

Lazy Data Structures

Roadmap for rest of semester

"Average" analysis of algorithms
↑
(w/out sacrificing worst-case robustness)

① Amortized analysis ("average" in hindsight)

② Randomized algorithms ("average" over random bits)

Both are very practical, different perspectives

Incrementing Binary Counters

`i++;`

`//increment i`

In bits:

0, 1, 10, 11, 100, 101, ~

how often total

- 1st* bit

every time n

- 2nd bit

every 2 times $\lfloor \frac{n}{2} \rfloor$

- 3rd bit

every 4 times $\lfloor \frac{n}{4} \rfloor$

⋮

- kth bit

every 2^{k-1} times $\lfloor \frac{n}{2^{k-1}} \rfloor$

[illegible]

	how often	total
• 1st [*] bit	every time	n
• 2nd bit	every 2 times	$\lfloor \frac{n}{2} \rfloor$
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n increments $\Rightarrow O(n)$ total time

each increment takes $O(1)$ on average

" $O(1)$ amortized time"

Amortized Analysis

	how often	total
• 1st [*] bit	every time	n
• 2nd bit	every 2 times	$\lfloor \frac{n}{2} \rfloor$
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"T amortized time"

$\Rightarrow$ n operations take $O(nT)$ time

Multiple operations $OP_1, \dots, OP_k$

" OP_1 takes T_1 amortized time, OP_2 take $\dots$

OP_k takes T_k amortized time"

Ways to do amortized analysis

- direct analysis (like above)
- credit schemes ("banker method")
- potential function method

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Credit schemes

Idea: buy credits ahead of time to pay for work later

$$(\text{running time}) + \alpha(1) \cdot (\Delta \text{ credit}) \leq \text{amortized time}$$

(net increase)

Credit schemes Idea: buy credits ahead of time to pay for work later

$$(\text{running time}) + \underbrace{O(1) \cdot (\Delta \text{ credit})}_{(\text{net increase})} \leq \text{amortized time}$$

e.g. for binary counter, when incrementing:

[illegible]

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put: 1 credit on first bit
 $\frac{1}{2}$ credit on 2nd bit
 $\frac{1}{4}$ credit on 3rd bit
 $\vdots$
 $+$ $\frac{1}{2^i}$ credits on i th bit

2 credits total

when we need to flip bit i , we have already saved 1 credit to pay for it

Credit schemes

Idea: buy credits ahead of time to pay for work later

$$(\text{running time}) + \underbrace{\alpha(i) \cdot (\Delta \text{ credit})}_{(\text{net increase})} \leq \text{amortized time}$$

Main rule:

Only spend credits that you already saved

eg. for binary counter, when incrementing:

0, 1, 10, 11, 100, 101, ...
11111111111111111111111111111111
10000000000000000000000000000000

	how often	total
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+ $\frac{1}{2^{i-1}}$ credits on ith bit

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when we need to flip bit i , we have already saved 1 credit to pay for it

Potential method

Invent "potential Φ "



Amortized cost of operation will be

$$(\text{real time}) + \Delta\Phi$$

(change in potential)

Potential method

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(real time) + $\Delta\Phi$
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e.g. binary counter

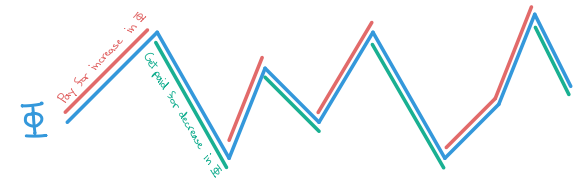
Φ = # bits set to 1

then for each inc.,

$$(\text{real time}) + \Delta \bar{\Phi} \leq O(1)$$

leach bit reset to 0 paid by $\Delta\Phi$)

"potential Φ "

[illegible]

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Potential method

Invent "potential Φ "



Pay for increase in Φ

Get paid for decrease in Φ

" Amortized cost of operation will be "

$$(\text{real time}) + \underbrace{\Delta\Phi}_{(\text{change in potential})}$$

why? suppose n operations

T_i = time of i th operation

Φ_i = Φ after i operations

$$\Delta\Phi_i = \Phi_i - \Phi_{i-1}$$

$$\sum_{i=1}^n (T_i + \Delta \Phi_i) = (\text{total time}) + \overset{\geq 0}{\Phi_n}$$

$$\geq (\text{total time})$$

$$(\text{total time}) \leq \sum_{i=1}^n (T_i + \Delta \Phi_i)$$

Ways to do amortized analysis

- direct analysis (like above)
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put: 1 credit on first bit
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+ $\frac{1}{2^{i-1}}$ credits on i th bit

2 credits total

- potential function method

$\Phi = \# \text{ bits set to } 1$

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" T amortized time"

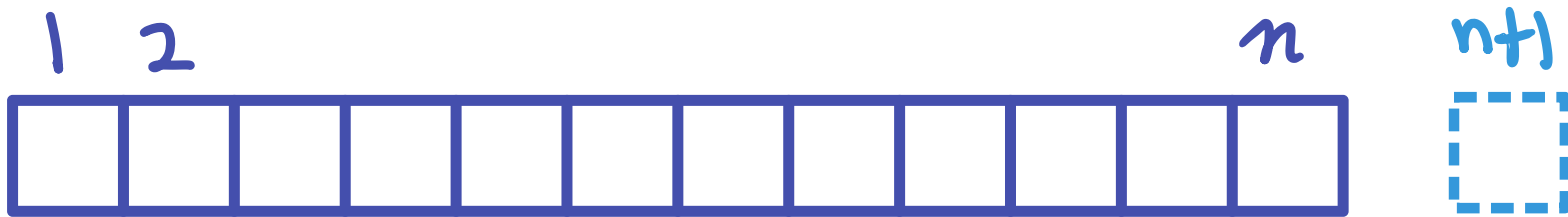
$\Rightarrow n$ operations take $O(nT)$ time

Multiple operations $OP_1, \dots, OP_k$

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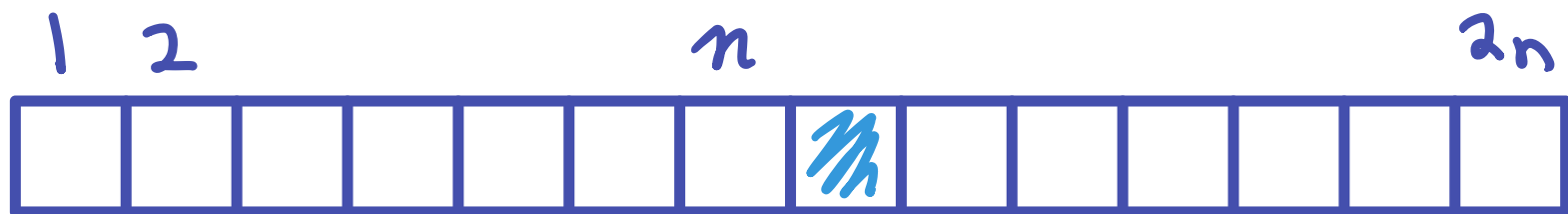
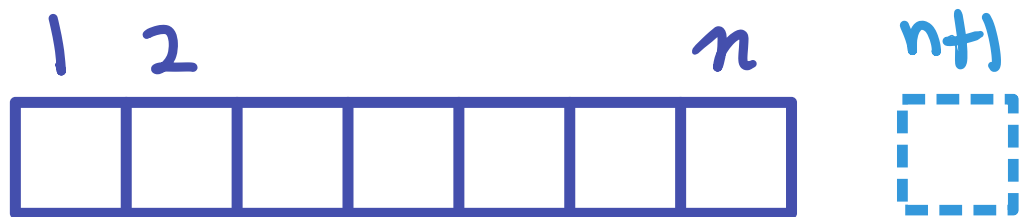
Array-backed lists



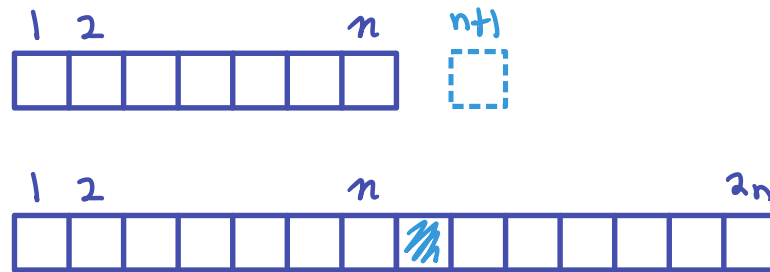
Good: $O(1)$ access by index

Bad: $O(n)$ append

Doubling Trick



Doubling Trick



Theorem

w/ doubling trick, arraylist has

- lookup in $O(1)$
- append in $O(1)$ amortized

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Proof

Doubling Trick



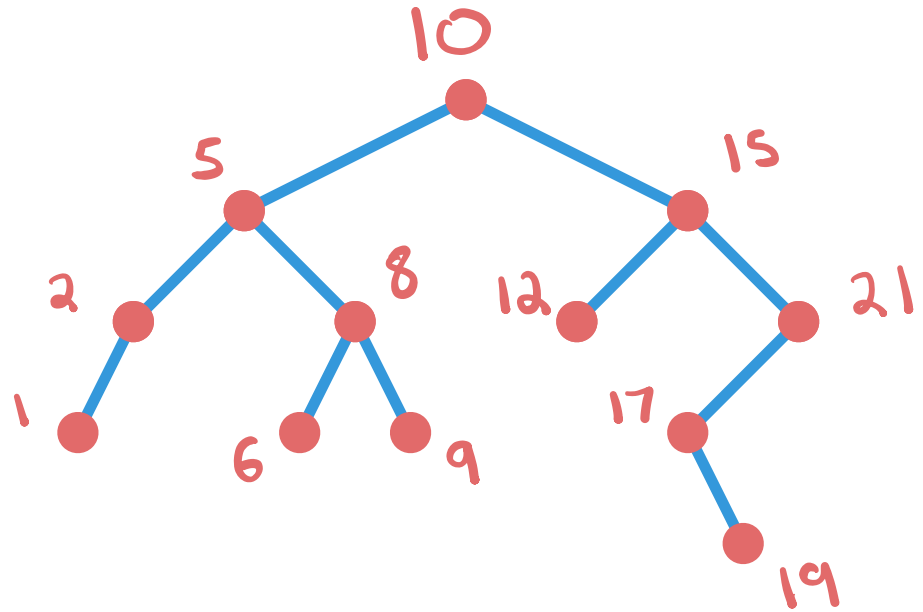
Search trees

organizes keys
in a tree

Invariant:

a node's # is

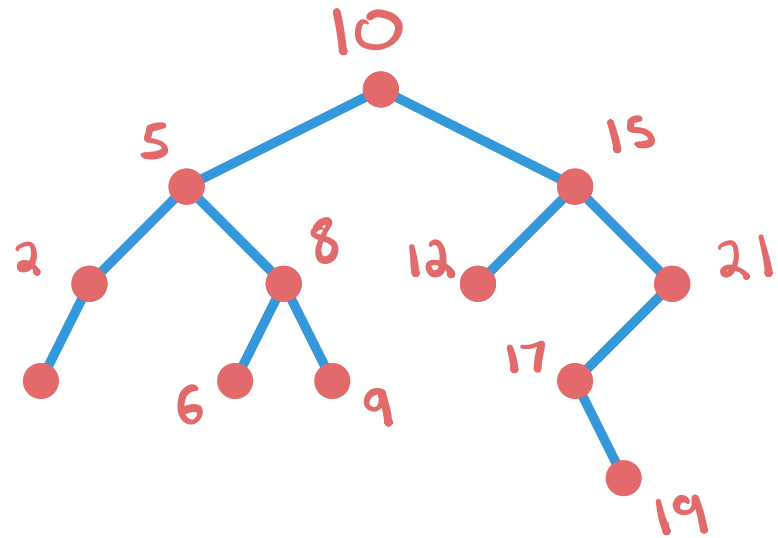
- $\geq$ any # in left subtree
- $\leq$ any # in right subtree



Invariant:

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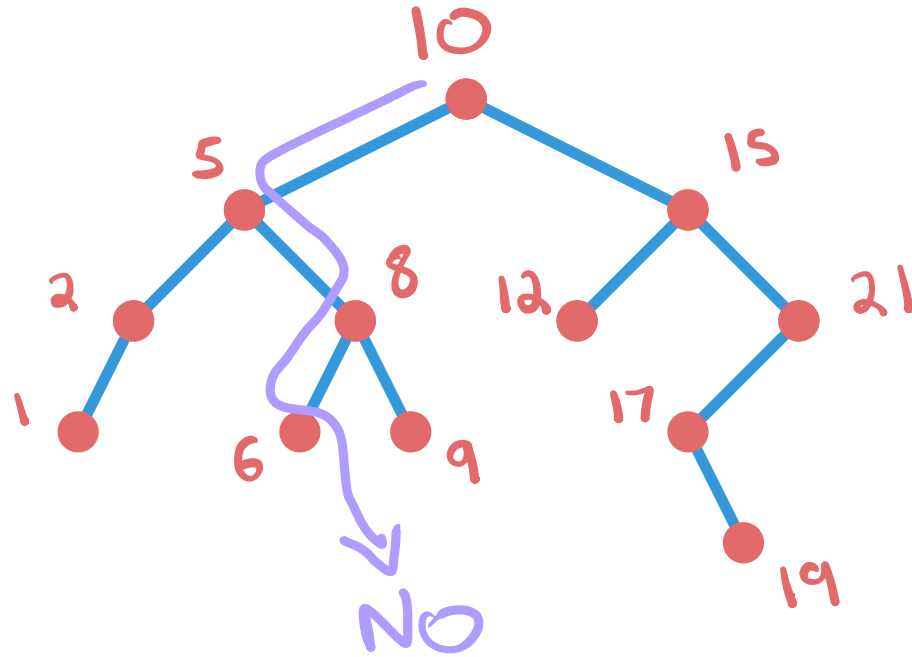
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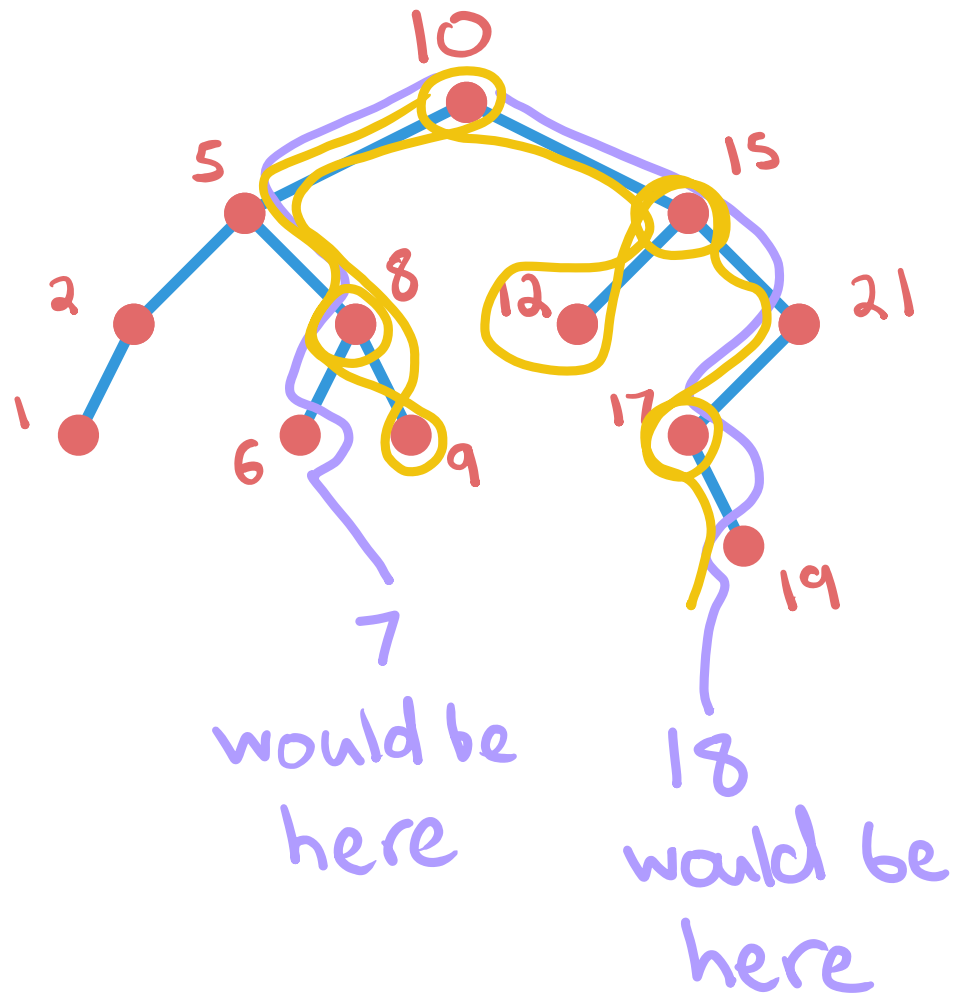
Leads to operations like:

- is a given key in the set?
- what is the first key $\geq x$
- list all keys between x and y
- how many keys are between x and y

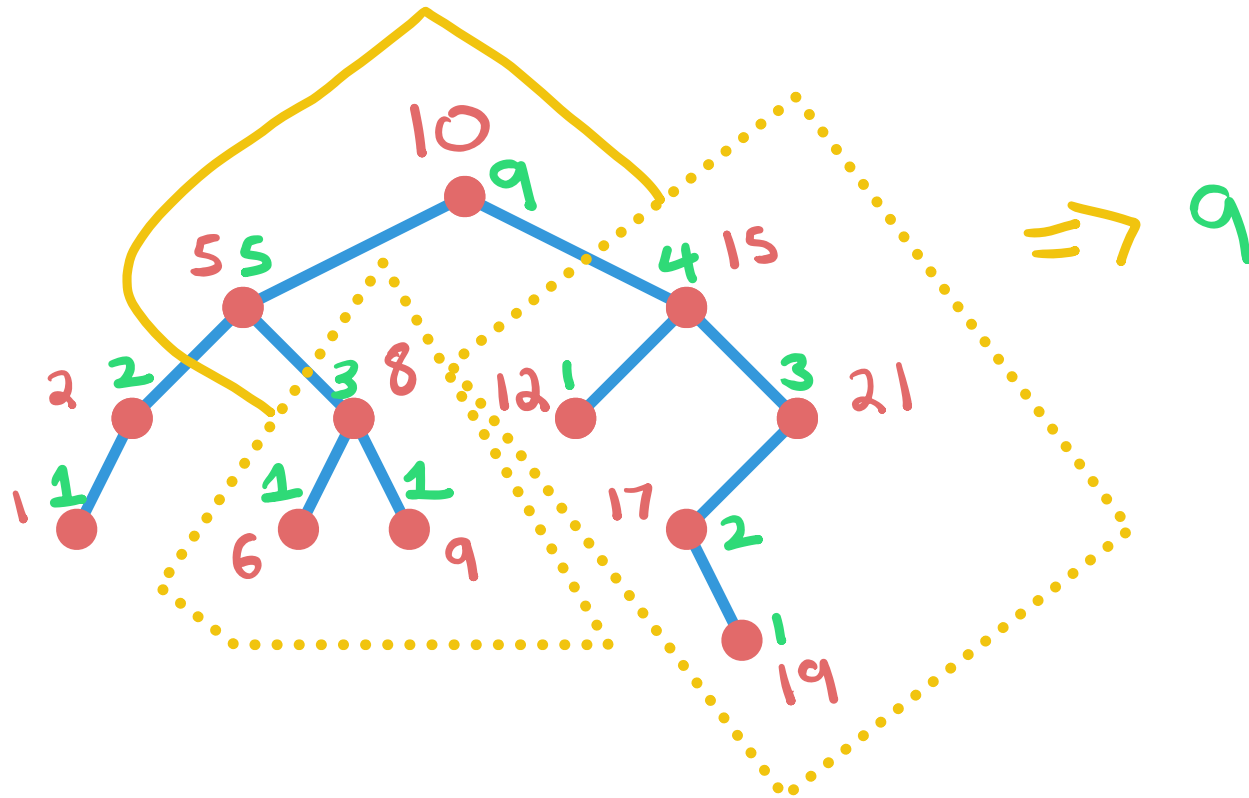
does the tree contain 7?



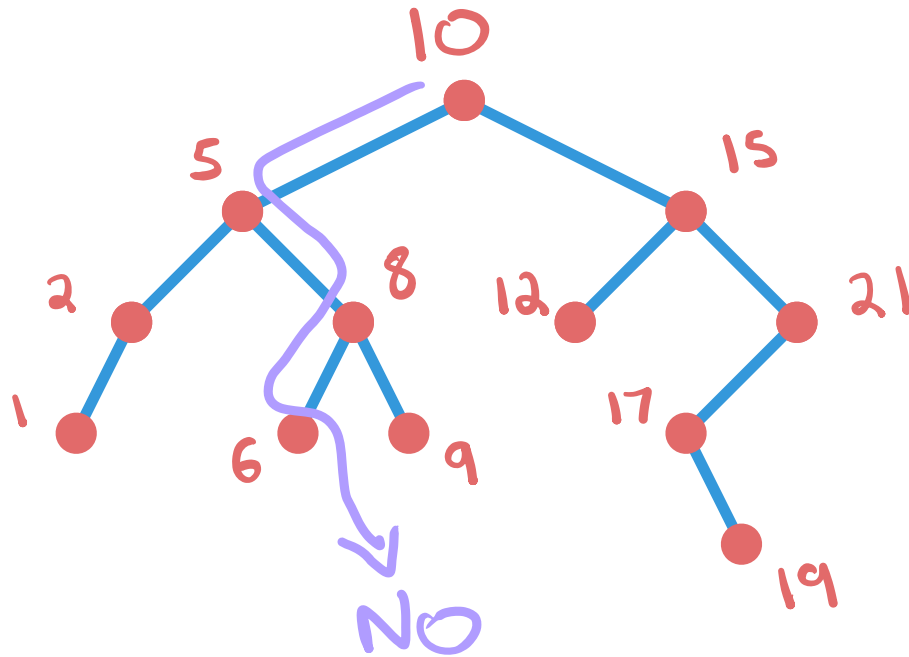
list all keys between 7 and 18



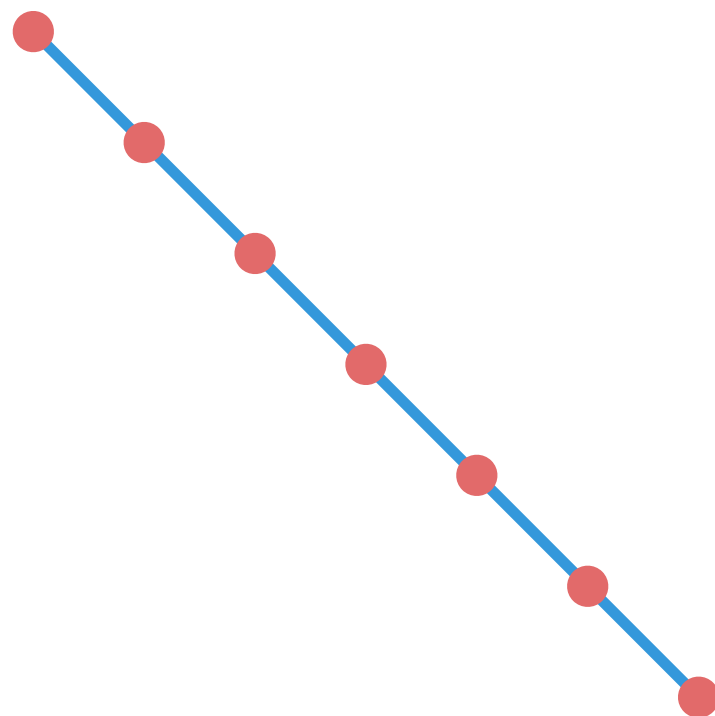
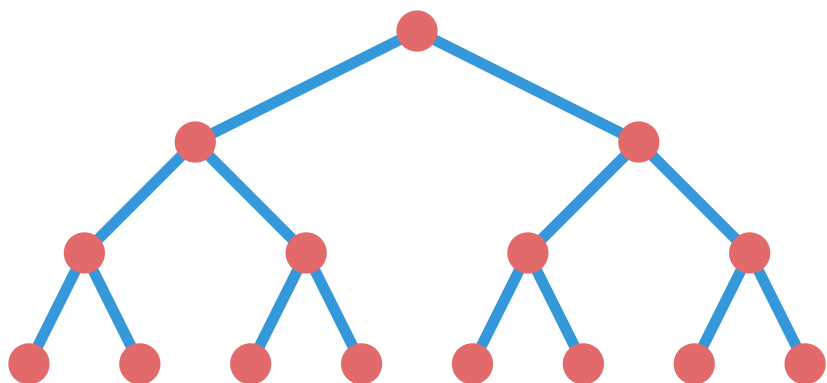
how many keys are between 5 and 25

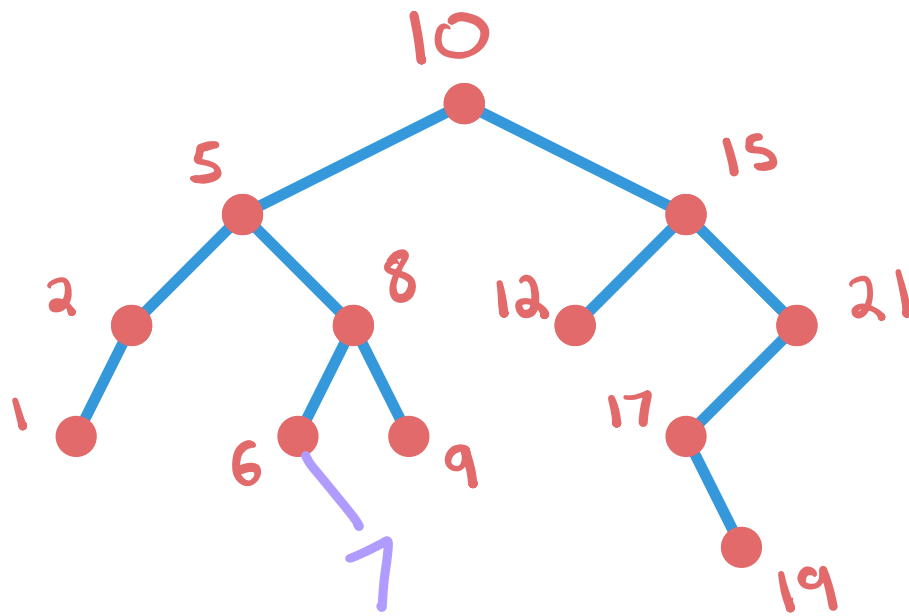


if we write down # nodes in each subtree, then faster



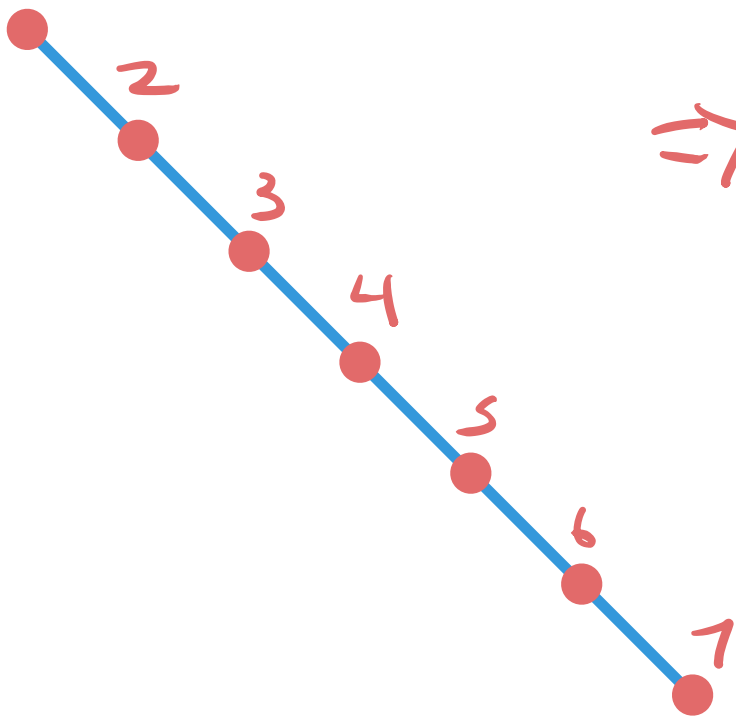
operations take time proportional
to the height of a tree



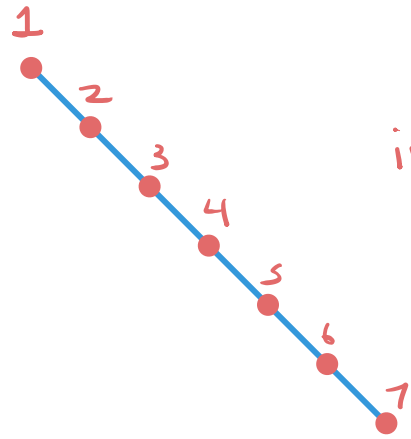


Most natural method for insertion
is as leaves (search for where
the key would be, and put it there)

1 insert 1, 2, 3, 4, 5, 6, 7



$\Rightarrow$ imbalanced



insert 1, 2, 3, 4, 5, 6, 7

$\Rightarrow$ imbalanced

How to keep a tree balanced?

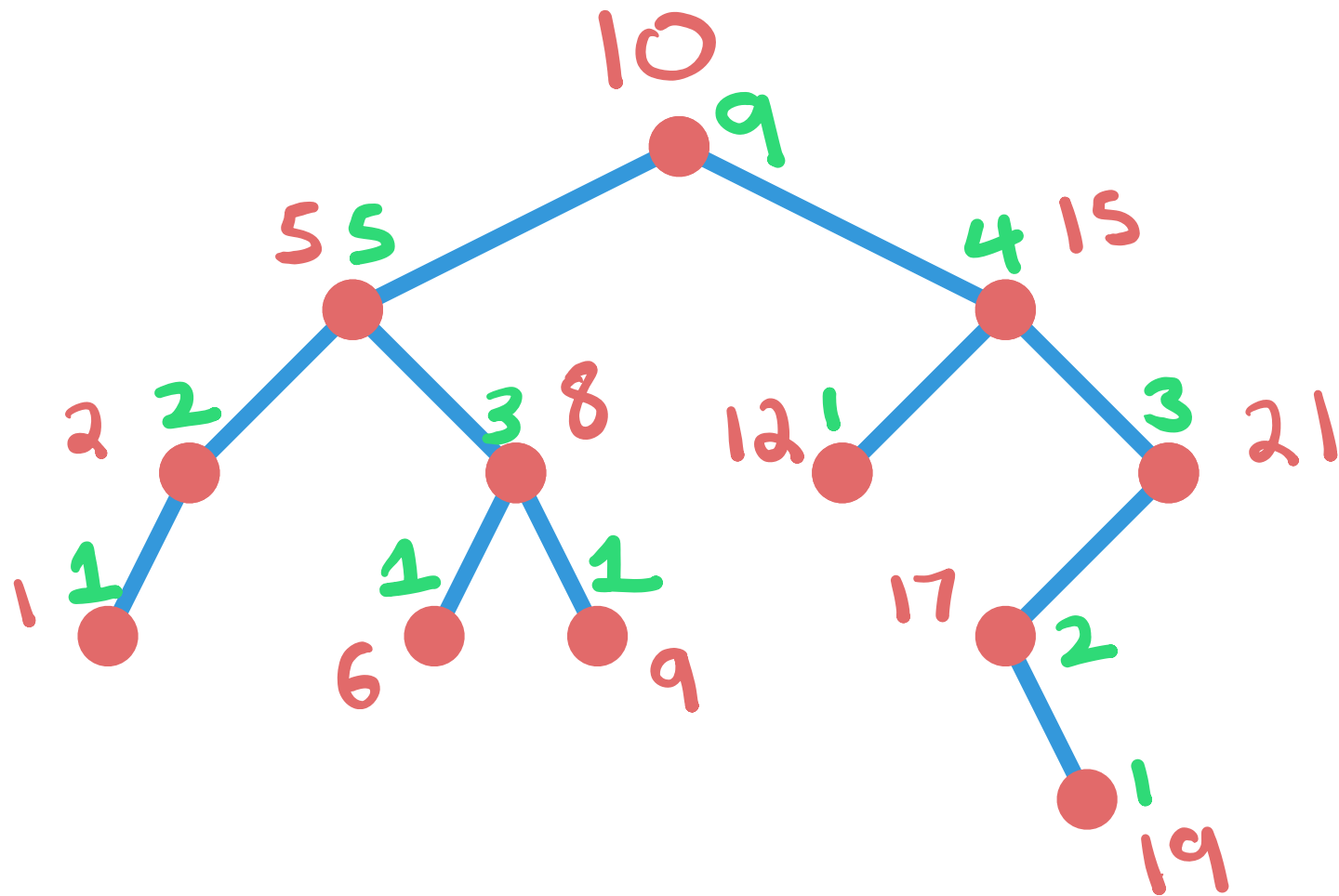
AVL trees

Red-black trees

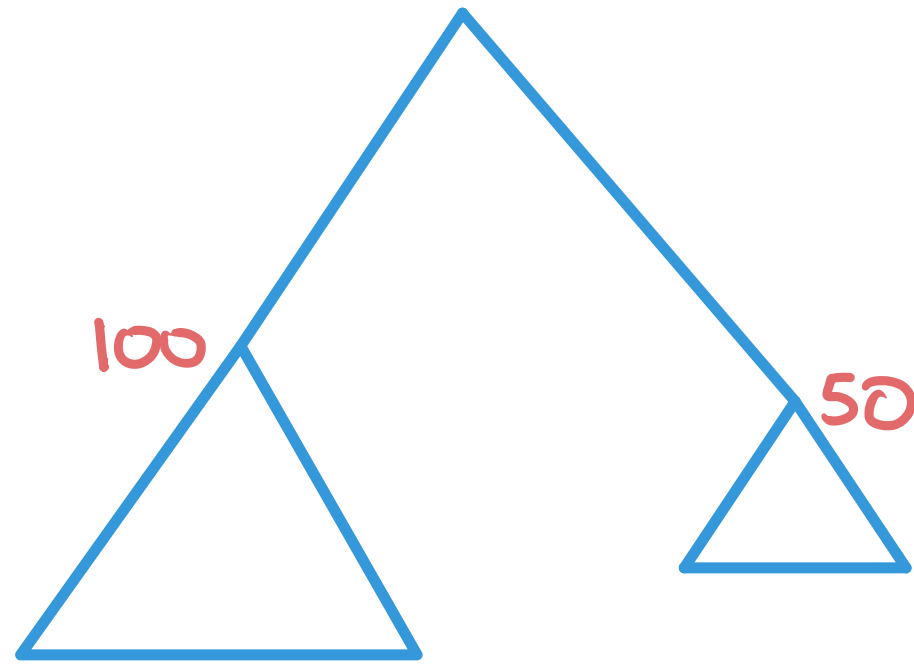
typically covered in
UG data structures

Today we will be very lazy

write down # nodes in each subtree



If we detect big imbalance:



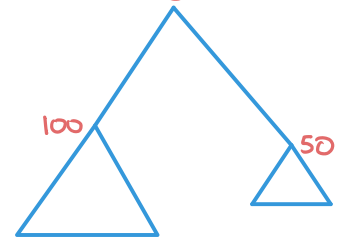
$$\left(\begin{array}{c} \# \text{ in one} \\ \text{subtree} \end{array} \right) > 2 \times \left(\begin{array}{c} \# \text{ in other} \\ \text{subtree} \end{array} \right),$$

rebuild entire subtree tree optimally

(choose median to be root of subtree, recurse) (linear time)

Lemma: height is $O(\log n)$
(always)

If we detect big imbalance:



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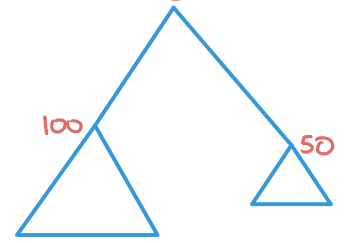
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Theorem insertion takes
 $O(\log n)$ amortized time

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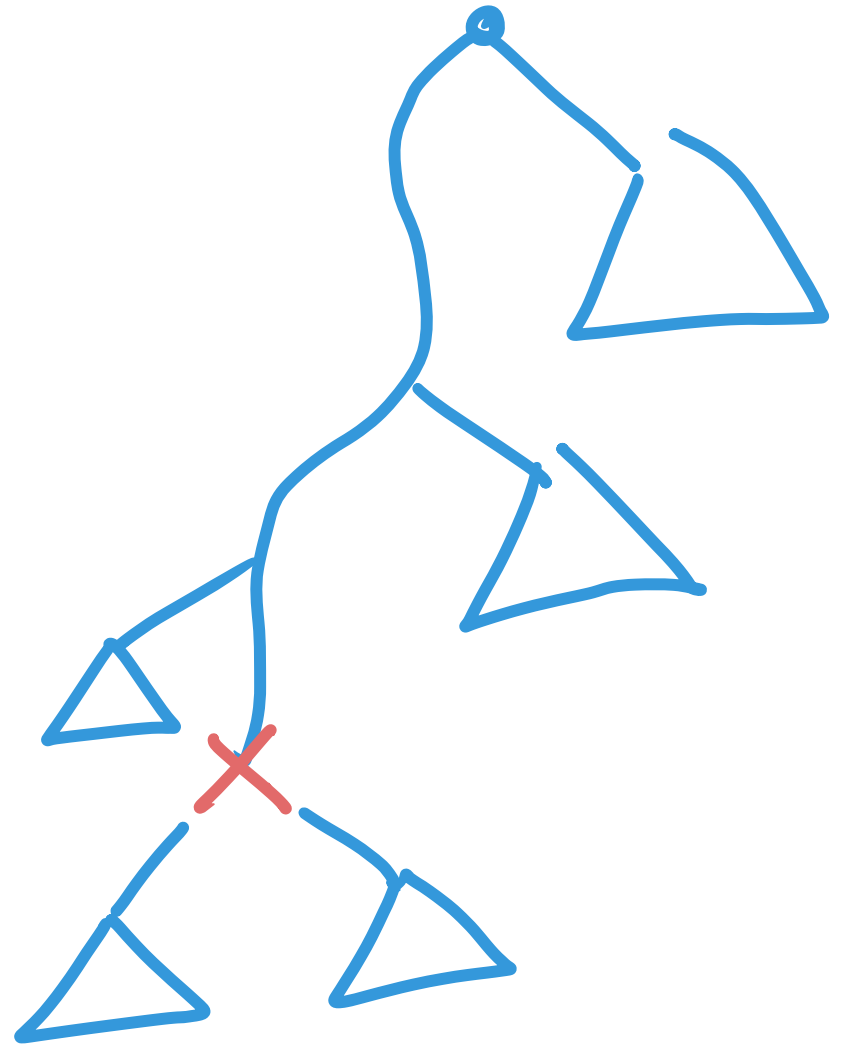
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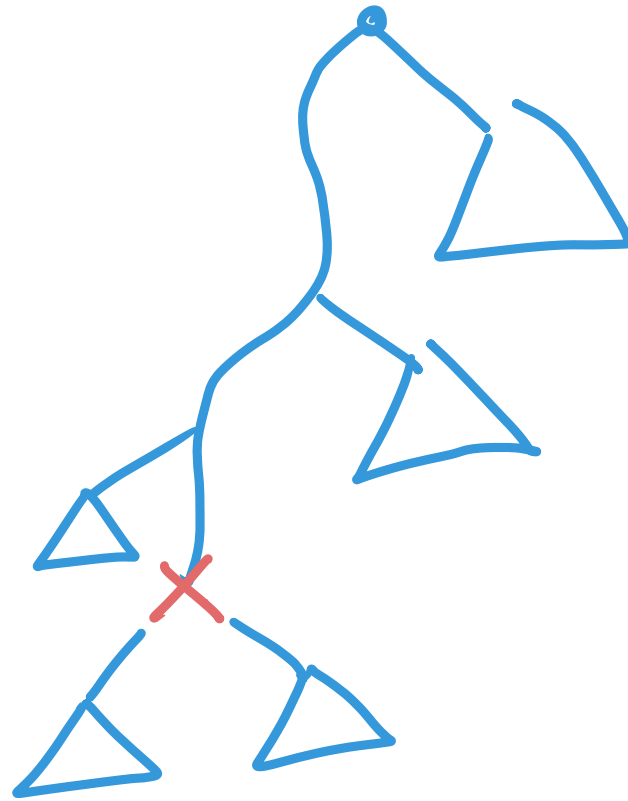
Deletions (remove key from BST)

Old-fashioned way:

① search for key

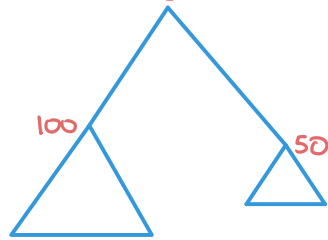
② If key is not a leaf:
chaos





Lazy idea: mark node as deleted
if $\geq 50\%$ marked for deletion,
rebuild optimally

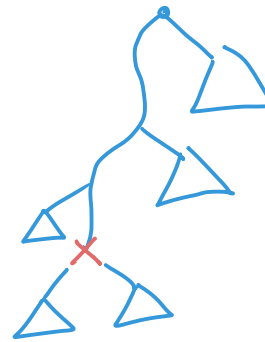
Is we detect big imbalance:



$(\# \text{ in one subtree}) > 2 \times (\# \text{ in other subtree})$,

rebuild entire subtree tree optimally

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Lazy idea: mark node as deleted

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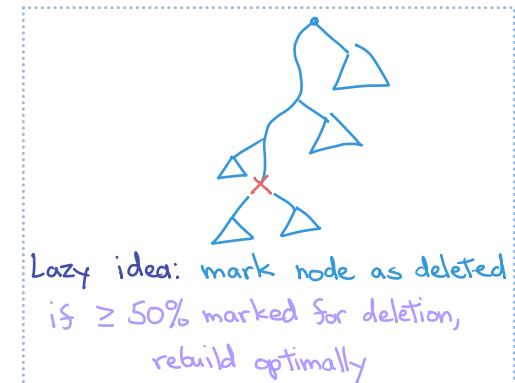
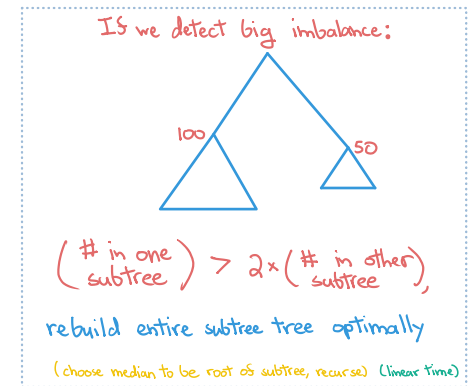
rebuild optimally

Theorem: lazy insertion and lazy deletion take

$O(\log n)$ amortized time

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Proof



Immutable data structures

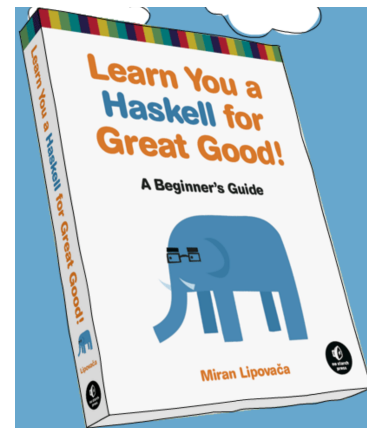
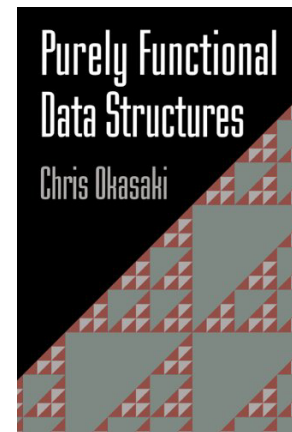
Once something is written, never changes

Restrictions bring benefits:

no side effects

simplifies concurrency

helps compiler



Immutable data structures

Once something is written, never changes

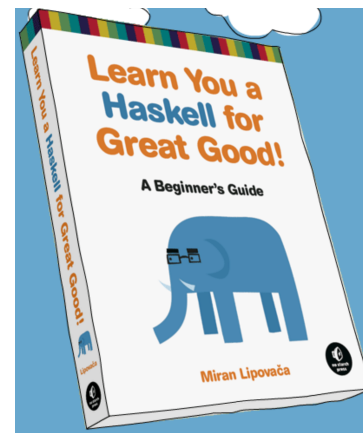
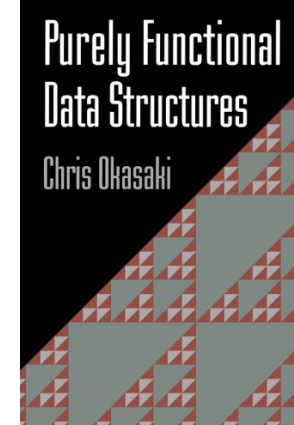
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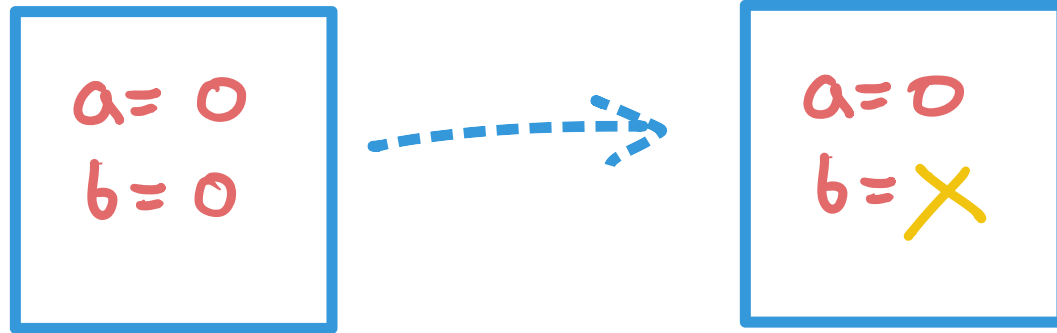
helps compiler

e.g. linked list

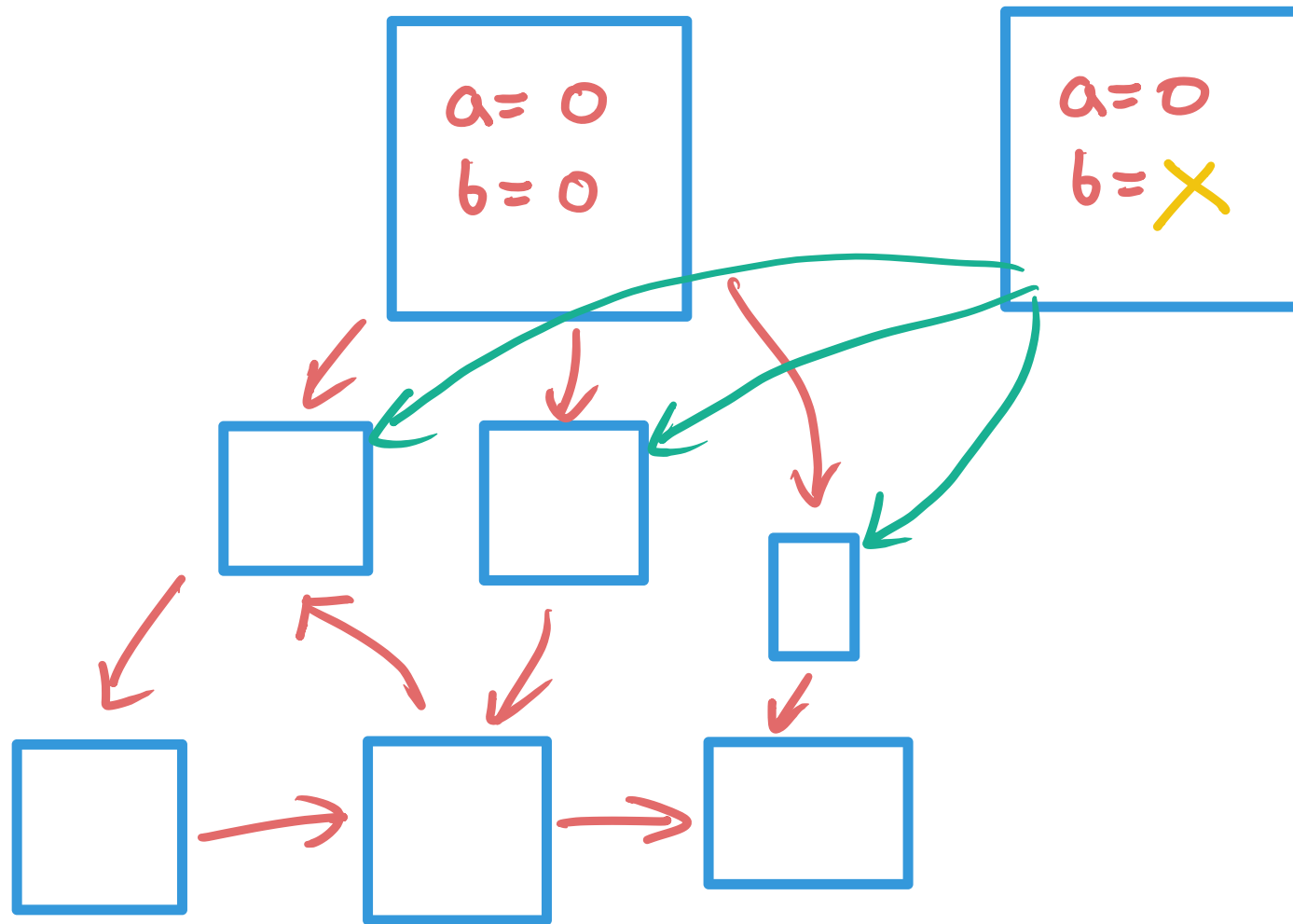


Editing objects by copying

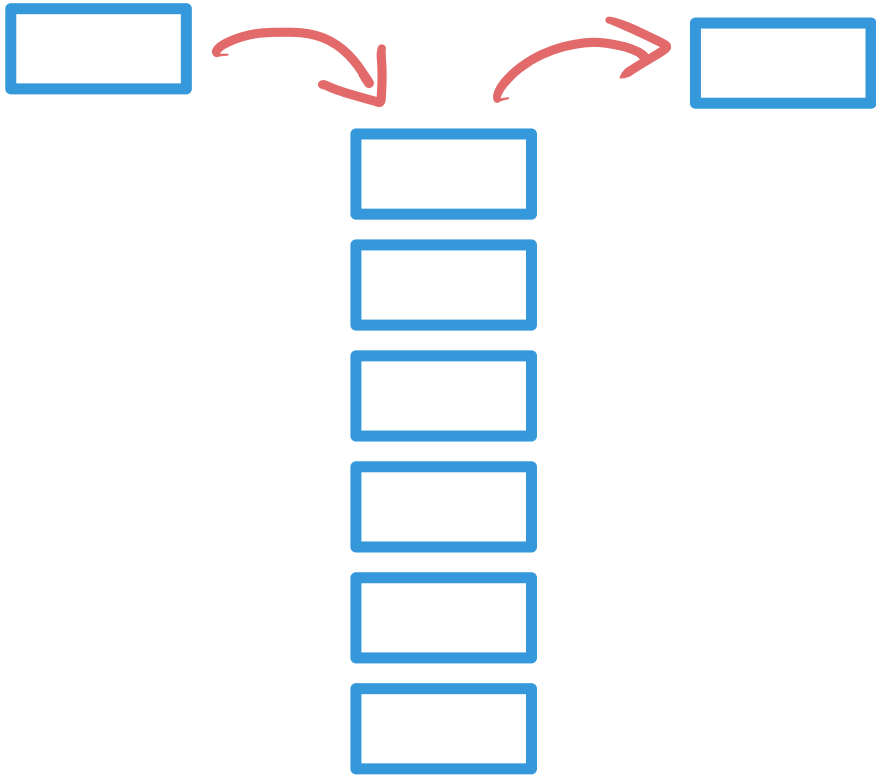
small change $\Rightarrow$ copy whole object



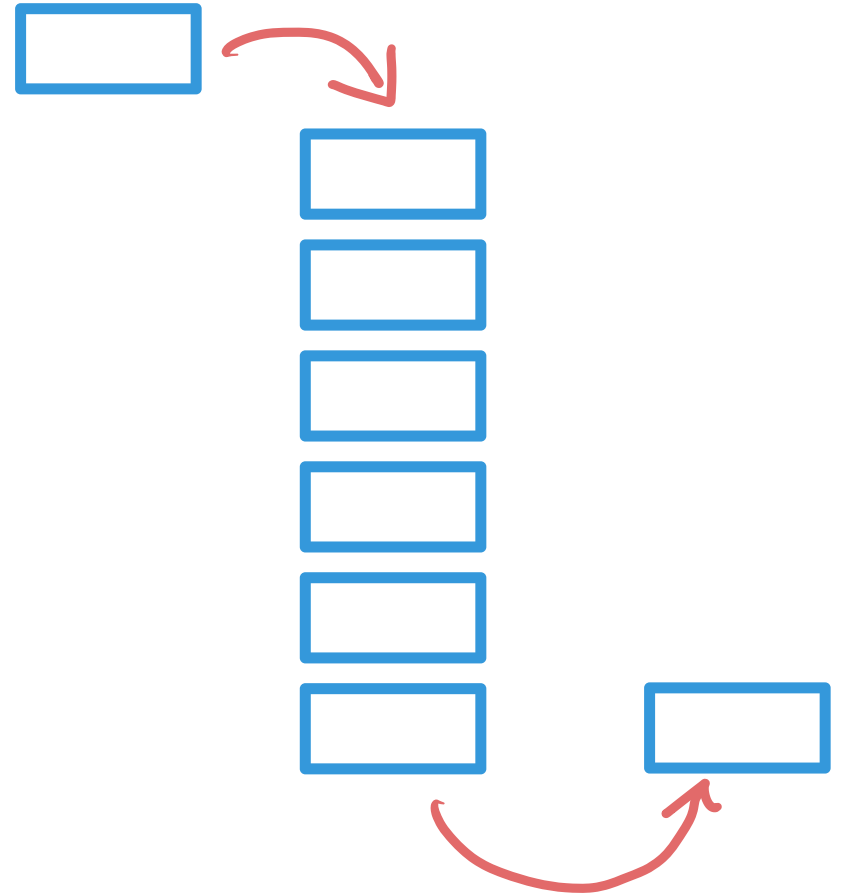
What about "deep" objects?



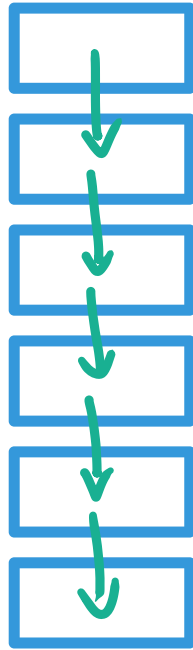
Stacks



Queues

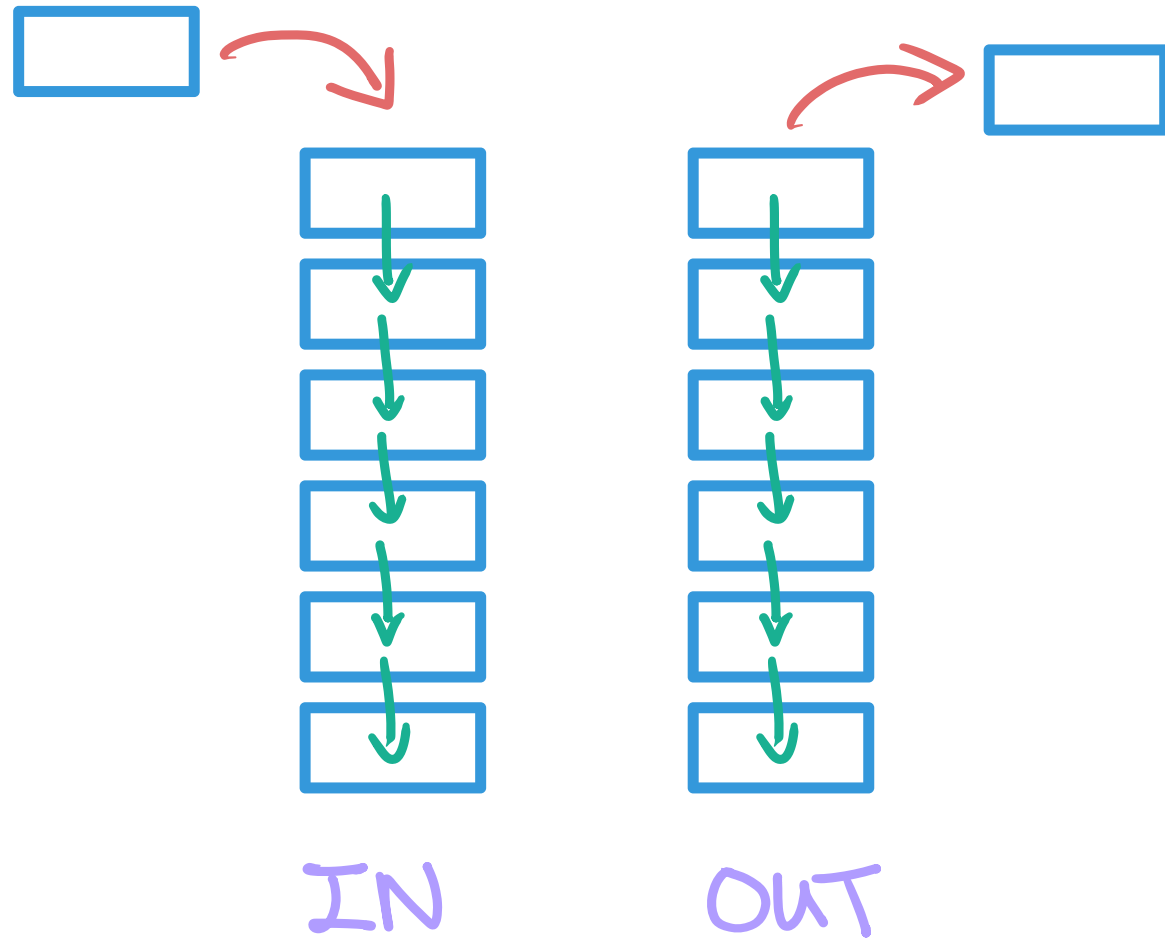


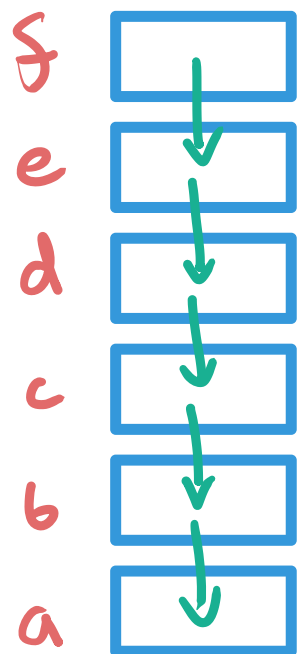
Immutable stacks



(just a linked list)

Immutable Queues

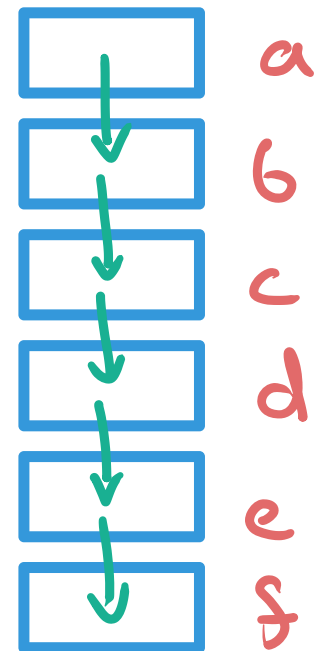




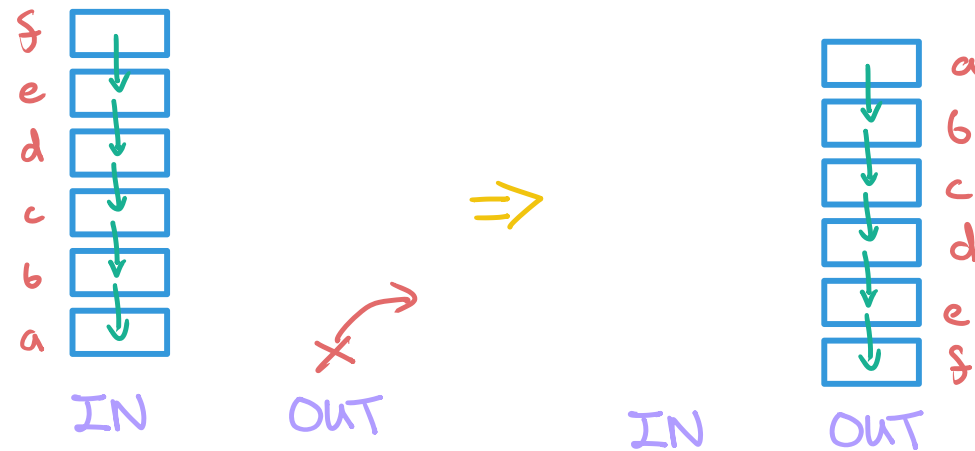
IN



IN



OUT



Theorem: insertion/deletion take $O(1)$ amortized