

# Unit-III

UNIT III : Greedy method: General method, applications-Job sequencing with dead lines, 0/1 knapsack problem, Minimum cost spanning trees, Single source shortest path problem.

Applications: Allocation of funds/resources based on the priority in the computer systems.

# Greedy Method

- Greedy algorithm obtains an **optimal** solution by making a **sequence** of decisions.
- Decisions are made **one by one** in some order.
- Each decision is made using a **greedy-choice property** or greedy criterion.
- A decision, once made, is (usually) **not changed** later.

- It gives an optimal solution when applied to problems with the **greedy-choice** property.
- A **feasible solution** is a solution that satisfies the constraints.
- An **optimal solution** is a feasible solution that optimizes the **objective** function.

## Greedy method control abstraction/ general method

**Algorithm** Greedy(a,n)

// a[1:n] contains the n inputs

{

    solution= //Initialize solution

**for** i=1 to n **do**

    {

        x:=Select(a);

**if** Feasible(solution,x) **then**

            solution=Union(solution,x)

    }

**return** solution;

}

# Example: Largest k-out-of-n Sum

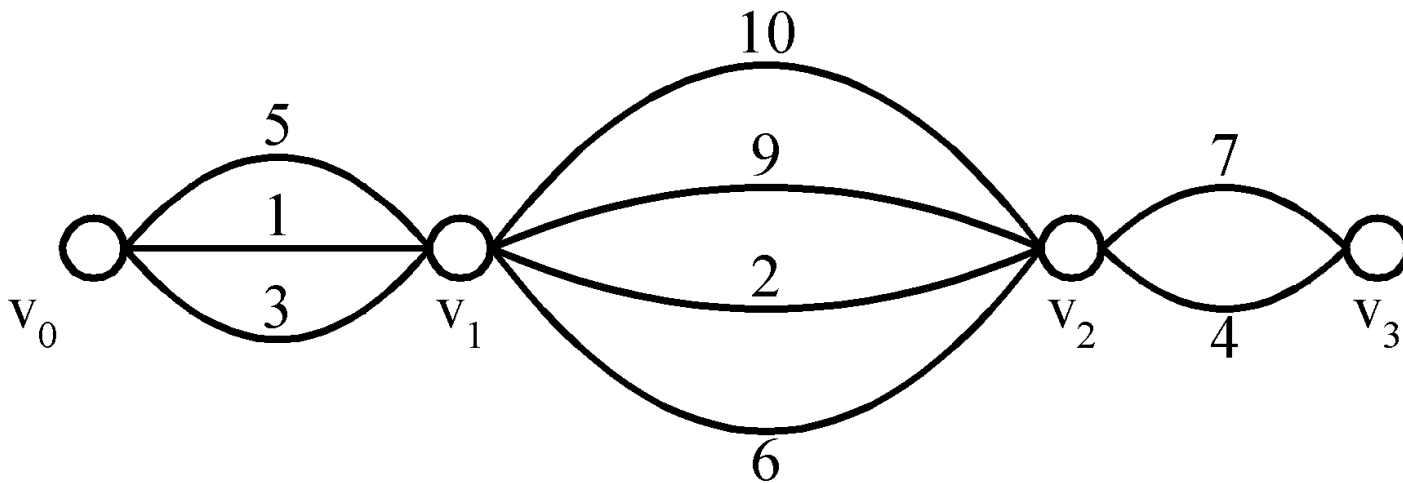
- Problem
  - Pick  $k$  numbers out of  $n$  numbers such that the **sum** of these  $k$  numbers is the **largest**.
- Exhaustive solution
  - There are  $C_k^n$  choices.
  - Choose the one with subset sum being the largest
- Greedy Solution *Is the greedy solution **always optimal**?*
  - FOR  $i = 1$  to  $k$ 
    - pick out the **largest** number and
    - delete** this number from the
    - input.
  - ENDFOR



# Example:

## Shortest Path on a Special Graph

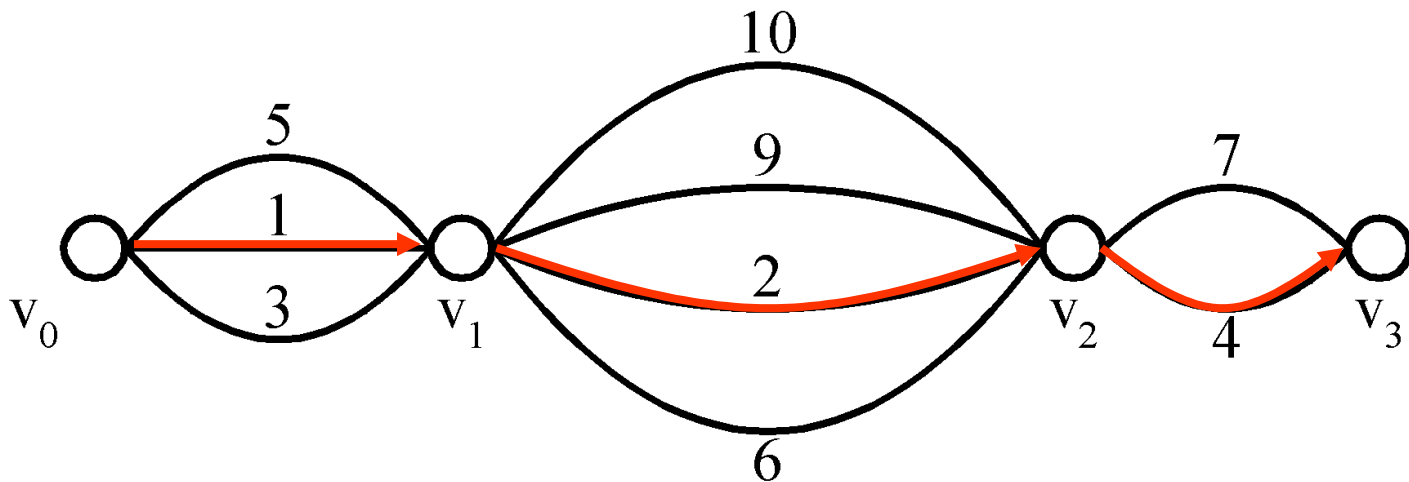
- Problem
  - Find a **shortest** path from  $v_0$  to  $v_3$
- Greedy Solution



# Example:

## Shortest Paths on a Special Graph

- Problem
  - Find a **shortest** path from  $v_0$  to  $v_3$
- Greedy Solution *Is the solution **optimal**?*

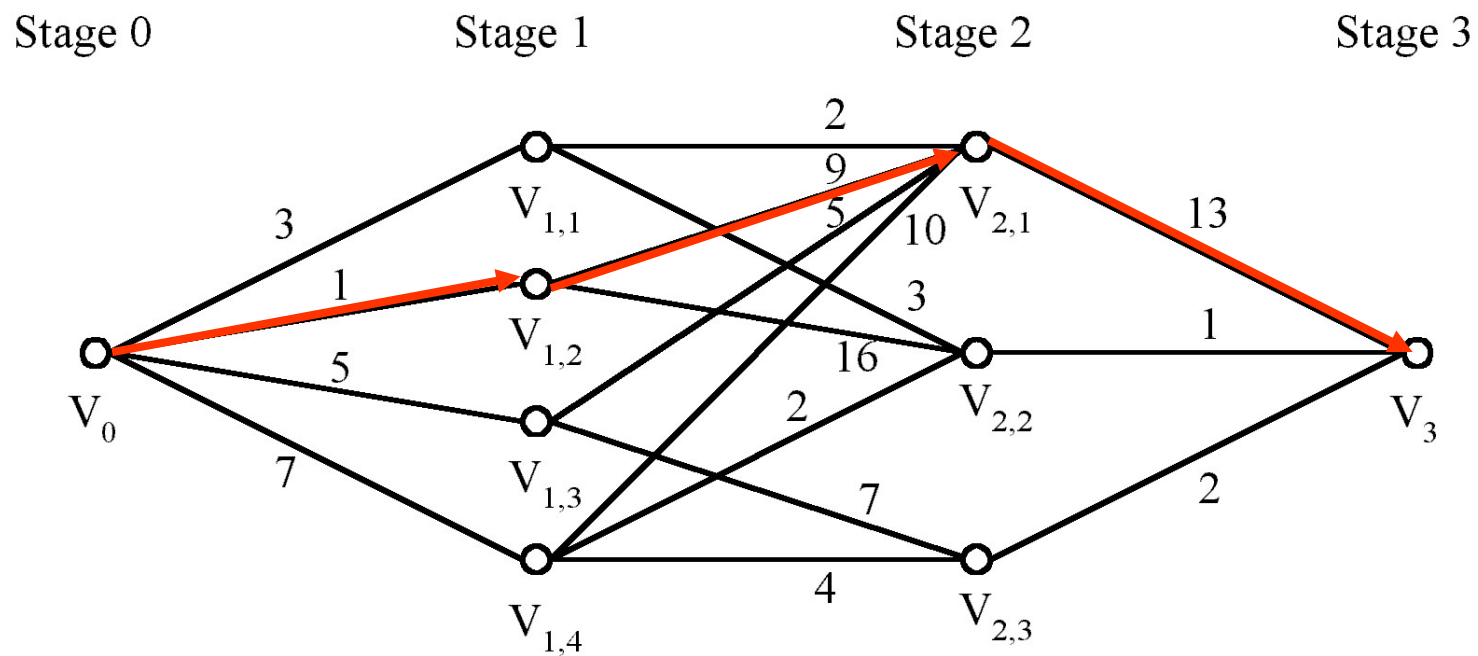


# Example:

## Shortest Paths on a Multi-stage Graph

*Is the greedy solution **optimal**?*

- Problem
  - Find a **shortest** path from  $v_0$  to  $v_3$



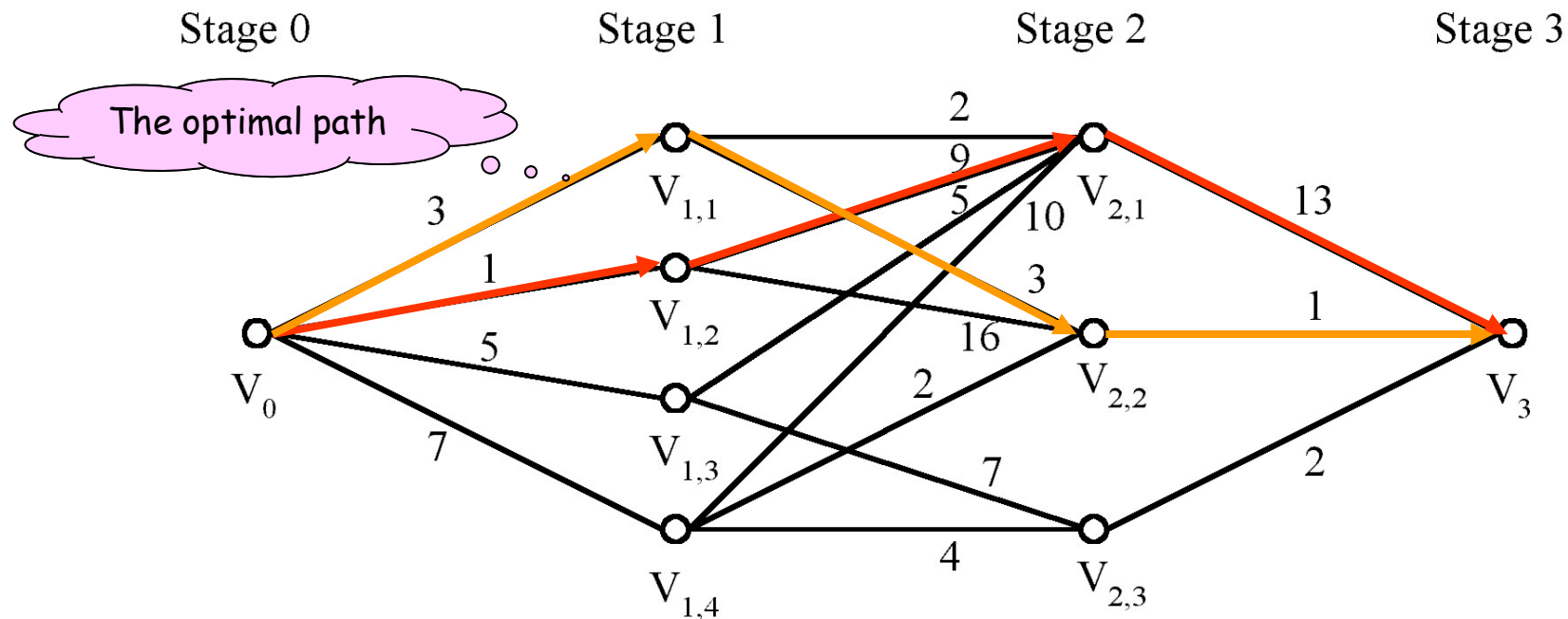


# Example:

## Shortest Paths on a Multi-stage Graph

*Is the greedy solution **optimal**? **X***

- Problem
  - Find a **shortest** path from  $v_0$  to  $v_3$



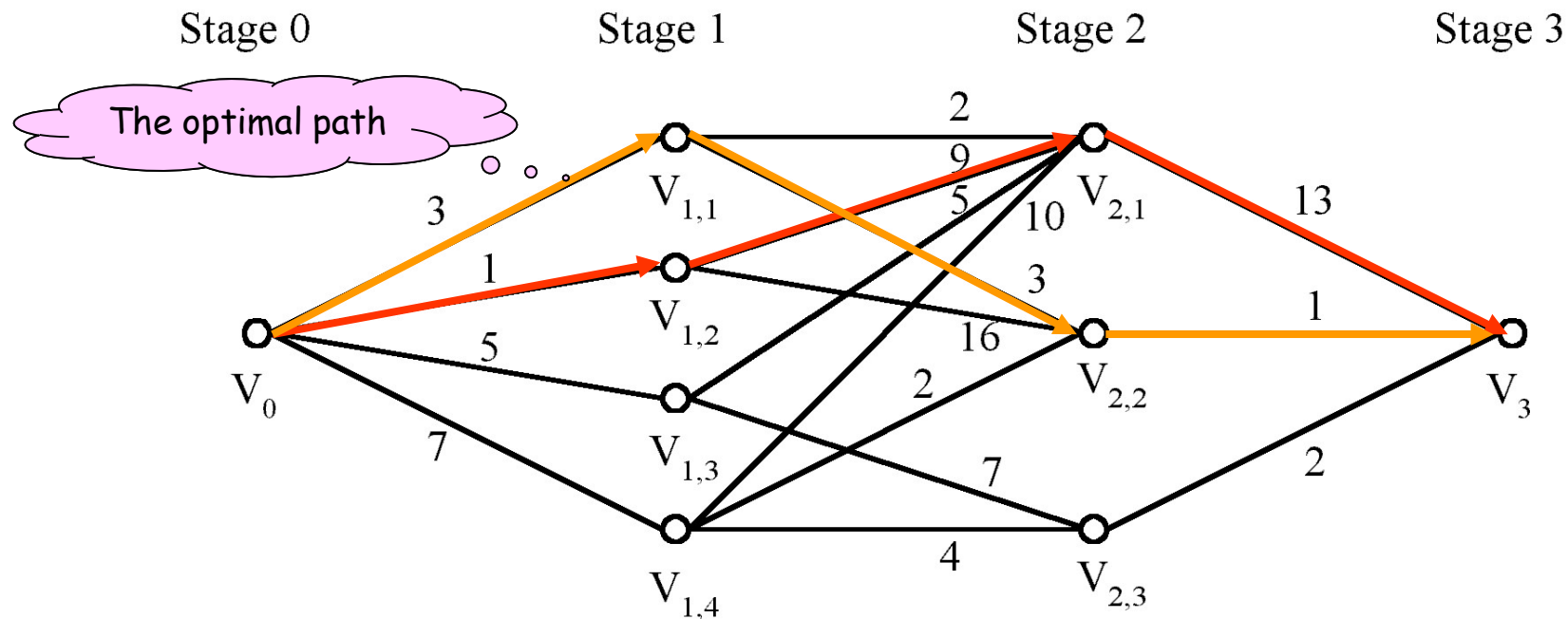
# Example:

## Shortest Paths on a Multi-stage Graph

*Is the greedy solution optimal?*

*What algorithm can be used to find the optimum?*

Find a **shortest** path from  $v_0$  to  $v_3$



# The Fractional Knapsack Problem

- Given: A set  $S$  of  $n$  items, with each item  $i$  having
  - $p_i$  - a positive profit
  - $w_i$  - a positive weight
- Goal: Choose items, allowing fractional amounts( $x_i$ ), to maximize total profit but with weight at most  $m$ .

$$\text{maximize } \sum_{1 \leq i \leq n} p_i x_i$$

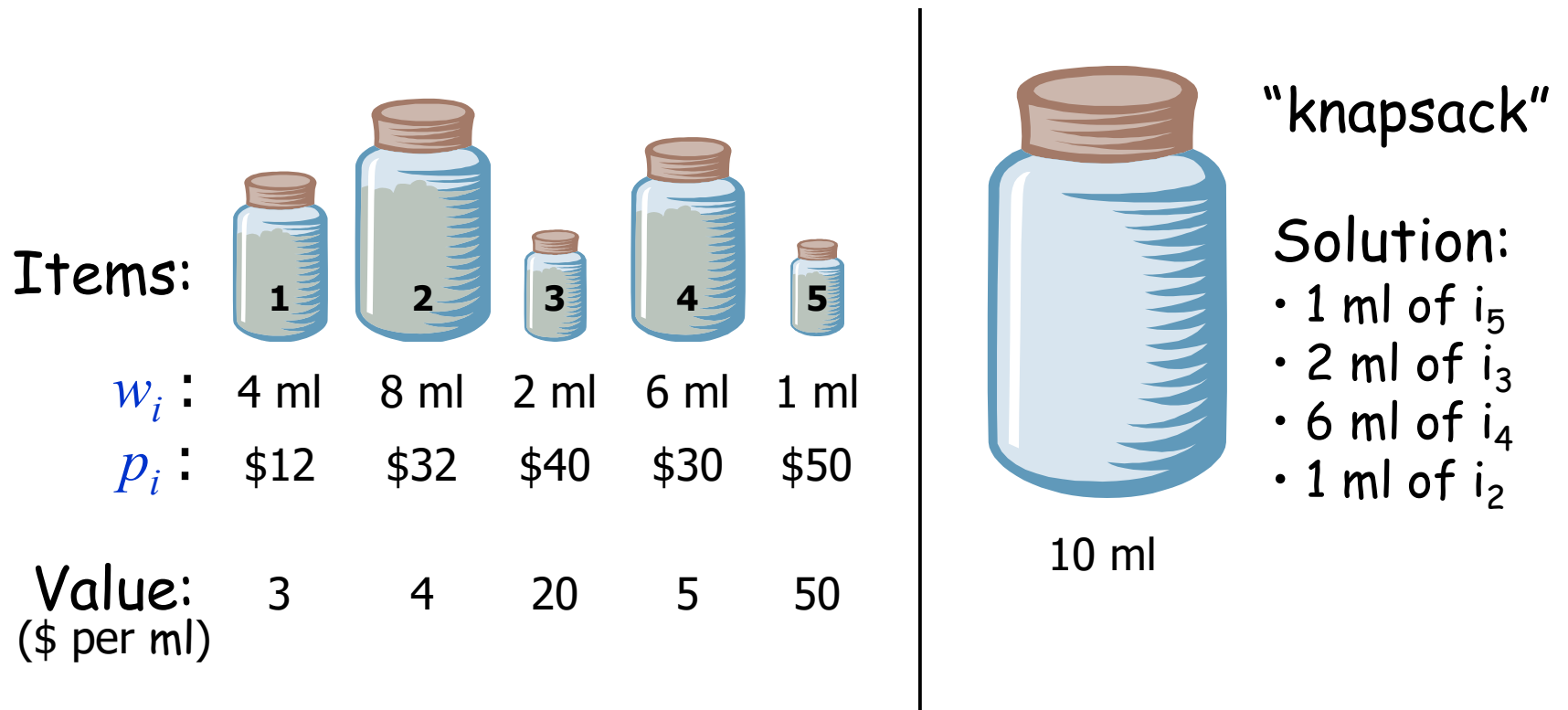
$$\text{subjected to } \sum_{1 \leq i \leq n} w_i x_i \leq m$$

$$\text{and } 0 \leq x_i \leq 1, \quad 1 \leq i \leq n$$

# The Fractional Knapsack Problem

Greedy decision property:-

Select items in **decreasing** order of **profit/weight**.



- Solution vector

$$(x_1, x_2, x_3, x_4, x_5) = (0, 1/8, 1, 1, 1)$$

- Profit  $= 12*0 + 32*1/8 + 40*1 + 30*1 + 50*1$   
 $= 0+4+40+30+50$   
 $= 124.$

Greedy algorithm for the fractional Knapsack problem

Algorithm GreedyKnapsack(m,n)

//P[1:n] and w[1:n] contain the profits and weights

// respectively of the n objects ordered such that

// $p[i]/w[i] \geq p[i+1]/w[i+1]$ .

//m is the knapsack size and x[1:n] is the solution

// Vector.

```
{
    for i=1 to n do x[i]=0; // Initialize x.
    U=m;
    for i=1 to n do
    {
        if ( w[i]>U ) then break;
        if x[i]=1; U=U-w[i];
    }
    if ( i <=n) then x[i]= U/w[i];
}
```

If you do not consider the time to sort the items, then the time taken by the above algorithm is  $O(n)$ .

# 0/1 Knapsack Problem

- An item is either included or not included into the knapsack.

Formally the problem can be stated as

$$\text{maximize } \sum p_i x_i$$

$$1 \leq i \leq n$$

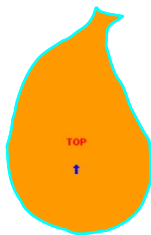
$$\text{subjected to } \sum w_i x_i \leq m$$

$$1 \leq i \leq n$$

$$\text{and } x_i = 0 \text{ or } 1, \quad 1 \leq i \leq n$$



Which items should be chosen  
to **maximize** the amount of  
**money** while still keeping the  
overall **weight under  $m$  kg** ?



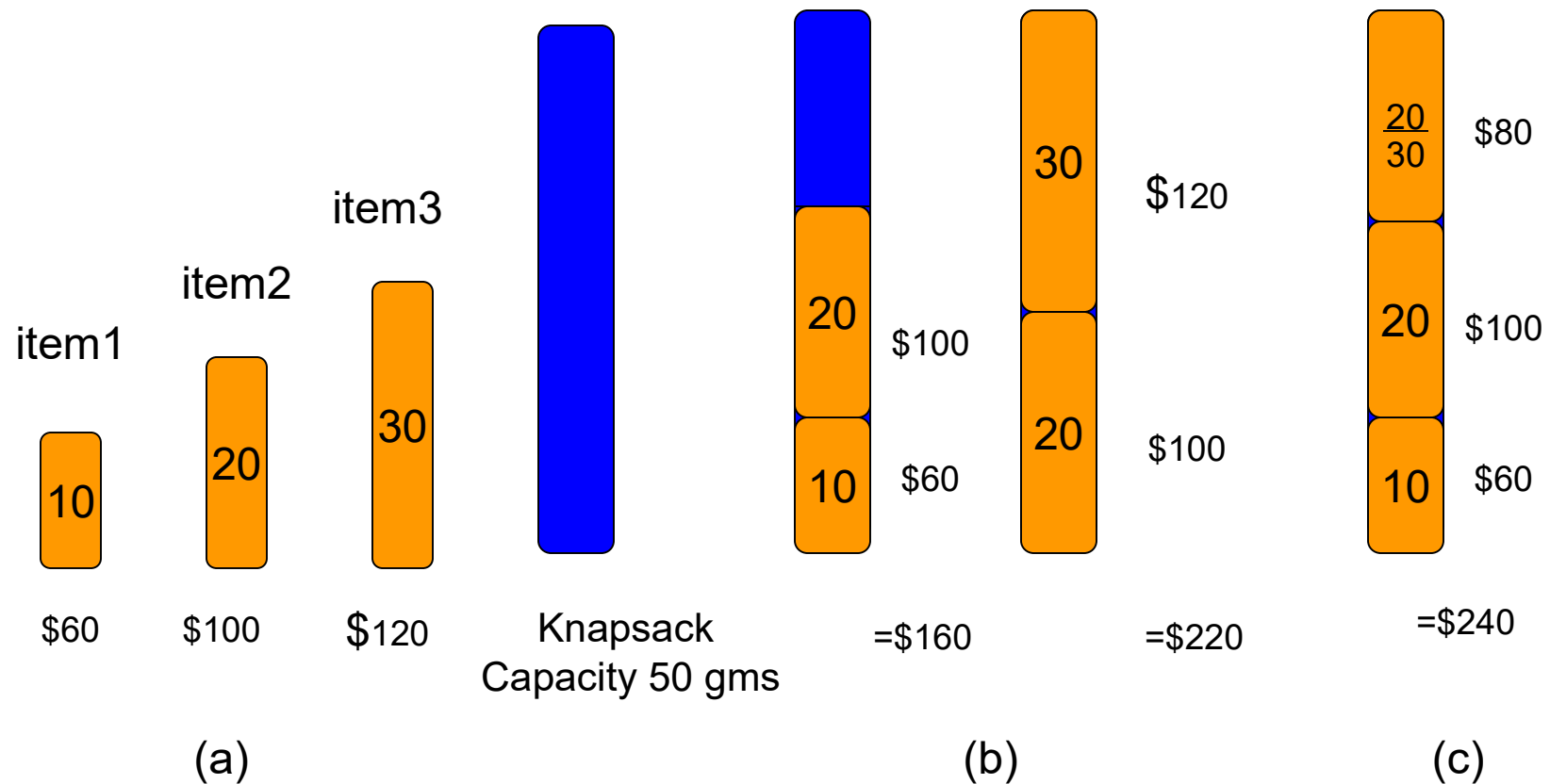
$m$



*Is the fractional knapsack algorithm applicable?*



- The greedy method works for **fractional** knapsack problem, but it does not for **0/1** knapsack problem.
- Ex:-



- There are 3 items, the knapsack can hold **50** gms.
- The value per gram of item 1 is 6, which is greater than the value per gram of either item2 or item3.
- The *greedy approach* ( Decreasing order of profit's/weight's), does not give an optimal solution.
- As we can see from the above fig., the *optimal solution* takes item2 and item3.
- For the *fractional* problem, the *greedy approach* (Decreasing order of profit's/weight's) gives an *optimal solution* as shown in fig c.

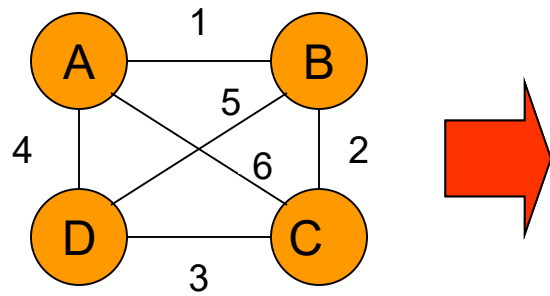
# *Spanning Tree*

- A *tree* is a connected undirected graph that contains *no cycles*.
- A *spanning tree* of a graph  $G$  is a subgraph of  $G$  that is a *tree* and contains *all* the vertices of  $G$ .

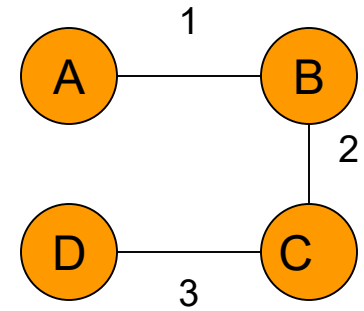
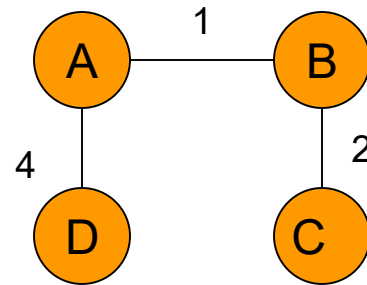
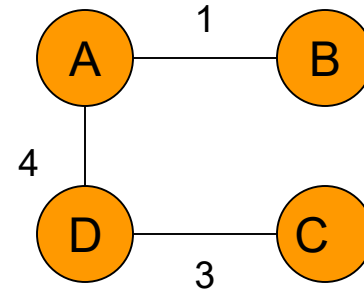
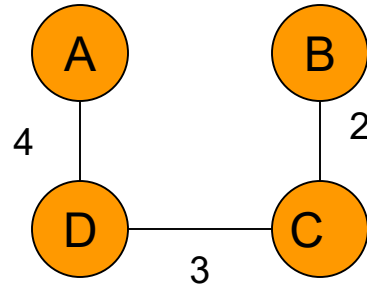
# Properties of a Spanning Tree

- The spanning tree of a  $n$ -vertex undirected graph has exactly  $n - 1$  edges.
- It connects all the vertices in the graph.
- A spanning tree has no cycles.

Ex:-



Undirected Graph

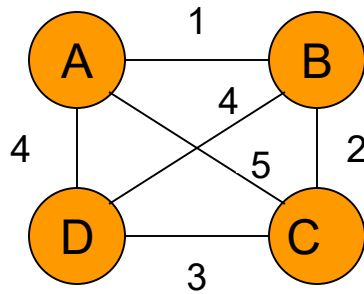


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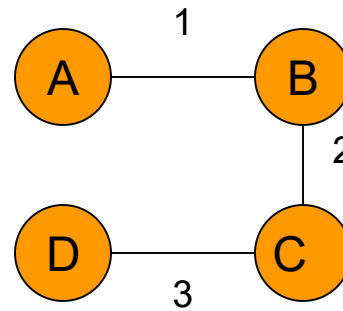
Some Spanning Trees

# Minimum Cost Spanning Tree / Minimum Spanning Tree (MST)

- A *minimum spanning tree* is the one among all the spanning trees with the *smallest total cost*.



Undirected Graph



Minimum Spanning Tree

# Applications of MSTs

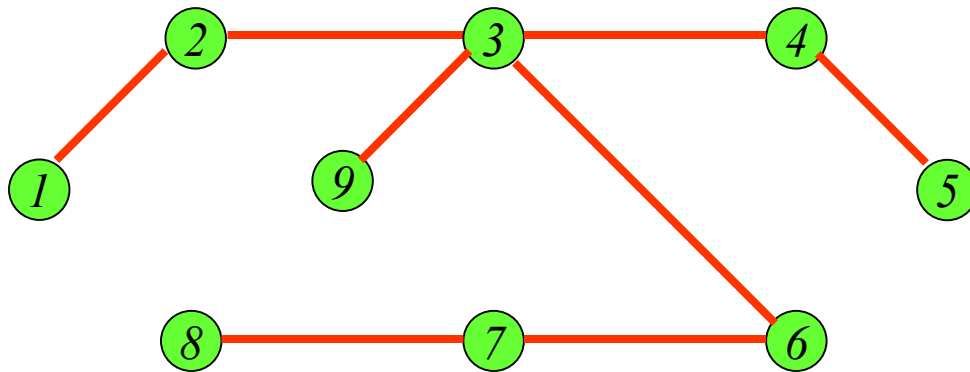
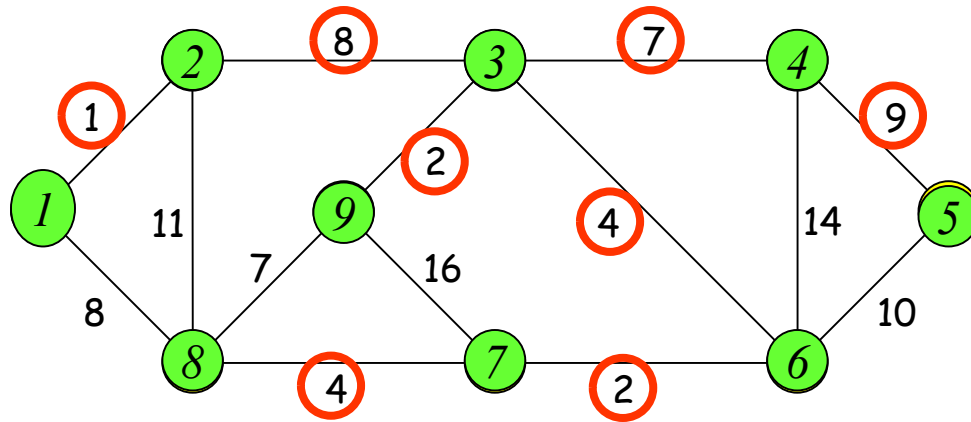
- Computer Networks
  - To **find** how to connect a set of computers using the **minimum amount of wire**.

# MST-Prim's Algorithm

- Start with minimum cost edge.
- Select next minimum cost edge ( $i,j$ ) such that  $i$  is a vertex already included in the tree,  $j$  is a vertex not yet included.
- Continue this process until the tree has  $n - 1$  edges.



# Prim's Algorithm

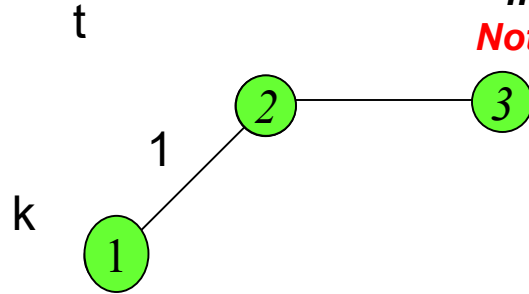


$t[1:n-1, 1:2]$

	1	2
1	1	2
2	2	3
	3	9
.	3	6
.	6	7
.	7	8
	3	4
n-1	4	5

1.  $\text{near}[j]$  is a vertex in the tree such that  $\text{cost}[j, \text{near}[j]]$  is minimum among all choices for  $\text{near}[j]$ .

**Note:** We define  $\text{near}[j] = 0$  for all vertices  $j$  that are already in the tree.



k

1

j

$\text{cost}[j, \text{near}[j]]$



1	$\text{near}[1]=0$
2	$\text{near}[2]=0$
3	$\text{near}[3]=0$

3

$\text{near}[3]=2$

$\text{cost}[3, 2]=8$

4

$\text{near}[4]=1$

$\text{cost}[4, 1]=\infty$

5

$\text{near}[5]=1$

$\text{cost}[5, 1]=\infty$

6

$\text{near}[6]=1$

$\text{cost}[6, 1]=\infty$

7

$\text{near}[7]=1$

$\text{cost}[7, 1]=\infty$

8

$\text{near}[8]=1$

$\text{cost}[8, 1]=8$

9

$\text{near}[9]=1$

$\text{cost}[9, 1]=\infty$

2. Select next min cost edge.

3. Next update  $\text{near}[j]$  for all vertices which are not yet included in the tree and then go to step 2.

4. Continue this procedure until tree contains  $n-1$  edges.

## Prim's Algorithm

```
1  Algorithm Prim(E, cost, n, t)
2  // E is the set of edges in G.
3  //cost[1:n,1:n] is the cost matrix such that cost[i,j] is either
4  // positive real number or  $\infty$  if no edge (i,j) exists. cost[i,j]=0, if i=j.
5  // A minimum spanning tree is computed and stored
6  // as a set of edges in the array t[1:n-1,1:2]
7  {
8      Let (k,l) be an edge of minimum cost in E

9      mincost=cost[k,l];
10     t[1,1]=k; t[1,2]=l;
11     near[k]=near[l]=0;

12     for i=1 to n do // initialize near
13         if( near[i]  $\neq$  0 ) then
14             if( cost[i,k]< cost[i, l] ) then near[i]=k;
15             else near[i]= l;
```

```

14  for i=2 to n-1 do
15      {
16          // Find n-2 additional edges for t.

17          Let j be an index such that near[j]≠0 and
18          cost[j,near[j]] is minimum;

19          t[i,1]=j; t[i,2]=near[j];
20          mincost=mincost+cost[j,near[j]];
21          near[j]=0;

22          for k=1 to n do // update near[]
23              if( ( near[k] ≠0 ) and (cost[k,near[k]]>cost[k,j])) then
24                  near[k]=j;
25      }
26  return mincost;
27 }

```

# Time complexity of Prim's algorithm

- Line 8 takes  $O(E)$ .
- The for loop of line 12 takes  $O(n)$ .
- 17 and 18 and the for loop of line 22 require  $O(n)$  time.
- Each iteration of the for loop of line 14 takes  $O(n)$  time.
- Therefore, the total time for the for loop of line 14 is  $O(n^2)$ .
- Hence, time complexity of Prim is  $O(n^2)$ .

# Kruskal's Method

- Start with a forest that has no edges.
- Add the next minimum cost edge to the forest if it will not cause a cycle.
- Continue this process until the tree has  $n - 1$  edges.

# Kruskal's Algorithm

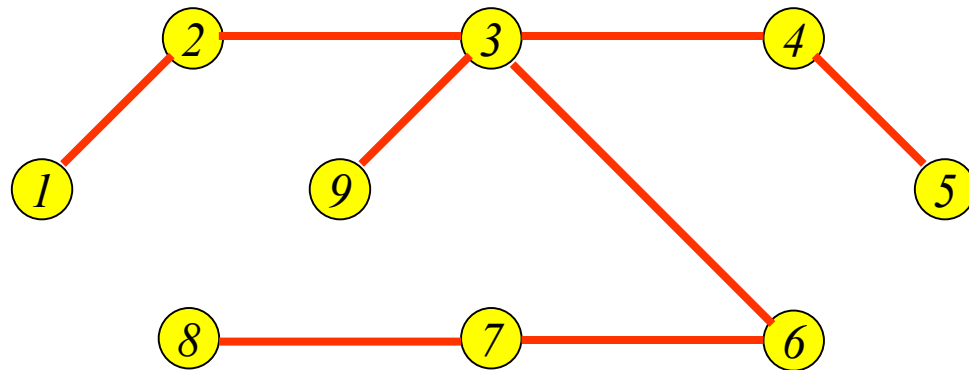
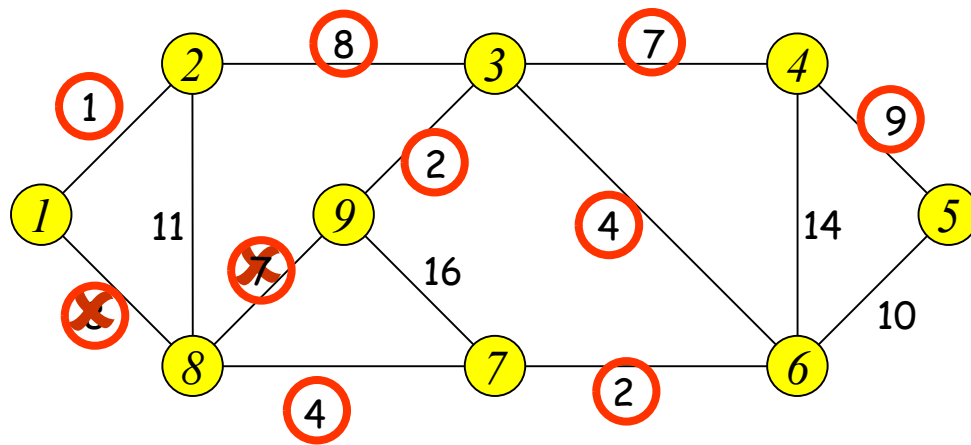




Diagram illustrating the formation of a cycle in a graph. Nodes 1, 2, 3, 4, 5 are yellow circles. Nodes 6, 7, 8, 9 are yellow circles. Red lines connect nodes 1-2, 2-3, 3-4, 4-5, 5-6, 6-7, 7-8, 8-9, 9-3, and 3-6. Dotted lines connect nodes 1-3, 2-4, 3-5, 4-6, 5-7, 6-8, 7-9, 8-1, 9-2, and 3-9. Arrows point from the text "Forms cycle" to the red line between nodes 1 and 2, and from the text "6" to the red line between nodes 5 and 6.



# Disjoint Sets

➤ Two sets A and B are said to be **disjoint** if there are no common elements i.e.,  $A \cap B = \emptyset$ .

➤ *Example:*

1)  $S_1 = \{1, 7, 8, 9\}$ ,  $S_2 = \{2, 5, 10\}$ , and  $S_3 = \{3, 4, 6\}$ .  
are three disjoint sets.

- We identify a set by choosing a *representative element* of the set. It doesn't matter which element we choose, but once chosen, it can't be changed.
- Disjoint set operations:
  - FIND-SET( $x$ ): Returns the representative of the set containing  $x$ .
  - UNION( $i, j$ ): Combines the two sets  $i$  and  $j$  into one new set. A new representative is selected.  
( Here  $i$  and  $j$  are the representatives of the sets )

# Disjoint Sets Example

- Make-Set(1)
- Make-Set(2)
- Make-Set(3 )
- Make-Set(4)
- Union(1,2)
- Union(3,4)
- Find-Set(2)      returns 1
- Find-Set(4)      returns 3
- Union(2,4)



# MST-Kruskal's Algorithm

Algorithm `kruskal(E, cost, n, t)`

//  $E$  is the set of edges in  $G$ .

// `cost[1:n, 1:n]` is the cost matrix such that `cost[i, j]` is either

// positive real number or  $\infty$  if no edge  $(i, j)$  exists. `cost[i, j] = 0`, if  $i = j$ .

// A minimum spanning tree is computed and stored

// as a set of edges in the array `t[1:n-1, 1:2]`.

{

  for  $i := 1$  to  $n$  do

**Make-Set**( $i$ ); // *each vertex is in a different set.*

*Sort the edges of  $E$  into increasing order by cost.*

```

mincost:=0; i:=1;
for each edge (u,v) ∈ E, taken in increasing order by cost do
{
  j:= Find-Set(u); k:= Find-Set(v)
  if( j≠k ) then
  {
    t[i,1]:=u; t[i,2]:=v;
    mincost:=mincost+cost[u,v];
    Union(j,k);
    i:=i+1;
  }
}
return mincost;
}

```

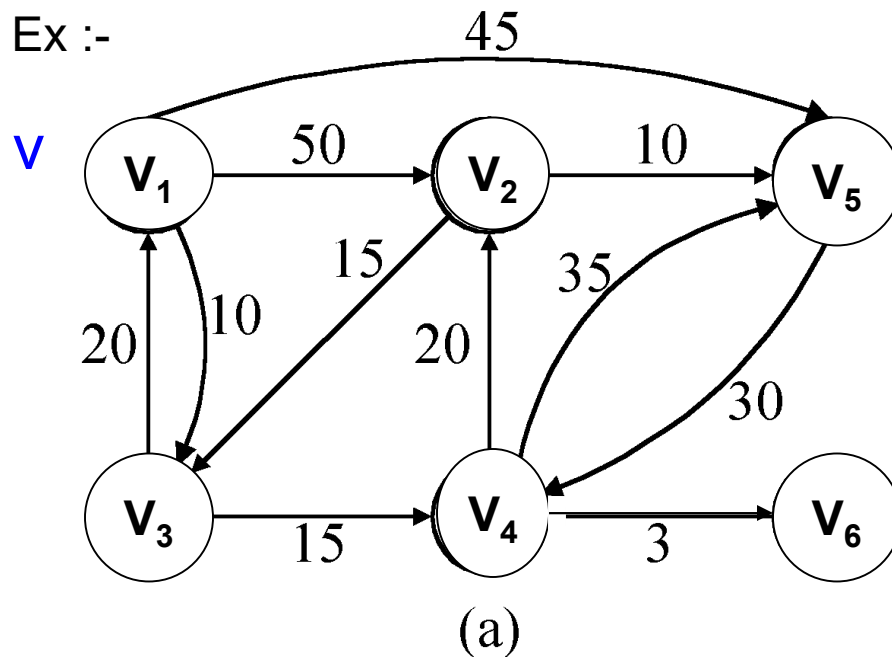
# Time complexity of kruskal's algorithm

- With an efficient **Find-set** and **union** algorithms, the running time of kruskal's algorithm will be dominated by the time needed for sorting the edge costs of a given graph.
- Hence, with an efficient sorting algorithm( **merge sort** ), the complexity of kruskal's algorithm is  $O(E \log E)$ .

# The Single-Source Shortest path Problem ( SSSP)

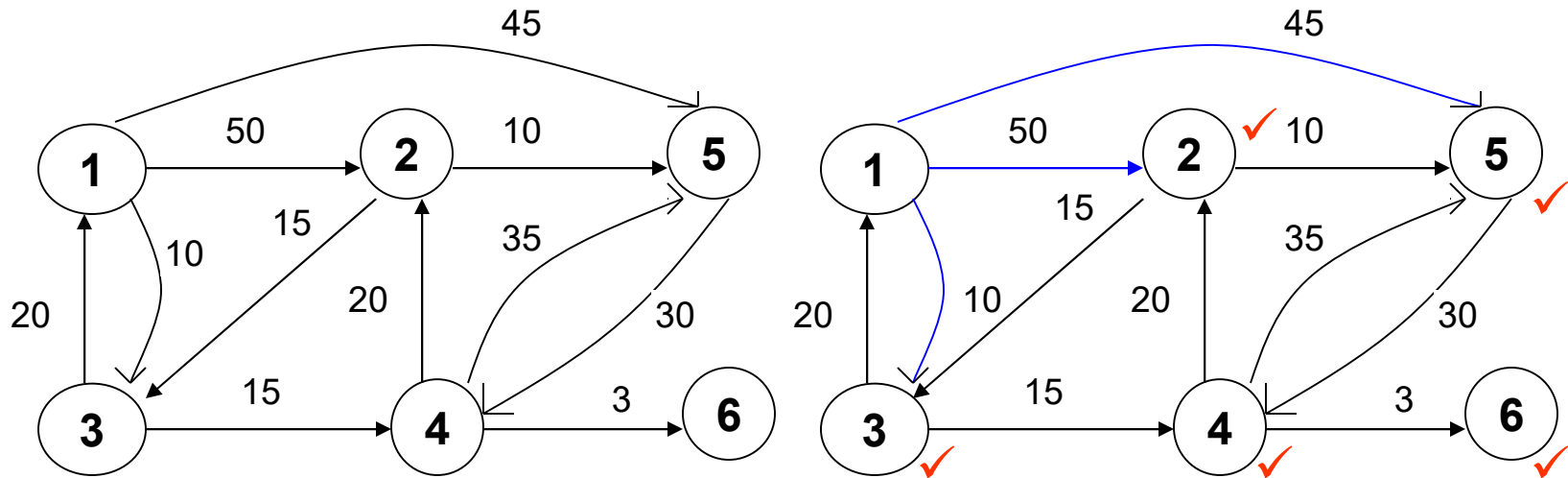
- Given a **positively** weighted directed graph G with a source vertex **v**, find the shortest paths **from v to all other vertices** in the graph.

Ex :-



	<u>Path</u>	<u>Length</u>
1)	$v_1 v_3$	10
2)	$v_1 v_3 v_4$	25
3)	$v_1 v_3 v_4 v_2$	45
4)	$v_1 v_5$	45
5)	$v_1 v_3 v_4 v_6$	<b>28</b>

(b)



Iteration	S	Dist[2]	Dist[3]	Dist[4]	Dist[5]	Dist[6]
Initial	{1}	50	10 ✓	∞	45	∞
1	{1,3}	50	10	25 ✓	45	∞
2	{1,3,4}	45	10	25	45	28 ✓
3	{1,3,4,6}	45	10	25	45 ✓	28
4	{1,3,4,5,6}	45 ✓	10	25	45	28



# SSSP-Dijkstra's algorithm

- Dijkstra's algorithm assumes that  $\text{cost}(e) \geq 0$  for each  $e$  in the graph.
- Maintains a set  $S$  of vertices whose SP from  $v$  (source) has been determined.
- a) Select the next minimum distance node  $u$ , which is not in  $S$ .
- (b) *for* each node  $w$  adjacent to  $u$  *do*
  - if(  $\text{dist}[w] > \text{dist}[u] + \text{cost}[u, w]$  ) then
  - $\text{dist}[w] := \text{dist}[u] + \text{cost}[u, w]$ ;
- Repeat step (a) and (b) until  $S = n$  (number of vertices).

# 1 Algorithm ShortestPaths( $v, cost, dist, n$ )

2 //dist[j],  $1 \leq j \leq n$ , is the length of the shortest path

3 //from vertex  $v$  to vertex  $j$  in a digraph  $G$  with  $n$  vertices.

4 // dist[v] is set to zero.  $G$  is represented by its cost adjacency

5 // matrix cost[1:n, 1:n].

6 {

7     for  $i := 1$  to  $n$  do

8     {     // Initialize S.

9          $s[i] := \text{false}$ ;  $dist[i] := cost[v, i]$ ;

10    }

11      $s[v] := \text{true}$ ; // put  $v$  in S.

```
12  for num:=2 to n do
13    {
14      Determine n-1 paths from v.
15      Choose u from among those vertices not in S such that
        dist[u] is minimum;

17      s[u]:=true; // Put u in S.
18      for ( each w adjacent to u with s[w]= false) do
19        // Uupdate distance
20        if( dist[w]>dist[u]+cost[u,w]) ) then
21          dist[w]:=dist[u]+cost[u,w];
22    }
23 }
```

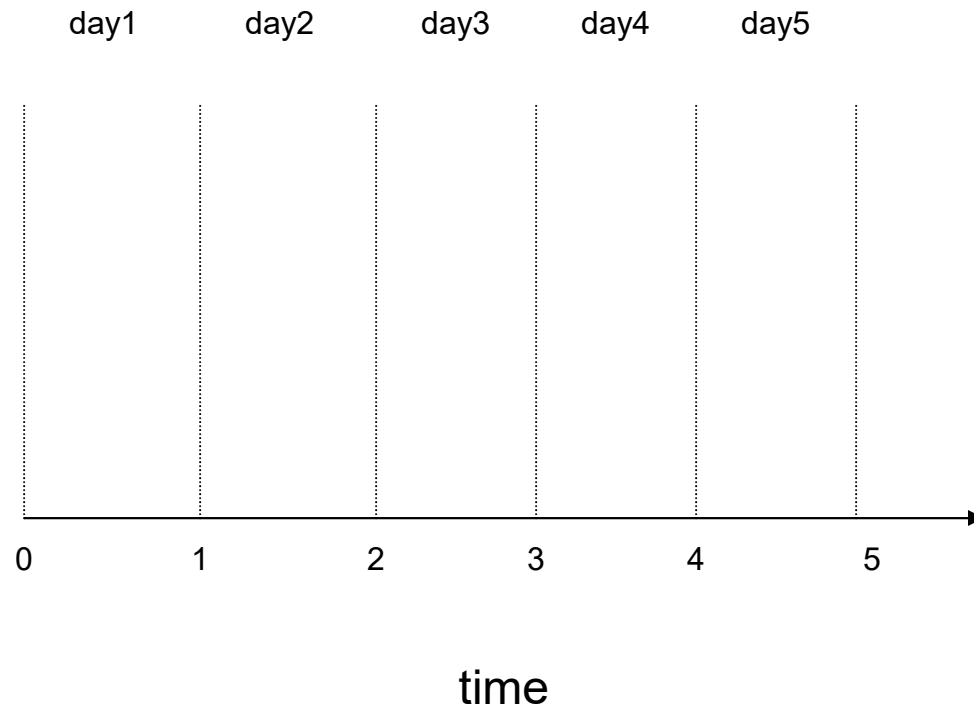
# Time complexity of Dijkstra's Algorithm

- The for loop of line 7 takes  $o(n)$ .
- The for loop of line 12 takes  $o(n)$ .
  - Each execution of this loop requires  $o(n)$  time at lines 15 and 18.
  - So the total time for this loop is  $o(n^2)$ .
- Therefore, **total time taken by this algorithm is  $o(n^2)$ .**

## Job sequencing with deadlines

- We are given a set of  $n$  jobs.
- *Deadline*  $d_i \geq 0$  and a *profit*  $p_i > 0$  are associated with each *job*  $i$ .
- For any job profit is earned if and only if the job is *completed by its deadline*.
- To complete a job, a job has to be processed by a machine for *one unit* of time.
- Only *one machine* is available for processing jobs.
- A *feasible solution* of this problem is a *subset of jobs* such that each job in this subset can be completed by its deadline
- The *optimal solution* is a feasible solution which will *maximize* the total profit.
- The *objective* is to find an *order of processing of jobs* which will *maximize the total profit*.

Ex:- $n=4$ ,  $(p_1, p_2, p_3, p_4) = (100, 10, 15, 27)$   
 $(d_1, d_2, d_3, d_4) = (2, 1, 2, 1)$



Ex:-n=4, ( p1,p2,p3,p4 )=( 100,10,15,27 )  
( d1,d2,d3,d4 )=( 2,1,2,1 )

The maximum deadline is 2 units, hence the feasible solution set must have  $\leq 2$  jobs.

	feasible solution	processing sequence	value
1.	(1,2)	2,1	110
2.	(1,3)	1,3 or 3,1	115
3.	(1,4)	4,1	127
4.	(2,3)	2,3	25
5.	(3,4)	4,3	42
6.	(1)	1	100
7.	(2)	2	10
8.	(3)	3	15
9.	(4)	4	27

Solution 3 is optimal.

# Greedy Algorithm for job sequencing with deadlines

1. Sort  $p_i$  into decreasing order. After sorting  
 $p_1 \geq p_2 \geq p_3 \geq \dots \geq p_i$ .
2. Add the next job  $i$  to the solution set if  $i$  can be completed by its deadline.
3. Stop if all jobs are examined. Otherwise, go to step 2.



Ex:- 1)  $n=5$ ,  $(p_1, \dots, p_5) = (20, 15, 10, 5, 1)$  and  
 $(d_1, \dots, d_5) = (2, 2, 1, 3, 3)$

The optimal solution is  $\{1, 2, 4\}$  with a profit of 40.

Ex:- 2)  $n=7$ ,  $(p_1, \dots, p_7) = (3, 5, 20, 18, 1, 6, 30)$  and  
 $(d_1, \dots, d_7) = (1, 3, 4, 3, 2, 1, 2)$

Find out an optimal solution.

## Algorithm JS(d,j,n)

*//d[i] ≥ 1,  $1 \leq i \leq n$  are the deadlines.*

*//The jobs are ordered such that  $p[1] \geq p[2] \dots \geq p[n]$*

*// j[i] is the  $i^{\text{th}}$  job in the optimal solution,  $1 \leq i \leq k$*

{

    d[0]=j[0]=0;   // Initialize

    j[1]=1; // Include job 1

    k=1;

**for** i=2 **to** n **do**

```
{  //Consider jobs in Descending order of p[i].
  // Find position for i and check feasibility of
  // insertion.
  r=k;
  while( ( d[j[r]] > d[i] ) and ( d[j[r]] > r ) ) do
    r = r-1;

  if( d[j[r]] ≤ d[i] and d[i] > r ) then
  {
    // Insert i into j[ ].
    for q=k to (r+1) step -1 do j[q+1] = j[q];

    j[r+1] :=i;
    k:=k+1;
  }
}
return k;
```

}

Time taken by this algorithm is  $O(n^2)$