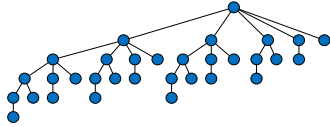


## Lecture 2. Amortized Analysis

**CpSc 8400: Algorithms and Data Structures**  
**Brian C. Dean**



**School of Computing**  
**Clemson University**  
**Spring, 2016**

### **Useful Analysis Technique: Think about an Algorithm from the Perspective of a Data Element...**

- Figure out how much work / running time is spent on a single generic element of data during the course of the algorithm.
- Add this up to get the total running time.  
(compared to adding up the time spent on each “operation”, summed over each operation in chronological order)

## Useful Analysis Technique: Think about an Algorithm from the Perspective of a Data Element...

Elements of Data  
←→

	Elem 1	Elem 2	Elem 3	Elem 4	Elem 5	
Step 1		1	1			"Swap elements 2 and 3"
Step 2						
Step 3				1		"Modify element 4"
Step 4						
Step 5	1	1	1	1	1	"Copy elements into a new array"

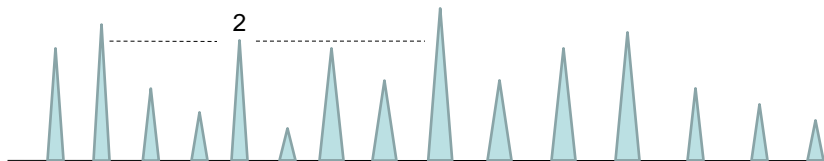
Steps Taken by Algorithm  
(in chronological order...)

Time/work done to each element at each  
major "step" of our algorithm's execution

(that is, sum the columns first, not the rows...)

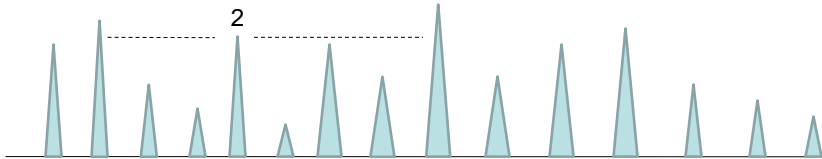
3

## Example: Domination Radius



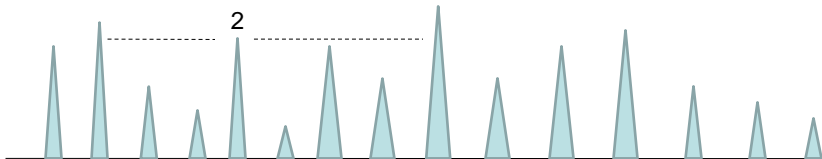
- Given the heights of  $N$  individuals standing in a line.
- **Goal:** find the domination radius of each individual.

## Example: Domination Radius



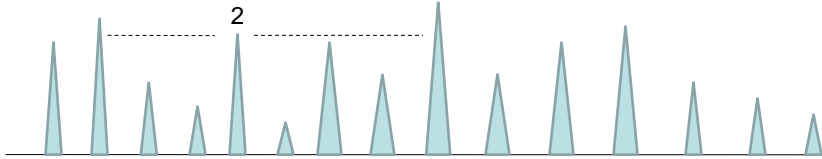
- Given the heights of  $N$  individuals standing in a line.
- **Goal:** find the domination radius of each individual.
- Simple algorithm: from each element, scan left until blocked, then scan right until blocked.

## Example: Domination Radius



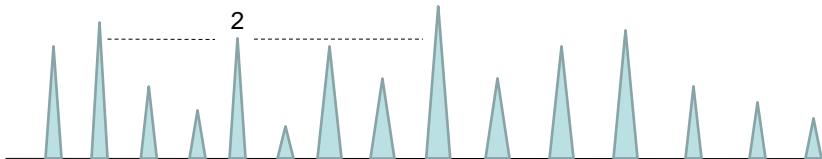
- Given the heights of  $N$  individuals standing in a line.
- **Goal:** find the domination radius of each individual.
- Simple algorithm: from each element, scan left until blocked, then scan right until blocked. ( $O(N^2)$  worst-case)

## Example: Domination Radius



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- **Goal:** find the domination radius of each individual.
- Simple algorithm: from each element, scan left until blocked, then scan right until blocked. ( $O(N^2)$  worst-case)
- Refinement: from each element, scan left and right simultaneously until blocked.

## Example: Domination Radius



- Given the heights of  $N$  individuals standing in a line.
- **Goal:** find the domination radius of each individual.
- Simple algorithm: from each element, scan left until blocked, then scan right until blocked. ( $O(N^2)$  worst-case)
- Refinement: from each element, scan left and right simultaneously until blocked. ( $O(N \log N)$  time!)
- $O(N)$  is even possible, using fancier data structures...

## Re-Sizing Memory Blocks

- Since memory blocks often cannot expand after allocation, what do we do when a memory block fills up?
- For example, suppose we allocate 100 words of memory space for a stack (implemented as an array), but then realize we have more than 100 elements to push onto the stack!

(yes, use of a linked list would have solved this problem, but suppose we really want to use arrays instead...)

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## Memory Allocation : Successive Doubling

- A common technique for block expansion: whenever our current block fills up, allocate a new block of twice its size and transfer the contents to the new block.
- Unfortunately, now some of our push operations will be quite slow!
  - Most push operations take only  $O(1)$  time.
  - However, a push operation resulting in an expansion (and a copy of the  $n$  elements currently in the stack) will take  $\Theta(n)$  time.
- This motivates the importance of **amortized analysis**...

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## How to Describe the Running Time of Push...?

- Push has a somewhat non-uniform running time profile:
  - $O(1)$  almost always
  - Except  $\Theta(N)$  every now and then.
- But just saying the running time is “ $\Theta(N)$  in the worst case” doesn’t tell the whole story...
  - Doesn’t do the structure justice.
  - People might be scared to use it for large input sizes...

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## How Expensive is Your Car to Maintain...?

Jan: \$10

Feb: \$10

...

Nov: \$10

Dec: \$130 = \$10 + yearly \$120 tune-up

- Same problem: saying it’s “\$130/month in the worst case” doesn’t tell the complete story...

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## Amortization of Costs

### Actual Cost

Jan: \$10

Feb: \$10

...

Nov: \$10

Dec: \$130

### Amortized Cost

Jan: \$20

Feb: \$20

...

Nov: \$20

Dec: \$20

- So our cost is “\$20/month, amortized”.
- This is a simpler, more accurate description of our cost structure.
- Compare with actually paying \$20/month...

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## Back to Push...

- How much does each push actually cost?

Op#:	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	...
Insert:	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	...
Copy:		1	2		4				8								16		...
Total:	1	2	3	1	5	1	1	1	9	1	1	1	1	1	1	1	17	1	...
Cumulative:	1	3	6	7	12	13	14	15	24	25	26	27	28	29	30	31	48	49	...

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## Back to Push...

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Insert:	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	...
Copy:		1	2		4				8								16		...
Total:	1	2	3	1	5	1	1	1	9	1	1	1	1	1	1	1	17	1	...
Cumulative:	1	3	6	7	12	13	14	15	24	25	26	27	28	29	30	31	48	49	...

- What about if we charge ourselves 3 units of work per operation instead...?

Total:	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	...
Cumulative:	3	6	9	12	15	18	21	24	27	30	33	36	39	42	45	48	51	54	...

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Copy:		1	2		4				8								16		...
Total:	1	2	3	1	5	1	1	1	9	1	1	1	1	1	1	1	17	1	...
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“True” cumulative cost after any sequence of  $k$  operations is upper bounded by “fictitious” cumulative cost of  $3k$ ...

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## Back to Push...

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Copy:		1	2		4				8								16		...
Total:	1	2	3	1	5	1	1	1	9	1	1	1	1	1	1	1	17	1	...
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Cumulative:	3	6	9	12	15	18	21	24	27	30	33	36	39	42	45	48	51	54	...

Total insert cost =  $k$

Total copy cost  $\leq 2k$

17

## Back to Push...

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Insert:	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	...
Copy:		1	2		4				8	+2	+2	+2	+2	+2	+2	+2	16		...
Total:	1	2	3	1	5	1	1	1	+2	1	1	1	1	1	1	1	17	1	...
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Copy:		1	2		4	+2	+2	+2	<del>8</del>	+2	+2	+2	+2	+2	+2	+2	<del>16</del>		...
Total:	1	2	3	1	+2	1	1	1	+2	1	1	1	1	1	1	1	17	1	...
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19

## Back to Push...

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Cumulative:	3	6	9	12	15	18	21	24	27	30	33	36	39	42	45	48	51	54	...

- So how different is our version of push from a version that takes 3 units in the worst case?

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## Amortized Analysis

- Any sequence of  $k$  pushes takes  $O(k)$  worst-case time, so we say that push takes  $O(1)$  **amortized** time.
- “On average”, each individual push therefore takes  $O(1)$  time.
- In general, an operation runs in  $O(f(n))$  amortized time if any sequence of  $k$  such operations runs in  $O(k f(n))$  time.

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## Amortized Analysis : Motivation

- Amortized analysis is an ideal way to characterize the worst-case running time of operations with highly non-uniform performance.
- It is still **worst-case** analysis, just averaged over an arbitrary sequence of operations.
- It gives us a much clearer picture of the true performance of a data structure that more faithfully describes the true performance.
  - E.g., “ $O(N)$  worst case vs.  $O(1)$  amortized”.

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## Amortized Analysis : Motivation

- Suppose we have 2 implementations of a data structure to choose from:
  - A:  $O(\log n)$  worst-case time / operation.
  - B:  $O(\log n)$  amortized time / operation.
- There is **no difference** if we use either A or B as part of a larger algorithm. For example, if our algorithm makes  $n$  calls to the data structure, the running time is  $O(n \log n)$  in either case.
- The choice between A and B only matters in a “real-time” setting when the response time of an individual operation is important.

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## Generalizing to Multiple Operations

- We say an operation A requires  $O(f(n))$  amortized time if *any* sequence of  $k$  invocations of A requires  $O(k f(n))$  time in the worst case.
- We say operations A and B have amortized running times of  $O(f_A(n))$  and  $O(f_B(n))$  if *any* sequence containing  $k_A$  invocations of A and  $k_B$  invocations of B requires  $O(k_A f_A(n) + k_B f_B(n))$  time in the worst case.
- And so on, for 3 or more operations...

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## **Aggregate Analysis: A Simple, but Often Limited, Method for Amortized Analysis**

- Compute the worst-case running time for an arbitrary sequence of  $k$  operations, then divide by  $k$ .
- Unfortunately, it is often hard to bound the running time of an arbitrary sequence of  $k$  operations (especially if the operations are of several types)...

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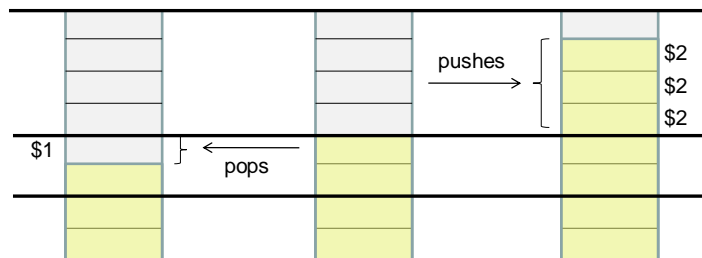
## **Recall our Initial Discussion: Think about an Algorithm from the Perspective of a Data Element...**

- Figure out how much work / running time is spent on a single generic element of data during the course of the algorithm.
- Add this up to get the total running time.
- In amortized analysis, this is often called the “accounting method”...

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## Accounting Method Analysis: Example Using Memory Re-Sizing

- Charge 3 units (i.e.,  $O(1)$  amortized time) for each *push* operation.
  - 1 unit for the immediate *push*.
  - “\$2” credit for future memory expansions.
- Charge 2 units per pop (1 unit for the immediate operation, “\$1” credit)



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## Make the New Elements Pay!

- When it comes time to expand our buffer from size  $n$  to  $2n$  (at a cost of  $n$ ), exactly  $n/2$  of the elements in our current buffer have been newly-added since the last memory expansion.
- All these elements have \$2 credit on them.
- So we have \$ $n$  worth of credit – enough to pay for the current memory expansion!
- After expansion, no credit remains (subsequently-added items will contribute toward next expansion).

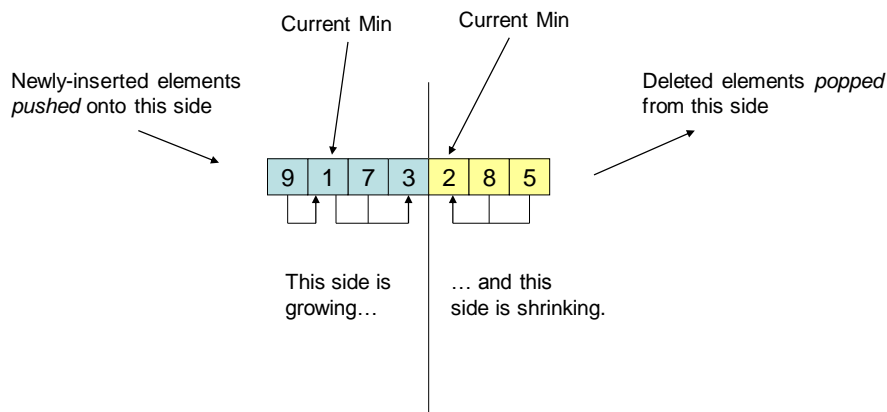
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## Example : The Min-Queue

- Using either a linked list or a (circular) array, it is easy to implement a FIFO queue supporting the *insert* and *delete* operations both in  $O(1)$  worst-case time.
- Suppose that we also want to support a *find-min* operation, which returns the value of the minimum element currently present in the queue.
- It is possible to implement a “min-queue” supporting *insert*, *delete*, and *find-min* all in  $O(1)$  worst-case time?

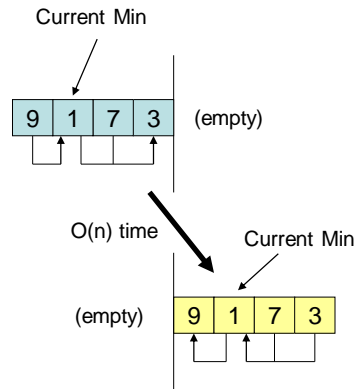
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## The Min-Queue as a Pair of “Back-to-Back” Min-Stacks



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## Expensive (but Rare) Operations



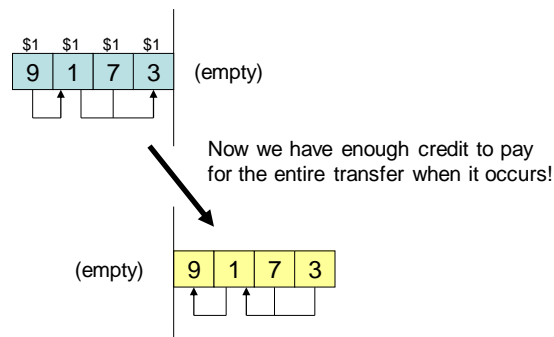
When yellow stack becomes empty, spend  $O(n)$  time and transfer the contents of blue stack into the yellow stack.

Worst-case running time for *delete*:  $O(n)$

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## Amortized analysis

Charge insert 2 units of time: 1 for the push, and \$1 in credit for each new element.



Final running times:  
 - *Insert* and *Delete*:  $O(1)$  amortized time  
 - *Find-Min*:  $O(1)$  worst-case time

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## Recap: Block Expansion and Contraction

- The approach:
  - Expand buffer (to size  $2m$ ) if  $n = m$ .
  - Contract buffer (to size  $m/2$ ) if  $n < m/4$ .
  - This ensures that  $m/4 \leq n \leq m$ .
- The accounting method shows that *push* and *pop* run in only  $O(1)$  amortized time.
  - When we expand, we need  $m$  units of credit.
  - When we contract, we need  $m/4$  units of credit.

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## Potential Functions

- A **potential function** provides a somewhat more formulaic way to perform amortized analysis.  
(although It's really just another way of looking at the accounting method)
- Express total amount of “credit” present in our data structure using a non-negative potential function of the state of our data structure.
  - Example: for the memory allocation problem, our potential function is:  $\phi = \begin{cases} 2n - m & \text{if } n \geq m/2 \\ m/2 - n & \text{if } n < m/2 \end{cases}$
  - If  $n = m/2$ , then  $\Phi = 0$ . No credit right after expansion or contraction.
  - If  $n = m$ , then  $\Phi = m$ . Just enough credit to expand!
  - If  $n = m/4$ , then  $\Phi = m/4$ . Just enough credit to contract!

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## Potential Functions

- Required properties of a potential function:
  - It should start out initially at zero (no credit initially).
  - It should be nonnegative (can't go into "debt").
- Some notation:
  - Let  $c_1, c_2, \dots, c_k$  denote the actual cost (running time) of each of  $k$  successive invocations of some operation.
  - Let  $\phi_j$  denote the potential function value right after the  $j$ th invocation.
- The amortized cost  $a_j$  of the  $j$ th operation is now:

$$a_j = \underbrace{c_j}_{\text{Actual cost}} + \underbrace{(\phi_j - \phi_{j-1})}_{\text{Change in potential (i.e., total credit added or consumed)}}$$

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## Potential Functions : Example

$$a_j = \underbrace{c_j}_{\text{Actual cost}} + \underbrace{(\phi_j - \phi_{j-1})}_{\text{Change in potential (i.e., total credit added or consumed)}}$$

$$\phi = \begin{cases} 2n - m & \text{if } n \geq m/2 \\ m/2 - n & \text{if } n < m/2 \end{cases}$$

- Amortized cost of *push*:
  - Without expansion:  $a_j = c_j + (\phi_j - \phi_{j-1}) \leq 1 + 2 = 3$ .  
(contributes 2 units of potential)
  - With expansion:  $a_j = c_j + (\phi_j - \phi_{j-1}) = 1 + m + (-m) = 1$ .  
(draws  $m$  units of potential to pay for expansion)
- Amortized cost of *pop*:
  - Without contraction:  $a_j = c_j + (\phi_j - \phi_{j-1}) \leq 1 + 1 = 2$ .  
(contributes 1 unit of potential)
  - With contraction:  $a_j = c_j + (\phi_j - \phi_{j-1}) = 1 + m/4 + (-m/4) = 1$ .  
(draws  $m/4$  units of potential to pay for contraction).

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## Amortized Running Times as Upper Bounds

Recall:  $a_j = \underbrace{c_j}_{\text{Actual cost}} + \underbrace{\varphi_j - \varphi_{j-1}}_{\text{Change in potential (i.e., total credit added or consumed)}}$

- Over a sequence of  $k$  operations:  

$$\sum_j a_j = \sum_j (c_j + \varphi_j - \varphi_{j-1}) = (\sum_j c_j) + \overbrace{\varphi_k}^{\geq 0} - \overbrace{\varphi_0}^0 \geq \sum_j c_j$$
- Therefore, over any sequence of operations, the total amortized running time gives us an upper bound on the total actual running time (as we expected!)

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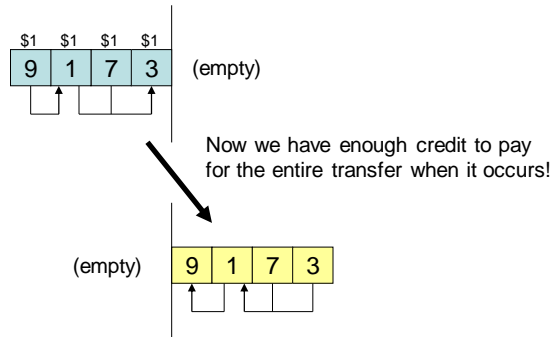
## Designing and Using Potential Functions

- Some potential functions look substantially more complicated than the ones we've seen so far.
- Although it is more or less equivalent to the accounting method, potential functions give us a widely-accepted "formulaic" means of performing amortized analysis.
  - State potential function.
  - Show that it's zero initially and always nonnegative.  
(and should only depend on *current* state)
  - Then use  $a_j = c_j + \varphi_j - \varphi_{j-1}$  to compute the amortized running time of each operation.

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## Example: The Min-Queue

Charge insert 2 units of time: 1 for the push, and \$1 in credit for each new element.



Final running times:

- *Insert* and *Delete*:  $O(1)$  amortized time
- *Find-Min*:  $O(1)$  worst-case time