Augmenting Data Structures, Dynamic Order Statistics, Interval Trees

Lecture 11

Dynamic order statistics

OS-SELECT(i, S): returns the ith smallest element in the dynamic set S.

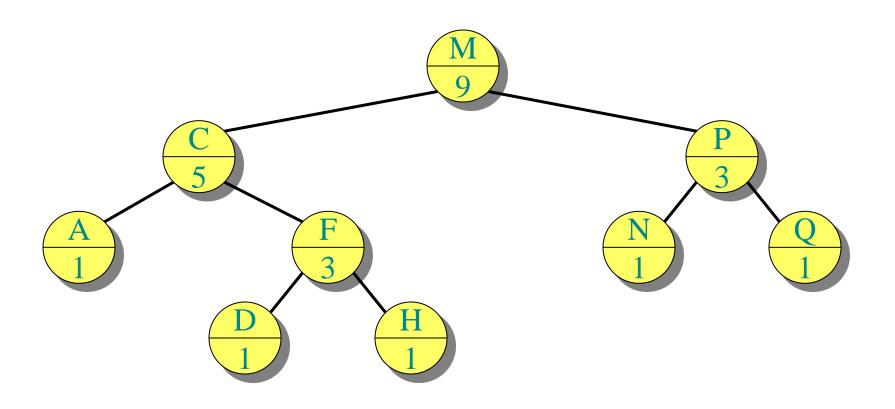
OS-RANK(x, S): returns the rank of $x \in S$ in the sorted order of S's elements.

IDEA: Use a red-black tree for the set *S*, but keep subtree sizes in the nodes.

Notation for nodes:



Example of an OS-tree



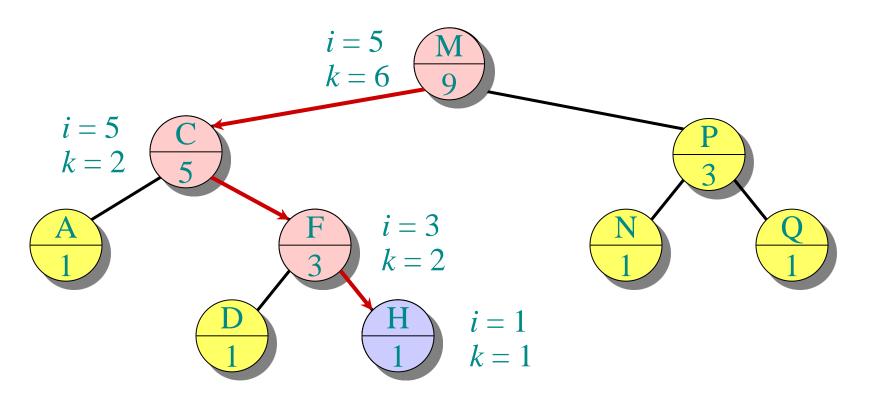
$$size[x] = size[left[x]] + size[right[x]] + 1$$

Selection

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Implementation trick: Use a sentinel
(dummy record) for NIL such that size[NIL] = 0.
OS-Select(x, i) > ith smallest element in the
                    subtree rooted at x
  k \leftarrow size[left[x]] + 1 \quad \triangleright k = rank(x)
  if i = k then return x
  if i < k
      then return OS-SELECT(left[x], i)
      else return OS-SELECT(right[x], i-k)
(OS-RANK is in the textbook.)
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Example

OS-SELECT(*root*, 5)



Running time = $O(h) = O(\lg n)$ for red-black trees.

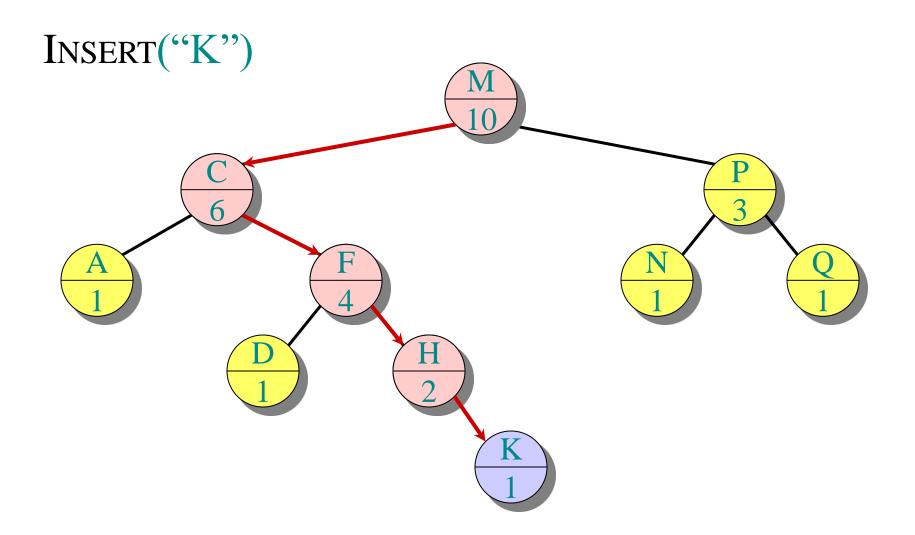
Data structure maintenance

- Q. Why not keep the ranks themselves in the nodes instead of subtree sizes?
- A. They are hard to maintain when the red-black tree is modified.

Modifying operations: Insert and Delete.

Strategy: Update subtree sizes when inserting or deleting.

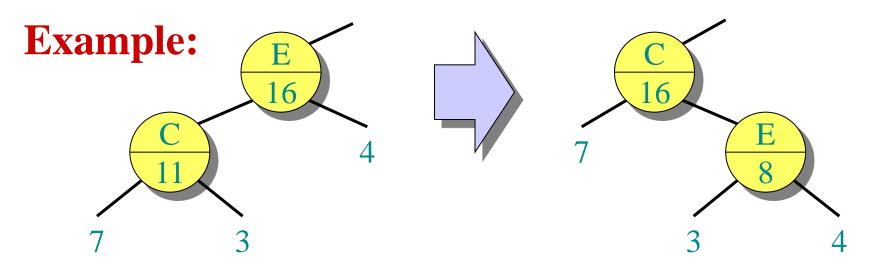
Example of insertion



Handling rebalancing

Don't forget that RB-Insert and RB-Delete may also need to modify the red-black tree in order to maintain balance.

- *Recolorings*: no effect on subtree sizes.
- *Rotations*: fix up subtree sizes in O(1) time.



 \therefore RB-Insert and RB-Delete still run in $O(\lg n)$ time.

Data-structure augmentation

Methodology: (e.g., order-statistics trees)

- 1. Choose an underlying data structure (*red-black trees*).
- 2. Determine additional information to be stored in the data structure (*subtree sizes*).
- 3. Verify that this information can be maintained for modifying operations (*RB-INSERT*, *RB-DELETE don't forget rotations*).
- 4. Develop new dynamic-set operations that use the information (*OS-SELECT and OS-RANK*).

These steps are guidelines, not rigid rules.

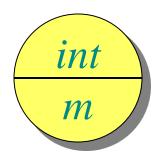
Interval trees

Goal: To maintain a dynamic set of intervals, such as time intervals.

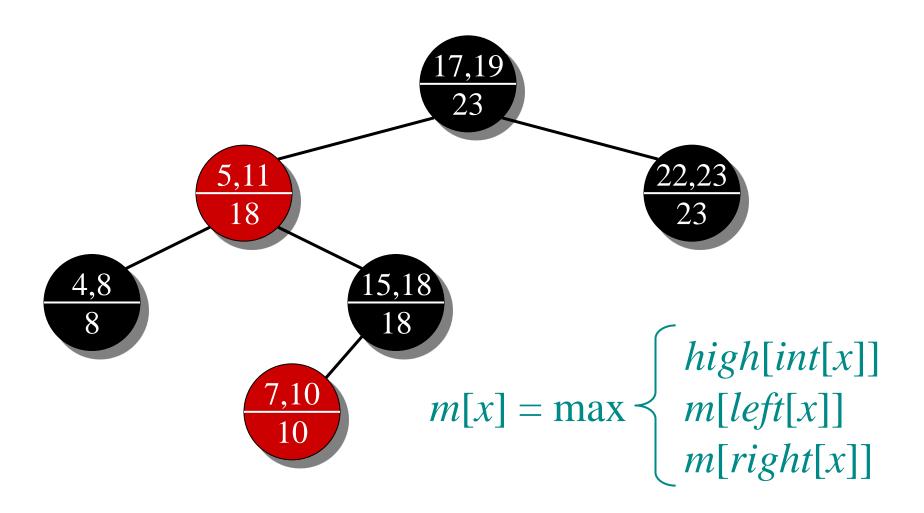
Query: For a given query interval i, find an interval in the set that overlaps i.

Following the methodology

- 1. Choose an underlying data structure.
 - Red-black tree keyed on low (left) endpoint.
- 2. Determine additional information to be stored in the data structure.
 - Store in each node x the largest value m[x] in the subtree rooted at x, as well as the interval int[x] corresponding to the key.

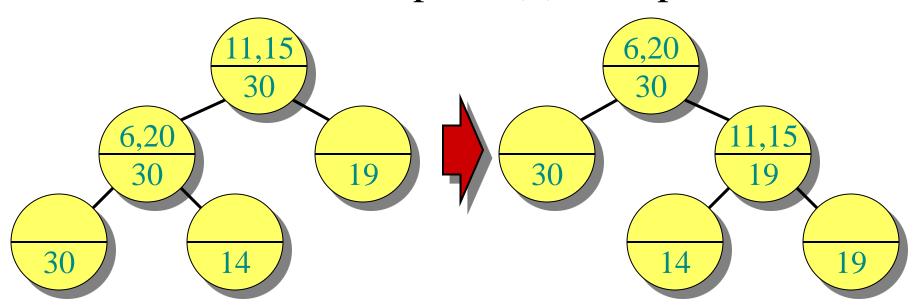


Example interval tree



Modifying operations

- 3. Verify that this information can be maintained for modifying operations.
 - Insert: Fix *m*'s on the way down.
 - Rotations Fixup = O(1) time per rotation:

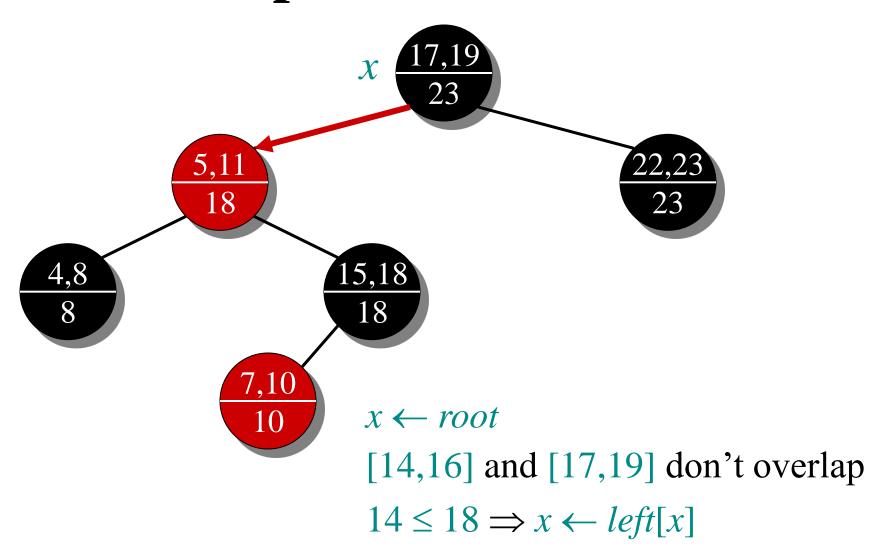


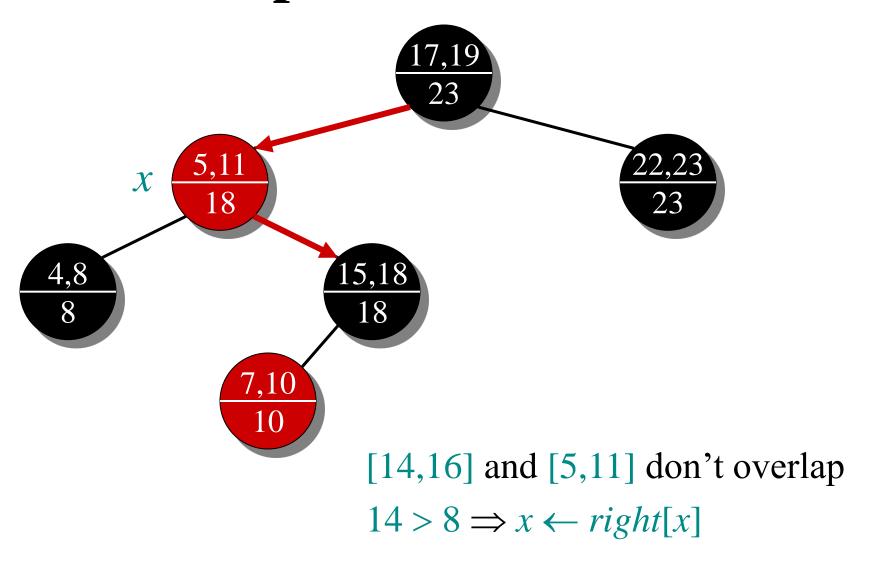
Total Insert time = $O(\lg n)$; Delete similar.

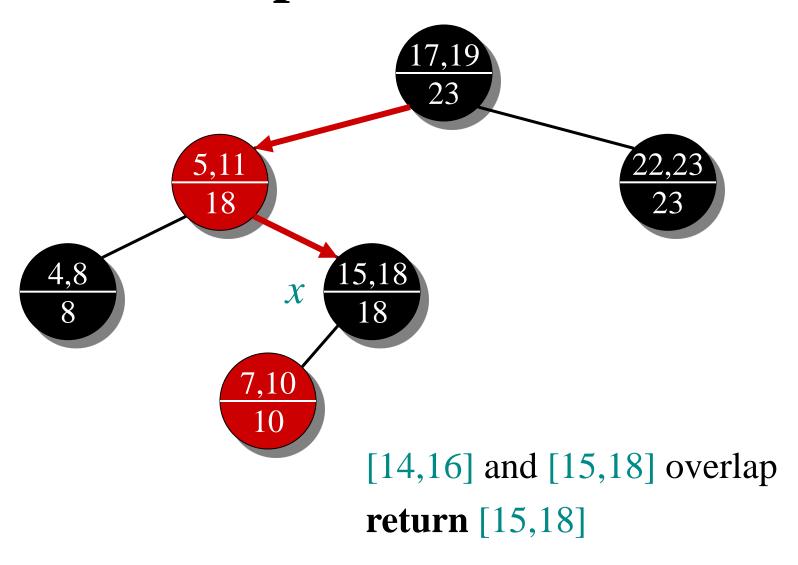
New operations

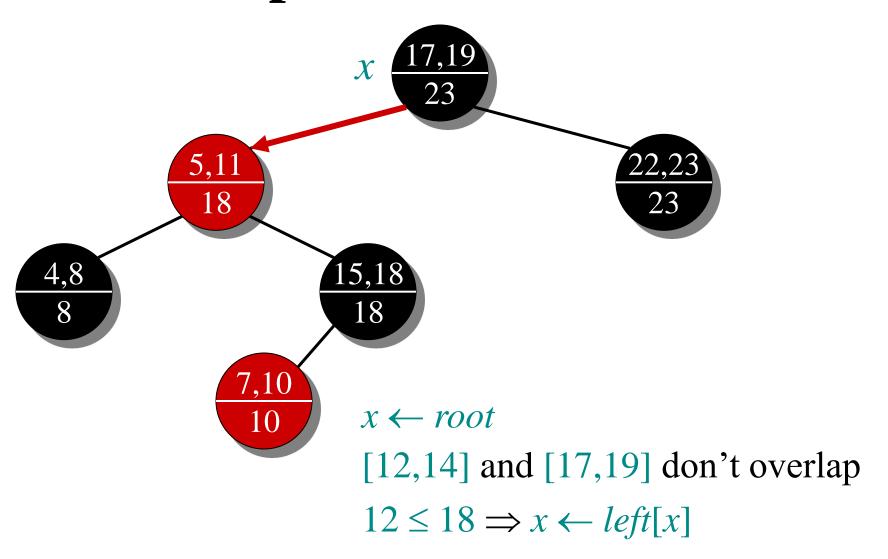
4. Develop new dynamic-set operations that use the information.

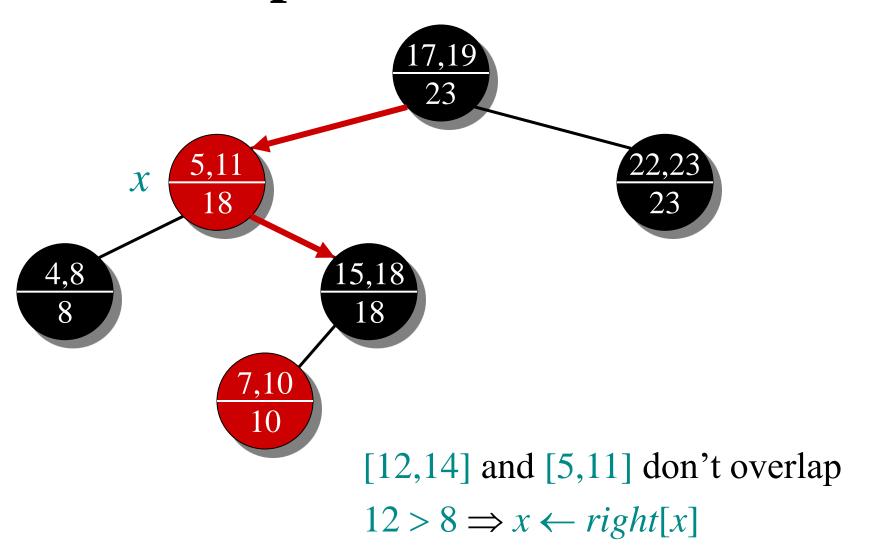
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INTERVAL-SEARCH(i)
    x \leftarrow root
    while x \neq NIL and (low[i] > high[int[x]])
                             or low[int[x]] > high[i])
        \mathbf{do} \triangleright i and int[x] don't overlap
            if left[x] \neq NIL and low[i] \leq m[left[x]]
                then x \leftarrow left[x]
                else x \leftarrow right[x]
    return x
```

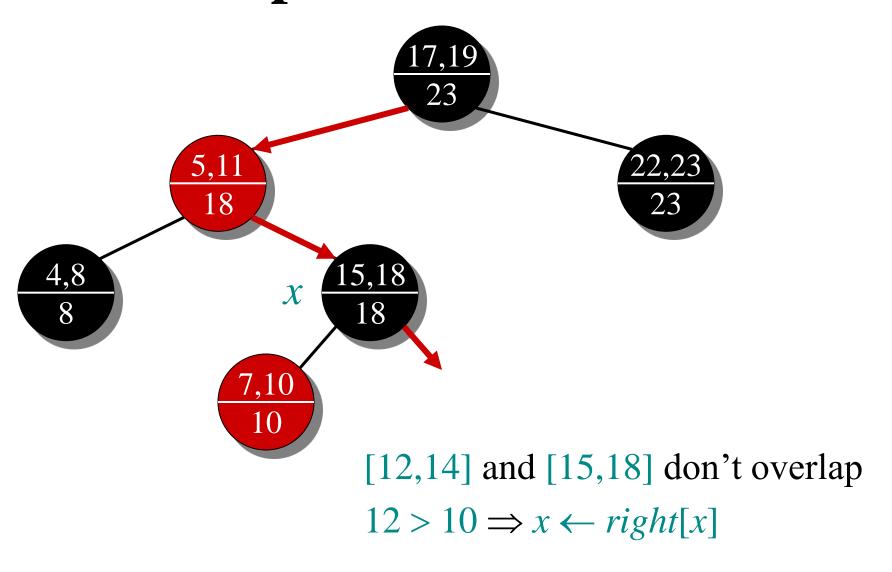


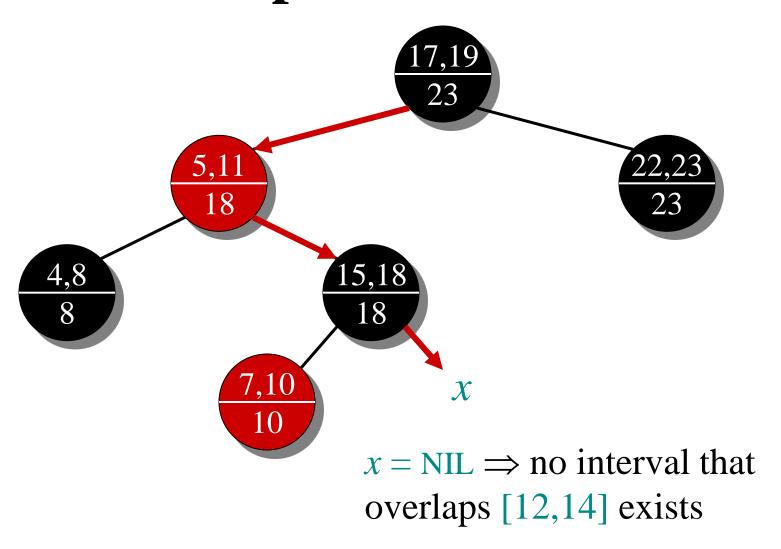












Analysis

Time = $O(h) = O(\lg n)$, since Interval-Search does constant work at each level as it follows a simple path down the tree.

List *all* overlapping intervals:

- Search, list, delete, repeat.
- Insert them all again at the end.

Time = $O(k \lg n)$, where k is the total number of overlapping intervals.

This is an *output-sensitive* bound.

Best algorithm to date: $O(k + \lg n)$.

Correctness

Theorem. Let L be the set of intervals in the left subtree of node x, and let R be the set of intervals in x's right subtree.

• If the search goes right, then

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\{i' \in L : i' \text{ overlaps } i\} = \emptyset.
```

• If the search goes left, then

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\{i' \in L : i' \text{ overlaps } i\} = \emptyset
 \Rightarrow \{i' \in R : i' \text{ overlaps } i\} = \emptyset.
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In other words, it's always safe to take only 1 of the 2 children: we'll either find something, or nothing was to be found.

Correctness proof

Proof. Suppose first that the search goes right.

- If left[x] = NIL, then we're done, since $L = \emptyset$.
- Otherwise, the code dictates that we must have low[i] > m[left[x]]. The value m[left[x]] corresponds to the right endpoint of some interval $j \in L$, and no other interval in L can have a larger right endpoint than high(j).

$$high(j) = m[left[x]]$$

$$low(i)$$

• Therefore, $\{i' \in L : i' \text{ overlaps } i\} = \emptyset$.

Proof (continued)

Suppose that the search goes left, and assume that $\{i' \in L : i' \text{ overlaps } i\} = \emptyset$.

- Then, the code dictates that $low[i] \le m[left[x]] = high[j]$ for some $j \in L$.
- Since $j \in L$, it does not overlap i, and hence high[i] < low[j].
- But, the binary-search-tree property implies that for all $i' \in R$, we have $low[j] \le low[i']$.
- But then $\{i' \in R : i' \text{ overlaps } i\} = \emptyset$.

