

15451 Fall 2022

Amortized Analysis

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Imagine some data structure

- Each operation takes **non-uniform** runtime
- An algorithm may make many calls to the data structure
- What matters: **average** cost per operation, also called **amortized** cost

Example: growing an array

- On item arrival, store in an array
- No prior knowledge of #items

What space should we preserve for the array?

- Allocate $O(1)$ upfront
- Whenever full, double the size

What is the amortized cost?



std: vector

- constructor: `vector<int> array`
- `push_back` ← add new item
- `pop_back` ← deletion
- index into: `array[i]`



- Allocate $O(1)$ upfront
- Whenever full, double the size
- Whenever $\frac{1}{4}$ loaded, half the size

This Lecture

- Learn how to do amortized analysis
- Design algorithms with good amortized runtime

Amortized algorithm design and analysis are useful in many applications!

Growing an array

$$\frac{N}{m} = 2$$

space reserved

actual # items

- initialize(): allocates an empty table of size 1 ($n = 1$, $s = 0$)
- insert(): add a new element to the table ($s++$)
 - if $s = n$ then grow(),
 - add the new elem to array[s] (costs 1)
- grow(): double the size from n to $2n$, costs $2n$

$$N \leq 2m$$

$$N \geq m$$
$$\frac{m}{2}$$

m

Suppose at the end, there are m elements in the array.

What is the amortized cost of such an array?

Let N be the space allocated at the end of the day

$$1 \rightarrow 2 \rightarrow 4 \rightarrow 8 \rightarrow \dots \rightarrow \frac{N}{2} \rightarrow N$$

$\underbrace{\quad\quad\quad}_2 \quad \underbrace{\quad\quad\quad}_4 \quad \underbrace{\quad\quad\quad}_8 \quad \quad \quad \underbrace{\quad\quad\quad}_m \quad \underbrace{\quad\quad\quad}_N$

$$2 + 4 + 8 + \dots + N \leq 2N \leq 4m$$

amortize cost = $4 + 1 = 5$

Another example: Binary Counter

n bits

0	0	0	0
1	0	0	1
2	0	1	0
3	0	1	1
4	0	1	0
5	0	1	1
6	1	0	0
7	1	0	1
8	1	1	0
9	1	1	1
10	1	0	0
11	1	0	1
12	1	1	0
13	1	1	1
14	1	1	0
15	1	1	1

- Suppose each bit flipped costs 1
- Amortized cost of the binary counter?

$$T = 2^n$$

$$1 + \frac{1}{2} + \frac{1}{4} + \dots \leq 2$$

$$T + \frac{T}{2} + \frac{T}{4} + \dots + \frac{T}{2^{n-1}} \leq 2T$$

$$\frac{2T}{T} = 2$$

$$\frac{T}{8} + \frac{T}{4} + \frac{T}{2} + T$$

The Potential Method

- Another method of counting
- Sometimes makes analysis easier
 - e.g., for more complex algorithms

The Potential Method

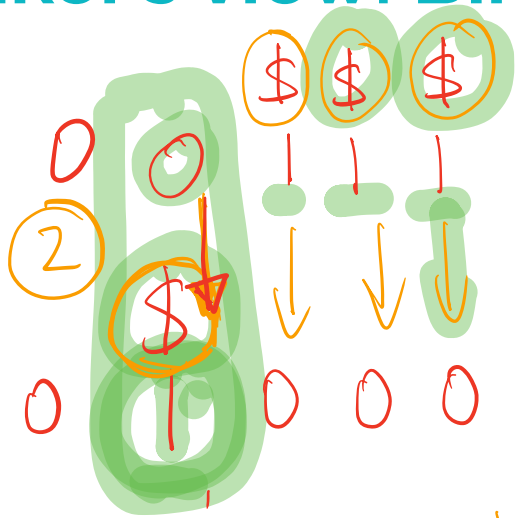
Banker's view

- initially bank is empty
- every step:
 - put coins into bank
 - pay for the work using (part of) the coins in the bank



How many coins should we deposit per step, s.t. we never run out of coins?

Banker's view: Binary Counter



total coins in bank $\rightarrow \phi_i$

3 ϕ_i

1 ϕ_{i+1}

#coins you need to put in in time step i

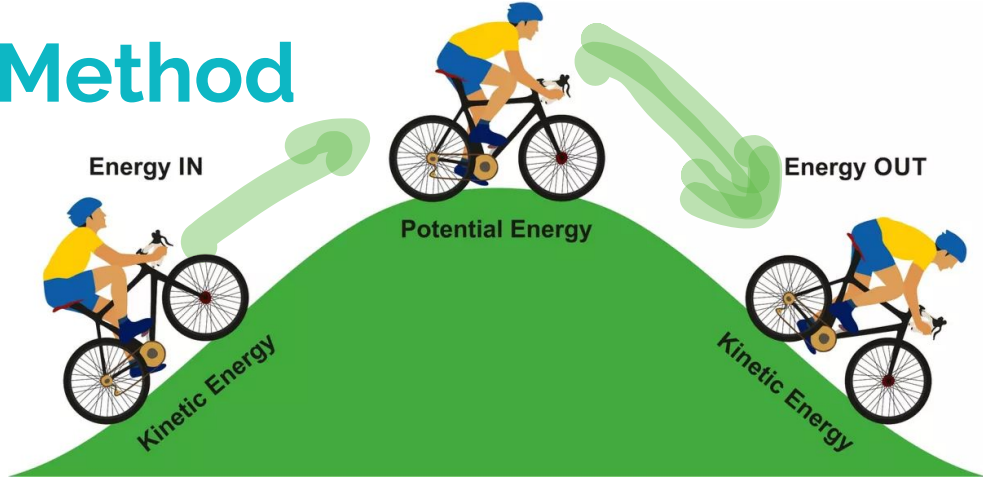
0 \downarrow = cost of step i + $\phi_{i+1} - \phi_i$

Banker's view: Binary Counter

- bank: 1 coin on each 1 bit
- every 0 \Rightarrow 1: deposit 2 coins
- every 1 \Rightarrow 0: use the coins on 1s to pay

The Potential Method

Physist's view



When compressed or stretched, a spring gains elastic potential energy.

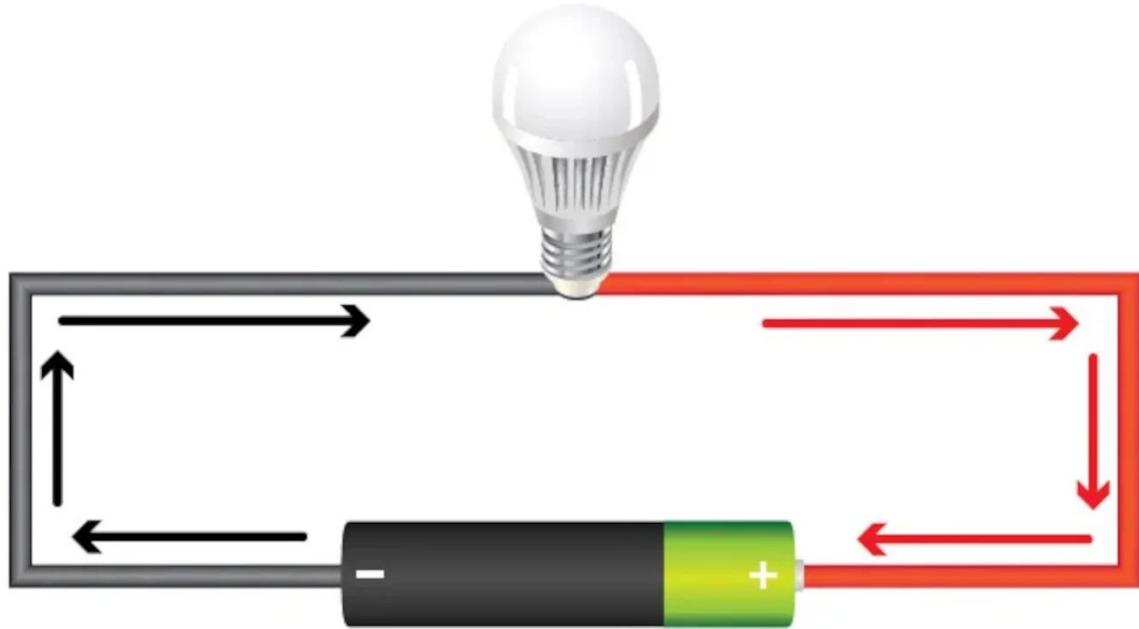


static



compressed

Electric potential = voltage



The Potential Method

Physist's view

- Need to pay to build up potential
- Whenever the algorithm incurs some cost, we can pay for it using the potential

How much should we pay per step, s.t. there is always enough potential to pay for the algorithm's cost?

amortized cost
of step i

Cost of the i th
operation

potential
at the end of
time step i

$$aC_i = C_i + \phi_i - \phi_{i-1}$$

(amortized cost) = (actual cost) + (change in potential).

$$\cancel{\phi_1 - \phi_0} + \cancel{\phi_2 - \phi_1} + \cancel{\phi_3 - \phi_2} + \cancel{\phi_4 - \phi_3} - \dots - \phi_n$$

$$aC_i = C_i + \phi_i - \phi_{i-1}$$

(amortized cost) = (actual cost) + (change in potential).

Summing both sides

$$\sum_i aC_i = \sum_i (C_i + \phi_i - \phi_{i-1}) = \phi_n - \phi_0 + \sum_i C_i$$

$$ac_i = c_i + \phi_i - \phi_{i-1}$$

(amortized cost) = (actual cost) + (change in potential).

Summing both sides

$$\sum_i ac_i = \sum_i (c_i + \phi_i - \phi_{i-1}) = \phi_n - \phi_0 + \sum_i c_i$$

$$\sum_i c_i = \sum_i ac_i + \phi_0 - \phi_n$$

Potential analysis: growing a table

space reserved \downarrow #items \swarrow

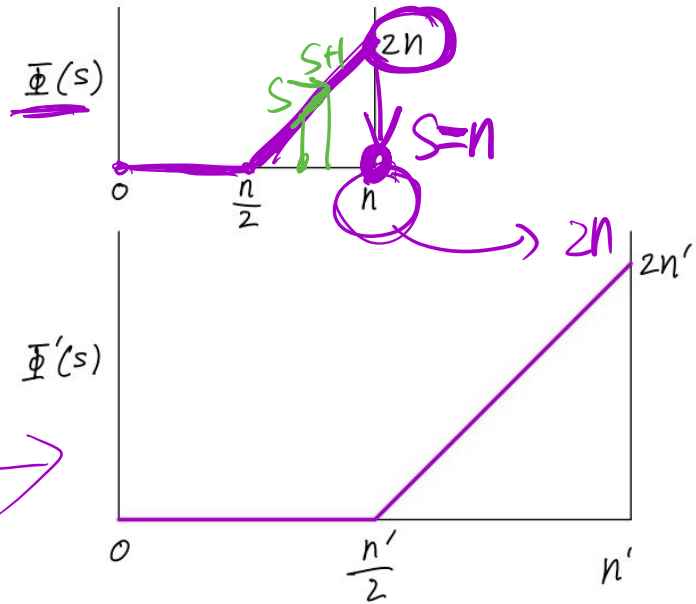
$$\Phi(n, s) = \begin{cases} 0 & \text{if } s \leq \frac{n}{2} \\ 4(s - \frac{n}{2}) & \text{otherwise} \end{cases}$$

whenever I don't need to grow:

$$ac = 1 + 4 = 5$$

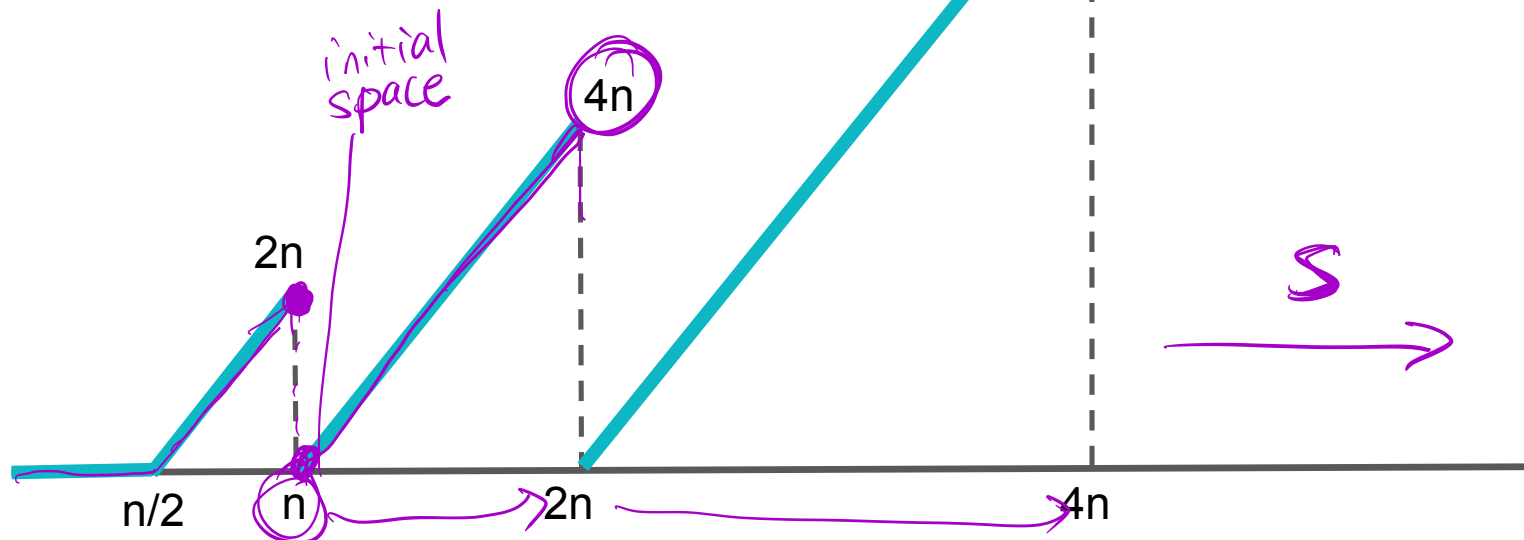
whenever I need to grow:

$$2n+1 - 2n = 1$$



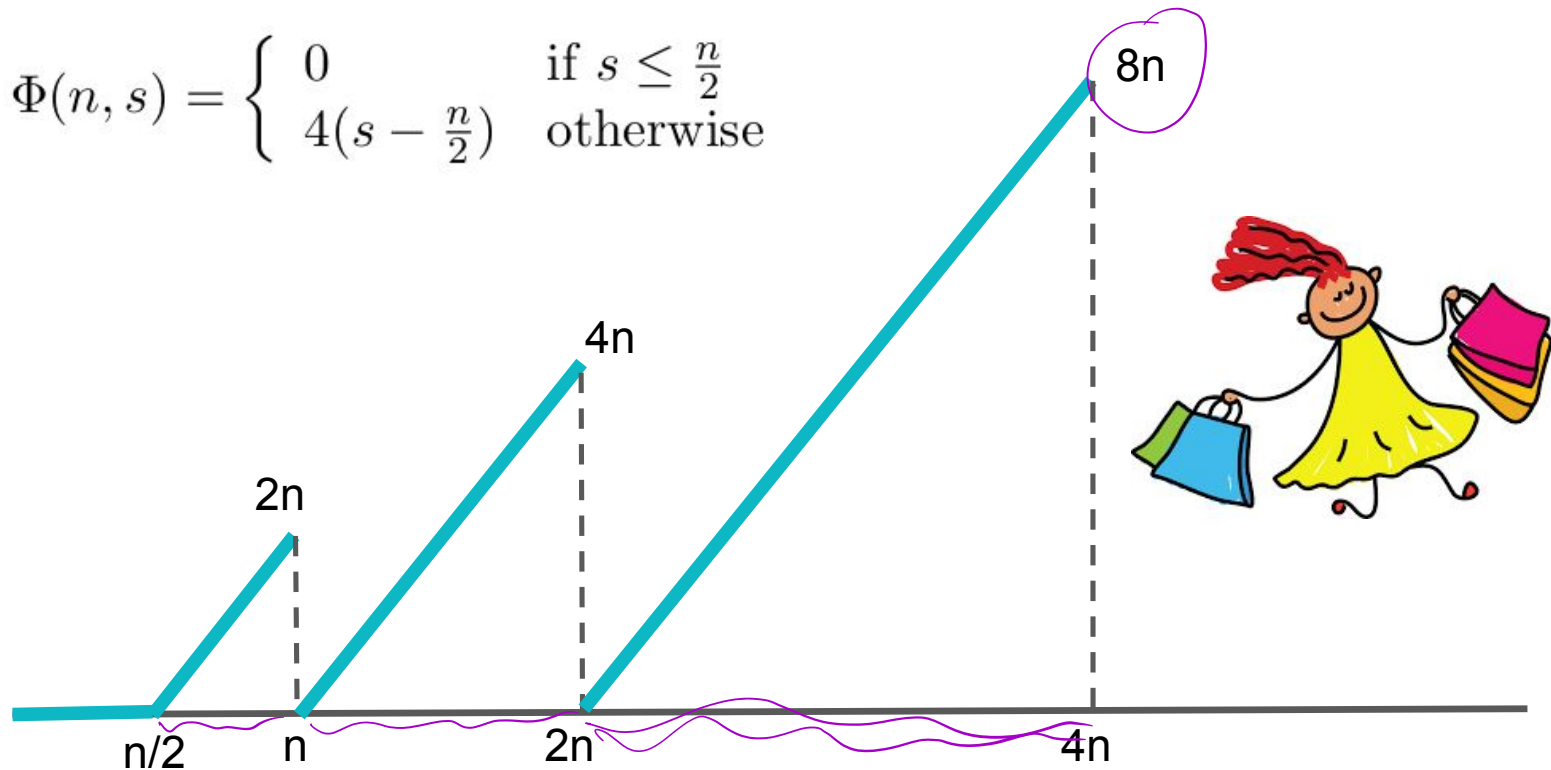
Potential analysis: growing a table

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Potential analysis: growing a table

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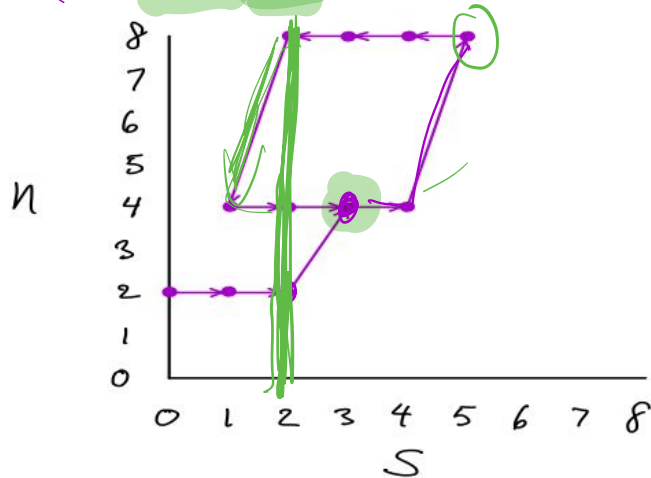
Potential analysis: growing and shrinking a table

- initialize(): allocates an empty table of size 2 ($n = 2$, $s = 0$)
- insert(): add a new element to the table ($s++$)
 - if $s = n$ then grow(),
 - add the new elem to array[s] (costs 1)
- delete(): delete the last elem from table ($s--$)
 - if $s = n/4$ and $n \geq 4$ then shrink()
 - delete last elem (costs 1)
- grow(): double the size from n to $2n$. costs $2n$
- shrink(): change the size of table to $n/2$. Costs n .

n \rightarrow $n/2$

Value of n depends not just on s, but also the history

$(0, 2), (1, 2), (2, 2), (3, 4), (4, 4), (5, 8), (4, 8), (3, 8), (2, 8), (1, 4), (2, 4), (3, 4)$

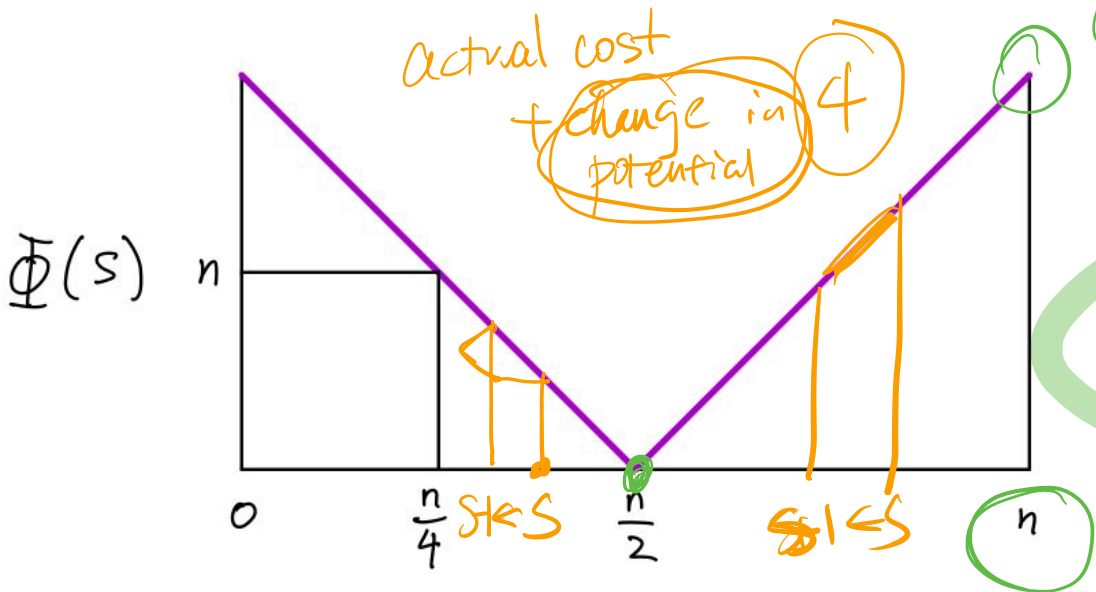


$$\Phi(n, s) := 4 \left| s - \frac{n}{2} \right|$$

$$n=2$$

$$s=0$$

$$n=2$$



$$\phi(n, s)$$

$$= 4$$

$$\phi_0 = 4$$

Theorem: total cost of N insertions and deletions is at most $5N + 4$.

Insertion:

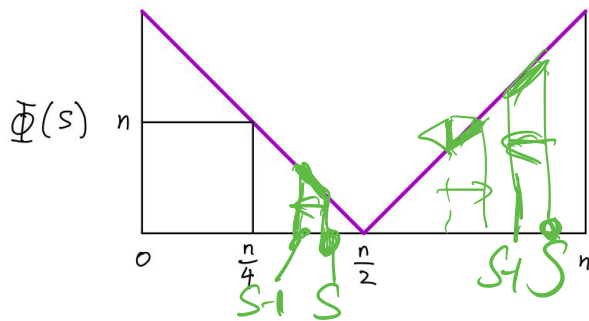
$$1 + 4 = 5$$

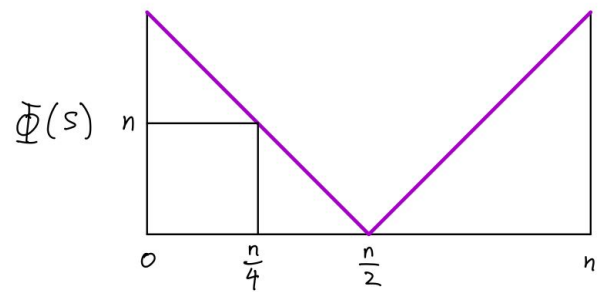
ϕ actual cost
 change in potential

$$\phi_0 = 4$$

Deletion:

$$1 + 4 = 5$$





The dictionary data structure

dict

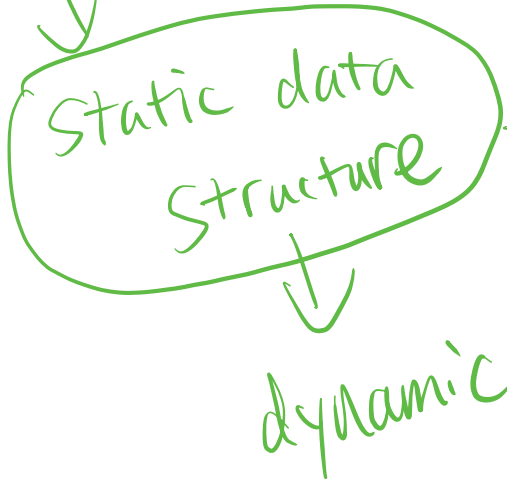
- insert(key, val)
- search(key)



Next lecture: splay tree

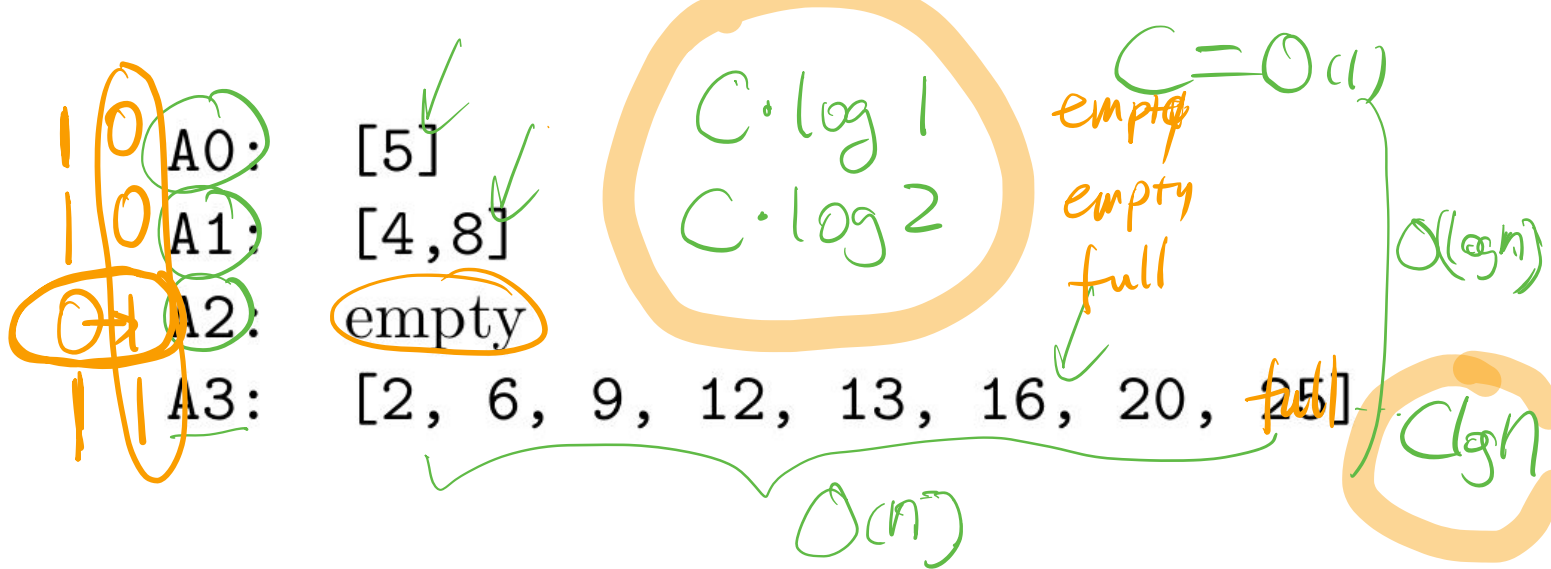
Today: a hierarchical data structure that is almost as good as splay tree.

- A sorted array can be searched in **$O(\log n)$** time
- Unfortunately insertion is slow



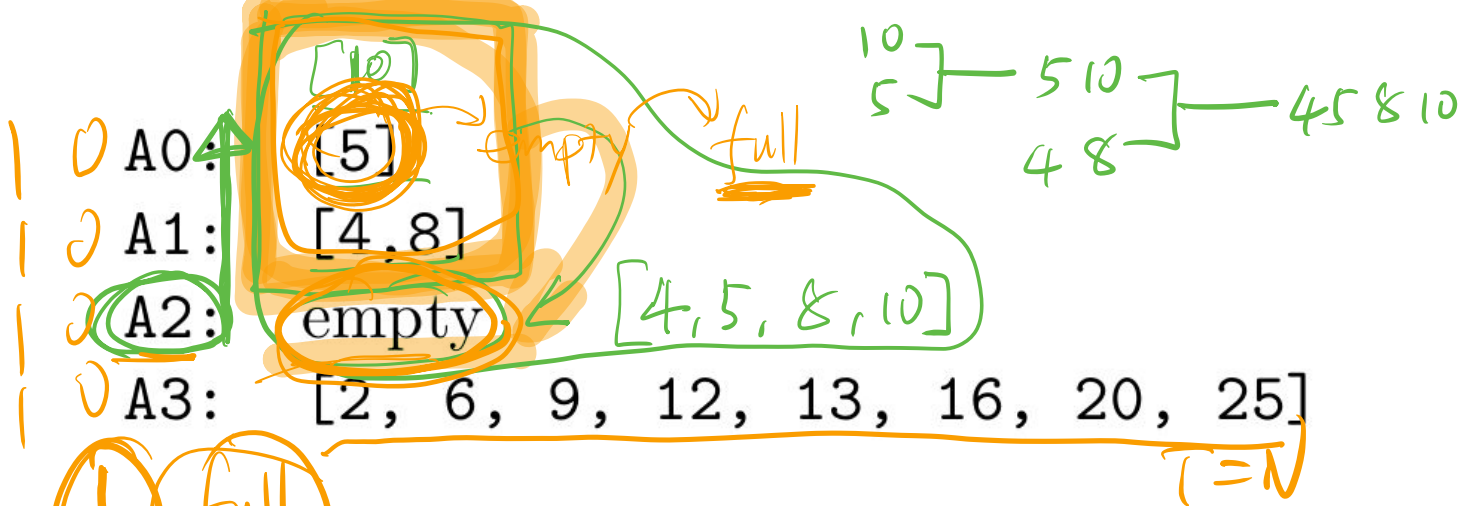
search ()

+ insert ()



- Search: binary search in each level

$$O(\log n \cdot \log n) = \underline{O(\log^2 n)}$$



① full

● Now we want to insert 10

every 2 steps: $C \cdot 1$
 every 4 steps: $C \cdot 2$
 every 8 steps: $C \cdot 4$

every N step: $C \cdot N$

$$\frac{N}{2} \cdot C \cdot 1 + \frac{N}{4} \cdot C \cdot 2 + \frac{N}{8} \cdot C \cdot 4 + \dots + \frac{N}{N} \cdot C \cdot N = O(N \log N)$$

After inserting 10

A0:

~~empty~~

[50]

A1:

empty

A2:

[4, 5, 8, 10]

A3:

[2, 6, 9, 12, 13, 16, 20, 25]

A4

empty

[55]

✓ [31]

[30]

[50][55]

A2: same

same

[2, 4, 5, 6, 8, 9, 10, 12, 13, 16, 20, 25, 30, 31, 50, 55]



What's the amortized cost of insertion?

This is a paradigm for compiling any static data structure into a dynamic one

JOURNAL OF ALGORITHMS 1, 301–358 (1980)

Decomposable Searching Problems I. Static-to-Dynamic Transformation*

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Received October 29, 1979; revised April 15, 1980