



Design and Analysis  
of Algorithms I

# Introduction

## Why Study Algorithms?

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- important for all other branches of computer science
- plays a key role in modern technological innovation
  - “Everyone knows Moore’s Law – a prediction made in 1965 by Intel co-founder Gordon Moore that the density of transistors in integrated circuits would continue to double every 1 to 2 years....in many areas, performance gains due to improvements in algorithms have vastly exceeded even the dramatic performance gains due to increased processor speed.”
    - Excerpt from *Report to the President and Congress: Designing a Digital Future*, December 2010 (page 71).

# Why Study Algorithms?

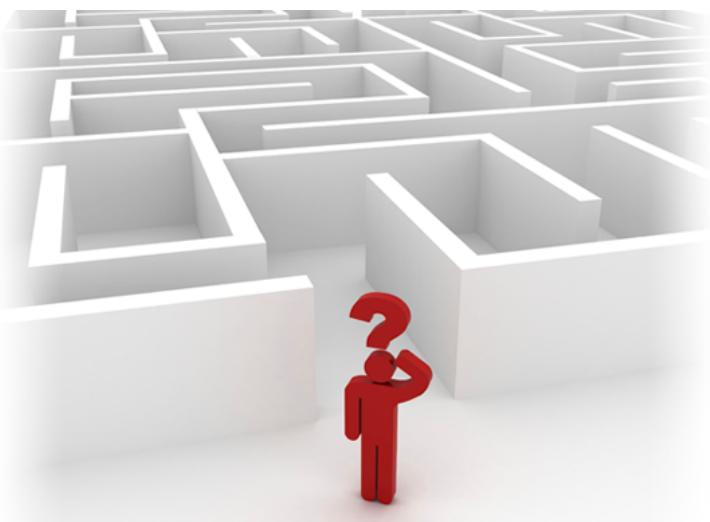
- important for all other branches of computer science
- plays a key role in modern technological innovation
- provides novel “lens” on processes outside of computer science and technology
  - quantum mechanics, economic markets, evolution

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- fun



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# Integer Multiplication

# Integer Multiplication

Input : 2 n-digit numbers  $x$  and  $y$

Output : product  $x*y$

“Primitive Operation” - add or multiply 2 single-digit numbers

# The Grade-School Algorithm

A handwritten multiplication problem is shown:

$$\begin{array}{r} 5678 \\ \times 1234 \\ \hline 22712 \\ 17034 \\ 11356 \\ \hline 7006652 \end{array}$$

The result is circled in red. A green bracket on the right side of the circled area indicates that there are roughly  $n$  operations per row up to a constant. A green arrow points from the text to the bracket.

# of operations overall  $\sim$  constant\*  $n^2$

# The Algorithm Designer's Mantra

“Perhaps the most important principle for the good algorithm designer is to refuse to be content.”

-Aho, Hopcroft, and Ullman, *The Design and Analysis of Computer Algorithms*, 1974

CAN WE DO BETTER ?  
[ than the “obvious” method]



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# Karatsuba Multiplication

# Example

$$x = \overbrace{5}^a \overbrace{6}^b \overbrace{7}^c \overbrace{8}^d$$
$$y = \overbrace{1}^e \overbrace{2}^f \overbrace{3}^g \overbrace{4}^h$$

Step 1: compute  $a \cdot c = 672$

Step 2: compute  $b \cdot d = 2652$

Step 3: compute  $(a+b)(c+d) = 134 \cdot 46 = 6164$

Step 4: compute  $\textcircled{3} - \textcircled{2} - \textcircled{1} = 2840$

Step 5:

$$\begin{array}{r} 6720000 \\ 2652 \\ \hline 2840000 \\ \hline 7006652 \end{array} = ((1234)(5678))$$

# A Recursive Algorithm

Write  $x = 10^{n/2}a + b$  and  $y = 10^{n/2}c + d$

Where  $a, b, c, d$  are  $n/2$ -digit numbers.

[example:  $a=56, b=78, c=12, d=34$ ]

$$\begin{aligned}\text{Then } x \cdot y &= (10^{n/2}a + b)(10^{n/2}c + d) \\ &= (10^n ac + 10^{n/2}(ad + bc) + bd\end{aligned}\quad (*)$$

Idea : recursively compute  $ac, ad, bc, bd$ , then  
compute  $(*)$  in the obvious way

Simple Base Case  
Omitted

# Karatsuba Multiplication

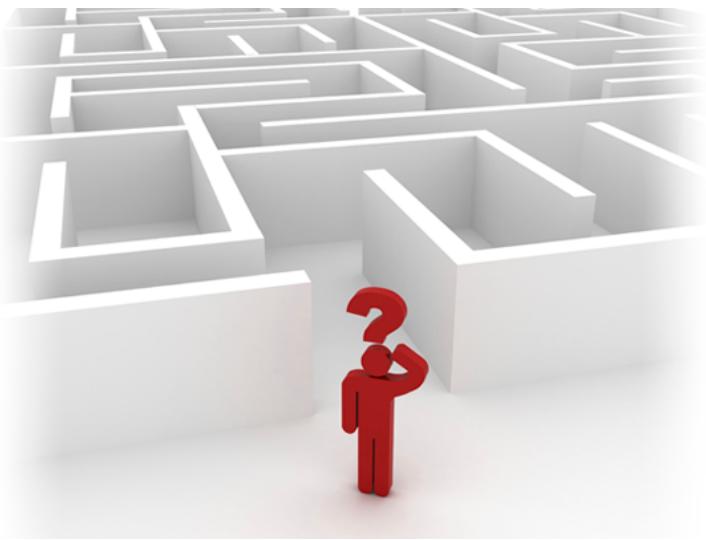
$$x \cdot y = (10^n ac + 10^{n/2}(ad + bc) + bd$$

1. Recursively compute  $ac$
2. Recursively compute  $bd$
3. Recursively compute  $(a+b)(c+d) = ac+bd+ad+bc$

Gauss' Trick :  $(3) - (1) - (2) = ad + bc$

Upshot : Only need 3 recursive multiplications (and some additions)

Q : which is the fastest algorithm ?



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## About The Course

# Course Topics

- Vocabulary for design and analysis of algorithms
- Divide and conquer algorithm design paradigm
- Randomization in algorithm design
- Primitives for reasoning about graphs
- Use and implementation of data structures

# Course Topics

- Vocabulary for design and analysis of algorithms
  - E.g., “Big-Oh” notation
  - “sweet spot” for high-level reasoning about algorithms

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- Vocabulary for design and analysis of algorithms
- Divide and conquer algorithm design paradigm
  - Will apply to: Integer multiplication, sorting, matrix multiplication, closest pair
  - General analysis methods (“Master Method/Theorem”)

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- Vocabulary for design and analysis of algorithms
- Divide and conquer algorithm design paradigm
- Randomization in algorithm design
  - Will apply to: QuickSort, primality testing, graph partitioning, hashing.

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- Divide and conquer algorithm design paradigm
- Randomization in algorithm design
- Primitives for reasoning about graphs
  - Connectivity information, shortest paths, structure of information and social networks.

# Course Topics

- Vocabulary for design and analysis of algorithms
- Divide and conquer algorithm design paradigm
- Randomization in algorithm design
- Primitives for reasoning about graphs
- Use and implementation of data structures
  - Heaps, balanced binary search trees, hashing and some variants (e.g., bloom filters)

# Topics in Sequel Course

- Greedy algorithm design paradigm

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- Greedy algorithm design paradigm
- Dynamic programming algorithm design paradigm
- NP-complete problems and what to do about them
- Fast heuristics with provable guarantees
- Fast exact algorithms for special cases
- Exact algorithms that beat brute-force search

# Skills You'll Learn

- Become a better programmer

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- Sharpen your mathematical and analytical skills

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- Become a better programmer
- Sharpen your mathematical and analytical skills
- Start “thinking algorithmically”
- Literacy with computer science’s “greatest hits”
- Ace your technical interviews

# Who Are You?

- It doesn't really matter. (It's a free course, after all.)

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- Ideally, you know some programming.
- Doesn't matter which language(s) you know.
  - But you should be capable of translating high-level algorithm descriptions into working programs in *some* programming language.

# Who Are You?

- It doesn't really matter. (It's a free course, after all.)
- Ideally, you know some programming.
- Doesn't matter which language(s) you know.
- Some (perhaps rusty) mathematical experience.
  - Basic discrete math, proofs by induction, etc.

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- Ideally, you know some programming.
- Doesn't matter which language(s) you know.
- Some (perhaps rusty) mathematical experience.
  - Basic discrete math, proofs by induction, etc.
- *Excellent free reference:* “Mathematics for Computer Science”, by Eric Lehman and Tom Leighton. (Easy to find on the Web.)

# Supporting Materials

- All (annotated) slides available from course site.

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  - Cormen/Leiserson/Rivest/Stein, *Introduction to Algorithms*, 2009 (3<sup>rd</sup> edition).
  - Mehlhorn/Sanders, *Data Structures and Algorithms: The Basic Toolbox*, 2008.

   
**Freely available online**

# Supporting Materials

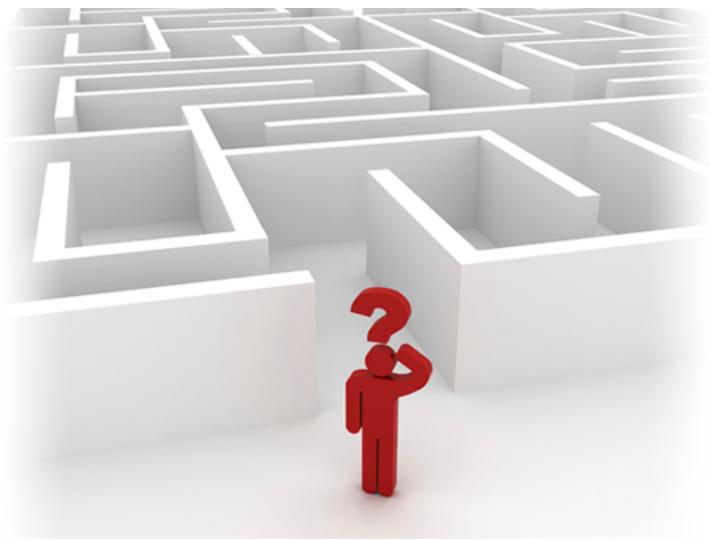
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  - Mehlhorn/Sanders, *Data Structures and Algorithms: The Basic Toolbox*, 2008.
- No specific development environment required.
  - But you should be able to write and execute programs.

# Assessment

- No grades per se. (Details on a certificate of accomplishment TBA.)
- Weekly homeworks.
  - Test understand of material
  - Synchronize students, greatly helps discussion forum
  - Intellectual challenge

# Assessment

- No grades per se. (Details on a certificate of accomplishment TBA.)
- Weekly homeworks.
- Assessment tools currently just a “1.0” technology.
  - We’ll do our best!
- Will sometimes propose harder “challenge problems”
  - Will not be graded; discuss solutions via course forum



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## Merge Sort (Overview)

# Why Study Merge Sort?

- Good introduction to divide & conquer
  - Improves over Selection, Insertion, Bubble sorts
- Calibrate your preparation
- Motivates guiding principles for algorithm analysis (worst-case and asymptotic analysis)
- Analysis generalizes to “Master Method”

# The Sorting Problem

Input : array of  $n$  numbers, unsorted.

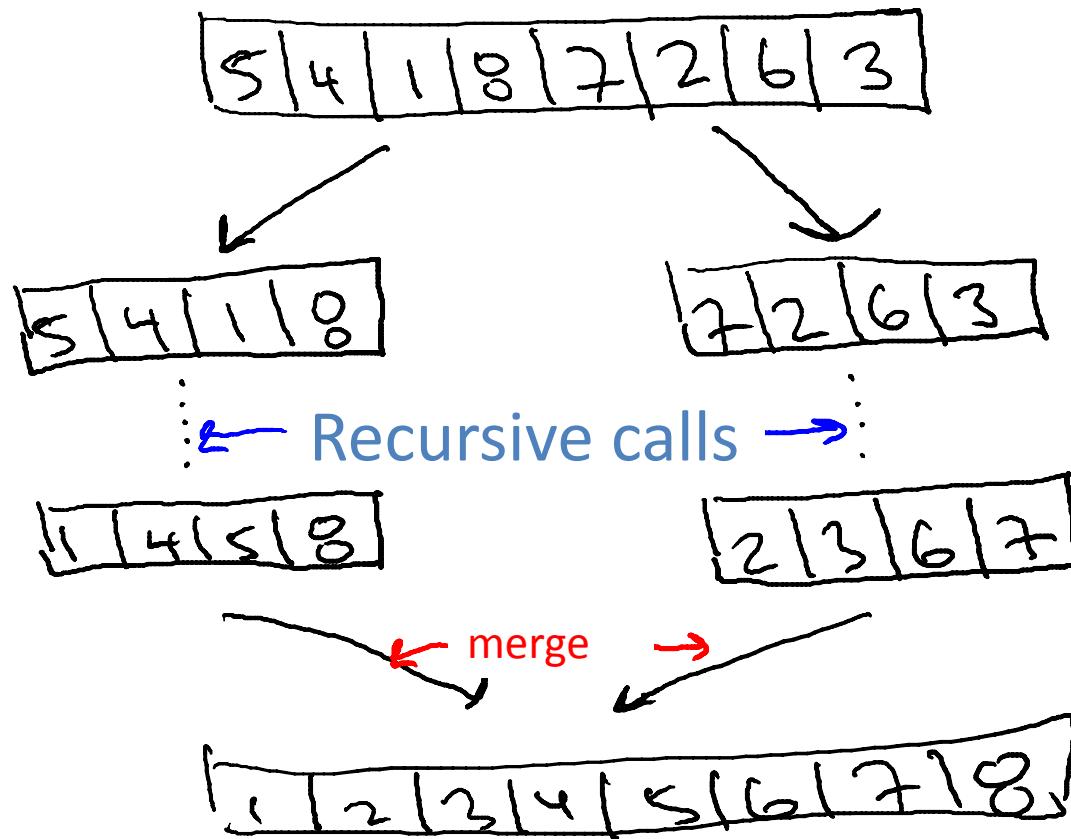
15|4|11|8|7|2|6|3|

Assume  
Distinct

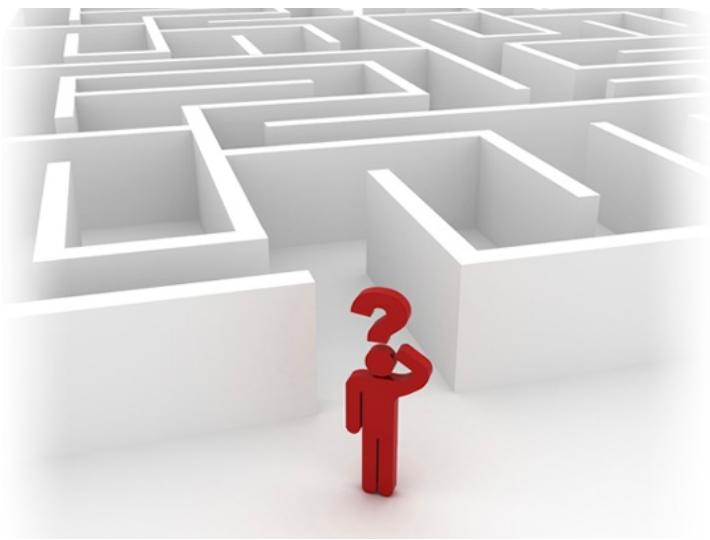
Output : Same numbers, sorted in increasing order

1|2|3|4|5|6|7|8|

# Merge Sort: Example



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## Merge Sort

## (Pseudocode)

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# Merge Sort: Pseudocode

```
-- recursively sort 1st half of the input array  
-- recursively sort 2nd half of the input array  
-- merge two sorted sublists into one  
[ignores base cases]
```

## Pseudocode for Merge:

$C = \text{output} [\text{length} = n]$

$A = 1^{\text{st}}$  sorted array [ $n/2$ ]

$B = 2^{\text{nd}}$  sorted array [ $n/2$ ]

$i = 1$

$j = 1$

for  $k = 1$  to  $n$

if  $A(i) < B(j)$

$C(k) = A(i)$

$i++$

else [ $B(j) < A(i)$ ]

$C(k) = B(j)$

$j++$

end

(ignores end cases)

# Merge Sort Running Time?

Key Question : running time of Merge Sort on array of  $n$  numbers ?

[running time  $\sim$  # of lines of code executed]

## Pseudocode for Merge:

$C = \text{output} [\text{length} = n]$

$A = 1^{\text{st}}$  sorted array  $[n/2]$

$B = 2^{\text{nd}}$  sorted array  $[n/2]$

$i = 1$

$j = 1$

} 2 operations

```
for k = 1 to n ✓  
    if A(i) < B(j) ✓  
        C(k) = A(i) -  
        i++ -  
    else [B(j) < A(i)]  
        C(k) = B(j) -  
        j++ -  
end  
(ignores end cases)
```

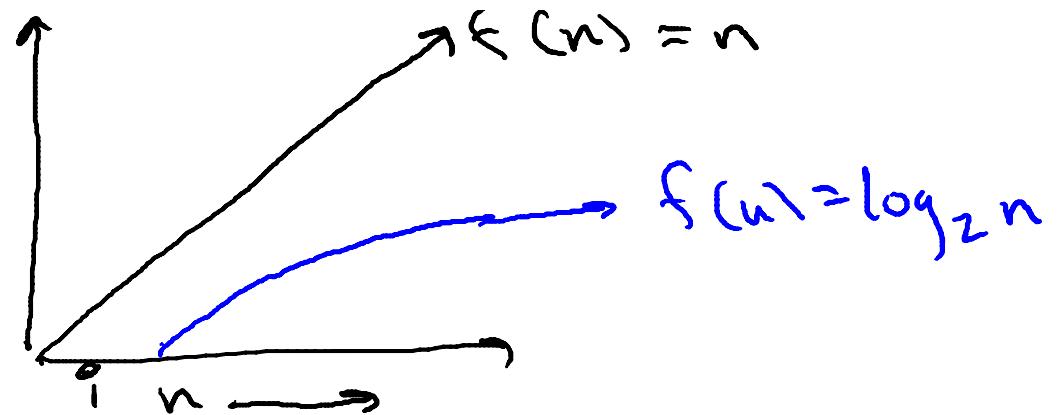
# Running Time of Merge

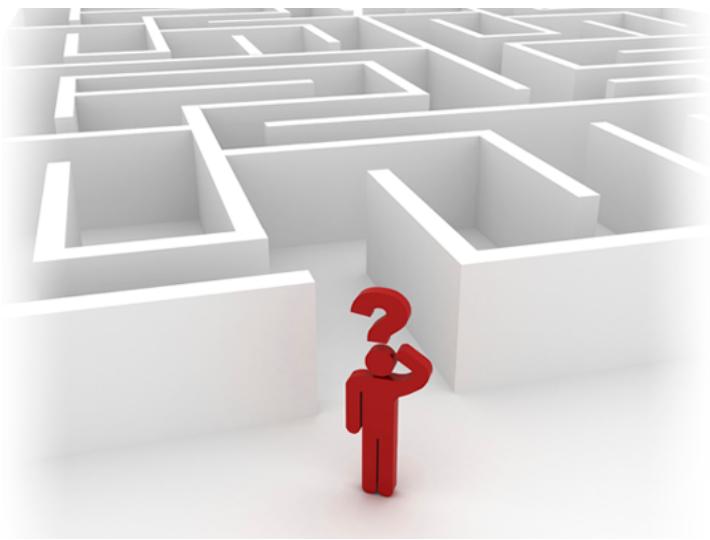
Upshot : running time of Merge on array of  $m$  numbers is  $\leq 4m + 2$   
 $\leq 6m$       (Since  $m \geq 1$ )

# Running Time of Merge Sort

Claim : Merge Sort requires  
 $\leq 6n \log_2 n + 6n$  operations  
to sort  $n$  numbers.

Recall :  $= \log_2 n$  is the #  
of times you divide by 2  
until you get down to 1





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## Merge Sort

### (Analysis)

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# Running Time of Merge Sort

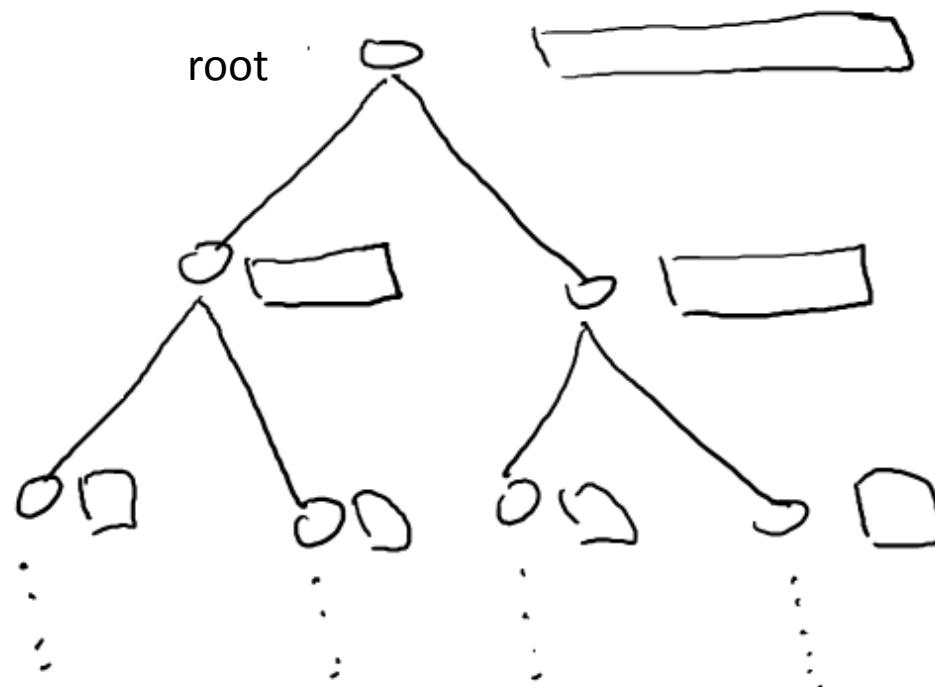
**Claim:** For every input array of  $n$  numbers, Merge Sort produces a sorted output array and uses at most  $6n \log_2 n + 6n$  operations.

## Proof of claim (assuming $n = \text{power of } 2$ ):

Level 0  
[outer call to  
Merge Sort]

Level 1  
(1<sup>st</sup> recursive  
calls)

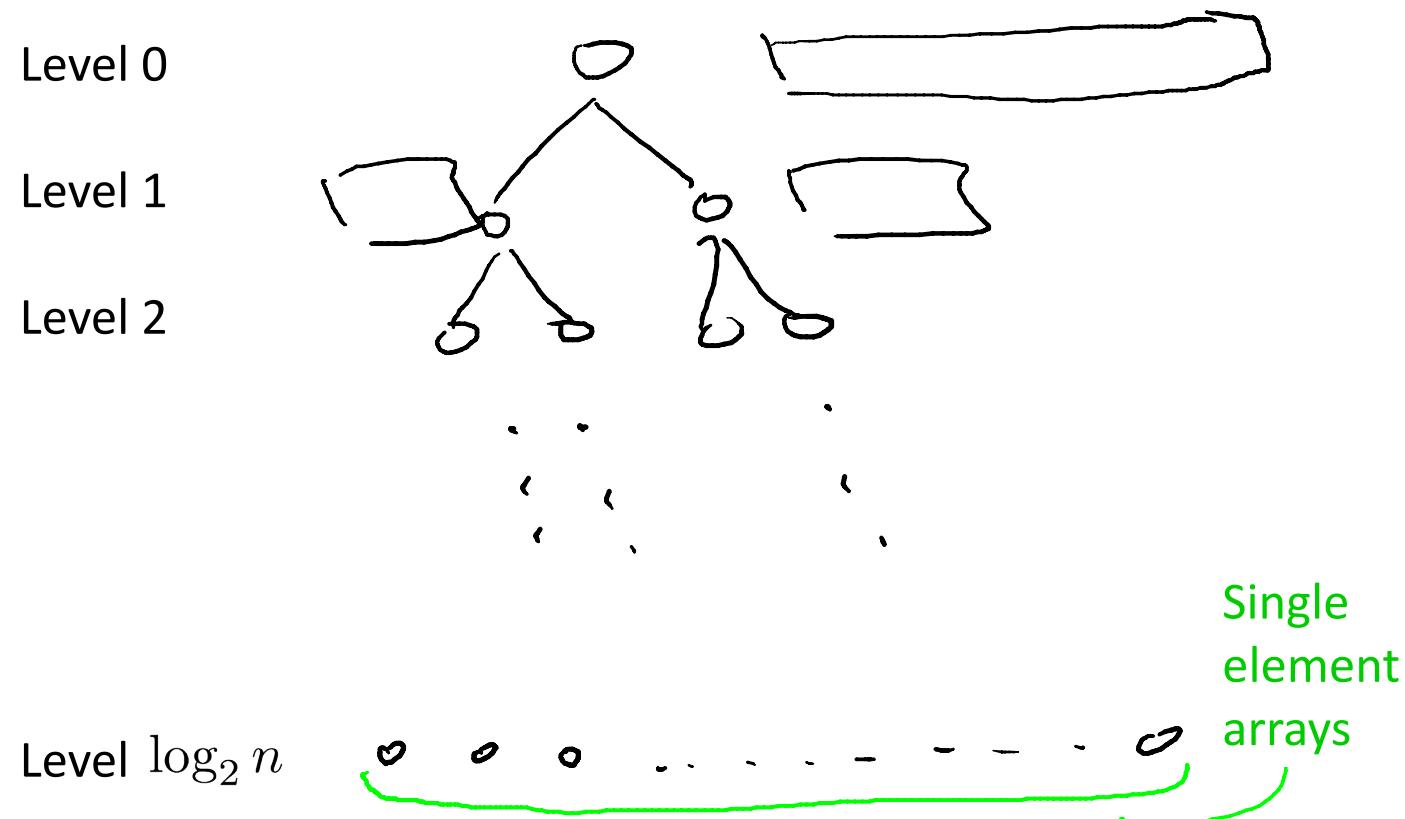
Level 2



Roughly how many levels does this recursion tree have (as a function of  $n$ , the length of the input array)?

- A constant number (independent of  $n$ ).
- $\log_2 n$        $(\log_2 n + 1)$  to be exact!
- $\sqrt{n}$
- $n$

Proof of claim (assuming  $n = \text{power of } 2$ ):



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What is the pattern ? Fill in the blanks in the following statement: at each level  $j = 0, 1, 2, \dots, \log_2 n$ , there are <blank> subproblems, each of size <blank>.

- $2^j$  and  $2^j$ , respectively
- $n/2^j$  and  $n/2^j$ , respectively
- $2^j$  and  $n/2^j$ , respectively
- $n/2^j$  and  $2^j$ , respectively

## Proof of claim (assuming $n = \text{power of 2}$ ) :

At each level  $j=0,1,2,\dots, \log_2 n$ ,

Total # of operations at level  $j = 0,1,2,\dots, \log_2 n$

$$\leq 2^j * 6\left(\frac{n}{2^j}\right) = 6n$$

# of level-j  
subproblems

Size of level-j  
subproblem

Work per level – j  
subproblem

Total

$$6n(\log_2 n + 1)$$

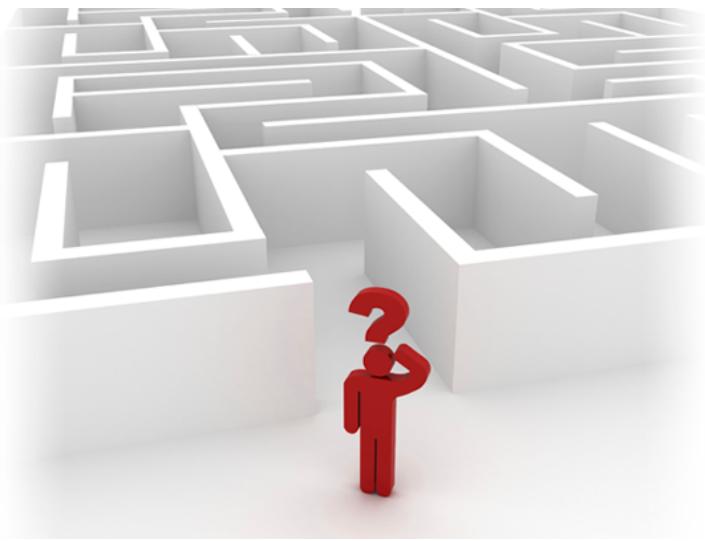
Work  
per level

# of  
levels

# Running Time of Merge Sort

**Claim:** For every input array of  $n$  numbers, Merge Sort produces a sorted output array and uses at most  $6n \log_2 n + 6n$  operations.

QED!



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# Introduction --- Guiding Principles

# Guiding Principle #1

“worst – case analysis” : our running time bound holds for every input of length  $n$ .

-Particularly appropriate for “general-purpose” routines

As Opposed to

--“average-case” analysis  
--benchmarks

REQUIRES DOMAIN  
KNOWLEDGE

BONUS : worst case usually easier to analyze.

# Guiding Principle #2

Won't pay much attention to constant factors,  
lower-order terms

## Justifications

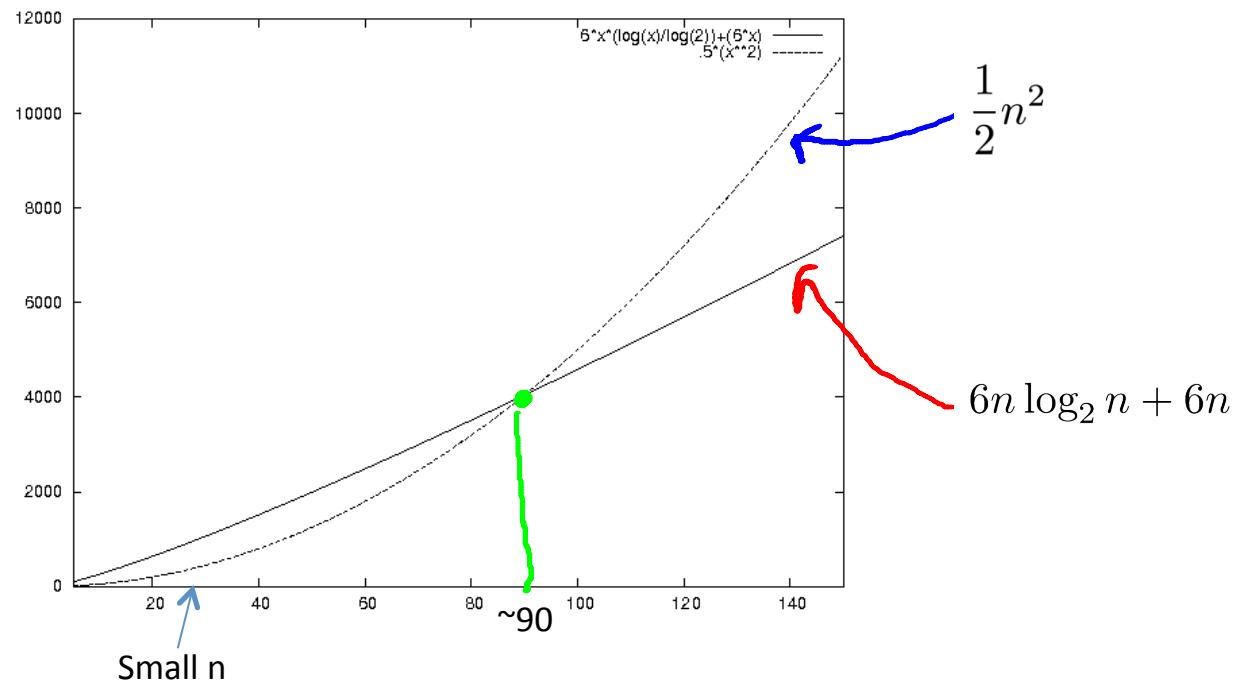
1. Way easier
2. Constants depend on architecture / compiler /  
programmer anyways
3. Lose very little predictive power  
(as we'll see)

# Guiding Principle #3

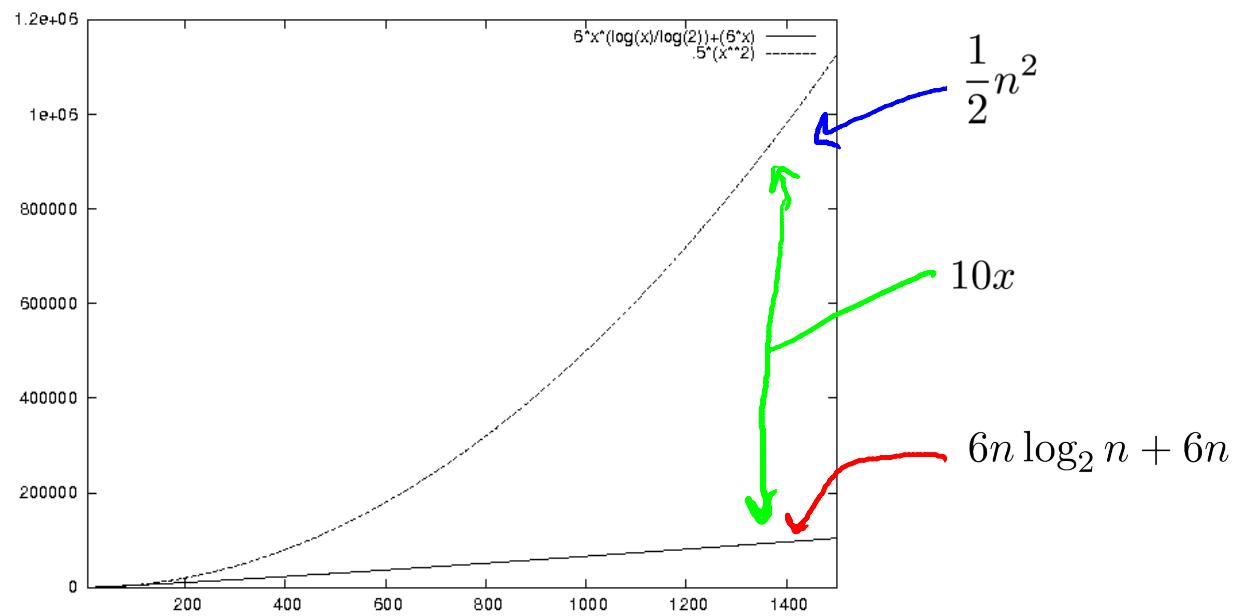
Asymptotic Analysis : focus on running time for large input sizes  $n$

Eg :  $\underbrace{6n \log_2 n + 6n}_{\text{MERGE SORT}}$  “better than”  $\underbrace{\frac{1}{2}n^2}_{\text{INSERTION SORT}}$

Justification: Only big problems are interesting!



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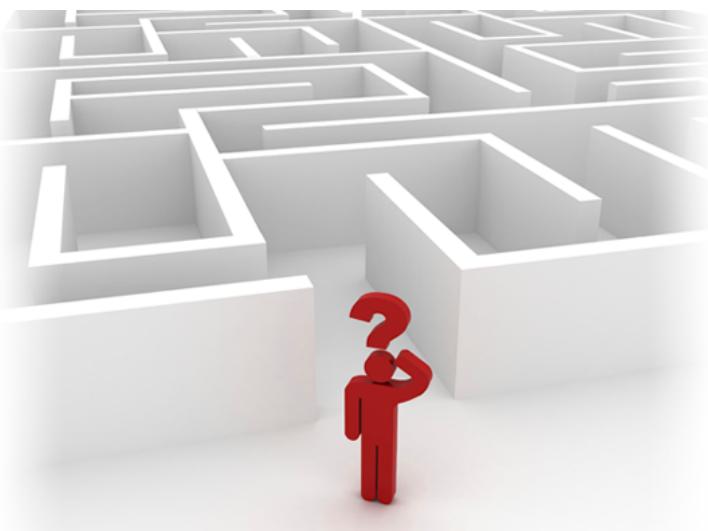
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# What Is a “Fast” Algorithm?

This Course : adopt these three biases as guiding principles

fast                       $\approx$               worst-case running time  
algorithm                  grows slowly with input size

Usually : want as close to linear ( $O(n)$ ) as possible



# Asymptotic Analysis

---

## The Gist

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# Motivation

**Importance:** Vocabulary for the design and analysis of algorithms  
(e.g. “big-Oh” notation).

- “Sweet spot” for high-level reasoning about algorithms.
- Coarse enough to suppress architecture/language/compiler-dependent details.
- Sharp enough to make useful comparisons between different algorithms, especially on large inputs (e.g. sorting or integer multiplication).

# Asymptotic Analysis

High-level idea: Suppress constant factors and lower-order terms

too system-dependent

irrelevant for large inputs

Example: Equate  $6n \log_2 n + 6$  with just  $n \log n$ .

Terminology: Running time is  $O(n \log n)$

[“big-Oh” of  $n \log n$ ]

where  $n$  = input size (e.g. length of input array).

# Example: One Loop

**Problem:** Does array  $A$  contain the integer  $t$ ? Given  $A$  (array of length  $n$ ) and  $t$  (an integer).

---

## Algorithm 1

---

```
1: for  $i = 1$  to  $n$  do
2:   if  $A[i] == t$  then
3:     Return TRUE
4: Return FALSE
```

---

**Question:** What is the running time?

- A)  $O(1)$
- C)  $O(n)$
- B)  $O(\log n)$
- D)  $O(n^2)$

# Example: Two Loops

Given  $A, B$  (arrays of length  $n$ ) and  $t$  (an integer). [Does  $A$  or  $B$  contain  $t$ ?]

---

## Algorithm 2

---

```
1: for  $i = 1$  to  $n$  do
2:   if  $A[i] == t$  then
3:     Return TRUE
4: for  $i = 1$  to  $n$  do
5:   if  $B[i] == t$  then
6:     Return TRUE
7: Return FALSE
```

---

**Question:** What is the running time?

- A)  $O(1)$
- C)  $O(n)$
- B)  $O(\log n)$
- D)  $O(n^2)$

# Example: Two Nested Loops

**Problem:** Do arrays  $A, B$  have a number in common? **Given arrays  $A, B$  of length  $n$ .**

---

## Algorithm 3

---

```
1: for  $i = 1$  to  $n$  do
2:   for  $j = 1$  to  $n$  do
3:     if  $A[i] == B[j]$  then
4:       Return TRUE
5: Return FALSE
```

---

**Question:** What is the running time?

A)  $O(1)$       C)  $O(n)$

B)  $O(\log n)$       D)  $O(n^2)$

## Example: Two Nested Loops (II)

**Problem:** Does array  $A$  have duplicate entries? Given arrays  $A$  of length  $n$ .

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### Algorithm 4

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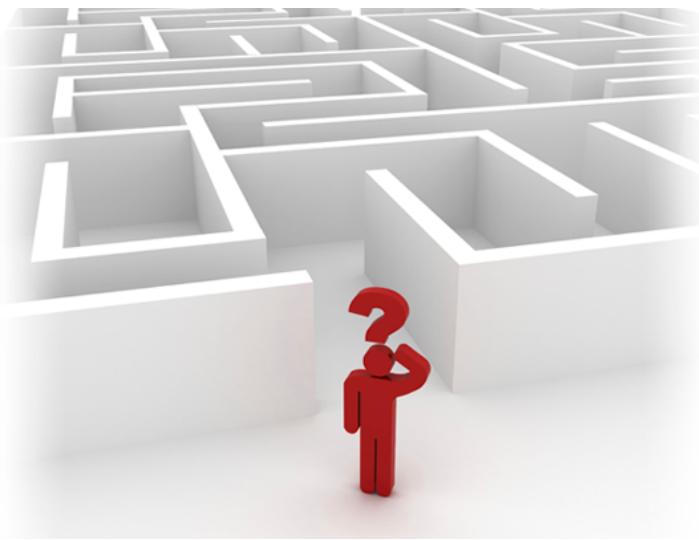
```
1: for  $i = 1$  to  $n$  do
2:   for  $j = i+1$  to  $n$  do
3:     if  $A[i] == A[j]$  then
4:       Return TRUE
5: Return FALSE
```

---

**Question:** What is the running time?

A)  $O(1)$       C)  $O(n)$

B)  $O(\log n)$       D)  $O(n^2)$



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# Asymptotic Analysis

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## Big-Oh: Definition

# Big-Oh: English Definition

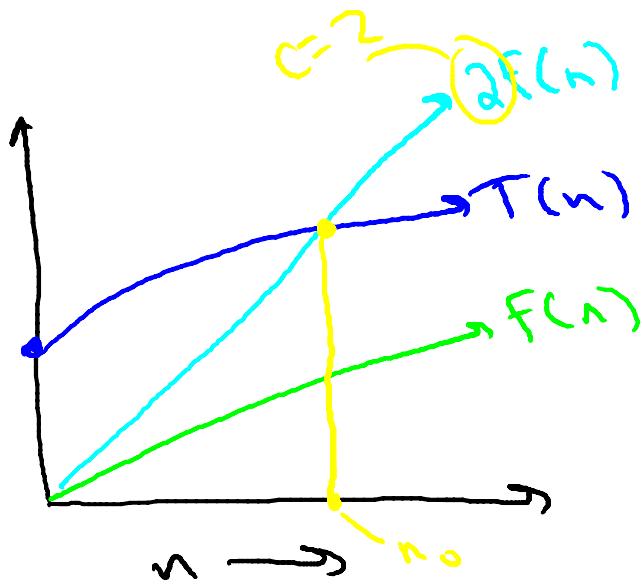
Let  $T(n)$  = function on  $n = 1, 2, 3, \dots$

[usually, the worst-case running time of an algorithm]

Q : When is  $T(n) = O(f(n))$  ?

A : if eventually (for all sufficiently large  $n$ ),  $T(n)$  is bounded above by a constant multiple of  $f(n)$

# Big-Oh: Formal Definition



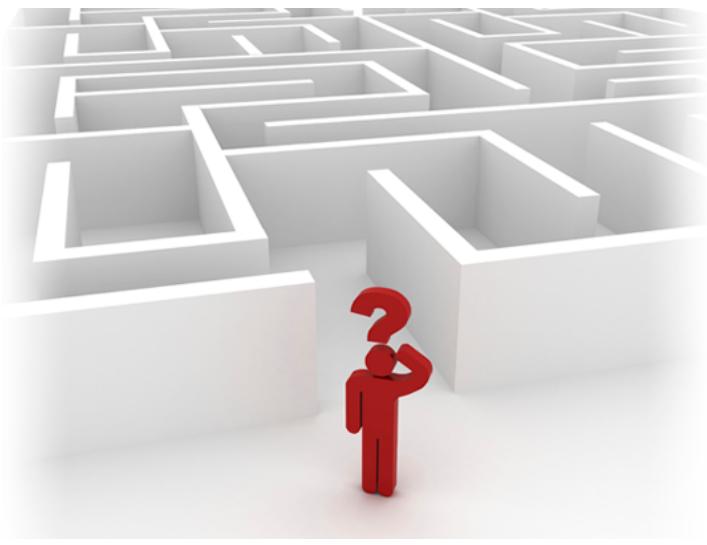
Formal Definition :  $T(n) = O(f(n))$  if and only if there exist constants  $c, n_0 > 0$  such that

$$T(n) \leq c \cdot f(n)$$

For all  $n \geq n_0$

Warning :  $c, n_0$  cannot depend on  $n$

Picture  $T(n) = O(f(n))$



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# Asymptotic Analysis

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## Big-Oh: Basic Examples

# Example #1

Claim : if  $T(n) = a_k n^k + \dots + a_1 n + a_0$  then

$$T(n) = O(n^k)$$

Proof : Choose  $n_0 = 1$  and  $c = |a_k| + |a_{k-1}| + \dots + |a_1| + |a_0|$

Need to show that  $\forall n \geq 1, T(n) \leq c \cdot n^k$

We have, for every  $n \geq 1$ ,

$$\begin{aligned} T(n) &\leq |a_k|n^k + \dots + |a_1|n + |a_0| \\ &\leq |a_k|n^k + \dots + |a_1|n^k + |a_0|n^k \\ &= c \cdot n^k \end{aligned}$$

## Example #2

Claim : for every  $k \geq 1$ ,  $n^k$  is not  $O(n^{k-1})$

Proof : by contradiction. Suppose  $n^k = O(n^{k-1})$

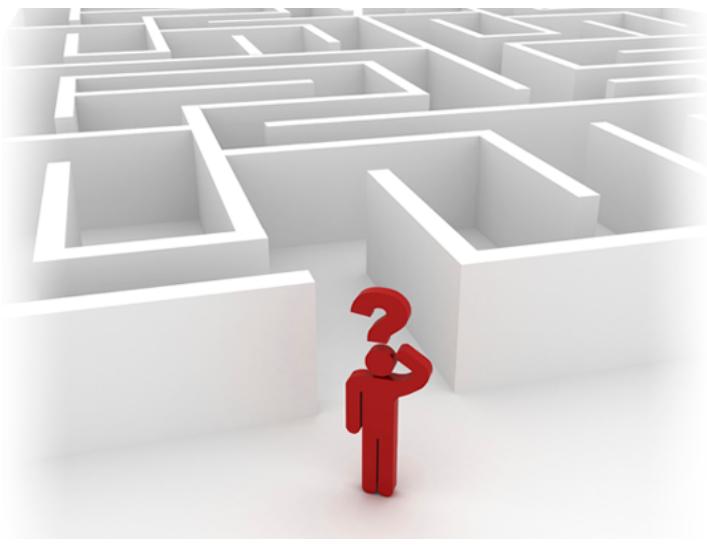
Then there exist constants  $c, n_0$  such that

$$n^k \leq c \cdot n^{k-1} \quad \forall n \geq n_0$$

But then [cancelling  $n^{k-1}$  from both sides]:

$$n \leq c \quad \forall n \geq n_0$$

Which is clearly False [contradiction].



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# Asymptotic Analysis

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## Big-Oh: Relatives (Omega & Theta)

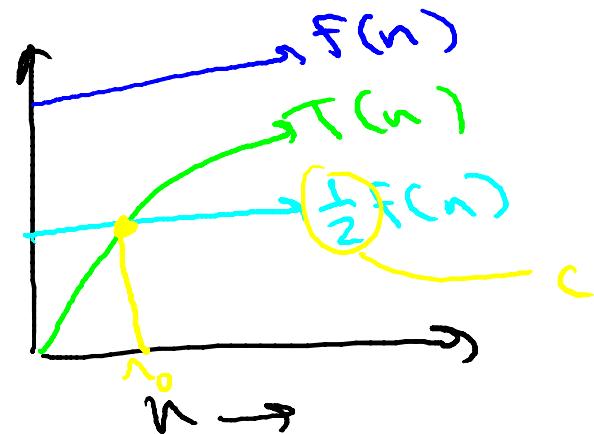
# Omega Notation

Definition :  $T(n) = \Omega(f(n))$

If and only if there exist constants  $c, n_0$  such that

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

Picture



$$T(n) = \Omega(f(n))$$

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# Theta Notation

Definition :  $T(n) = \theta(f(n))$  if and only if

$$T(n) = O(f(n)) \text{ and } T(n) = \Omega(f(n))$$

Equivalent : there exist constants  $c_1, c_2, n_0$  such that

$$c_1 f(n) \leq T(n) \leq c_2 f(n)$$

$$\forall n \geq n_0$$

Let  $T(n) = \frac{1}{2}n^2 + 3n$ . Which of the following statements are true? (Check all that apply.)

$T(n) = O(n)$ .

   $T(n) = \Omega(n)$ .  $[n_0 = 1, c = \frac{1}{2}]$

   $T(n) = \Theta(n^2)$ .  $[n_0 = 1, c_1 = 1/2, c_2 = 4]$

   $T(n) = O(n^3)$ .  $[n_0 = 1, c = 4]$

# Little-Oh Notation

Definition :  $T(n) = o(f(n))$  if and only if for all constants  $c > 0$ , there exists a constant  $n_0$  such that

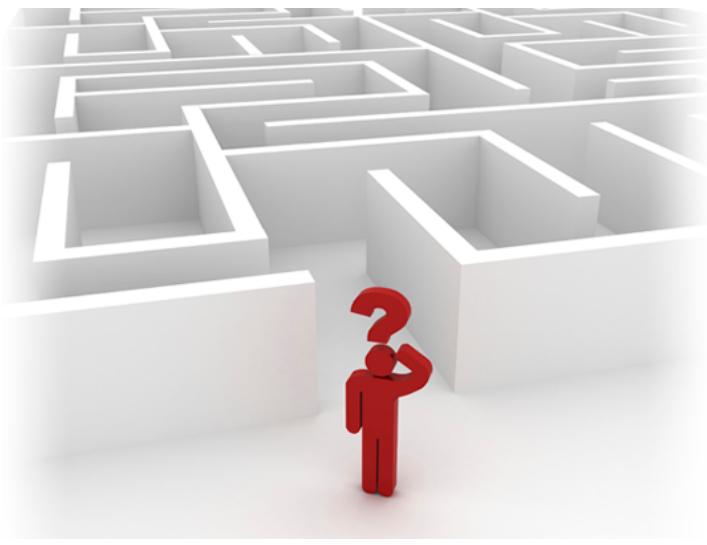
$$T(n) \leq c \cdot f(n) \quad \forall n \geq n_0$$

Exercise :  $\forall k \geq 1, n^{k-1} = o(n^k)$

# Where Does Notation Come From?

“On the basis of the issues discussed here, I propose that members of SIGACT, and editors of computer science and mathematics journals, adopt the  $O$ ,  $\Omega$ , and  $\Theta$  notations as defined above, unless a better alternative can be found reasonably soon”.

*-D. E. Knuth, “Big Omicron and Big Omega and Big Theta”, SIGACT News, 1976. Reprinted in “Selected Papers on Analysis of Algorithms.”*



Design and Analysis  
of Algorithms I

# Asymptotic Analysis

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## Additional Examples

# Example #1

Claim:  $2^{n+10} = O(2^n)$

Proof: need to pick constants  $c, n_0$  such that

$$(*) \quad 2^{n+10} \leq c \cdot 2^n \quad n \geq n_0$$

Note:  $2^{n+10} = 2^{10} \times 2^n = (1024) \times 2^n$

So if we choose  $c = 1024, n_0 = 1$  then  $(*)$  holds.

Q.E.D

## Example #2

Claim :  $2^{10n} \neq O(2^n)$

Proof : by contradiction. If  $2^{10n} = O(2^n)$  then there exist constants  $c, n_0 > 0$  such that

$$2^{10n} \leq c \cdot 2^n \quad n \geq n_0$$

But then [cancelling  $2^n$ ]

$$2^{9n} \leq c \quad \forall n \geq n_0$$

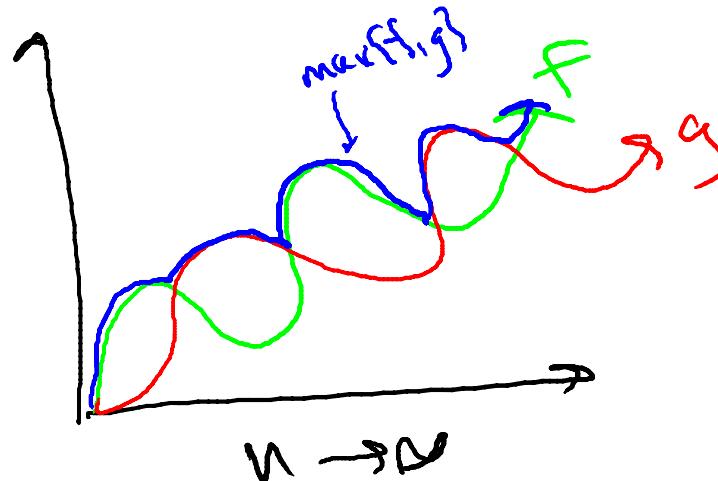
Which is certainly false.

Q.E.D

## Example #3

Claim : for every pair of (positive) functions  $f(n)$ ,  $g(n)$ ,

$$\max\{f, g\} = \theta(f(n) + g(n))$$



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## Example #3 (continued)

Proof:  $\max\{f, g\} = \theta(f(n) + g(n))$

For every  $n$ , we have

$$\max\{f(n), g(n)\} \leq f(n) + g(n)$$

And

$$2 * \max\{f(n), g(n)\} \geq f(n) + g(n)$$

Thus  $\frac{1}{2} * (f(n) + g(n)) \leq \max\{f(n), g(n)\} \leq f(n) + g(n) \quad \forall n \geq 1$   
 $\Rightarrow \max\{f, g\} = \theta(f(n) + g(n)) \quad [\text{where } n_0 = 1, c_1 = 1/2, c_2 = 1]$

Q.E.D

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Design and Analysis  
of Algorithms I

# Divide and Conquer

## Counting Inversions I

# The Problem

Input : array A containing the numbers 1,2,3,..,n in some arbitrary order

Output : number of inversions = number of pairs  $(i,j)$  of array indices with  $i < j$  and  $A[i] > A[j]$

# Examples and Motivation

Example

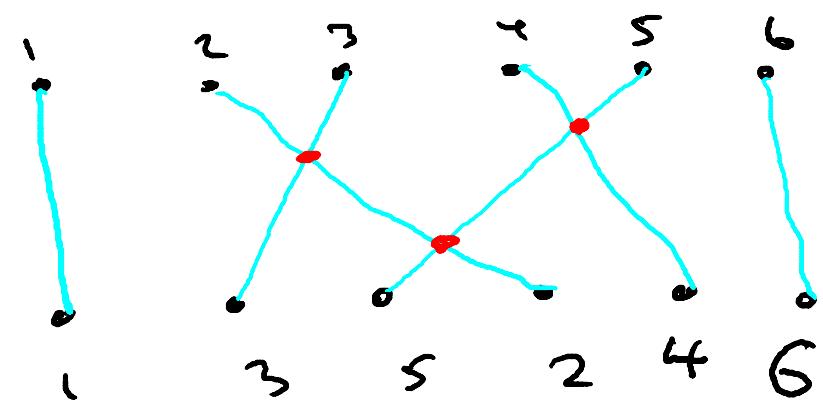
$(1, 3, 5, 2, 4, 6)$

Inversions :

$(3, 2), (5, 2), (5, 4)$

Motivation : numerical  
similarity measure

between two ranked lists eg: for collaborative filtering



What is the largest-possible number of inversions that a 6-element array can have?

- 15      In general,  $\binom{n}{2} = n(n - 1)/2$
- 21
- 36
- 64

# High-Level Approach

Brute-force :  $\theta(n^2)$  time

Can we do better ? Yes!

KEY IDEA # 1 : Divide + Conquer

Call an inversion  $(i,j)$  [with  $i < j$ ]

Left : if  $i,j < n/2$

Right : if  $i,j > n/2$

Split : if  $i \leq n/2 < j$

Note : can compute these  
recursively

need separate subroutine for  
these

# High-Level Algorithm

Count (array A, length n)

    if n=1, return 0

    else

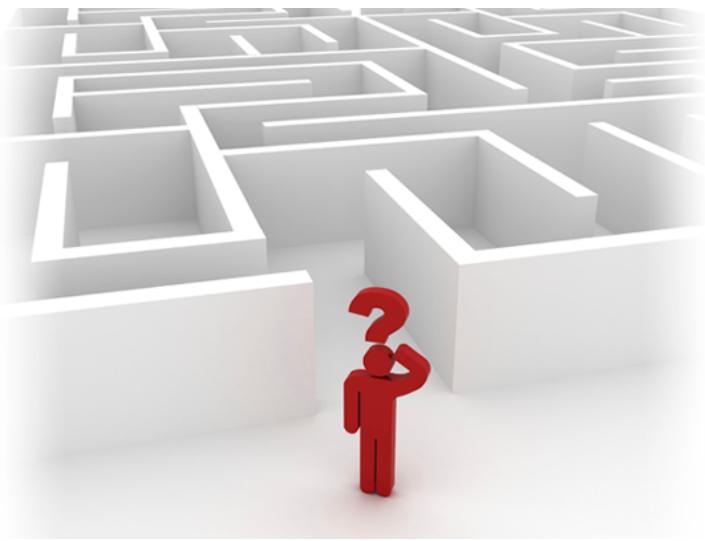
        X = Count (1<sup>st</sup> half of A, n/2)

        Y = Count (2<sup>nd</sup> half of A, n/2)

        Z = CountSplitInv(A,n) ← CURRENTLY UNIMPLEMENTED

    return x+y+z

Goal : implement CountSplitInv in linear ( $O(n)$ ) time then  
count will run in  $O(n \log(n))$  time [just like Merge Sort]



Design and Analysis  
of Algorithms I

# Divide and Conquer

## Counting Inversions II

# Piggybacking on Merge Sort

KEY IDEA # 2 : have recursive calls both count inversions and sort.  
[i.e. , piggy back on Merge Sort ]

Motivation : Merge subroutine naturally uncovers split inversions [as we'll see]

# High-Level Algorithm (revised)

Sort-and-Count (array A, length n)

if  $n=1$ , return 0  
else

Sorted version of 1<sup>st</sup> half → (B,X) = Sort-and-Count(1<sup>st</sup> half of A,  $n/2$ )  
Sorted version of 2<sup>nd</sup> half → (C,Y) = Sort-and-Count(2<sup>nd</sup> half of A,  $n/2$ )  
Sorted version of A → (D,Z) = CountSplitInv(A,n) ← CURRENTLY UNIMPLEMENTED

return X+Y+Z

Goal : implement CountSplitInv in linear ( $O(n)$ ) time  
=> then Count will run in  $O(n\log(n))$  time [just like Merge Sort ]

## Pseudocode for Merge:

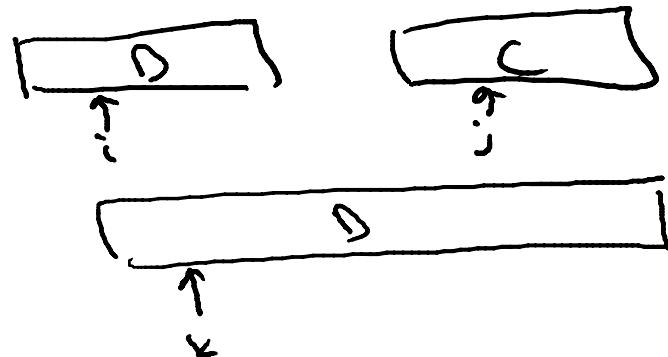
D = output [length = n]

B = 1<sup>st</sup> sorted array [n/2]

C = 2<sup>nd</sup> sorted array [n/2]

i = 1

j = 1



```
for k = 1 to n
    if B(i) < C(j)
        D(k) = B(i)
        i++
    else [C(j) < B(i)]
        D(k) = C(j)
        j++
end
(ignores end cases)
```

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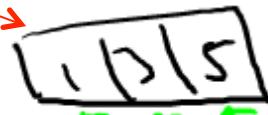
Suppose the input array A has no split inversions. What is the relationship between the sorted subarrays B and C?

- B has the smallest element of A, C the second-smallest, B, the third-smallest, and so on.
- All elements of B are less than all elements of C.
- All elements of B are greater than all elements of C.
- There is not enough information to answer this question.

# Example

Consider merging

B



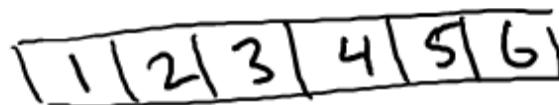
and

C



Output :

D



- ⇒ When 2 copied to output, discover the split inversions (3,2) and (5,2)
- ⇒ when 4 copied to output, discover (5,4)

# General Claim

Claim the split inversions involving an element  $y$  of the 2nd array  $C$  are precisely the numbers left in the 1<sup>st</sup> array  $B$  when  $y$  is copied to the output  $D$ .

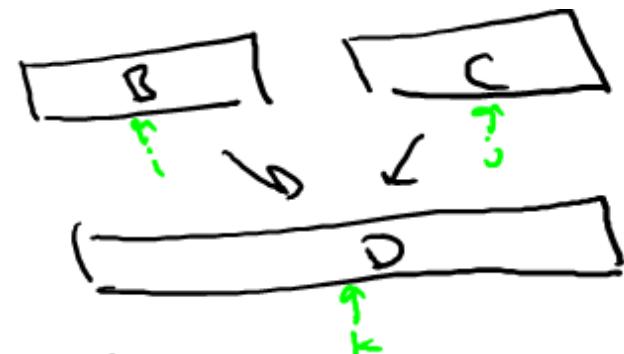
Proof : Let  $x$  be an element of the 1<sup>st</sup> array  $B$ .

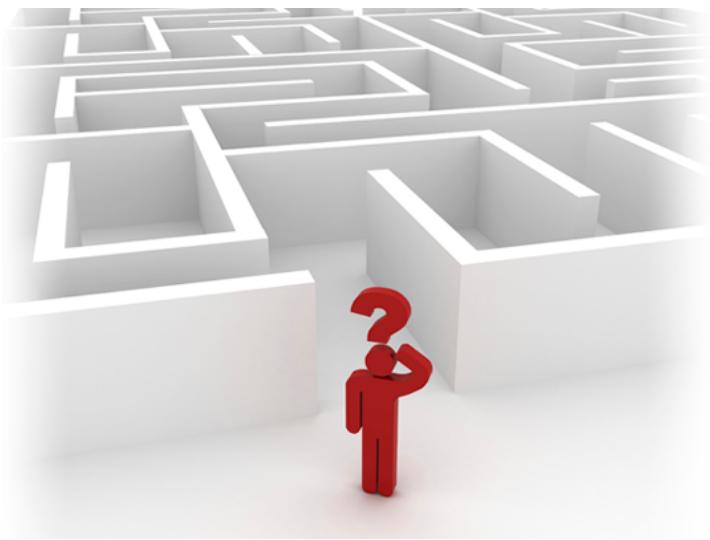
1. if  $x$  copied to output  $D$  before  $y$ , then  $x < y$   
⇒ no inversions involving  $x$  and  $y$
2. If  $y$  copied to output  $D$  before  $x$ , then  $y < x$   
=>  $X$  and  $y$  are a (split) inversion.

**Q.E.D**

# Merge\_and\_CountSplitInv

- while merging the two sorted subarrays, keep running total of number of split inversions
  - when element of 2<sup>nd</sup> array C gets copied to output D, increment total by number of elements remaining in 1<sup>st</sup> array B
- Run time of subroutine :  $O(n) + O(n) = O(n)$
- => Sort\_and\_Count runs in  $O(n \log(n))$  time [just like Merge Sort]

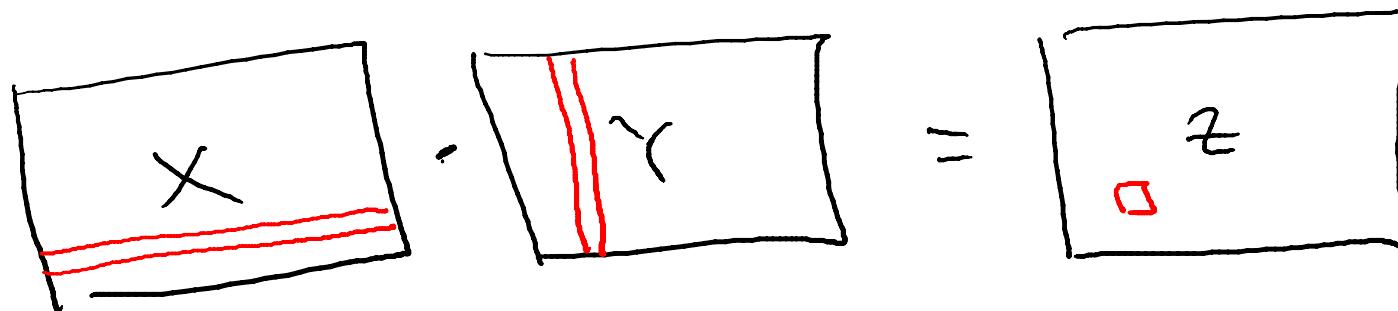




Design and Analysis  
of Algorithms I

# Divide and Conquer Matrix Multiplication

# Matrix Multiplication



( all  $n \times n$  matrices )

Where  $z_{ij} = (\text{i}^{\text{th}} \text{ row of } X) \cdot (\text{j}^{\text{th}} \text{ column of } Y)$

$$= \sum_{k=1}^n X_{ik} \cdot Y_{kj}$$

Note : input size  
 $= \theta(n^2)$

## Example (n=2)

$$\begin{pmatrix} a & b \\ c & d \end{pmatrix} \begin{pmatrix} e & f \\ g & h \end{pmatrix} = \begin{pmatrix} ae+bg & af+bh \\ ce+dg & cf+dh \end{pmatrix}$$

$$z_{ij} = \sum_{k=1}^n X_{ik} \cdot Y_{kj}$$

$$\theta(n)$$

What is the asymptotic running time of the straightforward iterative algorithm for matrix multiplication?

$\theta(n \log n)$

$\theta(n^2)$

   $\theta(n^3)$

$\theta(n^4)$

# The Divide and Conquer Paradigm

1. DIVIDE into smaller subproblems
2. CONQUER subproblems recursively.
3. COMBINE solutions of subproblems into one for the original problem.

# Applying Divide and Conquer

Idea :

Write  $X = \begin{pmatrix} A & B \\ C & D \end{pmatrix}$  and  $Y = \begin{pmatrix} E & F \\ G & H \end{pmatrix}$

[where A through H are all  $n/2$  by  $n/2$  matrices]

Then : (you check)

$$X \cdot Y = \begin{pmatrix} AE + BG & AF + BH \\ CE + DG & CF + DH \end{pmatrix}$$

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# Recursive Algorithm #1

Step 1 : recursively compute the 8 necessary products.

Step 2 : do the necessary additions ( $\theta(n^2)$  time)

Fact : runtime is  $\theta(n^3)$  [follows from the master method]

# Strassen's Algorithm (1969)

Step 1 : recursively compute only 7 (cleverly chosen) products

Step 2 : do the necessary (clever) additions + subtractions  
(still  $\theta(n^2)$  time)

Fact : better than cubic time!

[ see Master Method lecture ]

$$X = \begin{pmatrix} A & B \\ C & D \end{pmatrix}$$

## The Details

$$Y = \begin{pmatrix} E & F \\ G & H \end{pmatrix}$$

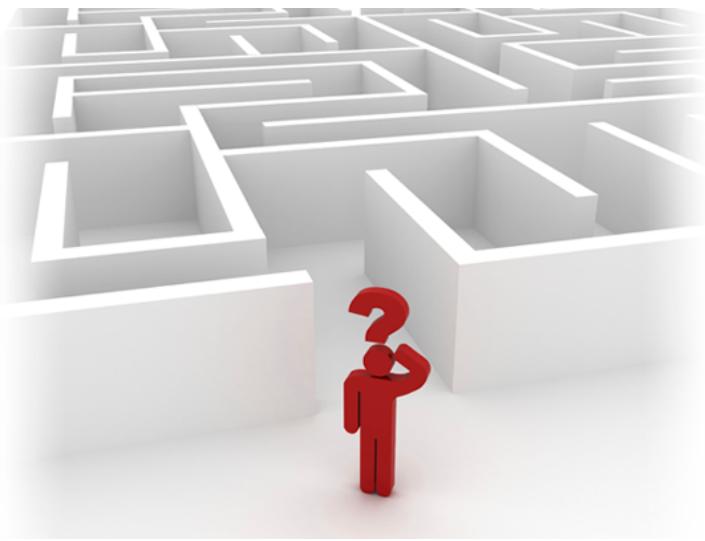
The Seven Products :  $P_1 = A(F-H)$ ,  $P_2 = (A+B)H$ ,  
 $P_3 = ((A+D)E$ ,  $P_4 = D(G-E)$ ,  $P_5 = (A+D)(E+F)$ ,  
 $P_6 = (B-D)(G+H)$ ,  $P_7 = (A-C)(E+F)$

Claim :  $X \cdot Y = \begin{pmatrix} AE + BG & AF + BH \\ CE + DG & CF + DH \end{pmatrix} = \begin{pmatrix} P_5 + P_4 - P_2 + P_6 \\ P_3 + P_4 \end{pmatrix} \begin{pmatrix} P_1 + P_2 \\ P_1 + P_5 - P_3 - P_7 \end{pmatrix}$

Proof:  ~~$AE + AH + DE + DH + DG - DE - AH - BH$~~   
 ~~$+ BG + BH - DG - DH$~~   $= AE + BG$  (remains)

Q.E.D

Question : where did this come from ? open!



Design and Analysis  
of Algorithms I

# Divide and Conquer

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## Closest Pair I

# The Closest Pair Problem

Input : a set  $P = \{p_1, \dots, p_n\}$  of  $n$  points in the plane  $\mathbb{R}^2$ .

Notation :  $d(p_i, p_j)$  = Euclidean distance

So if  $p_i = (x_i, y_i)$  and  $p_j = (x_j, y_j)$

$$d(p_i, p_j) = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2}$$

Output : a pair  $p^*, q^* \in P$  of distinct points that minimize  $d(p, q)$  over  $p, q$  in the set  $P$

# Initial Observations

Assumption : (for convenience) all points have distinct x-coordinates, distinct y-coordinates.

Brute-force search : takes  $\theta(n^2)$  time.

1-D Version of Closest Pair :



1. Sort points ( $O(n \log(n))$  time)
2. Return closest pair of adjacent points ( $O(n)$  time)

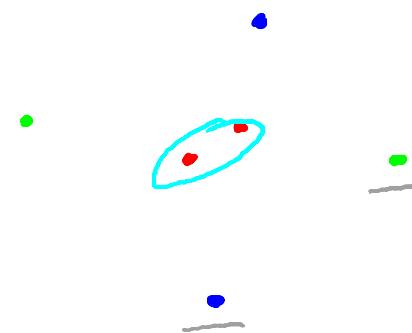
Goal :  $O(n \log(n))$  time algorithm for 2-D version.

# High-Level Approach

1. Make copies of points sorted by x-coordinate ( $P_x$ ) and by y-coordinate ( $P_y$ )  
[O(nlog(n)) time]

(but this is not enough!)

- ## 2. Use Divide+Conquer



# The Divide and Conquer Paradigm

1. DIVIDE into smaller subproblems.
2. CONQUER subproblems recursively.
3. COMBINE solutions of subproblems into one for the original problem.

# ClosestPair( $P_x, P_y$ )

BASE CASE  
OMITTED

1. Let  $Q = \text{left half of } P, R = \text{right half of } P$ . Form

$Q_x, Q_y, R_x, R_y$  [takes  $O(n)$  time]

2.  $(p_1, q_1) = \text{ClosestPair}(Q_x, Q_y)$
3.  $(p_2, q_2) = \text{ClosestPair}(R_x, R_y)$
4.  $(p_3, q_3) = \text{ClosestSplitPair}(P_x, P_y)$
5. Return best of  $(p_1, q_1), (p_2, q_2), (p_3, q_3)$

Suppose we can correctly implement the ClosestSplitPair subroutine in  $O(n)$  time. What will be the overall running time of the Closest Pair algorithm ? (Choose the smallest upper bound that applies.)

- $O(n)$
- $O(n \log n)$
- $O(n(\log n)^2)$
- $O(n^2)$

Key Idea : only need to bother computing the closest split pair in “unlucky case” where its distance is less than  $d(p_1, q_1)$  and  $d(p_2, q_2)$ .

**Result of 1<sup>st</sup> recursive call**

**Result of 2<sup>nd</sup> recursive call**

# ClosestPair( $P_x, P_y$ )

1. Let  $Q = \text{left half of } P$ ,  $R = \text{right half of } P$ . Form

BASE CASE  
OMITTED

$Q_x, Q_y, R_x, R_y$  [takes  $O(n)$  time]

2.  $(p_1, q_1) = \text{ClosestPair}(Q_x, Q_y)$

3.  $(p_2, q_2) = \text{ClosestPair}(R_x, R_y)$

4. Let  $\delta = \min\{d(p_1, q_1), d(p_2, q_2)\}$

5.  $(p_3, q_3) = \text{ClosestSplitPair}(P_x, P_y, \delta)$

6. Return best of  $(p_1, q_1), (p_2, q_2), (p_3, q_3)$

WILL DESCRIBE NEXT

## Requirements

1.  $O(n)$  time
2. Correct whenever closest pair of  $P$  is a split pair

# ClosestSplitPair( $P_x, P_y, \delta$ )

Let  $\bar{x}$  = biggest x-coordinate in left of  $P$ . (O(1) time)

Let  $S_y$  = points of  $P$  with x-coordinate in  
Sorted by y-coordinate (O(n) time)

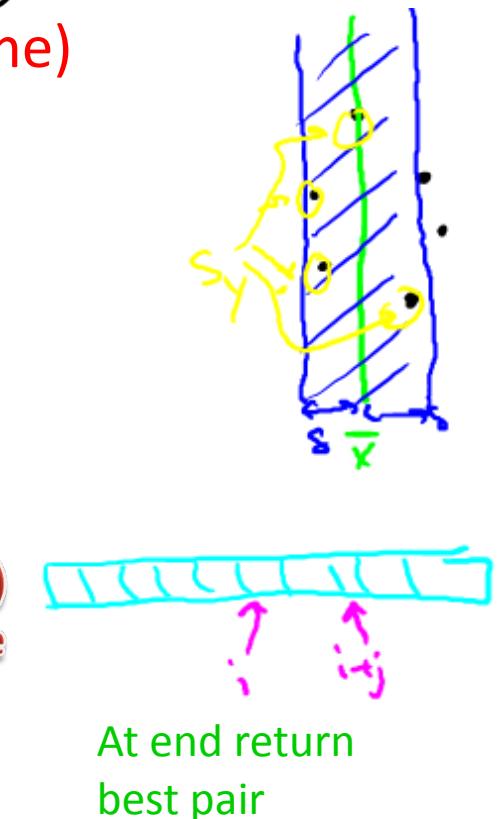
Initialize best =  $\delta$ , best pair = NULL

For  $i = 1$  to  $|S_y| - 7$

    For  $j = 1$  to 7

O(1)  
time      Let  $p, q = i^{\text{th}}, (i+j)^{\text{th}}$  points of  $S_y$   
        If  $d(p, q) < \text{best}$

            best pair =  $(p, q)$ ,  $\text{best} = d(p, q)$



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# Correctness Claim

Claim : Let  $p \in Q, q \in R$  be a split pair with  $d(p, q) < \delta$

$$\min\{d(p_1, q_1), d(p_2, q_2)\}$$

Then: (A) p and q are members of  $S_y$

(B) p and q are at most 7 positions apart in  $S_y$ .



Corollary1 : If the closest pair of P is a split pair, then the ClosestSplitPair finds it.

Corollary2 ClosestPair is correct, and runs in  $O(n \log(n))$  time.

Assuming  
claim is true!



Design and Analysis  
of Algorithms I

# Divide and Conquer

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## Closest Pair II

# Correctness Claim

Claim : Let  $p \in Q, q \in R$  be a split pair with  $d(p, q) < \delta$

Then: (A) p and q are members of  $S_y$

(B) p and q are at most 7 positions apart in  $S_y$ .

$$\min\{d(p_1, q_1), d(p_2, q_2)\}$$

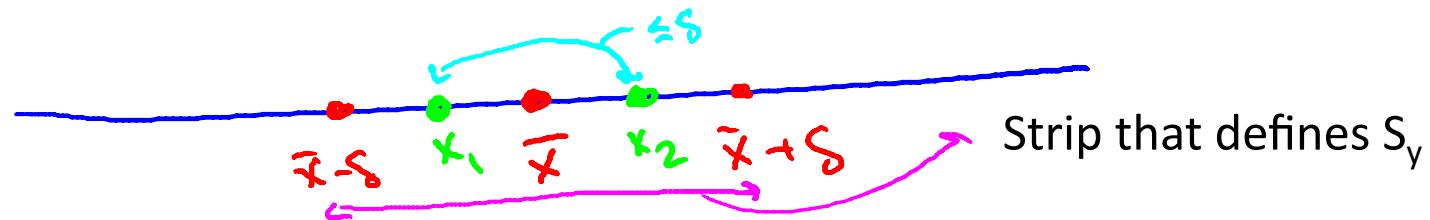


# Proof of Correctness Claim (A)

Let  $p = (x_1, y_1) \in Q$ ,  $q = (x_2, y_2) \in R$ ,  $d(p, q) \leq \delta$

Note : Since  $d(p, q) \leq \delta$ ,  $|x_1 - x_2| \leq \delta$  and  $|y_1 - y_2| \leq \delta$

Proof of (A) [p and q are members of  $S_y$  i.e.  $x_1, x_2 \in [\bar{x} - \delta, \bar{x} + \delta]$  ]



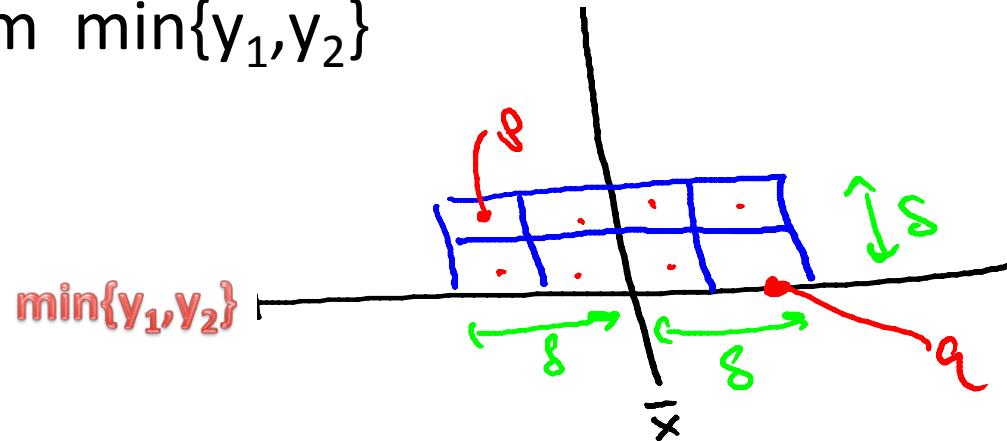
Note :  $p \in Q \Rightarrow x_1 \leq \bar{x}$  and  $q \in R \Rightarrow x_2 \geq \bar{x}$ .

$$\Rightarrow x_1, x_2 \in [\bar{x} - \delta, \bar{x} + \delta]$$

# Proof of Correctness Claim (B)

(B) :  $p = (x_1, y_1)$  and  $q = (x_2, y_2)$  are at most 7 positions apart in  $S_y$

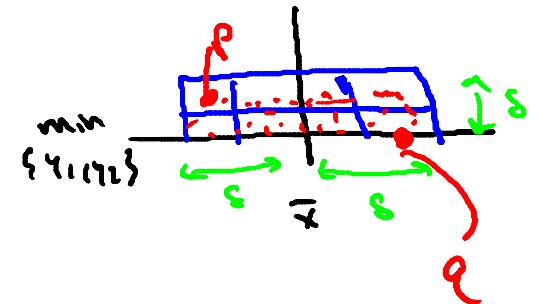
Key Picture : draw  $\delta/2 \times \delta/2$  boxes with center  $\bar{x}$  and bottom  $\min\{y_1, y_2\}$



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# Proof of Correctness Claim (B)

Lemma 1 : all points of  $S_y$  with y-coordinate between those of p and q, inclusive, lie in one of these 8 boxes.



Proof : First, recall y-coordinates of p,q differ by  $< \delta$   
Second, by definition of  $S_y$ , all have  
x-coordinates between  $\bar{x} - \delta$  and  $\bar{x} + \delta$

Q.E.D

# Proof of Correctness Claim (B)

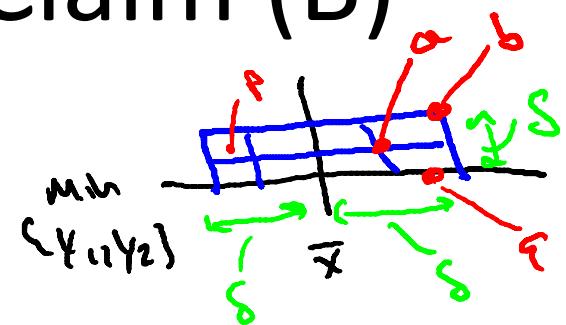
Lemma 2 : At most one point  
of P in each box.

Proof : by contradiction

Suppose a,b lie in the same box. Then :

- I. a,b are either both in Q or both in R
- II.  $d(a, b) \leq \frac{\delta}{2} \cdot \sqrt{2} \leq \delta$

But (i) and (ii) contradict the definition of  $\delta$   
(as smallest distance between pairs of points  
in Q or in R)



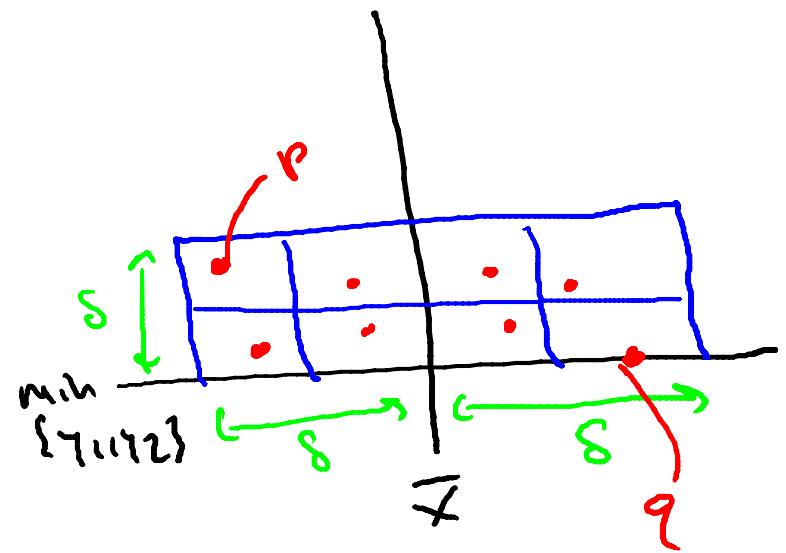
Q.E.D

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# Final Wrap-Up

Lemmas 1 and 2 => at most 8  
points in this picture  
(including p and q)

=> Positions of p,q in  $S_y$  differ  
by at most 7



Q.E.D

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