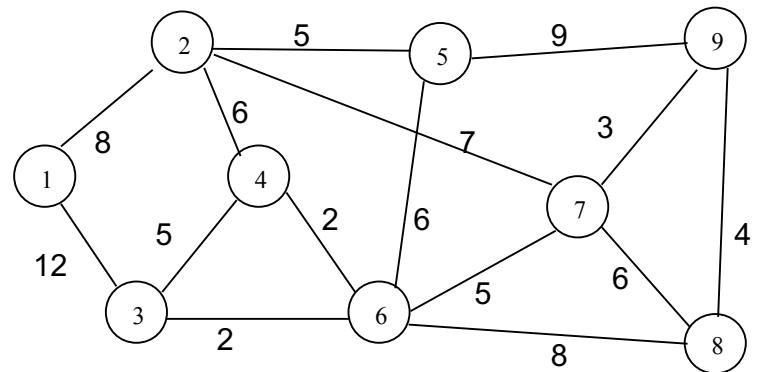
/ \ / \

6 4 9 8

Minimum Spanning Tree

3--6--4 7--9

3--6--4 7--9--8



Sorted edges

{3,6}, {4,6}, {7,9}, {8,9}, {3,4}, {6,7},
{2,5}, {2,4}, {5,6}, {7,8}, {2,7}, {1,2},
{6,8}, {5,9}, {1,3}

Example

Disjoint components:

5) Discard {3,4} (cycle); add {6,7}

3 1 2 5

/ | \

6 4 7

/ \

9 8

6) Add {2,5}

3 1 2

/ | \ \

6 4 7 5

/ \

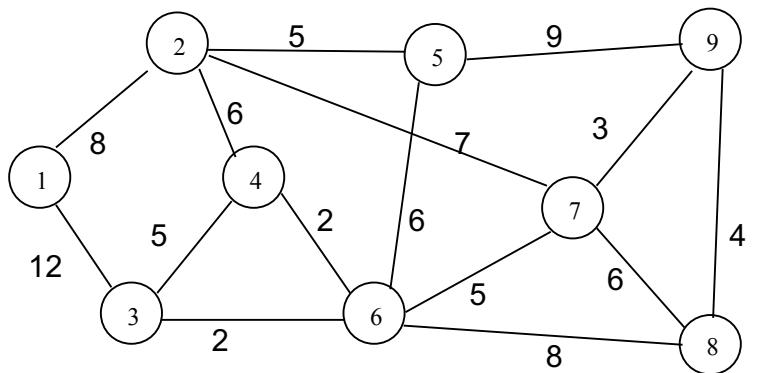
9 8

Minimum Spanning Tree

3--6--4

\

7--9--8



Sorted edges

$\{3,6\}, \{4,6\}, \{7,9\}, \{8,9\}, \{3,4\}, \{6,7\},$
 $\{2,5\}, \{2,4\}, \{5,6\}, \{7,8\}, \{2,7\}, \{1,2\},$
 $\{6,8\}, \{5,9\}, \{1,3\}$

Example

Disjoint components:

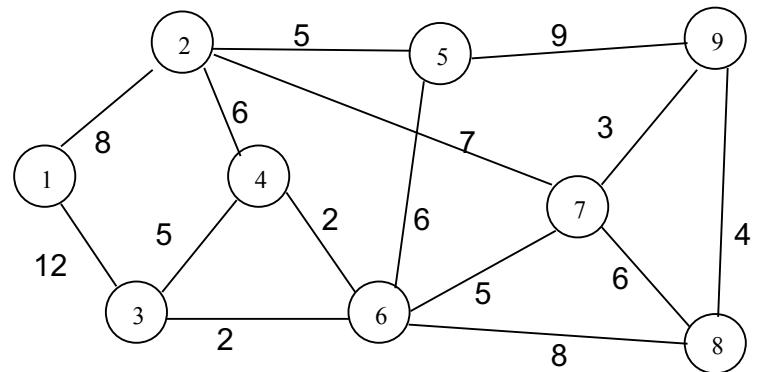
7) Add {2,4}

(3)	1
/		\	\
6	4	7	2
/	\	\	\
9	8	5	

Minimum Spanning Tree

3--6--4--2--5
\\
7--9--8

8) Discard $\{5,6\}, \{7,8\}, \{2,7\}$. Select arc $\{1,2\}$. DONE



Sorted edges

$\{3,6\}, \{4,6\}, \{7,9\}, \{8,9\}, \{3,4\}, \{6,7\},$
 $\{2,5\}, \{2,4\}, \{5,6\}, \{7,8\}, \{2,7\}, \{1,2\},$
 $\{6,8\}, \{5,9\}, \{1,3\}$

Different MST Algorithm: Prim-Jarmik

- ▶ Traverse $G = (V, E)$ starting at any node
 - ▶ Maintain priority queue of nodes (e.g. binary heap, Fibonacci heap)
 - ▶ set priority to weight of the cheapest edge that connects them to MST
- ▶ Un-added nodes start with priority ∞
- ▶ At each step
 - ▶ Add the node with lowest cost to MST
 - ▶ Update ("relax") neighbors as necessary
- ▶ Stop when all nodes added to MST

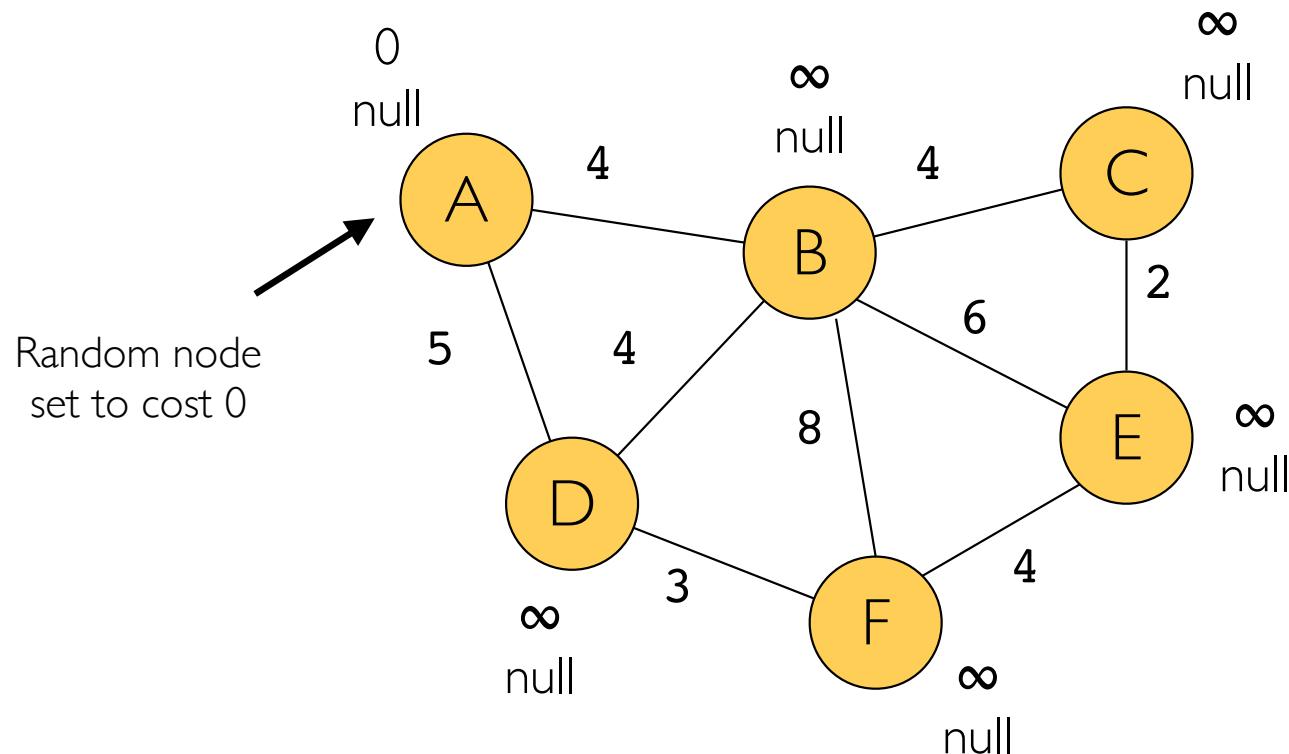
Different MST Algorithm: Prim-Jarnik

- › Traverse $G = (V, E)$ starting at any vertex v
- › Form priority queue PQ of nodes (e.g. binary heap, Fibonacci heap)
 - › Set $v.dist = 0$, $v'.dist = \infty$, v' different from v . $dist$ will be the key used in the priority queue
 - › Set parent of all vertices, $v.pred$ to NULL ; set $T = \emptyset$
- › At each step:
 - › Remove min from priority queue: call it v . If $v.pred$ not null, add $\{v, v.pred\}$ to T
 - › For all neighbors v' of v : if v' is in PQ and $w(v, v') < v'.dist$:
 - › Decrease $v'.dist$ to $w(v, v')$, update $v'.pred = v$
- › Stop when PQ is empty

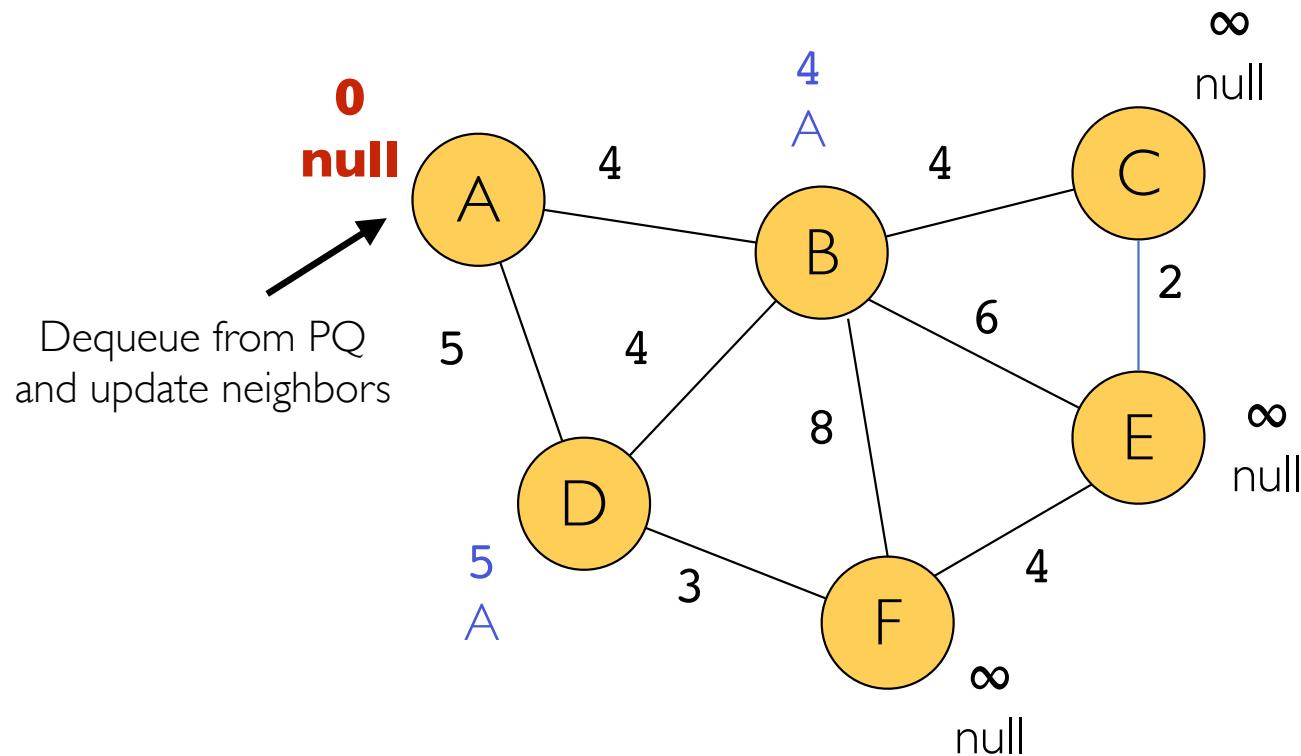
Pseudo-code

```
function prim(G):
    // Input: weighted, undirected graph G with vertices V
    // Output: list of edges in MST
    for all v in V:
        v.cost = ∞
        v.prev = null
    s = a random v in V // pick a random source s
    s.cost = 0
    MST = []
    PQ = PriorityQueue(V) // priorities will be v.cost values
    while PQ is not empty:
        v = PQ.removeMin()
        if v.prev != null:
            MST.append((v, v.prev))
        for all incident edges (v,u) of v such that u is in PQ:
            if u.cost > (v,u).weight:
                u.cost = (v,u).weight
                u.prev = v
                PQ.decreaseKey(u, u.cost)
    return MST
```

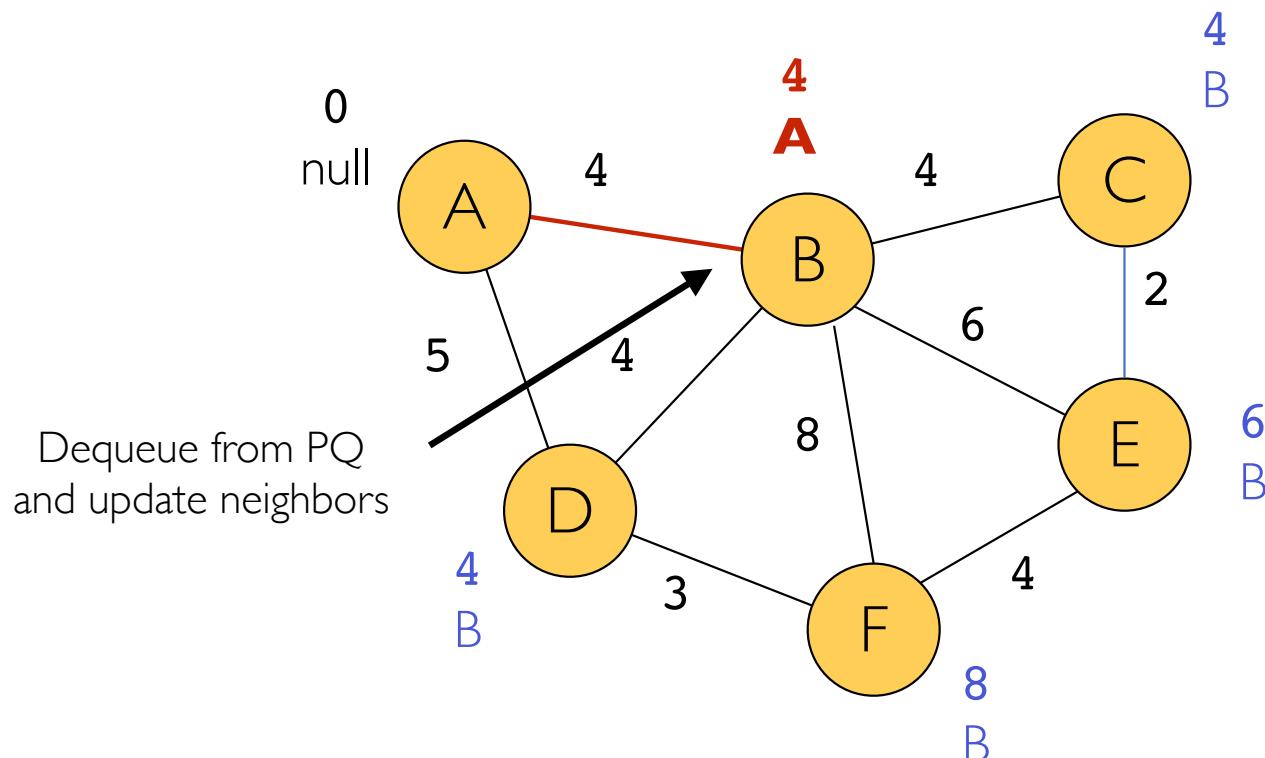
Example



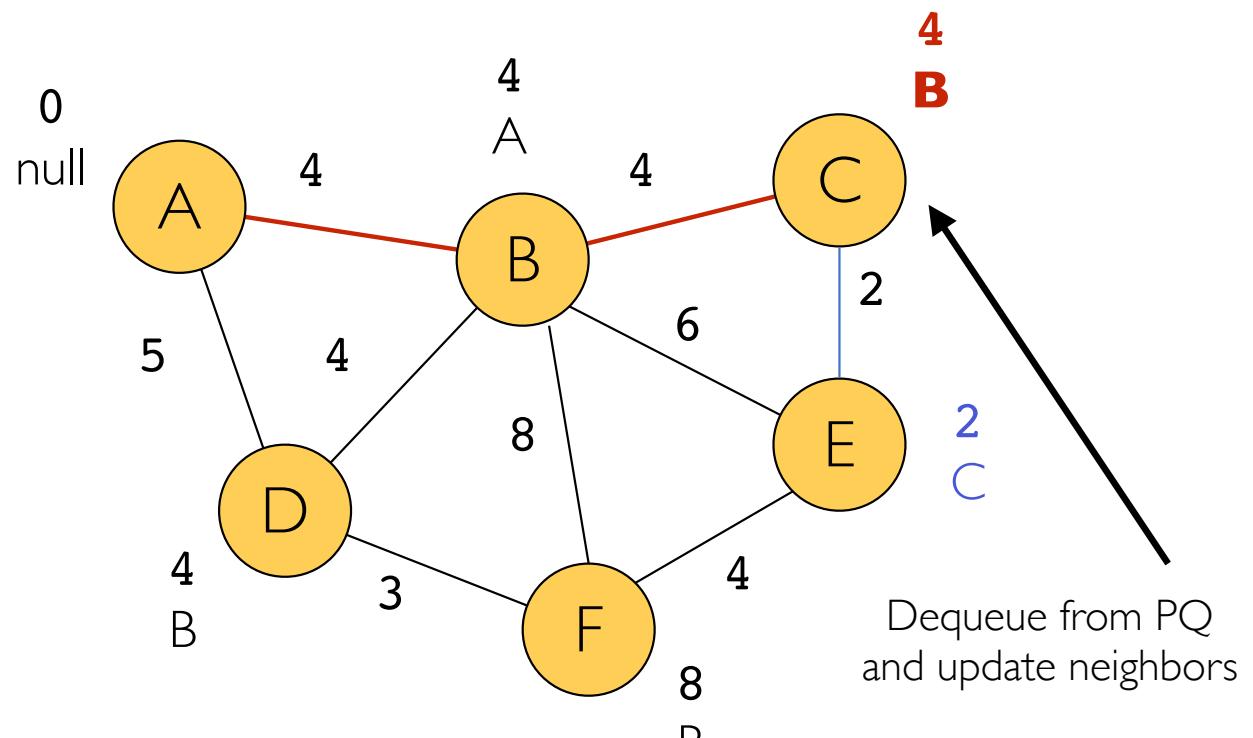
PQ = [(0, A), (∞ , B), (∞ , C), (∞ , D), (∞ , E), (∞ , F)]



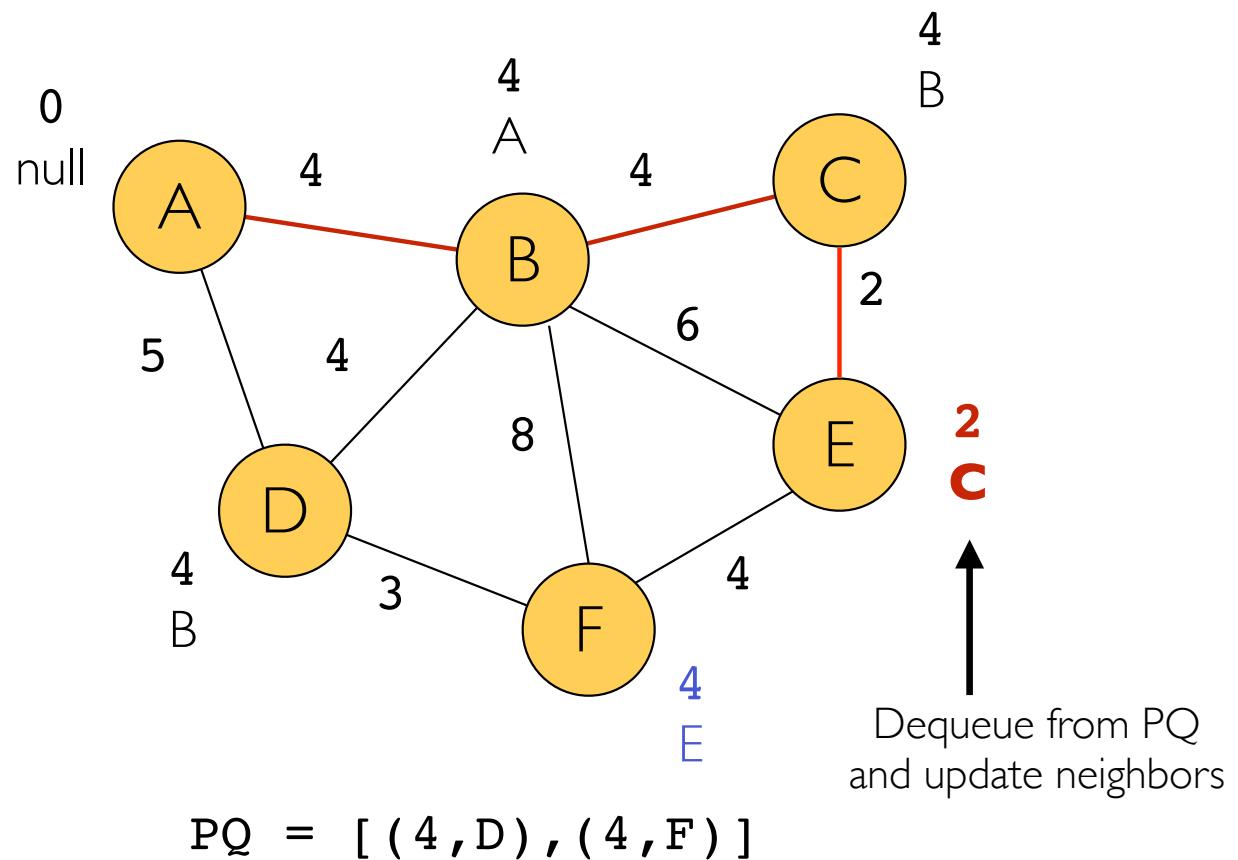
PQ = [(4, B), (5, D), (∞ , C), (∞ , E), (∞ , F)]

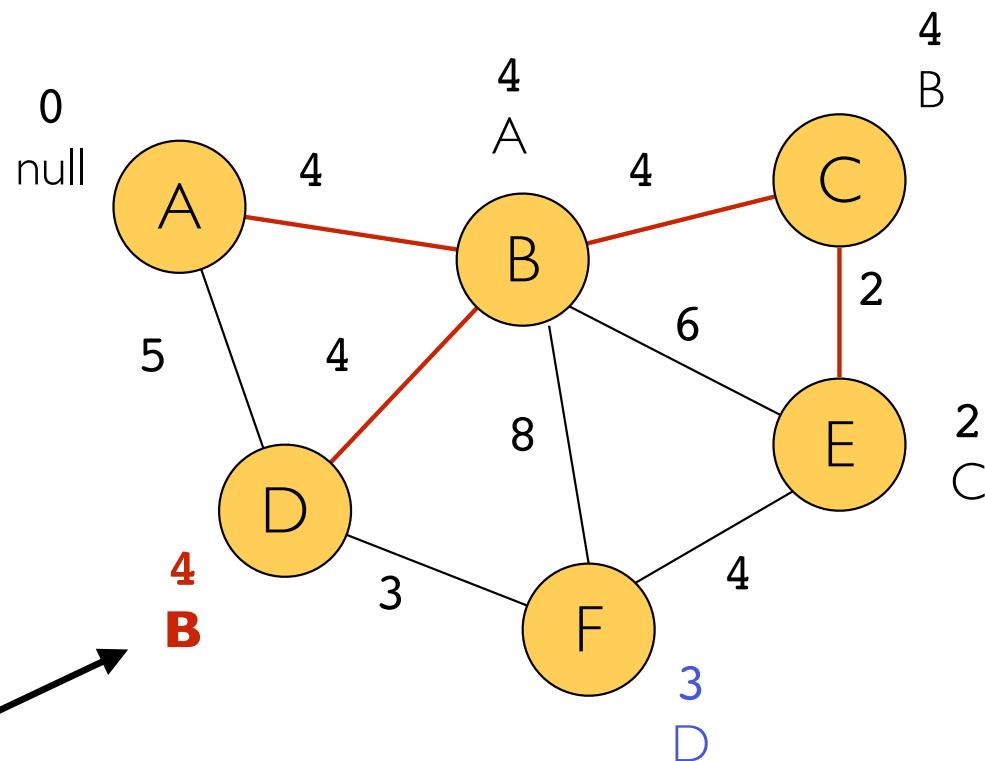


$$PQ = [(4, C), (4, D), (6, E), (8, F)]$$



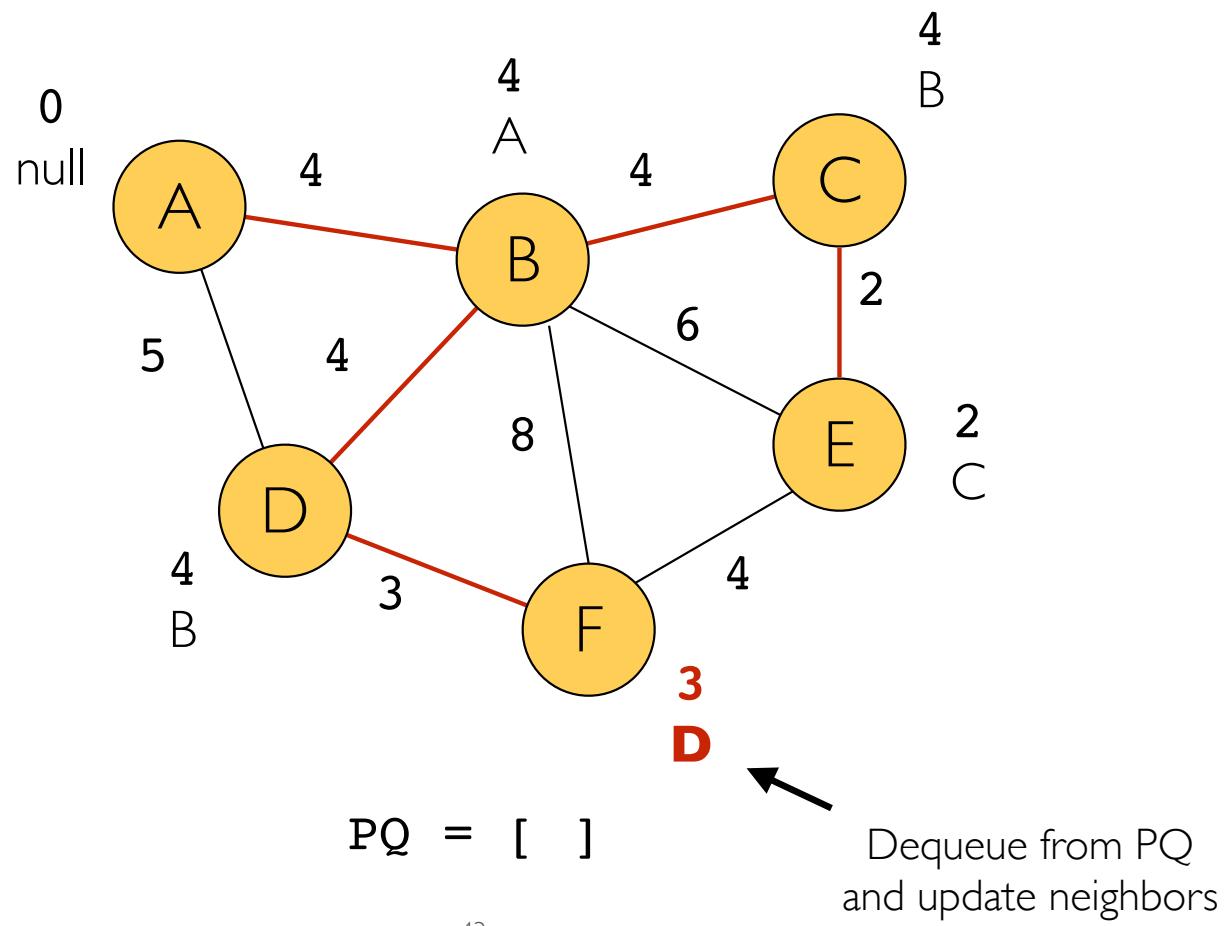
$$PQ = [(2, E), (4, D), (8, F)]$$

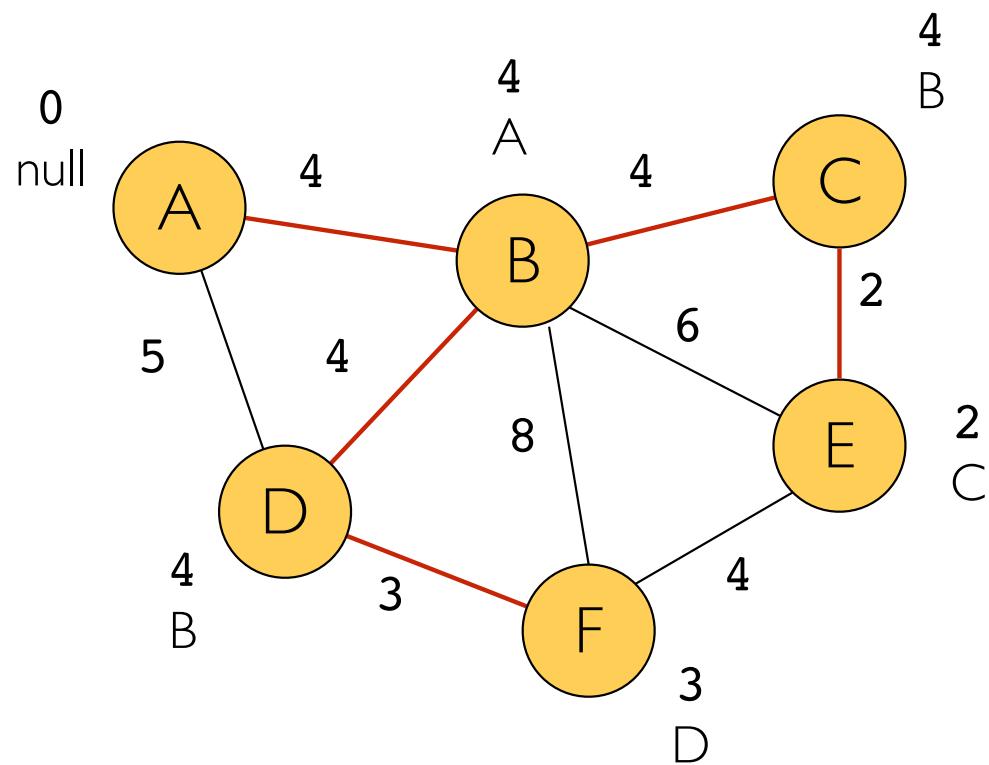




Dequeue from PQ
 and update neighbors

$PQ = [(3, F)]$





Proof of Correctness

- Let T be current tree at iteration step
- Claim: T is promising set
 - True initially, as $T = \emptyset$
 - Define $B = \text{vertices in } T$: t any stage, T is a tree over a subset of nodes $B \subset V$
 - Let v be min vertex in PQ ; then $\{v.\text{parent}, v\}$ leaves B
 - v has parent in B , and v is still in PQ , so it is not in B
 - If v in PQ , $v.\text{dist}$ is set by min weight edge leaving B
 - Thus, $\{v.\text{pred}, v\}$ is min-weight edge leaving B
 - Hence, $T \cup \{\{v.\text{pred}, v\}\}$ is promising set after remove min extracts v

Runtime Analysis

- Initializing nodes with distance and previous pointers is $O(|V|)$; putting nodes in PQ is $O(|V|)$
- While loop runs $|V|$ times
 - removing vertex from PQ is $O(\log|V|)$
 - So $O(|V|\log|V|)$
- For loop (in while loop) runs $|E|$ times in total
 - Determining whether v' is in PQ: $O(1)$ if we build index into PQ (need to find location; not easy!)
 - Decreasing vertex's key in the PQ is $\log|V|$ (binary heap), or amortized to $O(1)$ if we use Fibonacci or rank-pairing heaps
 - So $O(|E|)$ in complex data or $O(|E| \log|V|)$
- Overall runtime
 - $O(|V| + |V|\log|V| + |E|)$
 - = $O(|E| + |V|\log|V|)$ best

Example

Priority Q

(1,0)

(2,M)

(3,M)

(4,M) (5,M) (6,M) (7,M)

(8,M) (9,M)

1) Scan 1, reduce key of 2, 3; remove 1

(2,8)

(9,M)

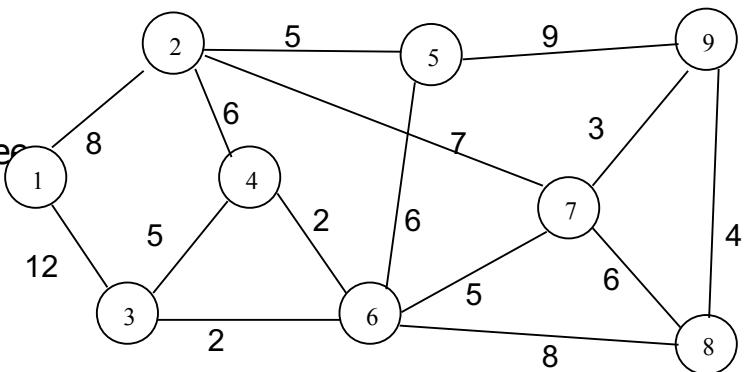
(3,12)

(4,M) (5,M) (6,M) (7,M)

(8,M)

Minimum Spanning Tree

Empty



Sorted edges

$\{3,6\}$, $\{4,6\}$, $\{7,9\}$, $\{8,9\}$, $\{3,4\}$, $\{6,7\}$,
 $\{2,5\}$, $\{2,4\}$, $\{5,6\}$, $\{7,8\}$, $\{2,7\}$, $\{1,2\}$,
 $\{6,8\}$, $\{5,9\}$, $\{1,3\}$

1

Example

2) Scan 2, reduce key of 4,5,7. Remove 2.

Priority Q

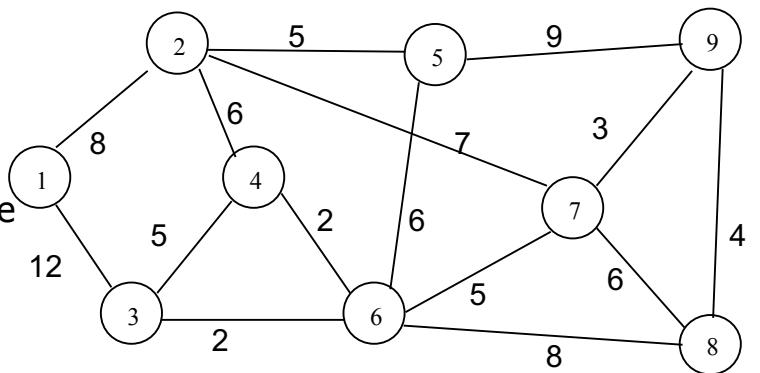
(5,5)	
(4,6)	(7,7)
(9,M)	(8,M)
(6,M)	(3,12)

3) Scan 5, reduce key of 6, 9; remove 5

(4,6)	
(9,9)	(6,6)
(3,12)	(8,M)
(7,7)	

Minimum Spanning Tree

1—2



Sorted edges

$\{3,6\}$, $\{4,6\}$, $\{7,9\}$, $\{8,9\}$, $\{3,4\}$, $\{6,7\}$,
 $\{2,5\}$, $\{2,4\}$, $\{5,6\}$, $\{7,8\}$, $\{2,7\}$, $\{1,2\}$,
 $\{6,8\}$, $\{5,9\}$, $\{1,3\}$

Example

4) Remove 4, reduce key of 3,6.

Priority Q	
(6,2)	
(3,5)	(7,7)
(9,9) (8,M)	

5) Remove 6, reduce key of 3, 7, 8;

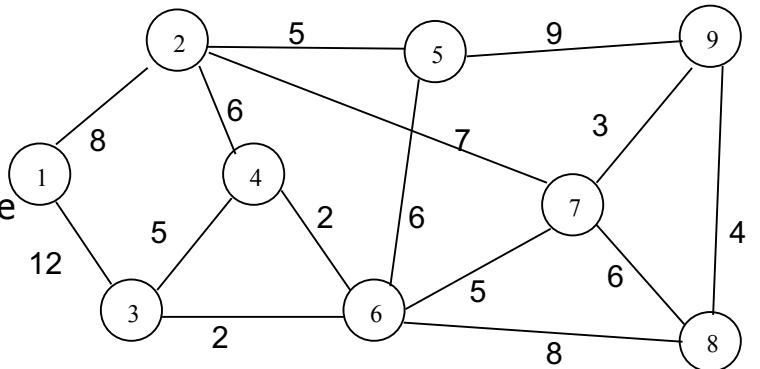
(3,2)	
(9,9)	(7,5)
(8,8)	

Minimum Spanning Tree

1—2—5

|

4



Sorted edges

1—2—5

|

4 — 6

{3,6}, {4,6},{7,9},{8,9},{3,4},{6,7},
{2,5},{2,4}{5,6},{7,8}, {2,7},{1,2},
{6,8},{5,9},{1,3}

Example

6) Remove 3.

Priority Q	
(7,5)	
(9,9)	(8,8)

5) Remove 7, reduce key of 8,9;

(9,3)
(8,6)

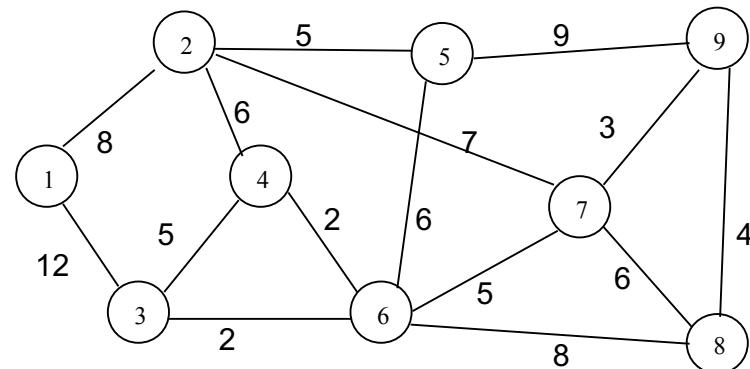
6) Remove 9, reduce key of 8

(8,4)

7) Remove 8. DONE

Minimum Spanning Tree

1—2—5
|
4 — 6 — 3



1—2—5

| /— 7
4 — 6 — 3

1—2—5

| /— 7—9—8

4 — 6 — 3

Sorted edges

{3,6}, {4,6}, {7,9}, {8,9}, {3,4}, {6,7}, {2,5}, {2,4}, {5,6}, {7,8}, {2,7}, {1,2}, {6,8}, {5,9}, {1,3}

Summary

- Initializing nodes with distance and previous pointers is $O(|V|)$; putting nodes in PQ is $O(|V|)$
- While loop runs $|V|$ times
 - removing vertex from PQ is $O(\log|V|)$
 - So $O(|V|\log|V|)$
- For loop (in while loop) runs $|E|$ times in total
 - Determining whether v' is in PQ: $O(1)$ if we build index into PQ (need to find location; not easy!)
 - Decreasing vertex's key in the PQ is $\log|V|$ (binary heap), or amortized to $O(1)$ if we use Fibonacci or rank-pairing heaps
 - So $O(|E|)$ in complex data or $O(|E| \log|V|)$
- Overall runtime
 - $O(|V| + |V|\log|V| + |E|)$
 - = $O(|E| + |V|\log|V|)$ best

Interesting Facts

- Cayley's theorem: The complete graph on n nodes has n^{n-2} spanning trees
- Suppose that you change the cost of every edge in G as follows. For which is every MST in G an MST in G' (and vice versa)?
 - $c'(e) = c(e) + 17$.
 - $c'(e) = 17 \times c(e)$.
 - Assume $c(e) > 0$; then, $c'(e) = \log_{17} c(e)$
 - All of the above.
- The highest weight edge in every cycle cannot be part of an MST
 - Reverse algorithm: throw out highest weight edges in cycles

Applications

- MST is fundamental problem with diverse applications.
 - Cluster analysis.
 - Max bottleneck paths.
 - Real-time face verification.
 - LDPC codes for error correction.
 - Image registration with Renyi entropy.
 - Find road networks in satellite and aerial imagery.
 - Model locality of particle interactions in turbulent fluid flows.
 - Reducing data storage in sequencing amino acids in a protein.
 - Autoconfig protocol for Ethernet bridging to avoid cycles in a network.
 - Approximation algorithms for NP-hard problems (e.g., TSP, Steiner tree).
 - Network design (communication, electrical, hydraulic, computer, road).

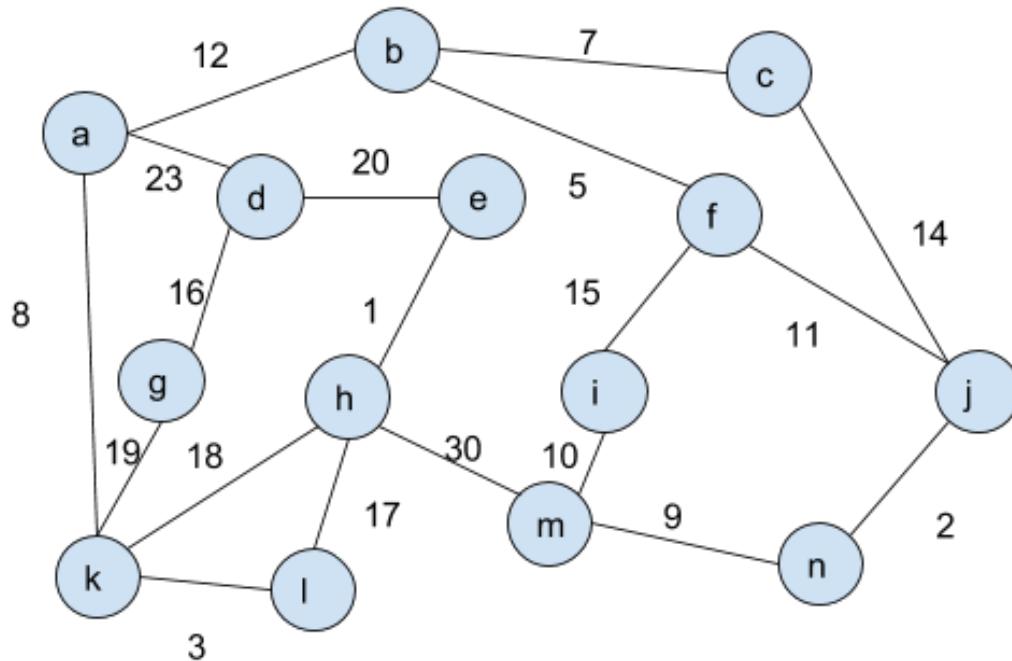
Borůvka's Algorithm

- Earliest MST algorithm: 1926. Application: design of power grid
- For **every** connected set in a forest,
 - Select smallest weight edge that leaves connected set
 - Add it to the MST
 - But don't add it twice if same edge selected by two connected sets
- In principle, merges at least half of the trees at each time: $O(\log(n))$ iterations
 - Easy to parallelize
- Each pass is $O(\#E)$

Example

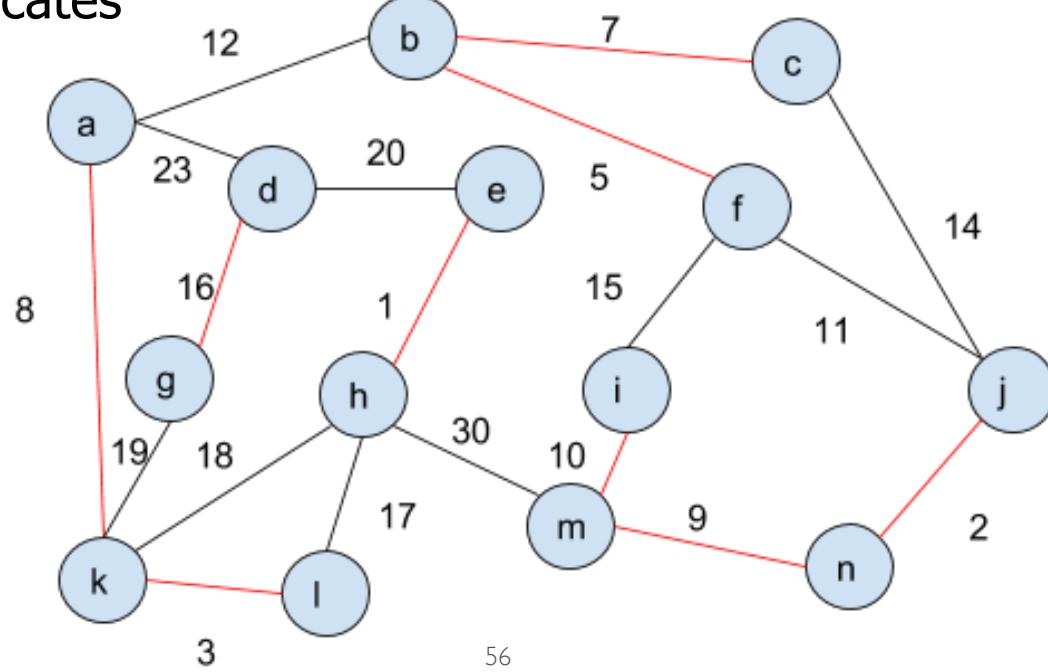
- Start with every vertex in a separate connected set, partial MST empty

▶



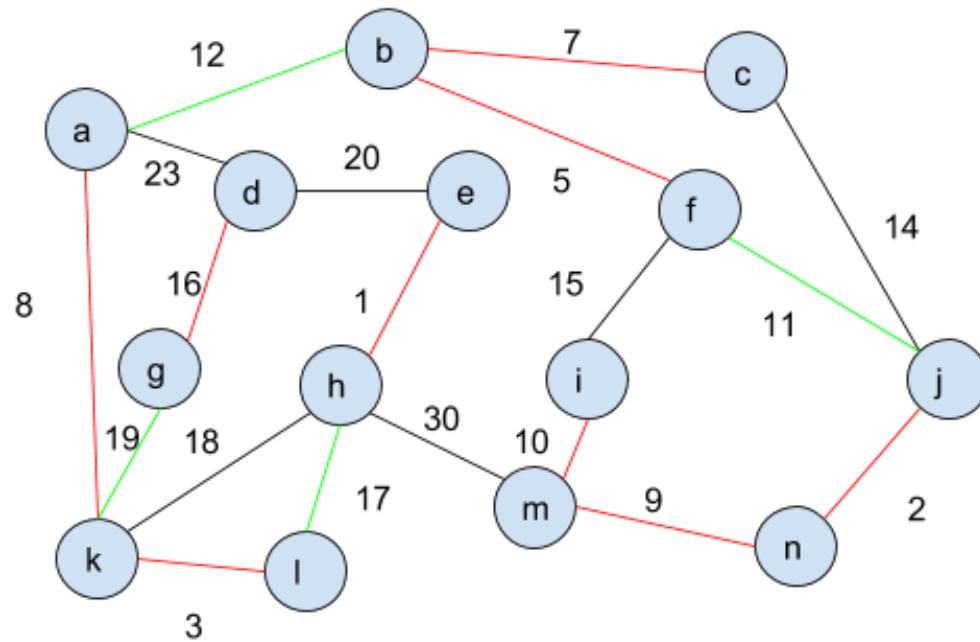
Example

- ▶ Find smallest weight edge connected to each set
 - ▶ Add all these edges to the partial MST
 - ▶ Avoid duplicates



Example

- ▶ Find smallest weight edge connected to each connected set
 - ▶ Add all these edges to the partial MST: Done!

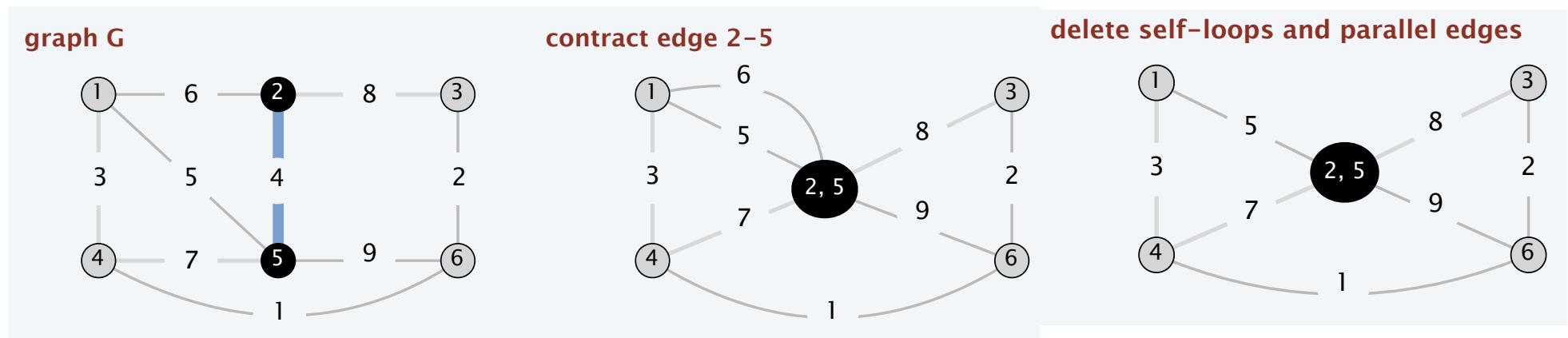


Borůvka's Algorithm

- Why does this work?
 - Can add edges sequentially and maintain promising set structure
 - Let $v \in V$ be any vertex in G . The minimum spanning tree for G must contain an edge (v, w) that is the minimum weight edge incident on v .
- What is hard to compute?
 - A bit of work to do: For each pass, need to avoid edges that form loops
 - Can do in $O(\log^*(\#V))$ with disjoint set data structure, or other tricks (graph contraction)
- Total complexity $O(\#E \log(\#V))$

Graph Contraction

- After each phase, contract each connected component to a single super-vertex
 - Delete self-loops and parallel edges (keeping only cheapest one)
- Borůvka iteration becomes: take cheapest edge incident to each super-vertex



Graph Contraction: $O(\#E)$

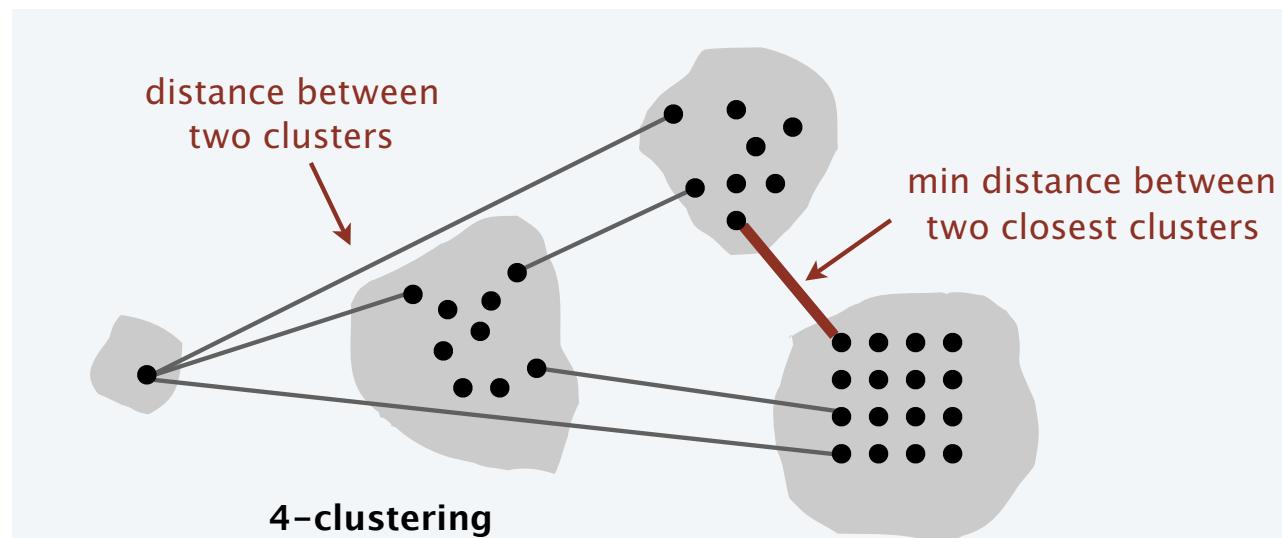
- ▶ Step 1: Let F be current edges in partial MST
 - ▶ Compute the n' connected components in (V, F) as super-vertices V'
 - ▶ Let $\text{id}[u] = \text{super-vertex index of vertex } u$
 - ▶ For each $e = \{u,v\} \in E$, add an edge $e' = \{\text{id}[u],\text{id}[v]\}$ to E' if and only if $\text{id}[u]$ differs from $\text{id}[v]$, and set $w(e') = w(e)$
- ▶ Step 2: Remove parallel edges
 - ▶ For each set $\{e': e' = \{j,k\} \text{ for } j, k \text{ in } V'\}$, keep only the edge with minimum weight
 - ▶ Can do this efficiently using a lexicographic sort (not comparison-based)

Further Work

- Hybrid: Combine Borůvka's and Prim-Jarnik, with $n = \#V$, $m = \#E$
 - Run Borůvka's for r phases: reduces super-vertices to $\leq \frac{n}{2^r}$, $O(mr)$
 - Run Prim-Jarnik on contracted graph G' : $O(m + \frac{n}{2^r} \log(\frac{n}{2^r}))$
- Choose r to balance complexity of both: $r = \log_2(\log_2(n))$
- Total complexity:
$$O(m \log_2(\log_2(n)) + m + \frac{n}{\log_2(n)} \log(\frac{n}{\log_2(n)})) = O(m \log_2(\log_2(n)))$$
- Much work trying to get it down to $O(m)$

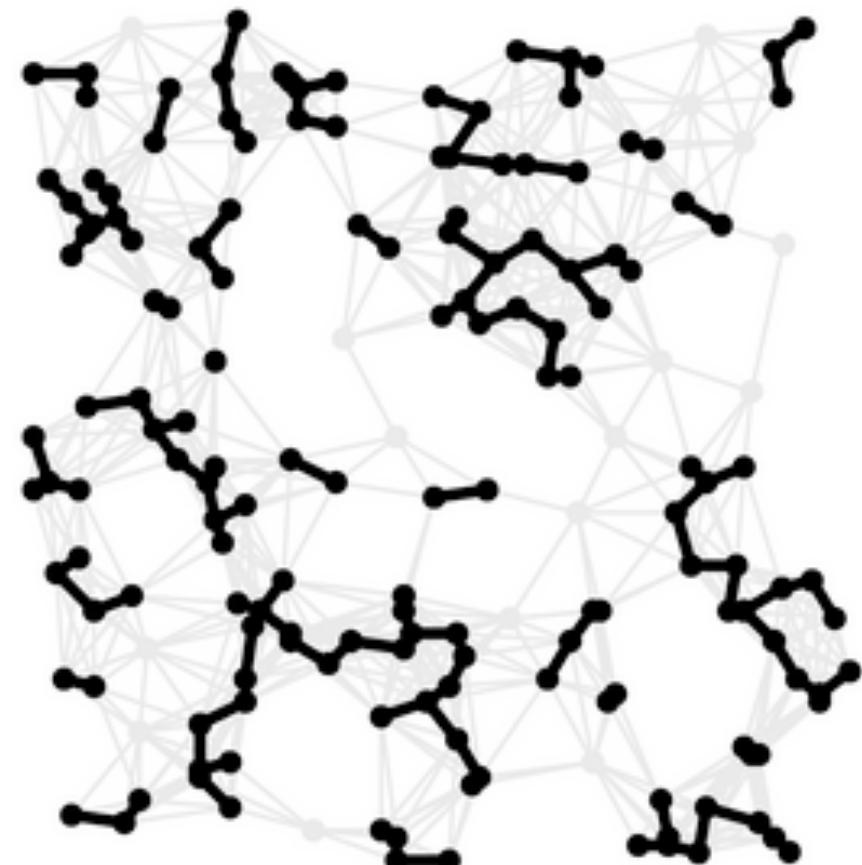
Application: Clustering

- Given a weighted graph $G = (V, E)$, where weight is distance, want to create k clusters such that we maximize the minimum distance between any pair of vertices in clusters



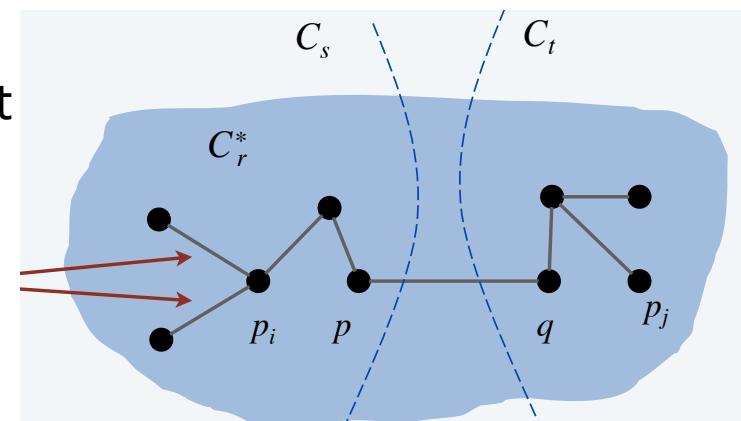
Solution

- › Approach 1: Run Kruskal's algorithm until there are only k connected components left
- › Approach 2: Run any MST algorithm, and delete the longest $k-1$ edges in MST



Why does this work?

- ▶ Theorem: Let $C^* = \{C_1^*, \dots, C_k^*\}$ denote the clustering formed by deleting the $k - 1$ longest edges of an MST. Then, C^* is a k -clustering of max spacing
 - ▶ Let d^* be min distance in C^* . Consider any other clustering $C = \{C_1, \dots, C_k\}$
 - ▶ Let v, w be in the same cluster in C^* (e.g. C_1^*) but not in C
 - ▶ Then, there is an edge $\{p, q\}$ on $v-w$ path in C_1^* , such that p in C_j , q in C_k , and j differs from k
 - ▶ $w(p, q) \leq d^*$ because it was added by Kruskal, so min distance in $C \leq d^*$

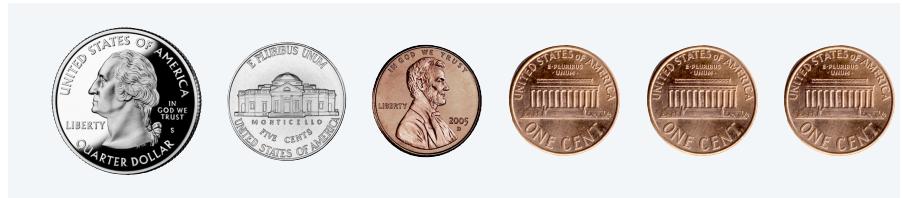


MHT Algorithms are Greedy Algorithms

- Greedy algorithm: an algorithm that builds a solution adding an element at a time that is the locally optimal choice at that time
 - Uses a simple rule e.g. MST adds edge with minimum weight across a cut
 - No backtracking (!!)
 - Greedy algorithms are not always optimal
 - Special classes of problems can be solved to optimality by greedy algorithms

Example: Coin Changing

- Given U. S. currency denominations { 1, 5, 10, 25, 100 }, devise a method to pay amount using fewest coins



- Greedy Algorithm

- At each iteration, add largest value coin that does not exceed amount
- e.g. for \$2.89,



- Is it optimal? Will this yield fewest coins for any amount?

Greedy Coin Changing in US

- ▶ For US denominations, optimal solution must satisfy:
 - ▶ Number of pennies ≤ 4 (if not, can reduce coins with a nickel)
 - ▶ Number of nickels ≤ 1 (otherwise, use dime)
 - ▶ Number of quarters ≤ 3 (otherwise, use Liberty \$)
 - ▶ Number of nickels + dimes ≤ 2 (otherwise, use quarters)



Greedy Coin Changing Optimal in US

- ▶ Prove by induction: Let c_k = value of coin k, x = amount to be paid
 - ▶ Assume greedy is optimal for $x < c_k$
 - ▶ If $c_k \leq x < c_{k+1}$, optimal solution must include at least one of coin k

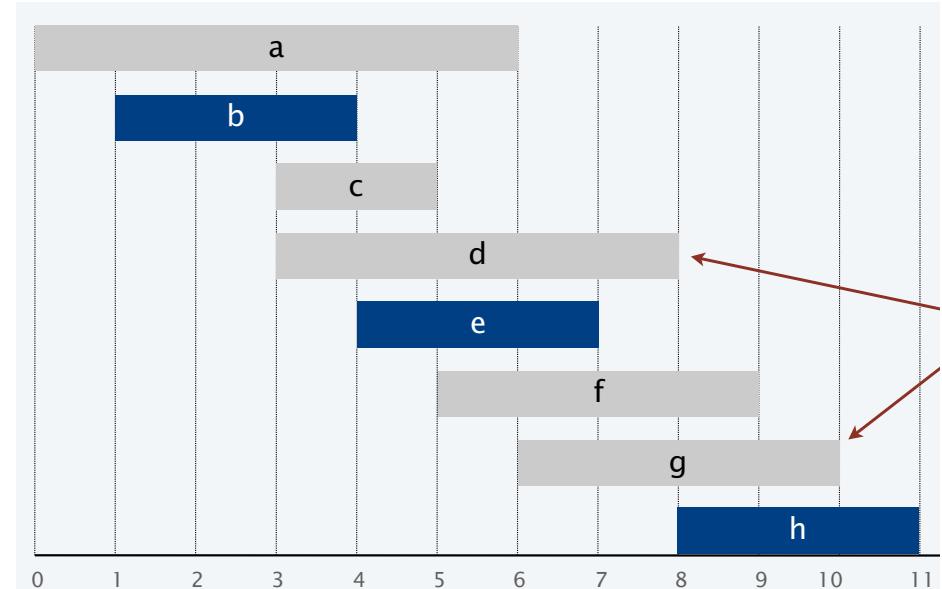
Otherwise, must match c_k with 1 lesser value coins, and it is not possible with US coins)

- ▶ Thus, optimal to use 1 of coin k, and then solve for $x - c_k$
- ▶ NOTE: not true for other denominations (e.g. stamps)

k	c_k	all optimal solutions must satisfy	max value of coin denominations c_1, c_2, \dots, c_{k-1} in any optimal solution
1	1	$P \leq 4$	-
2	5	$N \leq 1$	4
3	10	$N + D \leq 2$	$4 + 5 = 9$
4	25	$Q \leq 3$	$20 + 4 = 24$
5	100	<i>no limit</i>	$75 + 24 = 99$

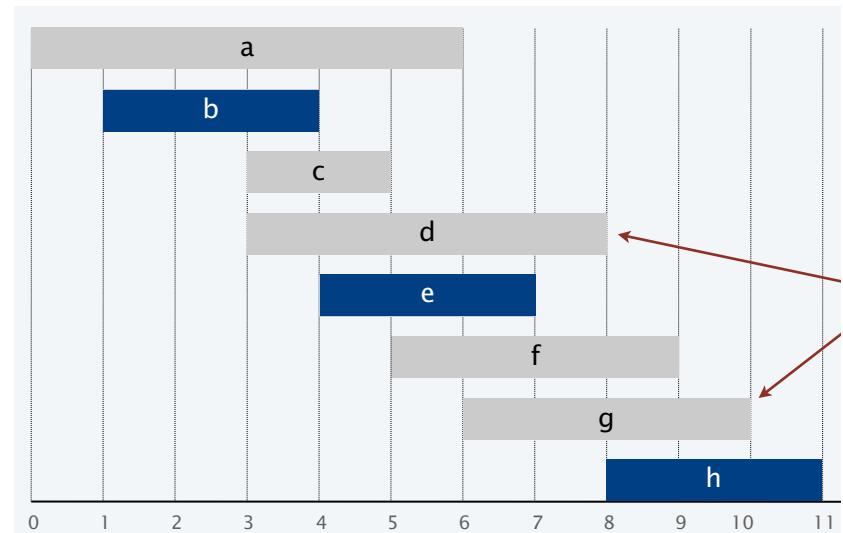
Interval Scheduling

- Jobs $\{1, 2, \dots, N\}$ occur at fixed times, with start times $s(j), f(j)$ for job j
- Single processor
- 2 jobs are compatible if they don't overlap
- Goal: Maximize number of jobs scheduled that are compatible



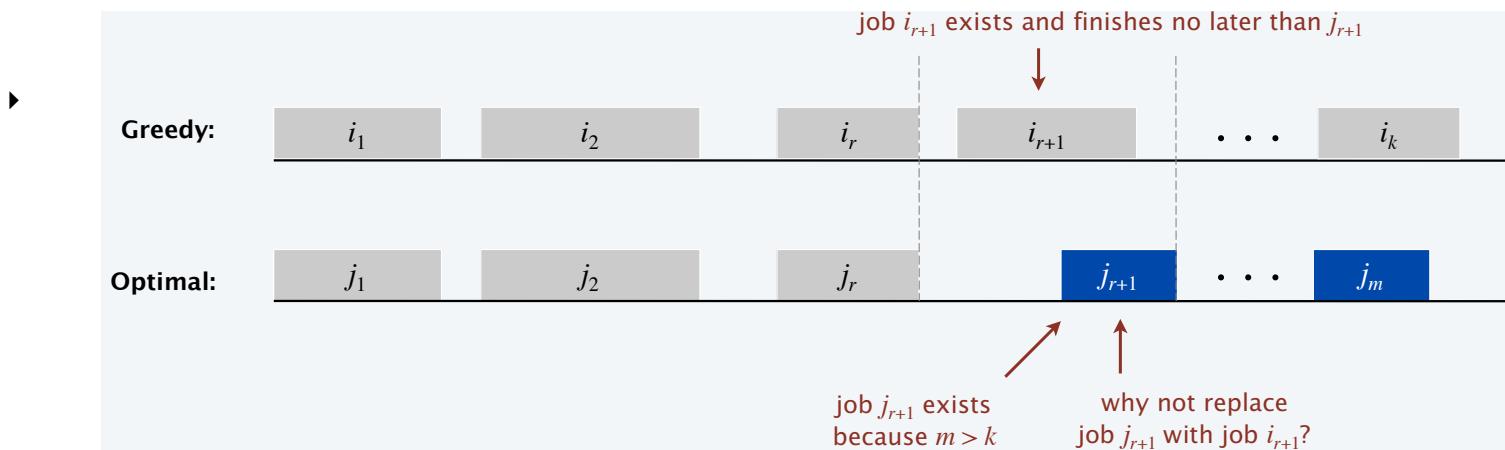
Interval Scheduling

- Quiz: Which is best? Sequence jobs by using an index, then add to schedule if compatible?
 - Earliest start time? (a,b,c,d,e,f,g,h)
 - Earliest finish time? (b,c,a,e,d,f,g,h)
 - Shortest interval? (c,b,e,h,f,g,d,a)
 - Least overlap? (h,b,c,g,a,e,f,d)



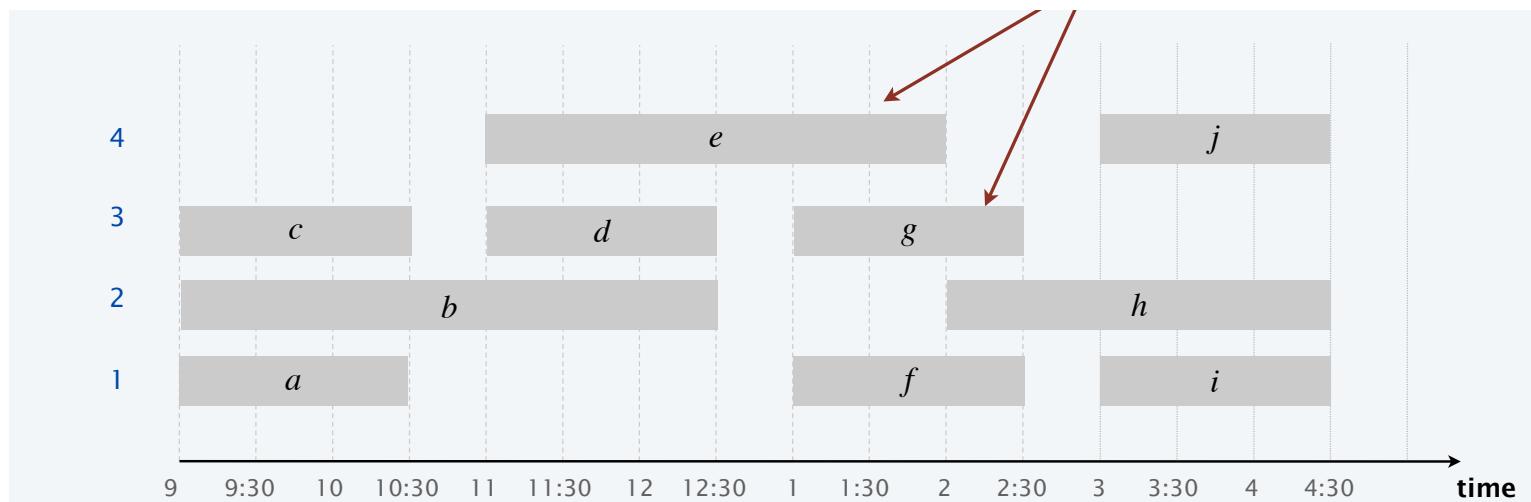
Interval Scheduling: Earliest finish time optimal

- Prove by contradiction
 - Let i_1, i_2, \dots, i_k denote set of jobs selected by EFT, and let j_1, j_2, \dots, j_m denote set of jobs in an optimal solution
 - Let r be largest value where $i_1 = j_1, \dots, i_r = j_r$ (schedules agree)
 - Note: i_{r+1} finishes no later than j_{r+1} (because of EFT choice)
 - So, can replace j_{r+1} with i_{r+1} and still be optimal for rest of schedule $J \rightarrow$ contradiction



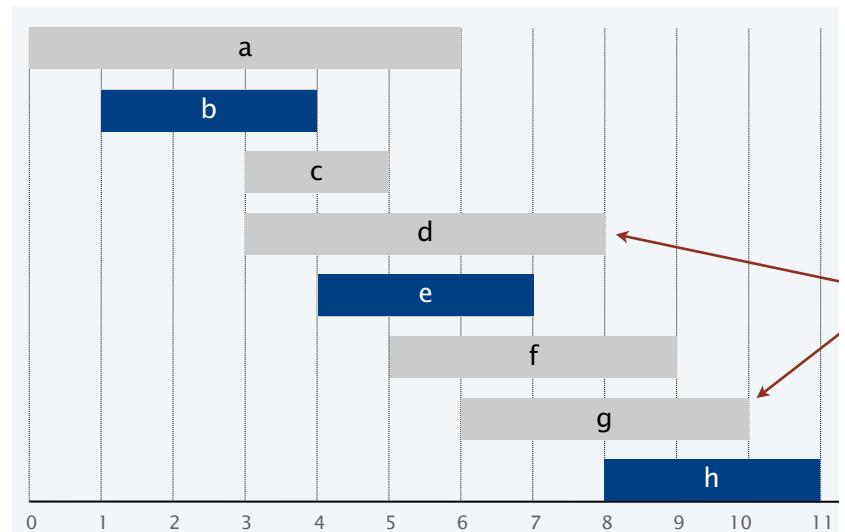
Scheduling Jobs on Parallel Processors

- Jobs $\{1, 2, \dots, N\}$ occur at fixed times, with start times $s(j)$, $f(j)$ for job j
- What is minimum number of parallel processors so we can schedule all jobs without conflict?
- The registrar problem: jobs are classes with start times, end times, and processors are classrooms (a bit more complicated if you add class sizes)



Parallel Job Scheduling

- Quiz: Which is best? Sequence jobs by using an index, then assign to first available processor?
 - Earliest start time? (a,b,c,d,e,f,g,h)
 - Earliest finish time? (b,c,a,e,d,f,g,h)
 - Shortest interval? (c,b,e,h,f,g,d,a)
 - Least overlap? (h,b,c,g,a,e,f,d)
 - ????

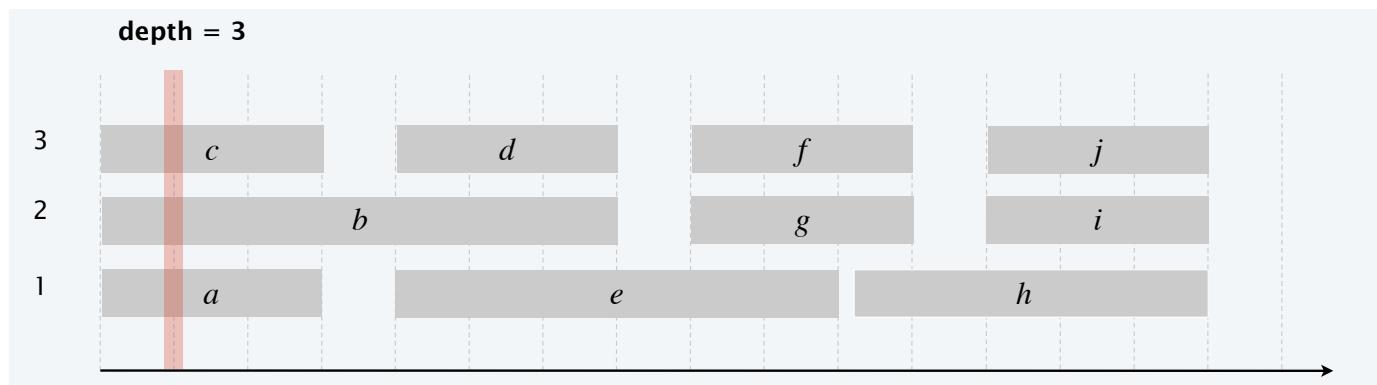


Optimal Algorithm

- Sequence by earliest start time: $s(1) \leq s(2) \leq \dots \leq s(n)$
 - Let $d = \text{number of allocated classrooms}$
 - For $j = 1$ to n :
 - If processor available at $s(j)$, assign $s(j)$ to processor
 - Else increase $d = d+1$, assign $s(j)$ to new processor
 - Alternative, sequence by earliest finishing time...would also work
 - $O(n \log(n)) \rightarrow$ need to sort
-

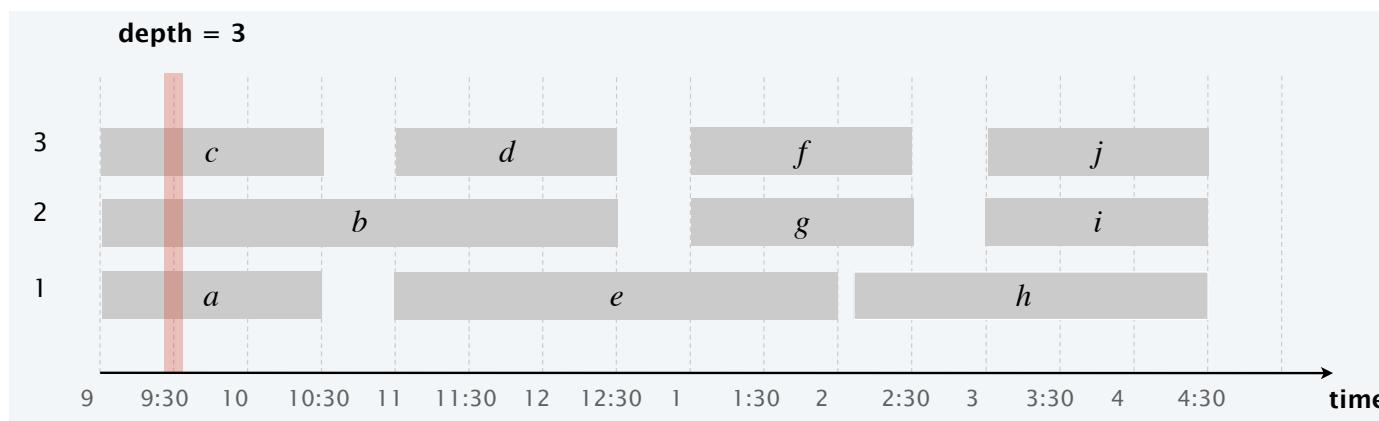
Concept: Depth of intervals

- ▶ Def. The depth of a set of open intervals is the maximum number of intervals that contain any given point.
- ▶ Key observation. Number of processors needed \geq depth.
- ▶ Q. Does minimum number of processors needed always equal depth?
 - ▶ Yes! Moreover, earliest-start-time-first algorithm finds a schedule whose number of processors equals the depth



Optimality

- › If you must add a processor to increase d in earliest-start-time algorithm for job j at $s(j)$, then depth is at least $d+1$ at time $s(j) + \epsilon$
- › Key observation. Number of processors needed \geq depth
- › Thus, EST algorithm achieves lower bound on number of processors, hence it is at least as good as any other algorithm \rightarrow it is optimal



Scheduling to minimize lateness

- Jobs $\{1, 2, \dots, N\}$, with required processing times t_j and deadlines d_j
 - If job j starts at time s , it finishes at $f_j = s + t_j$
 - Lateness measure $\ell_j = \max\{0, f_j - d_j\}$
 - Goal: schedule all jobs to minimize maximum lateness $L = \max_j \ell_j$

A Gantt chart illustrating task scheduling. The horizontal axis represents time from 0 to 15. The vertical axis lists tasks t_j and d_j along with their lateness values.

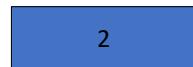
	1	2	3	4	5	6
t_j	3	2	1	4	3	2
d_j	6	8	9	9	14	15

The chart shows the following lateness values:

- Task t_j : lateness = 2 at position 8
- Task d_j : lateness = 0 at position 11
- max lateness: 15 at position 15

Example

Time



Deadline

2



4



Lateness 1



Lateness 3

Determine the minimum lateness

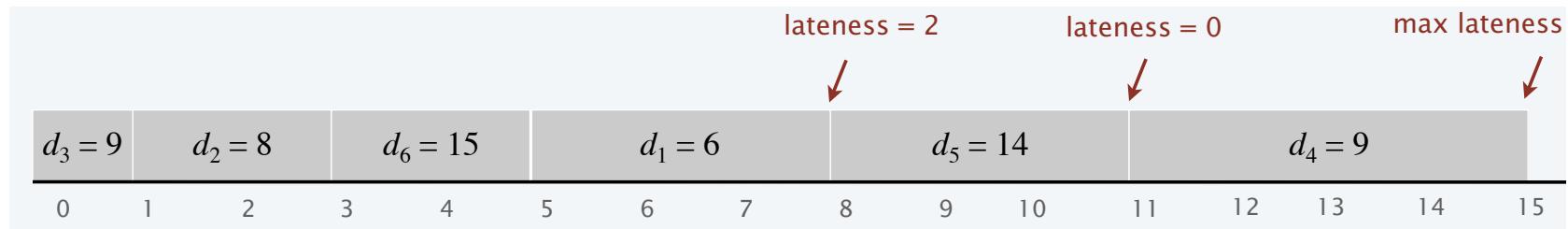
Time	Deadline
2	6
3	4
4	5
5	12



Deadline Scheduling

- Quiz: Which is best? Sequence jobs by using an index?
 - Shortest processing time?
 - Earliest deadline first?
 - Increasing order of slack $d_j - t_j$?
 - Something else?

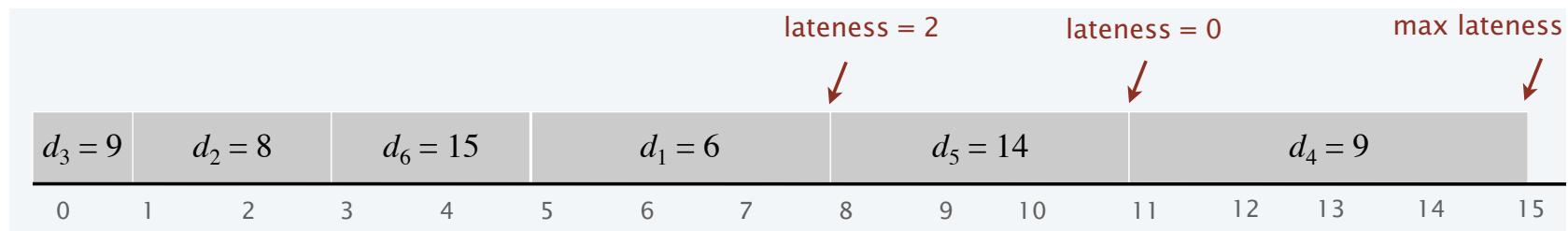
	1	2	3	4	5	6
t_j	3	2	1	4	3	2
d_j	6	8	9	9	14	15



Greedy algorithm: Earliest deadline first

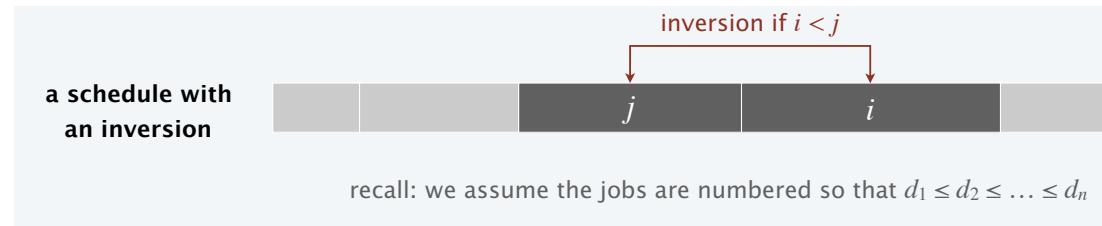
- › Sort jobs by deadline, so $d_1 \leq d_2 \leq \dots \leq d_N$
- › Start with $t = 0$
- › For $j=1$ to N :
 - › Schedule job j in $[t, t+d_j]$
 - › Increase $t = t+d_j$

	1	2	3	4	5	6
t_j	3	2	1	4	3	2
d_j	6	8	9	9	14	15



Observation: No idle time is optimal

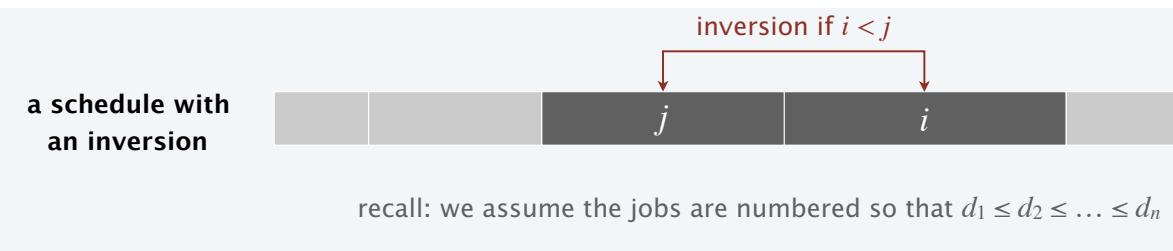
- › There exist an optimal schedule with no idle time (by contradiction, easy to perturb to eliminate idle time
 - › Earliest deadline schedule has no idle time
- › Definition: a schedule has an inversion if, for a particular pair $j < k$, job k is scheduled before job j
 - › Note: if an inversion exists, then there must exist a pair of adjacent jobs in a schedule with inversion



- › Earliest deadline schedule has no inversions

Minimizing Lateness

- Given a schedule S with inversions, exchanging the order of an adjacent, inverted pair j, k does not increase maximum lateness
- Proof: Let ℓ_m be the lateness of job m before the exchange, and ℓ'_m the lateness after the exchange
 - $\ell'_m = \ell_m$ for all $m \neq j, k$
 - $\ell'_j \leq \ell_j$ because we have moved it up
 - If job k is now late, $\ell'_k = f'_k - d_k = f_j - d_k \leq f_j - d_j = \ell_j$ (earliest deadline)
 - So, max lateness is not increased



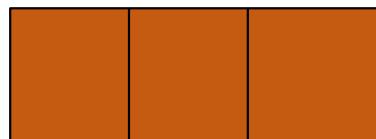
Optimality

- ▶ Earliest deadline first is optimal
- ▶ Proof:
 - ▶ Assume there is an optimal schedule that is not earliest deadline first that has the fewest number of inversions among optimal schedules
 - ▶ If number of inversions is 0, it is the EDF solution.
 - ▶ If not, there must be an adjacent inversion
 - ▶ Swapping the inversion does not increase the maximum lateness, and reduces the number of inversions, so we generate an optimal schedule which has less inversions
 - ▶ Contradiction

Optimal Caching

- ▶ Caching problem:
 - ▶ Maintain collection of items in local memory
 - ▶ Cache with capacity to store k items.
 - ▶ Sequence of m item requests d_1, \dots, d_m
 - ▶ Cache hit: item in cache when requested. Cache miss: item not in cache when requested (must evict item)
- ▶ Goal: Minimize number of items that result in cache misses

Caching example



A, B, C, D, A, E, B, A, D, A, C, B, D, A

Optimal Caching

- Non-causal: if we know the sequence of requests d_1, \dots, d_m , what is optimal replacement?
- Greedy algorithms
 - LIFO: evict most recent
 - FIFO: evict oldest
 - LRU: evict item with earliest recent access
 - LFU: evict least frequently requested

Optimal Caching

- Non-causal algorithm: evict item not requested until **farthest in future** (FF) sequence
- A reduced schedule is a schedule that brings an item d into the cache in step j only if there is a request for d in step j and d is not already in cache
- Given any unreduced schedule S, can transform it into a reduced schedule S' with no more evictions

an unreduced schedule

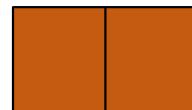
a	a	b	c
a	a	b	c
c	a	d	c
d	a	d	c
a	a	c	b
b	a	c	b
c	a	c	b
d	d	c	b
d	d	c	d

a reduced schedule

a	a	b	c
a	a	b	c
c	a	b	c
d	a	d	c
a	a	d	c
b	a	d	b
c	a	c	b
d	d	c	b
d	d	c	b

Farthest in the future algorithm

- Discard element used farthest in the future



A, B, C, A, C, D, C, B, C, A, D

Optimal Caching

- Theorem. FF is optimal eviction algorithm
 - Follows directly from the following invariant:
- There exists an optimal reduced schedule S that has the same eviction schedule as S_{FF} through the first j steps

Pf. [by induction] Base case: $j = 0$ obvious.

- Let S be reduced schedule that satisfies invariant through j steps; produce S' that satisfies invariant after $j + 1$ steps.
- Let d denote the item requested in step $j + 1$
- Since S and S_{FF} agreed until j , they have the same cache contents before step $j + 1$.
- **Case 1:** d is already in the cache. $S' = S$ satisfies invariant.
- **Case 2:** d is not in the cache and S and SFF evict the same item. $S' = S$ satisfies invariant.

Optimal Caching - 2

- ▶ **Case 3:** d is not in the cache; S_{FF} evicts e; S evicts $f \neq e$
 - ▶ begin construction of S' from S by evicting e instead of f



- ▶ S' agrees with S for first $j + 1$ steps; show that having item f in cache is no worse than having item e in cache
- ▶ let S' behave the same as S until S' is forced to take a different action (because either S evicts e; or because either e or f is requested)

Optimal Caching - 3

- ▶ **Case 3:** d is not in the cache; S_{FF} evicts e; S evicts $f \neq e$
 - ▶ Let j' be the first step after $j + 1$ that S' must take a different action from S; let g denote the item requested in step j'



- ▶ Possibilities:
 - a) $g=e$ cannot happen, because in S_{FF} e was evicted first, so f is accessed earlier
 - b) $g = f$. Since f is not in cache of S, f must evict e'.
 - if $e' = e$, then have the same cache after S, S' so same performance
 - if e' differs from e, make S' replace e' with e, and now S, S' have the same cache and performance
- ▶ S' can be transformed to reduced schedule that agrees with S for $j+1$ steps

Summary

- FF optimal for off-line cache optimization
 - Full sequence of requests known priori
- On-line approximation: LRU —> evict item whose last access was earliest
 - Like FF, but backwards in time...
- Strategies like FIFO and LIFO can be pretty bad

Other Scheduling Problems

1. Single server, N jobs

- › Job j has processing times $t(j)$
- › Select start time $s(j)$ for j , when server is idle; finish time $f(j) = s(j) + t(j)$
- › Objective: Schedule jobs to minimize total finishing time summed over jobs

$$\text{Min } \sum_{j=1}^N f(j)$$

- › Optimal solution: Greedy algorithm
 - › Sort jobs so $t(1) \leq t(2) \leq \dots \leq t(N)$ and schedule back-to-back in that order

Other Scheduling Problems

- ▶ Proof by contradiction:

Let P is an optimal schedule. Let p_j be job in position j in P

Assume P is not ordered according to increasing processing time

Find first j such that $t_{p_j} > t_{p_{j+1}}$ (must exist because of P ordering)

Swap these in schedule to get schedule P' , and show P' is better

Note: finishing time of p_1, \dots, p_{j-1} and p_{j+1}, \dots, p_N is the same under P, P'

Let T_{j-1} be finishing time p_{j-1} . Then,

Under P , finishing times of p_j and p_{j+1} are: $T_{j-1} + t_{p_j}, T_{j-1} + t_{p_j} + t_{p_{j+1}}$

Under P' , finishing times of p_j and p_{j+1} are: $T_{j-1} + t_{p_{j+1}}, T_{j-1} + t_{p_j} + t_{p_{j+1}}$

Since $t_{p_j} > t_{p_{j+1}}$, P' is better! So P cannot be optimal, contradiction.

Other Scheduling Problems

1. Single server, N jobs

- Job j has unit processing time, hard deadline $d(j)$, Value $V(j)$ if job completed on time
- Objective: Find sequence of jobs that will be scheduled to maximize value completed on time
- Concept: a set of jobs $\{j_1, \dots, j_k\}$ is feasible \iff there is an ordering of these jobs where each job is completed before its deadline
 - If a set of jobs is feasible, scheduling them by earliest deadline first is sufficient —> simple to show

Other Scheduling Problems

- Determining the best feasible set is the hard problem
- Algorithm:
 - Initialize feasible set S as empty; sort the jobs by decreasing value $V(j)$, into order j_1, \dots, j_N
 - Initialize step $k = 1$
 - At step k , add job j_k to S , and see if S is still a feasible set
 - If S is not feasible, remove j_k from S
 - If $k < N$, increment $k = k+1$ and repeat
- Claim: this will be an optimal feasible set
 - Important: every job takes the same amount of time