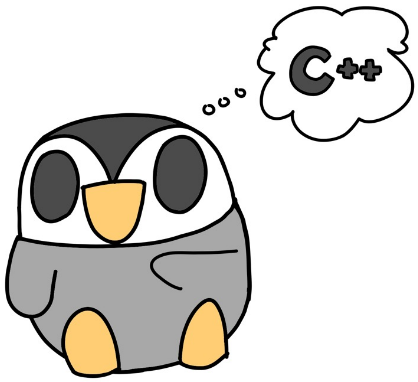
CS 225

Data Structures

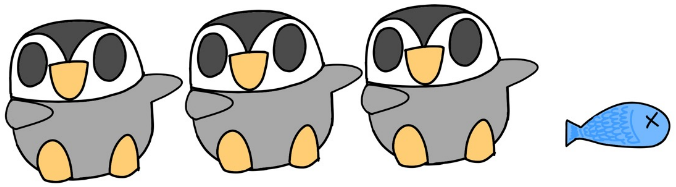
April 29 – The Story So Far…

G Carl Evans

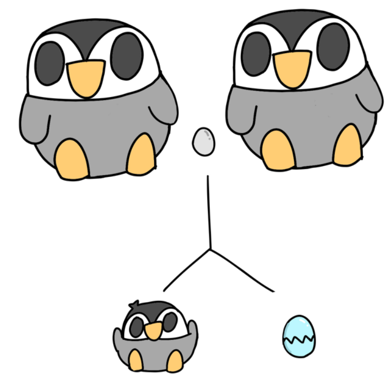
https://opportunities.cs.illinois.edu/


C++

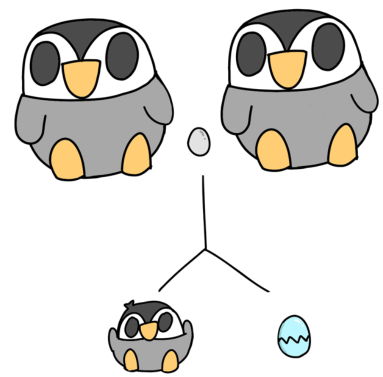
Lists



Trees

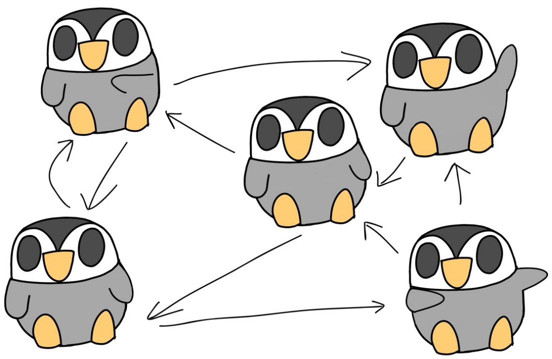


Huffman Trees



Disjoint Sets

Graphs



Hashing

Bloom Filters and MinHash

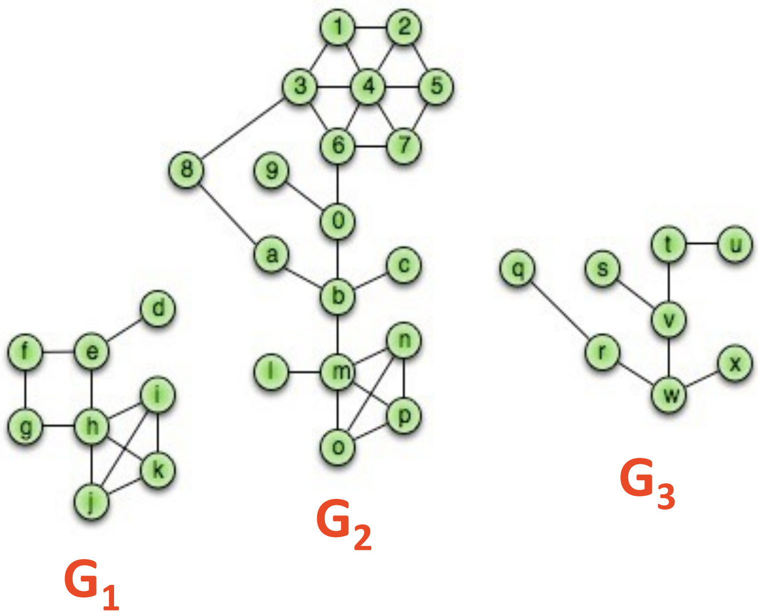
Final Exam

Remaining Slides by
Minghao Liu

Graph vocabulary

Graph vocabulary

A graph G is a tuple of a set of vertices V, and a set of edges E



$G = (V, E)$

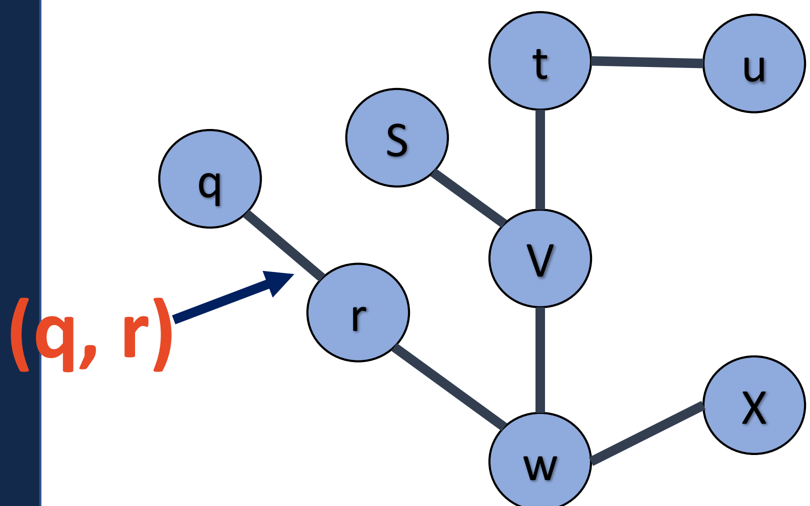
$|V| = n$ //number of vertices

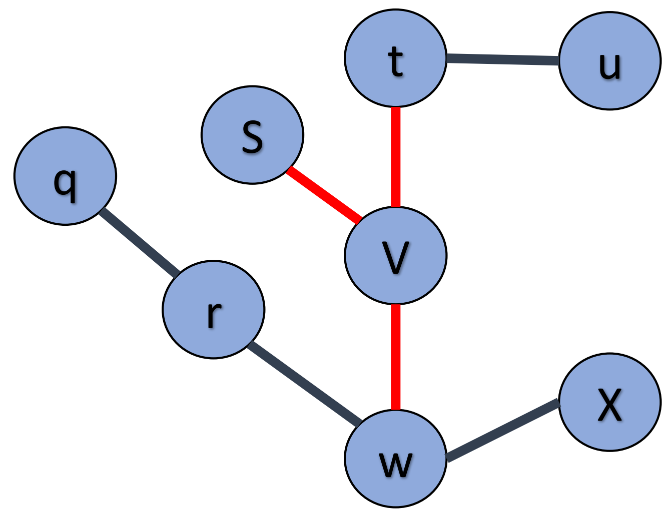
$|E| = m$ //number of edges

Graph vocabulary

We identify an edge by stating two vertices it connects.

- **Incident edges** → all edges that touch that node
  - $I(v) = \{\{x, v\}\ in\ E\}$

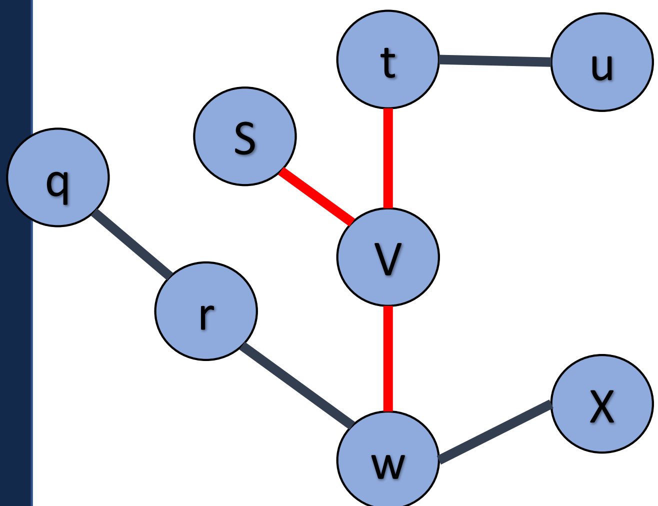




Incident edges for V are $(\boldsymbol{v}, \boldsymbol{s}), (\boldsymbol{v}, \boldsymbol{t}), (\boldsymbol{v}, \boldsymbol{w})$

Graph vocabulary

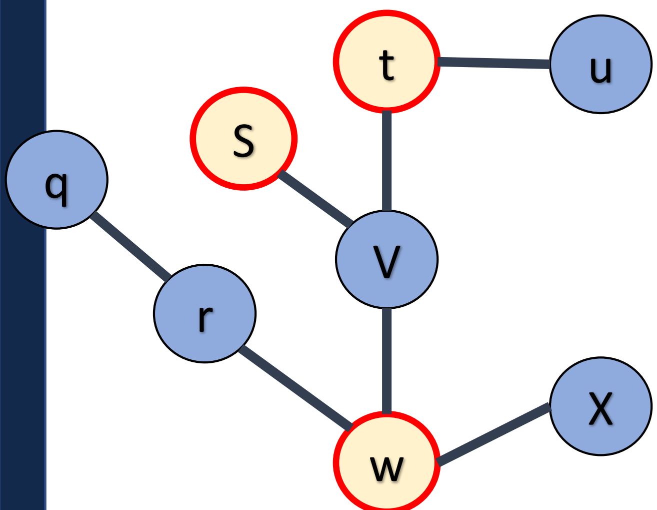
- **Degree** $\rightarrow$ the number of incident edges.
  - $Degree(v) \ = \ |I(v)|$



Degree(v) = 3

Graph vocabulary

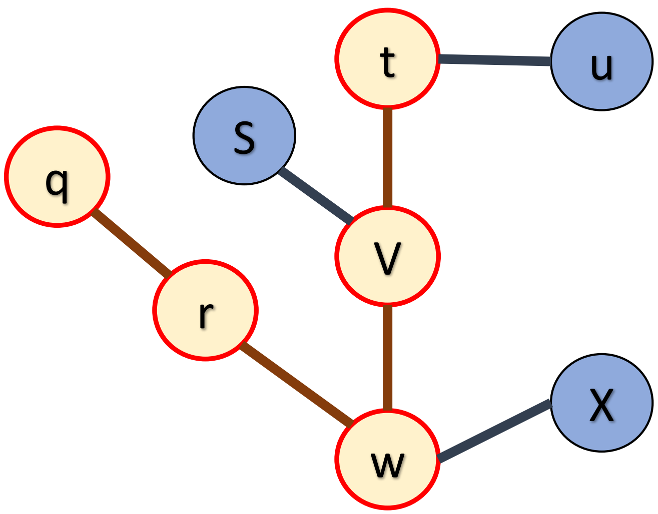
- **Adjacent vertex** → a vertex at the other end of the incident edge.
  - $A(v) = \{x: (x, v) in\ E\}$



$\boldsymbol{A(v) = \{s, w, t\}}$

Graph vocabulary

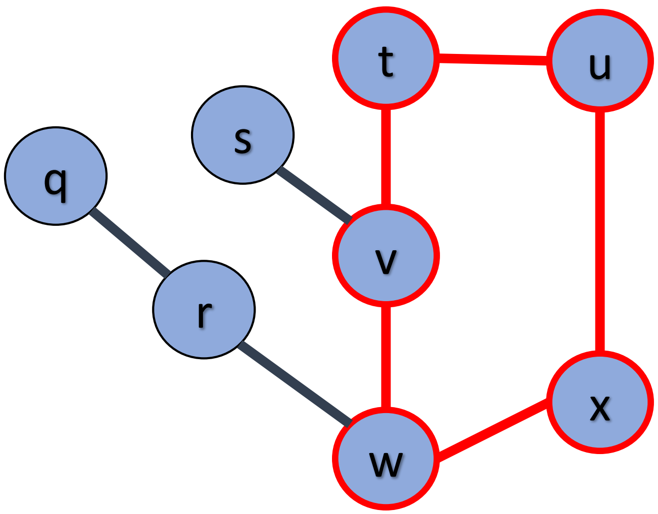
- **Path** → a sequence of vertices connected by edges.



Path from q to t is: $\{\boldsymbol{q}, \boldsymbol{r}, \boldsymbol{w}, \boldsymbol{v}, \boldsymbol{t}\}$

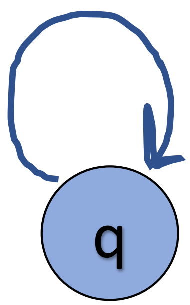
Graph vocabulary

- **Cycle** → a path with common beginning and end.

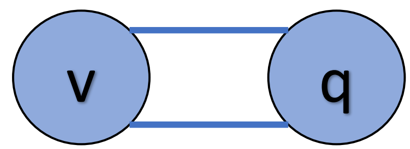


Graph vocabulary

- **Simple Graph** →A graph with **no** self loops and multi-edges



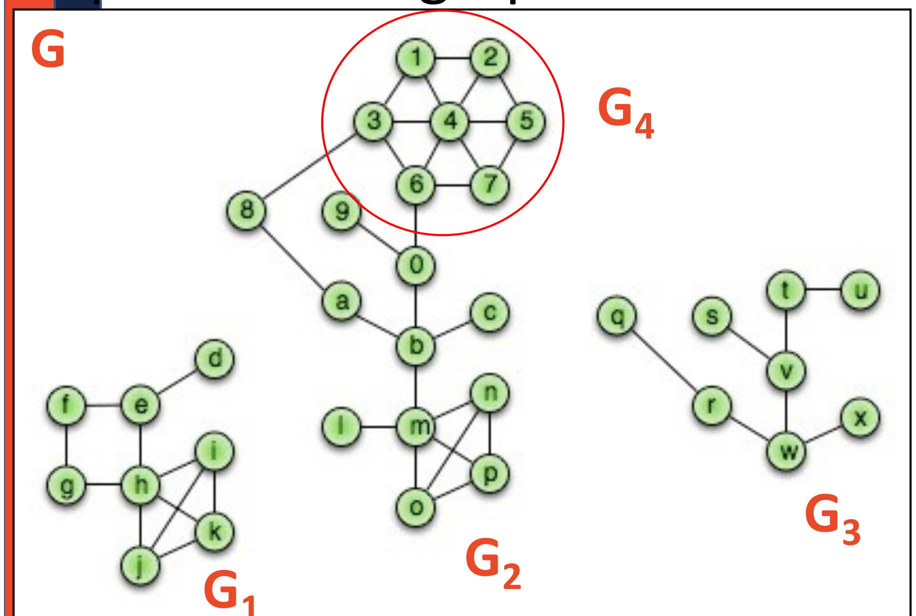
Self loop



Multi-edges

Graph vocabulary

- **Subgraph** →any subset of vertices such that every edge in the subgraph implies that both vertices that are incident to that edge are part of that graph



Subgraph(G):

G' = (V', E'):

V' ∈ V, E' ∈ E, and

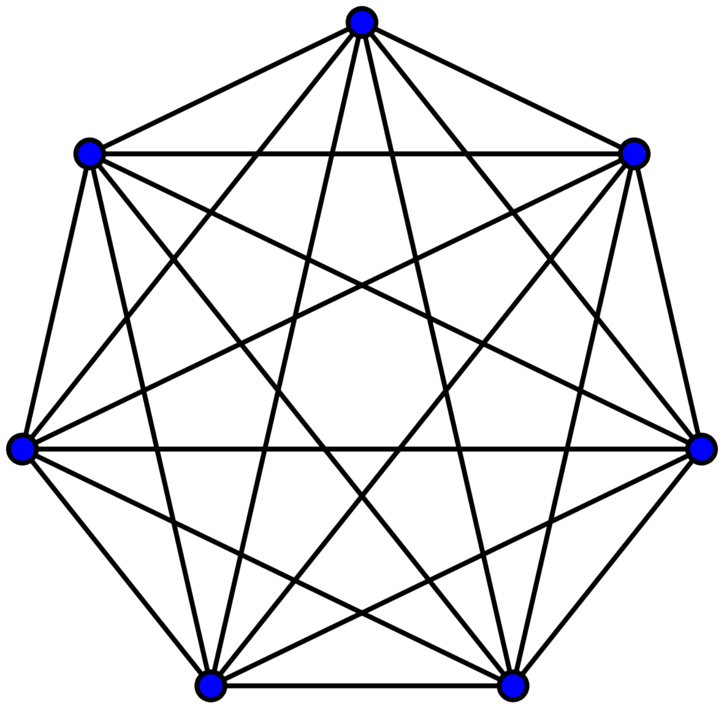
(u, v) ∈ E → u ∈ V', v ∈ V'

✓ G1 G2, G3 and G4 are subgraphs of G

✓ G4 is also a subgraph of G2

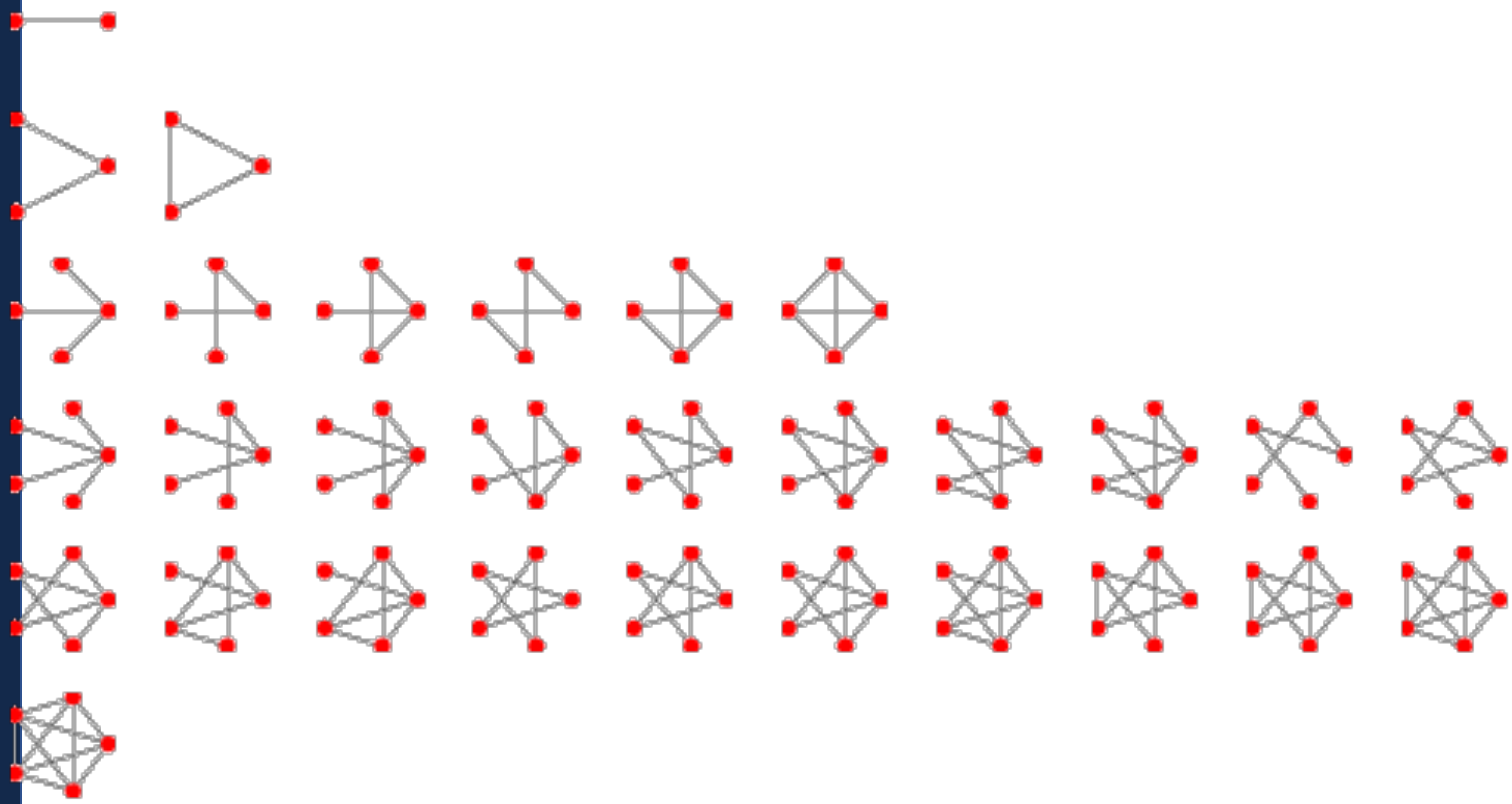
Graph vocabulary

- **Complete subgraph**: every two distinct vertices are adjacent.



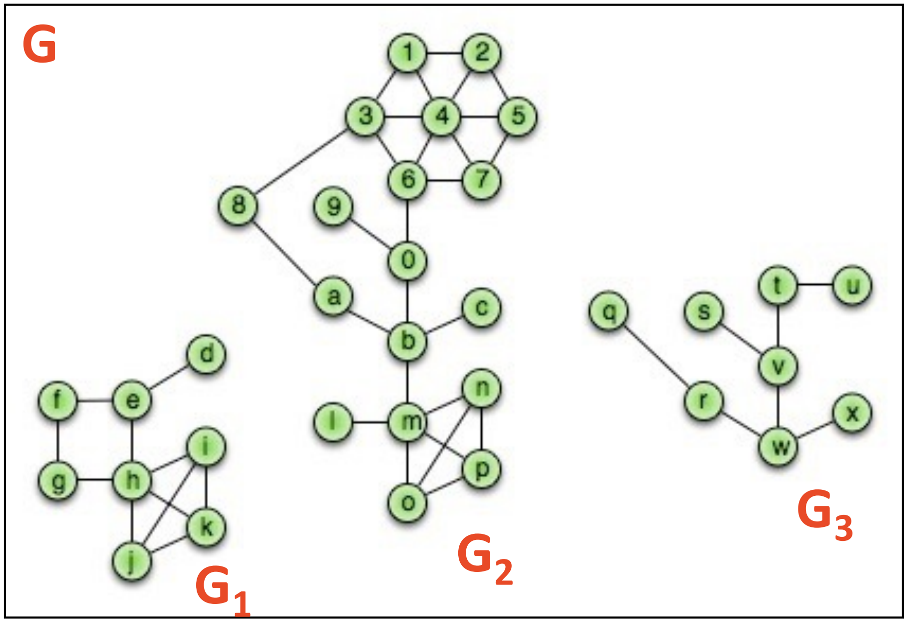
Graph vocabulary

- **Connected subgraph**: there is a path between every two vertices in the graph.



Graph vocabulary

- **Connected component**: a connected subgraph where non-of the vertices are connected to the rest of the graph.



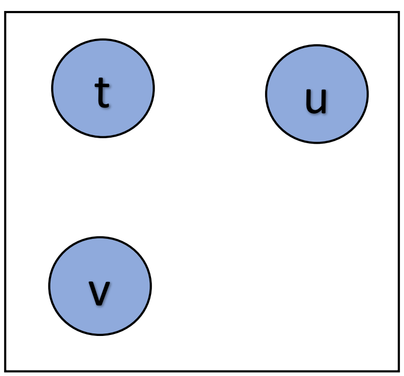
G1, G2 and G3 are connected components.

Properties of Graph

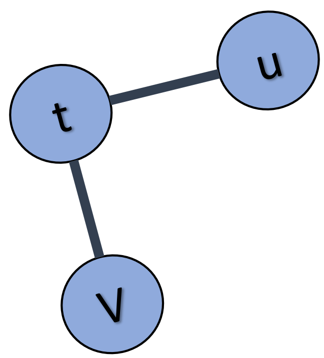
Properties of Graph

Running times are often reported by n (the number of vertices) but often depend on m (the number of edges).

- **Minimum number of edges (m):**
  - Not Connected: m = 0
  - Connected: m = n-1



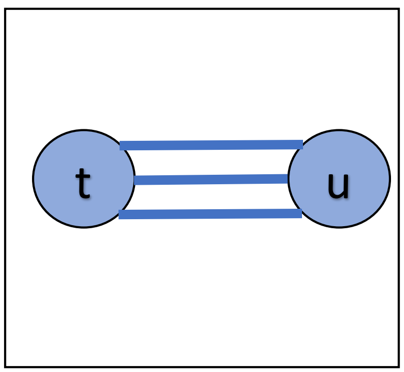
Example 1.

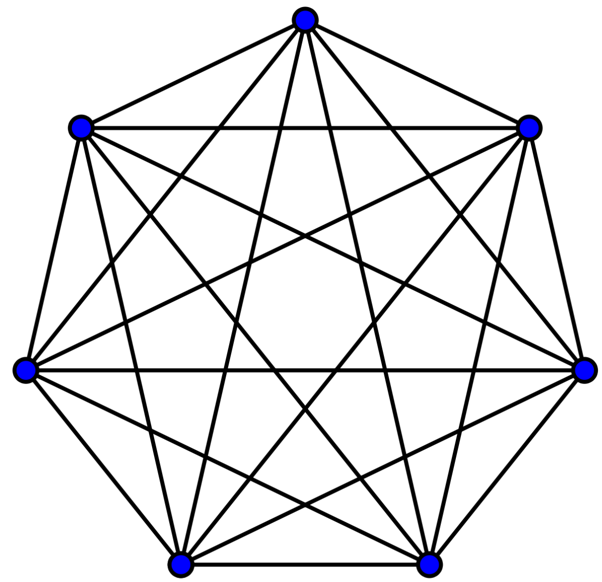


Example 2.

Properties of Graph

- **Maximum edges (m):**
  - Not simple**: m = ∞,** since we can have multiple edges between vertices.
  - Simple: $\frac{n(n-1)}{2}$

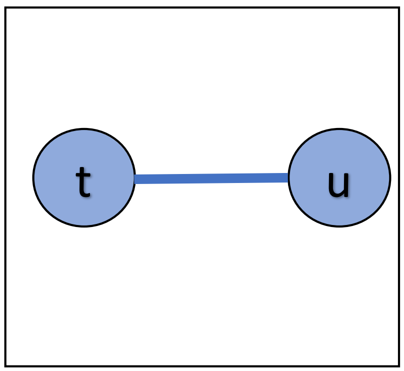




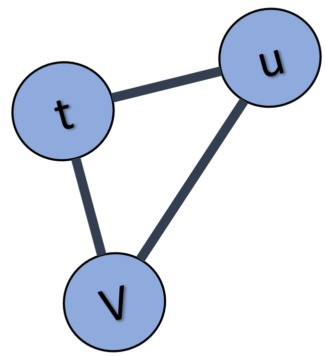
Properties of Graph

Sum of all degrees of all vertices:

$$\sum_{v \epsilon V} \deg(v) = 2 * m$$



$$\sum_{v \epsilon V} \deg(v) = 2$$

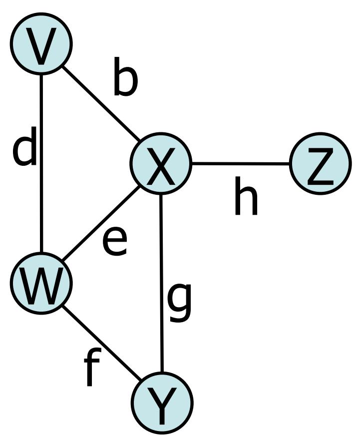


$$\sum_{v \epsilon V} \deg(v) = 6$$

Graph ADT

Graph ADT

Data:
- **Vertices**
- **Edges**
- **Some data structure maintaining the structure between vertices and edges.**

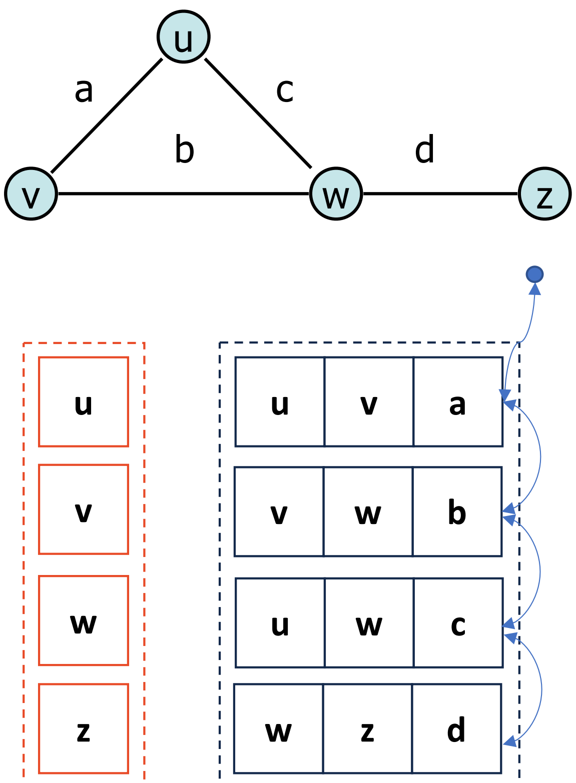


Functions:
- **insertVertex(K key);**
- **insertEdge(Vertex v1, Vertex v2, K key);**

- **removeVertex(Vertex v);**
- **removeEdge(Vertex v1, Vertex v2);**

- **incidentEdges(Vertex v);**
- **areAdjacent(Vertex v1, Vertex v2);**

Graph Implementation: Edge List



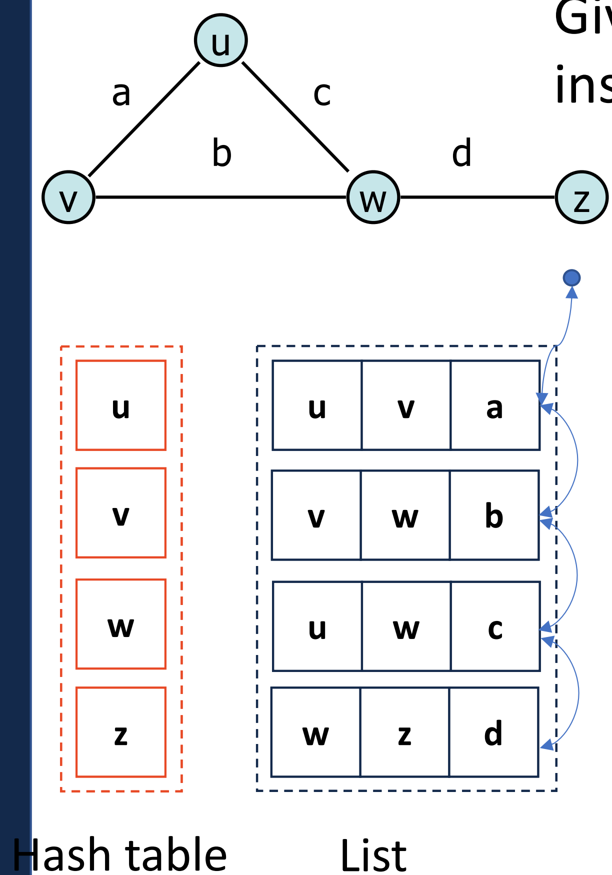
Vertex Collection:

- Hash table: find, insert and remove takes O(1) time

Edge Collection:

- Linked list

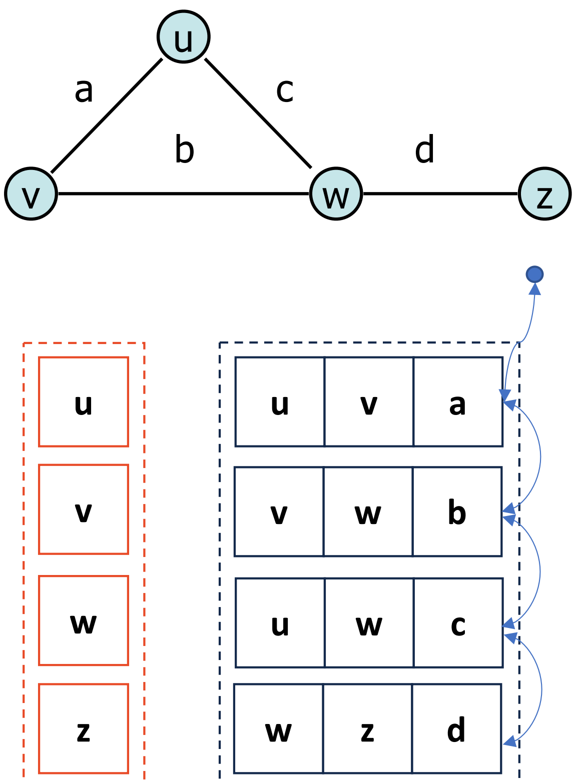
Graph Implementation: Edge List



Given we use list for edges, what is the running time of insertVertex and removeVertex?

- **insertVertex** take O(1) time, since inserting into hash table takes O(1) time.
- **removeVertex** - means removing vertex from hash table and removing corresponding edges from the list. Running time will be: O(1) + O(m)=O(m)

Graph Implementation: Edge List



insertVertex(K key) – O(1)

removeVertex(Vertex v) – O(m)

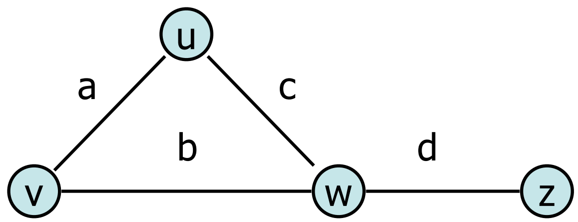
areAdjacent(Vertex v1, Vertex v2) – O(m)

incidentEdges(Vertex v) – O(m)

insertEdge(Vertex v1, Vertex v2, K key) – O(1)

The relationship between number of nodes and the number of edges can be n^2; which means that O(m) could in fact be $O(n^2)$

Graph Implementation: Adjacency Matrix



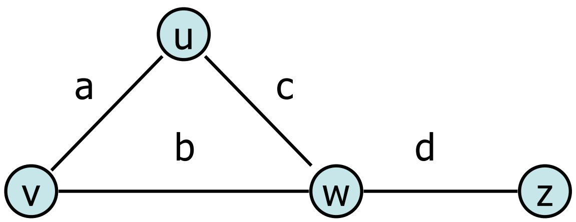
Space complexity $O(n^2)$

u
v
w
z

u	v	a
v	w	b
u	w	c
w	z	d

	u	v	w	z
u	-	1	1	0
v		-	1	0
w			-	1
z				-

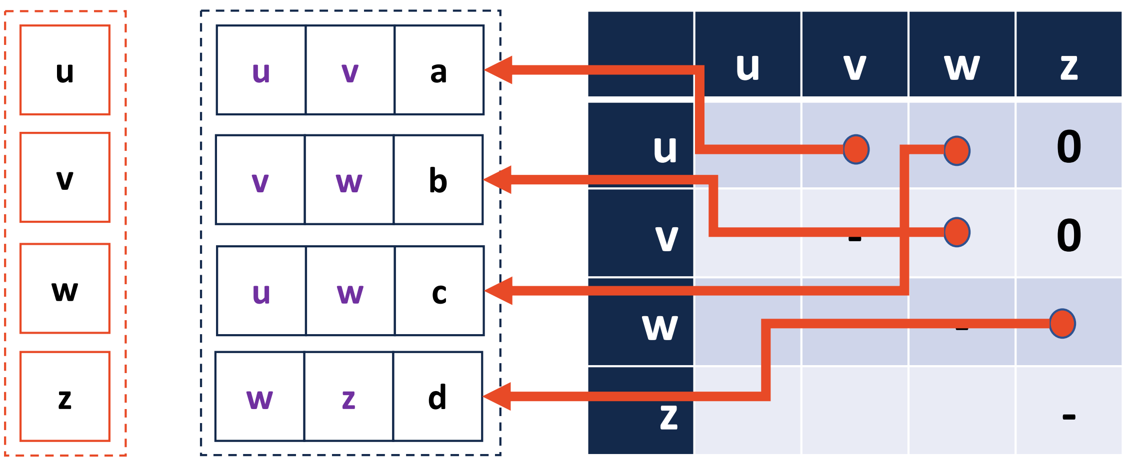
Graph Implementation: Adjacency Matrix



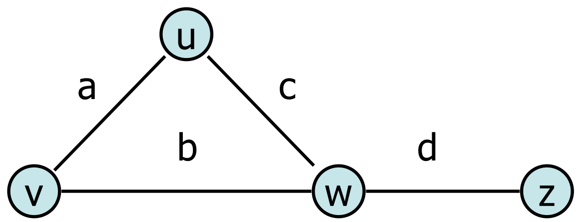
insertVertex(Vertex v):

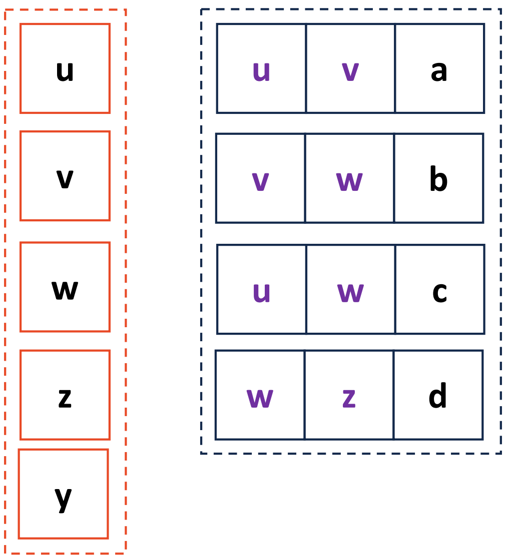
- **Add to the hash table: O(1)**
- **Add to adj. matrix (resize once in n element):**

$$\mathbf{O(n)^*} = \frac{\boldsymbol{O(n^2)}}{\boldsymbol{n}}$$



Graph Implementation: Adjacency Matrix





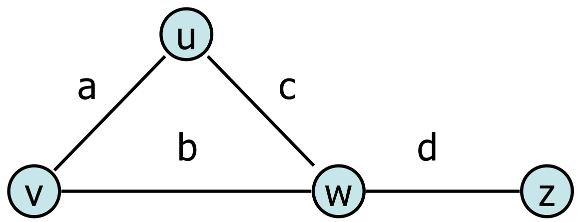
insertVertex(y):

- **Add to the hash table: O(1)**
- **Add to adj. matrix (resize once in n element):**

$$\mathbf{O(n)^*} = \frac{O(n^2)}{n}$$

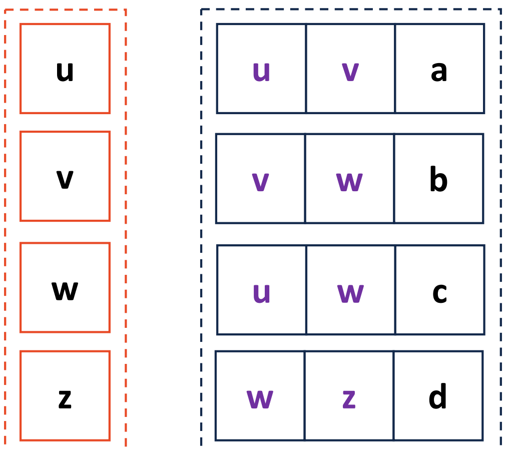
	u	v	w	z	y			
u	-	●	●	0				
v		-	●	0				
w			-	●				
z				-				
y					-			

Graph Implementation: Adjacency Matrix



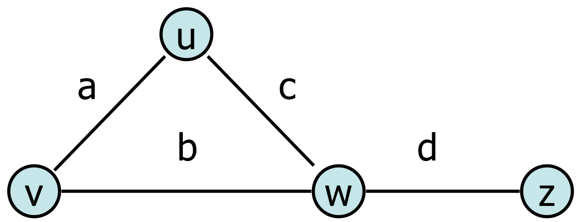
removeVertex(Vertex v) – O(n):

- **Remove from the hash table: O(1)**
- **Removing edges:**
  - **O(n) to check elements in row & column and if pointer exist remove the edge (O(1) for each) – O(n)**



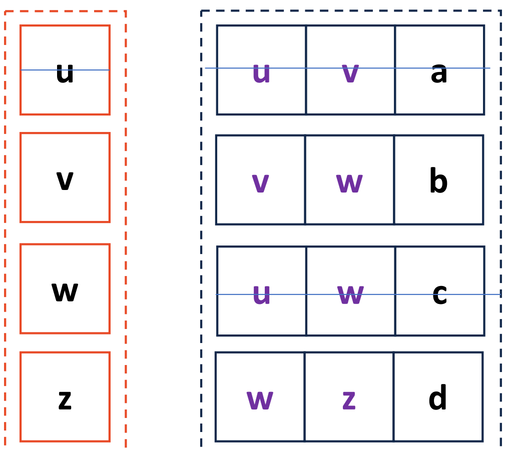
	u	v	w	z
u	-	●	●	0
v		-	●	0
w			-	●
z				-

Graph Implementation: Adjacency Matrix



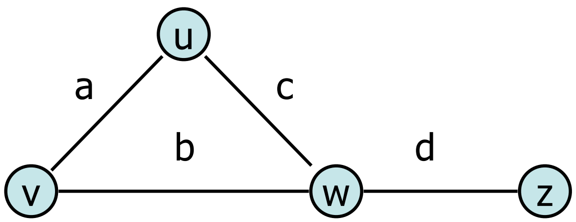
removeVertex(Vertex v) – O(n):

- **Remove from the hash table: O(1)**
- **Removing edges:**
  - **O(n) to check elements in row & column and if pointer exist remove the edge (O(1) for each remove) – O(n)**
- Repair structure of the table - …



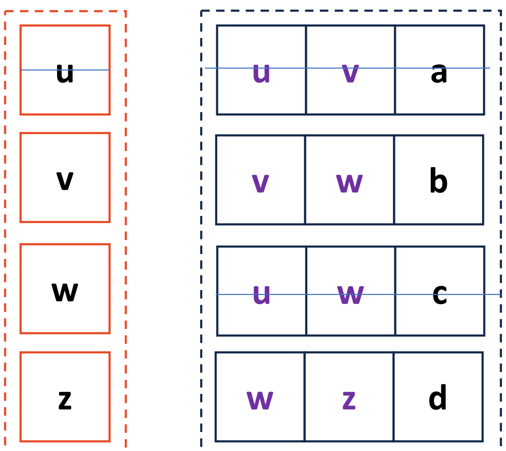
		v	w	z
v		-	●	0
w			-	●
z				-

Graph Implementation: Adjacency Matrix



removeVertex(Vertex v) – O(n):

- **Remove from the hash table: O(1)**
- **Removing edges:**
  - **O(n) to check elements in row & column and if pointer exist remove the edge (O(1) for each remove) – O(n)**
  - Repair structure of the table - O(n)

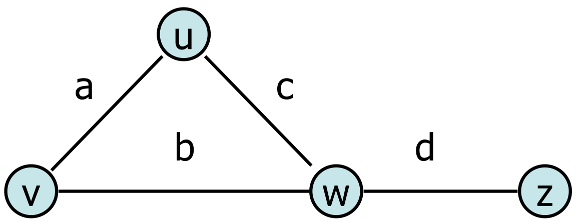


	z	v	w	
z	-	0	●	
v		-	●	
w			-	

Graph Implementation: Adjacency Matrix

incidentEdges(Vertex v) – O(n):

- Run through row/col $\rightarrow 2n \equiv O(n)$

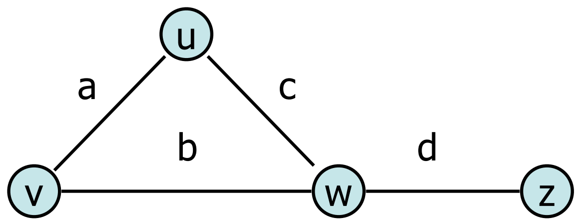


u
v
w
z

u	v	a
v	w	b
u	w	c
w	z	d

	u	v	w	z
u	-	●	●	0
v		-	●	0
w			-	●
z				-

Graph Implementation: Adjacency Matrix



areAdjacent(Vertex v1, Vertex v2) – O(1):

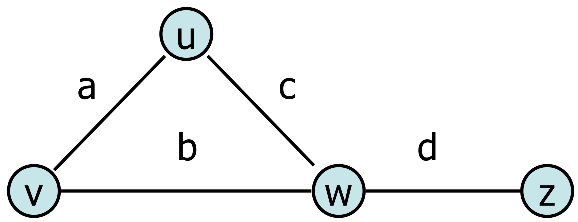
- Check the specific element in the adj. matrix – O(1)

u
v
w
z

u	v	a
v	w	b
u	w	c
w	z	d

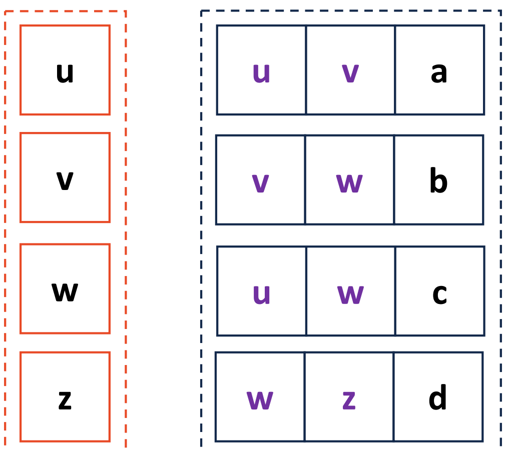
	u	v	w	z
u	-	●	●	0
v		-	●	0
w			-	●
z				-

Graph Implementation: Adjacency Matrix



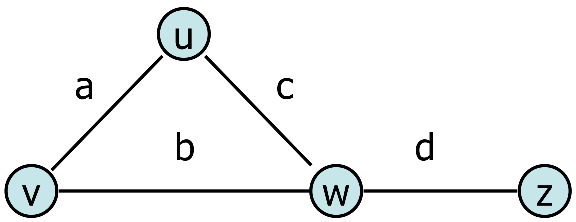
insertEdge(Vertex v1, Vertex v2, K key) – O(1):

- **Add edge to the edge list – O(1)**
- **update the pointer for the edge in adj. matrix – O(1)**



	u	v	w	z
u	-	●	●	0
v		-	●	0
w			-	●
z				-

Graph Implementation: Adjacency Matrix



insertEdge(u, z, key) – O(1):

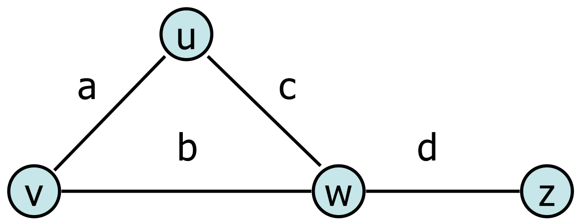
- **Add edge to the edge list – O(1)**
- **update the pointer for the edge in adj. matrix – O(1)**

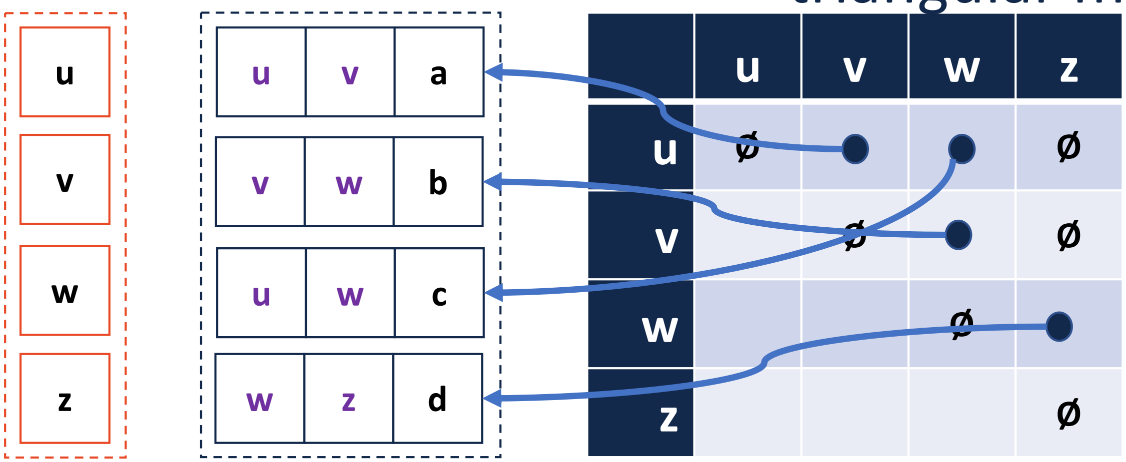
u
v
w
z

u	z	d
u	v	a
v	w	b
u	w	c
w	z	d

	u	v	w	z
u	-	●	●	●
v		-	●	0
w			-	●
z				-

Adjacency Matrix

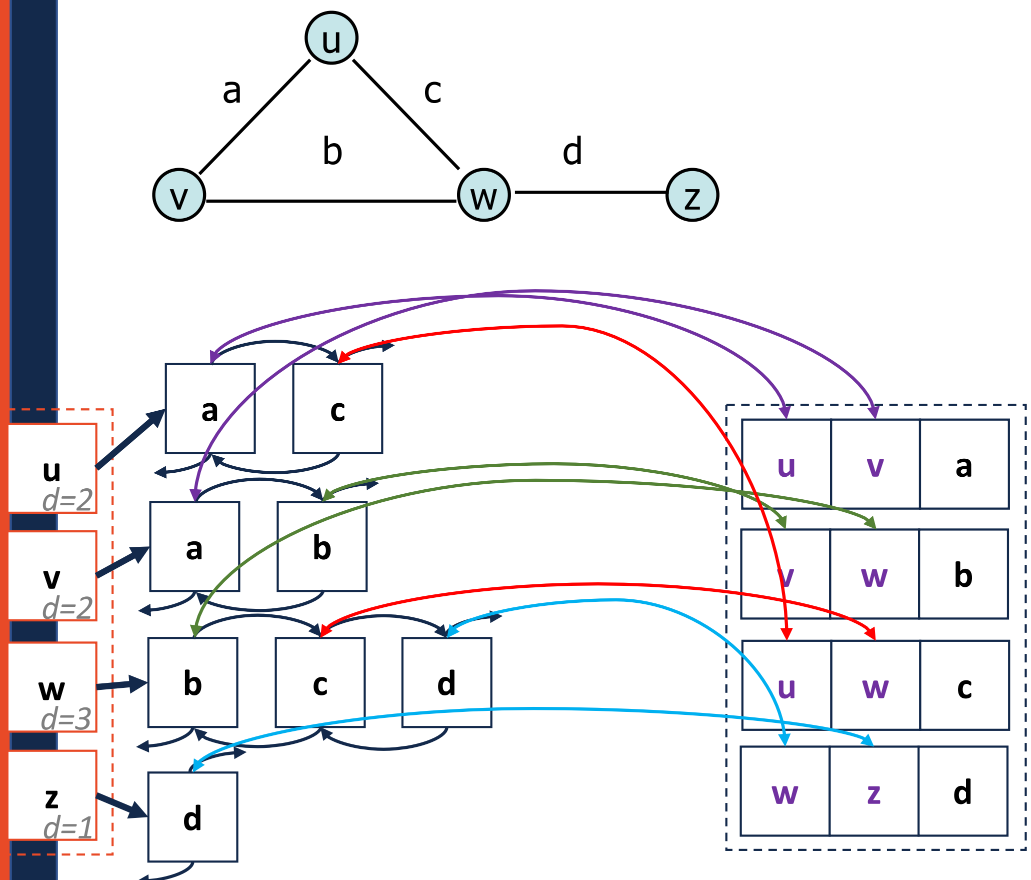




Key Ideas:

- Given a vertex, O(1) lookup in vertex list
- Given a pair of vertices (an edge), O(1) lookup in the matrix
- Undirected graphs can use an upper triangular matrix

Adjacency List



Key ideas:

-Given a vertex, O(1) lookup in vertex list;

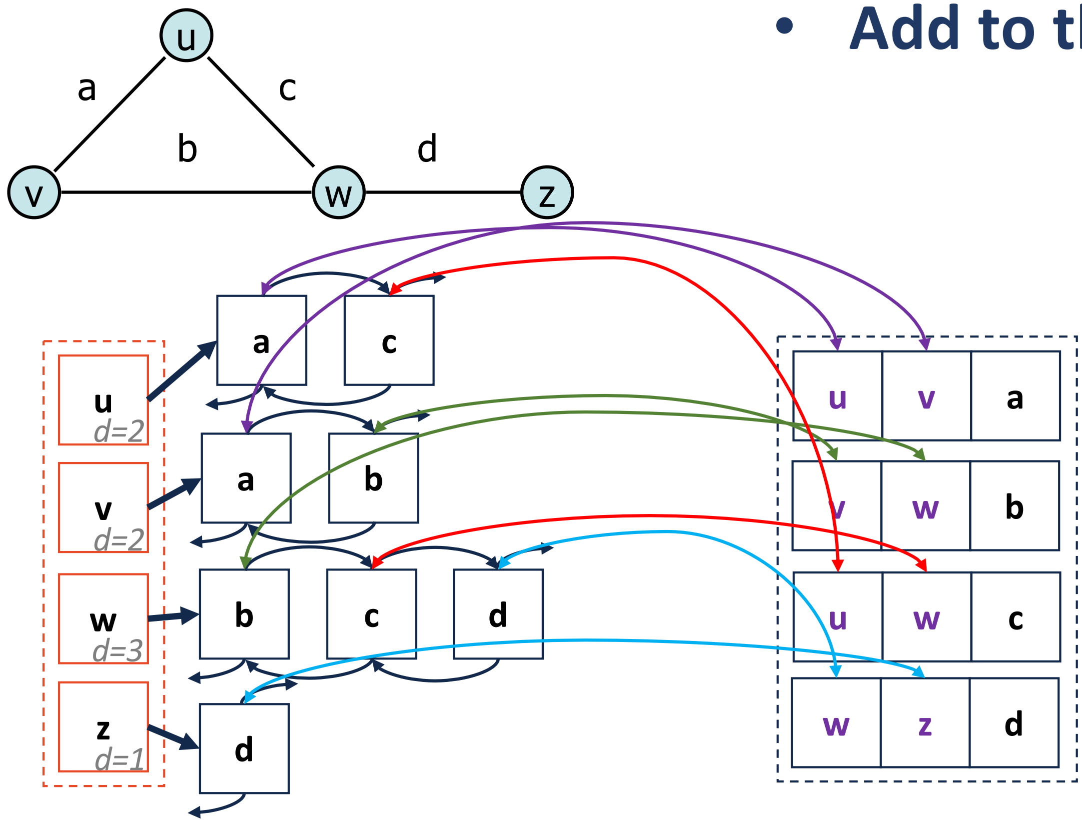
-Vertex list maintains a count of incident edges, or deg(v);

-Vertex list contains a doubly-linked adjacency list;

-O(1) access to the adjacent vertex's node in adjacency list (via the edge list);

-Many operations run in O(deg(v)), and deg(v) ≤ n-1, O(n).

Adjacency List



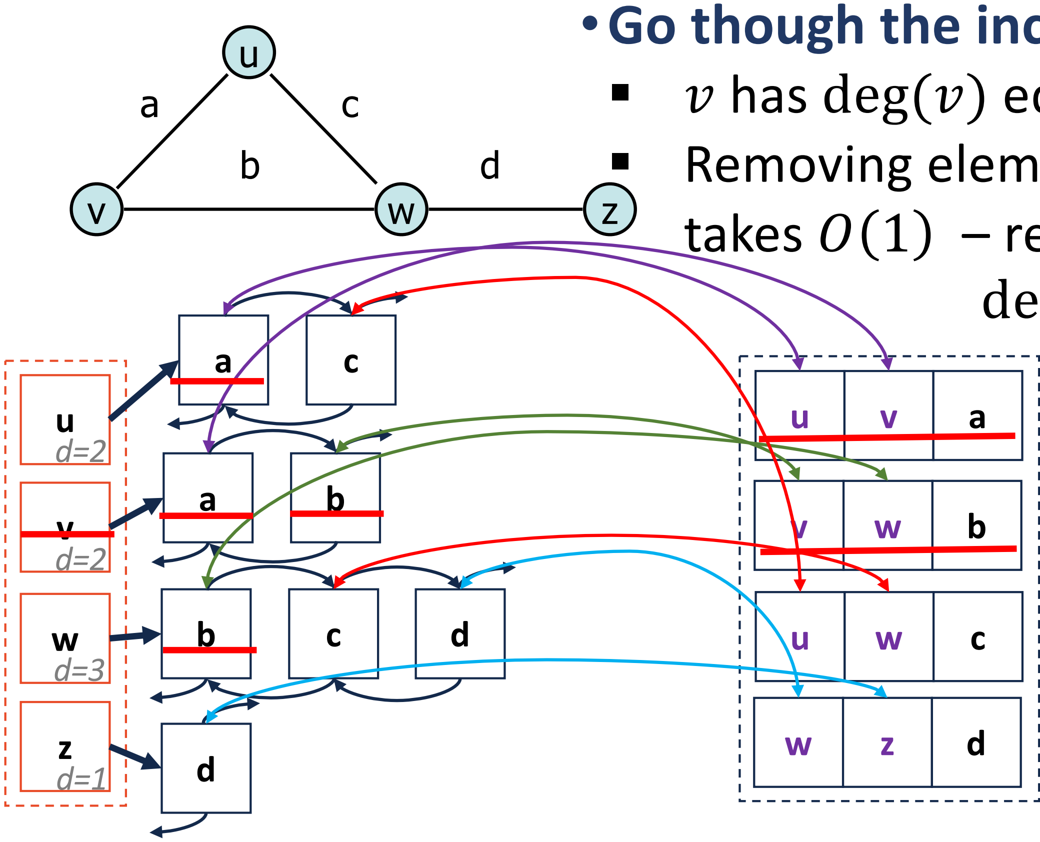
insertVertex(K key) – O(1):

- **Add to the hash table: O(1)**

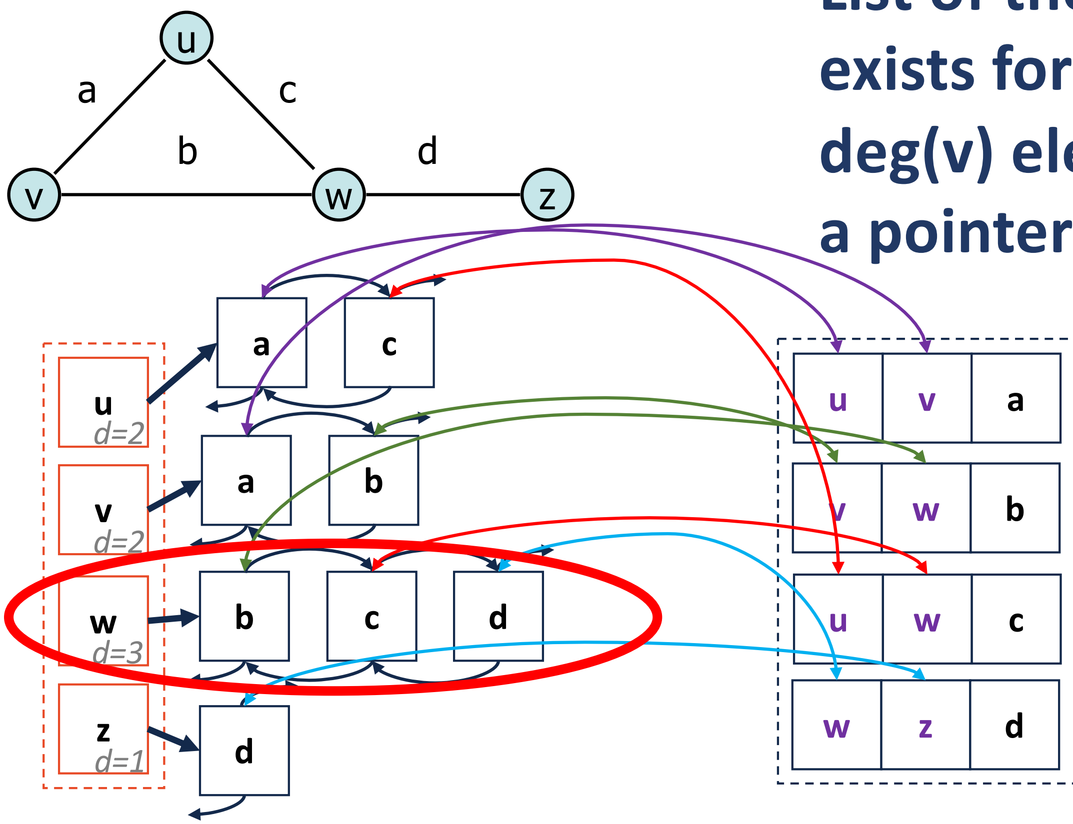
Adjacency List

removeVertex(Vertex v) – O(deg(v)):

- **Remove v from the hash table: O(1)**
- **Go though the incident list and remove all the edges:**
  - v has $\deg(v)$ edges in the list;
  - Removing element from the adj. lists and edge list takes $O(1)$ – removing all the edges will take $\deg(v) * O(1)$



Adjacency List

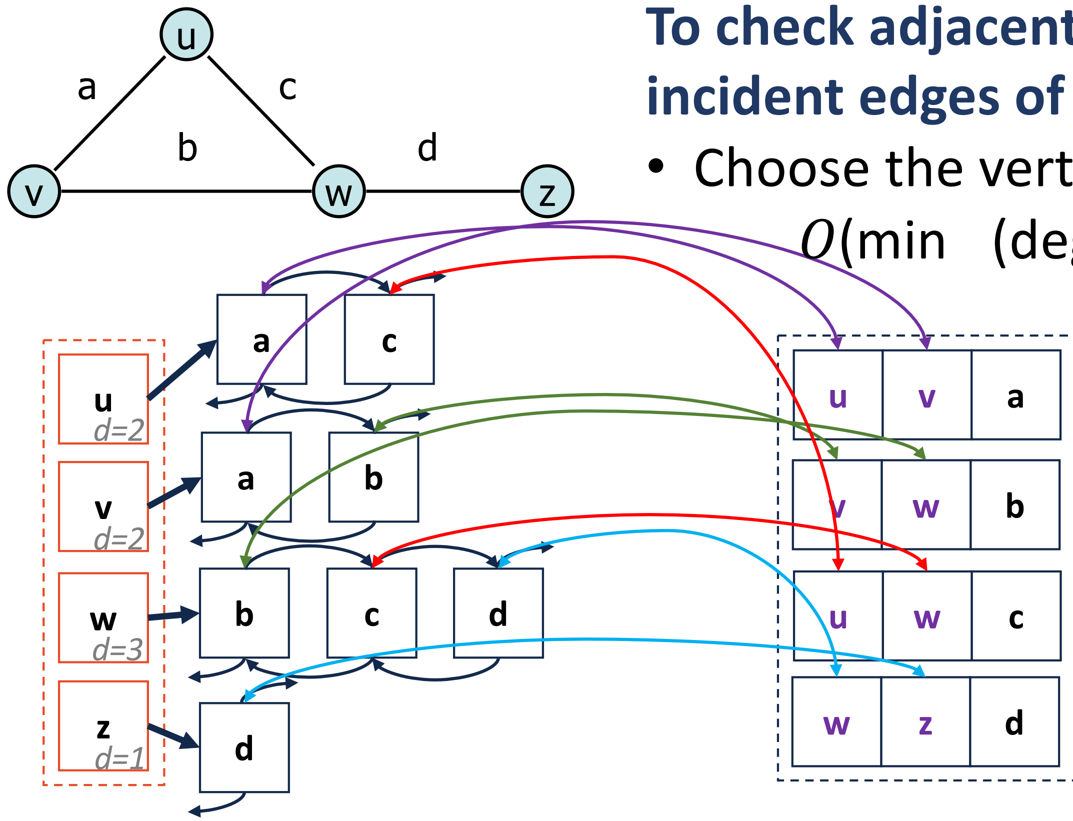


incidentEdges(Vertex v) – O(1):

- **List of the incident edges already exists for each vertex v and it has deg(v) elements but we can return a pointer to the front of the list.**

Adjacency List

areAdjacent(Vertex v1, Vertex v2) - $O(\min(\deg(v1), \deg(v2)))$



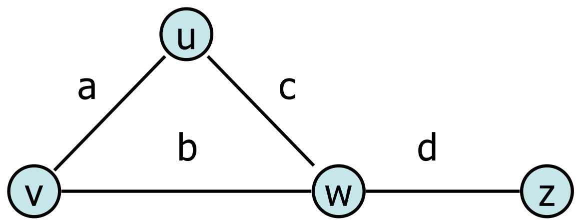
To check adjacent nodes, we need to go through incident edges of one of the vertices:

- Choose the vertex with smaller list:

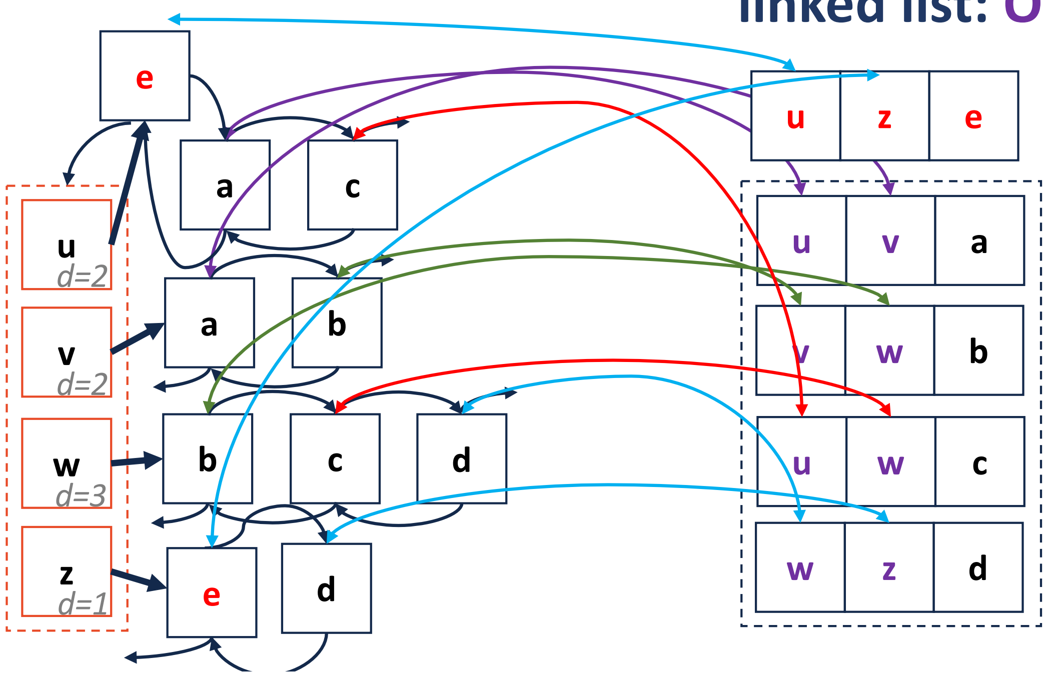
$$O(\min(\deg(v1), \deg(v2)))$$

Adjacency List

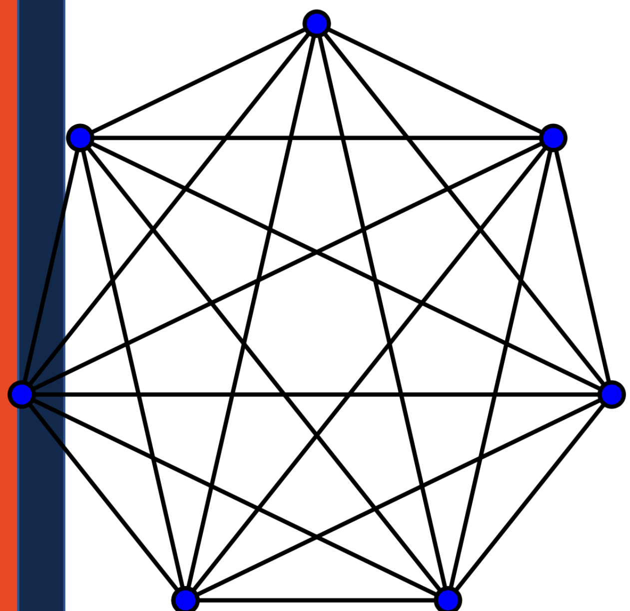
insertEdge(Vertex v1, Vertex v2, K key) - O(1)

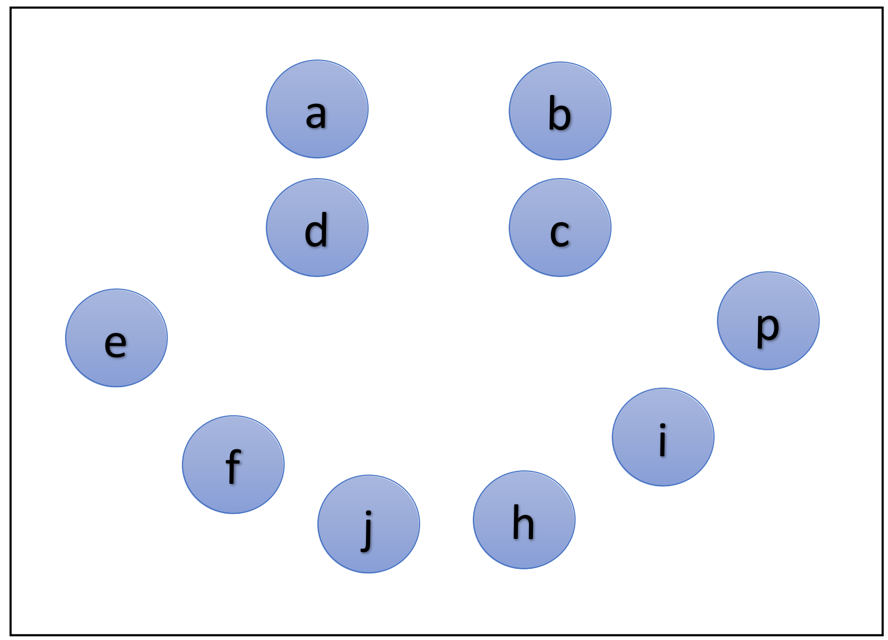


- insert edge in edge list: O(1)
- Find v1 in hashtable and insert edge in v1's linked list: O(1)
- Find v2 in hashtable and insert edge v2's linked list: O(1)



Better running time: O(n) or O(m)?





There is no clear winner!

Expressed as O(f)	Edge List	Adjacency Matrix	Adjacency List
Space	**n+m**	**n^2**	**n+m**
insertVertex(v)	**1**	**n**	**1**
removeVertex(v)	**m**	**n**	**deg(v)**
insertEdge(v, w, k)	**1**	**1**	**1**
removeEdge(v, w)	**1**	**1**	**1**
incidentEdges(v)	**m**	**n**	**deg(v)**
areAdjacent(v, w)	**m**	**1**	**min(deg(v), deg(w))**

Expressed as O(f)	Edge List	Adjacency Matrix	Adjacency List
Space	**n+m**	**n^2**	**n+m**
insertVertex(v)	**1 ☺**	**n**	**1 ☺**
removeVertex(v)	**m**	**n**	**deg(v) ☺**
insertEdge(v, w, k)	**1 ☺**	**1 ☺**	**1 ☺**
removeEdge(v, w)	**1 ☺**	**1 ☺**	**1 ☺**
incidentEdges(v)	**m**	**n**	**deg(v) ☺**
areAdjacent(v, w)	**m**	**1 ☺**	**min(deg(v), deg(w))**

Use cases:

Sparse graphs

The graph is not connected →

$$m < n \Rightarrow \deg(v) < n$$

Advantage to use: adjacency list

Dense graphs

The graph is almost fully connected →

$$m \sim n^2, \quad \mathrm{degree(v)} \sim \mathrm{n}$$

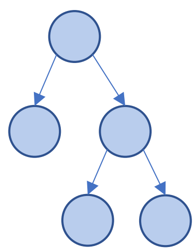
We can use either adjacency list or adjacency matrix.
It depends on the operations we need (areAdjacent or insertVertex).

Traversal:

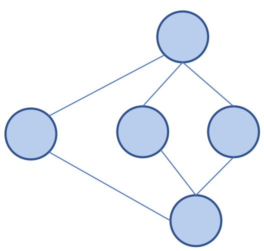
Objective: Visit every vertex and every edge in the graph.

Purpose: Search for interesting sub-structures in the graph.

Tree traversal vs Graph traversal



- Ordered
- Obvious Start
- Notion of doneness

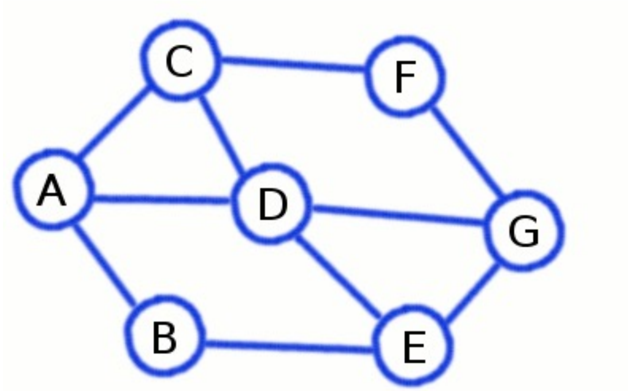


- Any order
- Arb. Starting point
- No notion of completeness

BFS

- ✓ Breadth-first search (BFS) is an algorithm for traversing or searching tree or graph data structures.

- ✓ It starts from some arbitrary node of a graph and explores all the neighbor nodes at the present depth prior to moving on to the nodes at the next depth level.



Algorithm setup:

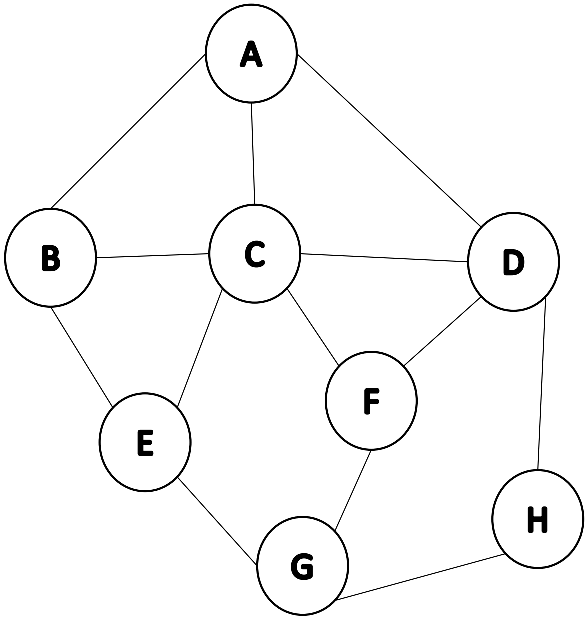
Label each edge:

- Discovery edge (bolded) or
- Cross edge (dashed)

Table of vertices with following features:

- Vertex name - key
- Boolean flag - visited
- Distance to the vertex
- Predecessor
- List of adjacent vertices

- Queue

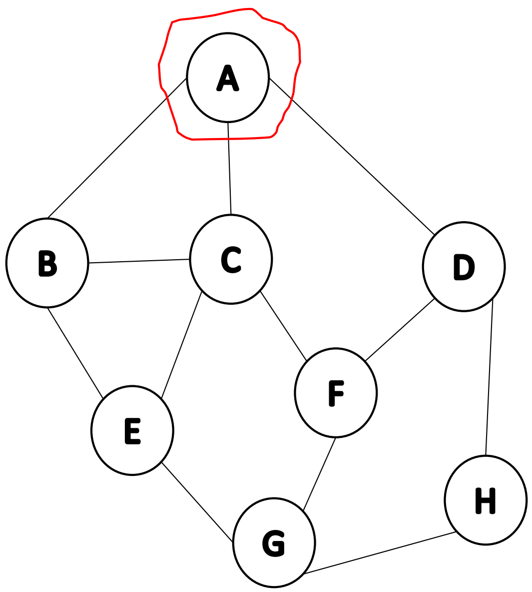


Queue

key	visited	dist.	pred.	adj. vertices
A				C B D
B				A E C
C				A B D E F
D				A C F H
E				B C G
F				C D G
G				E F H
H				D G

- Chose a starting point, add it to the queue, set its visited flag in the table, set distance value to 0, and predecessor value to null.

Starting point - A

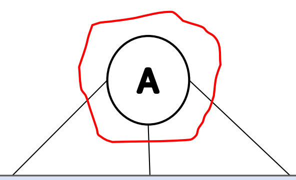


Queue

A

key	visited	dist.	pred.	adj. vertices
A	√	0	null	C B D
B				A E C
C				A B D E F
D				A C F H
E				B C G
F				C D G
G				E F H
H				D G

Starting point - A



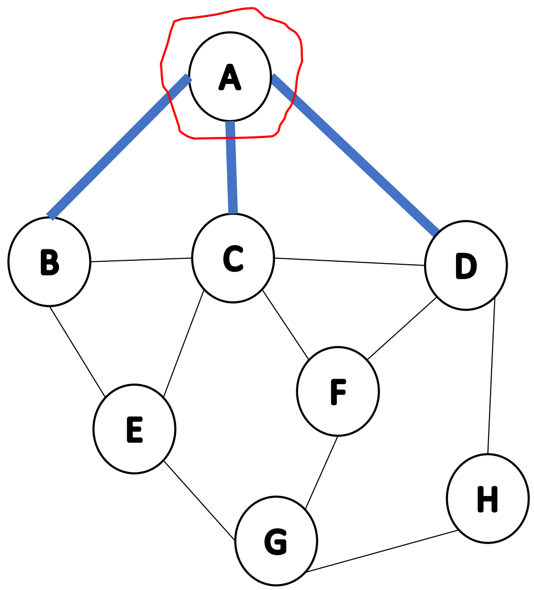
key	visited	dist.	pred.	adj. vertices
A	✓	0	null	C B D
B				A E C

Dequeue and loop over the adjacent vertices of the dequeued element.
Examine each adjacent vertex:

- **If the vertex has not been visited**, mark the edge to the vertex as discovery edge; update it’s visited flag, distance, and predecessor, and add the vertex to the queue.
- **Otherwise if the edge is not explored** yet just mark the edge as cross edge and move on to the next vertex.

We will dequeue A and examine vertices C, B, and D.

Starting point - A

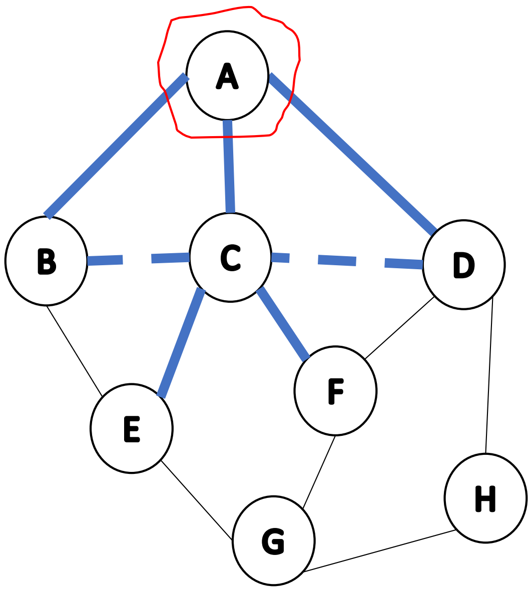


Queue

~~A~~	C	B	D

key	visited	dist.	pred.	adj. vertices
A	√	0	null	C B D
B	√	1	A	A E C
C	√	1	A	A B D E F
D	√	1	A	A C F H
E				B C G
F				C D G
G				E F H
H				D G

Starting point - A

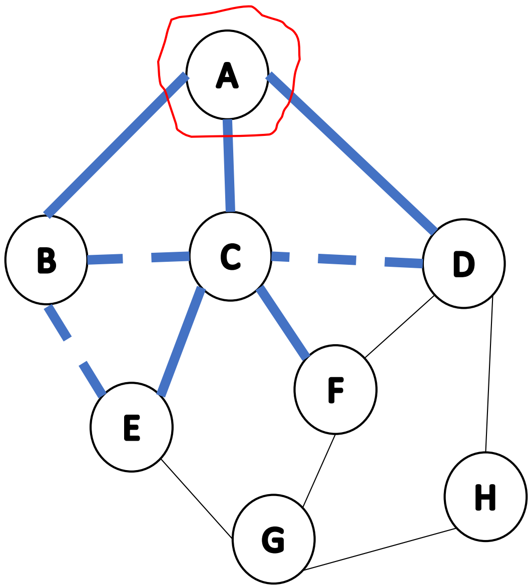


Queue

~~A~~	~~C~~	B	D	E	F

key	visited	dist.	pred.	adj. vertices
A	√	0	null	C B D
B	√	1	A	A E C
C	√	1	A	A B D E F
D	√	1	A	A C F H
E	√	2	C	B C G
F	√	2	C	C D G
G				E F H
H				D G

Starting point - A

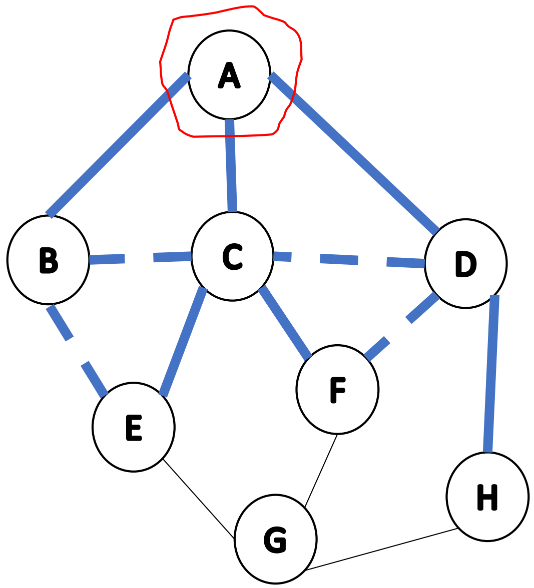


Queue

~~A~~	~~C~~	~~B~~	D	E	F

key	visited	dist.	pred.	adj. vertices
A	√	0	null	C B D
B	√	1	A	A E C
C	√	1	A	A B D E F
D	√	1	A	A C F H
E	√	2	C	B C G
F	√	2	C	C D G
G				E F H
H				D G

Starting point - A

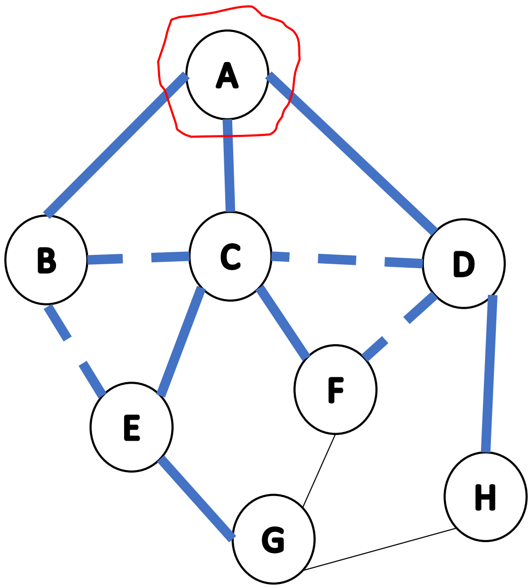


Queue

~~A~~	~~C~~	~~B~~	~~D~~	E	F	H

key	visited	dist.	pred.	adj. vertices
A	√	0	null	C B D
B	√	1	A	A E C
C	√	1	A	A B D E F
D	√	1	A	A C F H
E	√	2	C	B C G
F	√	2	C	C D G
G				E F H
H	√	2	D	D G

Starting point - A

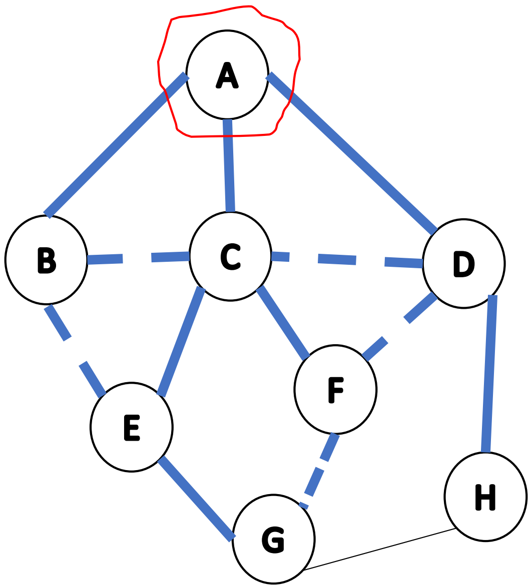


Queue

~~A~~	~~C~~	~~B~~	~~D~~	~~E~~	F	H	G

key	visited	dist.	pred.	adj. vertices
A	√	0	null	C B D
B	√	1	A	A E C
C	√	1	A	A B D E F
D	√	1	A	A C F H
E	√	2	C	B C G
F	√	2	C	C D G
G	√	3	E	E F H
H	√	2	D	D G

Starting point - A

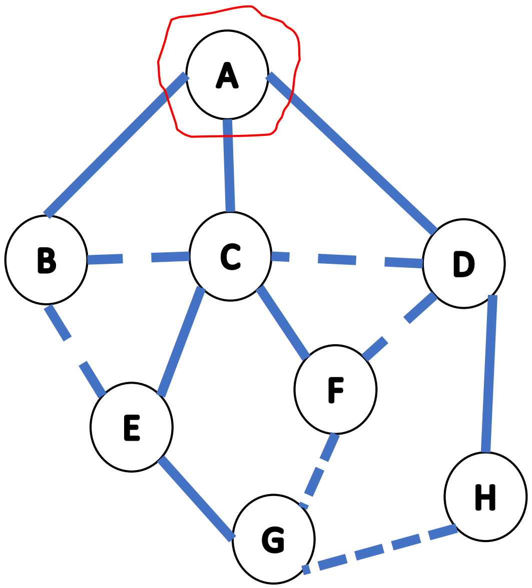


Queue

~~A~~	~~C~~	~~B~~	~~D~~	~~E~~	~~F~~	**H**	**G**

key	visited	dist.	pred.	adj. vertices
A	√	0	null	C B D
B	√	1	A	A E C
C	√	1	A	A B D E F
D	√	1	A	A C F H
E	√	2	C	B C G
F	√	2	C	C D G
G	√	3	E	E F H
H	√	2	D	D G

Starting point - A

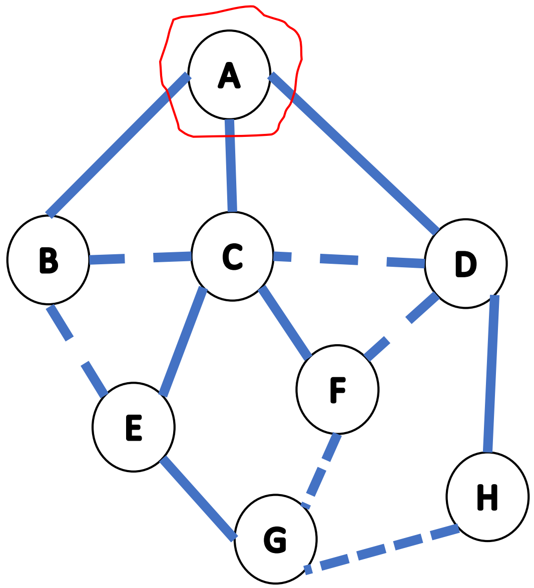


Queue

~~A~~	~~C~~	~~B~~	~~D~~	~~E~~	~~F~~	~~H~~	G

key	visited	dist.	pred.	adj. vertices
A	√	0	null	C B D
B	√	1	A	A E C
C	√	1	A	A B D E F
D	√	1	A	A C F H
E	√	2	C	B C G
F	√	2	C	C D G
G	√	3	E	E F H
H	√	2	D	D G

Starting point - A



Queue

~~A~~	~~C~~	~~B~~	~~D~~	~~E~~	~~F~~	~~H~~	~~G~~

key	visited	dist.	pred.	adj. vertices
A	√	0	null	C B D
B	√	1	A	A E C
C	√	1	A	A B D E F
D	√	1	A	A C F H
E	√	2	C	B C G
F	√	2	C	C D G
G	√	3	E	E F H
H	√	2	D	D G

Traversal: BFS

```
BFS(G):
  Input: Graph, G
  Output: A labeling of the edges on
      G as discovery and cross edges

  foreach (Vertex v : G.vertices()):
    setLabel(v, UNEXPLORED)
  foreach (Edge e : G.edges()):
    setLabel(e, UNEXPLORED)
  foreach (Vertex v : G.vertices()):
    if getLabel(v) == UNEXPLORED:
       BFS(G, v)
```

```
BFS(G, v):
  Queue q
  setLabel(v, VISITED)
  q.enqueue(v)

  while !q.empty():
    v = q.dequeue()
    foreach (Vertex w : G.adjacent(v)):
      if getLabel(w) == UNEXPLORED:
         setLabel(v, w, DISCOVERY)
         setLabel(w, VISITED)
         q.enqueue(w)
      elseif getLabel(v, w) == UNEXPLORED:
         setLabel(v, w, CROSS)
```

Traversal: BFS

```
BFS(G):
  Input: Graph, G
  Output: A labeling of the edges on
      G as discovery and cross edges

  foreach (Vertex v : G.vertices()):
    setLabel(v, UNEXPLORED)
  foreach (Edge e : G.edges()):
    setLabel(e, UNEXPLORED)
  foreach (Vertex v : G.vertices()):
    if getLabel(v) == UNEXPLORED:
       BFS(G, v)
```

```
BFS(G, v):
  Queue q
  setLabel(v, VISITED)
  q.enqueue(v)

  while !q.empty():
    v = q.dequeue()
    foreach (Vertex w : G.adjacent(v)):
      if getLabel(w) == UNEXPLORED:
         setLabel(v, w, DISCOVERY)
         setLabel(w, VISITED)
         q.enqueue(w)
      elseif getLabel(v, w) == UNEXPLORED:
         setLabel(v, w, CROSS)
```

Our implementation handles disjoint graphs.

How do we use this to count components?

Add component counter before BFS call;

Traversal: BFS

```
BFS(G):
  Input: Graph, G
  Output: A labeling of the edges on
      G as discovery and cross edges

  foreach (Vertex v : G.vertices()):
    setLabel(v, UNEXPLORED)
  foreach (Edge e : G.edges()):
    setLabel(e, UNEXPLORED)
  foreach (Vertex v : G.vertices()):
    if getLabel(v) == UNEXPLORED:
       comps++;
       BFS(G, v)
```

```
BFS(G, v):
  Queue q
  setLabel(v, VISITED)
  q.enqueue(v)

  while !q.empty():
    v = q.dequeue()
    foreach (Vertex w : G.adjacent(v)):
      if getLabel(w) == UNEXPLORED:
         setLabel(v, w, DISCOVERY)
         setLabel(w, VISITED)
         q.enqueue(w)
      elseif getLabel(v, w) == UNEXPLORED:
         setLabel(v, w, CROSS)
```

Our implementation handles disjoint graphs.

How do we use this to count components?

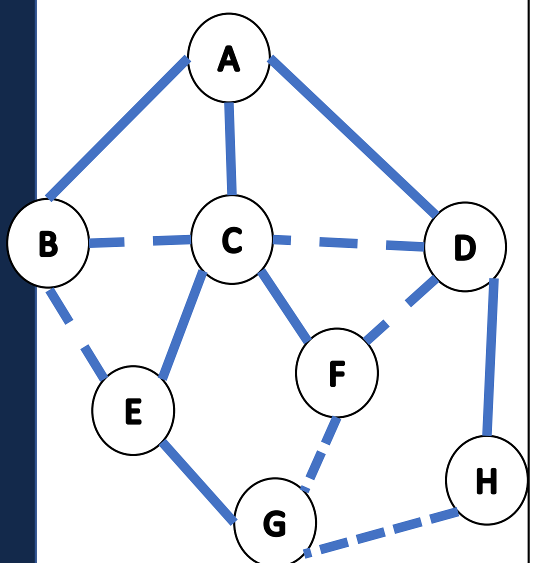
Add component counter before BFS call;

BFS Analysis

Q: Does our implementation detect a cycle?

- ***How do we update our code to detect a cycle?***

Yes. Existence of at least one cross edge guarantees cycle.




```
BFS(G, v):
  Queue q
  setLabel(v, VISITED)
  q.enqueue(v)

  while !q.empty():
    v = q.dequeue()
    foreach (Vertex w : G.adjacent(v)):
      if getLabel(w) == UNEXPLORED:
         setLabel(v, w, DISCOVERY)
         setLabel(w, VISITED)
         q.enqueue(w)
      elseif getLabel(v, w) == UNEXPLORED:
         setLabel(v, w, CROSS)
```

Running time of BFS - O(n+m)

```
BFS(G):
  Input: Graph, G
  Output: A labeling of the edges on
      G as discovery and cross edges

  foreach (Vertex v : G.vertices()):
    setLabel(v, UNEXPLORED)
  foreach (Edge e : G.edges()):
    setLabel(e, UNEXPLORED)
  foreach (Vertex v : G.vertices()):
    if getLabel(v) == UNEXPLORED:
       BFS(G, v)
```

```
BFS(G, v):
  Queue q
  setLabel(v, VISITED)
  q.enqueue(v)

  while !q.empty():
    v = q.dequeue()
    foreach (Vertex w : G.adjacent(v)):
      if getLabel(w) == UNEXPLORED:
         setLabel(v, w, DISCOVERY)
         setLabel(w, VISITED)
         q.enqueue(w)
      elseif getLabel(v, w) == UNEXPLORED:
         setLabel(v, w, CROSS)
```

This is optimal running time because we know we have to visit every edge and vertex, therefore we cannot do better than O(n+m).

BFS Observations

Q: What is a shortest path from **A** to **H**?

Path: A,D,H

Q: What is a shortest path from **E** to **H**?

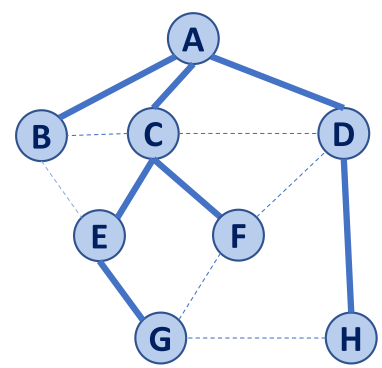
No information about this.

BFS finds shortest path only from starting vertex (in graphs without weights) ;

Q: What structure is made from discovery edges?

We get new graph structure: spanning tree!

d	p	v	Adjacent
0	A	A	C B D
1	A	B	A C E
1	A	C	B A D E F
1	A	D	A C F H
2	C	E	B C G
2	C	F	C D G
3	E	G	E F H
2	D	H	D G



BFS Observations

Obs. 1: Traversals can be used to count components.

Obs. 2: Traversals can be used to detect cycles.

Obs. 3: In BFS, **d** provides the shortest distance to every vertex.

Obs. 4: In BFS, the endpoints of a cross edge never differ in distance, **d**, by more than 1:

$$|d(u) - d(v)| = 1$$

DFS – Depth First Search

- ✓ Depth-first search (DFS) is an algorithm for traversing or searching tree or graph data structures.
- ✓ The algorithm starts from some arbitrary node and explores as far as possible along each branch before backtracking.

Algorithm setup:

Everything is the same as BFS except for:

- ❑ We will use stack instead of a queue.
- ❑ We will label cross edges as back edges.

Algorithm setup:

Label each edge:

- Discovery edge (bolded) or
- **back edge (dashed)**

Table of vertices with following features:

- Vertex name - key
- Boolean flag - visited
- Distance it took to get to the vertex
- Predecessor
- List of adjacent vertices

- **Stack (use recursion to replace)**

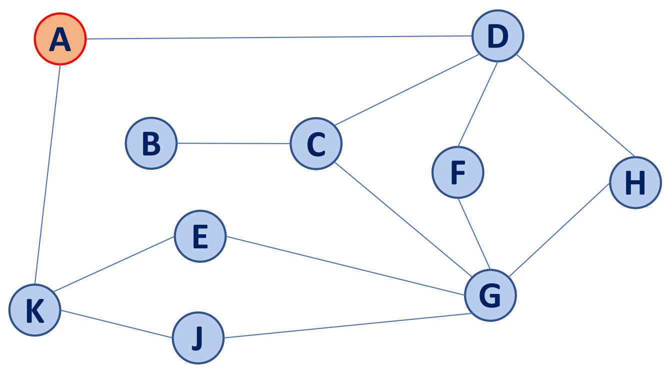
```
DFS(G):
  Input: Graph, G
  Output: A labeling of the edges on
      G as discovery and back edges

  foreach (Vertex v : G.vertices()):
    setLabel(v, UNEXPLORED)
  foreach (Edge e : G.edges()):
    setLabel(e, UNEXPLORED)
  foreach (Vertex v : G.vertices()):
    if getLabel(v) == UNEXPLORED:
       DFS(G, v)
```

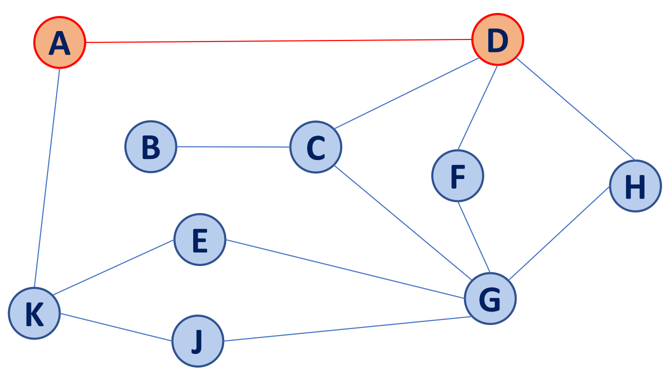
```
DFS(G, v):
  Queue q
  setLabel(v, VISITED)
  q.enqueue(v)

  while !q.empty():
    v = q.dequeue()
    foreach (Vertex w : G.adjacent(v)):
      if getLabel(w) == UNEXPLORED:
         setLabel(v, w, DISCOVERY)
         setLabel(w, VISITED)
         DFS(G, w)
      elseif getLabel(v, w) == UNEXPLORED:
         setLabel(v, w, BACK)
```

DFS with recursion:

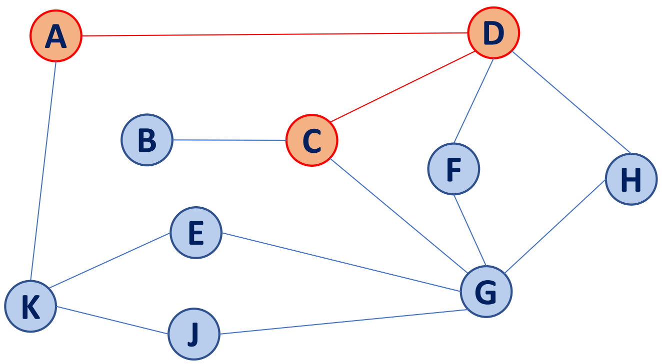


We visit D first and we are immediately recusing from D.

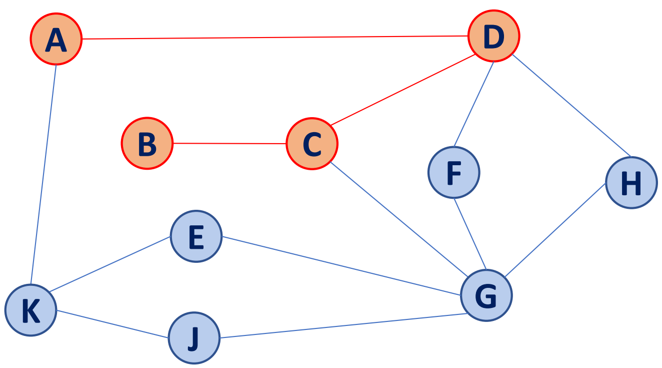


Order of vertices does not matter.

DFS with recursion:

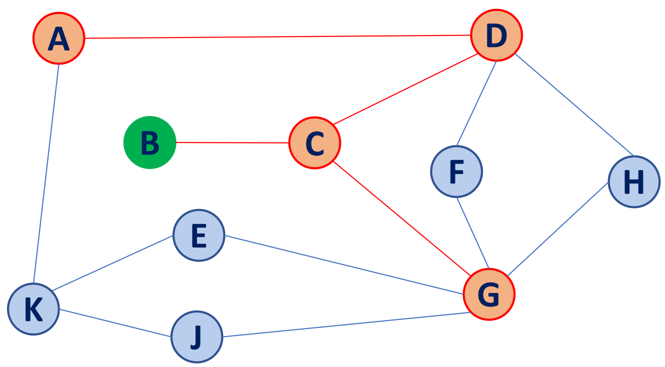


Next we visit C first and we are immediately recusing from C.

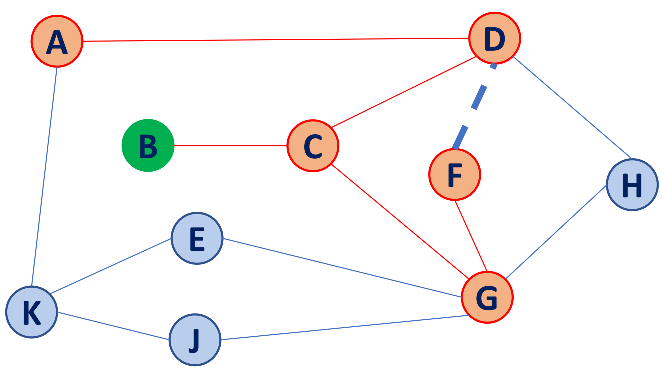


Next we visit B first.
We visited all neighbors for B, so we will go back to C.

DFS with recursion:

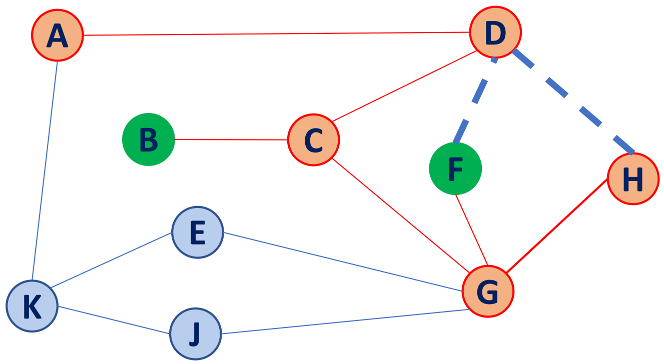


Next we visit G first and we are immediately recusing from G.

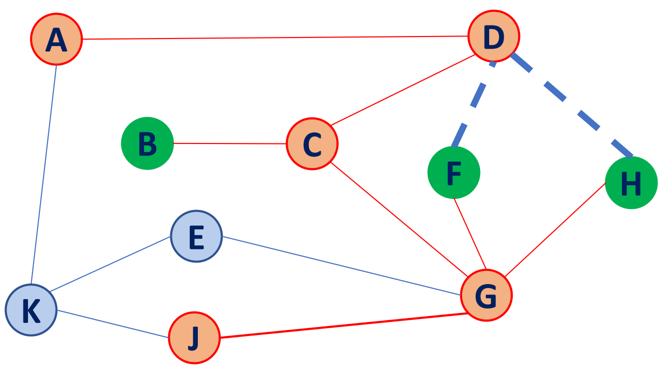


Next we visit F first.
Since D is already visited (F,D) is labeled as back edge.
F is done and we go back to G.

DFS with recursion:

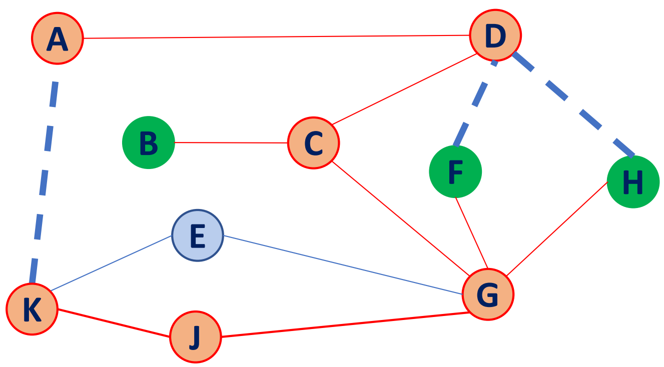


Next we visit H and we label another back edge (H,D). H will be done, we will go back to G.

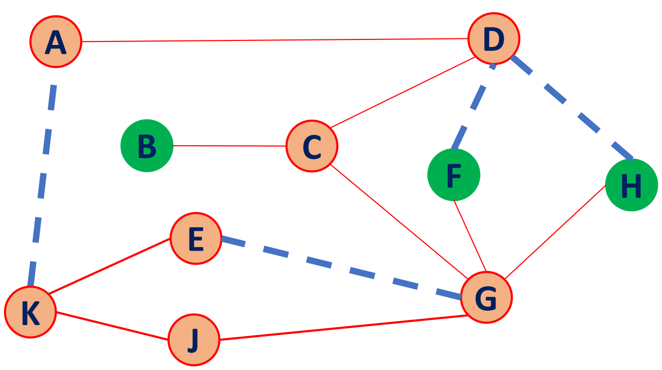


Next we visit J.

DFS with recursion:



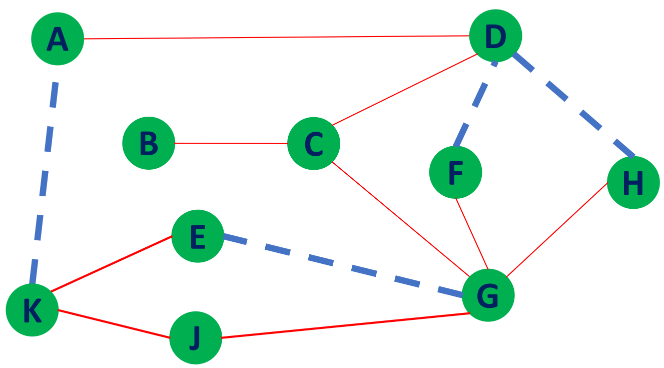
Next we visit K.
(A,K) labeled as back edge.



Next we visit E.
(E,G) becomes back edge and E will be done.

* You should also keep track of distance and parents.

DFS with recursion:



- Back edge is getting us closer to starting vertex;
- Existence of back edges means there is a cycle;
- Discovery edges gives us spanning tree;
- DFS can gives us component count;

Running time of DFS is **O(n+m)**

```
DFS(G):
  Input: Graph, G
  Output: A labeling of the edges on
      G as discovery and back edges

  foreach (Vertex v : G.vertices()):
    setLabel(v, UNEXPLORED)
  foreach (Edge e : G.edges()):
    setLabel(e, UNEXPLORED)
  foreach (Vertex v : G.vertices()):
    if getLabel(v) == UNEXPLORED:
       DFS(G, v)
```

```
DFS(G, v):
  Queue q
  setLabel(v, VISITED)
  q.enqueue(v)

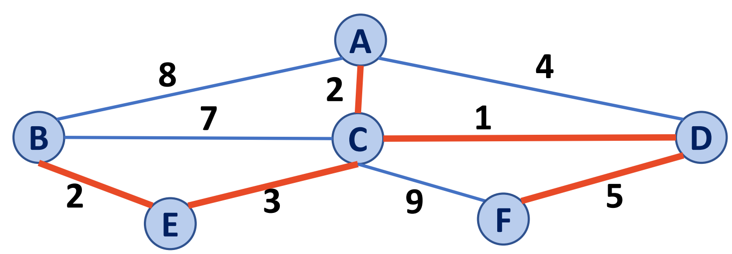
  while !q.empty():
    v = q.dequeue()
    foreach (Vertex w : G.adjacent(v)):
      if getLabel(w) == UNEXPLORED:
         setLabel(v, w, DISCOVERY)
         setLabel(w, VISITED)
         DFS(G, w)
      elseif getLabel(v, w) == UNEXPLORED:
         setLabel(v, w, BACK)
```

Minimum Spanning Tree Algorithms

Input: Connected, undirected graph **G** with edge weights (unconstrained, but must be additive)

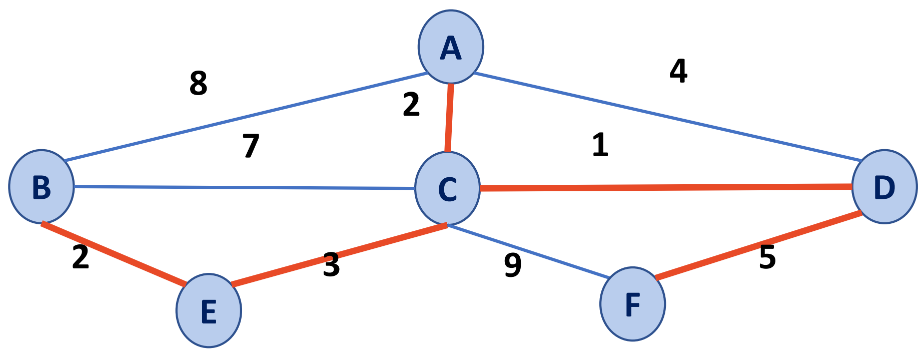
Output: A graph G' with the following properties:

- G' is a spanning graph of G
- G' is a tree (connected, acyclic)
- G' has a minimal total weight among all spanning trees



Minimum Spanning Tree Algorithms

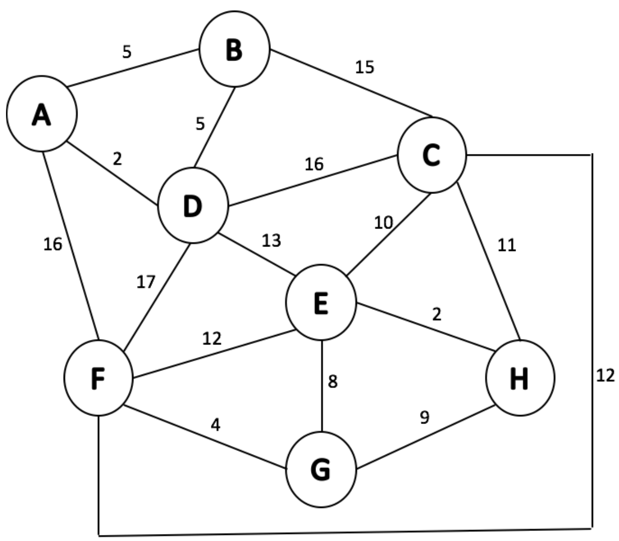
Graph can have multiple spanning trees ,but there will always be at least one minimum spanning tree.

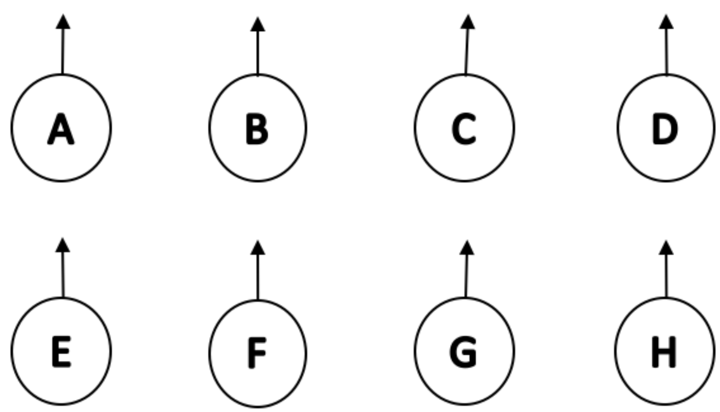


Kruskal’s Algorithm

Algorithm setup:

- Maintain a list of edges sorted by weight in increasing order → min heap.
- Initialize a disjoint set (up tree) for each vertex.





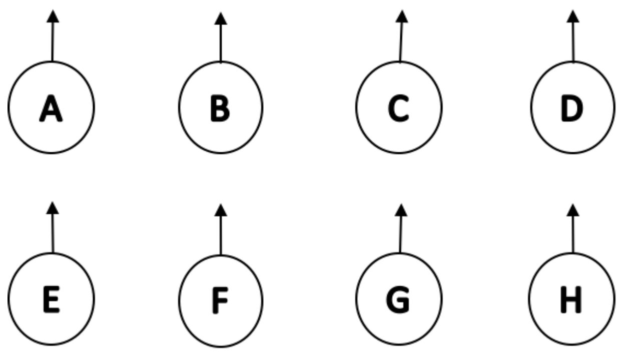
Sorted list of edges:

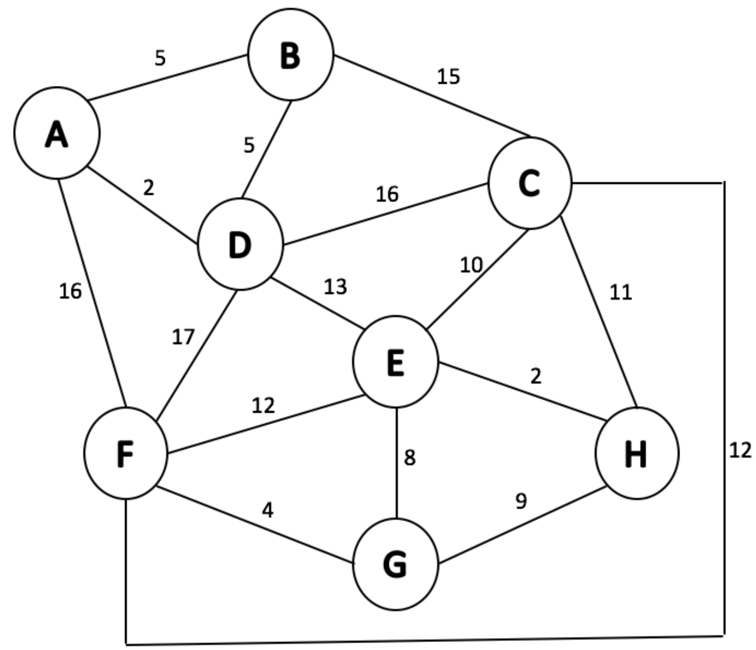
(A, D)
(E, H)
(F, G)
(A, B)
(B, D)
(G, E)
(G, H)
(E, C)
(C, H)
(E, F)
(F, C)
(D, E)
(B, C)
(C, D)
(A, F)
(D, F)

Kruskal’s Algorithm

- Remove minimum from the heap;
- Check that the two vertices, that form the removed edge, are in different disjoint sets.
  - If they are, add the edge to the spanning tree and union the two sets.
  - Otherwise, ignore that edge and move on.

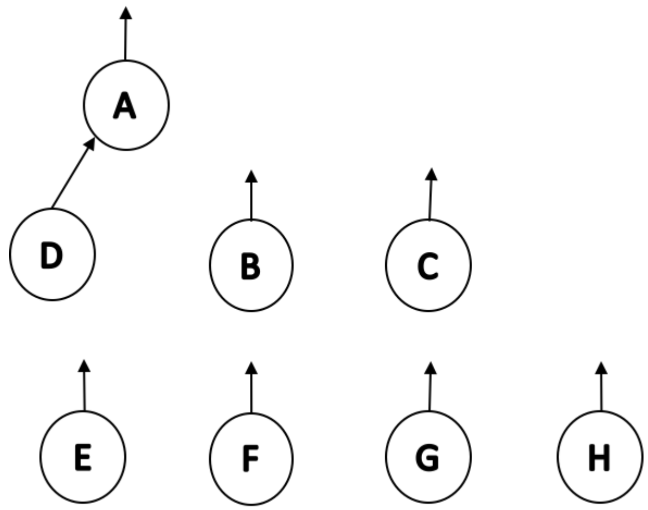
Kruskal's Algorithm

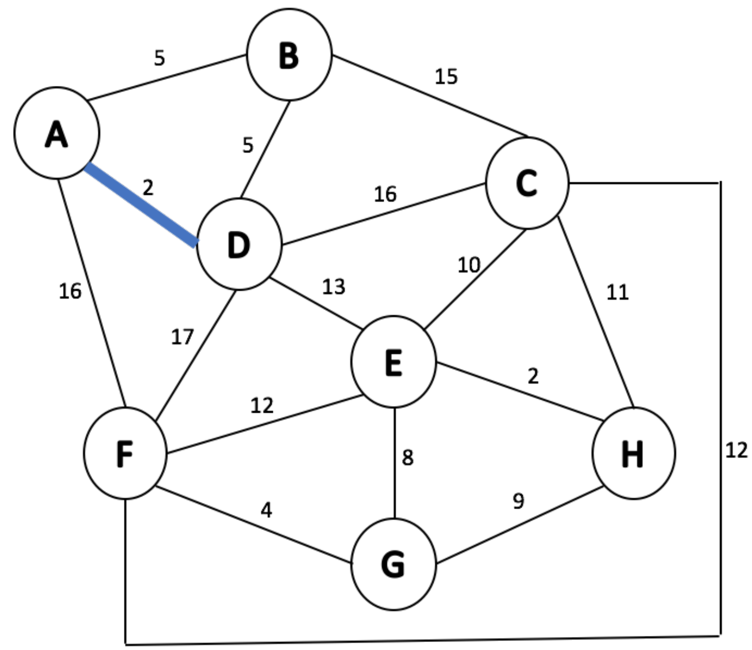




(A,D)
(E,H)
(F,G)
(A,B)
(B,D)
(G,E)
(G,H)
(E,C)
(C,H)
(E,F)
(F,C)
(D,E)
(B,C)
(C,D)
(A,F)
(D,F)

Kruskal’s Algorithm

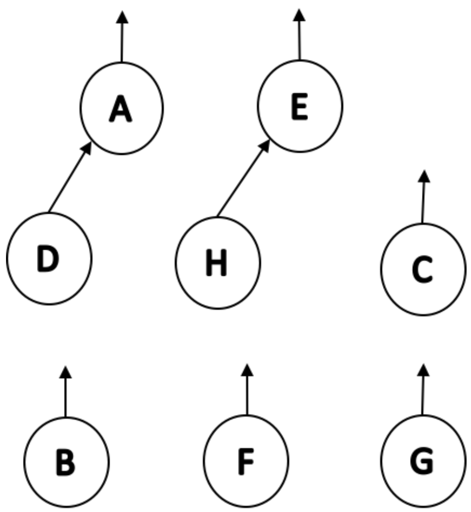


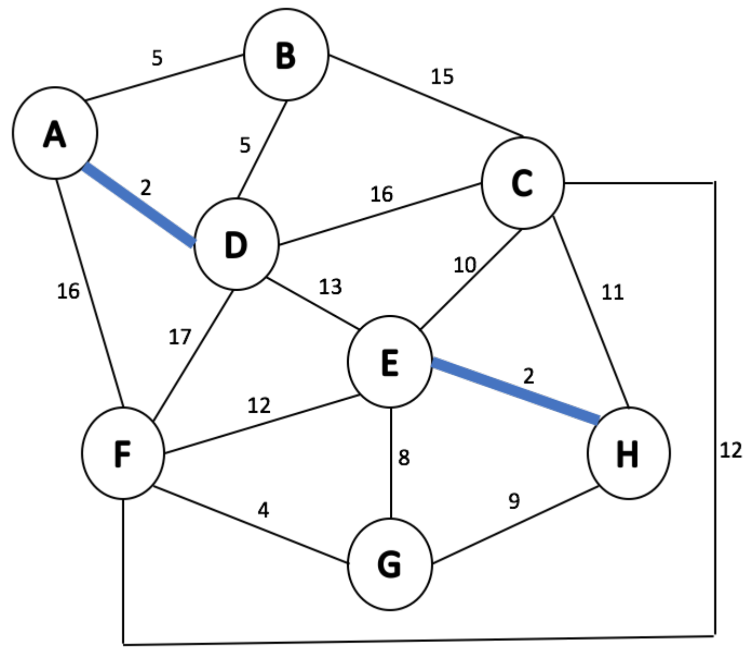


~~(A,D)~~
(E,H)
(F,G)
(A,B)
(B,D)
(G,E)
(G,H)
(E,C)
(C,H)
(E,F)
(F,C)
(D,E)
(B,C)
(C,D)
(A,F)
(D,F)

- remove edge (A, D) from the heap.
- Vertex A and vertex D are in different sets. Therefore, we can add edge (A, D) and union sets {A} and {D}.

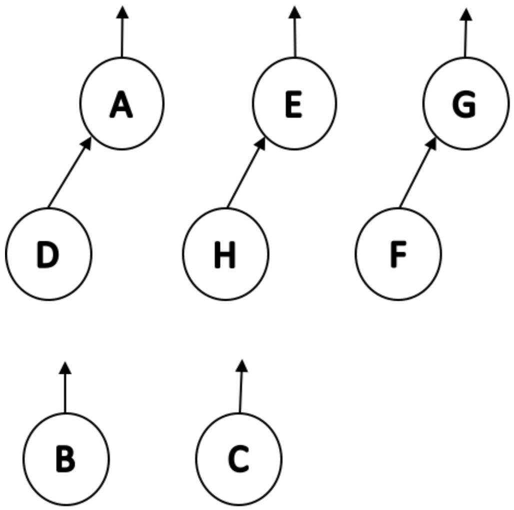
Kruskal's Algorithm

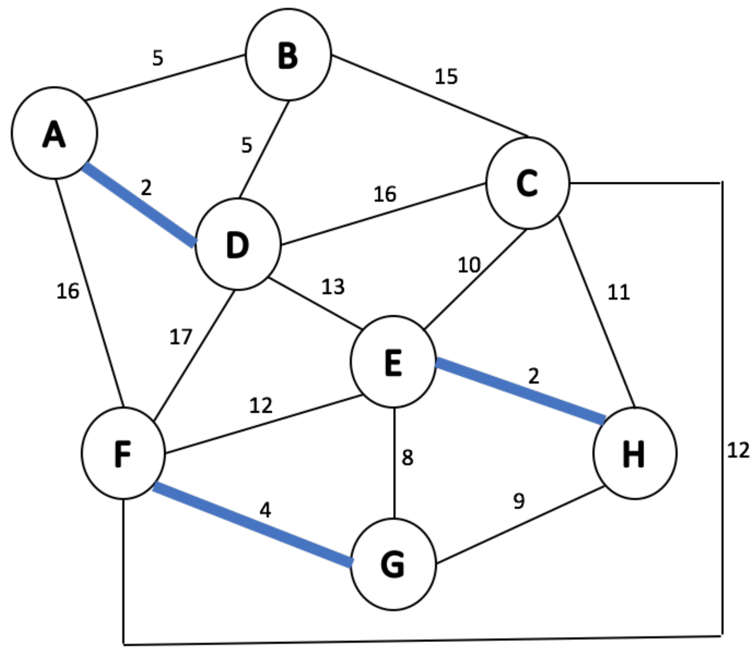




~~(A,D)~~
~~(E,H)~~
(F,G)
(A,B)
(B,D)
(G,E)
(G,H)
(E,C)
(C,H)
(E,F)
(F,C)
(D,E)
(B,C)
(C,D)
(A,F)
(D,F)

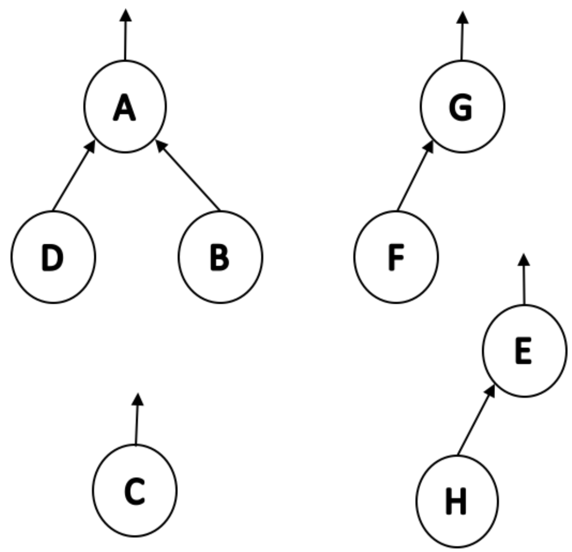
Kruskal's Algorithm

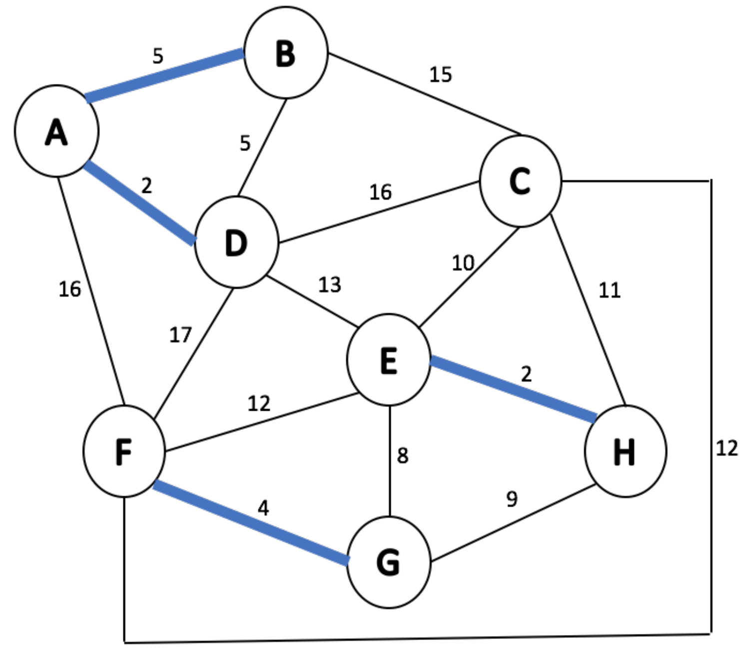




~~(A,D)~~
~~(E,H)~~
~~(F,G)~~
(A,B)
(B,D)
(G,E)
(G,H)
(E,C)
(C,H)
(E,F)
(F,C)
(D,E)
(B,C)
(C,D)
(A,F)
(D,F)

Kruskal's Algorithm

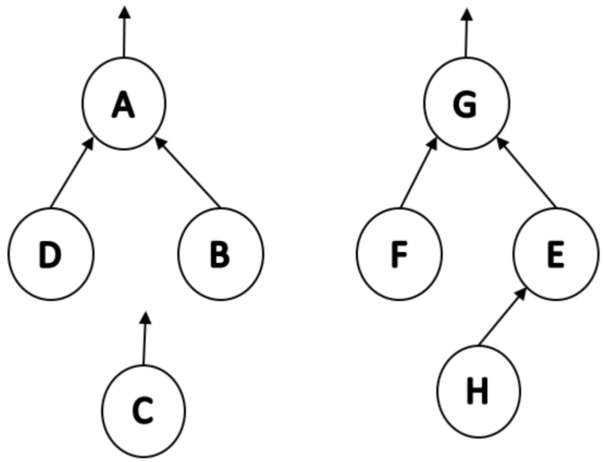


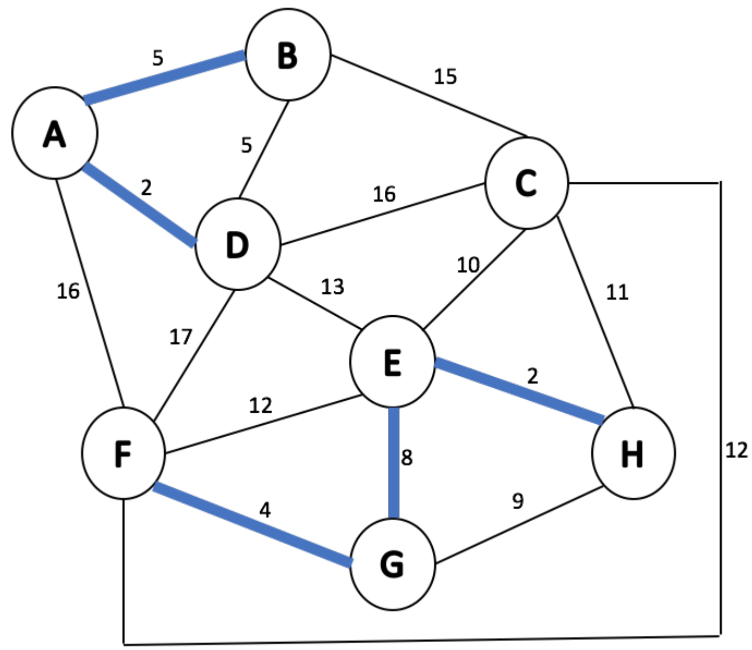


~~(A,D)~~
~~(E,H)~~
~~(F,G)~~
~~(A,B)~~
(B,D)
(G,E)
(G,H)
(E,C)
(C,H)
(E,F)
(F,C)
(D,E)
(B,C)
(C,D)
(A,F)
(D,F)

Next:
We skip (B,D) since they are in the same set.

Kruskal's Algorithm

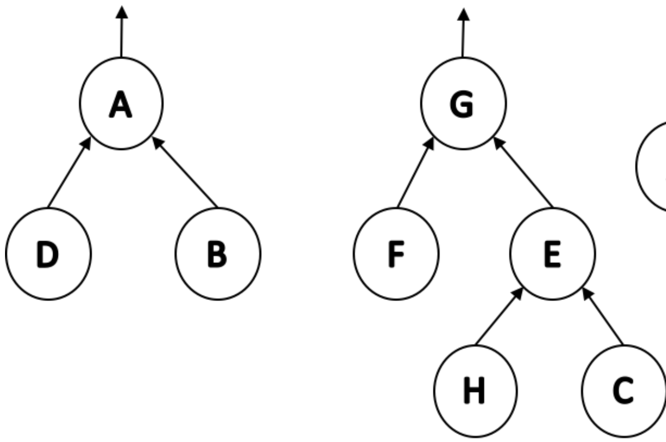


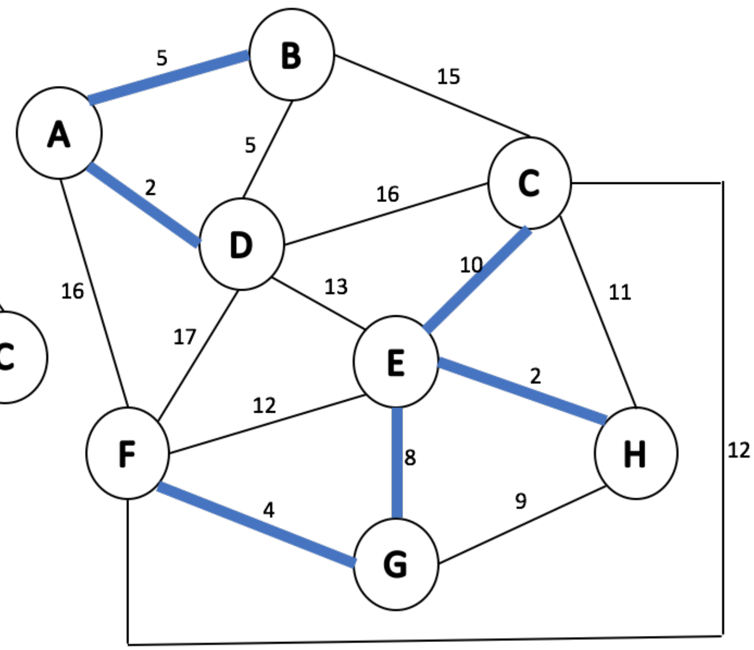


~~(A,D)~~
~~(E,H)~~
~~(F,G)~~
~~(A,B)~~
~~(B,D)~~
~~(G,E)~~
(G,H)
(E,C)
(C,H)
(E,F)
(F,C)
(D,E)
(B,C)
(C,D)
(A,F)
(D,F)

Next:
We skip (G,H) since they are in the same set.

Kruskal’s Algorithm

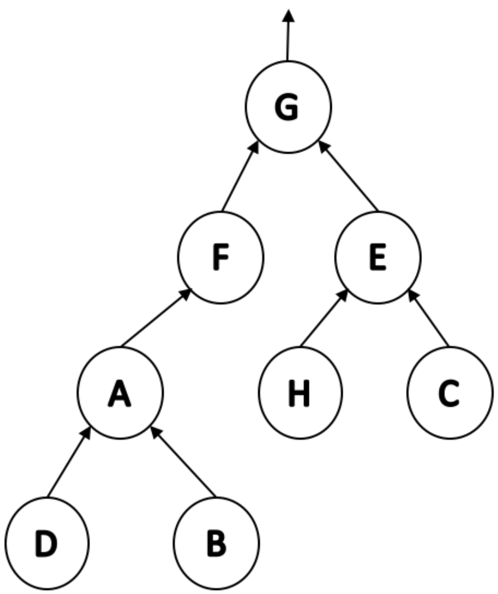


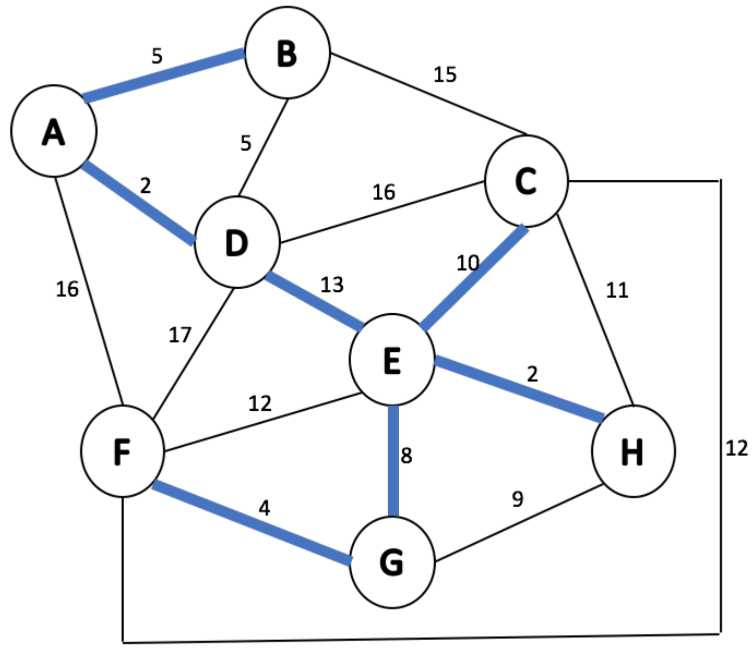


~~(A,D)~~
~~(E,H)~~
~~(F,G)~~
~~(A,B)~~
~~(B,D)~~
~~(G,E)~~
~~(G,H)~~
~~(E,C)~~
(C,H)
(E,F)
(F,C)
(D,E)
(B,C)
(C,D)
(A,F)
(D,F)

Next:
We skip (C, H), (E,F), (F,C) since they are in the same set.

Kruskal's Algorithm

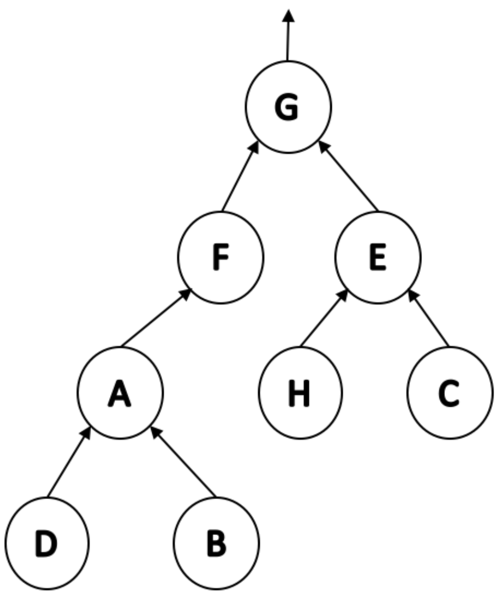


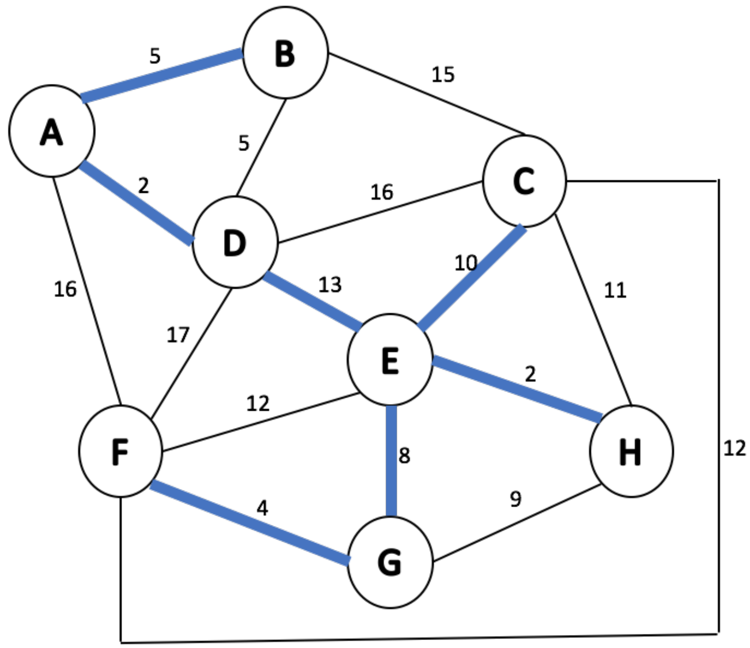


~~(A,D)~~
~~(E,H)~~
~~(F,G)~~
~~(A,B)~~
~~(B,D)~~
~~(G,E)~~
~~(G,H)~~
~~(E,C)~~
~~(C,H)~~
~~(E,F)~~
~~(F,C)~~
~~(D,E)~~
(B,C)
(C,D)
(A,F)
(D,F)

We pop the rest of the edges and ignore them all because now all vertices are in one set.

Kruskal's Algorithm





We have created an MST → total sum of all edges is the smallest possible on this graph.

Kruskal's Algorithm

```
KruskalMST(G):
  DisjointSets forest
  foreach (Vertex v : G):
    forest.makeSet(v)

  PriorityQueue Q    // min edge weight
  foreach (Edge e : G):
    Q.insert(e)

  Graph T = (V, {})

  while |T.edges()| < n-1:
    Vertex (u, v) = Q.removeMin()
    if forest.find(u) != forest.find(v):
       T.addEdge(u, v)
       forest.union( forest.find(u),
                     forest.find(v) )

  return T
```

Stopping condition:

`|T.edges()| < n-1`

Worst case:

We visit every edge

Kruskal's Algorithm - total running time:

$O(n + m)$ for set up with heap

$O(n + m \lg n)$ for set up with sorted array.

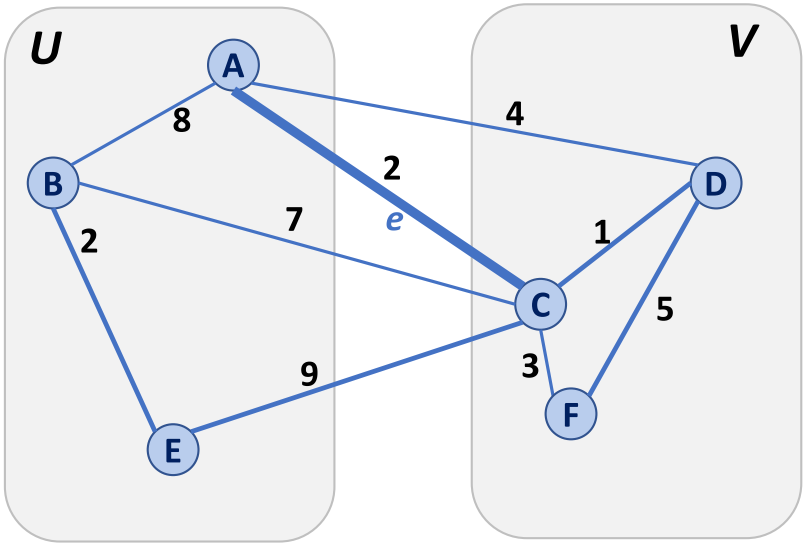
Priority Queue:	Total Running Time
Heap	$O(n + m) + O(m \lg n) = O(n + mlgn)$
Sorted Array	$O(n + m \lg n) + O(m) = O(n + mlgn)$

Partition Property

Consider an arbitrary partition of the vertices on **G** into two subsets **U** and **V**.

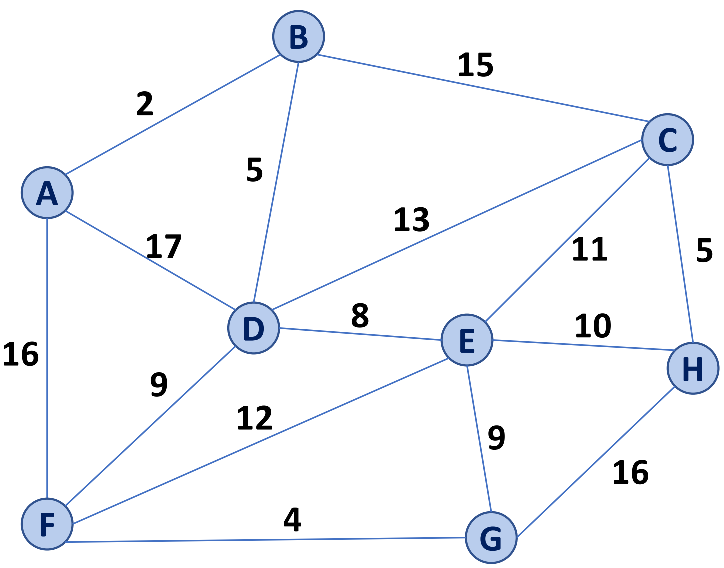
Let **e** be an edge of minimum weight across the partition.

Then **e** is part of some minimum spanning tree.

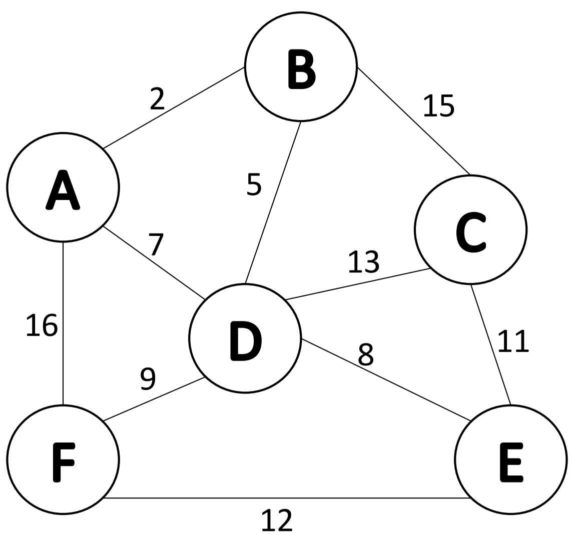


Partition Property

The partition property suggests an algorithm:



Prim's Algorithm




```
PrimMST(G, s):
  Input: G, Graph;
         s, vertex in G, starting vertex
  Output: T, a minimum spanning tree (MST) of G

  foreach (Vertex v : G):
    d[v] = +inf
    p[v] = NULL
  d[s] = 0

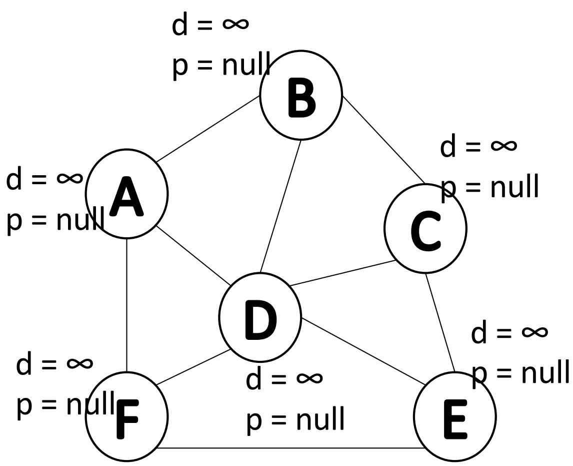
  PriorityQueue Q   // min distance, defined by d[v]
  Q.buildHeap(G.vertices())
  Graph T           // "labeled set"

  repeat n times:
    Vertex m = Q.removeMin()
    T.add(m)
    foreach (Vertex v : neighbors of m not in T):
      if cost(v, m) < d[v]:
        d[v] = cost(v, m)
        p[v] = m

  return T
```

Prim's Algorithm

A	∞
B	∞
C	∞
D	∞
E	∞
F	∞

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PrimMST(G, s):
  Input: G, Graph;
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    p[v] = NULL
  d[s] = 0

  PriorityQueue Q   // min distance, defined by d[v]
  Q.buildHeap(G.vertices())
  Graph T           // "labeled set"

  repeat n times:
    Vertex m = Q.removeMin()
    T.add(m)
    foreach (Vertex v : neighbors of m not in T):
      if cost(v, m) < d[v]:
        d[v] = cost(v, m)
        p[v] = m

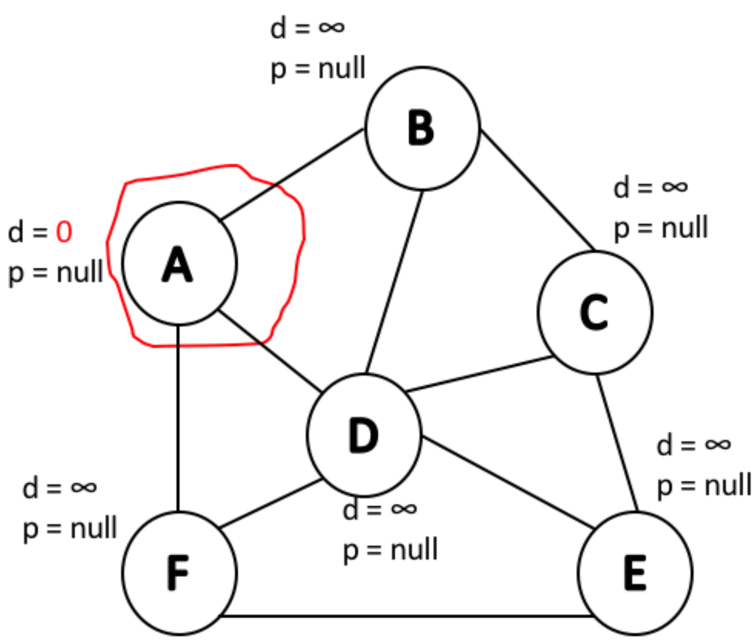
  return T
```

Prim’s Algorithm

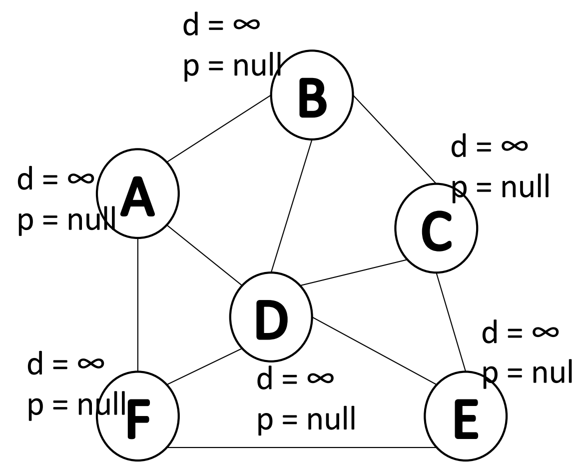
Algorithm logic:

Choose an arbitrary starting point and set its distance to 0.

Pop the starting vertex from the heap and update the distance/predecessor of adjacent vertices.



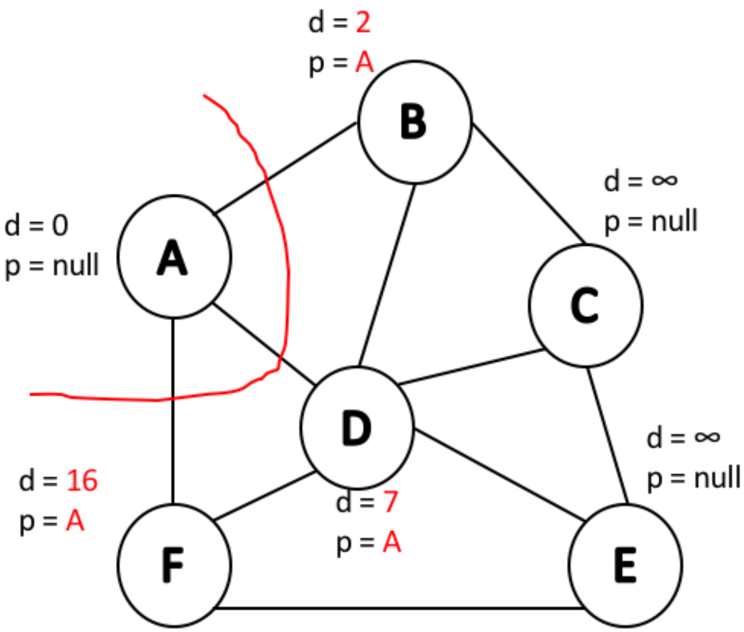
A	0
B	∞
C	∞
D	∞
E	∞
F	∞



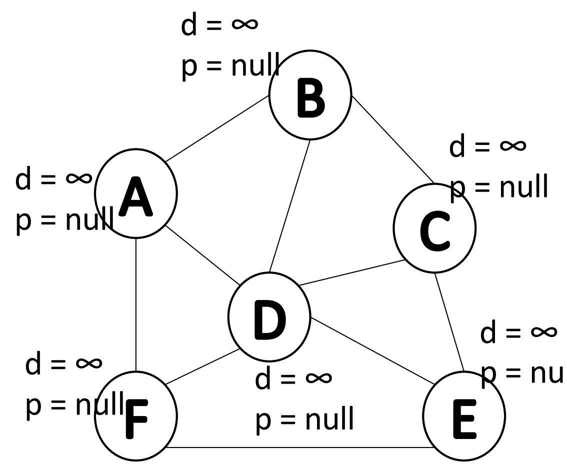
Prim’s Algorithm

We pop A and update adjacent vertices B, D, and F.

Next: remove minimum element from the heap and add the edge to the MST

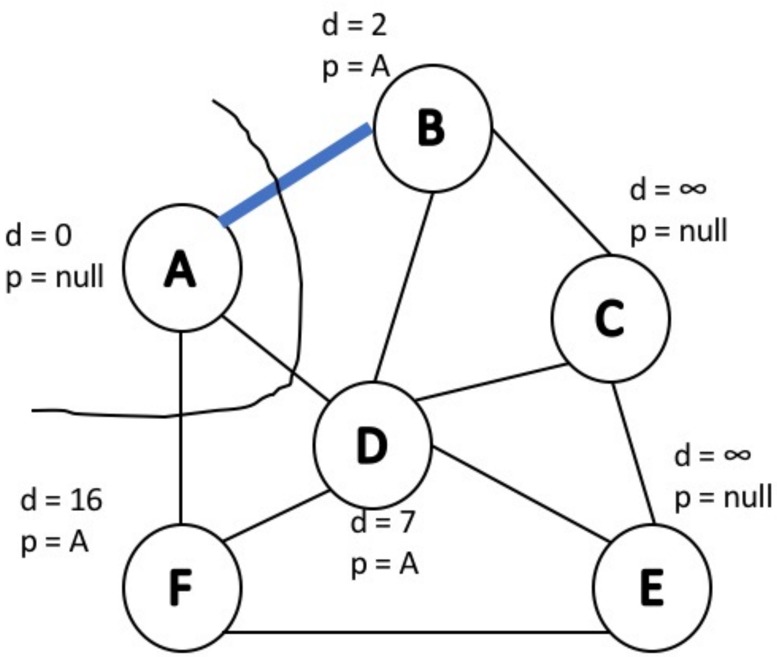


~~A~~	~~0~~
B	2
C	∞
D	7
E	∞
F	16

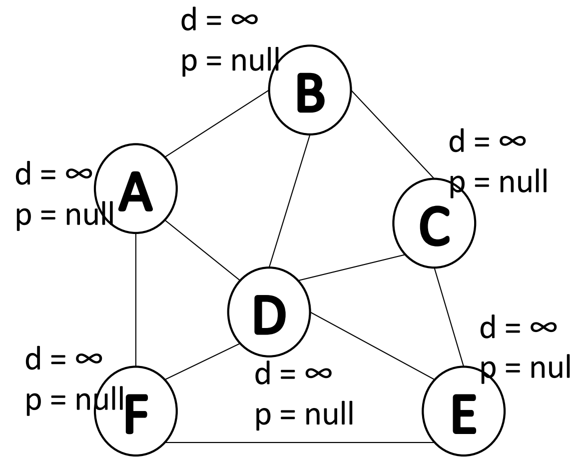


Prim’s Algorithm

Next, we pop a vertex with the smallest distance and update adjacent vertices. However, we update vertices only if the distance is smaller than the current.

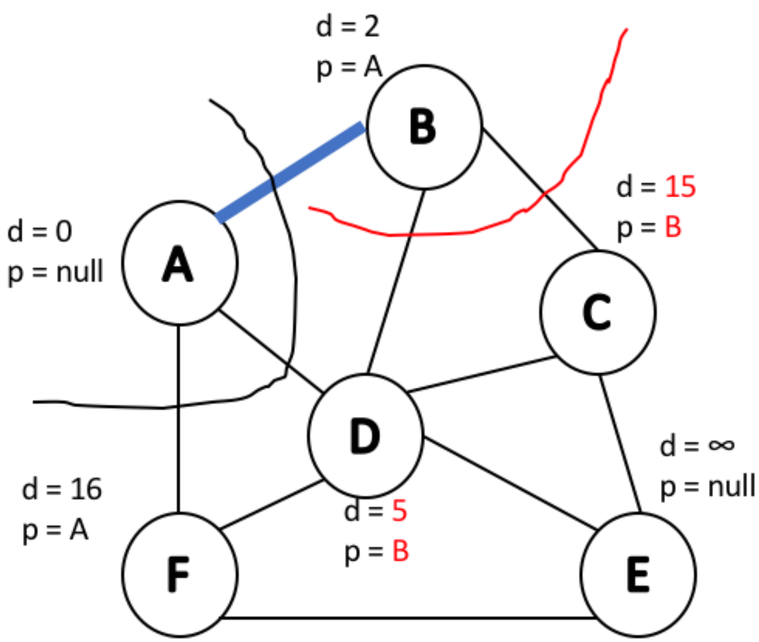


~~A~~	~~0~~
B	2
C	∞
D	7
E	∞
F	16

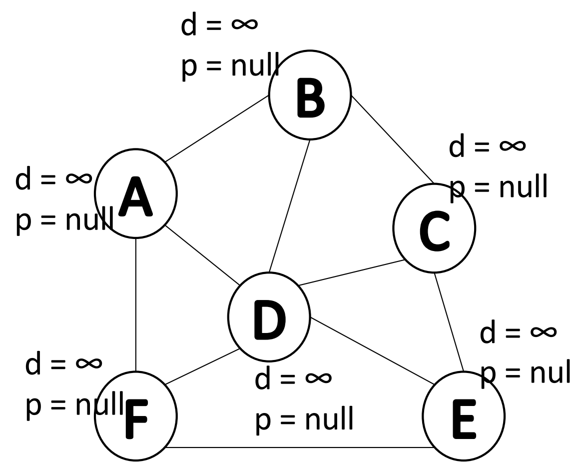


Prim’s Algorithm

Next: remove minimum element from the heap and add the edge to the MST
We will add edge (D, B)

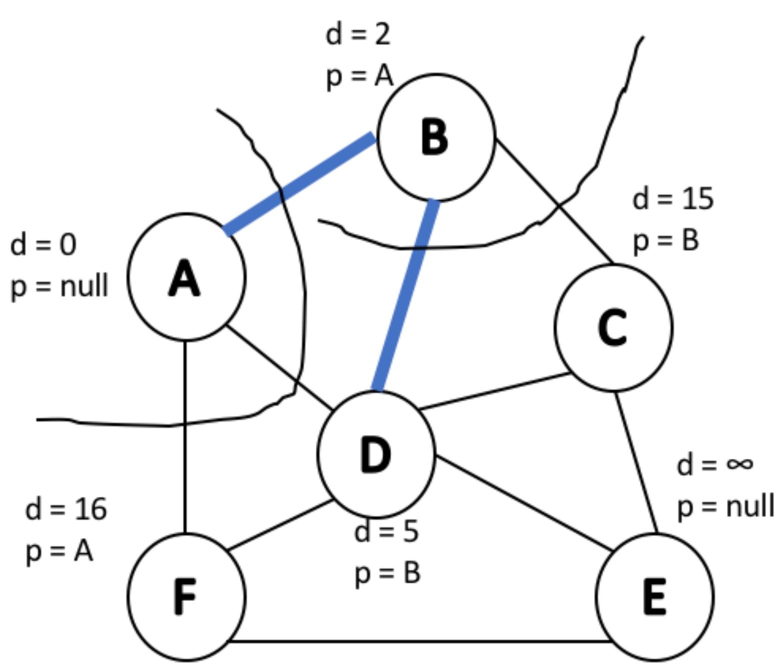


~~A~~	~~0~~
~~B~~	~~2~~
C	15
D	5
E	∞
F	16

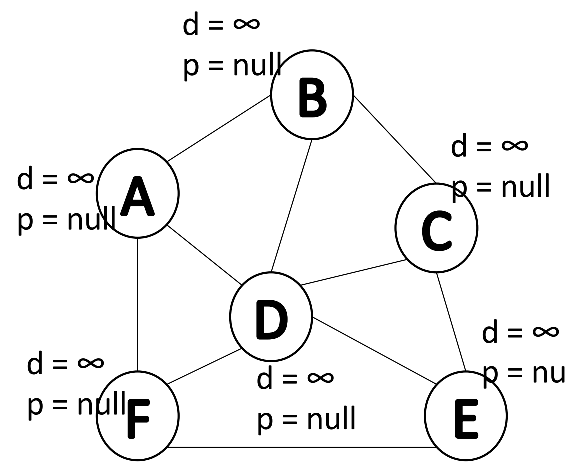


Prim's Algorithm

Next: pop a vertex with the smallest distance, update adjacent vertices if needed, and add the edge with the smallest distance.
These steps are repeated until the heap is empty .

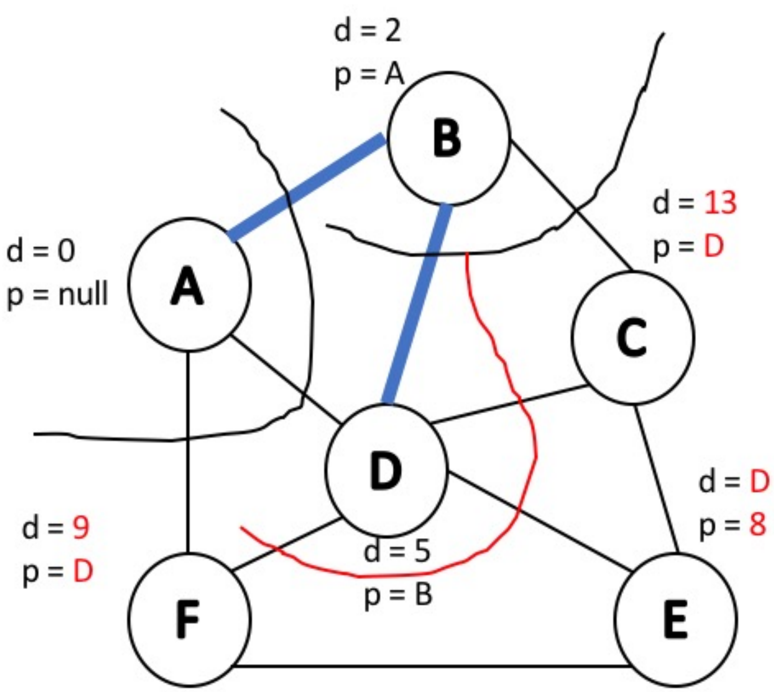


~~A~~	~~0~~
~~B~~	~~2~~
C	15
D	5
E	∞
F	16

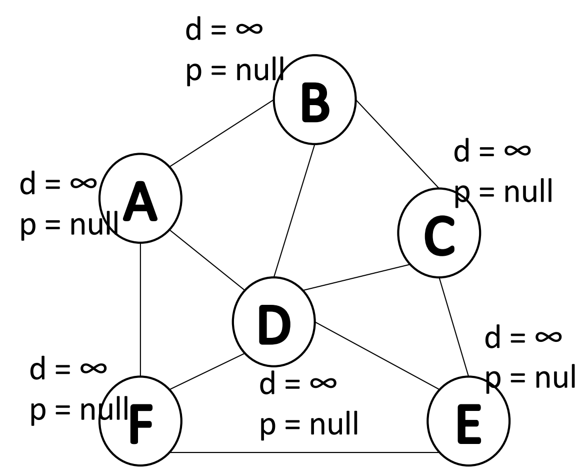


Prim’s Algorithm

we pop D and we update all its adjacent vertices F, E, and C

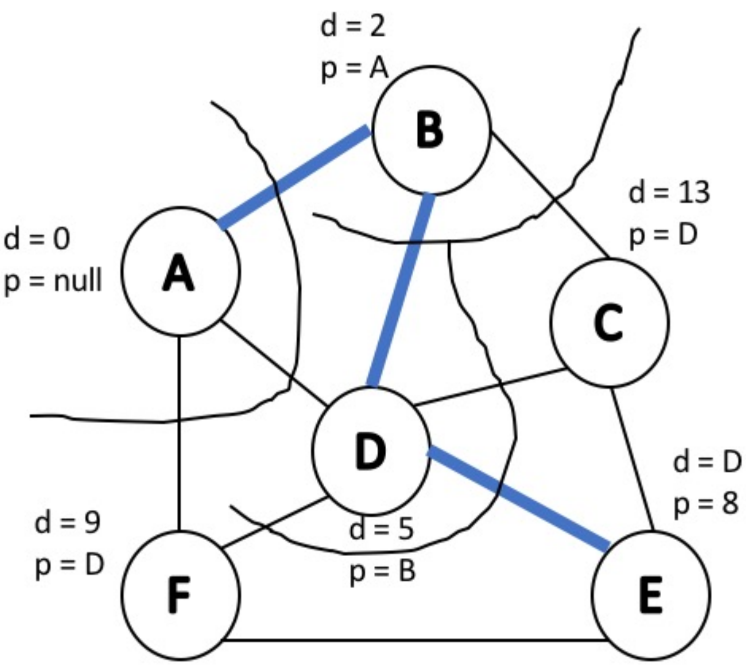


~~A~~	~~0~~
~~B~~	~~2~~
C	13
~~D~~	~~5~~
E	8
F	9

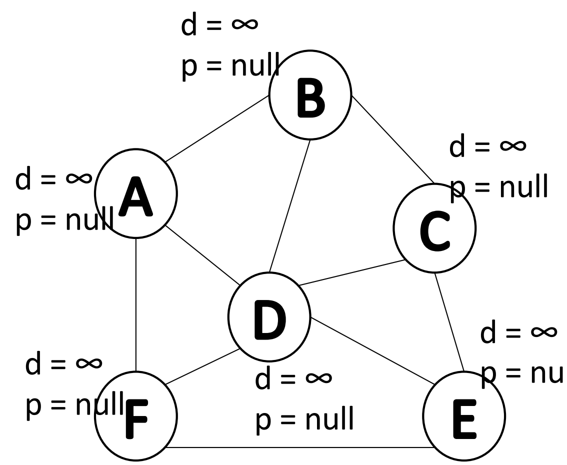


Prim's Algorithm

The next vertex with smallest distance is E. We add the edge from D to E.

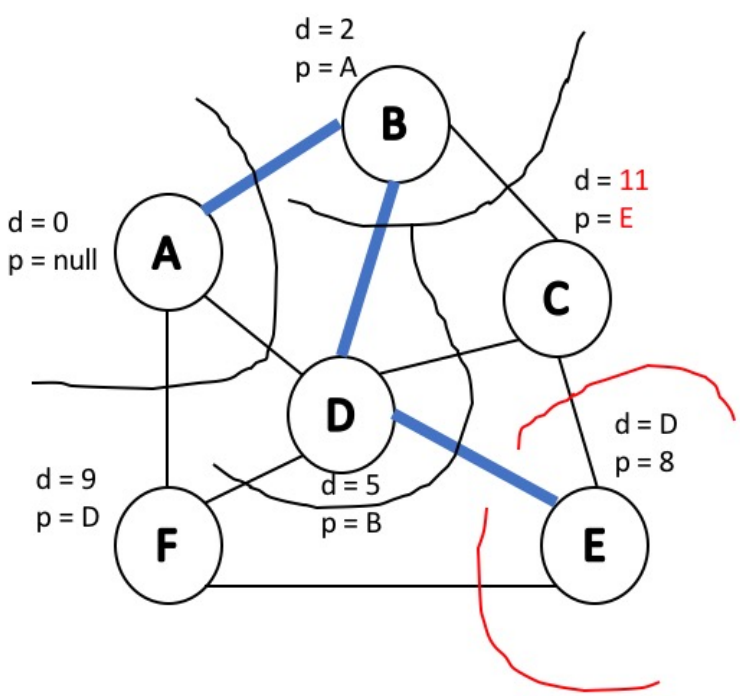


~~A~~	~~0~~
~~B~~	~~2~~
C	13
~~D~~	~~5~~
E	8
F	9

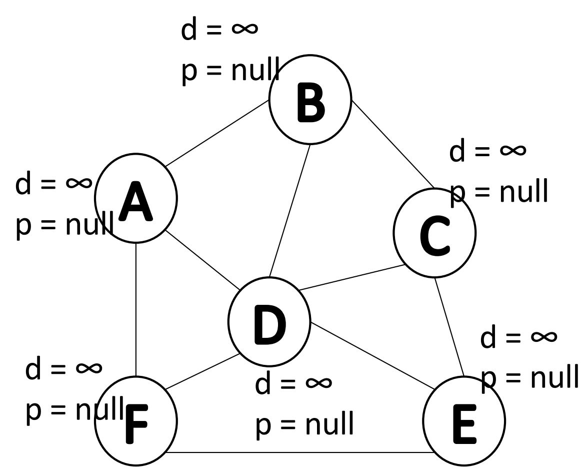


Prim's Algorithm

pop E and we only update C, because F's current distance is smaller than the one from E to F.

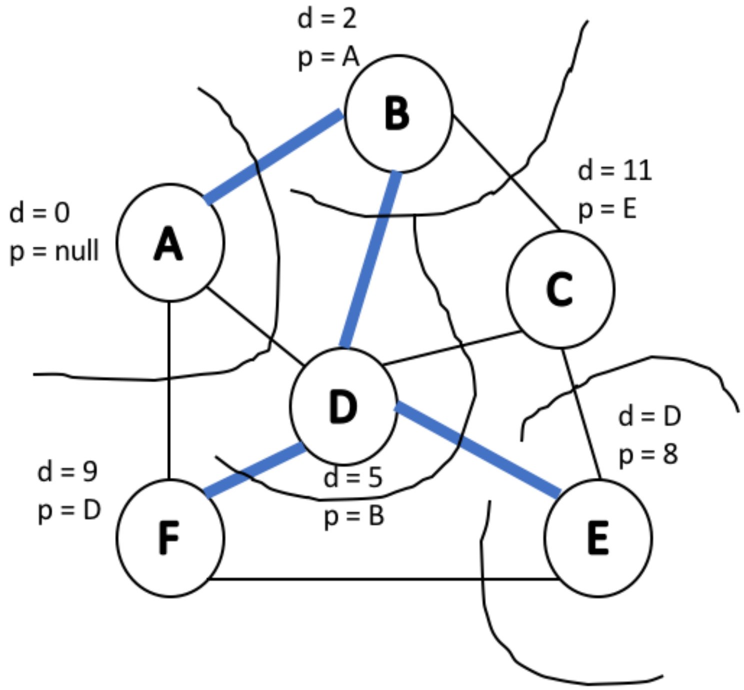


~~A~~	~~0~~
~~B~~	~~2~~
C	11
~~D~~	~~5~~
~~E~~	~~8~~
F	9

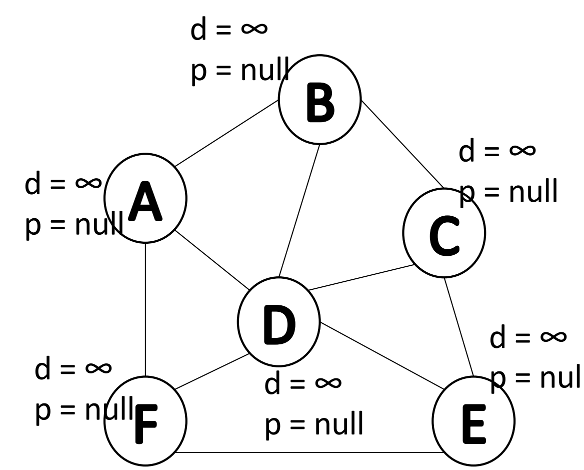


Prim’s Algorithm

- The shortest distance is from D to F, so we add that edge to the graph.
- We pop 9 and we don’t have anything to update because all neighboring edges have been added to the graph.

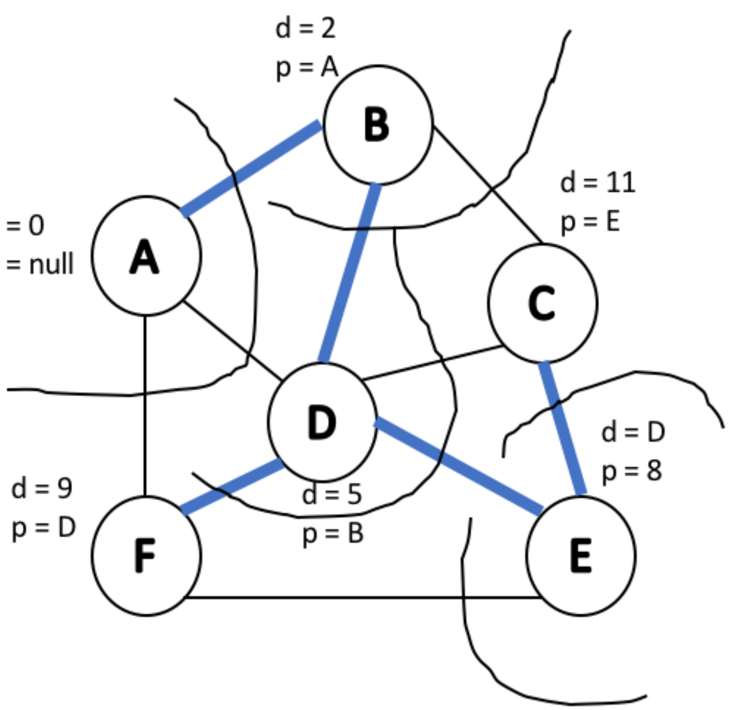


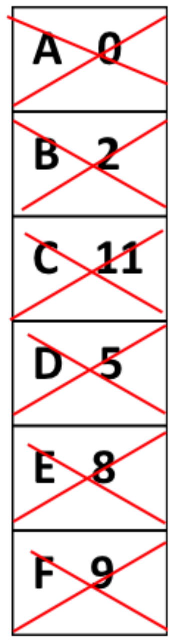
~~A~~	~~0~~
~~B~~	~~2~~
C	11
~~D~~	~~5~~
~~E~~	~~8~~
~~F~~	~~9~~

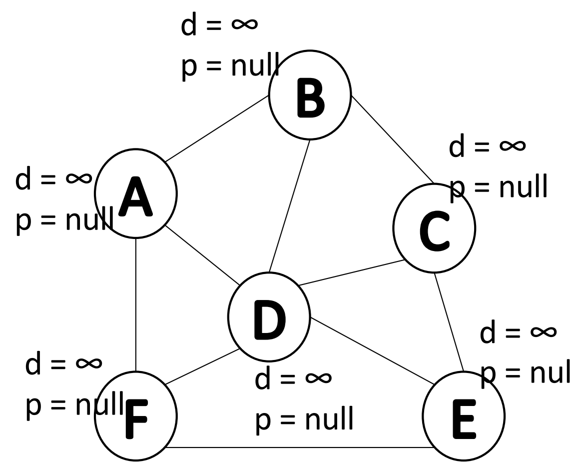


Prim's Algorithm

- Finally, we pop C and add an edge from E to C. After this step the heap is empty and we are done.







	Adj. Matrix	Adj. List
Heap	$O(n^2 + m \lg(n))$	$O(n \lg(n) + m \lg(n))$
Unsorted Array	$O(n^2)$	$O(n^2)$

- Case 1: the data is sparse → use (heap + adj list) and the running time will be O($nlog(n)$) $(n{\sim}m)$
- Case 2: the data is dense → use (unsorted array + adj matrix/list) and the running time will be O(n^2). $m{\sim}n^2$

MST Algorithm Runtime:

- Kruskal's Algorithm:

  O(n + m lg(n))

- Prim's Algorithm:

  O(n lg(n) + m lg(n))

- What must be true about the connectivity of a graph when running an MST algorithm?

  Graph is a connected graph.

  - How does n and m relate?

$$\boldsymbol{m \geq n - 1 \rightarrow O(m) = O(n)}$$

Running time: $m \lg n$

Fibonacci heap

Decrease key operation in Fibonacci heap takes O(1)* time.

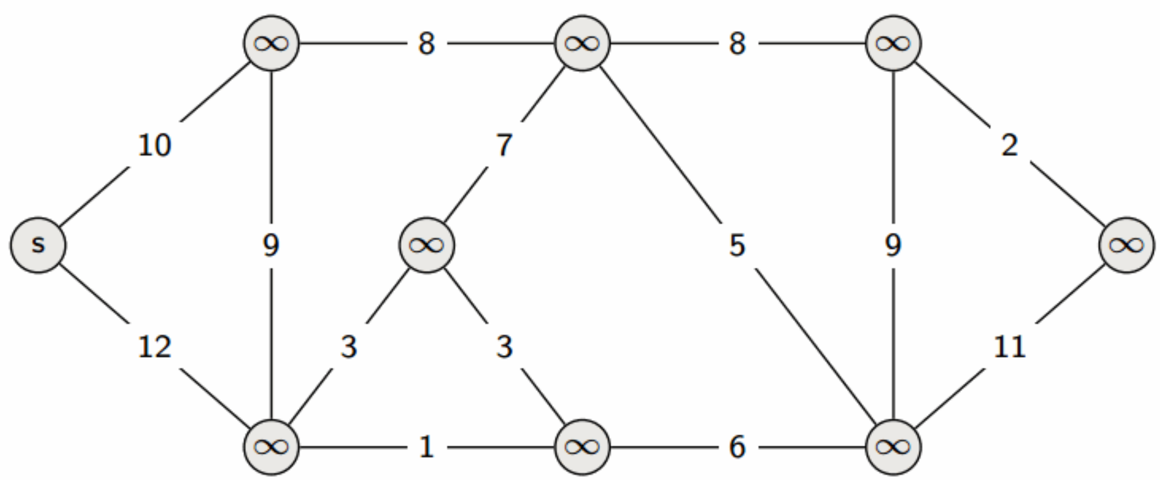
	Binary Heap	Fibonacci Heap
Remove Min	O(lg(n))	O(lg(n))
Decrease Key	O(lg(n))	O(1)*

If we use Fibonacci heap for our algorithm, updated value will take O(1) time, since we are always decreasing key.

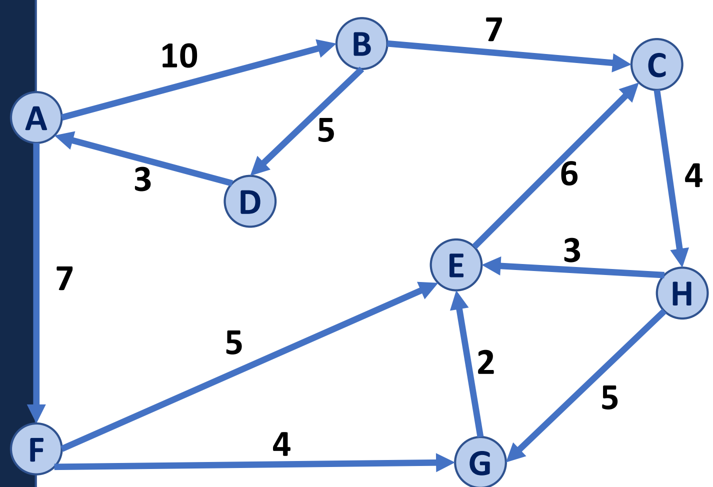
Adj. List with Fibonacci heap: $O(n \lg n + m) \ \rightarrow fastest\ running\ time\ for\ MST$

Dijkstra’s Algorithm

Dijkstra's algorithm is an algorithm for finding the shortest paths between starting node to every other nodes in a graph



Dijkstra's Algorithm



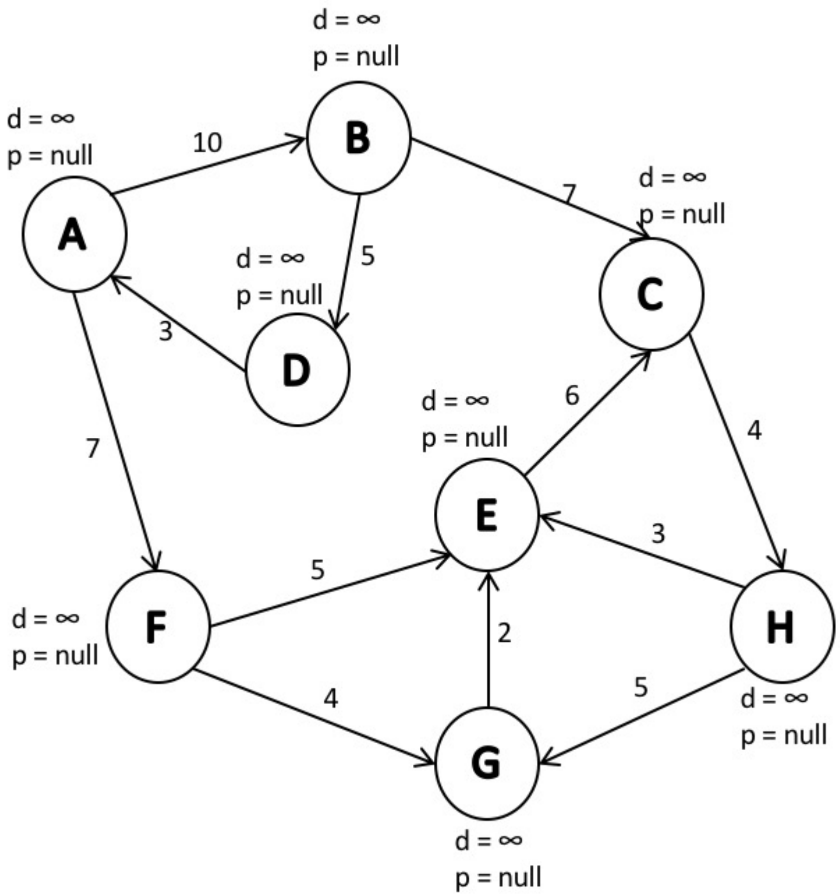

```
DijkstraSSSP(G, s):
  foreach (Vertex v : G):
    d[v] = +inf
    p[v] = NULL
  d[s] = 0

  PriorityQueue Q // min distance, defined by d[v]
  Q.buildHeap(G.vertices())
  Graph T          // "labeled set"

  repeat n times:
    Vertex m = Q.removeMin()
    T.add(u)
    foreach (Vertex v : neighbors of u not in T):
      if d[m] + cost(m, v) < d[v]:
        d[v] = d[m] + cost(m, v)
        p[v] = m
```

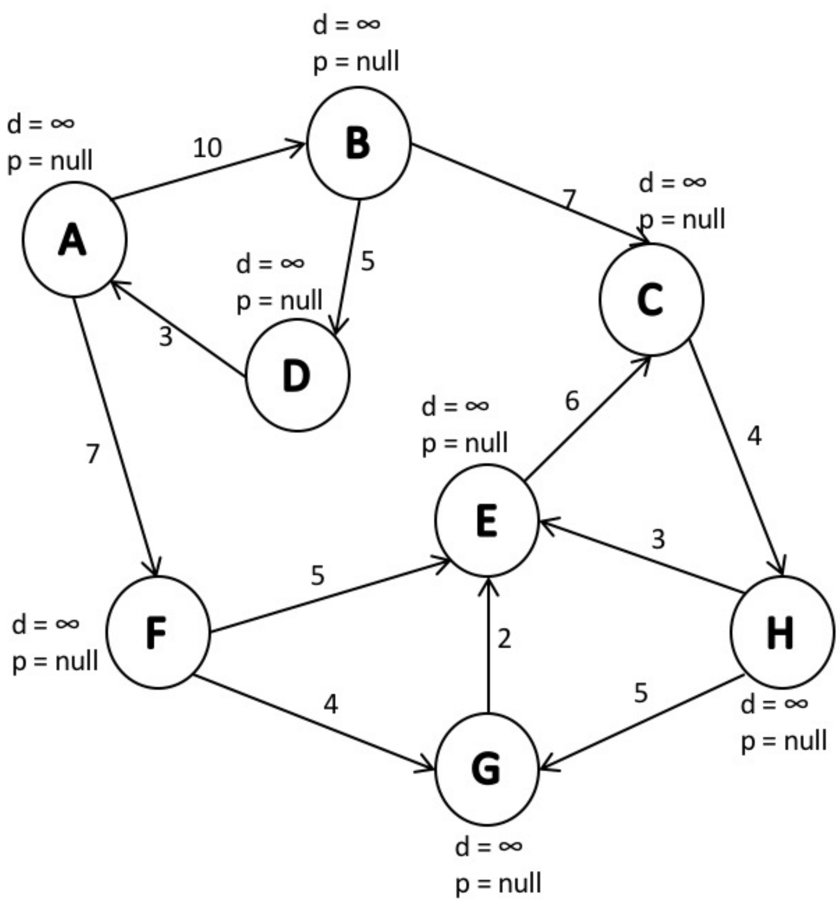
Very similar to Prim's Algorithm – only difference is when we update the distance, we use the path length instead of a single edge weight

Set up:



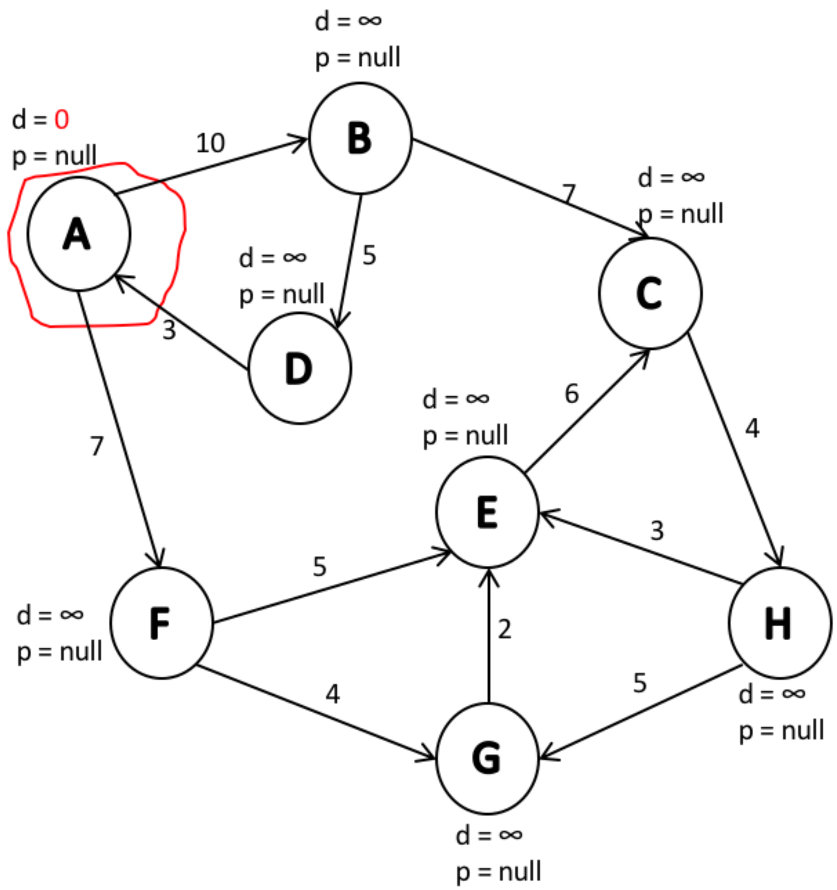
V	d	p
A	∞	null
B	∞	null
C	∞	null
D	∞	null
E	∞	null
F	∞	null
G	∞	null
H	∞	null

Choose an arbitrary starting point and set its distance to 0.



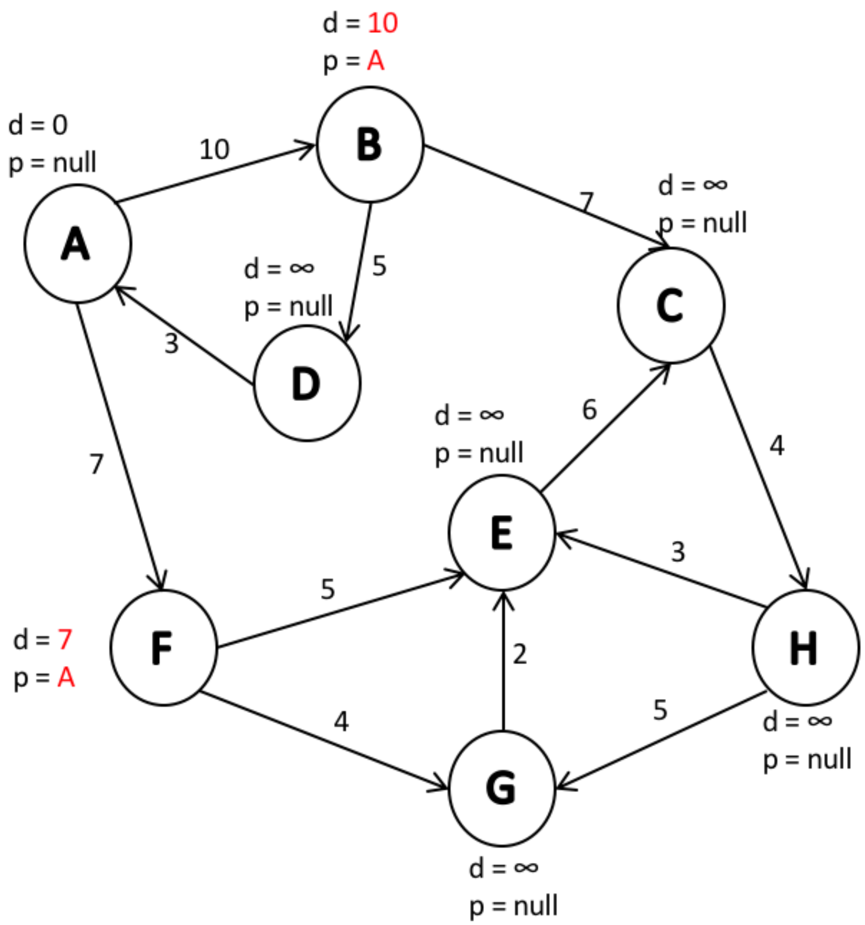
V	d	p
A	∞	null
B	∞	null
C	∞	null
D	∞	null
E	∞	null
F	∞	null
G	∞	null
H	∞	null

Starting point A.



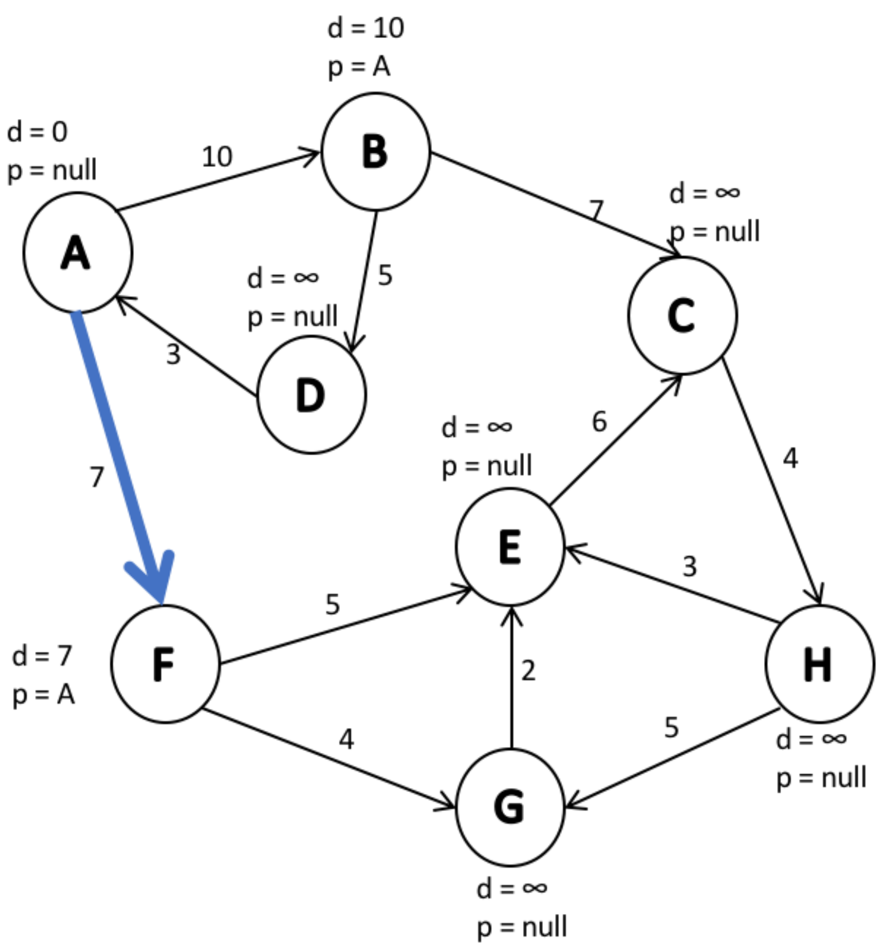
V	d	p
A	0	null
B	∞	null
C	∞	null
D	∞	null
E	∞	null
F	∞	null
G	∞	null
H	∞	null

We pop A and update adjacent vertices B and F. *Notice: edges are directed*



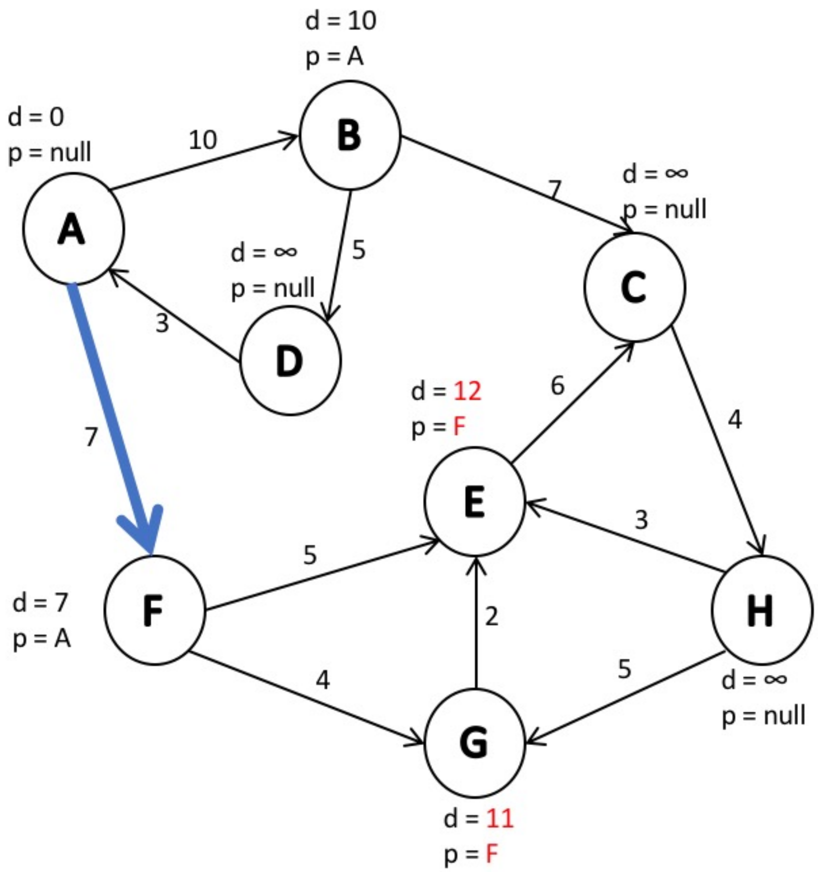
V	**d**	**p**
~~A~~	~~0~~	~~null~~
B	10	A
C	∞	null
D	∞	null
E	∞	null
F	7	A
G	∞	null
H	∞	null

add an edge to the node with the smallest distance



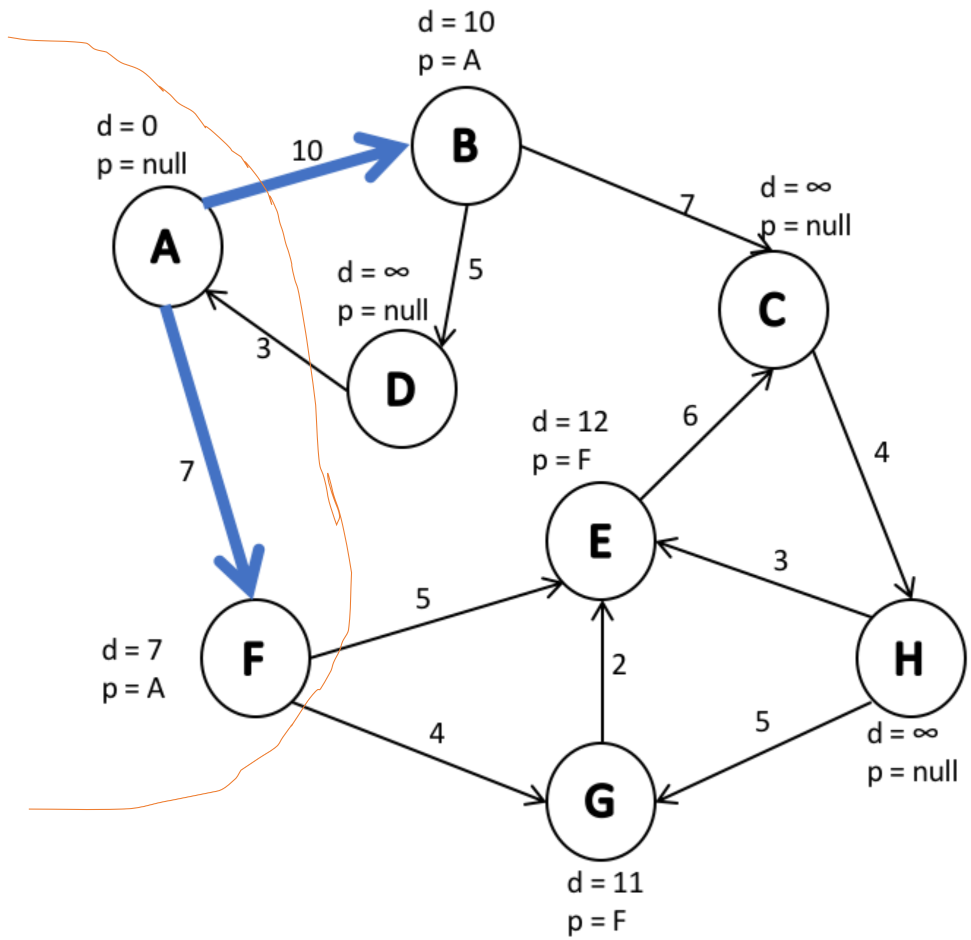
V	d	p
~~A~~	~~0~~	~~null~~
B	10	A
C	∞	null
D	∞	null
E	∞	null
F	7	A
G	∞	null
H	∞	null

Pop a vertex with the smallest distance and update adjacent vertices only if the distance from the start is smaller than the current d.



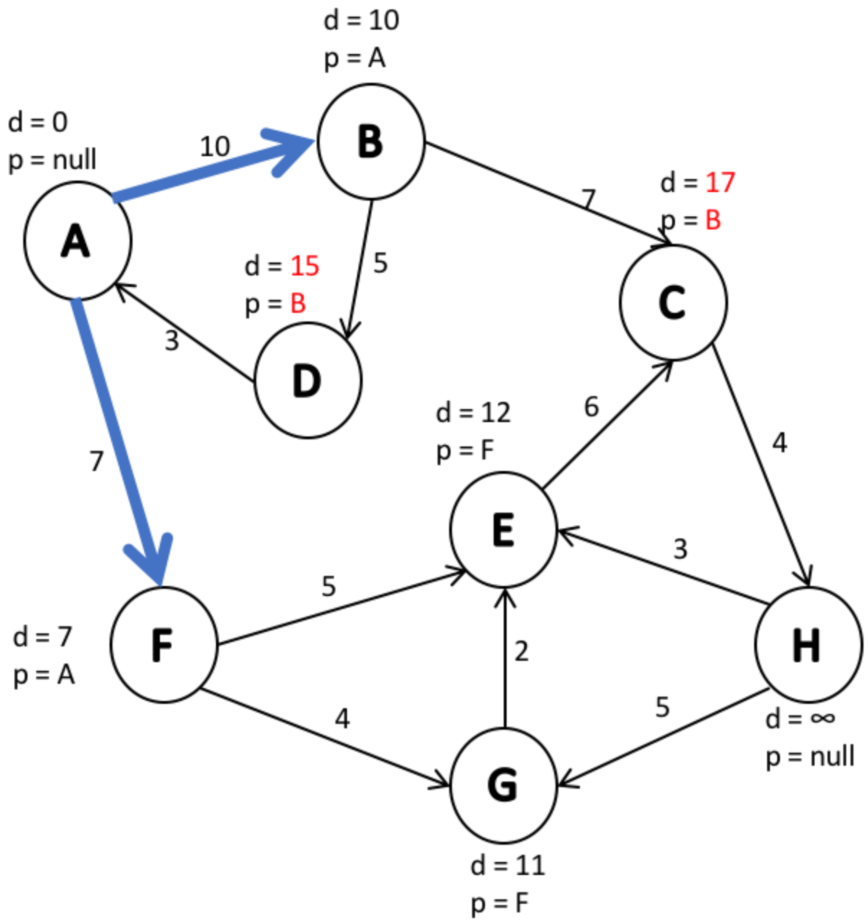
V	d	p
~~A~~	~~0~~	~~null~~
B	10	A
C	∞	null
D	∞	null
E	12	F
~~F~~	~~7~~	~~A~~
G	11	F
H	∞	null

Add an edge to the node with the smallest path



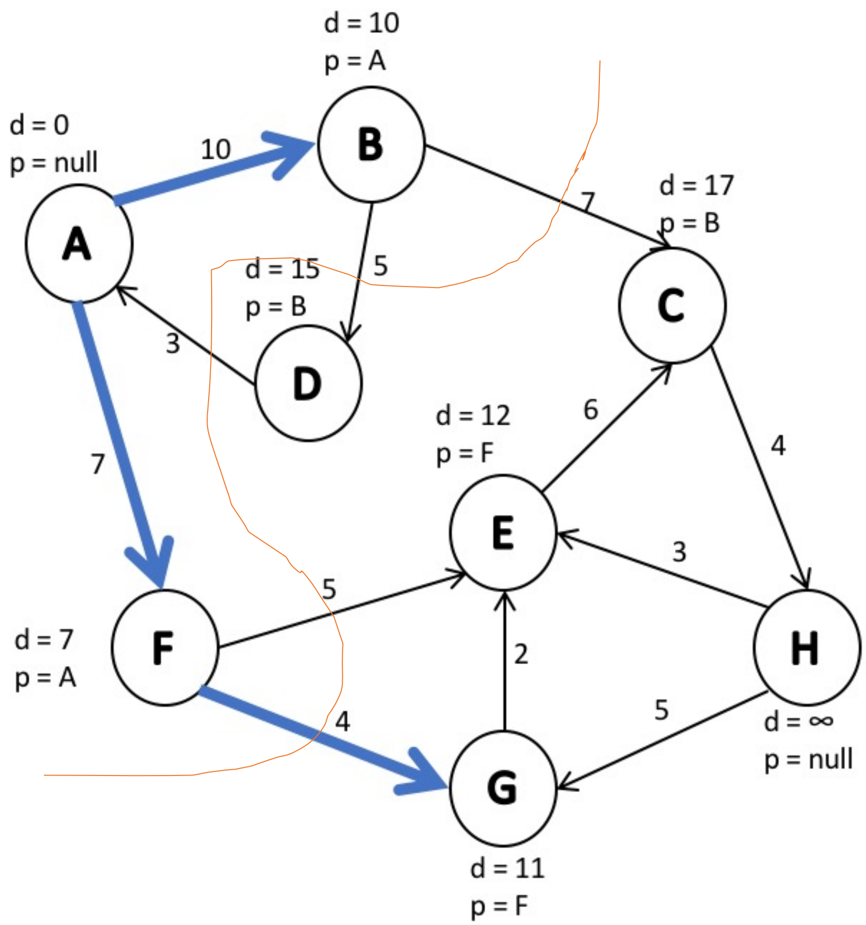
V	d	p
~~A~~	~~0~~	~~null~~
B	10	A
C	∞	null
D	∞	null
E	12	F
~~F~~	~~7~~	~~A~~
G	11	F
H	∞	null

Pop and update if needed:



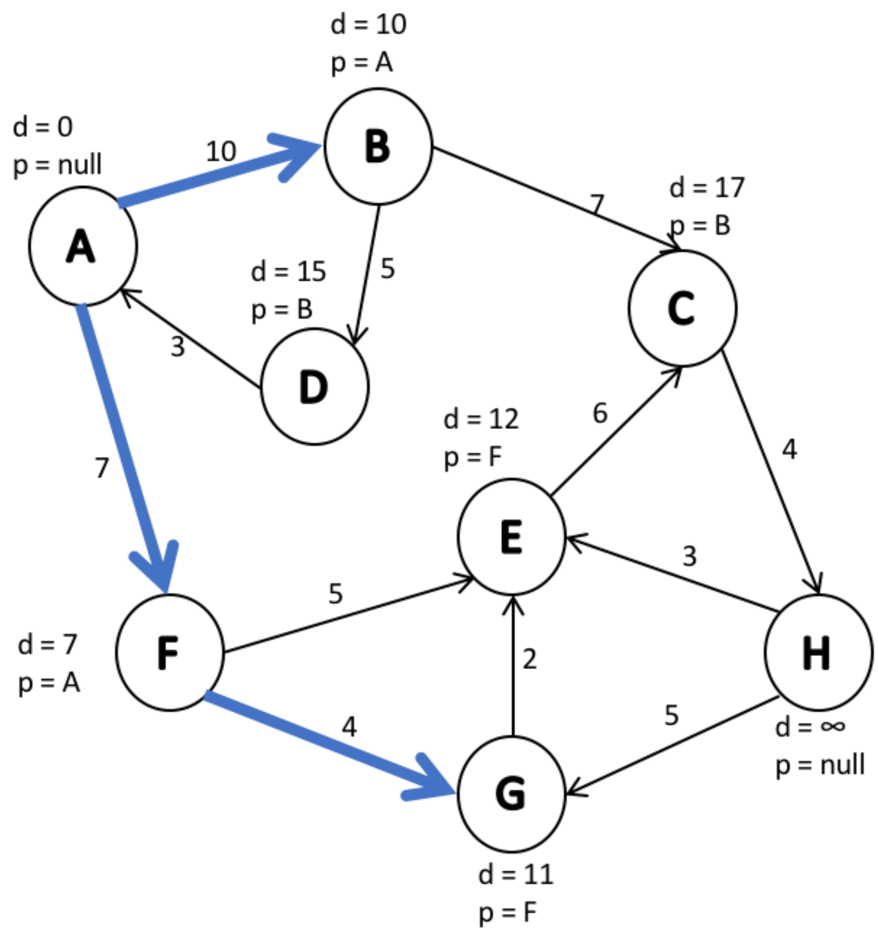
V	d	p
~~A~~	~~0~~	~~null~~
~~B~~	~~10~~	~~A~~
C	17	B
D	15	B
E	12	F
~~F~~	~~7~~	~~A~~
G	11	F
H	∞	null

Add the edge:



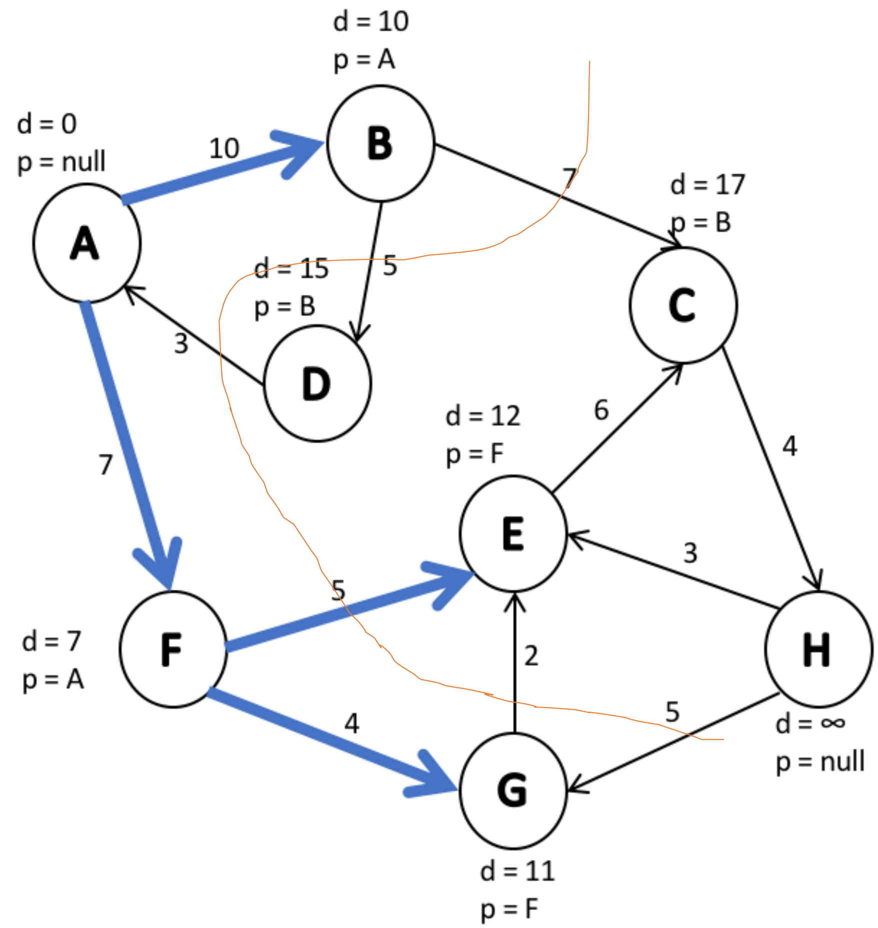
V	d	p
~~A~~	~~0~~	~~null~~
~~B~~	~~10~~	~~A~~
C	17	B
D	15	B
E	12	F
~~F~~	~~7~~	~~A~~
G	11	F
H	∞	null

Pop and update if needed:



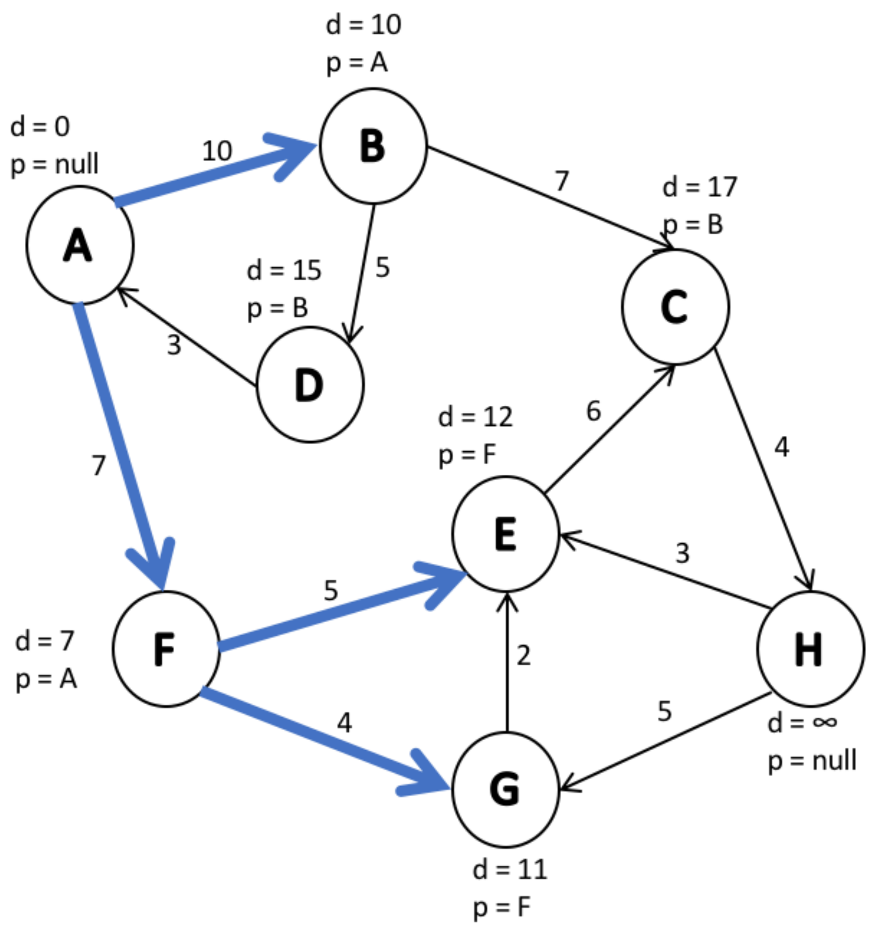
V	d	p
~~A~~	~~0~~	~~null~~
~~B~~	~~10~~	~~A~~
C	17	B
D	15	B
E	12	F
~~F~~	~~7~~	~~A~~
~~G~~	~~11~~	~~F~~
H	∞	null

Add the edge:



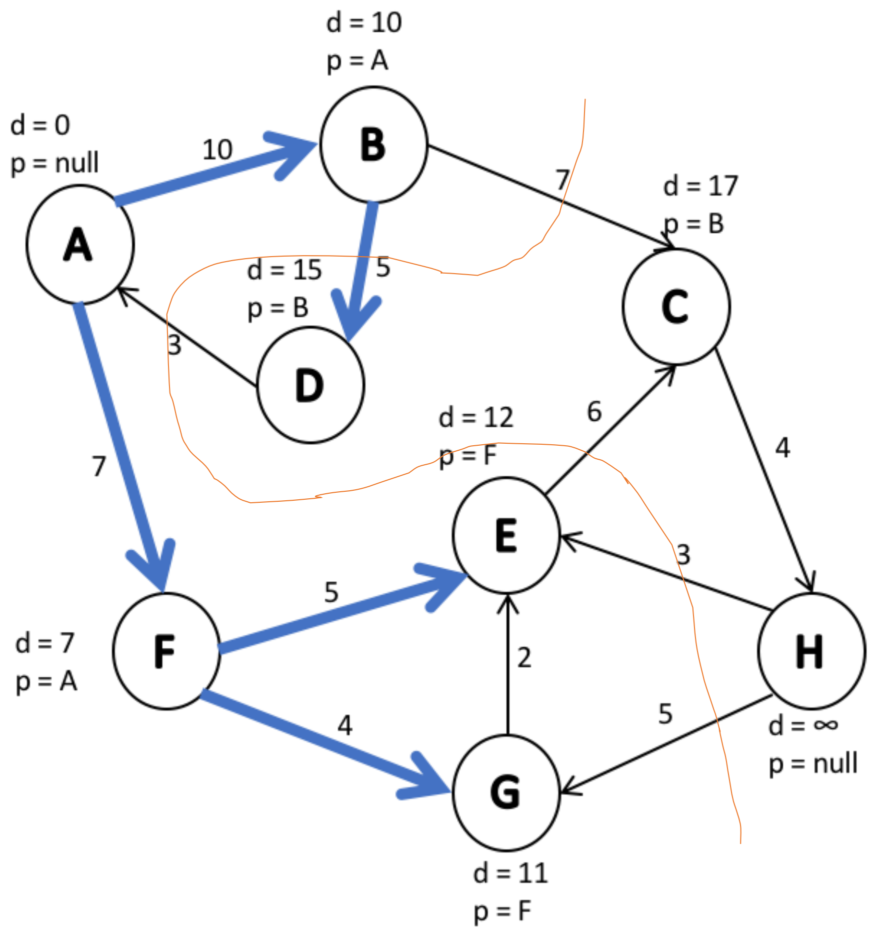
V	d	p
~~A~~	~~0~~	~~null~~
~~B~~	~~10~~	~~A~~
C	17	B
D	15	B
E	12	F
~~F~~	~~7~~	~~A~~
~~G~~	~~11~~	~~F~~
H	∞	null

Pop and update (nothing was updated)



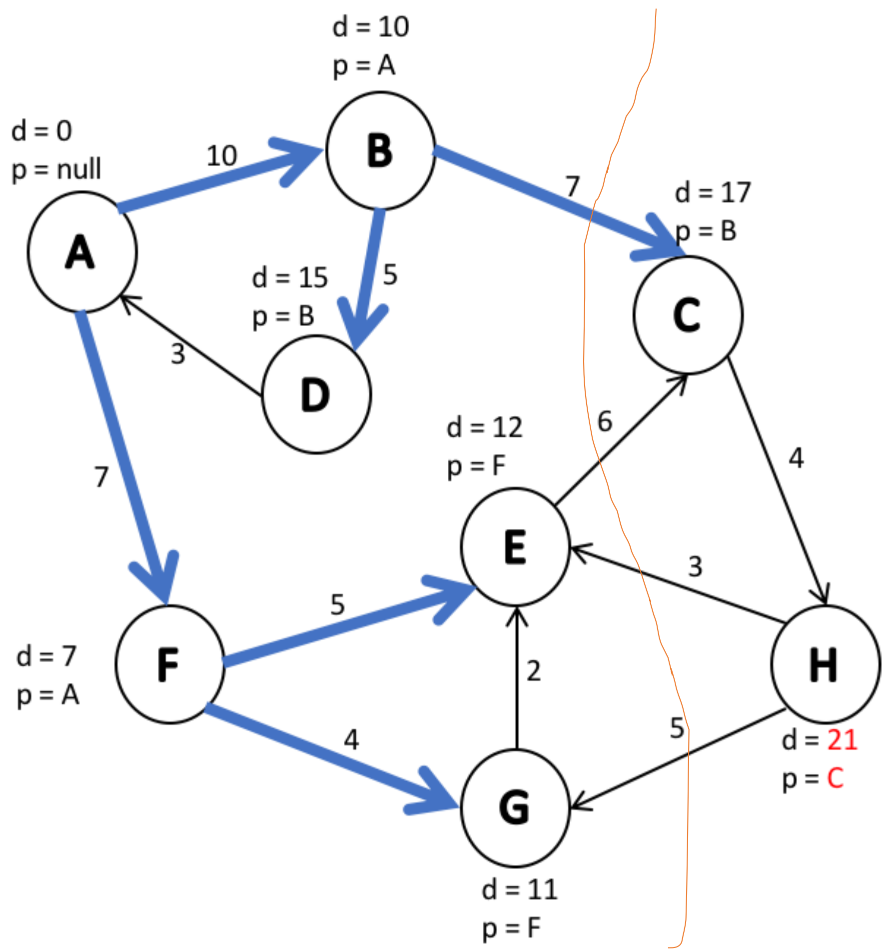
V	d	p
~~A~~	~~0~~	~~null~~
~~B~~	~~10~~	~~A~~
C	17	B
D	15	B
~~E~~	~~12~~	~~F~~
~~F~~	~~7~~	~~A~~
~~G~~	~~11~~	~~F~~
H	∞	null

Add the edge, pop D and update (nothing was updated)



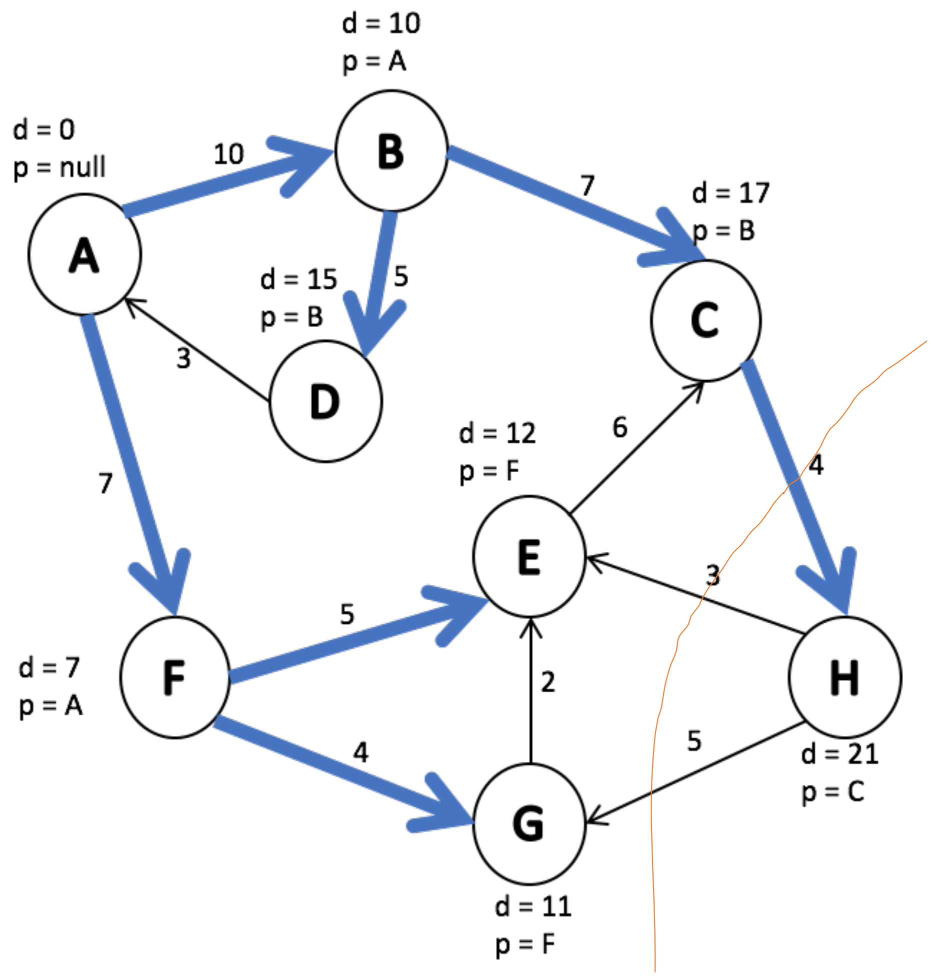
V	d	p
~~A~~	~~0~~	~~null~~
~~B~~	~~10~~	~~A~~
C	17	B
~~D~~	~~15~~	~~B~~
~~E~~	~~12~~	~~F~~
~~F~~	~~7~~	~~A~~
~~G~~	~~11~~	~~F~~
H	∞	null

Add the edge, pop C and update

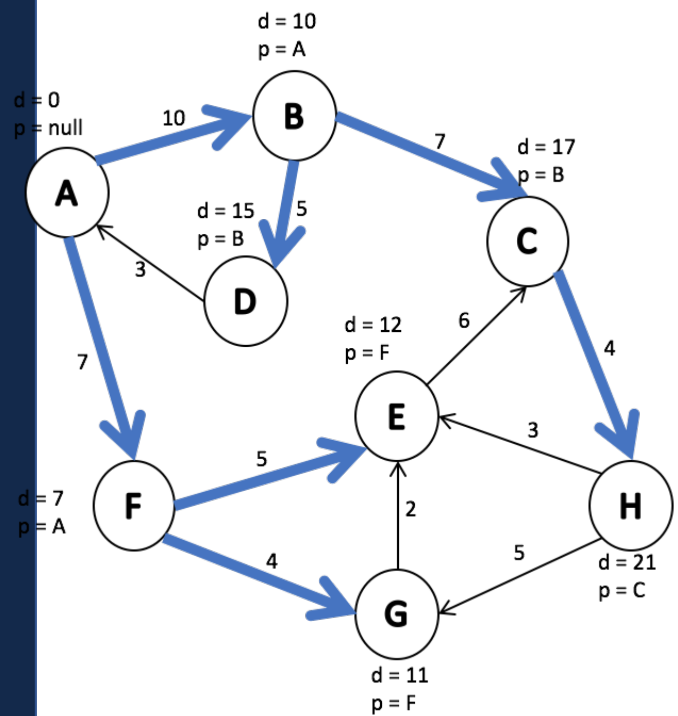


V	d	p
~~A~~	~~0~~	~~null~~
~~B~~	~~10~~	~~A~~
~~C~~	~~17~~	~~B~~
~~D~~	~~15~~	~~B~~
~~E~~	~~12~~	~~F~~
~~F~~	~~7~~	~~A~~
~~G~~	~~11~~	~~F~~
H	21	C

Add the edge from C to H and pop H. heap becomes empty



V	d	p
A	0	null
B	10	A
C	17	B
D	15	B
E	12	F
F	7	A
G	11	F
H	21	C



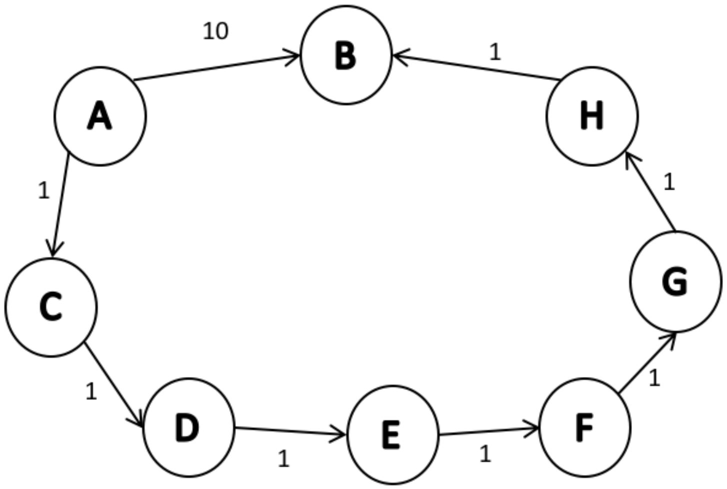
V	d	p
A	0	null
B	10	A
C	17	B
D	15	B
E	12	F
F	7	A
G	11	F
H	21	C

What is the path from A to H?
Start at H and trace back the predecessor nodes → A-B-C-H

V	d	p
A	0	null
B	10	A
C	17	B
D	15	B
E	12	F
F	7	A
G	11	F
H	21	C

The shortest path from A to H is 21.
The time to find this information is O(1).

If there is no path to a particular vertex, we will have infinity as distance.



The shortest path will be A-C-D-E-F-G-H-B instead of A-B because the first path has length 7 and the second path has length 10.

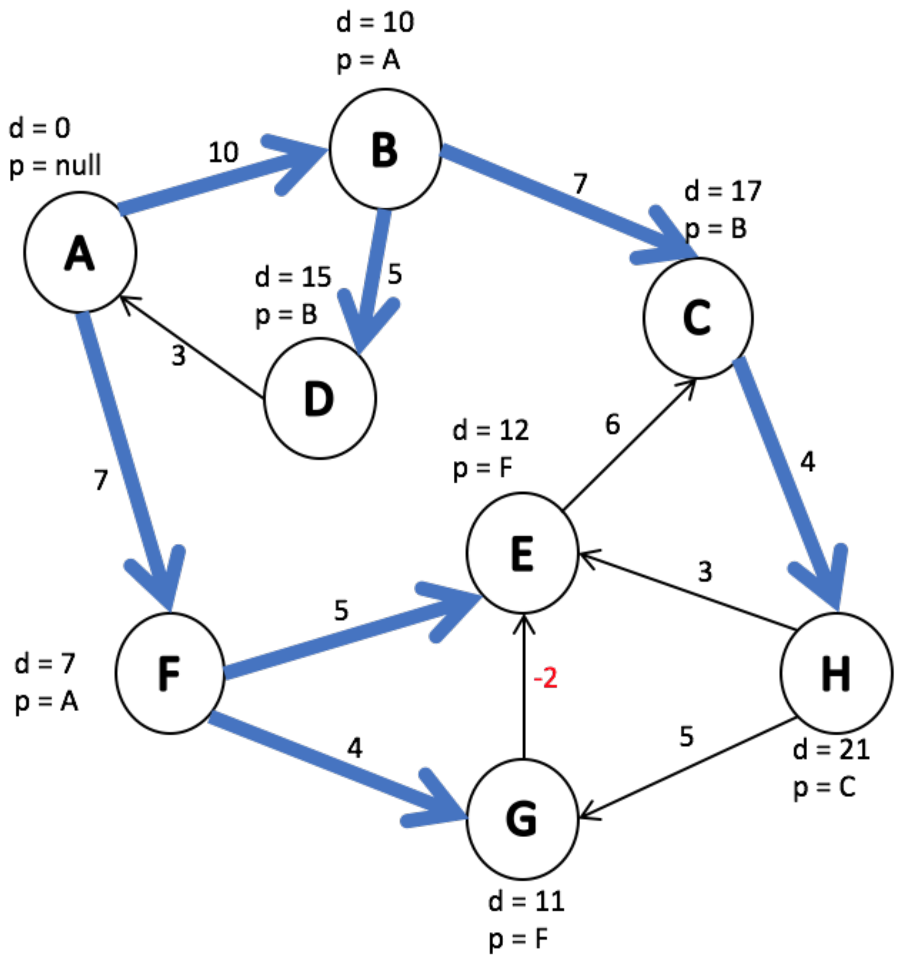
When there is a tie in path lengths, it is up to us to decide how we want to handle that.

Can Dijkstra's algorithm handle undirected graphs?
Yes, it can. It will not go back or in loop because that will increase the path length.

Can Dijkstra's algorithm handle graph with negative cycles?
No, because negative weight cycle doesn't have defined shortest path. We can always find a shorter path which leads to negative infinity.

Dijkstra's algorithm for graphs with negative edges *but with no negative cycles* <u>*will not produce the shortest path.*</u>
//We cant just add constant to every edge weights to make it 0!

Dijkstra's algorithm for graphs with negative edges (does not produce shortest path)



V	d	p
A	0	null
B	10	A
C	17	B
D	15	B
E	12	F
F	7	A
G	11	F
H	21	C

Running time of Dijkstra’s algorithm

Remember, we built Dijkstra’s algorithm on top of Prim’s algorithm.

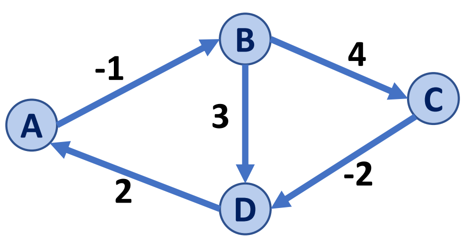
We only added two lines of code which take O(1).

Therefore, Dijkstra’s running time is the same as Prim’s.

Basic data structures	Fibonacci Heap
O(mlg(n))	O(nlg(n)+m)

Floyd-Warshall Algorithm

Floyd-Warshall's Algorithm is an alterative to Dijkstra in the presence of negative-weight edges (<u>not</u> negative weight cycles).

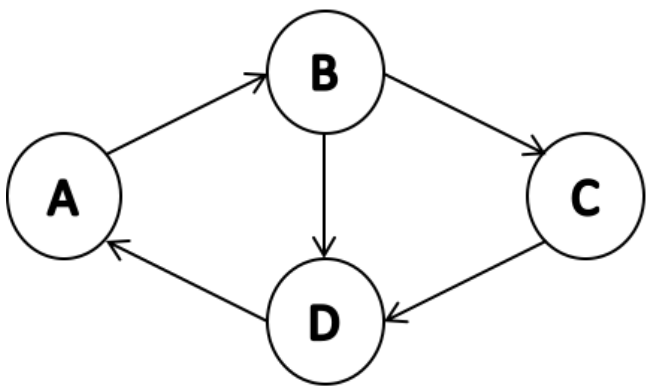



```
FloydWarshall(G):
  Let d be a adj. matrix initialized to +inf
  foreach (Vertex v : G):
    d[v][v] = 0
  foreach (Edge (u, v) : G):
    d[u][v] = cost(u, v)

  foreach (Vertex u : G):
    foreach (Vertex v : G):
      foreach (Vertex w : G):
        if d[u, v] > d[u, w] + d[w, v]:
          d[u, v] = d[u, w] + d[w, v]
```

Algorithm setup:

- Maintain a table (matrix) that has the shortest known paths between vertices.
- Initialize the table with three possible values:
  - self edges to 0
  - edges by edge weights
  - unknown paths to infinity

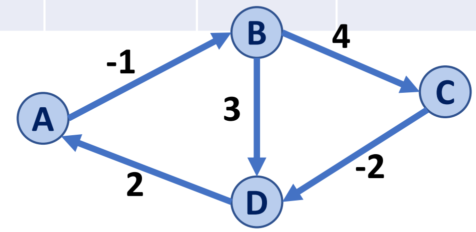


	A	B	C	D
A	0	-1	∞	∞
B	∞	0	4	3
C	∞	∞	0	-2
D	2	∞	∞	0

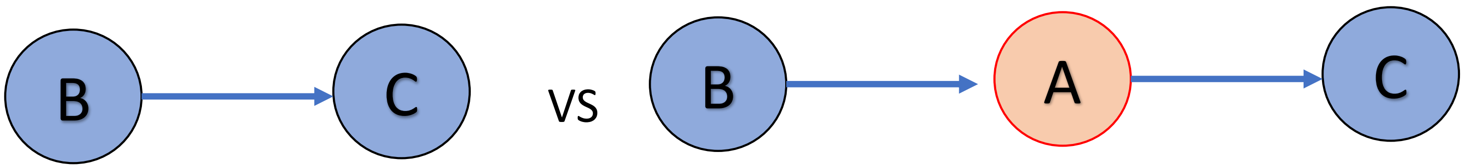
Floyd-Warshall Algorithm

```
foreach (Vertex u : G):
  foreach (Vertex v : G):
    foreach (Vertex k : G):
      if d[u, v] > d[u, k] + d[k, v]:
        d[u, v] = d[u, w] + d[w, v]
```

	A	B	C	D
A	0	-1	∞	∞
B	∞	0	4	3
C	∞	∞	0	-2
D	2	∞	∞	0



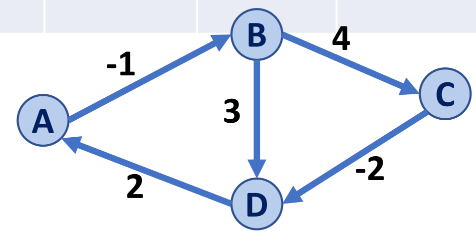
Can we add a vertex in between to vertices to make the distance shorter.



Floyd-Warshall Algorithm

```
foreach (Vertex u : G):
  foreach (Vertex v : G):
    foreach (Vertex k : G):
      if d[u, v] > d[u, k] + d[k, v]:
        d[u, v] = d[u, w] + d[w, v]
```

	A	B	C	D
A	0	-1	∞	∞
B	∞	0	4	3
C	∞	∞	0	-2
D	2	∞	∞	0



Let us consider k=A:

B → C 4 vs. B → A → C +∞

B → D 3 vs. B → A → D +∞

C → B +∞ vs. C → A → B +∞

C → D -2 vs. C → A → D +∞

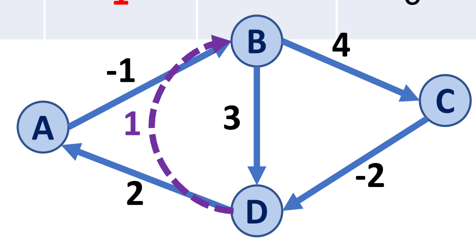
D → B +∞ vs. D → A → B **2+(-1) = 1**

D → C +∞ vs. D → A → C +∞

Floyd-Warshall Algorithm

```
foreach (Vertex u : G):
  foreach (Vertex v : G):
    foreach (Vertex k : G):
      if d[u, v] > d[u, k] + d[k, v]:
        d[u, v] = d[u, w] + d[w, v]
```

	A	B	C	D
A	0	-1	∞	∞
B	∞	0	4	3
C	∞	∞	0	-2
D	2	1	∞	0



Let us consider k=A:

B → C 4 vs. B → A → C +∞

B → D 3 vs. B → A → D +∞

C → B +∞ vs. C → A → B +∞

C → D -2 vs. C → A → D +∞

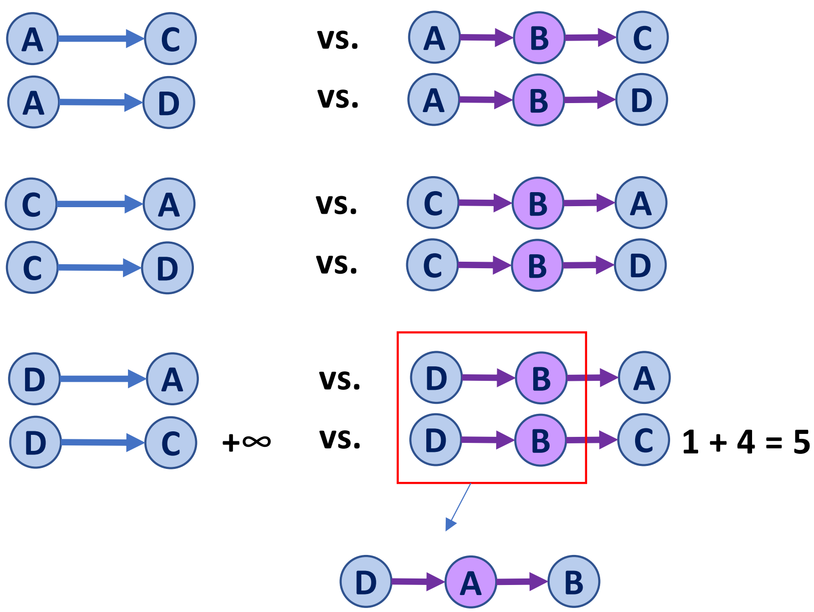
D → B +∞ vs. D → A → B 2+(-1) = 1

D → C +∞ vs. D → A → C +∞

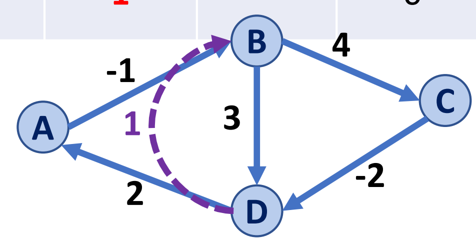
Floyd-Warshall Algorithm

```
  foreach (Vertex u : G):
    foreach (Vertex v : G):
      foreach (Vertex k : G):
        if d[u, v] > d[u, k] + d[k, v]:
          d[u, v] = d[u, w] + d[w, v]
```

Let us consider k=B:



	A	B	C	D
A	0	-1	∞	∞
B	∞	0	4	3
C	∞	∞	0	-2
D	2	1	∞	0



This edge does not actually gets created. Values in the matrix saves information about updated path values.

Floyd-Warshall Algorithm

Floyd-Warshall's algorithm explores all possible paths to determine the shortest path in $O(n^3)$

If we explored all possible paths with Dijkstra's algorithm:
$O(n^2 \lg n + m * n)$

Dense graph: Floyd-Warshall outperforms Dijkstra's algorithm
Sparse graph: Dijkstra's algorithm outperforms Floyd-Warshall

Floyd-Warshall works with negative edges!