Design and Analysis of Algorithms

CSE 5311

Lecture 16 Greedy Algorithms

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Department of Computer Science and Engineering



Graphs (review)

Definition. A directed graph (digraph)

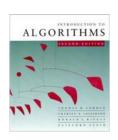
G = (V, E) is an ordered pair consisting of

- a set *V* of *vertices* (singular: *vertex*),
- a set $E \subseteq V \times V$ 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.)



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

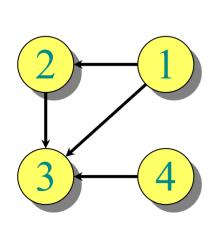
$$A[i,j] = \begin{cases} 1 & \text{if } (i,j) \in E, \\ 0 & \text{if } (i,j) \notin E. \end{cases}$$



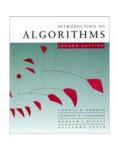
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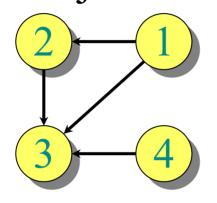


\boldsymbol{A}	1	2	3	4	
1	0	1	1	0	$\Theta(V^2)$ storage
2	0	0	1	0	\Rightarrow dense
3	0 0 0	0	0	0	representation.
4	0	0	1	0	



Adjacency-list representation

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



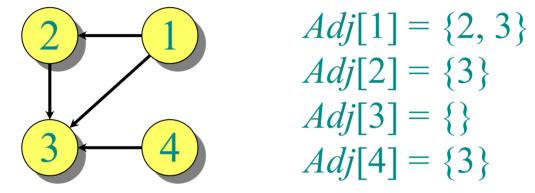
$$Adj[1] = \{2, 3\}$$

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



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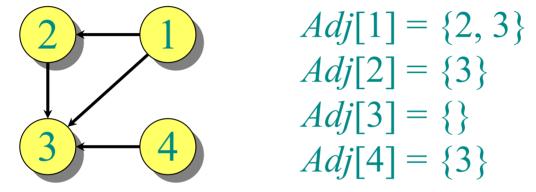


For undirected graphs, |Adj[v]| = degree(v). For digraphs, |Adj[v]| = out-degree(v).



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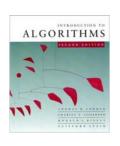
Handshaking Lemma: $\sum_{v \in V}^{\text{degree(v)}} 2|E|$ for undirected graphs \Rightarrow adjacency lists use $\Theta(V + E)$ storage — a *sparse* representation (for either type of graph).



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.)



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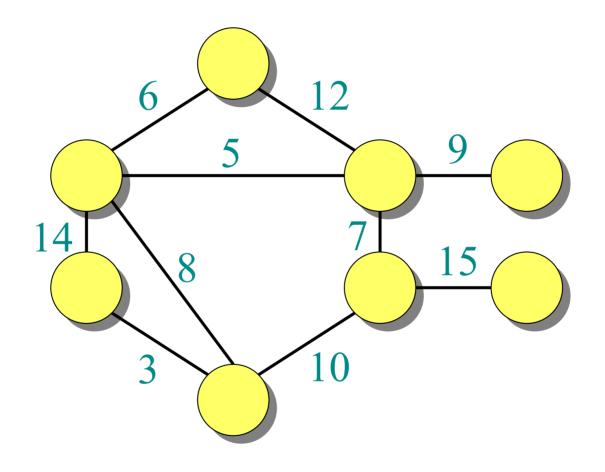
• For simplicity, assume that all edge weights are distinct. (CLRS covers the general case.)

Output: A *spanning tree* T — a tree that connects all vertices — of minimum weight:

$$w(T) = \sum_{(u,v)\in T} w(u,v).$$

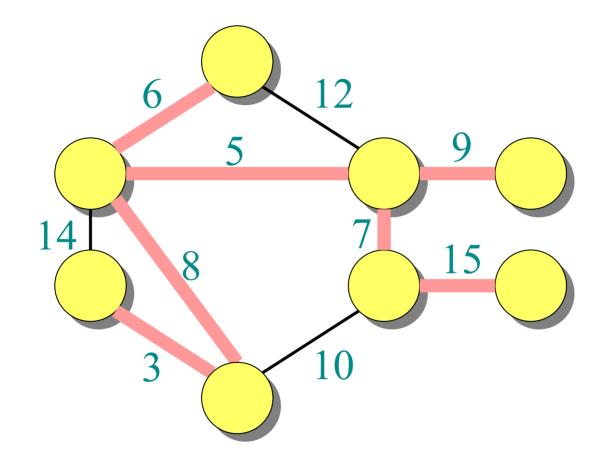


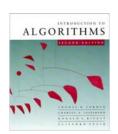
Example of MST





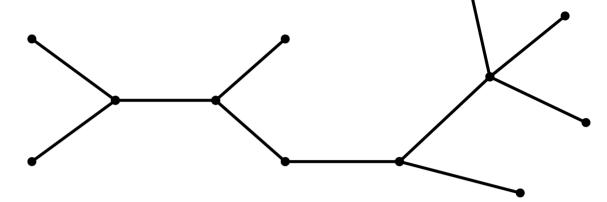
Example of MST





MST *T*:

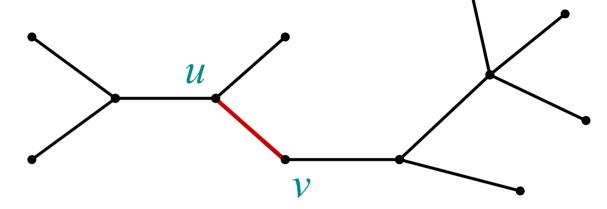
(Other edges of *G* are not shown.)



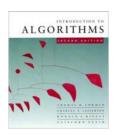


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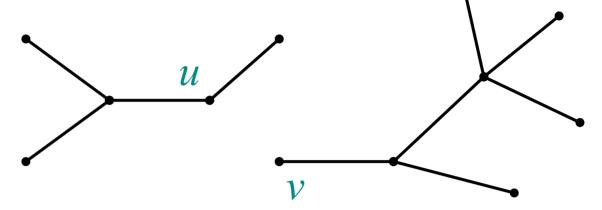


Remove any edge $(u, v) \in T$.

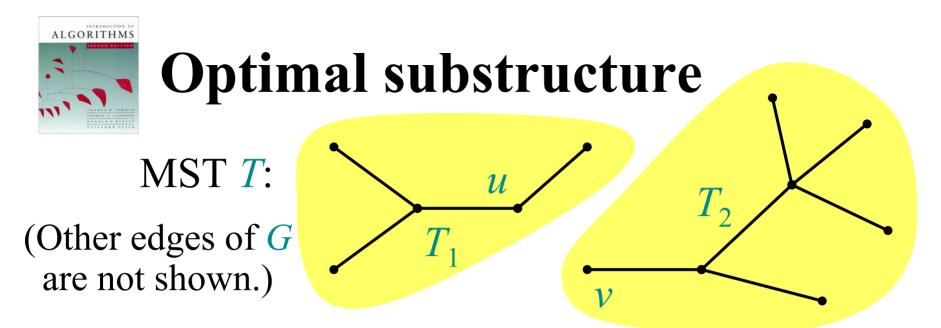


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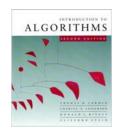
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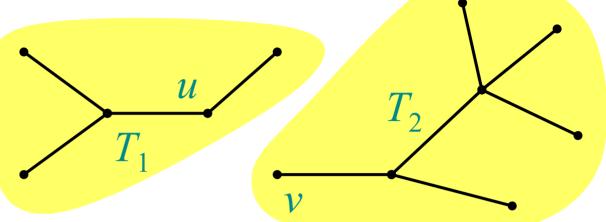


Remove any edge $(u, v) \in T$. Then, T is partitioned into two subtrees T_1 and T_2 .



MST T:

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



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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 :

$$V_1 = \text{vertices of } T_1,$$

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

Similarly for T_2 .



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.



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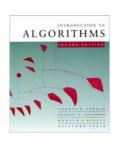
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Do we also have overlapping subproblems?

•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

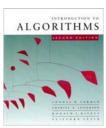
Greedy-choice property
A locally optimal choice
is globally optimal.

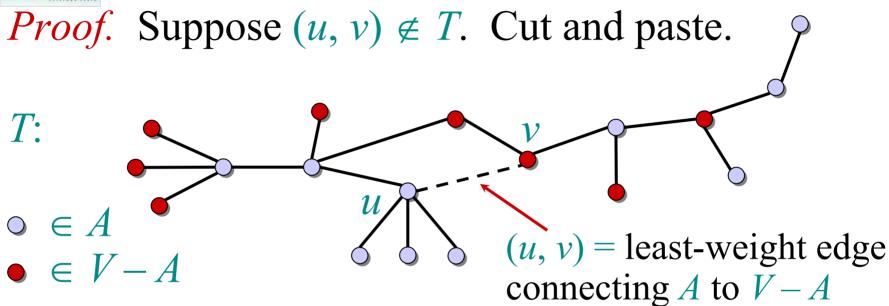


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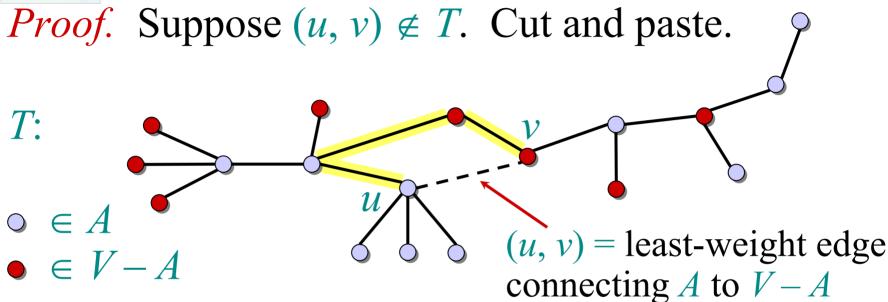
Greedy-choice property
A locally optimal choice
is globally optimal.

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, $(u, v) \in T$.



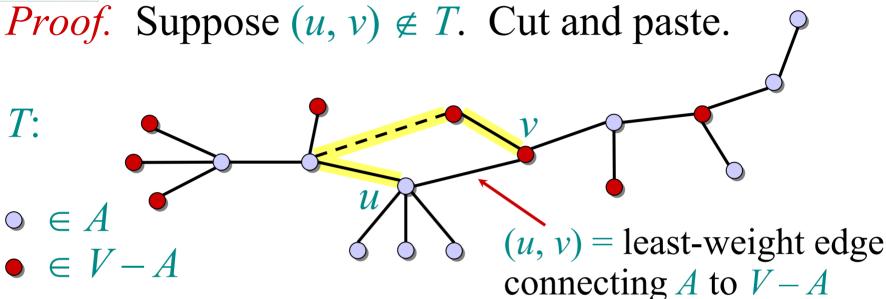




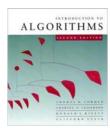


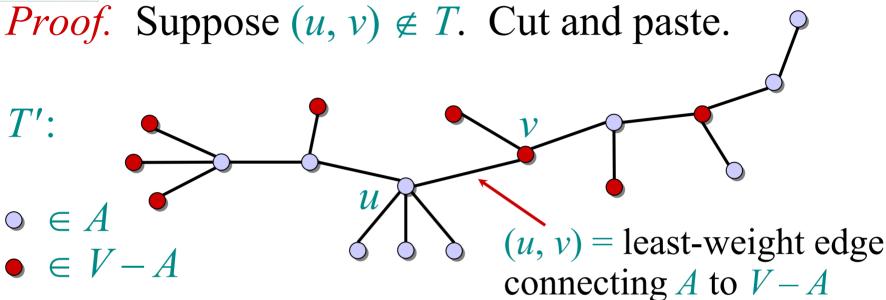
Consider the unique simple path from u to v in T.





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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.





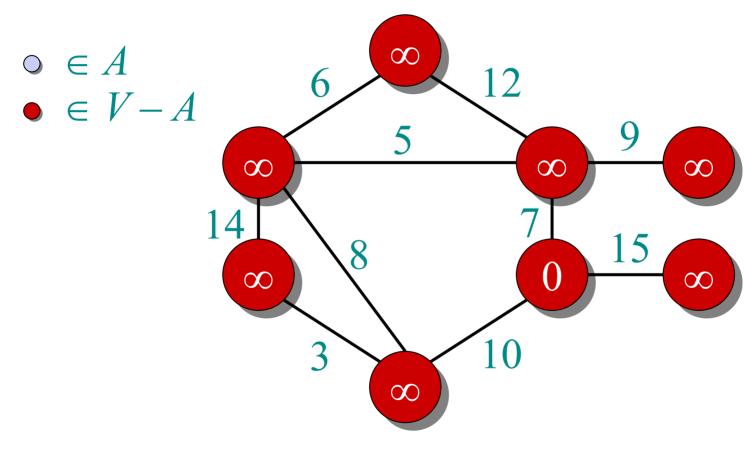
Prim's algorithm

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.

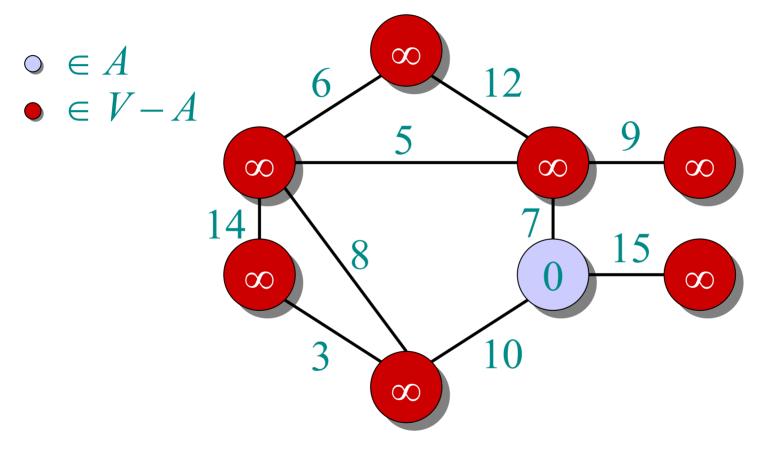
```
Q \leftarrow V
key[v] \leftarrow \infty for all v \in V
key[s] \leftarrow 0 for some arbitrary s \in V
while Q \neq \emptyset
do u \leftarrow \text{EXTRACT-MIN}(Q)
for each v \in Adj[u]
do if v \in Q and w(u, v) < key[v]
then key[v] \leftarrow w(u, v) \triangleright DECREASE-KEY
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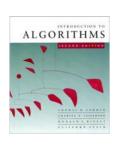
At the end, $\{(v, \pi[v])\}$ forms the MST.

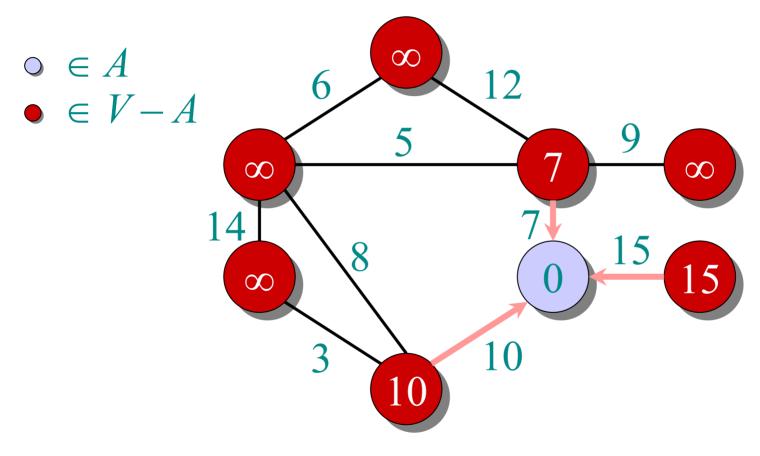


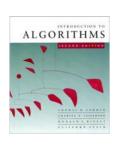


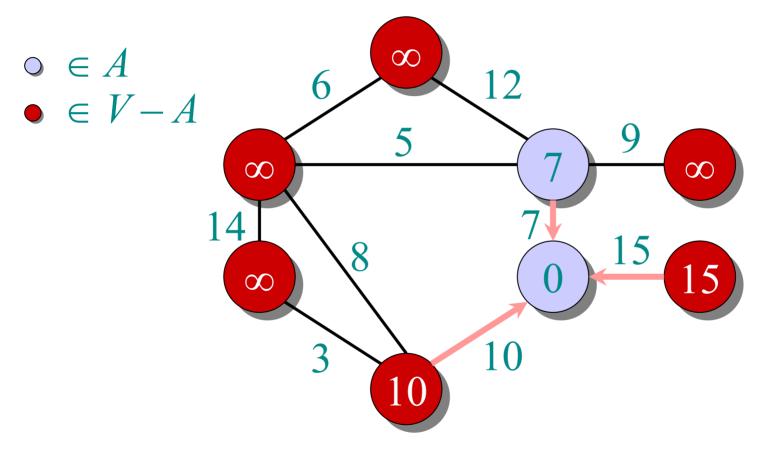


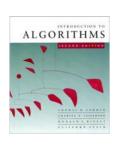


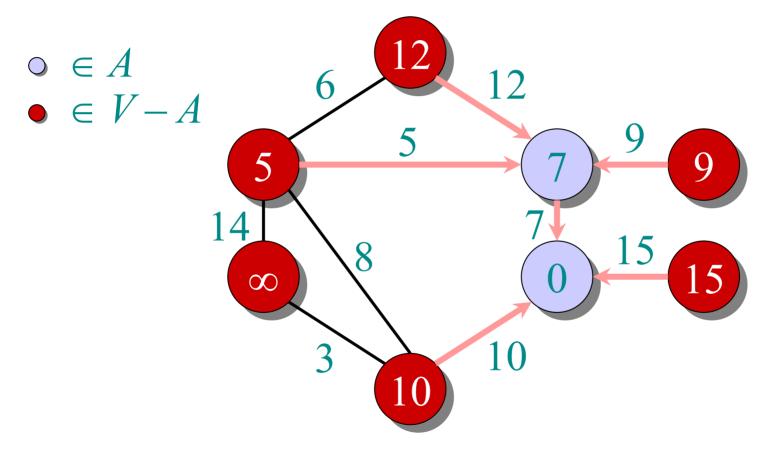




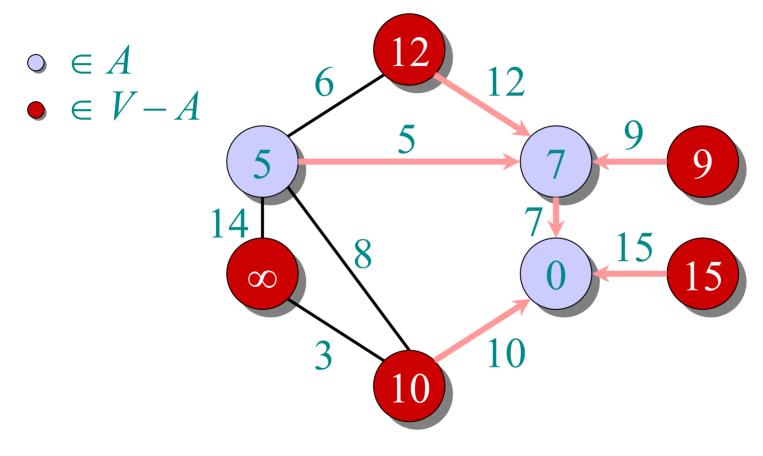


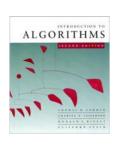


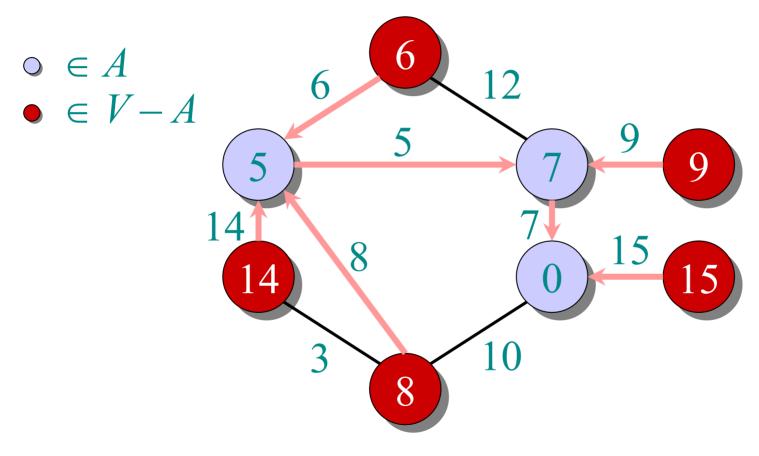




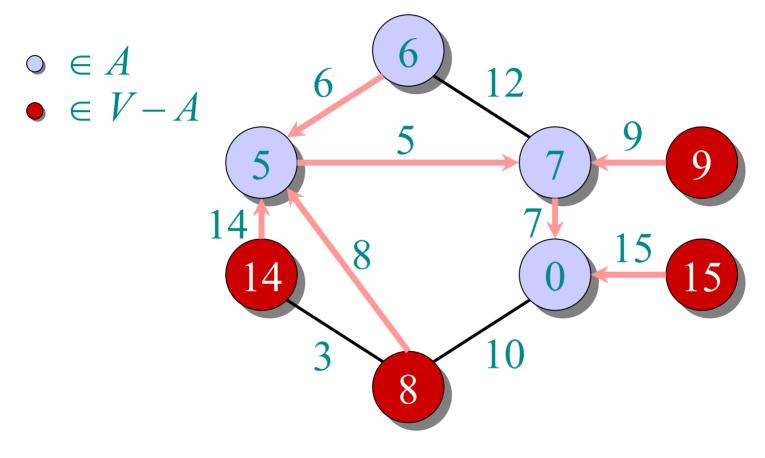


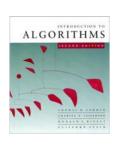


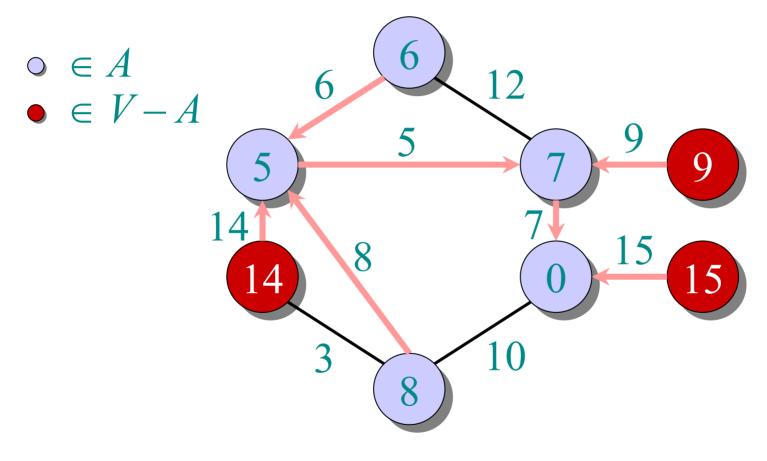


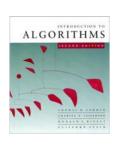


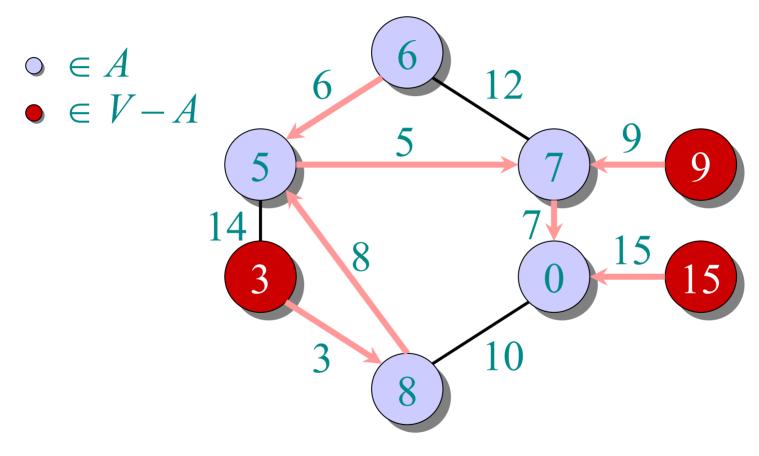






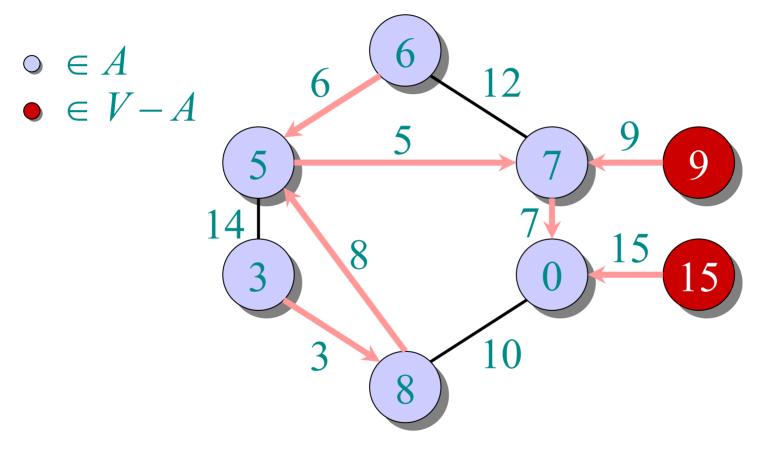


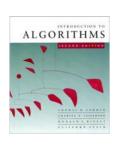




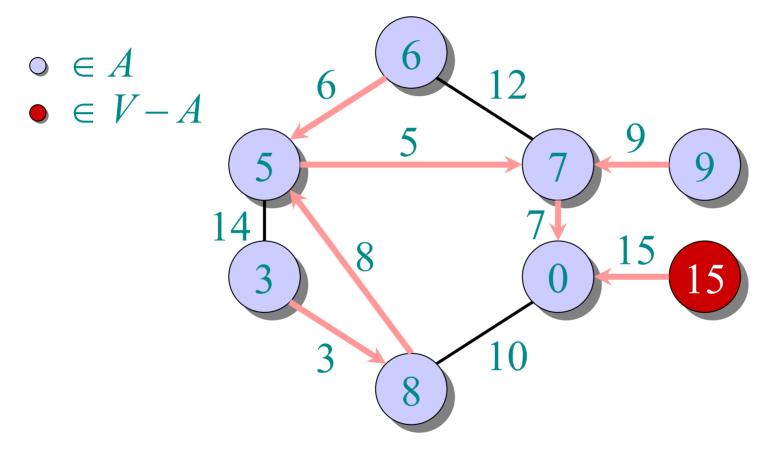


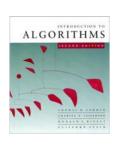
Example of Prim's algorithm



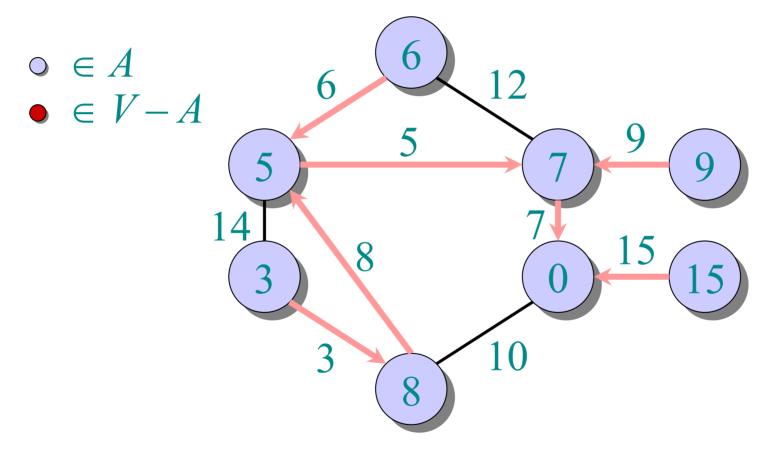


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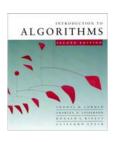


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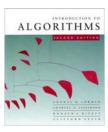




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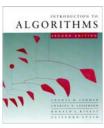
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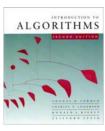


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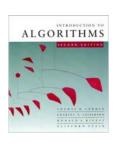
Handshaking Lemma $\Rightarrow \Theta(E)$ implicit Decrease-Key's.



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Handshaking Lemma $\Rightarrow \Theta(E)$ implicit Decrease-Key's.

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

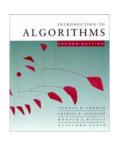


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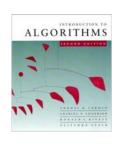
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Q $T_{\text{EXTRACT-MIN}}$ $T_{\text{DECREASE-Key}}$ Total



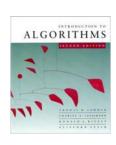
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Q $T_{
m EXTRACT-MIN}$ $T_{
m DECREASE-KEY}$ Total array O(V) O(1) $O(V^2)$



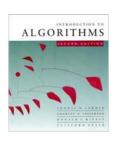
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Q	T _{EXTRACT-MIN}	T _{DECREASE-KEY}	Total
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array	O(V)	<i>O</i> (1)	$O(V^2)$
binary heap	$O(\lg V)$	$O(\lg V)$	$O(E \lg V)$
Fibonacci heap	i O(lg V) amortized	O(1) amortized	$O(E + V \lg V)$ worst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



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
- Running time = $O(E \lg V)$.

Best to date:

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