Introduction to Algorithms

Divide and Conquer

Divide and Conquer

- Divide and Conquer algorithms consist of two parts:
 - **Divide:** Smaller problems are solved recursively (except, of course, the base cases).
 - **Conquer:** The solution to the original problem is then formed from the solutions to the subproblems.

Divide and Conquer

- Traditionally
 - Algorithms which contain at least 2 recursive calls are called *divide and conquer* algorithms, while algorithms with one recursive call are not.
- Classic Examples
 - Mergesort and Quicksort
- Examples of recursive algorithms that are not Divide and Conquer
 - **Findset** in a Disjoint Set implementation is not divide and conquer.
 - Mostly because it doesn't "divide" the problem into smaller sub-problems since it only has one recursive call.
 - Even though the recursive method to compute the Fibonacci numbers has 2 recursive calls
 - It's really not divide and conquer because it doesn't divide the problem.

This Lecture

- *Divide-and-conquer* technique for algorithm design. Example problems:
 - Integer Multiplication
 - Subset Sum Recursive Problem
 - Closest Points Problem
 - Strassen's Algorithm

• The standard integer multiplication routine of 2 n-digit numbers

- Involves n multiplications of an n-digit number by a single digit
- Plus the addition of n numbers, which have at most 2 n digits

		<u>quantity</u>	<u>time</u>
<i>1)</i>	Multiplication n-digit by 1-digit	n	O(n)
<i>2)</i>	Additions 2n-digit by n-digit max	n	O(n)

Total time =
$$n*O(n) + n*O(n) = 2n*O(n) = O(n^2)$$

 Let's consider a Divide and Conquer Solution

- Imagine multiplying an n-bit number by another n-bit number.
 - We can split up each of these numbers into 2 halves.
 - ◆ Let the 1st number be I, and the 2nd number J
 - Let the "left half" of the 1^{st} number by I_h and the "right half" be I_l .
- So in this example: I is 1011 and J is 1111
 - I becomes $10*2^2 + 11$ where $I_h = 10*2^2$ and $I_l = 11$.
 - and $J_h = 11*2^2$ and $J_1 = 11$

- So for multiplying any n-bit integers I and J
 - We can split up I into $(I_h * 2^{n/2}) + I_1$
 - And J into $(J_h * 2^{n/2}) + J_1$
- Then we get
 - $I \times J = [(I_h \times 2^{n/2}) + I_1] \times [(J_h \times 2^{n/2}) + J_1]$
 - $I \times J = I_h \times J_h \times 2^n + (I_1 \times J_h + I_h \times J_1) \times 2^{n/2} + I_1 \times J_1$
- So what have we done?
 - We've broken down the problem of multiplying 2 n-bit numbers into
 - 4 multiplications of n/2-bit numbers plus 3 additions.
 - $T(n) = 4T(n/2) + \theta(n)$
 - Solving this using the master theorem gives us...
 - $T(n) = \theta(n^2)$

- So we haven't really improved that much,
 - Since we went from a $O(n^2)$ solution to a $O(n^2)$ solution
- Can we optimize this in any way?
 - We can re-work this formula using some clever choices...
 - Some clever choices of:

$$\begin{split} P_1 &= (I_h + I_l) \; x \; (J_h + J_l) = I_h x J_h \; + \; I_h x \; J_l \; + \; I_l x J_h \; + \; I_l x J_l \\ P_2 &= I_h \; x \; J_h \; , \; \text{and} \\ P_3 &= I_l \; x \; J_l \end{split}$$

■ Now, note that

$$P_1 - P_2 - P_3 = I_h x J_h + I_h x J_1 + I_1 x J_h + I_1 x J_1 - I_h x J_h - I_1 x J_1$$

= $I_h x J_1 + I_1 x J_h$

■ Then we can substitute these in our original equation:

$$I \times J = P_2 \times 2^n + [P_1 - P_2 - P_3] \times 2^{n/2} + P_3.$$

$$I \times J = P_2 \times 2^n + [P_1 - P_2 - P_3] \times 2^{n/2} + P_3.$$

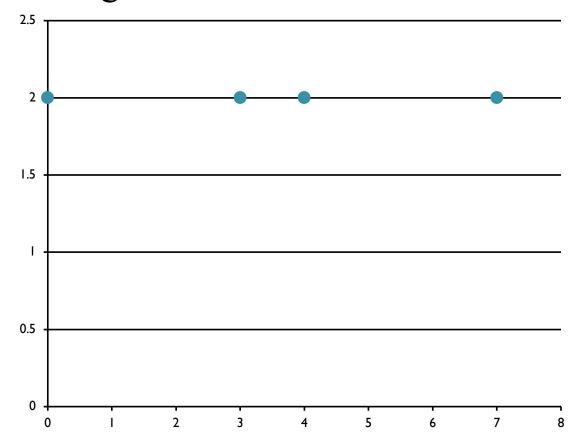
- Have we reduced the work?
 - Calculating P2 and P3 take n/2-bit multiplications.
 - P1 takes two n/2-bit additions and then one n/2-bit multiplication.
 - Then, 2 subtractions and another 2 additions, which take O(n) time.
- This gives us : $T(n) = 3T(n/2) + \theta(n)$
 - Solving gives us $T(n) = \theta(n^{(\log_2 3)})$, which is approximately $T(n) = \theta(n^{1.585})$, a solid improvement.

- Although this seems it would be slower initially because of some extra pre-computing before doing the multiplications, *for very large integers*, this will save time.
- Q: Why won't this save time for small multiplications?
 - A: The hidden constant in the $\theta(n)$ in the second recurrence is much larger. It consists of 6 additions/subtractions whereas the $\theta(n)$ in the first recurrence consists of 3 additions/subtractions.

Finding the Closest Pair of Points

• Problem:

■ Given n ordered pairs (x_1, y_1) , (x_2, y_2) , ..., (x_n, y_n) , find the distance between the two points in the set that are closest together.



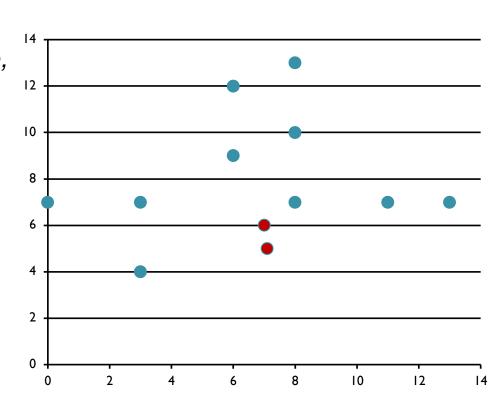
- Brute Force Algorithm
 - Iterate through all possible pairs of points, calculating the distance between each of these pairs. Any time you see a distance shorter than the shortest distance seen, update the shortest distance seen.

Since computing the distance between two points takes O(1) time,

And there are a total of $n(n-1)/2 = \theta(n^2)$ distinct pairs of points,

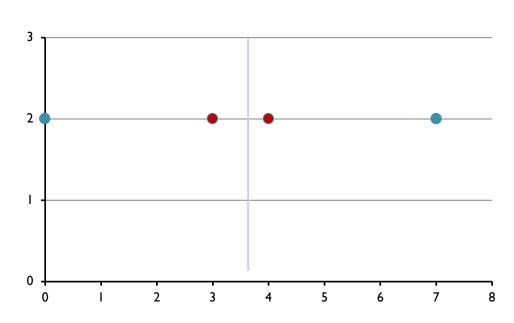
It follows that the running time of this algorithm is $\theta(n^2)$.

Can we do better?



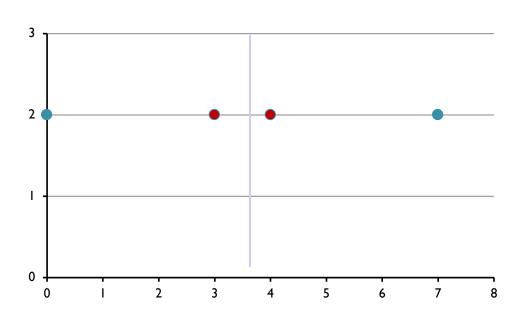
- Here's the idea:
 - 1) Split the set of n points into 2 halves by a vertical line.
 - Do this by sorting all the points by their x-coordinate and then picking the middle point and drawing a vertical line just to the right of it.
 - 2) Recursively solve the problem on both sets of points.
 - Return the smaller of the two values.

• What's the problem with this idea?



• The problem is that the actual shortest distance between any 2 of the original points MIGHT BE between a point in the 1st set and a point in the 2nd set! Like in this situation:

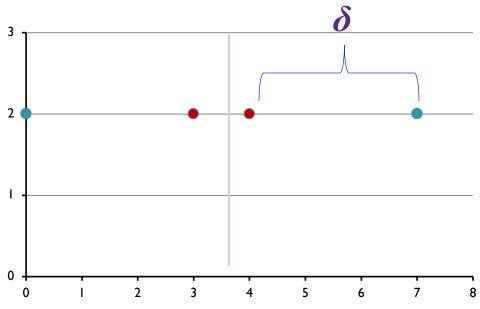
 So we would get a shortest distance of 3, instead of 1.



- Original idea:
 - 1) Split the set of n points into 2 halves by a vertical line.
 - Do this by sorting all the points by their x-coordinate and then picking the middle point and drawing a vertical line just to the right of it.
 - 2) Recursively solve the problem on both sets of points.
 - *3)* Return the smaller of the two values.

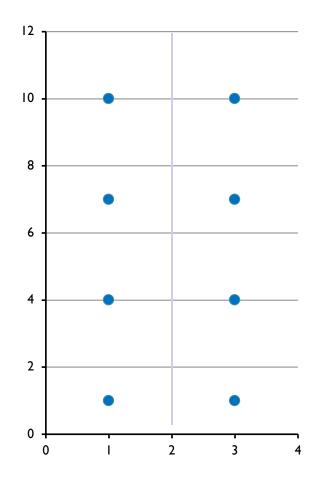
We must adapt our approach:

- In step 3, we can "save" the smaller of the two values (called δ), then we have to check to see if there are points that are closer than δ apart.
- Do we need to search thru all possible pairs of points from the 2 different sides?
 - NO, we can only consider points that are within δ of our dividing line.

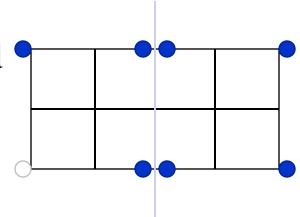


• However, one could construct a case where ALL the points on each side are within δ of the vertical line:

- So, this case is as bad as our original idea where we'd have to compare each pair of points to one another from the different groups.
- But, wait!! Is it really necessary to compare each point on one side with every other point on every other side???

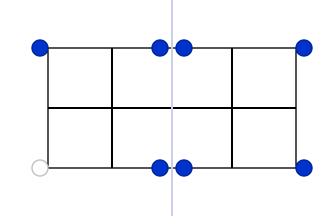


• Consider the following rectangle around the dividing line that is constructed by eight $\delta/2 \times \delta/2$ squares.



- Note that the diagonal of each square is $\delta/\sqrt{2}$, which is less than δ .
- Since each square lies on a single side of the dividing line, at most one point lies in each box
 - Because if 2 points were within a single box the distance between those 2 points would be less than δ .
- Therefore, there are at MOST 7 other points that could possibly be a distance of less than δ apart from a given point, that have a greater y coordinate than that point.
 - (We assume that our point is on the bottom row of this grid; we draw the grid that way.)

• Now we have the issue of how do we know *which 7 points* to compare a given point with?



- The idea is:
 - As you are processing the points recursively, **SORT** them based on the **y-coordinate**.
- Then for a given point within the strip, you only need to compare with the <u>next 7 points</u>.

- Now the Recurrence relation for the runtime of this problem is:
 - T(n) = 2T(n/2) + O(n)
 - Which is the same as Mergesort, which we've shown to be O(n log n).

Subset Sum Recursive Problem

- Given n items and a target value, T, determine whether there is a subset of the items such that their sum equals T.
 - Determine whether there is a subset S of $\{1, ..., n\}$ such that the elements of S add up to T.
- Two cases:
 - Either there is a subset S in items $\{1, ..., n-1\}$ that adds up to T.
 - Or there is a subset S in items $\{1,..., n-1\}$ that adds up to T n, where S U $\{n\}$ is the solution.
- The divide-and-conquer algorithm based on this recursive solution has a running time given by the recurrence:
 - T(n) = 2T(n-1) + O(1)

- A fundamental numerical operation is the multiplication of 2 matrices.
 - The standard method of matrix multiplication of two n x n matrices takes T(n) = O(n3).

$$\begin{bmatrix} a_{11} & a_{12} & a_{13} & a_{14} \\ a_{21} & a_{22} & a_{23} & a_{24} \\ a_{31} & a_{32} & a_{33} & a_{34} \\ a_{41} & a_{42} & a_{43} & a_{44} \end{bmatrix} \times \begin{bmatrix} b_{11} & b_{12} & b_{13} & b_{14} \\ b_{21} & b_{22} & b_{23} & b_{24} \\ b_{31} & b_{32} & b_{33} & b_{34} \\ b_{41} & b_{42} & b_{43} & b_{44} \end{bmatrix} = \begin{bmatrix} c_{11} \\ c_{12} \\ c_{13} \\ c_{11} \\ c_{12} \\ c_{13} \\ c_{14} \\ c_{15} \\$$

The following algorithm multiples n x n matrices A and B:

```
// Initialize C.

for i = 1 to n

for j = 1 to n

for k = 1 to n

C [i, j] += A[i, k] * B[k, j];
```

• We can use a Divide and Conquer solution to solve matrix multiplication by separating a matrix into 4 quadrants:

$$\begin{bmatrix} a_{11} & a_{12} & a_{13} & a_{14} \\ a_{21} & a_{22} & a_{23} & a_{24} \\ a_{31} & a_{32} & a_{33} & a_{34} \\ a_{41} & a_{42} & a_{43} & a_{44} \end{bmatrix} \times \begin{bmatrix} b_{11} & b_{12} & b_{13} & b_{14} \\ b_{21} & b_{22} & b_{23} & b_{24} \\ b_{31} & b_{32} & b_{33} & b_{34} \\ b_{41} & b_{42} & b_{43} & b_{44} \end{bmatrix} = \begin{bmatrix} c_{11} & c_{12} & c_{13} & c_{14} \\ c_{21} & c_{22} & c_{23} & c_{24} \\ c_{31} & c_{32} & c_{33} & c_{34} \\ c_{41} & c_{42} & c_{43} & c_{44} \end{bmatrix}$$

• Then we know have:

$$A = \begin{pmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{pmatrix} \quad B = \begin{pmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{pmatrix} \qquad C = \begin{pmatrix} c_{11} & c_{12} \\ c_{21} & c_{22} \end{pmatrix}$$

if
$$C=AB$$
 , then we have the following: $c_{11}=a_{11}b_{11}+a_{12}b_{21}$ $c_{12}=a_{11}b_{12}+a_{12}b_{22}$ $c_{21}=a_{21}b_{11}+a_{22}b_{21}$ $c_{22}=a_{21}b_{12}+a_{22}b_{22}$

8 n/2 * n/2 matrix multiples + 4 n/2 * n/2 matrix additions $T(n) = 8T(n/2) + O(n^2)$ If we solve using the master theorem we still have $O(n^3)$

- Strassen showed how two matrices can be multiplied using only 7 multiplications and 18 additions:
 - Consider calculating the following 7 products:

$$q_1 = (a_{11} + a_{22}) * (b_{11} + b_{22})$$

$$\cdot q_2 = (a_{21} + a_{22}) * b_{11}$$

$$q_3 = a_{11} * (b_{12} - b_{22})$$

$$\cdot \quad q_4 = a_{22} * (b_{21} - b_{11})$$

$$q_5 = (a_{11} + a_{12}) * b_{22}$$

$$\cdot q_6 = (a_{21} - a_{11}) * (b_{11} + b_{12})$$

$$\cdot q_7 = (a_{12} - a_{22}) * (b_{21} + b_{22})$$

■ It turns out that

$$c_{11} = q_1 + q_4 - q_5 + q_7$$

•
$$c_{12} = q_3 + q_5$$

•
$$c_{21} = q_2 + q_4$$

•
$$c_{22} = q_1 + q_3 - q_2 + q_6$$

• Let's verify one of these:

Given:
$$A = \begin{pmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{pmatrix}$$
 $B = \begin{pmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{pmatrix}$ $C = \begin{pmatrix} c_{11} & c_{12} \\ c_{21} & c_{22} \end{pmatrix}$

if
$$C=AB$$
 , we know: $c_{21}=a_{21}b_{11}+a_{22}b_{21}$

- Strassen's Algorithm states:
 - $c_{21} = q_2 + q_4$, where $q_4 = a_{22} * (b_{21} - b_{11})$ and $q_2 = (a_{21} + a_{22}) * b_{11}$

	Mult	Add	Recurrence Relation	Runtime
Regular	8	4	$T(n) = 8T(n/2) + O(n^2)$	$O(n^3)$
Strassen	7	18	$T(n) = 7T(n/2) + O(n^2)$	$O(n^{\log_2 7}) = O(n^{2.81})$

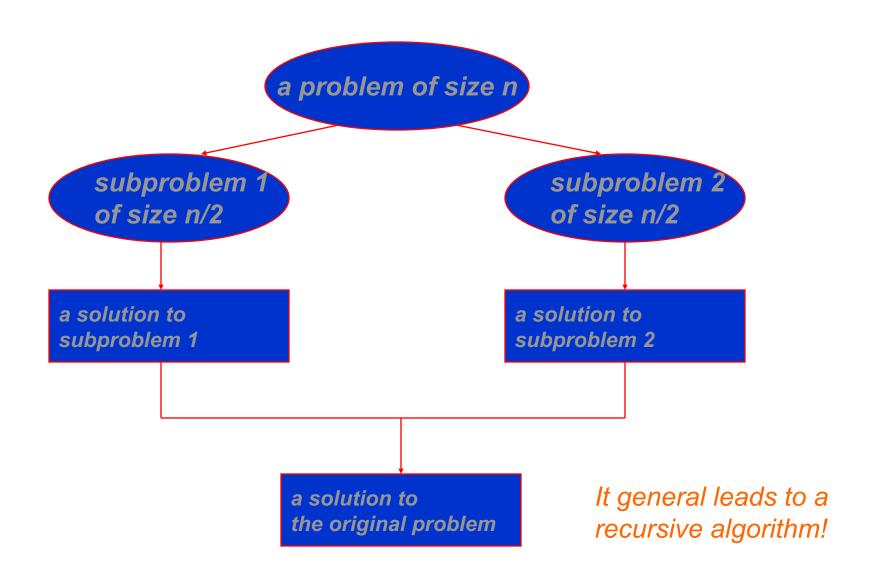
- I have no idea how Strassen came up with these combinations.
 - He probably realized that he wanted to determine each element in the product using less than 8 multiplications.
 - · From there, he probably just played around with it.
- If we let T(n) be the running time of Strassen's algorithm, then it satisfies the following recurrence relation:
 - $T(n) = 7T(n/2) + O(n^2)$
 - It's important to note that the hidden constant in the $O(n^2)$ term is larger than the corresponding constant for the standard divide and conquer algorithm for this problem.
 - However, for large matrices this algorithm yields an improvement over the standard one with respect to time.

Divide-and-Conquer Summary

The most-well known algorithm design strategy:

- 1. Divide instance of problem into two or more smaller instances
- 2. Solve smaller instances recursively
- 3. Obtain solution to original (larger) instance by combining these solutions

Divide-and-Conquer Technique



Divide-and-Conquer Examples

Sorting: mergesort and quicksort

- The Algorithms we've reviewed:
 - Integer Multiplication
 - Closest Pair of Points Problem
 - Subset Sum Recursive Problem
 - Strassen's Algorithm for Matrix Multiplication