

Greedy Design Technique

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Greedy Design Technique

The Greedy Approach can be described in general terms as follows.

- The Greedy technique suggests that one can devise an algorithm which works in stages, considering one input at a time.
- At each stage, a decision is made regarding whether or not a particular input is an optimal solution.
- This is done by considering the inputs in an order determined by some selection procedure.
- The selection procedure itself is based on some optimization measure.

Greedy Design Technique

The Greedy Approach can be described in general terms as follows.

- It is clear why such algorithms are called “greedy”: *at every step, the procedure chooses the best morsel it can swallow, without worrying about the future. It never changes its mind: once a candidate is included in the solution, it is there for good; once a candidate is excluded from the solution, it is never reconsidered.*
- The resulting solution may or may not be optimal, depending on the problem being solved (in other words, the greedy method does not work for all problems.)

Greedy Design Technique

- For convenience, we formulate Greedy Approach as a procedure.

Procedure **Greedy** (A,n)

// A(1:n) contains n inputs //

solution $\leftarrow \emptyset$ // initializes the solution to empty //

for i $\leftarrow$ 1 to n do

 x $\leftarrow$ **Select** (A)

 If **Feasible** (solution, x) Then

 solution $\leftarrow$ **Union** (solution,x)

repeat

return(solution)

End Greedy

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*.

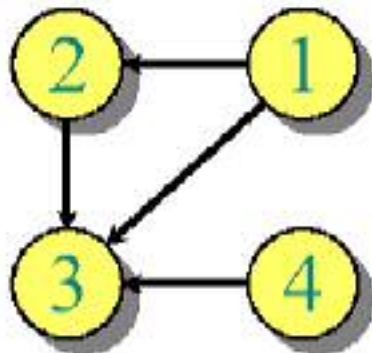
In an *undirected graph* $G = (V, E)$, the edge set E consists of *unordered* pairs of vertices.

In either case, we have $|E| = O(V^2)$. Moreover, if G is connected, then $|E| \geq |V| - 1$, which implies that $\lg |E| = \Theta(\lg V)$.

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

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

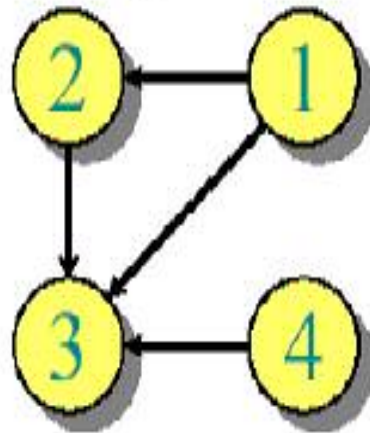


A	1	2	3	4
1	0	1	1	0
2	0	0	1	0
3	0	0	0	0
4	0	0	1	0

$\Theta(V^2)$ storage
 $\Rightarrow$ *dense*
representation.

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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, $|Adj[v]| = out-degree(v)$.

Greedy Design Technique

MST (Minimum Spanning Tree):

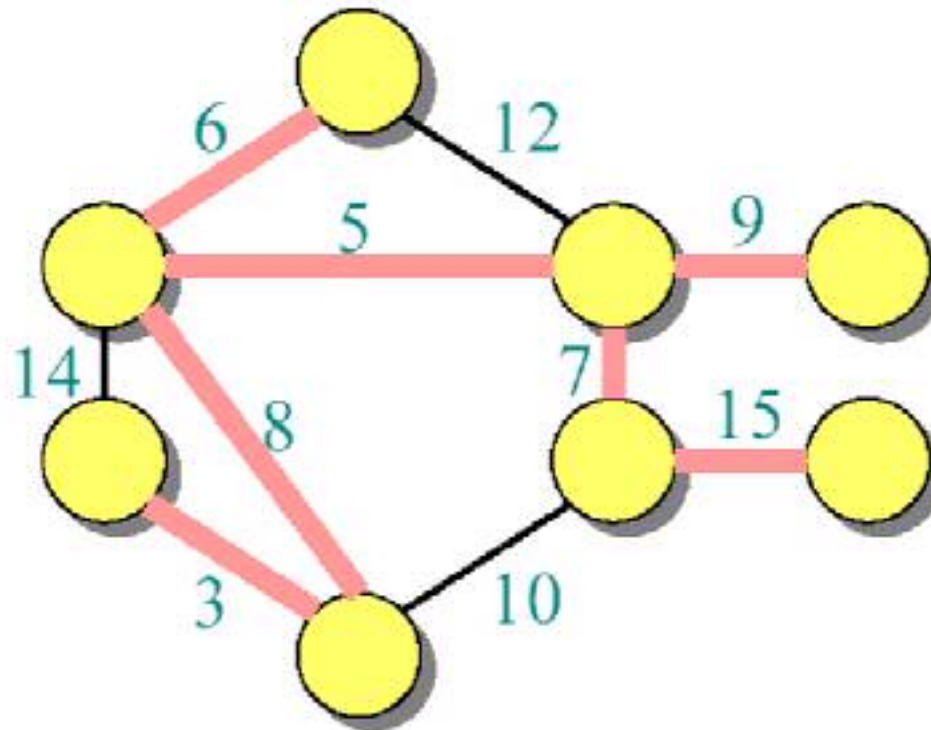
Problem Instance: a graph G in which each edge has a non-negative weight (or cost).

Feasible Solution: any spanning tree (a set of $(n-1)$ edges, and consequently all vertices, containing no cycles).

Objective Function: $c(T) = \sum_{e \in T} c(e)$, where T is a spanning tree of G and $c(e)$ is the cost of edge e .

Optimal Solution: the minimum cost spanning tree.

Greedy Design Technique



Geedy Design Technique

function kruskal ($G = \langle N, E \rangle$:graph; length: $E \rightarrow \mathbb{R}^+$): set of edges

{initialization}

Sort the edges, E , of G in ascending order of the costs

$n \leftarrow$ the number of nodes in N

$T \leftarrow \emptyset$ // initializes the solution to empty, will contain the edges of MST //

{greedy loop}

repeat

$e \leftarrow \{u, v\}$ // e be the next shortest edge of G in order of cost not yet considered//

$ucomp \leftarrow \text{find}(u)$ // which tells us in which connected node u is to be found//

$vcomp \leftarrow \text{find}(v)$ // which tells us in which connected node u is to be found//

// Check the feasibility, i.e., if $T \cup \{e\}$ does not contain a cycle //

if $ucomp \neq vcomp$ then

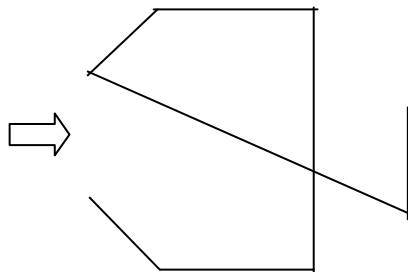
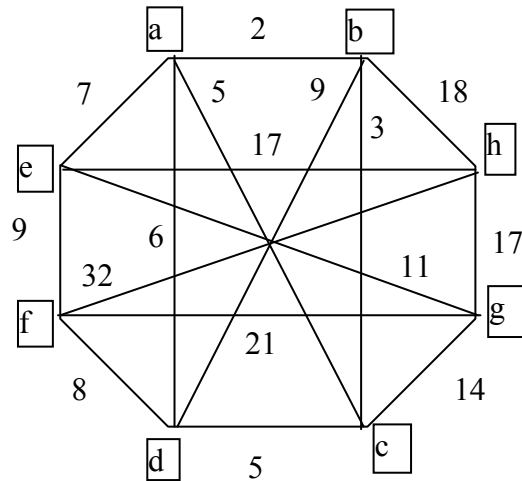
$\text{union}(ucomp, vcomp)$ //merges two connected components//

$T \leftarrow T \cup \{e\}$

until T contains $n-1$ edges

return T

Greedy Design Technique



Step	Edge considered	Cost of edge	Cycle Created	Connected Components
Initial	-	-	-	{a} {b} {c} {d} {e} {f} {g} {h}
1	{a,b}	2	none	{a, b} {c} {d} {e} {f} {g} {h}
2	{b,c}	3	none	{a, b, c} {d} {e} {f} {g} {h}
3	{c,a}	5	{a,b,c,a}	rejected
4	{c,d}	5	none	{a, b, c, d} {e} {f} {g} {h}
5	{d,a}	6	{a,b,c,d,a}	rejected
6	{a,e}	7	none	{a, b, c, d, e} {f} {g} {h}
7	{d,f}	8	none	{a, b, c, d, e, f} {g} {h}
8	{e,f}	9	{a,b,d,f,e,a}	rejected
9	{d,b}	9	{b,c,d,b}	rejected
10	{e,g}	11	none	{a, b, c, d, e, f, g} {h}
11	{c,g}	14	{e,a,b,c,g,e}	rejected
12	{g,h}	17	none	{a, b, c, d, e, f, g, h}
				$c(T) = 17+11+8+7+5+3+2 = 53$

Greedy Design Technique

We can evaluate the execution time of the algorithm as follows: On a graph with n nodes and E edges, the number of operations is in

- $\Theta(E \lg E)$ to sort the edges, which is equivalent to $\Theta(E \lg n)$ because $n-1 \leq E \leq n(n-1)/2$;
- $\Theta(n)$ to initialize the n disjoint sets
- There are at most $2E$ find operations and $(n-1)$ merge operations on a universe containing n elements.
- At worst $O(E)$ for the remaining operations
- We conclude that the total time for the algorithm is in $\Theta(E \lg E)$.

Greedy Design Technique

To prove that Kruskal's algorithm produces a MST, we must first enumerate some properties of spanning trees:

1. Any spanning tree in a graph G of n vertices has $n-1$ edges.
2. If T is a spanning tree in a graph G , and e is any edge in $G-T$, then $T+e$ contains a unique cycle C .
3. The removal of any edge e' of C from $T+e$ (as in 2 above) produces a spanning tree $T' = T + e - e'$.

Greedy Design Technique

Theorem: The spanning tree T produced by Kruskal's algorithm is a MST. Any other MST, T' , can be transformed to T by successively using the property (3).

Proof: Assume that $e_1, \dots, e_n$, the costs of the edges, are in increasing order. That is, $c(e_1) \leq \dots \leq c(e_n)$.

- Let also e_j be the first edge in T but not in T' . Then by property (2) above, $T' + e_j$ contains a unique cycle C .
- There must be some edge e_i of C that is not in T , for otherwise T would contain the cycle C , which is impossiblity.
- Then $T'' = T' + e_j - e_i$ is a spanning tree of G by property (3). The following cost relationship holds:
$$c(T'') = c(T') + c(e_j) - c(e_i)$$

Greedy Design Technique

The following cost relationship holds: $c(T'') = c(T') + c(e_j) - c(e_i)$

- $c(T'') \leq c(T')$ iff $j < i$, since the edges are sorted by cost in increasing order. Up to edge j , every edge in T is in T' .
- If $i < j$ and $e_i \notin T$, then adding e_i to T would have created a cycle C , all of whose edges precede e_j . However, if this were the case, C would be in T' , which is impossible (since T' is assumed to be a MST). Therefore, $c(T'') \leq c(T')$, but T' is a MST by our original assumption. Thus, $c(T'') = c(T')$, which can happen only if $c(e_j) = c(e_i)$.
- Now, T'' must be a MST with one more edge in common with T than with T' . We can repeat the above process starting with T'' and repeat this as often as necessary (at most $n-1$ times) to obtain T , which proves that T is a MST.

Prim's algorithm

IDEA: Maintain $V - A$ as a priority queue Q . Key each vertex in Q with the weight of the least-weight 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 $v \in \text{Adj}[u]$

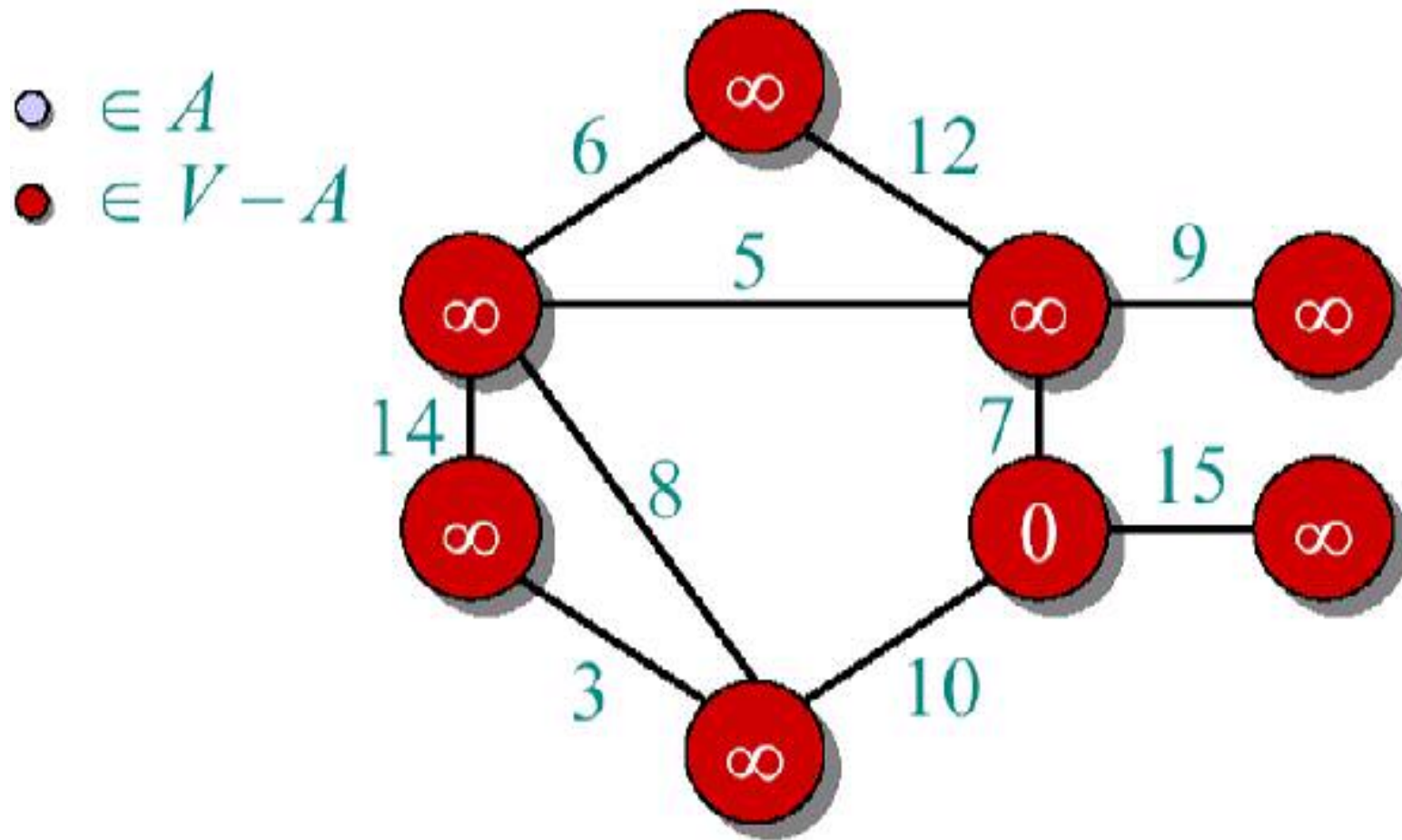
do if $v \in Q$ and $w(u, v) < key[v]$

then $key[v] \leftarrow w(u, v)$ $\triangleright$ DECREASE-KEY

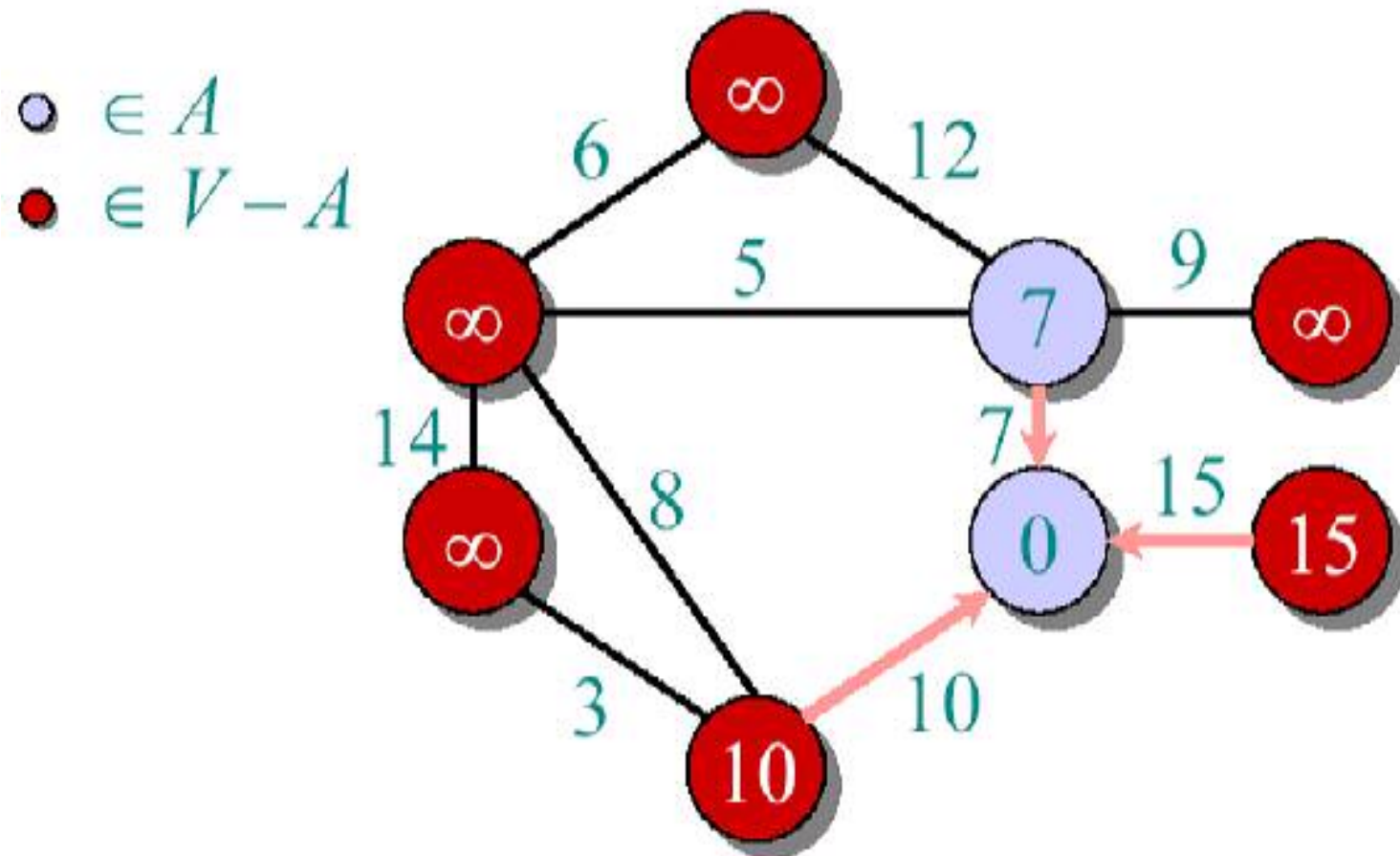
$\pi[v] \leftarrow u$

At the end, $\{(v, \pi[v])\}$ forms the MST.

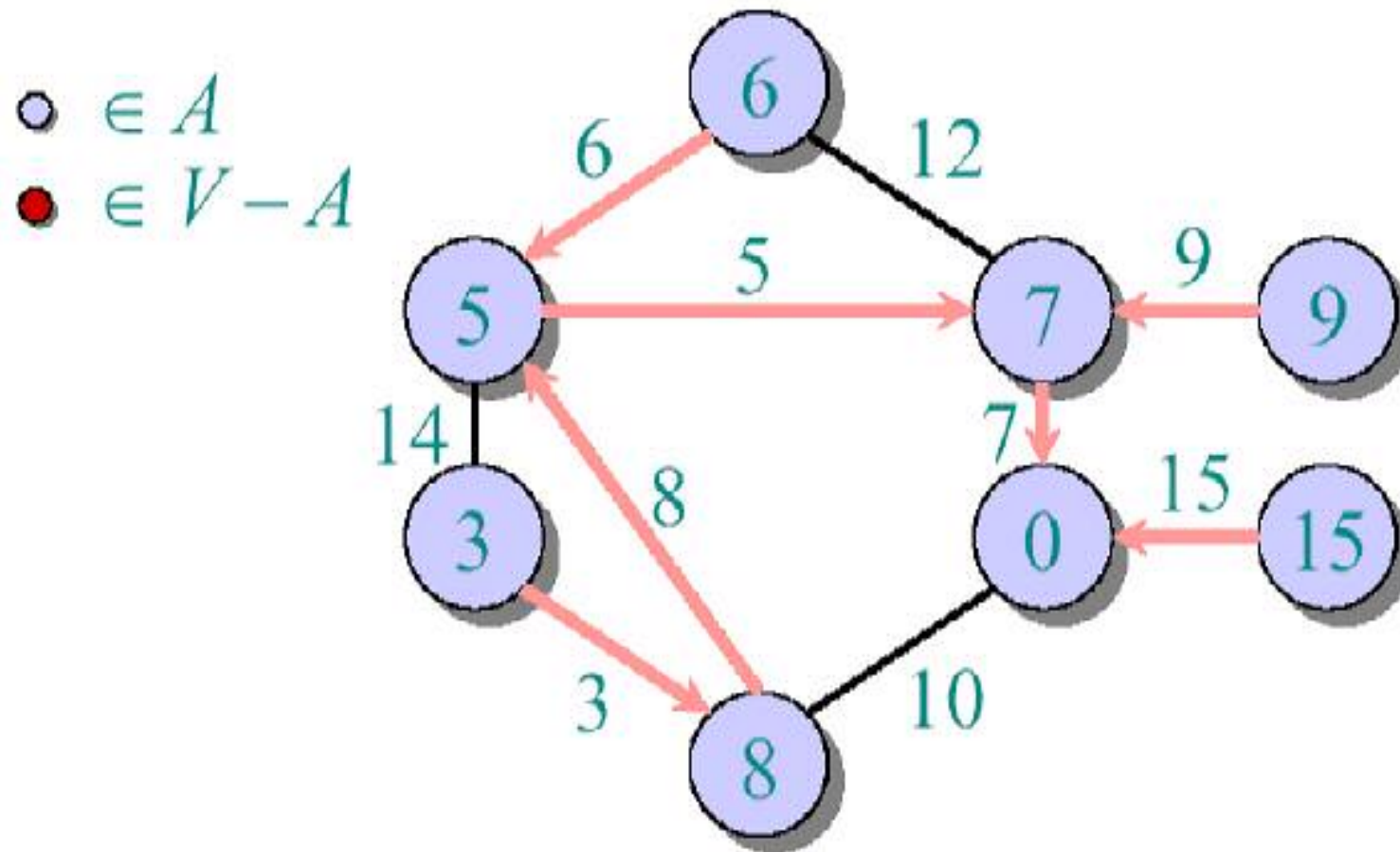
Example of Prim's algorithm



Example of Prim's algorithm



Example of Prim's algorithm



Analysis of Prim (continued)

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

Q	$T_{\text{EXTRACT-MIN}}$	$T_{\text{DECREASE-KEY}}$	Total
array	$O(V)$	$O(1)$	$O(V^2)$
binary heap	$O(\lg V)$	$O(\lg V)$	$O(E \lg V)$
Fibonacci heap	$O(\lg V)$ amortized	$O(1)$ amortized	$O(E + V \lg V)$ worst case

Geedy Design Technique

RKP(Rational Knapsack Problem):

Problem Instance: positive integers $w_1, \dots, w_n, p_1, \dots, p_n, M$ (we have n objects, where object i has weight w_i and profit p_i , and M is the capacity of the knapsack.)

Feasible Solution: a vector $(x_1, \dots, x_n)$, where $0 \leq x_i \leq 1$ and $\sum_{0 \leq i \leq n} w_i x_i \leq M$. In other words, the knapsack capacity cannot be exceeded. Note that we allow a fraction of an object to be placed into the knapsack.

Objective Function: $P = \sum_{0 \leq i \leq n} p_i x_i$, where P is the profit associated with $(x_1, \dots, x_n)$

Optimal Solution: the maximum profit feasible solution.

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Object Order	Profit
1, 2, 3	30 (highest profit 1 st)
1, 3, 2	30
3, 2, 1	34 (lowest weight 1 st)
3, 1, 2	29
2, 1, 3	35 (highest profit density 1 st)
2, 3, 1	34

Item	Profit	Weight	Density
1	30	10	3
2	20	5	4
3	2	1	2

Geedy Design Technique

```
function knapsack (w[1..n],p[1..n]): array [1..n]
```

{initialization}

```
for i = 1 to n do x[i] ← 0
```

$$\text{weight} \leftarrow 0$$

{greedy loop}

while weight < M do

i $\leftarrow$ the best remaining object (the objects are sorted in terms of the profit density)

if $\text{weight} + w[i] \geq M$ then $x[i] \leftarrow 1$

```
weight ← weight + w[i]
```

```
else x[i] ← (M – weight) / w[i]
```

$$\text{weight} \leftarrow M$$

```
return x
```

Greedy Design Technique

Theorem: If objects are selected in order of decreasing p_i/w_i , then algorithm knapsack finds an optimal solution.

Proof: Suppose that $p_1/w_1 \geq p_2/w_2 \geq \dots \geq p_n/w_n$. Let $X = (x_1 \dots x_n)$ be solution found by the greedy algorithm.

- If all the x_i are equal to 1, this solution is clearly optimal.
- Otherwise, let j be the smallest index such that $x_j \neq 1$. Looking at the way the algorithm works, it is clear that $x_i = 1$ for $1 \leq i < j$, $x_i = 0$ for $j < i \leq n$, and that $0 \leq x_j < 1$ and $\sum_{1 \leq i \leq n} w_i x_i = M$ and the value of the solution X be $P(X) = \sum_{1 \leq i \leq n} p_i x_i$.
- Now let $Y = (y_1 \dots y_n)$ be an optimal solution. Since Y is feasible, $\sum_{0 \leq i \leq n} w_i y_i = M$ and the value of the solution Y be $P(Y) = \sum_{1 \leq i \leq n} p_i y_i$.
- Let k be the least index such that $y_k \neq x_k$. Clearly, such a k must exist. It also follows that $y_k < x_k$. To see this, consider the three possibilities: $k < j$, $k=j$, or $k > j$.

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1. When $k < j$, $x_k = 1$. But $y_k \neq x_k$ and so $y_k < x_k$.
2. When $k = j$, then since $\sum_{1 \leq i \leq n} w_i y_i = M$ and $y_i = x_i$ for $1 \leq i < j$, it follows that either $y_k < x_k$ or $\sum_{1 \leq i \leq n} w_i y_i > M$.
3. When $k > j$, then $\sum_{1 \leq i \leq n} w_i y_i > M$ which is not possible.

- Now suppose we increase y_k to x_k and decrease as many of $(y_{k+1}, \dots, y_n)$ as is necessary so that the total capacity used is still M . This results in a new solution $Z = (z_1, \dots, z_n)$ with $z_i = x_i$, $1 \leq i \leq k$ and $\sum_{k < i \leq n} w_i (y_i - z_i) = w_k (z_k - y_k)$. Then for Z we have
- $$\begin{aligned} \sum_{1 \leq i \leq n} p_i z_i &= \sum_{1 \leq i \leq n} p_i y_i + (z_k - y_k) w_k p_k / w_k - \sum_{k < i \leq n} (y_i - z_i) w_i (p_j / w_j) \\ &\geq \sum_{1 \leq i \leq n} p_i y_i + [(z_k - y_k) w_k - \sum_{k < i \leq n} (y_i - z_i) w_i] p_k / w_k \\ &= \sum_{1 \leq i \leq n} p_i y_i \end{aligned}$$

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- If $\sum_{1 \leq i \leq n} p_i z_i > \sum_{1 \leq i \leq n} p_i y_i$ then Y could not have been an optimal solution. If these sums are equal then either $Z = X$ and X is optimal or $Z \neq X$. In this latter case, repeated use of the above argument will either show that Y is not optimal or will transform Y into X , showing that X too is optimal.

Greedy Design Technique

Example (The Task Sequencing Problem):

Problem Instance: a set of T of n tasks to be performed. For each task $t \in T$, there is a length $l(t)$, a weight (or penalty) $w(t)$ and a deadline $d(t)$, all entries are positive integers.

Feasible Solution: any schedule of a subset T_1 of T , in which at most one task is executed at a time, and such that each scheduled task finishes before its deadline. Scheduling function, $s(t)$ satisfies the following properties:

if $s(t) < s(t')$, then $s(t) + l(t) \leq s(t')$, $\forall t, t' \in T_1$

(each task terminates before any other one begins)

$s(t) + l(t) \leq d(t) \quad \forall t \in T_1$

(each task terminates before its deadline)

Objective Function: $W = \sum_{t \in T - T_1} w(t)$ = the sum of weights of unscheduled (tardy) tasks, i.e., the tardy task weight ($T - T_1$ are the ones not able to schedule).

Optimal Solution: the schedule with the minimum tardy task weight.

Geedy Design Technique

Example (The Task Sequencing Problem):

A *pseudo-code* description of the algorithm is as follows:

Sort the tasks so that $w_1 \geq w_2 \geq \dots \geq w_n$

$T1 \leftarrow \{\}$

For $i \leftarrow 1$ to n do

 If $T1 \cup \{t_i\}$ is feasible then

$T1 \leftarrow T1 \cup \{t_i\}$

$W = \sum_{t \in T-T1} w(t)$

Geedy Design Technique

Example: $T = \{t_1, t_2, t_3, t_4, t_5, t_6\}$

$w_1 = 7, w_2 = 5, w_3 = 4, w_4 = 3, w_5 = 2, w_6 = 1,$

$d_1 = 3, d_2 = 2, d_3 = 1, d_4 = 2, d_5 = 4, d_6 = 3,$

All lengths = 1.

Tasks considered (in increasing order of weights)	The schedule (based on the decreasing order of deadlines)
$T_1 \leftarrow \{\}$	$\{t_1\}$
$T_1 \leftarrow \{t_1\}$	$\{t_2, t_1\}$
$T_1 \leftarrow \{t_1, t_2\}$	$\{t_3, t_2, t_1\}$
$T_1 \leftarrow \{t_1, t_2, t_3\}$	$\{t_3, t_2, t_1\}$
$T_1 \leftarrow \{t_1, t_2, t_3, t_4\}$	not feasible
$T_1 \leftarrow \{t_1, t_2, t_3, t_5\}$	$\{t_3, t_2, t_1, t_5\}$
$T_1 \leftarrow \{t_1, t_2, t_3, t_5, t_6\}$	not feasible

- Since t_4 and t_3 have the same deadlines, 2, we could not add task t_4 to the list, $\{t_3, t_2, t_1, t_4\}$
- Is not feasible. Similarly, t_6 and t_1 have the same deadlines, 3.

Therefore, $W = w_4 + w_6 = 4$.

Geedy Design Technique

Theorem: If all tasks have length = 1, then the greedy algorithm determines the minimum tardy task weight.

Proof: We give only an outline of the proof. Let $T(G)$ denote the non-tardy tasks in the schedule found by the greedy algorithm and $T(O)$ be the non-tardy tasks in an optimal solution. Also, let $s(G)$ and $s(O)$ denote feasible schedules for the tasks in $T(G)$ and $T(O)$, respectively. We also assume that $s(G)$ schedules the tasks in $T(G)$ in increasing order by deadline, so $s(G)$ is feasible. The proof proceeds along the same lines as all previous proofs for greedy algorithms. That is, $s(O)$ is transformed into another optimal schedule, $s(O')$, which has one more task in common with $s(G)$ than does $s(O)$. This process is repeated as often as necessary and eventually it is shown that $s(G) = s(O)$.

Geedy Design Technique

Example (Multiprocessor Scheduling):

Problem Instance: a set of T of n tasks. For each task $t \in T$, there is a length $l(t)$, a positive integer. Also given a positive integer m , the number of available processors.

Feasible Solution: a schedule for all the tasks, such that each processor executes only one task at a time. All m processors are identical. Also, each task must be scheduled on only one processor without interruption.

Objective Function: the time when the last task finishes executing (this is the finishing time, denoted by FT)

Optimal Solution: the feasible schedule with the minimum finishing time.

- This problem is an NP-Complete problem, so we do not expect to find a polynomial time algorithm to solve it. A greedy approach does not do too badly, however. It can be shown that it always produces a schedule that is at most $1/3$ longer than optimal.

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Sort tasks so that $l_1 \geq l_2 \geq \dots \geq l_n$

For $i = 1$ to m do

$T(i) = 0$; // $T(i)$ keeps track of when processor i becomes free//

For $j = 1$ to n do

 Begin

$Mini = 1$;

 For $i = 2$ to m do

 If $T(i) < T(Mini)$ then

$Mini = i$; // this finds the next free processor//

 Assign t_j to processor $Mini$ at time $T(Mini)$

$T(Mini) = T(Mini) + l_j$;

 End

$FT = \max \{T(1), T(2), \dots, T(m)\}$

--

The complexity of this algorithm is $\Theta(n.m)$.

Geedy Design Technique

Example: Let us assume 7 jobs to be scheduled and their lengths are 5,5,4,4,3,3,3 and There are 3 processors available.

The greedy schedule is as follows:

Processor 1	5	3	3
-------------	---	---	---

Processor 2	5	3
-------------	---	---

Processor 3	4	4
-------------	---	---

FT = 11

The relative error is $2/9$. It can be shown that the maximum relative error is $1/3 - 1/(3m)$. In the case of $m = 3$, this is $1/3 - 1/9 = 2/9$.

5	4	
5	4	
3	3	3

Optimum Soln: FT = 9

Geedy Design Technique

Example (Compressing Data): Hoffman Coding

Problem Instance: a code, C , consists of a set of n characters. For each character $c \in C$, there is a frequency $f(c)$, a positive integer. Also there is a priority queue Q , keyed on f , is used to identify the two least-frequent objects to merge together.

Feasible Solution: a tree, T , for n characters, each character has a codeword representing the frequency of a character, $c \in C$, is the sum of the frequencies of all characters in the code.

Objective Function: the total frequencies = $f(T) = \sum_{f \in T} f(c_i)$, where $1 \leq i \leq n$, T is a tree of C and $f(c)$ is the frequency of c .

Optimal Solution: the minimum cost tree representing the Hoffman code.

Geedy Design Technique

Hoffman invented a greedy algorithm that constructs an optimal prefix code called a Huffman code. The algorithm builds the tree T corresponding to the optimal code in a bottom up manner. It begins with a set of $|C|$ leaves and performs a sequence of $|C| + 1$ “merging” operations to create the final tree.

HUFFMAN (C)

$n \leftarrow |C|$

$Q \leftarrow C$

For $i \leftarrow 1$ to $n-1$

 do $z \leftarrow \text{Allocate-Node}()$

$x \leftarrow \text{left}[z] \leftarrow \text{Extract-min}(Q)$

$y \leftarrow \text{right}[z] \leftarrow \text{Extract-min}(Q)$

$f[z] \leftarrow f[x] + f[y]$

 Insert (Q, z)

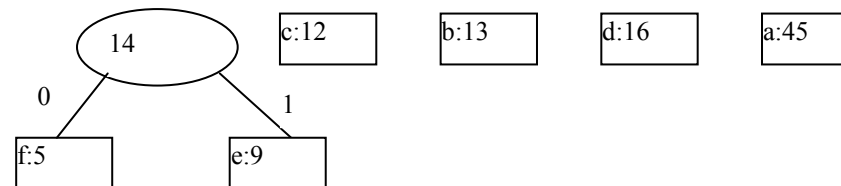
Return Extract-Min (Q)

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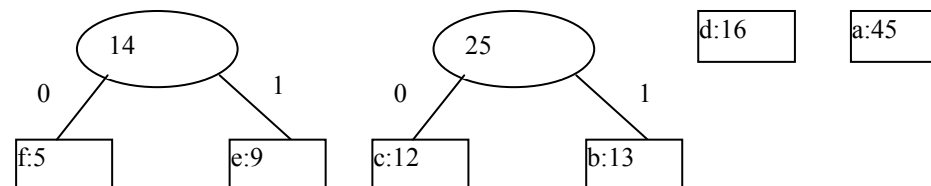
1. step:



2. step:

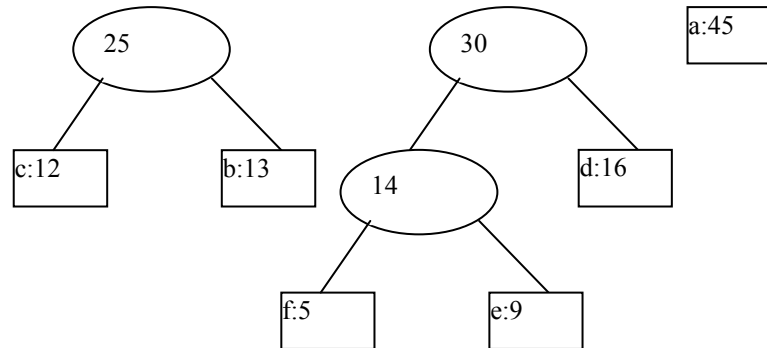


3. step:

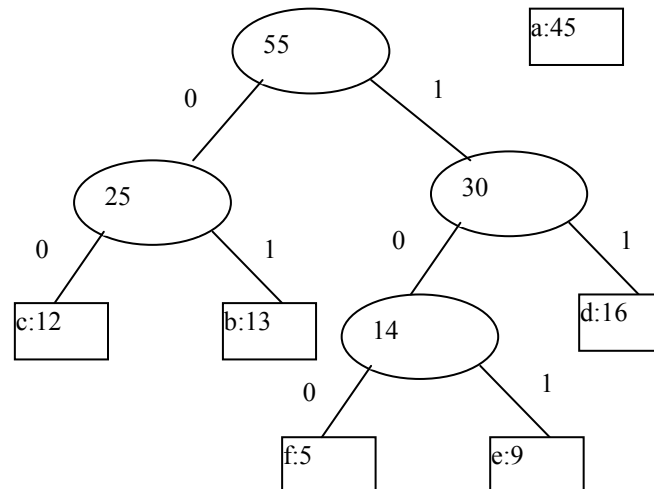


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4. step:

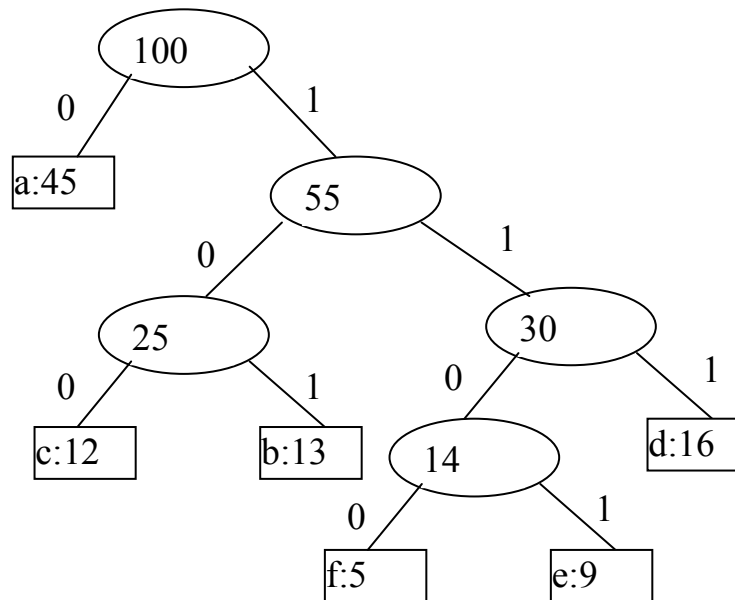


5.step:



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6.step:



	a	b	c	d	e	f
Frequency (in thousands)	45	13	12	16	9	5
Variable-length codeword	0	101	100	111	1101	1100

This code requires 224,000 bits = $((45*1 + 13*3 + 12*3 + 16*3 + 9*4 + 5*4) * 1000)$, which is an optimal character code for this file.

Geedy Design Technique

Complexity analysis:

- The analysis of the running time of Huffman's algorithm assumes that Q is implemented as a binary heap.
- For a set C of n characters, the initialization of Q can be performed in $O(n)$ time using *Build-heap* procedure.
- The for loop is executed exactly $n-1$ times, and since each heap operation requires time $O(\lg n)$, the loop contributes $O(n \lg n)$ to the running time.
- Therefore, the total running time of Huffman's algorithm on a set of n characters is $O(n \lg n)$.

CONCLUSIONS

Greedy Design technique does not guarantee the best solutions for all the problems that are applicable.

Therefore a proof must come with a solution.

- For some problems it finds the optimum soln.
- For some problems it is applicable to some specific instances of the problem.
- For some problems it finds a good solution, as an approximation algorithm.
- When it is applicable usually the computational complexity of the solution is quite good.