

CS 10: Problem solving via Object Oriented Programming

Runtime complexity

Main goals

- Characterize runtime complexity
 - Work for memory too
- Compare list implementations

Agenda

 1. Run-time complexity

2. Asymptotic notation

3. List analysis

Find an element in the list (unsorted)

27	11	3	42	18	7	15
----	----	---	----	----	---	----

Find an element in the list (unsorted)

27	11	3	42	18	7	15
----	----	---	----	----	---	----

Search algorithm (linear search):

```
for idx i = 0 ... n-1
```

```
    if list.get(i) equals target
```

```
        return i
```

```
return -1 (not found)
```

Best case?

Worst case?

Find an element in the list (sorted)

3	7	11	15	18	27	42
---	---	----	----	----	----	----

Find an element in the list (sorted)

3	7	11	15	18	27	42
---	---	----	----	----	----	----

Search algorithm (binary search):

```
min = 0
```

```
max = n-1
```

```
while min <= max
```

```
    idx = (min + max) / 2
```

```
    if list.get(i) equals target
```

```
        return idx
```

```
    if list.get(i) > target
```

```
        max = idx-1
```

```
    else
```

```
        min = idx +1
```

Best case?

Worst case?

Find the max element in the list (unsorted)

27	11	3	42	18	7	15
----	----	---	----	----	---	----

Max algorithm:

```
max_value = list.get(0)
for idx i = 1 ... n-1
    if list.get(i) > max_value
        max_value = list.get(i)
return max_value
```

Best case?

Worst case?

Find the max element in the list (sorted)

3	7	11	15	18	27	42
---	---	----	----	----	----	----

Max algorithm

```
return list.get(0)
```

Best case?

Worst case?

Comparing algorithms

Search algorithm (linear search):

```
for idx i = 0 ... n-1
    if list.get(i) equals target
        return i
return -1 (not found)
```

Search algorithm (binary search):

```
min = 0
max = n-1
while min <= max
    idx = (min + max) / 2
    if list.get(i) equals target
        return idx
    if list.get(i) > target
        max = idx-1
    else
        min = idx + 1
```

Comparing algorithms

Search algorithm (linear search):

```
for idx i = 0 ... n-1
    if list.get(i) equals target
        return i
return -1 (not found)
```

Worst case: check
every item in the list

Search algorithm (binary search):

```
min = 0
max = n-1
while min <= max
    idx = (min + max) / 2
    if list.get(i) equals target
        return idx
    if list.get(i) > target
        max = idx-1
    else
        min = idx + 1
```

Worst case: check half of
the items in the list (though
more operations)

Comparing algorithms

Search algorithm (linear search):

```
for idx i = 0 ... n-1
    if list.get(i) equals target
        return i
return -1 (not found)
```

Best case, immediately
found

Max algorithm:

```
max_value = list.get(0)
for idx i = 1 ... n-1
    if list.get(i) > max_value
        max_value = list.get(i)
return max_value
```

No best or worst case, need
to check entire list

How to compare efficiency?

Ideas:

- Time tests? But depends on specific hardware...
- Count # of operations? But will vary depending on size of list, and depends on exact implementation details...
- Do we compare best case, worst case, or average case?

How to compare efficiency?

- Key idea: typically in computer science, we measure how the # of operations grows with respect to the size of the input in the worst case
- “Size” is not always the length of a list or array, could also be the # characters in a string (as in SA-3), the # nodes in a binary tree, etc.

How to count operations?

- Examples of a single “operation”:
 - Assign value to variable, $x = 1$
 - Access element in array, $x = \text{array}[i]$
 - Perform arithmetic operation, $x = y + z$, $x++$, etc.
 - Compare two values, $x == y$, $x < y$, etc.
- In general, a single CPU computation or single read/write from memory

Example: Calculate sum of numbers from 1 to n

Algorithm 1:

$1+2+3+\dots+n$

```
int sum(int n) {  
    int total = 0  
    for (int i = 1; i <= sum; i++) {  
        total += i;  
    }  
    return total;  
}
```


Example: Calculate sum of numbers from 1 to n

Algorithm 1:

$$1+2+3+\dots+n$$

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int sum(int n) {  
    int total = 0  
    for (int i = 1; i <= sum; i++) {  
        total += i;  
    }  
    return total;  
}
```

operations

1

1; n+1; n

n

1

Total= 3n+4 operations

Example: Calculate sum of numbers from 1 to n

Algorithm 2:

$$1+(1+1)+(1+1+1)+\dots+(1+1+\dots+1)$$

```
int sum(int n) {  
    int total = 0  
    for (int i = 1; i <= sum; i++) {  
        for (int j = 1; j <= i; j++) {  
            total += 1;  
        }  
    }  
    return total;  
}
```

Example: Calculate sum of numbers from 1 to n

Algorithm 2:

$$1+(1+1)+(1+1+1)+\dots+(1+1+\dots+1)$$

```
int sum(int n) {  
    int total = 0  
    for (int i = 1; i <= sum; i++) {  
        for (int j = 1; j <= i; j++) {  
            total += 1;  
        }  
    }  
    return total;  
}
```

operations

1

1; n+1; n

n; (n+1)*(n+1)/2; n*(n+1)/2

n*(n+1)/2

1

Total= $\frac{3}{2}n^2 + \frac{11}{2}n + 4$

operations

Example: Calculate sum of numbers from 1 to n

Algorithm 3: $n*(n+1)/2$

```
int sum(int n) {  
    return n * (n+1) / 2;  
}
```

operations

4

Total= 4 operations

Example: Calculate sum of numbers from 1 to n

Algorithm 1:

$1+2+3+\dots+n$

$3n+4$

Algorithm 2:

$1+(1+1)+(1+1+1)+\dots+(1+1+\dots+1)$

$3/2n^2+11/2n+4$

Algorithm 3:

$n*(n+1)/2$

4

Example: Calculate sum of numbers from 1 to n

Algorithm 1:

$1+2+3+\dots+n$

$3n+4$

$O(n)$

Algorithm 2:

$1+(1+1)+(1+1+1)+\dots+(1+1+\dots+1)$

$3/2n^2+11/2n+4$

$O(n^2)$

Algorithm 3:

$n*(n+1)/2$

4

$O(1)$

Big O notation

- Ignore lower-order terms – the biggest term will dominate as the input size n grows asymptotically
- Ignore constant factors – depends on implementation details, not the core algorithm

Often run-time will depend on the number of elements an algorithm must process

Constant time $O(1)$ – does not depend on number of items
e.g., return first element of a list

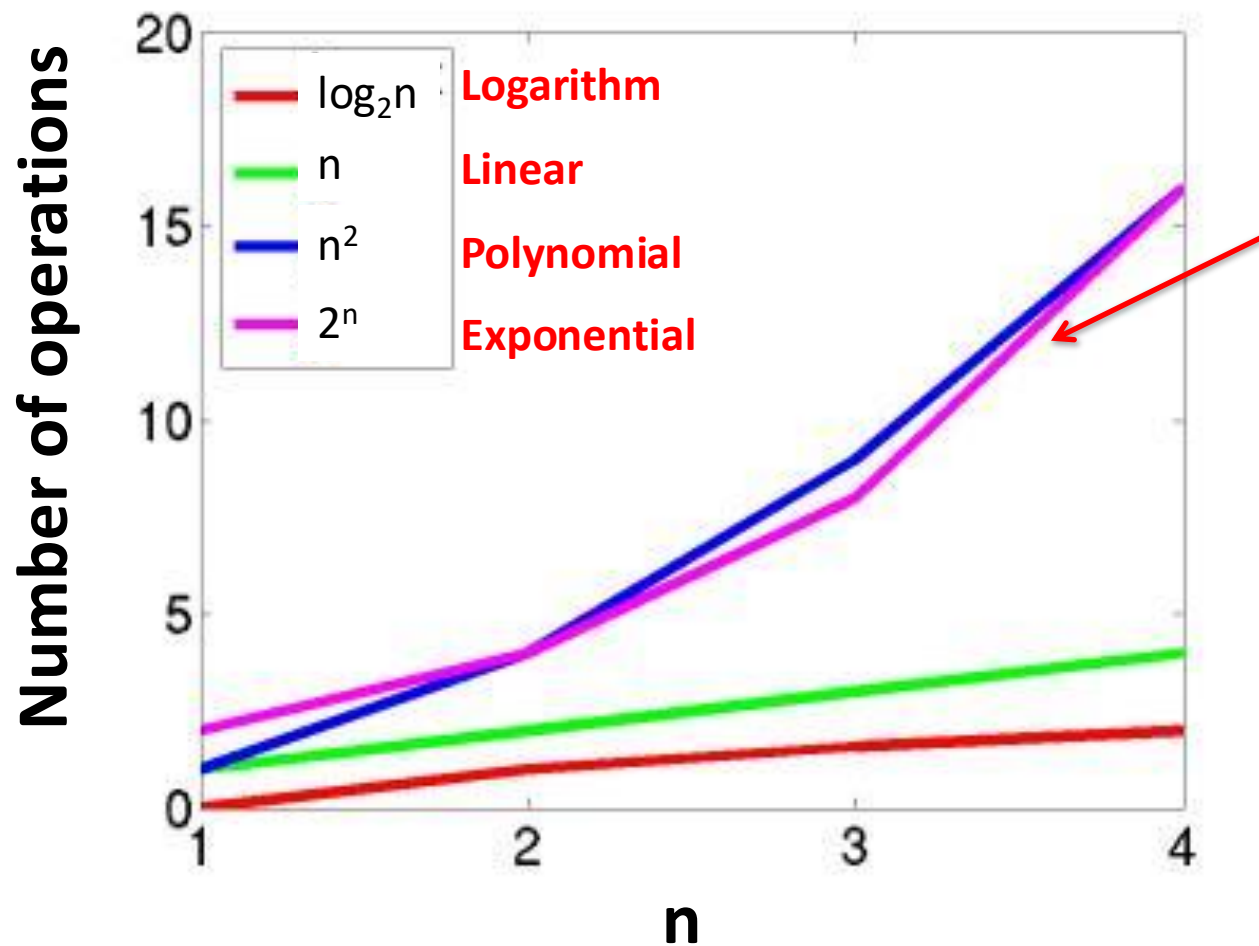
Linear time $O(n)$ – directly depends on number of items
e.g., find value in a list

Polynomial time $O(n^k)$ – depends on a polynomial function of number of items
e.g., nested loop in an image

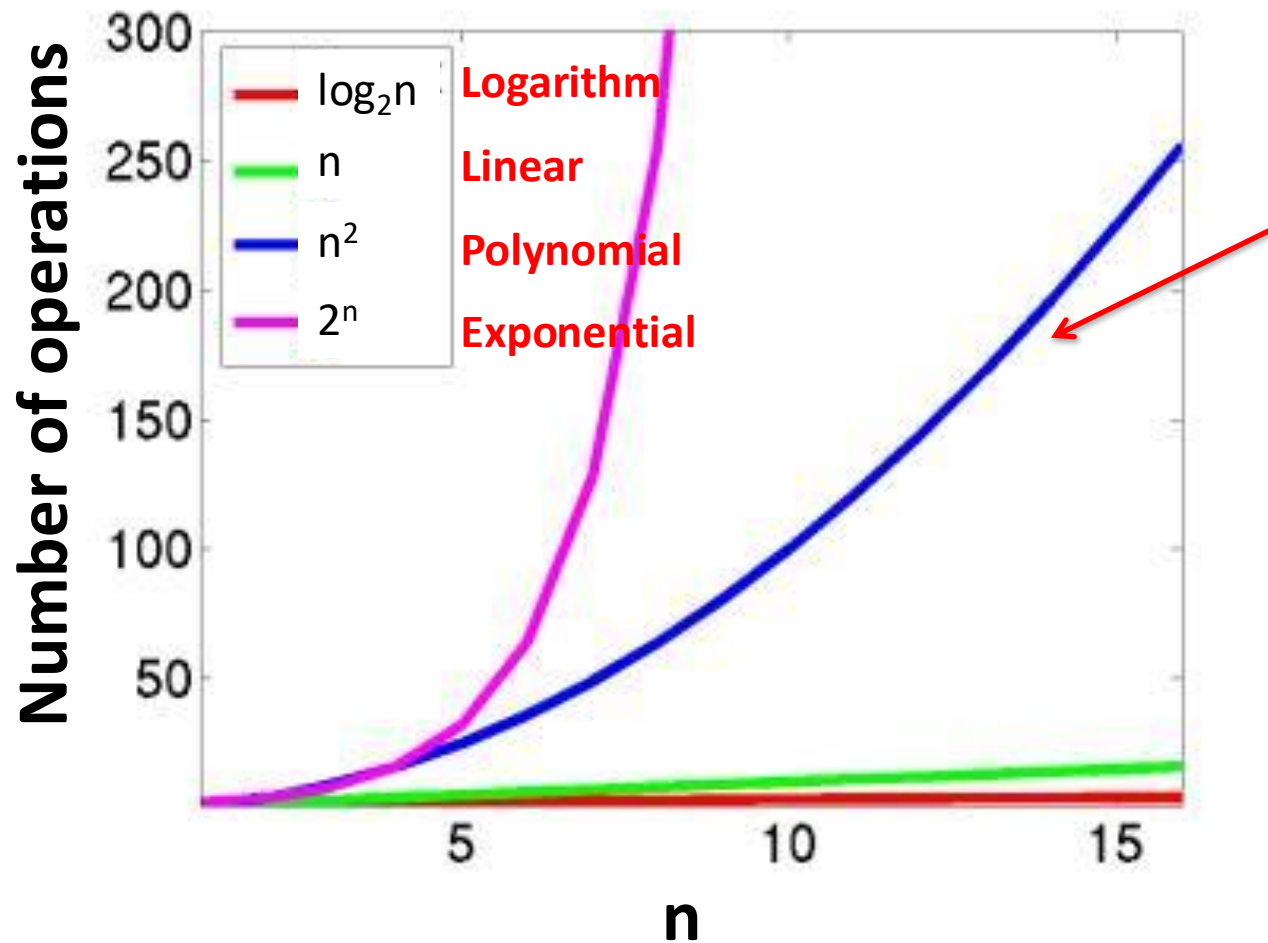
Logarithm time $O(\log n)$ – avoids operations on some items
e.g., binary search

Exponential time $O(2^n)$ – base raised to power
e.g., all possible bit combinations in n bits

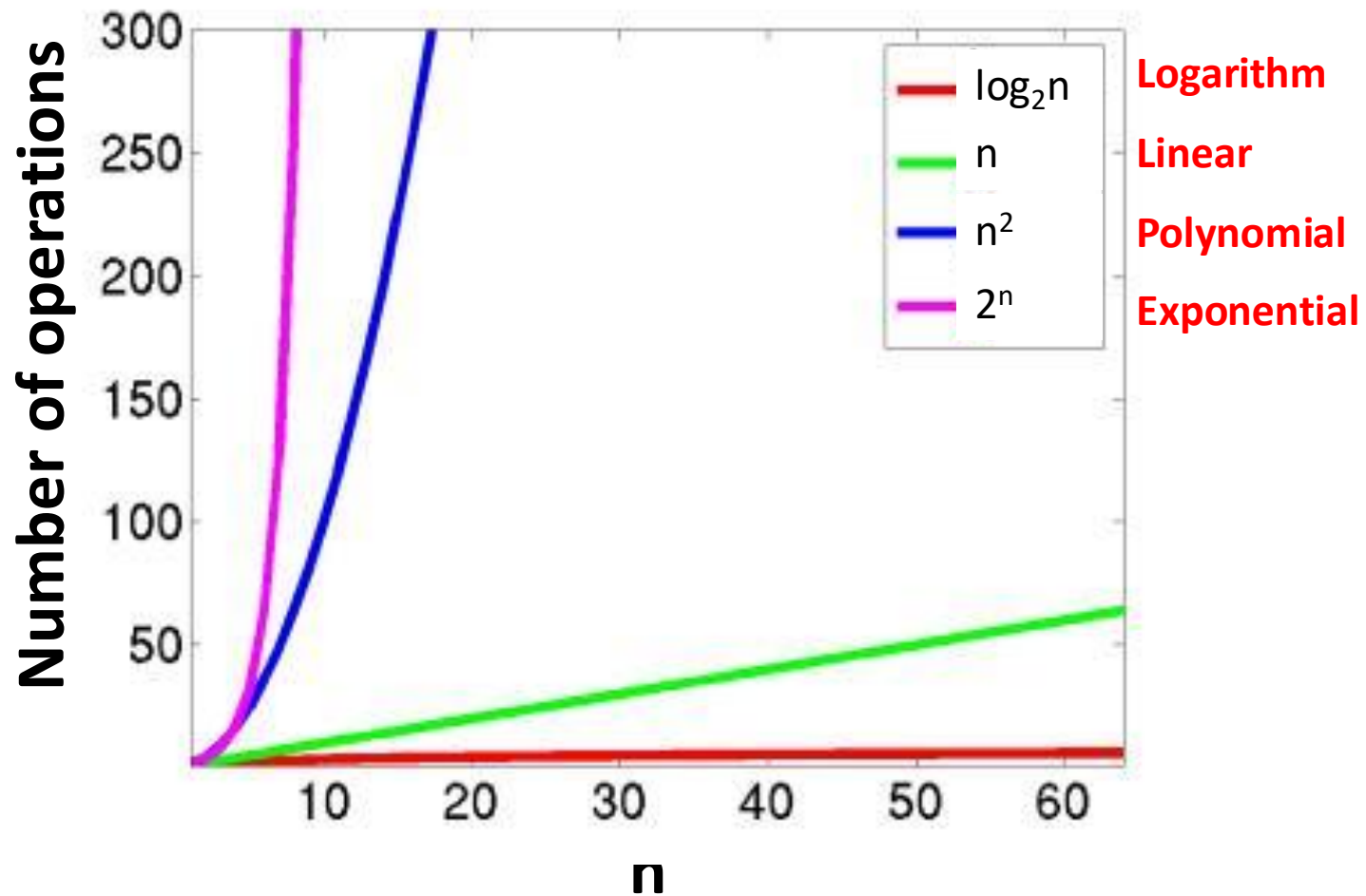
For small numbers of items, run time does not differ by much



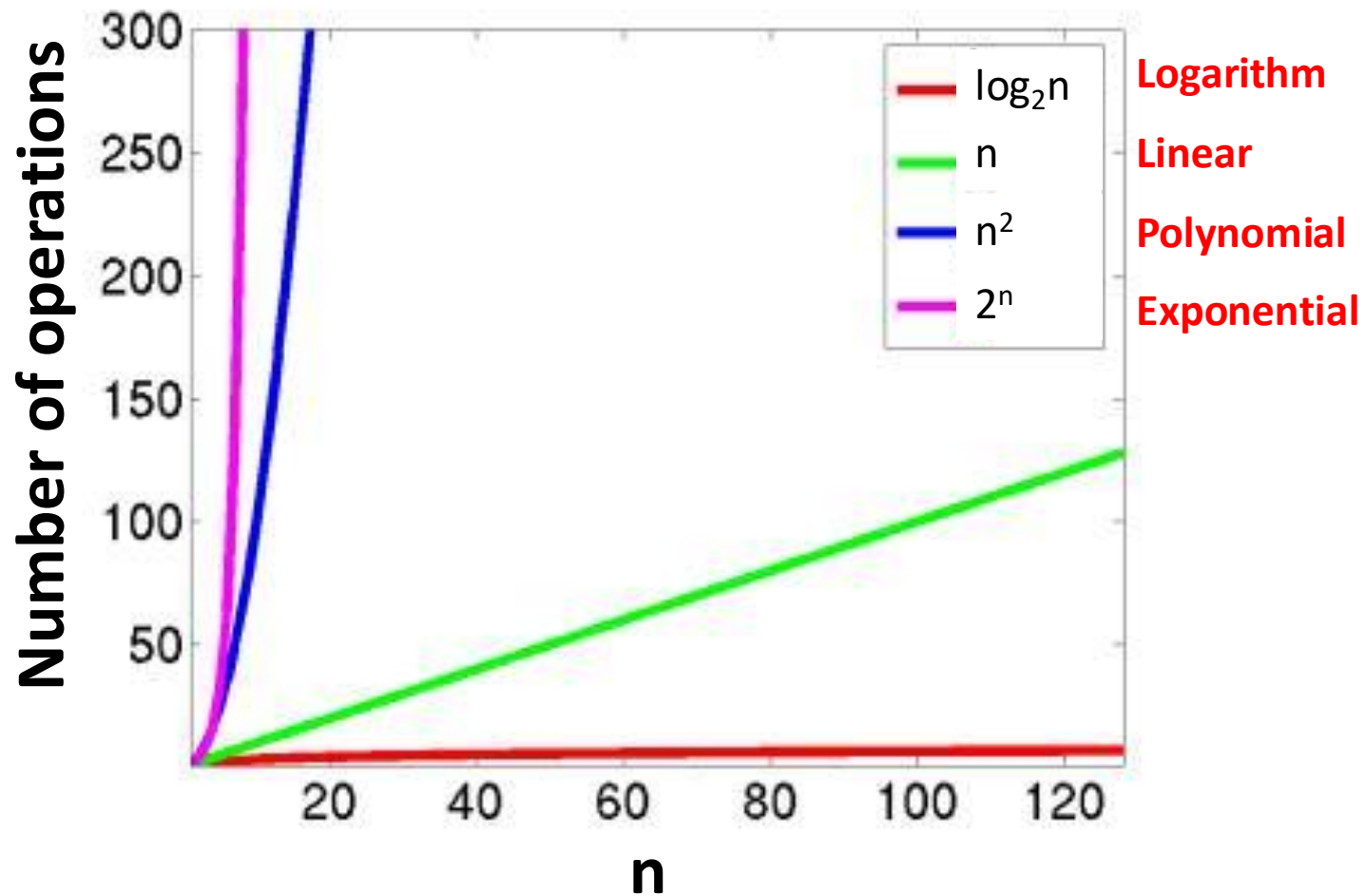
As n grows, number of operations between different algorithms begins to diverge



Even with only 60 items, there is a large difference in number of operations



Eventually, even with speedy computers,
some algorithms become impractical



Sometimes complexity can hurt us, sometimes it can help us



Hurts us

Can't brute force chess
algorithm 2^n



Helps us

Can't crack password
algorithm 2^n

Agenda

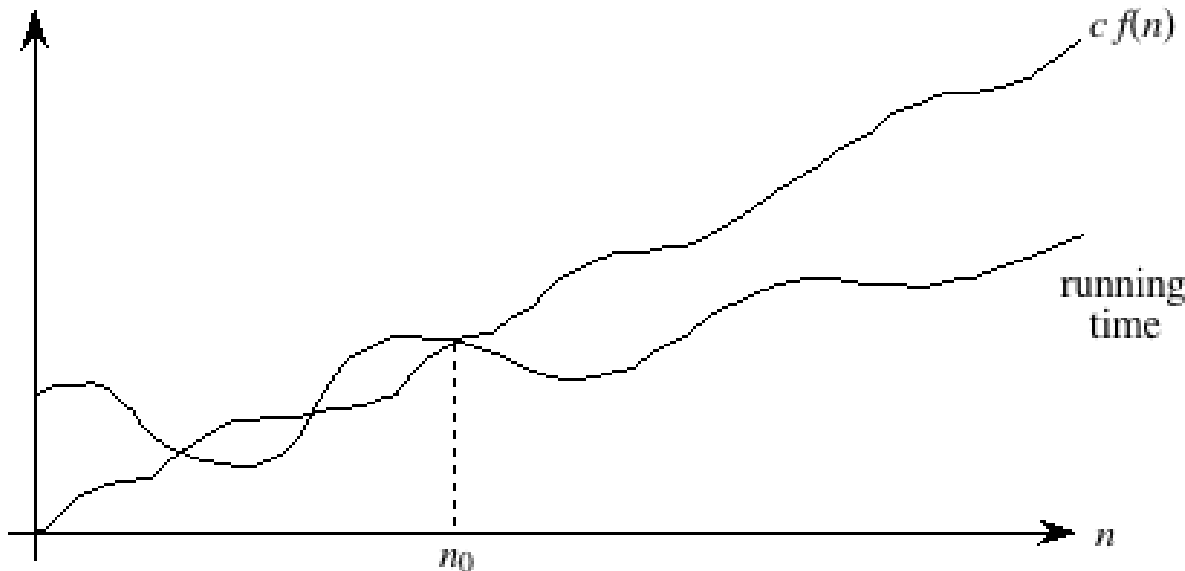
1. Run-time complexity

 2. Asymptotic notation

3. List analysis

We can extend Big Oh to any, not necessarily linear, function

O gives an asymptotic upper bounds

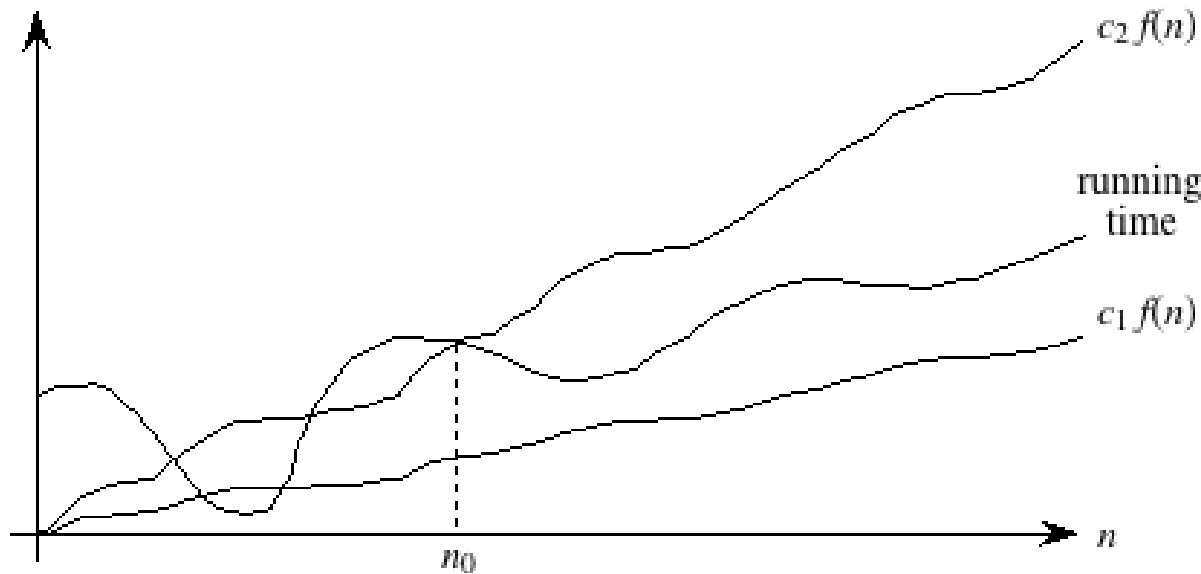


Run-time complexity is $O(f(n))$ if there exists constants n_0 and c such that:

- $\forall n \geq n_0$
- run time of size n is at most $cf(n)$, upper bound
- $O(f(n))$ is the worst case performance for large n , but actual performance could be better

Run time can also be Ω (Big Omega), where run time grows at least as fast

Ω gives an asymptotic lower bounds



Run-time complexity is $\Omega(f(n))$ if there exists constants n_0 and c_1 such that:

- $\forall n \geq n_0$
- run time of size n is at least $c_1 f(n)$, lower bound
- $\Omega(n)$ is the best case performance for large n , but actual performance can be worse

Comparison

Example: find *specific* item in a list

Example: find *largest* item in a list

Comparison

Example: find specific item in a list

- Might find item on first try
- Might not find it at all (must check all n items in list)
- Worst case (upper bound) is $O(n)$

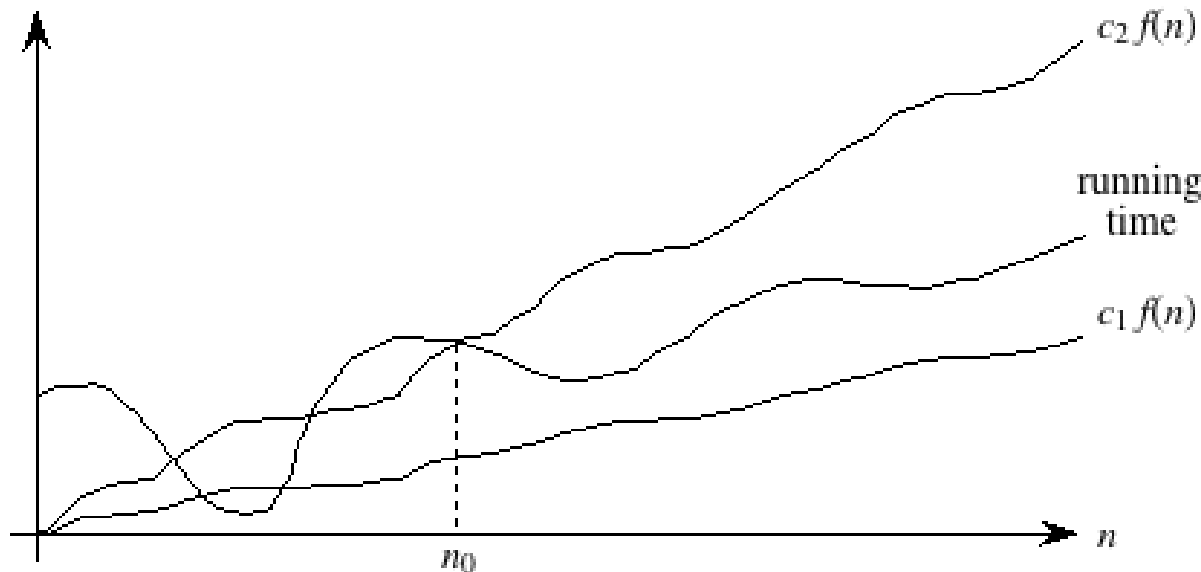
Example: find largest item in a list

- Must check each n items
- Largest item could be at end of list, can't stop early
- Can't do better than $\Omega(n)$

We use Θ (Big Theta) for tight bounds when we can define O and Ω

Θ gives an asymptotic tight bounds

If an algorithm is $O(f(n))$ and $\Omega(f(n))$, then it is $\Theta(f(n))$



Run-time complexity is $\Theta(f(n))$ if there exists constants n_0 and c_1 and c_2 such that:

- $\forall n \geq n_0$
- run time of size n is at least $c_1 f(n)$ and at most $c_2 f(n)$
- $\Theta(n)$ gives a tight bound, which means run time will be within a constant factor
- Generally we will use either O or Θ

Comparison: which has a tight bound?

Example: find specific item in a list

- Might find item on first try
- Might not find it at all (must check all n items in list)
- Worst case (upper bound) is $O(n)$

Example: find largest item in a list

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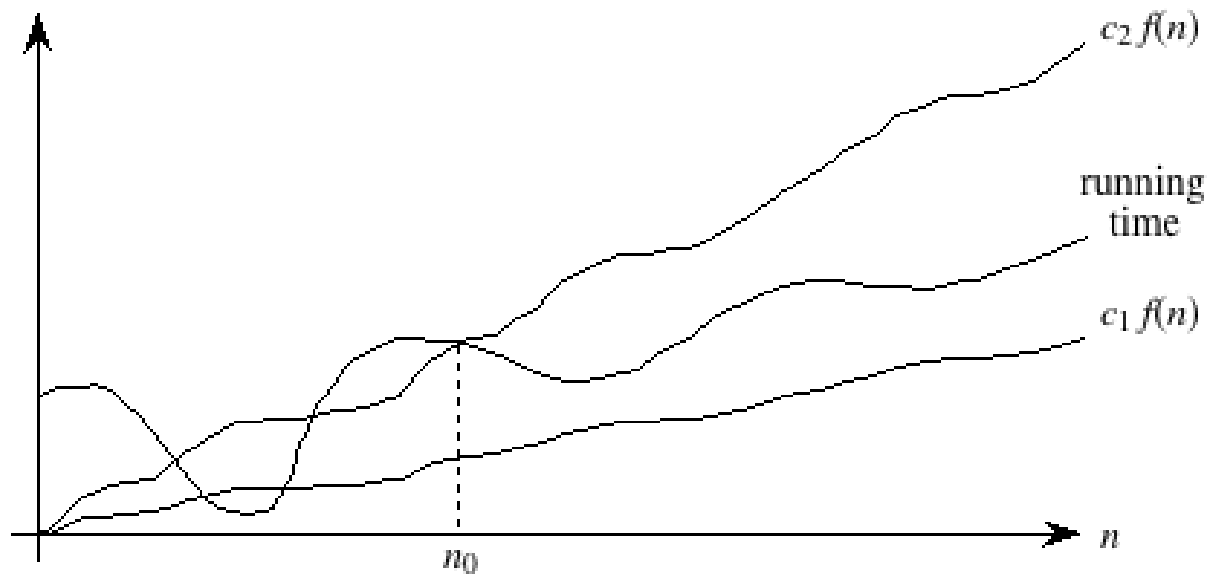
Example: find largest item in a list

- Must check each n items
- Largest item could be at end of list, can't stop early
- Can't do better than $\Omega(n)$
- Worst case: must check each item, so $O(n)$
- Because $\Omega(n)$ and $O(n)$ we say it is $\Theta(n)$

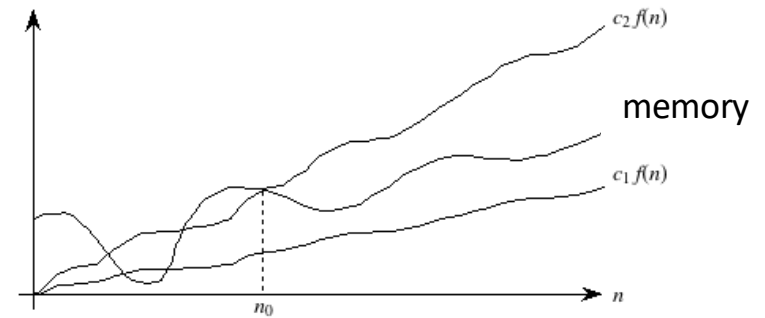
We ignore constants and low-order terms in asymptotic notation

Constants don't matter, just adjust c_1 and c_2

Low order terms don't matter either



These concepts are applicable for memory complexity as well



Agenda

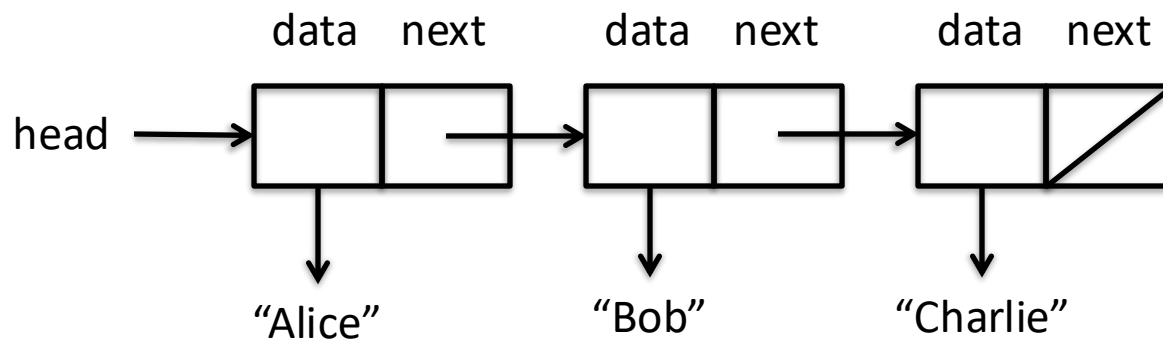
1. Run-time complexity

2. Asymptotic notation

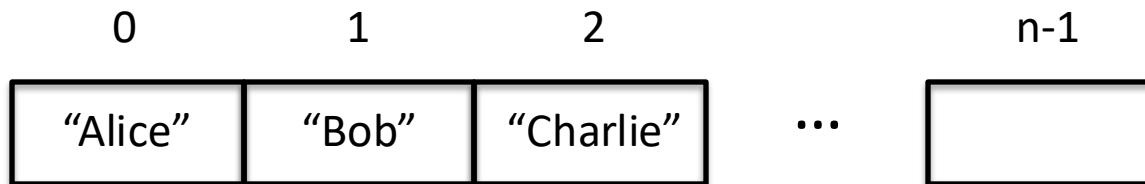
 3. List analysis

Difference between singly linked list and array

Singly linked list



Array



List ADT features

get()/set() element
anywhere in List

add()/remove() element
anywhere in List

No limit to number of
elements in List

Growing array is generally preferable to linked list, except maybe growth operation

Worst case run-time complexity

Linked list

Growing array

get(i)

set(i,e)

add(i,e)

remove(i)

Discussion

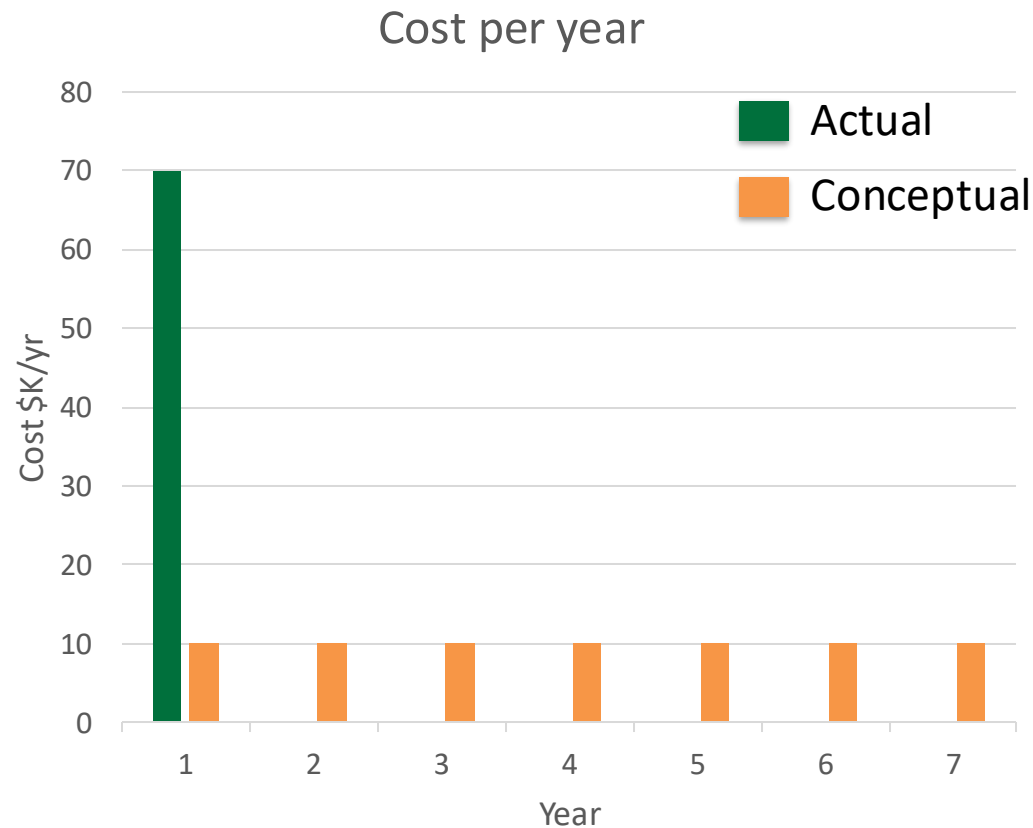
Growing array is generally preferable to linked list, except maybe growth operation

Worst case run-time complexity

	Linked list	Growing array
<i>get(i)</i>	$O(n)$	$O(1)$
<i>set(i,e)</i>	$O(n)$	$O(1)$
<i>add(i,e)</i>	$O(n)$	$O(n) + \text{growth}$
<i>remove(i)</i>	$O(n)$	$O(n)$

Amortization is a concept from accounting that allows us to spread costs over time

Amortized analysis

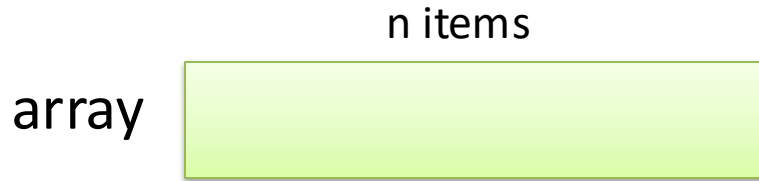


Accounting allows us to amortize costs over several years

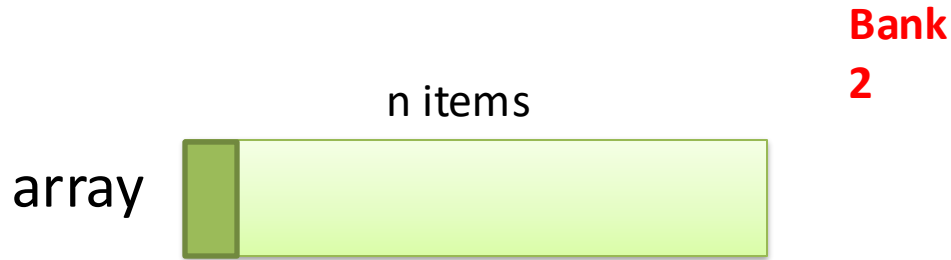
- Buy \$70K truck on year 1
- Truck is good for 7 years

Amortized analysis shows growing array is actually only $O(1)$!

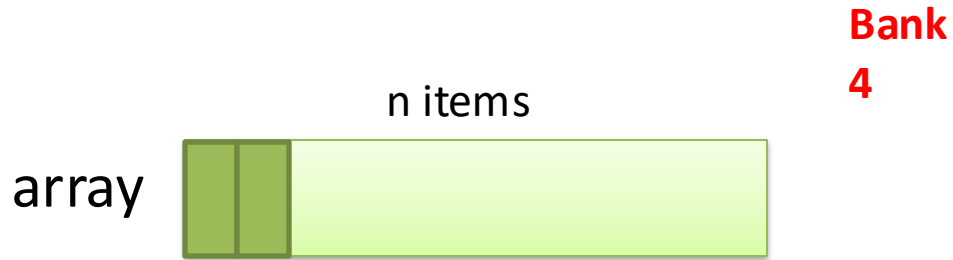
Amortized analysis



Amortized analysis shows growing array is actually only $O(1)$!



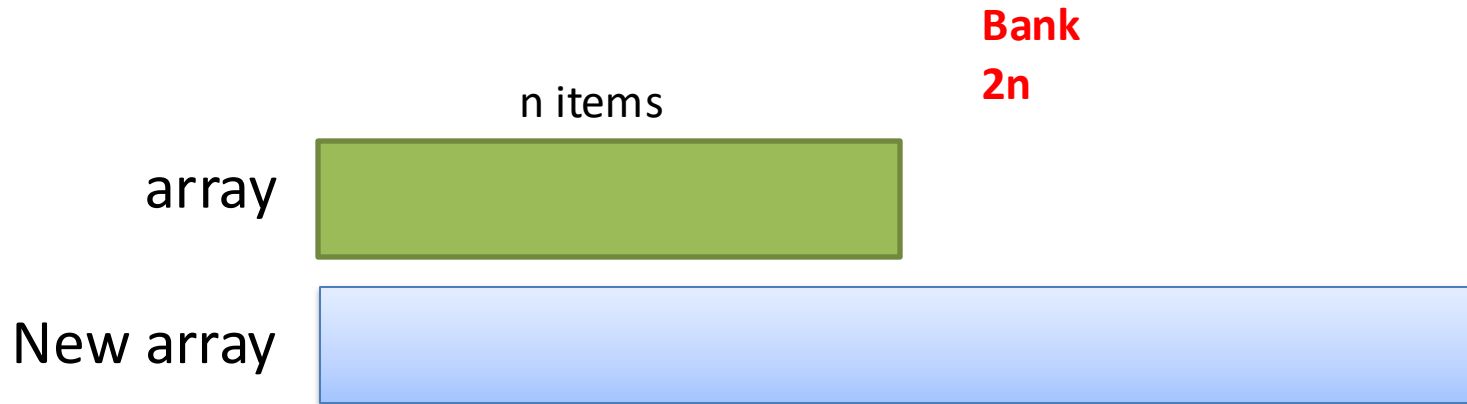
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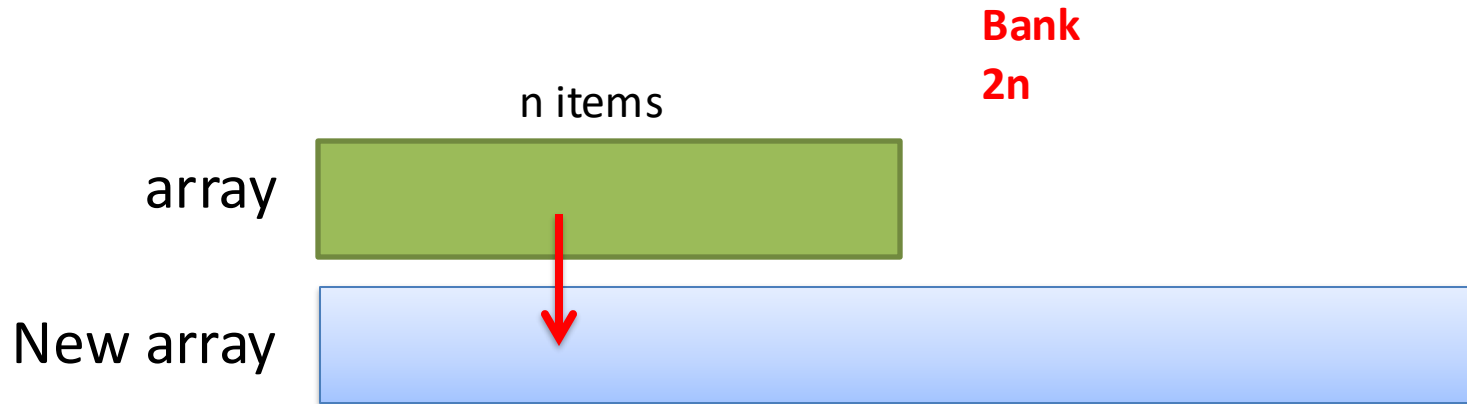
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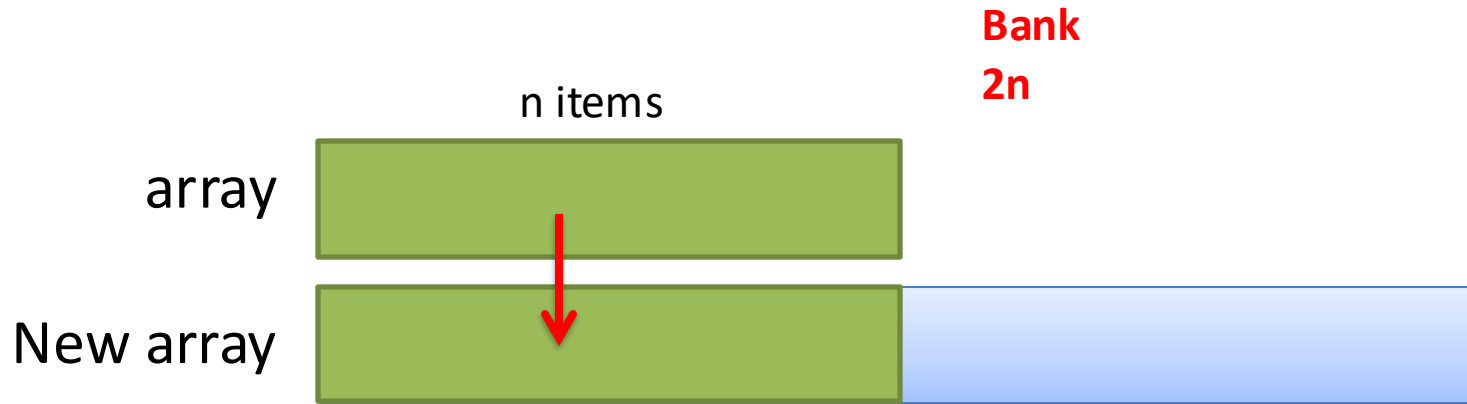
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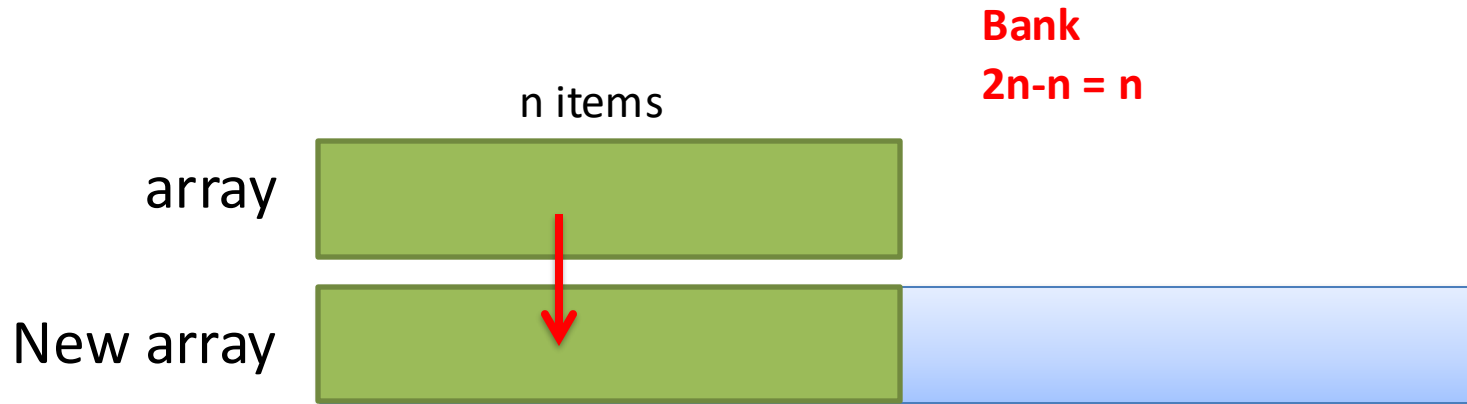
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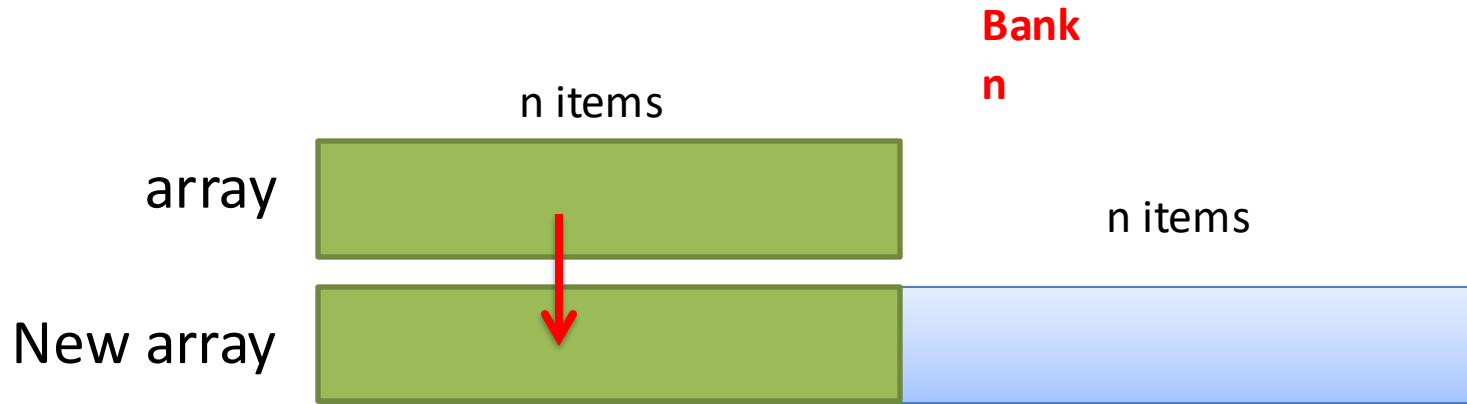
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Amortized analysis shows growing array is actually only $O(1)$!



Amortized analysis shows growing array is actually only $O(1)$!



Growing array is generally preferable to linked list

Worst case run-time complexity



	Linked list	Growing array
<i>get(i)</i>	$O(n)$	$O(1)$
<i>set(i,e)</i>	$O(n)$	$O(1)$
<i>add(i,e)</i>	$O(n)$	$O(n) + O(1) = O(n)$
<i>remove(i)</i>	$O(n)$	$O(n)$

Summary

- Runtime and memory complexity analysis
 - Asymptotic notation
 - $O(1)$ constant, $O(\log(n))$ logarithm, $O(n)$ linear, $O(n^2)$ polynomial, $O(2^n)$ exponential
- Runtime complexity analysis
 - Get/set $O(1)$
 - Add/remove $O(n)$
 - Amortized analysis for growth operation
- List analysis: SinglyLinkedList vs ArrayList
 - Growing array overall more efficient, unless specific assumptions on operations

Next

- Hierarchical relationships through trees

Additional Resources

RUN-TIME COMPLEXITY

How long does it take to find an item in a List?



Assume there are n items in the List (index 0 ... $n-1$)

Find index of "Paula" in List

What pseudo code would you use:

for $i = 0 \dots n-1$

 get item at index i

 if item is equal to search value

 return index i

return -1 (or otherwise indicate search term not in List)

How long to find the item? Should we time how long it takes?

Time would depend on

- Hardware
- Where Paula was located in the List

What is the best case?

What is the worst case?

What is the average case?

How long does it take to find an item in a List?



Instead of timing execution we will count how many operations are needed in the worst case

- Doesn't depend on hardware or software environment
- Could use average case, but average is hard to define sometimes because it would be based on the input's distribution
- Worst case tells us it won't take longer to execute
- Allows language-independent analysis based on number of elements

Operations to count

- Assign value to variable
- Following an object reference to heap memory
- Performing arithmetic operation (e.g., add two numbers)
- Compare two numbers (if statement)
- Access element in array
- Calling or returning from a method

Often run-time will depend on the number of elements an algorithm must process

Constant time – does not depend on number of items

- Returning the first element of a list takes a constant amount of time irrespective of the number of elements in the list
- Just return the first item
- No need to march down list to find the first element (*head*)
- Array *get()* implementation is also constant time (array *get()* is constant time everywhere, linked list only constant at *head*)

Linear time – directly depends on number of items

- Example: searching for a particular value stored in a list
- Start at first item, compare value with value trying to find
- Keep going until find item, or end up at end of list
- Could get lucky and find item right away, might not find it at all
- Worst case is we check all n items

Often run-time will depend on the number of elements an algorithm must process

Polynomial time – depends on a polynomial function of number of items

- Example: nested loop in image and graphic methods
- If changing all pixels in n by n image, must do a total of n^2 operations because inner and outer loops each run n times
- Normally runs slower than a constant or linear time algorithm

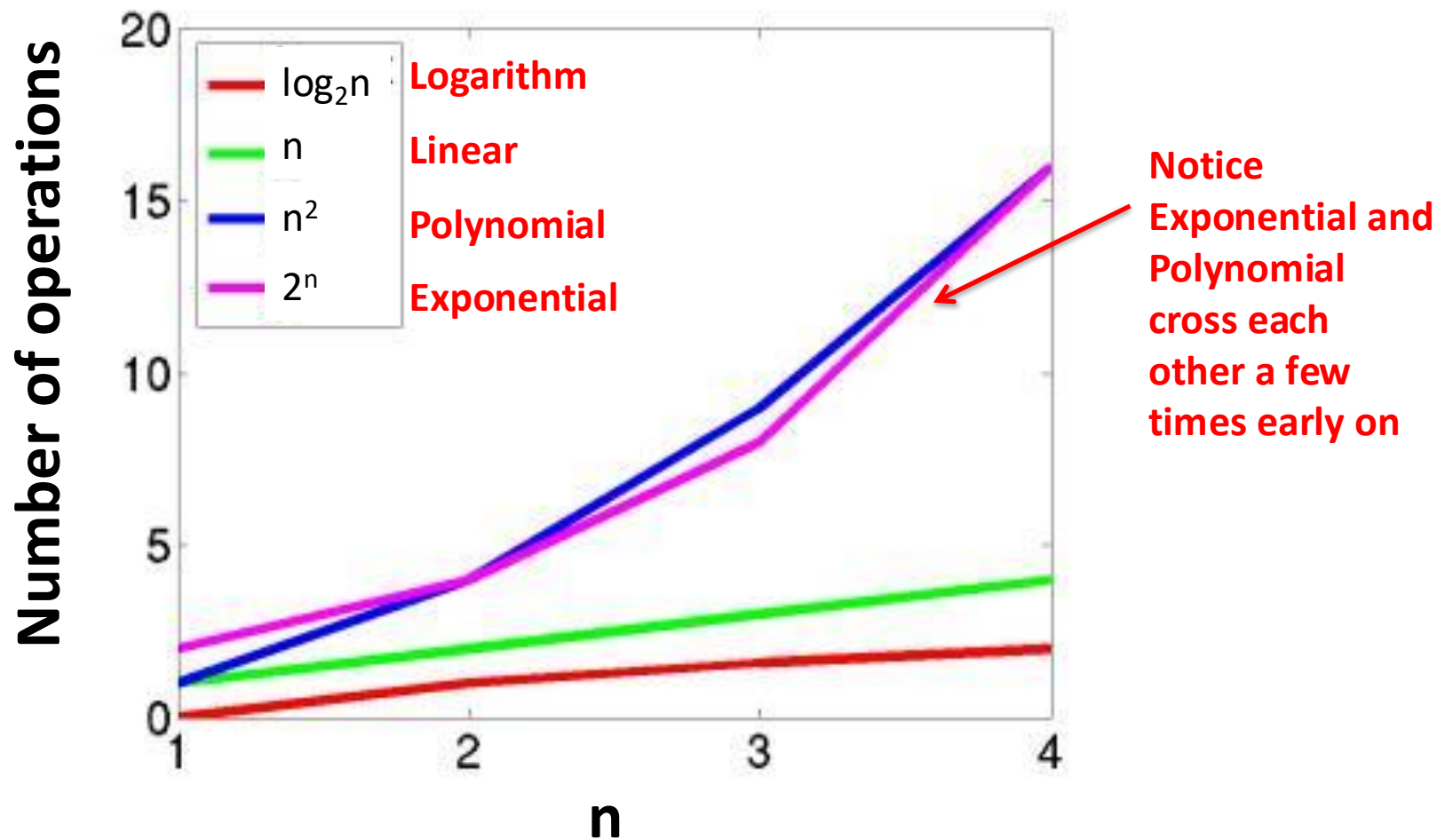
Logarithm time – avoids operations on some items

- Soon we will look at binary search
- Reduces the number of items algorithm must process (don't process all n items)
- Runs faster than linear or polynomial time (slower than constant)

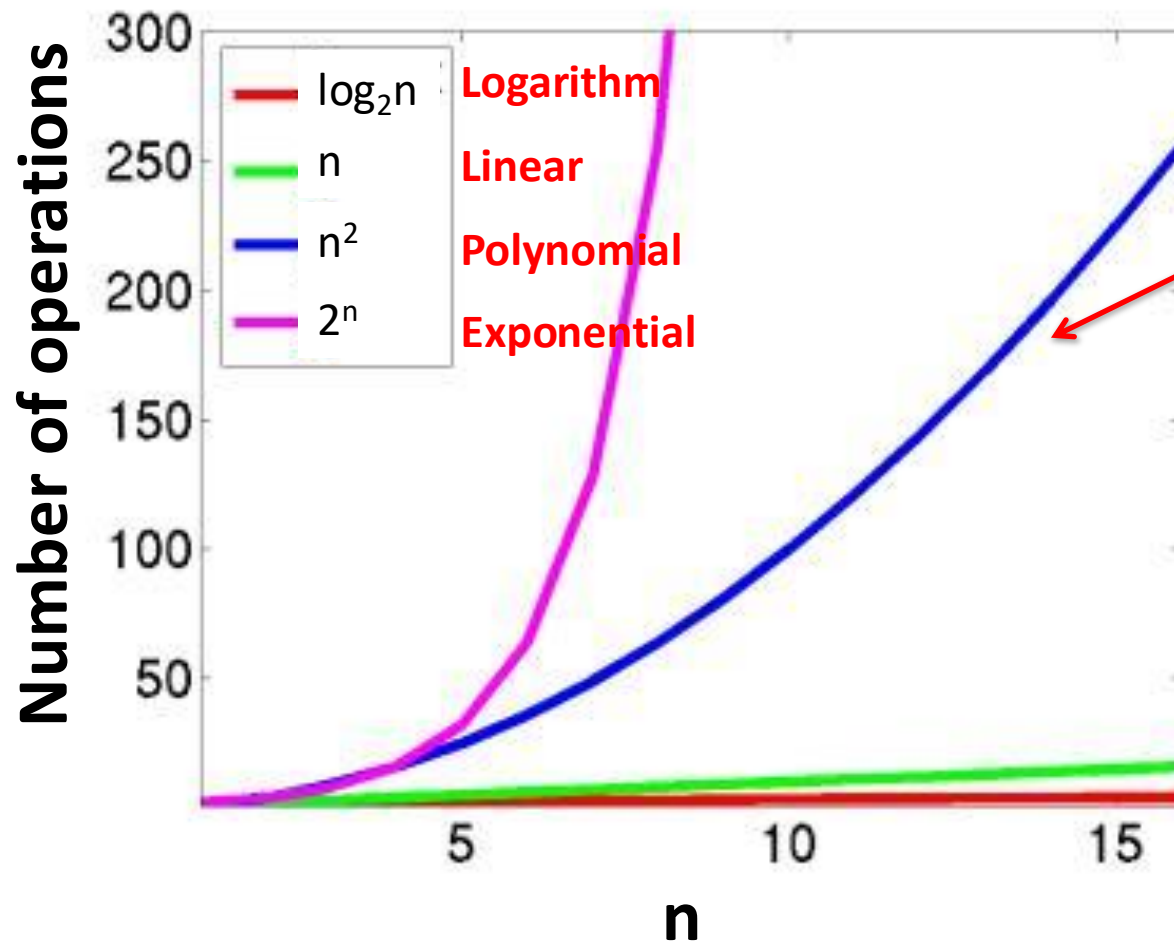
Exponential time – base raised to power

- Combination problems: all possible bit combinations in n bits = 2^n
- SLOW!

For small numbers of items, run time does not differ by much



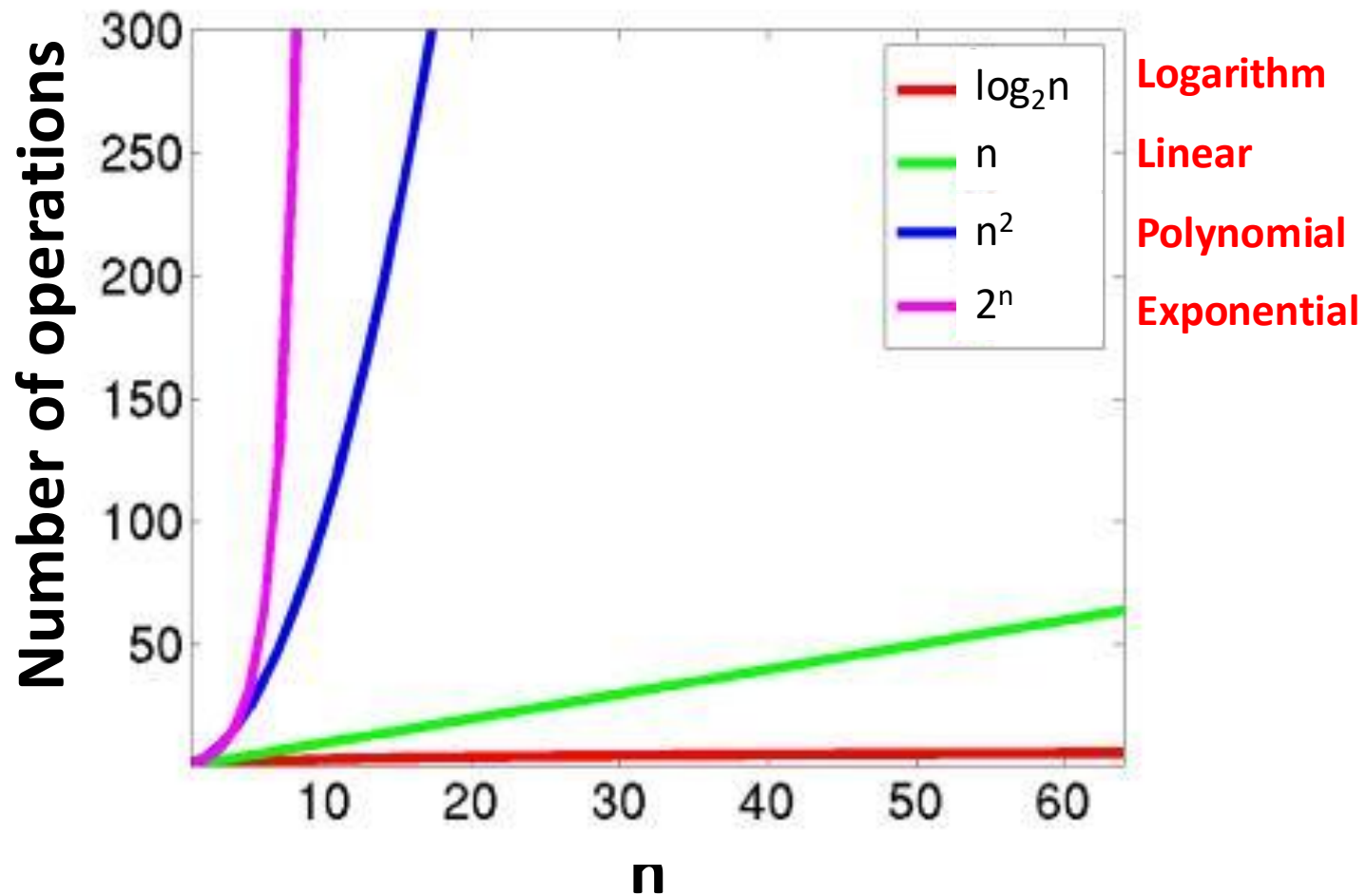
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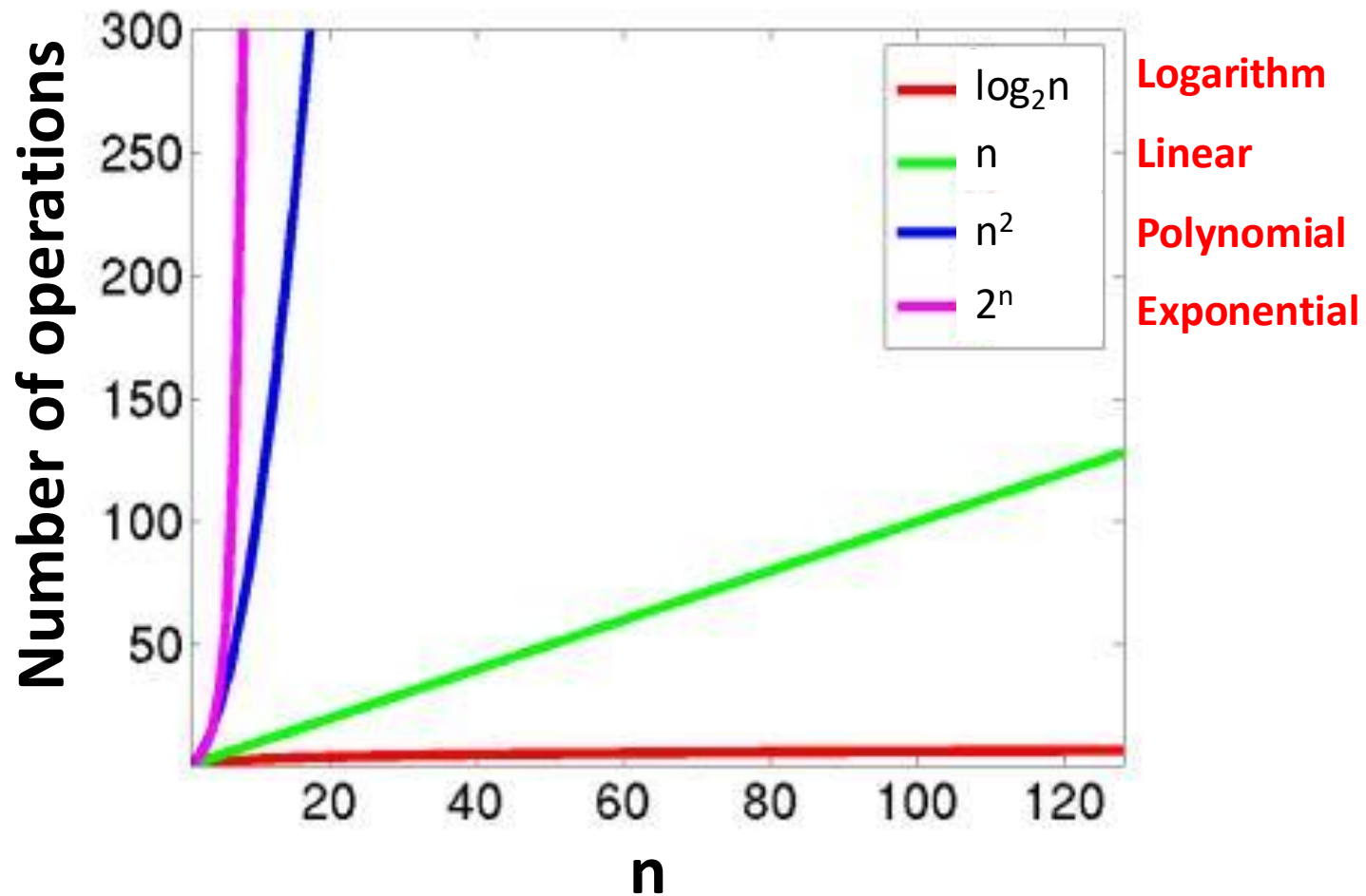
After $n=4$
Exponential is
always greater
than
Polynomial

We will use that
soon to define
 n_0 (standby for
more info)

Even with only 60 items, there is a large difference in number of operations



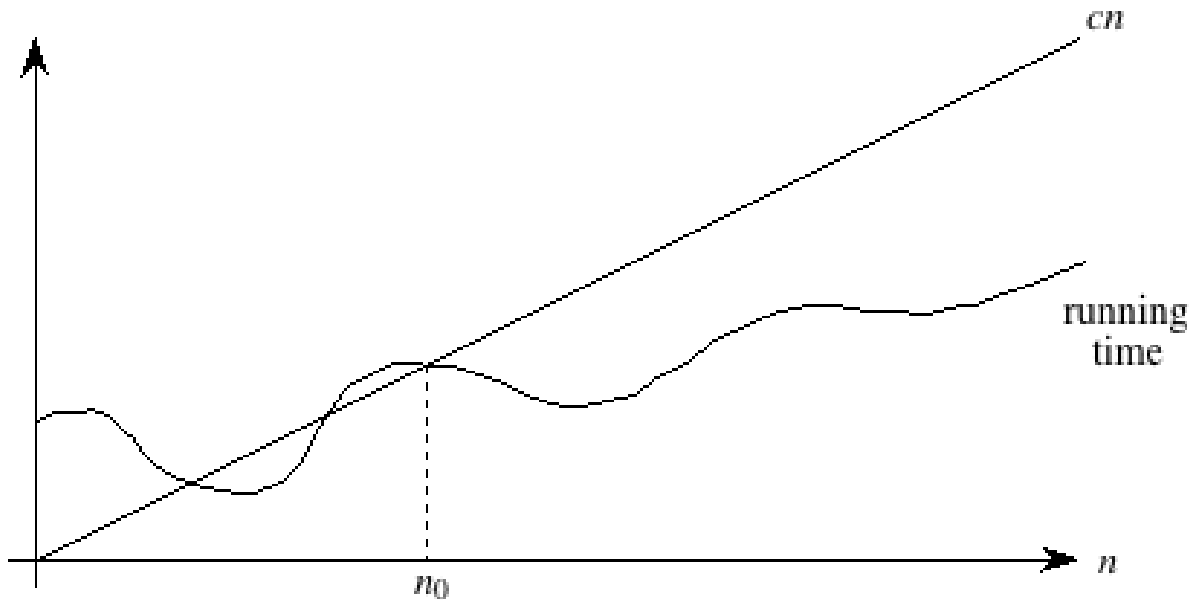
Eventually, even with speedy computers,
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ASYMPTOTIC NOTATION

Computer scientists describe upper bounds on orders of growth with “Big Oh” notation

O gives an asymptotic upper bounds



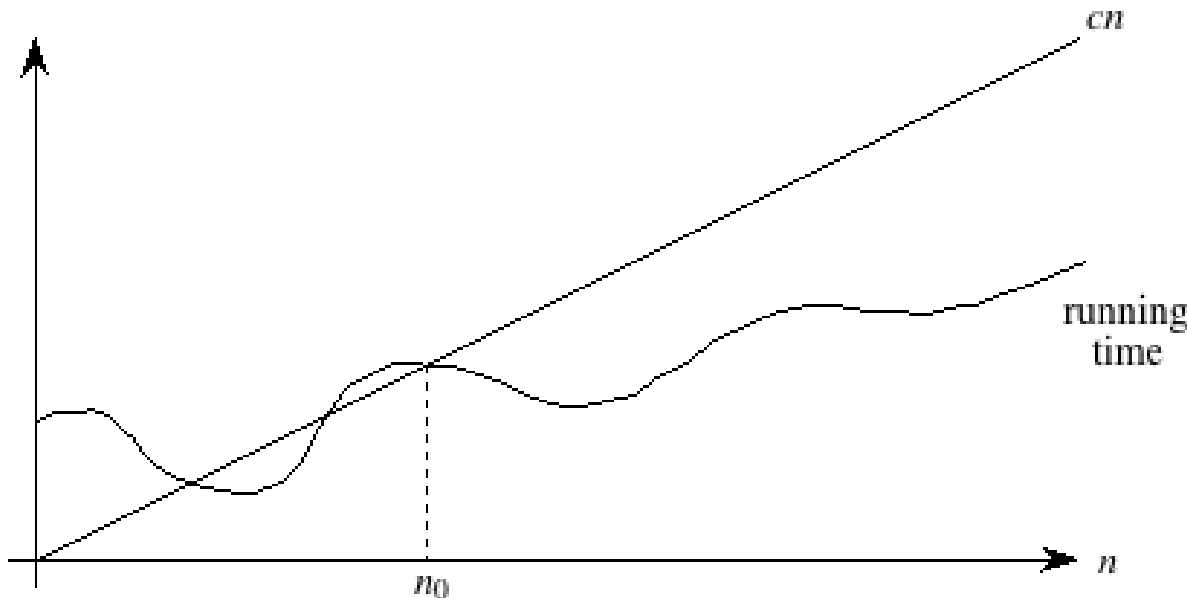
Run-time complexity is $O(n)$ if there exists constants n_0 and c such that:

- $\forall n \geq n_0$
- run time of size n is at most cn , upper bound

Computer scientists describe upper bounds on orders of growth with “Big Oh” notation

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“Big Oh of n ”, and “Oh of n ”, and “order n ”
all mean the same thing!



Example: find specific item in a list

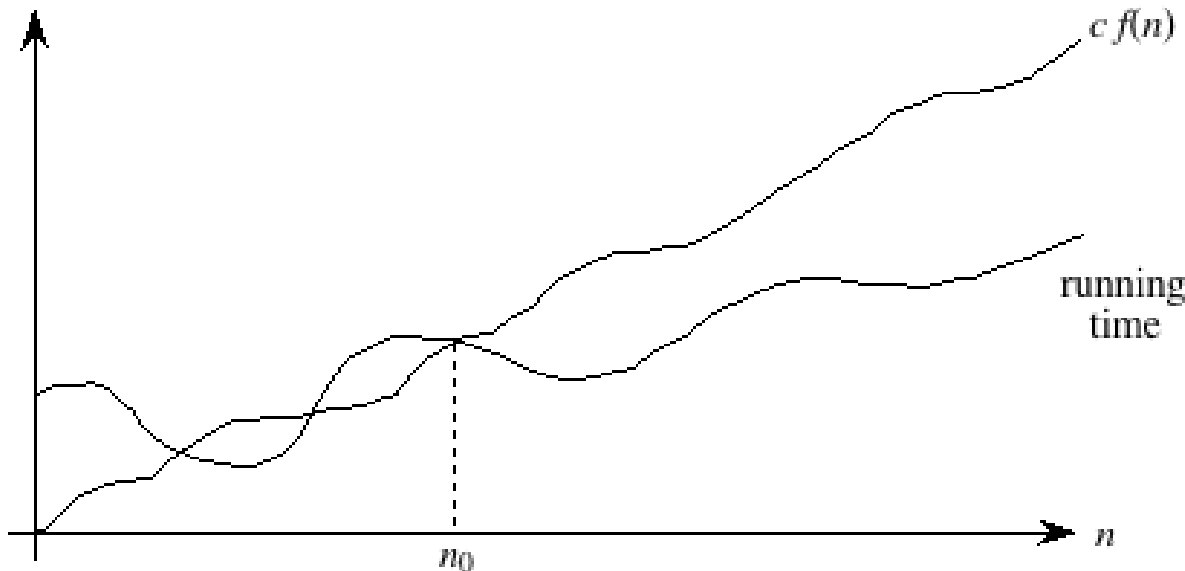
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- Might not find it at all (must check all n items in list)
- Worst case (upper bound) is $O(n)$

Run-time complexity is $O(n)$ if there exists constants n_0 and c such that:

- $\forall n \geq n_0$
- run time of size n is at most cn , upper bound
- $O(n)$ is the worst case performance for large n , but actual performance could be better
- $O(n)$ is said to be “linear” time
- $O(1)$ means constant time

We can extend Big Oh to any, not necessarily linear, function

O gives an asymptotic upper bounds

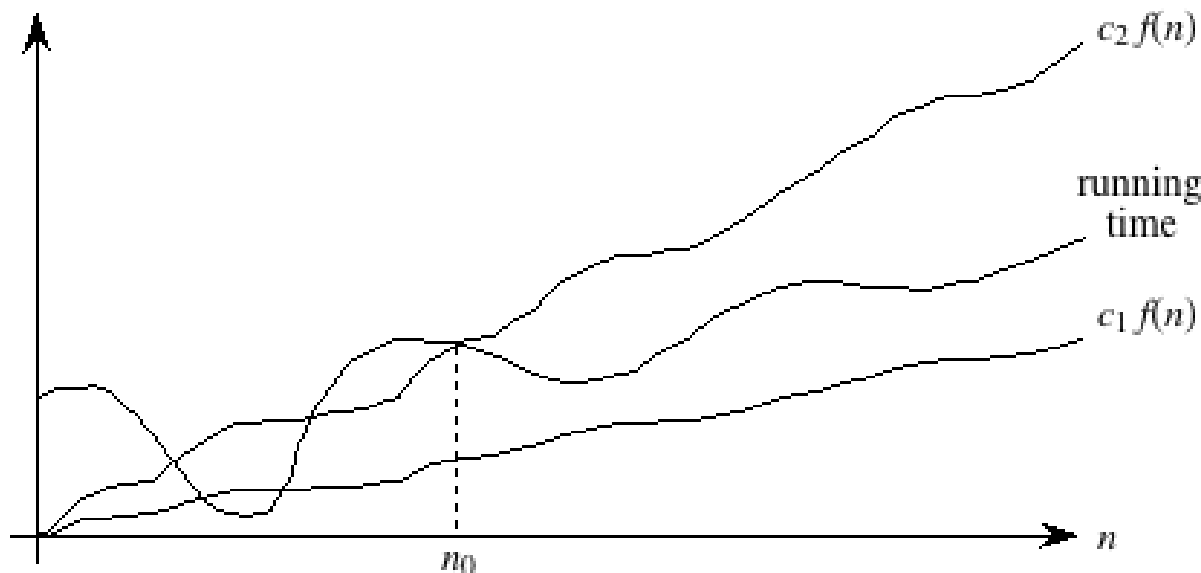


Run-time complexity is $O(f(n))$ if there exists constants n_0 and c such that:

- $\forall n \geq n_0$
- run time of size n is at most $cf(n)$, upper bound
- $O(f(n))$ is the worst case performance for large n , but actual performance could be better
- $f(n)$ can be a non-linear function such as n^2 or $\log(n)$
- In that case $O(n^2)$ or $O(\log n)$

Run time can also be Ω (Big Omega), where run time grows at least as fast

Ω gives an asymptotic lower bounds



Example: find largest item in a list

- Must check each n items
- Largest item could be at end of list, can't stop early
- Can't do better than $\Omega(n)$

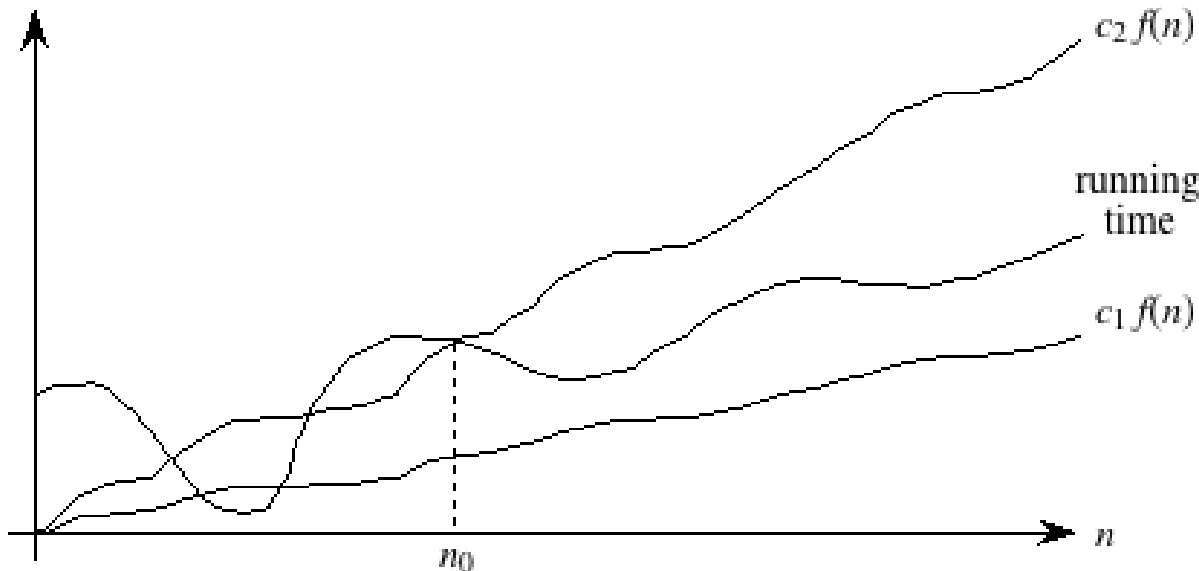
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We use Θ (Big Theta) for tight bounds
when we can define O and Ω

Θ gives an asymptotic tight bounds

We can also apply these concepts to how much memory an algorithm uses (not just run-time complexity)



Example: find *largest* item in a list

- Best case: already seen it is $\Omega(n)$
- Worst case: must check each item, so $O(n)$
- Because $\Omega(n)$ *and* $O(n)$ we say it is $\Theta(n)$

Run-time complexity is $\Theta(f(n))$ if there exists constants n_0 and c_1 and c_2 such that:

- $\forall n \geq n_0$
- run time of size n is at least $c_1 f(n)$ and at most $c_2 f(n)$
- $\Theta(n)$ gives a tight bound, which means run time will be within a constant factor
- Generally we will use either O or Θ
- **O, Ω, Θ called asymptotic notation**

We ignore constants and low-order terms in asymptotic notation

Constants don't matter, just adjust c_1 and c_2

- Constant multiplicative factors are absorbed into c_1 (and c_2)
- Example: $1000n^2$ is $O(n^2)$ because we can choose c_1 to be 1000 (remember bounded by c_1n)
- Do care in practice – if an operation takes a constant time, $O(1)$, but more than 24 hours to complete, can't run it everyday

Low order terms don't matter either

- If $n^2 + 1000n$, then choose $c_1 = 1$, so now $n^2 + 1000n \geq c_1n^2$
- Now must find c_2 such that $n^2 + 1000n \leq c_2n^2$
- Subtract n^2 from both sides and get $1000n \leq c_2n^2 - n^2 = (c_2 - 1)n^2$
- Divide both sides by $(c_2 - 1)n$ gives $1000/(c_2 - 1) \leq n$
- Pick $c_2 = 2$ and $n_0 = 1000$, then $\forall n \geq n_0, 1000 \leq n$
- So, $n^2 + 1000n \leq c_2n^2$, try with $n=1000$ get $n^2 + 1000^2 = 2 * n^2$
- **In practice, we simply ignore constants and low order terms**

How to write them

Constant time
 $O(1)$

Linear time
 $O(n)$

Polynomial time
 $O(n^2)$

DESCRIPTION OF PROS AND CONS

At first arrays seem to be a poor choice to implement the List ADT

List ADT features	Linked List	Array
<i>get()/set()</i> element anywhere in List	• Start at head and march down to index in list • Slow to find element, but fast once there	• Contiguous block of memory • Random access aspect of arrays makes <i>get()/set()</i> easy and fast
<i>add()/remove()</i> element anywhere in List	• Start at head and march down to index in list • Slow to find element, but fast once there	• Fast to find element, but slow once there • Have to make (or fill) hole by copying over
No limit to number of elements in List	• Built in feature of how linked lists work • Just create a new element and splice it in	• Arrays declared of fixed size

ArrTest.java

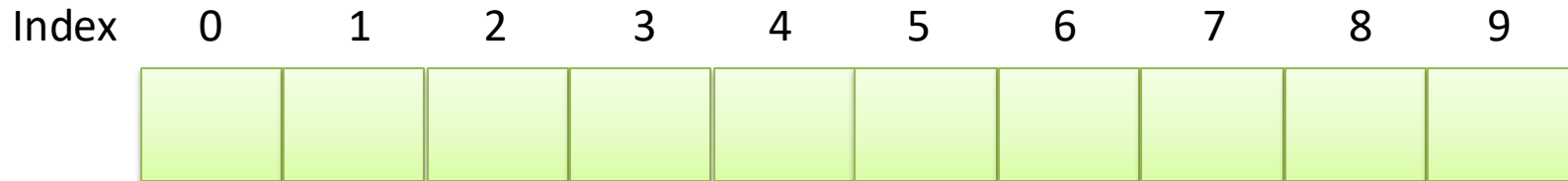
ANNOTATED SLIDES

Random access aspect of arrays makes it easy to get or set any element

```
1
2 public class ArrTest {
3
4     public static void main(String[] args) {
5         //declare array
6         int[] numbers = new int[10]; //indices 0..9
7
8         //set some elements
9         numbers[2] = 2;
10        numbers[5] = 10;
11
12        //get some elements
13        int a = numbers[2];
14        int b = numbers[5];
15        int c = numbers[1]; //we did not set this
16        System.out.println("a="+a+" b="+b+" c="+c);
17    }
18 }
19
```

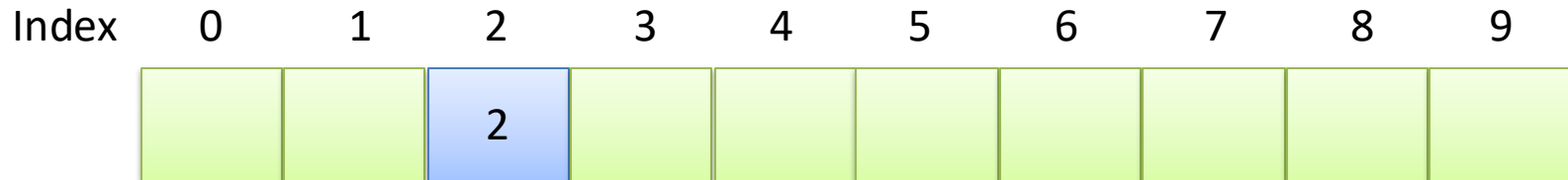
- Array reserves a contiguous block of memory
- Big enough to hold specified number of elements (10 here) times size of each element (4 bytes for integers) = 40 bytes
- Indices are 0...9

Random access aspect of arrays makes it easy to get or set any element



```
2 public class ArrTest {
3
4     public static void main(String[] args) {
5         //declare array
6         int[] numbers = new int[10]; //indices 0..9
7
8         //set some elements
9         numbers[2] = 2;
10        numbers[5] = 10;
11
12        //get some elements
13        int a = numbers[2];
14        int b = numbers[5];
15        int c = numbers[1]; //we did not set this
16        System.out.println("a="+a+" b="+b+" c="+c);
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```

Random access aspect of arrays makes it easy to get or set any element



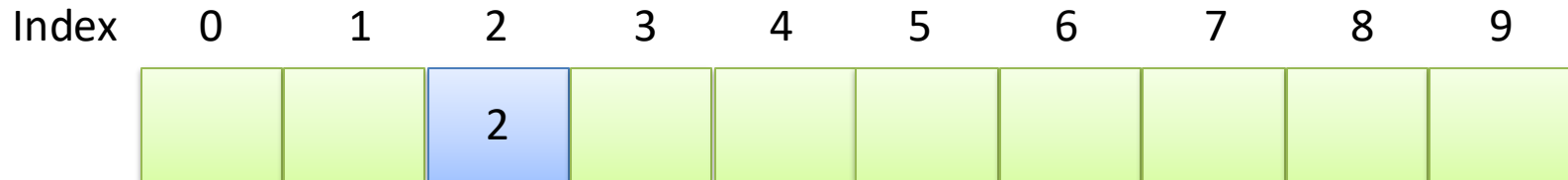
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16        System.out.println("a="+a+" b="+b+" c="+c);
17    }
18 }
19
```

No need to march down list to get or set element

To find element:

- Start at base address of array (this is where “*numbers*” array points)
- Element at index *idx* is at address:
*base addr + idx*size(element)*

Random access aspect of arrays makes it easy to get or set any element



```
2 public class ArrTest {
3
4     public static void main(String[] args) {
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6         int[] numbers = new int[10]; //indices 0..9
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17    }
18 }
19
```

No need to march down list to get or set element

To find element:

- Start at base address of array (this is where “*numbers*” array points)
- Element at index *idx* is at address:
*base addr + idx*size(element)*
- Index 2 at *base addr + 2*4 bytes*
- Time to access element is constant anywhere in array (just simple math operation to calculate any index)
- With linked list have to march down list, takes longer to find elements at end

Random access aspect of arrays makes it easy to get or set any element

Index	0	1	2	3	4	5	6	7	8	9
			2			10				

```
2 public class ArrTest {
3
4     public static void main(String[] args) {
5         //declare array
6         int[] numbers = new int[10]; //indices 0..9
7
8         //set some elements
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Random access aspect of arrays makes it easy to get or set any element

Index	0	1	2	3	4	5	6	7	8	9
			2			10				

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16        System.out.println("a="+a+" b="+b+" c="+c);  
17    }  
18 }  
19
```

What values will a, b and c have?

Random access aspect of arrays makes it easy to get or set any element

Index	0	1	2	3	4	5	6	7	8	9
			2			10				

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17    }
18 }
19
```

What values will a, b and c have?

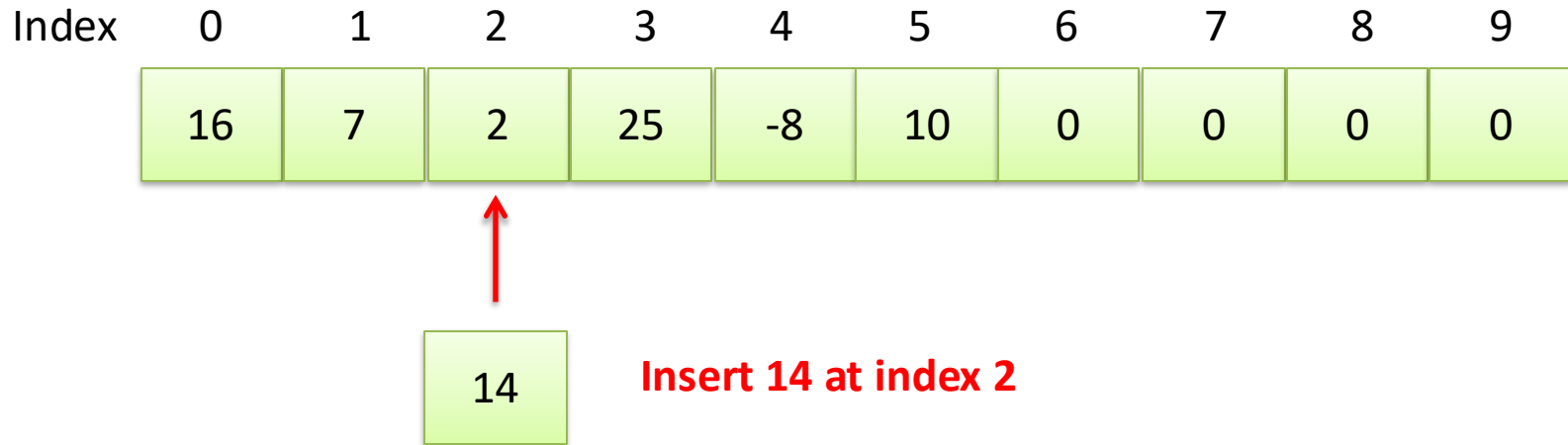
Problems Javadoc Declaration Console Debug Expressions Error Log Call Hierarchy

<terminated> ArrTest [Java Application] /Library/Java/JavaVirtualMachines/jdk1.8.0_112.jdk/Contents/Home/bin/java (Dec 31, 2017, 6:

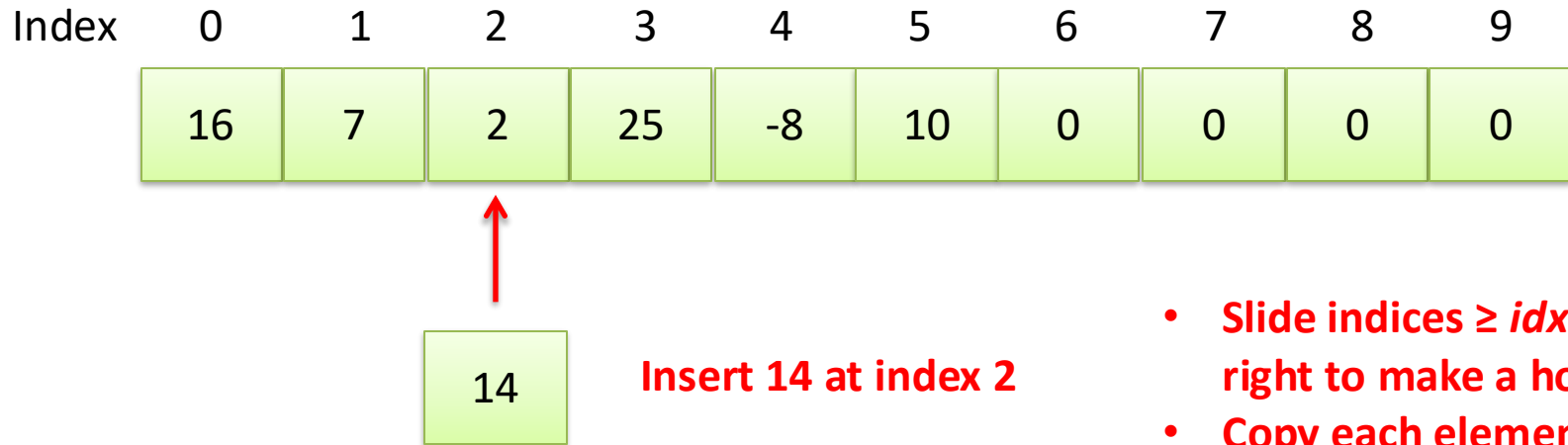
a=2 b=10 c=0

EXAMPLE OF INSERTION IN ARRAYLIST

Because arrays are a contiguous block of memory, hard to insert (except at end)

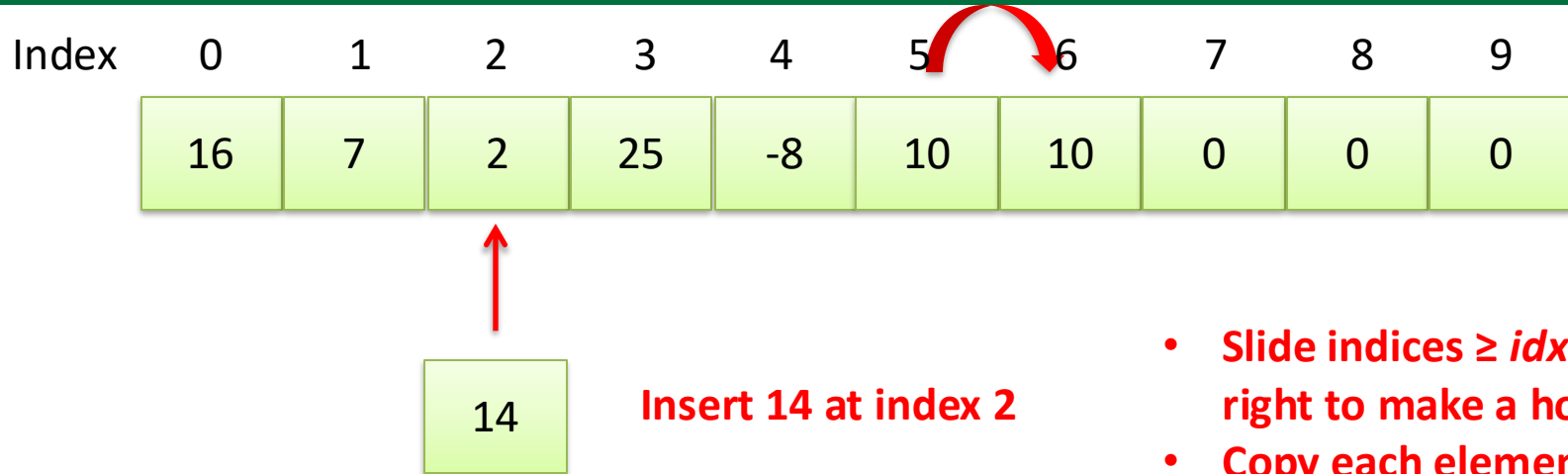


Because arrays are a contiguous block of memory, hard to insert (except at end)



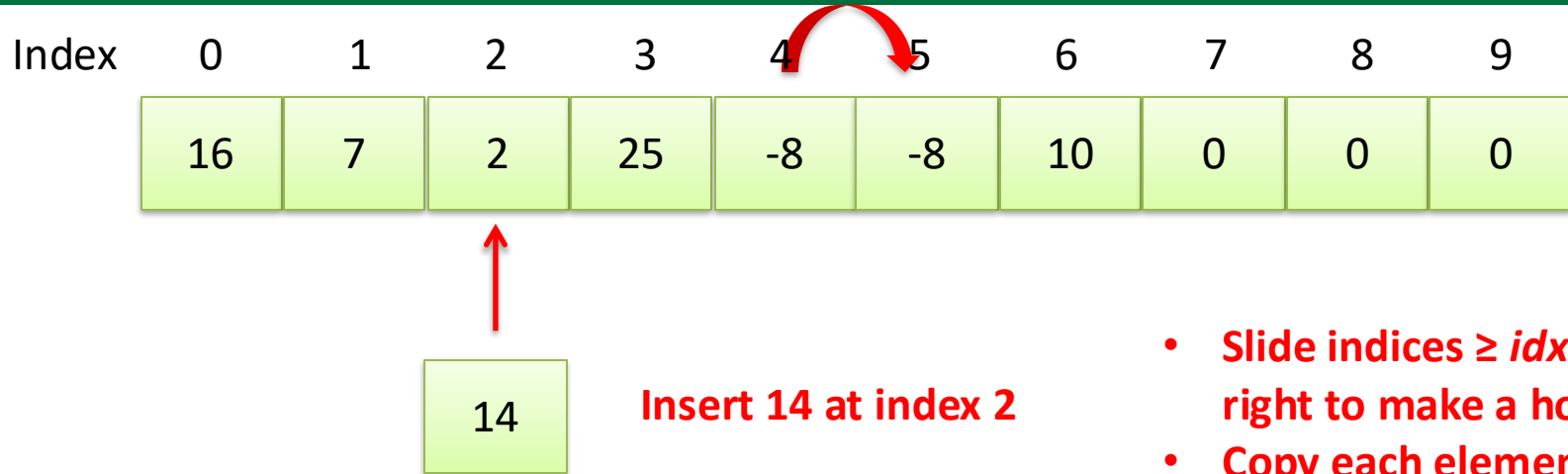
- Slide indices $\geq idx$ to the right to make a hole
- Copy each element to next index

Because arrays are a contiguous block of memory, hard to insert (except at end)



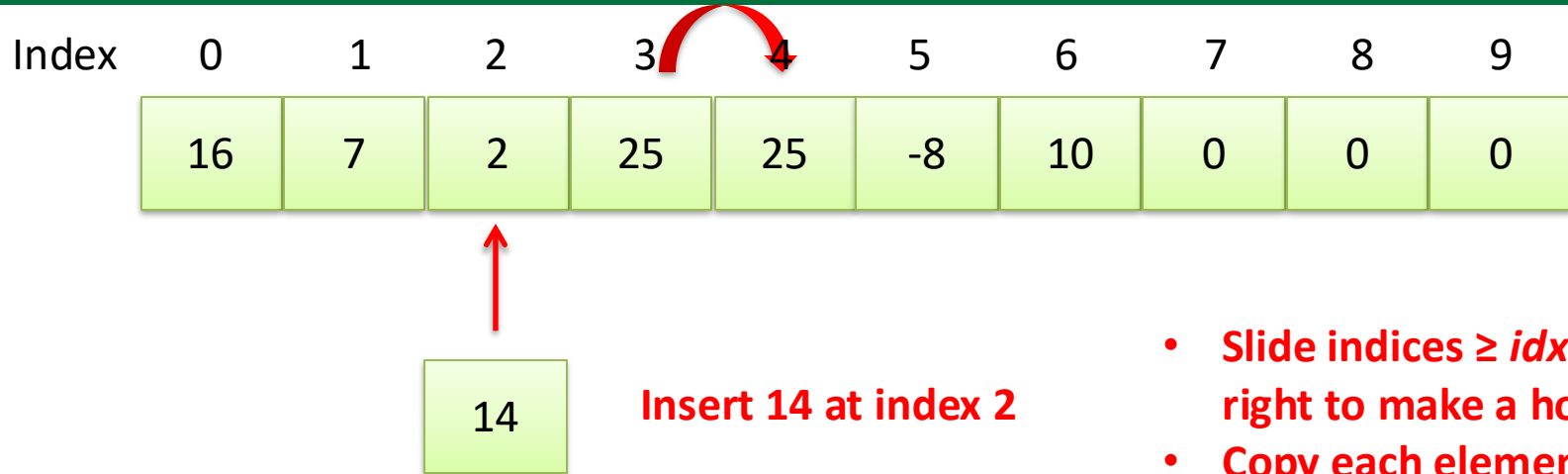
- Slide indices $\geq idx$ to the right to make a hole
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Because arrays are a contiguous block of memory, hard to insert (except at end)



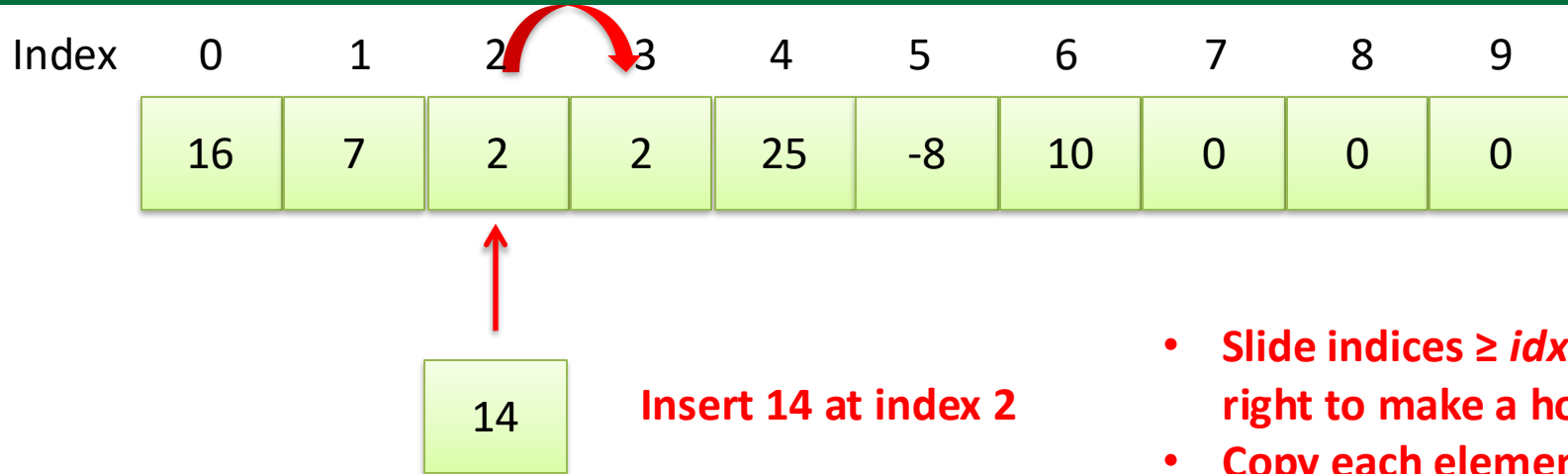
- Slide indices $\geq idx$ to the right to make a hole
- Copy each element to next index

Because arrays are a contiguous block of memory, hard to insert (except at end)



- Slide indices $\geq idx$ to the right to make a hole
- Copy each element to next index

Because arrays are a contiguous block of memory, hard to insert (except at end)



- Slide indices $\geq idx$ to the right to make a hole
- Copy each element to next index

Because arrays are a contiguous block of memory, hard to insert (except at end)

Index	0	1	2	3	4	5	6	7	8	9
	16	7	2	2	25	-8	10	0	0	0



Insert 14 at index 2

Copy new element
into index

- Slide indices $\geq idx$ to the right to make a hole
- Copy each element to next index

Because arrays are a contiguous block of memory, hard to insert (except at end)

Index	0	1	2	3	4	5	6	7	8	9
	16	7	14	2	25	-8	10	0	0	0

- Works, but takes a lot of time (said to be “expensive”)
- Especially expensive with respect to time if the array is large and we insert at the front
- Linked list is slow to find the right place (have to march down list starting from head), but fast to insert, just update two pointers and you’re done
- Linked list is fast, however, if only dealing with head
- With arrays, easy to find right place, but slow afterward due to copying to make a hole

EXAMPLE OF GROWING ARRAYLIST

Arrays are of fixed size, but List ADT allows for growth

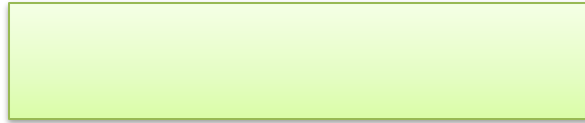
Index	0	1	2	3	4	5	6	7	8	9
	16	7	14	2	25	-8	10	52	-19	6

What do we do when the array is full, but we want to add more elements?

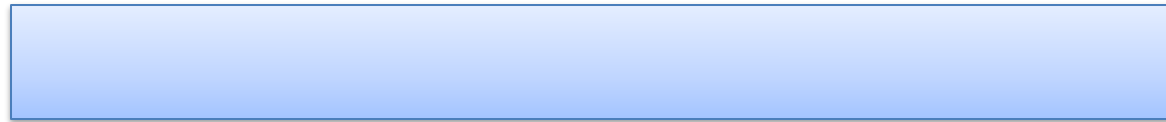
Answer: create another, larger array, and copy elements from old array into new array

Arrays are of fixed size, but List ADT allows for growth

Old array



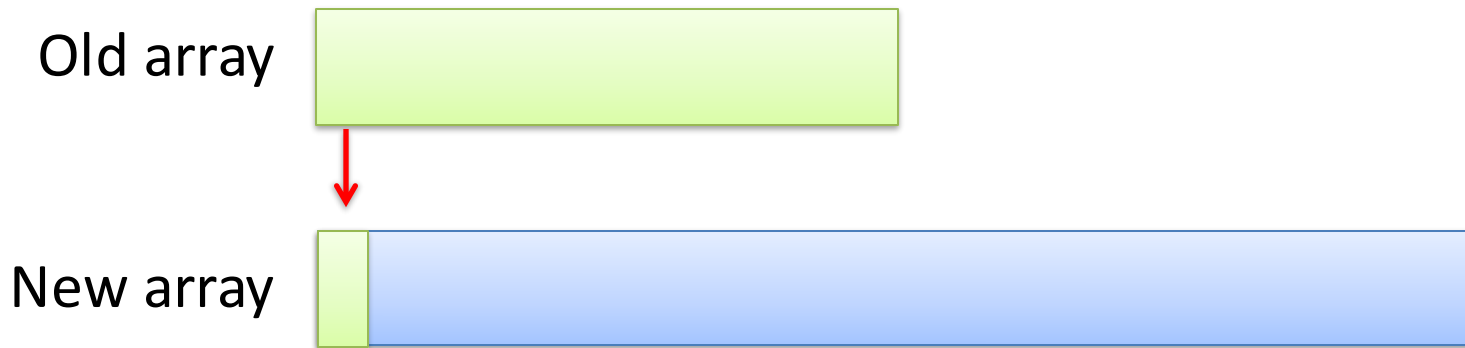
New array



Grow array

1. Make new array, say 2 times larger than old array

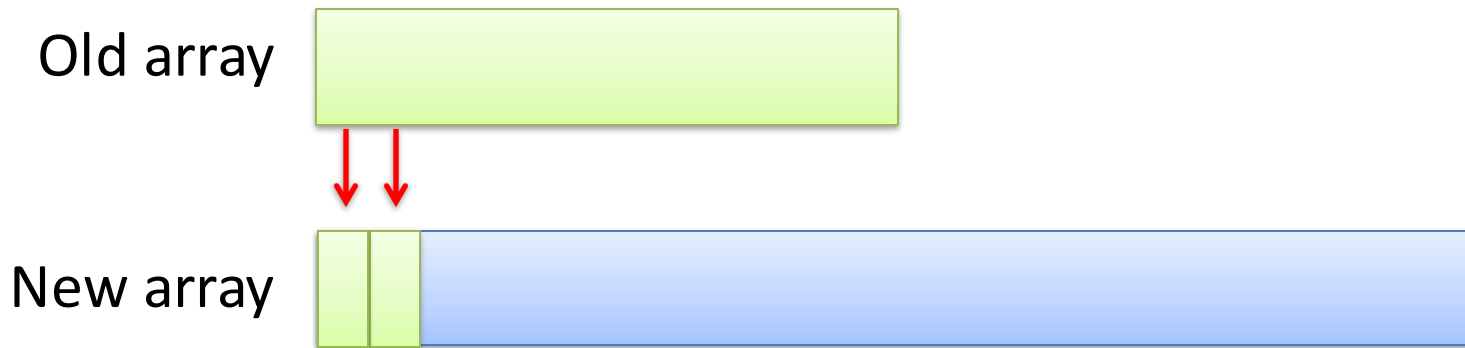
Arrays are of fixed size, but List ADT allows for growth



Grow array

- 1. Make new array, say 2 times larger than old array**
- 2. Copy elements one at a time from old array to new**

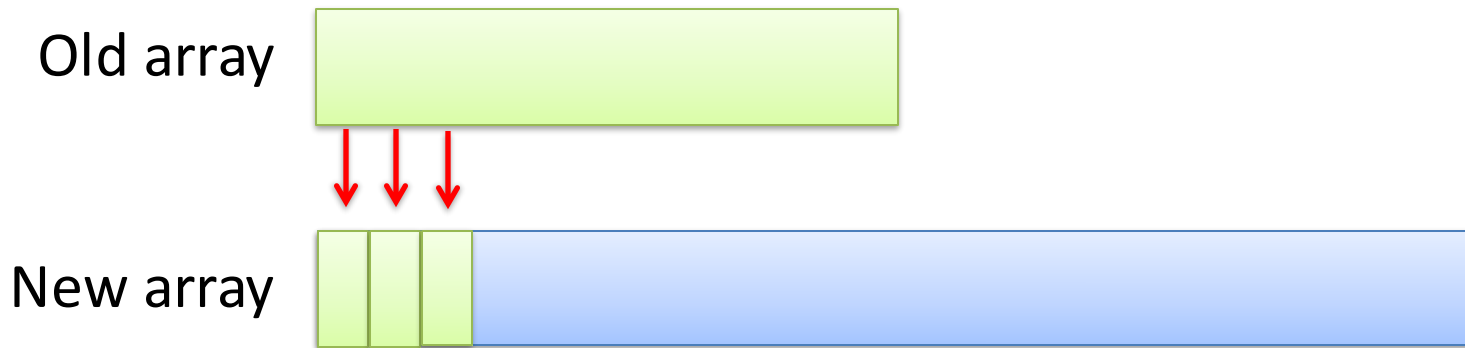
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Grow array

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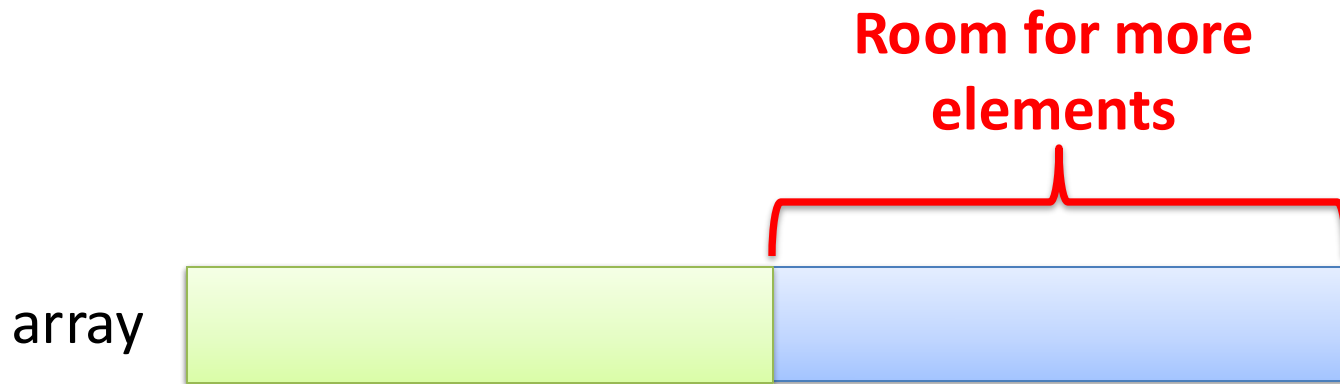
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Grow array

- 1. Make new array, say 2 times larger than old array**
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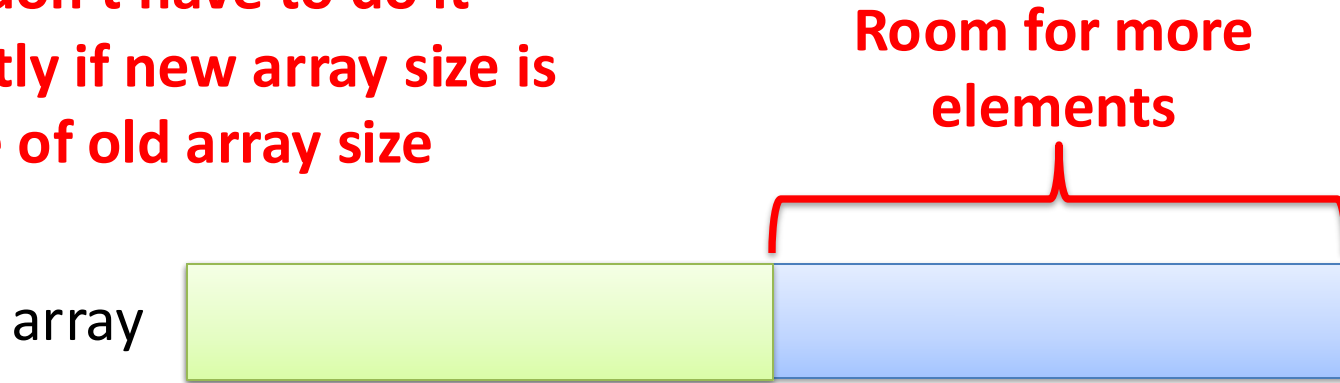


Grow array

1. Make new array, say 2 times larger than old array
2. Copy elements one at a time from old array to new
3. Set instance variable to point at new array (old array will be garbage collected)

Arrays are of fixed size, but List ADT allows for growth

Growing is expensive operation,
but we don't have to do it
frequently if new array size is
multiple of old array size



Grow array

1. Make new array, say 2 times larger than old array
2. Copy elements one at a time from old array to new
3. Set instance variable to point at new array (old array will be garbage collected)

GrowingArray.java

ANNOTATED SLIDES

GrowingArray.java: implements List ADT using an array instead of a linked list

```
public class GrowingArray<T> implements SimpleList<T>, Iterable<T> {
```

Implements SimpleList and Iterable from last class

```
    private T[] array;
```

```
    private int size; // how much of the array is actually filled up so far
```

```
    private static final int initCap = 10; // how big the array should be initially
```

Array is now the data structure used to store elements in List

```
    public GrowingArray() {
```

```
        array = (T[]) new Object[initCap]; // java generics oddness – cast array of objects
```

```
        size = 0;
```

```
    }
```

- Array initially sized to 10 Objects (note the funky Java allocation syntax, must cast to array of generic type)
- Remember, arrays are of fixed size, but the List ADT does not specify a size

```
    /**
```

```
     * Return the number of elements in the List (they are indexed 0..size-1)
```

```
     * @return number of elements
```

```
     */
```

```
    public int size() {
```

```
        return size;
```

```
    }
```

Track size

Will increment on each *add* and decrement on each *remove*

Run-time complexity?

O(1)

GrowingArray.java: *get()/set()* are easy and fast with an array implementation

```
/**
 * Return item at index idx
 * @param idx index of item to return
 * @return item stored at index idx
 * @throws Exception invalid index
 */
public T get(int idx) throws Exception {
    if (idx >= 0 && idx < size) return array[idx];
    else throw new Exception("invalid index");
}
```

Get and set are easy, just make sure index is valid, then return or set item

Notice: no curly braces!

Only next line in if statement

Run-time complexity?

$O(1)$ for any index!

Just two math operations to compute memory address

```
/**
 * Overwrite item at index idx with item parameter
 * @param idx index of item to get
 * @param item overwrite existing item at index idx with this item
 * @throws Exception invalid index
 */
public void set(int idx, T item) throws Exception {
    if (idx >= 0 && idx < size) array[idx] = item;
    else throw new Exception("invalid index");
}
```


GrowingArray.java: With growing trick, can implement the List interface with an array

```
public void add(int idx, T item) throws Exception {  
    if (idx > size || idx < 0) throw new Exception("invalid index");  
    if (size == array.length) {  
        // Double the size of the array, to leave more space  
        T[] copy = (T[]) new Object[size*2];  
        // Copy it over  
        for (int i=0; i<size; i++) copy[i] = array[i];  
        array = copy;  
    }  
    // Shift right to make room  
    for (int i=size-1; i>=idx; i--) array[i+1] = array[i];  
    array[idx] = item;  
    size++;  
}
```

array.length is how many elements array can hold

size has how many elements array does hold

add() makes a new, larger array if needed

GrowingArray.java: With growing trick, can implement the List interface with an array

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Copy elements one at a time into new array

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}
```

array.length is how many elements array can hold

size has how many elements array does hold

add() makes a new, larger array if needed

Copy elements one at a time into new array

Update instance variable to new array

GrowingArray.java: With growing trick, can implement the List interface with an array

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public void add(int idx, T item) throws Exception {  
    if (idx > size || idx < 0) throw new Exception("invalid index");  
    if (size == array.length) {  
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        // Copy it over  
        for (int i=0; i<size; i++) copy[i] = array[i];  
        array = copy;  
    }  
    // Shift right to make room  
    for (int i=size-1; i>=idx; i--) array[i+1] = array[i];  
    array[idx] = item;  
    size++;  
}
```

- Here we know we have enough room to add a new element
- Now do insert
- Start from last item and copy to one index larger
- Stop at index *idx*
- Set item at *idx* to item

GrowingArray.java: With growing trick, can implement the List interface with an array

```
public void add(int idx, T item) throws Exception {
    if (idx > size || idx < 0) throw new Exception("invalid index");
    if (size == array.length) {
        // Double the size of the array, to leave more space
        T[] copy = (T[]) new Object[size*2];
        // Copy it over
        for (int i=0; i<size; i++) copy[i] = array[i];
        array = copy;
    }
    // Shift right to make room
    for (int i=size-1; i>=idx; i--) array[i+1] = array[i];
    array[idx] = item;
    size++;
}

public void add(T item) throws Exception {
    add(size, item);
}
```

Add an item at the end is easy
Just call *add* with *size* as index

What did we call it when two
methods have the same name but
different variables?
Overloading

Run-time complexity
 $O(1)$

GrowingArray.java: With growing trick, can implement the List interface with an array

```
/**
 * Remove and return the item at index idx. Move items left to fill hole.
 * @param idx index of item to remove
 * @return the value previously at index idx
 * @throws Exception invalid index
 */
public T remove(int idx) throws Exception {
    if (idx > size-1 || idx < 0) throw new Exception("invalid index");
    T data = array[idx];
    // Shift left to cover it over
    for (int i=idx; i<size-1; i++) array[i] = array[i+1];
    size--;
    return data;
}
```

remove() slides
elements left one slot
for index > idx



Run-time complexity?
O(n)

LIST ANALYSIS

Growing array is generally preferable to linked list, except maybe growth operation

Worst case run-time complexity

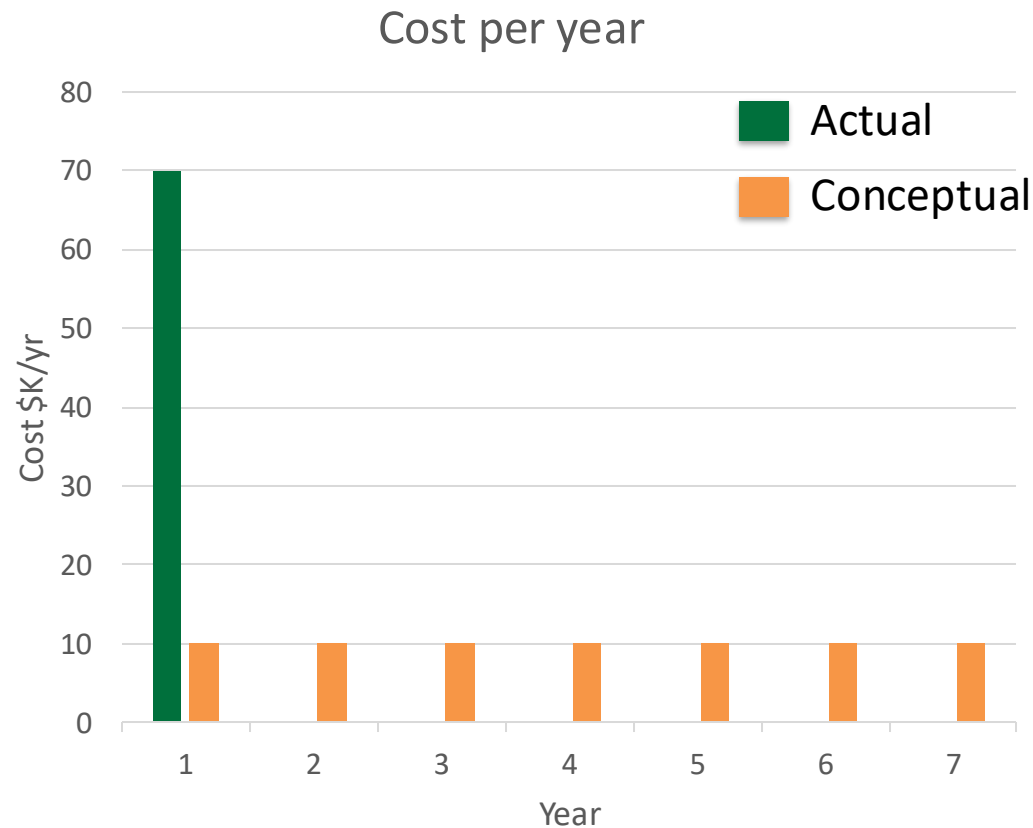
	Linked list	Growing array
<i>get(i)</i>	$O(n)$	$O(1)$
<i>set(i,e)</i>	$O(n)$	$O(1)$
<i>add(i,e)</i>	$O(n)$	$O(n) + \text{growth}$
<i>remove(i)</i>	$O(n)$	$O(n)$

- Start at *head* and march down to find index *i*
- Slow to get to index, $O(n)$
- Once there, operations are fast $O(1)$
- Best case: all operations on head

- Faster *get()/set()* than linked list
- Tie with linked list on *remove()*
- Best case: all operation at tail
- *add()* might cause expensive growth operation
- How should be think about that?

Amortization is a concept from accounting that allows us to spread costs over time

Amortized analysis

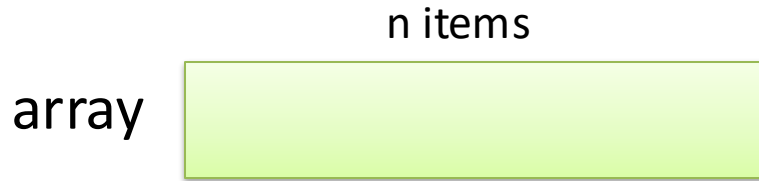


Accounting allows us to amortize costs over several years

- Buy \$70K truck on year 1
- Truck is good for 7 years
- Can think of the cost as \$10K/year instead of one payment of \$70K on year 1
- Actually pay \$70K on year 1, but this is equivalent to paying \$10K/year for 7 years
- Idea is to spread the cost (“amortize” the cost) over the lifetime of the truck
- We will use this concept to “pre-pay” for expensive growth operation

Amortized analysis shows growing array is actually only $O(1)$!

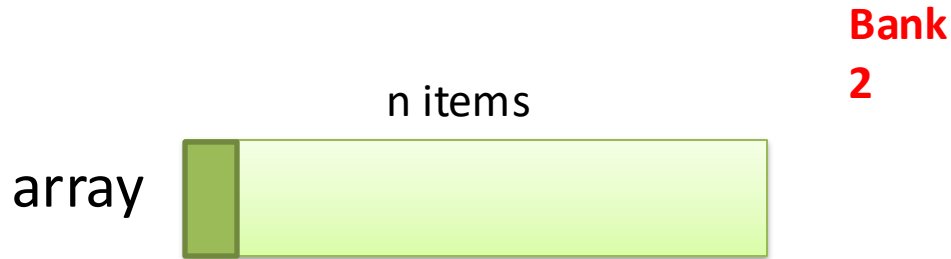
Amortized analysis



Each time add an item to array, conceptually charge 3 “tokens”

- One token pays for current add()
- Two tokens go into “Bank”
- We are spread out (amortizing) the cost of the expensive, but infrequent growth operation

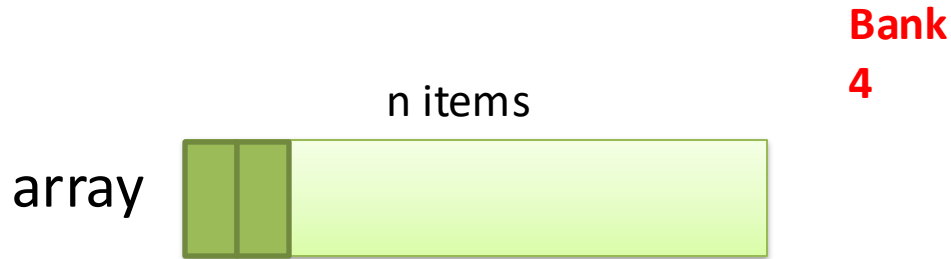
Amortized analysis shows growing array is actually only $O(1)$!



Each time add an item to array, conceptually charge 3 “tokens”

- One token pays for current `add()`
- Two tokens go into “Bank”
- We are spread out (amortizing) the cost of the expensive, but infrequent growth operation

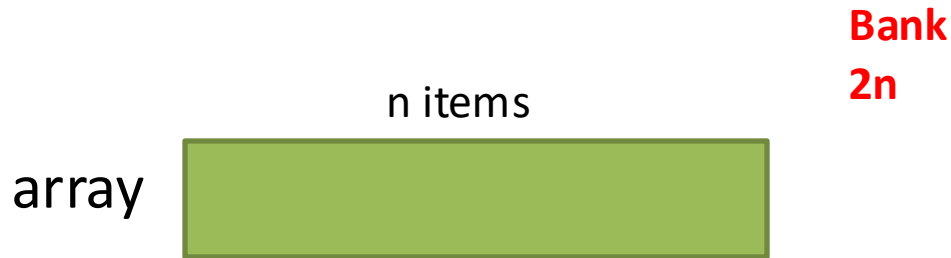
Amortized analysis shows growing array is actually only $O(1)$!



Each time add an item to array, conceptually charge 3 “tokens”

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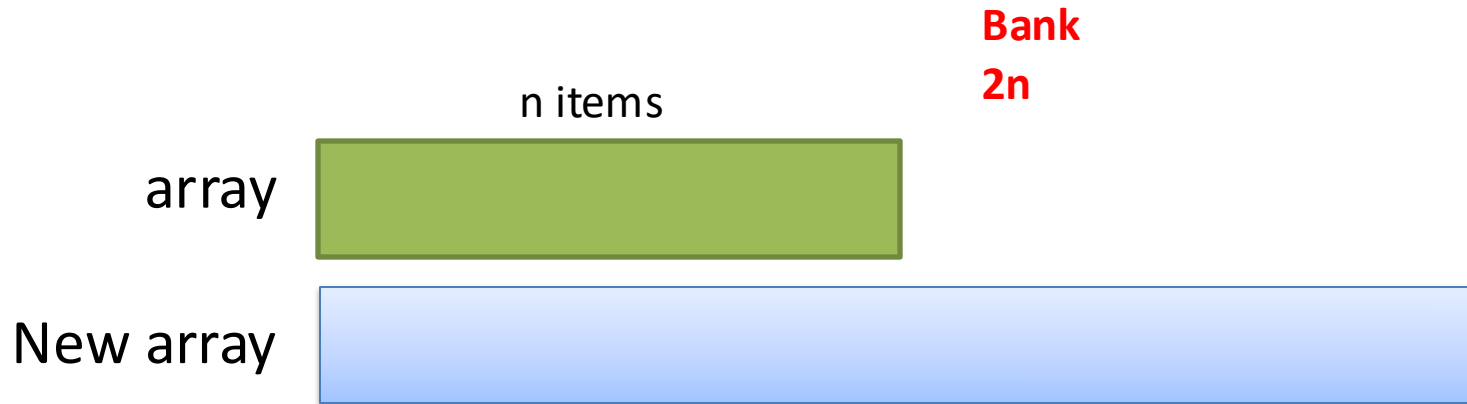


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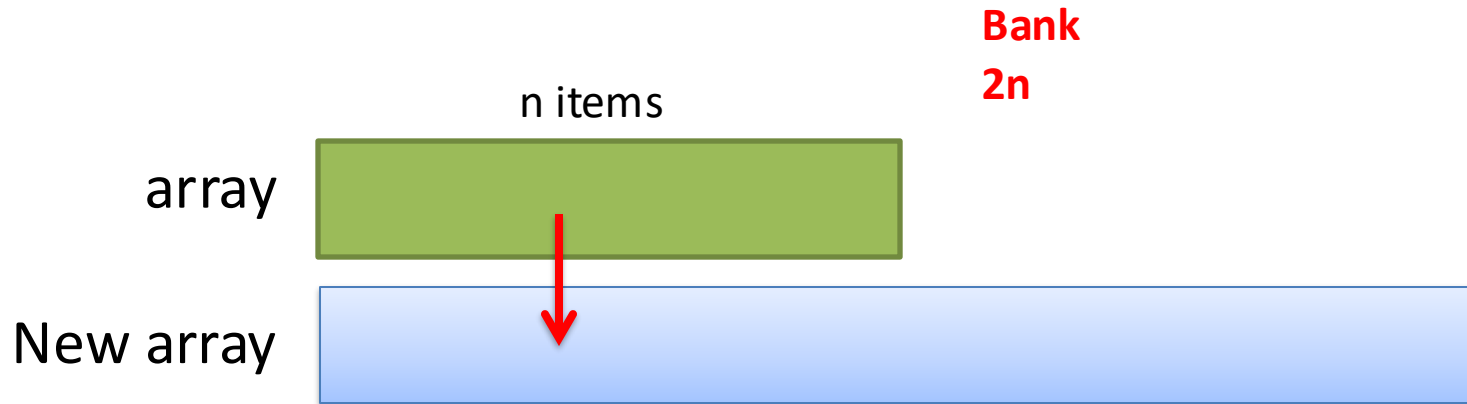
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Allocate new 2X larger array

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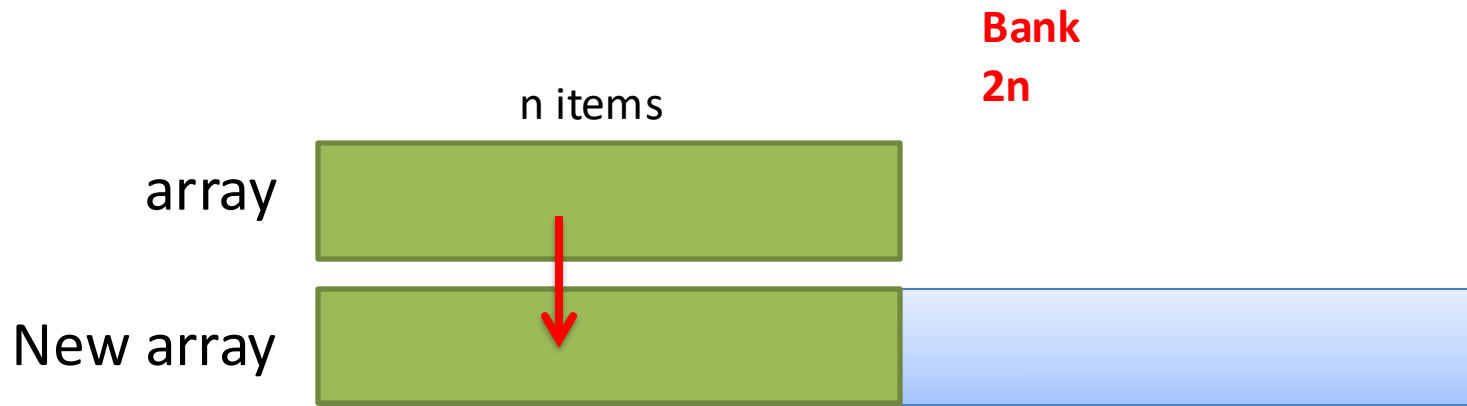
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Allocate new 2X larger array

Copy elements from old array to new array

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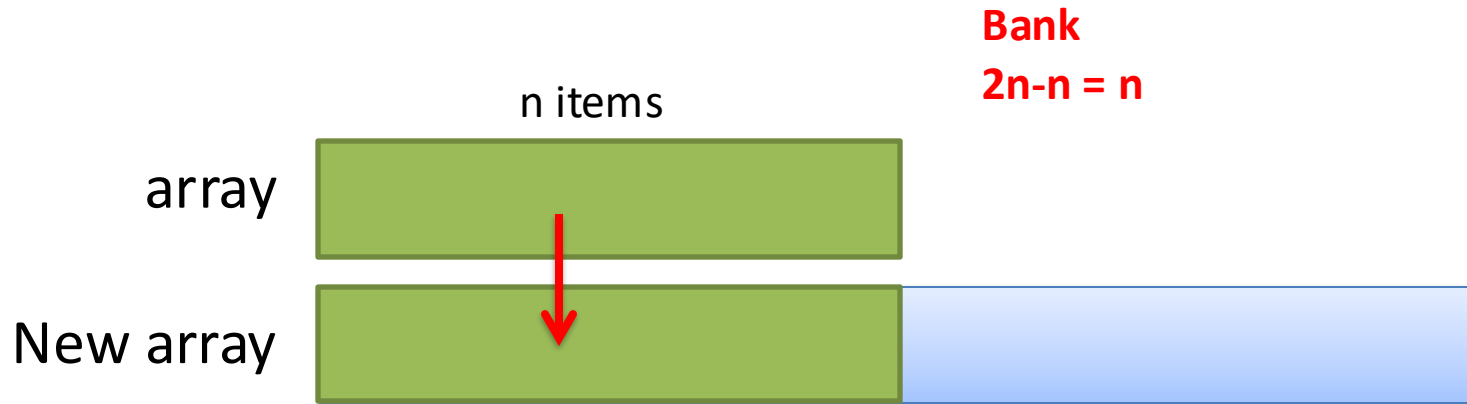
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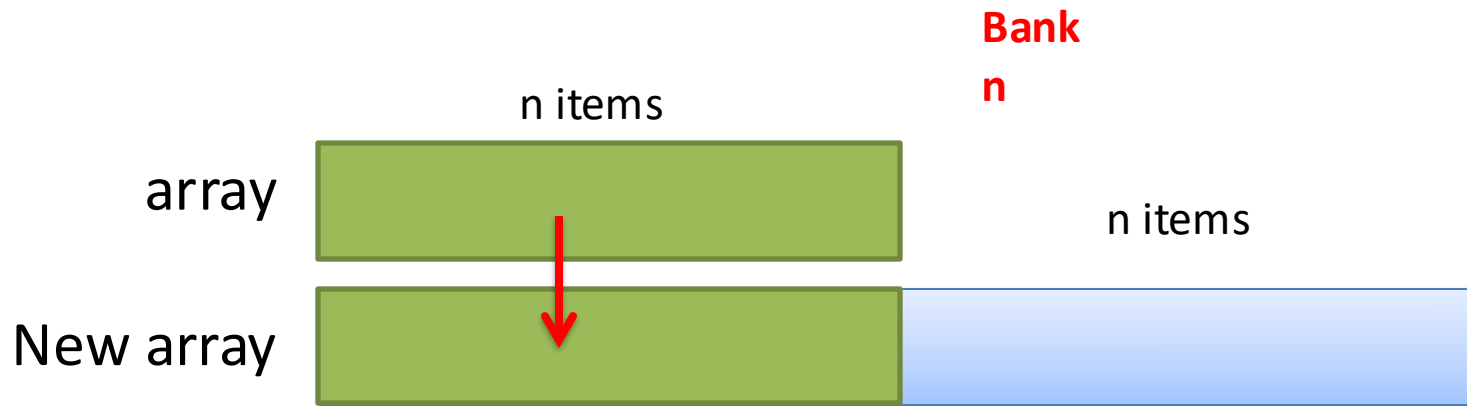
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Copy elements from old array to new array

Have to copy n items, so charge n pre-paid tokens from bank

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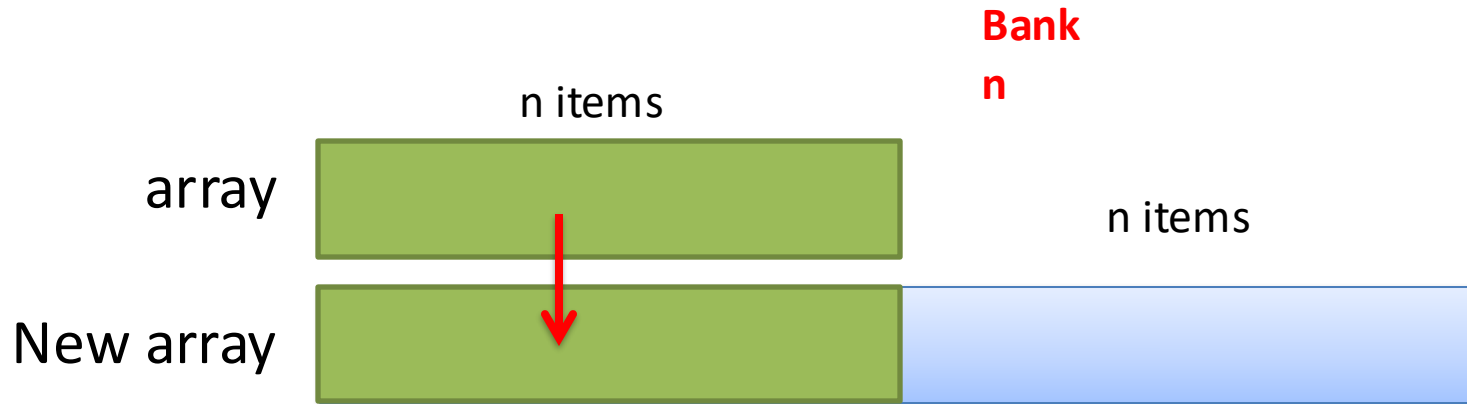
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Remaining n items in bank “pay for” empty n spaces

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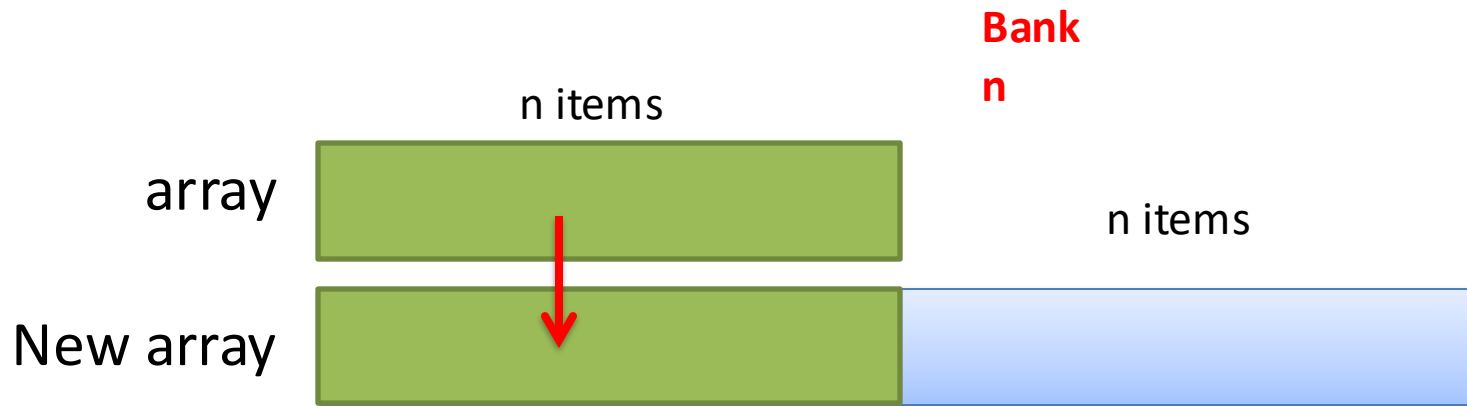
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Charging a little extra for each `add` spreads out cost for infrequent growth operation

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The charge, however, is a constant, so $O(3) = O(1)$

Growing array is generally preferable to linked list

Worst case run-time complexity



	Linked list	Growing array
<i>get(i)</i>	$O(n)$	$O(1)$ Amortized analysis shows infrequent growth operation is constant time
<i>set(i,e)</i>	$O(n)$	$O(1)$
<i>add(i,e)</i>	$O(n)$	$O(n) + O(1) = O(n)$
<i>remove(i)</i>	$O(n)$	$O(n)$ Pay a constant amount more on each <i>add()</i> to pay for the occasional expensive growth
- Start at <i>head</i> and march down to find index <i>i</i> - Slow to get to index, $O(n)$ - Once there, operations are fast $O(1)$ - Best case: all operations on head		- Faster <i>get()/set()</i> than linked list - Tie with linked list on <i>remove()</i> - Best case: all operations on tail <i>add()</i> might cause expensive growth operation