

LECTURE 15: ALL-PAIRS SHORTEST PATHS (APSP) + REVISION

Harold Soh harold@comp.nus.edu.sg

ı

### **ADMINISTRATIVE ISSUES**

Quiz1, Quiz 2, and PS1 scores are on Luminus

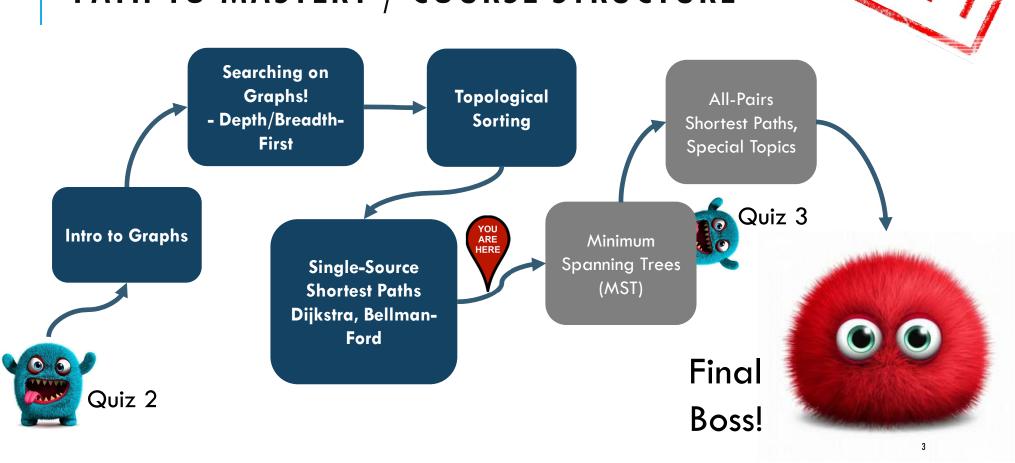
#### **Please Verify**

- verify all your scores = 1 participation point
- If something is incorrect, please let us know.

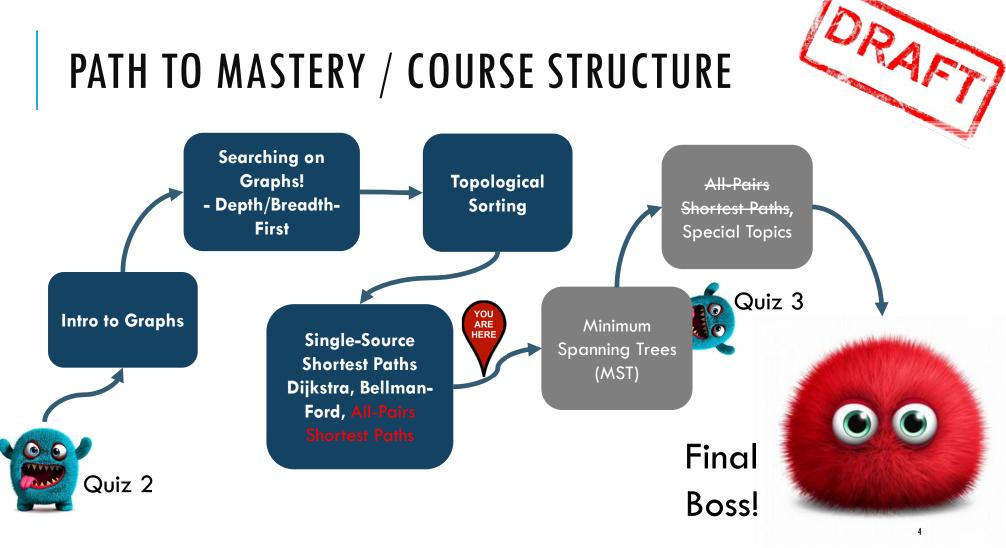
PS2 scores coming soon (just a few more to check).

Quiz 2 to be returned during Friday's tutorial.

## PATH TO MASTERY / COURSE STRUCTURE



## PATH TO MASTERY / COURSE STRUCTURE



### **TODAY: LEARNING OUTCOMES**

By the end of this session, students should be able to:

- State the all-pairs shortest-paths (APSP) problem
- Explain Floyd-Warshall and apply it to solve the APSP problem.
- Analyze the computational complexity of Floyd-Warshall.

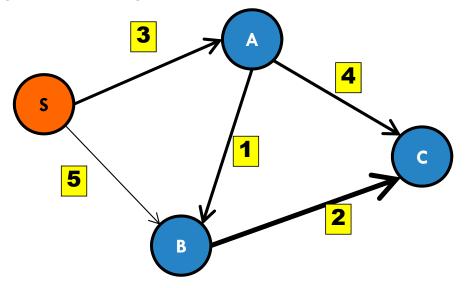
### **SINGLE-SOURCE** SHORTEST PATHS

#### Input:

- Directed, weighted graph G = (V,E)
- Given source s and target t

#### **Output:**

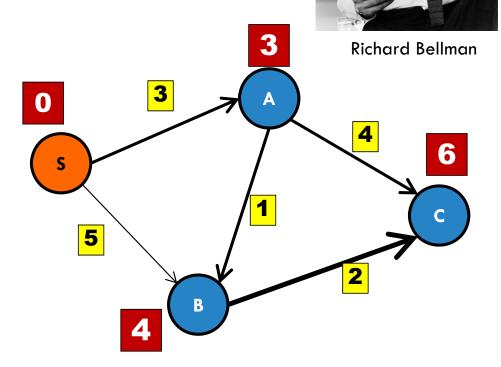
min-distance(s, t)



In fact, you can now compute shortestpaths from 1 source to **ALL** other nodes.

# BELLMAN-FORD ALGORITHM FOR SINGLE-SOURCE SHORTEST PATHS

n = V.length
for i = 1 to n-1
 for Edge e in Graph
 relax(e)



### **SPECIAL CASES**

Condition	Algorithm	Time Complexity
No Negative Weight Cycles	Bellman-Ford Algorithm	O(VE)
On Unweighted Graph (or equal weights)	BFS	O(V+E)
No Negative Weights	Dijkstra's Algorithm	$O((V+E)\log V)$
On Tree	BFS / DFS	O(V)
On DAG	Topological Sort	O(V+E)

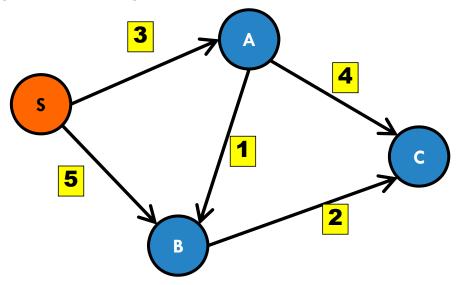
### **SINGLE-SOURCE** SHORTEST PATHS

#### Input:

- Directed, weighted graph G = (V,E)
- Given source s and target t

#### **Output:**

min-distance(s, t)



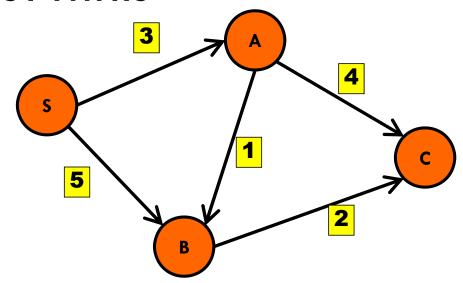
### **SINGLE-SOURCE** SHORTEST PATHS

#### Input:

- Directed, weighted graph G = (V,E)
- Given source s and target t

#### **Output:**

min-distance(s, t)



But what if we have queries involving many different source nodes?

### ALL PAIRS SHORTEST PATHS (APSP) PROBLEM

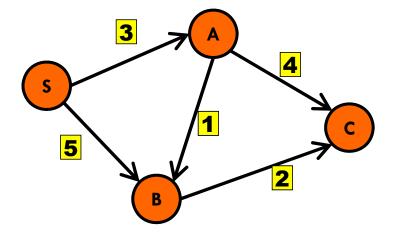
Compute distances between ALL pairs of nodes.

Simple solution (using what you have learnt)?

Run Bellman-Ford / Dijkstra for all nodes

#### **Running time?**

- Bellman-Ford:  $O(V^2 E)$
- Djikstra:  $O((V^2 + VE) \log V)$



## FLOYD-WARSHALL (1962)

#### **All Pairs Shortest Paths**

Computes distances between ALL pairs of nodes.

#### Slide from the Lecture on Heaps!

#### **REMEMBER ROBERT FLOYD?**

FROM HEAPS: CLEVER CREATION IN O(n) TIME



#### Invented by Robert Floyd in 1964

- invented invariants (among other things)
- we'll hear about him again in when we meet graphs!

#### The idea:

- View the input array as a binary tree
- "Bottom up" fixing of the tree to satisfy MaxHeap property

### FLOYD-WARSHALL (1962)

#### **All Pairs Shortest Paths**

Computes distances between ALL pairs of nodes.

The original algorithm was invented by Bernard Roy in 1959.





## STIGLER'S LAW OF EPONYMY

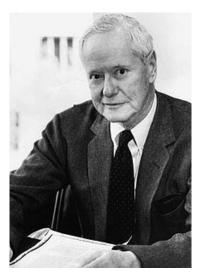
No scientific discovery is named after its original discoverer.

proposed by University of Chicago statistics professor Stephen Stigler.

Stigler named Columbia University sociology professor **Robert K. Merton** as the original discoverer of "Stigler's law"

Stigler's law follows Stigler's law.





### FLOYD-WARSHALL (1962)

#### **All Pairs Shortest Paths**

Computes distances between ALL pairs of nodes.

Key Idea: Shortest paths have "optimal sub-structure":

If P is the shortest path  $(u \rightarrow v \rightarrow w)$ , then P contains the shortest path from  $(u \rightarrow v)$  and from  $(v \rightarrow w)$ .



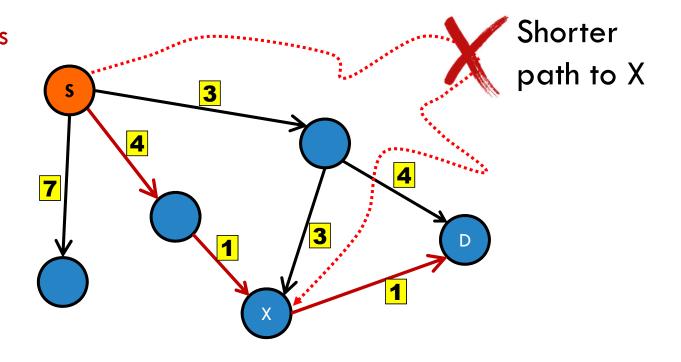
Many shortest path calculations depends on the same sub-pieces.

# **RECALL:** SUBPATHS OF SHORTEST PATHS ARE SHORTEST PATHS

**Key property:** If p is the shortest path from S to D,

and if p goes through X,

then p is also the shortest path from S to X (and from X to D).



### FLOYD-WARSHALL (1962)

The original algorithm was invented by Bernard Roy in 1959.

#### **All Pairs Shortest Paths**

Computes distances between ALL pairs of nodes.

Key Idea: Shortest paths have "optimal sub-structure":

If P is the shortest path  $(u \rightarrow v \rightarrow w)$ , then P contains the shortest path from  $(u \rightarrow v)$  and from  $(v \rightarrow w)$ .



Many shortest path calculations depends on the same sub-pieces.

Is a **Dynamic Programming** solution

#### DYNAMIC PROGRAMMING

Actually isn't really about "PROGRAMMING" "Programming" refers to a "tabular method"

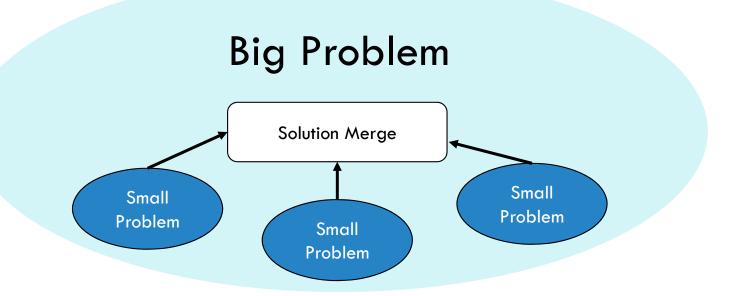
#### 4 basic steps:

- Figure out the subproblems.
- Relate the subproblem solutions.
- Recurse and memoize ("memorize")
- Solve the original problem via subproblems.

#### DYNAMIC PROGRAMMING BASICS

#### **Optimal sub-structure:**

 Optimal solution can be constructed from optimal solutions to smaller subproblems.

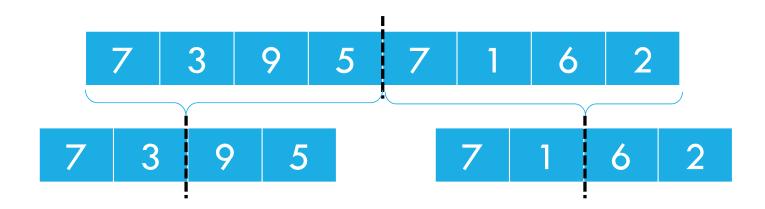


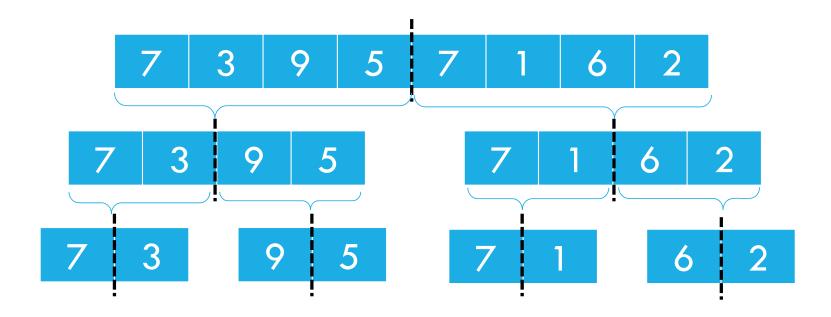
### OPTIMAL SUB-STRUCTURE

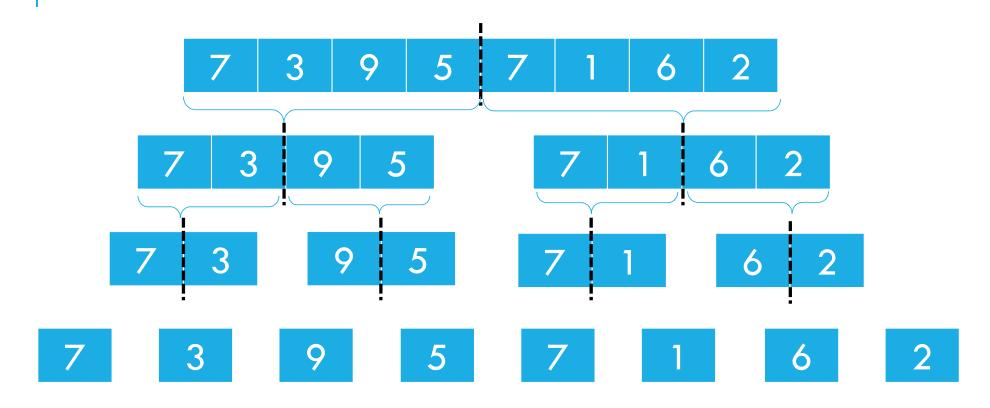
#### Property of many problems we study:

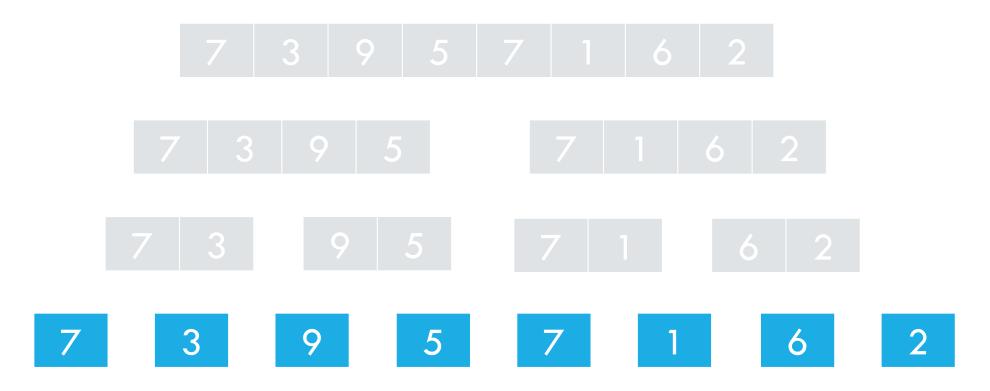
- GREEDY algorithms
  - Dijkstra's Algorithm
  - Minimum Spanning Tree algorithms
- Divide-and-conquer algorithms
  - MergeSort

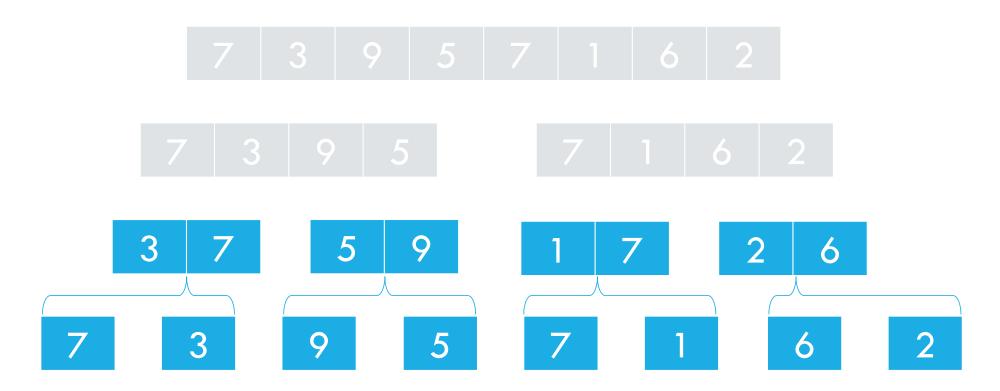


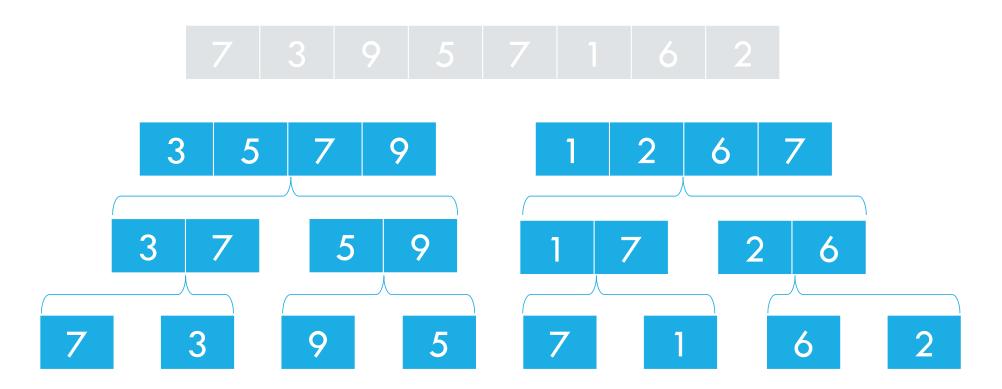


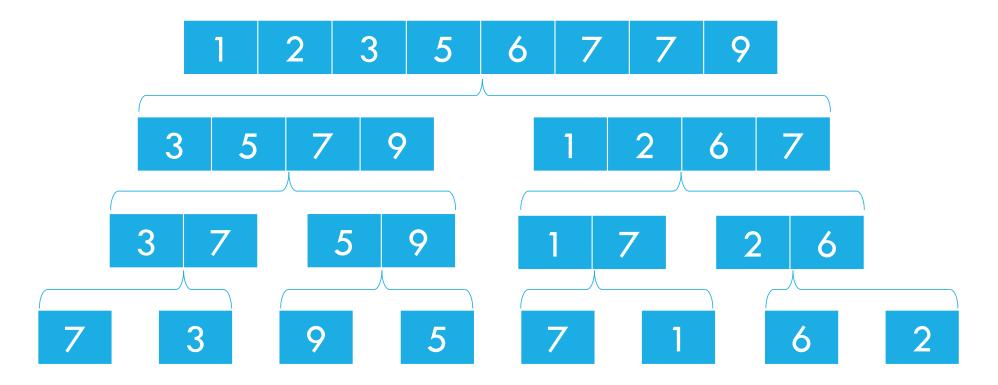










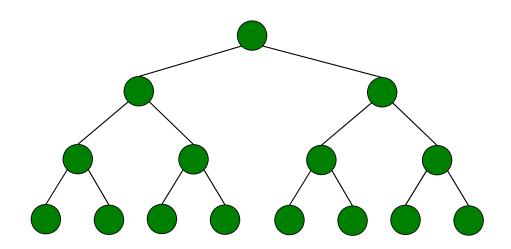


### OPTIMAL SUB-STRUCTURE

#### Property of many problems we study:

- GREEDY algorithms
  - Dijkstra's Algorithm
  - Minimum Spanning Tree algorithms
- Divide-and-conquer algorithms
  - MergeSort

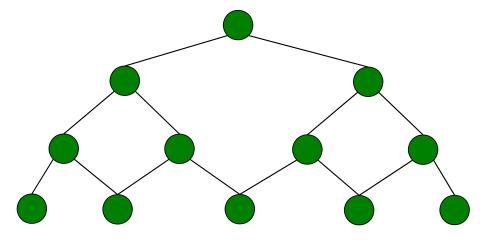
### **OPTIMAL SUB-STRUCTURE**



### **OVERLAPPING** SUB-PROBLEMS

The same smaller problem is used to solve multiple different bigger

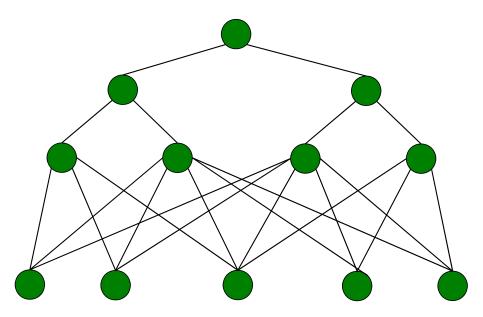
problems.



### **OVERLAPPING** SUB-PROBLEMS

The same smaller problem is used to solve multiple different bigger

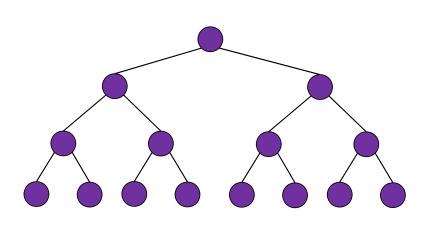
problems.



#### Both have optimal substructure

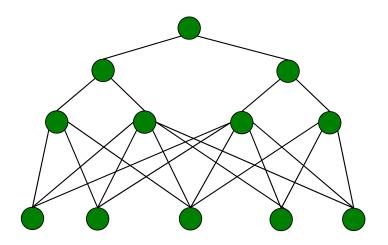
### DYNAMIC PROGRAMMING

#### No overlapping subproblems



Divide-and-Conquer

#### Overlapping subproblems



**Dynamic Programming** 

### FLOYD-WARSHALL (1962)



#### **Dynamic programming:**

Shortest paths have optimal sub-structure:

If P is the shortest path  $(u \rightarrow v \rightarrow w)$ , then P contains the shortest path from  $(u \rightarrow v)$  and from  $(v \rightarrow w)$ .

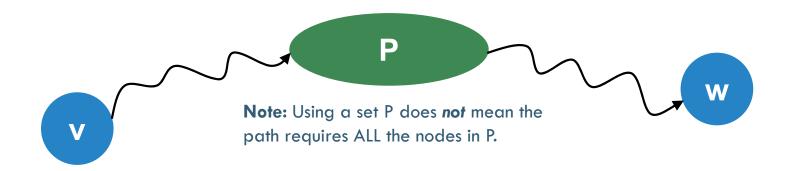
Shortest paths have overlapping subproblems

Many shortest path calculations depends on the same sub-pieces.

Hard question: what are the right subproblems?

### FLOYD-WARSHALL

Let S[v, w, P] be the distance (of the shortest path) from v to w that **only** uses intermediate nodes in the set P.

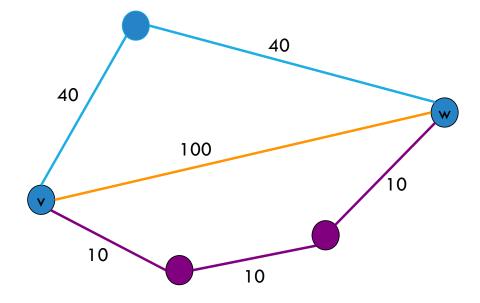


Let S[v, w, P] be the distance (of the shortest path) from v to w that only uses intermediate nodes in the set P.

 $P_1$  = no nodes (empty set)

 $P_2$  = blue nodes

 $P_3$  = purple nodes



Let S[v, w, P] be the distance (of the shortest path) from v to w that only uses intermediate nodes in the set P.

 $P_1$  = no nodes (empty set)

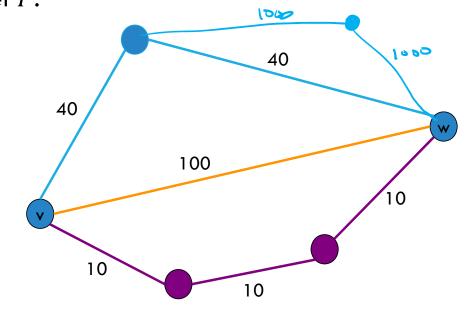
 $P_2$  = blue nodes

 $P_3$  = purple nodes

$$S(v, w, P_1) = 100$$

$$S(v, w, P_2) = 80$$

$$S(v, w, P_3) = 30$$

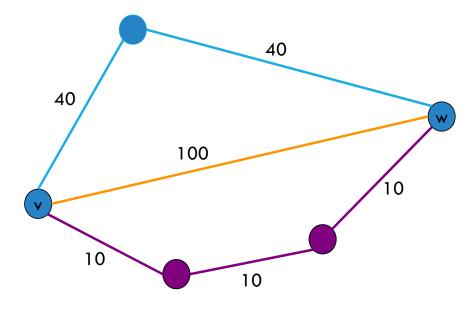


Let S[v, w, P] be the distance (of the shortest path) from v to w that only uses intermediate nodes in the set P.

#### Base case:

$$S[v, w, \emptyset] = E[v, w]$$

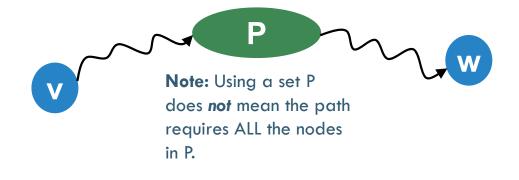
$$E[v, w] = \text{weight of}$$
  
edge from  $v$  to  $w$ .  
(if no edge:  $E[v, w] = \infty$ )



Which sets P do we need to check for a graph with n nodes (nodes are labelled from 1, 2, ..., n)?

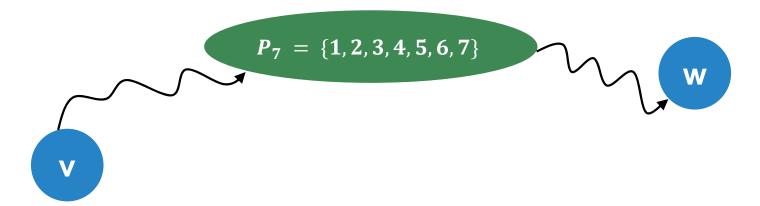
#### Check increasingly large sets:

$$\begin{array}{l} P_0 = \varnothing \\ P_1 = \{1\} \\ P_2 = \{1,2\} \\ P_3 = \{1,2,3\} \\ P_4 = \{1,2,3,4\} \\ \dots \\ P_n = \{1,2,3,4,\dots,n\} \end{array}$$



#### Use the **precalculated** subproblems:

Assume we have calculated  $S[v, w, P_7] = 42$ . How do we calculate  $S[v, w, P_8]$ ?



#### Slide from the previous lecture!

### REMEMBER RELAX?

Maintain estimate for each distance: relax(S, A)

#### The idea:

relax(w,v):

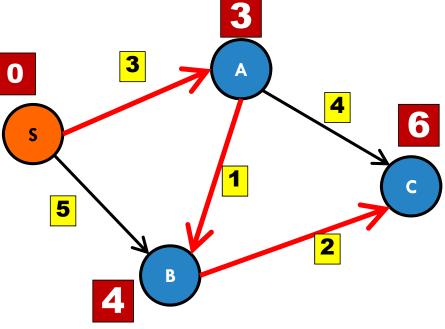
Test if the best way to get from  $s \to v$  is to go from  $s \to w$ , then  $w \to v$ .

#### If yes:

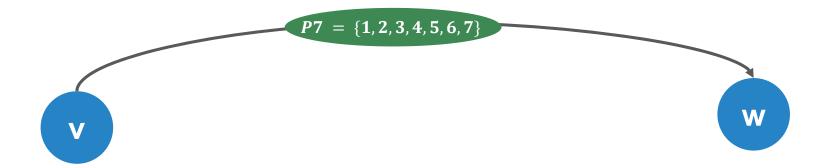
- Update dist[v]
- Update edgeTo[v]

relax(int u, int v) {
 if (dist[v] > dist[u] + weight(u,v))
 dist[v] = dist[u] + weight(u,v);
 edgeTo[v] = u; //update predecessor/parent

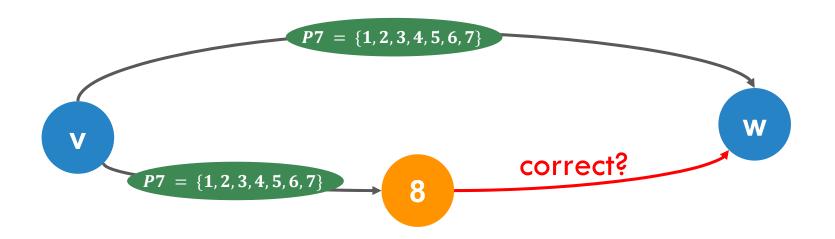
This creates a predecessor subgraph



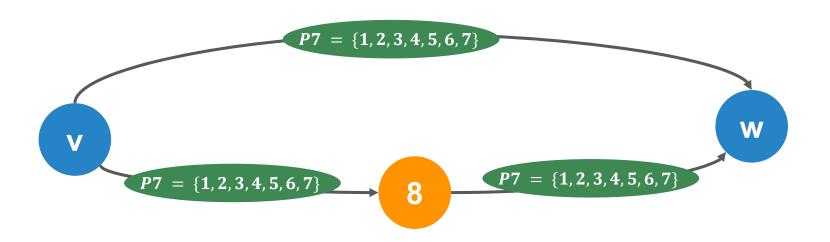
$$S[v, w, P_8] = \min(S[v, w, P_7],$$
?



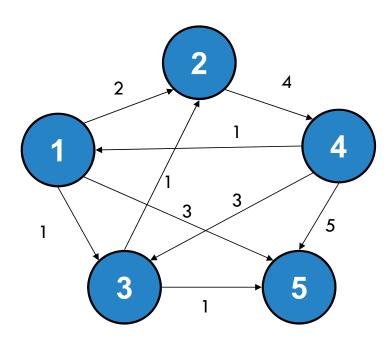
$$S[v, w, P_8] = \min(S[v, w, P_7], S[v, 8, P_7] + E[8, w])$$



$$S[v, w, P_8] = \min(S[v, w, P_7], S[v, 8, P_7] + S[8, w, P_7])$$

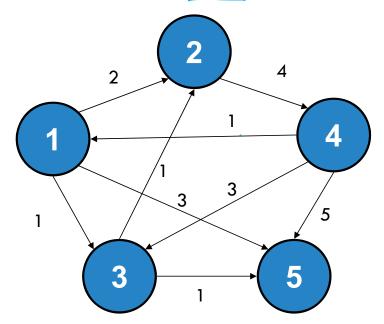


### **EXAMPLE**



### INITIALIZATION

 $S[v, w, P_0] = E[v, w]$ 

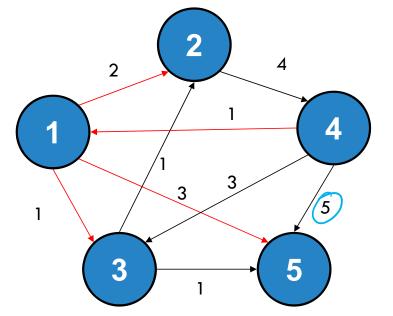


	1	2	3	4	5
1	0	2	1	$\infty$	3
2	$\infty$	0	$\infty$	4	$\infty$
3	$\infty$	1	0	$\infty$	1
4	1	$\infty$	3	0	5
5	$\infty$	$\infty$	$\infty$	$\infty$	0

# STEP: $P_1 = \{1\}$

 $S[v, w, P_1] = \min(S[v, w, P_0], S[v, 1, P_0] + S[1, w, P_0])$ 

$$P_0 = \{\}$$



	1	2	3	4	5
1	0	2	1	$\infty$	3
2	$\infty$	0	$\infty$	4	$\infty$
3	$\infty$	1	0	$\infty$	1
4	1	$\infty$	3	0	5
5	$\infty$	$\infty$	$\infty$	$\infty$	0

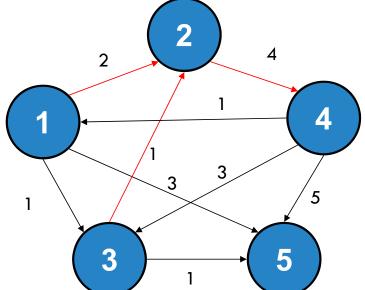


	1	2	3	4	5
1	0	2	1	$\infty$	3
2	$\infty$	0	$\infty$	4	$\infty$
3	$\infty$	1	0	$\infty$	1
4	1	3	2	0	4
5	$\infty$	$\infty$	$\infty$	$\infty$	0

## STEP: $P_2 = \{1,2\}$

 $S[v, w, P_2] = \min(S[v, w, P_1], S[v, 2, P_1] + S[2, w, P_1])$ 

$$P_1 = \{1\}$$

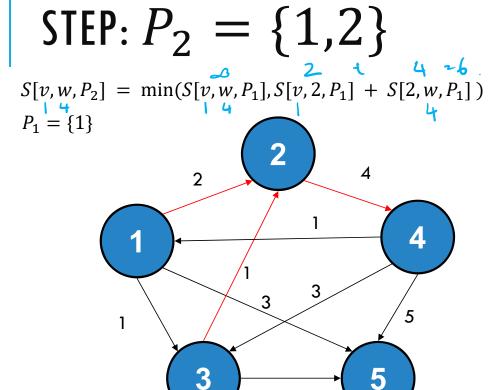


	1	2	3	4	5
1	0	2	1	$\infty$	3
2	$\infty$	0	$\infty$	4	$\infty$
3	$\infty$	1	0	$\infty$	1
4	1	3	2	0	4
5	$\infty$	$\infty$	$\infty$	$\infty$	0

•	<b>\</b> .		
$\boldsymbol{\mathcal{L}}$	•	•	7
		1	
		1	
		1	
		ı	
		_	

54,6	, Y2 >			•		
=		1	2	3	4	5
	1	0	2	2)1	?	3
	2	$\infty$	0	$\infty$	4	$\infty$
	3	$\infty$	1	0	?	1
	4	1	3	2	0	4
	5	$\infty$	$\infty$	$\infty$	$\infty$	0

#### 3(1,4,1)



	1	2	3	4	5
1	0	2	1	$\infty$	3
2	$\infty$	0	$\infty$	4	$\infty$
3	$\infty$	1	0	$\infty$	1
4	1	3	2	0	4
5	$\infty$	$\infty$	$\infty$	$\infty$	0

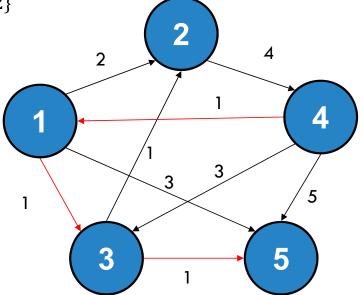


	1	2	3	4	5
1	0	2	1)	6	3
2	$\infty$	0	$\infty$	4	$\infty$
3	$\infty$	1	0	5	1
4	1	3	2	0	4
5	$\infty$	$\infty$	$\infty$	$\infty$	0

## STEP: $P_3 = \{1,2,3\}$

 $S[v, w, P_3] = \min(S[v, w, P_2], S[v, 3, P_2] + S[3, w, P_2])$ 





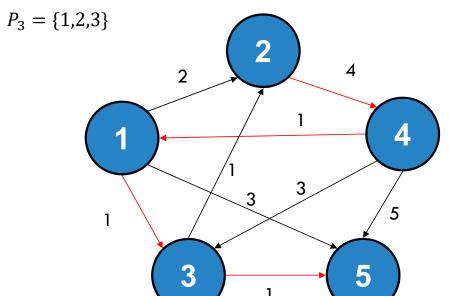
	1	2	3	4	5
1	0	2	1	6	3
2	$\infty$	0	$\infty$	4	$\infty$
3	$\infty$	1	0	5	1
4	1	3	2	0	4
5	$\infty$	$\infty$	$\infty$	$\infty$	0



	1	2	3	4	5
1	0	2	1	6	2
2	$\infty$	0	$\infty$	4	$\infty$
3	$\infty$	1	0	5	1
4	1	3	2	0	3
5	$\infty$	$\infty$	$\infty$	$\infty$	0

## STEP: $P_4 = \{1,2,3,4\}$

 $S[v, w, P_4] = \min(S[v, w, P_3], S[v, 4, P_3] + S[4, w, P_3])$ 



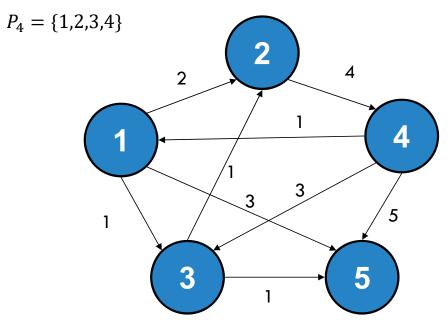
	1	2	3	4	5
1	0	2	1	6	2
2	$\infty$	0	$\infty$	4	$\infty$
3	$\infty$	1	0	5	1
4	1	3	2	0	3
5	$\infty$	$\infty$	$\infty$	$\infty$	0



	1	2	3	4	5
1	0	2	1	6	2
2	5	0	6	4	7
3	6	1	0	5	1
4	1	3	2	0	3
5	$\infty$	$\infty$	$\infty$	$\infty$	0

## STEP: $P_5 = \{1,2,3,4,5\}$

 $S[v, w, P_5] = \min(S[v, w, P_4], S[v, 5, P_4] + S[5, w, P_4])$ 

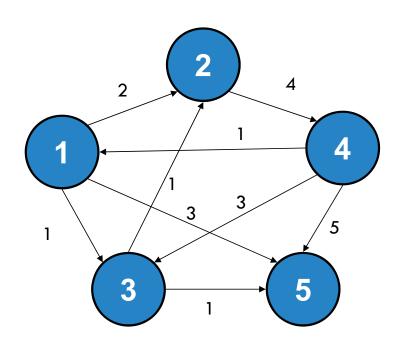


	1	2	3	4	5
1	0	2	1	6	2
2	5	0	6	4	7
3	6	1	0	5	1
4	1	3	2	0	3
5	$\infty$	$\infty$	$\infty$	$\infty$	0



	1	2	3	4	5
1	0	2	1	6	2
2	5	0	6	4	7
3	6	1	0	5	1
4	1	3	2	0	3
5	$\infty$	$\infty$	$\infty$	$\infty$	0

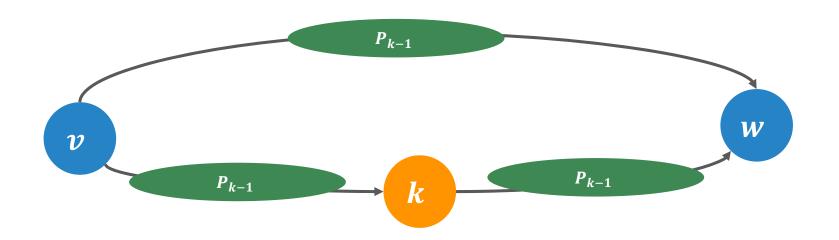
## DONE!



	1	2	3	4	5
1	0	2	1	6	2
2	5	0	6	4	7
3	6	1	0	5	1
4	1	3	2	0	3
5	$\infty$	$\infty$	$\infty$	$\infty$	0

$$S[v, w, P_k] = \min(S[v, w, P_{k-1}],$$

$$S[v, k, P_{k-1}] + S[k, w, P_{k-1}]$$
)



### FLOYD-WARSHALL: PSEUDOCODE

#### Function FloydWarshall(G)

What is the running time?  $O(V^3)$ 

### **TODAY: LEARNING OUTCOMES**

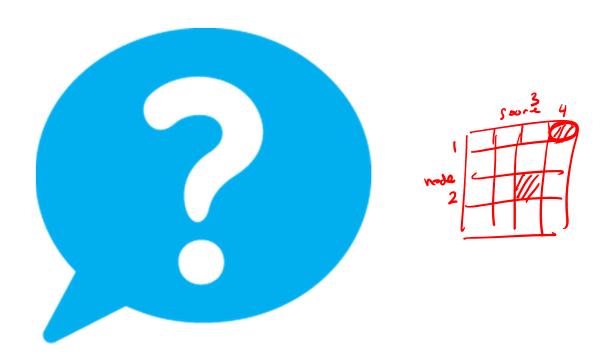
By the end of this session, students should be able to:

- State the all-pairs shortest-paths (APSP) problem
- Explain Floyd-Warshall and apply it to solve the APSP problem.
- Analyze the computational complexity of Floyd-Warshall algorithm.





## QUESTIONS?



### QUIZ 3

Will cover everything up to SSSP
No Minimum Spanning Trees (MSTs)
Focus on topics not in Quiz 1 or 2.

- Hashing
- Graph Searching
- Single-source Shortest Paths





### **ADVICE:**

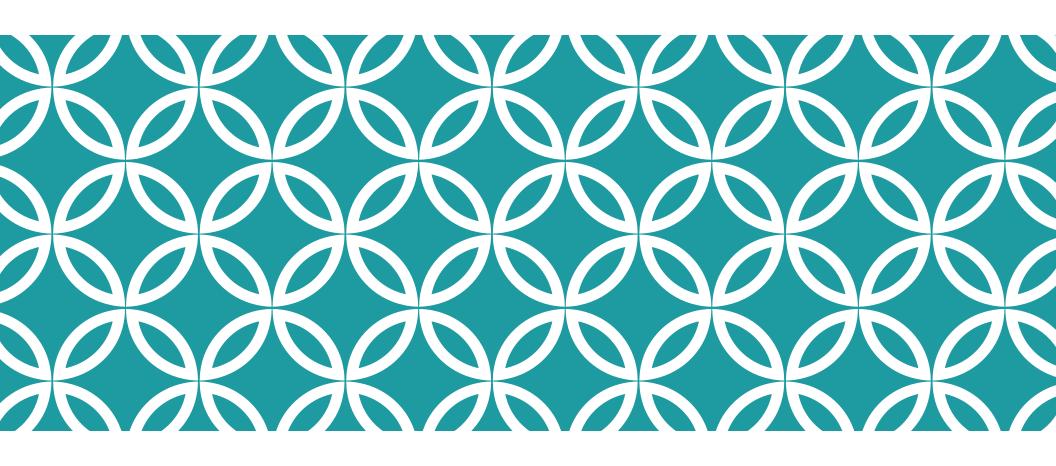
**Understanding + Analyzing** the problem is usually 50-90% of the battle.

Read the question properly. If you are unsure, ask.

The solution may **not** be obvious at first.

It may take some hard thinking to "see" it.

The **best solution** is **often not obvious** at first.



### HASH TABLES

Harold Soh harold@comp.nus.edu.sg

### HASH TABLES

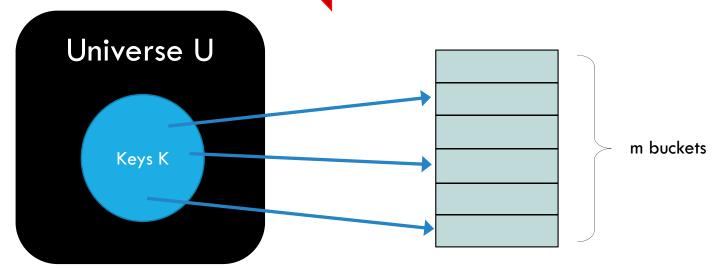


Data Structure	Avg. Insert Time	Avg. Search Time	Avg. Max/Min	Avg. Floor/ Ceiling
Unordered Array / Linked List	O(1)	O(n)	O(n)	O(n)
Ordered Array / Linked List	O(n)	O(1)	O(1)	O(log n)
Balanced Binary Search Tree (AVL)	O(log n)	O(log n)	O(log n)	O(log n)
Hash Table	O(1)	O(1)	O(n)	O(n)

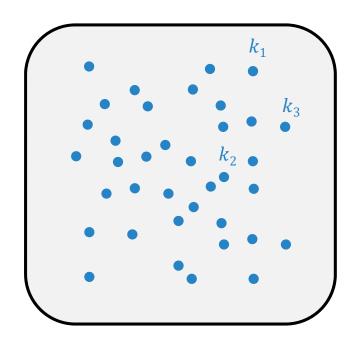
### HASH FUNCTIONS

Define a hash function  $h: U \to \{0, ..., m-1\}$ 

- Store key k in bucket h(k)
- Time complexity: Time to compute h + Time to access bucket
- Assume: computing h takes  $\mathit{O}(1)$  **This may not be true in practice!**

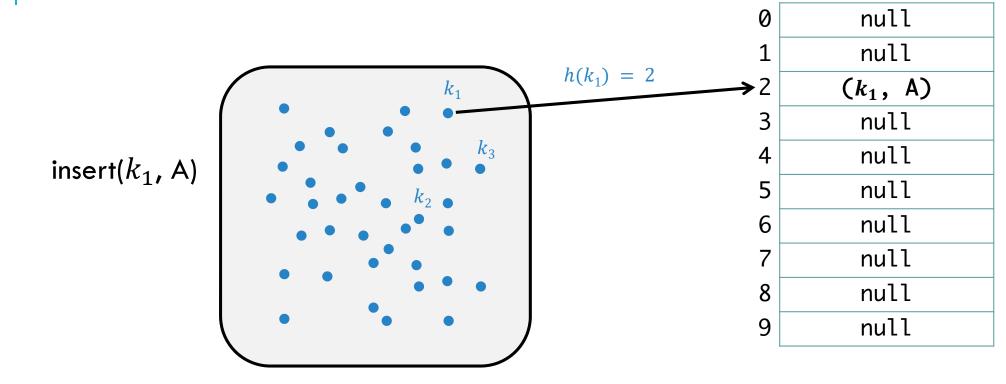


### HASHING EXAMPLE

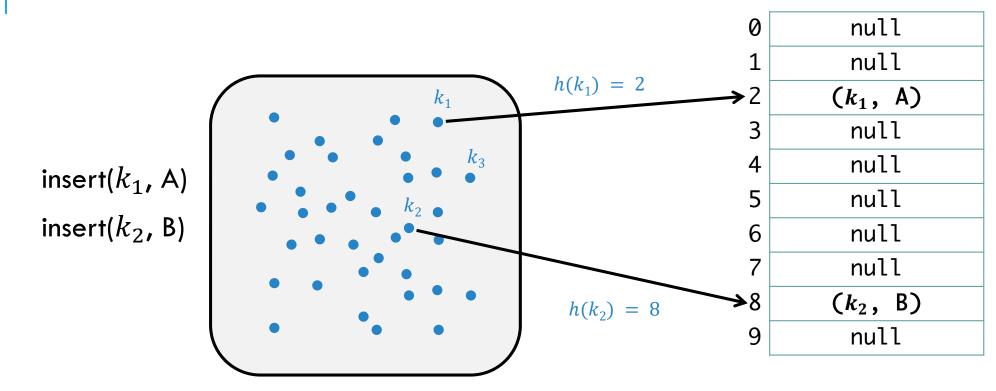


0	null
1	null
2	null
3	null
4	null
5	null
6	null
7	null
8	null
9	null

### HASHING EXAMPLE



### HASHING EXAMPLE

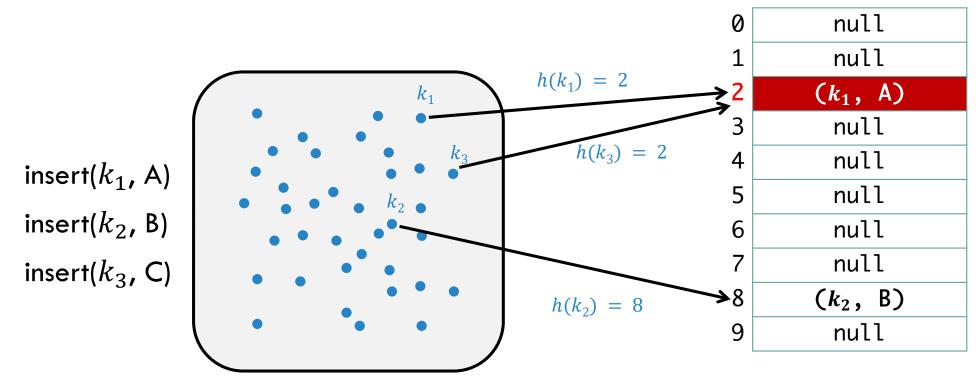


#### Collision!

### HASHING EXAMPLE

Two distinct keys  $k_1$  and  $k_2$  collide if:

$$h(k_1) = h(k_2)$$



### COLLISIONS ARE A FACT OF LIFE

If you don't know the keys in advance.

 Otherwise, you can derive a perfect hash (google gperf)

Have a policy for handling collisions:



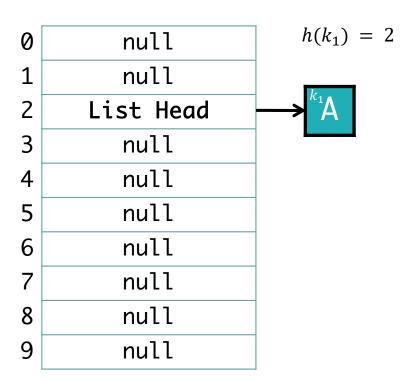
- Chaining (or Separate Chaining)
- Open Addressing



Idea: Each bucket stores a linked list.

If there is a collision, we add the item to the linked list.

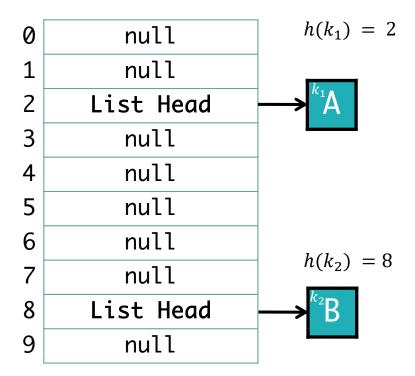
 $insert(k_1, A)$ 



Idea: Each bucket stores a linked list.

If there is a collision, we add the item to the linked list.

insert( $k_1$ , A) insert( $k_2$ , B)



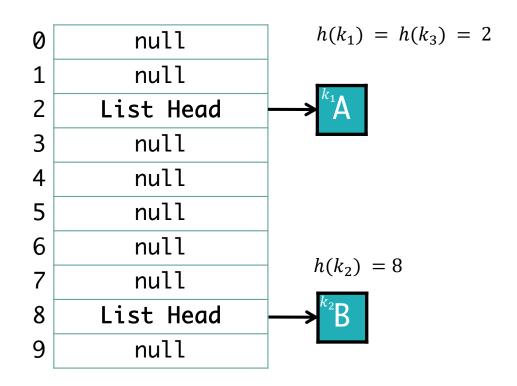
Idea: Each bucket stores a linked list.

If there is a collision, we add the item to the linked list.

insert( $k_1$ , A) insert( $k_2$ , B) insert( $k_3$ , C)

#### Collision.

#### but it's ok!



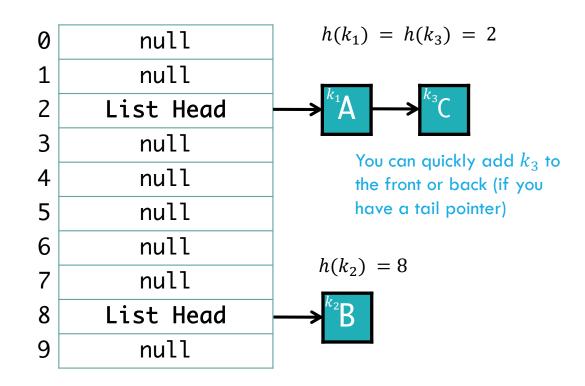
Idea: Each bucket stores a linked list.

If there is a collision, we add the item to the linked list.

insert( $k_1$ , A) insert( $k_2$ , B) insert( $k_3$ , C)

#### Collision.

#### but it's ok!



## SIMPLE UNIFORM HASHING ASSUMPTION

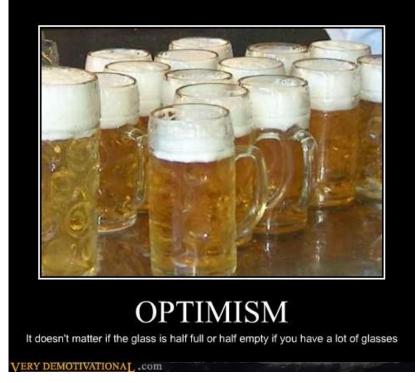
#### An optimistic assumption:

Every key is **equally likely** to map to every bucket

Keys are mapped independently.

#### Intuition:

- Each key is put in a random bucket.
- As long as enough buckets, not too many keys in any one bucket.



## WHAT IS THE AVERAGE SEARCH TIME...

under the simple uniform hashing assumption (SUHA)

#### We have:

- m buckets
- n items
- Assume  $n = \alpha m$  and  $m \ge n$
- $\alpha$  is the "load factor"

Expected search time = 1 + expected # items per bucket

hashing + array access | linked list traversal

What is the average search time under SUHA?

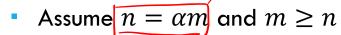
- A. O(m)
- B. O(n)
- Why?
- $\mathbf{C.} \quad \boldsymbol{O}(1)$
- D. O(m+n)
- E. I thought we were doing some fingerprint stuff?

## WHAT IS THE AVERAGE SEARCH TIME... = P(sxcos)

under the simple uniform hashing assumption (SUHA)

#### We have:

- m buckets
- n items



 $\alpha$  is the "load factor"

Expected search time = 1 + expected # items per buckethashing + array access linked list traversal

#### **Proof Sketch:**

Indicator random variables

$$X(i,j) = 1$$
 if item i is in bucket  $j$  (Jucus)  $X(i,j) = 0$  otherwise

Expected number of items in bucket b:

$$\mathbb{E}\left[\sum_{i}^{n} X(i,b)\right] = \sum_{i}^{n} \mathbb{E}[X(i,b)],$$

$$= \sum_{i}^{n} \frac{1}{m} = \frac{n}{\underline{m}} = \underline{\alpha}$$
Since  $m > n$ 

$$\mathbb{E}\left[\sum_{i}^{n} X(i,b)\right] = O(1)$$

## COLLISIONS ARE A FACT OF LIFE

If you don't know the keys in advance.

 Otherwise, you can derive a perfect hash (google gperf)

Have a policy for handling collisions:

Chaining (or Separate Chaining)



Open Addressing



# OPEN ADDRESSING: LINEAR PROBING

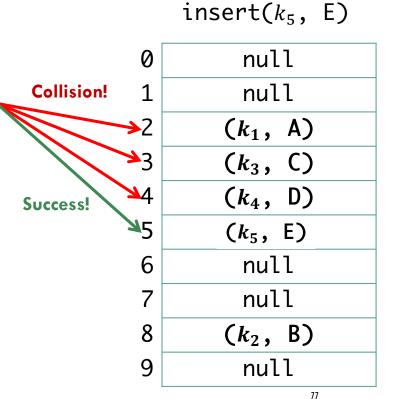
**Idea:** On collision, probe until you find an empty slot.

 $h(k_5) =$ 

Question: How to probe?

**Linear Probing:** keep checking next bucket until you find an empty slot.

index 
$$i = (h(k) + \text{step} \times 1) \mod m$$



## A PROBLEM: PRIMARY CLUSTERS

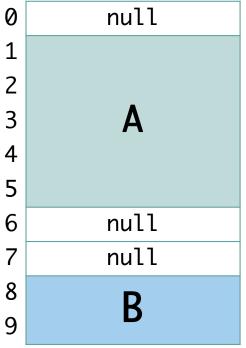
cluster = collection of consecutive occupied slots

In a hash table of size 10, consider 2 clusters:

- A: size 5
- B: size 2

Probability that a new inserted key k has a bucket in:

- cluster A? 5/10
- cluster B? 2/10



## OPEN ADDRESSING: QUADRATIC PROBING

Linear probing: index  $i = (h(k) + \text{step} \times 1) \mod m$ 



Quadratic probing: index  $i = (h(k)^{\bullet} + \text{step}^2) \mod m$ 

#### **Example:**

- h(k) = 3, m = 7
- Step 0: i = h(k) = 3
- Step 1:  $i = (h(k) + 1) \mod 7 = 4$
- Step 2:  $i = (h(k) + 4) \mod 7 = 0$
- Step 3:  $i = (h(k) + 9) \mod 7 = 5$

Is this a good probing method?

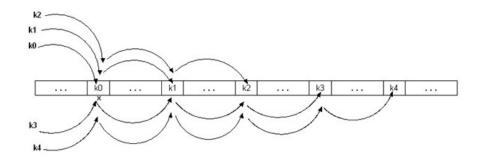
## ONE PROBLEM: SECONDARY CLUSTERING

Milder form of the clustering problem.

Because: if two keys have the same probe position, their probe sequences are the same.

Clustering around different points (rather than the primary probe point)

 $i = (h(k) + step^2) \mod m$ 



How many probe sequences can there be? m

## **DOUBLE HASHING**

Use a second hashing:

$$index i = (h_1(k) + step \times h_2(k)) mod m$$

Avoids secondary clustering by providing more unique probing sequences.

#### Intuition:

- $h_1(k)$  provides good "random" base address
- $h_2(k)$  provides good "random" sequence

Up to how many unique indexing sequences does double hashing provide?

A. *m* 

B. 2m

C.  $m^2$ 

D.  $2^{m}$ 

E.



81

#### **DOUBLE HASHING**

Use a second hashing:

$$index i = (h_1(k) + step \times h_2(k)) \mod m$$

Avoids secondary clustering by providing p to  $m^2$  probing sequences.

#### To work:

- Needs careful choice for  $h_1$  and  $h_2$
- Make m prime and  $h_2 < m$
- Also,  $h_2(k) \neq 0$  Why?

One technique is to choose:

$$h_2 = (ak \ mod \ b) + 1$$
 where  $b < m$ 







### SUHA IS A DREAM!

Simple Uniform Hashing doesn't exist (in general).

**BUT:** Tells us properties of a "good" hashing function:

- A. Consistent: same key maps to same bucket.
- B. Fast to compute, O(1)
- C. Scatter the keys into different buckets as uniformly as possible  $\in [0..m-1]$



## DESIGNING HASH FUNCTIONS

**Want:** Hash function whose values *look* random

Similar to pseudorandom number generators

Two common hashing techniques:

- Division Method
- Multiplication Method

A linear congruential generator (LCG) pseudorandom number generator:

$$x_{n+1} = (ax_n + c) \bmod m$$

For special choices of a, c and m, LCGs can produce numbers that pass formal tests of randomness.





### REGULARITY AND COMMON DIVISORS

Division method:  $h(k) = k \mod m$ If k and m have a common divisor dthen:

$$k = im + k \mod m$$
divisible divisible divisible by  $d$  by  $d$  by  $d$ 

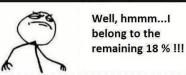
Assume chaining. How much of the table do we use if both x and m have a common divisor d?

- $\mathsf{A}.$  d
- B. 2d
- C.  $1/d^2$
- D. 1/d

E.



75 % of all students are good at maths!



8

#### REGULARITY AND COMMON DIVISORS

Division method:  $h(k) = k \mod m$ If k and m have a common divisor dthen:

$$k = im + k \mod m$$
divisible divisible divisible by  $d$  by  $d$  by  $d$ 

Choose m such that it has no common factors with any k

will only use 1 out of every d slots!

0	$(k_1, A)$
1	null
2	null
d=3	$(k_2, B)$
4	null
5	null
2d=6	$(k_3, C)$
7	null
8	null
3d=9	$(k_4, D)$

## **DIVISION METHOD**

Choose m to be prime

Avoid powers of 2 and powers of 10

In practice: popular and easy

But not always the most effective.

Slow (no more shifts)



## DESIGNING HASH FUNCTIONS

**Want:** Hash function whose values *look* random

Similar to pseudorandom number generators

Two common hashing techniques:

Division Method



Multiplication Method

A linear congruential generator (LCG) pseudorandom number generator:

$$x_{n+1} = (ax_n + c) \bmod m$$

For special choices of a, c and m, LCGs can produce numbers that pass formal tests of randomness.

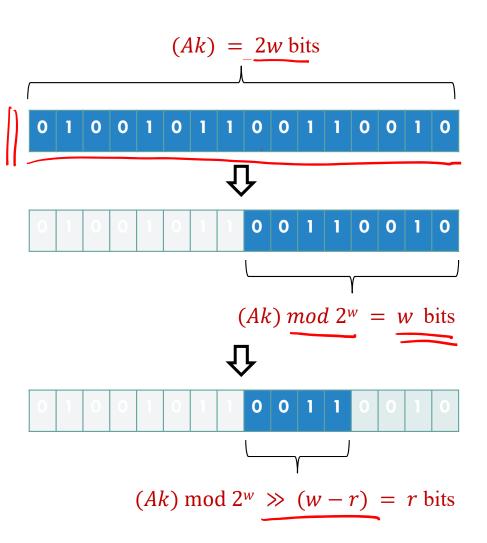
### MULTIPLICATION METHOD

#### Fix

- table size:  $m = 2^r$
- word size: W (size of a key in bits)
- constant:  $2^{w-1} < A < 2^w$

#### Then:

$$h(k) = (Ak) \bmod 2^w \gg (w - r)$$



#### MULTIPLICATION METHOD

• table size:  $m = 2^r$ 

• constant:  $2^{w-1} < A < 2^w$ 

## (Ak) = 2w bits 0 0 0 0 0 0 0 0 0 0 0 0 $(Ak) \mod 2^w = w \text{ bits}$

#### Then:

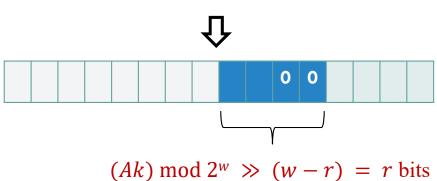
Fix

$$h(k) = (Ak) \bmod 2^w \gg (w - r)$$

word size: w (size of a key in bits)

Consider what happens when A is even, say  $2^{w-1} + 64$ . (see example in the right)

**Point:** even numbers cause at least one bit of information loss.

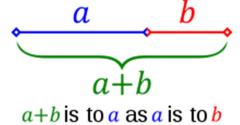


## MULTIPLICATION METHOD

Choose A, r carefully

In practice: works well with A is chosen well (e.g., odd)

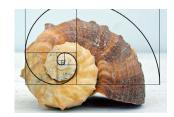
Knuth recommends  $A \approx \frac{\sqrt{5}-1}{2} \cdot 2^{32}$  for w = 32 bit words



**Donald Knuth** 



wrote The Art of Computer Programming (TAOCP)





## DESIGNING HASH FUNCTIONS

**Want:** Hash function whose values *look* random

Similar to pseudorandom number generators

Two common hashing techniques:

- Division Method
- Multiplication Method

A linear congruential generator (LCG) pseudorandom number generator:

$$x_{n+1} = (ax_n + c) \bmod m$$

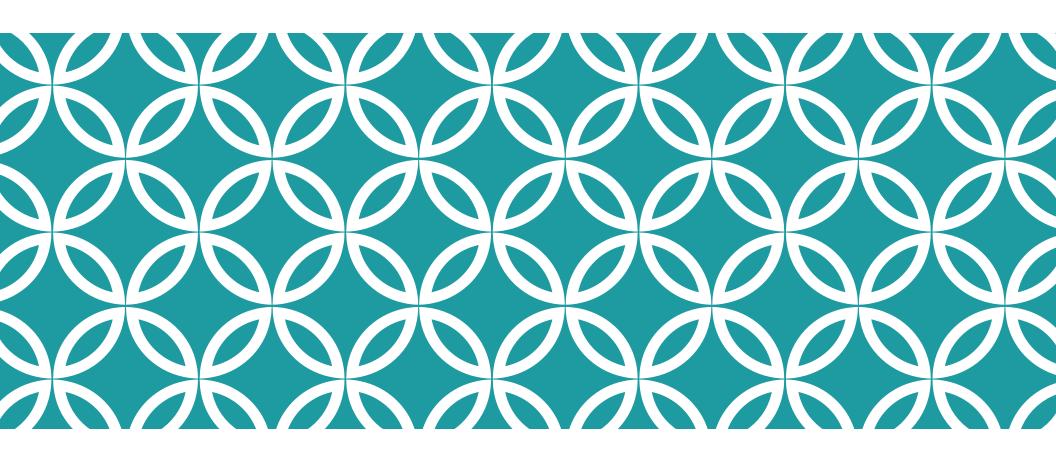
For special choices of a, c and m, LCGs can produce numbers that pass formal tests of randomness.





## QUESTIONS?





# SAMPLE PROBLEM: NEAREST REPEATED WORDS (WARMUP)

Harold Soh
<a href="mailto:harold@comp.nus.edu.sg">harold@comp.nus.edu.sg</a>

## NEAREST REPEATED WORDS

"I am so happy we're getting more problems to solve. Nothing pleases me more than solving problems. I love solving problems. Especially tough problems. The harder the better! Give me more problems!"

#### Difficulty level 2 (out of 5).

#### NEAREST REPEATED WORDS

"I am so happy we're getting more problems to solve. Nothing pleases me more than solving problems. I love solving problems. Especially tough problems. The harder the better! Give me more problems!"

Assume words are given to you in a list. Describe the most efficient algorithm you can think of for finding the *distance* (in terms of number of words) between the *closest* repeated word. You do not need to provide pseudocode. Ignore punctuation and capitalization.

**Extra:** Can you provide an algorithm for the case when memory is limited. Minimize the amount of memory required for your algorithm. What are the trade-offs?

#### NEAREST REPEATED WORD

#### Idea:

Assume words are in a list maintain a minimum distance, dmin loop through the words.

For each word w at position i, find the closest repetition by scanning forward in the list until the same word is found, say at position j.

if the distance d = j-i is less than dmin, update dmin = d

the
harder
the
better
give
me
more
problems

#### NEAREST REPEATED WORD: COMPLEXITY?

#### Idea:

Assume words are in a list maintain a minimum distance, dmin loop through the words.

For each word w at position i, find the closest repetition by scanning forward in the list until the same word is found, say at position j.

if the distance d = j-i is less than dmin, update dmin = d

Looping through each word takes n time. for each word, we need to scan forwards.  $(n-1) + (n-2) + \cdots + (n-(n-1))$  $= 1 + 2 + \ldots + (n-1) = O(n^2)$ 

#### Can we do better?

#### NEAREST REPEATED WORD: IDEA

#### Idea:

Assume words are in a list maintain a minimum distance, dmin loop through the words.

For each word w at position i, find the closest repetition by scanning forward in the list until the same word is found, say at position j.

if the distance d = j-i is less than dmin, update dmin = d

the harder the position the better give me more problems

#### NEAREST REPEATED WORD: VERSION 2

#### Idea:

Assume words are in a list maintain a minimum distance, dmin maintain a hash table H with word keys and last seen position

for each word w at position i,

- lookup the word in H
- if H contains w, check if the distance d=i-H[w]. If d < dmin, update dmin = d.</p>
- Then update: H[w] = i

#### NEAREST REPEATED WORD: VERSION 2: COMPLEXITY

#### Idea:

Assume words are in a list maintain a minimum distance, dmin maintain a hash table H with word keys and last seen position

for each word w at position i,

- lookup the word in H
- if H contains w, check if the distance d=i-H[w]. If d < dmin, update dmin = d.</p>
- Then update: H[w] = i

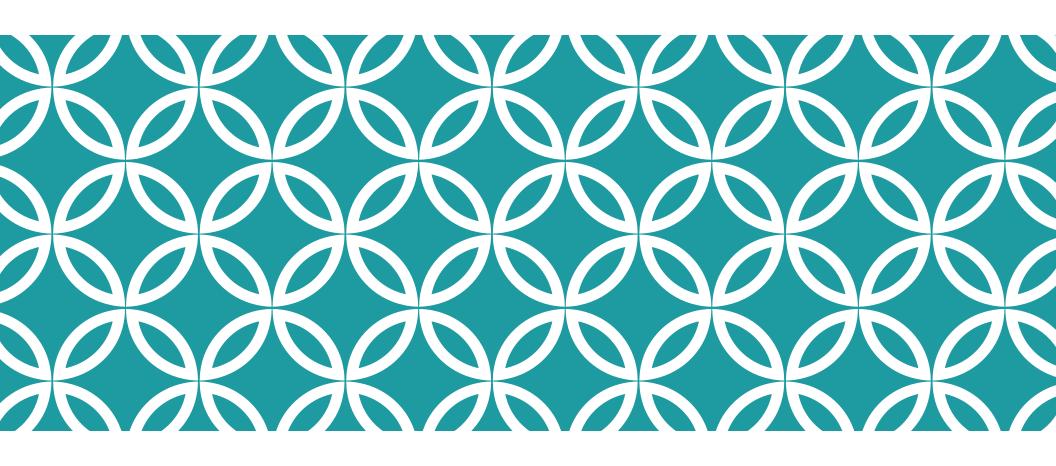
Looping through each word takes n time. for each word, we check hash table O(1) so, total O(n).

Here we have assumed the hashing function is O(1). If the max length of a word is m, then the cost is O(mn) assuming a linear hash function or a trie is used.



## QUESTIONS?





## ON TO GRAPHS!

Harold Soh harold@comp.nus.edu.sg

#### TERMINOLOGY SUMMARY

Graph:  $G = \langle V, E \rangle$ 

Degree of a node: number of edges connected to it

Diameter: longest shortest path between two different nodes

Connected Graph: path between any two nodes

Clique: fully connected graph

Line Graph: a line (duh!)

**Star:** central node connected to all other nodes.

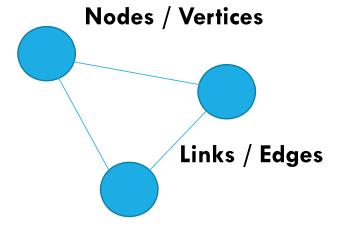
## UNDIRECTED GRAPHS: A FORMAL DEFINITION

Graph  $G = \langle V, E \rangle$  ("a tuple of two sets")

- V is a set of nodes
- E is a set of edges
  - $E \subseteq \{(v, w): v, w \in V\}$

#### Simple Graph:

- e = (v, w) for  $v \neq w$  ("no self loops")
- $\forall e_1, e_2 \in E : e_1 \neq e_2$  ("only one edge per pair of nodes")



## **DIRECTED** GRAPHS

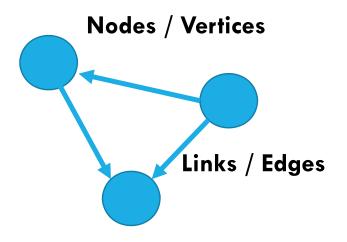
Graph  $G = \langle V, E \rangle$  ("a tuple of two sets")

- V is a set of nodes
- E is a set of edges

• 
$$E \subseteq \{(v,w): v,w \in V\}$$

Order matters!

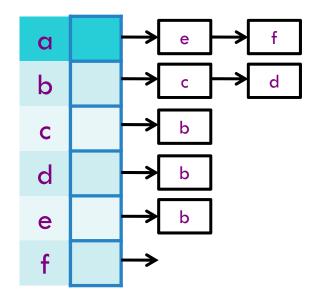
(v, w) means an edge pointing from  $v \to w$ 

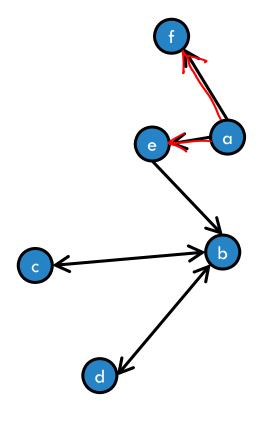


## **ADJACENCY LIST**

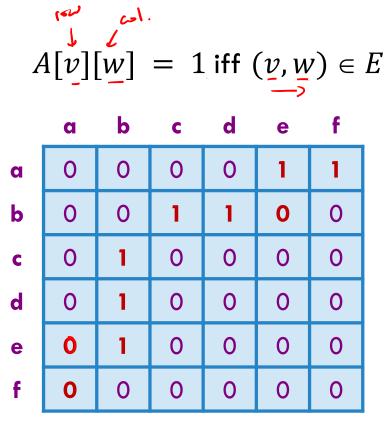
#### **Directed** Graph consists of:

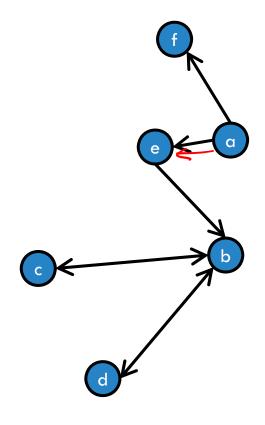
- Nodes: stored in an array
- Outgoing Edges: linked list per node





### ADJACENCY MATRIX





### SEARCHING A GRAPH

#### Goal:

- Start at some vertex s = start.
- Find some other vertex f = finish.
   Or: visit all the nodes in the graph

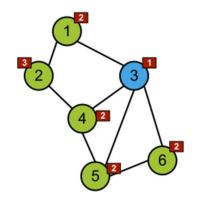
#### Two basic techniques:

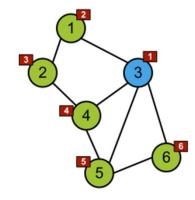
- Breadth-First Search (BFS)
- Depth-First Search (DFS)

#### Graph representation:

Adjacency list

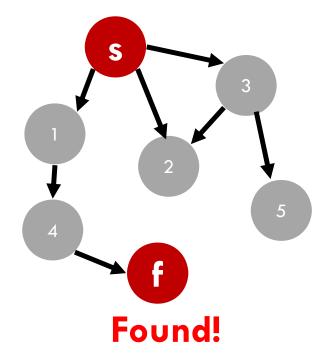
#### Breadth-First vs. Depth-First Search





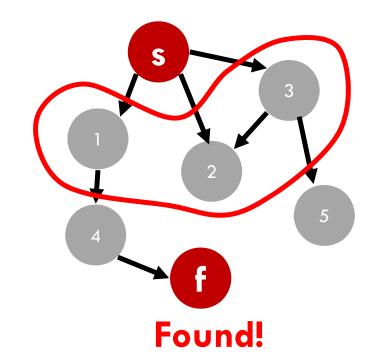
### **BFS: STEP-BY-STEP**

```
BFS(G, s, f)
  visit(s)
  Queue.add(s)
  while not Queue.empty()
    curr = Queue.dequeue()
    if curr == f
       return curr
    for each neighbor u of curr
       if u is not visited
            visit(u)
            Queue.enqueue(u)
  return null
```



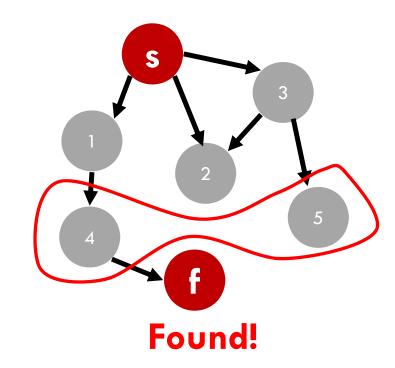
### **BFS: STEP-BY-STEP**

```
BFS(G, s, f)
  visit(s)
  Queue.add(s)
while not Queue.empty()
  curr = Queue.dequeue()
  if curr == f
     return curr
  for each neighbor u of curr
   if u is not visited
     visit(u)
     Queue.enqueue(u)
return null
```



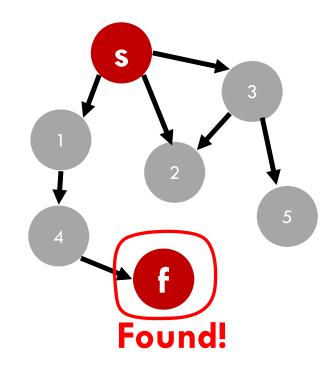
### **BFS: STEP-BY-STEP**

```
BFS(G, s, f)
  visit(s)
  Queue.add(s)
while not Queue.empty()
  curr = Queue.dequeue()
  if curr == f
     return curr
  for each neighbor u of curr
   if u is not visited
     visit(u)
     Queue.enqueue(u)
return null
```



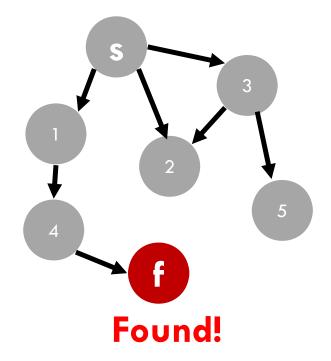
### **BFS: STEP-BY-STEP**

```
BFS(G, s, f)
  visit(s)
  Queue.add(s)
while not Queue.empty()
  curr = Queue.dequeue()
  if curr == f
     return curr
  for each neighbor u of curr
     if u is not visited
       visit(u)
       Queue.enqueue(u)
return null
```



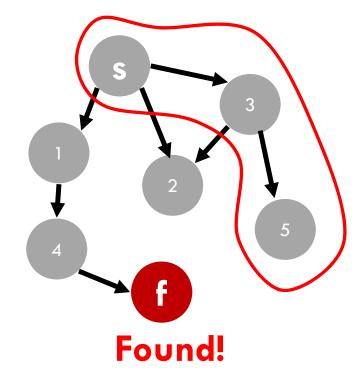
### **DFS: STEP-BY-STEP**

```
DFS(G, s, f)
  visit(s)
  Stack.push(s)
  while not Stack.empty()
    curr = Stack.pop()
    if curr == f
       return curr
    for each neighbor u of curr
       if u is not visited
            visit(u)
            Stack.push(u)
  return null
```



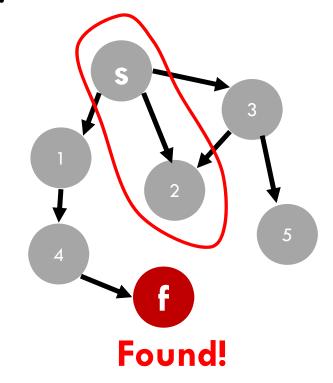
### **DFS: STEP-BY-STEP**

```
DFS(G, s, f)
  visit(s)
  Stack.push(s)
  while not Stack.empty()
    curr = Stack.pop()
    if curr == f
       return curr
    for each neighbor u of curr
       if u is not visited
            visit(u)
            Stack.push(u)
  return null
```



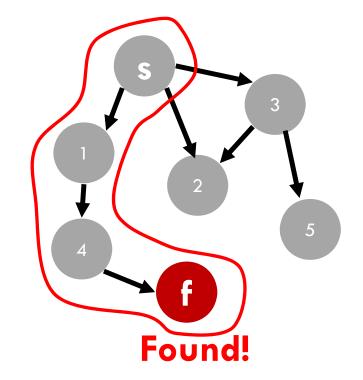
### **DFS: STEP-BY-STEP**

```
DFS(G, s, f)
  visit(s)
  Stack.push(s)
  while not Stack.empty()
    curr = Stack.pop()
    if curr == f
       return curr
    for each neighbor u of curr
       if u is not visited
            visit(u)
            Stack.push(u)
  return null
```



### **DFS: STEP-BY-STEP**

```
DFS(G, s, f)
  visit(s)
  Stack.push(s)
  while not Stack.empty()
    curr = Stack.pop()
    if curr == f
       return curr
    for each neighbor u of curr
       if u is not visited
            visit(u)
            Stack.push(u)
  return null
```



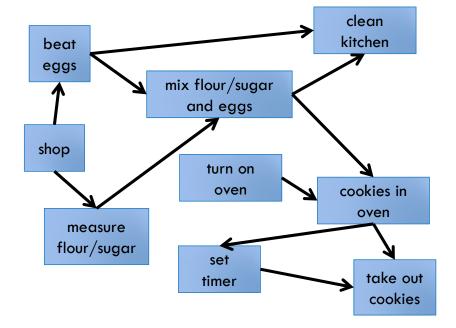
### TOPOLOGICAL SORT

#### Input(s):

- Input is a graph. Any graph?
- A DAG!
- Represented as a?
- Adjacency list

#### Output(s):

- A list of nodes in topological order.
  - No node in the list can have an incoming edge from a node that appears later (in the list).



### KAHN'S ALGORITHM

Start at any node v with no incoming edges.

Add v to our list

Remove v and all its outgoing edges.

Repeat

#### Pseudocode:

```
L = list()
S = list()
add all nodes with no incoming edge to S
while S is not empty:
    remove node v from S
    add v to tail of L
    for each of v's neighbors u
        remove edge e where source is v
        if u has no other incoming edges
        add u to S
```

#### What is the time complexity? O(V + E)



### TOPOLOGICAL SORT USING DFS (ASSUME DAG)

Idea: Process node when it is "last" visited.

```
L = list()
while there are unvisited nodes
v = select unvisited node
DFS(G, v, L)
```

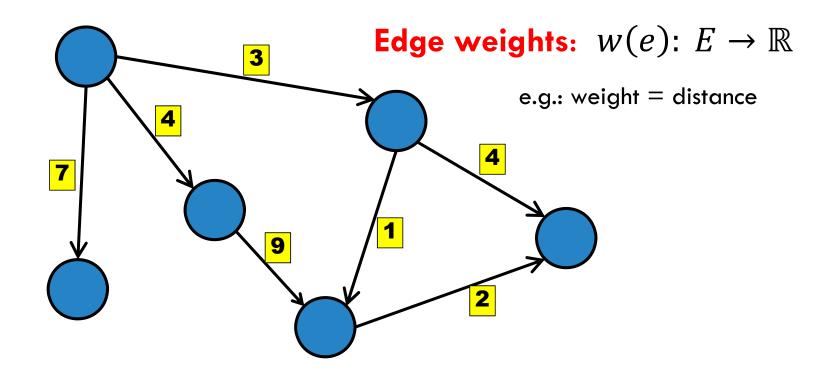
How can we quickly check if there are unvisited nodes or select unvisited nodes?

List/ Hash Table / Set

```
if v is visited
    return
else
    for each of v's neighbor u
        DFS(G, u, L) /
visit(v) /
L.pushFront(v) /
```

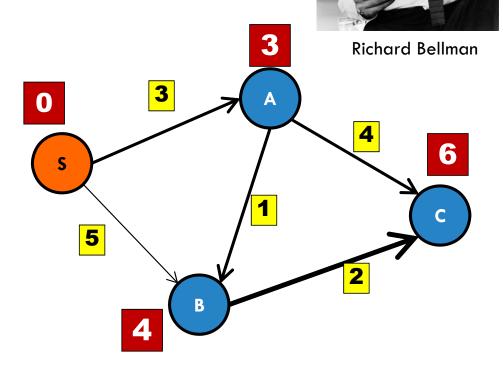
DFS (G, V, L)

### WEIGHTED GRAPHS



# BELLMAN-FORD ALGORITHM FOR SINGLE-SOURCE SHORTEST PATHS

n = V.length
for i = 1 to n-1
 for Edge e in Graph
 relax(e)



### **SPECIAL CASES**

Condition	Algorithm	Time Complexity
No Negative Weight Cycles	Bellman-Ford Algorithm	O(VE)
On Unweighted Graph (or equal weights)	BFS	O(V+E)
No Negative Weights	Dijkstra's Algorithm	$O((V+E)\log V)$
On Tree	BFS / DFS	O(V)
On DAG	Topological Sort	O(V+E)



### QUESTIONS?

