CMSC 420 (Advanced Data Structures)

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Textbook: none
Type: #class

Topics: Data Structures Trees

Amortized Analysis

- Motivation: common for data structures to have:
 - · Lots of cheap operations
 - Some expensive operations
 - Suppose we take a sequence of n operations (as bad as possible); what is avg per-op cost?
 - Examples
 - Ex: we randomly choose a binary tree with 3 nodes (all equally likely). What do we expect the height to be?
 - 4 cases with height 2, 1 case with height 1, so

$$\frac{4}{5} \cdot 2 + \frac{1}{5} \cdot 1 = \frac{9}{5}$$

- This type of thinking is useful for average case analysis/counting structures
- Ex: consider the below pseudocode

```
function sum(n)
    sum = 0
    for i = 1 to n
        sum = sum + 7
        if i is an integer power of 3
            sum = sum + i
        end if
    end for
    return sum
end function
```

- · Can we find a closed form for the above?
 - For arbitrary n, we have

$$(7+1)+(7)+(7+3)+(7)+(7)+(7)+(7)+(7)+(7+9)+\cdots$$

Separating this, we have

$$(7n) + (1+3+9+\cdots)$$

where the last power of three is the largest power of 3 \leq n, or largest k such that $3^k \leq n$

- This means $k \leq \log_3(n)$; as $k \in \mathbb{Z}$, we have $k = \lfloor \log_3 n \rfloor$
- So, a closed formula for our sum is

$$egin{align} 7n + \sum_{i=0}^{\lfloor \log_3 n
floor} 3^i &= 7n + rac{3^{\lfloor \log_3 n + 1
floor} - 1}{3-1} \ &= 7n + rac{3^{\lfloor \log_3 n
floor} + 1 - 1}{2} \end{aligned}$$

- Ex: List deletion
 - Consider a 0-indexed list of length n; choose an index at random and delete that element. All
 elements to the right shift left by 1; each shift takes 0.2ms; on average, how long will a deletion
 take?
 - If we delete an element at index i, how many elts get shifted? n-i-1
 - This takes 0.2(n-i-1) time, so on average, the EV is

$$\sum_{i=0}^{n-1} rac{1}{n} \cdot 0.2 \cdot (n-i-1) = rac{0.2}{n} iggl[\sum_{i=0}^{n-1} n - \sum_{i=0}^{n-1} i - \sum_{I=0}^{n-1} 1 iggr]$$

- Ex: Suppose we have $m \ge 2$ and h represent the height of a tree with the following properties
 - All leaves are at the same level (tree is perfect)
 - Each node contains m-1 keys
 - ullet Each node except the leaves has m children
 - ullet Each node except the leaves has m children
 - Q: in general, for an unknown h, m, how many keys are there? Make a table:

level	# nodes	$\# \mathrm{keys}$
0	1	m-1
1	m	m(m-1)
2	m^2	$m^2(m-1)$
:	÷	:
h	m^h	$m^h(m-1)$

- Techniques for amortized analysis
 - Aggregate method
 - Given a situation, think of a sequence of n operations for which the total cost C(n) is as bad as possible
 - Def: If the total cost of an operation is C(n), the **amortized cost** is $AC(n) = \frac{C(n)}{n}$
 - Ex: suppose we have a data structure with the following:
 - Insertion + deletion each cost 1
 - When we have a multiple of 10 objects in the structure, there is an additional cost of 8
 - Suppose we perform n operations starting with an empty structure; to obtain worst-case, we would continuously insert, resulting in a total cost and amortized cost of

$$C(n) = n + 8 \left\lfloor rac{n}{10}
ight
floor \ AC(n) = rac{C(n)}{n} = rac{n + 8 \left\lfloor rac{n}{10}
ight
floor}{n}$$

As |x| < x, we have

$$AC(n) \leq rac{n+8\left(rac{n}{10}
ight)}{n} = 1+rac{8}{10} = rac{9}{5}$$

so
$$AC(n)\in \mathcal{O}(1)$$

• Ex: we allocate space for a stack, starting with 0 bytes. We can push/pop, each costing 1. If we overflow the allocated space we allocate more space and copy all the old stuff over, then push. Suppose the allocation + copy costs a value equal to the size of the new space; how do we reallocate?

Option 1: Always allocate 1 more byte. In the worst-case, all we do is push, which will cost a

$$C(n) = (1+1) + (2+1) + (3+1) + \dots + (n+1) = n + \frac{n(n+1)}{2} \in \mathcal{O}(n^2)$$

• Option 2: when we need to reallocate, double the space. In the worst-case, we have

$$C(n) = n + (1 + 2 + \dots + 2^k)$$

for some k. Since we allocate to make space, we know $2^k \ge n$, so we need the smallest k such that $2^k \ge n$, or $k \ge \log_2 n$, which implies $k = \lceil \log_2 n \rceil$. Thus, we have

$$C(n) = n + \sum_{i=0}^{\lceil \log_2 n
ceil} 2^i = n + \left[2^{\lceil \log_2 n
ceil} - 1
ight]$$

so

$$egin{split} AC(n) &= rac{C(n)}{n} = rac{n + 2^{\lceil \log_2 n
ceil + 1} - 1}{n} \ &\leq rac{n + 2^{\log_2 n + 1 + 1} - 1}{n} \ &\leq rac{n + 4n - 1}{n} = rac{5n - 1}{n} = 5 - rac{1}{n} \leq 5 \end{split}$$

- So $AC(n) \in \mathcal{O}(n)$
- More examples
 - Ex: we randomly choose a binary tree with 3 nodes (all equally likely). What do we expect the height to be?
 - · 4 cases with height 2, 1 case with height 1, so

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:	÷	:
h	m^h	$m^h(m-1)$

- Token (banker's) method (described in Justin's notes)
 - Typically used when worst-case situation can be divided into runs (segments) in which each run consists of
 a sequence of cheap operations ending with an expensive operation
 - Ex: Suppose we're looking at lunch costs for the week (a run); from Sunday t Friday you spend \$8 per day and on Sat, you spend \$29
 - On average how much did you spend per day? $rac{8\cdot 6+29}{7}=11$ per day
 - This is an aggregate analysis
 - Rephrased example: every day you put β into the bank and withdraw as needed for lunch. What must be true of β to ensure enough? As we have 7 days and put β per day, we need $7\beta \geq 77 \geq 8 \cdot 6 + 29$, so $\beta \geq 11$
 - Instead of money, think of time; we've calculated the pre-operation cost
 - Ex: stack allocation; if we overflow our stack we double the space allocated
 - A run will start after a reallocation + push and will stop after the next reallocation + push; more rigorously, for some k
 - ullet Run starts: we reallocated from 2k to 4k and there are 2k+1 elts on stack
 - Run stops: we reallocate from 4k to 8k and there are 4k + 1 elts on stack
 - Total run cost: push cost + reallocation cost = 2k + 8k = 10k; we want β such that $\beta(2k) \ge 10k$, so $\beta \ge 5$, so $\beta = \mathcal{O}(1)$

- Ex: stack allocation; when we reallocate, go to the next perfect square (e.g. $0 \to 1 \to 4 \to 9 \to 16 \to \cdots$), for some k
 - Run start: we reallocate k^2 to $(k+1)^2$ and (k^2+1) elts on the stack
 - Run stops: we reallocate $(k+1)^2$ to $(k+2)^2$ and $(k+1)^2+1$ elts on the stack
 - Total operations: $[(k+1)^2 + 1] [k^2 + 1] = k^2 + 2k + 2 k^2 1 = 2k + 1$ (like the number of days in above ex)
 - Total run cost: push cost + reallocation cost = $2k + 1 + (k + 2)^2 = k^2 + 6k + 5$ (like the total meal cost in above ex)
 - So $\beta(2k+1) \geq k^2+6k+5$, implying $\beta \geq \frac{1}{2}k+\frac{11}{4}+\frac{9/4}{2k+1}$, which implies

$$eta \geq rac{1}{2}k + rac{11}{4} + rac{9}{4}$$
 $eta \geq rac{1}{2}k + rac{20}{4}$ $eta \geq rac{1}{2}k + 5$

• What about this k? We must have $k \ge 1$ and as we're pushing n items we must have $(k+1)^2 + 1 \le n$ which is $k \le \sqrt{n-1} - 1$, so together we have

$$1 \le k \le \sqrt{n-1} - 1$$

- If we have $\beta \geq \frac{1}{2}(\sqrt{n-1}-1)+5$ then we will be safe, but in addition we want β as small as possible so we let $\beta = \frac{1}{2}(\sqrt{n-1}-1)+5$, so $\beta = \mathcal{O}(\sqrt{n})$
- Potential method

Trees

- Motivation: why will we look at so many trees?
 - They work; if managed well, good runtimes for insertion/deletion/querying
 - · "Easy" to understand
 - Some properties of trees
 - · Binary search tree property
 - For any node, it's key is less than all keys in the right subtree and greater than all keys in the left subtree
 - Max heap property
 - For any node, its value is greater than or equal to all the values of its children
 - Tree height: the length is the length of the longest path from root to the leaf (path length is equal to the number of edges)
 - Tree levels
 - Typically 0-indexed from the root down
 - There are rare, weird alternative defns of tree levels (see AA trees for example)
 - Traversal types
 - Breadth-first
 - Depth-first
 - Pre-order
 - Post-order
 - In-order
 - Storing trees
 - Balanced trees: what could it mean for a tree to be balanced?
 - · Weight (size) balanced

- weight(L.subtree) = weight(R.subtree)
- Height balanced
 - For every node, we have height(L.subtree) = height(R.subtree)
 - AVL trees/scapegoat trees

Binary Search Trees

- Operations: search, insertion, delete
 - Deletion: search(x)
 - Steps: start at the root, go left or right depending on how x compares to the node's key, and keep going until
 we find x (or fall out and error)
 - Suppose we have a BST with n nodes
 - Best case search is $\Theta(1)$ and worst-case is $\Theta(n)$
 - Average case is tricky, because for a tree with n nodes, it could have been created with just inserts or with inserts and deletions
 - This matters because deletion and associated choices can affect this result
 - Insertion: insert(x)
 - Steps:
 - "Search" for x
 - · When we reach bottom of tree, search concludes
 - Time complexity
 - Best-case, worst case are $\Theta(1)$, $\Theta(n)$, respectively
 - Deletion: delete(x)
 - Steps:
 - Search for x
 - · If it is a leaf, drop if off
 - If it has one child, we remove the node and promote the child
 - If it has two children, we have two options
 - In-order predecessor, the largest node/key smaller than x
 - In-order successor, the smallest node/key larger than x
 - Pick one of the above, replace it with x, and recursively delete that node/key (this replacement is
 easy to delete because it will have at worst one child)
 - Average case of insertion/deletion/search depends on the average height of the tree
 - For a BST with n nodes, we have
 - (a) Max height: $\Theta(n)$
 - (b) Min height: $\Theta(\log_2 n)$ if the BST is perfect
 - (c) Average height; to find this, we can
 - ullet (a) Look at all binary trees with n nodes and take the average height
 - This has been proven to be $\Theta(\log_2 n)$
 - (b) Look at all possible constructions of BST using insertion/deletion, which ends up with n nodes
 - If we always use the same option between in-order predecessor and in-order successor for deletion, then it is $\Theta(\sqrt{n})$ (worse than $\Theta(\log_2 n)$
 - If we choose randomly between in-order predecessor and in-order successor, the data suggests $\Theta(\log_2 n)$ again (has not been proved)

AVL Trees

Main issue with binary search trees

- Insert, search, delete operations are worst-case $\mathcal{O}(n)$ because BSTs can become unbalanced
- · Can we tweak our BST so it always stays balanced?
- Definitions
 - If x is a node in a binary search tree, define

$$balance(x) = height(x. rightsubtree) - height(x. leftsubtree)$$

- Recall height(emptytree) = -1
- A binary search tree satisfies the **AVL balance condition** (is an AVL tree) if for all nodes x, balance $(x) \in \{-1, 0, 1\}$
- Height bound: if an AVL tree has height $\mathcal{O}(\log n)$, the operations insert/deletion/search should be faster
 - Thm: suppose an AVL tree has n nodes and height h. Then $h \in \mathcal{O}(\log n)$.
 - Proof: Define N(h) to be the minimum number of nodes in an AVL tree with height h (e.g. N(0) = 1). Now, for every h, we have N(h-1) > N(h-2) because the h-1 term is taller/higher, so it has more nodes. Also, N(h) = 1 + N(h-1) + N(h-2) because the tree is an AVL tree (but there are as few nodes as possible on each side). From here, we have

$$N(h) = 1 + N(h-1) + N(h-2) \ N(h) > 1 + N(h-2) + N(h-2) \
ightarrow N(h) > 2n(h-2)$$

Now, we have $N(h)>2N(h-2)>2^2N(h-4)>2^3N(h-6)>\dots$ We now have two cases:

- Case 1: h is even. This ends at $N(h)>2^{h/2}N(0)$. Since N(h) is the minimum number of nodes in an AVL tree with height h for any AVL tree of height h, we have $n\geq N(h)$, so $n>2^{h/2}N(0)$. As N(0)=1, we have $n>2^{h/2}$, implying $h/2<\log_2 n$, or $h<2\log_2 n$.
- Case 2: h is odd. This is similar to the above case>

Thus, we have $h \in \mathcal{O}(\log_2 n)$, as desired.

- Note that inserts/deletions could ruin the balance condition; this brings us to the concept of rotations
 - Rotations
 - Left rotation
 - Right rotation (mirror image of a left rotation)
 - Left-right rotation
 - Step 1: Left rotation at left child
 - · Step 2: Right rotation on parent
 - Right-left rotation
 - Step 1: Right rotation on right child
 - Step 2: Left rotation on parent
- Operations
 - Insertion
 - Step 1: First insert as with a vanilla BST
 - Step 2: Nodes along path from newly inserted leaf node up to root may be unbalanced
 - Traverse up to tree looking for node x with $balance(x) \notin \{-1,0,1\}$
 - If no unbalanced node is found, we are done
 - Step 3: If unbalanced node is found
 - Cases
 - Unbalance arises in left subtree (left-heavy)
 - Left-left heavy: do a right rotation
 - Left-right heavy: do a left-right rotation

- Unbalanced arises in right subtree (right-heavy)
 - Right-right heavy: do a left rotation
 - Right-left heavy: do a right-left rotation
- Things to note
 - In all four of the above cases, the balance of the root is 0
 - Height of resulting subtree is same as it was before insertion (all nodes above subtree) will be balanced
- Worst-case time complexity
 - Rebalancing is $\mathcal{O}(1)$, but we may need $\mathcal{O}(\log_2 n)$ height inspections to find an unbalanced node, so total worst-case time complexity of insertion is $\mathcal{O}(\log_2 n)$
- Deletion
 - Step 1: delete as with a vanilla binary search tree (including replacement). Then go to parent of the deleted node (or replacement node) and similar to insertion, go up looking for unbalanced nodes
 - · Step 2: If an unbalanced node is found
 - Cases
 - Right-right heavy (and possibly right-left heavy): left rotation will fix
 - Right-left heavy (not right-right heavy): right-left rotation will fix
 - Left-left heavy: symmetric to right-right heavy
 - Left-right heavy: symmetric to right-lefty heavy
 - Worst-case time complexity
 - Steps
 - Step 1: Finding the node and possibly a replacement takes $\Theta(\log_2 n)$ because of the height of the tree
 - Step 2: Deletion (chop, splice, promote) is $\Theta(1)$
 - Step 3: Checking every node back to the root is $\Theta(\log_2 n)$ nodes
 - Step 4: Each fix (via a rotation) is $\Theta(1)$
 - Total worst-case time complexity is $\Theta(\log_2 n)$

B-Trees

- A multiway search tree is a generalization of a BST: if a node has keys $a_1 < a_2 < \ldots < a_k$, the children are roots of subtrees A_1, \ldots, A_{k+1} with keys satisfying $A_1 < a_1 < A_2 < a_2 < \ldots < a_k < A_{k+1}$
- A **B-tree** of order $m \ge 3$ is a multiway search tree (MST) with the following properties:
 - It is **perfect** (all leaves are at the same level)
 - The root node has between 1 and m-1 keys; if the root node has children then c=1+k, so the number of children c is between 2 and m
 - Non-root nodes have between $\lceil \frac{m}{2} \rceil 1$ and m-1 keys
 - ullet If the non-root has children than c=1+k, so the number of children is between $\lceil rac{m}{2}
 ceil$ and m
 - Note: we allow the root to have down to 1 key because we need to allow (for example) a B-tree with just 1 key
 - Note: we do not allow all nodes to have down to 1 key because it would permit the B-tree to degenerate to a
 vanilla BST, defeating the purpose of the B-tree
- Height theorem: Suppose a B-tree has order $m \geq 3$ and height h;. Then, the following properties hold:
 - (a) The minimum number of keys in the tree is $2\lceil \frac{m}{2} \rceil^h 1$
 - (b) In general, $k \geq 2\lceil \frac{m}{2} \rceil^h 1$
 - (c) $h = \mathcal{O}(\log k)$
 - Proof
 - To prove part (a), we will build a tree with the minimum number of keys via a table:

level	$\# \ \mathrm{nodes}$	$\# \ \mathrm{keys}$
0	1	1
1	2	$2(\lceil m/2 \rceil - 1)$
2	$\lceil m/2 ceil$	$2\lceil m/2\rceil(\lceil m/2\rceil-1)$
3	$2\lceil m/2 ceil^2$	$2\lceil m/2 ceil^2 (\lceil m/2 ceil - 1)$
:	:	÷
h	$2\lceil m/2 ceil^{h-1}$	$igg \ 2\lceil m/2 ceil^{h-1}(\lceil m/2 ceil-1)$

So the total number of keys is

$$1 + \sum_{i=0}^{h-1} 2 \lceil m/2 \rceil^i (\lceil m/2 \rceil - 1)$$

This is a geometric series which sums to $2\lceil m/2 \rceil^h - 1$, proving part (a). Part (b) follows directly from part (a). Using this result, we can obtain $h \leq \log_{\lceil m/2 \rceil} \left(\frac{k+1}{2} \right)$, proving $h = \mathcal{O}(\log k)$, as desired.

- Remark: we've shown that for a given m, h that $2\lceil m/2 \rceil^h 1 \le k \le m^{h+1} 1$, which says that given m, h, k is in that range. This *does not imply* that for each k in this range, which
- Example: suppose m=7
 - If h=4 then the minimum number of keys is $2\left\lceil \frac{7}{2}\right\rceil 4-1=161$
 - If k=40000 then $h \leq \log \lceil 9/2 \rceil \left(rac{40001}{2}
 ight) pprox 9.02$ so $h \leq 9$
- Advantages of using B-trees
 - Less balancing required following insertions/deletions
 - Easier to do rang queries
- Restructuring
 - An **overfull node** is a node with m+1 children (m keys)
 - An **underfull node** is a node with $\lceil m/2 \rceil 1$ children and $\lceil m/2 \rceil 2$ keys
 - Rotation operations
 - Key rotations: required when a node is over/underfull but there are extra keys in an adjacent sibling that we can use to restructure the tree

Scapegoat Trees

- · Scapegoat trees are interesting because they involve several thought-provoking concepts
 - Time is analyzed via amortized analysis
 - Tree + subtree rebuilding
 - Weight-balancing
 - · Balancing with insertion/deletion is very different
 - Very little additional info to store
- Balancing
 - Def: For a node x in a tree define size(x) to be the number of nodes in the subtree rooted at x
 - Some ideas
 - For each node x we might require that size(x. left) = size(x. right) (this is too rigid)
 - For each node x, define $\mathrm{size}(x.\operatorname{left}) = \mathrm{size}(x.\operatorname{right})$, or equivalently $\frac{\operatorname{size}(x.\operatorname{child})}{\operatorname{size}(x)} pprox \frac{1}{2}$
 - But 1/2 is too rigid and defining an approximation is difficult (we need some formality)
 - Def: Let α be a real number with $\frac{1}{2} < \alpha < 1$. Define a **scapegoat** to be a node x with $\frac{\text{size}(x.\text{child})}{\text{size}(x)} > \alpha$
 - Typically, $\alpha=\frac{2}{3}$ is used, so a scapegoat has $rac{\mathrm{size}(x.\mathrm{child})}{\mathrm{size}(x)}>rac{2}{3}$
 - We might think that a scapegoat tree is a tree with no scapegoats, but that is not where this is going
- A scapegoat is someone who is blamed for something they did not do (e.g. they are a sacrifice); a scapegoat tree is
 a binary tree which is only modified if it gets "badly unbalanced"

Operations

- Some formality
 - · We will store only two things other than the tree
 - n, which is the number of nodes/keys
 - *m*, which is the maximum number of nodes which have been in the tree since it was created or since the last total rebuild due to deletion
 - Ex: start with an empty tree, so n=0 and m=0. Then, do the following operations:
 - Insert 17 keys, making n=17 and m=17
 - Delete 3 keys, making n=14 and m=17 (assume no rebuild)
 - Insert 1 key to obtain n=15 and m=17

Goals:

- 1. Height of the tree should be $\lfloor \log_{3/2} n \rfloor + 1$ or less
- 2. The tree should be "balanced" whenever possible

Sub(tree) rebuilding

- Suppose we have a tree or subtree; we can rebuild it as follows:
 - First do an in-order traversal to get the keys in a list in order
 - If the list has length k, pick the entry with index $\lfloor k/2 \rfloor$ that becomes the new root
 - · Then, all smaller keys go left via recursion
 - · All larger keys go right via recursion

Insertion

- Informal def: Insert as in a standard BST; if the insertion node is too deep (how deep? We will revisit this) we go back up the tree until we find a scapegoat (why must a scapegoat exist?) and we rebuild the subtree (what does this mean?) rooted at that scapegoat
- Formal def: Insert as with a standard BST. Let d be the depth of the inserted node. If $d>\log_{3/2}n$, then go up the tree until we find a scapegoat and rebuild the subtree rooted at the scapegoat. We choose 3/2 as the base of the logarithm because $1/\alpha=3/2$

Deletion

- Informal def: If we delete too many nodes (how many?) without inserting to compensate, we panic and rebuild the entire tree
- Formal def: Delete as with a standard BST. If $n < \frac{2}{3}m$, rebuild the entire tree and set m = n

· Important results

- Thm: Rebuilding a tree with i nodes takes time $\mathcal{O}(i)$
 - Proof: The inorder traversal via recursion can write to an array in $\mathcal{O}(j)$ time. As rebuilding is a recursive divide-and-conquer algorithm, the entire process takes time $\mathcal{O}(j)$
- Thm: A rebuilt tree with j nodes will have height equal to $|\log j|$
 - Proof: Done by strong induction on j and is left to the reader
- Scapegoat existence; if the depth of the inserted node is greater than $\log_{3/2} n$, then it has an ancestor which is a scapegoat
 - Thm: For a BST with n nodes suppose p is a freshly inserted node satisfying $\operatorname{depth}(p) > \log_{3/2} n$. Then, an ancestor of p is a scapegoat.
 - Proof: Proceed by contradiction; suppose for every note u from the root to p we have $\frac{\text{size}(u.\text{childonpath})}{\text{size}(u)} \leq \frac{2}{3}$

Following the path from the root r to node p, we have the following:

$$egin{aligned} n &= \operatorname{size}(r) \ &\geq rac{3}{2} \operatorname{size}(r.\operatorname{childonpath}) \ &\geq \left(rac{3}{2}
ight)^2 \operatorname{size}(r.\operatorname{childonpath.childonpath}) \ &\geq \dots \ &\geq \left(rac{3}{2}
ight)^{\operatorname{depth}(p)} \operatorname{size}(p) = \left(rac{3}{2}
ight)^{\operatorname{depth}(p)} \end{aligned}$$

So,
$$n \geq \left(\frac{3}{2}\right)^{\operatorname{depth}(p)}$$
, which implies $\operatorname{depth}(p) \leq \log_{3/2} n$

- Keeping track of size: size calculations do not slow processes down because they are in $\mathcal O$ of the size of a subtree
- · Height theorems
 - Thm: The height of a scapegoat tree with $n \geq 1$ satisfies $h \leq \lfloor \log_{3/2} n \rfloor + 1$
 - Proof: Sketch in Justin's notes (more rigorous proof in Galperin/Rivest).
 - · Ideas from proof:
 - A tree is height-balanced if $h \leq \lfloor \log_{3/2} n \rfloor$ and loosely height-balanced if $h \leq \lfloor \log_{3/2} n \rfloor + 1$ (an empty tree is height-balanced by default)
 - Corollary: The height of a scapegoat tree satisfies $h(n) = \mathcal{O}(\log n)$
 - Proof: Follows immediately from previous theorem.
- Time complexity
 - Search worst-case: as $\mathcal{O}(\log n)$, search is also worst-case $\mathcal{O}(\log n)$
 - Insertion/deletion: $\mathcal{O}(n)$
 - Amortized analysis
 - While insertion/deletion is worst-case $\mathcal{O}(n)$, such operations do not happen repeatedly (e.g. we will never do a rebuild immediately after a rebuild)
 - Thm: Starting with an empty tree, any sequence of k insertions/deletions has an amortized cost of $\mathcal{O}(\log k)$ per operation (including rebuilding)
 - See Justin's notes for a more detailed description

Splay Trees

- Motivation: we want an efficient self-balancing tree that easily gives access to nodes we need more access to
- Splay operations
 - **Zig**: when target node x is left or right child of p, do a right or left rotation at p, respectively
 - Zag: when target node x is left-left or right-right child of root g, do a right-right or left-left rotation at g, respectively
 - **Zig-Zag**: when target node x is left-right or right-left child of root g, rotate right at parent p and left at g in the first case or left at parent p and right at g
- Implementing splay
 - We splay a node when that node is the not the root of the tree and we wish to transport it to the root; we have the following four cases:
 - (a) If x is the root, we are done
 - (b) If x is a left-left child or a right-right child, Zig-Zig
 - (c) If x is a right-left child or a left-right child, Zig-Zag
 - (d) If none of the above apply, go back to (a)
- Tree operations
 - Search
 - Call splay on target key; if key exists, it will be at root (otherwise, throw an error)
 - Even if key is not at root, tree will be cleaner (more balanced and reorganized) after process

- Insert
 - Algorithm 1: Described well in Justin's notes
 - · Algorithm 2: Insert as with a vanilla BST
- Delete
 - Algorithm 1: Described well in Justin's notes
 - Algorithm 2: Delete as with a standard BST and splay parent of that key to root
- Time complexity
 - Amortized cost of a single operation is $\mathcal{O}(\log n)$ because splay trees tend to be balanced
 - Worst-case is O(n), since there is technically nothing stopping the splay tree from turning into a linked list

KD Trees

- Motivation: we want to store keys in an n-dimensional space
- Cycle splitting
 - Insert using cycle splitting (for 2 dimensions, alternate between x and y coordinates to insert)
- Deletion
 - Must use inorder successor since we decided equal coordinates go right
 - If u (the node to be deleted) is a leaf, delete it and we are done
 - Otherwise, if u has a right subtree, let α be the coordinate that u splits on
 - Find a replacement node r in u. right for which r_{α} (the α coordinate of r is minimal)
 - Copy r's point α to u (overwriting u's point)
 - ullet Recursively call delete on the old r
 - If u does not have a right subtree, it has a left subtree, let α be the coordinate that u splits on
 - Find a replacement node l in u. left for which l_{α} (the α coordinate of l) is minimal
 - Copy l's point to u (overwriting u's point) and move u's left subtree to become u's right subtree
 - Recursively call delete on the old l
 - Why does this work?
 - All other nodes in u. left have α -coordinate greater than or equal to r_{α} , so when u. left is moved to u. right, all nodes in u. right are correctly positioned with respect to r_{α}

Extended KD-Trees

- Motivation: all data is at leaf nodes and internal nodes only contains coordinate to split on and splitting coordinate value (these are splitting nodes)
- Insertion
 - · Note: we always go right on an equal coordinate
 - · Insert at leaf; if leaf is overfull, split
 - · Splitting leaf nodes
 - When we split, we create a parent splitting node that requires a splitting coordinate and value
 - Two possible approaches to splitting: cycle split or spread split

Character Tries

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