

Week 1

Arrays

- Accessable by *indexing*
- Continuous area of storage (in most programming languages)
 - Provides constant-time access to an indexed memory location
- Used at the core of many data structures
- Need to indicate number of elements the array has when initiating it.
e.g. in Java

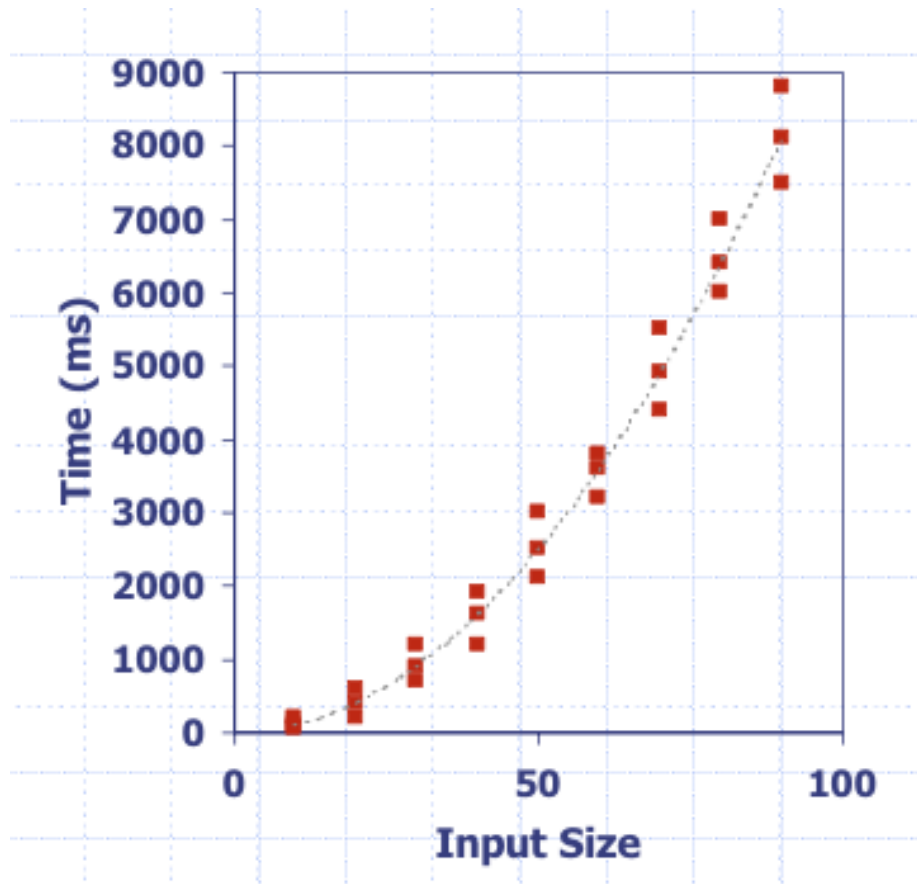
```
int [] array = new int[4];
```

Algorithm Analysis - Intro

How does an algorithm's runtime and memory usage increase with the size of the input. - Most algorithms transform input data into output data - Running time of an algorithm typically grows with input size - Averagecase time is often difficult to determine - We focus on the worstcase running time - easier to analyse - crucial for games, finance, robotics, eScience, .. ### Space Usage - Algorithms require space to store intermediate results - Space usage can vary dramatically depending on - algorithm implementation - iteration or recursion - Average-case space usage is often difficult to determine - We also focus on the worst-case space usage - easier to analyse - *crucial* for embedded systems - Data structures need space to hold data elements - We will focus primarily on runtime analysis

Experimental Studies

- Write program implementing the algorithm
- Run program with inputs of varying size and composition
- Use a method like `System.currentTimeMillis()` to measure actual running time
- Plot the results



Limitations of Experiments - Need to implement the algorithm - May be difficult - Results may not be indicative of the running time on other inputs not included in the experiment - Comparing algorithms requires the same hardware and software environments.

Theoretical Analysis

- Use a high-level description of the algorithm
 - instead of an implementation
 - Characterises running time as a function of input size, n
 - Takes into account all possible inputs
 - at least those that are “bad”
 - Evaluation is independent of the hardware and software environment ####
- Theoretical Analysis Steps

1. Express algorithm as pseudo-code
2. Count primitive operations
3. Describe algorithm as $f(n)$

- function of n
4. Preform asymptotic analysis
- express in **asymptotic notation** ## Pseudo-Code

```

Algorithm arrayMax( $A, n$ )
Input array  $A$  of  $n$  integers
Output maximum element of  $A$ 

 $currentMax \leftarrow A[0]$ 
for  $i \leftarrow 1$  to  $n - 1$  do
    if  $A[i] > currentMax$  then
         $currentMax \leftarrow A[i]$ 
    { increment counter  $i$  }
return  $currentMax$ 

```

Pseudo-code

```

public int arrayMax(int[]  $A$ ) {
    int  $currentMax = A[0]$ ;

    for(int  $i=1$ ;  $i < A.length$ ;  $i++$ ) {
        if ( $A[i] > currentMax$ ) {
             $currentMax = A[i]$ ;
        } // increment counter  $i$ 
    }
    return  $currentMax$ ;
}

```

Java code

- High level description of an algorithm

Counting Promative Operations

Assignment $int\ num = 10$; // 1 operation
 1. Assigning a value to a variable
 $int\ num = A[10]$; // 2 operations
 1. Indexing into an array
 2. Assigning a value to a variable

Loops

```

while( $i < 10$ ) { // 1 operation per iteration + 1
    // operations
}
do {
    // operations
} while( $i < 10$ ) // 1 operation per iteration

for(int  $i = 0$ ;  $i < n$ ;  $i++$ ) { // 1 + ( $n + 1$ )
    ... let counted operations =  $X$  //  $n * X$ 
} //  $n$ 

int  $i = 0$  // executed once
 $i < m$  // conditional is evaluated  $n + 1$  times
 $i++$  // increment is evaluated  $n$  times
{ /*body*/ } //  $X$  instructions within loop are evaluated  $n$  times

```

Describe as $f(n)$ - Function of n

- By inspecting the psuedo-code, we can determine the **maximum** number of primitives operations executed by an algoritthm as a function of the input size.

```

Algorithm arrayMax(A, n)                                # Operations
  currentMax <- A[0]                                    # 2
  for i <- 1 to n - 1 do                                # 1 + 2 * n or 2 + n
    if A[i] > currentMax then                            # 2 * (n - 1)
      currentMax <- A[i]                                # 2 * (n - 1)
      { increment counter i }                            # n - 1
  return currentMax                                     # 1
Total:                                                  # 7 * n [+ lower order terms]

```

- `arrayMax` execute seven and primitive operations in the worst case
 - a = time taken by the fastest primitive operation
 - b = time taken by the slowest primitive operation
- Let $T(n)$ be the worst time case of `arrayMax`
 - $a\tilde{n} \leq T(n) \leq b\tilde{n}$
- Run time $T(n)$, is bounded by two linear functions
-

Growth Rate

- Seven functions that often appear in algorith analysis

Name	Math	Found
Constant	≈ 1	
Logarithmic	$\approx \log_2 n$	Searching a sorted list
Linear	$\approx n$	Searching an unsorted list
N-Log-N	$\approx n \log_2 n$	
Quadratic	$\approx n^2$	Nested loops
Cubic	$\approx n^3$	Nested nested loops
Exponential	$\approx 2^n$	Loop where the number of operations doubles each iteration

Effect of growth rate

```

n <- 64
k <- 1
for i <- 0 to n-1 do
  for j <- 0 to k-1 do
    pick()
    { increment counter j }
  k <- k * 2
  { increment counter i }

```

- Suppose pick takes 10-9s to execute
- This harmless looking loop would take 585 years to run

- assuming 82 109instructions per secq
- Would still take 7 years if pick takes a single instruction(unrealistic)

Comparision of Two Algorithms

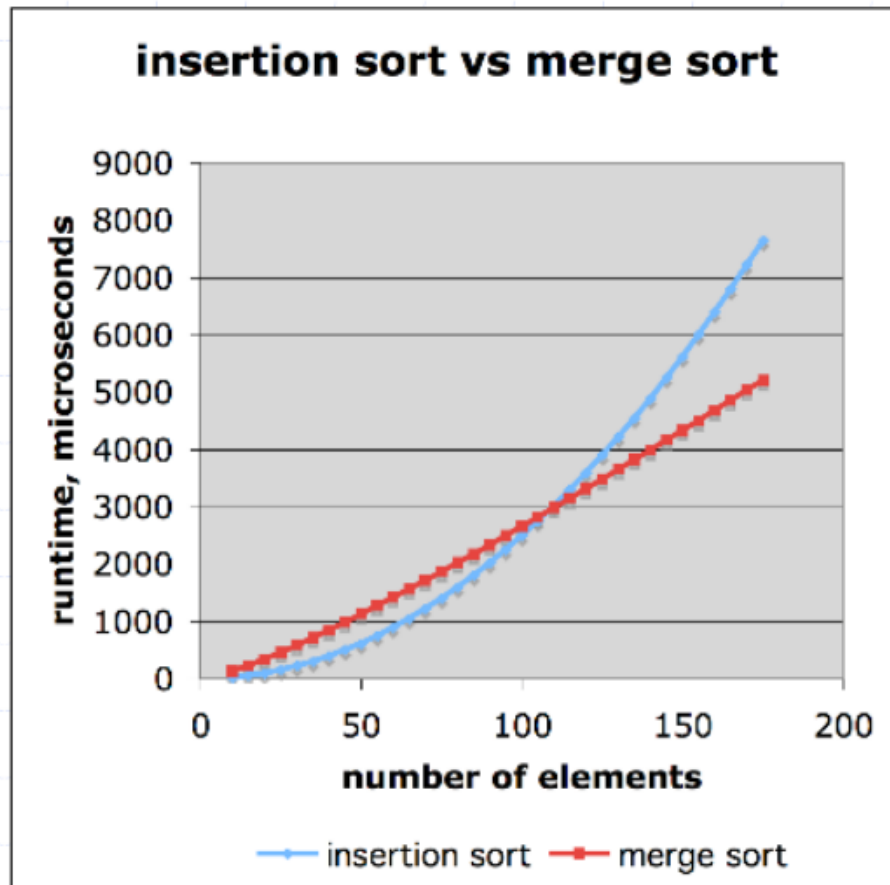


Figure 1: graph comparing insertation sprt and merge sort

Name	Complexity
Insertation sort	$\frac{n^2}{4}$
Merge sort	$2 \log_2(n)$

If it takes merge sort 0.5s to sort a list of a million items, it would take insertation sort 40m

Analysis Process

- To perform an asymptotic analysis of the worst-case running time of an algorithm
 - find the worst-case number of primitive operations executed as a function of the input size $f(n)$
 - * since constant factors and lower-order terms do not affect the growth rate for large n they are usually disregarded when counting primitive operations
 - express this function with big-O notation

What Difference do Lower-Order Terms Make?

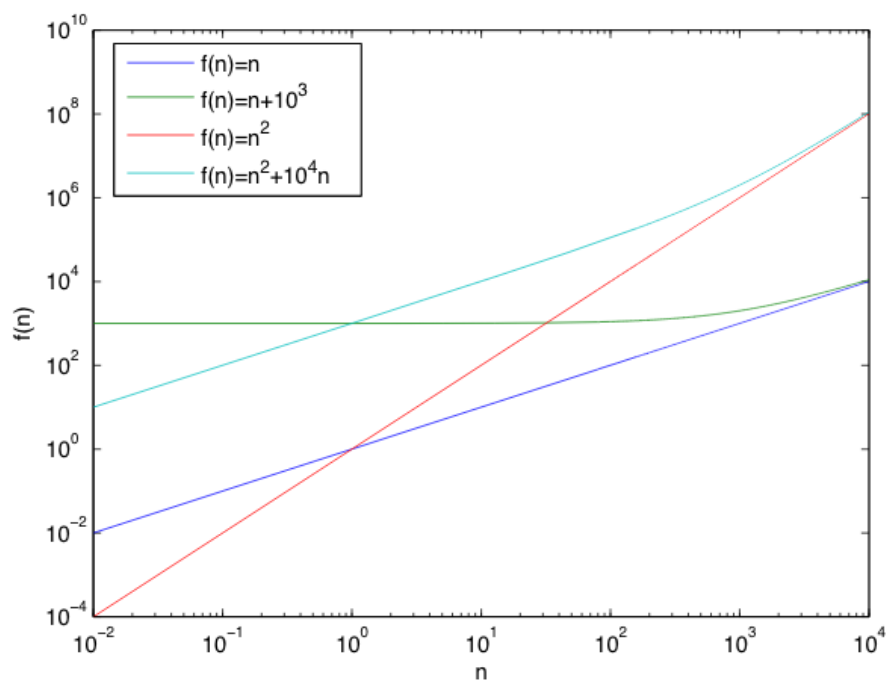


Figure 2: Graph showing how functions with the lower order terms included converge on the ones without them

What Difference Does a Constant Factor Make?

Big-O Notation

- Big-O notation describes an upper bound on a function
- $f(n)$ is $O(g(n))$ if $f(n)$ is asymptotically less than or equal to $g(n)$

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

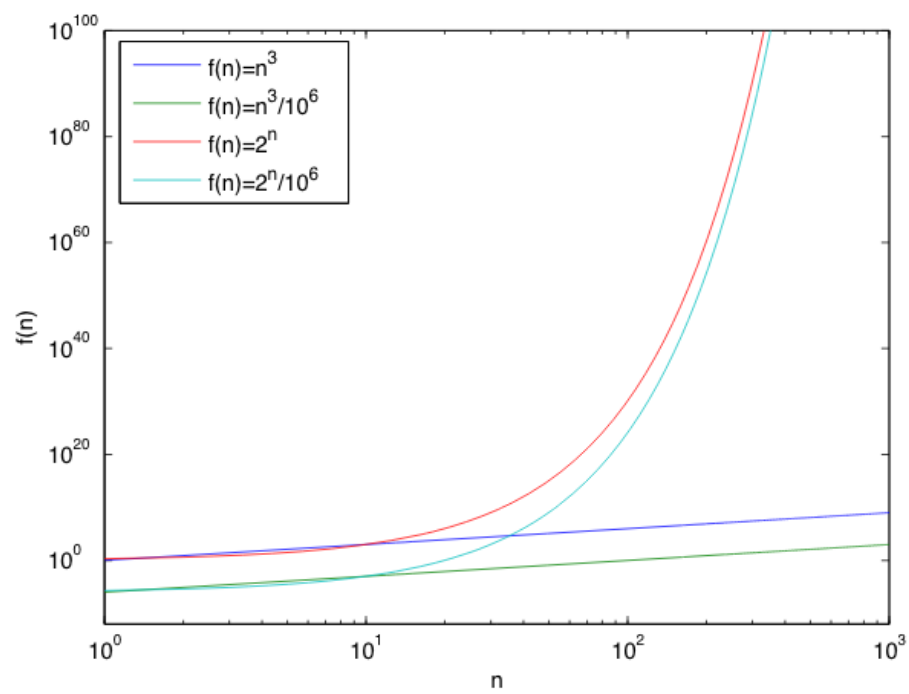


Figure 3: Graph showing convergence of constant factor

$f(n)$ is $O(g(n))$

if there are positive constants c and n_0 such that

$$f(n) \leq cg(n) \text{ for } n \geq n_0$$

Big-O and Growth Rate

	$f(n)$ is $O(g(n))$	$g(n)$ is $O(f(n))$
$g(n)$ grows more	yes	no

Big-O Rules

- **Rule 1** - If $f(n)$ is a polynomial of degree d , then $f(n)$ is $O(n^d)$
 - drop lower-order terms
 - drop constant factors (coefficients)

e.g. $3n^4 + 7n^3 + 5$ is $O(n^4)$

- **Rule 2** - Use the smallest possible class of functions (the “tightest” possible bound)
- “ $2n$ is $O(n)$ ” instead of “ $2n$ is $O(n^2)$ ”

___ Rule 3 ___ Use the simplest expression of the class - “ $3n + 5$ is $O(n)$ ” instead of “ $3n + 5$ is $O(3n)$ ”

Big-O Examples

$7n - 2$ is $O(n)$ - need $c > 0$ and $n_0 \geq 1$ such that $7n - 2 \leq c \times n$ for $N \geq N_0$ true for $c = 7$ and $n_0 = 1$
 $3n^3 + 20n^2 + 5$ is $O(n^3)$ - need $c > 0$ and $n_0 \geq 1$ such that $3n^3 + 20n^2 + 5 \leq c \times n^3$ for $N \geq N_0$ true for $c = 4$ and $n_0 = 21$
 $3 \log(n) + 5$ is $O(\log(n))$ - need $c > 0$ and $n_0 \geq 1$ such that $3 \log(n) + 5 \leq c \times \log(n)$ for $N \geq n_0$ true for $c = 7$ and $n_0 = 1$