## Algorithm Analysis

## What is an algorithm ?

- A clearly specifiable set of instructions
- to solve a problem
- Given a problem
- decide that the algorithm is correct
- Determine how much resource the algorithm will require
- Time Complexity
- Space Complexity


## Analysis of Algorithms

- How much resource is required?
- Measures for efficiency
- Execution time $\rightarrow$ time complexity
- Memory space $\rightarrow$ space complexity
- Observation :
- The larger amount of input data an algorithm has, the larger amount of resource it requires.
- Complexities are functions of the amount of input data (input size).


## What do we use for a yardstick?

- The same algorithm will run at different speeds and will require different amounts of space.
- When run on different computers, different programming languages, different compilers.
- But algorithms usually consume resources in some fashion that depends on the size of the problem they solve.
- Some parameter n (for example, number of elements to sort).


## Sorting integers

```
void sort (int A[], int N)
{
    int i, j, x;
    for (i=1; i<N; i++)
    {
        x = A[i];
        for (j=i; j>0 && x<A[j-1]; j--)
            A[j] = A[j-1];
            A[j] = x;
    }
}
```

- We run this sorting algorithm on two different computers, and note the time (in ms ) for different sizes of input.

| Array Size <br> n | Home <br> Computer | Desktop <br> Computer |
| :---: | :---: | :---: |
| 125 | 12.5 | 2.8 |
| 250 | 49.3 | 11.0 |
| 500 | 195.8 | 43.4 |
| 1000 | 780.3 | 72.9 |
| 2000 | 3114.9 | 690.5 |



## Contd.

- Home Computer :

$$
f_{1}(n)=0.0007772 n^{2}+0.00305 n+0.001
$$

- Desktop Computer :

$$
f_{2}(n)=0.0001724 n^{2}+0.00040 n+0.100
$$

- Both are quadratic function of $n$.
- The shape of the curve that expresses the running time as a function of the problem size stays the same.


## Complexity classes

- The running time for different algorithms fall into different complexity classes.
- Each complexity class is characterized by a different family of curves.
- All curves in a given complexity class share the same basic shape.
- The O-notation is used for talking about the complexity classes of algorithms.


## Introducing the language of O-notation

- For the quadratic function
$f(n)=a n^{2}+b n+c$
we will say that $f(n)$ is $O\left(n^{2}\right)$.
- We focus on the dominant term, and ignore the lesser terms; then throw away the coefficient.


## Mathematical background

- $T(N)=O(f(N))$ if there exists positive constants $c$ and $n_{0}$ such that $T(N) \leq c f(N)$ when $N \geq \boldsymbol{n}_{0}$.
- Meaning :
- As $N$ increases, $T(N)$ grows no faster than $f(N)$.
- The function $T$ is eventually bounded by some multiple of $f(N)$.
- $f(N)$ gives an upper bound in the behavior of $T(N)$.
- $T(N)=\Omega(g(N))$ if there are positive constants $c$ and $n_{0}$ such that $T(N) \geq c f(N)$ when $N \geq \boldsymbol{n}_{0}$.
- Meaning :
- As $N$ increases, $T(N)$ grows no slower than $g(N)$.
- $T(N)$ grows at least as fast as $g(N)$.


## Examples

- $\log _{e} n=O(n)$
- $\mathrm{n}^{10}=\mathrm{o}\left(\mathbf{2}^{\mathrm{n}}\right)$


## Concepts in Analysis

1. Worst Case
2. Average case (expected value)
3. Operator count

Why is the analysis of algorithms important?
Can advance on hardware overcome inefficiency of your algorithm ?
$\rightarrow$ NO!

## Model of computation

- A normal computer, instructions executed sequentially.
- addition, multiplication, comparison, assignment, etc.
- all are assumed to take a single time unit.


## Running time of algorithms

## Assume speed S is $10^{7}$ instructions per second.

| size n | $\mathbf{1 0}$ | $\mathbf{2 0}$ | $\mathbf{3 0}$ | $\mathbf{5 0}$ | $\mathbf{1 0 0}$ | $\mathbf{1 0 0 0}$ | $\mathbf{1 0 0 0 0}$ |
| :---: | :--- | :--- | :--- | :--- | :--- | :--- | :--- |
| $\mathbf{n}$ | .001 ms | .002 ms | .003 ms | .005 ms | .01 ms | .1 ms | 1 ms |
| $\mathbf{n l o g n}$ | .003 ms | .008 ms | .015 ms | .03 ms | .07 ms | 1 ms | 13 ms |
| $\mathbf{n}^{\mathbf{2}}$ | .01 ms | .04 ms | .09 ms | .25 ms | 1 ms | 100 ms | 10 s |
| $\mathbf{n}^{\mathbf{3}}$ | .1 ms | .8 ms | 2.7 ms | 12.5 ms | 100 ms | 100 s | 28 h |
| $\mathbf{2}^{\mathrm{n}}$ | ..1 <br> ms | .1 s | 100 s | 3 y | $3 \times 10^{13} \mathrm{c}$ | inf | $\inf$ |

## Maximum size solvable within 1 hour

| speed <br> complexity | $1 \mathbf{S}$ | 100 S | 1000 S |
| :---: | :---: | :---: | :---: |
| $\mathbf{n}$ | $\mathrm{~N} 1=3.6 \times 10^{10}$ | 100 N 1 | 1000 N 1 |
| $\mathrm{n} \log _{\mathbf{2}} \mathbf{n}$ | $\mathrm{N} 2=1.2 \times 10^{9}$ | 85 N 2 | 750 N 2 |
| $\mathbf{n}^{2}$ | $\mathrm{~N} 3=2 \times 10^{5}$ | 10 N 3 | 30 N 3 |
| $\mathbf{2}^{\mathbf{n}}$ | $\mathrm{N} 4=35$ | $\mathrm{~N} 4+7$ | $\mathrm{~N} 4+10$ |

## Observations

- There is a big difference between polynomial time complexity and exponential time complexity.
- Hardware advances affect only efficient algorithms and do not help inefficient algorithms.


## Maximum subsequence sum problem

- Given (possibly negative) integers $<A_{1} A_{2} \ldots A_{N}>$ find the maximum value of $\sum_{\mathrm{k}=\mathrm{i}} \mathrm{A}_{\mathrm{k}}$.
- For convenience, the maximum subsequence sum is considered to be 0 if all the integers are negative.
- Example :
- For input $<-2,11,-4,13,-5,2>$ the answer is 20 ( $A_{2}$ to $A_{4}$ )


## Algorithm 1

```
int MaxSubSum (int A[], int N) {
    int thissum, maxsum, i,j,k;
1. maxsum = 0;
2. for (i=0; i<N; i++)
3. for (j=i; j<N; j++) {
4. thissum = 0;
5. for (k=i; k <= j; k++)
6.
7.
8.
    }
9. return maxsum;
}
```

- The loop at line 2 is of size $\mathbf{N}$.
- The second loop has size N-i.
- The third loop has size j-i+1.
- Total : about $\mathrm{N}^{3}$ steps

$$
\begin{aligned}
& \sum_{k=i}^{j} 1=j-i+1 \\
& \sum_{k=i}^{j}(j-i+1)=(N-i+1)(N-i) / 2 \\
& \Sigma^{N-1}{ }_{i=0}(N-i+1)(N-i) / 2=\left(N^{3}+3 N^{2}+2 N\right) / 6
\end{aligned}
$$

## Improve the running time

- Remove the second for loop
- Observe :

$$
-\sum_{k=i}^{j} A_{k}=A_{j}+\sum_{k=i}^{j-1} A_{k}
$$

## Algorithm 2

```
int MaxSubSum2 (int A[], int N)
{
    int thissum, maxsum, i, j;
1. maxsum = 0;
2. for (i=0; i<N; i++)
3. {
3. thissum = 0;
4. for (j=i; j < N; j++)
5. {
5. thissum += A[j];
6. if (thissum > maxsum)
7. maxsum = thissum;
    }
    }
8. return maxsum;
}
```


## Recursive algorithm

- Divide \& Conquer :
- Divide: Split the problem into two roughly equal subproblems, and solve recursively.
- Conquer: Patch together the 2 solutions of the subproblems, and some additional work to get a solution for the whole problem.


## Divide \& Conquer

- The maximum subsequence sum can be in one of three places:
- occurs entirely in the left half of the input
- occurs entirely in the right half
- crosses the middle and is in both halves.
- 1 \& 2 can be solved recursively.
- 3 can be solved by finding the largest sum in the first half that includes the last element of the first half, and the largest element in the 2nd half that includes the 1st element in the 2nd half, and adding the two.

| First half |  |  | Second half |  |  |  |  |
| :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- |
| 4 | -3 | 5 | -2 | -1 | 2 | 6 | -2 |

## Algorithm 3

```
int maxsum (int A[], int left, int right)
{
    int maxlsum, maxrtsum, maxlbsum, maxrbsum, lbsum,rbsum;
    int i, centre;
1. if (left == right)
2. if (A[left]>0) return A[left];
3. else return 0;
4. centre = (left + right)/2;
5. maxlsum = maxsubsum(A,left,center);
6. maxrtsum = maxsubsum(A, center+1, right);
7. maxlbsum = lbsum = 0;
8. for (i=centre; i>=left; i--) {
9. lbsum += A[i];
10. if (lbsum > maxlbsum) maxlbsum = lbsum;
    }
```


## Algorithm 3 : continued

```
11 maxrbsum = rbsum = 0;
12 for (i=centre+1; i<=right; i++) {
        rbsum += A[i];
        if (rbsum > maxrbsum) maxrbsum = rbsum;
    }
15 return max (maxlsum, maxrtsum,
        maxlbsum + maxrbsum);
}
int maxsubsum3 (int A[], int N) {
    return maxsum (A, 0, N-1);
}
```


## Complexity

$$
\begin{aligned}
\mathrm{T}(1) & =1 \\
\mathrm{~T}(\mathrm{~N}) & =2 \mathrm{~T}(\mathrm{~N} / 2)+\mathrm{O}(\mathrm{~N}) \\
& =2 \mathrm{~T}(\mathrm{~N} / 2)+\mathrm{cN}
\end{aligned}
$$

$$
\begin{aligned}
& \mathrm{T}(2)=4 \\
& \mathrm{~T}(4)=12
\end{aligned}
$$

## $\mathrm{T}\left(\mathbf{2}^{\mathrm{k}}\right)=\mathrm{N}^{*}(\mathrm{k}+1)=\mathrm{N} \log \mathrm{N}+\mathrm{N}$ $=\mathbf{O}(\mathrm{N} \log \mathrm{N})$

## Algorithm 4

```
int MaxSubSum4 (int A[], int N)
{
    int thissum, maxsum, j;
1. thissum = maxsum = 0;
2. for (j=0; j<N; j++) {
3. thissum += A[j];
4. if (thissum > maxsum)
            maxsum = thissum;
        else if (thissum < 0)
        thissum = 0;
    }
8. return maxsum;
}
```


## Complexity : O(N)

## Search in a sorted array

- Given an integer X , and integers $<\mathrm{A}_{0} \mathrm{~A}_{1} \ldots \mathrm{~A}_{\mathrm{N}-1}>$ which are presorted and already in memory, find $i$ such that $A_{i}=X$, or return $\mathrm{i}=-1$ if X is not in the input.


## Linear Search

```
int search (int A[], int X, int N)
{
    int i;
    for (i=0; i<N; i++)
        if (A[i] == X)
            return i;
    return -1;
}
```


## Binary Search

```
int BinarySearch (int A[], int X, int N)
{
    int low, mid, high;
    while (low <= high) {
        mid = (low+high)/2;
        if (A[mid] < X) low = mid+1;
        else if (A[mid] > X) high = mid-1;
        else return mid;
    }
    return -1;
}
```


## Binary Search Illustrated

$\square$possible positions for what we are looking for

$\square$ruled out as a possible position for what we are looking for


## Analysis of binary search

- All the work done inside the loop takes O(1) time per iteration.
- Number of times the loop is executed :
- The loop starts with high -low = N-1
- Finishes with high -low $\geq 1$
- Every time through the loop the value of high low is at least halved from its previous value.
is at most $\left\lceil\log _{2}(\mathrm{~N}-1)\right\rceil+2=\mathrm{O}(\log \mathrm{N})$.


## Sorting integers

```
void sort (int A[], int N) {
    int i, j, x;
    for (i=1; i<N; i++)
    {
        x = A[i];
        for (j=i; j>0 && x<A[j-1]; j--)
        A[j] = A[j-1];
            A[j] = x;
    }
}
```


## Explosive Example

```
int boom (int M, int X) {
    if (M == 0) return H(X);
    return boom (M-1, Q(X)) + boom(M-1, R(X);
}
```

$$
\begin{aligned}
\mathrm{T}(\mathrm{~N})= & 2 \mathrm{~T}(\mathrm{~N}-1)+1 \\
= & 2(2 \mathrm{~T}(\mathrm{~N}-2)+1)+1 \\
& \cdots \\
= & 2(\ldots(2.0+1)+1) \ldots+1 \\
& =\sum_{\mathrm{M}}^{2(\mathrm{~L} \leq \mathrm{j} \leq M-1} 2^{j} \\
M & =2^{M}-1
\end{aligned}
$$

## Worst Case Analysis

- Suppose that all the cases fall in one of $\mathbf{n}$ cases:
x1, x2, ... , xn
ci denotes the cost for case xi.
- Worst case complexity $=\max \{c i \mid 1<=i<=n\}$
- Example : Sequential search on a table.
- There are n+1 cases
- Worst case time complexity = n


## Average Case Analysis

- Suppose that all the cases fall in one of $n$ cases: $\mathrm{x}_{1}, \mathrm{x}_{2}, \ldots, \mathrm{x}_{\mathrm{n}}$
$c_{i}$ denotes the cost for case $x_{i}$.
$\mathrm{p}_{\mathrm{i}}$ denotes the probability of $\mathrm{x}_{\mathrm{i}}$.
- Average case complexity $=\Sigma^{n}{ }_{i=1} p_{i} c_{i}$
- Example : Sequential search on a table (the key is in the table and every key is equally likely)
- There are n cases, each w.p. 1/n.
- Average case time complexity $=\Sigma^{n}{ }_{i=1} i / n$ $=(n+1) / 2$

