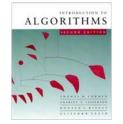
CS60020: Foundations of Algorithm Design and Machine Learning

Sourangshu Bhattacharya



Graphs (review)

Definition. A *directed graph (digraph)* G = (V, E) is an ordered pair consisting of • a set *V* of *vertices* (singular: *vertex*), • a set $E \subset V \times V$ of *edges*. In an *undirected graph* G = (V, E), the edge set *E* consists of *unordered* pairs of vertices. In either case, we have $|E| = O(V^2)$. Moreover, if G is connected, then $|E| \ge |V| - 1$, which implies that $\lg |E| = \Theta(\lg V)$.

(Review CLRS, Appendix B.)

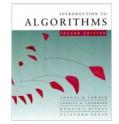
November 9, 2005Copyright © 2001-5 by Erik D. Demaine and Charles E. LeisersonL16.2



Adjacency-matrix representation

The *adjacency matrix* of a graph G = (V, E), where $V = \{1, 2, ..., n\}$, is the matrix A[1 ... n, 1 ... n] given by $A[i, i] = \begin{cases} 1 & \text{if } (i, j) \in E, \end{cases}$

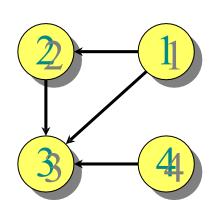
$$4[i,j] = \begin{cases} 0 & \text{if } (i,j) \notin E. \end{cases}$$



Adjacency-matrix representation

The *adjacency matrix* of a graph G = (V, E), where $V = \{1, 2, ..., n\}$, is the matrix A[1 ... n, 1 ... n] given by

$$A[i,j] = \begin{cases} 1 & \text{if } (i,j) \in \mathcal{E}, \\ 0 & \text{if } (i,j) \notin \mathcal{E}. \end{cases}$$



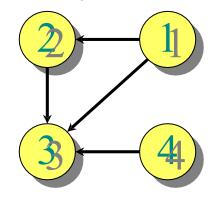
$\Theta(V^2) \text{ storage} \\ \Rightarrow \textbf{dense}$

representation.



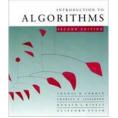
Adjacency-list representation

An *adjacency list* of a vertex $v \in V$ is the list Adj[v] of vertices adjacent to v.



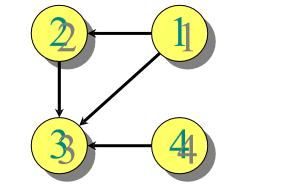
$$Adj[1] = \{2, 3\}$$

 $Adj[2] = \{3\}$
 $Adj[3] = \{\}$
 $Adj[4] = \{3\}$



Adjacency-list representation

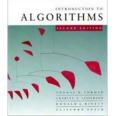
An *adjacency list* of a vertex $v \in V$ is the list Adj[v] of vertices adjacent to v.



$$Adj[1] = \{2, 3\}$$

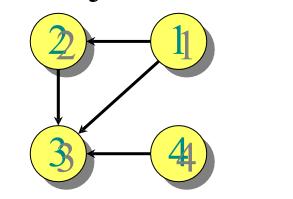
 $Adj[2] = \{3\}$
 $Adj[3] = \{\}$
 $Adj[4] = \{3\}$

For undirected graphs, |Adj[v]| = degree(v). For digraphs, |Adj[v]| = out-degree(v).



Adjacency-list representation

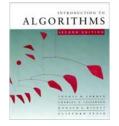
An *adjacency list* of a vertex $v \in V$ is the list Adj[v] of vertices adjacent to v.



 $Adj[1] = \{2, 3\}$ $Adj[2] = \{3\}$ $Adj[3] = \{\}$ $Adj[4] = \{3\}$

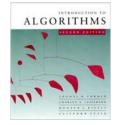
For undirected graphs, |Adj[v]| = degree(v). For digraphs, |Adj[v]| = out-degree(v).

Handshaking Lemma: $\sum_{v \in V} \operatorname{Adj}[v] = 2 |E|$ for undirected graphs \Rightarrow adjacency lists use $\Theta(V + E)$ storage — a *sparse* representation (for either type of graph).



Minimum spanning trees

- **Input:** A connected, undirected graph G = (V, E) with weight function $w : E \to \mathbb{R}$.
- For simplicity, assume that all edge weights are distinct. (CLRS covers the general case.)

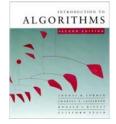


Minimum spanning trees

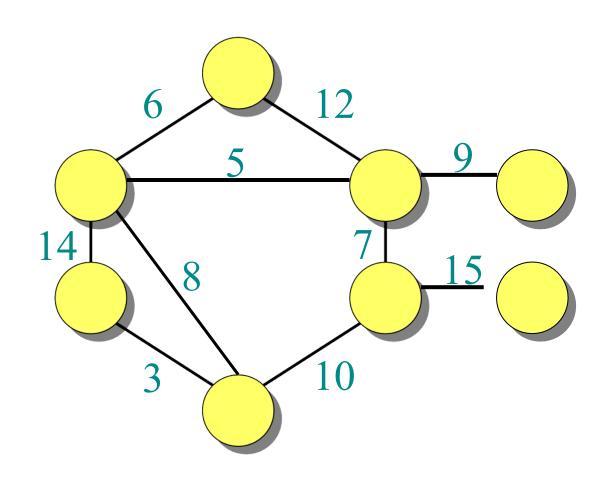
Input: A connected, undirected graph G = (V, E) with weight function $w : E \to R$.

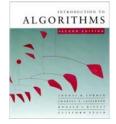
• For simplicity, assume that all edge weights are distinct. (CLRS covers the general case.)

Output: A *spanning tree* T — a tree that connects all vertices — of minimum weight: $w(T) = \sum_{(u,v) \in T} w(u,v).$

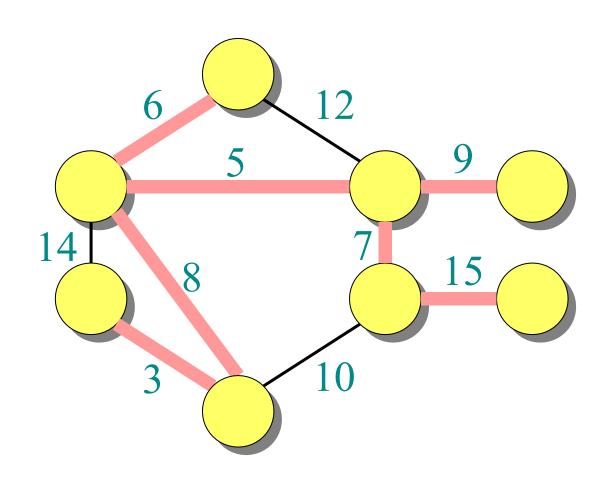


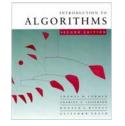
Example of MST





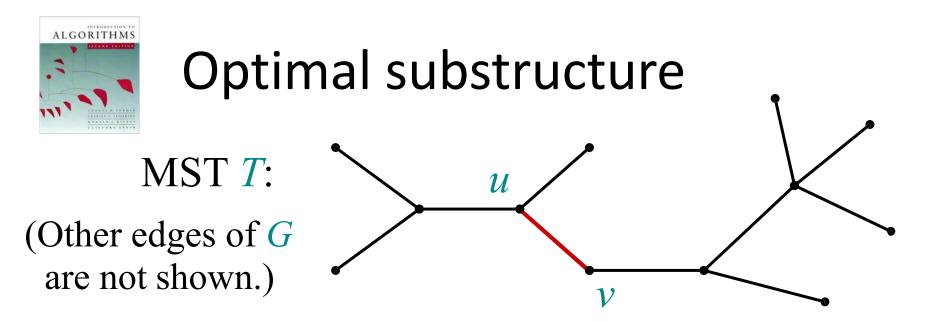
Example of MST



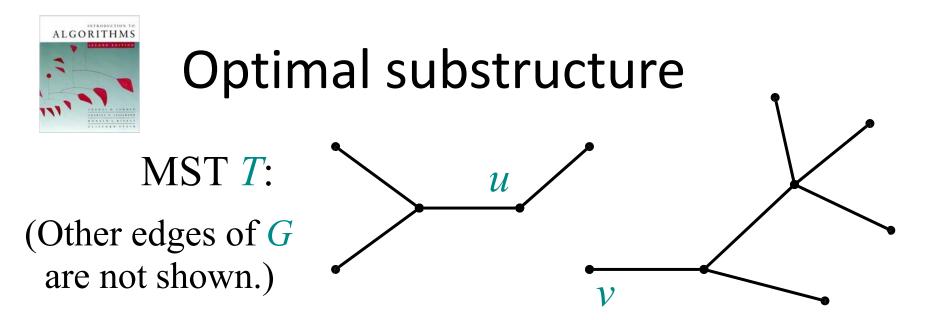


Optimal substructure

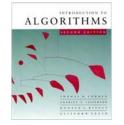
MST *T*: (Other edges of *G* are not shown.)



Remove any edge $(u, v) \in T$.



Remove any edge $(u, v) \in T$.



Optimal substructure

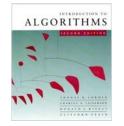
(Other edges of *G* are not shown.)

MST T:

Remove any edge $(u, v) \in T$. Then, *T* is partitioned into two subtrees T_1 and T_2 .

 \mathcal{U}

12



Optimal substructure

(Other edges of *G* are not shown.)

MST T:

Remove any edge $(u, v) \in T$. Then, *T* is partitioned into two subtrees T_1 and T_2 .

 \mathcal{U}

1)

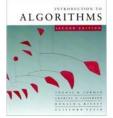
Theorem. The subtree T_1 is an MST of $G_1 = (V_1, E_1)$, the subgraph of *G induced* by the vertices of T_1 :

$$V_1 =$$
vertices of T_1 ,

 $E_1 = \{ (x, y) \in E : x, y \in V_1 \}.$

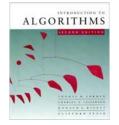
Similarly for T_2 .

November 9, 2005 Copyright © 2001-5 by Erik D. Demaine and Charles E. Leiserson L16.16



Proof of optimal substructure

Proof. Cut and paste: $w(T) = w(u, v) + w(T_1) + w(T_2).$ If T_1 were a lower-weight spanning tree than T_1 for G_1 , then $T' = \{(u, v)\} \cup T_1 \cup T_2$ would be a lower-weight spanning tree than T for G.



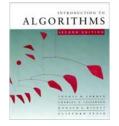
Proof of optimal substructure

Proof. Cut and paste:

 $w(T) = w(u, v) + w(T_1) + w(T_2).$

If T_1 were a lower-weight spanning tree than T_1 for G_1 , then $T' = \{(u, v)\} \cup T_1 \cup T_2$ would be a lower-weight spanning tree than T for G.

Do we also have overlapping subproblems? • Yes.



Proof of optimal substructure

Proof. Cut and paste:

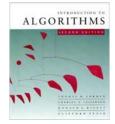
 $w(T) = w(u, v) + w(T_1) + w(T_2).$

If T_1 were a lower-weight spanning tree than T_1 for G_1 , then $T' = \{(u, v)\} \cup T_1 \cup T_2$ would be a lower-weight spanning tree than T for G.

Do we also have overlapping subproblems? • Yes.

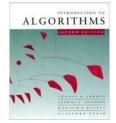
Great, then dynamic programming may work!

• Yes, but MST exhibits another powerful property which leads to an even more efficient algorithm.



Hallmark for "greedy" algorithms

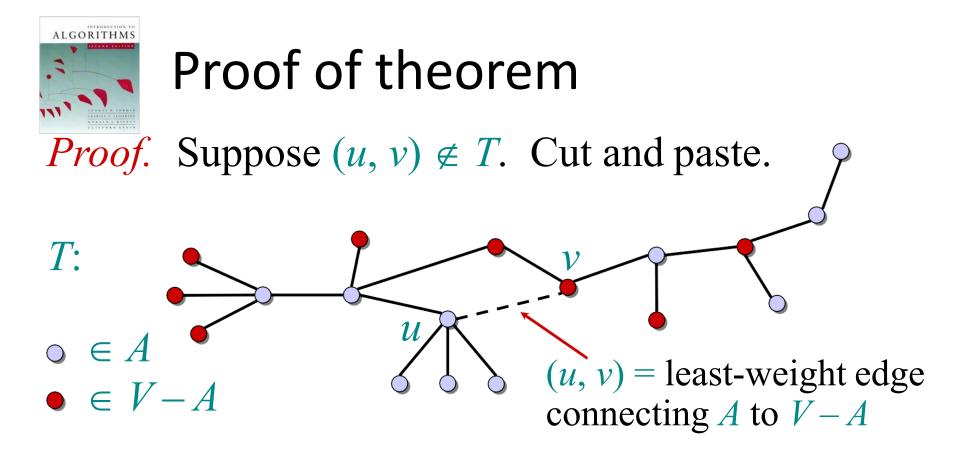
Greedy-choice property A locally optimal choice is globally optimal.

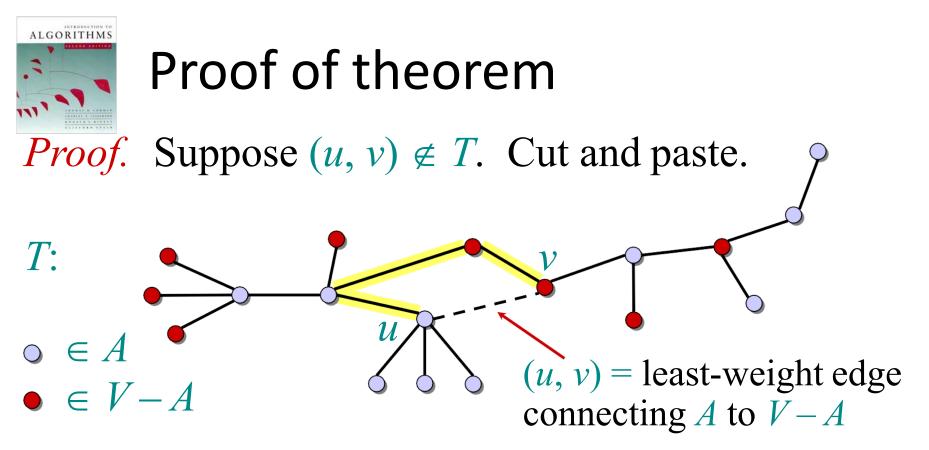


Hallmark for "greedy" algorithms

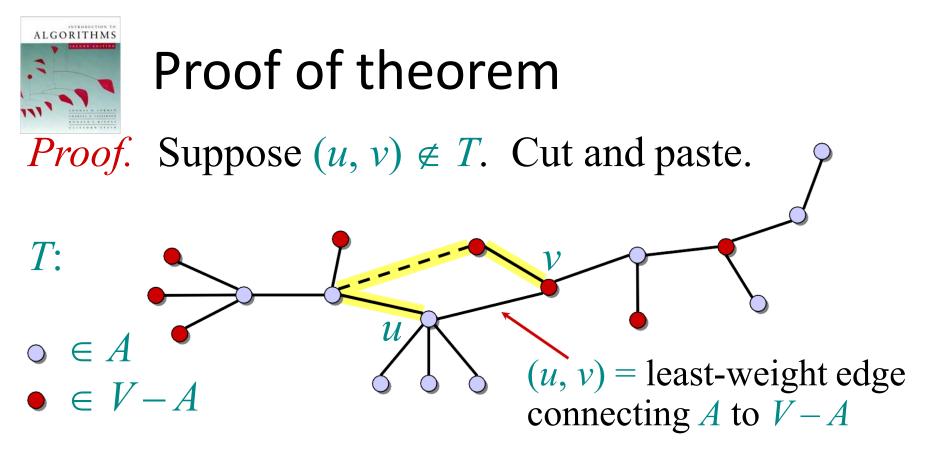
Greedy-choice property A locally optimal choice is globally optimal.

Theorem. Let *T* be the MST of G = (V, E), and let $A \subseteq V$. Suppose that $(u, v) \in E$ is the least-weight edge connecting *A* to V - A. Then, $(u, v) \in T$.

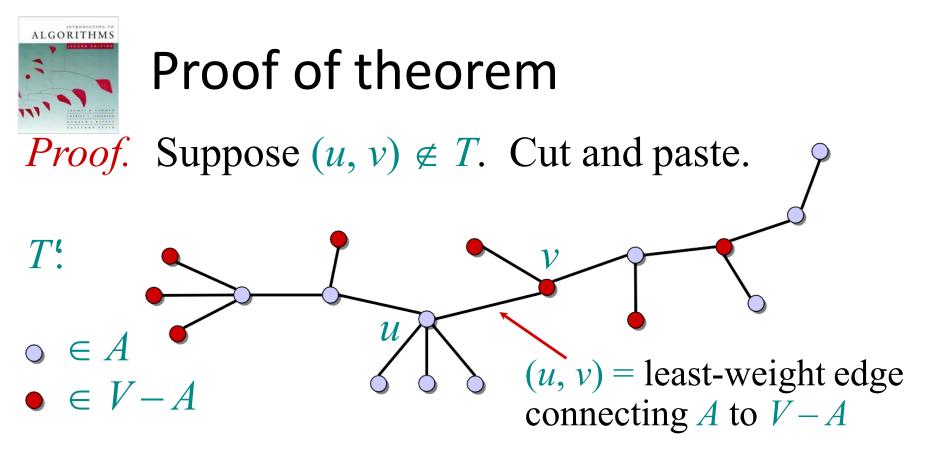




Consider the unique simple path from u to v in T.



Consider the unique simple path from u to v in T. Swap (u, v) with the first edge on this path that connects a vertex in A to a vertex in V-A.



Consider the unique simple path from u to v in T. Swap (u, v) with the first edge on this path that connects a vertex in A to a vertex in V-A. A lighter-weight spanning tree than T results.

November 9, 2005 Copyright © 2001-5 by Erik D. Demaine and Charles E. Leiserson L16.25

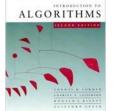
Kruskal's Algorithm

```
MST-KRUSKAL(G, w)
```

1 $A = \emptyset$

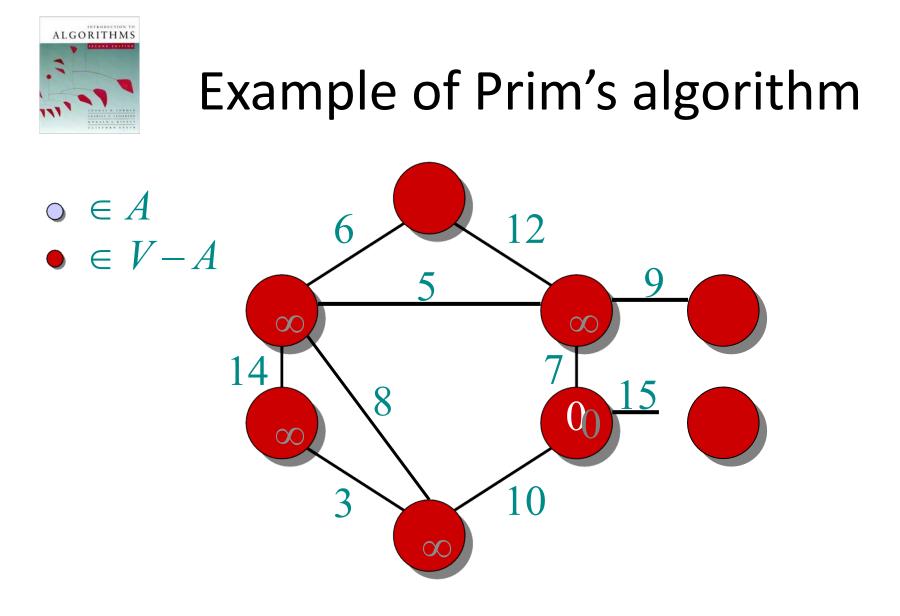
- 2 for each vertex $\nu \in G.V$
- 3 MAKE-SET (ν)
- 4 sort the edges of G.E into nondecreasing order by weight w
- 5 for each edge $(u, v) \in G.E$, taken in nondecreasing order by weight
- 6 **if** FIND-SET $(u) \neq$ FIND-SET(v)
 - $A = A \cup \{(u, v)\}$
- 8 UNION(u, v)
- 9 return A

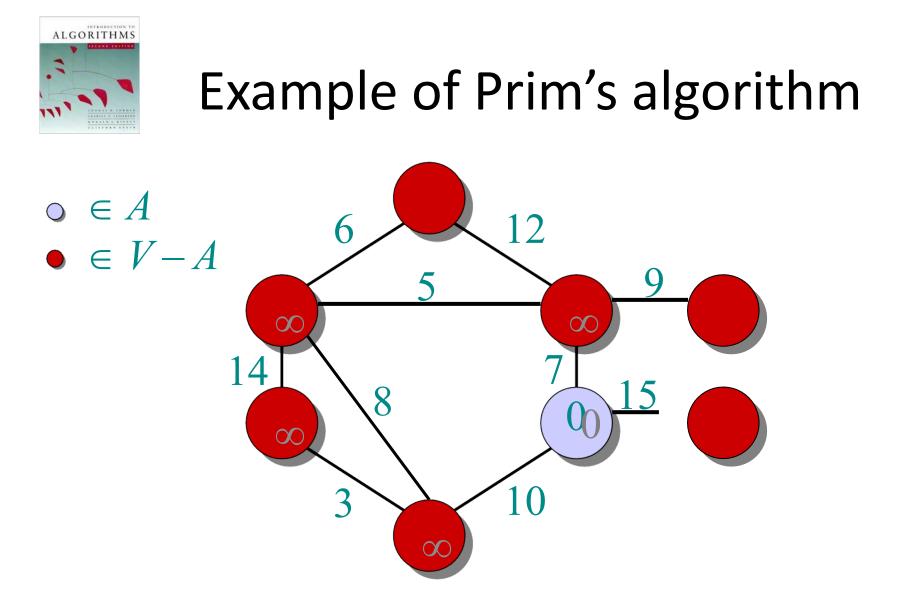
7

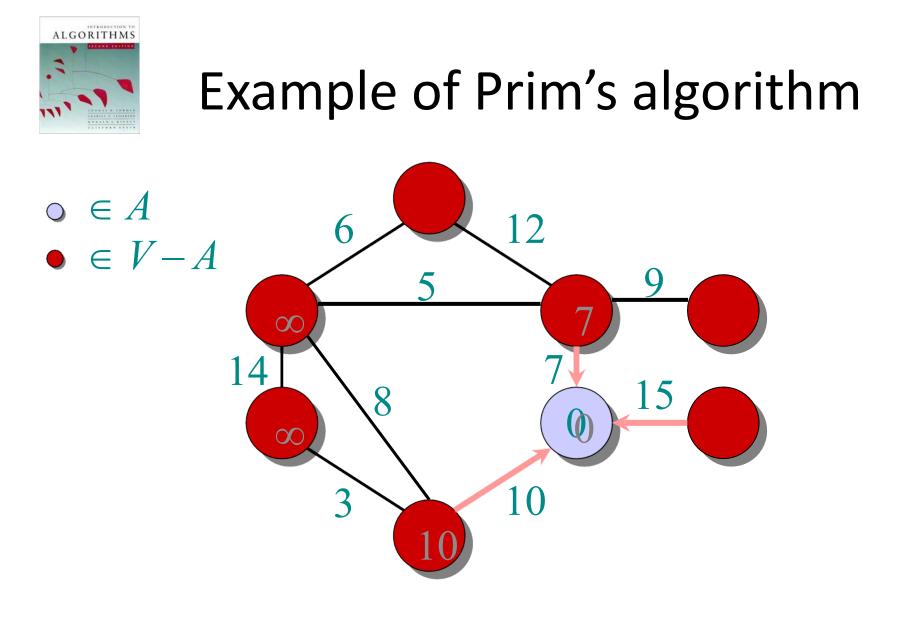


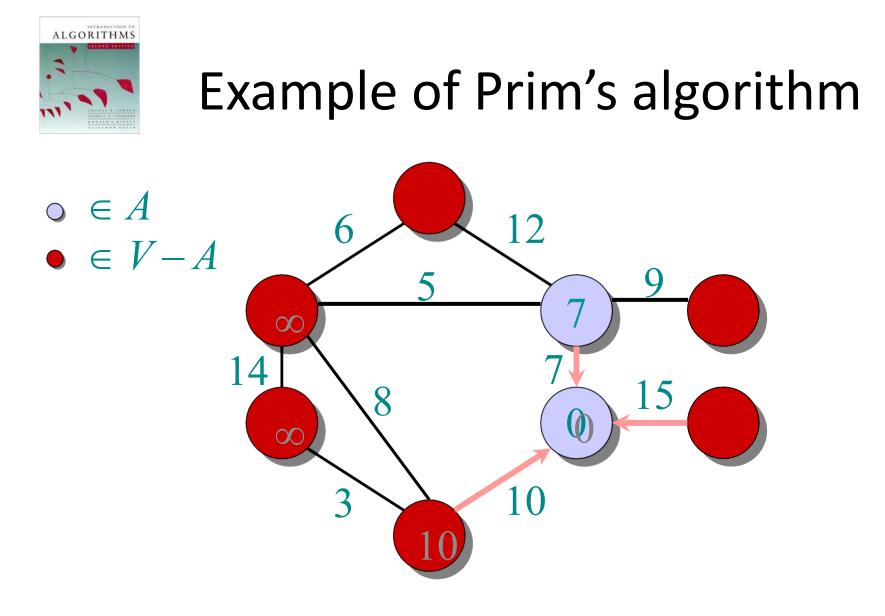
Prim's algorithm

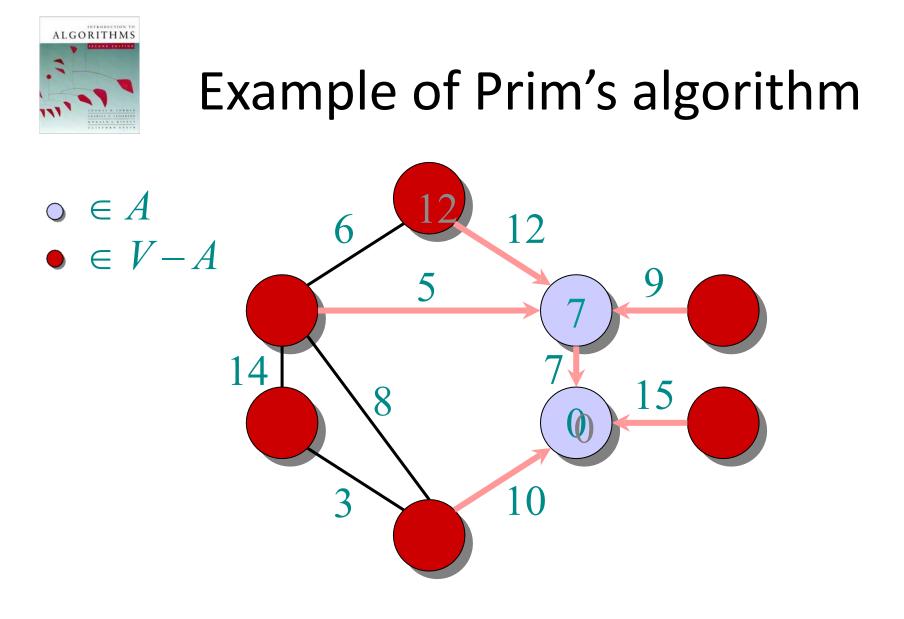
IDEA: Maintain V - A as a priority queue Q. Key each vertex in Q with the weight of the leastweight edge connecting it to a vertex in A. $Q \leftarrow V$ $kev[v] \leftarrow \infty$ for all $v \in V$ $key[s] \leftarrow 0$ for some arbitrary $s \in V$ while $Q \neq \emptyset$ **do** $u \leftarrow \text{EXTRACT-MIN}(Q)$ for each $v \in Adj[u]$ **do if** $v \in Q$ and w(u, v) < kev[v]then $key[v] \leftarrow w(u, v)$ DECREASE-KEY $\pi[v] \leftarrow u$ At the end, $\{(v, \pi[v])\}$ forms the MST.

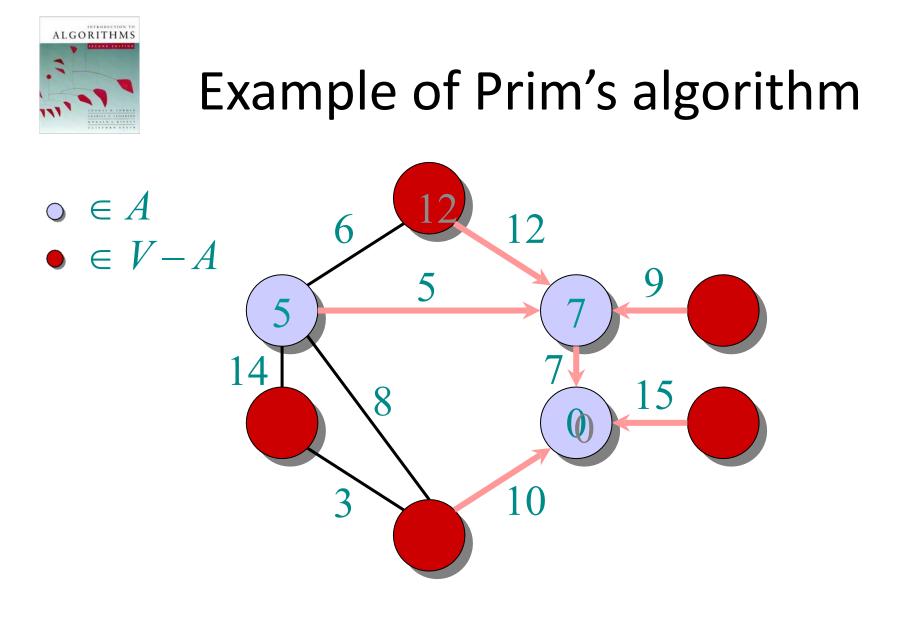


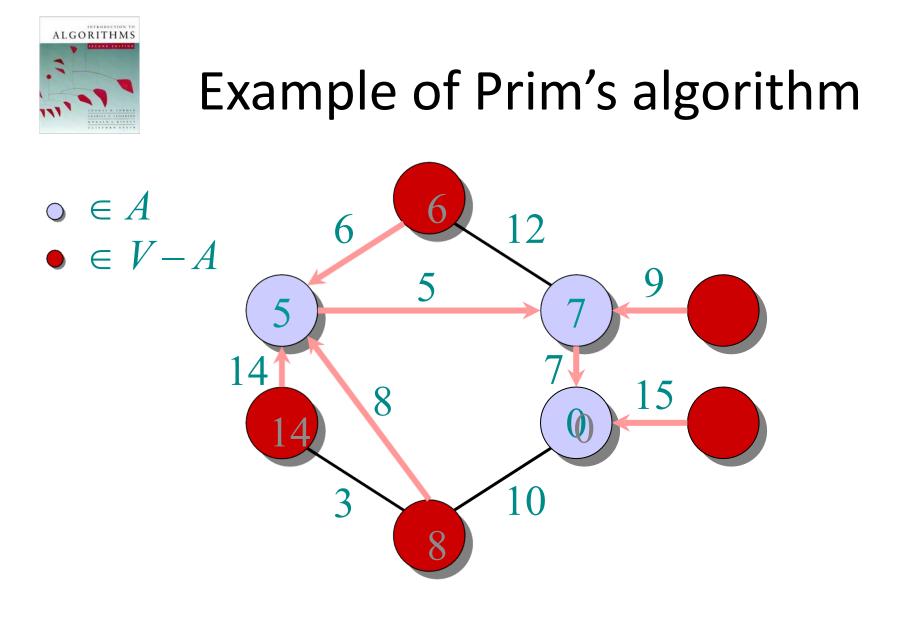


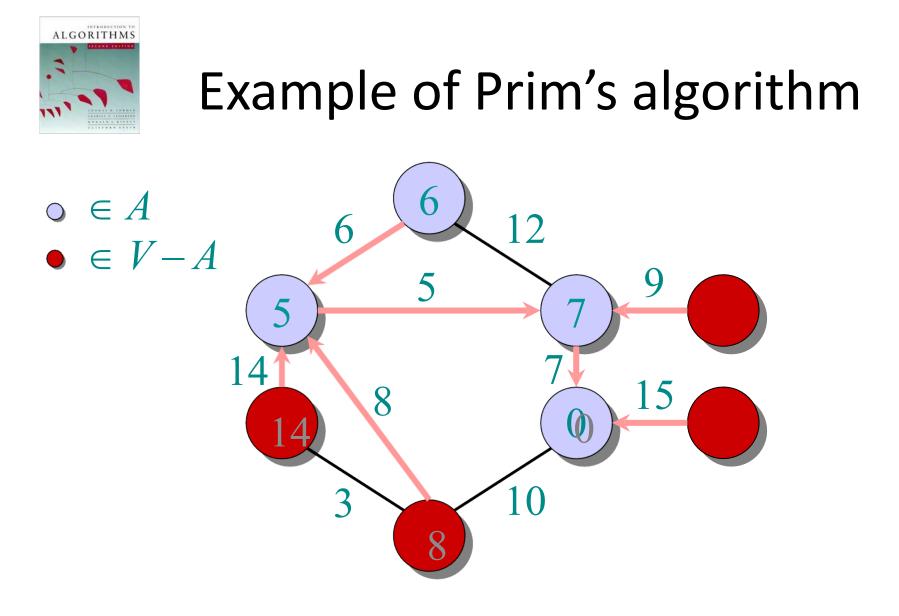


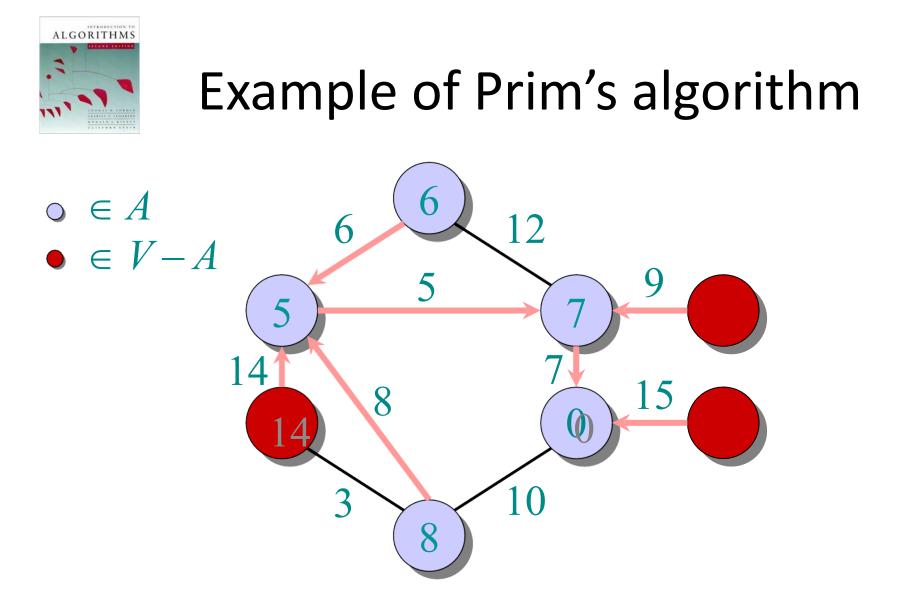


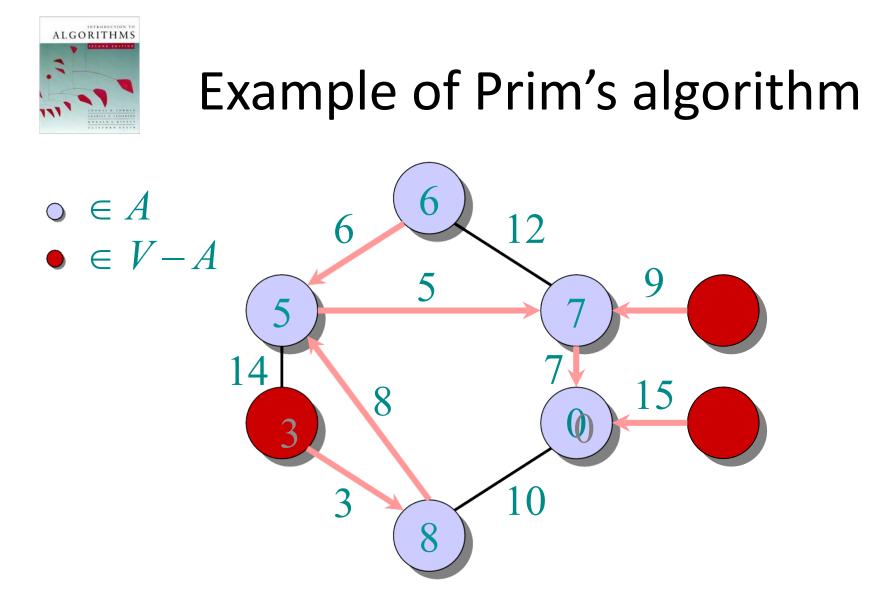


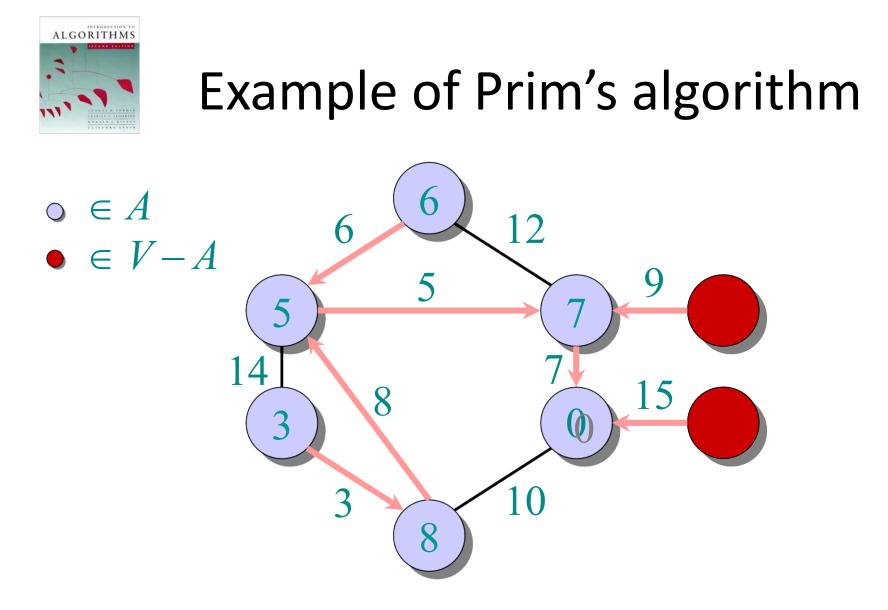


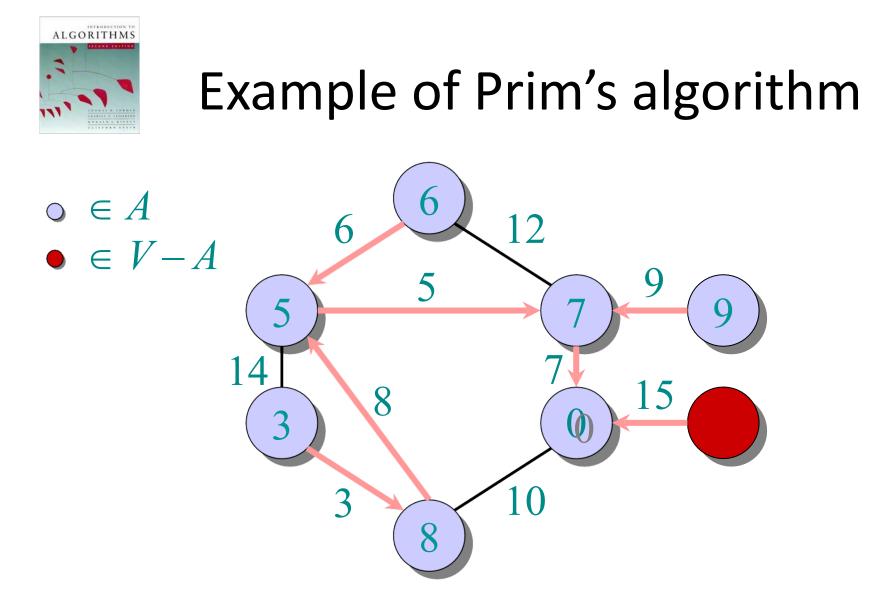


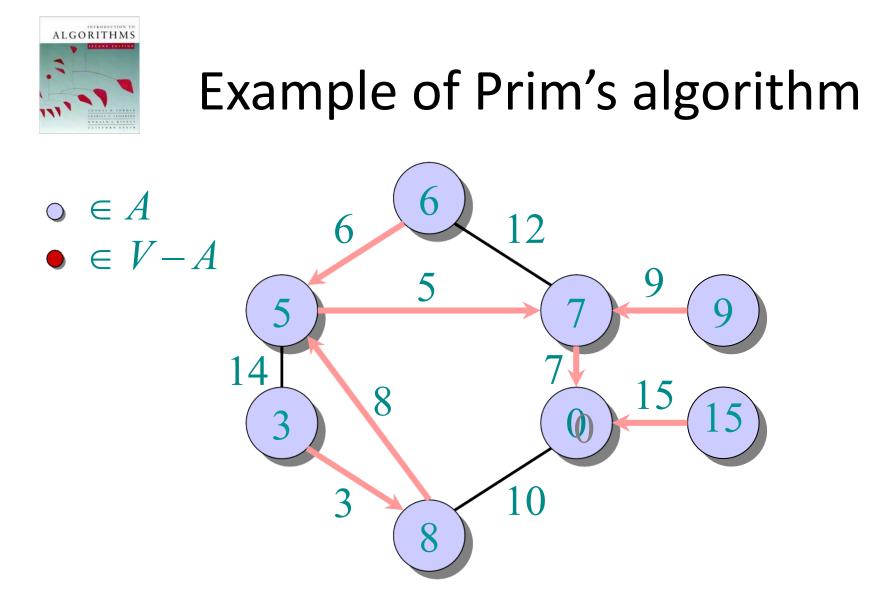


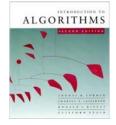






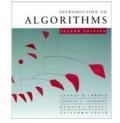






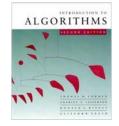
Analysis of Prim

 $Q \leftarrow V$ $kev[v] \leftarrow \infty$ for all $v \in V$ $kev[s] \leftarrow 0$ for some arbitrary $s \in V$ while $Q \neq \emptyset$ **do** $u \leftarrow \text{EXTRACT-MIN}(O)$ for each $v \in Adj[u]$ **do if** $v \in Q$ and w(u, v) < key[v]then $kev[v] \leftarrow w(u, v)$ $\pi[v] \leftarrow u$



Analysis of Prim

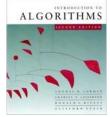
 $\Theta(V) \begin{cases} Q \leftarrow V \\ key[v] \leftarrow \infty \text{ for all } v \in V \\ key[s] \leftarrow 0 \text{ for some arbitrary } s \in V \end{cases}$ while $Q \neq \emptyset$ **do** $u \leftarrow \text{EXTRACT-MIN}(Q)$ for each $v \in Adj[u]$ **do if** $v \in Q$ and w(u, v) < key[v]then $key[v] \leftarrow w(u, v)$ $\pi[v] \leftarrow u$



 $\Theta(V)$ total

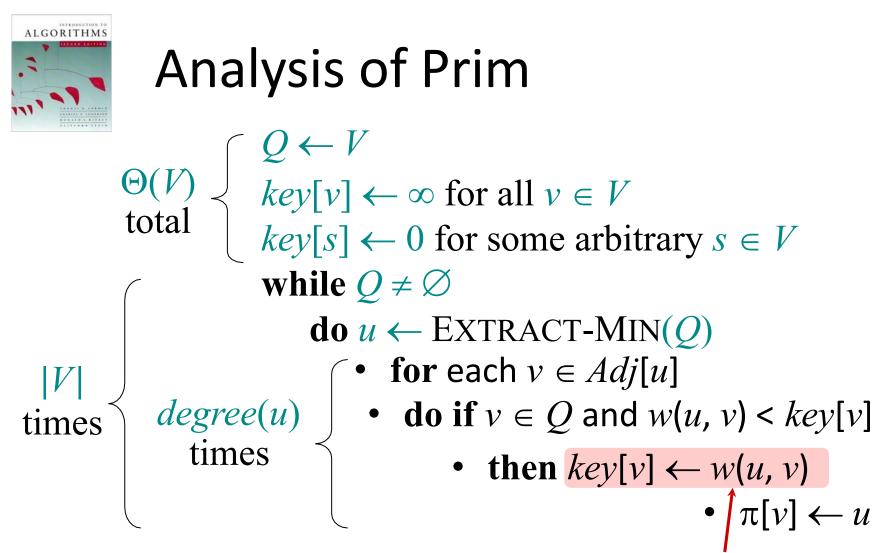
Analysis of Prim

 $\sum_{k \in V} [v] \leftarrow \infty \text{ for all } v \in V$ $key[s] \leftarrow 0 \text{ for some arbitrary } s \in V$ while $Q \neq \emptyset$ **do** $u \leftarrow \text{EXTRACT-MIN}(Q)$ for each $v \in Adj[u]$ **do if** $v \in Q$ and w(u, v) < key[v]then $key[v] \leftarrow w(u, v)$ $\pi[v] \leftarrow u$

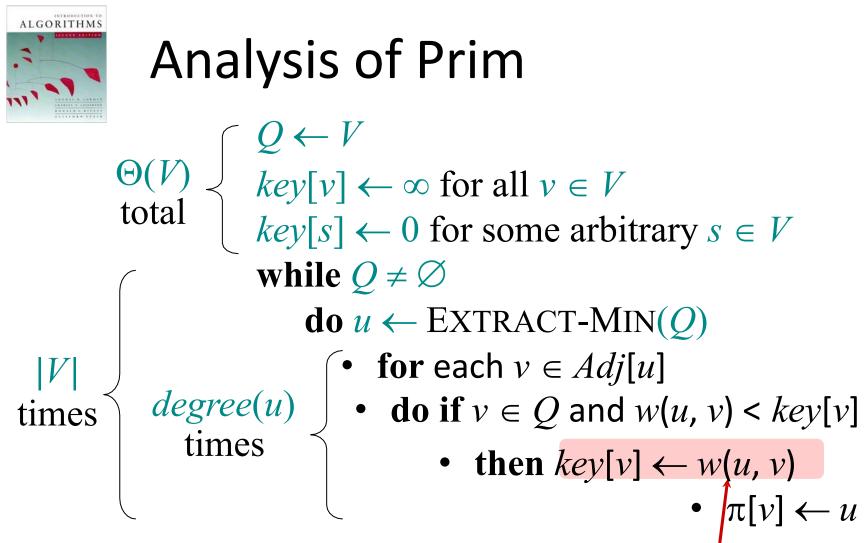


Analysis of Prim

 $\Theta(V) \begin{cases} \varphi(V) \\ key[v] \leftarrow \infty \text{ for all } v \in V \\ key[s] \leftarrow 0 \text{ for some arbitrary } s \in V \end{cases}$ while $Q \neq \emptyset$ **do** $u \leftarrow \text{EXTRACT-MIN}(Q)$ for each v ∈ Adj[u]
do if v ∈ Q and w(u, v) < key[v] degree(u) times < times • then $key[v] \leftarrow w(u, v)$ • $\pi[v] \leftarrow u$



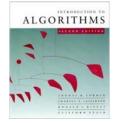
Handshaking Lemma $\Rightarrow \Theta(E)$ implicit DECREASE-KEY's.



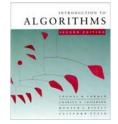
Handshaking Lemma $\Rightarrow \Theta(E)$ implicit DECREASE-KEY's.

Time = $\Theta(V) \cdot T_{\text{EXTRACT-MIN}} + \Theta(E) \cdot T_{\text{DECREASE-KEY}}$

November 9, 2005 Copyright © 2001-5 by Erik D. Demaine and Charles E. Leiserson L16.45

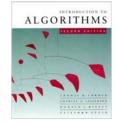


Time = $\Theta(V) \cdot T_{\text{EXTRACT-MIN}} + \Theta(E) \cdot T_{\text{DECREASE-KEY}}$



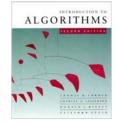
Time = $\Theta(V) \cdot T_{\text{EXTRACT-MIN}} + \Theta(E) \cdot T_{\text{DECREASE-KEY}}$

$Q \quad T_{\text{EXTRACT-MIN}} \quad T_{\text{DECREASE-KEY}} \quad \text{Total}$



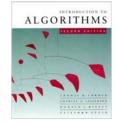
Time = $\Theta(V) \cdot T_{\text{EXTRACT-MIN}} + \Theta(E) \cdot T_{\text{DECREASE-KEY}}$

$\begin{array}{ccc} Q & T_{\text{EXTRACT-MIN}} & T_{\text{DECREASE-KEY}} & \text{Total} \\ \\ \text{array} & O(V) & O(1) & O(V^2) \end{array}$



Time = $\Theta(V) \cdot T_{\text{EXTRACT-MIN}} + \Theta(E) \cdot T_{\text{DECREASE-KEY}}$

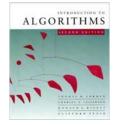
Q $T_{\text{EXTRACT-MIN}}$ $T_{\text{DECREASE-KEY}}$ TotalarrayO(V)O(1) $O(V^2)$ binary
heap $O(\lg V)$ $O(\lg V)$ $O(E \lg V)$



Time = $\Theta(V) \cdot T_{\text{EXTRACT-MIN}} + \Theta(E) \cdot T_{\text{DECREASE-KEY}}$

Q	T _{EXTRACT} -MIN	T _{DECREASE-KEY}	Total
array	O(V)	<i>O</i> (1)	$O(V^2)$
binary heap	<i>O</i> (lg <i>V</i>)	<i>O</i> (lg <i>V</i>)	$O(E \lg V)$
Fibonacci heap	<i>O</i> (lg <i>V</i>) amortized	<i>O</i> (1) amortized	$O(E + V \lg V)$ worst case

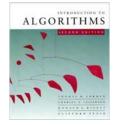
November 9, 2005 Copyright © 2001-5 by Erik D. Demaine and Charles E. Leiserson L16.50



MST algorithms

Kruskal's algorithm (see CLRS):

- Uses the *disjoint-set data structure* (Lecture 10).
- Running time = $O(E \lg V)$.



MST algorithms

Kruskal's algorithm (see CLRS):

- Uses the *disjoint-set data structure* (Lecture 10).
- Running time = $O(E \lg V)$.

Best to date:

- Karger, Klein, and Tarjan [1993].
- Randomized algorithm.
- O(V + E) expected time.