

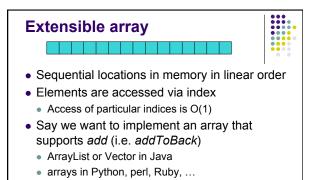
Admin

- Looking for summer researchers in CS at Middlebury
 - Deadline Friday
 - Come talk to me if you want to hear more...
- CS lunch
- Looking ahead...
 - Take-home midterm the week before spring break
 - open notes and book
 - will be timed
- Review on Tuesday of that week

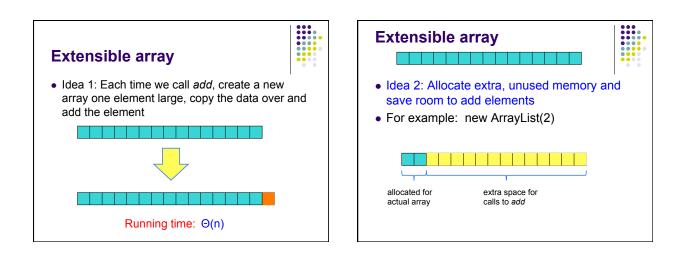
Admin

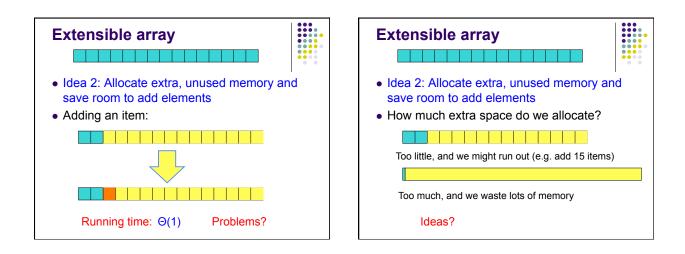
- Assignment averages
 - 1: 28.7/30
 - 2: 42.3/49
 - 3: 21.4/23
 - 4: 26.7/32
 - 5: 18.8/20

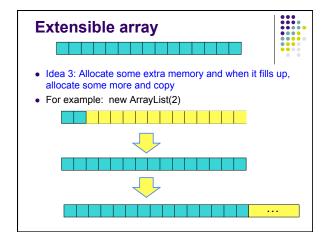


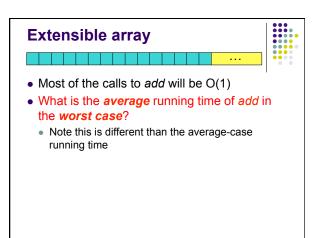


• How can we do it?









Amortized analysis

- There are many situations where the worst case running time is bad
- However, if we average the operations over *n* operations, the average time is more reasonable
- This is called *amortized* analysis
 - This is different than average-case running time, which requires probabilistic reasoning about input
 - The worse case running time doesn't change

Amortized analysis

- Many approaches for calculating the amortized analysis
 - we'll just look at the counting method
 - book has others
- aggregate method
 - figure out the big-O runtime for a sequence of *n* calls
- divide by *n* to get the average run-time per call

Amortized analysis

What is the aggregate cost of *n* calls?

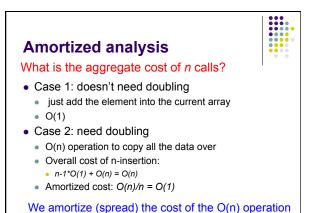
Let's assume it's O(1) and then prove it

Base case: size 1 array, add an element: O(1)

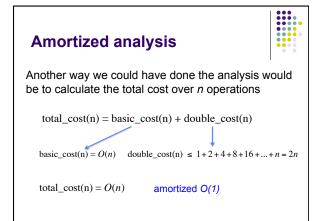
Inductive case: assume n-1 calls are O(1), show that *n*th call is O(1)

Two cases:

- array need to be doubled
- array does need to be doubled

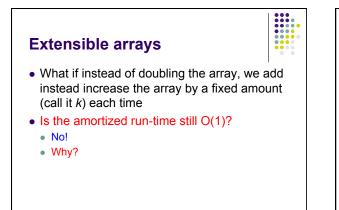


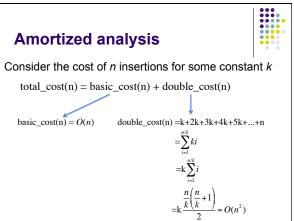
over all of the previous O(1) operations



Amortized analysis vs. worse case

- What is the worse case of add?
 - Still O(n)
 - If you have an application that needs it to be O(1), this implementation will not work!
- amortized analysis give you the cost of n operations (i.e. average cost) not the cost of any individual operation



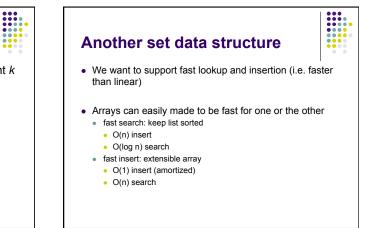


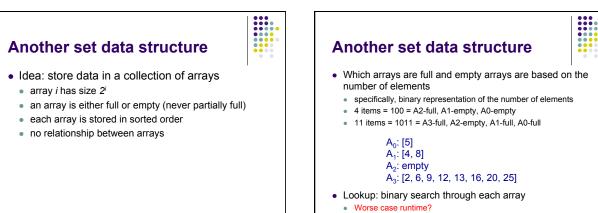


Consider the cost of *n* insertions for some constant *k*

 $total_cost(n) = O(n) + O(n^2)$ $= O(n^2)$

amortized O(n)!





Another set data structure

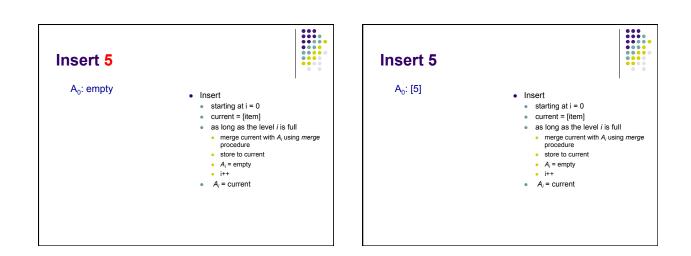
A₀: [5] A₁: [4, 8] A₂: empty A₃: [2, 6, 9, 12, 13, 16, 20, 25]

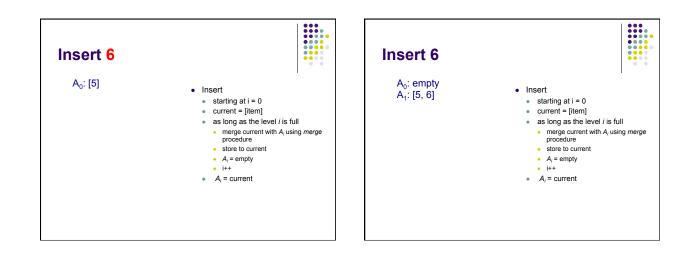
- Lookup: binary search through each array
- Worse case: all arrays are full
 - number of arrays = number of digits = log n
 - binary search cost for each array = O(log n)
 - O(log n log n)

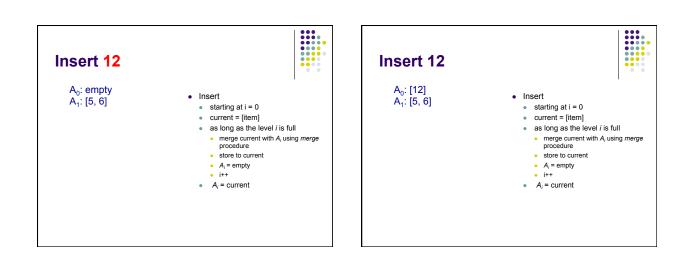


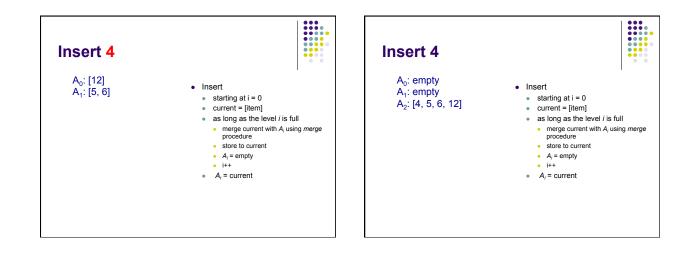


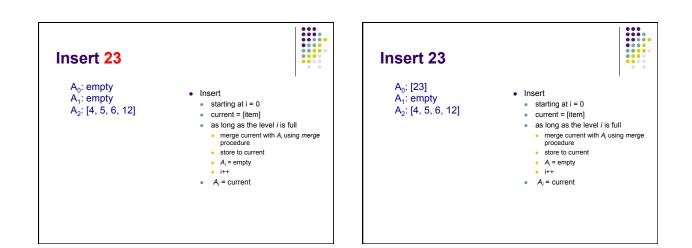
- Insert
 - starting at i = 0
 - current = [item]
 - as long as the level *i* is full
 - merge current with A_i using merge procedure
 - store to current
 - A_i = empty
 - i++
 - A_i = current

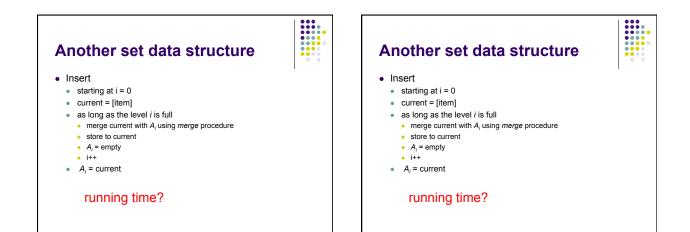




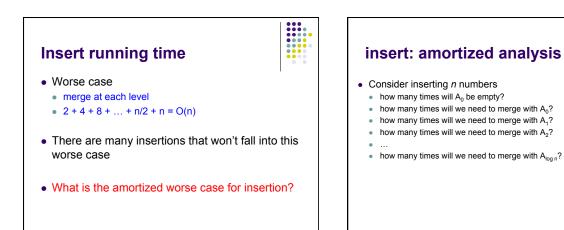








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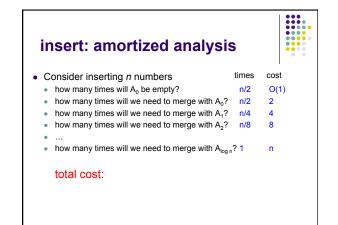
• Consider inserting *n* numbers

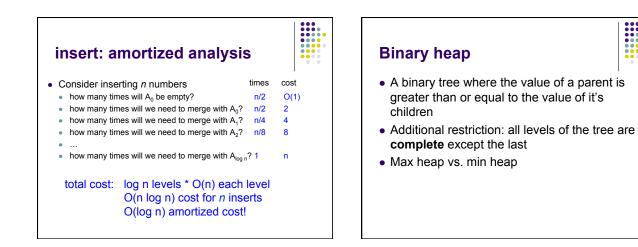
- how many times will A₀ be empty?
- how many times will we need to merge with A₀? n/2
- how many times will we need to merge with A1? n/4
- how many times will we need to merge with A_2 ? n/8
- ...
- how many times will we need to merge with A_{log n}? 1

cost of each of these steps?

times

n/2





Binary heap - operations

- Maximum(S) return the largest element in the set
- ExtractMax(S) Return and remove the largest element in the set
- Insert(S, val) insert val into the set
- IncreaseElement(S, x, val) increase the value of element x to val
- BuildHeap(A) build a heap from an array of elements

