

Data Structures Review

CS 225
Brad Solomon

December 6, 2023



UNIVERSITY OF
ILLINOIS
URBANA - CHAMPAIGN

Department of Computer Science



Material covered here is not only material in class!

Represents only an attempt to provide some helpful resources.

Requested: Iterators

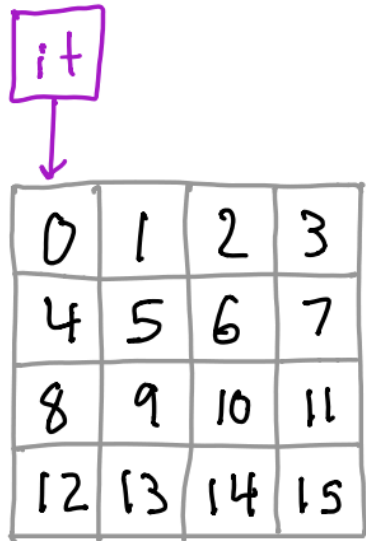
```
1
2  std::vector<Animal> zoo;
3
4
5  /* Full text snippet */
6
7  for ( std::vector<Animal>::iterator it = zoo.begin(); it != zoo.end(); ++it ) {
8      std::cout << (*it).name << " " << (*it).food << std::endl;
9  }
10
11
12 /* Auto Snippet */
13
14 for ( auto it = zoo.begin(); it != zoo.end(); ++it ) {
15     std::cout << animal.name << " " << animal.food << std::endl;
16 }
17
18 /* For Each Snippet */
19
20 for ( const Animal & animal : zoo ) {
21     std::cout << animal.name << " " << animal.food << std::endl;
22 }
23
```

Iterators

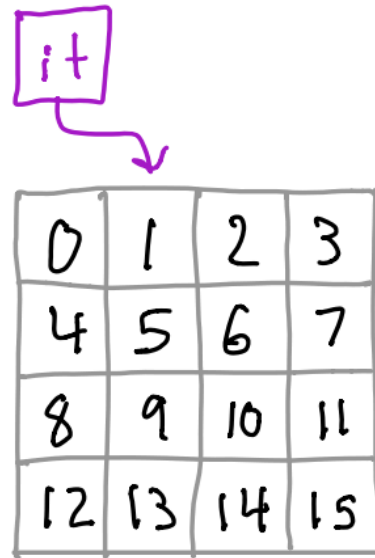
Iterators defined inside a class (and as part of class)

```
1 template <class T>
2 class List {
3
4     class ListIterator : public
5     std::iterator<std::forward_iterator_tag, T> {
6         public:
7
8             ListIterator& operator++();
9
10            bool operator!=(const ListIterator& rhs);
11
12            const T& operator*();
13        };
14
15        ListIterator begin() const;
16
17        ListIterator end() const;
18    };
19
```

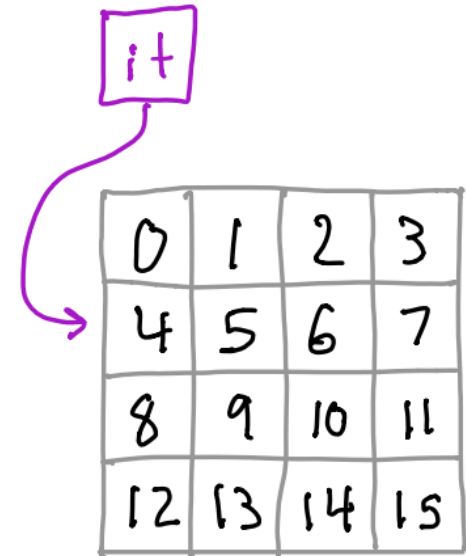
Iterators (225 Webpage Resources)



end



end

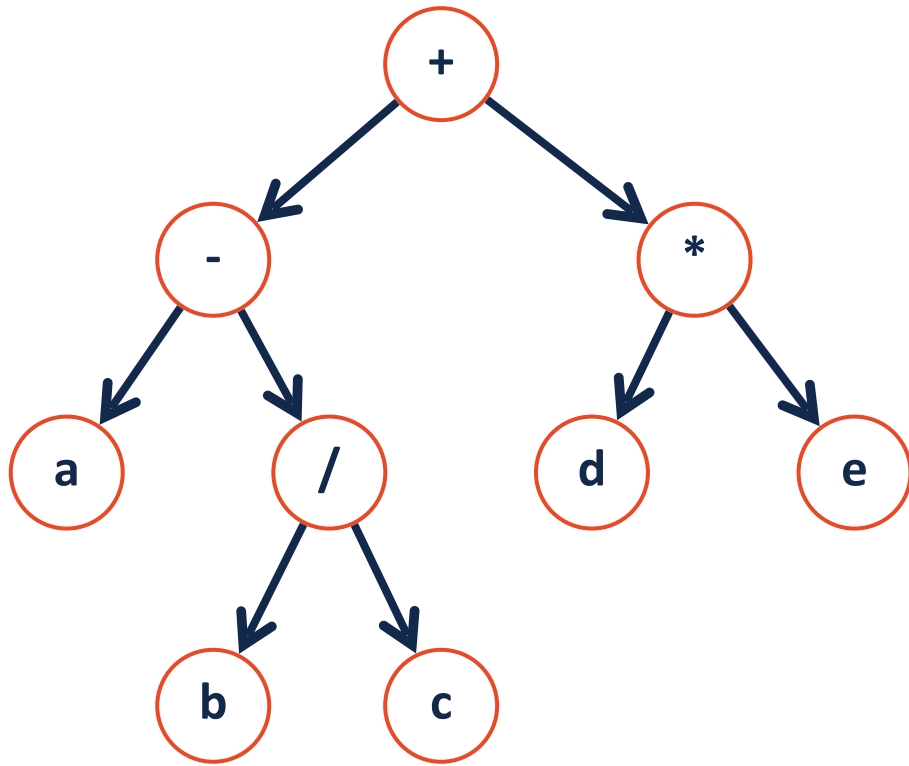


end



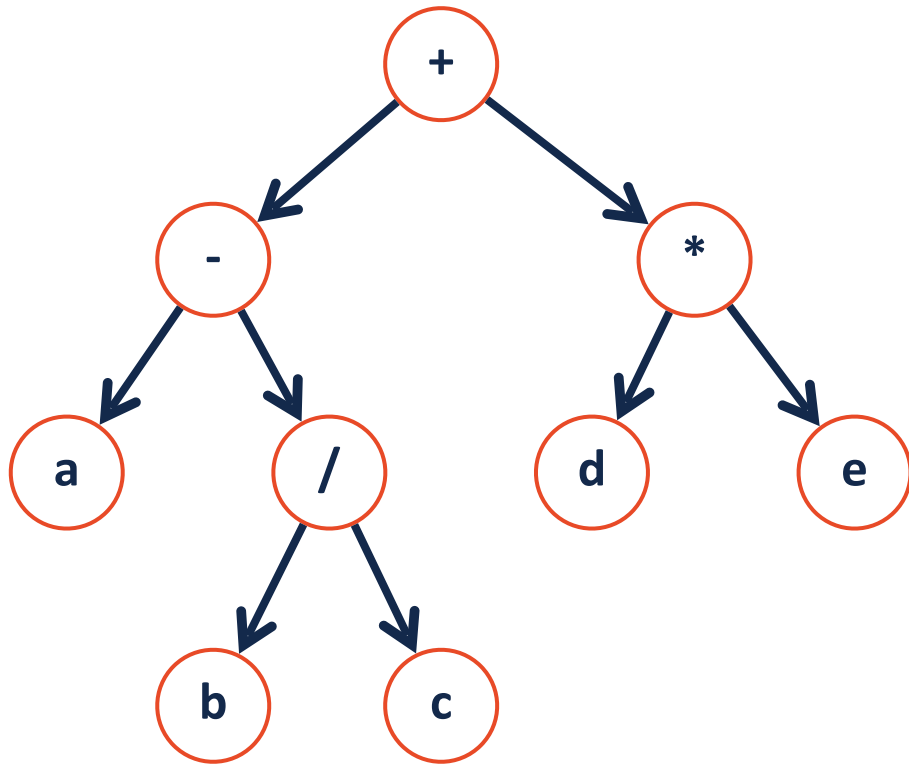
Requested: Tree Traversals

Traversals



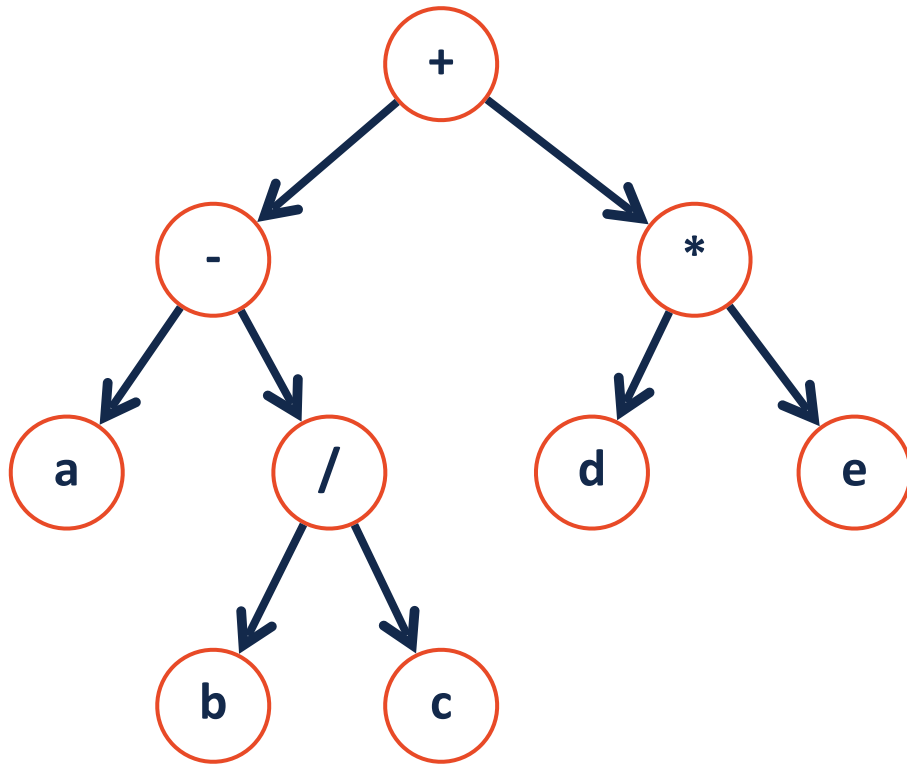
```
1 template<class T>
2 void BinaryTree<T>::_____Order(TreeNode * root)
3 {
4
5     if (root) {
6
7         _____;
8
9         _____Order(root->left);
10
11        _____;
12
13        _____Order(root->right);
14
15        _____;
16
17    }
18
19
20
21 }
```

Traversals



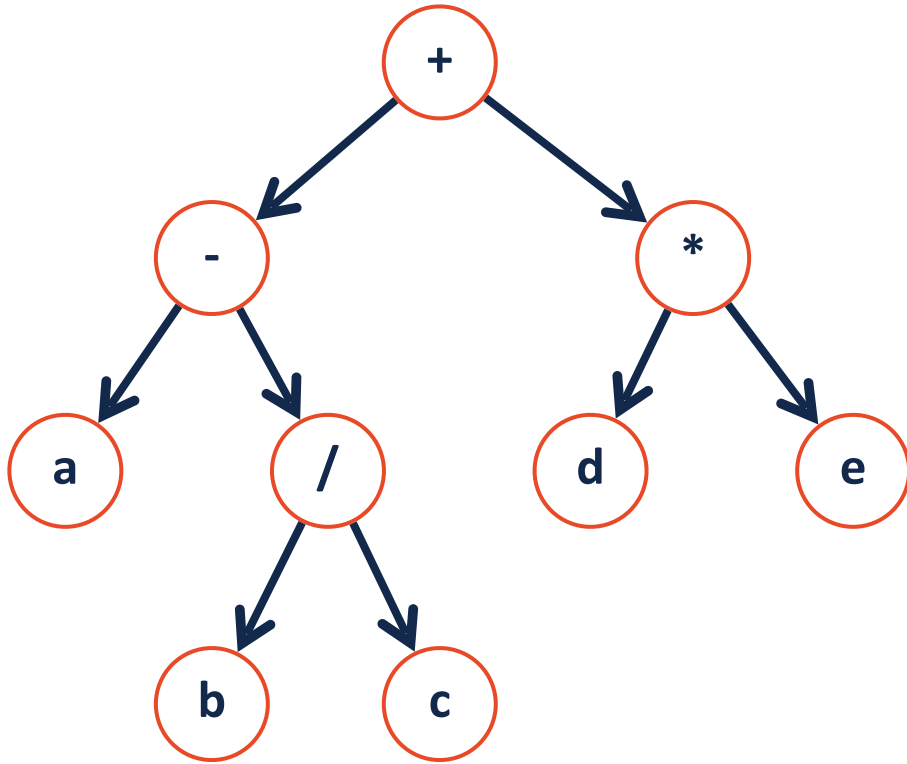
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14
15         _____;
16
17     }
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19
20
21 }
```


Traversals



```
1 template<class T>
2 void BinaryTree<T>::_____Order (TreeNode * root)
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10
11         _____;
12
13         _____Order (root->right) ;
14
15         _____;
16
17     }
18
19
20
21 }
```

Level-Order Traversal



```
1 template<class T>
2 void BinaryTree<T>::lOrder(TreeNode * root)
3 {
4
5     Queue<TreeNode*> q;
6     q.enqueue(root);
7
8     while( q.empty() == False){
9
10        TreeNode* temp = q.head();
11        process(temp);
12
13        q.dequeue();
14
15        q.enqueue(temp->left);
16        q.enqueue(temp->right);
17
18    }
19 }
```

Requested: Amortized Analysis

When an algorithm has an infrequent 'costly' step.

What algorithms *should* we consider from an amortized point of view?

Resize Strategy: x2 elements every time

Total copies for n inserts: $2n - 1$

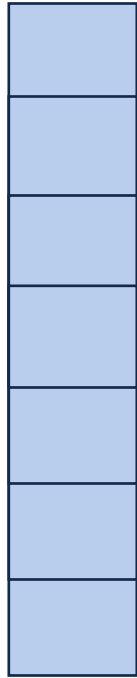




Resize Strategy: x2 elements every time

Resizing a hash table

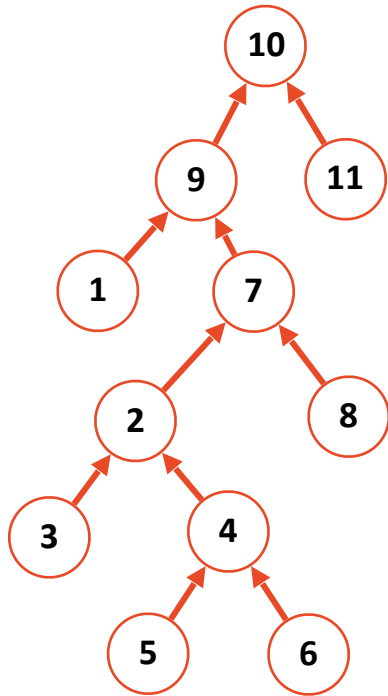
How do you resize?



Amortized Time (Rank w/ Path Compression)

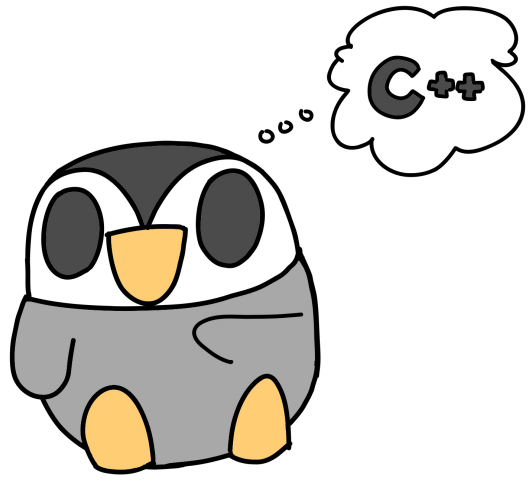
We have **n items** in an Uptree. We make **m find()** calls.

We are interested in the **worst case work** possible **over m calls**.

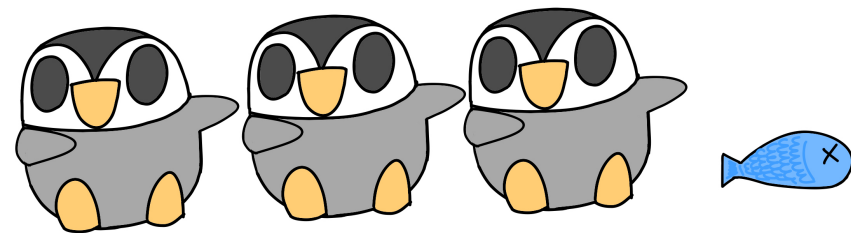




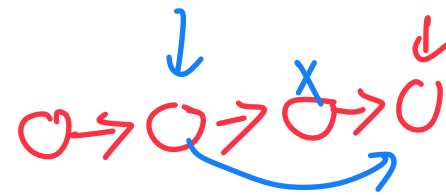
A partial review of topics in CS 225



Lists



Array Implementation



	Singly Linked List	Array
Look up arbitrary location ↳ index (random access)	$O(n)$	$O(1)$
Insert after given element ↳ pointer to object (*4)	$O(1)$	$O(n)$
Remove after given element	$O(1)$	$O(n)$
Insert at arbitrary location	$O(n)$	$O(n)$
Remove at arbitrary location	$O(n)$	$O(n)$
Search for an input value	$O(n)$	$O(n)$

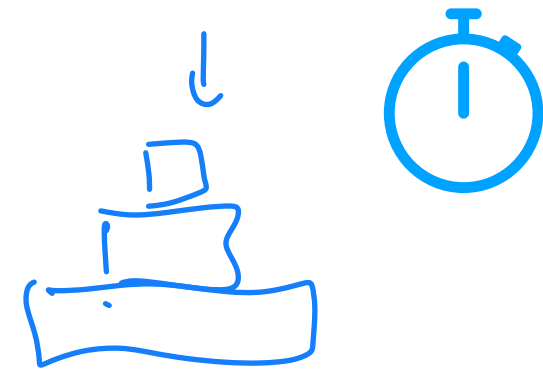
LL. insert (3)

Array Implementation

	Singly Linked List	Array
Look up arbitrary location <i>Random Access</i>	$O(n)$	$O(1)$
Insert after given element <i>Given pointer to object</i>	$O(1)$	$O(n)$
Remove after given element	$O(1)$	$O(n)$
Insert at arbitrary location	$O(n)$	$O(n)$
Remove at arbitrary location	$O(n)$	$O(n)$
Search for an input value	$O(n)$	$O(n)$

Stack ADT

- [Order]: Last in first out (LIFO)



- [Implementation]: Vector / deque ← C++
LL or array list

- [Runtime]: push() $O(1)$
pop() $O(1)$



Queue ADT

• [Order]: First in first out $FIFO$

• [Implementation]: LL w/ head and tail
Circular array list*
↳ worst case for array is $O(n)$

• [Runtime]: Enqueue
Dequeue $O(1)$ *
b/c resize

Iterators

class List
private
linked list

The actual iterator is defined as a class **inside** the outer class:

1. It must be of base class **std::iterator** (std::vector)

2. It must implement at least the following operations:

Iterator& operator ++() - pre-increment (point to next object)

const T & operator *() - de-reference

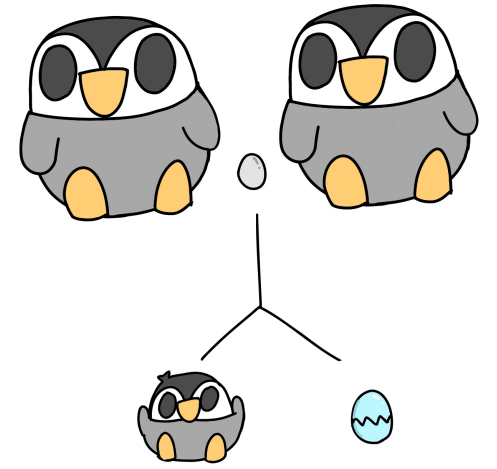
bool operator !=(const Iterator &) - check if two iterators - pointers are same



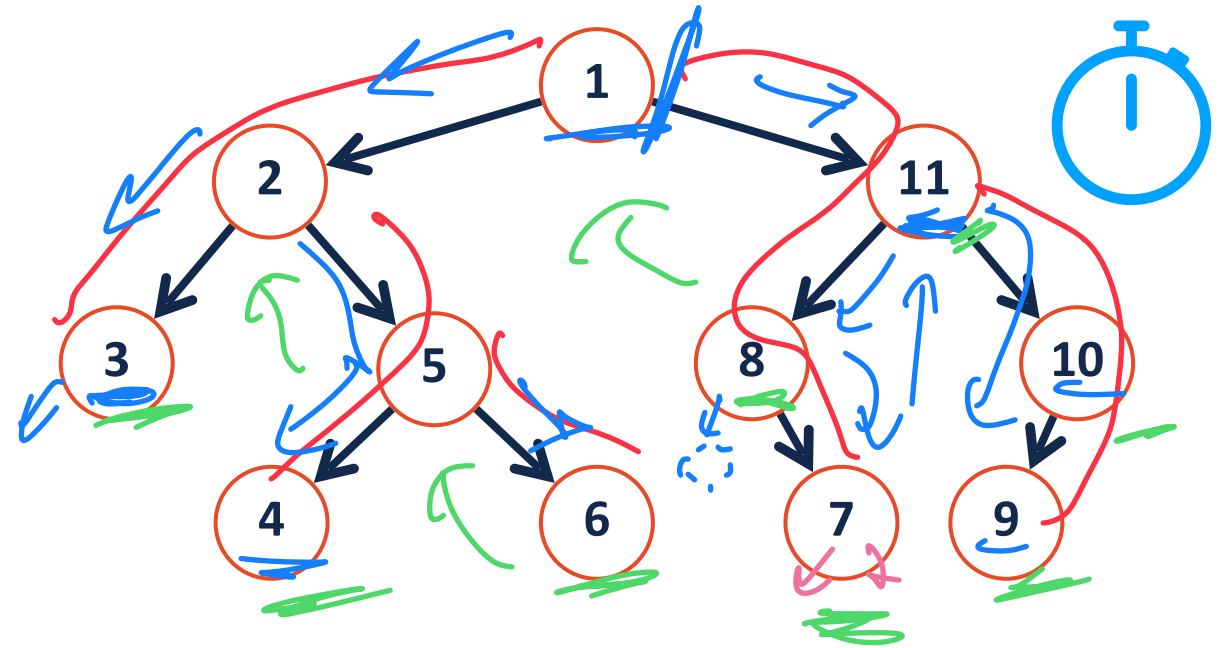
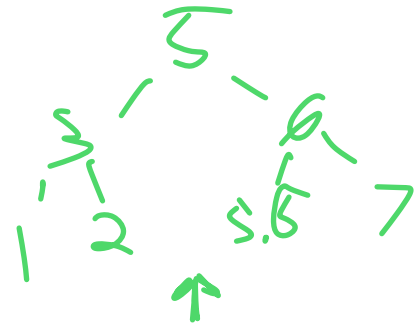
```
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2 std::vector<Animal> zoo;
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4
5 /* Full text snippet */
6
7 for ( std::vector<Animal>::iterator it = zoo.begin(); it != zoo.end(); ++it ) {
8     std::cout << (*it).name << " " << (*it).food << std::endl;
9 }
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11
12 /* Auto Snippet */
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14 for ( auto it = zoo.begin(); it != zoo.end(); ++it ) {
15     std::cout << animal.name << " " << animal.food << std::endl;
16 }
17
18 /* For Each Snippet */
19
20 for ( const Animal & animal : zoo ) {
21     std::cout << animal.name << " " << animal.food << std::endl;
22 }
23
24
25
```

for each animal in zoo
cast Animal

Trees



Tree Traversals



Pre-order:

1 2 3 5 4 6 11 8 7 10 9

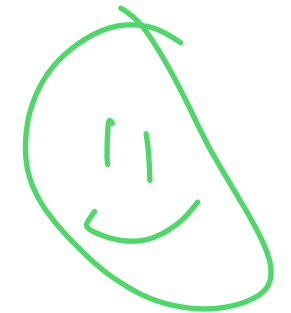
In-order:

left curr right

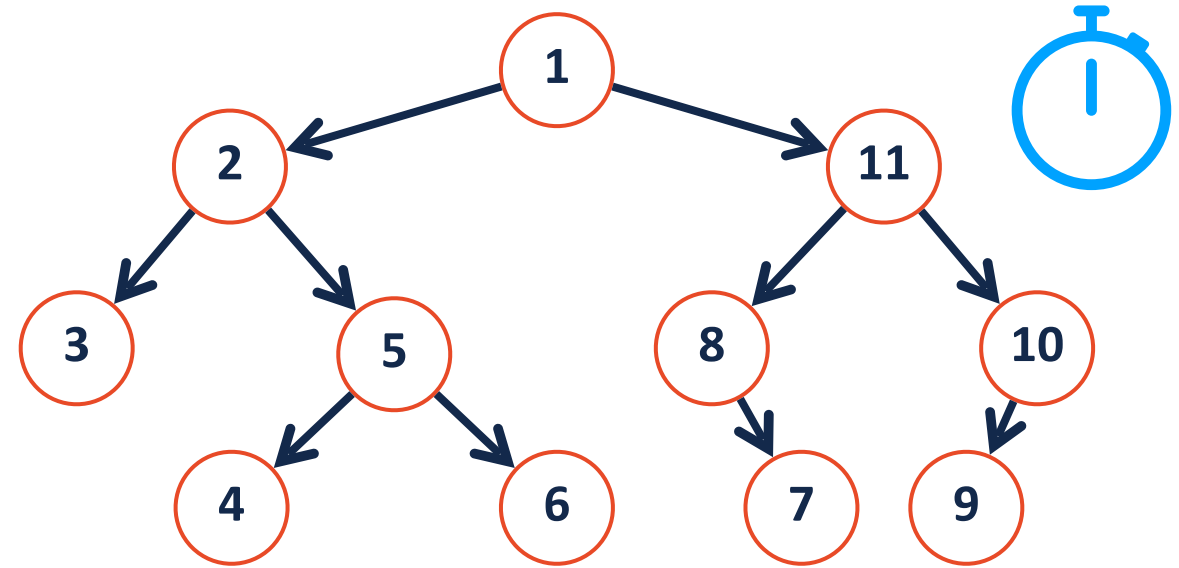
2 4 5 6 3 8 7 11 9 10

Post-order:

4 6 5 2 7 8 9 10 11 1



Tree Traversals



Pre-order: 1, 2, 3, 5, 4, 6, 11, 8, 7, 10, 9

In-order: 3, 2, 4, 5, 6, 1, 8, 7, 11, 9, 10

Post-order: 3, 4, 6, 5, 2, 7, 8, 9, 10, 11, 1

Depth First Search

September 18 (BST Lecture)

Explore as far along one path as possible before backtracking

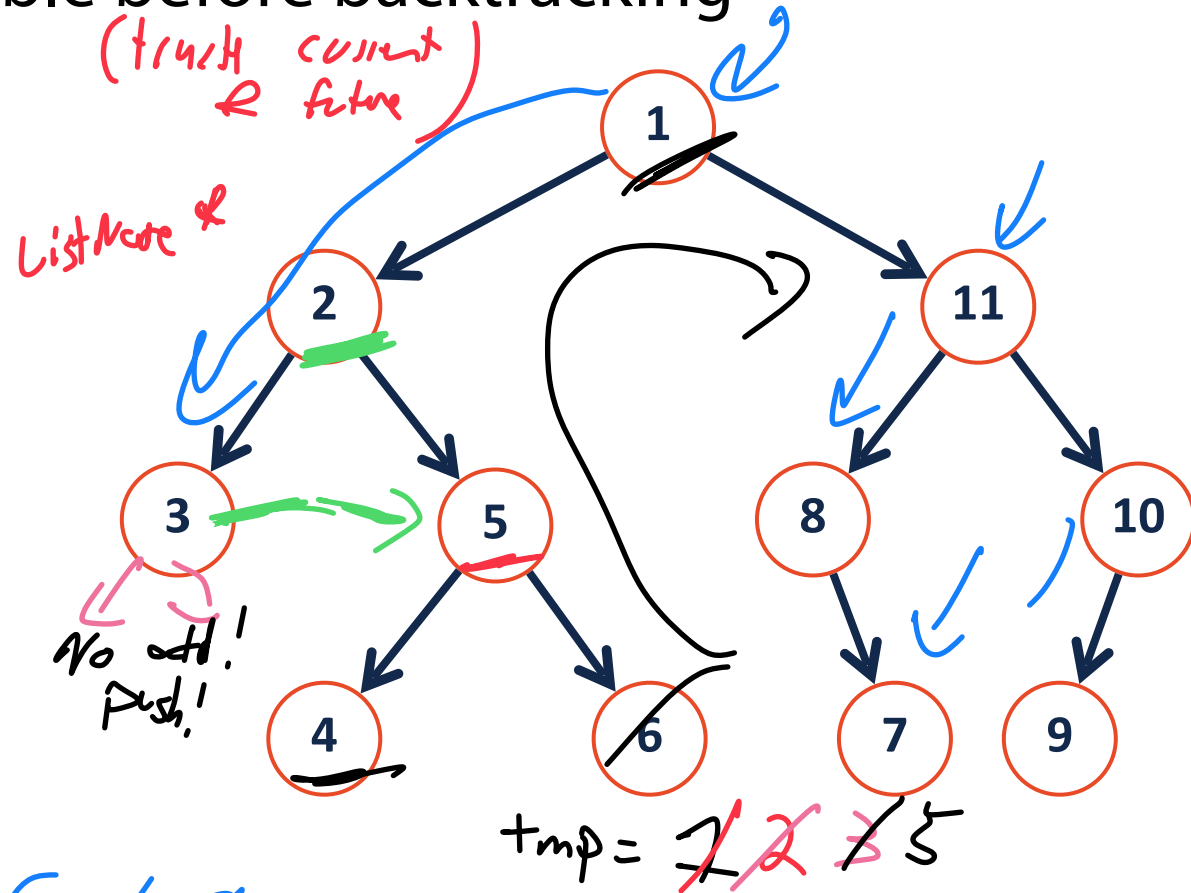
- 1) Make a stack initialized to root
- 2) While stack is not empty
 - * \rightarrow $tmp = \text{stack.pop()}$ (remove top element)
 - Print(tmp)

Stack.push($tmp \rightarrow \text{right}$)
Stack.push($tmp \rightarrow \text{left}$)

\uparrow 1 1 2 5 3 6 4

stack: \uparrow 1 1 2 5 3 6 4 11 8 7 9

print: 1 2 3 5 4 6 11 8 7 10 9



pre order

Breadth First Search

Fully explore depth i before exploring depth $i+1$

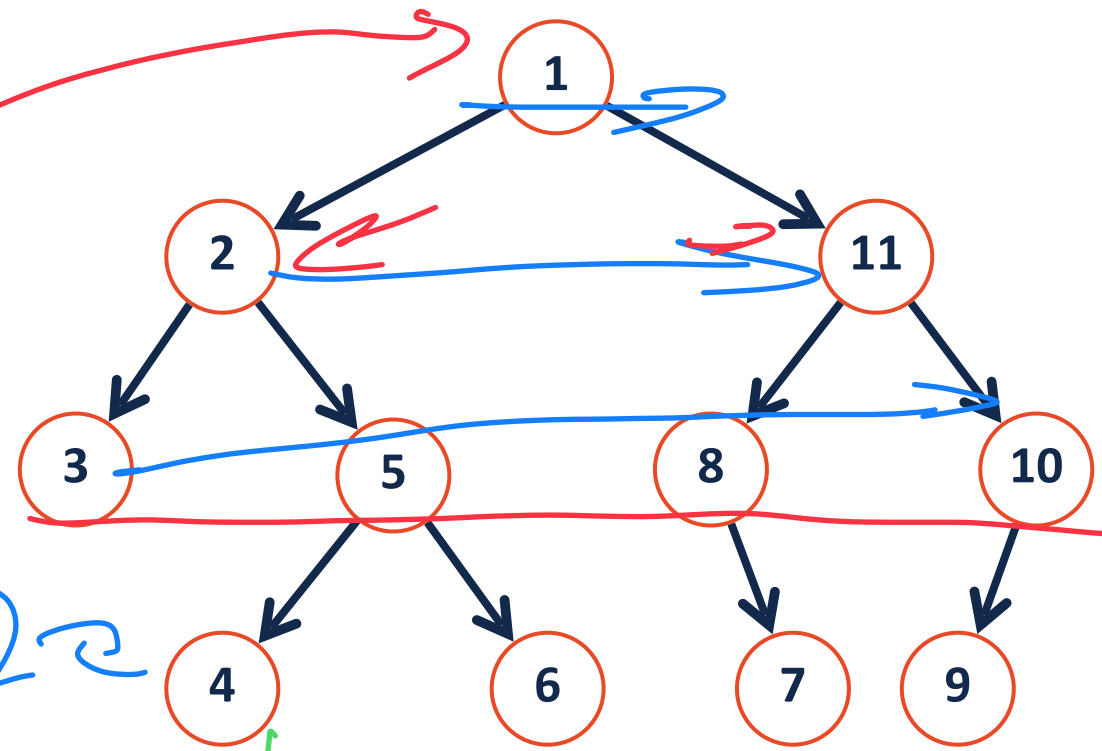
1) Make a queue init to root

2) while queue is not empty
 tmp = queue.dequeue() ~~is free Node *~~

print tmp

queue.enqueue(tmp.left)
 queue.enqueue(tmp.right)

pre recursion
 in recursion
 post



Local entire level

front												
Queue:	1	2	11	3	5	8	10	4	6	7	9	
Print:	1	2	11	3	5	8	10	4	6	7	9	

~~tmp = 2~~

To insert \Rightarrow remove I need find

BST Find

1) Start at root node

1.3) check if root is null \rightarrow return root;
 if so

2) Check value of root \rightarrow key

\hookrightarrow if root \rightarrow key $\underline{=}$ query

\hookrightarrow if yes, return root

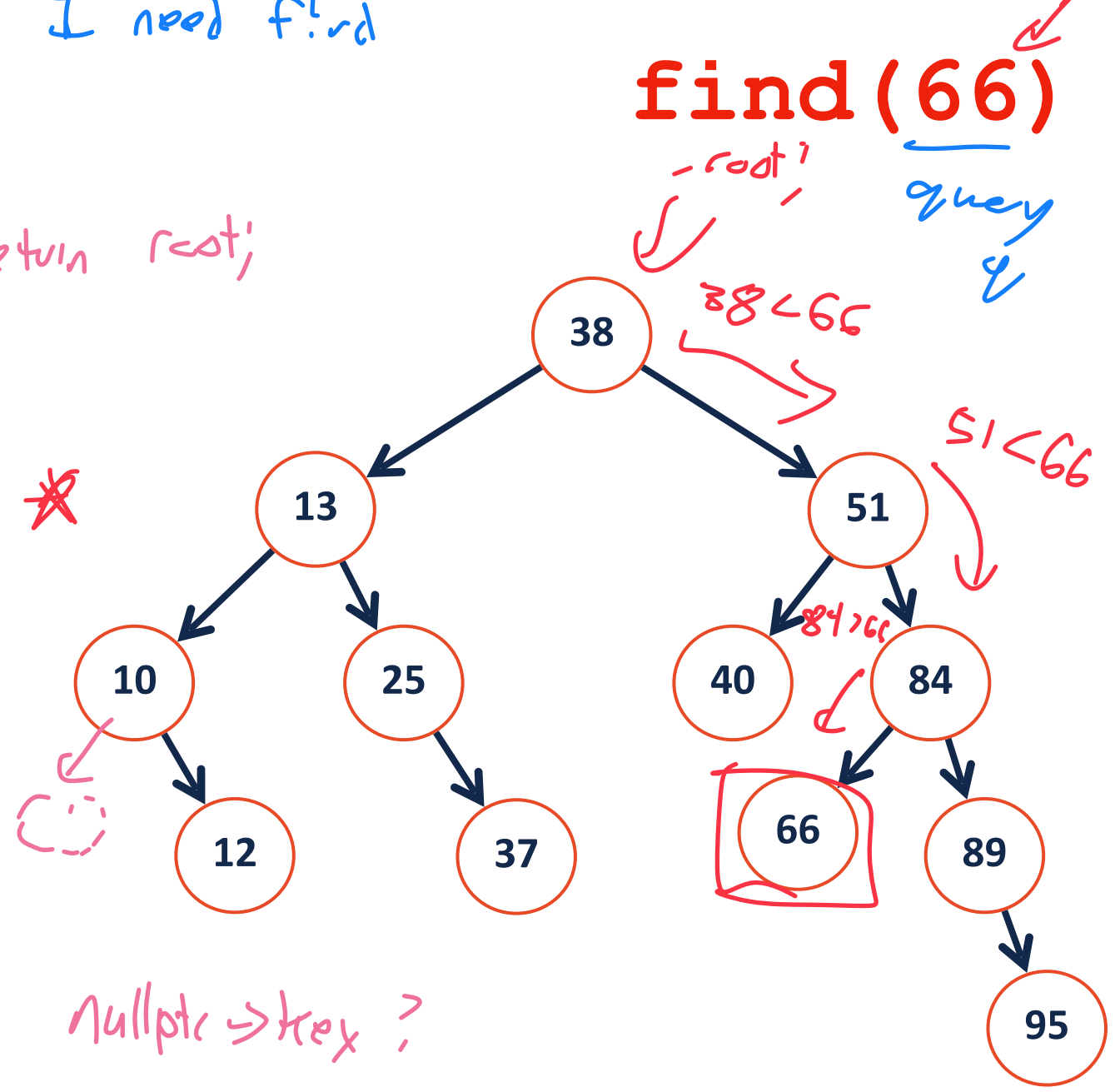
if root \rightarrow key $<$ query

recurse right

if root \rightarrow key $>$ query

recurse left

find(66)





```

1 template<typename K, typename V>
2
3 void _insert(const K & key, const V & val) {
4
5     return _insert(root, key, val);
6 }
7

```

helper function

T^E data

```

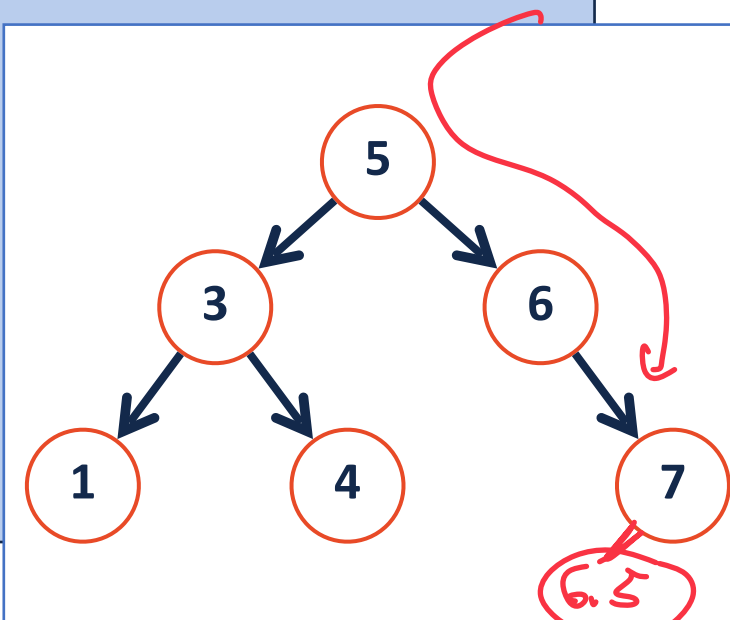
1 template<typename K, typename V>
2
3 void _insert(TreeNode *& root, const K & key, const V & val) {
4
5
6
7
8
9
10
11
12
13
14
15
16 }

```

1) Do a find (↓)

2) Insert new Node

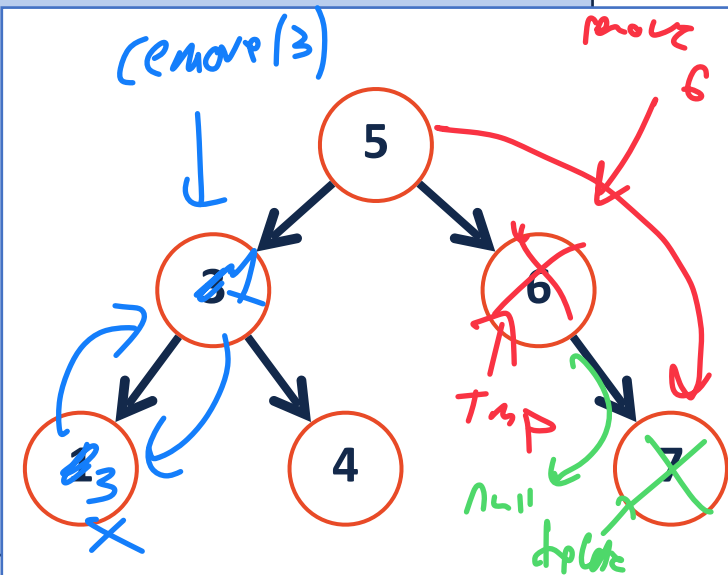
6.5



```

1 template<typename K, typename V>
2
3 void _remove(TreeNode *& root, const K & key) {
4
5     1) find (G) ← *p
6
7     2) 3 cases:
8
9         0 - child remove
10
11         1 - child removal
12           ↳ LL remove
13
14         2 - child removal
15           ↳ find TOP / IOS
16           ↳ swap TOP w/ root
17           ↳ remove (key)
18
19
20
21
22
23 }

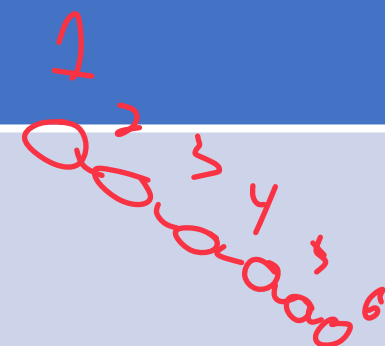
```



BST Analysis – Running Time



Operation	BST Worst Case
<u>find</u>	$O(h)$ → where h is height h is $O(n)$
<u>insert</u>	find $O(h)$ insert $O(1)$ → $O(h)$
<u>remove</u>	find $O(h)$ + find $O(h)$ + 1 ↳ remove obj ↳ JOP/JOS $O(h)$
<u>traverse</u>	$O(n)$



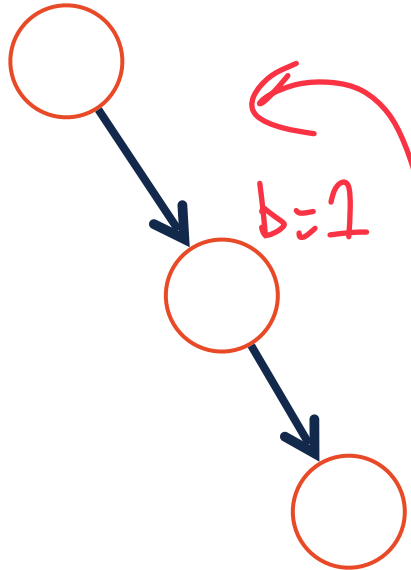
BST Analysis – Running Time

Operation	BST Worst Case
find	$O(h) = O(n)$
insert	$O(h) = O(n)$
remove	$O(h) = O(n)$
traverse	$O(n)$

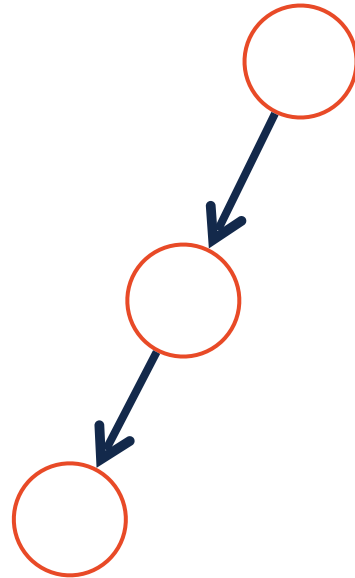
AVL Rotations

$b=2$

Simple

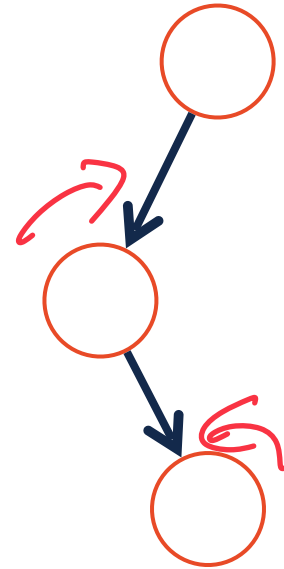


Left

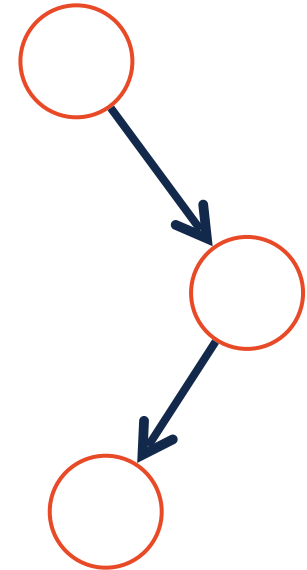


Right

Complex



Left Right



Right Left

Very
important!

AVL Tree Analysis

For an AVL tree of height h :

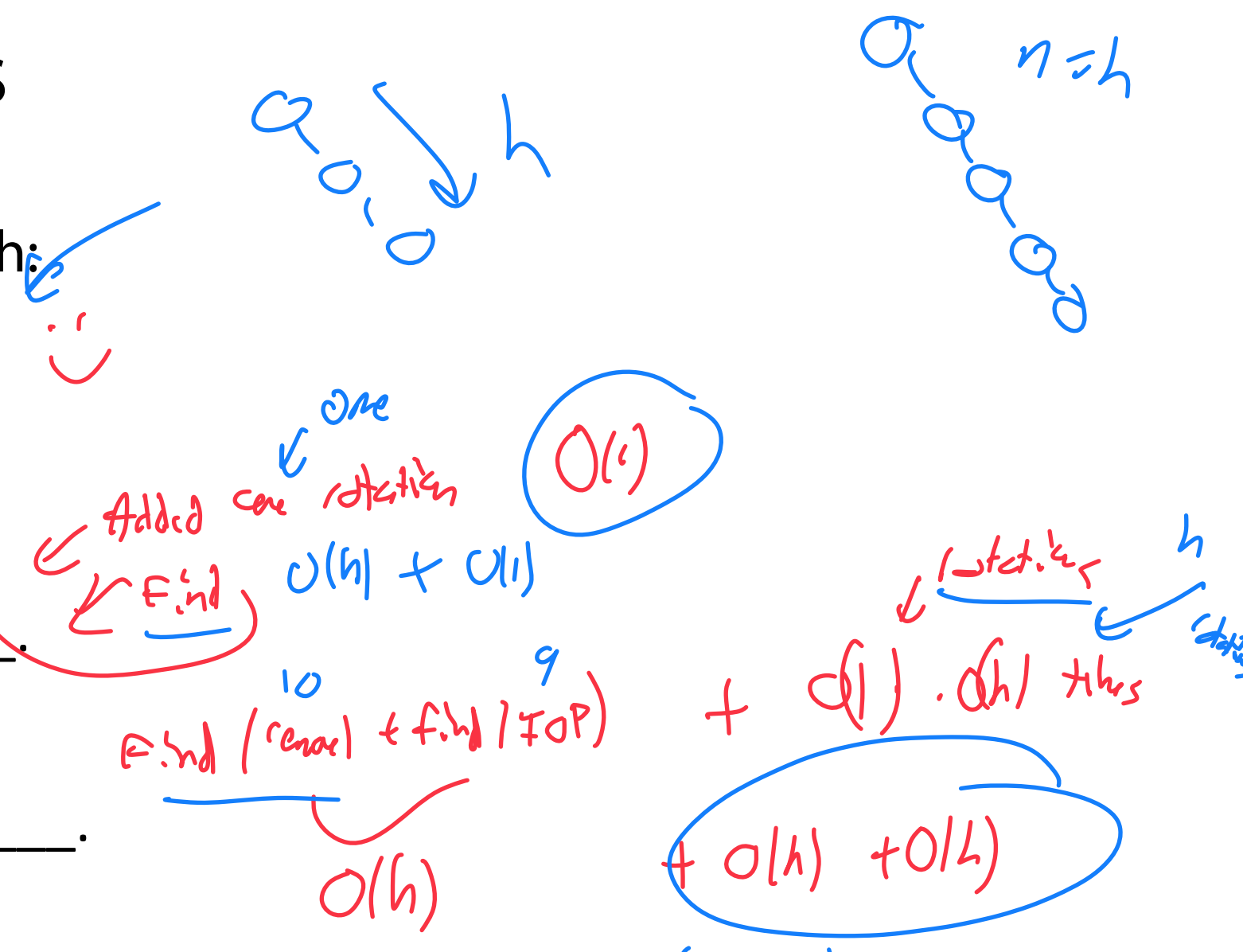
Find runs in: $O(h)$.

Insert runs in: $O(h)$.

Remove runs in: $O(h)$.

Claim: The height of the AVL tree with n nodes is: $O(\log n)$.

September 27 (AVL analysis)



Nearest Neighbor: k-d tree

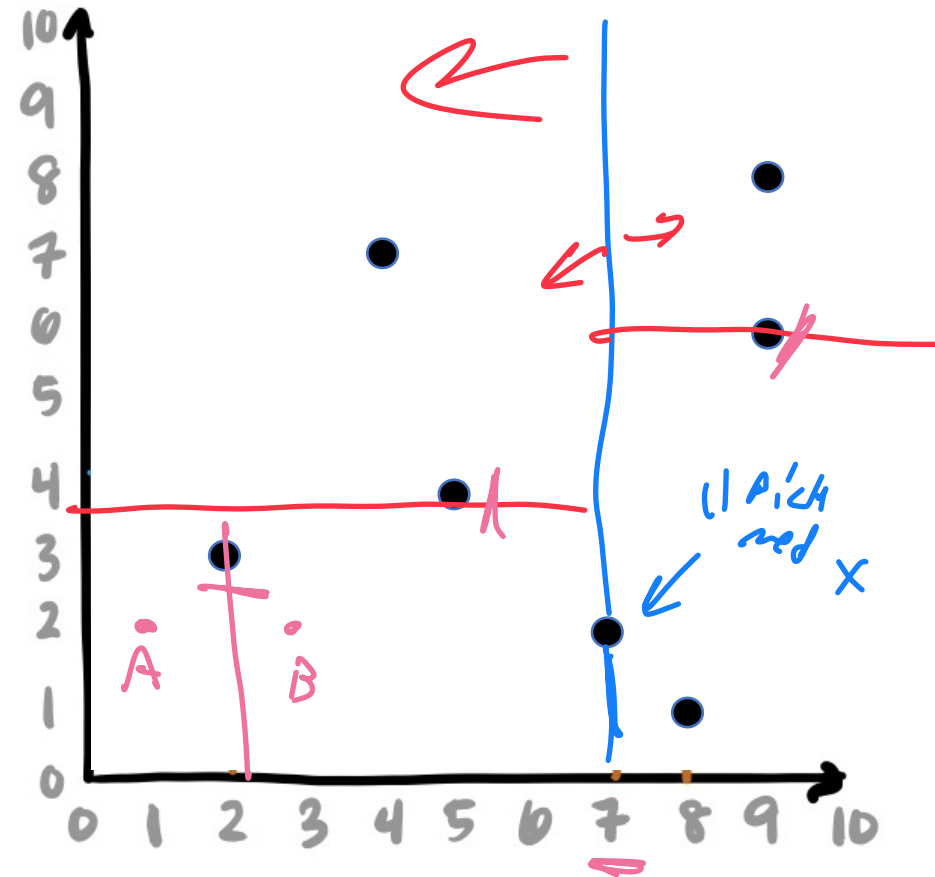
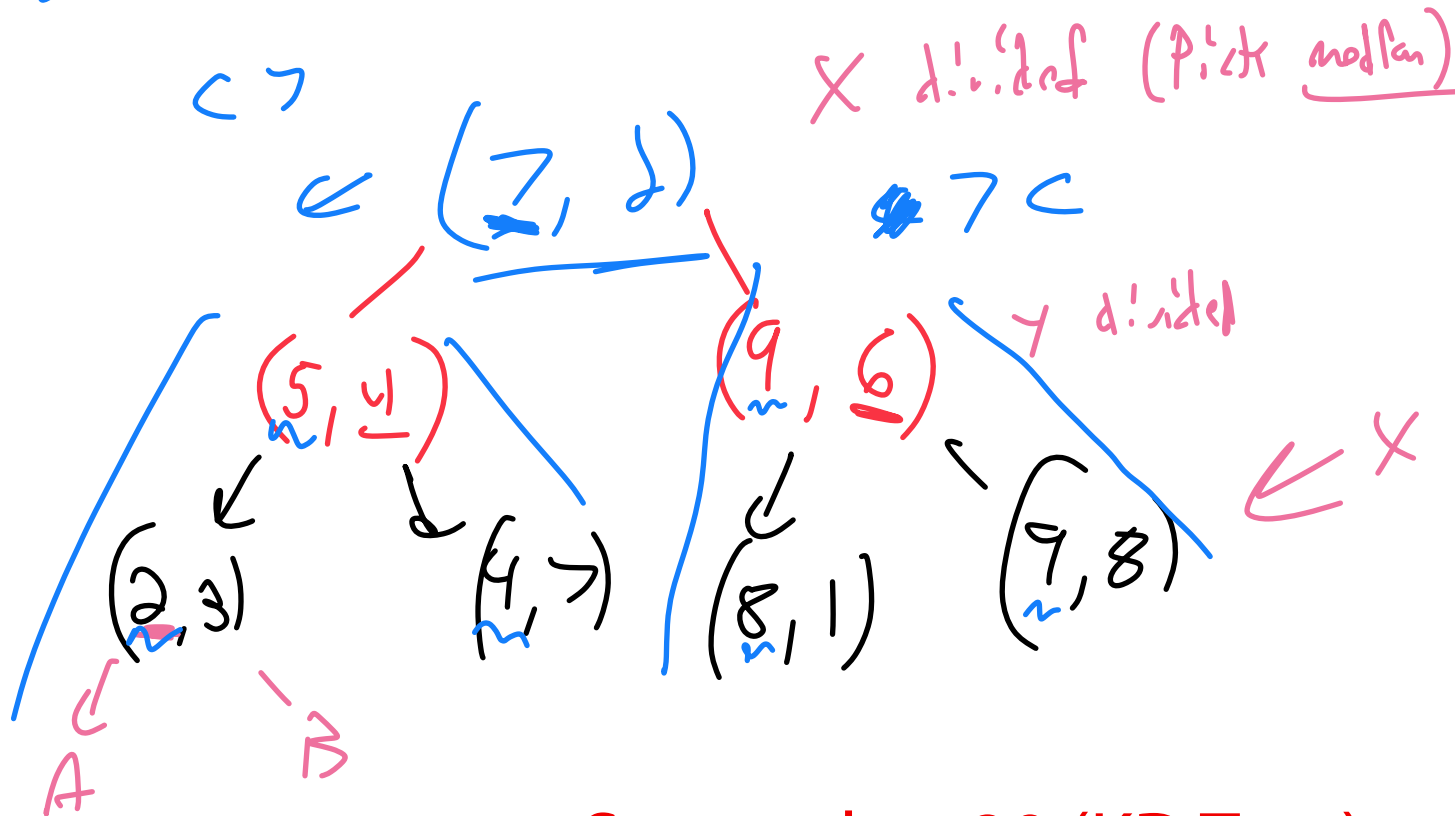
(x, y, z)

(x, y)

A **k-d tree** is similar but splits on points:

$(7, 2), (5, 4), (9, 6), (4, 7), (2, 3), (8, 1), (9, 8)$

start - / x-div.





BTree Properties



A **BTree** of order **m** is an m-ary tree and by definition:

- All keys within a node are ordered
- All nodes contain no more than **m-1** keys.
- All internal nodes have exactly **one more child than keys**

Review

Root nodes can be a leaf or have $[2, m]$ children.

at least at most

Derived from insert

All non-root, internal nodes have $[\lceil \frac{m}{2} \rceil, m]$ children.

at least at most m

All leaves in the tree are at the same level.

??



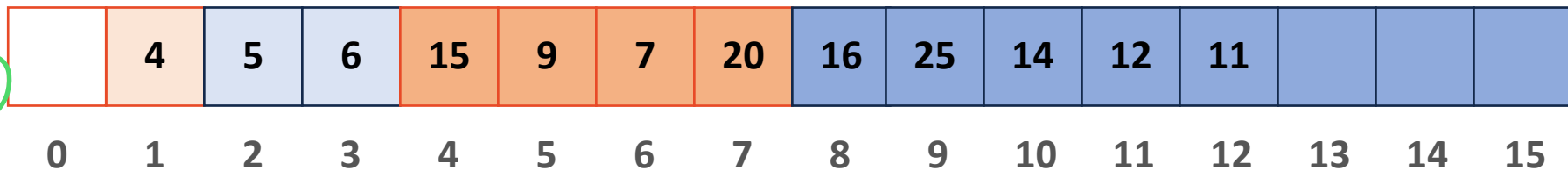
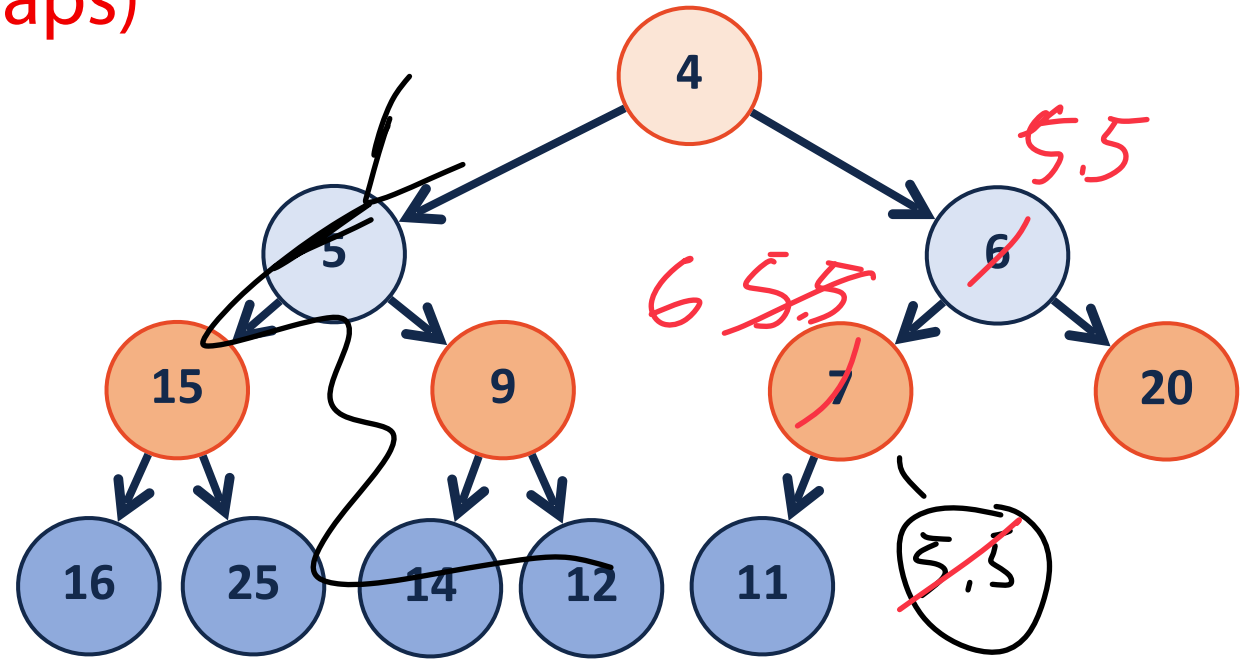
Heaps

(min)Heap October 13 (Heaps)

Insert (i)
↳ Array push back (i)
↳ Swap until heap again
↳ 'heapify up'

$$O(\log n) \equiv O(h)$$

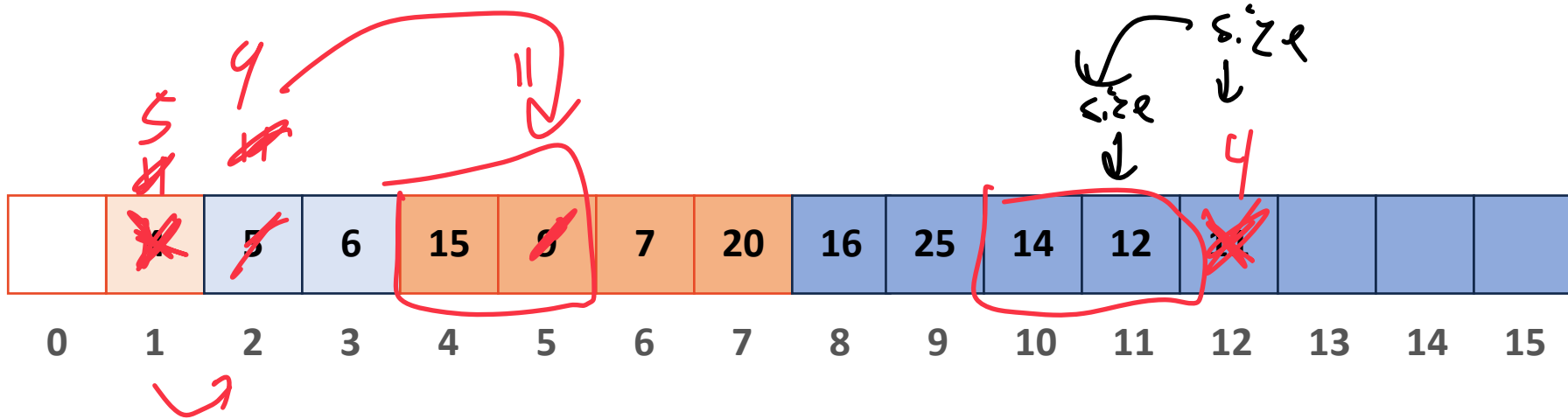
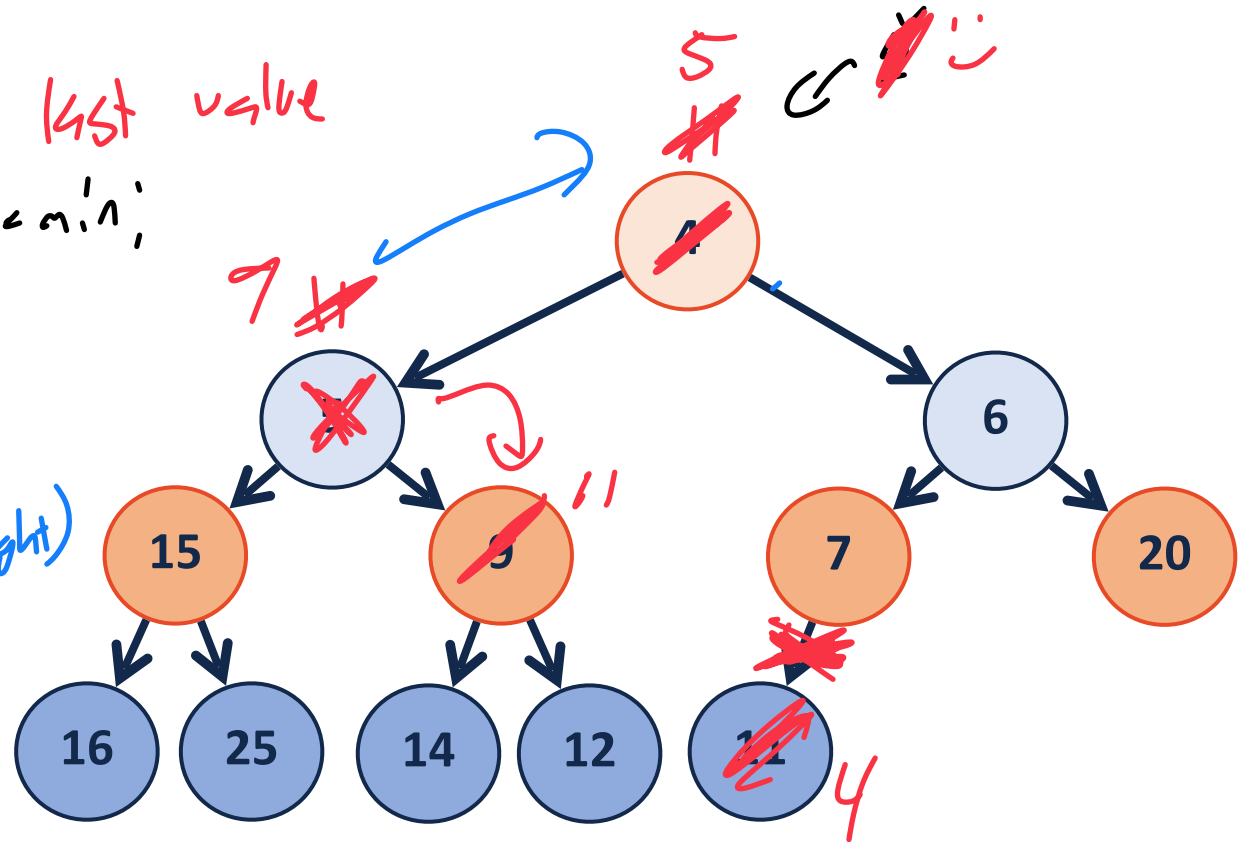
complete tree is balanced



This is a design decision!

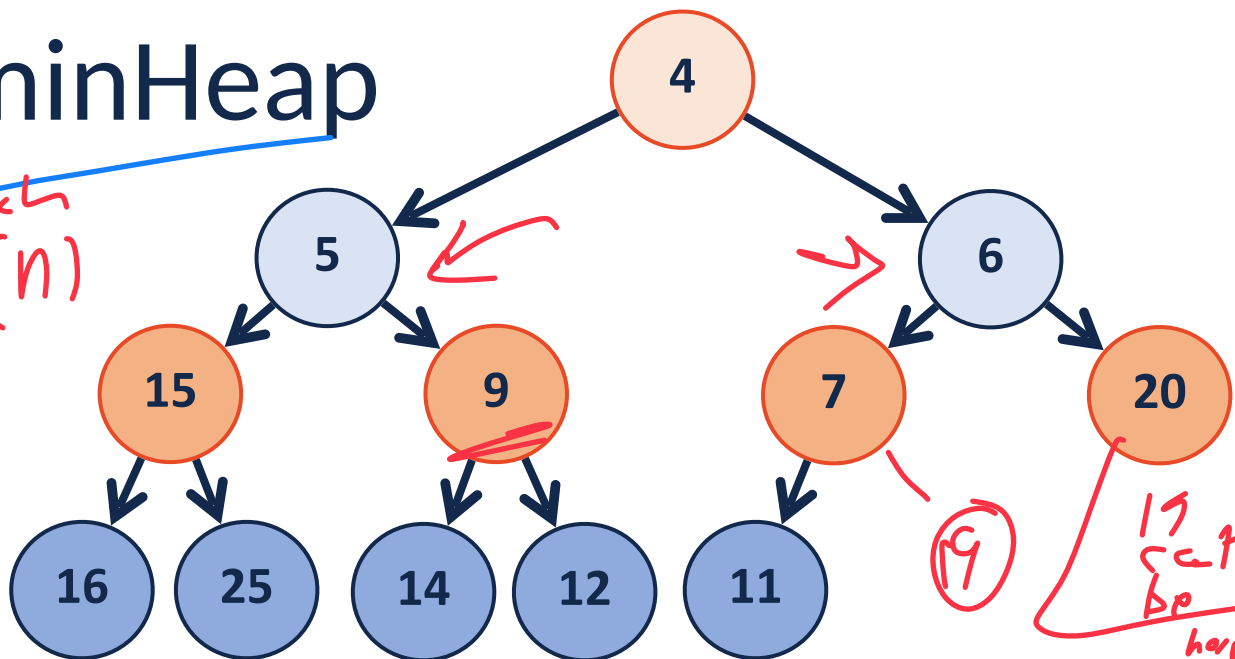
removeMin → and return

- 1) SWAP min value (root) w/ last value
→ temp = min;
- 2) Delete min by size--
- 3) heapify Down (root)
↳ swap root w/ min (left, right)
recursively



minHeap

Search $O(n)$



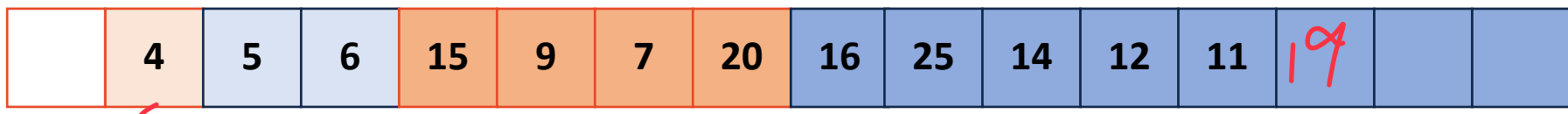
1. Construction $\rightarrow O(n)$



2. Insert $\rightarrow O(\log n)$

3. RemoveMin $\rightarrow O(\log n)$

Just an array in storage



minHeap is a good example of tradeoffs:

Nearly optimal* for every function

Cost of access!

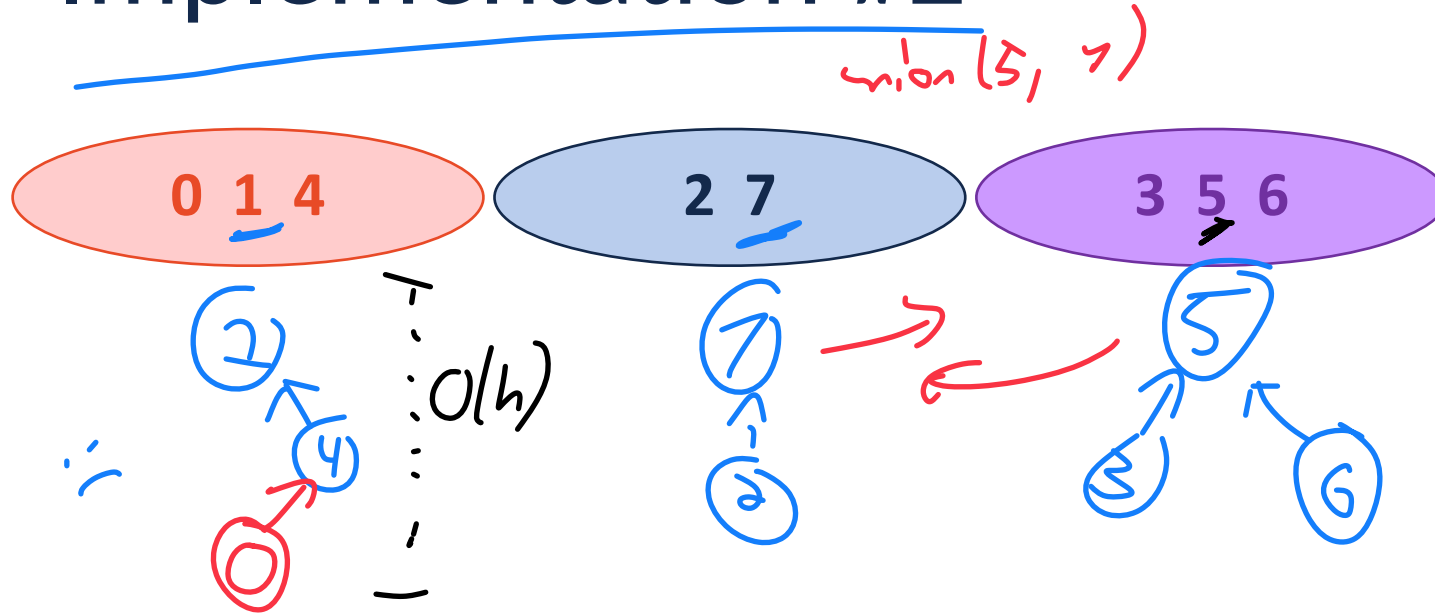
Not suitable for random access & find



Disjoint Sets

Implementation #2

October 18 (Sets 2)



0	1	2	3	4	5	6	7
4	-1	7	5	2	-1	5	-1

Find(k): $O(h)$

↳ last class: $O(1)$
w/ array

↳ A little slower

Union(k_1, k_2): $O(1)$

↳ last class: $O(h)$

b/c we draw one arrow
(we change one value)

up tree

- 1) All non-canonical elements point to canonical (or 'root')
- 2) Canonical (root) elements store -1

Disjoint Sets Representation

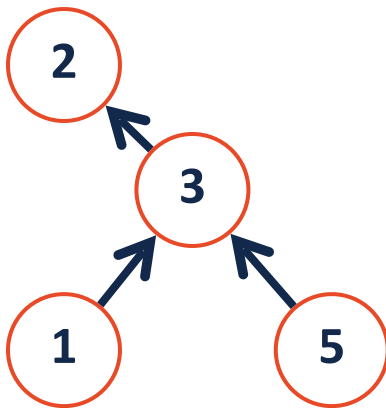


We can represent a disjoint set as an array where the key is the index

The values inside the array stores our sets as a pseudo-tree (UpTree)

The value **-1** is our representative element (the root)

All other set members store the index to a parent of the UpTree



Disjoint Sets Find

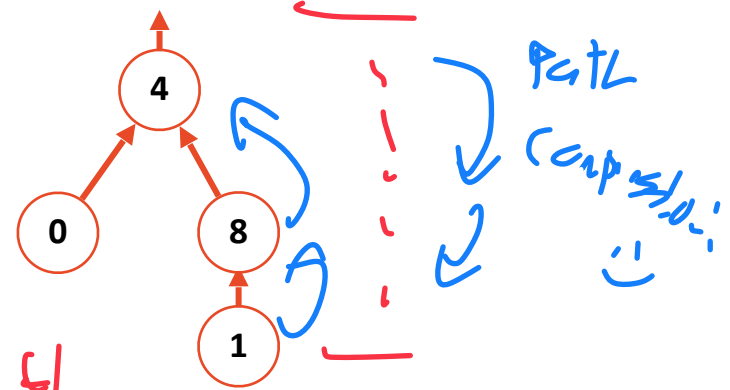
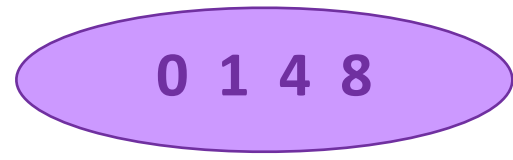
-1 is canonical

Find(1)

```

1 int DisjointSets::find(int i) {
2   if ( s[i] < 0 ) { return i; }
3   else { return find( s[i] ); }
4 }
    
```

↘ reverse UP



Running time? $O(h)$

return 4

What is ideal UpTree? height 1, 0, 0



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

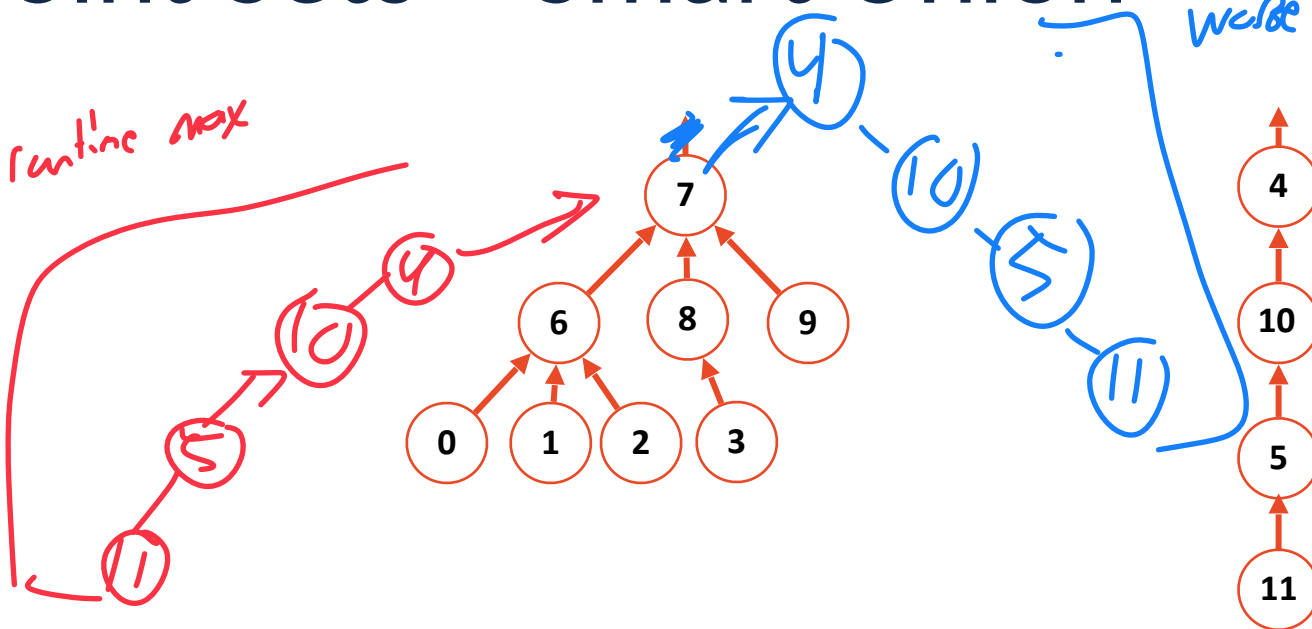


Disjoint Sets – Smart Union



Worse runtime max

Worse average performance



Union by height

0	1	2	3	4	5	6	7	8	9	10	11
6	6	6	8		10	7		7	7	4	5

Idea: Keep the height of the tree as small as possible.

Union by size

0	1	2	3	4	5	6	7	8	9	10	11
6	6	6	8		10	7		7	7	4	5

Idea: Minimize the number of nodes that increase in height

Claim that both guarantee the height of the tree is: $\log_2 n$.



Final Result

We have **n items** in an Uptree. We make **m find()** calls. Total work is:

cost between buckets

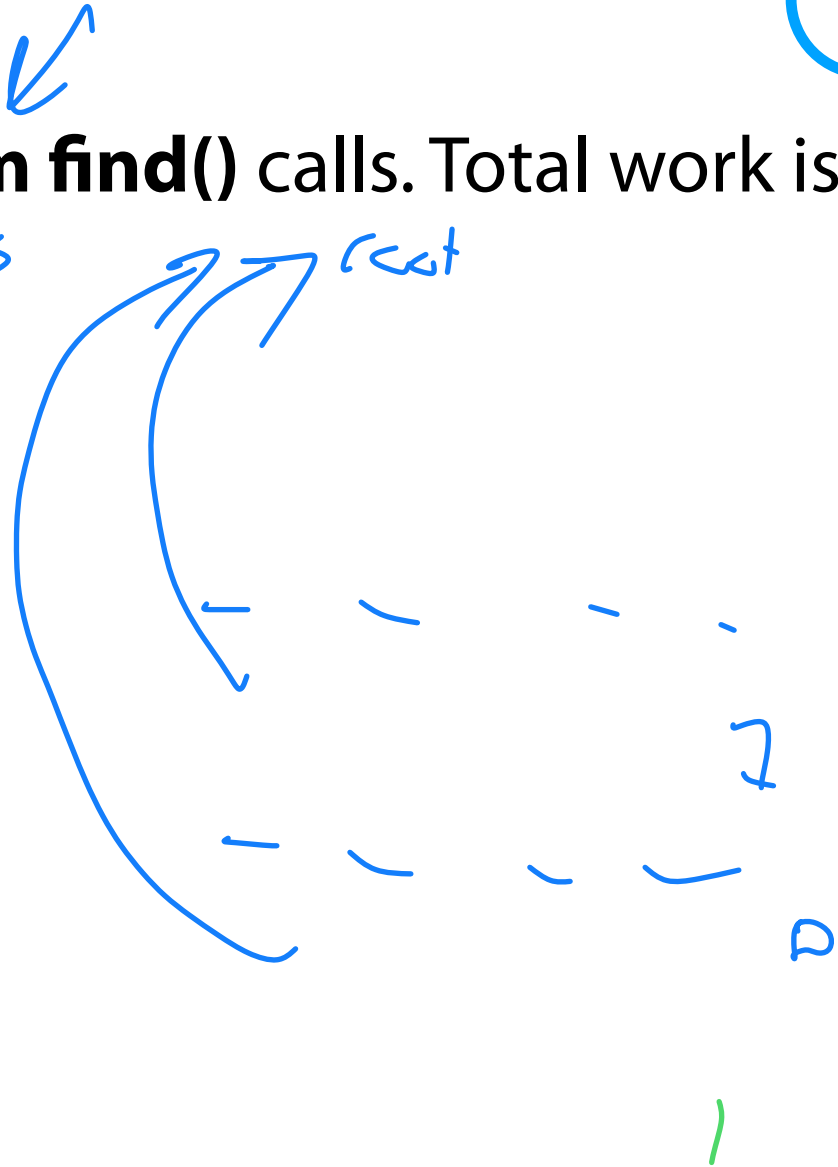
$$m \cdot \log^* n$$

cost inside buckets

$$+ n \cdot \log^* n$$

$$(m+n) \log^* n$$

≠ virtually my finds we just this





Probability in CS



Probabilistic Data Structures

A Hash Table based Dictionary

October 30 (Hashing 2)

User Code (is a map):

```
1 Dictionary<KeyType, ValueType> d;  
2 d[k] = v;
```

A **Hash Table** consists of three things:

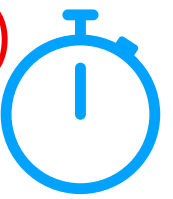
1. A hash function

Data → *int*

2. A data storage structure

Array

3. A method of addressing *hash collisions*



Hash Table (Separate Chaining)

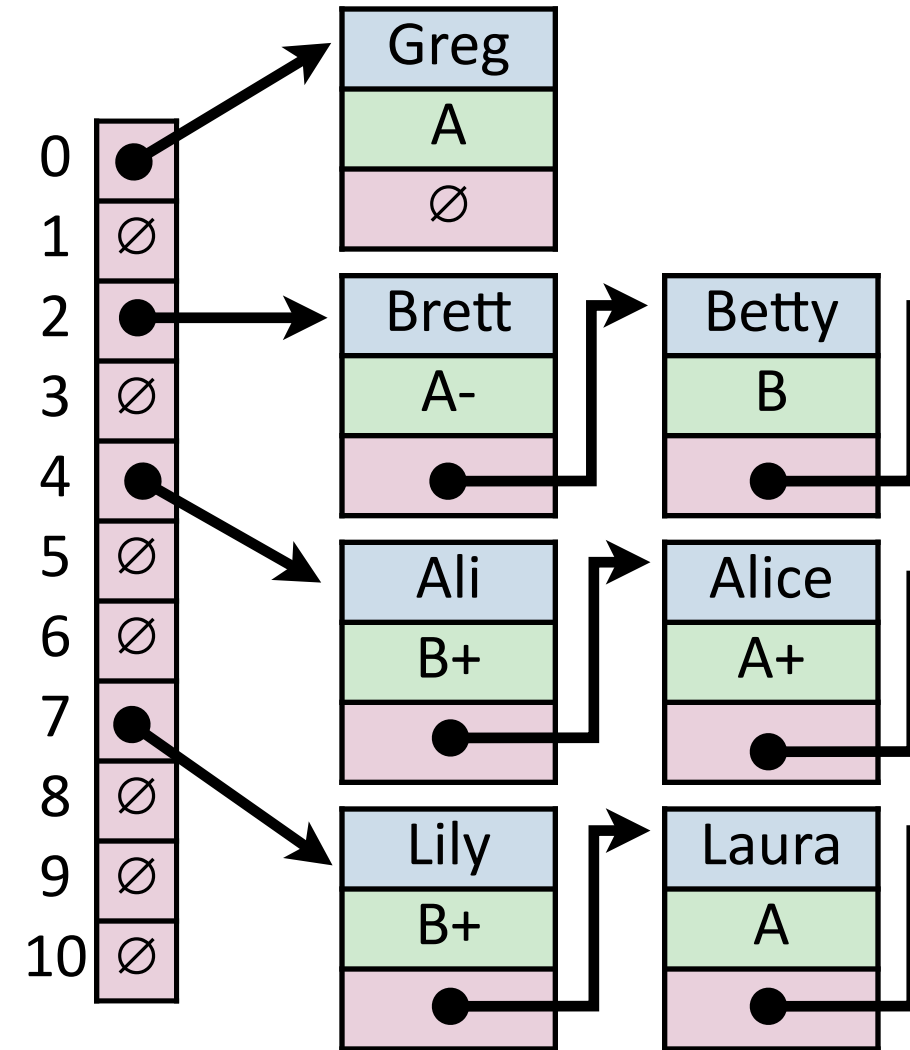
For hash table of size m and n elements:

Find runs in: $O(n)$

Insert runs in: $O(1)$ ☺

Remove runs in: $O(n)$

↳ B/c of collisions!



Simple Uniform Hashing Assumption

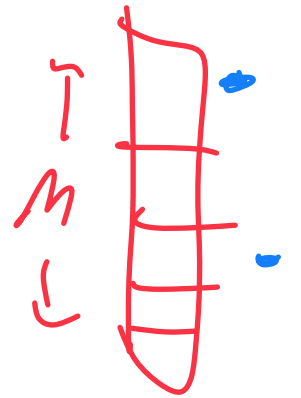
October 30

Given table of size m , a simple uniform hash, h , implies

$$\forall k_1, k_2 \in U \text{ where } k_1 \neq k_2, \Pr(h[k_1] = h[k_2]) = \frac{1}{m}$$

Uniform: All keys equally likely to hash any value

$$\Pr(h(k_i) = X) = \frac{1}{m}$$



Independent: All keys hash independently of each other

Separate Chaining Under SUHA

we set those constants



Under SUHA, a hash table of size m and n elements:

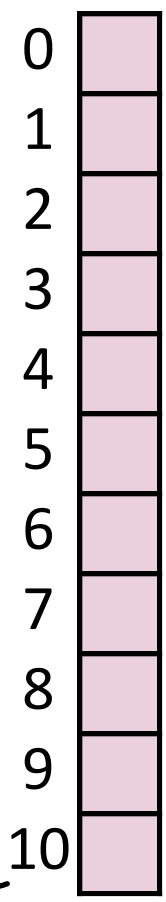
Find runs in: $2 + \alpha$

$2 + \alpha + n/m$



hash

uniform indep randomness



Insert runs in: $O(2)$

$\alpha = \lceil n/m \rceil$

m
we control m

α
Load Factor

Remove runs in: $2 + \alpha$

expected # of items in bucket

Expectations Not Big O

Running Times *(Don't memorize these equations, no need.)*

The expected number of probes for find(key) under SUHA

Linear Probing:

- Successful: $\frac{1}{2}(1 + 1/(1-\alpha))$
- Unsuccessful: $\frac{1}{2}(1 + 1/(1-\alpha))^2$

Double Hashing:

- Successful: $1/\alpha * \ln(1/(1-\alpha))$
- Unsuccessful: $1/(1-\alpha)$

Separate Chaining:

- Successful: $1 + \alpha/2$
- Unsuccessful: $1 + \alpha$

OH: $\alpha \rightarrow \infty$

CH: $0 \leq \alpha < 1$

Don't let α 's be 1

Instead, observe:

- As α increases:

Search time $\rightarrow \infty$

- If α is constant:

↳ Runtime is constant

IF $n=100, m > 100$

$m = 200$:-

Running Times

The expected number of probes for $\text{find}(\text{key})$ under SUHA



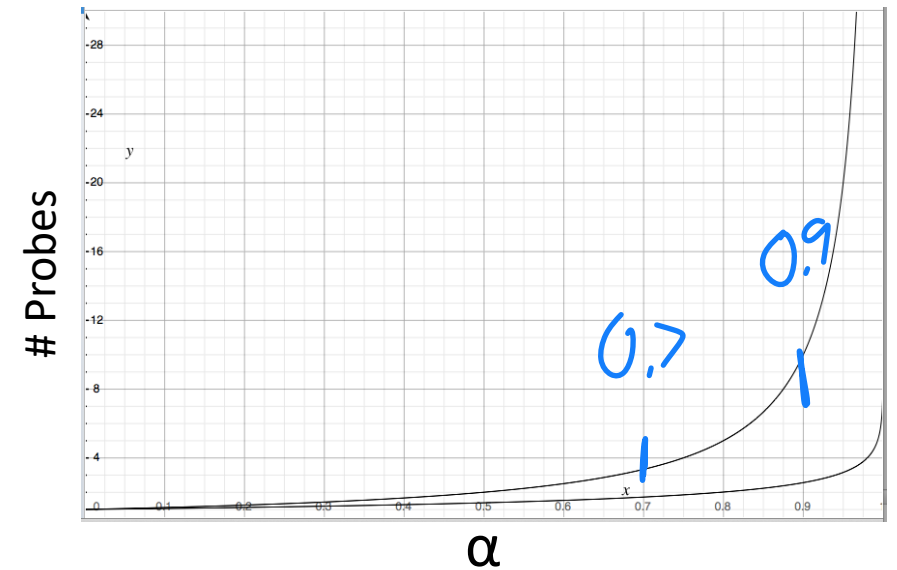
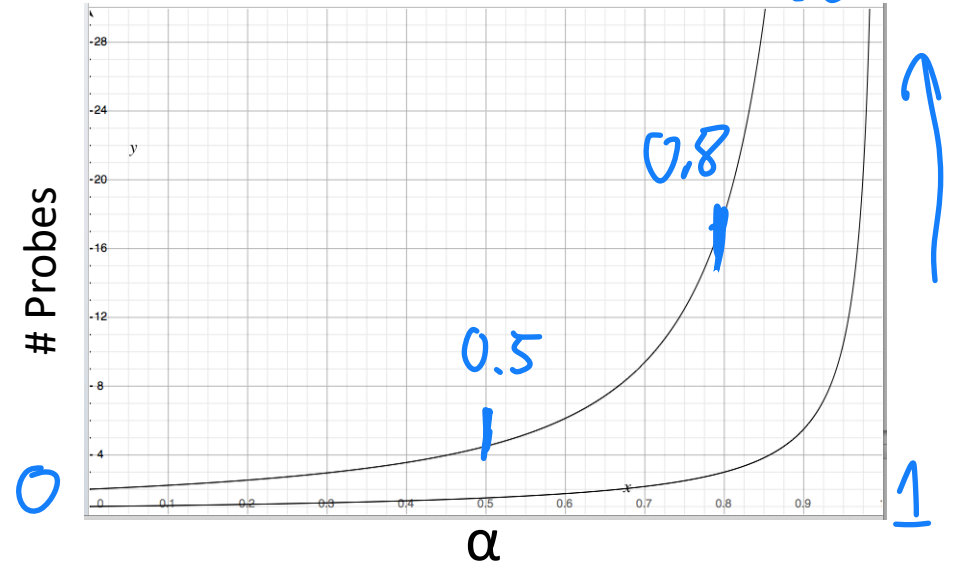
Linear Probing:

- Successful: $\frac{1}{2}(1 + \frac{1}{1-\alpha})$
- Unsuccessful: $\frac{1}{2}(1 + \frac{1}{(1-\alpha)^2})$

Double Hashing:

- Successful: $\frac{1}{\alpha} * \ln(\frac{1}{1-\alpha})$
- Unsuccessful: $\frac{1}{1-\alpha}$

When do we resize? $\alpha \sim \underline{0.7 - 0.9}$



Running Times

$\log 2$



	Hash Table	AVL	Linked List
Find	Expectation*: <u>$O(1)$</u> Worst Case: $O(n)$	$O(\log n)$	$O(n)$ ←
Insert	Expectation*: <u>$O(1)$</u> Worst Case: $O(n)$	$O(\log n)$	$O(1)$ ←
Storage Space	$O(m) \sim \underline{O(n)}$	<u>$O(n)$</u>	<u>$O(n)$</u>

↑
constant μ 's



Bloom Filter

A probabilistic data structure storing a set of values

$$H = \{h_1, h_2, \dots, h_k\}$$

Built from a bit vector of length m and k hash functions

Insert / Find runs in: $O(k) \sim O(1)$

Delete is not possible (yet)!

\hookrightarrow One sided error b/c we don't delete

0
0
1
0
0
1
0
1
0
0



Imagine we have a **bloom filter** that **stores malicious sites...**

predictor

Bit Value = 1

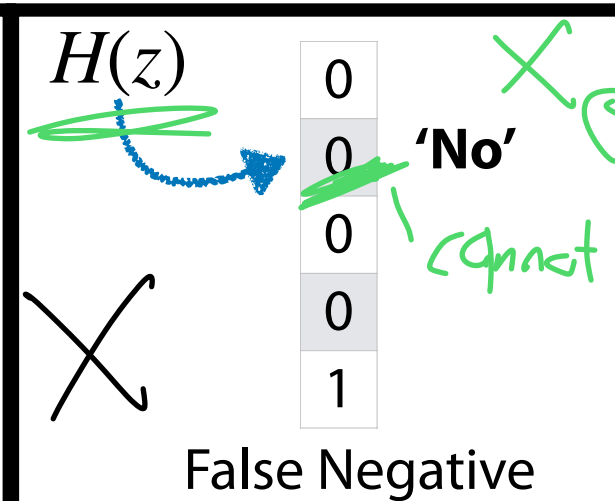
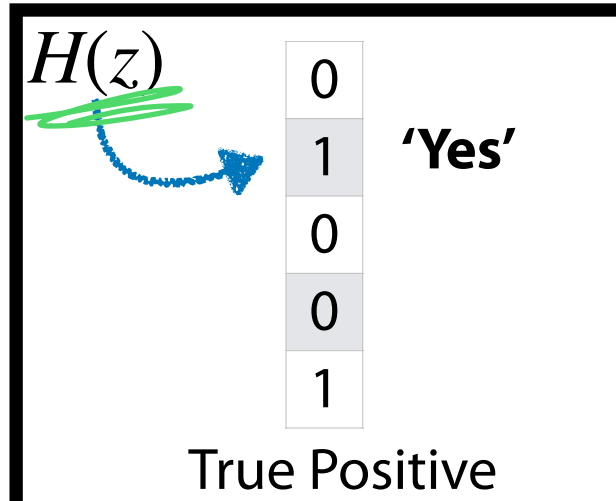
↳ Yes

Bit Value = 0

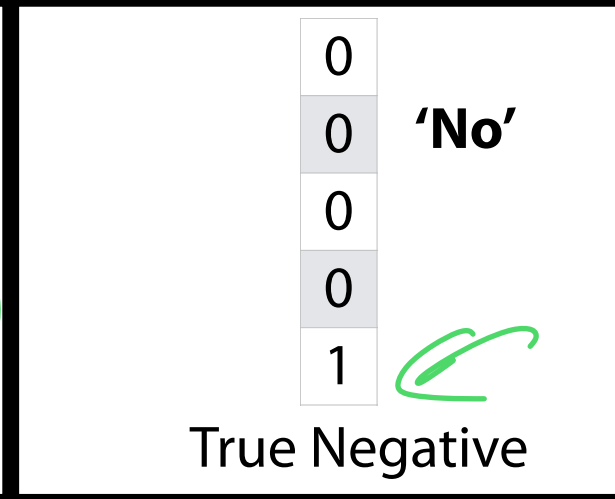
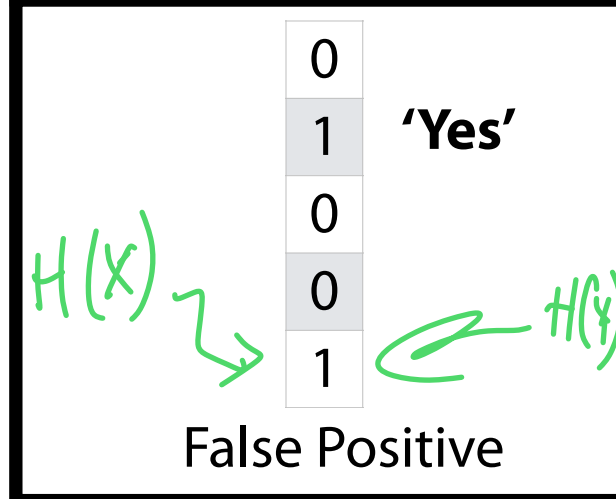
↳ No

Actual truth

Item Inserted



Item NOT inserted

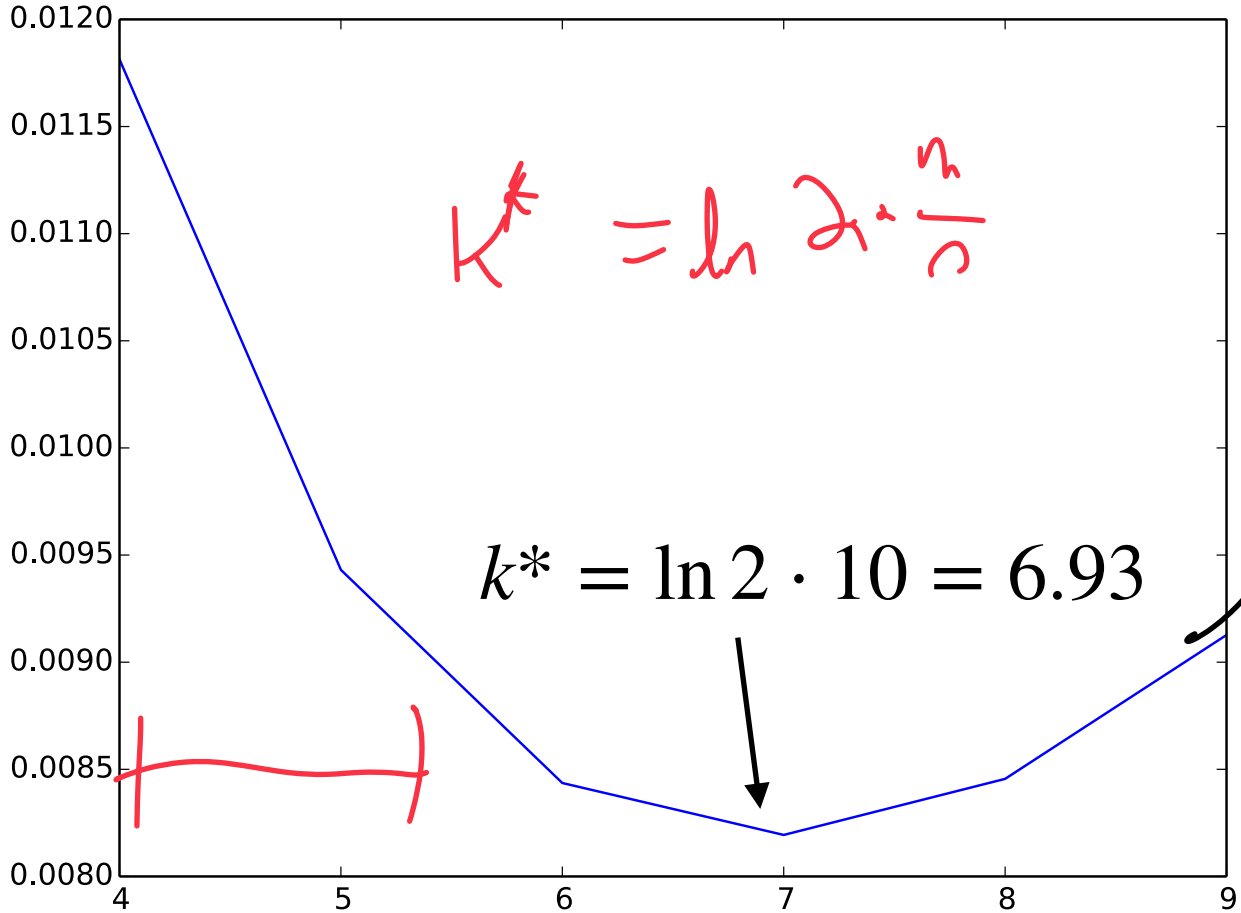


One sided error

Bloom Filter: Error Rate

$m/n = 10$

$$FPR = \left(1 - e^{-\frac{nk}{m}}\right)^k$$



$$k^* = \ln 2 \cdot \frac{n}{m}$$

$$k^* = \ln 2 \cdot 10 = 6.93$$

*k is too small
not enough random trials*

*Saturate
my
filter,*

Figure by Ben Langmead



Cardinality Estimation

Let $\min = 95$. Can we estimate N , the cardinality of the set?



Conceptually: If we scatter N points randomly across the interval, we end up with $N + 1$ partitions, each about $1000/(N + 1)$ long

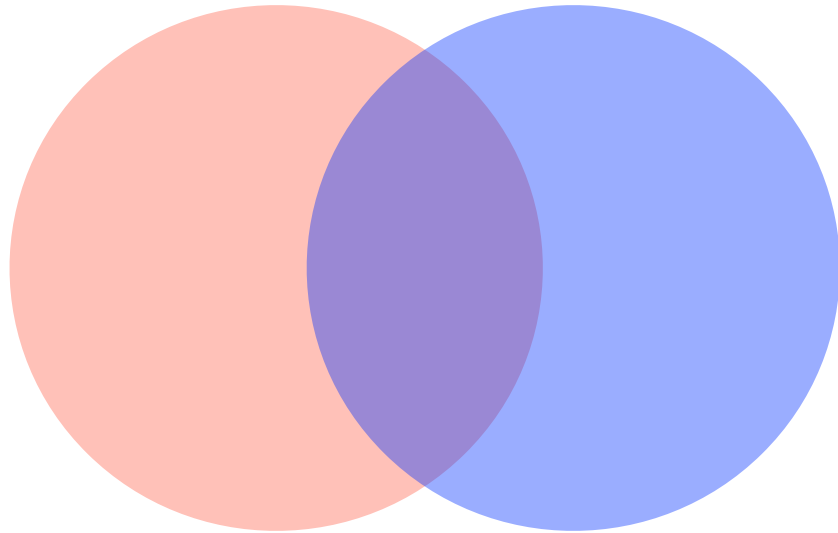
Assuming our first 'partition' is about average: $95 \approx 1000/(N + 1)$

$$N + 1 \approx 10.5$$

$$N \approx 9.5$$

Set Similarity Review

To measure **similarity** of A & B , we need both a measure of how similar the sets are but also the total size of both sets.



$$J = \frac{|A \cap B|}{|A \cup B|}$$

J is the **Jaccard coefficient**

MinHash Sketch

Claim: Under SUHA, set similarity can be estimated by sketch similarity!

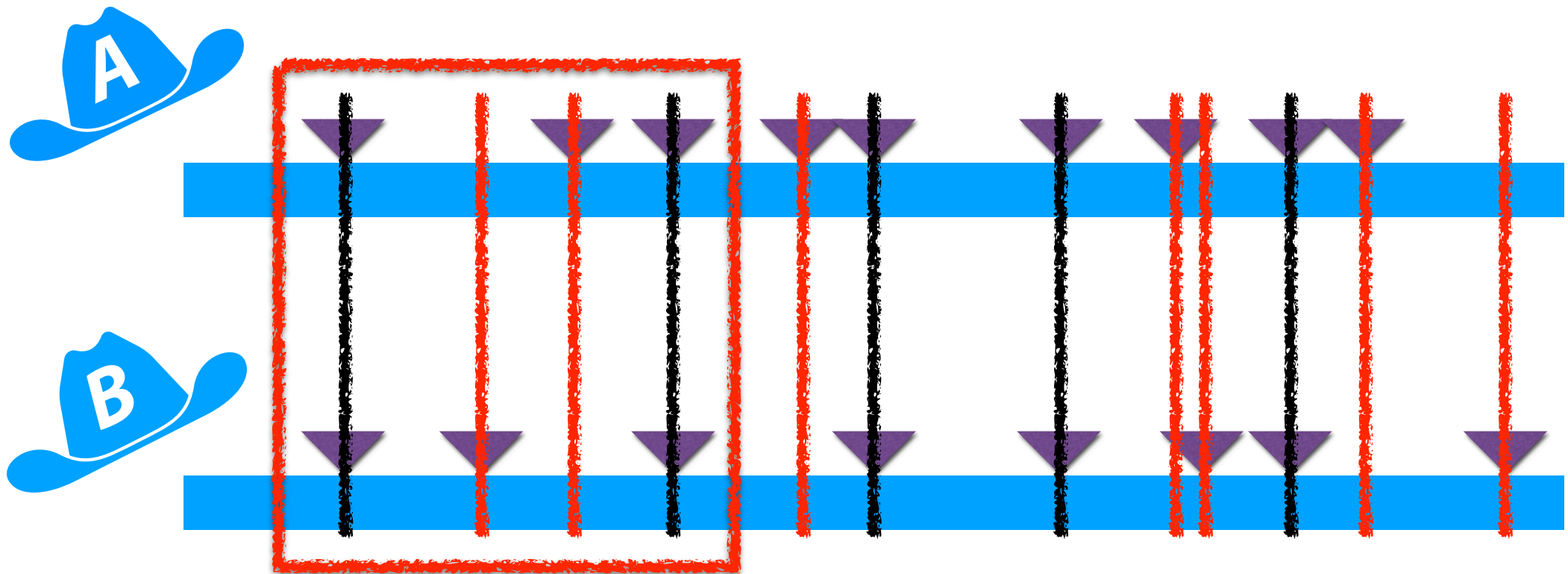
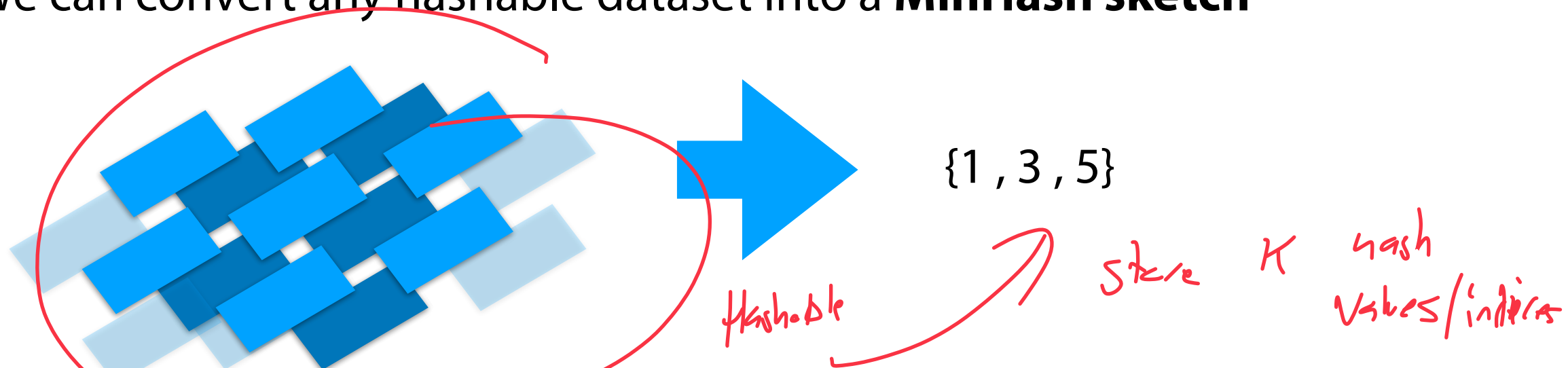


Image inspired by: Ondov B, Starrett G, Sappington A, Kostic A, Koren S, Buck CB, Phillippy AM. **Mash Screen: high-throughput sequence containment estimation for genome discovery.** *Genome Biol* 20, 232 (2019)



MinHash Sketch

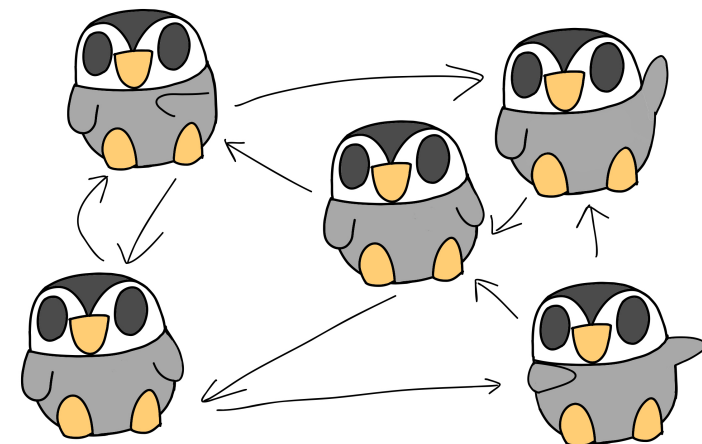
We can convert any hashable dataset into a **MinHash sketch**



We lose our original dataset, but we can still estimate two things:

1. Cardinality (k min hash is best estimate)
2. Similarity (Directly or indirectly)

Graphs

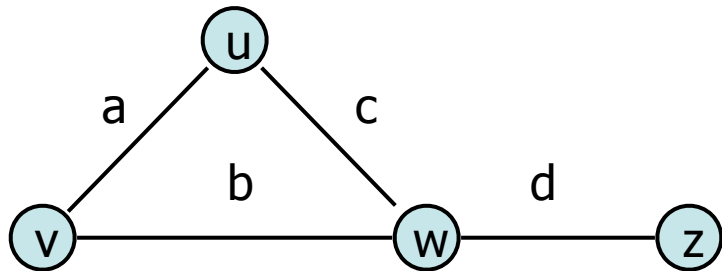


Graph Implementation: Edge List

$|V| = n, |E| = m$

$O(n)$ list

$O(1)$ array or not LL



Big O

insertVertex(K key):

insertEdge(Vertex v1, Vertex v2, K key):

List Vertices $|n|$

List Edges $|m|$

removeVertex(Vertex v):

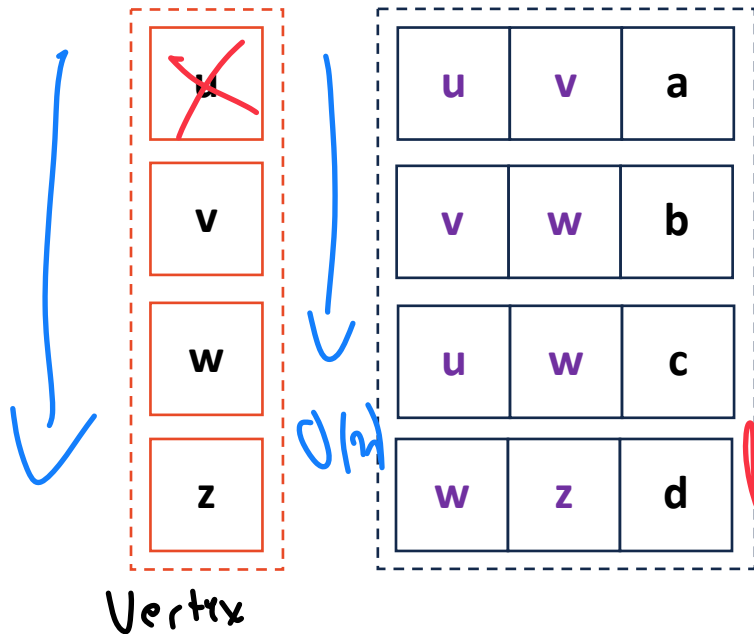
removeEdge(Vertex v1, Vertex v2, K key):

find & remove

incidentEdges(Vertex v):

areAdjacent(Vertex v1, Vertex v2):

$O(m)$



$O(n+m)$

$O(m)$

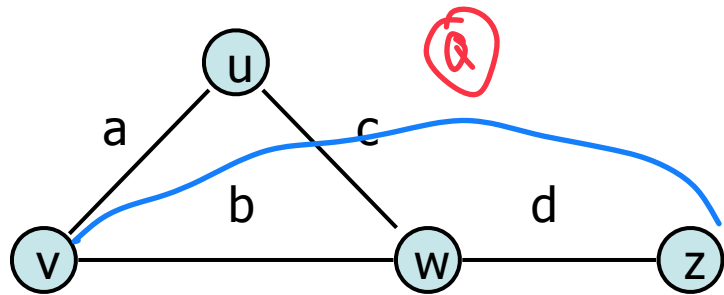
find all edges

$O(m)$

Graph Implementation: Adjacency Matrix



$|V| = n, |E| = m$



insertVertex(K key): $O(n)$ *weight*

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

removeVertex(Vertex v): $O(n)$

removeEdge(Vertex v1, Vertex v2, ~~K key~~): $O(1)$

incidentEdges(Vertex v): $O(n)$

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

Great for dense graphs!

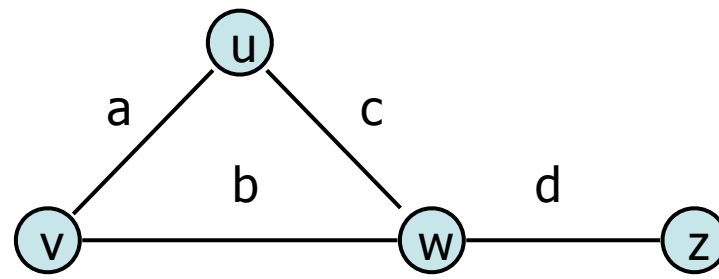
vertex list H.T.

Edges Adj matrix $O(n^2)$

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

Adjacency List

$|V| = n, |E| = m$

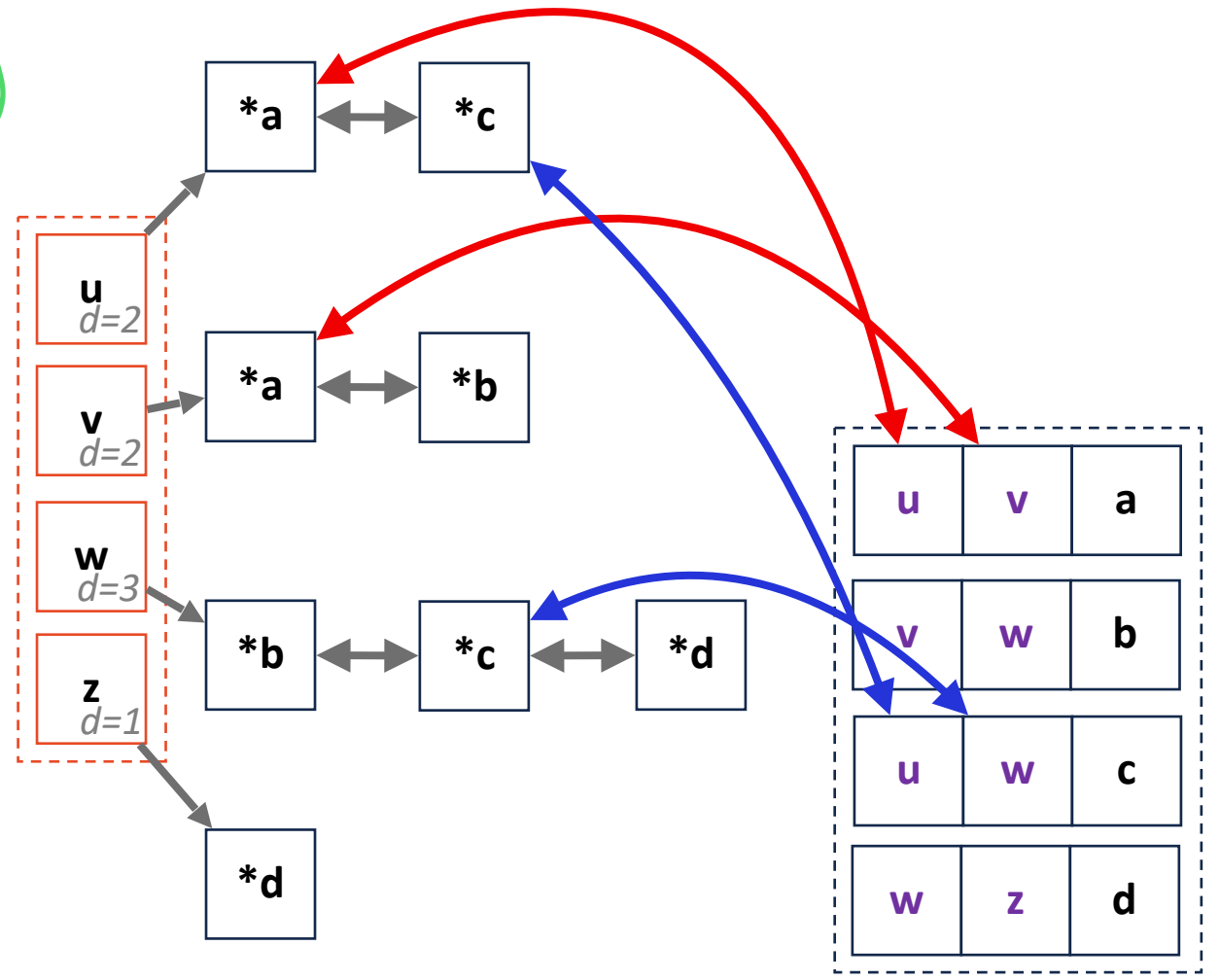


Adj List Node: Bidirectional LL (w/ tail pointer)
3 pointers

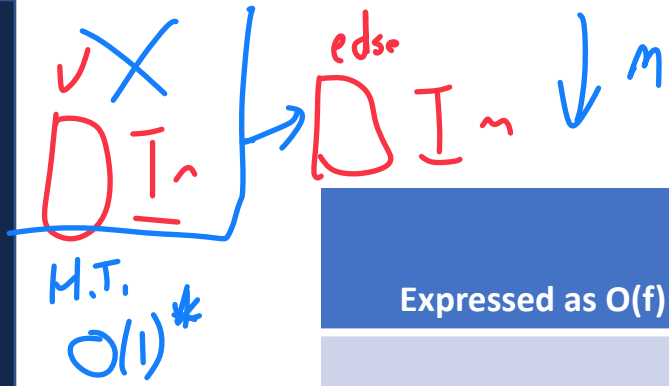
Prev	Edge	Next
------	------	------

Edge List: Edge list + 2 pointers

V1	V2	Weight
*V1	*V2	



$$|V| = n, |E| = m$$



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	$\text{deg}(v)$
insertEdge(u, v)	1	1	1^*
removeEdge(u, v)	m	1	$\text{min}(\text{deg}(u), \text{deg}(v))$
incidentEdges(v)	m	n	$\text{deg}(v)$
areAdjacent(u, v)	m	1	$\text{min}(\text{deg}(u), \text{deg}(v))$

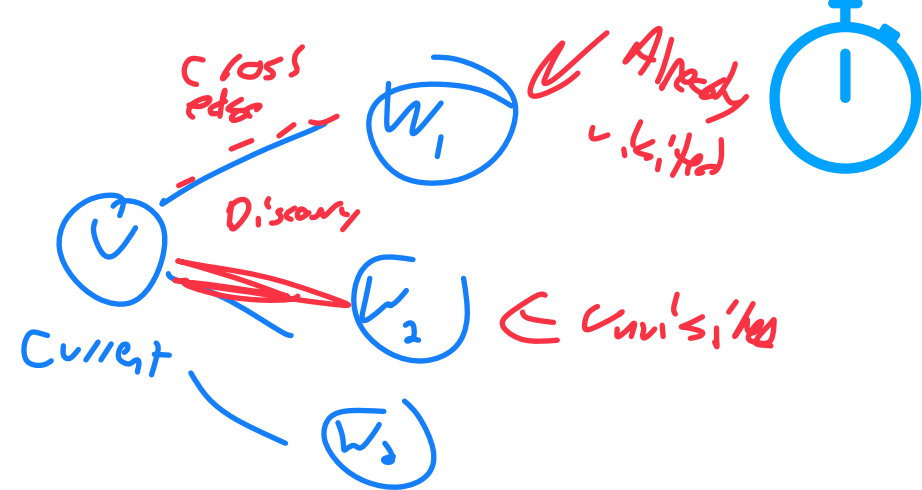
$M+n$

amortized $O(1)$ H.T. expected $O(1)$

```

1 BFS (G) :
2   foreach (Vertex v : G.vertices()) :
3     setPred(v, NULL)
4     setDist(v, -1)
5
6   foreach (Edge e : G.edges()) :
7     setLabel(e, UNEXPLORED)
8
9   foreach (Vertex v : G.vertices()) :
10    if getDist(v) == -1:
11      BFS (G, v)

```



```

12 BFS (G, v) :
13   Queue q
14   setDist(v, 0)
15   q.enqueue(v)
16
17   while !q.empty():
18     v = q.dequeue()
19
20   foreach (Vertex w : G.adjacent(v)) :
21     if( getDist(w) == -1):
22       setLabel((v, w), DISCOVERY)
23       setPred(w, v)
24       setDist(w, v + 1)
25       q.enqueue(w)
26   else * if edge unlabeled &
27     setLabel((v, w), CROSS)

```

initialize

Look at edge

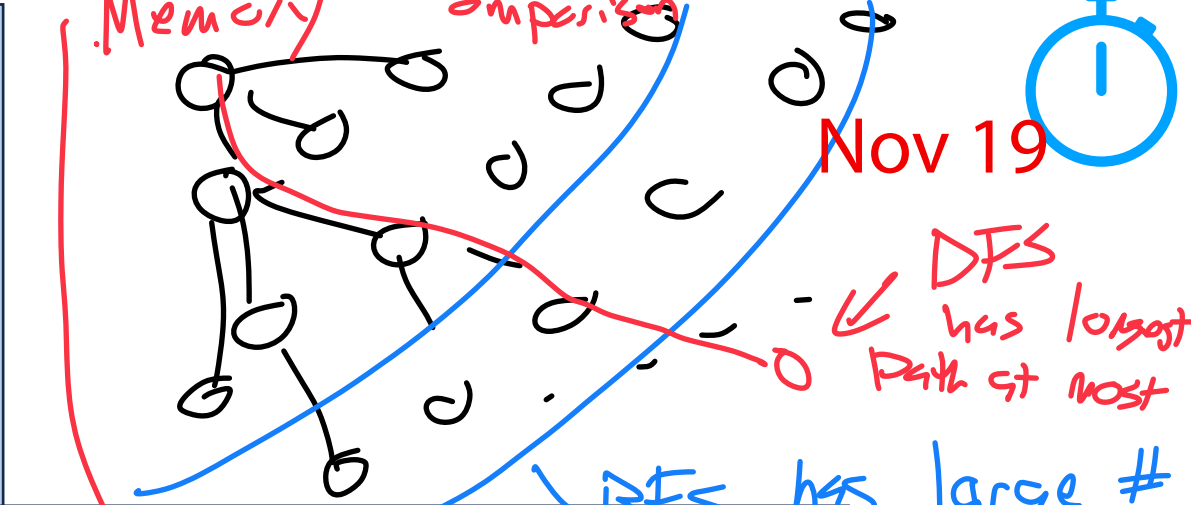
unvisited vertex / edge sets label

November 17
(Graph Traversal)

```

1 DFS (G) :
2   foreach (Vertex v : G.vertices()) :
3     setPred(v, NULL)
4     setDist(v, -1)
5
6   foreach (Edge e : G.edges()) :
7     setLabel(e, UNEXPLORED)
8
9   foreach (Vertex v : G.vertices()) :
10    if getDist(v) == -1:
11      DFS (G, v)

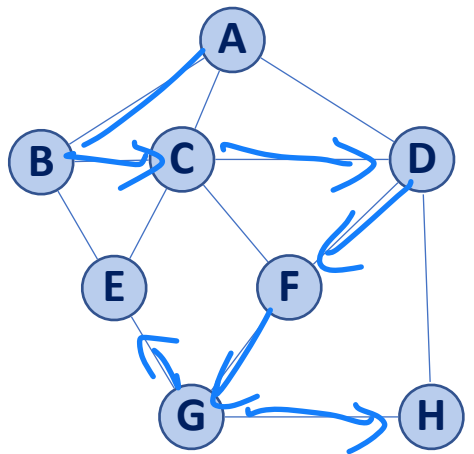
```



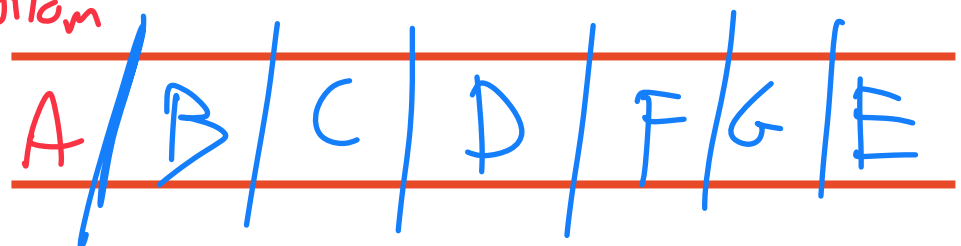
```

12 DFS (G, v) :
13
14   foreach (Vertex w : G.adjacent(v)) :
15     if( getDist(w) == -1):
16       setLabel((v, w), DISCOVERY)
17       setPred(w, v)
18       setDist(w, v + 1)
19       DFS (G, w)
20   else:
21     setLabel((v, w), BACK)

```



Bottom



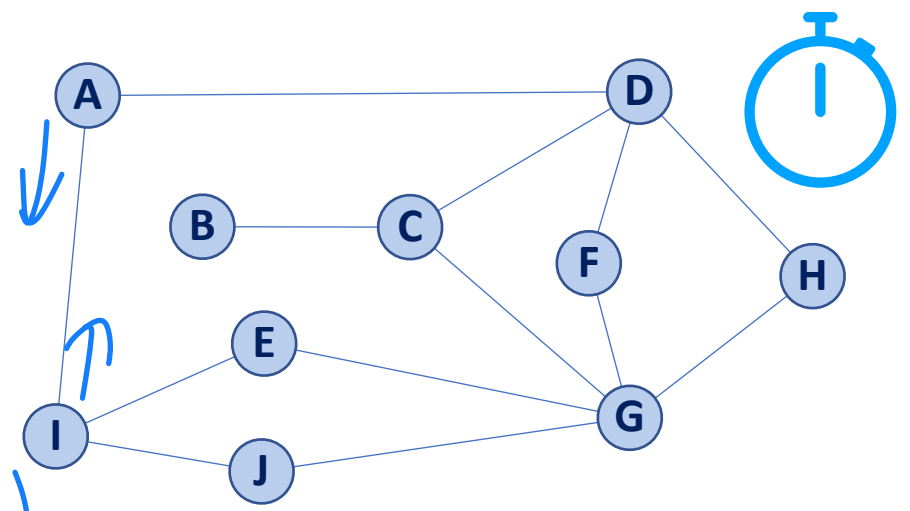
A → [B] C, D
 ↳ stop!
 DFS(B) → DFS(C) → DFS(D)

Running time of DFS $|V| = n$ $|E| = m$

Labeling:

- Vertex: $O(n)$
- Edge: $O(m)$

BFS: $O(n + m)$
DFS: $O(n + m)$



Traversal:

- Vertex: Each vertex looks at all neighbors
 look at all vertices

$$\sum_v \deg(v) = 2E = 2n \quad O(m)$$

- Edge: $O(m)$

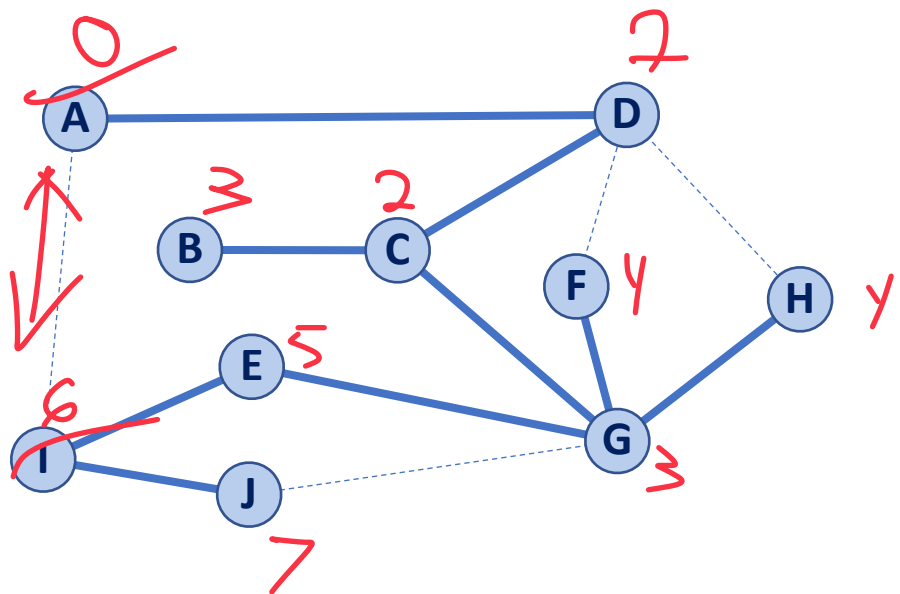
<p><u>BFS</u></p> <ul style="list-style-type: none"> ↳ MST, <u>shortest path</u>, cycles, ↳ Memory Hog! 	<p><u>DFS</u> → mem is bounded by longest path</p> <ul style="list-style-type: none"> ↳ MST, cycles ↳ If early termination
---	--



BFS Observations

1. BFS can be used to count components
2. BFS can be used to detect cycles
3. The BFS 'distance' value is always the shortest distance from source to any vertex (and the discovery edges form a MST)
4. The endpoints of a cross edge never differ in distance by more than 1.

Traversal: DFS



Do we still make a spanning tree?

↳ Yes it makes an MST*

* on unweighted graphs

Does distance have meaning here?

↳ Has no real meaning!

————— Discovery Edge

..... Back Edge

Do our edge labels have meaning here?

↳ Back edge still implies cycle

Not cross b/c cross implies $\text{dist}(u,v) \leq 1$

Kruskal's Algorithm

Priority Queue:	Total Running Time
Heap	$O(n + m + m \log(n))$ *
Sorted Array	$O(n + m \log(n) + m)$

Construction \log / remove Min

1) Disjoint Set
 ↓
 Priority Queue

* Destructive

Sorted array persist

```

1  KruskalMST (G) :
2  DisjointSets forest
3  foreach (Vertex v : G) :
4      forest.makeSet (v)
5
6  PriorityQueue Q // min edge weight
7  Q.buildFromGraph (G)
8
9  Graph T = (V, {})
10
11 while |T.edges()| < n-1:
12     Vertex (u, v) = Q.removeMin()
13     if forest.find(u) != forest.find(v):
14         T.addEdge (u, v)
15         forest.union( forest.find(u),
16                       forest.find(v) )
17
18 return T
19
    
```

} $O(n)$



Prim's Algorithm

Sparse Graph: $O(n) \leq O(m) \leq O(n^2)$

$\hookrightarrow m \sim n$ $\rightarrow O(n \log n)$

\hookrightarrow at; 1st heap is best

Dense Graph: $m \sim n^2$

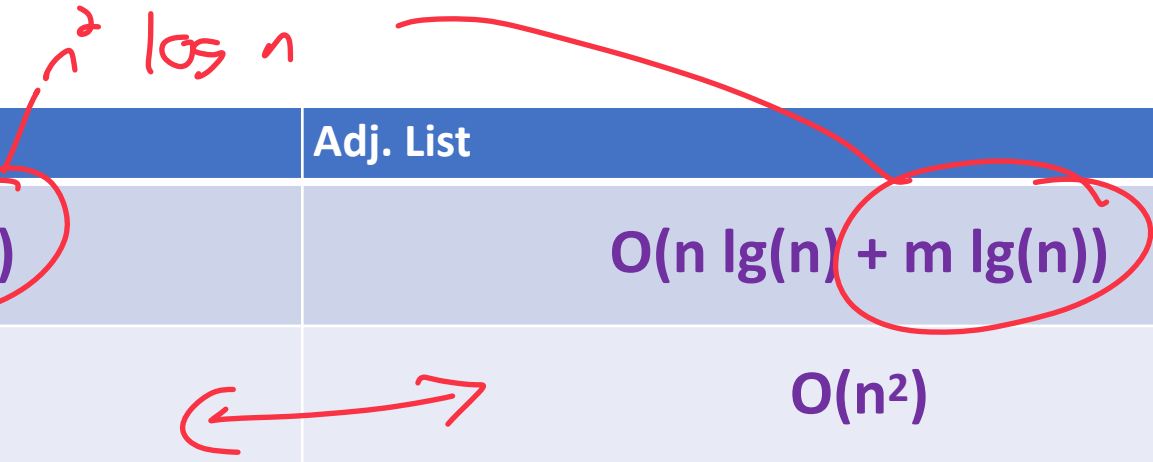
\hookrightarrow unsorted array is better than heap on dense graph

```

6 PrimMST(G, s):
7   foreach (Vertex v : G.vertices()):
8     d[v] = +inf
9     p[v] = NULL
10  d[s] = 0
11
12  PriorityQueue Q // min distance, defined by d[v]
13  Q.buildHeap(G.vertices())
14  Graph T // "labeled set"
15
16  repeat n times:
17    Vertex m = Q.removeMin()
18    T.add(m)
19    foreach (Vertex v : neighbors of m not in T):
20      if cost(v, m) < d[v]:
21        d[v] = cost(v, m)
22        p[v] = m
23

```

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





Dijkstra's Algorithm (SSSP)

What is the running time of Dijkstra's Algorithm? Running time \approx Prim

using Fib heap
 $O(m + n \log n)$

$n \log n$ or n

Min heap
 $O(\log n)$
 $O(\log n)$

Fib heap
 $O(\log n)$
 $O(1)$

remove min
updates
decreasing KEY

```

DijkstraSSSP(G, s):
6  foreach (Vertex v : G):
7      d[v] = +inf
8      p[v] = NULL
9  d[s] = 0
10
11  PriorityQueue Q // min distance, defined by d[v]
12  Q.buildHeap(G.vertices())
13  Graph T // "labeled set"
14
15  repeat n times:
16      Vertex u = Q.removeMin()
17      T.add(u)
18      foreach (Vertex v : neighbors of u not in T):
19          if cost(u, v) + d[u] < d[v]:
20              d[v] = cost(u, v) + d[u]
21              p[v] = u
22
23  return T

```

$O(n)$

$O(n)$

$O(\log n) \rightarrow O(n)$

$O(1)$ Fib heap
 $O(\log n)$

total of m edges

Dijkstra's Algorithm (SSSP)



Dijkstra's Algorithm works efficiently only on non-negative weights * ^{no} cycles allowed

Optimal implementation:

Fib heap
On dense graph \rightarrow ties
inserted list

Optimal runtime:

$$O(m + n \log n)$$

$$O(n^2)$$

```
DijkstraSSSP(G, s):
6   foreach (Vertex v : G):
7       d[v] = +inf
8       p[v] = NULL
9   d[s] = 0
10
11  PriorityQueue Q // min distance, defined by d[v]
12  Q.buildHeap(G.vertices())
13  Graph T // "labeled set"
14
15  repeat n times:
16      Vertex u = Q.removeMin()
17      T.add(u)
18      foreach (Vertex v : neighbors of u not in T):
19          if cost(u, v) + d[u] < d[v]:
20              d[v] = cost(u, v) + d[u]
21              p[v] = u
22
23  return T
```

Floyd-Warshall Algorithm

→ easy to mult! th read

Running time?

$O(n^3)$

, easy to code!

↳ text book dynamic program

$O(n)$
 $O(m)$
 $O(n^3)$

```
FloydWarshall(G):  
6   Let d be a adj. matrix initialized to +inf  
7   foreach (Vertex v : G):  
8     d[v][v] = 0  
9   foreach (Edge (u, v) : G):  
10    d[u][v] = cost(u, v)  
11  
12    foreach (Vertex w : G):  $n \times$   
13      foreach (Vertex u : G):  $n \times$   
14        foreach (Vertex v : G):  $n \times$   
15          if (d[u, v] > d[u, w] + d[w, v])  
16            d[u, v] = d[u, w] + d[w, v]
```

$O(n^3)$