# x-Fast and y-Fast Tries

#### Outline for Today

#### • Data Structures on Integers

 How can we speed up operations that work on integer data?

#### x-Fast Tries

Bit manipulation meets tries and hashing.

#### y-Fast Tries

• Combining RMQ, strings, balanced trees, amortization, and randomization!

#### Working with Integers

- Many practical problems involve working specifically with integer values.
  - *CPU Scheduling:* Each thread has some associated integer priority, and we need to maintain those priorities in sorted order.
  - *Network Routing:* Each computer has an associated IP address, and we need to figure out which connections are active.
  - *ID Management:* We need to store social security numbers, zip codes, phone numbers, credit card numbers, etc. and perform basic lookups and range searches on them.
- We've seen many general-purpose data structures for keeping things in order and looking things up.
- *Question:* Can we improve those data structures if we know in advance that we're working with integer data?

#### Working with Integers

- Integers are interesting objects to work with:
  - Their values can directly be used as indices in lookup tables.
  - They can be treated as strings of bits, so we can use techniques from string processing.
  - They fit into machine words, so we can process the bits in parallel with individual word operations.
- The data structures we'll explore over the next few lectures will give you a sense of what sorts of techniques are possible with integer data.

## An Auxiliary Motive

- Integer data structures are also a great place to see just how much you've learned over the quarter!
- Today's data structures cover every single unit from the quarter (RMQ, strings, balanced trees, amortization, and randomization).
- I hope this gives you a chance to pause and reflect on just how far you've come!

The Setup

#### Our Machine Model

- We will assume we're working on a machine where memory is segmented into w-bit words.
  - Although on any one fixed machine *w* is a constant, in general, don't assume this is the case. 32-bit was the norm until fairly recently, and before that 16-bit was standard.
- We will assume that, if we build a data structure that holds n elements, then  $w = \Omega(\log n)$ .
  - This is called the *transdichotomous machine model*. Essentially, your word size has to be big enough to hold the size of your input.
- We'll assume C integer operators work in constant time, and won't assume other integer operations (say, finding most significant bits, counting 1 bits set) are available.

Besting BSTs

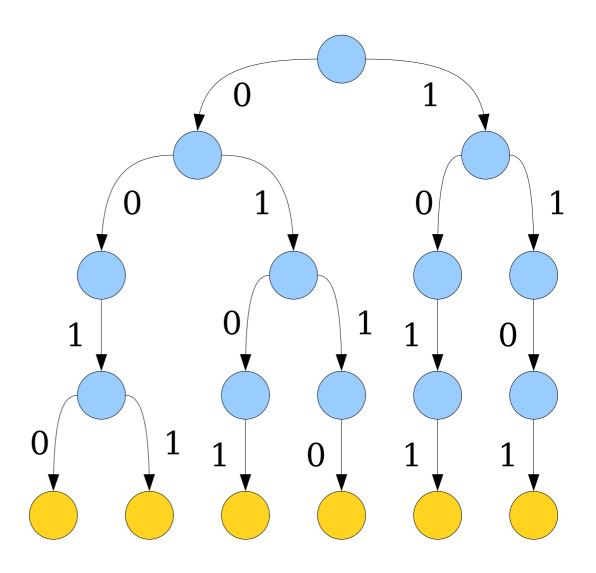
#### Besting BSTs

- BSTs store their elements in sorted order, which enables them to quickly answer each of the following queries:
  - *lookup*(x), which returns whether  $x \in S$ ;
  - insert(x), which adds x to S;
  - *delete*(*x*), which removes *x* from *S*;
  - max() / min(), which return the max/min element of S;
  - *successor*(*x*), which returns the smallest element of *S* greater than *x*; and
  - predecessor(x), which returns the largest element of S smaller than x.
- *Question:* Can we build another data structure that answers these same queries, but does so faster than a BST?

A Start: Bitwise Tries

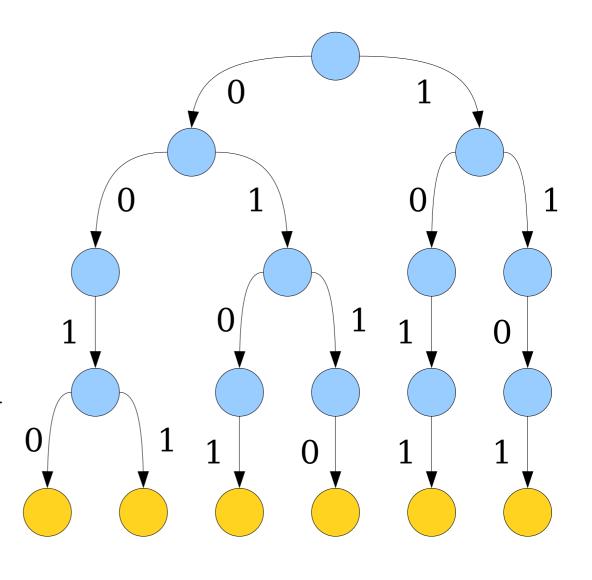
#### Tries Revisited

- **Recall:** A trie is a simple data structure for storing strings.
- Integers can be thought of as strings of bits.
- *Idea:* Store integers in a *bitwise trie*.



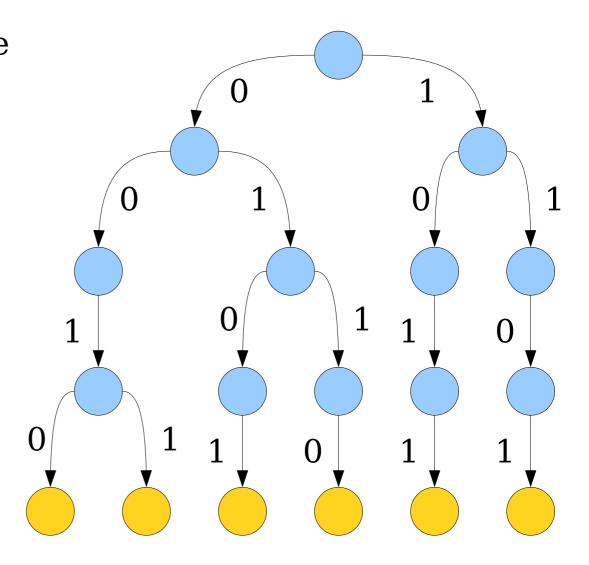
#### Finding Successors

- To compute successor(x), do the following:
  - Search for *x*.
  - If *x* is a leaf node, its successor is the next leaf.
  - If you don't find x, back up until you find a node with a 1 child not already followed, follow the 1, then take the cheapest path down.



#### Bitwise Trie Efficiency

- All operations on bitwise tries take time proportional to the number of bits in each number.
- Runtime for each operation: O(w).
  - This is worse than a BST's  $O(\log n)$ .
- Can we do better?



#### Speeding up Successors

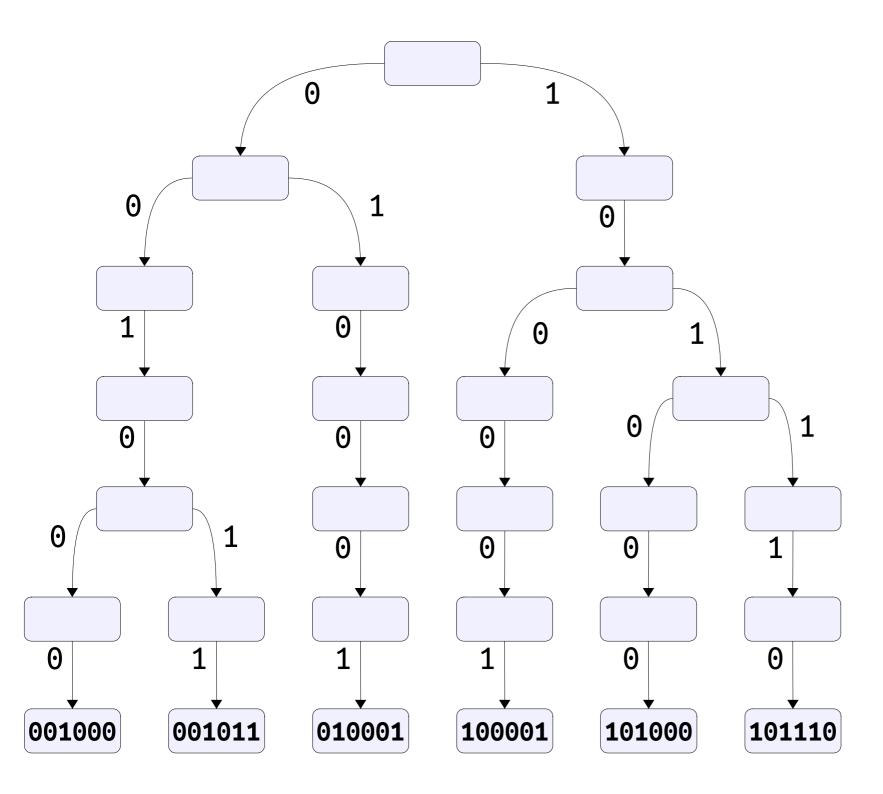
- There are two independent pieces that contribute to the O(w) runtime:
  - Need to walk down the trie following the bits of x, and there are  $\Theta(w)$  of those.
  - From there, need to back up to a branching node where we can find the successor.
- Can we speed up those operations? Or at least work around them?

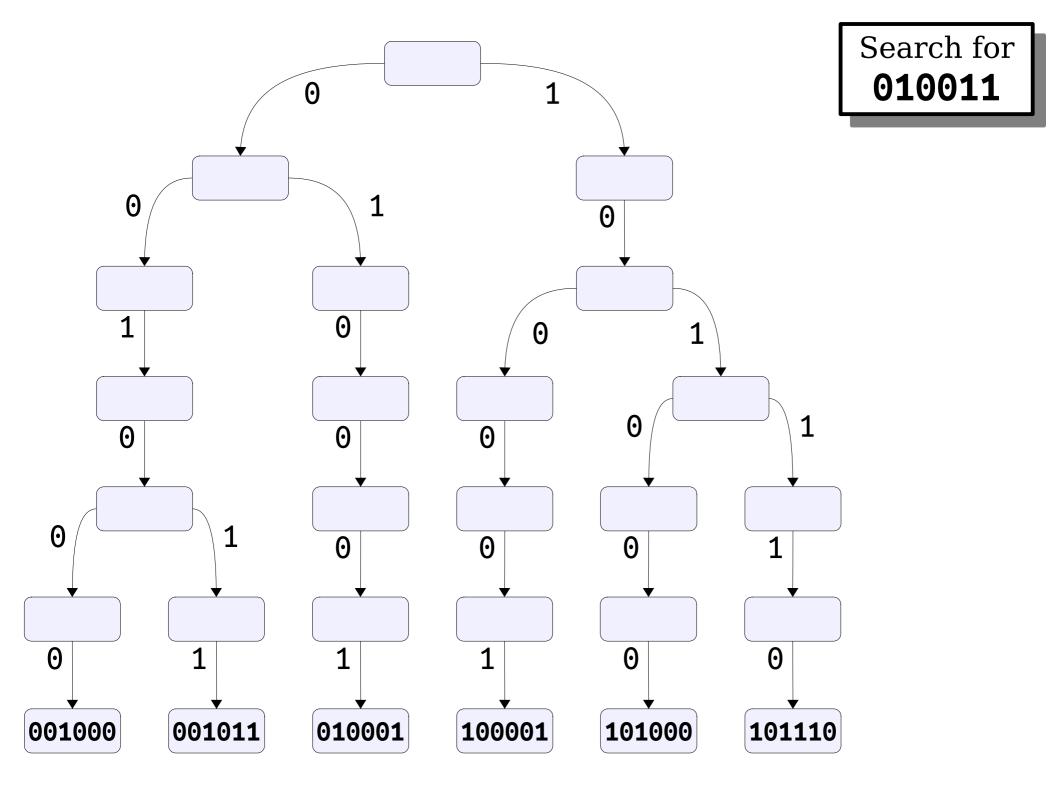
#### A Quick Algorithms Problem

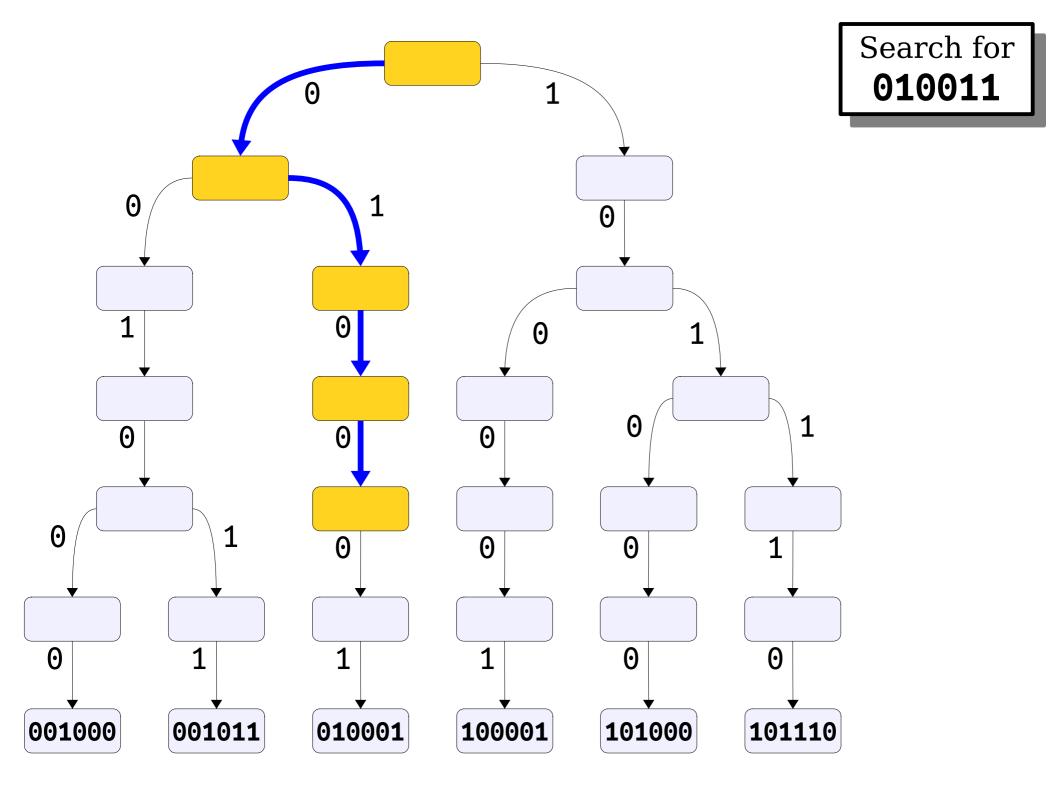
 You're given an array consisting of some number of Y's followed by some number of N's. There are k total letters.

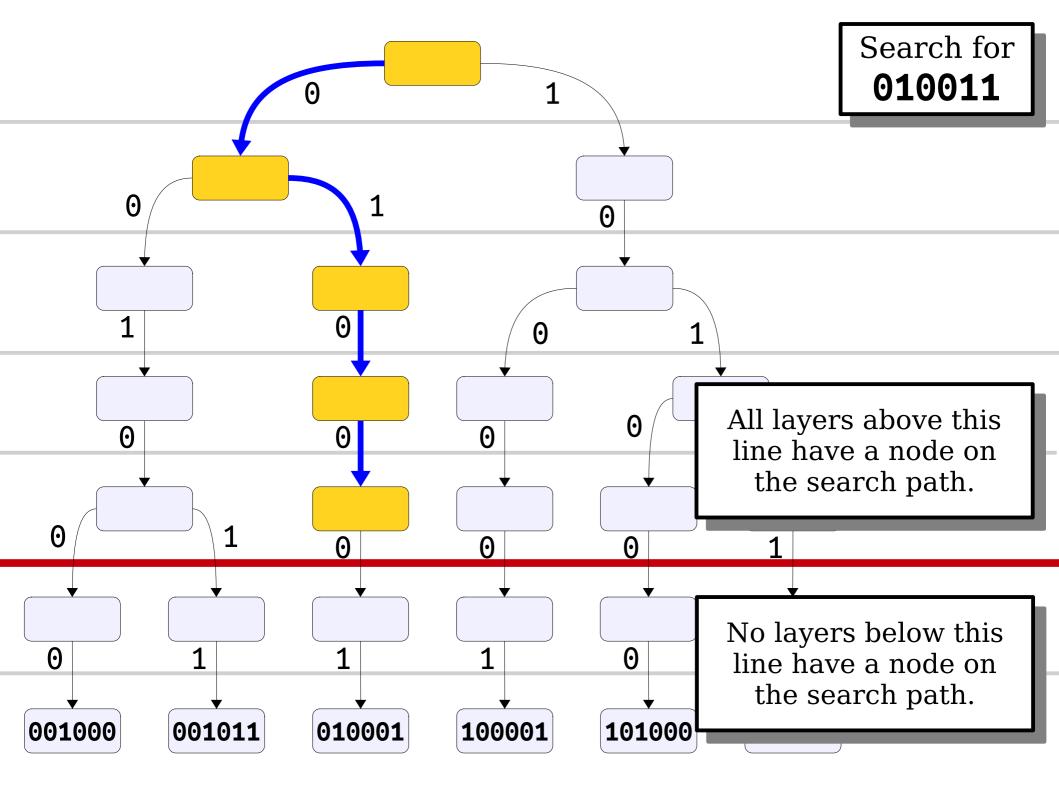
#### YYYYYY...YYYNNNN...NN

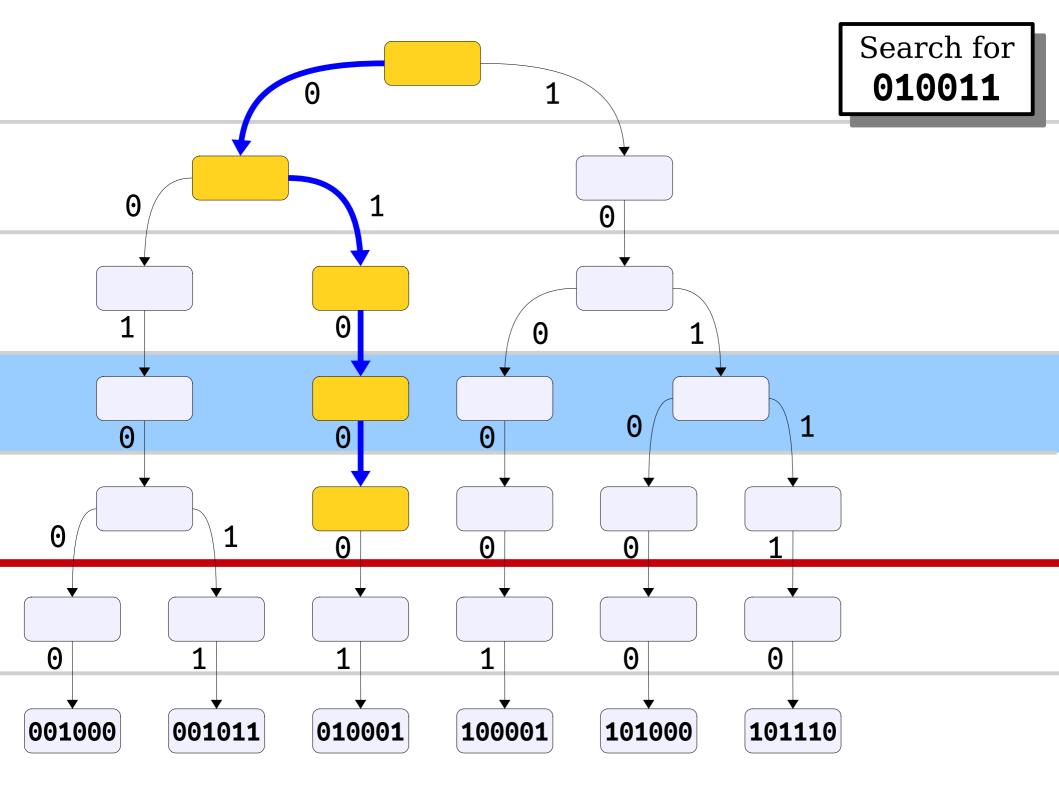
- How quickly can you find the last Y?
- *Answer*: Can be done in time  $O(\log k)$  using a binary search.

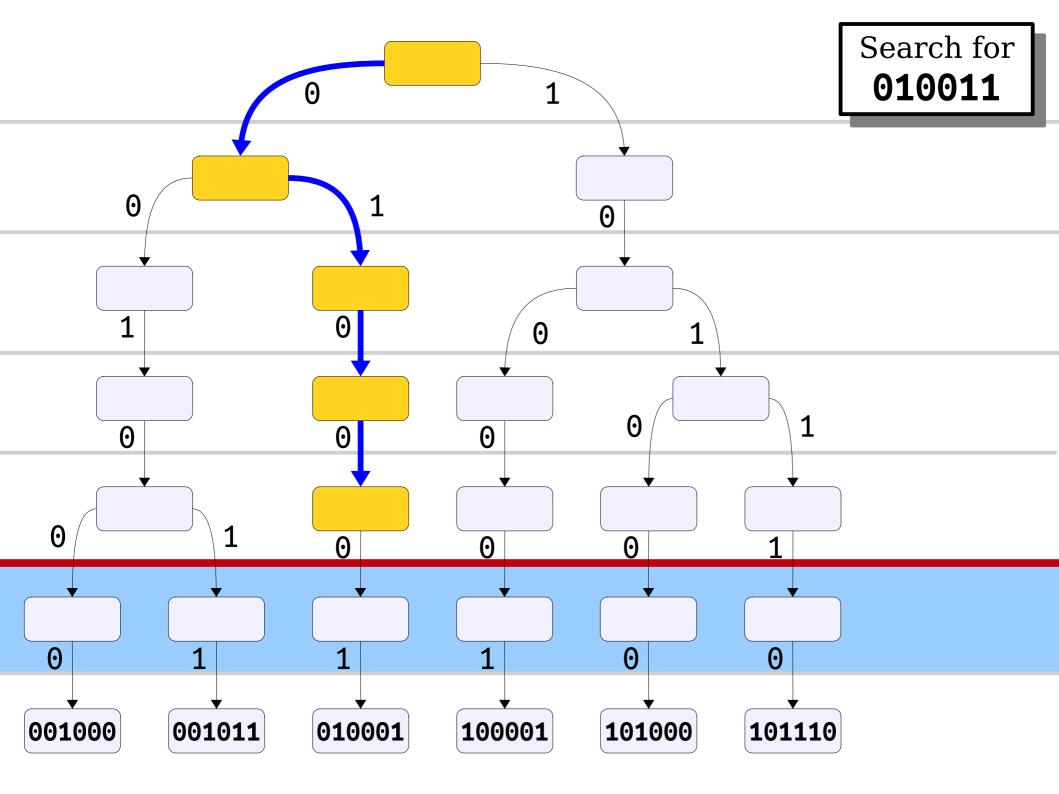


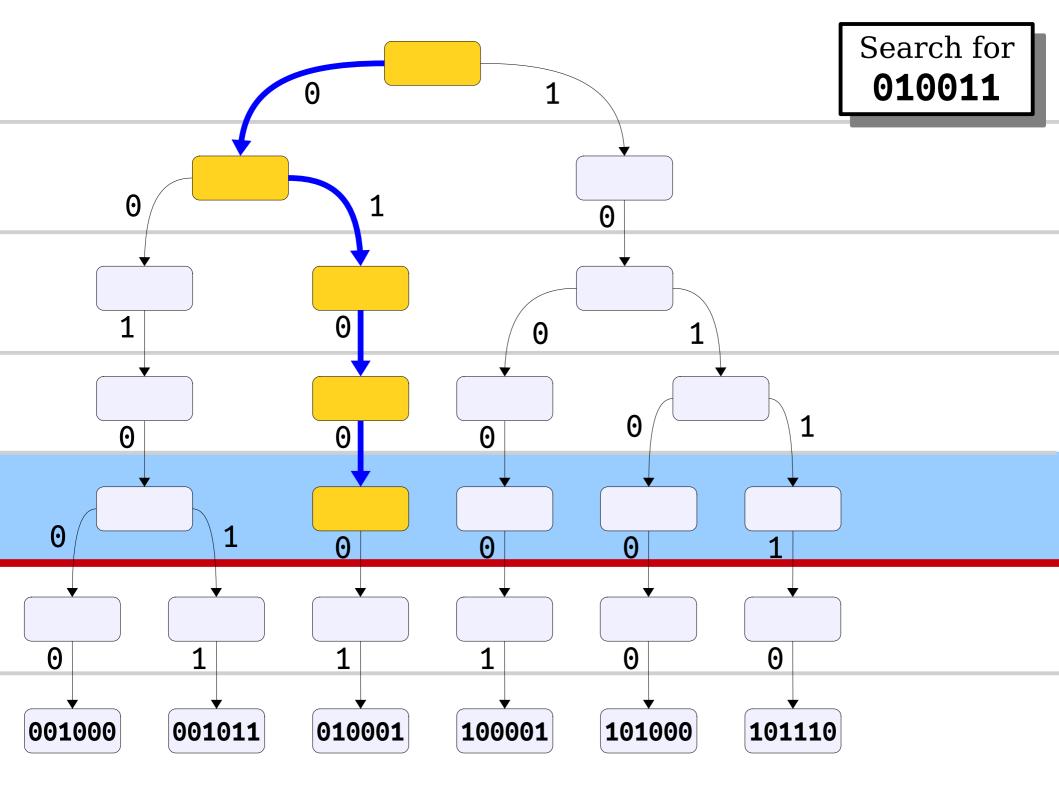


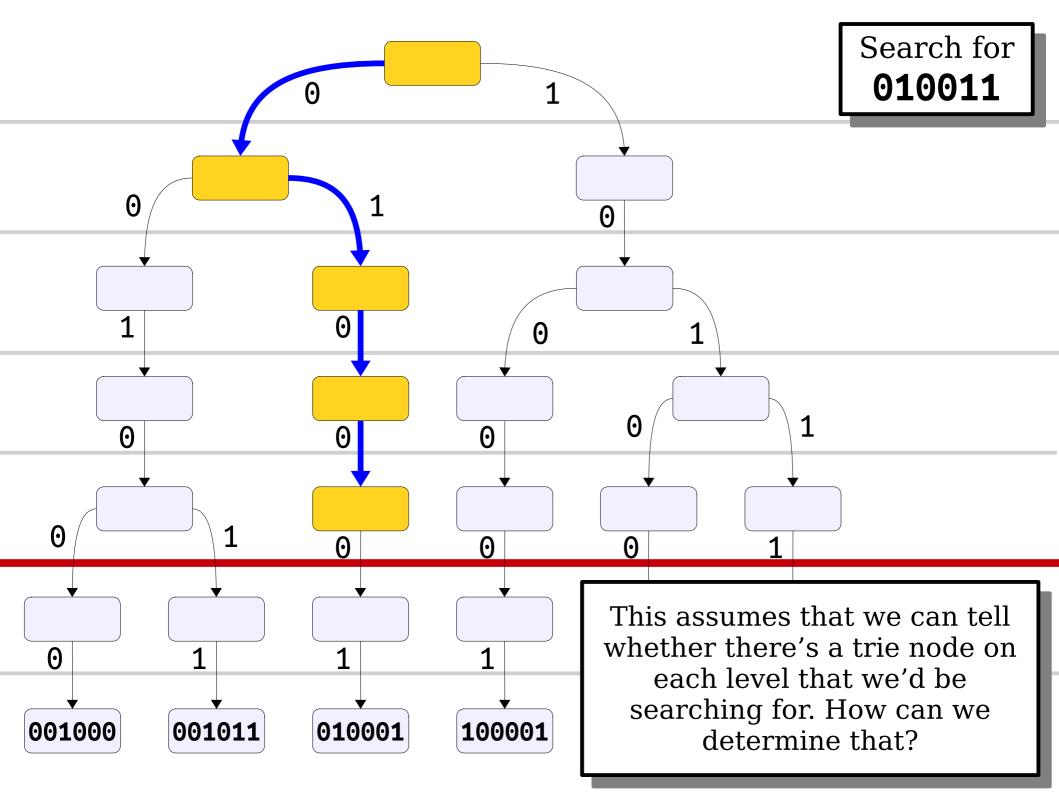


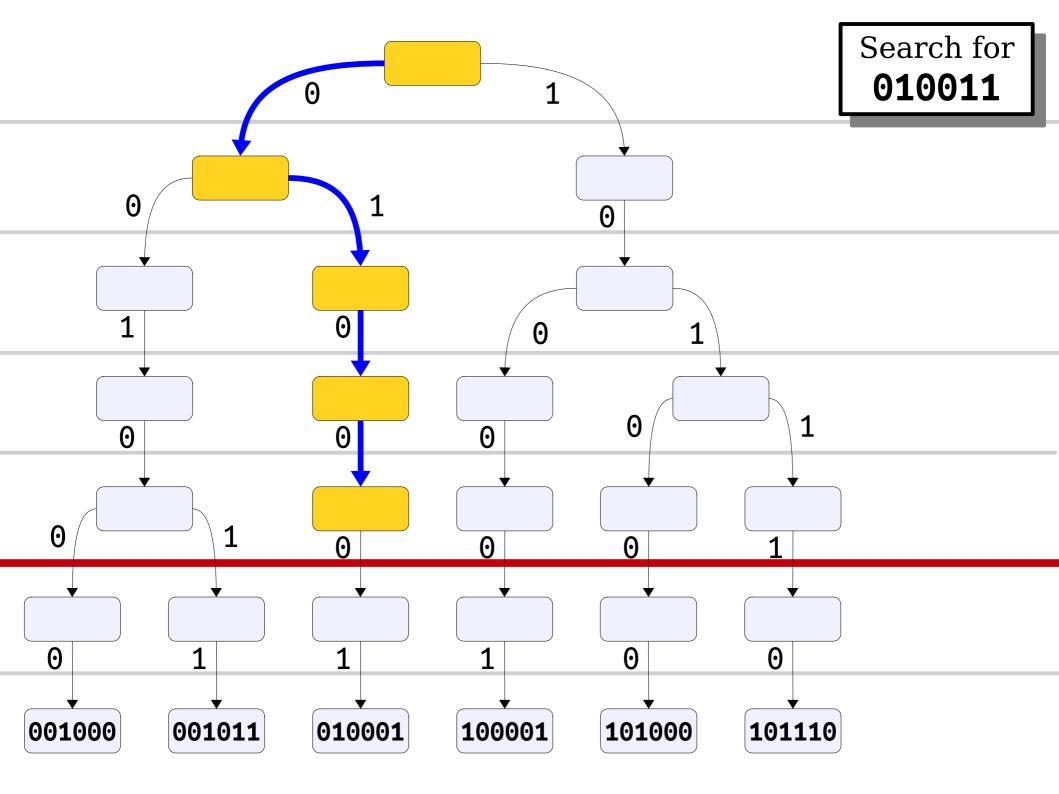


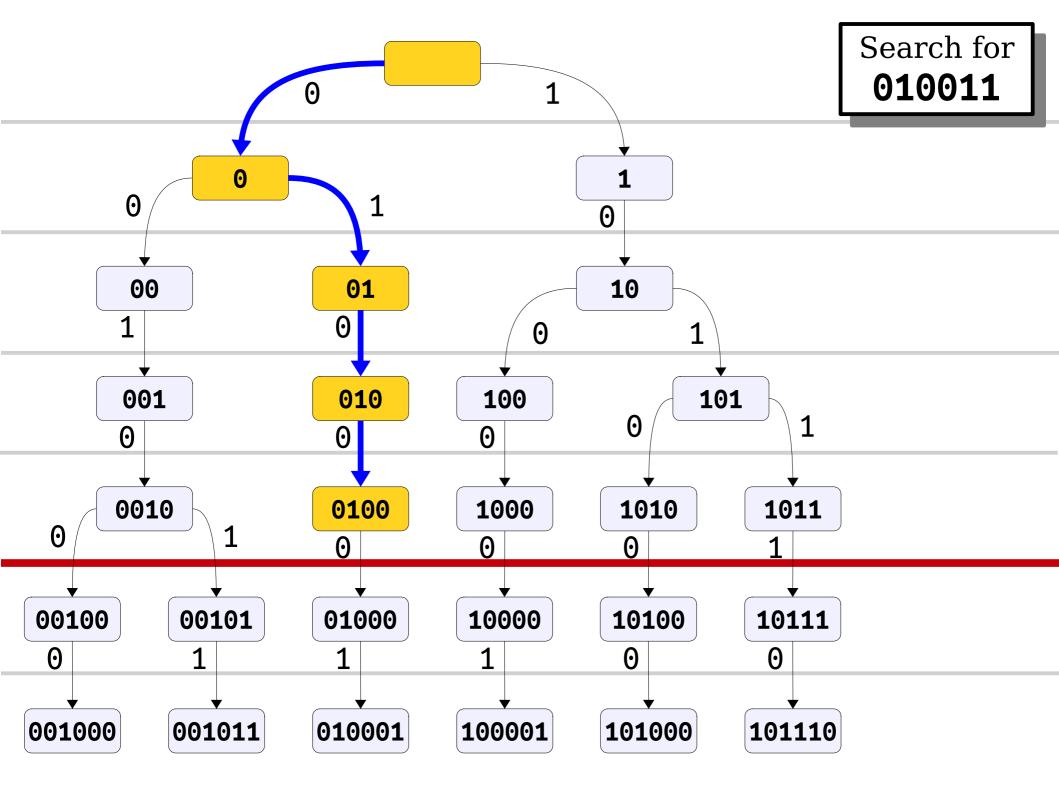


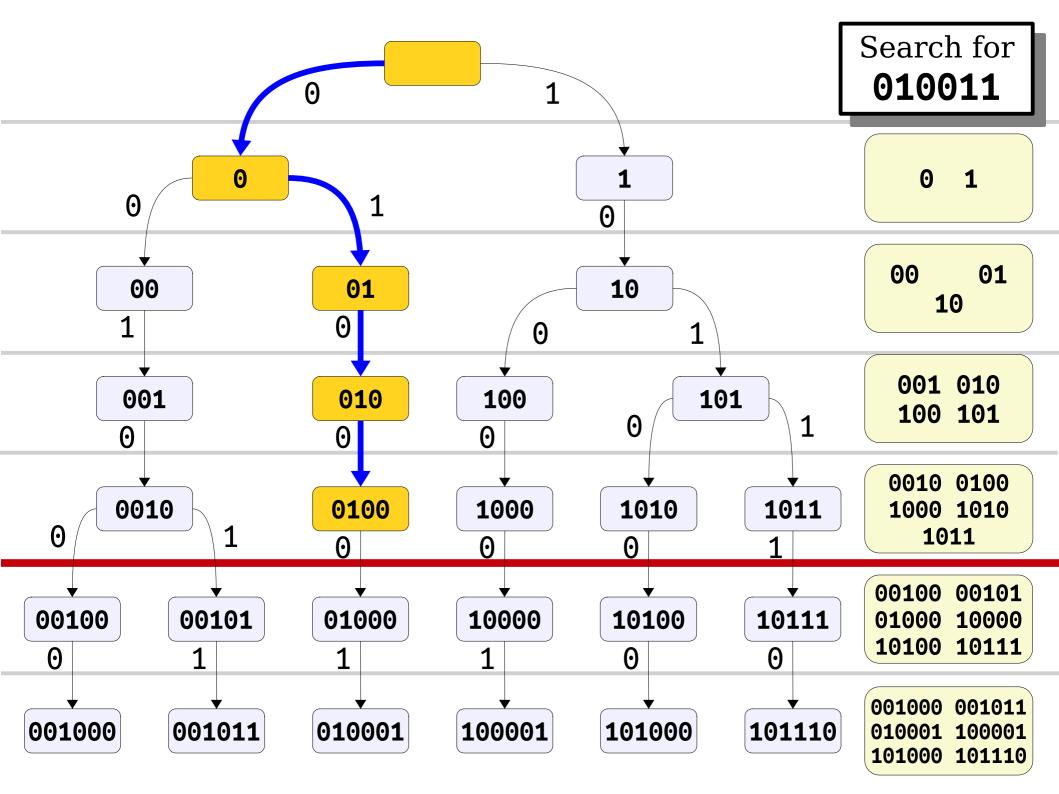


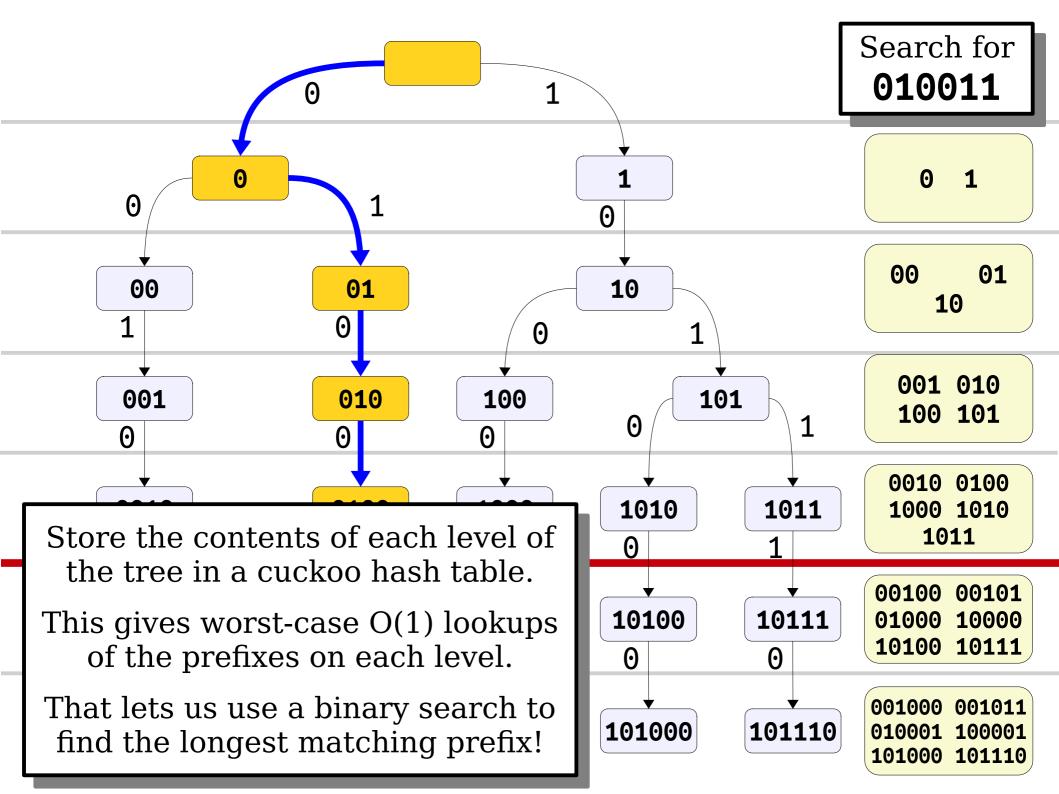












#### One Speedup

- *Goal:* Encode the trie so that we can do a binary search over its layers.
- *One Solution:* Store an array of cuckoo hash tables, one per layer of the trie, that holds all the nodes in that layer.
- Can now query, in worst-case time O(1), whether a node's prefix is present on a given layer.
- There are O(w) layers in the trie.
- Binary search will take worst-case time  $O(\log w)$ . This is *much* better than  $O(\log n)$  for any reasonable value of n.

- This binary search assumes that, given a number x and a length k, we can extract the first k bits of x in time O(1).
- Fortunately, we can do this!

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uint64_t x = /* ... */;
uint64_t mask = (uint64_t(1) << (64 - k));
uint64_t prefix = x & mask;</pre>
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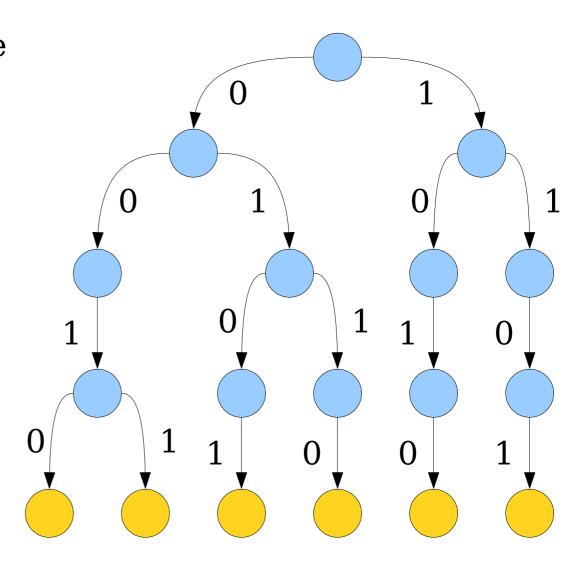
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uint64_t x = /* ... */;
uint64_t mask = ~(uint64_t(1) << (64 - k));
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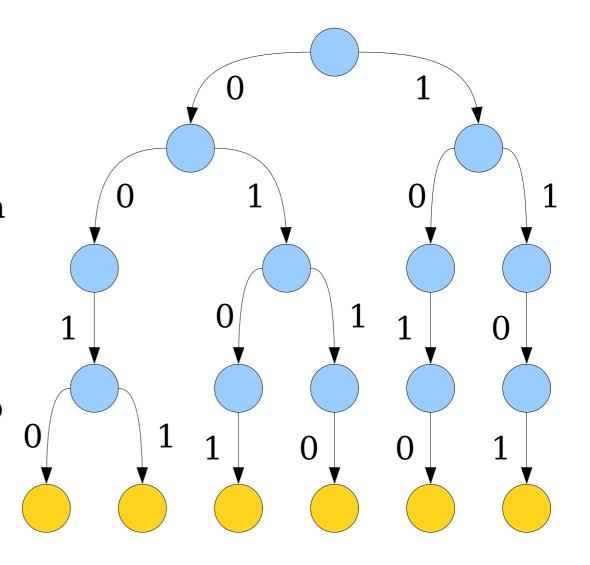
## Finding Successors

- We can now find the node where the successor search would initially arrive in time O(log w).
- At this point, we'd normally back up until we find a branching node where we can follow a 1 child pointer, then descend from there to the leaves.
- This will take time O(w).
- Can we do better?

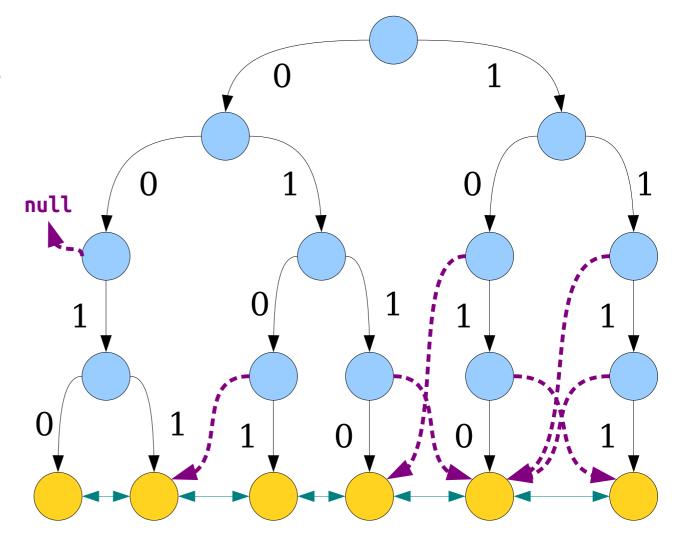


# Finding Successors

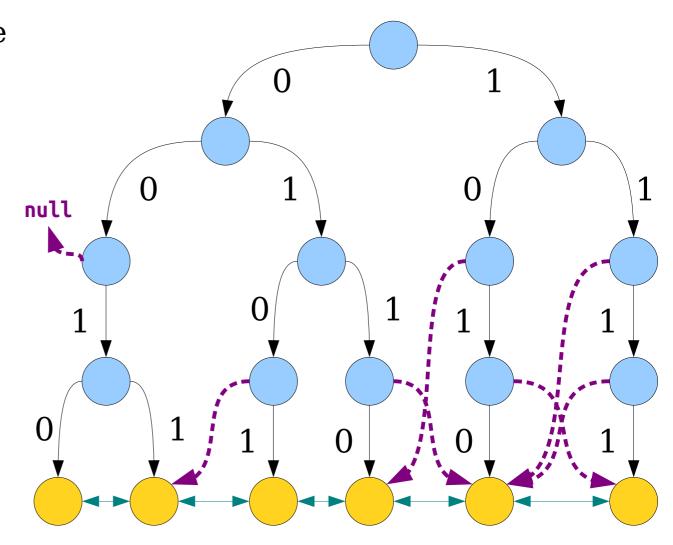
- *Claim:* If the binary search terminates at a node *v*, that node must have at most one child.
- If it doesn't, it has both a 0 child and a 1 child, so there's a longer prefix that can be matched.
- *Idea*: Steal the missing pointers and use them to speed up successor and predecessor searches.



- An x-fast trie is a modified binary trie.
- Each missing 1 pointer points to a node's successor.
- Each missing 0 pointer points to a node's predecessor.
- Each layer of the tree is stored in a cuckoo hash table for fast binary search.



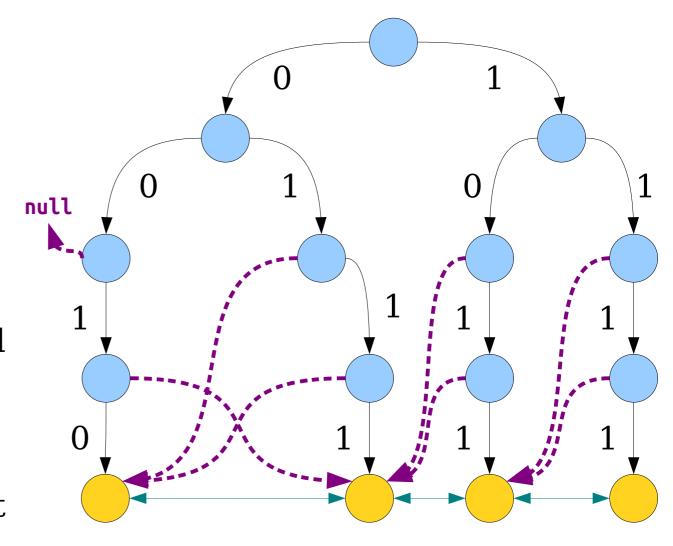
- Claim: Can determine successor(x) in time  $O(\log w)$ .
- Binary search for the longest prefix of *x*.
- If that node has a missing 1 pointer, it points to the successor.
- Otherwise, it has a missing 0 pointer.
   Follow it to a leaf, then follow the leaf's 1 pointer.



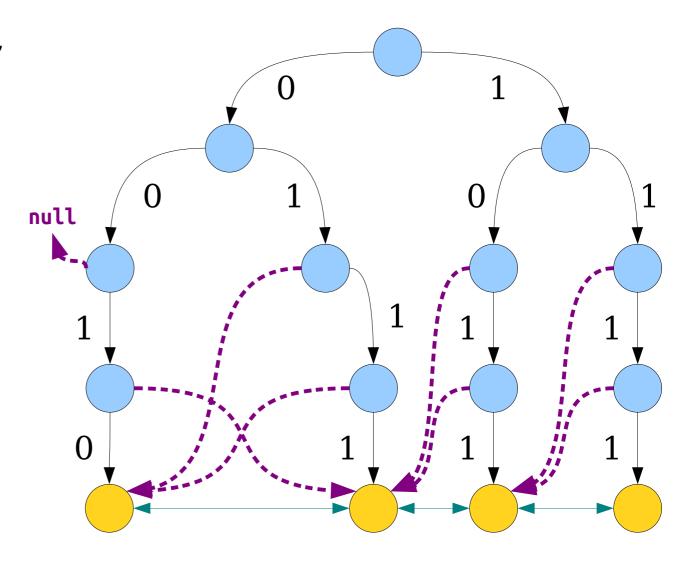
### x-Fast Trie Maintenance

- Based on what we've seen:
  - *lookup* takes worst-case time O(1).
  - successor and predecessor queries take worst-case time  $O(\log w)$ .
  - min and max can be done in time O(1), assuming we cache those values.
- How efficiently can we support *insert* and *delete*?

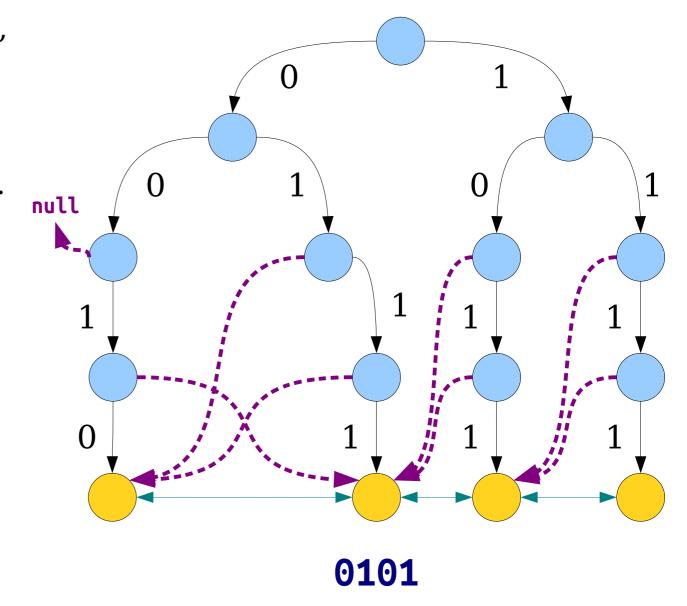
- If we insert(x), we need to
  - add some new nodes to the trie;
  - wire x into the doubly-linked list of leaves; and
  - update the thread pointers to include *x*.
- Worst-case will be  $\Omega(w)$  due to the first and third steps.



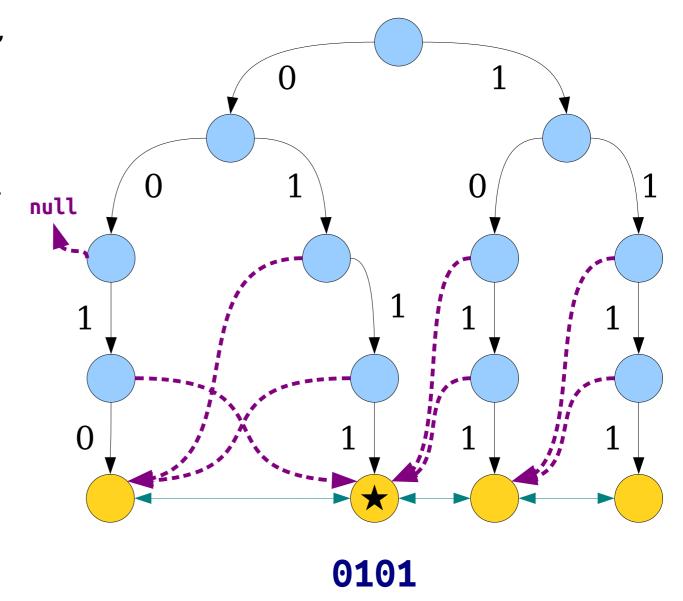
- Here is an (amortized, expected) O(w)-time algorithm for insert(x):
  - Find successor(x).
  - Add *x* to the trie.
  - Using the successor from before, wire x into the linked list.
  - Walk up from x, its successor, and its predecessor and update threads.



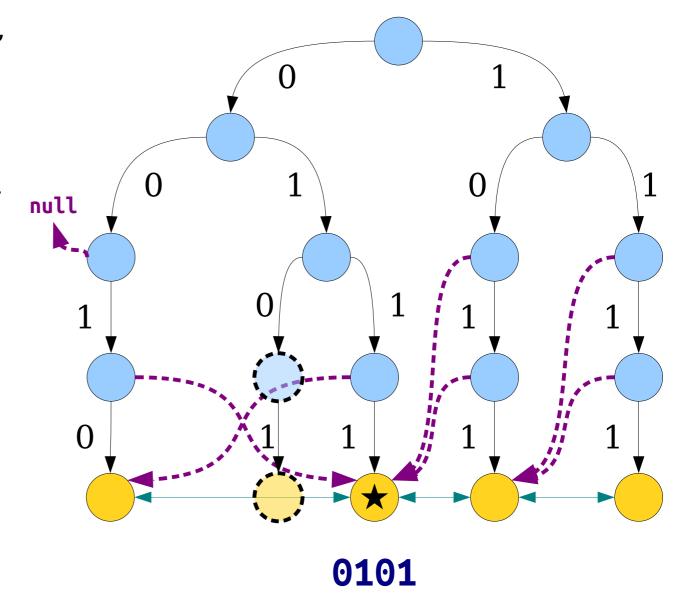
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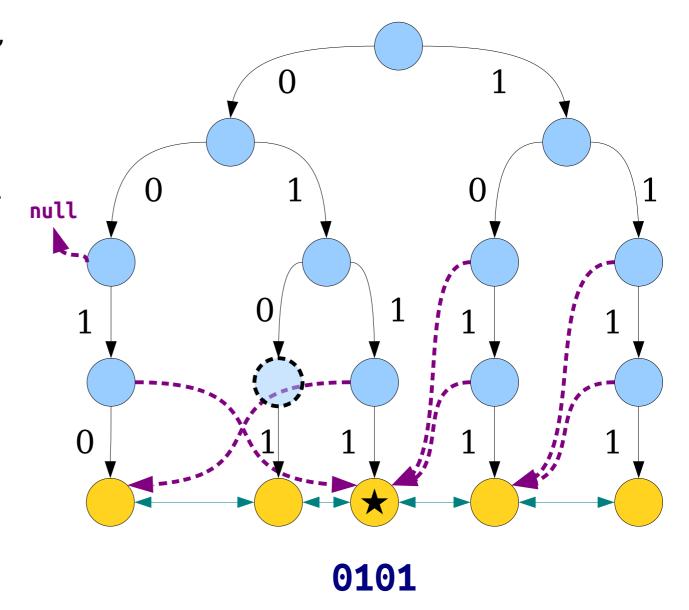
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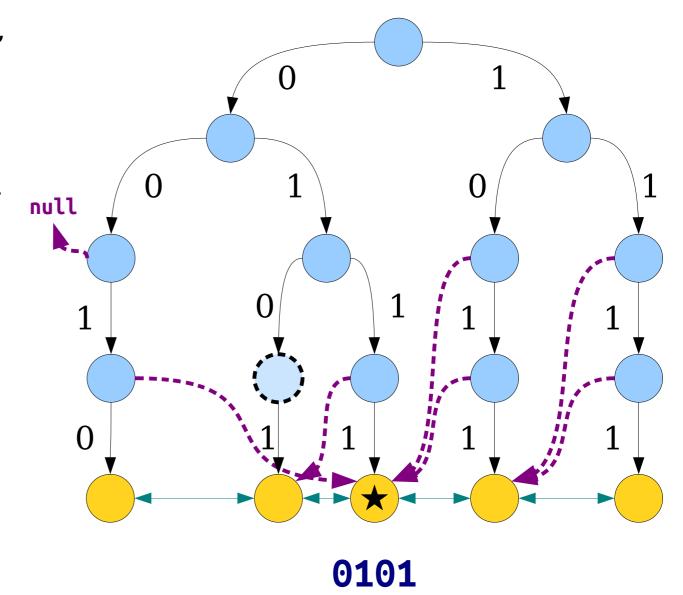
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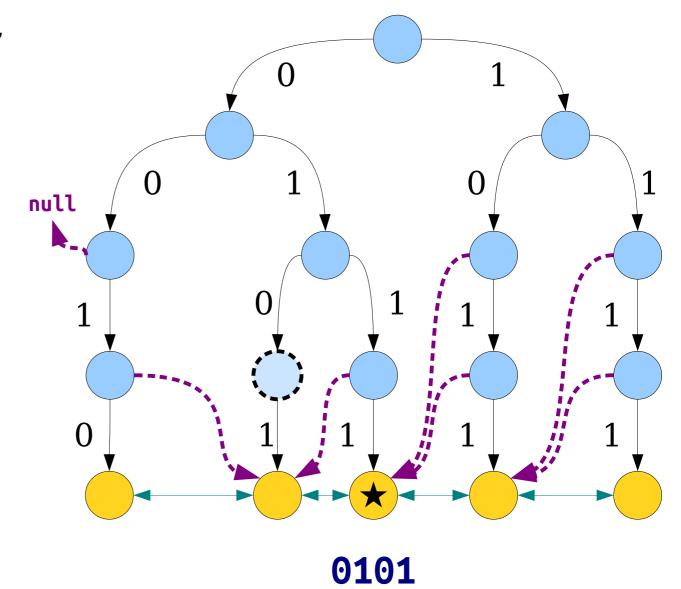
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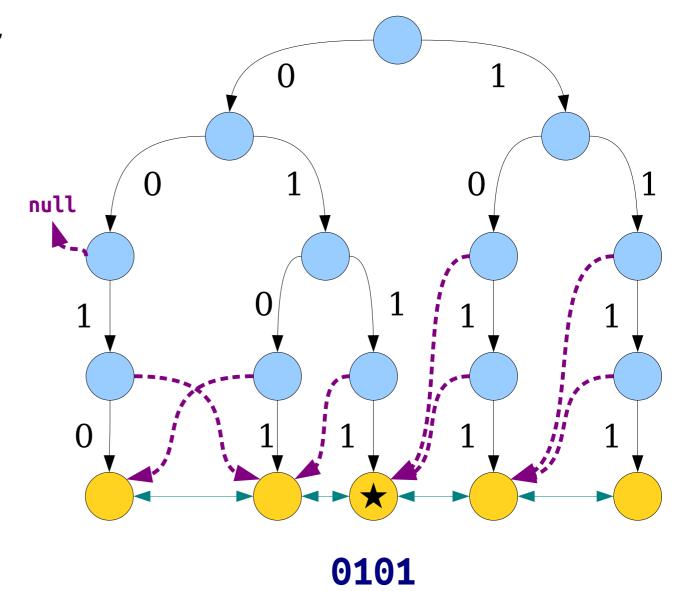
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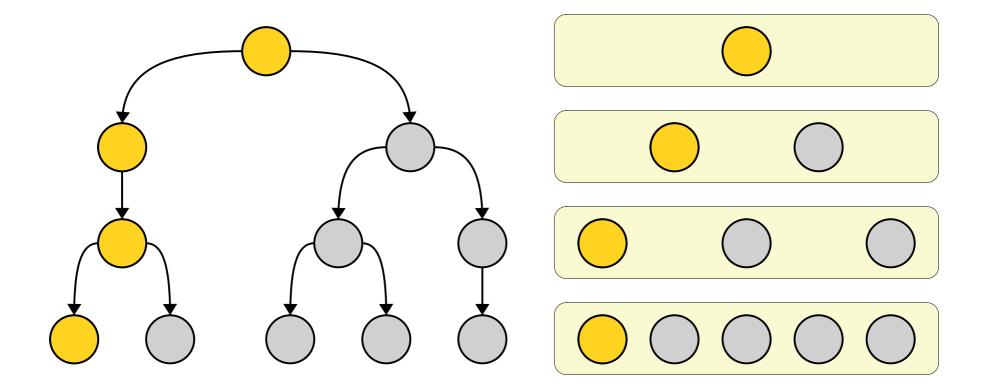


## Deletion

- To delete(x), we need to
  - Remove *x* from the trie.
  - Splice *x* out of its linked list.
  - Update thread pointers from *x*'s former predecessor and successor.
- Runs in expected, amortized time O(w).
- Full details are left as a proverbial Exercise to the Reader. ②

## Space Usage

- Each leaf node (item stored in the x-fast trie) contributes at most O(w) nodes in the trie and at most O(w) entries into the hash tables.
- Total space: O(nw).



## Where We Stand

- Right now, we have a reasonably fast data structure for storing a sorted set of integers.
- If we have a *static* set of integers that we want to make lots of queries on, this is pretty good as-is!
- As you'll see, though, we can make this even better with some kitchen sink techniques.

- *lookup*: O(1)
- insert:  $O(w)^*$
- **delete**:  $O(w)^*$
- max: O(1)
- *succ*: O(log *w*)
- *is-empty*: O(1)
- Space: O(nw)
- \* Expected, amortized

## Where We Stand

- Where is there room for improvement in this data structure?
- Ideally, we'd like to improve these highlighted costs, which are places where this structure currently is beaten by a standard BST.

- *lookup*: O(1)
- *insert*: **O**(*w*)\*
- **delete**: **O**(**w**)\*
- max: O(1)
- *succ*: O(log *w*)
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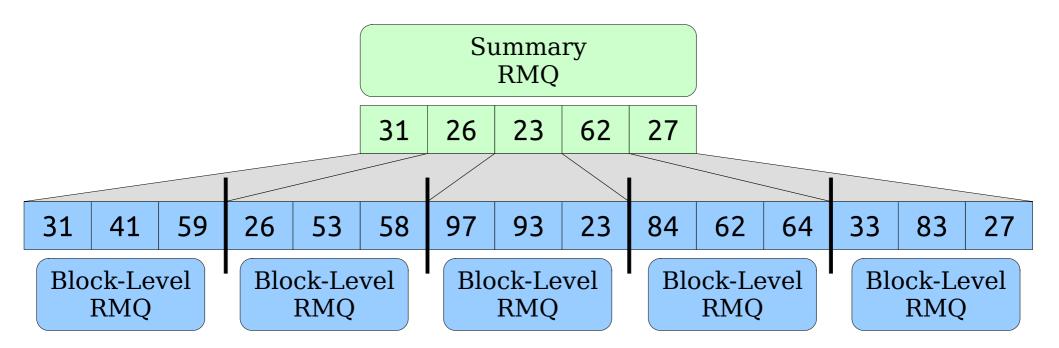
# Shaving Off Logs

- We're essentially at a spot where we need to shave off a factor of w from a couple of operations.
- Figure that w is kinda sorta ish like log n, so this is like shaving off a log factor.
- Question: What techniques have we developed so far to do this?

- *lookup*: O(1)
- *insert*: **O**(*w*)\*
- **delete**: **O**(**w**)\*
- *max*: O(1)
- *succ*: O(log *w*)
- *is-empty*: O(1)
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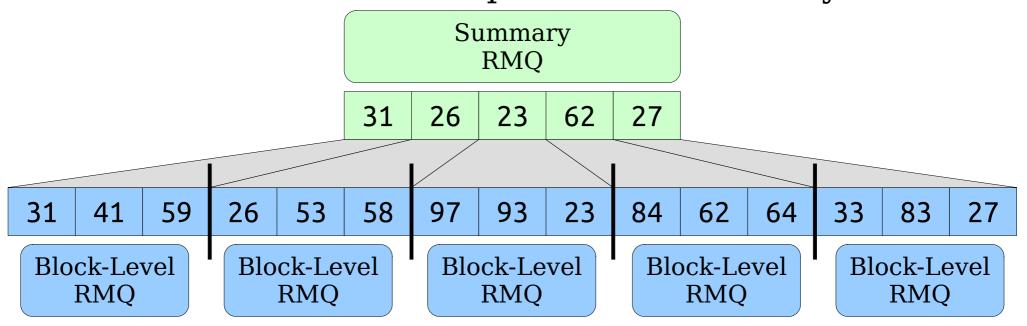
## Two-Level Structures

- Think back to the hybrid approach we used for solving RMQ.
- It consisted of a two-tiered structure:
  - A bunch of small, lower-level structures that each solve the problem in small cases.
  - A single, larger, top-level structure that helps aggregate those solutions together.



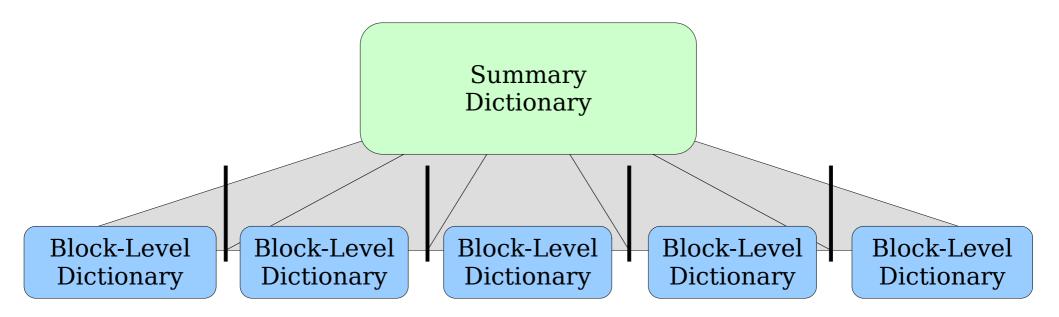
## Two-Level Structures

- *Main Idea:* Partition the input into blocks that are really, really small.
- Small blocks make the block-level structures run quickly.
- Assuming they're not "too small," small blocks reduce the size of the inputs to the summary as well.



## The Idea

- Build a two-level ordered dictionary out of existing ordered dictionaries.
- Split the keys apart into logarithmic-sized blocks.
- Build ordered dictionaries for each of the block-level dictionaries.
- Build a summary dictionary to aggregate the blocks together.



The *y*-Fast Trie

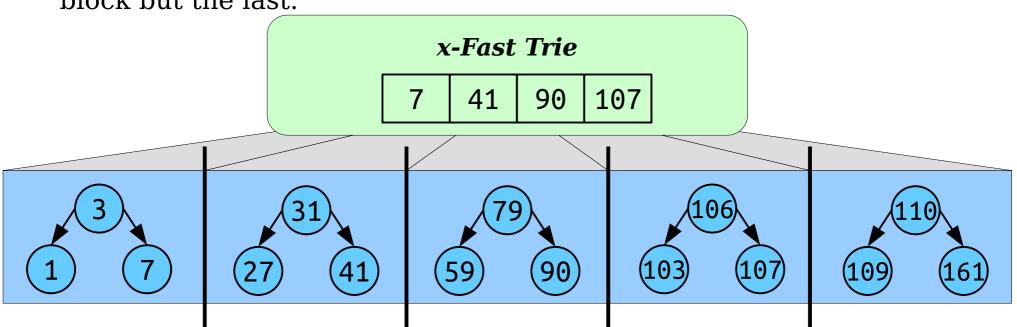
## The Setup

- For now, assume all keys are given to us in advance, in sorted order.
- Split the keys apart into blocks of size  $\Theta(w)$  and store them in balanced BSTs.

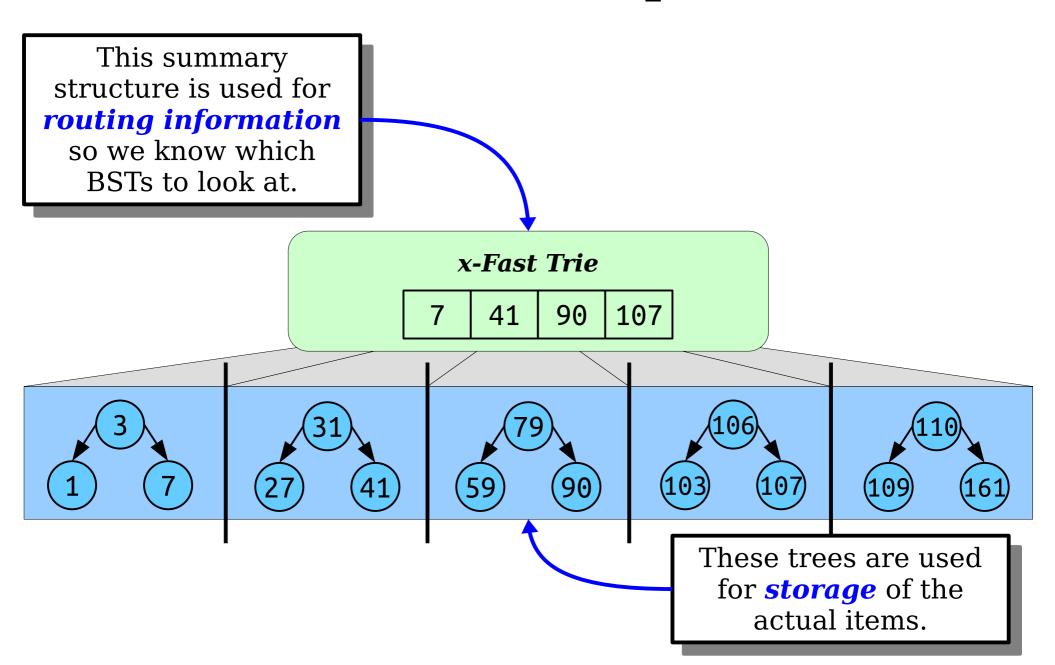


## The Setup

- For now, assume all keys are given to us in advance, in sorted order.
- Split the keys apart into blocks of size  $\Theta(w)$  and store them in balanced BSTs.
- Create a summary *x*-fast trie that stores the maximum key from each block but the last.



## The Setup



# Performing a Lookup

• Suppose we want to perform *lookup*(90).

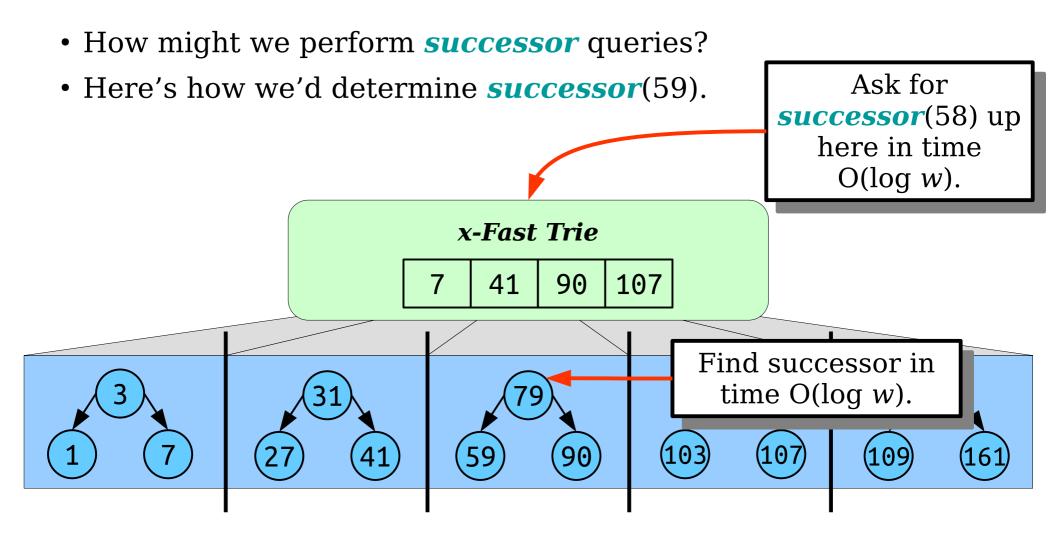
• *Idea*: figure out which block 90 would belong to, then search within the BST in that block. Ask for • Cost: **O(log w)**. successor(89) up here in time  $O(\log w)$ . x-Fast Trie 90 107 41 90 41 (107)59 Search this BST in time  $O(\log w)$ .

# Performing a Lookup

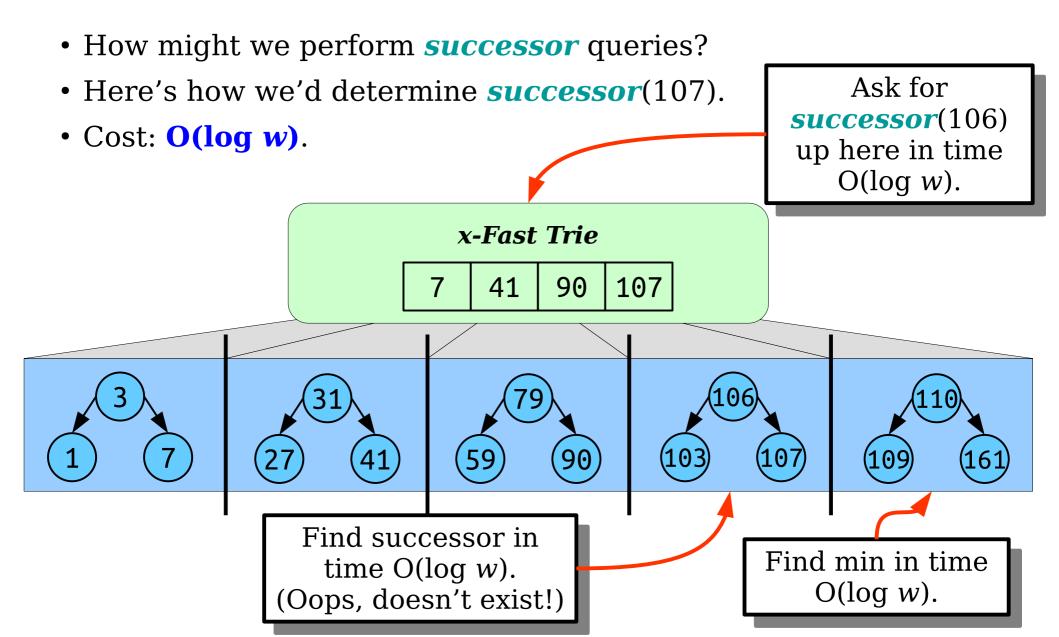
• Suppose we want to perform *lookup*(110).

• *Idea*: figure out which block 109 would belong to, then search within the BST in that block. Ask for • Cost:  $O(\log w)$ . successor(109) in time  $O(\log w)$ . (Oops, doesn't exist!) x-Fast Trie 107 41 90 90 41 59 (103)(107)Search this BST in time  $O(\log w)$ .

## Successor Queries



## Successor Queries



 With a major caveat, insertions follow the same procedure as before. Ask for • Here's how we'd **insert**(6) **successor**(5) in time  $O(\log w)$ . **insert** into this BST in time x-Fast Trie  $O(\log w)$ 107 41 90 (90) (41)(59)(107) (103)

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 With a major caveat, insertions follow the same procedure as before. Ask for • Here's how we'd *insert*(4) **successor**(3) in time  $O(\log w)$ . **insert** into this BST in time x-Fast Trie  $O(\log w)$ 107 41 90 (90)41 (107)(59) (103)

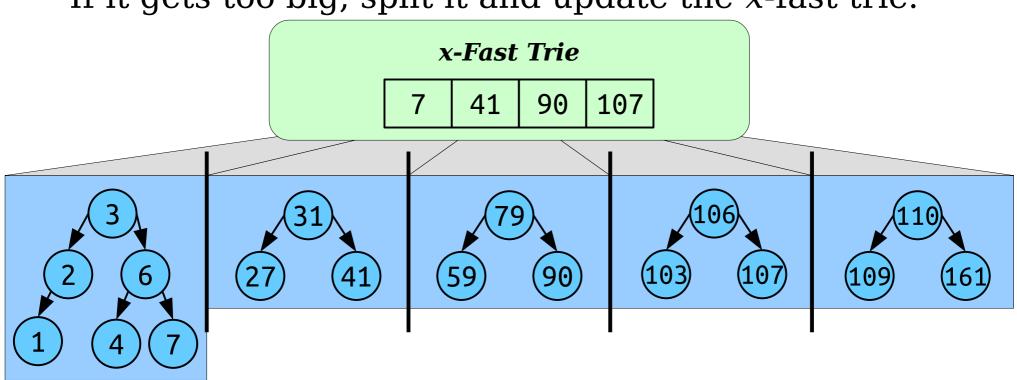
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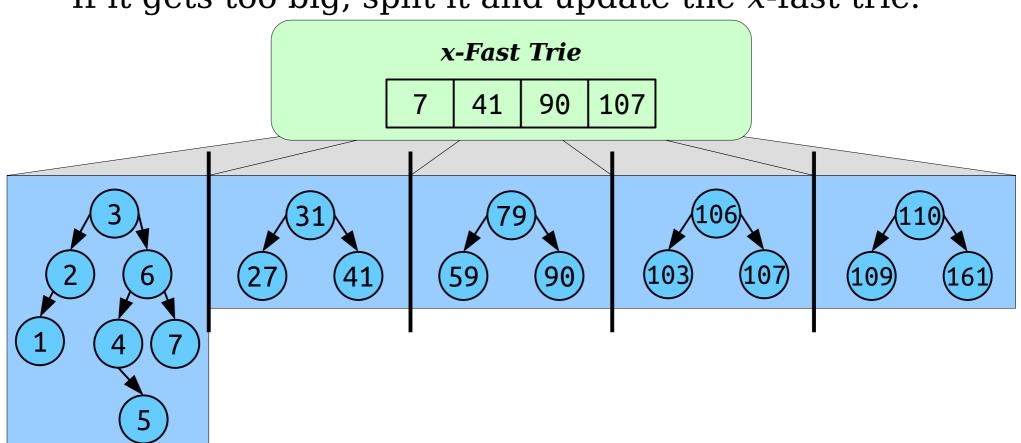
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## The Problem

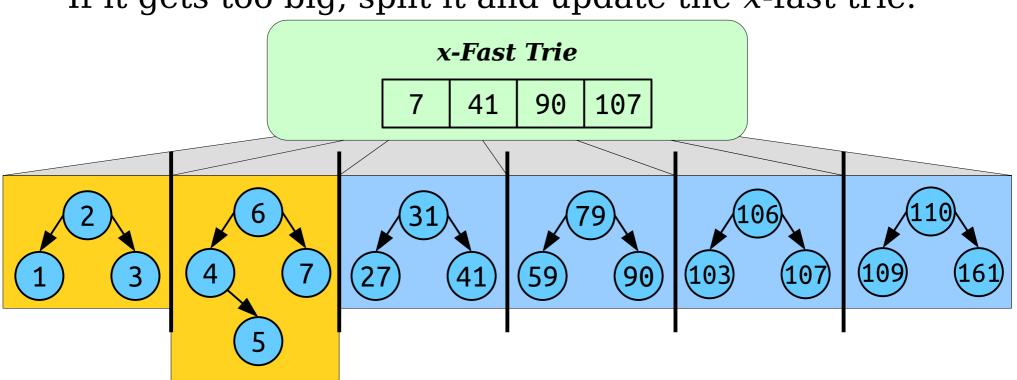
- If our trees get too big, we may lose our O(log w) time bound. (Why?)
- *Idea*: Require each tree to have at most 2*w* elements. If it gets too big, split it and update the *x*-fast trie.



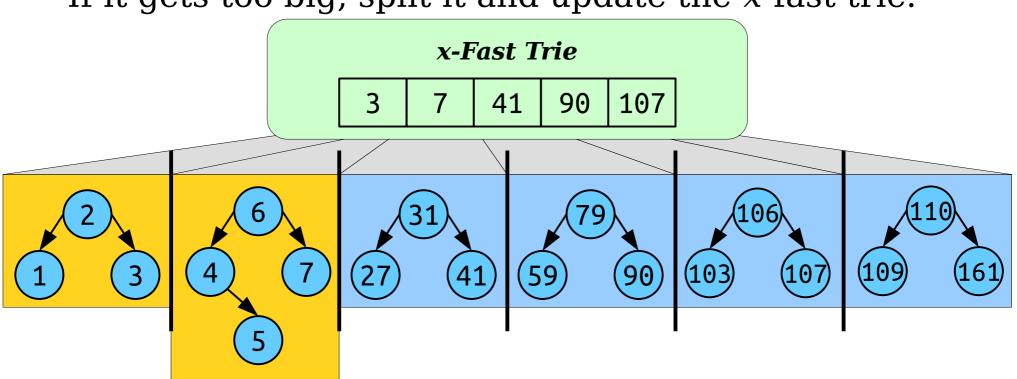
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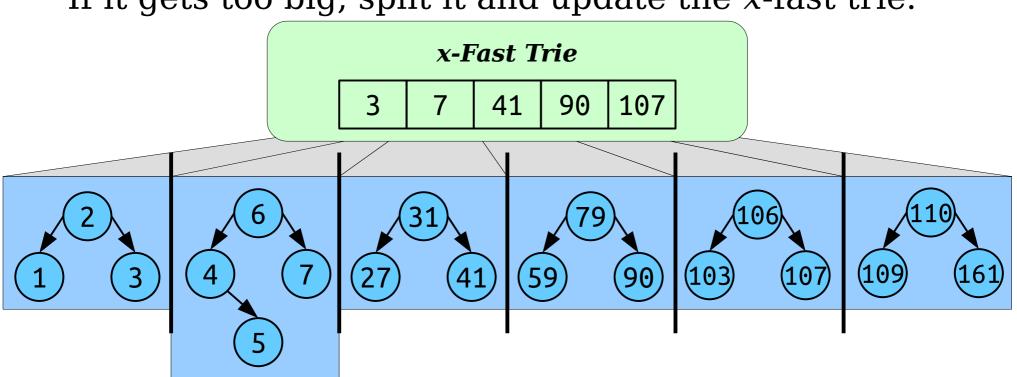
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## Analyzing an Insertion

- If we perform an *insert* and don't end up doing a resize, the cost is O(log w).
- If we perform an *insert* and *do* have to do a resize, the work done is
  - O(log w) to split the binary search tree (say, using a splay tree), and
  - O(w) to insert into the *x*-fast trie.
- Total work: O(w).

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  - O(log w) to *split* the binary search tree (say, using a splay tree), and
  - O(w) to insert into the x-fast trie.
- Total work: O(w).

But this is uncommon!
We only do this if a tree
got way too big.

## An Amortized Analysis

- Whenever we do an insertion, place a credit on the newly-inserted element.
  - Cost of a "light" *insert* still O(log w).
- If we have to split a tree, the tree size was above 2w, so there must be w credits on it (one for each element above w).
- The *amortized* cost of a "heavy" insert is then

$$O(\log w) + O(w) - \Theta(w) = O(\log w).$$

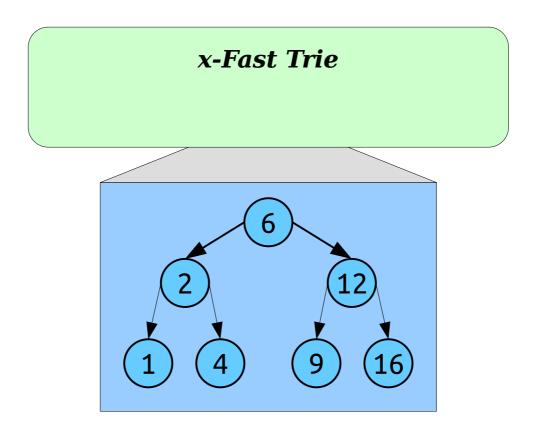
Cost of a regular insert, plus the tree split.

Cost of adding to the *x*-fast trie.

Credits spent.

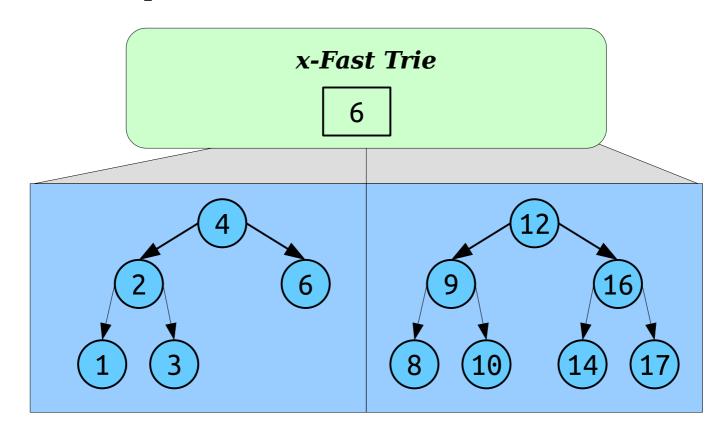
### A Nice Side-Effect

- We can now abandon our assumption that we're given all the keys in sorted order in advance.
- Each insertion takes amortized time O(log *w*), so we can build the structure up from scratch!



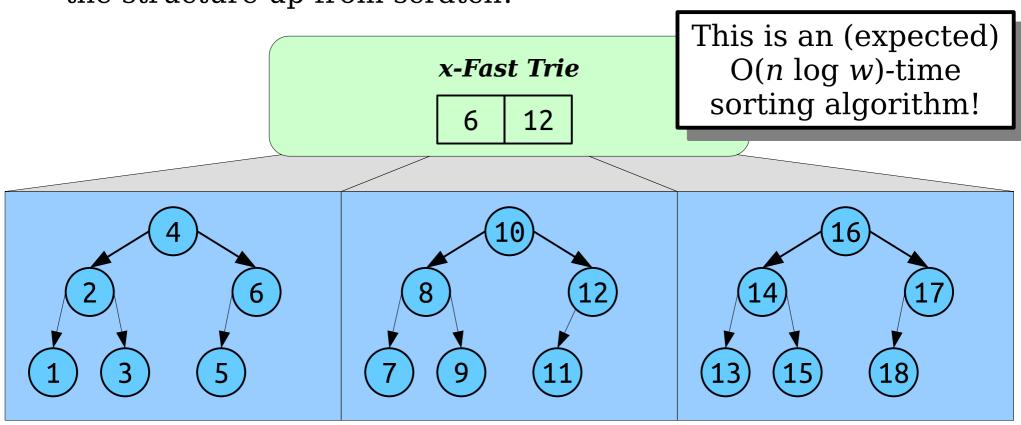
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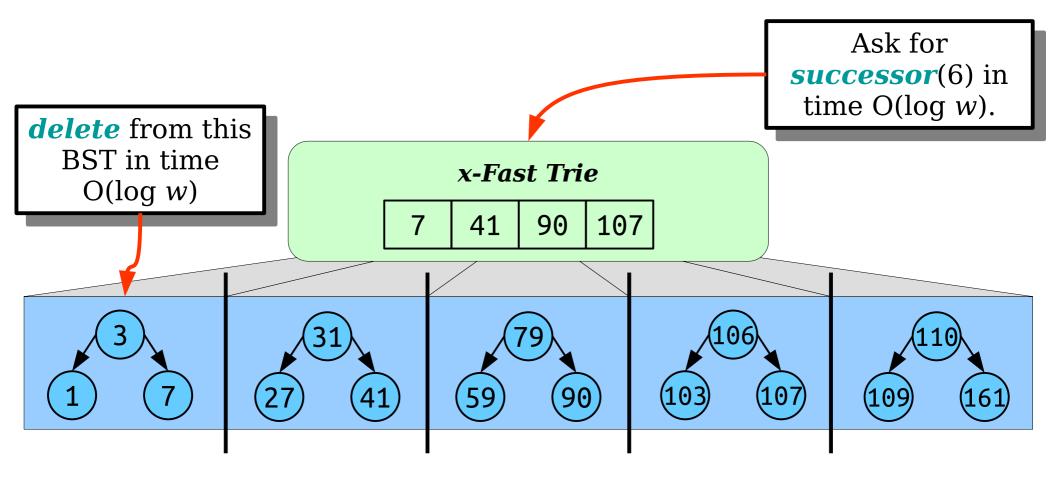


# Making Edits

- With a major caveat, deletions follow the same procedure as insertions.
- Here's how we'd *delete*(7).

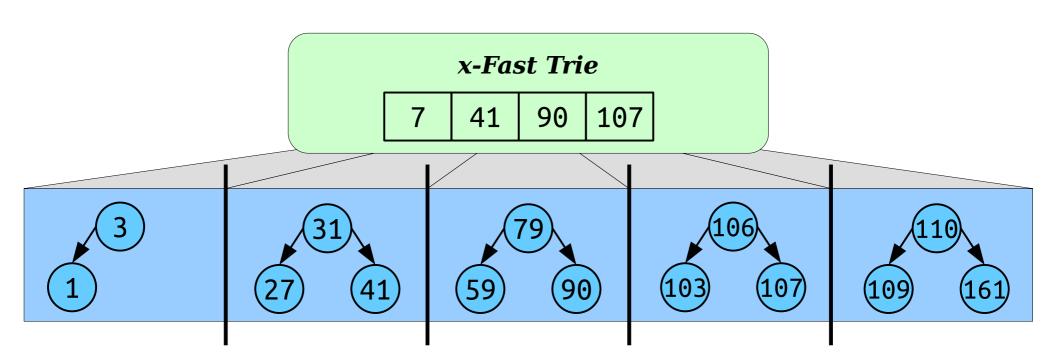
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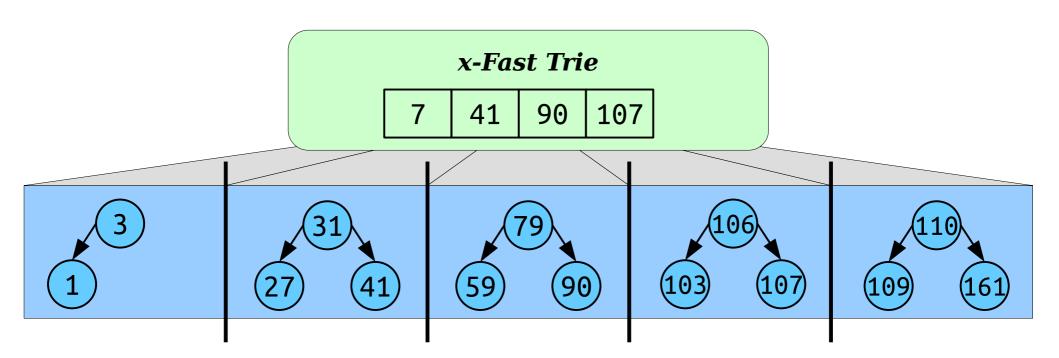
## Making Edits

- Our *x*-fast trie still holds 7, even though 7 is no longer present.
- That's not a problem those keys just serve as "routing information" to tell us which BSTs to look at.
- *Intuition:* The *x*-fast trie keys act as partitions between BSTs. They don't need to actually be present in our data structure.



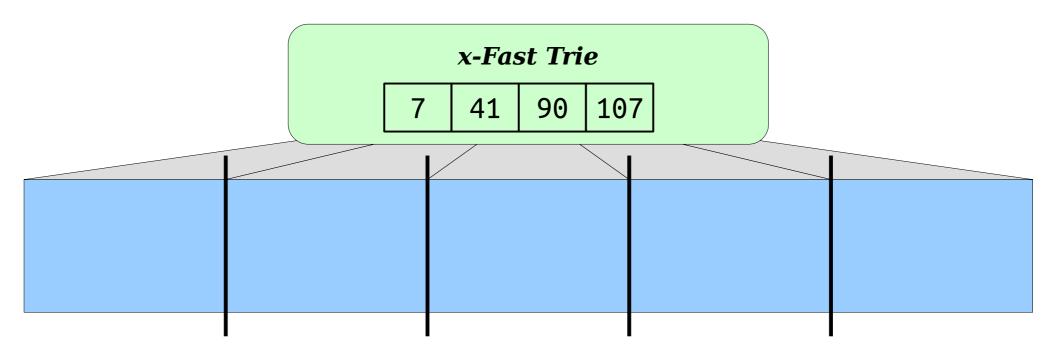
# Shrinking our Structure

• What happens if we remove all the elements from our structure without touching the *x*-fast trie?



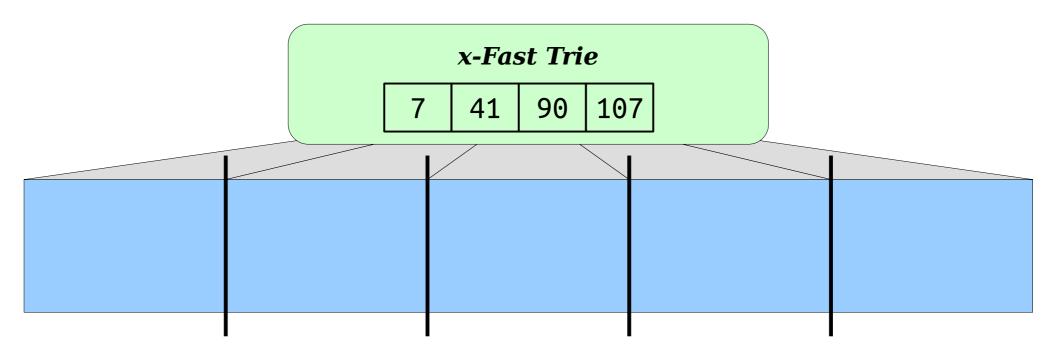
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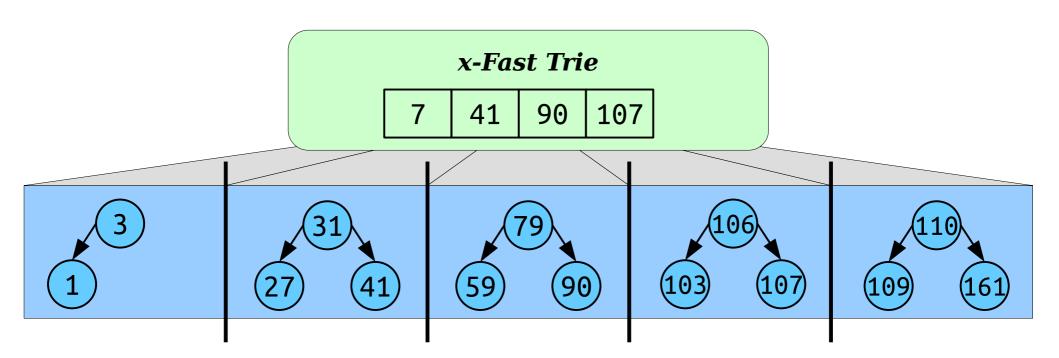
# Shrinking our Structure

- What happens if we remove all the elements from our structure without touching the *x*-fast trie?
- Each operation still takes time  $O(\log w)$ .
- But now our space usage depends on the maximum size we reached, not the current size!



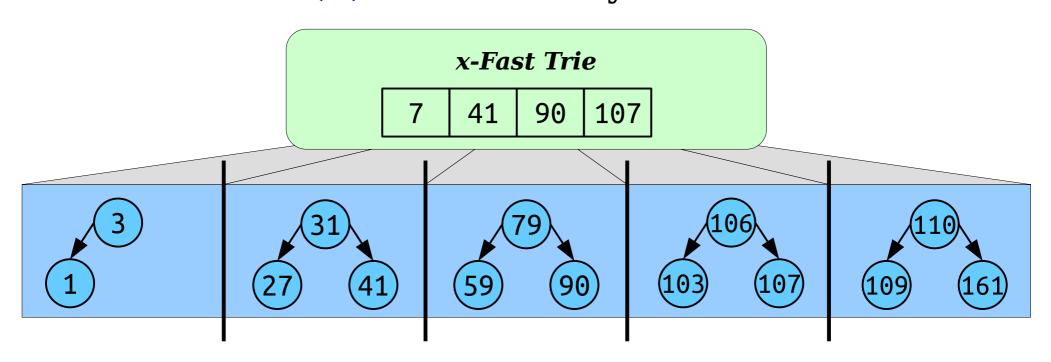
# Achieving a Balance

- *Invariant:* Require each tree to have between  $\frac{1}{2}w$  and 2w elements.
- If a tree gets too small:
  - Merge with the tree next to you, editing the *x*-fast trie as appropriate.
  - If the resulting tree is too big, split it in half, editing the *x*-fast trie.
- This does O(w) on the *x*-fast trie only once every  $\Theta(w)$  operations, so this amortizes out to  $O(\log w)$  work per operation.



# Achieving a Balance

- If each tree has  $\Theta(w)$  elements in it, then our space usage is
  - $\Theta(n)$  for all the trees, plus
  - $\Theta((n / w) w) = \Theta(n)$  for the x-fast trie,
- This uses  $\Theta(n)$  total memory.



### What We've Seen

- Here's the final scorecard for the y-fast trie.
- Assuming  $n = \omega(w)$ , which it probably is, this is faster than a binary search tree!
- And it gives rise to an O(n log w)-expectedtime sorting algorithm!

#### The y-Fast Trie:

- *lookup*: O(log *w*)
- insert:  $O(\log w)^*$
- **delete**:  $O(\log w)^*$
- max: O(log w)
- *succ*: O(log *w*)
- Space:  $\Theta(n)$ 
  - \* Expected, amortized.

### What We Needed

- An *x*-fast trie requires *tries* and *cuckoo hashing*.
- The y-fast trie requires amortized analysis and split/join on balanced BSTs.
- y-fast tries also use the "blocking" technique from *RMQ* we used to shave off log factors.

# What's Missing

- There's still a little gap between where BSTs dominate and where *y*-fast tries take over.
  - Specifically, what if  $n = \Theta(w)$ ?
- Our solution still involves randomness.
  - We need that in the cuckoo hash tables at each level.
- *Question:* Can we build a solution with neither of these weaknesses?

### Next Time

#### • Word-Level Parallelism

Treating arithmetic as parallel computation.

#### Sardine Trees

• A fast ordered dictionary for truly tiny integers.

### • Finding the Most Significant Bit

• An astonishing algorithm for a deceptively tricky problem.