



Lecture 4: Data Structures I

COMP526: Efficient Algorithms

Updated: October 15, 2024

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Announcements

1. Second Quiz, due Friday

- Similar format to before
 - One question, select all correct answers
 - 20 minute time limit
- Covers asymptotic (Big-O) notation
 - Lectures 03 and 04
 - Relevant reading from **CLRS** — *Intro to Algorithms*
- Quiz is **closed resource**
 - No books, notes, internet, etc.
 - Do not discuss until after submission deadline (Friday night, after midnight)

2. Programming Assignment 1: Discuss on Thursday

- Due 13 November

3. Attendance Code:

239179

Meeting Goals

- Finish discussion of asymptotic notation
- Introduce Abstract Data Types:
 - Stack
 - Queue
 - Priority Queue
- Discuss array-backed and linked list-backed implementations of Stacks and Queues
- Introduce amortized analysis

Asymptotic Notation

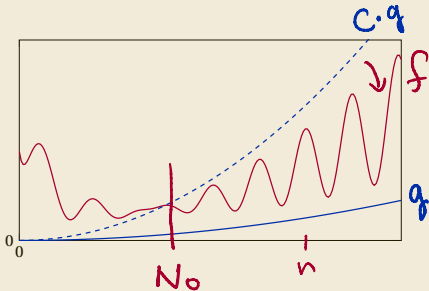
From Last Time

Definition

Suppose f and g are functions from \mathbf{N} to \mathbf{R}^+ . Then we say that $f = O(g)$ (read: f is big O of g) if there exist constants $N_0 \in \mathbf{N}$ and $C \in \mathbf{R}$ such that for all $n \in \mathbf{N}$

$$n \geq N_0 \implies f(n) \leq Cg(n).$$

Equivalently, $f = O(g) \iff \limsup \frac{f(n)}{g(n)} < \infty$



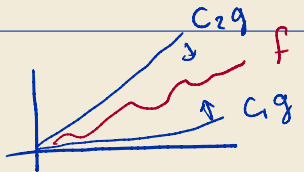
Proposition

Suppose $f, f_1, f_2, g, g_1, g_2, h$ are functions and a is any constant. Then:

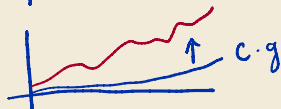
1. $(\forall n f(n) \leq a) \implies f = O(1)$
2. $(\forall n f(n) \leq g(n)) \implies f = O(g)$
3. $f = O(g) \implies a \cdot f = O(g)$
4. $f = O(g)$ and $g = O(h) \implies f = O(h)$
5. $f = O(h)$ and $g = O(h) \implies f + g = O(h)$
6. $f_1 = O(g_1)$ and $f_2 = O(g_2) \implies f_1 \cdot f_2 = O(g_1 \cdot g_2)$

Variations of O

- $f = \Theta(g)$ if $f = O(g)$ and $g = O(f)$
 - Example: $4n^2 + 3n + 7 = \Theta(n^2)$



- $f = \Omega(g)$ if $g = O(f)$
 - Example: $0.01n^2 - 7n = \Omega(n^2)$



- $f = o(g)$ if for every $\epsilon > 0$, there exists N_0 such that $n \geq N_0 \implies \frac{f(n)}{g(n)} < \epsilon$.
Informally: f much smaller than g



- Equivalently:

$$f = o(g) \iff \lim_{n \rightarrow \infty} \frac{f(n)}{g(n)} = 0$$

- Example: $n^{1.999} = o(n^2)$

- $f = \omega(g)$ if $g = o(f)$
 - Example: $0.01n^{2.01} = \omega(n^2)$ *Informally f grows significantly faster than g*

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Mnemonic for Variations

Big-O	(in)equality
ω	$>$
Ω	\geq
Θ	\approx
O	\leq
o	$<$

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More Properties

- $f_1 = O(g_1)$ and $f_2 = o(g_2) \implies f_1 \cdot f_2 = o(g_1 \cdot g_2)$
- $f_1 = \Omega(g_1)$ and $f_2 = \omega(g_2) \implies f_1 \cdot f_2 = \omega(g_1 \cdot g_2)$

Interpretation

Suppose:

- two algorithms A and B for solving the same problem
- running time of A is f , running time of B is g

$f = o(g)$ f grows strictly slower than g

Consider running A on a **slow** machine M_1 and B on a **fast** machine M_2 .

Then: regardless of how much slower M_1 is than M_2 , for *sufficiently large* inputs, A will complete faster than B .

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- $f = o(g)$

Consider running A on a **slow** machine M_1 and B on a **fast** machine M_2 .
Then: regardless of how much slower M_1 is than M_2 , for *sufficiently large* inputs, A will complete faster than B .

The Moral. Efficient *algorithms* are better than faster hardware.

- little- o notation gives the “right” abstraction to formalize this relationship

Common Orders of Growth

Named orders of growth:

name	asymptotic growth
constant	$O(1)$
logarithmic	$O(\log n)$
polylogarithmic	$O(\log^c n)$
linear	$O(n)$
almost linear	$O(n \log^c n)$
quadratic	$O(n^2)$
polynomial	$O(n^c)$
exponential	$O(c^n)$

base of log doesn't matter for big O notation:
 $\log_b a = \frac{\log_2 a}{\log_2 b}$
const. = const.

$= (\log n)^c$

$c =$ any constant value

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↑ increasing rates of growth ↓

Relationships

Between classes:
For all $a, b > 0$ *constant*

- $\underline{a} = o(\underline{\log^b n})$
- $\underline{\log^a n} = o(\underline{n^b})$
- $\underline{n^a} = o(\underline{b^n})$

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exponential	$O(c^n)$

If $f = o(g)$ then
 $f = O(g)$

$$n! = \underline{n} \times \underline{(n-1)} \times \underline{(n-2)} \cdots 1 < n^n$$

Relationships

Between classes:

For all $a, b > 0$

- $a = o(\log^b n)$
- $\log^a n = o(n^b)$
- $n^a = o(b^n)$

Within classes:

For all $a, b, a < b$

- $\log^a n = o(\log^b n)$
- $n^a = o(n^b)$
- $a^n = o(b^n)$

$$\underbrace{n \cdot (n-1) \cdots \frac{n}{2}}_{\text{faster than exp.}} > \left(\frac{n}{2}\right)^{\frac{n}{2}}$$

Example

Example

Compare the asymptotic growth of the following functions:

- $f(n) = 2n^2 + 2^{n/2}$
- $g(n) = \log^2 n + \sqrt{n}$
- $h(n) = n + n \log n + n^{3/2}$

polynomial

Exponential

$$a^n$$

$$\frac{1}{2} \cdot 2^n$$

$$2^{n/2} = 2^{\frac{1}{2} \cdot n} = (2^{1/2})^n$$

$$\sqrt{n} = n^{1/2}$$

c^n for $c = 1.4 \dots$

$$g(n) = \Theta(n^{1/2})$$

$$o(c^n) + \Theta(c^n) = \Theta(c^n)$$

Also $\Omega(c^n) \implies \Theta(c^n)$

$n \log n \stackrel{?}{=} n \cdot n^{1/2}$

$\log n = o(n^{1/2})$

$\implies n \log n = o(n^{3/2})$

$h(n) = \Theta(n^{3/2})$

$(a^b)^c = a^{b \cdot c}$

$f = \omega(g)$

$g = o(h)$

Linear ADTs and Data Structures

Abstract Data Types and Data Structures

Abstract Data Types (ADTs)

An **abstract data type** gives a formal specification of a **task** to be performed:

many operations

- List of supported operations (**syntax**)
- The effects of applying the operations (**semantics**)

Abstract Data Types and Data Structures

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Specify WHAT

Data Structures

A **data structure** specifies

- **how** data is represented
- **how** the supported operations are performed (i.e., what algorithms are used)
- what are the **costs** of the operations

Specify HOW

Abstract Data Types and Data Structures

Abstract Data Types (ADTs)

An **abstract data type** gives a formal specification of a task to be performed:

- List of supported operations ([syntax](#))
- The effects of applying the operations ([semantics](#))

Question. Why is it useful to separate ADTs from Data Structure?

- Can swap different data structures for same ADT
 - applications *using* the functionality will not be broken
 - different data structures may be more efficient in some applications
- Better abstractions
- Generic lower bounds

Data Structures

A **data structure** specifies

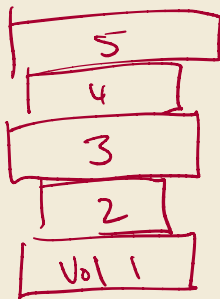
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The Stack ADT

Stacks, Intuitively

Goal: to store a *collection* of elements

- elements arranged as in a stack of books
- can only access top-most element:
 - put a new book on the stack
 - look at the top-most book
 - remove the top-most book



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Stacks, Formally

- S is the state of the stack, initially $S = \emptyset$ *concatenation*
- $S.PUSH(x) : S \mapsto Sx$
- $S.TOP() : \text{returns } x_{n-1}$ where $S = x_0x_1 \cdots x_{n-1}$ *last elt. in S*
- $S.POP() : Sx \mapsto S$, returns x
- $S.EMPTY()$ returns $TRUE \iff S = \emptyset$

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Tons of Applications!

- Executing programs (call stack)
- Parsing/evaluating arithmetic expression
- Syntax checking (parenthesis)
- ...

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Try It Yourself!

PollEverywhere Question

What is the result of calling TOP() after the following sequence stack operations:

PUSH(1)

PUSH(2)

PUSH(3)

POP()

PUSH(4)

PUSH(5)

POP()

PUSH(6)

POP()

POP()



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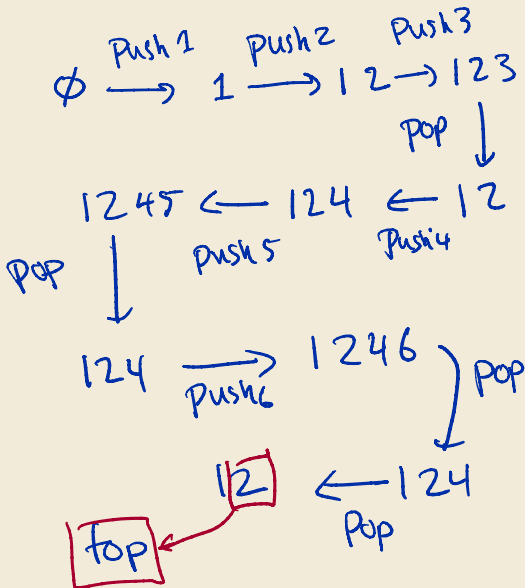
PUSH(5)

POP()

PUSH(6)

POP()

POP()



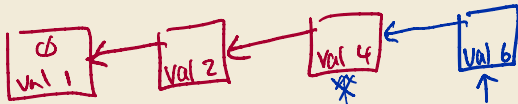
Linked List Backed Stack Implementation

Idea

- Store each element in a NODE
- Each NODE stores
 - the value of an element in the stack
 - a *reference* to the NODE storing the next element

```
1: class NODE
2:   datavalue
3:   NODE next
4: end class
```

) points to node "below" in stack



State $S = 124$
push(6)

ignores empty stack condition

```
1: class LISTSTACK
2:   NODE head
3:   procedure PUSH(x)
4:     n ← new NODE
5:     n.data ← x
6:     → n.next ← head
7:     head ← n
8:   end procedure
9:   procedure POP
10:    n ← head
11:    head ← n.next
12:    return n.data
13:  end procedure
14:  procedure TOP
15:    return head.data
16:  end procedure
17: end class
```

Issues with Linked List Stacks

Issues

- NODES waste space
 - must store reference for each entry

Memory
bad

- Following chains of reference is costly
 - memory access is **non-local**
 - **sequential** memory access is more efficient

```
1: class LISTSTACK
2:   NODE head ← ∅
3:   procedure PUSH(x)
4:     n ← new NODE
5:     n.data ← x
6:     n.next ← head
7:     head ← n
8:   end procedure
9:   procedure POP
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13:  end procedure
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Arrays as ADTs

Informally, arrays are indexed lists of elements:

$a =$	0	1	2	3	4	5	6	7	8
	<i>l</i>	<i>i</i>	<i>v</i>	<i>e</i>	<i>r</i>	<i>r</i>	<i>o</i>	<i>o</i>	<i>l</i>

Array Operations (ADT):

- **create** an array of size n
- **get** the element at index i :
 - $a[4]$ returns r
- **set** the value at index i to a prescribed value
 - $a[5] \leftarrow c$

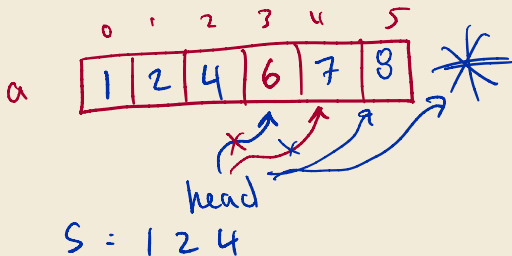
Array Operation Costs (Data Structure)

- **create** an array of size n has cost $O(n)$
 - **get** and **set** have cost $O(1)$
- ← arrays are great!

Array Backed Stack Implementation

Idea:

- Store elements in the stack in an array
 - access array values by *index*
 - neighboring values at adjacent indices
 - ⇒ sequential access
- Only overhead: store index of head (top)



```
1: class ARRAYSTACK
2:   a ← new array
3:   head ← 0
4:   procedure PUSH(x)
5:     a[head] ← x
6:     head ← head + 1
7:   end procedure
8:   procedure POP
9:     head ← head - 1
10:    return a[head]
11:  end procedure
12:  procedure TOP
13:    return a[head - 1]
14:  end procedure
15: end class
```

push(6)
push(7)

push(8)
push(9)

Array Backed Stack Implementation

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1: class ARRAYSTACK
2:    $a \leftarrow$  new array
3:   head  $\leftarrow$  0
4:   procedure PUSH(x)
5:      $a[\text{head}] \leftarrow x$ 
6:     head  $\leftarrow$  head + 1
7:   end procedure
8:   procedure POP
9:     head  $\leftarrow$  head - 1
10:    return  $a[\text{head}]$ 
11:  end procedure
12:  procedure TOP
13:    return  $a[\text{head} - 1]$ 
14:  end procedure
15: end class
```

What is the issue here?

Arrays have fixed size.

Resizing Arrays

The Problem: Arrays are *fixed size!*

- What if we don't know the (maximum) size of the stack in advance?

Resizing Arrays

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- What if we don't know the (maximum) size of the stack in advance?

A Solution: Make a larger array when necessary!

- Must copy contents of old array into new array...
... this is costly!

Increasing stack capacity

```
1: class ARRAYSTACK
2:    $a \leftarrow$  new array
3:   ...
4:   procedure INCREASECAPACITY( $k$ )
5:      $n \leftarrow$  SIZE( $a$ )
6:      $b \leftarrow$  new array of size  $n+k$ 
7:     for  $i = 0, 1, \dots, n-1$  do
8:        $b[i] \leftarrow a[i]$ 
9:     end for
10:    head  $\leftarrow$   $n$   $n$  in  $b$ 
11:  end procedure
12: end class
```

Handwritten annotations:

- A red bracket on line 4: INCREASECAPACITY(k)
- A red box around $n+k$ on line 6, with an arrow pointing to the text "additional space" below.
- Red handwritten text " ~~n~~ n in b " next to line 10.

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Question. What is the running time of INCREASECAPACITY?

Increasing stack capacity

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6:      $b \leftarrow$  new array of size  $n + k$ 
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8:        $b[i] \leftarrow a[i]$ 
9:     end for
10:     $\text{head} \leftarrow b$ 
11:  end procedure
12: end class
```

Handwritten annotations: $O(1)$ is written next to line 5. $O(n+k)$ is written next to line 6. $O(n)$ is written next to the for loop (lines 7-8). $O(1)$ is written next to line 10. A red bracket on the right side of the code spans from line 6 to line 10.

$O(n+k)$

Two Strategies

Design Question. When our array runs out of room, by how much should we increase the stack capacity?

Strategy 1. Increase the capacity by $k = 1$ each time.

- Why increase the size more than we need to?

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Strategy 2. Increase the capacity by n each time!

- Maybe we'll need more extra space?

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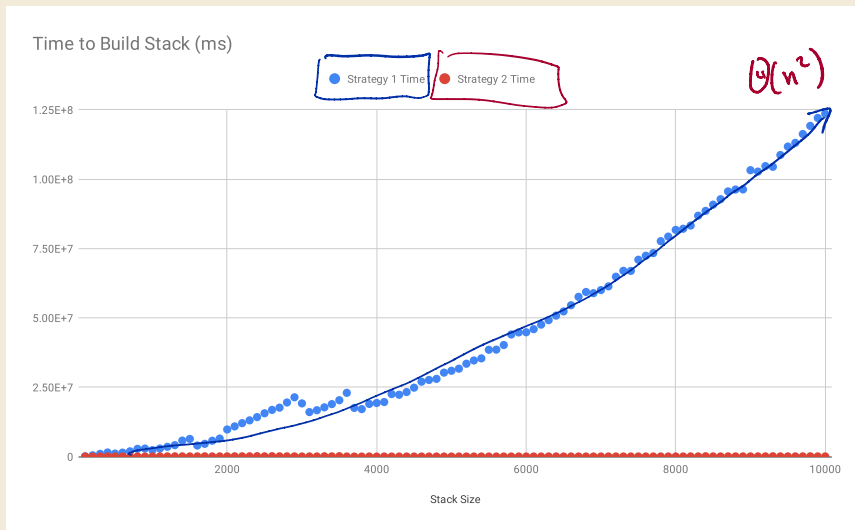
PollEverywhere Question

Which strategy will lead to better performance?



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Running Time Comparison



Understanding the Discrepancy

Question. Why was the difference in running time so **dramatic**?

Observation. Both strategies have *worst-case* running time of $\Theta(n)$ for INCREASECAPACITY

- Strategy 1 may incur this on *every* PUSH operation
 - Overall running time $\Theta(n^2)$

Understanding the Discrepancy

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Observation. Both strategies have *worst-case* running time of $\Theta(n)$ for INCREASECAPACITY

- Strategy 1 may incur this on *every* PUSH operation
 - Overall running time $\Theta(n^2)$
- For Strategy 2, INCREASECAPACITY only gets called when the stack size is $1, 2, 4, 8, \dots, 2^k, \dots, n$.
 - If cost of resizing n' is $c \cdot n'$, what is total resize cost?

$$c \cdot 1 + c \cdot 2 + c \cdot 4 + c \cdot 8 + \dots + cn$$

$$c \cdot 1 + c \cdot 2 \quad \dots \quad c \frac{n}{4} + c \frac{n}{2} + cn$$

$$cn \left(1 + \frac{1}{2} + \frac{1}{4} + \frac{1}{8} + \dots \right) \leq 2$$

$$2 \cdot cn = \Theta(n)$$

On average
each push
is $\Theta(1)$

Amortized Analysis

Goal. To analyze the worst-case running time of a *sequence* of operations.

- Amortized cost = largest **average** cost per operation averaged over all sequences.

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Banker's View

- Each operation has a (financial) **cost**
- Cost can be paid:
 - from pocket
 - from **bank account**
- For each operation, can
 - withdraw from account
 - deposit to account

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Example $c=10$
- OP cost 2
 \Rightarrow pay 2 franc
for OP
deposit $c-2=8$
to bank
 \rightarrow new bal
 $= 50$

$B=100$
- next OP cost 60
- pay of 10 out of pocket
an 50 from bank

A sequence of operations has **amortized cost** c if for each operation:

1. the operation is paid for (from pocket or bank account)
2. at most c value is paid from pocket and/or *deposited* during each operation

Amortized Analysis of Strategy 2

Setup. Suppose we apply Strategy 2 (double the capacity when full):

- PUSH(x) has cost $\underline{c_1} = O(1)$ if the array is not full,
- PUSH(x) has cost $\underline{c_2} = O(n)$ if the array is full.

Amortized Analysis of Strategy 2

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- PUSH(x) has cost $c_2 = O(n)$ if the array is full.

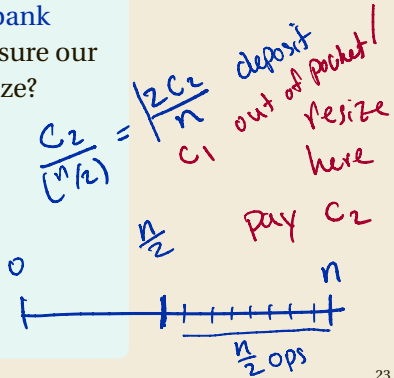
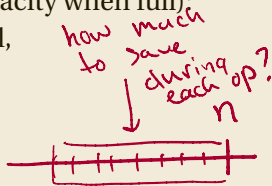
PollEverywhere Question

How much money must we add to our bank account after each (not full) PUSH to ensure our balance is at least c_2 before the next resize?

$$\frac{2c_2}{n} + c_1 = O(1)$$



pollev.com/comp526



Amortized Analysis of Strategy 2

Setup. Suppose we apply Strategy 2 (double the capacity when full):

- PUSH(x) has cost $c_1 = O(1)$ if the array is not full,
- PUSH(x) has cost $c_2 = O(n)$ if the array is full.

Completing the analysis:

- If current capacity is n , last resize was at capacity $n/2$
- There were (at least) $n/2$ non-resizing PUSH operations before next resize
- Must pay c_2 for next resize
- It suffices to put $c_2/(n/2) = 2c_2/n$ in bank each operation

← because double the size

On each non-resizing operation, we pay c_1 out of pocket, and $2c_2/n$ into the bank

⇒ the amortized cost is $c_1 + 2c_2/n = O(1) + \frac{1}{n}O(n) = \boxed{O(1)}$.

The Moral. A single resize may cost $\Theta(n)$, but the average cost over sequences of operations is always $O(1)$ (if we're careful).

The Queue ADT

Queues, Intuitively

Goal: to store a *collection* of elements

- elements arranged as in a queue at Tesco
- new people enter the **back** of the queue
- only the person at the **front** of the queue can be removed (serviced)

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Queues, Formally

- S is the state of the queue, initially $S = \emptyset$
- $S.ENQUEUE(x) : S \mapsto xS$
- $S.FRONT() : \text{returns } x_{n-1}$ where $S = x_0x_1 \cdots x_{n-1}$
- $S.DEQUEUE() : Sx \mapsto S$, returns x
- $S.EMPTY()$ returns $TRUE \iff S = \emptyset$

The Queue ADT

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- new people enter the **back** of the queue
- only the person at the **front** of the queue can be removed (serviced)

Tons of Applications!

- Scheduling
- Messaging
- ...

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List Backed Queues

Idea

- Store each element in a NODE
- Store references to NODE:
 - head at the front of the queue
 - tail at the back of the queue

```
1: class LISTQUEUE
2:   NODE head
3:   NODE tail
4:   procedure ENQUEUE(x)
5:     n ← new NODE
6:     n.data ← x
7:     tail.next ← n
8:     tail ← n
9:   end procedure
10:  procedure DEQUEUE
11:    n ← head
12:    head ← n.next
13:    return n.data
14:  end procedure
15: end class
```


List Backed Queues

Idea

- Store each element in a NODE
- Store references to NODE:
 - head at the front of the queue
 - tail at the back of the queue

Issues:

- Similar to linked list stack implementation
 - Locality of reference
 - NODE memory overhead

```
1: class LISTQUEUE
2:   NODE head
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4:   procedure ENQUEUE(x)
5:     n ← new NODE
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13:    return n.data
14:  end procedure
15: end class
```

Array Backed Queues

Idea:

- Store elements in the stack in an array
- Maintain indices of head and tail

Ignores resizing/checking if full

```
1: class ARRAYQUEUE
2:    $a \leftarrow$  new array, size  $n$ 
3:   head, tail  $\leftarrow$  0
4:   procedure ENQUEUE( $x$ )
5:      $a[\text{tail}] \leftarrow x$ 
6:     tail  $\leftarrow$  tail + 1
7:   end procedure
8:   procedure DEQUEUE
9:     head  $\leftarrow$  head + 1
10:    return  $a[\text{head} - 1]$ 
11:  end procedure
12: end class
```

Array Backed Queues

Idea:

- Store elements in the stack in an array
- Maintain indices of head and tail

What is the problem here?

Ignores resizing/checking if full

```
1: class ARRAYQUEUE
2:    $a \leftarrow$  new array, size  $n$ 
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10:    return  $a[\text{head} - 1]$ 
11:  end procedure
12: end class
```

Array Backed Queues

Idea:

- Store elements in the stack in an **array**
- Maintain indices of head and tail

The fix:

- Use *circular arrays*
- Perform index arithmetic *modulo n* (array size)
- All operations are then $O(1)$
 - **amortized** $O(1)$ time if resizing by doubling size

Ignores resizing/checking if full

```
1: class ARRAYQUEUE
2:    $a \leftarrow$  new array, size  $n$ 
3:   head, tail  $\leftarrow$  0
4:   procedure ENQUEUE( $x$ )
5:      $a[\text{tail}] \leftarrow x$ 
6:     tail  $\leftarrow$  tail + 1 mod  $n$ 
7:   end procedure
8:   procedure DEQUEUE
9:     head  $\leftarrow$  head + 1 mod  $n$ 
10:    return  $a[\text{head} - 1 \bmod n]$ 
11:  end procedure
12: end class
```

The (Min) Priority Queue ADT

Priority Queues, Intuitively

Goal: to store a *collection* of elements

- Each element x has an associated *priority*, $p(x)$
- New elements **inserted** with prescribed priorities
- Can access/remove element with the *minimum* priority in the collection

The (Min) Priority Queue ADT

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Priority Queues, Formally

- S is the state of the queue, initially $S = \emptyset$
- $S.\text{INSERT}(x, p(x)) : S \mapsto xS$
- $S.\text{MIN}() : \text{returns } x_0$ where $S = x_0x_1 \cdots x_{n-1}$
- $S.\text{REMOVEMIN}() : xS \mapsto S$, returns x
- $S.\text{DECREASEKEY}(x, p')$
 $S = x_0x_1 \cdots x_{i-1}xx_{i+1} \cdots x_{n-1} \mapsto x_0x_1 \cdots x_{j-1}xx_jx_{i-1}x_{i+1} \cdots x_{n-1}$
 - $p(x_j) \leq p'(x) < p(x_{j+1})$

The (Min) Priority Queue ADT

Priority Queues, Intuitively

Goal: to store a *collection* of elements

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- New elements **inserted** with prescribed priorities
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For Next Time

- Think about implementing min priority queues with linked lists and stacks
- Consider the running times of the priority queue operations

Priority Queues, Formally

- S is the state of the queue, initially $S = \emptyset$
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 $S = x_0x_1 \cdots x_{i-1}xx_{i+1} \cdots x_{n-1} \mapsto x_0x_1 \cdots x_{j-1}xx_jx_{i-1}x_{i+1} \cdots x_{n-1}$
 - $p(x_j) \leq p'(x) < p(x_{j+1})$

Next Time: Trees!

- Heaps
- Binary Search Trees
- Balanced Binary Trees

Scratch Notes
