



Algorithmic Complexity - I

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ES103: Course Summary

- Estimating algorithmic complexities
- Tools like Recursion, Iteration
- ADT
 - Linear data organizations like Arrays, Stacks, queues, Linked lists
 - Non-linear data organizations like hashing, trees (and its many variances), graphs (and many variances)
 - Examples
- Standard Problems: Searching and Sorting
- Standard Problem Solving Approaches



Algorithm

“An algorithm is a sequence of computational steps that transform the input into the output”

An Example: **Sorting Problem**

Input: A sequence of n numbers a_1, a_2, \dots, a_n

Output: Output: A permutation (reordering) $\{a'_1, a'_2, \dots, a'_n\}$ of the input sequence such that $a'_1 \leq a'_2 \leq \dots \leq a'_n$



Algorithms as a tool

- What kinds of problems are solved by Algorithms?
 - Internet
 - Operating Systems
 - Machine Learning
 - Design and Manufacturing
 - E-Commerce
 - Workflows
 - ...



Algorithm

- Can be expressed in many kind of notations, like
 - Natural languages,
 - Pseudocode,
 - Flowcharts,
 - Programming Languages

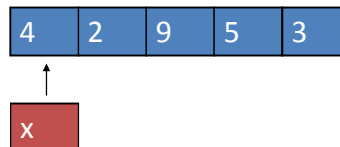


Search

Example: **Searching Problem**

Input: A sequence of n numbers a_1, a_2, \dots, a_n and an element x to be search

Output: Output: return the index of the element x if present, else, return 'not found'





Sequential Search – C Code

```
int sequentialSearch(int c[], int s_element){
```

```
    int i;
    int array_size = size_of_array(c);
    for (i=0; i < array_size and s_element != c[i]; i++);
```

```
    if (i == array_size)
        return -1;
    else
        return i;
}
```

```
int sequentialSearch(int c[], int s_element){
```

```
    int i;
    int array_size = size_of_array(c);
    for (i=0; i < array_size; i++){
        if (s_element == c[i])
            break;
```

```
    }
    if (i == array_size)
        return -1;
    else
        return i;
}
```



Sequential Search – C Code

```
int sequentialSearch(int c[], int s_element){
```

```
    int i;
    int array_size = size_of_array(c);
    for (i=0; i < array_size and s_element != c[i]; i++);
```

```
    if (i == array_size)
        return -1;
    else
        return i;
}
```

```
int sequentialSearch(x, A)
```

```
int i;
for (i=0; i < length[A] and x <> A[i]; i++);
if (i == length[A])
    return (-1)
else
    return (i)
```

Algorithm



Sequential Search – Analysis

```
int sequentialSearch(x, A)
int i;
for (i=0; i < length[A]; i++) {
    if x == A[i]
        then break;
}
if (i == length[A])
    return (-1)
else
    return (i)
```

```
1
1
1 - length[A]
0 - length[A]
1
1
1
1
1
```

Best Case : when x is the first element (No of comparisons = 1) : O(1)

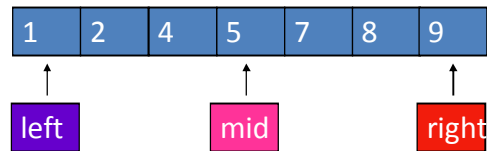
Worst Case : when x is absent (No of comparisons = n) : O(n)

Average Case : $\frac{1}{n} \sum_{i=1}^n i = \frac{(n+1)}{2} = O(n)$



Binary Search

```
BinarySearch(x, A)
left = 0;
right = length(A) - 1;
while (left <= right) {
    mid = (left + right) / 2
    if (A[mid] == x)
        return mid;
    else if (A[mid] > value)
        right = mid - 1
    else
        left = mid + 1
}
return -1 // not found
```



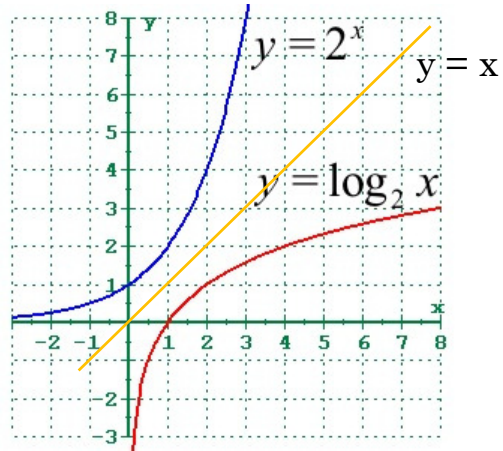
Best Case : when x is mid element (No of comparisons = 1) : O(1)

Worst Case : when x is absent (No of comparisons = n) : O(log n)

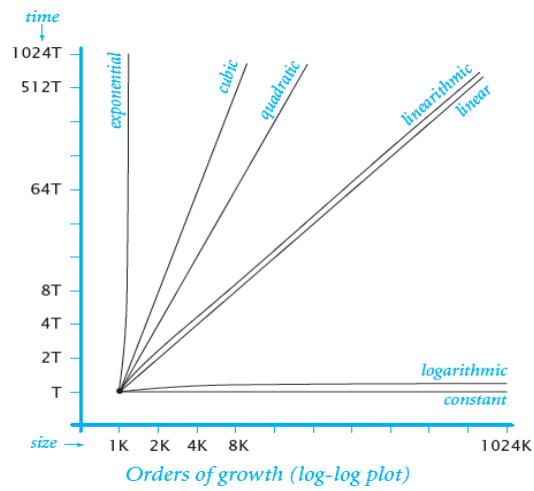
Average Case : O(log n)



Comparing Performance



Comparing Performance





Finding Minimum of a Collection

```
int findMin(int[] x) {
    int k = 0; int n = x.length;
    for (int i = 1; i < n; i++) {
        if (x[i] < x[k]) {
            k = i;
        }
    }
    return k;
}
```

Time	Space
	n
	1+1
n	
1	
1	
1	
n+3	n+2
O(n)	O(n)



C Code for Binary Search

```
int Bin-Search(){
    first = 0;
    last = n - 1;
    middle = (first+last)/2;

    while( first <= last )
    {
        if ( array[middle] < search )
            first = middle + 1;
        else if ( array[middle] == search )
        {
            printf("%d found at location %d.\n", search, middle+1);
            break;
        }
        else
            last = middle - 1;

        middle = (first + last)/2;
    }
    if ( first > last )
        printf("Not found! %d is not present in the list.\n", search);

    return 0;
}
```



How good is your program?

- Sequence of computational steps
- Efficient
 - Speed (Time)
 - Space (Memory)
- Evaluation of “Goodness” should be independent of
 - Language
 - Processor
- Algorithmic Evaluation



How good is your program?

- Running Time
 - Types of operations
 - H/W
 - Compiler
 - Inputs
- Number of Basic Operations
 - Different types
 - Inputs and size
 - Complex

```
scanf("%d", &x);  
if (x < 10)  
    x++;  
else  
    for (i = 0, i < 10, i++);
```

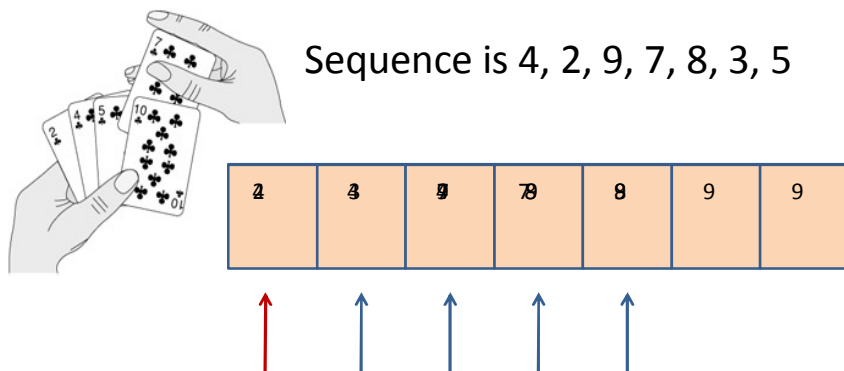



How good is your program?

- Running time as a function of input size
 - Input type and size is known
 - Compute number of times each statement is going to be executed (expressed in terms of input size)
 - Replace operation times with constants
 - Different operations take different (but constant) time
 - Compute
$$T(n) = \sum \text{time taken by } i^{\text{th}} \text{ statement}$$



An Example: Insertion Sort



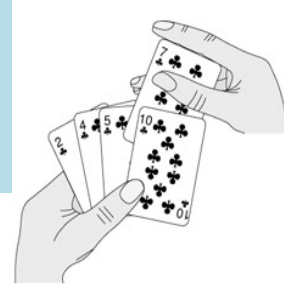
The figure is taken from the Book by Cormen et. al. – Introduction to Algorithms



Algorithm: Insertion sort

```

void insertion-sort(A)
1 for (i ← 2; i < length[A]; i++) {
2   key ← A[i];
   //Insert A[j] into the sorted sequence A[1 ] to A[j - 1].
3   j ← i - 1;
4   while (j > 0 and A[j] > key) {
5     A[j + 1] ← A[j];
6     j ← j - 1;
   }
7   A[j + 1] ← key;
}
    
```



Insertion sort: Time Taken

S. No.	Steps	cost	times
1	for (i ← 2; i < length[A]; i++)	c1	n-1
2	key ← A[i];	c2	n-1
	//Insert A[j] into the sorted sequence A[1] to A[j - 1].		
3	j ← i - 1	c3	n-1
4	while (j > 0 and A[j] > key)	c4	$\sum_{j=2}^n t_j$
5	A[j + 1] ← A[j];	c5	$\sum_{j=2}^n (t_j - 1)$
6	j ← j - 1;	c6	$\sum_{j=2}^n (t_j - 1)$
7	A[j + 1] ← key	c7	n-1

$$T(n) = c1(n-1) + c2(n-1) + c3(n-1) + c4 \sum_{j=2}^n t_j + c5 \sum_{j=2}^n (t_j - 1) + c6 \sum_{j=2}^n (t_j - 1) + c7(n-1)$$



Insertion Sort: Time Taken

- Best Case
- Worse Case
- Average Case



Why Worse Case?

- Act as the “Upper Bound”
- Worse case do occur in practice
 - Ex: a record not found in the database
- Average case is often (roughly) as bad as the worse case



Algorithmic Complexity

- A measure of the performance of an algorithm with respect to input size
 - Space complexity
 - Time complexity (Mostly used)
- Expressed in terms of Asymptotic Notations
 - Big-Oh (O), Big-Theta (Θ), Big-Omega (Ω)
- What to measure
 - Worst case performance
 - Average case
 - Best case

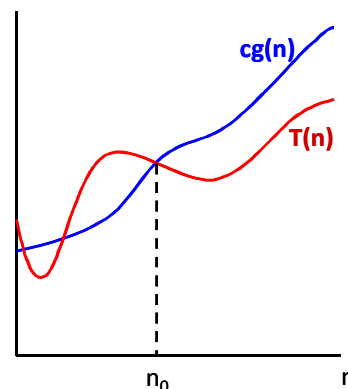


Big-Oh (O)

- An indicator of the worst case performance (upper bound)
- Defined as a function $T(n)$ which is said to be of $O(g(n))$ if there exist positive constants c_0 and n_0 such that for all $n \geq n_0$, we have

$$T(n) \leq c_0 g(n)$$

- $T(n)$ is asymptotically smaller than or equal to $g(n)$



$$T(n) \leq c_0 g(n)$$



Big-Oh (O): Examples

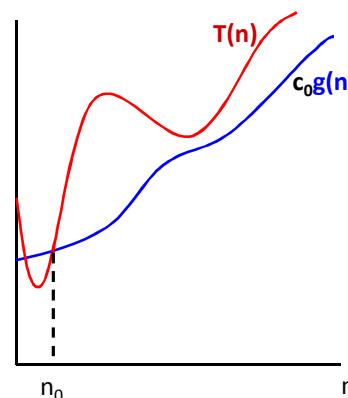
- $T(n) = 3n^2 + 4n = O(n^2)$
- $T(n) = 3n^2 + 4n = O(n^3)$
- $T(n) = 3n^2 + 4n \neq O(n)$
- $T(n) = (n+1)^2 = O(n^2)$



Big-Omega (Ω)

- An indicator of the best case performance (lower bound)
- Defined as a function $T(n)$ which is said to be of $\Omega(g(n))$ if there exist positive constants c_0 and n_0 such that for all $n \geq n_0$, we have

$$T(n) \geq c_0 g(n)$$
- $T(n)$ is asymptotically greater than or equal to $g(n)$



$$T(n) \geq c_0 g(n)$$



Big-Omega (Ω): Examples

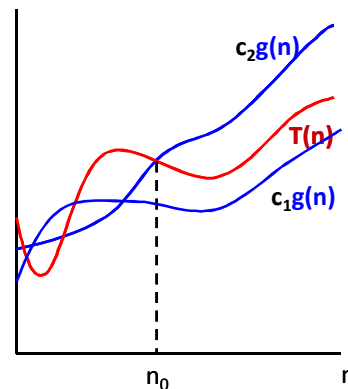
- $T(n) = 3n^2 + 4n = \Omega(n^2)$
- $T(n) = 3n^2 + 4n = \Omega(n)$
- $T(n) = 4n + 2 = \Omega(n)$
- $T(n) = 4n + 2 = \Omega(1)$



Big-Theta (Θ)

- An indicator of the worst case and best case performance (asymptotically tight bound)
- Defined as a function $T(n)$ which is said to be of $\Theta(g(n))$ if there exist positive constants c_1 , c_2 and n_0 such that for all $n \geq n_0$, we have

$$c_1 g(n) \leq T(n) \leq c_2 g(n)$$
- $T(n)$ is asymptotically equal to $g(n)$



$$T(n) \leq c_0 g(n)$$



Big-Theta (Θ): Examples

- $T(n) = 3n^2 + 4n = \Theta(n^2)$
- $T(n) = 3n^2 + 4n \neq \Theta(n)$
- $Tn = 4n + 2 = \Theta(n)$
- $Tn = 4n + 2 \neq \Theta(1)$



Order of Growth

Analysis Type	Mathematical Expression	Relative Rates of Growth
Big O	$T(N) = O(F(N))$	$T(N) \leq F(N)$
Big Ω	$T(N) = \Omega(F(N))$	$T(N) \geq F(N)$
Big θ	$T(N) = \theta(F(N))$	$T(N) = F(N)$

$$1 < \log n < n < n \log n < n^2 < n^3 < 2^n < n!$$



Name Convention

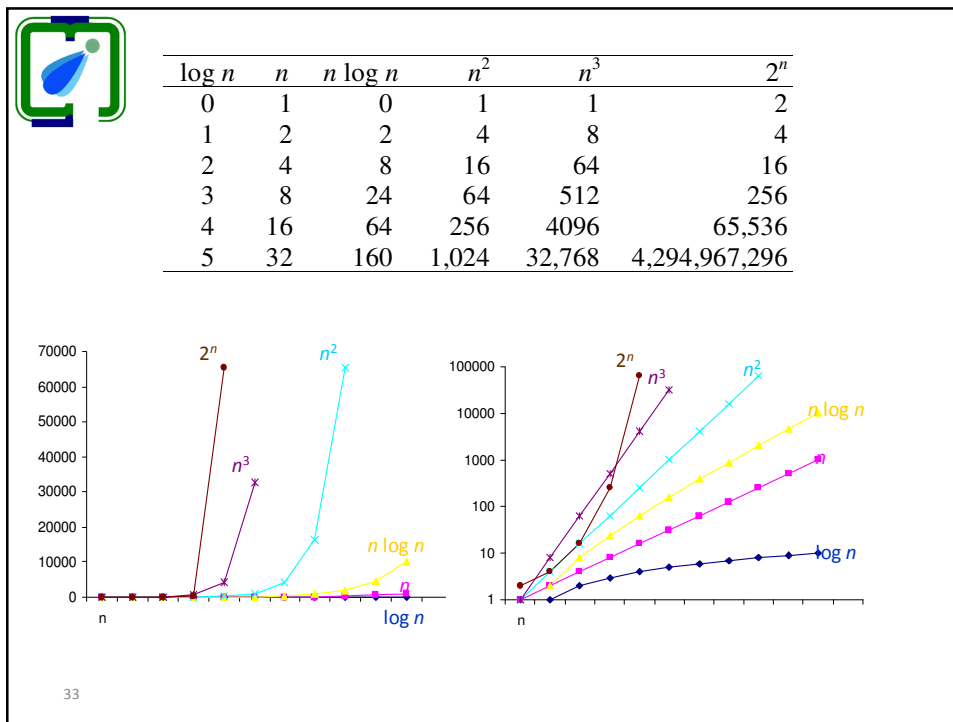
- $O(1)$ Constant
- $O(\log_c n)$ Logarithmic (same order $\forall c$)
- $O(\log^c n)$ Polylogarithmic
- $O(n)$ Linear
- $O(n^c)$ Polynomial
- $O(c^n), c > 1$ Exponential
- $O(n!)$ Factorial



Complexity and Tractability

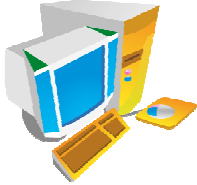
n	$T(n)$						
	n	$n \log n$	n^2	n^3	n^4	n^{10}	2^n
10	.01 μ s	.03 μ s	.1 μ s	1 μ s	10 μ s	1s	1 μ s
20	.02 μ s	.09 μ s	.4 μ s	8 μ s	160 μ s	2.84h	1ms
30	.03 μ s	.15 μ s	.9 μ s	27 μ s	810 μ s	6.83d	1s
40	.04 μ s	.21 μ s	1.6 μ s	64 μ s	2.56ms	121d	18m
50	.05 μ s	.28 μ s	2.5 μ s	125 μ s	6.25ms	3.1y	13d
100	.1 μ s	.66 μ s	10 μ s	1ms	100ms	3171y	4×10^{13} y
10^3	1 μ s	9.96 μ s	1ms	1s	16.67m	3.17×10^{13} y	32×10^{283} y
10^4	10 μ s	130 μ s	100ms	16.67m	115.7d	3.17×10^{23} y	
10^5	100 μ s	1.66ms	10s	11.57d	3171y	3.17×10^{33} y	
10^6	1ms	19.92ms	16.67m	31.71y	3.17×10^7 y	3.17×10^{43} y	

Assume the computer does 1 billion ops per sec.




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Time Complexity – How much it matters?




Computer - A
 10^9 instructions/sec
 Insertion sort
 $(2n^2)$

One million number

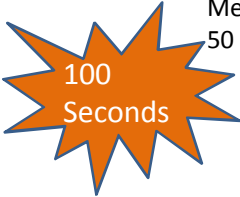




Computer - B
 10^7 instructions/sec
 Merge sort
 $50 n \log n$



2000
Seconds



100
Seconds



Summary

- Algorithms are omnipresent in computational domain
- Time complexity of algorithm does matter
- Time complexity of an algorithm is measured as rate of growth of the running time wrt input size
- Time complexity is normally expressed
 - Big-Oh (O) ----- upper bound (most Popular)
 - Big-theta (Θ) ----- tight (upper & lower) bound
 - Big-omega (Ω) ----- lower bound
- Can you measure time complexity of a given algorithm?



To-Do

- Do assignment #1