

# CS 457, Fall 2019

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Drexel University, Department of Computer Science

Lecture 15



# Maximum Subarray Problem

- Can you provide a **dynamic programming** solution to this problem?
  - How would you break this problem into sub-problems?
  - You want the solutions to the subproblems to help you solve larger subproblems faster
- If you knew the best subarray **ending at  $A[i]$** , could you find the best subarray **ending at  $A[i + 1]$** ?
  - Let's create a new array  $B$  and store the sum of the best subarray ending at  $A[i]$  in  $B[i]$
  - The best ending at  $A[i + 1]$  is either the best **ending at  $A[i]$  plus  $A[i + 1]$** , or just  **$A[i + 1]$**
  - This means that  $B[i + 1] = \max\{B[i] + A[i + 1], A[i + 1]\}$
  - How quickly can you check which one is best?
  - How quickly can you compute the best subarray ending at  **$A[i]$**  for every  $i \in \{1, \dots, n\}$ ?
  - Can you compute the optimal solution using this information?

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
A	13	-3	-25	20	-3	-16	-23	18	20	-7	12	-5	-22	15	-4	7

maximum subarray



# Matrix-Chain Multiplication

- Given sequence  $\langle A_1, A_2, \dots, A_n \rangle$  of  $n$  matrices, compute the product  $A_1 A_2 \cdots A_n$ 
  - Matrix multiplication is associative so all parenthesizations yield the same product
  - But, do they all take the same amount of time?
  - E.g., say that  $n=3$  and the dimensions are  $10 \times 100$ ,  $100 \times 5$ , and  $5 \times 50$

MATRIX-MULTIPLY( $A, B$ )

```
1  if  $A.columns \neq B.rows$ 
2      error "incompatible dimensions"
3  else let  $C$  be a new  $A.rows \times B.columns$  matrix
4      for  $i = 1$  to  $A.rows$ 
5          for  $j = 1$  to  $B.columns$ 
6               $c_{ij} = 0$ 
7              for  $k = 1$  to  $A.columns$ 
8                   $c_{ij} = c_{ij} + a_{ik} \cdot b_{kj}$ 
9  return  $C$ 
```

If  $A$  is  $p \times q$  and  $B$  is  $q \times r$ , then step 8 is executed  $pqr$  times

- Find the optimal multiplication order using dynamic programming



# Matrix-Chain Multiplication

- The minimum cost of parenthesizing the product  $A_i A_{i+1} \cdots A_j$  is

$$m[i, j] = \begin{cases} 0 & \text{if } i = j, \\ \min_{i \leq k < j} \{m[i, k] + m[k + 1, j] + p_{i-1} p_k p_j\} & \text{if } i < j. \end{cases}$$

- Input is  $p = \langle p_0, p_1, \dots, p_n \rangle$  where  $p_{i-1} \times p_i$  are the dimensions of matrix  $A_i$
- Recursive algorithm would require exponential time
- But, how many subproblems have we defined?
  - One for each pair  $(i, j)$  so  $\Theta(n^2)$  subproblems
  - Each subproblem depends on  $\Theta(n)$  subproblems
- Output is a table  $m$  and a table  $s$ 
  - Table  $m$  stores cost of each  $m[i, j]$
  - Table  $s$  records index of  $k$  that achieved that cost

## MATRIX-CHAIN-ORDER( $p$ )

```
1   $n = p.length - 1$ 
2  let  $m[1..n, 1..n]$  and  $s[1..n - 1, 2..n]$  be new tables
3  for  $i = 1$  to  $n$ 
4       $m[i, i] = 0$ 
5  for  $l = 2$  to  $n$  //  $l$  is the chain length
6      for  $i = 1$  to  $n - l + 1$ 
7           $j = i + l - 1$ 
8           $m[i, j] = \infty$ 
9          for  $k = i$  to  $j - 1$ 
10              $q = m[i, k] + m[k + 1, j] + p_{i-1} p_k p_j$ 
11             if  $q < m[i, j]$ 
12                  $m[i, j] = q$ 
13                  $s[i, j] = k$ 
14  return  $m$  and  $s$ 
```



# Today's Lecture

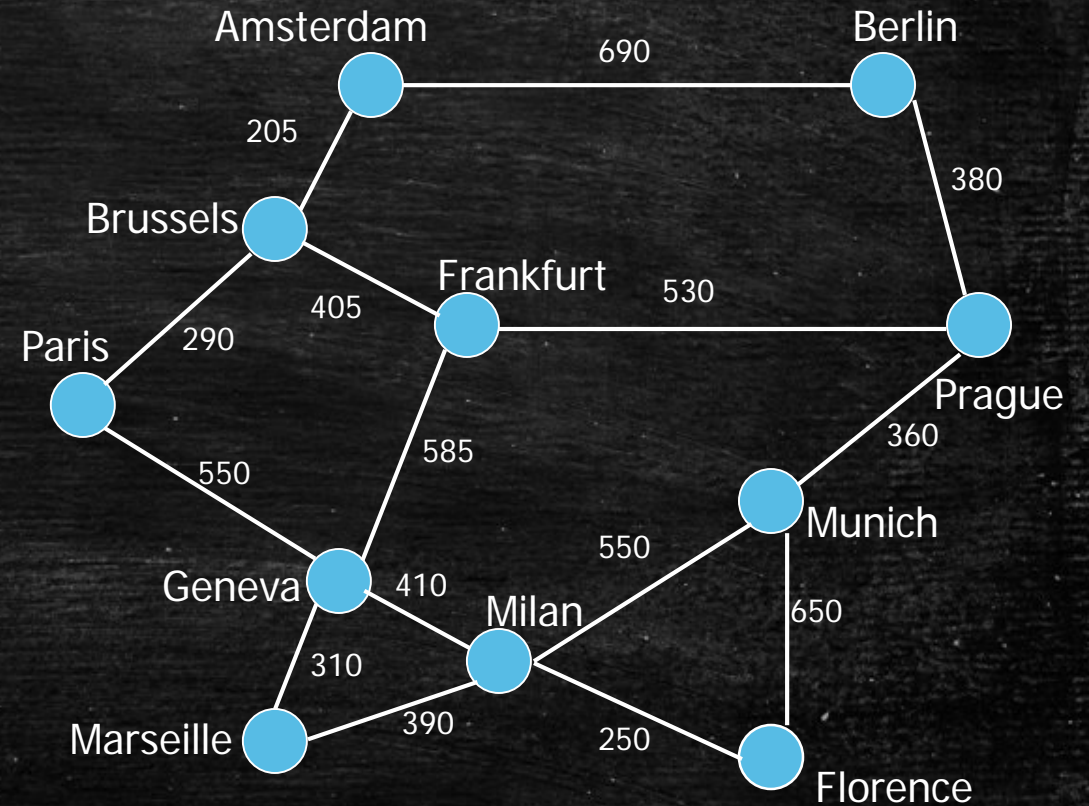
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- We now transition into graph algorithms
  - Minimum Spanning Tree
  - Breadth First Search
  - Depth First Search
  - Topological Sorting
  - Strongly Connected Components



# Graphs

- Things to know:
  - Path
  - Cycle
  - Sub-graph
  - Degree of a vertex
  - Maximum and minimum degree
  - Maximum number of edges
  - Connected components
  - Shortest path (weighted & unweighted)
  - Distance of two vertices
  - Tree (rooted tree)
  - Spanning tree of a graph
  - Acyclic graph
  - Bipartite graph





# Definitions

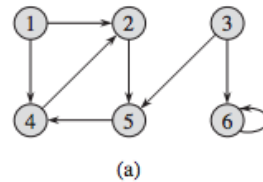
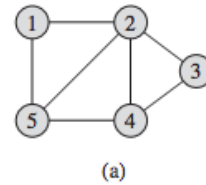
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- Given A graph  $G=(V,E)$ , where
  - $V$  is its vertex set,  $|V|=n$ ,
  - $E$  is its edge set, with  $|E|=m=O(n^2)$
- If  $G$  is **connected** then for every pair of vertices  $u,v$  in  $G$ , there is path connecting them
- In an **undirected graph**, an edge  $(u, v)=(v, u)$ .
- In a **directed graph**,  $(u, v)$  is different from  $(v, u)$ .
- In a **weighted graph** there are weights associated with edges and/or vertices.
- **Running time** of graph algorithms are usually expressed in terms of  $n$  or  $m$ .



# Graph Representations

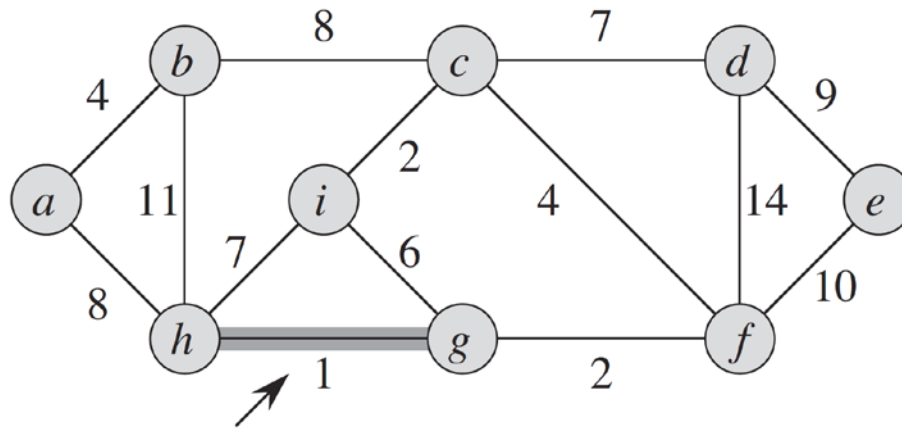
- Adjacency List
  - Good for sparse graphs
- Adjacency Matrix
  - Quick edge existence query
  - Simple





# Minimum Spanning Tree of a Weighted Graph

- Let  $G=(V,E)$  be a graph on  $n$  vertices,  $m$  edges, and a **weight**  $w$  on edges in  $E$ .
- Sub-graph  $T=(V,E')$  with  $E' \subseteq E$  with no cycles is a **spanning tree**
- The **weight of  $T$**  is the sum of the weights of its edges:  $w(T) = \sum_{(u,v) \in E'} w(u,v)$





# Set Operations

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- We will use the following set operations:
  - **Make-Set( $v$ )**: creates a set containing element  $v$ , i.e.,  $\{v\}$
  - **Find-Set( $v$ )**: returns the set to which  $v$  belongs to
  - **Union( $u, v$ )**: creates a set which is the union of two sets, the one containing  $v$  and the one containing  $u$

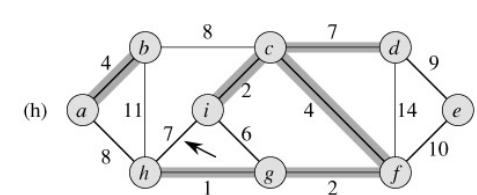
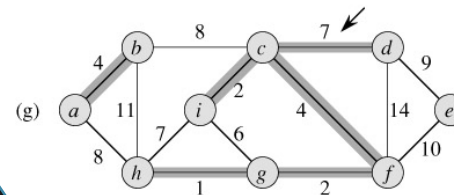
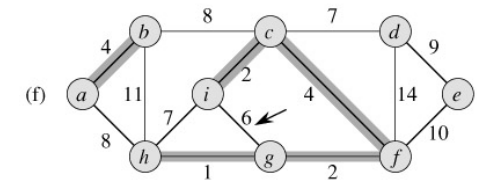
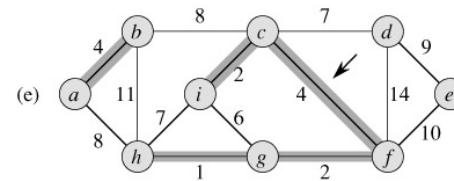
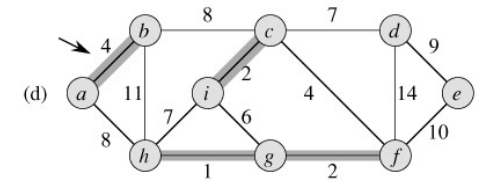
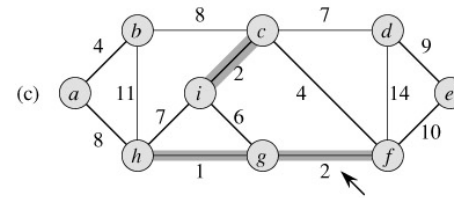
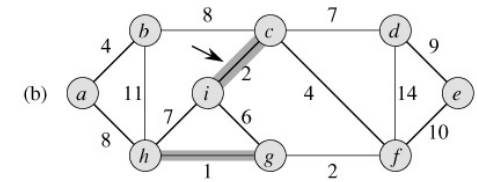
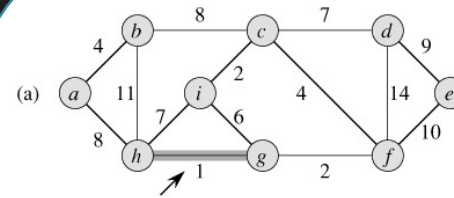


# Kruskal's Algorithm

MST-KRUSKAL( $G, w$ )

```

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



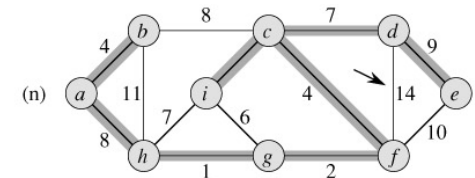
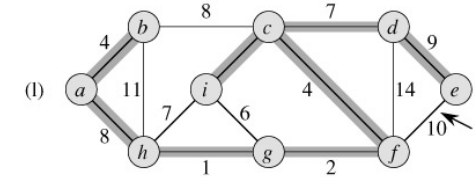
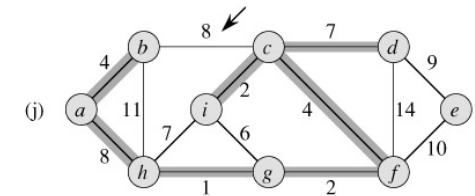
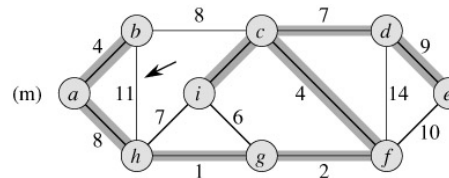
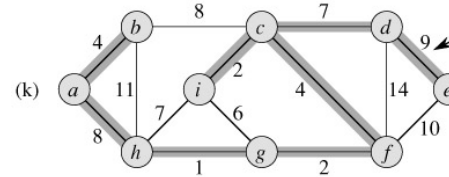
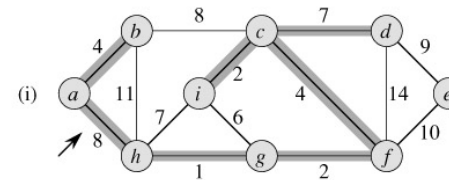


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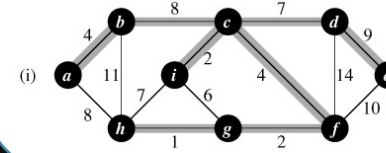
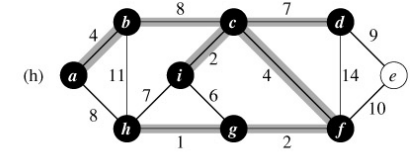
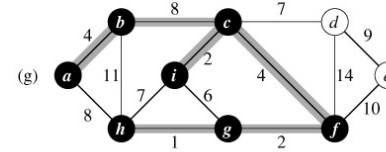
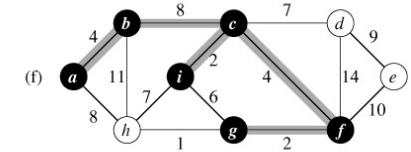
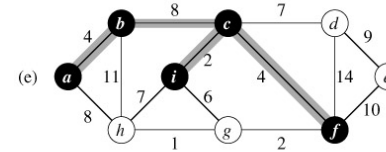
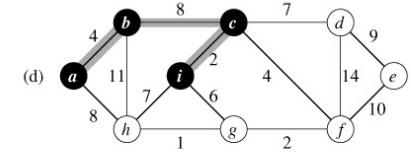
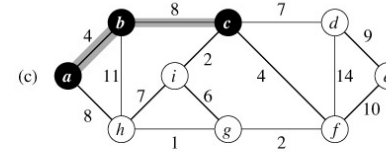
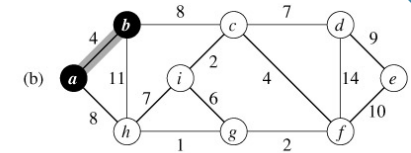
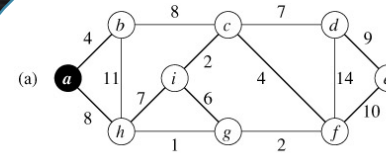
# Prim's Algorithm

MST-PRIM( $G, w, r$ )

```

1  for each  $u \in G.V$ 
2     $u.key = \infty$ 
3     $u.\pi = \text{NIL}$ 
4   $r.key = 0$ 
5   $Q = G.V$ 
6  while  $Q \neq \emptyset$ 
7     $u = \text{EXTRACT-MIN}(Q)$ 
8    for each  $v \in G.Adj[u]$ 
9      if  $v \in Q$  and  $w(u, v) < v.key$ 
10        $v.\pi = u$ 
11        $v.key = w(u, v)$ 

```





# Practice Problem

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- Is the path between two vertices in an MST necessarily a shortest path between the two vertices in the full graph? Give a proof or a counterexample.
  - Answer: No it is not. For example, consider a graph that forms a single  $n$ -vertex cycle. The minimum spanning tree will remove just one edge  $(u, v)$ , significantly increasing the distance between  $u$  and  $v$



# Breadth First Search (BFS)

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- Given a graph  $G = (V, E)$ , BFS starts at some **source vertex  $s$**  and discovers which vertices are **reachable from  $s$**
- The **distance** between a vertex  $v$  and  $s$  is the minimum number of edges on a path from  $s$  to  $v$  (the shortest path length)
- BFS discovers vertices in increasing order of distance, and hence can be used as an algorithm for computing **shortest paths** from  $s$
- At any given time there is a **frontier** of vertices that have been discovered, but not yet processed.
- BFS first visits all vertices across the **breadth** of this frontier (hence the name)



# BFS: coloring

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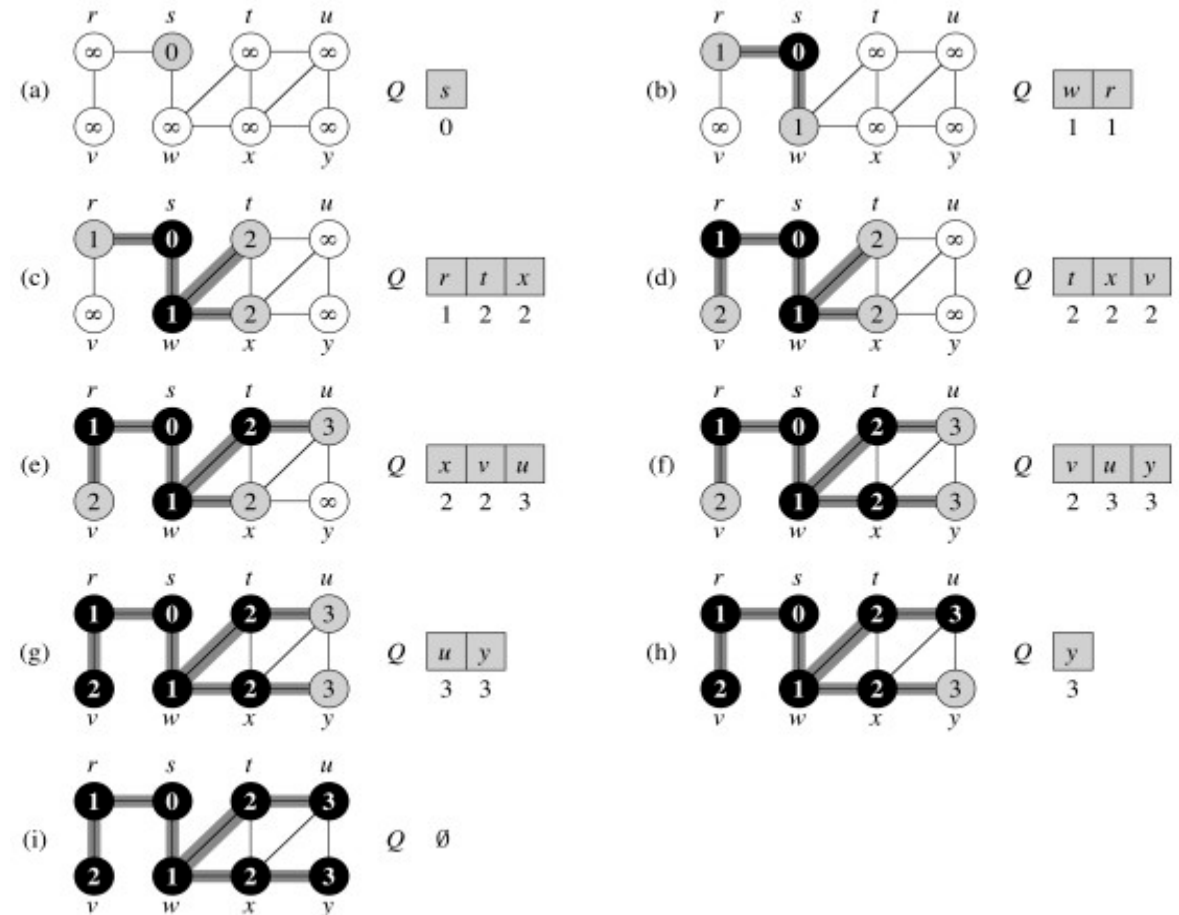
- We use a coloring procedure to show the status of BFS at each time:
  - Initially all vertices (except the source) are **white**: they are **undiscovered**
  - When a vertex is first **discovered**, it becomes **gray** (and is part of the frontier)
  - When a gray vertex is **processed**, it becomes **black**



# BFS Algorithm

## BFS ( $G, s$ )

1. for each  $u \in G.V - \{s\}$
2.      $u.color = WHITE$
3.      $u.d = \infty$
4.      $u.\pi = NIL$
5.  $s.color = GRAY$
6.  $s.d = 0$
7.  $s.\pi = NIL$
8.  $Q = \emptyset$
9. ENQUEUE( $Q, s$ )
10. while  $Q \neq \emptyset$
11.      $u = DEQUEUE(Q)$
12.     for each  $v \in G.Adj[u]$
13.         if  $v.color == WHITE$
14.              $v.color = GRAY$
15.              $v.d = u.d + 1$
16.              $v.\pi = u$
17.             ENQUEUE( $Q, v$ )
18.      $u.color = BLACK$





# BFS predecessor subgraph of $G$

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For a graph  $G = (V, E)$  with source  $s$  the predecessor subgraph of  $G$  is:

- $G_\pi = (V_\pi, E_\pi)$ , where
- $V_\pi = \{v \in V : v.\pi \neq \text{NIL}\} \cup \{s\}$
- $E_\pi = \{(v.\pi, v) : v \in V_\pi - \{s\}\}$



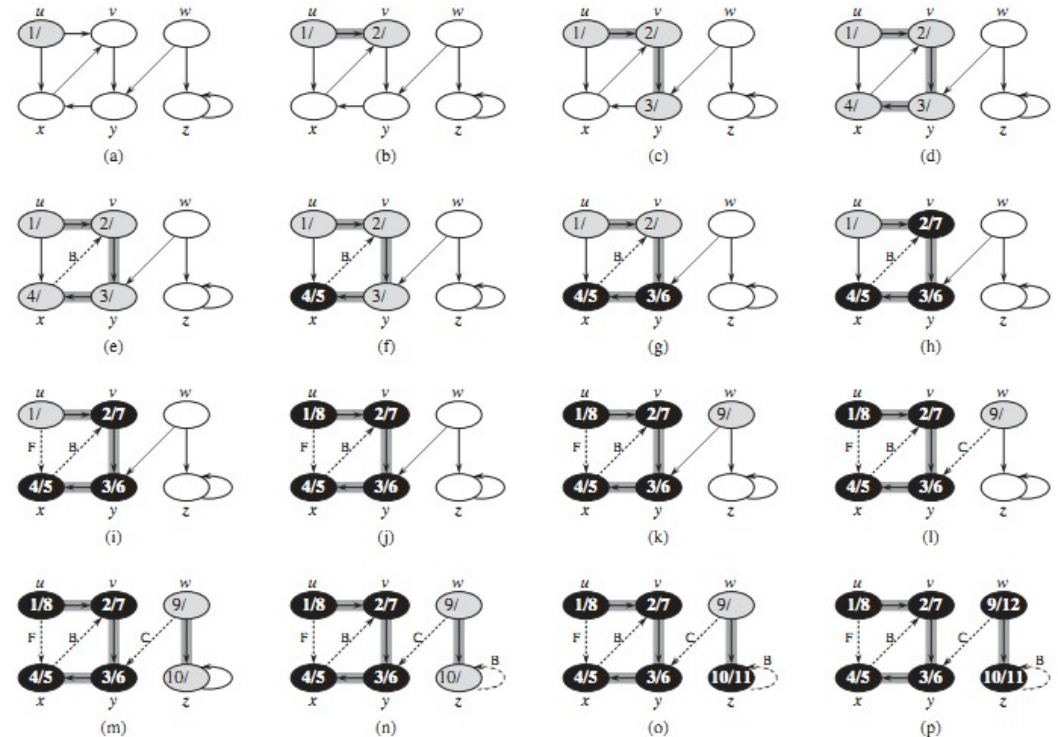
# DFS Algorithm

## DFS( $G$ )

1. for each vertex  $u \in G.V$
2.      $u.color = WHITE$
3.      $u.\pi = NIL$
4. time = 0
5. for each vertex  $u \in G.V$
6.     if  $u.color = WHITE$
7.         DFS-Visit( $G, u$ )

## DFS-Visit( $G, u$ )

1. time = time + 1
2.  $u.d = time$
3.  $u.color = GRAY$
4. for each vertex  $v \in G.Adj[u]$
5.     if  $v.color == WHITE$
6.          $v.\pi = u$
7.         DFS-Visit( $G, v$ )
8.  $u.color = BLACK$
9. time = time + 1
10.  $u.f = time$



**Figure 22.4** The progress of the depth-first-search algorithm DFS on a directed graph. As edges are explored by the algorithm, they are shown as either shaded (if they are tree edges) or dashed (otherwise). Nontree edges are labeled B, C, or F according to whether they are back, cross, or forward edges. Timestamps within vertices indicate discovery time/finishing times.