CS583 Lecture 06

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Structures for Dynamic Sets

Many slides here are based on E. Demaine, D. Luebke slides

Review: Radix Sort

• Radix sort:

Assumption: input has d digits ranging from 0 to k Basic idea:

Sort elements by digit starting with *least* significant Use a stable sort (like counting sort) for each stage Each pass over n numbers with d digits takes time O(n + k), so total time O(dn + dk)

When d is constant and k=O(n), takes O(n) time Fast! Stable! Simple!

Doesn't sort in place

Review: Bucket Sort

· Bucket sort

Assumption: input is n reals from [0, 1)

Basic idea:

Create *n* linked lists (*buckets*) to divide interval

[0,1) into subintervals of size 1/n

Add each input element to appropriate bucket and sort buckets with insertion sort

Uniform input distribution \rightarrow O(1) bucket size

Therefore the expected total time is O(n)

These ideas will return when we study hash tables

Review: Order Statistics

- The *i*th *order statistic* in a set of *n* elements is the *i*th smallest element
- The *minimum* is thus the 1st order statistic
- The *maximum* is (duh) the *n*th order statistic
- The *median* is the *n*/2 order statistic If *n* is even, there are 2 medians
- Could calculate order statistics by sorting Time: O(n lg n) w/ comparison sort We can do better

Review: The Selection Problem

- The *selection problem*: find the *i*th smallest element of a set
- Two algorithms:

A practical randomized algorithm with O(n) expected running time

A cool algorithm of theoretical interest only with O(n) worst-case running time

Review: Randomized Selection

```
RandomizedSelect(A, p, r, i)
    if (p == r) then return A[p];
    q = RandomizedPartition(A, p, r)
   k = q - p + 1;
    if (i == k) then return A[q]; // not in
 book
    if (i < k) then
        return RandomizedSelect(A, p, q-1, i);
    else
        return RandomizedSelect(A, q+1, r, i-
 k);
           k
         \leq A[q]
                                  \geq A[q]
                         q
                                              r
 p
```

Review: Randomized Selection

• Average case

For upper bound, assume *i*th element always falls in larger side of partition:

$$T(n) \le \frac{1}{n} \sum_{k=0}^{n-1} T(\max(k, n-k-1)) + \Theta(n)$$

$$\leq \frac{2}{n} \sum_{k=n/2}^{n-1} T(k) + \Theta(n)$$

We then showed that T(n) = O(n) by substitution

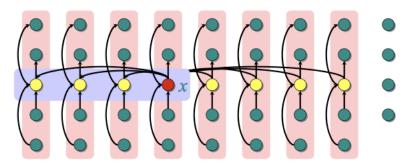
Worst-Case Linear-Time Selection

- The algorithm in words:
 - 1. Divide *n* elements into groups of 5
 - 2. Find median of each group (*How? How long?*)
 - 3. Use Select() recursively to find median x of the $\lfloor n/5 \rfloor$ medians
 - 4. Partition the *n* elements around *x*. Let k = rank(x)
 - 5. **if** (i == k) **then** return x

if (i < k) **then** use Select() recursively to find *i*th smallest element in first partition

else (i > k) use Select() recursively to find (i-k)th smallest element in last partition

Worst-Case Linear-Time Selection



At least half the group medians are $\leq x$, which is at least $\lfloor \lfloor n/5 \rfloor / 2 \rfloor = \lfloor n/10 \rfloor$ group medians.

- Therefore, at least $3\lfloor n/10\rfloor$ elements are $\leq x$.
- Similarly, at least $3 \lfloor n/10 \rfloor$ elements are $\geq x$.

Worst-Case Linear-Time Selection

- (Sketch situation on the board)
- How many of the 5-element medians are $\leq x$? At least 1/2 of the medians = | | n/5 | / 2 | = | n/10 |
- How many elements are $\leq x$? At least $3 \mid n/10 \mid$ elements
- For large n, $3 \lfloor n/10 \rfloor \ge n/4$ (How large?)
- So at least n/4 elements $\leq x$
- Similarly: at least n/4 elements $\ge x$

Worst-Case Linear-Time Selection

$$T(n)$$
SELECT(i , n) $\Theta(n)$ 1. Divide the n elements into groups of 5. Find the median of each 5-element group by rote. $T(n/5)$ 2. Recursively SELECT the median x of the $\lfloor n/5 \rfloor$ group medians to be the pivot.3. Partition around the pivot x . Let $k = \text{rank}(x)$.4. if $i = k$ then return x elseif $i < k$ then recursively SELECT the i th smallest element in the lower part else recursively SELECT the $(i-k)$ th smallest element in the upper part

Worst-Case Linear-Time Selection

- Thus after partitioning around x, step 5 will call Select() on at most 3n/4 elements
- The recurrence is therefore:

$$T(n) \le T(\lfloor n/5 \rfloor) + T(3n/4) + \Theta(n)$$

 $\le T(n/5) + T(3n/4) + \Theta(n)$
 $\le cn/5 + 3cn/4 + \Theta(n)$ $\lfloor n/5 \rfloor \le n/5$
 $= 19cn/20 + \Theta(n)$ Substitute $T(n) = cn$
 $= cn - (cn/20 - \Theta(n))$ Combine fractions
 $\le cn$ if c is big enough Express in desired form
 c has to be 20 times larger then constant associated Theta(n)

Worst case linear time seletion

• Why not to use groups of 3 – instead of 5?

Linear-Time Median Selection

- Given a "black box" O(n) median algorithm, what can we do?
- *i*th order statistic:

Find median x

Partition input around *x*

if $(i \le (n+1)/2)$ recursively find *i*th element of first half

else find (i - (n+1)/2)th element in second half

T(n) = T(n/2) + O(n) = O(n)

Can you think of an application to sorting?

Structures...

- Done with sorting and order statistics for now
- Next part of class will focus on data structures
- Many applications require dynamic set that supports operations Insert, Search, Delete
- E.g. compiler symbol table keys are the identifier strings
- One options static array A size is the number of all possible keys (very large an

Review: Hashing Tables

- Motivation: symbol tables
- A compiler uses a *symbol table* to relate symbols to associated data
- Symbols: variable names, procedure names,
- Associated data: memory location, call graph, etc.
- For a symbol table (also called a *dictionary*), we care about search, insertion, and deletion
- We typically don't care about sorted order

Review: Hash Tables

- More formally:
- Given a table *T* and a record *x*, with key (= symbol) and satellite data, we need to support:

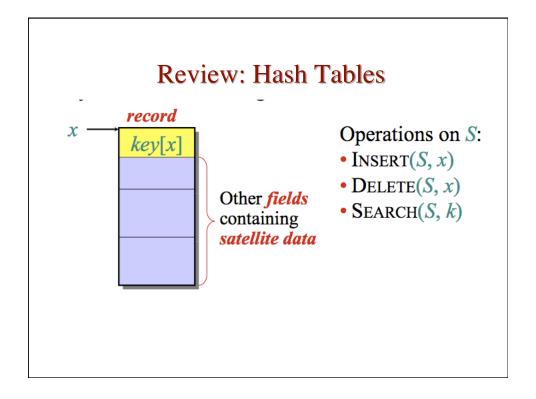
Insert (T, x)

Delete (T, x)

Search(T, x)

We want these to be fast, but don't care about sorting the records

• The structure we will use is a *hash table* Supports all the above in O(1) expected time!



Review: Hash Tables

- Example maintain 250 IP addresses of active customers of your web service
- Each IP 32-bit number 128.32.168.80
- How to organize the customers so we can retrieve, add, delete them fast
- Option 1: array indexed by IP address
- Option 2: linked list of all addresses

Hashing: Keys

- In the following discussions we will consider all keys to be (possibly large) natural numbers
- How can we convert floats to natural numbers for hashing purposes?
- How can we convert ASCII strings to natural numbers for hashing purposes? (radix notation)

Review: Direct Addressing

- Suppose
- The range of keys is 0..*m*-1
- Keys are distinct
- The idea:

```
Set up an array T[0..m-1] in which T[i] = x if x \in T and key[x] = i T[i] = NULL otherwise This is called a direct-address table Operations take O(1) time!
```

So what's the problem?

The Problem With Direct Addressing

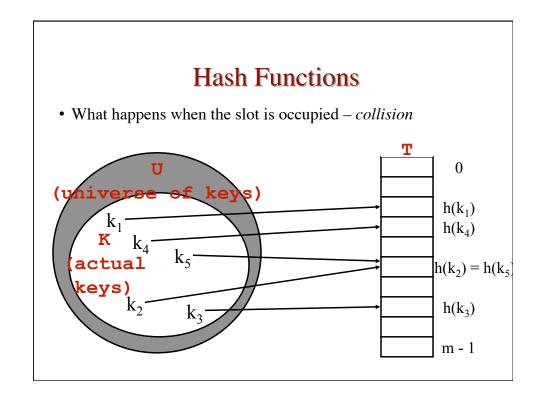
- Direct addressing works well when the range *m* of keys is relatively small
- But what if the keys are 32-bit integers?

Problem 1: direct-address table will have

 2^{32} entries, more than 4 billion

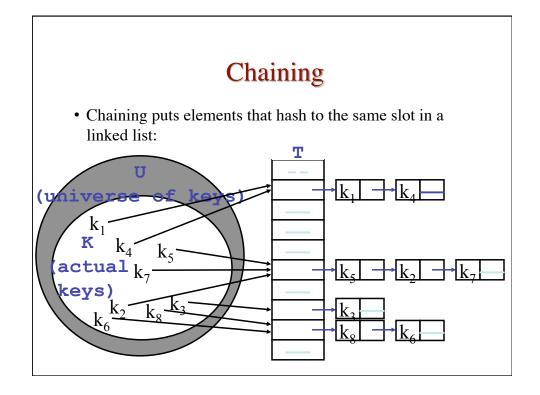
Problem 2: even if memory is not an issue, the time to initialize the elements to NULL may be

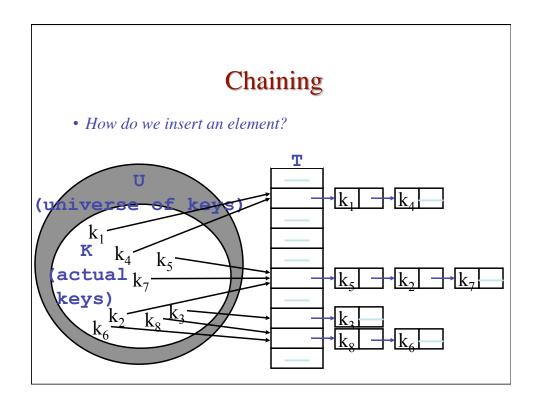
- Solution: map keys to smaller range 0..*m*-1
- This mapping is called a hash function

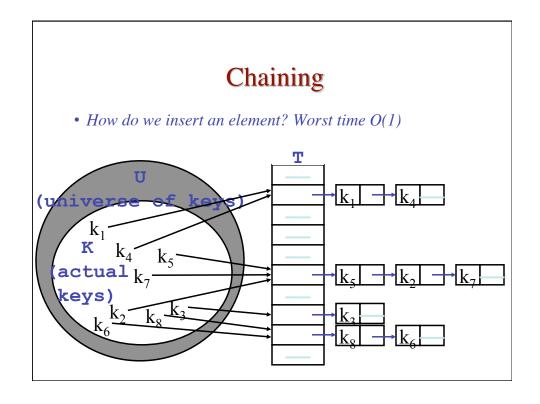


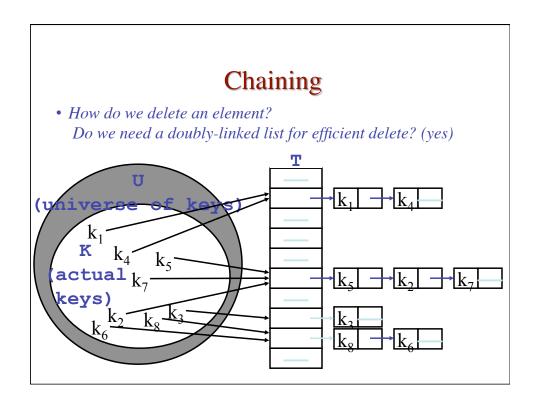
Resolving Collisions

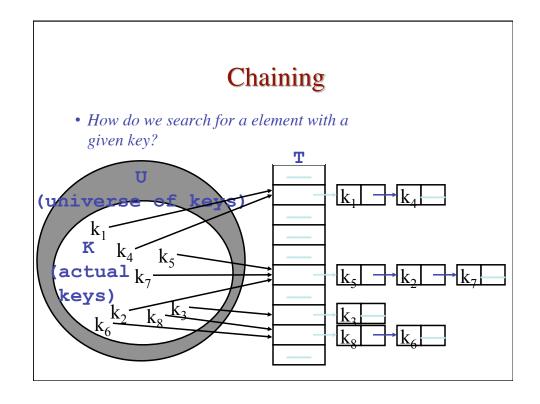
- How can we solve the problem of collisions?
- Solution 1: chaining
- Solution 2: open addressing











Analysis of Chaining

- Assume *simple uniform hashing*: each key in table is equally likely to be hashed to any slot
- Given n keys and m slots in the table: the load factor $\alpha = n/m =$ average # keys per slot
- What will be the average cost of an unsuccessful search for a key?

Analysis of Chaining

- Assume *simple uniform hashing*: each key in table is equally likely to be hashed to any slot
- Given *n* keys and *m* slots in the table, the load factor $\alpha = n/m = \text{average } \# \text{ keys per slot}$
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- What will be the average cost of a successful search?

Analysis of Chaining

- Assume *simple uniform hashing*: each key in table is equally likely to be hashed to any slot
- Given n keys and m slots in the table, the load factor α = n/m = average # keys per slot
- What will be the average cost of an unsuccessful search for a key? A: $O(1+\alpha)$
- Each list is equally likely be searched, α average length of the list
- What will be the average cost of a successful search? A: $O(1 + \alpha/2) = O(1 + \alpha)$
- Slightly different analysis list to be searched is proportional to the expected number of elements in it expected size to searched is $\alpha/2$

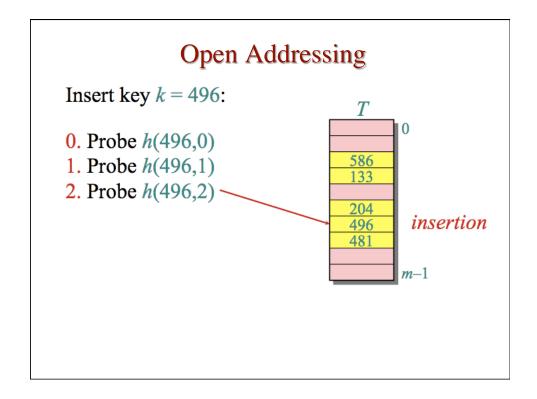
Analysis of Chaining Continued

- So the cost of searching = $O(1 + \alpha)$
- If the number of keys n is proportional to the number of slots in the table, what is α ?
- A: $\alpha = O(1)$

In other words, we can make the expected cost of searching constant if we make α constant

Open Addressing

- Basic idea (details in Section 12.4):
- To insert: if slot is full, try another slot, ..., until an open slot is found (*probing*)
- To search, follow same sequence of probes as would be used when inserting the element
- If reach element with correct key, return it
- If reach a NULL pointer, element is not in table
- Good for fixed sets (adding but no deletion) Example: spell checking
- Table needn't be much bigger than *n*
- We will return to this later



Choosing A Hash Function

- Clearly choosing the hash function well is crucial
- What will a worst-case hash function do?
- What will be the time to search in this case?
- What are desirable features of the hash function
- Should distribute keys uniformly into slots
- Should not depend on patterns in the data, i.e. regularity in the data should not affect its uniformity (e.g. all even numbers)
- Three methods: hashing by division, multiplication, universal hashing

Hash Functions: The Division Method

- $h(k) = k \mod m$
- In words: hash *k* into a table with *m* slots using the slot given by the remainder of *k* divided by *m*
- What happens to elements with adjacent values of k?
- What happens if m is a power of 2 (say 2^{P})?
- What if m is a power of 10?
- Upshot: pick table size *m* = prime number not too close to a power of 2 (or 10)

Hash Functions: The Division Method

- $h(k) = k \mod m$
- In words: hash *k* into a table with *m* slots using the slot given by the remainder of *k* divided by *m*
- What happens to elements with adjacent values of k?
- What happens if m is a power of 2 (say 2^{P}) hashing on p lower order bits?
- What if m is a power of 10? hashing on p least sign. Digits
- What if m is divisible by two and all numbers are even?

Hash Functions: The Division Method

- $h(k) = k \mod m$
- Upshot: pick table size m = prime number not too close to a power of 2 (or 10), given some desirable load factor
- (e.g. 2000 elements, load factor around 3, 2000/3
- 701 is a prime number which is close to 2000/3, but not near any power of 2)

Hash Functions: The Multiplication Method

- For a constant A, 0 < A < 1:
- h(k) = [m(kA [kA])]

What does this term represent?

Hash Functions: The Multiplication Method

- For a constant A, 0 < A < 1:
- h(k) = [m(kA [kA])]

Fractional part of kA

- h(k) = | m(k A mod 1) |
- Value of m is not critical, Choose $m = 2^p$
- Choose A not too close to 0 or 1
- Knuth: Good choice for $A = (\sqrt{5} 1)/2$
- Example

Hash Functions: The Multiplication Method

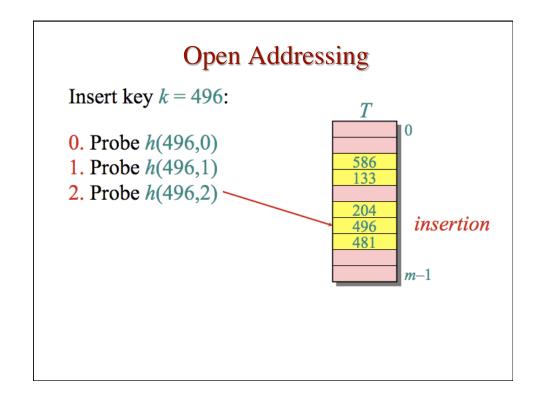
- For a constant A, 0 < A < 1:
- $h(k) = \lfloor m(kA \lfloor kA \rfloor) \rfloor$ $h(k) = \lfloor m(k \ A \ mod \ 1) \rfloor$

Fractional part of kA

• $h(k) = (A \ k \ mod \ s) \ rsh(w - p)$ where $s = 2^w, m = 2^p$

Open Addressing

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Open Addressing

- Basic idea (details in Section 12.4):
- To insert: if slot is full, try another slot, ..., until an open slot is found (*probing*)
- Idea: for every key define a probe sequence
- h(k,0), h(k,1), h(k,2), h(k,3)
- Linear probing

$$h(k,i) = (h'(k) + i) \operatorname{mod} m$$

Quadratic probing

$$h(k,i) = (h'(k) + c_1 i + c_2 i^2) \mod m$$

Double hashing

$$h(k,i) = (h_1(k) + ih_2(k)) \bmod m$$

Hash Functions: Worst Case Scenario

• Scenario:

You are given an assignment to implement hashing You will self-grade in pairs, testing and grading your partner's implementation

In a blatant violation of the honor code, your partner: Analyzes your hash function Picks a sequence of "worst-case" keys, causing your implementation to take O(n) time to search

• What's an honest CS student to do?

Review: Choosing A Hash Function

- Choosing the hash function well is crucial
 Bad hash function puts all elements in same slot
 A good hash function:
 Should distribute keys uniformly into slots
 Should not depend on patterns in the data
- We discussed three methods: Division method Multiplication method Universal hashing

Review: The Division Method

- $h(k) = k \mod m$ In words: hash k into a table with m slots using the slot given by the remainder of k divided by m
- Elements with adjacent keys hashed to different slots: good
- If keys bear relation to *m*: bad
- Upshot: pick table size m = prime number not too close to a power of 2 (or 10)

Review: The Multiplication Method

- For a constant A, 0 < A < 1:
- h(k) = [m(kA [kA])]

Fractional part of kA

• Upshot:

Choose $m = 2^P$

Choose A not too close to 0 or 1

Knuth: Good choice for $A = (\sqrt{5} - 1)/2$

Hash Functions: Universal Hashing

- As before, when attempting to foil an malicious adversary: randomize the algorithm
- *Universal hashing*: pick a hash function randomly in a way that is independent of the keys that are actually going to be stored
- Guarantees good performance on average, no matter what keys adversary chooses

Universal Hashing

- Let \mathcal{H} be a (finite) collection of hash functions ...that map a given universe U of keys... ...into the range $\{0, 1, ..., m-1\}$.
- \mathcal{H} is said to be *universal* if: for each pair of distinct keys $x, y \in U$, the number of hash functions $h \in \mathcal{H}$ for which h(x) = h(y) is $|\mathcal{H}|/m$ In other words:

With a random hash function from \mathcal{H} , the chance of a collision between x and y is exactly 1/m $(x \neq y)$

Universal Hashing

• Theorem 11.3:

Choose h from a universal family of hash functions Hash n keys into a table of m slots, $n \le m$ Then the expected number of collisions involving a particular key x is less than 1 (is less then n/m)

Proof:

For each pair of keys y, z, let $c_{yx} = 1$ if y and z collide, 0 otherwise

 $E[c_{yz}] = 1/m$ (by definition)

Let C_x be total number of collisions involving key x

$$E[C_x] = \sum_{\substack{y \in T \\ y \neq x}} E[c_{xy}] = \frac{n-1}{m}$$

Since $n \le m$, we have $E[C_r] < 1$

A Universal Hash Function

- · How to design an universal class of hash functions
- Choose table size *m* to be prime
- Decompose key x into r+1 digits, so that x = {x₀, x₁, ..., x_r}
 Only requirement is that max value of digit < m (representation in terms of base of m)
 Let a = {a₀, a₁, ..., a_r} denote a sequence of r+1 elements chosen randomly from {0, 1, ..., m 1}
 Define corresponding hash function h_a ∈ H:

$$h_a(x) = \sum_{i=0}^r a_i x_i \bmod m$$

With this definition, \mathcal{H} has m^{r+1} members

A Universal Hash Function

- \mathcal{H} is a universal collection of hash functions (Theorem 12.4)
- How to use:
 Pick r based on m and the range of keys in U
 Pick a hash function by (randomly) picking the a's Use that hash function on all keys

The end

Dynamic Sets

- Another example of data structure
- In particular, structures for dynamic sets
 Elements have a key and satellite data
 Dynamic sets support queries such as:
 Search(S, k), Minimum(S), Maximum(S),
 Successor(S, x), Predecessor(S, x)
 They may also support modifying operations like:

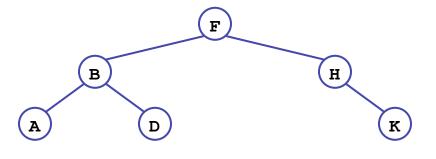
Insert(S, x), Delete(S, x)

Binary Search Trees

- *Binary Search Trees* (BSTs) are an important data structure for dynamic sets
- In addition to satellite data, elements have: key: an identifying field inducing a total ordering left: pointer to a left child (may be NULL) right: pointer to a right child (may be NULL) p: pointer to a parent node (NULL for root)

Binary Search Trees

- BST property: $key[left(x)] \le key[x] \le key[right(x)]$
- Example:



Inorder Tree Walk

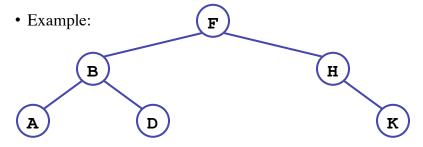
• What does the following code do?

```
TreeWalk(x)
    TreeWalk(left[x]);
    print(x);
    TreeWalk(right[x]);
```

- A: prints elements in sorted (increasing) order
- This is called an *inorder tree walk*Preorder tree walk: print root, then left, then right

 Postorder tree walk: print left, then right, then root

Inorder Tree Walk



- How long will a tree walk take?
- Prove that inorder walk prints in monotonically increasing order

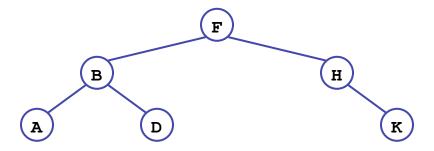
Operations on BSTs: Search

• Given a key and a pointer to a node, returns an element with that key or NULL:

```
TreeSearch(x, k)
    if (x = NULL or k = key[x])
        return x;
    if (k < key[x])
        return TreeSearch(left[x],
k);
    else
        return TreeSearch(right[x],
k);</pre>
```

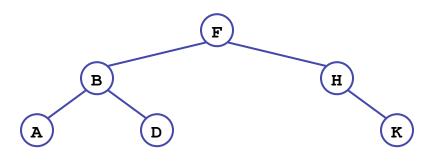
BST Search: Example

• Search for *D* and *C*:



BST Search: Example

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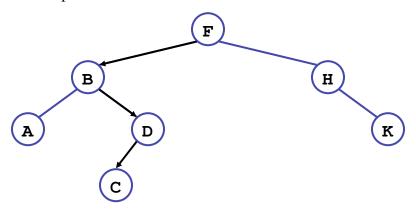


Operations of BSTs: Insert

- Adds an element x to the tree so that the binary search tree property continues to hold
- The basic algorithm
- Like the search procedure above
- Insert x in place of NULL Use a "trailing pointer" to keep track of where you came from (like inserting into singly linked list)

BST Insert: Example

• Example: Insert *C*



BST Search/Insert: Running Time

- What is the running time of TreeSearch() or TreeInsert()?
- A: O(h), where h = height of tree
- What is the height of a binary search tree?
- A: worst case: h = O(n) when tree is just a linear string of left or right children

We'll keep all analysis in terms of h for now Later we'll see how to maintain $h = O(\lg n)$

Sorting With Binary Search Trees

• Informal code for sorting array A of length *n*:

```
BSTSort(A)
    for i=1 to n
        TreeInsert(A[i]);
    InorderTreeWalk(root);
```

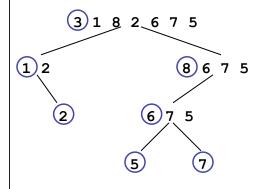
- Argue that this is $\Omega(n \lg n)$
- What will be the running time in the Worst case?

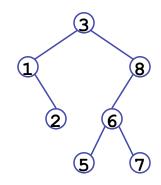
Average case? (hint: remind you of anything?)

Sorting With BSTs

• Average case analysis It's a form of quicksort!

for i=1 to n
 TreeInsert(A[i]);
InorderTreeWalk(root);





Sorting with BSTs

• Same partitions are done as with quicksort, but in a different order

In previous example

Everything was compared to 3 once

Then those items < 3 were compared to 1 once Etc.

Same comparisons as quicksort, different order! Example: consider inserting 5

Sorting with BSTs

- Since run time is proportional to the number of comparisons, same time as quicksort: O(n lg n)
- Which do you think is better, quicksort or BSTsort? Why?

Sorting with BSTs

- Since run time is proportional to the number of comparisons, same time as quicksort: O(n lg n)
- Which do you think is better, quicksort or BSTSort? Why?
- A: quicksort
 Better constants
 Sorts in place
 Doesn't need to build data structure

More BST Operations

- BSTs are good for more than sorting. For example, can implement a priority queue
- What operations must a priority queue have?
 Insert
 Minimum
 Extract-Min

BST Operations: Minimum

- How can we implement a Minimum() query?
- What is the running time?

BST Operations: Successor

- For deletion, we will need a Successor() operation
- Draw Fig 13.2
- What is the successor of node 3? Node 15? Node 13?
- What are the general rules for finding the successor of node x? (hint: two cases)

BST Operations: Successor

- Two cases:
 - x has a right subtree: successor is minimum node in right subtree
 - x has no right subtree: successor is first ancestor of x whose left child is also ancestor of x

Intuition: As long as you move to the left up the tree, you're visiting smaller nodes.

• Predecessor: similar algorithm

BST Operations: Delete

• Deletion is a bit tricky
• 3 cases:

x has no children:
Remove x

x has one child:
Splice out x

x has two children:
Swap x with successor
Perform case 1 or 2 to delete it

BST Operations: Delete

- Why will case 2 always go to case 0 or case 1?
- A: because when x has 2 children, its successor is the minimum in its right subtree
- Could we swap x with predecessor instead of successor?
- A: yes. Would it be a good idea?
- A: might be good to alternate

The End

• Up next: guaranteeing a O(lg n) height tree