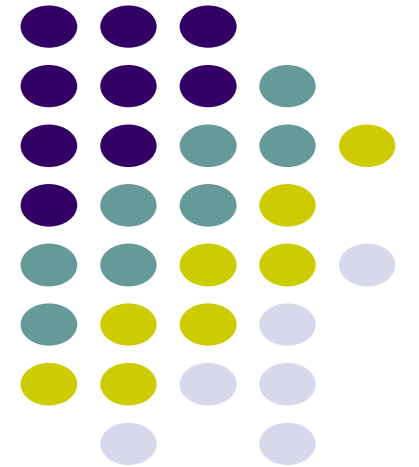


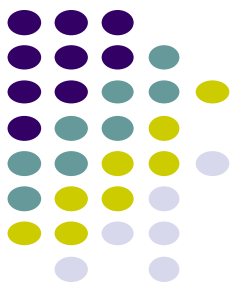
Divide and Conquer Algorithms

Recurrence Relations

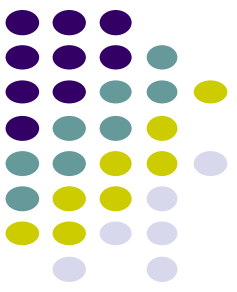
Dr. Navjot Singh
Design and Analysis of Algorithms



Divide and Conquer



- Recursive in structure
 - **Divide** the problem into sub-problems that are similar to the original but smaller in size
 - **Conquer** the sub-problems by solving them **recursively**. If they are small enough, just solve them in a straightforward manner.
 - **Combine** the solutions to create a solution to the original problem

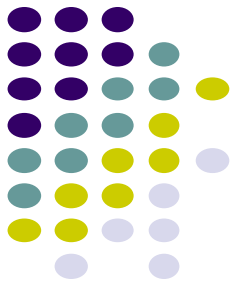


An Example: Merge Sort

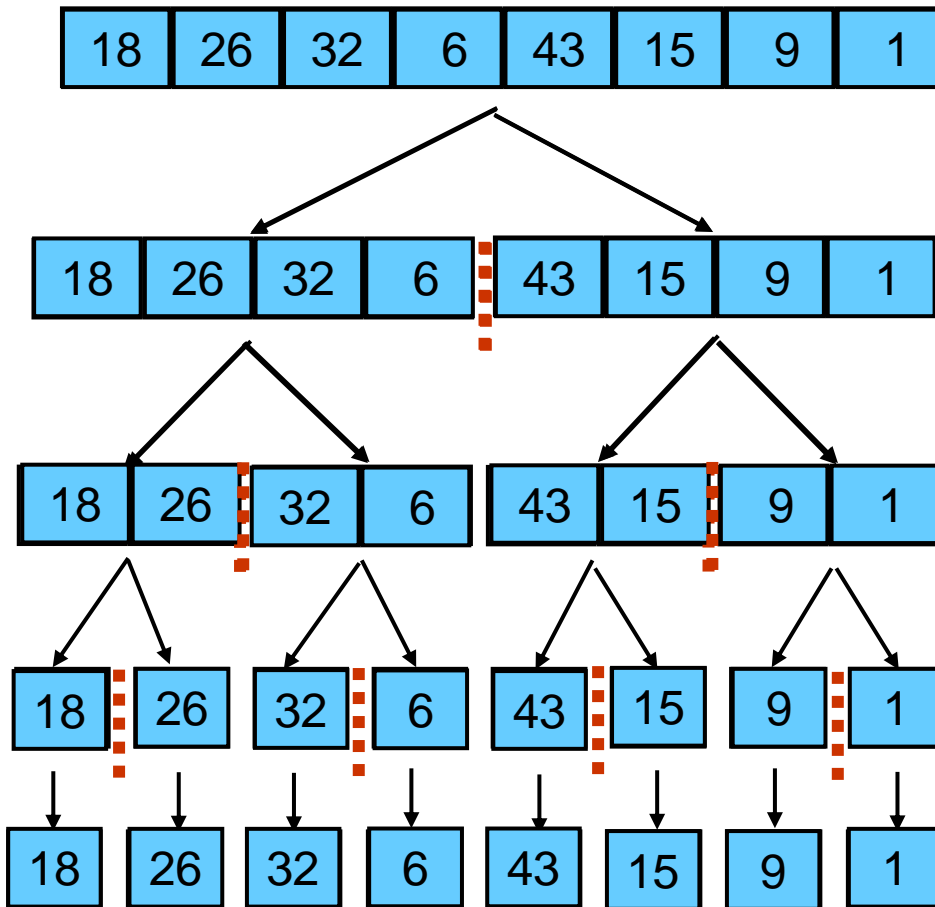
Sorting Problem: Sort a sequence of n elements into non-decreasing order.

- **Divide:** Divide the n -element sequence to be sorted into two subsequences of $n/2$ elements each
- **Conquer:** Sort the two subsequences recursively using merge sort.
- **Combine:** Merge the two sorted subsequences to produce the sorted answer.

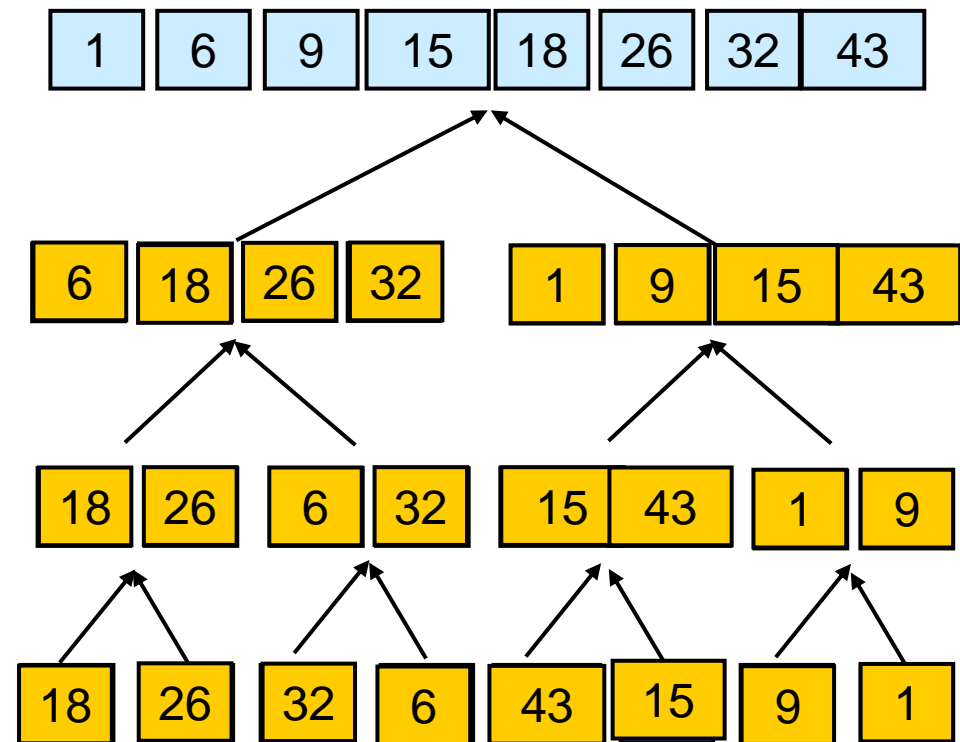
Merge Sort – Example

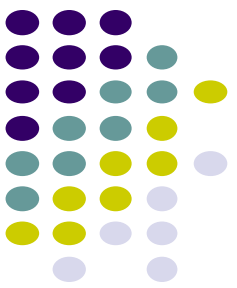


Original Sequence



Sorted Sequence





Merge-Sort (A, p, r)

INPUT: a sequence of n numbers stored in array A

OUTPUT: an ordered sequence of n numbers

```
MergeSort ( $A, p, r$ ) // sort  $A[p..r]$  by divide & conquer
1  if  $p < r$ 
2    then  $q \leftarrow \lfloor (p+r)/2 \rfloor$ 
3         MergeSort ( $A, p, q$ )
4         MergeSort ( $A, q+1, r$ )
5         Merge ( $A, p, q, r$ ) // merges  $A[p..q]$  with  $A[q+1..r]$ 
```

Initial Call: *MergeSort*($A, 1, n$)

Procedure Merge



Merge(A, p, q, r)

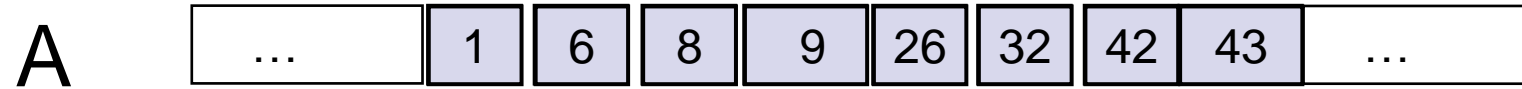
```
1  $n_1 \leftarrow q - p + 1$ 
2  $n_2 \leftarrow r - q$ 
3   for  $i \leftarrow 1$  to  $n_1$ 
4     do  $L[i] \leftarrow A[p + i - 1]$ 
5   for  $j \leftarrow 1$  to  $n_2$ 
6     do  $R[j] \leftarrow A[q + j]$ 
7    $L[n_1 + 1] \leftarrow \infty$ 
8    $R[n_2 + 1] \leftarrow \infty$ 
9    $i \leftarrow 1$ 
10   $j \leftarrow 1$ 
11  for  $k \leftarrow p$  to  $r$ 
12    do if  $L[i] \leq R[j]$ 
13      then  $A[k] \leftarrow L[i]$ 
14            $i \leftarrow i + 1$ 
15      else  $A[k] \leftarrow R[j]$ 
16            $j \leftarrow j + 1$ 
```

Input: Array containing sorted subarrays $A[p..q]$ and $A[q+1..r]$.

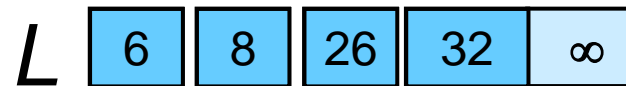
Output: Merged sorted subarray in $A[p..r]$.

Sentinels, to avoid having to check if either subarray is fully copied at **each step**.

Merge – Example



k

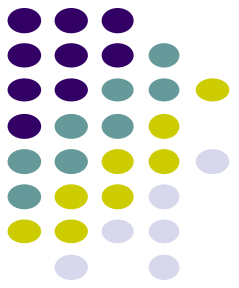


i



j

Correctness of Merge



Merge(A, p, q, r)

```
1  $n_1 \leftarrow q - p + 1$ 
2  $n_2 \leftarrow r - q$ 
3   for  $i \leftarrow 1$  to  $n_1$ 
4     do  $L[i] \leftarrow A[p + i - 1]$ 
5   for  $j \leftarrow 1$  to  $n_2$ 
6     do  $R[j] \leftarrow A[q + j]$ 
7    $L[n_1 + 1] \leftarrow \infty$ 
8    $R[n_2 + 1] \leftarrow \infty$ 
9    $i \leftarrow 1$ 
10   $j \leftarrow 1$ 
11  for  $k \leftarrow p$  to  $r$ 
12    do if  $L[i] \leq R[j]$ 
13      then  $A[k] \leftarrow L[i]$ 
14             $i \leftarrow i + 1$ 
15      else  $A[k] \leftarrow R[j]$ 
16             $j \leftarrow j + 1$ 
```

Loop Invariant for the for loop

At the start of each iteration of the for loop:

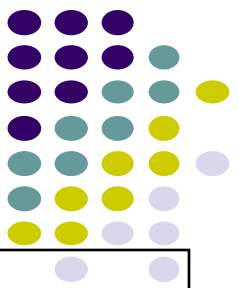
Subarray $A[p..k - 1]$ contains the $k - p$ smallest elements of L and R in sorted order. $L[i]$ and $R[j]$ are the smallest elements of L and R that have not been copied back into A .

Initialization:

Before the first iteration:

- $A[p..k - 1]$ is empty.
- $i = j = 1$.
- $L[1]$ and $R[1]$ are the smallest elements of L and R not copied to A .

Correctness of Merge



Merge(A, p, q, r)

```
1  $n_1 \leftarrow q - p + 1$ 
2  $n_2 \leftarrow r - q$ 
3   for  $i \leftarrow 1$  to  $n_1$ 
4     do  $L[i] \leftarrow A[p + i - 1]$ 
5   for  $j \leftarrow 1$  to  $n_2$ 
6     do  $R[j] \leftarrow A[q + j]$ 
7    $L[n_1 + 1] \leftarrow \infty$ 
8    $R[n_2 + 1] \leftarrow \infty$ 
9    $i \leftarrow 1$ 
10   $j \leftarrow 1$ 
11  for  $k \leftarrow p$  to  $r$ 
12    do if  $L[i] \leq R[j]$ 
13      then  $A[k] \leftarrow L[i]$ 
14            $i \leftarrow i + 1$ 
15      else  $A[k] \leftarrow R[j]$ 
16            $j \leftarrow j + 1$ 
```

Maintenance:

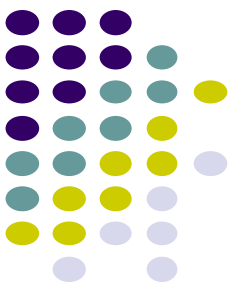
Case 1: $L[i] \leq R[j]$

- By LI, A contains $p - k$ smallest elements of L and R in sorted order.
 - By LI, $L[i]$ and $R[j]$ are the smallest elements of L and R not yet copied into A .
 - Line 13 results in A containing $p - k + 1$ smallest elements (again in sorted order).
- Incrementing i and k reestablishes the LI for the next iteration.

Similarly for $L[i] > R[j]$.

Termination:

- On termination, $k = r + 1$.
 - By LI, A contains $r - p + 1$ smallest elements of L and R in sorted order.
 - L and R together contain $r - p + 3$ elements.
- All but the two sentinels have been copied back into A .



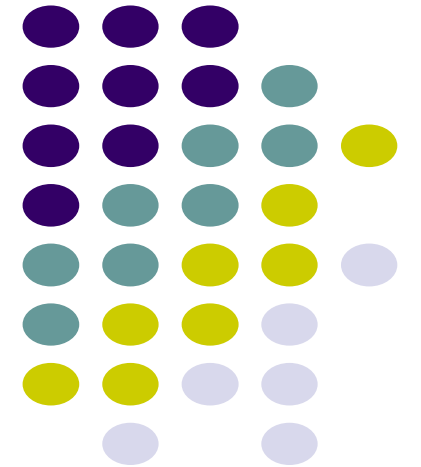
Analysis of Merge Sort

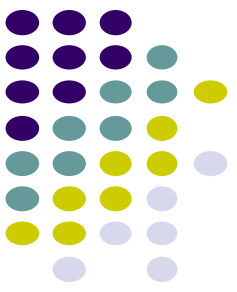
- Running time $T(n)$ of Merge Sort:
- Divide: computing the middle takes $\Theta(1)$
- Conquer: solving 2 subproblems takes $2T(n/2)$
- Combine: merging n elements takes $\Theta(n)$
- Total:

$$\begin{aligned} T(n) &= \Theta(1) && \text{if } n = 1 \\ T(n) &= 2T(n/2) + \Theta(n) && \text{if } n > 1 \end{aligned}$$

$$\Rightarrow T(n) = \Theta(n \lg n)$$

Recurrence Relations





Recurrence Relations

- Equation or an inequality that characterizes a function by its values on smaller inputs.
- **Solution Methods**
 - Substitution Method.
 - Recursion-tree Method.
 - Master Method.
- Recurrence relations **arise when we analyze the running time of iterative or recursive algorithms.**
 - **Ex:** Divide and Conquer.
$$T(n) = \Theta(1) \quad \text{if } n \leq c$$
$$T(n) = a T(n/b) + D(n) + C(n) \quad \text{otherwise}$$



Substitution Method

- Guess the form of the solution, then use mathematical induction to show it correct.
 - Substitute guessed answer for the function when the inductive hypothesis is applied to smaller values – hence, the name.
- Works well when the solution is easy to guess.
- No general way to guess the correct solution.

Substitution method



Guess the form of the solution

Then prove it's correct by induction

$$T(n) = T(n / 2) + d$$

Halves the input then constant amount of work

Similar to binary search:

Guess: $O(\log_2 n)$

Proof?



$$T(n) = T(n / 2) + d = O(\log_2 n)?$$

Ideas?

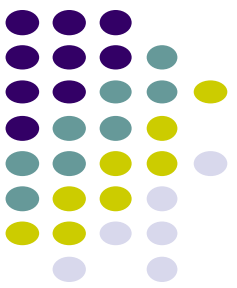
Proof?



$$T(n) = T(n / 2) + d = O(\log_2 n)?$$

Proof by induction!

- Assume it's true for smaller $T(k)$, i.e. $k < n$
- prove that it's then true for current $T(n)$



$$T(n) = T(n / 2) + d$$

Assume $T(k) = O(\log_2 k)$ for all $k < n$

Show that $T(n) = O(\log_2 n)$

From our assumption, $T(n/2) = O(\log_2 n)$:

$$O(g(n)) = \left\{ f(n) : \begin{array}{l} \text{there exists positive constants } c \text{ and } n \text{ such that} \\ 0 \leq f(n) \leq cg(n) \text{ for all } n \geq n_0 \end{array} \right\}$$

From the definition of big-O: $T(n/2) \leq c \log_2(n/2)$

How do we now prove $T(n) = O(\log n)$?

$$T(n) = T(n/2) + d$$

To prove that $T(n) = O(\log_2 n)$ identify the appropriate constants:

$$O(g(n)) = \left\{ f(n) : \begin{array}{l} \text{there exists positive constants } c \text{ and } n \text{ such that} \\ 0 \leq f(n) \leq cg(n) \text{ for all } n \geq n_0 \end{array} \right\}$$

i.e. some constant c' such that $T(n) \leq c' \log_2 n$

$$T(n) = T(n/2) + d$$

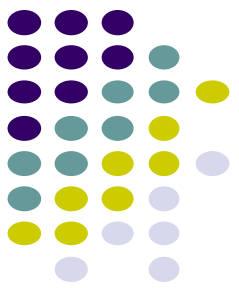
$$\leq c \log_2(n/2) + d \quad \text{from our inductive hypothesis}$$

$$\leq c \log_2 n - c \log_2 2 + d$$

$$\leq c \log_2 n - c + d \quad \text{residual}$$

Key question: does a constant exist such that:

$$T(n) \leq c' \log_2 n$$



$$T(n) = T(n/2) + d$$

To prove that $T(n) = O(\log_2 n)$ identify the appropriate constants:

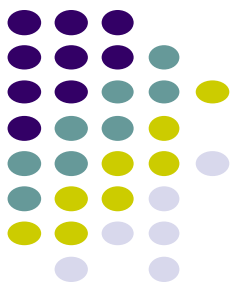
$$O(g(n)) = \left\{ f(n) : \begin{array}{l} \text{there exists positive constants } c \text{ and } n \text{ such that} \\ 0 \leq f(n) \leq cg(n) \text{ for all } n \geq n_0 \end{array} \right\}$$

i.e. some constant c_2 such that $T(n) \leq c_2 \log_2 n$

Key question: does a constant exist such that:
 $T(n) \leq c' \log_2 n$

$$T(n) \leq c \log_2 n - \underbrace{c + d}$$

if $c \geq d$, then, yes!
 (if not, just let $c' = d$)



Base case?



For an inductive proof we need to show two things:

- Assuming it's true for $k < n$ show it's true for n
- *Show that it holds for some base case*

What is the base case in our situation?

$$T(n) = \begin{cases} \Theta(1) & \text{if } n \text{ is small} \\ T(n/2) + d & \text{otherwise} \end{cases}$$

$$T(n) = T(n-1) + n$$

Guess the solution?

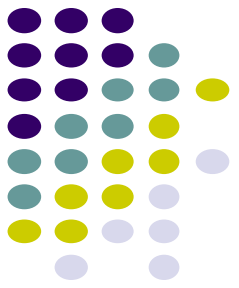
At each iteration, does a linear amount of work (i.e. iterate over the data) and reduces the size by one at each step

$$O(n^2)$$

Assume $T(k) = O(k^2)$ for all $k < n$

- again, this implies that $T(n-1) \leq c(n-1)^2$

Show that $T(n) = O(n^2)$, i.e. $T(n) \leq c'n^2$





$$\begin{aligned}T(n) &= T(n-1) + n \\&\leq c(n-1)^2 + n \quad \text{from our inductive hypothesis} \\&= c(n^2 - 2n + 1) + n \\&= cn^2 - 2cn + c + n \quad \text{residual}\end{aligned}$$

$$\text{if } -2cn + c + n \leq 0$$

then let $c' = c$ and there exists a constant such that $T(n) \leq c'n^2$



$$\begin{aligned}T(n) &= T(n-1) + n \\&\leq c(n-1)^2 + n \quad \text{from our inductive hypothesis} \\&= c(n^2 - 2n + 1) + n \\&= cn^2 - 2cn + c + n \quad \text{residual}\end{aligned}$$

$$-2cn + c + n \leq 0$$

$$-2cn + c \leq -n$$

$$c(-2n + 1) \leq -n$$

$$c \geq \frac{n}{2n-1}$$

$$c \geq \frac{1}{2-1/n}$$

which holds for any
 $c \geq 1$ for $n \geq 1$



$$T(n) = 2T(n/2) + n$$

Guess the solution?

Recurses into 2 sub-problems that are half the size
and performs some operation on all the elements

$O(n \log n)$

What if we guess wrong, e.g. $O(n^2)$?

Assume $T(k) = O(k^2)$ for all $k < n$

- again, this implies that $T(n/2) \leq c(n/2)^2$

Show that $T(n) = O(n^2)$



$$\begin{aligned}T(n) &= 2T(n/2) + n \\&\leq 2c(n/2)^2 + n \quad \text{from our inductive hypothesis} \\&= 2cn^2 / 4 + n \\&= 1/2cn^2 + n \\&= cn^2 - (1/2cn^2 - n) \quad \text{residual}\end{aligned}$$

if

$$-(1/2cn^2 - n) \leq 0$$

$$-1/2cn^2 + n \leq 0$$

$$cn \geq 2$$

overkill?

$$T(n) = 2T(n/2) + n$$

What if we guess wrong, e.g. $O(n)$?

Assume $T(k) = O(k)$ for all $k < n$

- again, this implies that $T(n/2) \leq c(n/2)$

Show that $T(n) = O(n)$

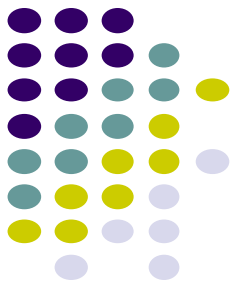
$$T(n) = 2T(n/2) + n$$

$$\leq 2cn/2 + n$$

$$= cn + n$$

$$\leq cn$$

factor of n so we can
just roll it in?





$$T(n) = 2T(n/2) + n$$

What if we guess wrong, e.g. $O(n)$?

Assume $T(k) = O(k)$ for all $k < n$

- again, this implies that $T(n/2) \leq c(n/2)$

Show that $T(n) = O(n)$

$$T(n) = 2T(n/2) + n$$

$$\leq 2cn/2 + n$$

$$= cn + n$$

$$\leq cn$$

Must prove the
exact form!

$cn + n \leq cn$??

factor of n so we can
just roll it in?

$$T(n) = 2T(n/2) + n$$

Prove $T(n) = O(n \log_2 n)$

Assume $T(k) = O(k \log_2 k)$ for all $k < n$

- again, this implies that $T(k) = ck \log_2 k$

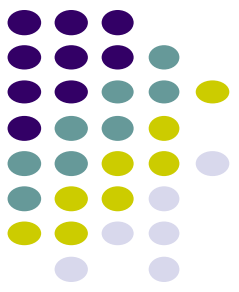
Show that $T(n) = O(n \log_2 n)$

$$\begin{aligned} T(n) &= 2T(n/2) + n \\ &\leq 2cn/2 \log(n/2) + n \\ &\leq cn(\log_2 n - \log_2 2) + n \\ &\leq cn \log_2 n - cn + n \quad \text{residual} \\ &\leq cn \log_2 n \end{aligned}$$

if $cn \geq n$, $c > 1$



Changing variables



$$T(n) = 2T(\sqrt{n}) + \log n$$

Guesses?

We can do a variable change: let $m = \log_2 n$
(or $n = 2^m$)

$$T(2^m) = 2T(2^{m/2}) + m$$

Now, let $S(m) = T(2^m)$

$$S(m) = 2S(m/2) + m$$

Changing variables



$$S(m) = 2S(m/2) + m$$

Guess? $S(m) = O(m \log m)$

$$T(n) = T(2^m) = S(m) = O(m \log m)$$

substituting $m = \log n$

$$T(n) = O(\log n \log \log n)$$



Recursion-tree Method

- Making a **good guess** is sometimes **difficult** with the substitution method.
- Use **recursion trees** to devise good guesses.
- Recursion Trees
 - Show successive expansions of recurrences using trees.
 - Keep track of the time spent on the subproblems of a divide and conquer algorithm.
 - Help organize the algebraic bookkeeping necessary to solve a recurrence.



Recursion Tree – Example

- Running time of Merge Sort:

$$T(n) = \Theta(1) \quad \text{if } n = 1$$

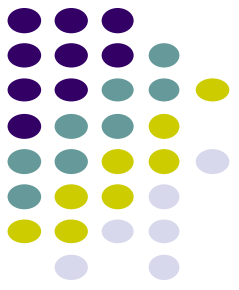
$$T(n) = 2T(n/2) + \Theta(n) \quad \text{if } n > 1$$

- Rewrite the recurrence as

$$T(n) = c \quad \text{if } n = 1$$

$$T(n) = 2T(n/2) + cn \quad \text{if } n > 1$$

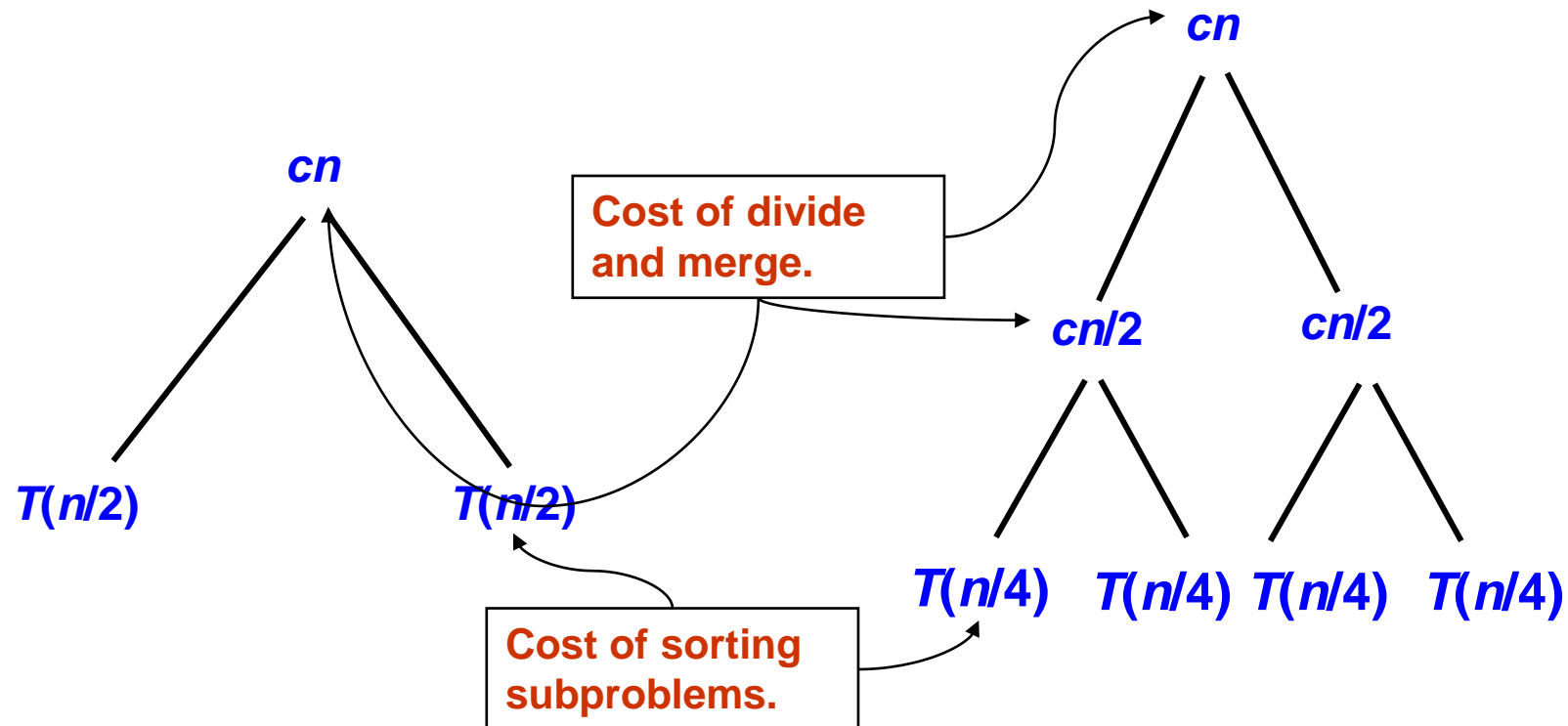
$c > 0$: Running time for the base case and time per array element for the divide and combine steps.



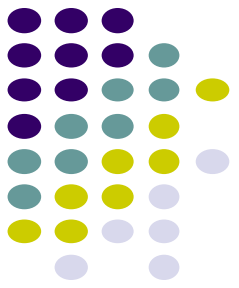
Recursion Tree for Merge Sort

For the original problem, we have a cost of cn , plus two subproblems each of size $(n/2)$ and running time $T(n/2)$.

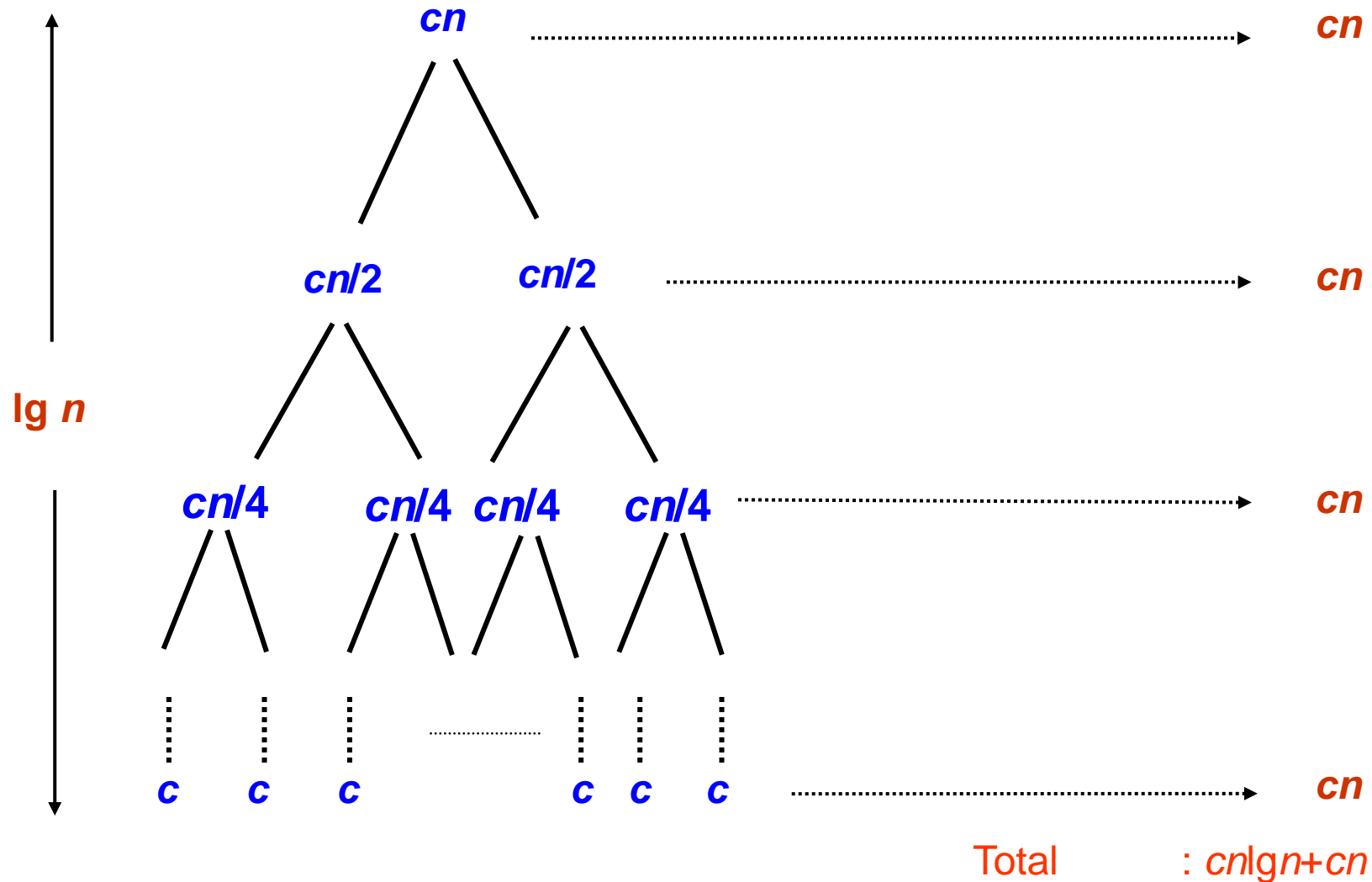
Each of the size $n/2$ problems has a cost of $cn/2$ plus two subproblems, each costing $T(n/4)$.



Recursion Tree for Merge Sort



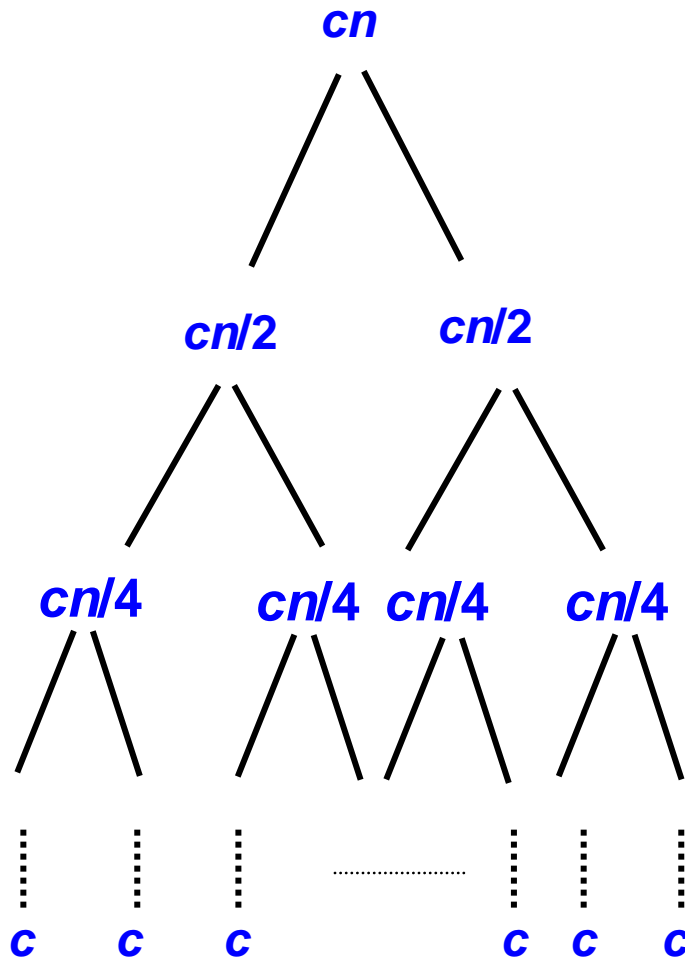
Continue expanding until the problem size reduces to 1.



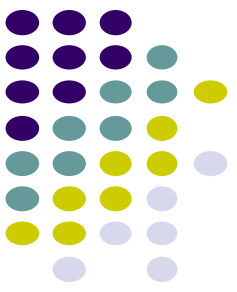


Recursion Tree for Merge Sort

Continue expanding until the problem size reduces to 1.



- Each level has total cost cn .
- Each time we go down one level, the number of subproblems doubles, but the cost per subproblem halves \Rightarrow *cost per level remains the same*.
- There are $\lg n + 1$ levels, height is $\lg n$. (Assuming n is a power of 2.)
- Can be proved by induction.
- Total cost = sum of costs at each level
 $= (\lg n + 1)cn = cn \lg n + cn = \Theta(n \lg n)$.



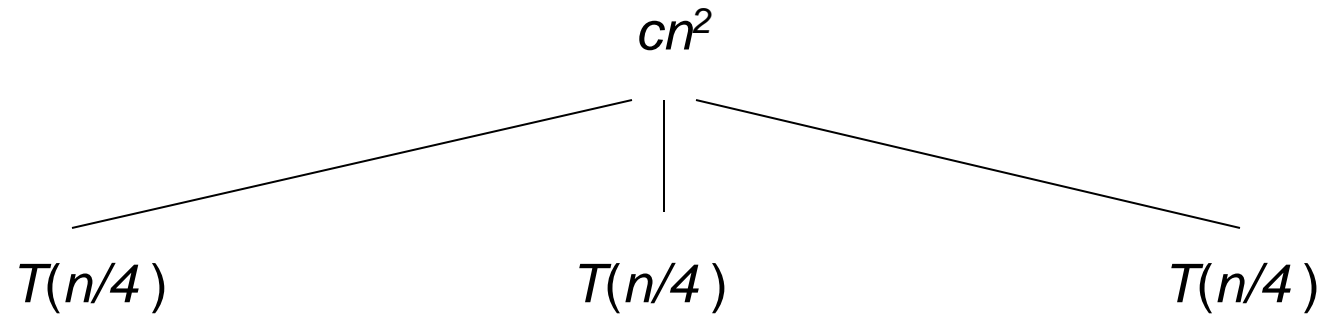
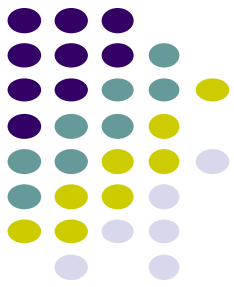
Other Examples

- Use the recursion-tree method to determine a guess for the recurrences
 - $T(n) = 3T(\lfloor n/4 \rfloor) + \Theta(n^2)$.
 - $T(n) = T(n/3) + T(2n/3) + O(n)$.

$$T(n) = 3T(n/4) + n^2$$

cost

cn^2

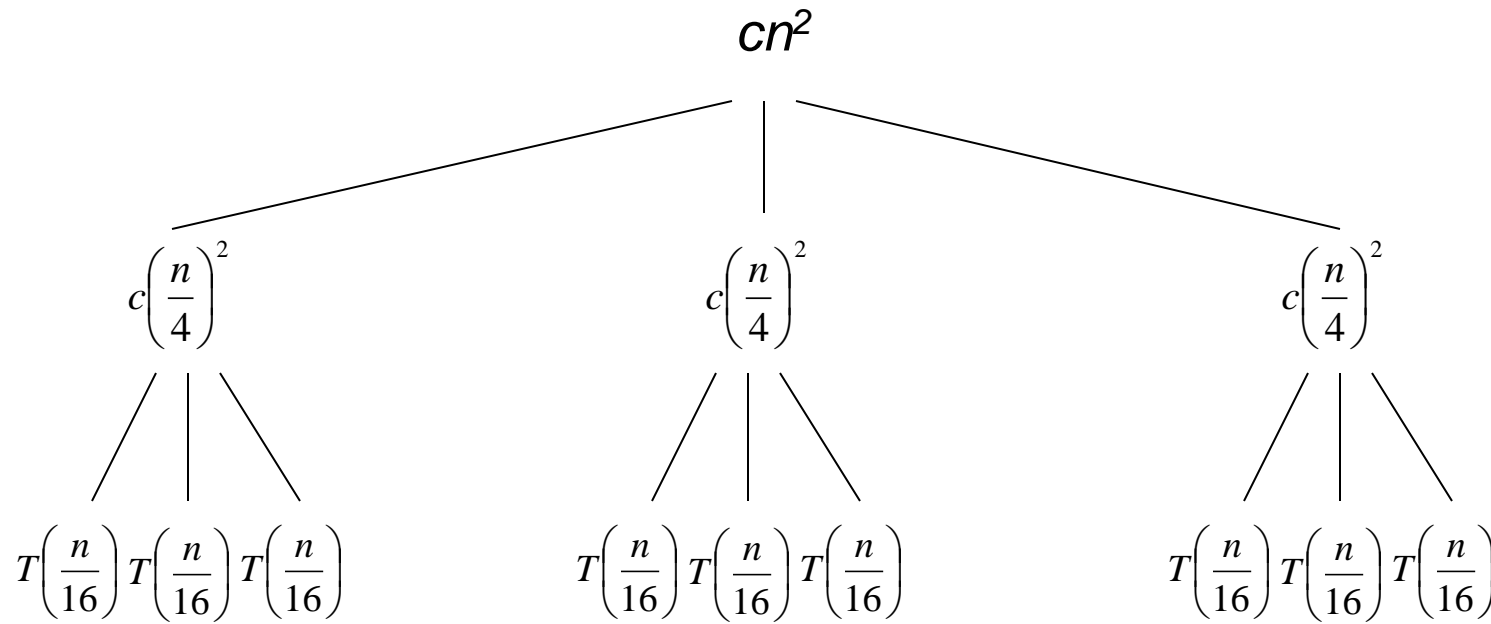
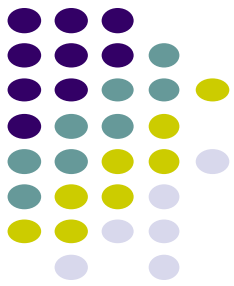


$$T(n) = 3T(n/4) + n^2$$

cost

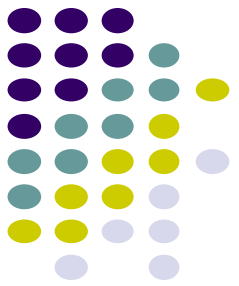
$$cn^2$$

$$3/16cn^2$$

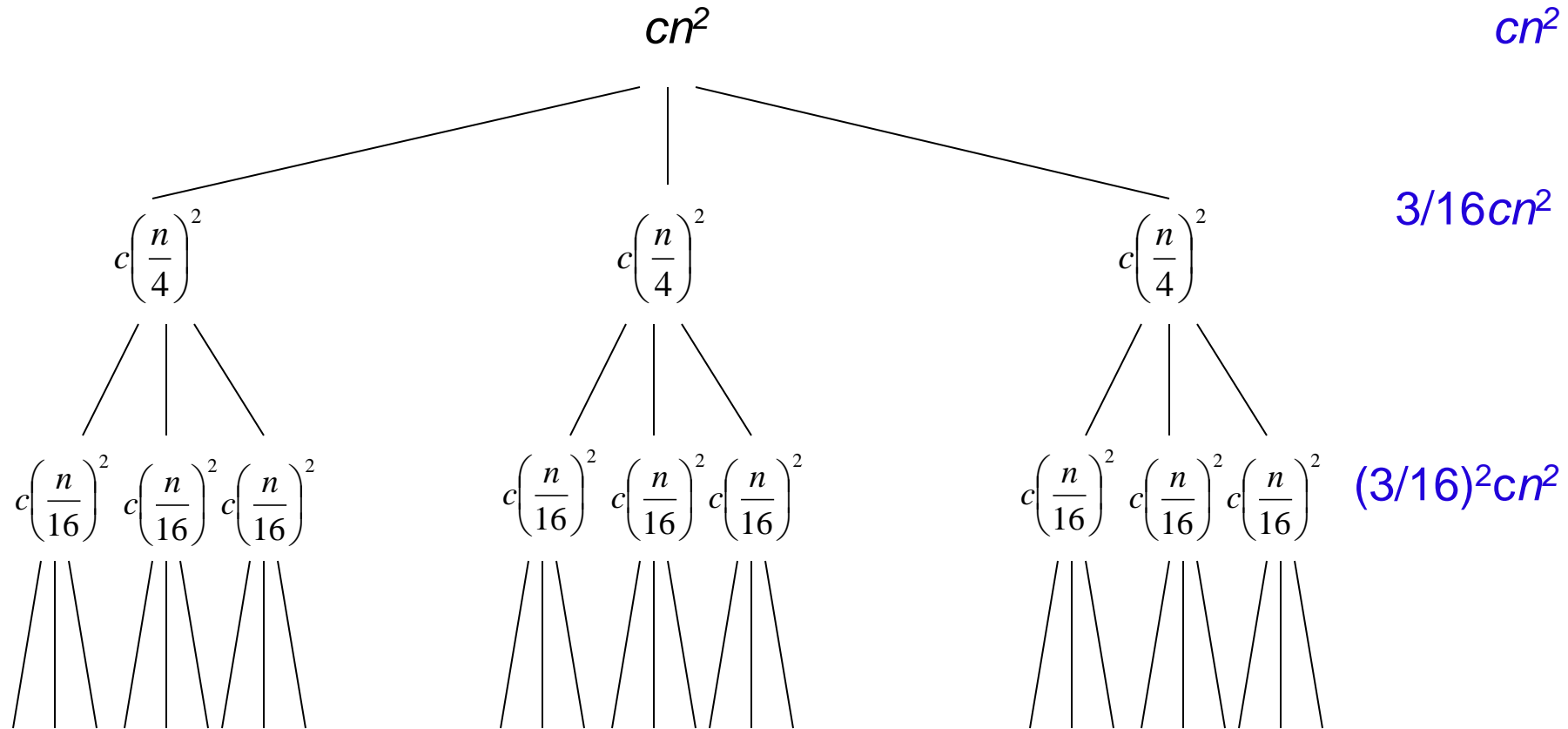


$$T(n) = 3T(n/4) + n^2$$

cost



$$cn^2$$



What is the cost at each level?

$$\left(\frac{3}{16}\right)^d cn^2$$



What is the depth of the tree?

At each level, the size of the data is divided by 4

$$\frac{n}{4^d} = 1$$

$$\log\left(\frac{n}{4^d}\right) = 0$$

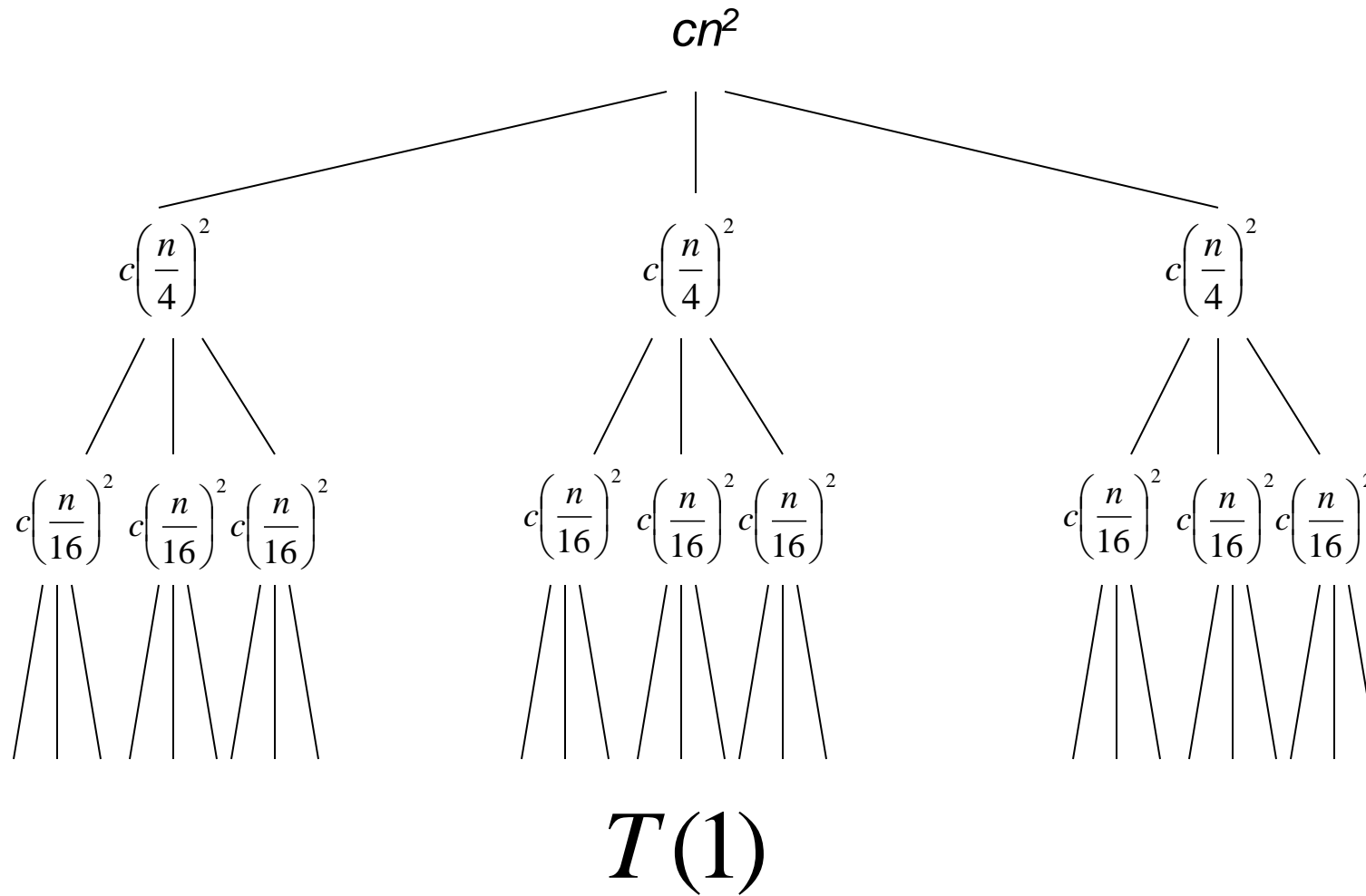
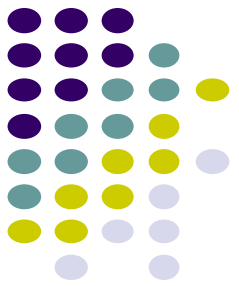
$$\log n - \log 4^d = 0$$

$$d \log 4 = \log n$$

$$d = \log_4 n$$

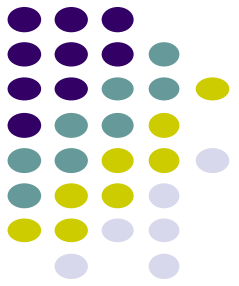


$$T(n) = 3T(n/4) + n^2$$



How many leaves are there?

How many leaves?



How many leaves are there in a complete ternary tree of depth d ?

$$3^d = 3^{\log_4 n}$$

Total cost



$$T(n) = cn^2 + \frac{3}{16}cn^2 + \left(\frac{3}{16}\right)^2 cn^2 + \dots + \left(\frac{3}{16}\right)^{d-1} cn^2 + \Theta(3^{\log_4 n})$$

$$= cn^2 \sum_{i=0}^{\log_4 n - 1} \left(\frac{3}{16}\right)^i + \Theta(3^{\log_4 n})$$

$$< cn^2 \sum_{i=0}^{\infty} \left(\frac{3}{16}\right)^i + \Theta(3^{\log_4 n})$$

$$= \frac{1}{1 - (3/16)} cn^2 + \Theta(3^{\log_4 n})$$

$$= \frac{16}{13} cn^2 + \Theta(3^{\log_4 n}) \quad ?$$

$$\sum_{k=0}^{\infty} x^k = \frac{1}{1-x}$$

let $x = 3/16$

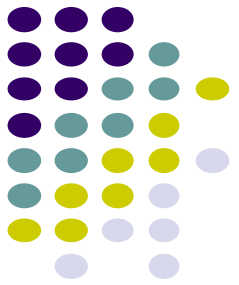
Total cost

$$T(n) = \frac{16}{13}cn^2 + \Theta(3^{\log_4 n})$$

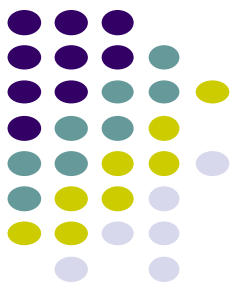
$$\begin{aligned} 3^{\log_4 n} &= 4^{\log_4 3^{\log_4 n}} \\ &= 4^{\log_4 n \log_4 3} \\ &= 4^{\log_4 n^{\log_4 3}} \\ &= n^{\log_4 3} \end{aligned}$$

$$T(n) = \frac{16}{13}cn^2 + \Theta(n^{\log_4 3})$$

$$T(n) = O(n^2)$$



Verify solution using substitution



$$T(n) = 3T(n/4) + n^2$$

Assume $T(k) = O(k^2)$ for all $k < n$

Show that $T(n) = O(n^2)$

Given that $T(n/4) = O((n/4)^2)$, then

$$O(g(n)) = \left\{ f(n) : \begin{array}{l} \text{there exists positive constants } c \text{ and } n \text{ such that} \\ 0 \leq f(n) \leq cg(n) \text{ for all } n \geq n_0 \end{array} \right\}$$

$$T(n/4) \leq c(n/4)^2$$

$$T(n) = 3T(n/4) + n^2$$

To prove that Show that $T(n) = O(n^2)$ we need to identify the appropriate constants:

$$O(g(n)) = \left\{ f(n) : \begin{array}{l} \text{there exists positive constants } c \text{ and } n \text{ such that} \\ 0 \leq f(n) \leq cg(n) \text{ for all } n \geq n_0 \end{array} \right\}$$

i.e. some constant c such that $T(n) \leq cn^2$

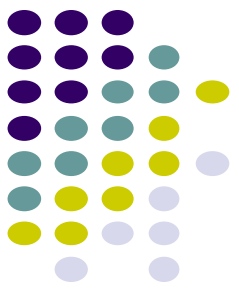
$$T(n) = 3T(n/4) + n^2$$

$$\leq 3c(n/4)^2 + n^2$$

$$= cn^2 3/16 + n^2$$

$$= cn^2 - cn^2 * \frac{13}{16} + n^2 \quad \text{residual}$$

a constant exists if, if $-cn^2 * \frac{13}{16} + n^2 \leq 0$



$$T(n) = 3T(n/4) + n^2$$

To prove that Show that $T(n) = O(n^2)$ we need to identify the appropriate constants:

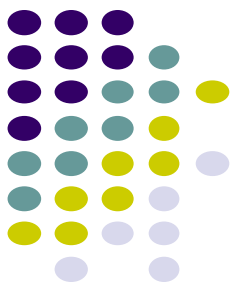
$$O(g(n)) = \left\{ f(n) : \begin{array}{l} \text{there exists positive constants } c \text{ and } n \text{ such that} \\ 0 \leq f(n) \leq cg(n) \text{ for all } n \geq n_0 \end{array} \right\}$$

i.e. some constant c such that $T(n) \leq cn^2$

$$-cn^2 * \frac{13}{16} + n^2 \leq 0$$

$$cn^2 * \frac{13}{16} \geq n^2$$

$$c \geq \frac{16}{13}$$





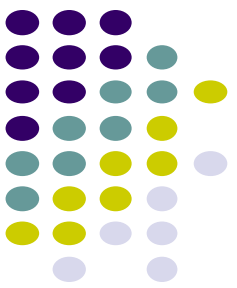
Recursion Trees – Caution Note

- Recursion trees **only generate guesses**.
 - Verify guesses using substitution method.
- A small amount of “sloppiness” can be tolerated. [Why?](#)
- **If careful** when drawing out a recursion tree and summing the costs, **can be used as direct proof**.



The Master Method

- Based on the **Master theorem**.
- “**Cookbook**” approach for solving recurrences of the form
$$T(n) = aT(n/b) + f(n)$$
 - $a \geq 1, b > 1$ are constants.
 - $f(n)$ is asymptotically positive.
 - n/b may not be an integer, but we ignore floors and ceilings. [Why?](#)
- Requires memorization of three cases.



The Master Theorem

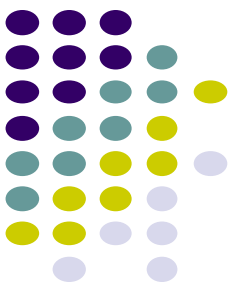
Theorem

Let $a \geq 1$ and $b > 1$ be constants, let $f(n)$ be a function, and

Let $T(n)$ be defined on nonnegative integers by the recurrence
 $T(n) = aT(n/b) + f(n)$, where we can replace n/b by $\lfloor n/b \rfloor$ or $\lceil n/b \rceil$.

$T(n)$ can be bounded asymptotically in three cases:

1. If $f(n) = O(n^{\log_b a - \epsilon})$ for some constant $\epsilon > 0$, then $T(n) = \Theta(n^{\log_b a})$.
2. If $f(n) = \Theta(n^{\log_b a})$, then $T(n) = \Theta(n^{\log_b a} \lg n)$.
3. If $f(n) = \Omega(n^{\log_b a + \epsilon})$ for some constant $\epsilon > 0$,
and if, for some constant $c < 1$ and all sufficiently large n ,
we have $a \cdot f(n/b) \leq c f(n)$, then $T(n) = \Theta(f(n))$.
(regularity condition)



The Master Theorem: Examples

- $T(n) = 16T(n/4) + n$
 - $a = 16, b = 4, n^{\log_b a} = n^{\log_4 16} = n^2.$
 - $f(n) = n = O(n^{\log_b a - \varepsilon}) = O(n^{2 - \varepsilon})$, where $\varepsilon = 1 \Rightarrow$ **Case 1.**
 - Hence, $T(n) = \Theta(n^{\log_b a}) = \Theta(n^2).$
- $T(n) = T(3n/7) + 1$
 - $a = 1, b = 7/3$, and $n^{\log_b a} = n^{\log_{7/3} 1} = n^0 = 1$
 - $f(n) = 1 = \Theta(n^{\log_b a}) \Rightarrow$ **Case 2.**
 - Therefore, $T(n) = \Theta(n^{\log_b a} \lg n) = \Theta(\lg n)$



The Master Theorem: Examples

- $T(n) = 3T(n/4) + n \lg n$
 - $a = 3, b=4$, thus $n^{\log_b a} = n^{\log_4 3} = O(n^{0.793})$
 - $f(n) = n \lg n = \Omega(n^{\log_4 3 + \varepsilon})$ where $\varepsilon \approx 0.2$
 - Is $3n/4 \lg 3n/4 \leq c n \lg n$ for $c < 1$? – It holds for $c=3/4 \Rightarrow$ **Case 3**.
 - Therefore, $T(n) = \Theta(f(n)) = \Theta(n \lg n)$.
- $T(n) = 2T(n/2) + n \lg n$
 - $a = 2, b=2, f(n) = n \lg n$, and $n^{\log_b a} = n^{\log_2 2} = n$
 - $f(n)$ is asymptotically larger than $n^{\log_b a}$, but **not polynomially larger**.
The ratio $\lg n$ is asymptotically less than n^ε for any positive ε . Thus, the Master Theorem **doesn't** apply here.



$$T(n) = T(n/2) + 2^n$$

if $f(n) = O(n^{\log_b a - \varepsilon})$ for $\varepsilon > 0$, then $T(n) = \Theta(n^{\log_b a})$

if $f(n) = \Theta(n^{\log_b a})$, then $T(n) = \Theta(n^{\log_b a} \log n)$

if $f(n) = \Omega(n^{\log_b a + \varepsilon})$ for $\varepsilon > 0$ and $af(n/b) \leq cf(n)$ for $c < 1$
then $T(n) = \Theta(f(n))$

$$\begin{array}{ll} a &= 1 \\ b &= 2 \\ f(n) &= 2^n \end{array} \qquad \begin{array}{ll} n^{\log_b a} &= n^{\log_2 1} \\ &= n^0 \end{array}$$

Case 3?

is $2^n = O(n^{0-\varepsilon})$?

is $2^n = \Theta(n^0)$?

is $2^n = \Omega(n^{0+\varepsilon})$?

is $2^{n/2} \leq c2^n$ for $c < 1$?

$$T(n) = T(n/2) + 2^n$$

if $f(n) = O(n^{\log_b a - \varepsilon})$ for $\varepsilon > 0$, then $T(n) = \Theta(n^{\log_b a})$

if $f(n) = \Theta(n^{\log_b a})$, then $T(n) = \Theta(n^{\log_b a} \log n)$

if $f(n) = \Omega(n^{\log_b a + \varepsilon})$ for $\varepsilon > 0$ and $af(n/b) \leq cf(n)$ for $c < 1$
then $T(n) = \Theta(f(n))$

is $2^{n/2} \leq c2^n$ for $c < 1$?

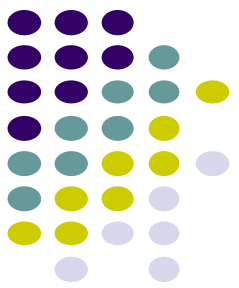
Let $c = 1/2$

$$2^{n/2} \leq (1/2)2^n$$

$$2^{n/2} \leq 2^{-1}2^n$$

$$2^{n/2} \leq 2^{n-1}$$

$$T(n) = \Theta(2^n)$$



$$T(n) = 2T(n/2) + n$$

if $f(n) = O(n^{\log_b a - \varepsilon})$ for $\varepsilon > 0$, then $T(n) = \Theta(n^{\log_b a})$

if $f(n) = \Theta(n^{\log_b a})$, then $T(n) = \Theta(n^{\log_b a} \log n)$

if $f(n) = \Omega(n^{\log_b a + \varepsilon})$ for $\varepsilon > 0$ and $af(n/b) \leq cf(n)$ for $c < 1$
then $T(n) = \Theta(f(n))$

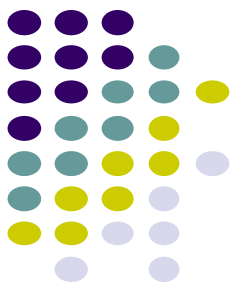
$$\begin{array}{ll} a &= 2 \\ b &= 2 \\ f(n) &= n \end{array} \qquad \begin{array}{ll} n^{\log_b a} &= n^{\log_2 2} \\ &= n^1 \end{array}$$

is $n = O(n^{1-\varepsilon})$?

is $n = \Theta(n^1)$?

is $n = \Omega(n^{1+\varepsilon})$?

Case 2: $\Theta(n \log n)$



$$T(n) = 16T(n/4) + n!$$

if $f(n) = O(n^{\log_b a - \varepsilon})$ for $\varepsilon > 0$, then $T(n) = \Theta(n^{\log_b a})$

if $f(n) = \Theta(n^{\log_b a})$, then $T(n) = \Theta(n^{\log_b a} \log n)$

if $f(n) = \Omega(n^{\log_b a + \varepsilon})$ for $\varepsilon > 0$ and $af(n/b) \leq cf(n)$ for $c < 1$
then $T(n) = \Theta(f(n))$

$$\begin{array}{ll} a &= 16 \\ b &= 4 \\ f(n) &= n! \end{array} \qquad \begin{array}{l} n^{\log_b a} = n^{\log_4 16} \\ = n^2 \end{array}$$

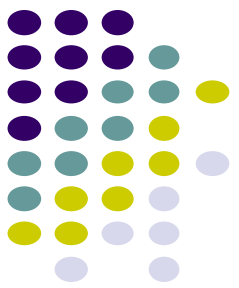
Case 3?

is $n! = O(n^{2-\varepsilon})$?

is $n! = \Theta(n^2)$?

is $n! = \Omega(n^{2+\varepsilon})$?

is $16(n/4)! \leq cn!$ for $c < 1$?



$$T(n) = 16T(n/4) + n!$$

if $f(n) = O(n^{\log_b a - \varepsilon})$ for $\varepsilon > 0$, then $T(n) = \Theta(n^{\log_b a})$

if $f(n) = \Theta(n^{\log_b a})$, then $T(n) = \Theta(n^{\log_b a} \log n)$

if $f(n) = \Omega(n^{\log_b a + \varepsilon})$ for $\varepsilon > 0$ and $af(n/b) \leq cf(n)$ for $c < 1$
then $T(n) = \Theta(f(n))$

is $16(n/4)! \leq cn!$ for $c < 1$?

Let $c = 1/2$

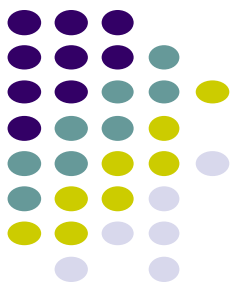
$$cn! = 1/2n!$$

$$> (n/2)!$$

$$T(n) = \Theta(n!)$$

therefore,

$$16(n/4)! \leq (n/2)! < 1/2n!$$



$$T(n) = \sqrt{2}T(n/2) + \log n$$

if $f(n) = O(n^{\log_b a - \varepsilon})$ for $\varepsilon > 0$, then $T(n) = \Theta(n^{\log_b a})$

if $f(n) = \Theta(n^{\log_b a})$, then $T(n) = \Theta(n^{\log_b a} \log n)$

if $f(n) = \Omega(n^{\log_b a + \varepsilon})$ for $\varepsilon > 0$ and $af(n/b) \leq cf(n)$ for $c < 1$
then $T(n) = \Theta(f(n))$

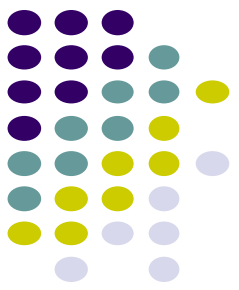
$$\begin{aligned} a &= \sqrt{2} & n^{\log_b a} &= n^{\log_2 \sqrt{2}} \\ b &= 2 & &= n^{\log_2 2^{1/2}} \\ f(n) &= \log n & &= \sqrt{n} \end{aligned}$$

is $\log n = O(n^{1/2 - \varepsilon})$?

is $\log n = \Theta(n^{1/2})$?

is $\log n = \Omega(n^{1/2 + \varepsilon})$?

Case 1: $\Theta(\sqrt{n})$



$$T(n) = 4T(n/2) + n$$

if $f(n) = O(n^{\log_b a - \varepsilon})$ for $\varepsilon > 0$, then $T(n) = \Theta(n^{\log_b a})$

if $f(n) = \Theta(n^{\log_b a})$, then $T(n) = \Theta(n^{\log_b a} \log n)$

if $f(n) = \Omega(n^{\log_b a + \varepsilon})$ for $\varepsilon > 0$ and $af(n/b) \leq cf(n)$ for $c < 1$
then $T(n) = \Theta(f(n))$

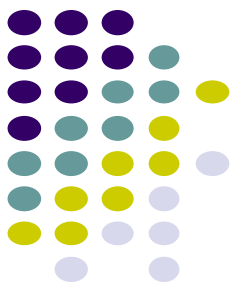
$$\begin{array}{ll} a &= 4 \\ b &= 2 \\ f(n) &= n \end{array} \qquad \begin{array}{ll} n^{\log_b a} &= n^{\log_2 4} \\ &= n^2 \end{array}$$

is $n = O(n^{2-\varepsilon})$?

is $n = \Theta(n^2)$?

is $n = \Omega(n^{2+\varepsilon})$?

Case 1: $\Theta(n^2)$



Recurrences



$$T(n) = 2T(n/3) + d$$

$$T(n) = 7T(n/7) + n$$

if $f(n) = O(n^{\log_b a - \varepsilon})$ for $\varepsilon > 0$, then $T(n) = \Theta(n^{\log_b a})$

if $f(n) = \Theta(n^{\log_b a})$, then $T(n) = \Theta(n^{\log_b a} \log n)$

if $f(n) = \Omega(n^{\log_b a + \varepsilon})$ for $\varepsilon > 0$ and $af(n/b) \leq cf(n)$ for $c < 1$

then $T(n) = \Theta(f(n))$

$$T(n) = T(n-1) + \log n$$

$$T(n) = 8T(n/2) + n^3$$



Acknowledgements

- Cormen, T.H., Leiserson, C.E., Rivest, R.L. and Stein, C., Introduction to algorithms. MIT press, 2009
- Dr. David Kauchak, Pomona College
- Prof. David Plaisted, The University of North Carolina at Chapel Hill