

# CSE 326 Data Structures

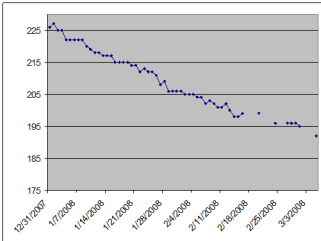
Dave Bacon

Final Review

Stay on Target....Stay on Target

# Logisitics

- Hand in Homework 7
- Friday: Games and NP completeness
- **Final for Section A:**  
Thursday March 15, 8:30-10:20 MGH 231



April 15th

# Final Logistics

- Example Final ~~Example~~ (up soon)
- Final Exam Review Material (up soon)
- Homework 7 will not be returned before final, but homework solution will be posted shortly
  
- Regular office hours next week, plus, I'll be in my office (CSE 460) 9-5. Stop by or email for a good time to meet.

# Final Material

- “Everything is fair game”
- BUT ~~80~~-90% of the material will come from material covered after the midterm

→ splay trees

- This means: Splay trees onward
- This means: Up to Kruskal's

← Floyd-Warshall  
Huffman Coding.  
↑

# Final Material Rough Map

• Stuff before the midterm

• Splay Trees, B-Trees, Memory Hierarchy

• Hashing

• Disjoint Sets

• Sorting

• Graph Algorithms

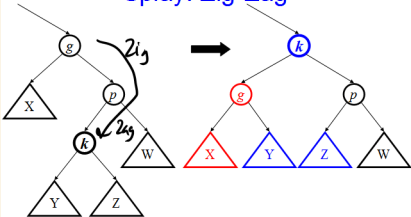
# Splay Trees

*self adjusting.*

- Blind adjusting version of AVL trees
  - Why worry about balances? Just rotate anyway!
- Amortized time per operations is  $O(\log n)$
- Worst case time per operation is  $O(n)$ 
  - But guaranteed to happen rarely

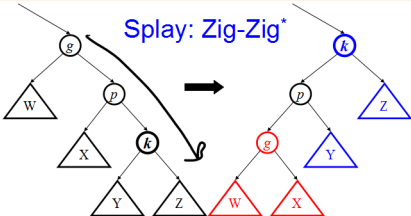
**Insert/Find always rotate node *to the root!***

# Splay: Zig-Zag\*

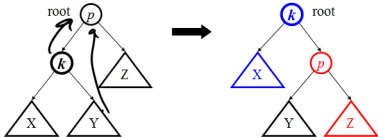




# Splay: Zig-Zig\*



# Special Case for Root: Zig



# Splay Operations: Find

- Find the node in normal BST manner
- Splay the node to the root
  - if node not found, splay what would have been its parent

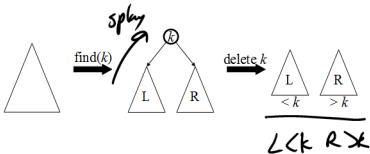


when in doubt splay  
nothing

# Splay Operations: Insert

- Insert the node in normal BST manner
- Splay the node to the root

# Splay Operations: Remove



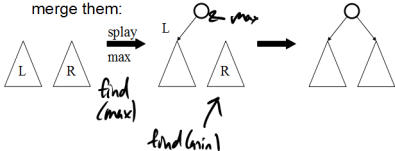
Now what?

~~Array~~ Join

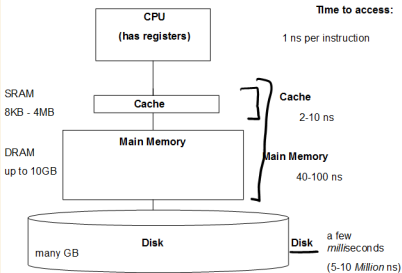
# Join

Join(L, R):

given two trees such that (stuff in L) < (stuff in R),  
merge them:



**Splay on the maximum element in L, then  
attach R**



# Solution: B\*-Trees

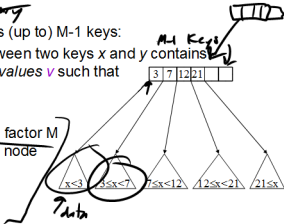
- specialized *M*-ary search trees

*binary*

- Each **node** has (up to) *M*-1 keys:



- subtree between two keys *x* and *y* contains leaves with *values v* such that  $x \leq v < y$

- Pick branching factor M such that each node takes one full {page, block} of memory





# B<sup>+</sup>-Tree Properties ‡

- Data is stored at the **leaves** 
- All **leaves** are at the same depth and contains between  $\lceil L/2 \rceil$  and  $L$  data items
- **Internal** nodes store up to  $M-1$  keys *mostly full*
- **Internal** nodes have between  $\lceil M/2 \rceil$  and  $M$  children
- **Root** (special case) has  between 2 and  $M$  children (or root could be a leaf)

‡These are technically B<sup>+</sup>-Trees

# Insertion Algorithm

1. Insert the key in its leaf
2. If the leaf ends up with  $L+1$  items, **overflow!**
  - Split the leaf into two nodes:
    - original with  $\lceil (L+1)/2 \rceil$  items
    - new one with  $\lfloor (L+1)/2 \rfloor$  items
  - Add the new child to the parent
  - If the parent ends up with  $M+1$  items, **overflow!**
3. If an internal node ends up with  $M+1$  items, **overflow!**
  - Split the node into two nodes:
    - original with  $\lceil (M+1)/2 \rceil$  items
    - new one with  $\lfloor (M+1)/2 \rfloor$  items
  - Add the new child to the parent
  - If the parent ends up with  $M+1$  items, **overflow!**

This makes the tree deeper!

4. Split an overflowed root in two and hang the new nodes under a new root

# Deletion Algorithm

1. Remove the key from its leaf
2. If the leaf ends up with fewer than  $\lceil L/2 \rceil$  items, **underflow!**
  - Adopt data from a sibling; update the parent
  - If adopting won't work, delete node and merge with neighbor
  - If the parent ends up with fewer than  $\lceil M/2 \rceil$  items, **underflow!**

# Hash Tables

- Constant time accesses!
- A **hash table** is an array of some  $0$  fixed size, usually a prime number.
- General idea:

hash table

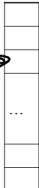


hash function:

$h(K)$



$h(\text{Cont\_ID})$



key space (e.g., integers, strings)

$\text{Cont\_ID}$

$\text{TableSize} - 1$

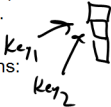
designing good hash functions

# Collision Resolution

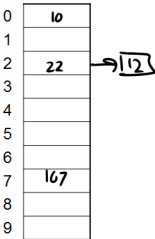
**Collision:** when two keys map to the same location in the hash table.

Two ways to resolve collisions:

1. Separate Chaining
2. Open Addressing (linear probing, quadratic probing, double hashing)



# “Separate Chaining”



Insert:

10

22

107

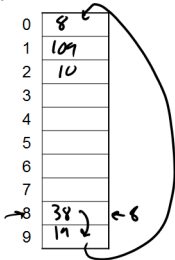
12

42

- Separate chaining: All keys that map to the same hash value are kept in a list (or “bucket”).

# Open Addressing

Find (8)



Insert:

38

19

8

109

10

- **Linear Probing:**  
after checking spot  $h(k)$ , try spot  $h(k)+1$ , if that is full, try  $h(k)+2$ , then  $h(k)+3$ , etc.

# Terminology Alert!

“Open Hashing”  
equals

“Closed Hashing”  
equals

“Separate Chaining”

“Open Addressing”

Weiss

↙

↙



# Load Factor in Linear Probing

- For any  $\lambda < 1$ , linear probing will find an empty slot

$$\text{load factor } \lambda = \frac{\# \text{ keys}}{\text{size table}}$$

- Expected # of probes (for large table sizes)

– successful search:  $\frac{1}{2} \left( 1 + \frac{1}{(1-\lambda)} \right)$  ~~2.5~~  $\lambda = \frac{1}{2}$  1.5 probes

– unsuccessful search:  $\frac{1}{2} \left( 1 + \frac{1}{(1-\lambda)^2} \right)$   
 $\lambda = \frac{1}{2}$  2.5 probes

- Linear probing suffers from **primary clustering**
- Performance quickly degrades for  $\lambda > 1/2$  ↙

# Quadratic Probing

Less likely  
to encounter  
Primary  
Clustering

$$f(i) = i^2$$

- Probe sequence:

$$0^{\text{th}} \text{ probe} = h(k) \bmod \text{TableSize}$$

$$1^{\text{th}} \text{ probe} = (h(k) + 1) \bmod \text{TableSize}$$

$$2^{\text{th}} \text{ probe} = (h(k) + 4) \bmod \text{TableSize}$$

$$3^{\text{th}} \text{ probe} = (h(k) + 9) \bmod \text{TableSize}$$

...

$$i^{\text{th}} \text{ probe} = (h(k) + i^2) \bmod \text{TableSize}$$

# Quadratic Probing: ↳ less than half full.

## Success guarantee for $\lambda < 1/2$

- If size is prime and  $\lambda < 1/2$ , then quadratic probing will find an empty slot in size/2 probes or fewer.

– show for all  $0 \leq i, j \leq \text{size}/2$  and  $i \neq j$

$$(h(x) + i^2) \bmod \text{size} \neq (h(x) + j^2) \bmod \text{size}$$

– by contradiction: suppose that for some  $i \neq j$ :

$$(h(x) + i^2) \bmod \text{size} = (h(x) + j^2) \bmod \text{size}$$

$$\Rightarrow i^2 \bmod \text{size} = j^2 \bmod \text{size}$$

$$\Rightarrow (i^2 - j^2) \bmod \text{size} = 0$$

$$\Rightarrow [(i + j)(i - j)] \bmod \text{size} = 0$$

BUT size does not divide  $(i-j)$  or  $(i+j)$

# Double Hashing

$$f(i) = i * g(k)$$

where g is a second hash function

- Probe sequence:

$$0^{\text{th}} \text{ probe} = h(k) \bmod \text{TableSize}$$

$$1^{\text{th}} \text{ probe} = (h(k) + g(k)) \bmod \text{TableSize}$$

$$2^{\text{th}} \text{ probe} = (h(k) + 2 * g(k)) \bmod \text{TableSize}$$

$$3^{\text{th}} \text{ probe} = (h(k) + 3 * g(k)) \bmod \text{TableSize}$$

...

$$i^{\text{th}} \text{ probe} = (h(k) + i * g(k)) \bmod \text{TableSize}$$

Rehashing 

# Disjoint Sets

## Chapter 8

# Disjoint Union - Find

$\{1,3\}, \{2\}, \dots$

- Maintain a set of pairwise disjoint sets.
  - $\{3,5,7\}, \{4,2,8\}, \{9\}, \{1,6\}$
- Each set has a unique name, one of its members

–  $\{3, \underline{5}, 7\}, \{4, 2, \underline{8}\}, \{\underline{9}\}, \{\underline{1}, 6\}$

↑            ↑    ↑    ↑

Find(4) → 8

# Union

- Union(x,y) – take the union of two sets named x and y
  - {3,5,7}, {4,2,8}, {9}, {1,6}
  - Union(5,1)  
{3,5,7,1,6}, {4,2,8}, {9},

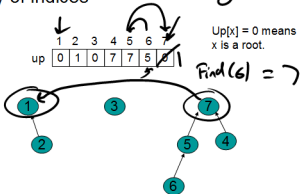
# Find

- Find(x) – return the name of the set containing x.
  - {3,5,7,1,6}, {4,2,8}, {9},
  - Find(1) = 5 ←
  - Find(4) = 8



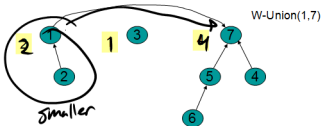
# Simple Implementation

- Array of indices



# Weighted Union

- Weighted Union
  - Always point the *smaller* (total # of nodes) tree to the root of the larger tree



# Analysis of Weighted Union

With weighted union an up-tree of height  $h$  has weight *at least*  $2^h$ .

- Proof by induction
  - **Basis**:  $h = 0$ . The up-tree has one node,  $2^0 = 1$
  - **Inductive step**: Assume true for all  $h' < h$ .

Minimum weight  
up-tree of height  $h$   
formed by  
weighted unions



$$W(T_1) \geq W(T_2) \geq 2^{h-1}$$

Weighted union      Induction hypothesis

$$W(T) \geq 2^{h-1} + 2^{h-1} = 2^h$$

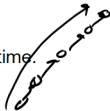
## Analysis of Weighted Union (cont)

Let  $T$  be an up-tree of weight  $n$  formed by weighted union. Let  $h$  be its height.

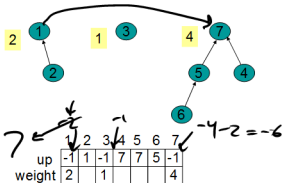
$$n \geq 2^h$$

$$\log_2 n \geq h$$

- Find(x) in tree  $T$  takes  $O(\log n)$  time.



# Array Implementation



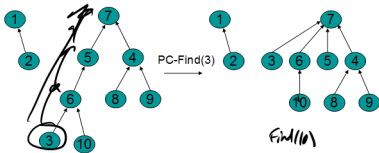
# Nifty Storage Trick

- Use the same array representation as before
- Instead of storing  $-1$  for the root, simply store  $-size$

[Read section 8.4, page 276]

# Path Compression

- On a Find operation point all the nodes on the search path directly to the root.



# Complex Complexity of Union-by-Size + Path Compression

Tarjan proved that, with these optimizations,  $p$  union and find operations on a set of  $n$  elements have worst case complexity of  $O(p \cdot \alpha(p, n))$

For all practical purposes this is amortized constant time:

$O(p \cdot 4)$  for  $p$  operations!

$O(4p)$  amortize

$$\frac{O(4p)}{p} = O(1)$$

- Very complex analysis – worse than splay tree analysis etc. that we skipped!

disjoint sets



# Sorting: *The Big Picture*

Given  $n$  comparable elements in an array, sort them in an increasing (or decreasing) order.

Simple algorithms:  
 $O(n^2)$

Fancier algorithms:  
 $O(n \log n)$

Comparison lower bound:  
 $\Omega(n \log n)$

Specialized algorithms:  
 $O(n)$

Handling huge data sets

Insertion sort  
Selection sort  
Bubble sort  
Shell sort  
...

Heap sort  
Merge sort  
Quick sort  
...

↑  
decision trees.

Bucket sort  
Radix sort

External sorting

Handwritten annotations: "Behind" and "Violate bound" with arrows pointing to the comparison lower bound box.



# Insertion Sort: Idea

- At the  $k^{\text{th}}$  step, put the  $k^{\text{th}}$  input element in the correct place among the first  $k$  elements
- Result: After the  $k^{\text{th}}$  step, the first  $k$  elements are sorted.

*Runtime:*

worst case :  $O(n^2)$   
best case :  $O(n)$   
average case :  $O(n^2)$

## Selection Sort: idea

- Find the smallest element, put it 1<sup>st</sup>
- Find the next smallest element, put it 2<sup>nd</sup>
- Find the next smallest, put it 3<sup>rd</sup>
- And so on ...

$$O(n^2)$$

# HeapSort: Using Priority Queue ADT (heap)

---



Shove all elements into a priority queue,  
take them out smallest to largest.

$$\text{Build} = N$$

$$\text{Delete } n_n = \log N$$

*Runtime:*  $O(N \log N)$

# Merge Sort

MergeSort (Array [1..n])

1. Split Array in half
2. Recursively sort each half
3. Merge two halves together



Merge (a1[1..n], a2[1..n])

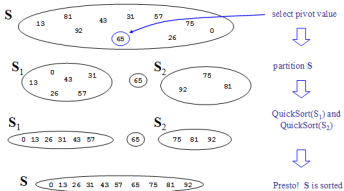
i1=1, i2=1

```
While (i1<n, i2<n) {  
    if (a1[i1] < a2[i2]) {  
        Next is a1[i1]  
        i1++  
    } else {  
        Next is a2[i2]  
        i2++  
    }  
}
```

Now throw in the dregs..

*“The 2-pointer method”*

# The steps of QuickSort



OK

picking pivot, threshold <sup>[Weiss]</sup>

# BucketSort (aka BinSort)

If all values to be sorted are *known* to be between 1 and K, create an array `count` of size K, increment counts while traversing the input, and finally output the result.

**Example**  $K=5$ . Input = (5,1,3,4,3,2,1,1,5,4,5)

count array	
1	
2	
3	
4	
5	




2<sup>32</sup>



Running time to sort  $n$  items?

$O(N+K)$

# Fixing impracticality: RadixSort

- Radix = “The base of a number system”
  - We’ll use 10 for convenience, but could be anything
- Idea: BucketSort on each **digit**,  
least significant to most significant  
(lsd to msd) 



# Internal versus External Sorting

- Need sorting algorithms that minimize disk/tape access time
- **External sorting** – Basic Idea:
  - Load chunk of data into RAM, sort, store this “run” on disk/tape
  - Use the Merge routine from Mergesort to merge runs
  - Repeat until you have only one run (one sorted chunk)
  - Text gives some examples

# Graphs

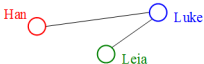
Chapter 9 in Weiss

# Graph Definitions

In *directed* graphs, edges have a specific direction:



In *undirected* graphs, they don't (edges are two-way):



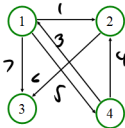
$v$  is *adjacent* to  $u$  if  $(u, v) \in E$

# Representation

- adjacency matrix:

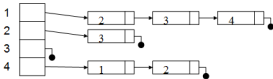
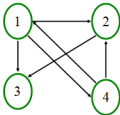
$$A[u][v] = \begin{cases} \text{weight} & , \text{ if } (u, v) \in E \\ 0 & , \text{ if } (u, v) \notin E \end{cases}$$

	1	2	3	4
1	0	1	7	0
2				
3				
4				



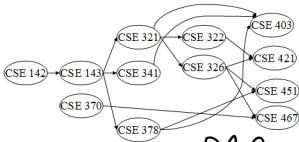
# Representation

- adjacency **list**:



# Application: Topological Sort

Given a directed graph,  $G = (V, E)$ , output all the vertices in  $V$  such that no vertex is output before any other vertex with an edge to it.



DAG

*Is the output unique?*

# Graph Traversals

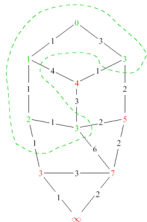
- Breadth-first search (and depth-first search) work for arbitrary (directed or undirected) graphs - not just mazes!
  - Must mark visited vertices so you do not go into an infinite loop!
- Either can be used to determine connectivity:
  - Is there a path between two given vertices?
  - Is the graph (weakly) connected?
- Which one:
  - Uses a queue?
  - Uses a stack?
  - Always finds the **shortest path** (for unweighted graphs)?

# Single Source Shortest Paths (SSSP)

Given a graph  $G$ , edge costs  $c_{i,j}$ , and vertex  $s$ , find the shortest paths from  $s$  to all vertices in  $G$ .



# Dijkstra's Algorithm: Idea

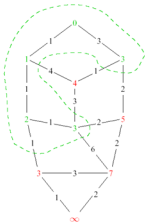


Adapt BFS to handle weighted graphs

Two kinds of vertices:

- Finished or **known** vertices
  - Shortest distance has been computed
- **Unknown** vertices
  - Have tentative distance

# Dijkstra's Algorithm: Idea



At each step:

- 1) Pick closest **unknown** vertex
- 2) Add it to **known** vertices
- 3) Update distances

# Dijkstra's Algorithm: Pseudocode

Initialize the cost of each node to  $\infty$

Initialize the cost of the source to 0

While there are **unknown** nodes left in the graph

    Select an **unknown** node  $b$  with the lowest cost

    Mark  $b$  as **known**

    For each node  $a$  adjacent to  $b$

$a$ 's cost =  $\min(a$ 's old cost,  $b$ 's cost + cost of  $(b, a)$ )

# Dijkstra's Algorithm: a Greedy Algorithm

*Greedy* algorithms always make choices that *currently* seem the best

- Short-sighted - no consideration of long-term or global issues
- Locally optimal - does not always mean globally optimal!!

# Minimum Spanning Trees

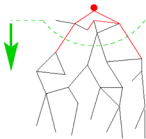
Given an undirected graph  $G=(V,E)$ , find a graph  $G'=(V, E')$  such that:

- $E'$  is a subset of  $E$
- $|E'| = |V| - 1$
- $G'$  is connected
- $\sum_{(u,v) \in E'} c_{uv}$  is minimal

$G'$  is a **minimum spanning tree**.

**Applications:** wiring a house, power grids, Internet connections

# Two Different Approaches



Prim's Algorithm

Almost identical to Dijkstra's

*greedy node*



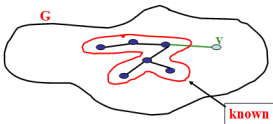
Kruskal's Algorithm

Completely different!

*greedy edges*

# Prim's algorithm

**Idea:** Grow a tree by adding an edge from the “known” vertices to the “unknown” vertices. Pick the edge with the smallest weight.



# Prim's Algorithm for MST

## A *node-based greedy algorithm*

Builds MST by greedily adding nodes

1. Select a node to be the "root"
  - mark it as *known*
  - Update cost of all its neighbors
2. While there are *unknown* nodes left in the graph
  - a. Select an *unknown* node *b* with the smallest cost from some *known* node *a*
  - b. Mark *b* as *known*
  - c. Add (*a*, *b*) to MST
  - d. Update cost of all nodes adjacent to *b*

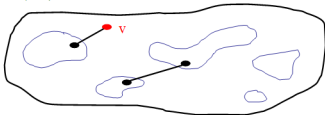
Note: cost from some *a*,  
not from root



# Kruskal's MST Algorithm

**Idea:** Grow a **forest** out of edges that do not create a cycle. Pick an **edge with the smallest weight**.

$G=(V,E)$



# Kruskal's Algorithm for MST

## An edge-based greedy algorithm

Builds MST by greedily adding edges

1. Initialize with
  - empty MST
  - all vertices marked unconnected
  - all edges **unmarked**
2. While there are still **unmarked** edges
  - a. Pick the lowest cost edge  $(u, v)$  and mark it
  - b. If  $u$  and  $v$  are not already connected, add  $(u, v)$  to the MST and mark  $u$  and  $v$  as connected to each other

*Doesn't it sound familiar?*

