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.
- We'll assume our integers are drawn from some set [U], where $\lg U = O(w)$.
 - In other words, we assume our integers fit into a constant number of machine words.
- We'll assume that the C integer operators work in constant time, and will not assume we have access to operators beyond them.

Ordered Dictionaries

Ordered Dictionaries

- An *ordered dictionary* maintains a set S drawn from an ordered universe \mathscr{U} and supports these operations:
 - *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 maximum or minimum 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.
- For context:

Ordered Dictionary : BST :: Queue : Linked List

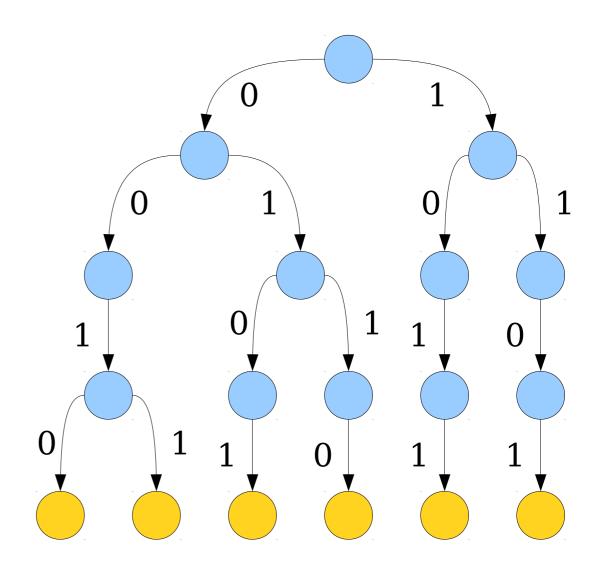
Ordered Dictionaries

- Balanced BSTs support all ordered dictionary operations in time $O(\log n)$ each.
- Hash tables support insertion, lookups, and deletion in expected time O(1), but require time O(n) for max, min, successor, and predecessor.
- Question: Can we improve upon these bounds if we know that we're working with integers drawn from [U]?

A Start: Bitwise Tries

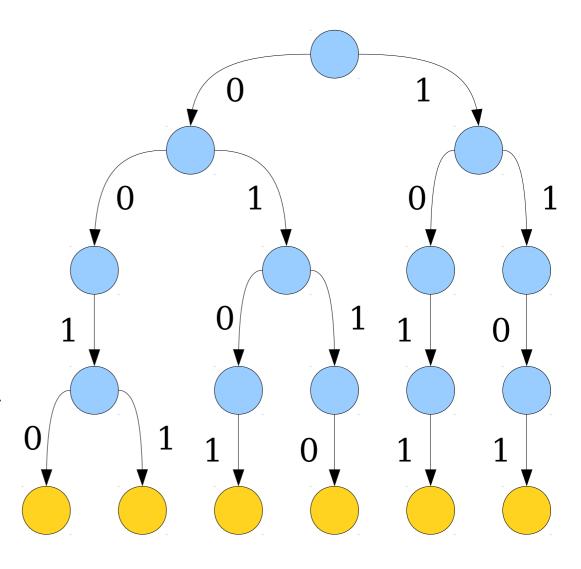
Tries Revisited

- **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*.



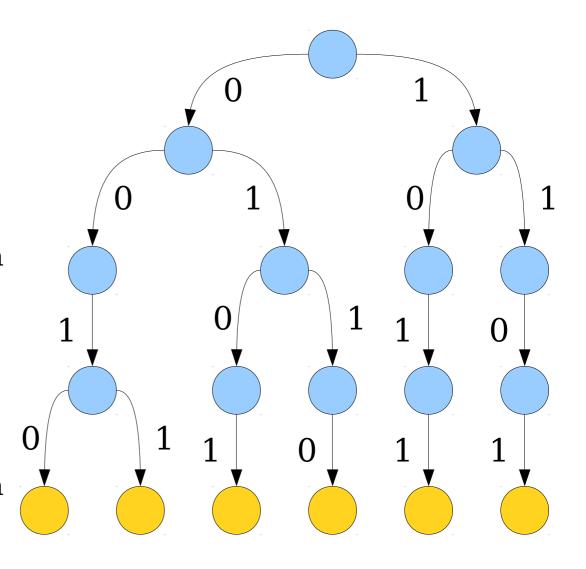
Finding Successors

- 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.



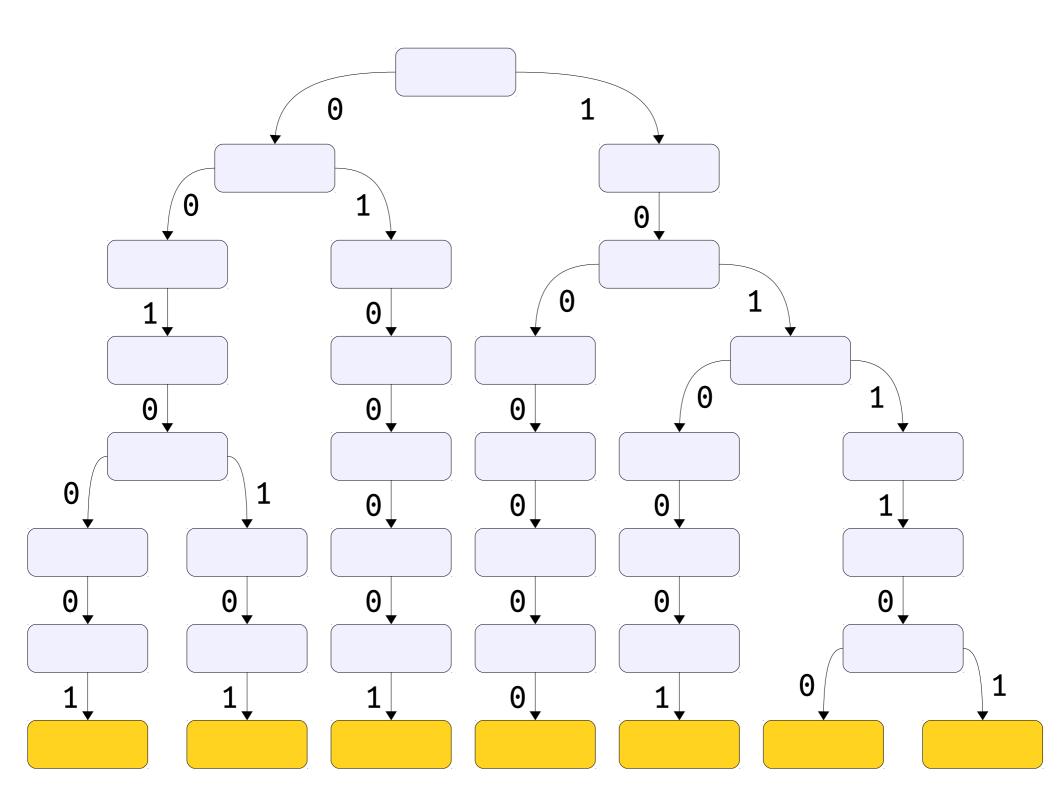
Bitwise Trie Efficiency

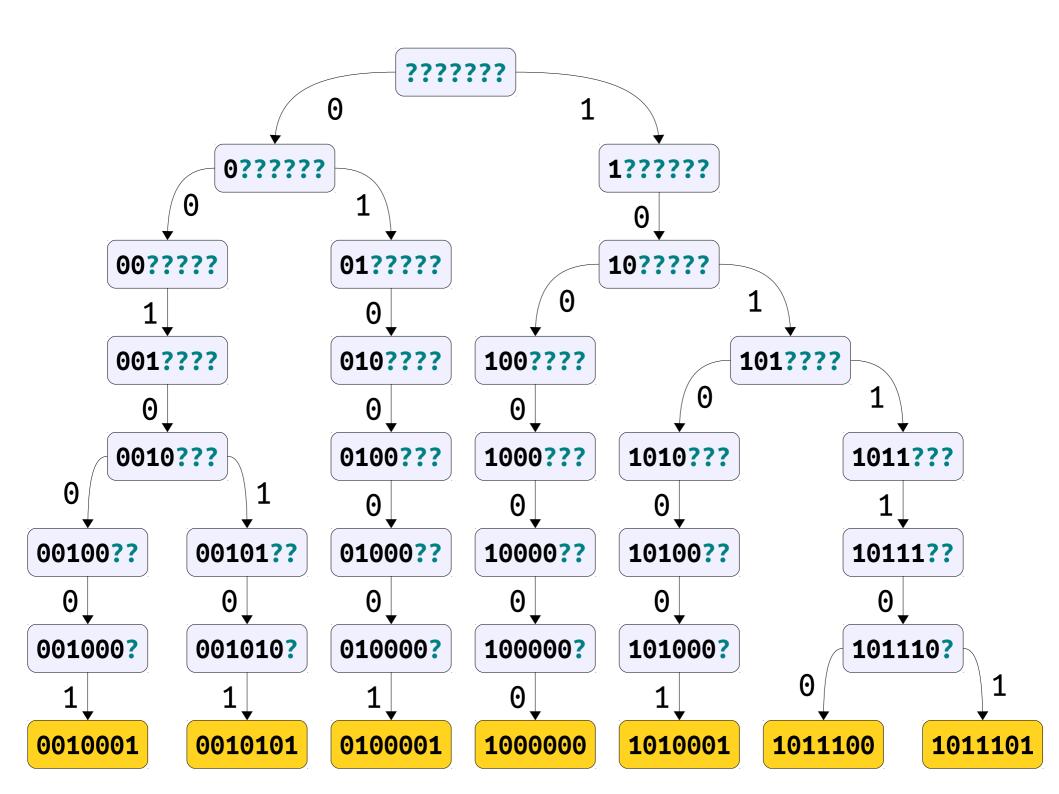
- All operations on bitwise tries take time proportional to the number of bits in each number.
- Runtime for each operation: $O(\log U)$.
 - This is probably worse than $O(\log n)$.
- For each number stored, we need to store $\Theta(\log U)$ internal nodes.
- Space usage: $O(n \log U)$.
 - This is probably worse than a BST.
- Can we do better?

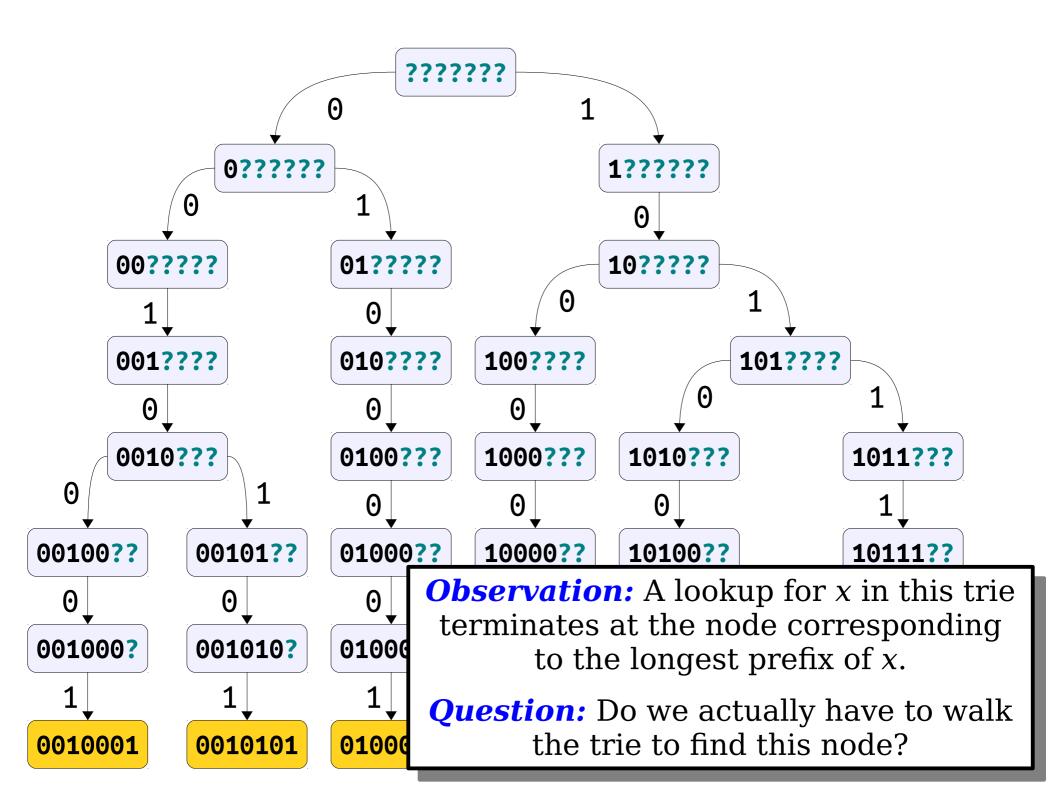


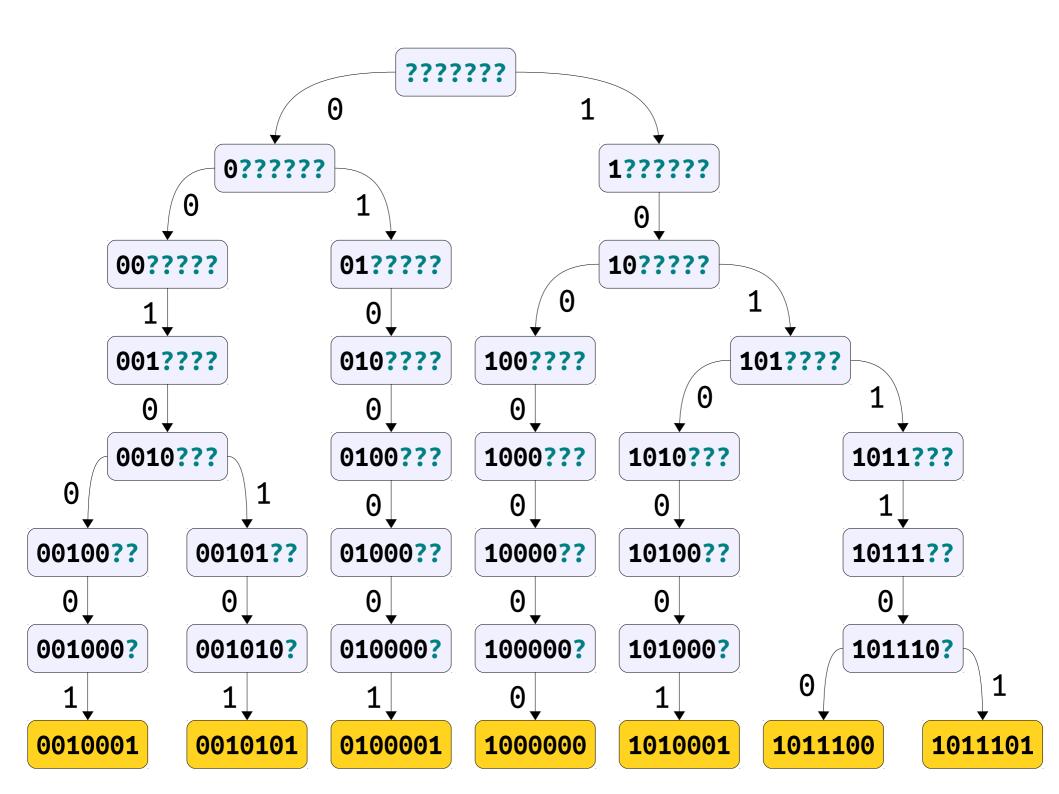
Speeding up Successors

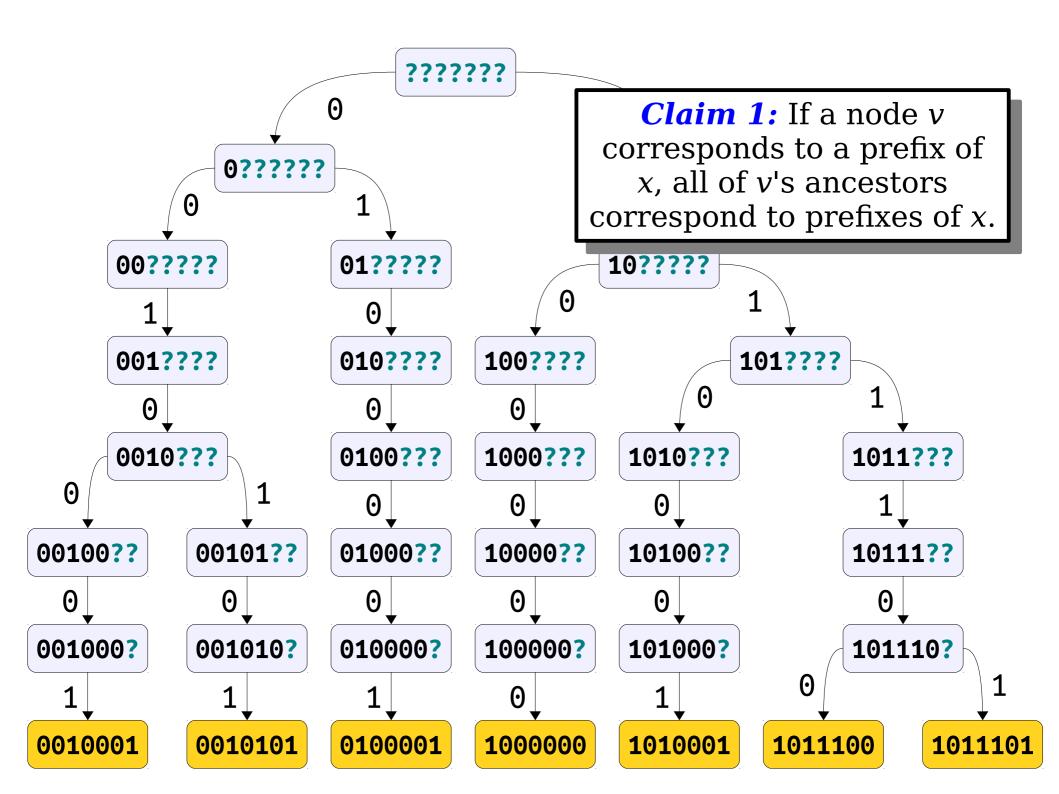
- There are two independent pieces that contribute to the $O(\log U)$ runtime:
 - Need to walk down the trie following the bits of x, and there are $\Theta(\log U)$ of those.
 - From there, need to back up to a branching node where we can find the successor.
- Can we speed up those operations? Or at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

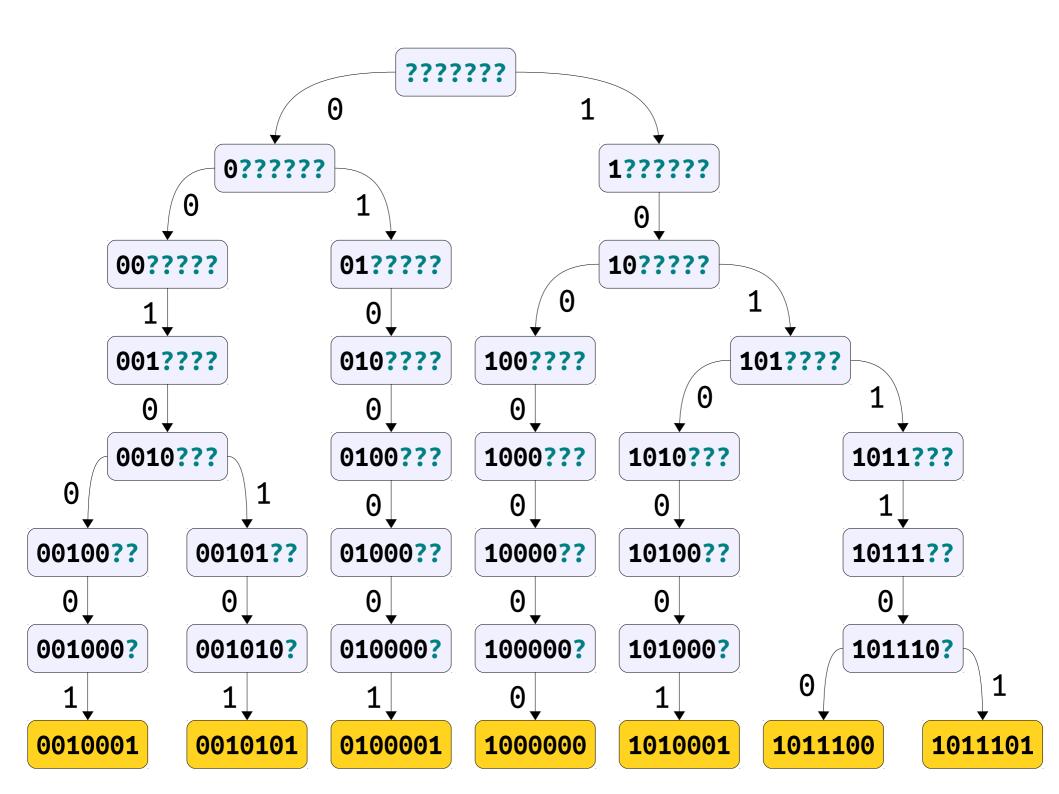


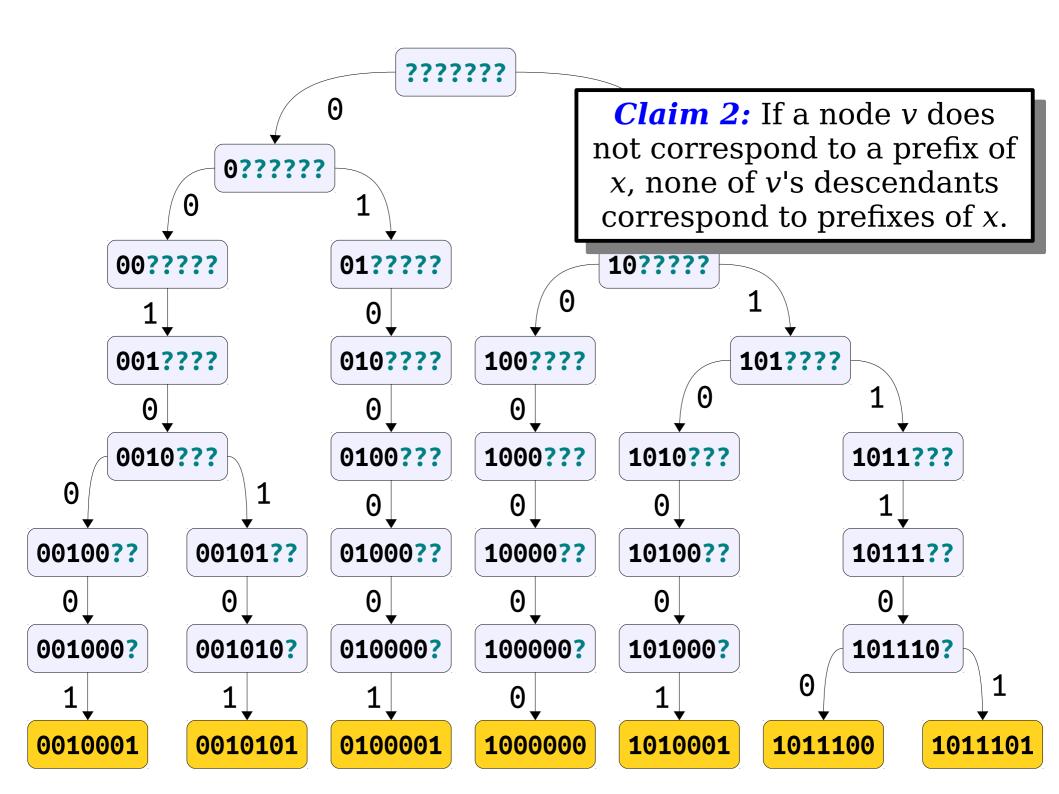


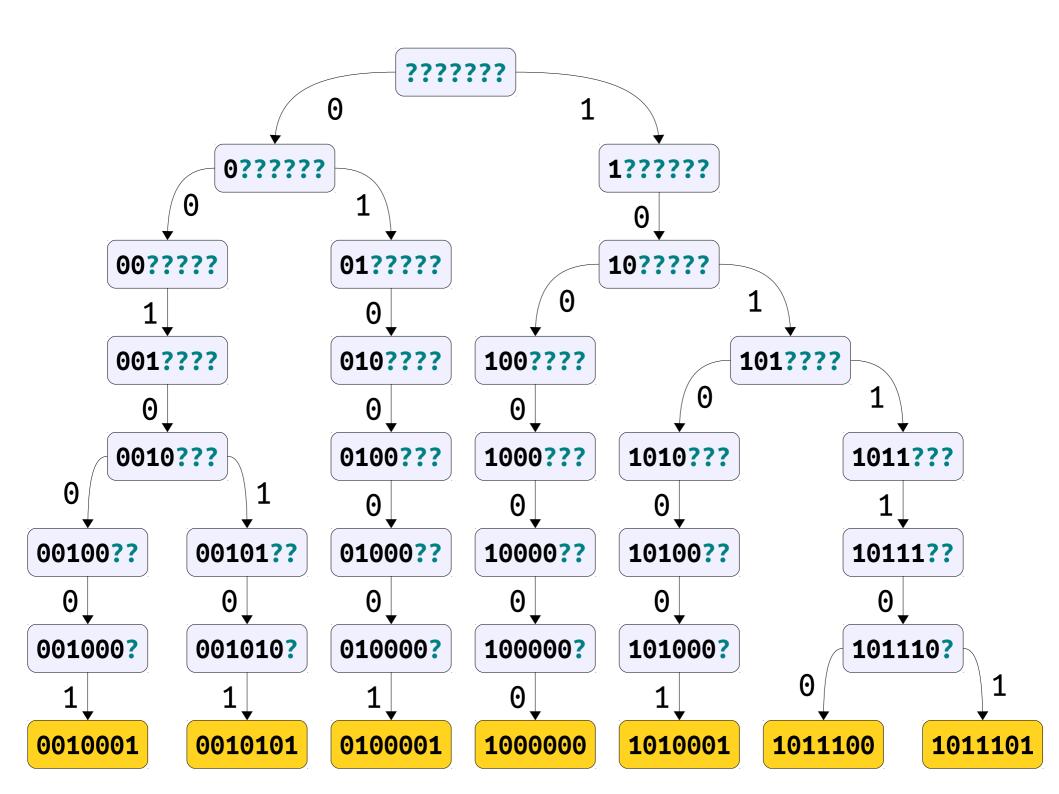


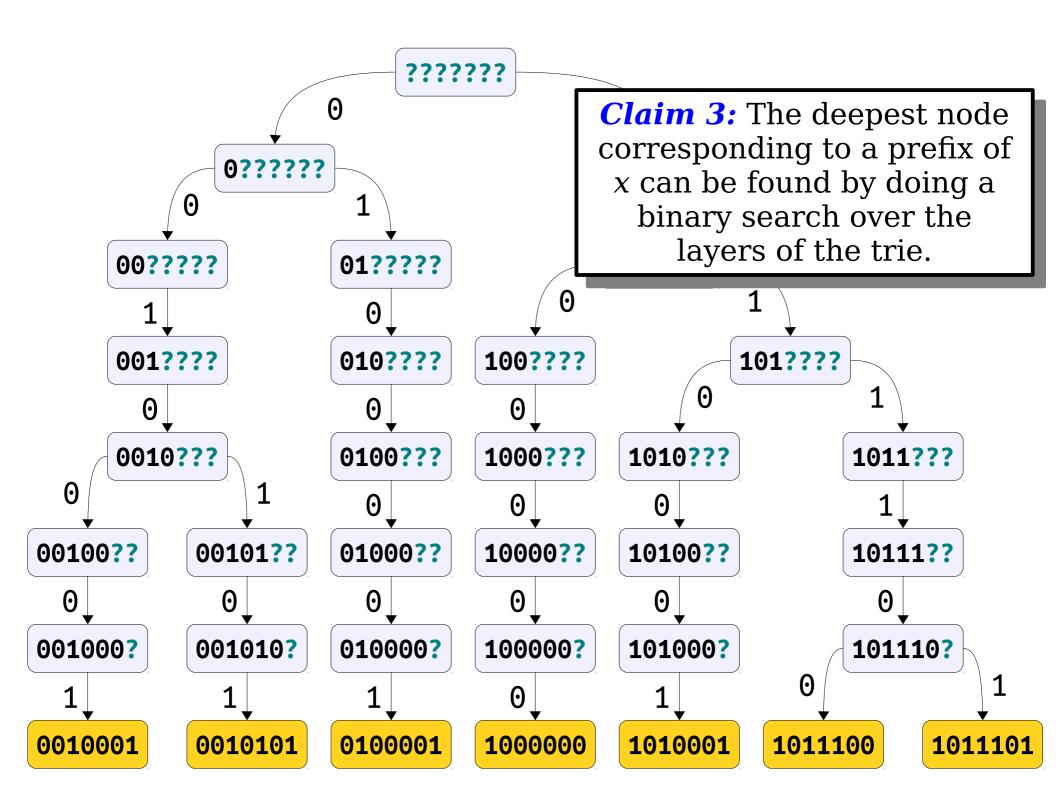












One Speedup

- *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 $O(\log U)$ layers in the trie.
- Binary search will take worst-case time $O(\log \log U)$.
- *Nice side-effect:* Queries are now worst-case O(1), since we can just check the hash table at the bottom layer.

- 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 = something magical;
uint64_t prefix = x & mask;
```

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```
      x
      11011100
      101111011
      11000100
      11010110
      11110011
      01111011
      11110000
      10001100

      mask
      00000000
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```

```
uint64_t x = /* ... */;
uint64_t mask = (uint64_t(1) << (64 - k));
uint64_t prefix = x & mask;</pre>
```

- 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!

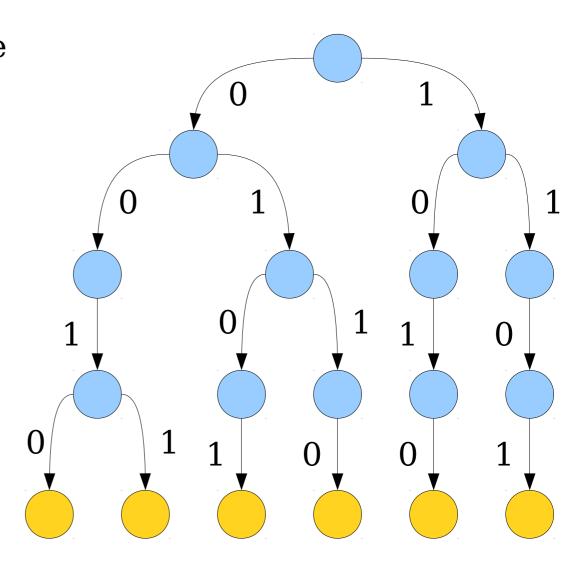
```
uint64_t x = /* ... */;
uint64_t mask = ~(uint64_t(1) << (64 - k));
uint64_t prefix = x & mask;</pre>
```

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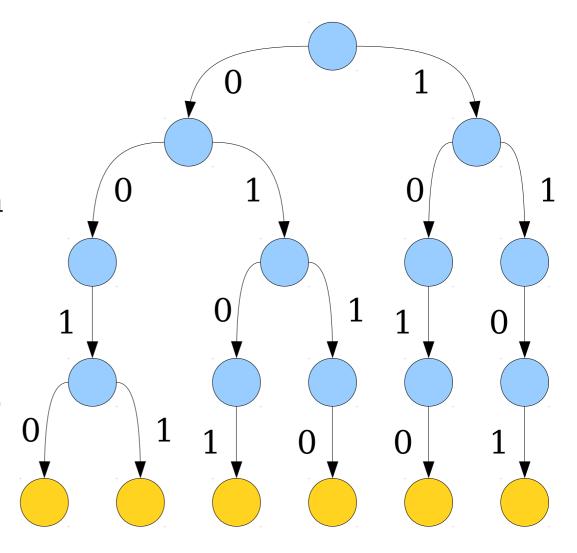
Finding Successors

- We can now find the node where the successor search would initially arrive.
- 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 $O(\log U)$.
- Can we do better?



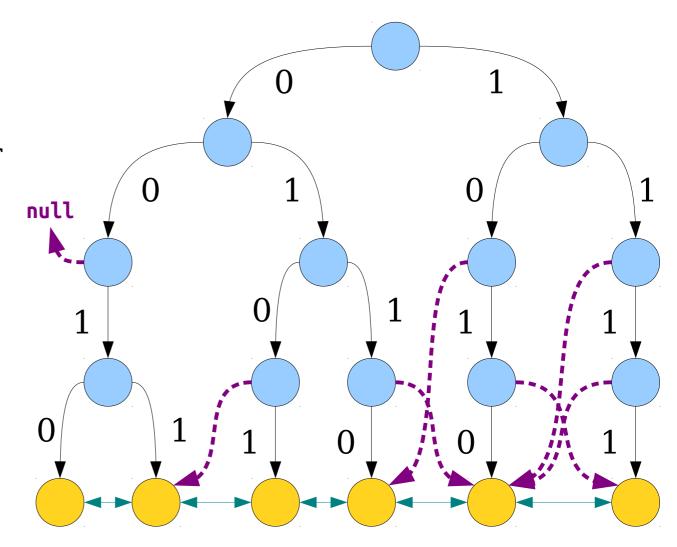
Finding Successors

- *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.



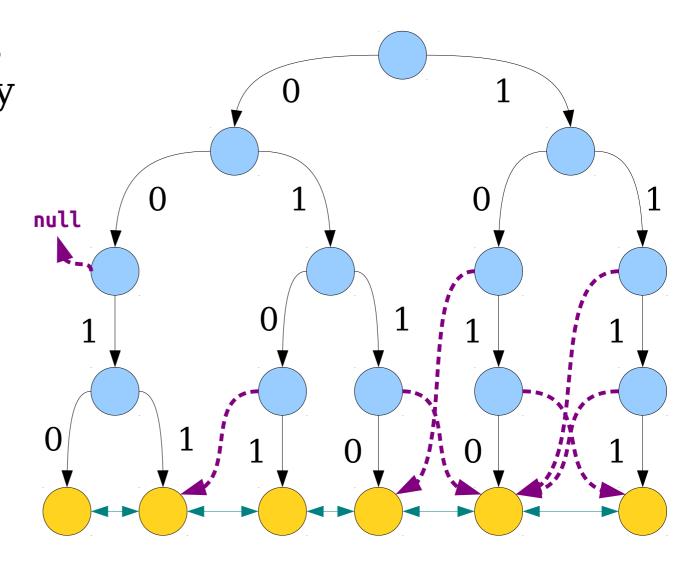
Threaded Binary Tries

- A threaded binary tree where
 - each missing 0 pointer points to the inorder predecessor of the node and
 - each missing 1 points to the inorder successor of the node.
- Notice that the leaves end up in a doublylinked list.

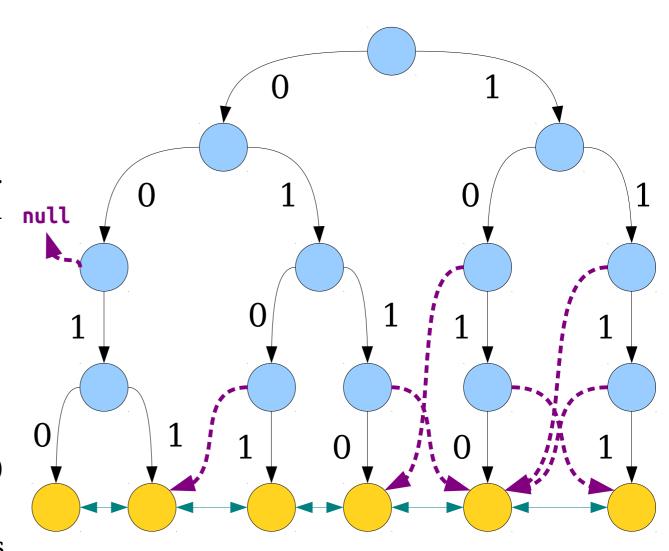


x-Fast Tries

- An x-Fast Trie is a threaded binary trie with a cuckoo hash table at each level that stores the nodes at that level.
- Can do lookups in time O(1).



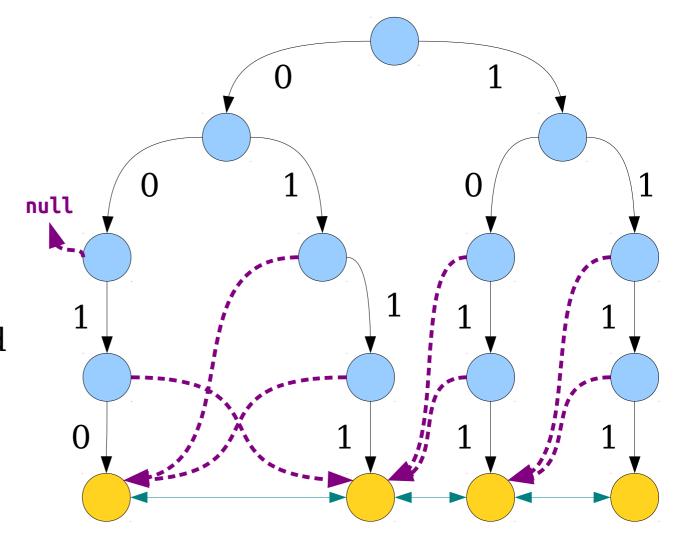
- Claim: Can determine successor(x) in time $O(\log \log U)$.
- Start by binary searching for the longest prefix of x.
- If that node has a missing 1 pointer, it points directly to the successor.
- Otherwise, it has a missing 0 pointer.
- If that pointer is null, return the minimum value (we can cache this.)
- Otherwise, follow it to a leaf, then follow the leaf's 1 pointer.



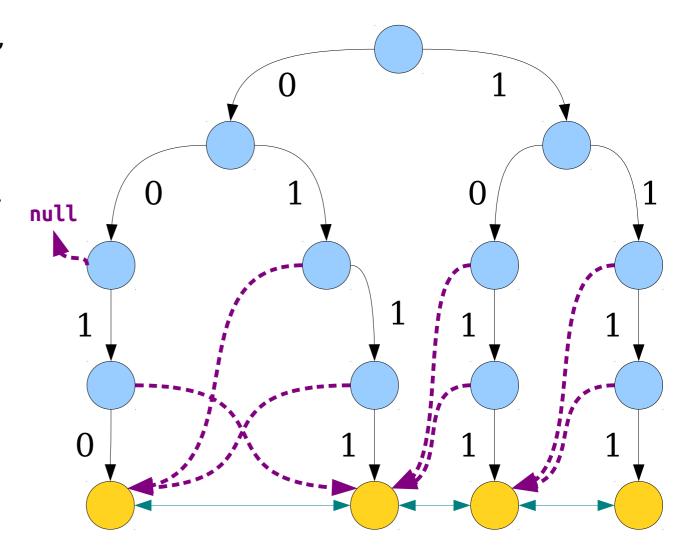
x-Fast Trie Maintenance

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

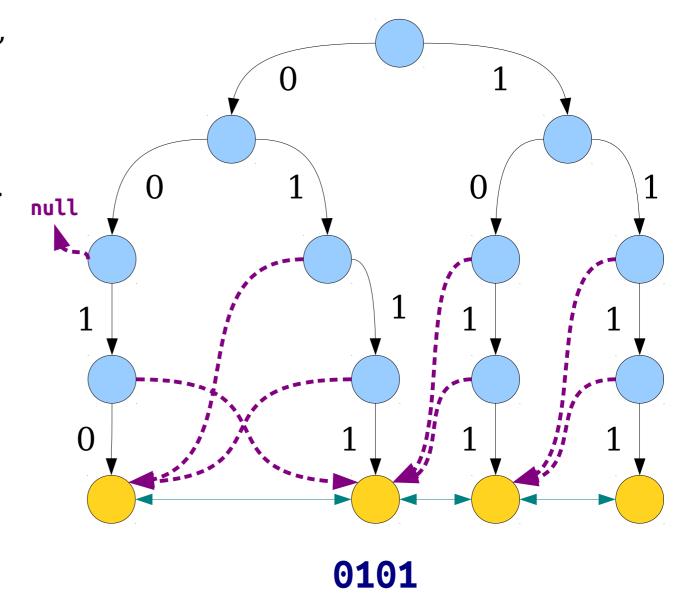
- If we insert(x), we need to
 - add some new nodes to the trie;
 - wire x into the doubly-linked list of leaves; and
 - update the thread pointers to include *x*.
- Worst-case will be $\Omega(\log U)$ due to the first and third steps.



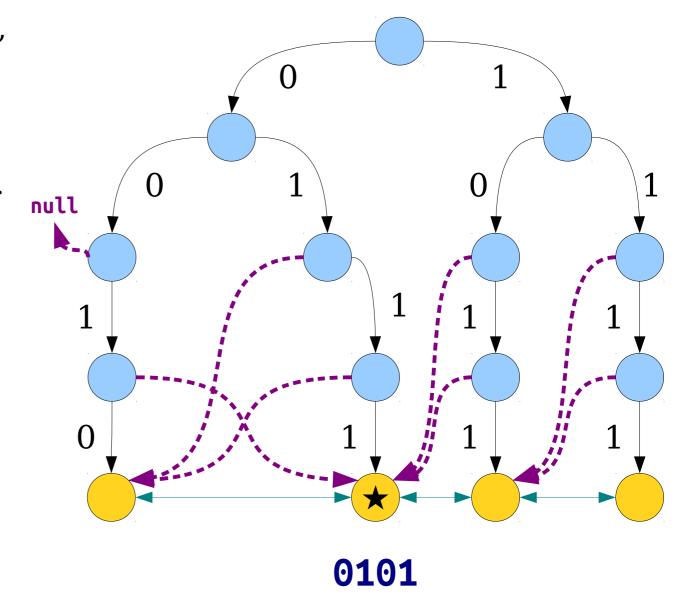
- Here is an (amortized, expected) O(log *U*) time algorithm for *insert*(x):
 - Find successor(x).
 - Add *x* to the trie.
 - Using the successor from before, wire x into the linked list.
 - Walk up from x, its successor, and its predecessor and update threads.



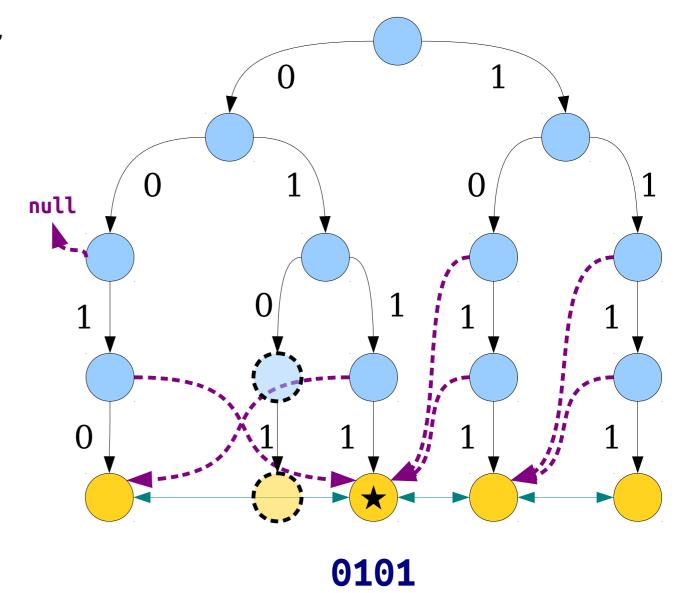
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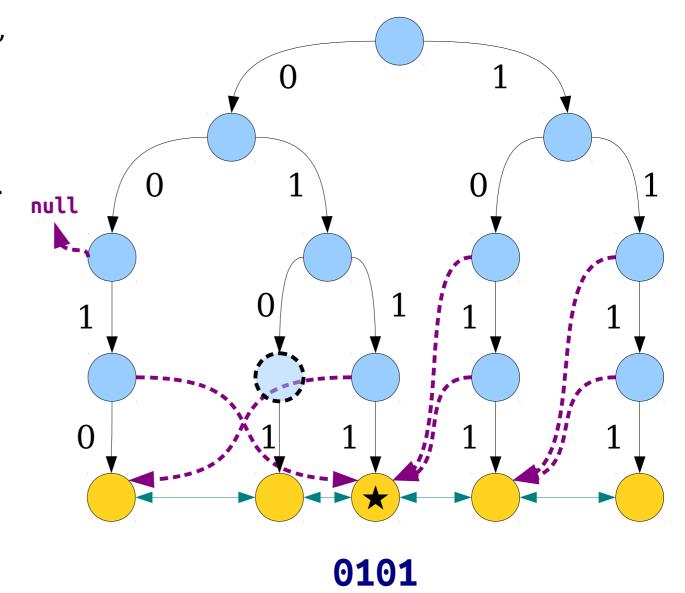
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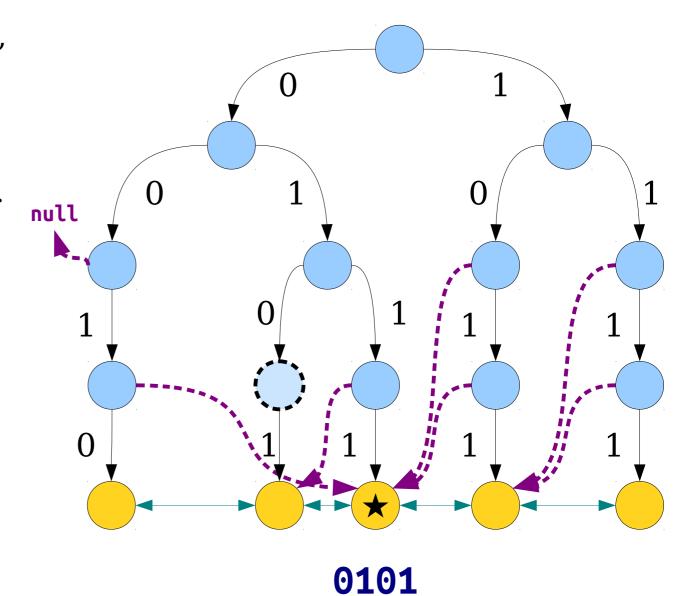
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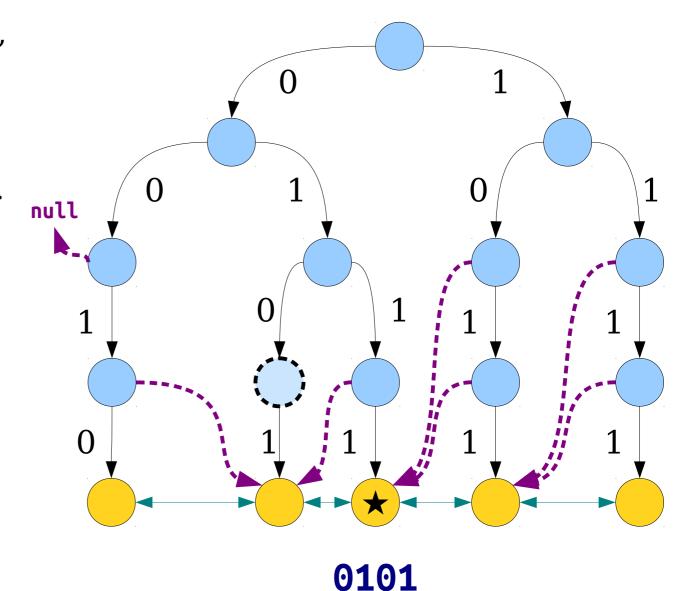
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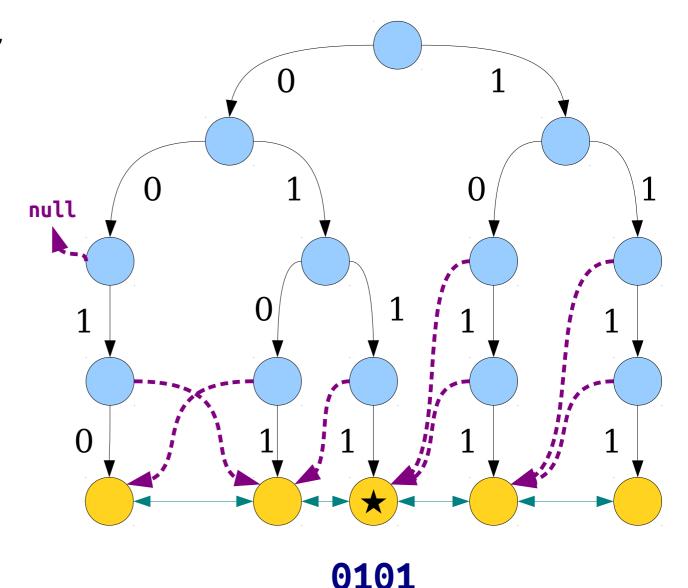
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 - Find successor(x).
 - Add *x* to the trie.
 - Using the successor from before, wire x into the linked list.
 - Walk up from x, its successor, and its predecessor and update threads.



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 $O(\log U)$.
- Full details are left as a proverbial Exercise to the Reader. ☺

Space Usage

- How much space is required in an x-fast trie?
- Each leaf node contributes at most $O(\log U)$ nodes in the trie.
- Total space usage for hash tables is proportional to total number of trie nodes.
- Total space: $O(n \log U)$.

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*: $O(\log U)^*$
- **delete**: $O(\log U)^*$
- max: O(1)
- **succ**: O(log log *U*)
- *is-empty*: O(1)
- Space: $O(n \log U)$
- * Expected, amortized

Time-Out for Announcements!

Midterm Logistics

- Our midterm will be held next Tuesday from 7:00PM 10:00PM in *Hewlett 200*.
- Exam is closed-book, closed-computer, and limited-note. You can bring a double-sided $8.5" \times 11"$ sheet of notes with you to the exam.
- Topic coverage is material from PS1 PS5. Topics from this week won't be tested, but are an excellent review of the concepts.
- We've released a set of practice problems to help you prepare for the exam. They're up on the course website.
- Can't make the exam time? Have OAE accommodations?
 Let us know ASAP so that we can set up an alternate time.

Final Project Presentations

- Final project presentations will run from *Monday*, *June 4* to *Thursday*, *June 7*.
- Use this link to sign up for a time slot:

http://www.slottr.com/cs166-2018

- You can view the available time slots starting today. The form will be open from *noon on Thursday, May 24* until noon on Thursday, May 31. It's first-come, first-served.
- Presentations will be 15-20 minutes, plus five minutes for questions. Please arrive five minutes early to get set up.
- Presentations are open to the public, so feel free to stop by any of the presentations you're interested in.

Back to CS166!

Where We Stand

- Right now, we have a reasonably fast data structure for storing a sorted set of integers.
- To make this really shine, we need to improve the highlighted costs.

- *lookup*: O(1)
- *insert*: O(log *U*)*
- *delete*: O(log *U*)*
- max: O(1)
- **succ**: O(log log *U*)
- *is-empty*: O(1)
- Space: $\Theta(n \log U)$
- * Expected, amortized

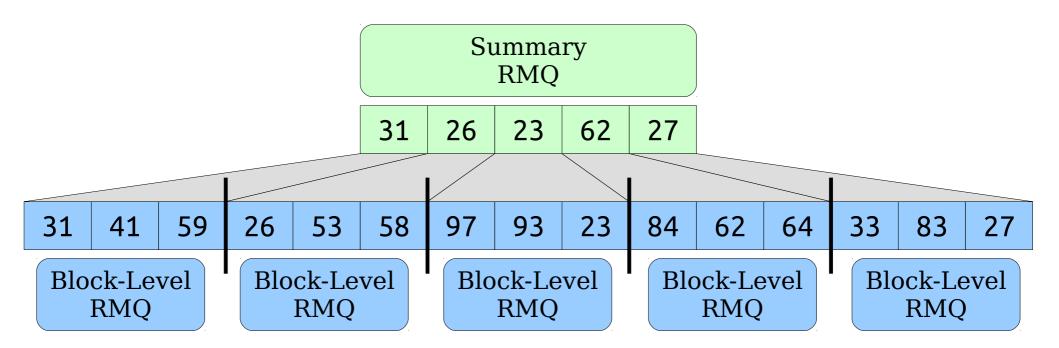
Shaving Off Logs

- We're essentially at a spot where we need to shave off a log factor from a couple of operations.
- Question: What techniques have we developed so far to do this?

- *lookup*: O(1)
- *insert*: O(log *U*)*
- *delete*: O(log *U*)*
- *max*: O(1)
- **succ**: O(log log *U*)
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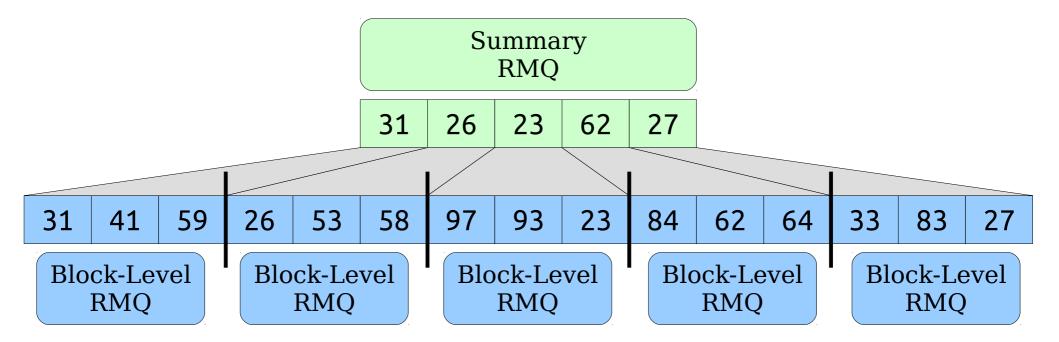
Two-Level Structures

- 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.



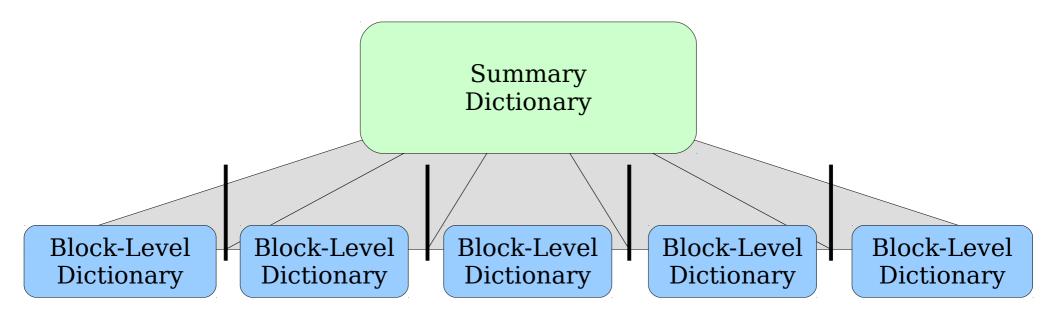
Two-Level Structures

- One of the fastest RMQ hybrids in practice is the $(O(n), O(\log n))$ hybrid structure built with blocks of size $\Theta(\log n)$ where
 - the summary structure is a $(O(n \log n), O(1))$ sparse table, and
 - the block-level structures are (O(1), O(n)) no-preprocessing RMQ structures.
- By breaking the input apart into blocks of size $\Theta(\log n)$
 - the summary structure only takes time O(n) to build, and
 - the linear terms in the blocks become $O(\log n)$ terms.



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

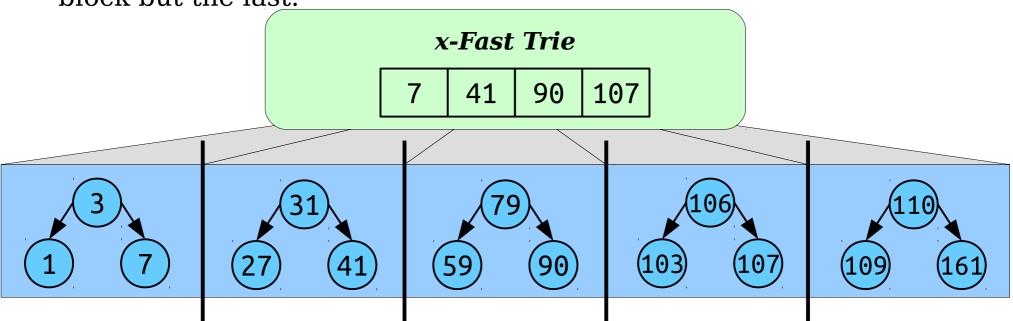
- For now, assume all keys are given to us in advance, in sorted order.
- Split the keys apart into blocks of size $\Theta(\log U)$ and store them in balanced BSTs.

1	3	7	27	31	41	59	79	90	103	106	107	109	110	161

The Setup

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

• Create a summary *x*-fast trie that stores the maximum key from each block but the last.



Performing a Lookup

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

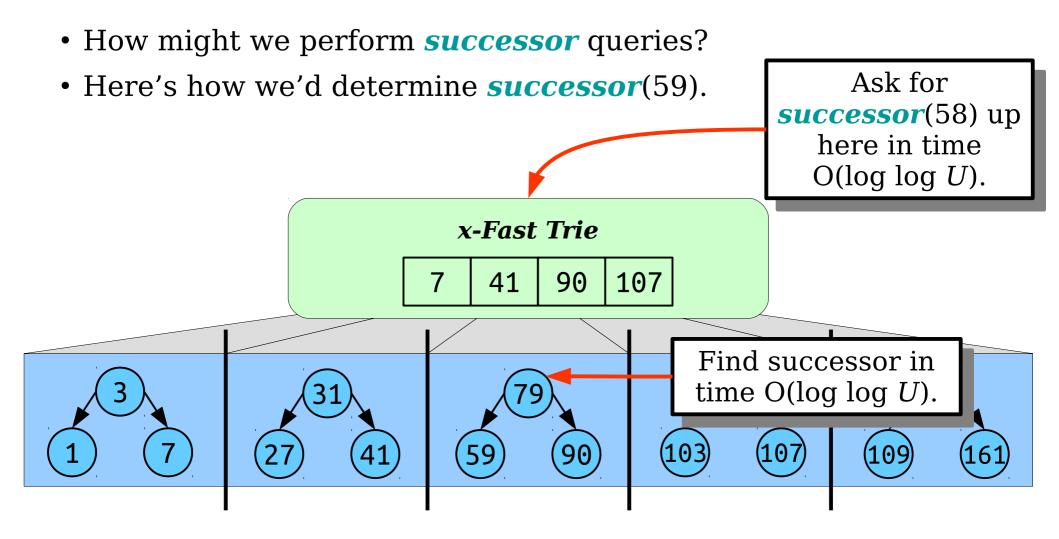
• *Idea*: figure out which block 90 would belong to, then search within the BST in that block. Ask for • Cost: $O(\log \log U)$. **successor**(89) up here in time $O(\log \log U)$. x-Fast Trie 90 107 41 90 41 59 107 Search this BST in time $O(\log \log U)$.

Performing a Lookup

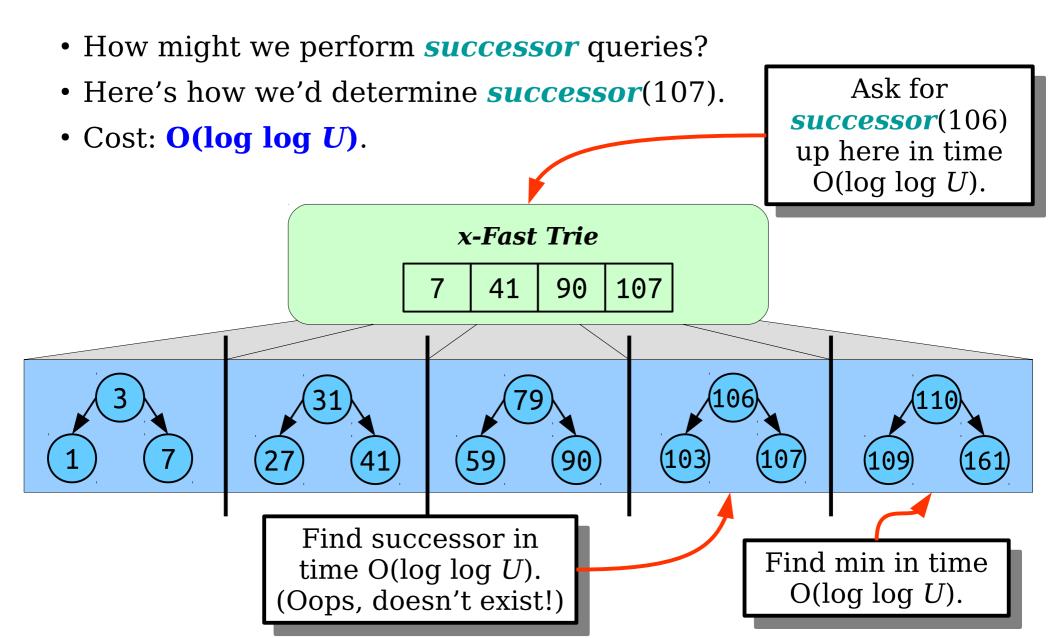
• Suppose we want to perform *lookup*(110).

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

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 $O(\log \log U)$. **insert** into this BST in time x-Fast Trie $O(\log \log U)$ 107 41 90 90 41 59 (107)(103)

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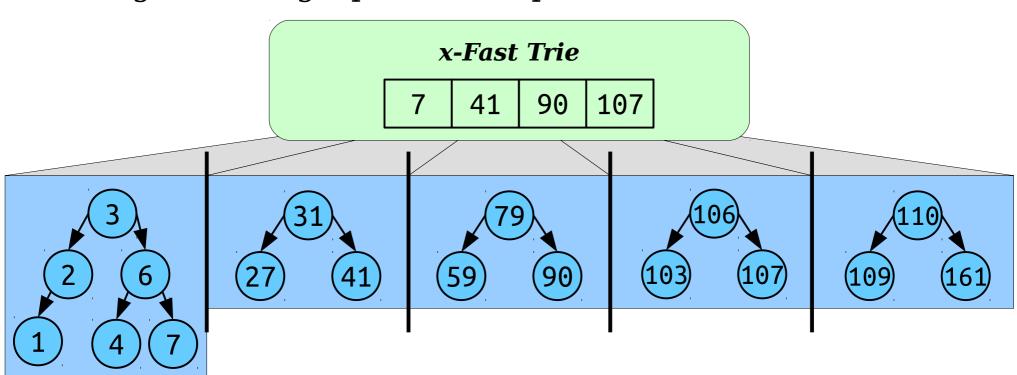
 With a major caveat, insertions follow the same procedure as before. Ask for • Here's how we'd *insert*(4) **successor**(3) in time $O(\log \log U)$. **insert** into this BST in time x-Fast Trie $O(\log \log U)$ 107 41 90 90 41 59 (107)(103)

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

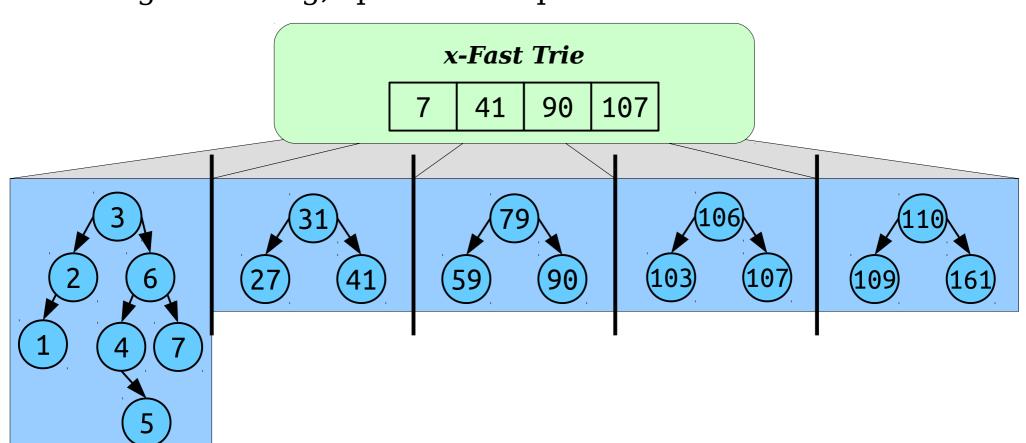
 With a major caveat, insertions follow the same procedure as before. Ask for • Here's how we'd *insert*(2) **successor**(1) in time $O(\log \log U)$. **insert** into this BST in time x-Fast Trie $O(\log \log U)$ 107 41 90 90 41 59 (107)(103)

 With a major caveat, insertions follow the same procedure as before. Ask for • Here's how we'd *insert*(2) **successor**(1) in time $O(\log \log U)$. **insert** into this BST in time x-Fast Trie $O(\log \log U)$ 107 41 90 90 41 59 (107)(103)

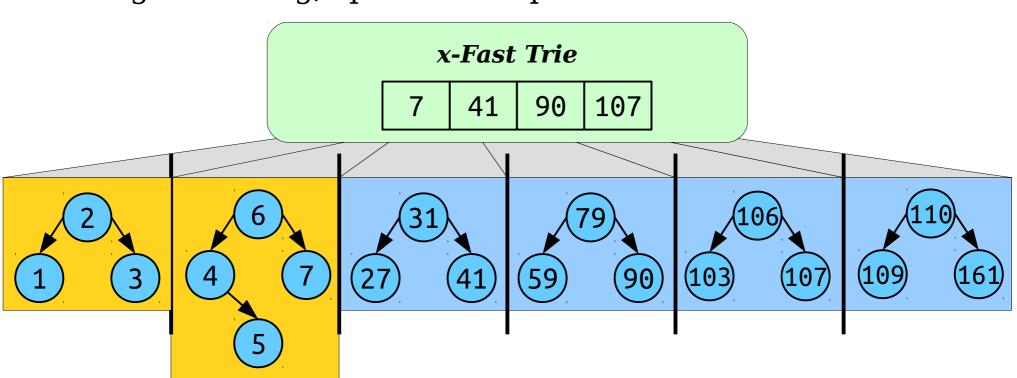
- If our trees get too big, we may lose our $O(\log \log U)$ time bound.
- *Idea*: Require each tree to have at most $2 \cdot \lg U$ elements. If it gets too big, split it and update the x-fast trie.



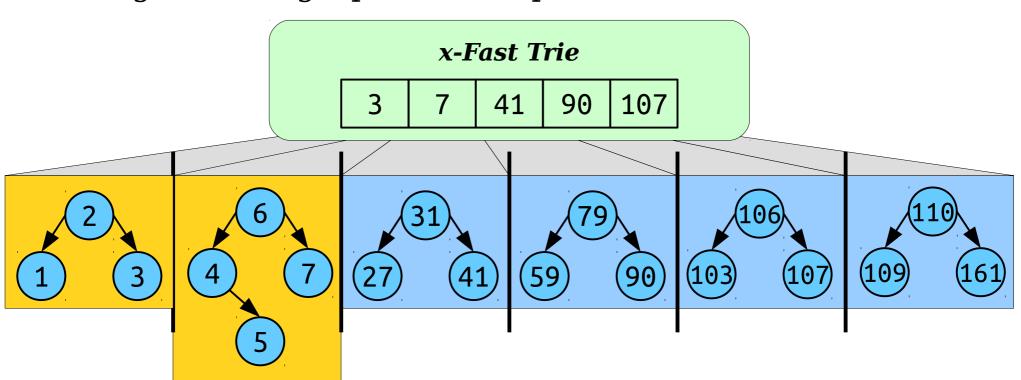
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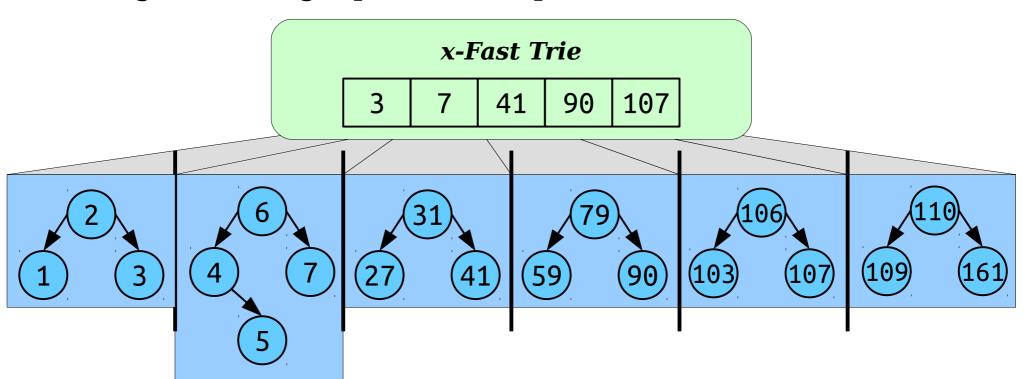
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Analyzing an Insertion

- If we perform an *insert* and don't end up doing a resize, the cost is $O(\log \log U)$.
- If we perform an *insert* and *do* have to do a resize, the work done is
 - O($\log \log U$) to *split* the binary search tree, and
 - $O(\log U)$ to insert into the *x*-fast trie.
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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 log U).
- If we have to split a tree, the tree size was above 2 lg *U*, so there must be lg *U* credits on it (one for each element above lg *U*).
- The *amortized* cost of a "heavy" insert is then

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

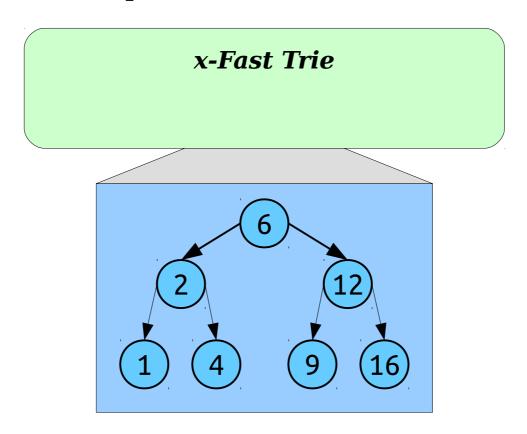
Cost of a regular insert, plus the tree split.

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

Credits spent.

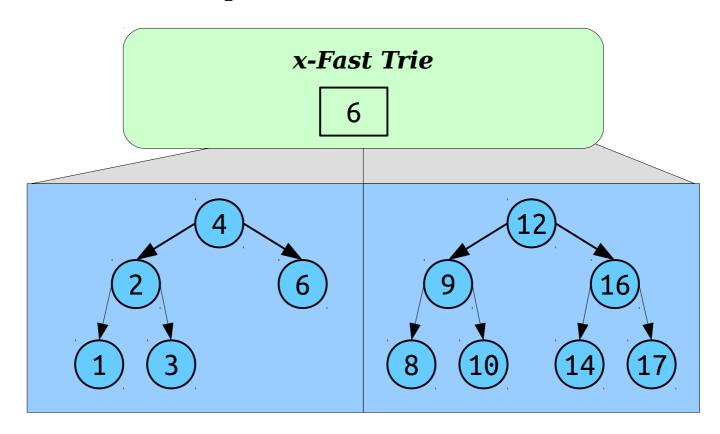
A Nice Side-Effect

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



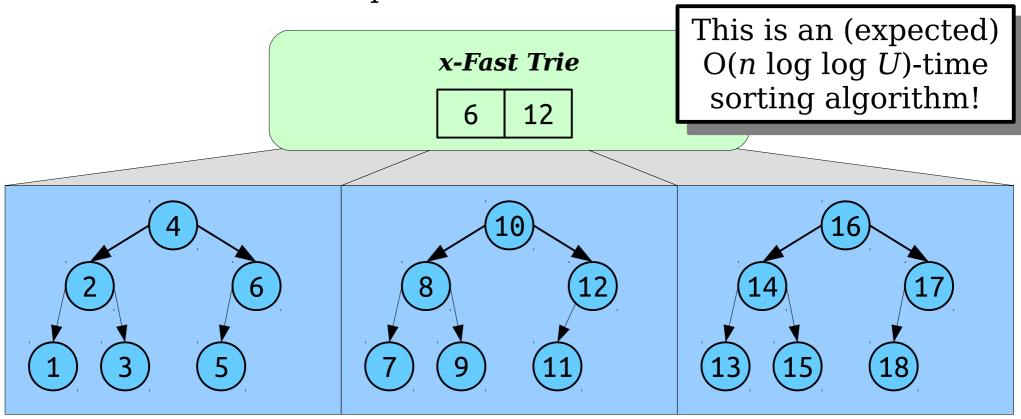
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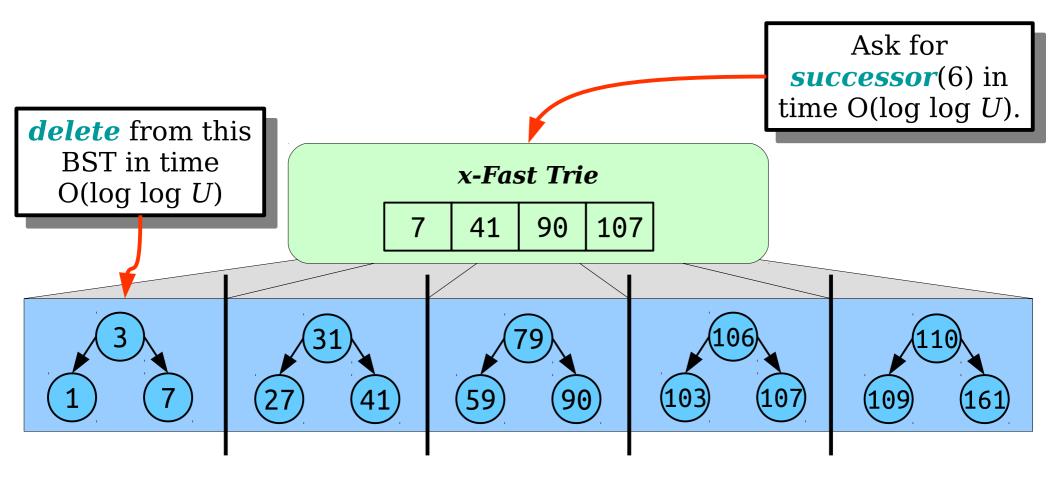
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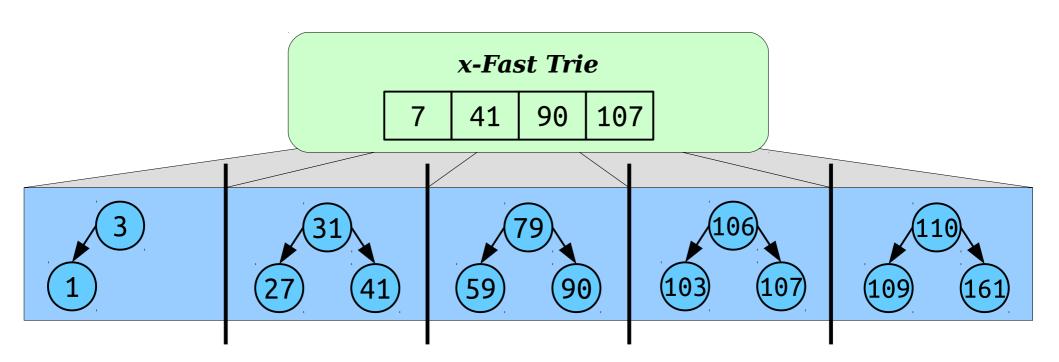


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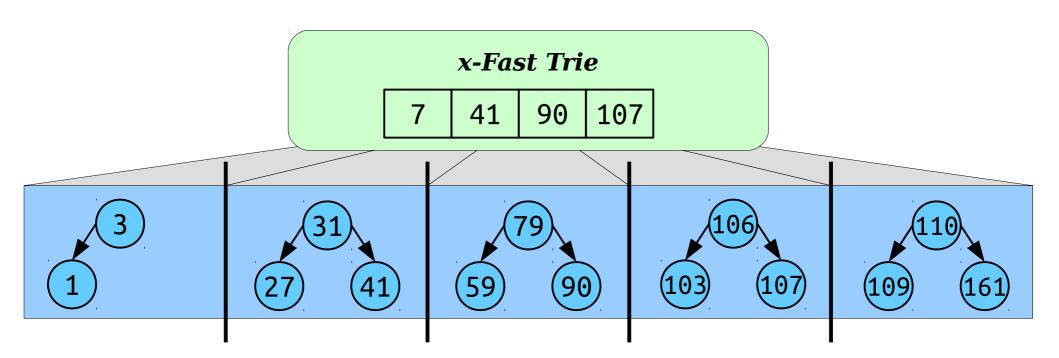


- Our *x*-fast trie still holds 7, even though 7 is no longer present.
- That's not a problem those keys just serve as "routing information" to tell us which BSTs to look at.
- *Intuition:* The *x*-fast trie keys act as partitions between BSTs. They don't need to actually be present in our data structure.



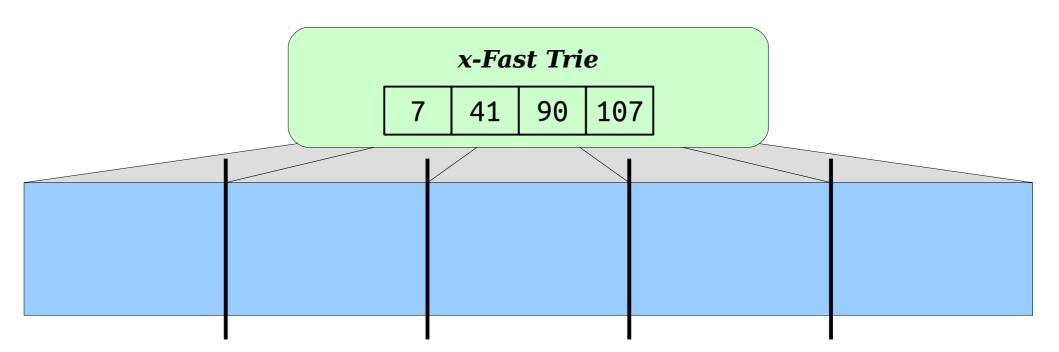
Shrinking our Structure

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



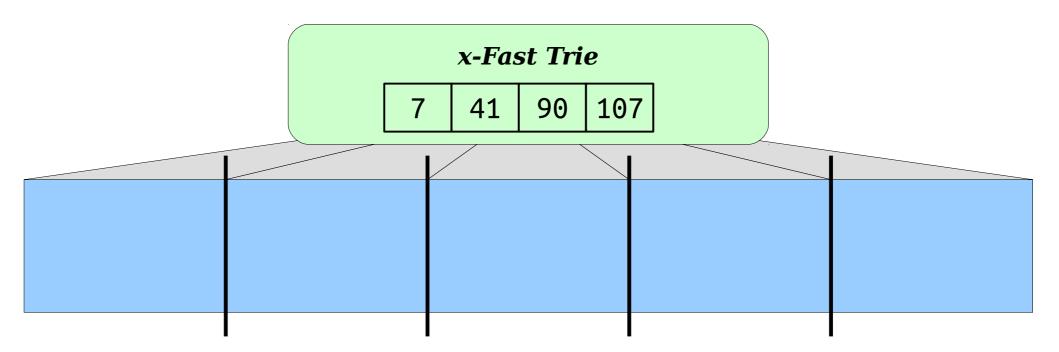
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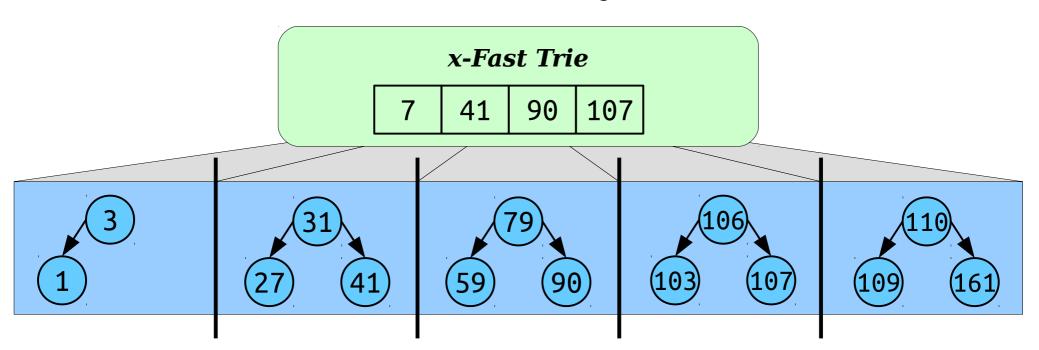


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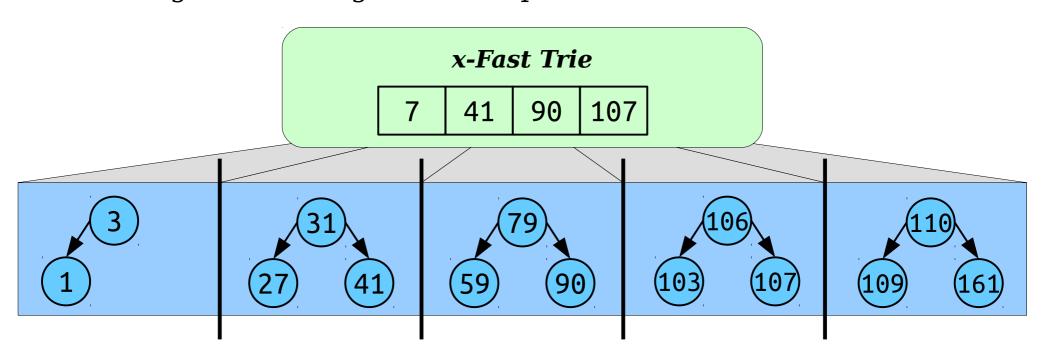
- What happens if we remove all the elements from our structure without touching the *x*-fast trie?
- Each operation still takes time $O(\log \log U)$.
- But now our space usage depends on the maximum size we reached, not the current size!



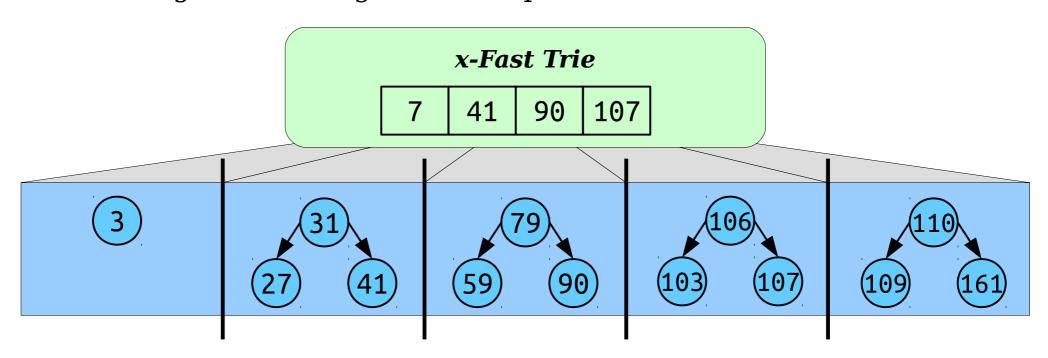
- If each tree has $\Theta(\log U)$ elements in it, then our space usage is
 - $\Theta(n)$ for all the trees, plus
 - $\Theta((n / \log U) \log U) = \Theta(n)$ for the *x*-fast trie,
- This uses $\Theta(n)$ total memory.



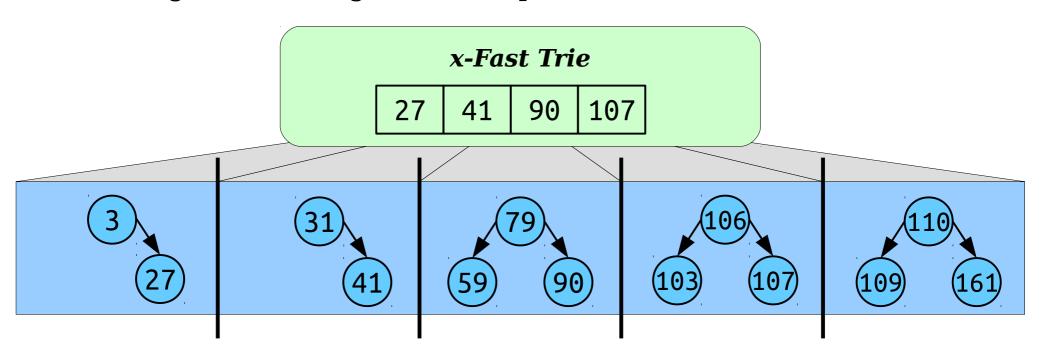
- *Invariant:* Require each tree to have between $\frac{1}{2}$ lg U and 2 lg U elements.
- If a tree gets too small, either
 - borrow lots of elements from a neighbor and update the *x*-fast trie, or
 - merge with a neighbor and update the *x*-fast trie.



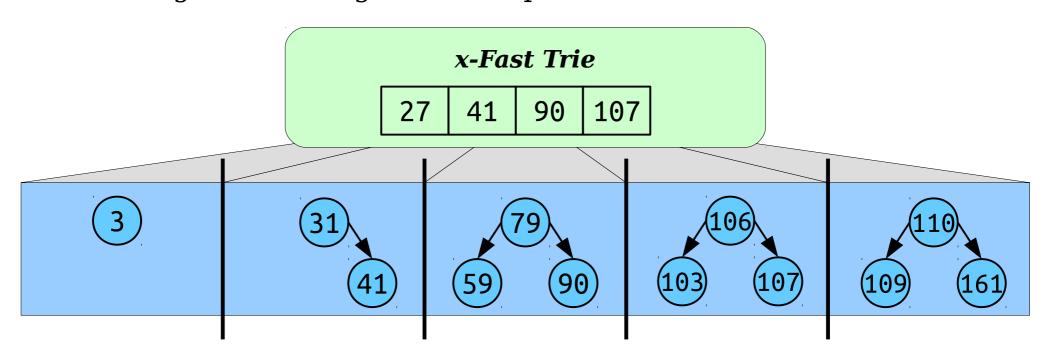
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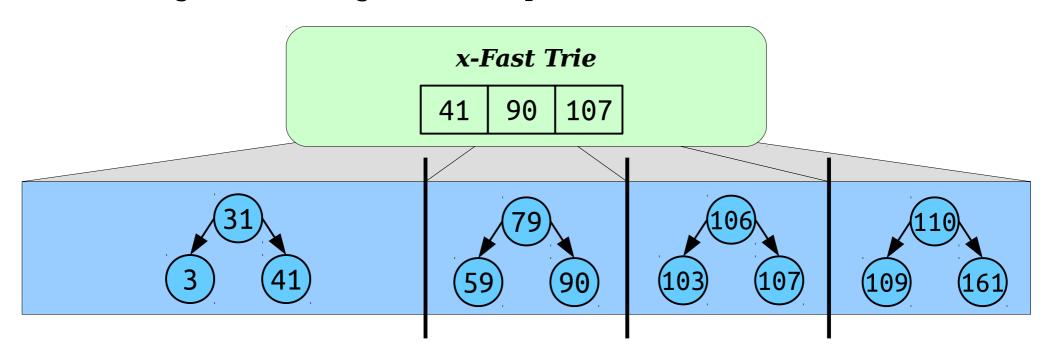
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What We've Seen

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

The *y*-Fast Trie:

- lookup: O(log log U)
- *insert*: $O(\log \log U)^*$
- **delete**: $O(\log \log U)^*$
- max: O(log log U)
- *succ*: O(log log *U*)
- *is-empty*: O(1)
- 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 $n = O(\log U)$?
- 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

 Parallel processing via addition, subtraction, and the like.

• Sardine Trees

A fast ordered dictionary for truly tiny trees.