## Algorithms

Review for Final

## Final Exam

- Coverage: the whole semester
- Goal: doable in 2 hours
- Cheat sheet: you are allowed two 8 ' 11 " sheets, both sides


## Final Exam: Study Tips

- Study tips:
- Study each lecture
- Study the homework and homework solutions
- Study the midterm exams
- Re-make your previous cheat sheets

■ I recommend handwriting or typing them

- Think about what you should have had on it the first time...cheat sheets is about identifying important concepts


## Graph Representation

- Adjacency list
- Adjacency matrix
- Tradeoffs:
- What makes a graph dense?
- What makes a graph sparse?
- What about planar graphs?


## Basic Graph Algorithms

- Breadth-first search
- What can we use BFS to calculate?
- A: shortest-path distance to source vertex
- Depth-first search
- Tree edges, back edges, cross and forward edges
- What can we use DFS for?
- A: finding cycles, topological sort


## Topological Sort, MST

- Topological sort
- Examples: getting dressed, project dependency
- To what kind of graph does topological sort apply?
- Minimum spanning tree
- Optimal substructure
- Min edge theorem (enables greedy approach)


## MST Algorithms

- Prim's algorithm
- What is the bottleneck in Prim's algorithm?
- A: priority queue operations
- Kruskal's algorithm
- What is the bottleneck in Kruskal's algorithm?
- Answer: depends on disjoint-set implementation
- As covered in class, disjoint-set union operations
- As described in book, sorting the edges


## Single-Source Shortest Path

- Optimal substructure
- Key idea: relaxation of edges
- What does the Bellman-Ford algorithm do?
- What is the running time?
- What does Dijkstra's algorithm do?
- What is the running time?

■ When does Dijkstra's algorithm not apply?

## Disjoint-Set Union

- We talked about representing sets as linked lists, every element stores pointer to list head
- What is the cost of merging sets $A$ and $B$ ?
- $\mathrm{A}: \mathrm{O}(\max (|\mathrm{Al},|\mathrm{BI}|))$
- What is the maximum cost of merging $n$ 1 -element sets into a single n-element set?
- A: O( $n^{2}$ )
- How did we improve this? By how much?
- A: always copy smaller into larger: $\mathrm{O}(n \lg n)$


## Amortized Analysis

- Idea: worst-case cost of an operation may overestimate its cost over course of algorithm
- Goal: get a tighter amortized bound on its cost
- Aggregate method: total cost of operation over course of algorithm divided by \# operations
- Example: disjoint-set union
- Accounting method: "charge" a cost to each operation, accumulate unused cost in bank, never go negative
- Example: dynamically-doubling arrays


## Dynamic Programming

- Indications: optimal substructure, repeated subproblems
- What is the difference between memoization and dynamic programming?
- A: same basic idea, but:
- Memoization: recursive algorithm, looking up subproblem solutions after computing once
- Dynamic programming: build table of subproblem solutions bottom-up


## LCS Via Dynamic Programming

- Longest common subsequence (LCS) problem:

■ Given two sequences $x[1 . . m]$ and $y[1 . . n]$, find the longest subsequence which occurs in both

- Brute-force algorithm: $2^{\mathrm{m}}$ subsequences of x to check against $n$ elements of $\mathrm{y}: \mathrm{O}\left(n 2^{m}\right)$
- Define $c[i, j]=$ length of LCS of $x[1 . . i], y[1 . . j]$
- Theorem:

$$
c[i, j]= \begin{cases}c[i-1, j-1]+1 & \text { if } x[i]=y[j] \\ \max (c[i, j-1], c[i-1, j]) & \text { otherwise }\end{cases}
$$

## Greedy Algorithms

- Indicators:
- Optimal substructure

■ Greedy choice property: a locally optimal choice leads to a globally optimal solution

- Example problems:
- Activity selection: Set of activities, with start and end times. Maximize compatible set of activities.
■ Fractional knapsack: sort items by \$/lb, then take items in sorted order
- MST


## NP-Completeness

- What do we mean when we say a problem is in $\boldsymbol{P}$ ?
- A: A solution can be found in polynomial time
- What do we mean when we say a problem is in NP?
- A: A solution can be verified in polynomial time
- What is the relation between $\mathbf{P}$ and $\mathbf{N P}$ ?
- A: $\mathbf{P} \subseteq \mathbf{N P}$, but no one knows whether $\mathbf{P}=\mathbf{N P}$


## Review: NP-Complete

- What, intuitively, does it mean if we can reduce problem P to problem Q?
- P is "no harder than" Q
- How do we reduce $P$ to $Q$ ?
- Transform instances of P to instances of Q in polynomial time s.t. Q: "yes" iff P: "yes"
- What does it mean if $Q$ is NP-Hard?
- Every problem $\mathrm{P} \in \mathbf{N P} \leq_{\mathrm{p}} \mathrm{Q}$
- What does it mean if $Q$ is NP-Complete?
- Q is NP-Hard and $\mathrm{Q} \in \mathbf{N P}$


## Review: <br> Proving Problems NP-Complete

- What was the first problem shown to be NP-Complete?
- A: Boolean satisfiability (SAT), by Cook
- How do we usually prove that a problem $R$ is NP-Complete?
- A: Show $\mathrm{R} \in \mathbf{N P}$, and reduce a known NP-Complete problem Q to R


## Review: Reductions

- Review the reductions we've covered:
- Directed hamiltonian cycle $\rightarrow$ undirected hamiltonian cycle
- Undirected hamiltonian cycle $\rightarrow$ traveling salesman problem
- 3-CNF $\rightarrow k$-clique
- $k$-clique $\rightarrow$ vertex cover
- Homework 7


## Next: Detailed Review

- Up next: a detailed review of the first half of the course
- The following 100+ slides are intended as a resource for your studying
- Since you probably remember the more recent stuff better, I just provide this for the early material


## Review: Induction

- Suppose
- $\mathrm{S}(\mathrm{k})$ is true for fixed constant k
- Often $\mathrm{k}=0$
- $\mathrm{S}(\mathrm{n}) \wedge \mathrm{S}(\mathrm{n}+1)$ for all $\mathrm{n}>=\mathrm{k}$
- Then $S(n)$ is true for all $n>=k$


## Proof By Induction

- Claim: $S(n)$ is true for all $n>=k$
- Basis:
- Show formula is true when $\mathrm{n}=\mathrm{k}$
- Inductive hypothesis:
- Assume formula is true for an arbitrary n
- Step:
- Show that formula is then true for $\mathrm{n}+1$


## Induction Example: Gaussian Closed Form

- Prove $1+2+3+\ldots+n=n(n+1) / 2$
- Basis:
- If $\mathrm{n}=0$, then $0=0(0+1) / 2$

■ Inductive hypothesis:

- Assume $1+2+3+\ldots+n=n(n+1) / 2$
- Step (show true for $\mathrm{n}+1$ ):

$$
\begin{aligned}
& 1+2+\ldots+\mathrm{n}+\mathrm{n}+1=(1+2+\ldots+\mathrm{n})+(\mathrm{n}+1) \\
& =\mathrm{n}(\mathrm{n}+1) / 2+\mathrm{n}+1=[\mathrm{n}(\mathrm{n}+1)+2(\mathrm{n}+2)] / 2 \\
& =(\mathrm{n}+1)(\mathrm{n}+2) / 2=(\mathrm{n}+1)(\mathrm{n}+1+1) / 2
\end{aligned}
$$

## Induction Example: Geometric Closed Form

- Prove $a^{0}+a^{1}+\ldots+a^{n}=\left(a^{n+1}-1\right) /(a-1)$ for all a != 1
$\square$ Basis: show that $a^{0}=\left(a^{0+1}-1\right) /(a-1)$

$$
\mathrm{a}^{0}=1=\left(\mathrm{a}^{1}-1\right) /(\mathrm{a}-1)
$$

- Inductive hypothesis:
- Assume $a^{0}+a^{1}+\ldots+a^{n}=\left(a^{n+1}-1\right) /(a-1)$

■ Step (show true for $\mathrm{n}+1$ ):

$$
\begin{aligned}
& a^{0}+a^{1}+\ldots+a^{n+1}=a^{0}+a^{1}+\ldots+a^{n}+a^{n+1} \\
& =\left(a^{n+1}-1\right) /(a-1)+a^{n+1}=\left(a^{n+1+1}-1\right)(a-1)
\end{aligned}
$$

## Review: Analyzing Algorithms

- We are interested in asymptotic analysis:
- Behavior of algorithms as problem size gets large

■ Constants, low-order terms don't matter

## An Example: Insertion Sort



## An Example: Insertion Sort



## An Example: Insertion Sort



## An Example: Insertion Sort



## An Example: Insertion Sort



## An Example: Insertion Sort



## An Example: Insertion Sort



## An Example: Insertion Sort



## An Example: Insertion Sort



## An Example: Insertion Sort



## An Example: Insertion Sort



## An Example: Insertion Sort



## An Example: Insertion Sort



## An Example: Insertion Sort



## An Example: Insertion Sort



## An Example: Insertion Sort



## An Example: Insertion Sort



## An Example: Insertion Sort



## An Example: Insertion Sort



## An Example: Insertion Sort



## An Example: Insertion Sort



## An Example: Insertion Sort



## An Example: Insertion Sort



## An Example: Insertion Sort



## An Example: Insertion Sort



## An Example: Insertion Sort



## An Example: Insertion Sort



## An Example: Insertion Sort



## An Example: Insertion Sort



## Insertion Sort

```
Statement
InsertionSort (A, n) \{
    for \(i=2\) to \(n\) \{
            key = A[i]
            j = i - 1;
            while (j > 0) and (A[j] > key) \{
                \(A[j+1]=A[j]\)
                j \(=\) j - 1
            \}
            \(\mathrm{A}[\mathrm{j}+1]=\) key
    \}
\}
\(T=t_{2}+t_{3}+\ldots+t_{n}\) where \(t_{i}\) is number of while expression evaluations for the \(i^{\text {th }}\) for loop iteration
```


## Analyzing Insertion Sort

- $\mathrm{T}(\mathrm{n})=\mathrm{c}_{1} \mathrm{n}+\mathrm{c}_{2}(\mathrm{n}-1)+\mathrm{c}_{3}(\mathrm{n}-1)+\mathrm{c}_{4} \mathrm{~T}+\mathrm{c}_{5}(\mathrm{~T}-(\mathrm{n}-1))+\mathrm{c}_{6}(\mathrm{~T}-(\mathrm{n}-1))+\mathrm{c}_{7}(\mathrm{n}-1)$

$$
=\mathrm{c}_{8} \mathrm{~T}+\mathrm{c}_{9} \mathrm{n}+\mathrm{c}_{10}
$$

- What can T be?

■ Best case -- inner loop body never executed
$\circ t_{i}=1 \wedge T(n)$ is a linear function
■ Worst case -- inner loop body executed for all previous elements
$\circ \mathrm{t}_{\mathrm{i}}=\mathrm{i} \wedge \mathrm{T}(\mathrm{n})$ is a quadratic function

- If $T$ is a quadratic function, which terms in the above equation matter?


## Upper Bound Notation

- We say InsertionSort's run time is $O\left(n^{2}\right)$
- Properly we should say run time is in $\mathrm{O}\left(\mathrm{n}^{2}\right)$
- Read O as "Big-O" (you'll also hear it as "order")
- In general a function
- $\mathrm{f}(\mathrm{n})$ is $\mathrm{O}(\mathrm{g}(\mathrm{n})$ ) if there exist positive constants $c$ and $n_{0}$ such that $\mathrm{f}(\mathrm{n}) \leq \mathrm{c} \cdot \mathrm{g}(\mathrm{n})$ for all $\mathrm{n} \geq n_{0}$
- Formally
- $\mathrm{O}(\mathrm{g}(\mathrm{n}))=\left\{\mathrm{f}(\mathrm{n}): \exists\right.$ positive constants $c$ and $n_{0}$ such that $\mathrm{f}(\mathrm{n}) \leq \mathrm{c} \cdot \mathrm{g}(\mathrm{n}) \forall \mathrm{n} \geq n_{0}$


## Big O Fact

- A polynomial of degree k is $\mathrm{O}\left(\mathrm{n}^{\mathrm{k}}\right)$
- Proof:
$■$ Suppose $f(n)=b_{k} n^{k}+b_{k-1} n^{k-1}+\ldots+b_{1} n+b_{0}$
- Let $a_{i}=\left|b_{i}\right|$
$■ f(n) \leq \mathrm{a}_{\mathrm{k}} \mathrm{n}^{\mathrm{k}}+\mathrm{a}_{\mathrm{k}-1} \mathrm{n}^{\mathrm{k}-1}+\ldots+\mathrm{a}_{1} \mathrm{n}+\mathrm{a}_{0}$

$$
\leq n^{k} \sum a_{i} \frac{n^{i}}{n^{k}} \leq n^{k} \sum a_{i} \leq c n^{k}
$$

## Lower Bound Notation

- We say InsertionSort's run time is $\Omega(\mathrm{n})$
- In general a function
- $\mathrm{f}(\mathrm{n})$ is $\Omega(\mathrm{g}(\mathrm{n}))$ if $\exists$ positive constants $c$ and $n_{0}$ such that $0 \leq \mathrm{c} \cdot \mathrm{g}(\mathrm{n}) \leq \mathrm{f}(\mathrm{n}) \quad \forall \mathrm{n} \geq n_{0}$


## Asymptotic Tight Bound

- A function $\mathrm{f}(\mathrm{n})$ is $\Theta(\mathrm{g}(\mathrm{n}))$ if $\exists$ positive constants $c_{1}, c_{2}$, and $n_{0}$ such that

$$
c_{1} \mathrm{~g}(\mathrm{n}) \leq \mathrm{f}(\mathrm{n}) \leq c_{2} \mathrm{~g}(\mathrm{n}) \forall \mathrm{n} \geq n_{0}
$$

## Other Asymptotic Notations

- A function $f(n)$ is $o(g(n))$ if $\exists$ positive constants $c$ and $n_{0}$ such that

$$
\mathrm{f}(\mathrm{n})<c \mathrm{~g}(\mathrm{n}) \forall \mathrm{n} \geq n_{0}
$$

- A function $f(n)$ is $\omega(g(n))$ if $\exists$ positive constants $c$ and $n_{0}$ such that

$$
c \mathrm{~g}(\mathrm{n})<\mathrm{f}(\mathrm{n}) \forall \mathrm{n} \geq n_{0}
$$

- Intuitively,
- o() is like $<$
- $\omega()$ is like $>$
- $\Theta()$ is like $=$
$■ \mathrm{O}()$ is like $\leq \quad \Omega()$ is like $\geq$


## Review: Recurrences

- Recurrence: an equation that describes a function in terms of its value on smaller functions

$$
\begin{array}{cc}
s(n)=\left\{\begin{array}{cc}
0 & n=0 \\
c+s(n-1) & n>0
\end{array}\right. & s(n)=\left\{\begin{array}{cc}
0 & n=0 \\
n+s(n-1) & n>0
\end{array}\right. \\
T(n)=\left\{\begin{array}{cc}
c & n=1 \\
2 T\left(\frac{n}{2}\right)+c & n>1
\end{array}\right. & T(n)=\left\{\begin{array}{cc}
c & n=1 \\
a T\left(\frac{n}{b}\right)+c n & n>1
\end{array}\right.
\end{array}
$$

## Review: Solving Recurrences

- Substitution method
- Iteration method
- Master method


## Review: Substitution Method

- Substitution Method:
- Guess the form of the answer, then use induction to find the constants and show that solution works
■ Example:
$\circ T(n)=2 T(n / 2)+\Theta(n) \wedge T(n)=\Theta(n \lg n)$
$\circ T(n)=2 T(2 n / 2 g+n A ? ? ?$


## Review: Substitution Method

- Substitution Method:
- Guess the form of the answer, then use induction to find the constants and show that solution works
- Examples:

$$
\begin{aligned}
& \circ T(n)=2 T(n / 2)+\Theta(n) \Delta T(n)=\Theta(n \lg n) \\
& \circ T(n)=2 T\left(\_n / 2 g\right)+n \Delta T(n)=\Theta(n \lg n)
\end{aligned}
$$

$■$ We can show that this holds by induction

## Substitution Method

- Our goal: show that

$$
T(n)=2 T(\lfloor n / 2\rfloor)+n=\mathrm{O}(n \lg n)
$$

- Thus, we need to show that $T(n) \leq c n \lg n$ with an appropriate choice of $c$
■ Inductive hypothesis: assume
$T(\lfloor n / 2\rfloor) \leq c\lfloor n / 2\rfloor \lg \lfloor n / 2\rfloor$
- Substitute back into recurrence to show that $T(n) \leq c n \lg n$ follows, when $c \geq 1$ (show on board)


## Review: Iteration Method

- Iteration method:
- Expand the recurrence $k$ times
- Work some algebra to express as a summation
- Evaluate the summation

Review: $s(n)=\left\{\begin{array}{cc}0 & n=0 \\ c+s(n-1) & n>0\end{array}\right.$

- $s(\mathrm{n})=$

$$
\begin{aligned}
& c+s(n-1) \\
& c+c+s(n-2) \\
& 2 c+s(n-2) \\
& 2 c+c+s(n-3) \\
& 3 c+s(n-3)
\end{aligned}
$$

$$
\mathrm{kc}+\mathrm{s}(\mathrm{n}-\mathrm{k})=\mathrm{ck}+\mathrm{s}(\mathrm{n}-\mathrm{k})
$$

Review: $s(n)=\left\{\begin{array}{cc}0 & n=0 \\ c+s(n-1) & n>0\end{array}\right.$

- So far for $\mathrm{n}>=\mathrm{k}$ we have

■ $\mathrm{s}(\mathrm{n})=\mathrm{ck}+\mathrm{s}(\mathrm{n}-\mathrm{k})$

- What if $\mathrm{k}=\mathrm{n}$ ?
- $\mathrm{s}(\mathrm{n})=\mathrm{cn}+\mathrm{s}(0)=\mathrm{cn}$

Review: $T(n)=\left\{\begin{array}{cc}c & n=1 \\ 2 T\left(\frac{n}{2}\right)+c & n>1\end{array}\right.$

- $\mathrm{T}(\mathrm{n})=$
$2 \mathrm{~T}(\mathrm{n} / 2)+\mathrm{c}$
$2(2 \mathrm{~T}(\mathrm{n} / 2 / 2)+\mathrm{c})+\mathrm{c}$
$2^{2} \mathrm{~T}\left(\mathrm{n} / 2^{2}\right)+2 \mathrm{c}+\mathrm{c}$
$2^{2}\left(2 \mathrm{~T}\left(\mathrm{n} / 2^{2} / 2\right)+\mathrm{c}\right)+3 \mathrm{c}$
$2^{3} \mathrm{~T}\left(\mathrm{n} / 2^{3}\right)+4 \mathrm{c}+3 \mathrm{c}$
$2^{3} \mathrm{~T}\left(\mathrm{n} / 2^{3}\right)+7 \mathrm{c}$
$2^{3}\left(2 \mathrm{~T}\left(\mathrm{n} / 2^{3} / 2\right)+\mathrm{c}\right)+7 \mathrm{c}$
$2^{4} \mathrm{~T}\left(\mathrm{n} / 2^{4}\right)+15 \mathrm{c}$
$2^{\mathrm{k}} \mathrm{T}\left(\mathrm{n} / 2^{\mathrm{k}}\right)+\left(2^{\mathrm{k}}-1\right) \mathrm{c}$

Review: $T(n)=\left\{\begin{array}{cc}c & n=1 \\ 2 T\left(\frac{n}{2}\right)+c & n>1\end{array}\right.$

- So far for $\mathrm{n}>2 \mathrm{k}$ we have
$■ \mathrm{~T}(\mathrm{n})=2^{\mathrm{k}} \mathrm{T}\left(\mathrm{n} / 2^{\mathrm{k}}\right)+\left(2^{\mathrm{k}}-1\right) \mathrm{c}$
- What if $\mathrm{k}=\lg \mathrm{n}$ ?
- $T(n)=2^{\lg n} T\left(n / 2^{\lg n}\right)+\left(2^{\lg n}-1\right) c$
$=\mathrm{nT}(\mathrm{n} / \mathrm{n})+(\mathrm{n}-1) \mathrm{c}$
$=\mathrm{n} T(1)+(\mathrm{n}-1) \mathrm{c}$
$=\mathrm{nc}+(\mathrm{n}-1) \mathrm{c}=(2 \mathrm{n}-1) \mathrm{c}$


## Review: The Master Theorem

- Given: a divide and conquer algorithm
- An algorithm that divides the problem of size $n$ into $a$ subproblems, each of size $n / b$
- Let the cost of each stage (i.e., the work to divide the problem + combine solved subproblems) be described by the function $f(n)$
- Then, the Master Theorem gives us a cookbook for the algorithm's running time:


## Review: The Master Theorem

- if $T(n)=a T(n / b)+f(n)$ then

$$
T(n)=\left\{\begin{array}{ll}
\Theta\left(n^{\log _{b} a}\right) & f(n)=O\left(n^{\log _{b} a-\varepsilon}\right) \\
\Theta\left(n^{\log _{b} a} \log n\right) & f(n)=\Theta\left(n^{\log _{b} a}\right) \\
\Theta(f(n)) & f(n)=\Omega\left(n^{\log _{b} a+\varepsilon}\right) \text { AND } \\
& a f(n / b)<c f(n) \text { for large } n
\end{array}\right\}
$$

## Review: Merge Sort

```
MergeSort(A, left, right) {
    if (left < right) {
        mid = floor((left + right) / 2);
        MergeSort(A, left, mid);
        MergeSort(A, mid+1, right);
        Merge(A, left, mid, right);
    }
}
```

// Merge() takes two sorted subarrays of A and
// merges them into a single sorted subarray of $A$.
// Merge()takes $O(n)$ time, $n=$ length of $A$

## Review: Analysis of Merge Sort

```
Statement
Effort
```

```
MergeSort(A, left, right) {
```

MergeSort(A, left, right) {
T(n)
T(n)
if (left < right) { \Theta(1)
if (left < right) { \Theta(1)
mid = floor((left + right) / 2); \Theta(1)
mid = floor((left + right) / 2); \Theta(1)
MergeSort (A, left, mid); T(n/2)
MergeSort (A, left, mid); T(n/2)
MergeSort (A, mid+1, right); T(n/2)
MergeSort (A, mid+1, right); T(n/2)
Merge(A, left, mid, right); \Theta(n)
Merge(A, left, mid, right); \Theta(n)
}
}

- So $T(n)=\Theta(1)$ when $n=1$, and

$$
2 \mathrm{~T}(\mathrm{n} / 2)+\Theta(\mathrm{n}) \text { when } \mathrm{n}>1
$$

```
- Solving this recurrence (how?) gives \(\mathrm{T}(\mathrm{n})=\mathrm{n} \lg \mathrm{n}\)

\section*{Review: Heaps}
- A heap is a "complete" binary tree, usually represented as an array:


\section*{Review: Heaps}
- To represent a heap as an array: Parent (i) \{ return \i/2」; \} Left(i) \{ return 2*i; \} right (i) \{ return \(2 * i+1 ;\) \}

\section*{Review: The Heap Property}
- Heaps also satisfy the heap property:
\(\mathrm{A}[\operatorname{Parent}(i)] \geq \mathrm{A}[i] \quad\) for all nodes \(i>1\)
\(■\) In other words, the value of a node is at most the value of its parent
- The largest value is thus stored at the \(\operatorname{root}(\mathrm{A}[1])\)
- Because the heap is a binary tree, the height of any node is at most \(\Theta(\lg n)\)

\section*{Review: Heapify()}
- Heapify () : maintain the heap property
- Given: a node \(i\) in the heap with children \(l\) and \(r\)
\(■\) Given: two subtrees rooted at \(l\) and \(r\), assumed to be heaps
- Action: let the value of the parent node "float down" so subtree at \(i\) satisfies the heap property
\(\circ\) If \(\mathrm{A}[\mathrm{i}]<\mathrm{A}[1]\) or \(\mathrm{A}[\mathrm{i}]<\mathrm{A}[\mathrm{r}]\), swap \(\mathrm{A}[\mathrm{i}]\) with the largest of \(\mathrm{A}[1]\) and \(\mathrm{A}[\mathrm{r}]\)
- Recurse on that subtree
\(■\) Running time: \(\mathrm{O}(h), \mathrm{h}=\) height of heap \(=\mathrm{O}(\lg n)\)

\section*{Review: BuildHeap()}
- BuildHeap () : build heap bottom-up by running Heapify () on successive subarrays
■ Walk backwards through the array from \(\mathrm{n} / 2\) to 1 , calling Heapify () on each node.
- Order of processing guarantees that the children of node \(i\) are heaps when \(i\) is processed
- Easy to show that running time is \(\mathrm{O}(n \lg n)\)
- Can be shown to be \(\mathrm{O}(n)\)

■ Key observation: most subheaps are small

\section*{Review: Heapsort()}
- Heapsort () : an in-place sorting algorithm:
- Maximum element is at A[1]
- Discard by swapping with element at A[n]
- Decrement heap_size[A]
- \(\mathrm{A}[\mathrm{n}]\) now contains correct value
- Restore heap property at \(\mathrm{A}[1]\) by calling Heapify ()
- Repeat, always swapping A[1] for A[heap_size(A)]
- Running time: \(\mathrm{O}(n \lg n)\)
- BuildHeap: O(n), Heapify: \(n\) * \(\mathrm{O}(\lg n)\)

\section*{Review: Priority Queues}
- The heap data structure is often used for implementing priority queues
- A data structure for maintaining a set \(S\) of elements, each with an associated value or key
■ Supports the operations Insert (), Maximum (), and ExtractMax ()
■ Commonly used for scheduling, event simulation

\section*{Priority Queue Operations}
- Insert( \(\mathbf{S}, \mathbf{x}\) ) inserts the element x into set S
- Maximum(S) returns the element of \(S\) with the maximum key
- ExtractMax(S) removes and returns the element of \(S\) with the maximum key

\section*{Implementing Priority Queues}
```

HeapInsert(A, key) // what's running time?
{
heap_size[A] ++;
i = heap_size[A];
while (i > 1 AND A[Parent(i)] < key)
{
A[i] = A[Parent(i)];
i = Parent(i);
}
A[i] = key;
}

```

\section*{Implementing Priority Queues}

HeapMaximum (A)
\{
// This one is really tricky:
return A[i];
\}

\section*{Implementing Priority Queues}
```

HeapExtractMax(A)
{
if (heap_size[A] < 1) { error; }
max = A[1];
A[1] = A[heap_size[A]]
heap_size[A] --;
Heapify(A, 1);
return max;
}

```

\section*{Example: Combat Billiards}
- Extract the next collision \(\mathrm{C}_{i}\) from the queue
- Advance the system to the time \(\mathrm{T}_{i}\) of the collision
- Recompute the next collision(s) for the ball(s) involved
- Insert collision(s) into the queue, using the time of occurrence as the key
- Find the next overall collision \(\mathrm{C}_{i+1}\) and repeat

\section*{Review: Quicksort}
- Quicksort pros:
\(\square\) Sorts in place
- Sorts O(n \(\lg \mathrm{n})\) in the average case
- Very efficient in practice
- Quicksort cons:
- Sorts \(\mathrm{O}\left(\mathrm{n}^{2}\right)\) in the worst case

■ Naïve implementation: worst-case = sorted
- Even picking a different pivot, some particular input will take \(\mathrm{O}\left(\mathrm{n}^{2}\right)\) time

\section*{Review: Quicksort}
- Another divide-and-conquer algorithm
- The array \(\mathrm{A}[\mathrm{p} . \mathrm{r}]\) is partitioned into two nonempty subarrays \(\mathrm{A}[\mathrm{p} . . \mathrm{q}]\) and \(\mathrm{A}[\mathrm{q}+1 . . \mathrm{r}]\)
- Invariant: All elements in \(A[p . . q]\) are less than all elements in \(\mathrm{A}[\mathrm{q}+1 . . \mathrm{r}]\)
- The subarrays are recursively quicksorted
- No combining step: two subarrays form an already-sorted array

\section*{Review: Quicksort Code}

Quicksort (A, p, r)
\{
if ( \(\mathrm{p}<\mathrm{r}\) )
\{
q = Partition(A, p, r);
Quicksort (A, \(\mathrm{P}, \mathrm{q}\) ) ;
Quicksort(A, q+1, r);
\}
\}

\section*{Review: Partition Code}
```

Partition(A, p, r)
x = A[p];
i = p - 1;
j = r + 1;
while (TRUE)
repeat
j--;
until A[j] <= x;
repeat
partition() runs in O(n) time
until A[i] >= x;
if (i < j)
Swap(A, i, j);
else
return j;

```

\section*{Review: Analyzing Quicksort}
- What will be the worst case for the algorithm?
- Partition is always unbalanced
- What will be the best case for the algorithm?
- Partition is perfectly balanced
- Which is more likely?
- The latter, by far, except...
- Will any particular input elicit the worst case?
- Yes: Already-sorted input

\section*{Review: Analyzing Quicksort}
- In the worst case:
\(\mathrm{T}(1)=\Theta(1)\)
\[
T(n)=T(n-1)+\Theta(n)
\]
- Works out to
\[
T(n)=\Theta\left(n^{2}\right)
\]

\section*{Review: Analyzing Quicksort}
- In the best case:
\[
\mathrm{T}(\mathrm{n})=2 \mathrm{~T}(\mathrm{n} / 2)+\Theta(\mathrm{n})
\]
- Works out to
\[
T(n)=\Theta(n \lg n)
\]

\section*{Review: Analyzing Quicksort}
- Average case works out to \(T(n)=\Theta(n \lg n)\)
- Glance over the proof (lecture 6) but you won't have to know the details
- Key idea: analyze the running time based on the expected split caused by Partition()

\section*{Review: Improving Quicksort}
- The real liability of quicksort is that it runs in \(\mathrm{O}\left(\mathrm{n}^{2}\right)\) on already-sorted input
- Book discusses two solutions:

■ Randomize the input array, OR
- Pick a random pivot element
- How do these solve the problem?
- By insuring that no particular input can be chosen to make quicksort run in \(\mathrm{O}\left(\mathrm{n}^{2}\right)\) time

\section*{Sorting Summary}
- Insertion sort:
- Easy to code
- Fast on small inputs (less than \(\sim 50\) elements)
- Fast on nearly-sorted inputs
- \(\mathrm{O}\left(\mathrm{n}^{2}\right)\) worst case
- \(\mathrm{O}\left(\mathrm{n}^{2}\right)\) average (equally-likely inputs) case
- \(\mathrm{O}\left(\mathrm{n}^{2}\right)\) reverse-sorted case

\section*{Sorting Summary}
- Merge sort:
- Divide-and-conquer:
- Split array in half
- Recursively sort subarrays
- Linear-time merge step
- O(n \(\lg \mathrm{n})\) worst case
- Doesn't sort in place

\section*{Sorting Summary}
- Heap sort:
- Uses the very useful heap data structure
- Complete binary tree
- Heap property: parent key > children's keys
- \(\mathrm{O}(\mathrm{n} \lg \mathrm{n})\) worst case
- Sorts in place
- Fair amount of shuffling memory around

\section*{Sorting Summary}
- Quick sort:
- Divide-and-conquer:
- Partition array into two subarrays, recursively sort
- All of first subarray < all of second subarray
- No merge step needed!
- \(\mathrm{O}(\mathrm{n} \lg \mathrm{n})\) average case
- Fast in practice
- \(\mathrm{O}\left(\mathrm{n}^{2}\right)\) worst case
- Naïve implementation: worst case on sorted input
- Address this with randomized quicksort

\section*{Review: Comparison Sorts}
- Comparison sorts: \(\mathrm{O}(\mathrm{n} \lg \mathrm{n})\) at best
- Model sort with decision tree
- Path down tree = execution trace of algorithm

■ Leaves of tree = possible permutations of input
■ Tree must have n ! leaves, so \(\mathrm{O}(\mathrm{n} \lg \mathrm{n})\) height

\section*{Review: Counting Sort}

\section*{- Counting sort:}
- Assumption: input is in the range 1..k
- Basic idea:
- Count number of elements \(k \leq\) each element \(i\)
- Use that number to place \(i\) in position \(k\) of sorted array

■ No comparisons! Runs in time \(\mathrm{O}(\mathrm{n}+\mathrm{k})\)
- Stable sort
- Does not sort in place:
- O(n) array to hold sorted output
- \(\mathrm{O}(\mathrm{k})\) array for scratch storage

\section*{Review: Counting Sort}
\begin{tabular}{lc}
1 & CountingSort \((A, B, k)\) \\
2 & for \(i=1\) to \(k\) \\
3 & \(C[i]=0 ;\) \\
4 & for \(j=1\) to \(n\) \\
5 & \(C[A[j]]+=1 ;\) \\
6 & for \(i=2\) to \(k\) \\
7 & \(C[i]=C[i]+C[i-1] ;\) \\
8 & for \(j=n \operatorname{downto~}\) \\
9 & \(B[C[A[j]]]=A[j] ;\) \\
10 & \(C[A[j]]-=1 ;\)
\end{tabular}

\section*{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 \(\mathrm{O}(n+k)\), so total time \(\mathrm{O}(d n+d k)\)
- When \(d\) is constant and \(k=\mathrm{O}(n)\), takes \(\mathrm{O}(n)\) time
- Fast! Stable! Simple!
- Doesn’t sort in place

\section*{Review: 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)

\section*{Review: Binary Search Trees}
- BST property:
\(\operatorname{key}[\operatorname{left}(\mathrm{x})] \leq \operatorname{key}[\mathrm{x}] \leq \operatorname{key}[\operatorname{right}(\mathrm{x})]\)
- Example:


\section*{Review: Inorder Tree Walk}
- An inorder walk prints the set in sorted order: TreeWalk (x)

TreeWalk(left[x]);
print(x);
TreeWalk(right[x]);
- Easy to show by induction on the BST property
- Preorder tree walk: print root, then left, then right
- Postorder tree walk: print left, then right, then root

\section*{Review: BST Search}

TreeSearch (x, k)
\[
\begin{aligned}
& \text { if }(x=\text { NULL or } k=\text { key }[x]) \\
& \quad \text { return } x ; \\
& \text { if }(k<\operatorname{key}[x]) \\
& \quad \text { return TreeSearch (left }[x], k) \text {; } \\
& \text { else }
\end{aligned}
\]
return TreeSearch (right[x], k);

\section*{Review: BST Search (Iterative)}

IterativeTreeSearch (x, k)
```

while (x != NULL and k != key[x])
if (k < key[x])
x = left[x];
else
x = right[x];
return x;

```

\section*{Review: BST 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)
- Like search, takes time \(\mathrm{O}(h), h=\) tree height

\section*{Review: Sorting With BSTs}
- Basic algorithm:
- Insert elements of unsorted array from \(1 . . n\)
- Do an inorder tree walk to print in sorted order
- Running time:

■ Best case: \(\Omega(n \lg n)\) (it's a comparison sort)
- Worst case: \(\mathrm{O}\left(\mathrm{n}^{2}\right)\)
- Average case: \(\mathrm{O}(n \lg n)\) (it's a quicksort!)

\section*{Review: Sorting With BSTs}
- Average case analysis
- It's a form of quicksort!

```

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

```


\section*{Review: More BST Operations}
- Minimum:
- Find leftmost node in tree
- Successor:
- 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 to successor

\section*{Review: More BST Operations}
- Delete:
- x has no children:
- Remove x
- x has one child:
- Splice out x

- Swap x with successor
- Perform case 1 or 2 to delete it

\section*{Review: Red-Black Trees}
- Red-black trees:
- Binary search trees augmented with node color
- Operations designed to guarantee that the height \(h=\mathrm{O}(\lg n)\)

\section*{Red-Black Properties}
- The red-black properties:
1. Every node is either red or black
2. Every leaf (NULL pointer) is black
- Note: this means every "real" node has 2 children
3. If a node is red, both children are black
- Note: can't have 2 consecutive reds on a path
4. Every path from node to descendent leaf contains the same number of black nodes
5. The root is always black
- black-height: \# black nodes on path to leaf
- Lets us prove RB tree has height \(h \leq 2 \lg (n+1)\)

\section*{Operations On RB Trees}
- Since height is \(\mathrm{O}(\lg n)\), we can show that all BST operations take \(\mathrm{O}(\lg n)\) time
- Problem: BST Insert() and Delete() modify the tree and could destroy red-black properties
- Solution: restructure the tree in \(\mathrm{O}(\lg n)\) time

■ You should understand the basic approach of these operations

■ Key operation: rotation

\section*{RB Trees: Rotation}
- Our basic operation for changing tree structure:

- Rotation preserves inorder key ordering
- Rotation takes \(\mathrm{O}(1)\) time (just swaps pointers)

\section*{Review: Skip Lists}
- A relatively recent data structure
- "A probabilistic alternative to balanced trees"
- A randomized algorithm with benefits of r-b trees
- \(\mathrm{O}(\lg n)\) expected search time
- O(1) time for Min, Max, Succ, Pred
- Much easier to code than r-b trees

■ Fast!

\section*{Review: Skip Lists}
- The basic idea:
level 3
level 2
level 1

- Keep a doubly-linked list of elements
\(\square\) Min, max, successor, predecessor: \(\mathrm{O}(1)\) time
- Delete is \(\mathrm{O}(1)\) time, Insert is \(\mathrm{O}(1)+\) Search time
- Add each level \(-i\) element to level \(i+1\) with probability \(p\) (e.g., \(p=1 / 2\) or \(p=1 / 4\) )

\section*{Review: Skip List Search}
- To search for an element with a given key:
- Find location in top list
- Top list has O(1) elements with high probability
- Location in this list defines a range of items in next list
- Drop down a level and recurse
- O(1) time per level on average
- \(\mathrm{O}(\lg n)\) levels with high probability
- Total time: \(\mathrm{O}(\lg n)\)

\section*{Review: Skip List Insert}
- Skip list insert: analysis
- Do a search for that key
- Insert element in bottom-level list
- With probability \(p\), recurse to insert in next level
- Expected number of lists \(=1+\mathrm{p}+\mathrm{p}^{2}+\ldots=\) ???
\[
=1 /(1-\mathrm{p})=\mathrm{O}(1) \text { if } p \text { is constant }
\]
- Total time \(=\) Search \(+\mathbf{O}(1)=\mathbf{O}(\lg n)\) expected
- Skip list delete: \(\mathrm{O}(1)\)

\section*{Review: Skip Lists}
- \(\mathrm{O}(1)\) expected time for most operations
- \(\mathrm{O}(\lg n)\) expected time for insert
- \(\mathrm{O}\left(n^{2}\right)\) time worst case

■ But random, so no particular order of insertion evokes worst-case behavior
- \(\mathrm{O}(n)\) expected storage requirements
- Easy to code

\section*{Review: Hashing Tables}
- Motivation: symbol tables
- A compiler uses a symbol table to relate symbols to associated data
- Symbols: variable names, procedure names, etc.
- 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

\section*{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 ( \(T, x\) )
- \(\operatorname{Search}(T, x)\)

■ Don't care about sorting the records
- Hash tables support all the above in \(\mathrm{O}(1)\) expected time

\section*{Review: Direct Addressing}
- Suppose:
- The range of keys is \(0 . . m-1\)
- Keys are distinct
- The idea:
- Use key itself as the address into the table
- Set up an array T[0..m-1] in which
- \(\mathrm{T}[i]=x\)
if \(x \in T\) and \(\operatorname{key}[x]=i\)
- T \([i]=\) NULL \(\quad\) otherwise
- This is called a direct-address table

\section*{Review: Hash Functions}
- Next problem: collision


\section*{Review: Resolving Collisions}
- How can we solve the problem of collisions?
- Open addressing
- To insert: if slot is full, try another slot, and another, until an open slot is found (probing)
- To search, follow same sequence of probes as would be used when inserting the element
- Chaining

■ Keep linked list of elements in slots
■ Upon collision, just add new element to list

\section*{Review: Chaining}
- Chaining puts elements that hash to the same slot in a linked list:


\section*{Review: Analysis Of Hash Tables}
- Simple uniform hashing: each key in table is equally likely to be hashed to any slot
- Load factor \(\alpha=n / m=\) average \# keys per slot
- Average cost of unsuccessful search \(=O(1+\alpha)\)
- Successful search: \(O(1+\alpha / 2)=O(1+\alpha)\)
- If \(n\) is proportional to \(m, \alpha=\mathrm{O}(1)\)
- So the cost of searching \(=O(1)\) if we size our table appropriately

\section*{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

\section*{Review: The Division Method}
- \(h(k)=k \bmod m\)
- 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)

\section*{Review: The Multiplication Method}
- For a constant \(A, 0<A<1\) :
- \(\mathrm{h}(\mathrm{k})=\lfloor m \underbrace{(k A-\lfloor k A\rfloor)}_{\text {Fractional part of } k A}\rfloor\)
- Upshot:
- Choose \(m=2^{P}\)
- Choose \(A\) not too close to 0 or 1
- Knuth: Good choice for \(A=(\sqrt{ } 5-1) / 2\)

\section*{Review: Universal Hashing}
- When attempting to foil an malicious adversary, randomize the algorithm
- Universal hashing: pick a hash function randomly when the algorithm begins (not upon every insert!)
■ Guarantees good performance on average, no matter what keys adversary chooses
■ Need a family of hash functions to choose from

\section*{Review: Universal Hashing}
- Let \(\varsigma\) be a (finite) collection of hash functions
- ...that map a given universe \(U\) of keys...

■ ...into the range \(\{0,1, \ldots, m-1\}\).
- If \(\varsigma\) is universal if:
- for each pair of distinct keys \(x, y \in U\), the number of hash functions \(\mathrm{h} \in \boldsymbol{\zeta}\) for which \(h(x)=h(y)\) is \(\mid \mathrm{s} / m\)
- In other words:
- With a random hash function from \(\varsigma\), the chance of a collision between \(x\) and \(y(x \neq y)\) is exactly \(1 / m\)

\section*{Review: A Universal Hash Function}
- Choose table size \(m\) to be prime
- Decompose key \(x\) into \(r+1\) bytes, so that \(x=\left\{x_{0}, x_{1}, \ldots, x_{r}\right\}\)
\(■\) Only requirement is that max value of byte \(<m\)
\(\square\) Let \(a=\left\{a_{0}, a_{1}, \ldots, a_{r}\right\}\) denote a sequence of \(r+1\) elements chosen randomly from \(\{0,1, \ldots, m-1\}\)

■ Define corresponding hash function \(h_{a} \in \varsigma\).
\[
h_{a}(x)=\left(\sum_{i=0}^{r} a_{i} x_{i}\right) \bmod m
\]
- With this definition, \(\varsigma\) has \(m^{r+1}\) members

\section*{Review: Dynamic Order Statistics}
- We've seen algorithms for finding the \(i\) th element of an unordered set in \(\mathrm{O}(n)\) time
- OS-Trees: a structure to support finding the \(i\) th element of a dynamic set in \(\mathrm{O}(\lg n)\) time
■ Support standard dynamic set operations (Insert(), Delete(), Min(), Max(), Succ(), Pred())
- Also support these order statistic operations: void OS-Select (root, i); int OS-Rank(x);

\section*{Review: Order Statistic Trees}
- OS Trees augment red-black trees:
- Associate a size field with each node in the tree
\(■ \mathbf{x}->\boldsymbol{s i z e}\) records the size of subtree rooted at \(\mathbf{x}\), including \(\mathbf{x}\) itself:


\section*{Review: OS-Select}
- Example: show OS-Select(root, 5):
```

OS-Select(x, i)
{
r = x->left->size + 1;
if (i == r)
return x;
else if (i < r)
return OS-Select(x->left, i);
else
return OS-Select(x->right, i-r);
}

```


\section*{Review: OS-Select}
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```

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- Example: show OS-Select(root, 5):
```

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```


\section*{Review: OS-Select}
- Example: show OS-Select(root, 5):
```

OS-Select(x, i)
{
r = x->left->size + 1;
if (i == r)
return x;
else if (i < r)
return OS-Select(x->left, i);
else
return OS-Select(x->right, i-r);
}

```


Note: use a sentinel NIL element at the leaves with size \(=0\) to simplify code, avoid testing for NULL

\section*{Review: Determining The Rank Of An Element}

Idea: rank of right child x is one more than its parent's rank, plus the size of x's left subtree
```

OS-Rank(T, x)

```
\{
\(r=x->l e f t->s i z e+1 ;\)
y = \(\mathbf{x}\);
while ( y ! \(=\mathrm{T}->\) root)
    if ( \(y==y->p->r i g h t)\)
        \(r\) = r + y->p->left->size + 1;
    \(y=y^{->p ;}\)
return r;

\section*{Review: Determining The Rank Of An Element}

Example 1:
find rank of element with key \(H\)

OS-Rank (T, x)
\{
\[
r=x->l e f t->s i z e+1
\]
\[
y=x ;
\]
while (y != T->root)
if (y == y->p->right)
\[
r=r+y->p->l e f t->\text { size }+1
\]
\[
y=y^{->p} ;
\]
return r;

\section*{Review: Determining The Rank Of An Element}

\section*{Example 1:}
find rank of element with key H

OS-Rank (T, x)
\{
\[
\begin{aligned}
& \mathrm{r}=\mathrm{x}->\text { left->size }+1 ; \\
& \mathrm{y}=\mathrm{x} ; \\
& \text { while }(\mathrm{y}!=\mathrm{T}->\text { root }) \\
& \quad \text { if }(\mathrm{y}==\mathrm{y}->\mathrm{p}->\text { right }) \\
& \quad \mathrm{r}=\mathrm{r}+\mathrm{y}->\mathrm{p}->\text { left->size }+1 ;
\end{aligned} \quad \begin{aligned}
& \mathrm{y}=\mathrm{y}->\mathrm{p} ;
\end{aligned} \text { return } \mathrm{r} \text {; }
\]

\section*{Review: Determining The Rank Of An Element}

Example 1:
find rank of element with key \(H\)

OS-Rank (T, x)
\{
\[
r=x->l e f t->s i z e+1 ;
\]
\[
y=x ;
\]
while (y != T->root)
if (y == y->p->right)
\[
r=r+y->p->\text { left->size }+1
\]
\[
y=y^{->p} ;
\]
return \(r\);

\section*{Review: Determining The Rank Of An Element}

Example 1:
find rank of element with key \(H\)

OS-Rank (T, x)
\{
\[
r=x->l e f t->s i z e+1
\]
\[
\mathbf{y}=\mathbf{x} ;
\]
while (y != T->root)

if (y == y->p->right)
\[
r=r+y->p->l e f t->\text { size }+1
\]
\[
y=y->p ;
\]
return r;

\section*{Review: Maintaining Subtree Sizes}
- So by keeping subtree sizes, order statistic operations can be done in \(\mathrm{O}(\lg n)\) time
- Next: maintain sizes during Insert() and Delete() operations
■ Insert(): Increment size fields of nodes traversed during search down the tree
- Delete(): Decrement sizes along a path from the deleted node to the root
■ Both: Update sizes correctly during rotations

\section*{Reivew: Maintaining Subtree Sizes}

- Note that rotation invalidates only \(x\) and \(y\)
- Can recalculate their sizes in constant time
- Thm 15.1: can compute any property in \(\mathrm{O}(\lg n)\) time that depends only on node, left child, and right child

\section*{Review: Interval Trees}
- The problem: maintain a set of intervals
- E.g., time intervals for a scheduling program:
\[
7 \longmapsto 10
\]
\(5 \curvearrowleft 11\) \(17 \bullet \longrightarrow\)


■ Query: find an interval in the set that overlaps a given query interval
- [14,16] \(\rightarrow[15,18]\)
\(\circ[16,19] \rightarrow[15,18]\) or \([17,19]\)
\(\circ[12,14] \rightarrow\) NULL

\section*{Interval Trees}
- Following the methodology:
- Pick underlying data structure
- Red-black trees will store intervals, keyed on \(i \rightarrow l o w\)
- Decide what additional information to store
- Store the maximum endpoint in the subtree rooted at \(i\)
- Figure out how to maintain the information
- Insert: update max on way down, during rotations
- Delete: similar

■ Develop the desired new operations

\section*{Searching Interval Trees}
```

IntervalSearch(T, i)
{
x = T->root;
while (x != NULL \&\& !Overlap(i, x->interval))
if (x->left != NULL \&\& x->left->max \geq i->low)
x = x->left;
else
x = x->right;
return x
}

- Running time: O(lg n)

```

\section*{Review: Correctness of IntervalSearch()}
- Key idea: need to check only 1 of node's 2 children
- Case 1: search goes right
- Show that \(\exists\) overlap in right subtree, or no overlap at all
- Case 2: search goes left
- Show that \(\exists\) overlap in left subtree, or no overlap at all

\section*{Review: Correctness of IntervalSearch()}
- Case 1 : if search goes right, \(\exists\) overlap in the right subtree or no overlap in either subtree
- If \(\exists\) overlap in right subtree, we're done
- Otherwise:
- \(\mathrm{x} \rightarrow\) left \(=\) NULL, or \(\mathrm{x} \rightarrow\) left \(\rightarrow\) max \(<\mathrm{x} \rightarrow\) low (Why?)
- Thus, no overlap in left subtree!
```

while (x != NULL \&\& !overlap(i, x->interval))
if (x->left != NULL \&\& x->left->max \geq i->low)
x = x->left;
else
x = x->right;
return x;

```

\section*{Review: Correctness of IntervalSearch()}
- Case 2: if search goes left, \(\exists\) overlap in the left subtree or no overlap in either subtree
- If \(\exists\) overlap in left subtree, we're done
- Otherwise:
- \(\mathrm{i} \rightarrow\) low \(\leq \mathrm{x} \rightarrow\) left \(\rightarrow\) max, by branch condition
- \(\mathrm{x} \rightarrow\) left \(\rightarrow\) max \(=\mathrm{y} \rightarrow\) high for some y in left subtree
- Since i and y don't overlap and \(\mathrm{i} \rightarrow\) low \(\leq \mathrm{y} \rightarrow\) high, i \(\rightarrow\) high \(<\) y \(\rightarrow\) low
- Since tree is sorted by low's, \(\mathrm{i} \rightarrow\) high < any low in right subtree
- Thus, no overlap in right subtree
```

while (x != NULL \&\& !overlap(i, x->interval))
if (x->left != NULL \&\& x->left->max \geq i->low)
x = x->left;
else
x = x->right;
return x;

```
```

