



Design & Analysis of Algorithms

Lecture # 02

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Today's Topic

- **Problem :- Given number M and N , Find the Greatest Common Divisor.**
- **Algorithm 1: Simple school level algorithm.**
- **Euclid Algorithm.**



Middle School Algorithm for GCD

Middle-school procedure

Step 1 Find the prime factorization of m

Step 2 Find the prime factorization of n

Step 3 Find all the common prime factors

Step 4 Compute the product of all the common prime factors
and return it as $\text{gcd}(m,n)$

Is this an algorithm?

Euclid's Algorithm

Problem: Find $\text{gcd}(m,n)$, the greatest common divisor of two nonnegative

Examples: $\text{gcd}(60,24) = 12$, $\text{gcd}(60,0) = 60$, $\text{gcd}(0,0) = ?$

```
Euclid (m,n){  
    while m does not divides n  
         $r \leftarrow n \bmod m$   
         $n \leftarrow m$   
         $m \leftarrow r$   
    end while  
    return m  
}
```

- 
- 
- $m=434$ $n=966$
 - #####first Iteration#####
 - 434 divides 966 (No)
 - $r=966 \bmod 434 = 98$
 - $n=434$
 - $m=98$
 - ##### 2nd Iteration#####
 - $r= 434 \bmod 98= 98 \times 4 + 42$
 - $n=98$
 - $m=42$
 - #####3Rd Iteration #####
 - $r= 98 \bmod 42 =14$
 - $n=42$
 - $m=14$
 - ,

Proof of Correctness

Examples: $\text{gcd}(60,24) = 12$, $\text{gcd}(60,0) = 60$
 $\text{gcd}(0,0) = ?$

- If m divides n then $\text{GCD}(m,n) = m$
- Otherwise $\text{GCD}(m,n) = \text{GCD}(n \bmod m, m)$
- The value of m and n changing in every iteration.
- If you want to calculate $\text{GCD}(m,n)$ you have to calculate $\text{GCD}(n \bmod m, m)$
- We will maintain such integers m and n in each iteration whose GCD will be the GCD of original m and n
- Loop Invariant

```
Euclid (m,n){  
    while  $m$  does not divides  $n$   
         $r \leftarrow n \bmod m$   
         $n \leftarrow m$   
         $m \leftarrow r$   
    end while  
    return  $m$ 
```

Proof of Termination

- Why and when we will exit from the loop?
- Compare value after one iteration.
- Is $n \bmod m$ will be smaller than m ?
- Always decreasing at least by one
- How much ? Will it become zero?
- Loop terminates.



Types of Analysis

- **Priory Analysis**
 - Algorithms
 - Independent of Language
 - Hardware Independence
 - Time and Space as function
- **Posteriori Analysis**
 - Program
 - Language dependent
 - Machine oriented (Hardware dependent)
 - Calculate time and space by program execution.



Problem and Instance

- **Specification of valid input and what are the acceptable outputs for each valid input**
 - **Computing GCD of two numbers.**
 - **GCD(48,36)**
 - **Finding shortest path in map.**
 - **Karachi to Quetta**
 - **Meaning of word in dictionary**
 - **“Evolution”**
 - **Given an image and determine any disease**
 - **“X-Ray”**



Problem and Instance

- A value X is an input instance for problem P , if X is a valid input as per specification.
- Can be single value or set of value.
- Size of instance number of bits required to store instance



Mathematical Model

- **Mathematical Model of Computer (Generic)**
 - **Executer Algorithm on that model (Mentally)**
- **Time required to execute instruction.**
- **What is input data? (Execution time depends on data)**
- **how does this model relate to real computer?**
 - **If Model terribly different, conclusions will not be applicable on real computers.**



Mathematical Model

- **Random Access Machine (RAM)**
 - **Processor +Memory**
- **Memory is Collection of elements, accessible Randomly.**
- **Assigning operation.**
- **Arithmetic operations.**
- **Jumps and conditional jumps**
- **Pointer instruction**
- **Array operations**
- **Functional calls**



Complex Instruction

- We assume that each basic operation takes the same constant time to execute.
- The RAM model does a good job of describing the computational power of most modern (nonparallel) machines.
- $x=y;$
- $Z=a +b;$
- $Z=w[10]$
- $X=a+b*c-d$

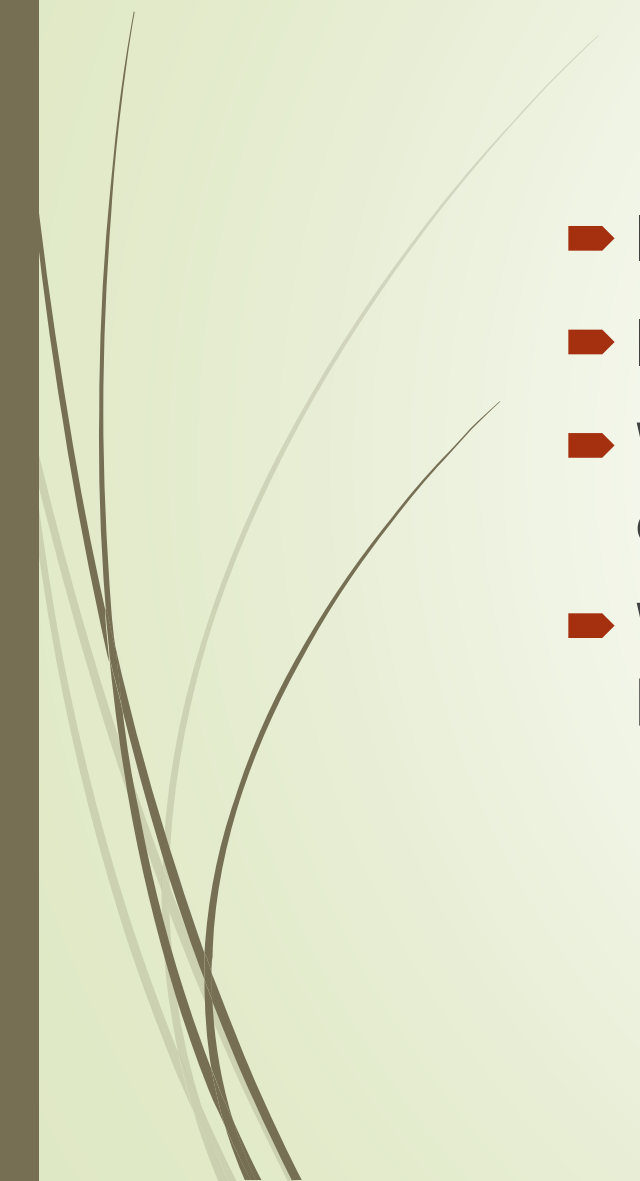


Relation to Reality

- Real computers are complicated
 - Different kinds of memories
- Pipeline
- Memory to register copy instruction
- Computation is done only in register
- Intelligent Compilers



Relation to Reality

- Idealized model of computer
 - It differs from real computer
 - We are not talking about compiler and what actually executed on machine
 - What ever apply on our idealized model can be mimic by real computer.
- 



General Analysis Strategy

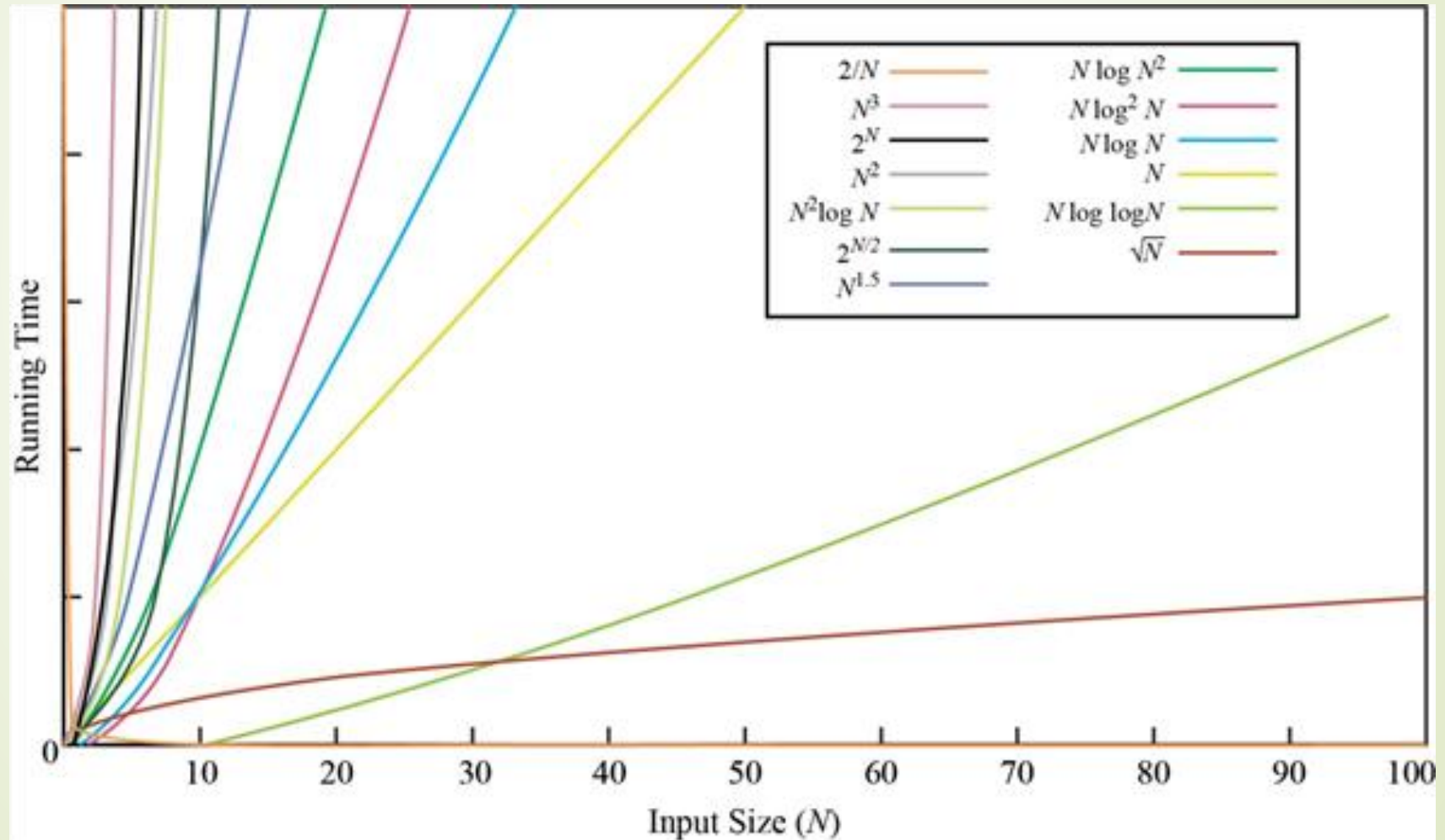
- $T(n)$: Maximum time taken by algorithm to solve any instance of size n .
- $T(n)$: Measure of goodness
 - How good or bad indicated by function
- The function will indicate how good is algorithm.
- Conservative Definition “Worst Case”



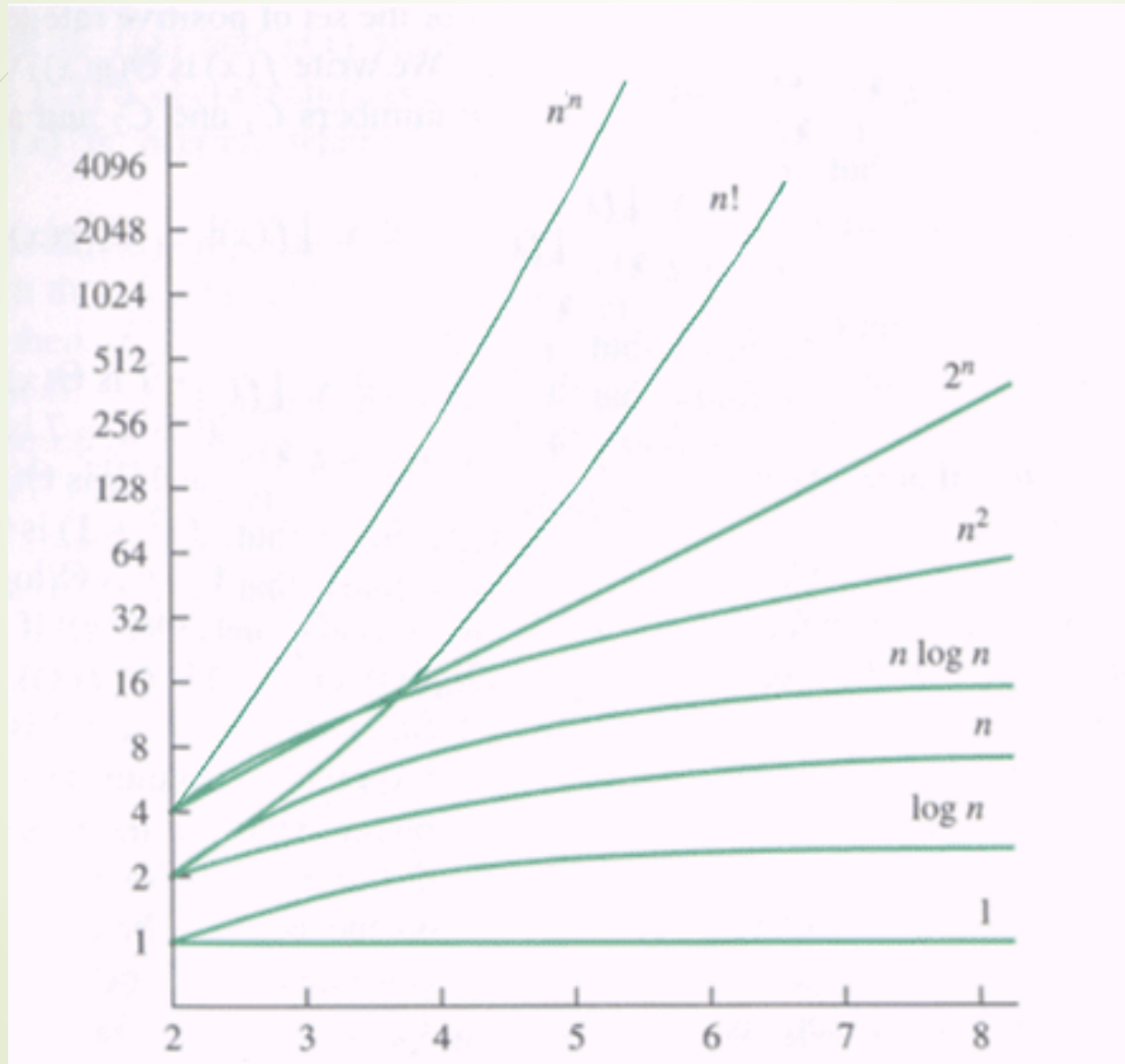
General Analysis Strategy

- Form of $T(n)$ (independent from machine)
 - “Linear”, “Cubic”, “Quadratic” etc.
- Bounds of $T(n)$:
 - Upper bound, Lower bound
- Large n is Important
 - As n become larger and larger which algorithm is better

Growth of Function $T(n)$



Growth of Function $T(n)$





Running Time Analysis

- The running time depends upon the input size, e.g. n
- Different inputs of the same size may result in different running time.
- Criteria for measuring running time.
 - Worst-Case Time (Maximum running time over legal input of size n)

Running Time analysis

- Criteria Worst-case time:
- Let I denote an input instance
- let $|I|$ denote its length, and
- let $T(I)$ denote the running time of algorithm on input I

$$T_{\text{worst}}(n) = \max_{|I|=n} T(I)$$


Running Time analysis

- **Average- Case time is the average running time over all inputs of size n .**
- **Let $p(I)$ denote the probability of seeing this input.**
- **Average case time is the weighted sum of running times with weights being the probabilities.**

$$T_{\text{avg}}(n) = \sum_{|I|=n} p(I)T(I)$$



Running Time Analysis

- We will almost always work with worst-case time
 - Average-case time is more difficult to calculate; it is difficult to specify probability distribution on inputs
 - Worst-case time will specify an upper limit on the running time.
- 

Example: 2-dimension maxima

Example: 2-dimension maxima

The car selection problem can be modelled this way:
For each car we associate (x, y) pair where

- x is the speed of the car and
- y is the negation of the price.



Example: 2-dimension maxima

Example: 2-dimension maxima

- High y value means a cheap car and low y means expensive car.
- Think of y as the money left in your pocket after you have paid for the car.
- Maximal points correspond to the fastest and cheapest cars.

Example: 2-dimension maxima

Example: 2-dimension maxima

2-dimensional Maxima:

- Given a set of points $P = \{p_1, p_2, \dots, p_n\}$ in 2-space,
- output the set of maximal points of P ,
- i.e., those points p_i such that p_i is not dominated by any other point of P .

Example: 2-dimension maxima

Example: 2-dimension maxima

Here is how we might model this as a formal problem.

- Let a point p in 2-dimensional space be given by its integer coordinates, $p = (p.x, p.y)$.
- A point p is said to be *dominated* by point q if $p.x \leq q.x$ and $p.y \leq q.y$.

Example: 2-dimension maxima

Example: 2-dimension maxima

- Given a set of n points, $P = \{p_1, p_2, \dots, p_n\}$ in 2-space a point is said to be *maximal* if it is not dominated by any other point in P .



Example: 2-dimension maxima

Example: 2-dimension maxima

The car selection problem can be modelled this way:
For each car we associate (x, y) pair where

- x is the speed of the car and
- y is the negation of the price.

Example: 2-dimension maxima

Example: 2-dimension maxima

```
MAXIMA(int n, Point P[1 . . . n])
1  for i ← 1 to n
2  do maximal ← true
3    for j ← 1 to n
4    do
5      if (i ≠ j) and (P[i].x ≤ P[j].x) and
        (P[i].y ≤ P[j].y)
6      then maximal ← false; break
```

Example: 2-dimension maxima

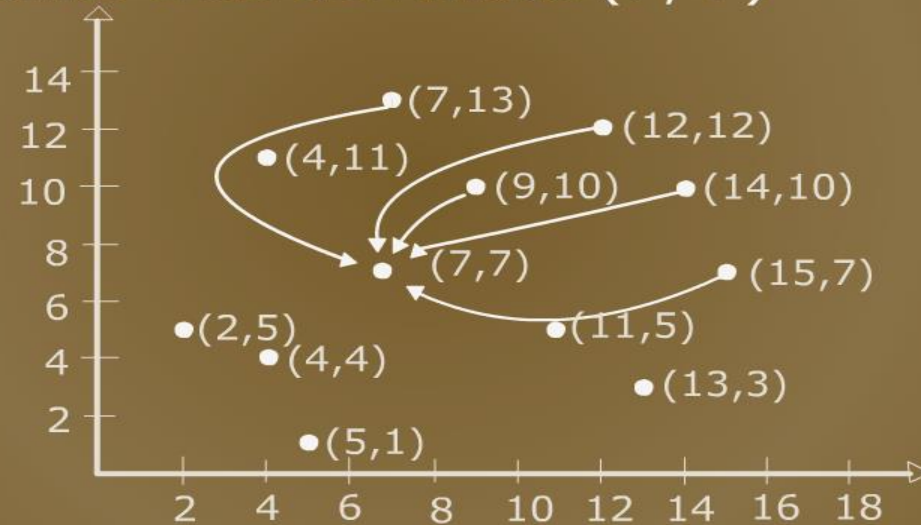
Example: 2-dimension maxima

```
3   for  $j \leftarrow 1$  to  $n$ 
4   do
5       if  $(i \neq j)$  and  $(P[i].x \leq P[j].x)$  and
         $(P[i].y \leq P[j].y)$ 
6       then  $maximal \leftarrow false$ ; break
7   if  $(maximal = true)$ 
8       then output  $P[i]$ 
```

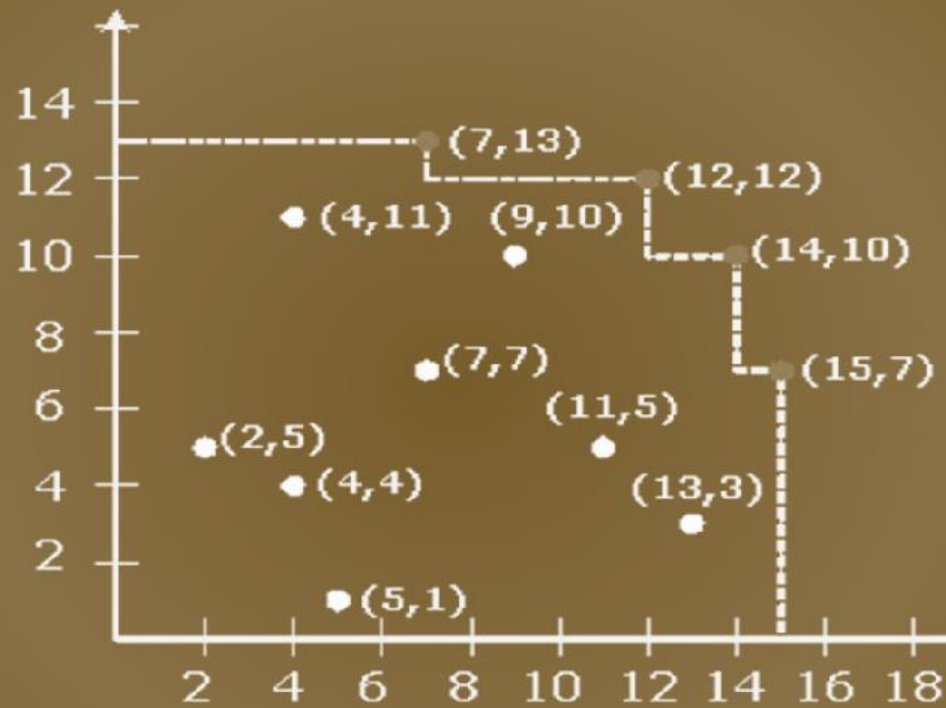

Example: 2-dimension maxima

Example: 2-dimension maxima

Points that dominate (7, 7)



Graph



Analysis of 2-dimension maxima

Example: 2-dimension maxima

```
MAXIMA(int n, Point P[1 . . . n])
1  for i ← 1 to n      n times
2  do maximal ← true
3    for j ← 1 to n    n times
4    do
5      if (i ≠ j) & (P[i].x ≤ P[j].x) &
        (P[i].y ≤ P[j].y)  4 accesses
6      then maximal ← false; break
```

Example: 2-dimension *maxima*

```
2 do maximal  $\leftarrow$  true
3   for  $j \leftarrow 1$  to  $n$  n times
4   do
5     if  $(i \neq j) \ \& \ (P[i].x \leq P[j].x) \ \&$ 
6        $(P[i].y \leq P[j].y)$  4 accesses
7       then maximal  $\leftarrow$  false; break
8   if maximal
9     then output  $P[i].x,$ 
10               $P[i].y$  2 accesses
```

Analysis of 2-dimension maxima

Analysis of 2-dimension maxima

Worst-case running time:

Pair of nested summations, one for i-loop and the other for the j-loop

$$T(n) = \sum_{i=1}^n \left(2 + \sum_{j=1}^n 4 \right)$$

Analysis of 2-dimension maxima

Analysis of 2-dimension maxima

Worst-case running time:

$$T(n) = \sum_{i=1}^n \left(2 + \sum_{j=1}^n 4 \right)$$

$$\left(\sum_{j=1}^n 4 \right) = 4n, \text{ and so}$$

$$\begin{aligned} T(n) &= \sum_{i=1}^n (4n + 2) \\ &= (4n + 2) \cdot n = 4n^2 + 2n \end{aligned}$$



Analysis of 2-dimension maxima

Analysis of 2-dimension maxima

- For small values of n , any algorithm is fast enough.
- What happens when n gets large?
- Running time does become an issue.
- When n is large, n^2 term will be much larger than the n term and will dominate the running time.



Analysis of 2-dimension maxima

Analysis of 2-dimension maxima

- We will say that the worst-case running time is $\Theta(n^2)$.
- This is called the *asymptotic growth rate* of the function.
- We will discuss this Θ -notation more formally later.



Summations

Summations

- The analysis involved computing a summation.
- Summation should be familiar but let us review a bit here.

Summations

Summations

- Given a finite sequence of values a_1, a_2, \dots, a_n ,
- their sum $a_1 + a_2 + \dots + a_n$ is expressed in summation notation as

$$\sum_{i=1}^n a_i$$

Summations

Summations

Some facts about summation:

- If c is a constant

$$\sum_{i=1}^n ca_i = c \sum_{i=1}^n a_i$$

and

$$\sum_{i=1}^n (a_i + b_i) = \sum_{i=1}^n a_i + \sum_{i=1}^n b_i$$

Summations

Summations

Some important summations that should be committed to memory.

Arithmetic series:

$$\begin{aligned}\sum_{i=1}^n i &= 1 + 2 + \dots + n \\ &= \frac{n(n+1)}{2} = \Theta(n^2)\end{aligned}$$

Summations

Summations

Quadratic series:

$$\begin{aligned}\sum_{i=1}^n i^2 &= 1 + 4 + 9 + \dots + n^2 \\ &= \frac{2n^3 + 3n^2 + n}{6} = \Theta(n^3)\end{aligned}$$

Summations

Summations

Geometric series:

$$\sum_{i=1}^n x^i = 1 + x + x^2 + \dots + x^n$$

$$= \frac{x^{(n+1)} - 1}{x - 1} = \Theta(n^2)$$

Summations

Summations

Harmonic series: For $n \geq 0$

$$\begin{aligned} H_n &= \sum_{i=1}^n \frac{1}{i} \\ &= 1 + \frac{1}{2} + \frac{1}{3} + \dots + \frac{1}{n} \approx \ln n \\ &= \Theta(\ln n) \end{aligned}$$

A harder Example

A Harder Example

NESTED-LOOPS()

1 for $i \leftarrow 1$ to n

2 do

3 for $j \leftarrow 1$ to $2i$

4 **do** $k = j \dots$

5 **while** ($k \geq 0$)

6 **do** $k = k - 1 \dots$

How do we analyze the running time of an algorithm that has complex nested loop?

A harder Example

A Harder Example

NESTED-LOOPS()

1 for $i \leftarrow 1$ to n

2 do

3 for $j \leftarrow 1$ to $2i$

4 **do** $k = j \dots$

5 **while** ($k \geq 0$)

6 **do** $k = k - 1 \dots$

To convert loops into summations, we work from inside-out.

A harder Example

A Harder Example

NESTED-LOOPS()

1 for $i \leftarrow 1$ to n

2 do

3 for $j \leftarrow 1$ to $2i$

4 **do** $k = j \dots$

5 **while** ($k \geq 0$)

6 **do** $k = k - 1 \dots$

The answer is we write out the loops as summations and then solve the summations.

A harder Example

A Harder Example

NESTED-LOOPS()

```
1 for i ← 1 to n
2 do
3   for j ← 1 to 2i
4   do k = j . . .
5     while (k ≥ 0)
6     do k = k - 1 . . .
```

The answer is we write out the loops as summations and then solve the summations.

A harder Example

A Harder Example

NESTED-LOOPS()

```
1 for i ← 1 to n
2 do for j ← 1 to 2i
3   do k = j
4     while (k ≥ 0) ◀
5     do k = k - 1
```

- Consider the inner most *while* loop.
- It is executed for $k=j, j-1, j-2, \dots, 0$.

A harder Example

A Harder Example

NESTED-LOOPS()

```
1 for i ← 1 to n
2 do for j ← 1 to 2i
3   do k = j
4   while (k ≥ 0) ◀
5   do k = k - 1
```

- Time spent inside the while loop is constant.
- Let $I()$ be the time spent in the while loop.

Thus:

$$I(j) = \sum_{k=0}^j 1 = j + 1$$

A harder Example

A Harder Example

NESTED-LOOPS()

```
1 for i ← 1 to n
2 do for j ← 1 to 2i
3   do k = j
4   while (k ≥ 0)
5     do k = k - 1
```

- Consider the *middle* for loop.

- It's running time is determined by i.

A harder Example

A Harder Example

NESTED-LOOPS()

1 for i ← 1 to n

2 do for j ← 1 to 2i

3 do k = j

4 while (k ≥ 0)

5 do k = k - 1

- Let M() be the time spent in the for loop:

$$M(i) = \sum_{j=1}^{2i} I(j)$$

A harder Example

A Harder Example

$$\begin{aligned} M(i) &= \sum_{j=1}^{2i} I(j) = \sum_{j=1}^{2i} (j + 1) \\ &= \sum_{j=1}^{2i} j + \sum_{j=1}^{2i} 1 \\ &= \frac{2i(2i + 1)}{2} + 2i \\ &= 2i^2 + 3i \end{aligned}$$

A harder Example

A Harder Example

NESTED-LOOPS()

```
1 for i ← 1 to n ◁
2 do for j ← 1 to 2i
3   do k = j
4   while (k ≥ 0)
5   do k = k - 1
```

- Finally the outer-most for loop.
- Let $T()$ be running time of the entire algorithm:

$$T(n) = \sum_{i=1}^n M(i)$$

A harder Example

A Harder Example

$$\begin{aligned}T(n) &= \sum_{i=1}^n M(i) = \sum_{i=1}^n (2i^2 + 3i) \\&= \sum_{i=1}^n 2i^2 + \sum_{i=1}^n 3i \\&= 2 \frac{2n^3 + 3n^2 + n}{6} + 3 \frac{n(n+1)}{2} \\&= \frac{4n^3 + 15n^2 + 11n}{6} \\&= \Theta(n^3)\end{aligned}$$