Analysis of Algorithms

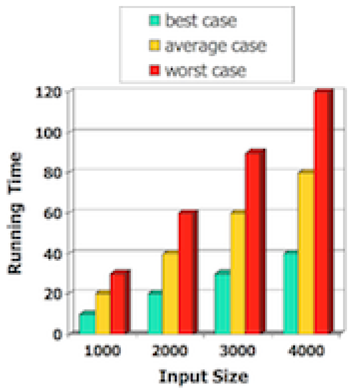
Running Time

An algorithm is a step-by-step procedure

- for solving a problem
- in a finite amount of time

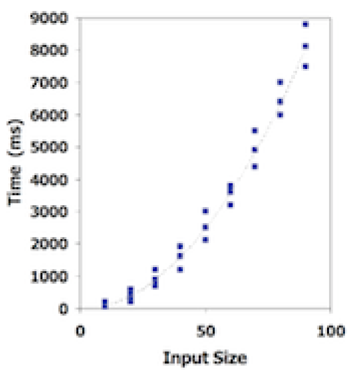
Most algorithms map input to output

- running time typically grows with input size
- *average time* often difficult to determine
- Focus on *worst case* running time
  - easier to analyse
  - crucial to many applications: finance, robotics, games, ...



Empirical Analysis

1. Write program that implements an algorithm
2. Run program with inputs of varying size and composition
3. Measure the actual running time
4. Plot the results



Limitations:

- requires to implement the algorithm, which may be difficult
- results may not be indicative of running time on other inputs
- same hardware and operating system must be used in order to compare two algorithms

---

Theoretical Analysis

- Uses high-level description of the algorithm instead of implementation ("pseudocode")
- Characterises running time as a function of the input size, *n*
- Takes into account all possible inputs
- Allows us to evaluate the speed of an algorithm independent of the hardware/software environment

---

Pseudocode

Example: Find maximal element in an array

```
arrayMax(A):
|  Input  array A of n integers
|  Output maximum element of A
|
|  currentMax=A[0]
|  for all i=1..n-1 do
|  |  if A[i]>currentMax then
|  |     currentMax=A[i]
|  |  end if
|  end for
|  return currentMax
```

... Pseudocode

Control flow

- **if** ... **then** ... [**else**] ... **end if**
- **while .. do** ... **end while**
  repeat ... **until**
  for [all][each] .. do ... **end for**

Function declaration

- f(arguments):
  Input ...
  Output ...
  ...

Expressions

- = assignment
- = equality testing
- n^2 superscripts and other mathematical formatting allowed
- swap A[i] and A[j] verbal descriptions of *simple* operations allowed

---

... Pseudocode

- More structured than English prose
- Less detailed than a program
- Preferred notation for describing algorithms
- Hides program design issues

Exercise #1: Pseudocode

Formulate the following verbal description in pseudocode:

To reverse the order of the elements on a stack S with the help of a queue:

1. *In the first phase, pop one element after the other from S and enqueue it in queue Q until the stack is empty.*
2. *In the second phase, iteratively dequeue all the elements from Q and push them onto the stack.*

As a result, all the elements are now in reversed order on S.

Sample solution:

```
while S is not empty do
   pop e from S, enqueue e into Q
end while
while Q is not empty do
   dequeue e from Q, push e onto S
end while
```

Exercise #2: Pseudocode

Implement the following pseudocode instructions in C

1. `A` is an array of `int`s

   ```
   ...
   swap A[i] and A[j]
   ...
   ```

2. `S` is a stack

   ```
   ...
   swap the top two elements on S
   ...
   ```

1. `int temp = A[i];`
   `A[i] = A[j];`
   `A[j] = temp;`

2. `x = StackPop(S);`
   `y = StackPop(S);`
   `StackPush(S, x);`
   `StackPush(S, y);`

The following pseudocode instruction is problematic. Why?

```
...
swap the two elements at the front of queue Q
...
```

The Abstract RAM Model

16/89

RAM = Random Access Machine

- A CPU (central processing unit)
- A potentially unbounded bank of memory cells
  - each of which can hold an arbitrary number, or character
- Memory cells are numbered, and accessing any one of them takes CPU time

Primitive Operations

17/89

- Basic computations performed by an algorithm
- Identifiable in pseudocode
- Largely independent of the programming language
- Exact definition not important (we will shortly see why)
- Assumed to take a constant amount of time in the RAM model

Examples:

- evaluating an expression
- indexing into an array
- calling/returning from a function

Counting Primitive Operations

18/89

By inspecting the pseudocode …

- we can determine the maximum number of primitive operations executed by an algorithm
- as a function of the input size

Example:

```
arrayMax(A):
|  Input  array A of n integers
|  Output maximum element of A
|
|  currentMax=A[0]              1
|  for all i=1..n-1 do           n+(n-1)
|  |  if A[i]>currentMax then    2(n-1)
|  |     currentMax=A[i]        n-1
|  |  end if
|  end for
|  return currentMax             1
                                --------
                         Total  5n-2
```


Estimating Running Times

Algorithm `arrayMax` requires $5n – 2$ primitive operations in the *worst* case

- *best* case requires $4n – 1$ operations   (why?)

Define:

- *a* ... time taken by the fastest primitive operation
- *b* ... time taken by the slowest primitive operation

Let *T(n)* be worst-case time of `arrayMax`. Then

$a \cdot (5n - 2) \leq T(n) \leq b \cdot (5n - 2)$

Hence, the running time *T(n)* is bound by two linear functions

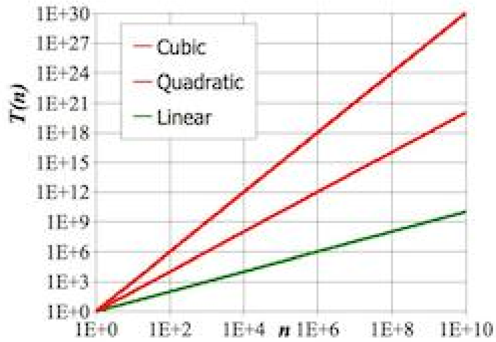
... Estimating Running Times

Seven commonly encountered functions for algorithm analysis

- Constant ≅ 1
- Logarithmic ≅ $\log n$
- Linear ≅ n
- N-Log-N ≅ $n \log n$
- Quadratic ≅ n^2
- Cubic ≅ n^3
- Exponential ≅ 2^n

... Estimating Running Times

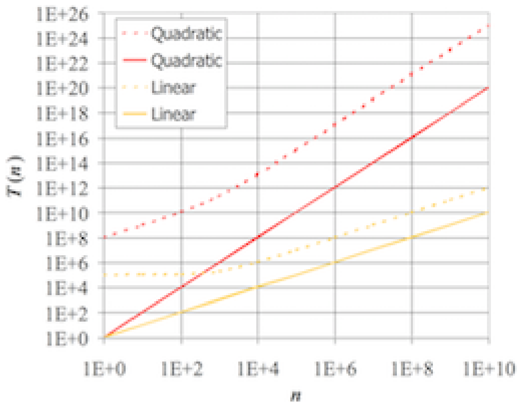
In a log-log chart, the slope of the line corresponds to the growth rate of the function



... Estimating Running Times

The growth rate is not affected by constant factors or lower-order terms

- Examples:
  - $10^2n + 10^5$ is a linear function
  - $10^5n^2 + 10^8n$ is a quadratic function



... Estimating Running Times

Changing the hardware/software environment

- affects *T(n)* by a constant factor
- but does not alter the growth rate of *T(n)*

⇒ *Linear* growth rate of the running time *T(n)* is an intrinsic property of algorithm `arrayMax`

Exercise #3: Estimating running times

Determine the number of primitive operations

```
matrixProduct(A,B):
|  Input  n×n matrices A, B
|  Output n×n matrix A•B
|
|  for all i=1..n do
|  |  for all j=1..n do
|  |  |  C[i,j]=0
|  |  |  for all k=1..n do
```

```
|   |   |      C[i,j]=C[i,j]+A[i,k]•B[k,j]
|   |   |   end for
|   |   end for
|   end for
|   return C
```

```
matrixProduct(A,B):
|   Input  n×n matrices A, B
|   Output n×n matrix A•B
|
|   for all i=1..n do                         2n+1
|   |   for all j=1..n do                     n(2n+1)
|   |   |   C[i,j]=0                        n^2
|   |   |   for all k=1..n do                n^2(2n+1)
|   |   |      C[i,j]=C[i,j]+A[i,k]•B[k,j]   n^3•4
|   |   |   end for
|   |   end for
|   end for
|   return C                                  1
                                            ------------
                                   Total    6n^3+4n^2+3n+2
```

Big-Oh

Big-Oh Notation

Given functions f(n) and g(n), we say that

$$f(n) \in O(g(n))$$

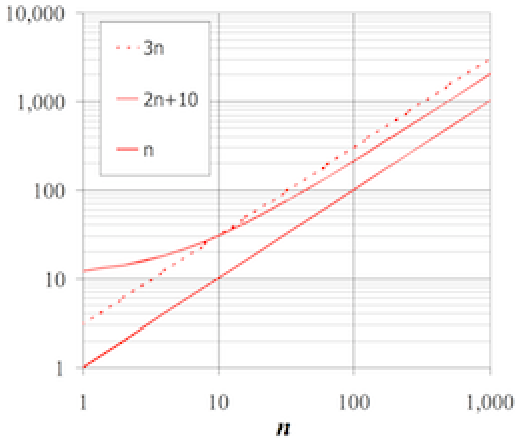
if there are positive constants c and n_0 such that

$$f(n) \leq c \cdot g(n) \quad \forall n \geq n_0$$

Hence: *O(g(n)) is the set of all functions that do not grow faster than g(n)*

... Big-Oh Notation

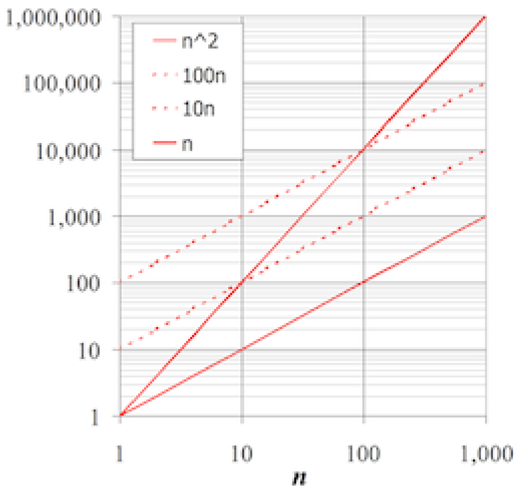
Example: function 2n + 10 is in O(n)



- $2n+10 \le c \cdot n$
  $\Rightarrow$ $(c-2)n \ge 10$
  $\Rightarrow$ $n \ge 10/(c-2)$
- pick c=3 and n_0=10

... Big-Oh Notation

Example: function n^2 is not in O(n)



- $n^2 \le c \cdot n$
  $\Rightarrow$ $n \le c$
- inequality cannot be satisfied since c must be a constant

Exercise #4: Big-Oh

Show that

1. 7n-2 is in O(n)
2. $3n^3 + 20n^2 + 5$ is in O(n^3)
3. 3·log n + 5 is in O(log n)

---

1. 7n-2 ∈ O(n)
   need $c>0$ and $n_0 \ge 1$ such that $7n-2 \le c \cdot n$ for $n \ge n_0$

⇒ true for $c=7$ and $n_0=1$

2. $3n^3 + 20n^2 + 5 \in O(n^3)$

   need $c>0$ and $n_0 \geq 1$ such that $3n^3+20n^2+5 \leq c \cdot n^3$ for $n \geq n_0$

   ⇒ true for $c=4$ and $n_0=21$

3. $3 \cdot \log n + 5 \in O(\log n)$

   need $c>0$ and $n_0 \geq 1$ such that $3 \cdot \log n+5 \leq c \cdot \log n$ for $n \geq n_0$

   ⇒ true for $c=8$ and $n_0=2$

Big-Oh and Rate of Growth

- Big-Oh notation gives an upper bound on the growth rate of a function
  - "$f(n) \in O(g(n))$" means growth rate of $f(n)$ no more than growth rate of $g(n)$
- use big-Oh to rank functions according to their rate of growth

	$f(n) \in O(g(n))$	$g(n) \in O(f(n))$
g(n) grows faster	yes	no
f(n) grows faster	no	yes
same order of growth	yes	yes

Big-Oh Rules

- If $f(n)$ is a polynomial of degree d ⇒ $f(n)$ is $O(n^d)$
  - lower-order terms are ignored
  - constant factors are ignored
- Use the smallest possible class of functions
  - say "$2n$ is $O(n)$" instead of "$2n$ is $O(n^2)$"
    - but keep in mind that, $2n$ is in $O(n^2)$, $O(n^3)$, ...
- Use the simplest expression of the class
  - say "$3n + 5$ is $O(n)$" instead of "$3n + 5$ is $O(3n)$"

Exercise #5: Big-Oh

Show that $\sum_{i=1}^{n} i = 1 + 2 + 3 + ... + n$ is $O(n^2)$

$$\sum_{i=1}^{n} i = \frac{n(n+1)}{2} = \frac{n^2+n}{2}$$

which is $O(n^2)$

Asymptotic Analysis of Algorithms

36/89

Asymptotic analysis of algorithms determines running time in big-Oh notation:

- find worst-case number of primitive operations as a function of input size
- express this function using big-Oh notation

Example:

- algorithm `arrayMax` executes at most 5n – 2 primitive operations
  ⇒ algorithm `arrayMax` *"runs in O(n) time"*

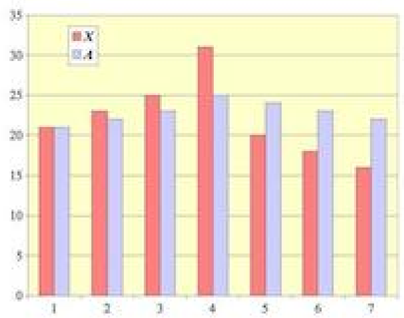
Constant factors and lower-order terms eventually dropped
⇒ can disregard them when counting primitive operations

Example: Computing Prefix Averages

37/89

- The *i-th prefix average* of an array X is the average of the first i elements:

A[i] = (X[0] + X[1] + ... + X[i]) / (i+1)



NB. computing the array A of prefix averages of another array X has applications in financial analysis

... Example: Computing Prefix Averages

38/89

A *quadratic* algorithm to compute prefix averages:

```
prefixAverages1(X):
|  Input  array X of n integers
|  Output array A of prefix averages of X
|
|  for all i=0..n-1 do          O(n)
|  |  s=X[0]                   O(n)
|  |  for all j=1..i do         O(n^2)
|  |     s=s+X[j]              O(n^2)
|  |  end for
|  |  A[i]=s/(i+1)             O(n)
```

```
|  end for
|  return A                      O(1)
```

$$2 \cdot O(n^2) + 3 \cdot O(n) + O(1) = O(n^2)$$

⇒ *Time complexity* of algorithm `prefixAverages1` is $O(n^2)$

... Example: Computing Prefix Averages

The following algorithm computes prefix averages by keeping a running sum:

```
prefixAverages2(X):
|  Input  array X of n integers
|  Output array A of prefix averages of X
|
|  s=0
|  for all i=0..n-1 do             O(n)
|     s=s+X[i]                    O(n)
|     A[i]=s/(i+1)                O(n)
|  end for
|  return A                        O(1)
```

Thus, `prefixAverages2` is $O(n)$

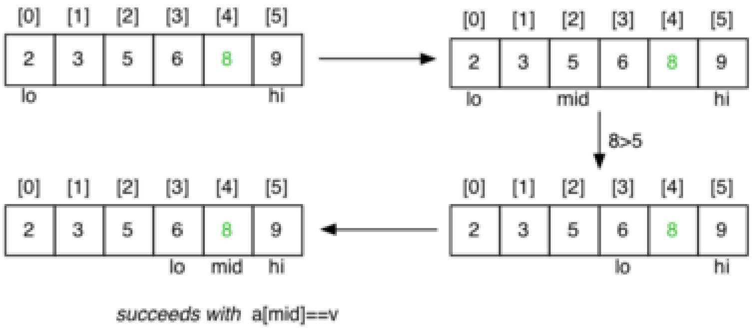
Example: Binary Search

The following recursive algorithm searches for a value in a *sorted* array:

```
search(v,a,lo,hi):
|  Input  value v
|         array a[lo..hi] of values
|  Output true if v in a[lo..hi]
|         false otherwise
|
|  mid=(lo+hi)/2
|  if lo>hi then return false
|  if a[mid]=v then
|     return true
|  else if a[mid]<v then
|     return search(v,a,mid+1,hi)
|  else
|     return search(v,a,lo,mid-1)
|  end if
```

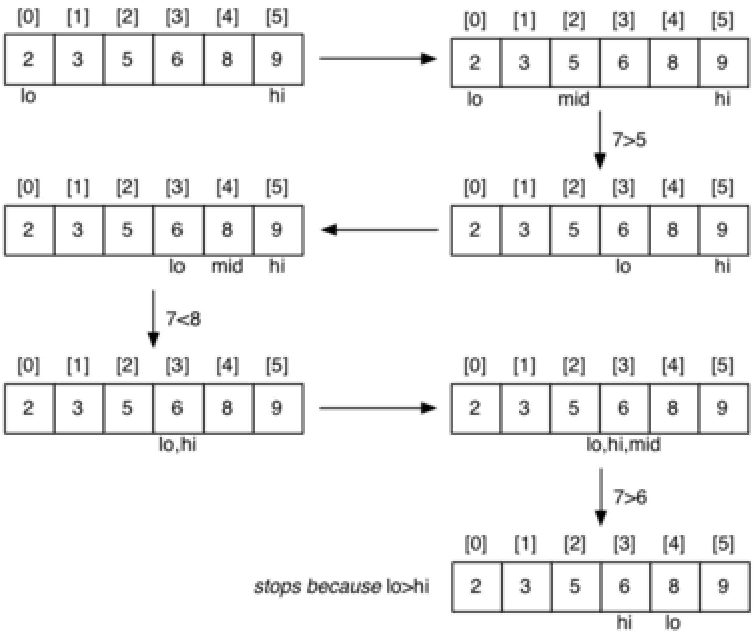
... Example: Binary Search

Successful search for a value of 8:



... Example: Binary Search

Unsuccessful search for a value of 7:



... Example: Binary Search

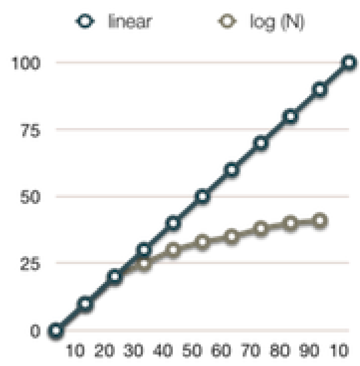
Cost analysis:

- C_i = #calls to `search()` for array of length i
- for best case, $C_n = 1$
- for `a[i..j]`, `j<i` (length=0)
  - $C_0 = 0$
- for `a[i..j]`, `i≤j` (length=n)
  - $C_n = 1 + C_{n/2} \Rightarrow C_n = \log_2 n$

Thus, binary search is $O(\log_2 n)$ or simply $O(\log n)$ (why?)

... Example: Binary Search

Why logarithmic complexity is good:



Math Needed for Complexity Analysis

- Logarithms
  - $\log_b (xy) = \log_b x + \log_b y$
  - $\log_b (x/y) = \log_b x - \log_b y$
  - $\log_b x^a = a \log_b x$
  - $\log_a x = \log_b x \cdot (\log_c b / \log_c a)$
- Exponentials
  - $a^{(b+c)} = a^b a^c$
  - $a^{bc} = (a^b)^c$
  - $a^b / a^c = a^{(b-c)}$
  - $b = a^{\log_a b}$
  - $b^c = a^{c \cdot \log_a b}$
- Proof techniques
- Summation (addition of sequences of numbers)
- Basic probability (for average case analysis, randomised algorithms)

Exercise #6: Analysis of Algorithms

What is the complexity of the following algorithm?

```
enqueue(Q,Elem):
|  Input  queue Q, element Elem
|  Output Q with Elem added at the end
|
|  Q.top=Q.top+1
|  for all i=Q.top down to 1 do
|     Q[i]=Q[i-1]
|  end for
|  Q[0]=Elem
|  return Q
```

Answer: $O(|Q|)$

Exercise #7: Analysis of Algorithms

What is the complexity of the following algorithm?

```
insertionSort(A):
|  Input array A[0..n-1] of n elements
|
|  for all i=1..n-1 do
|  |  element=A[i], j=i-1
|  |  while j≥0 and A[j]>element do
|  |     A[j+1]=A[j]
|  |     j=j-1
|  |  end while
|  |  A[j+1]=element
|  end for
```

Answer: $O(n^2)$

Best known sorting algorithms are $O(n \cdot \log n)$. Example: Quicksort (→ week 10)

Exercise #8: Analysis of Algorithms

What is the complexity of the following algorithm?

```
binaryConversion(n):
|  Input  positive integer n
|  Output binary representation of n on a stack
|
|  create empty stack S
|  while n>0 do
|  |  push (n mod 2) onto S
|  |  n=⌊n/2⌋
|  end while
|  return S
```

Assume that creating a stack and pushing an element both are O(1) operations ("constant")

Answer: $O(\log n)$

Relatives of Big-Oh

big-Omega

- $f(n) \in \Omega(g(n))$ if there is a constant $c > 0$ and an integer constant $n_0 \geq 1$ such that

$$f(n) \geq c \cdot g(n) \quad \forall n \geq n_0$$

big-Theta

- $f(n) \in \Theta(g(n))$ if there are constants $c',c'' > 0$ and an integer constant $n_0 \geq 1$ such that

$$c' \cdot g(n) \le f(n) \le c'' \cdot g(n) \quad \forall n \ge n_0$$

... Relatives of Big-Oh

- f(n) belongs to O(g(n)) if f(n) is asymptotically *less than or equal* to g(n)
- f(n) belongs to Ω(g(n)) if f(n) is asymptotically *greater than or equal* to g(n)
- f(n) belongs to Θ(g(n)) if f(n) is asymptotically *equal* to g(n)

... Relatives of Big-Oh

Examples:

- $\frac{1}{4}n^2 \in \Omega(n^2)$
  - need $c > 0$ and $n_0 \ge 1$ such that $\frac{1}{4}n^2 \ge c \cdot n^2$ for $n \ge n_0$
  - let $c=\frac{1}{4}$ and $n_0=1$
- $\frac{1}{4}n^2 \in \Omega(n)$
  - need $c > 0$ and $n_0 \ge 1$ such that $\frac{1}{4}n^2 \ge c \cdot n$ for $n \ge n_0$
  - let $c=1$ and $n_0=4$
- $\frac{1}{4}n^2 \in \Theta(n^2)$
  - since $\frac{1}{4}n^2$ belongs to $\Omega(n^2)$ and $O(n^2)$

Complexity Analysis: Arrays vs. Linked Lists

Static/Dynamic Sequences

Previously we have used an *array* to implement a stack

- fixed size collection of homogeneous elements
- can be accessed via index or via "moving" pointer

The "fixed size" aspect is a potential problem:

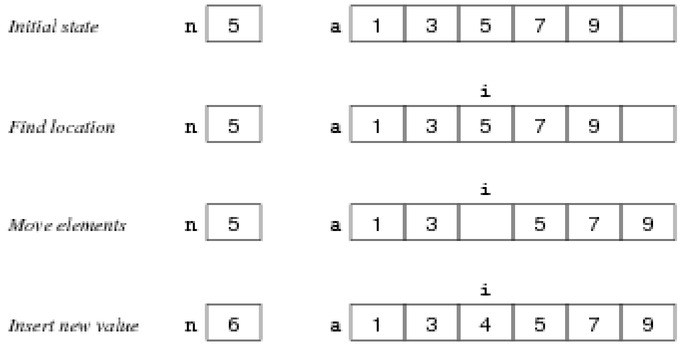
- how big to make the (dynamic) array? (big ... just in case)
- what to do if it fills up?

The rigid sequence is another problems:

- inserting/deleting an item in middle of array

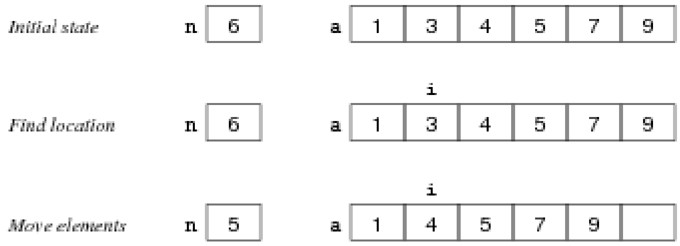
... Static/Dynamic Sequences

Inserting a value (*4*) into a sorted array a with n elements:



... Static/Dynamic Sequences

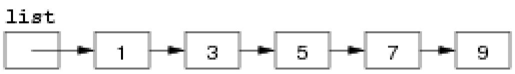
Deleting a value (*3*) from a sorted array `a` with `n` elements:



... Static/Dynamic Sequences

The problems with using arrays can be solved by

- allocating elements individually
- linking them together as a "chain"



Benefits:

- insertion/deletion have minimal effect on list overall
- only use as much space as needed for values

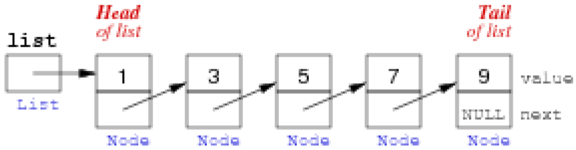
Self-referential Structures

To realise a "chain of elements", need a *node* containing

- a value
- a link to the next node

To represent a chained (linked) *list* of nodes:

- we need a *pointer* to the first node
- each node contains a pointer to the next node
- the `next` pointer in the last node is `NULL`



... Self-referential Structures

Linked lists are more flexible than arrays:

- values do not have to be adjacent in memory
- values can be rearranged simply by altering pointers
- the number of values can change dynamically
- values can be added or removed in any order

Disadvantages:

- it is not difficult to get pointer manipulations wrong
- each value also requires storage for `next` pointer

... Self-referential Structures

Create a new list node:

```
makeNode(v)
|  Input   value v
|  Output new linked list node with value v
|
|  new.value=v       // initialise data
|  new.next=NULL     // initialise link to next node
|  return new         // return pointer to new node
```

Exercise #9: Creating a Linked List

Write pseudocode to create a linked list of three nodes with values 1, 42 and 9024.

```
mylist=makeNode(1)
mylist.next=makeNode(42)
(mylist.next).next=makeNode(9024)
```

Iteration over Linked Lists

When manipulating list elements

- typically have pointer `p` to current node
- to access the data in current node: `p.value`
- to get pointer to next node: `p.next`

To iterate over a linked list:

- set p to point at first node (head)
- examine node pointed to by p
- change p to point to next node
- stop when p reaches end of list (NULL)

... Iteration over Linked Lists

66/89

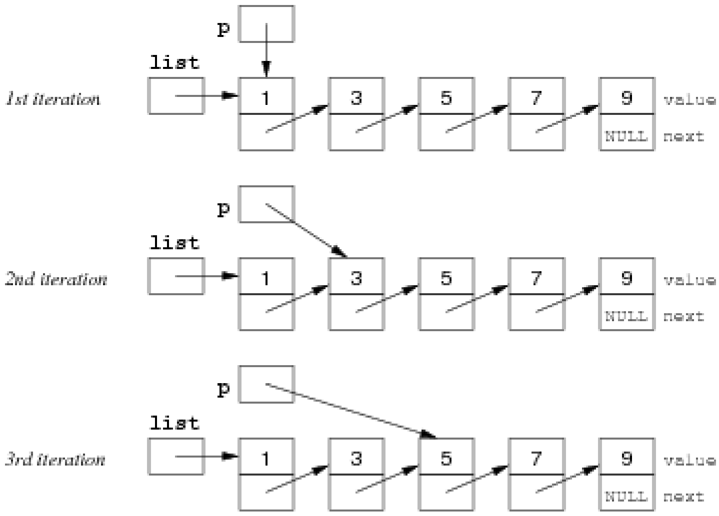
Standard method for scanning all elements in a linked list:

```
list  // pointer to first Node in list
p     // pointer to "current" Node in list

p=list
while p≠NULL do
|   ⋯ do something with p.value ⋯
|   p=p.next
end while
```

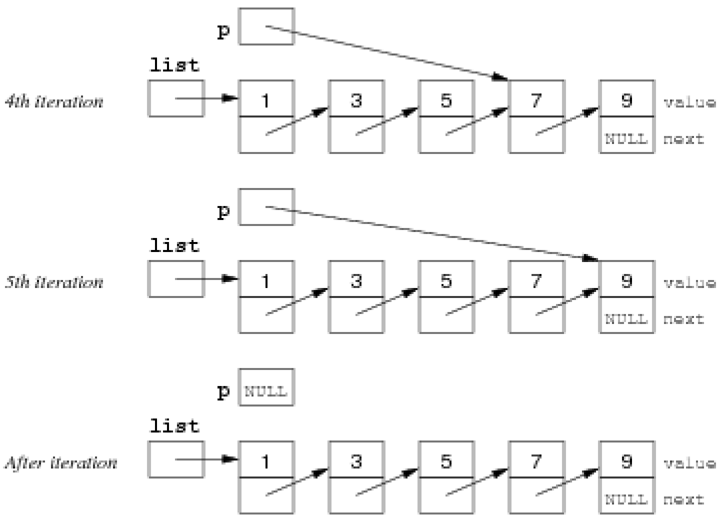
... Iteration over Linked Lists

67/89



... Iteration over Linked Lists

68/89



... Iteration over Linked Lists

Check if list contains an element:

```
inLL(L,d):
|  Input  linked list L, value d
|  Output true if d in list, false otherwise
|
|  p=L
|  while p≠NULL do
|  |  if p.value=d then   // element found
|  |     return true
|  |  end if
|  |  p=p.next
|  end while
|  return false          // element not in list
```

Time complexity: O(|L|)

... Iteration over Linked Lists

Print all elements:

```
showLL(L):
|  Input linked list L
|
|  p=L
|  while p≠NULL do
|     print p.value
|     p=p.next
|  end while
```

Time complexity: O(|L|)

Exercise #10: Traversing a linked list

What does this code do?

```
1  p=list
2  while p≠NULL do
3  |  print p.value
4  |  if p.next≠NULL then
5  |     p=p.next.next
6  |  else
7  |     p=NULL
8  |  end if
9  end while
```

What is the purpose of the conditional statement in line 4?

Every second list element is printed.

If p happens to be the last element in the list, then p.next.next does not exist.
The if-statement ensures that we do not attempt to assign an undefined value to pointer p in line 5.

Exercise #11: Traversing a linked list

Rewrite showLL() as a recursive function.

```
showLL(L):
|  Input linked list L
|
|  if L≠NULL do
|     print L.value
|     showLL(L.next)
|  end if
```

Modifying a Linked List

Insert a new element at the beginning:

```
insertLL(L,d):
|  Input  linked list L, value d
|  Output L with d prepended to the list
|
|  new=makeNode(d)  // create new list element
|  new.next=L       // link to beginning of list
|  return new        // new element is new head
```

Time complexity: O(1)

... Modifying a Linked List

Delete the *first* element:

```
deleteHead(L):
|  Input  non-empty linked list L, value d
|  Output L with head deleted
|
|  return L.next    // move to second element
```

Time complexity: O(1)

Delete a *specific* element (recursive version):

```
deleteLL(L,d):
|  Input  linked list L
|  Output L with element d deleted
|
```

```
|  if L=NULL then            // element not in list
|     return L
|  else if L.value=d then     // d found at front
|     return deleteHead(L)   // delete first element
|  else                      // delete element in tail list
|     L.next=deleteLL(L.next,d)
|  end if
|  return L
```

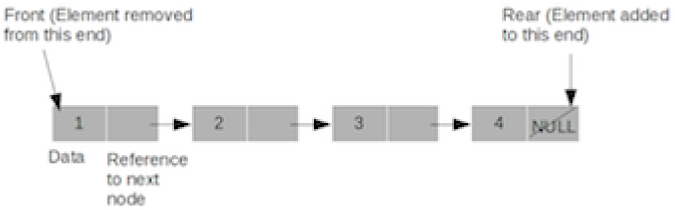
Time complexity: O(|L|)

Exercise #12: Implementing a Queue as a Linked List

Develop a datastructure for a queue based on linked lists such that ...

- enqueuing an element takes constant time
- dequeuing an element takes constant time

Use pointers to both ends



Dequeue from the front ...

```
dequeue(Q):
|  Input  non-empty queue Q
|  Output front element d, dequeued from Q
|
|  d=Q.front.value        // first element in the list
|  Q.front=Q.front.next   // move to second element
|  return d
```

Enqueue at the rear ...

```
enqueue(Q,d):
|  Input queue Q
|
|  new=makeNode(d)      // create new list element
|  Q.rear.next=new      // add to end of list
|  Q.rear=new           // link to new end of list
```

Comparison Array vs. Linked List

Complexity of operations, *n* elements

	array	linked list
insert/delete at	*O(n)*	*O(1)*

beginning		
insert/delete at end	*O(1)*	*O(1)* ("doubly-linked" list, with pointer to rear)
insert/delete at middle	*O(n)*	*O(n)*
find an element	*O(n)* (*O(log n)*, if array is sorted)	*O(n)*
index a specific element	*O(1)*	*O(n)*

Complexity Classes

Complexity Classes

81/89

Problems in Computer Science ...

- some have *polynomial* worst-case performance (e.g. n^2)
- some have *exponential* worst-case performance (e.g. 2^n)

Classes of problems:

- *P* = problems for which an algorithm can compute answer in polynomial time
- *NP* = includes problems for which no *P* algorithm is known

Beware: NP stands for "nondeterministic, polynomial time (on a theoretical *Turing Machine*)"

... Complexity Classes

82/89

Computer Science jargon for difficulty:

- tractable ... have a polynomial-time algorithm (useful in practice)
- intractable ... no tractable algorithm is known (feasible only for small *n*)
- non-computable ... no algorithm can exist

Computational complexity theory deals with different degrees of intractability

---

Generate and Test

83/89

In scenarios where

- it is simple to test whether a given state is a solution
- it is easy to generate new states (preferably likely solutions)

then a *generate and test* strategy can be used.

It is necessary that states are generated systematically

- so that we are guaranteed to find a solution, or know that none exists
  - some randomised algorithms do not require this, however (more on this later in this course)

... Generate and Test

Simple example: checking whether an integer *n* is prime

- generate/test all possible factors of *n*
- if none of them pass the test ⇒ *n* is prime

Generation is straightforward:

- produce a sequence of all numbers from 2 to *n-1*

Testing is also straightforward:

- check whether next number divides *n* exactly

... Generate and Test

Function for primality checking:

```
isPrime(n):
|  Input  natural number n
|  Output true if n prime, false otherwise
|
|  for all i=2..n-1 do      // generate
|  |  if n mod i = 0 then   // test
|  |     return false       // i is a divisor => n is not prime
|  |  end if
|  end for
|  return true              // no divisor => n is prime
```

Complexity of `isPrime` is O(n)

Can be optimised: check only numbers between 2 and $\lfloor\sqrt{n}\rfloor$ ⇒ O($\sqrt{n}$)

Example: Subset Sum

Problem to solve ...

Is there a subset *S* of these numbers with $\Sigma_{x\in S}\, x = 1000$?

```
 34,  38,  39,  43,  55,  66,  67,  84,  85,  91,
101, 117, 128, 138, 165, 168, 169, 182, 184, 186,
234, 238, 241, 276, 279, 288, 386, 387, 388, 389
```

General problem:

- given *n* arbitrary integers and a target sum *k*
- is there a subset that adds up to exactly *k*?

... Example: Subset Sum

Generate and test approach:

```
subsetsum(A,k):
|  Input  set A of n integers, target sum k
|  Output true if Σx∈Sx=k for some S⊆A
|         false otherwise
|
|  for each subset B⊆A do
|  |  if Σb∈Bb=k then
|  |     return true
|  |  end if
|  end for
|  return false
```

- How many subsets are there of *n* elements?
- How could we generate them?

... Example: Subset Sum

Given: a set of `n` distinct integers in an array `A` ...

- produce all subsets of these integers

A method to generate subsets:

- represent sets as *n* bits (e.g. *n=4*, `0000`, `0011`, `1111` etc.)
- bit *i* represents the *i* th input number
- if bit *i* is set to 1, then `A[i]` is in the subset
- if bit *i* is set to 0, then `A[i]` is not in the subset
- e.g. if `A[]=={1,2,3,5}` then `0011` represents `{1,2}`

... Example: Subset Sum

Algorithm:

```
subsetsum1(A,k):
|  Input  set A of n integers, target sum k
|  Output true if Σx∈Sx=k for some S⊆A
|         false otherwise
|
|  for s=0..2^n-1 do
|  |  if k = Σ(ith bit of s is 1) A[i] then
|  |     return true
|  |  end if
|  end for
|  return false
```

Obviously, `subsetsum1` is $O(2^n)$

... Example: Subset Sum

Alternative approach ...

`subsetsum2(A,n,k)`
(returns true if any subset of A[0..*n*-1] sums to *k*; returns false otherwise)

- if the n^{th} value A[*n*-1] is part of a solution ...
  - then the first *n*-1 values must sum to *k* – A[*n*-1]
- if the n^{th} value is not part of a solution ...
  - then the first *n*-1 values must sum to *k*
- base cases: *k*=0 (solved by {}); *n*=0 (unsolvable if *k*>0)

```
subsetsum2(A,n,k):
|  Input  array A, index n, target sum k
|  Output true if some subset of A[0..n-1] sums up to k
|         false otherwise
|
|  if k=0 then
|     return true   // empty set solves this
|  else if n=0 then
|     return false  // no elements => no sums
|  else
|     return subsetsum(A,n-1,k-A[n-1]) or subsetsum(A,n-1,k)
|  end if
```

... Example: Subset Sum

Cost analysis:

- C_i = #calls to `subsetsum2()` for array of length i
- for worst case,
  - $C_1 = 2$
  - $C_n = 2 + 2 \cdot C_{n-1} \quad \Rightarrow C_n \cong 2^n$

Thus, `subsetsum2` also is $O(2^n)$

... Example: Subset Sum

Subset Sum is typical member of the class of *NP-complete problems*

- intractable ... only algorithms with exponential performance are known
  - increase input size by 1, double the execution time
  - increase input size by 100, it takes 2^{100} = 1,267,650,600,228,229,401,496,703,205,376 times as long to execute
- but if you can find a polynomial algorithm for Subset Sum, then any other *NP*-complete problem becomes *P* ...

Summary

- Big-Oh notation
- Asymptotic analysis of algorithms
- Examples of algorithms with logarithmic, linear, polynomial, exponential complexity
- Linked lists vs. arrays

- Suggested reading:
  - Sedgewick, Ch. 2.1-2.4, 2.6

Produced: 19 Sep 2022