Imperial College London

CO202 – Software Engineering – Algorithms **Divide and Conquer**

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Algorithm Design

How to design an (efficient) algorithm?

Structure the problem!*

Make use of algorithmic schemes/design paradigms

- Incremental Approach
- Divide and Conquer (this week)
- Dynamic Programming upcoming weeks
 Greedy Algorithms

*Take some time and think!

Divide and Conquer

Solve a problem recursively, apply three steps:

- 1. Divide the problem into a number of subproblems that are smaller instances of the same problem
- 2. Conquer the subproblems by solving them recursively. If the subproblem sizes are small enough, just solve them in a straightforward manner
- **3. Combine** the solutions to the subproblems into the solution for the original problem

D&C Principle

In Divide and Conquer, we solve a problem recursively

 When the subproblems are large enough to solve recursively, we call that the recursive case

 Once the subproblems become small enough, we say the recursion "bottoms out" and we have gotten down to the base case

Example: Sorting Problem

• **Input**: Sequence of n numbers $\langle a_1, a_2, ..., a_n \rangle$

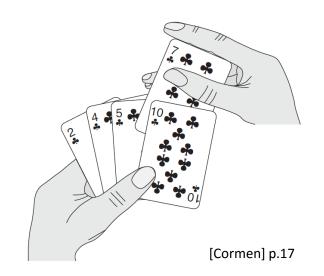
• Output: Permutation (reordering) $\langle a_1', a_2', ..., a_n' \rangle$ such that $a_1' \le a_2' \le \cdots \le a_n'$

Reminder: Insertion Sort

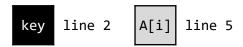
Incremental Approach

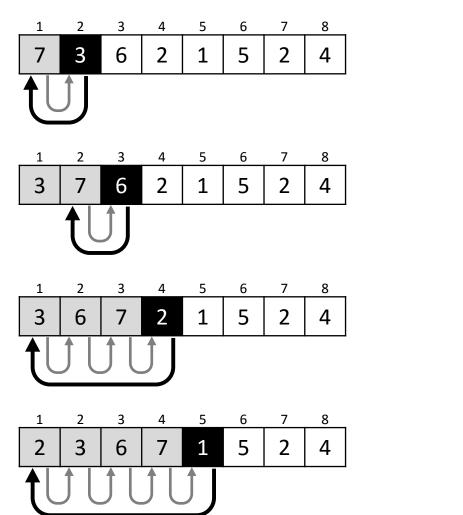
1	2	3	4	5	6	7	8
7	3	6	2	1	5	2	4

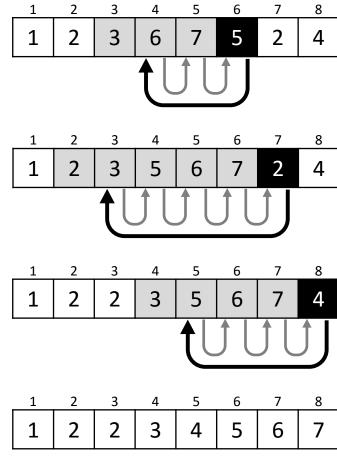
```
INSERTION-SORT(A)
 1: for j = 2 to A.length
       key = A[j]
2:
3:
       # Insert A[j] into the sorted sequence A[1..j-1].
4: i = j-1
       while i > 0 and A[i] > key
 5:
           A[i+1] = A[i]
6:
           i = i-1
7:
       A[i+1] = key
8:
```



Reminder: Insertion Sort (cont'd)







Running Time of Insertion Sort

Depends on the length of the sequence n = A.1ength

```
INSERTION-SORT(A)
                                                 cost
                                                          times
1: for j = 2 to A.length
2: key = A[j]
3: # Insert A[j]...
4: i = j-1
5: while i > 0 and A[i] > key
6:
           A[i+1] = A[i]
            i = i-1
7:
     A[i+1] = key
8:
      T(n) = c_1 n + c_2 (n-1) + c_4 (n-1)
          +c_5 \sum_{i=2}^{n} t_j + c_6 \sum_{i=2}^{n} (t_j - 1) + c_7 \sum_{i=2}^{n} (t_j - 1) + c_8(n-1)
```

Running Time of Insertion Sort

Depends on the length of the sequence n = A.1ength

```
INSERTION-SORT(A)
                                                      cost
                                                                times
 1: for j = 2 to A.length
                                                                n
                                                      C_1
 2: key = A[j]
                                                                n-1
                                                      C_2
 3: # Insert A[j]...
                                                      0
                                                               n-1
 4: i = j-1
                                                                n-1
                                                      \mathsf{C}_\mathtt{A}
                                                      c_5 \qquad \sum_{j=2}^n t_j
 5: while i > 0 and A[i] > key
                                                      c_6 \qquad \sum_{j=2}^{n} (t_j - 1)
6:
           A[i+1] = A[i]
                                                      c_7 \qquad \sum_{j=2}^n (t_j - 1)
             i = i-1
7:
   A[i+1] = key
 8:
                                                         n-1
                                                      C_{8}
```

$$T(n) = c_1 n + c_2 (n - 1) + c_4 (n - 1)$$

$$+ c_5 \sum_{i=2}^{n} t_i + c_6 \sum_{i=2}^{n} (t_i - 1) + c_7 \sum_{i=2}^{n} (t_i - 1) + c_8 (n - 1)$$

Running Time of Insertion Sort (cont'd)

Depends also on the nature of the input

• Best-case (already sorted): $t_i = 1$

$$T_{\text{best}}(n) = c_1 n + c_2 (n-1) + c_4 (n-1) + c_5 (n-1) + c_8 (n-1)$$

• Worst-case (reversely sorted): $t_i = j$

$$T_{\text{worst}}(n) = c_1 n + c_2 (n-1) + c_4 (n-1)$$

$$\sum_{j=2}^{n} j = \frac{n(n+1)}{2} - 1$$

$$\sum_{j=2}^{n} (j-1) = \frac{n(n-1)}{2}$$

$$+c_5\left(\frac{n(n+1)}{2}-1\right)+c_6\left(\frac{n(n-1)}{2}\right)+c_7\left(\frac{n(n-1)}{2}\right)+c_8(n-1)$$

Running Time of Insertion Sort (cont'd)

Depends also on the nature of the input

• Best-case (already sorted): $t_j = 1$

$$T_{\text{best}}(n) = \text{linear}$$

• Worst-case (reversely sorted): $t_i = j$

$$T_{\text{worst}}(n) = \text{quadratic}$$

$$\sum_{j=2}^{n} j = \frac{n(n+1)}{2} - 1$$

$$\sum_{j=2}^{n} (j-1) = \frac{n(n-1)}{2}$$

Worst-case Running Time

We usually focus on the worst-case running time:

 It provides an upper bound on the running time for any input. It is guaranteed that the algorithm will never take any longer.

 Worst-case can occur fairly often, e.g. in searching a database for a piece of information that is not present.

"Average-case" is often roughly as bad as the worst-case

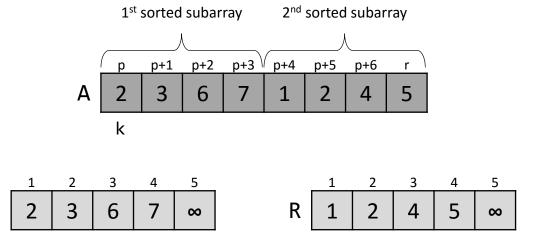
Merge Sort

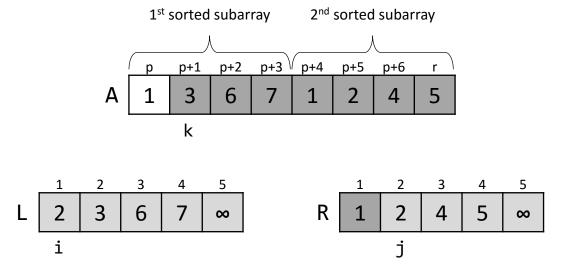
Divide & Conquer Approach

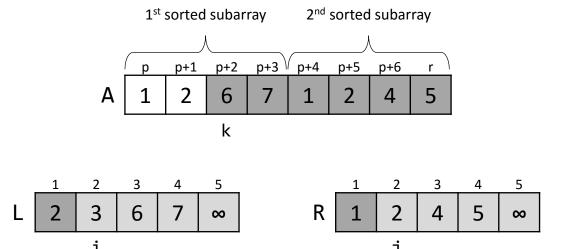
- **1. Divide** the n-element sequence to be sorted into two subsequences of n/2 elements each
- 2. Conquer: Sort the two subsequences recursively using merge sort
- **3. Combine:** Merge the two sorted subsequences to produce the sorted answer

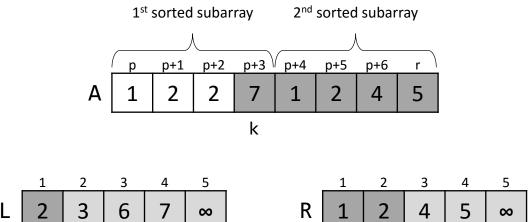
Combine: Merge

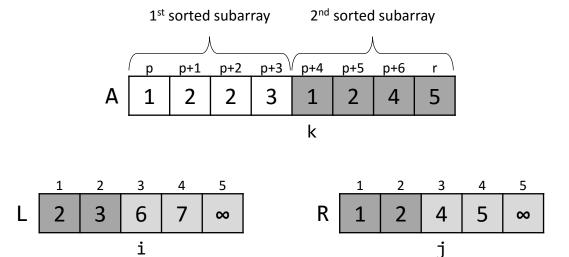
```
MERGE(A,p,q,r)
                                                    # length of 1<sup>st</sup> subarray
 1: n_1 = q-p+1
                                                    # length of 2<sup>nd</sup> subarray
 2: n_2 = r - q
 3: let L[1...n_1+1] and R[1...n_2+1] be new arrays
 4: for i = 1 to n_1
 5: L[i] = A[p+i-1]
                                                    # copy values to 1<sup>st</sup> array
 6: for j = 1 to n_2
 7: R[j] = A[q+j]
                                                    # copy values to 2<sup>nd</sup> array
 8: L[n_1+1] = \infty
                                                    # set sentinel
9: R[n_2+1] = \infty
                                                    # set sentinel
10: i = 1
11: j = 1
12: for k = p to r
                                                    # merge subarrays
13:
        if L[i] ≤ R[j]
14: A[k] = L[i]
15:
            i = i+1
16: else
17: A[k] = R[j]
            j = j+1
18:
```

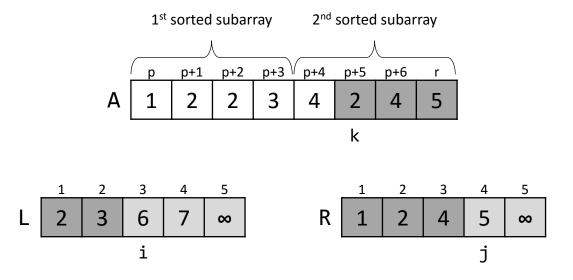


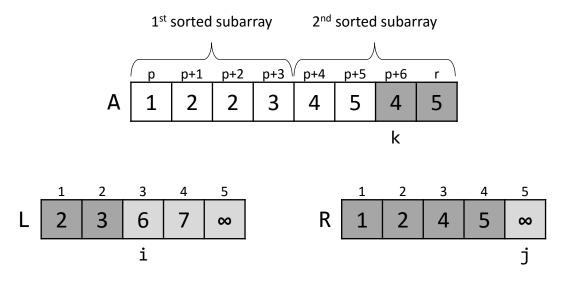


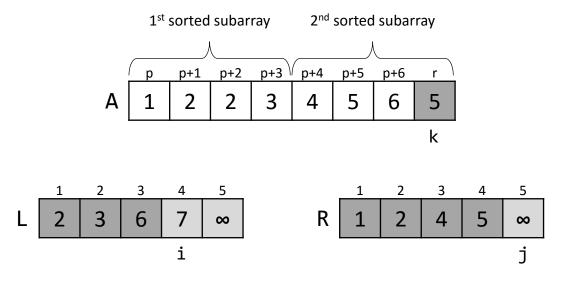


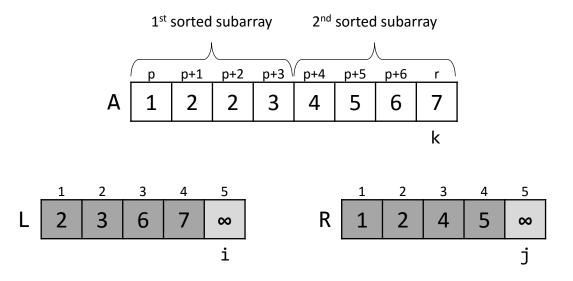








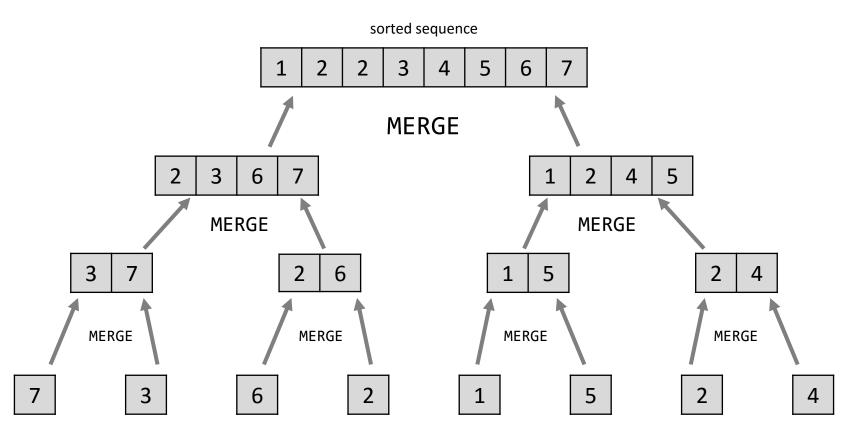




Merge Sort (cont'd)

Divide and Conquer Approach

Merge Sort (cont'd)



initial sequence

Running Time of Merge Sort

How to deal with recursion in running time analysis?

MERGE	E-SORT(A,p,r)	cost	times
1: i	.f p < r	c_1	?
2:	q = floor((p+r)/2)	c_2	?
3:	<pre>MERGE-SORT(A,p,q)</pre>	c_3	?
4:	<pre>MERGE-SORT(A,q+1,r)</pre>	c_4	?
5:	<pre>MERGE(A,p,q,r)</pre>	c ₅	?

Recurrences

A recurrence is an equation (or inequality) that describes a function in terms of its value on smaller inputs

Recurrence for Divide & Conquer

- Trivial problems $n \leq c$ can be solved in constant time
- Suppose division yields a subproblems each of size 1/b
- Divide takes time D(n) and combine takes C(n)

$$T(n) = \begin{cases} \Theta(1), & n \le c \\ aT(n/b) + D(n) + C(n), & \text{otherwise} \end{cases}$$

Divide & Conquer

Merge Sort Recurrence

$$T(n) = \begin{cases} \Theta(1), & n \le c \\ aT(n/b) + D(n) + C(n), & \text{otherwise} \end{cases}$$

- **Base case**: Merge Sort on one element takes constant time: c=1
- **Divide**: Computes the middle of the subarray in constant time: $D(n) = \Theta(1)$
- Conquer: Recursively solve two subproblems of size n/2, thus: a=2, b=2
- Combine: The MERGE procedure on an n-element subarray takes linear time, so $\mathcal{C}(n) = \Theta(n)$

$$T(n) = \begin{cases} \Theta(1), & n = 1 \\ 2T\binom{n}{2} + \Theta(1) + \Theta(n), & n > 1 \end{cases}$$

$$\Theta(n) \qquad T(n) = \begin{cases} \Theta(1), & n = 1 \\ 2T\binom{n}{2} + \Theta(n), & n > 1 \end{cases}$$

Technicalities in Recurrences

Calling MERGE-SORT on n elements when n is odd yields

$$T(n) = \begin{cases} \Theta(1), & n = 1 \\ T(\lceil \frac{n}{2} \rceil) + T(\lceil \frac{n}{2} \rceil) + \Theta(n), & n > 1 \end{cases}$$

We neglect certain technical details, because in many cases it doesn't make a difference

- Omit the boundary conditions (constant for small n)
- Omit floors and ceilings, assume n is power of b (which is 2 above)

Solving Recurrences

The three main methods for solving recurrences, and obtaining asymptotic bounds on the running time

 Substitution Method: Guess a bound and use induction to prove it is correct

 Recursion Tree Method: Convert recurrence into a tree whose nodes represent the costs at different levels

Master Method: Look-up bounds for recurrences of

$$T(n) = aT(n/b) + f(n)$$

Substitution Method

Two steps:

- 1. Guess the form of the solution
- 2. Use mathematical induction to show it's correct

- Making a good guess can be difficult and requires experience (and sometimes creativity)
- Inductive proof can be tricky and sometimes needs a bit of algebraic mastery

Substitution Method (cont'd)

Example

$$T(n) = 2T(^n/_2) + n$$

Guess: $O(n \lg n)$

Prove that $T(n) \le c(n \lg n)^*$

Assume this holds for all positive m < n (strong induction), in particular for $m \le n/2$, yielding $T(n/2) \le c(n/2 \lg n/2)$

By substitution:

$$T(n) \le 2(c(n/2 \lg n/2)) + n$$

$$= cn \lg n/2 + n$$

$$= cn \lg n - cn \lg 2 + n$$

$$= cn \lg n - cn + n$$

$$\le cn \lg n \qquad \text{holds for } c \ge 1$$

What about the base case? $T(1) = 1 \le c1 \lg 1 = 0$

Need to choose a suitable n_0 , such that $\forall n \geq n_0$. $T(2) = 4 \leq c2 \lg 2 = c2$ holds for $c \geq 2$

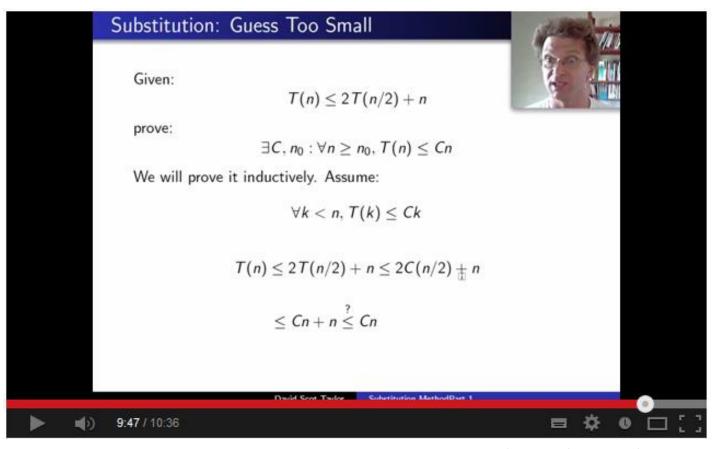
$$*O(g(n)) = \{f(n): \exists c, n_0 > 0 \text{ such that } \forall n \ge n_0 \ 0 \le f(n) \le cg(n)\}$$

Divide & Conquer

Substitution Method (cont'd)

What happens if guess is too small?

http://youtu.be/ad5zs6Uin3U?t=9m11s



by David Scot Taylor, SJSU

Substitution Method Subtleties

Sometimes the guess is correct...

$$T(n) = 4T(^n/_2) + n$$

Guess: $O(n^2)$

Prove that $T(n) \leq cn^2$

Assume
$$T\left(\frac{n}{2}\right) \le c\left(\frac{n}{2}\right)^2$$

By substitution:

$$T(n) \le 4\left(c\left(\frac{n}{2}\right)^2\right) + n$$

$$= 4\left(c\frac{n^2}{4}\right) + n$$

$$= cn^2 + n$$

$$\le cn^2$$

...but the math fails to work.

Substitution Method Subtleties (cont'd)

Subtracting lower-order terms can help

$$T(n) = 4T(^n/_2) + n$$

Guess: $O(n^2)$

Prove that $T(n) \leq cn^2 - bn$

Assume
$$T\left(\frac{n}{2}\right) \le c\left(\frac{n}{2}\right)^2 - b\frac{n}{2}$$

By substitution:

$$T(n) \le 4\left(c\left(\frac{n}{2}\right)^2 - b\frac{n}{2}\right) + n$$

$$= cn^2 - 2bn + n$$

$$= cn^2 - n(2b+1)$$

$$\le cn^2 - bn$$

holds for $c \ge 1$ and b = 1

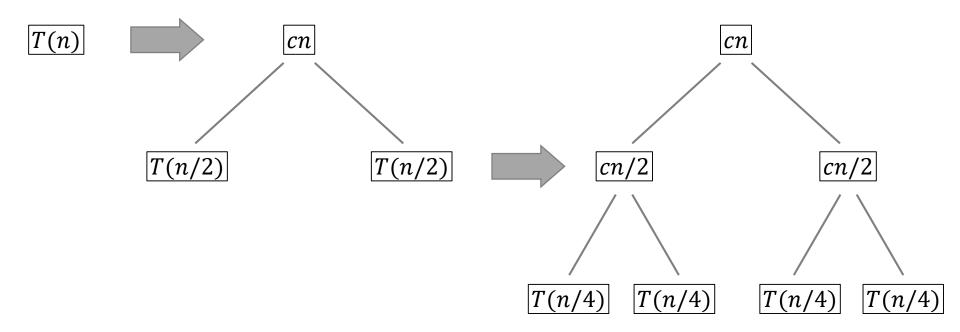
Skipping the base case here.

Recursion Tree: Merge Sort

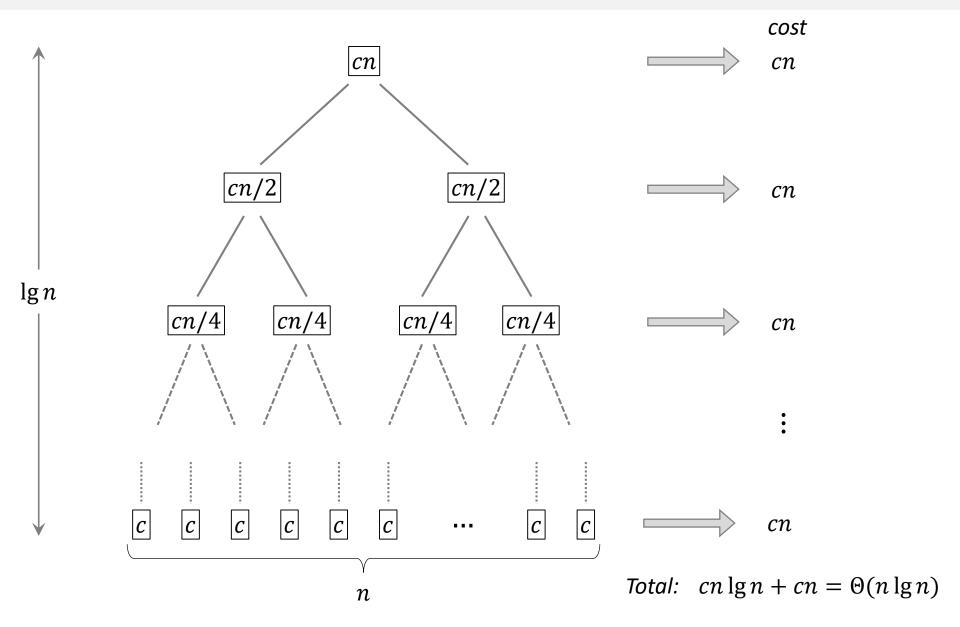
$$T(n) = \begin{cases} \Theta(1), & n = 1 \\ 2T\binom{n}{2} + \Theta(n), & n > 1 \end{cases}$$

$$T(n) = \begin{cases} c, & n = 1 \\ 2T\binom{n}{2} + cn, & n > 1 \end{cases}$$

Replace constant operations by c

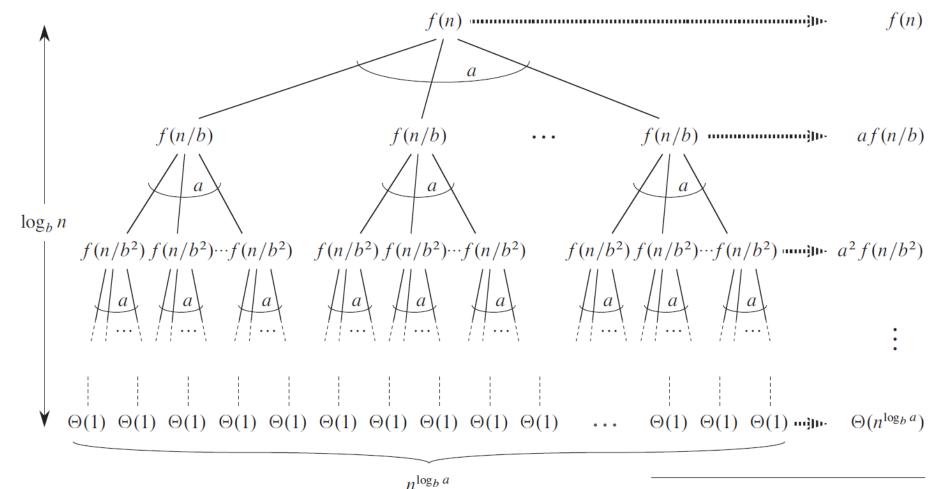


Recursion Tree: Merge Sort (cont'd)



The D&C Recursion Tree

$$T(n) = aT(n/b) + f(n)$$



[Cormen] p.99

Total: $\Theta(n^{\log_b a}) + \sum_{j=0}^{\log_b n-1} a^j f(n/b^j)$

The D&C Recursion Tree - Remarks

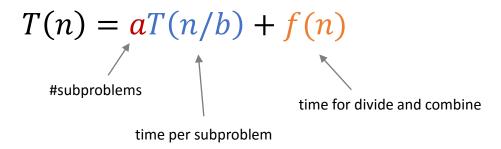
- The height of a tree is the number of levels 1
- The height of a recursion tree is given by $\log_b n$
- We have $\log_b n$ levels of recursion (including the root, but without the bottom level of base cases)
- The cost of divide and combine is given by summing the operations for each recursion level: $\sum_{j=0}^{\log_b n-1} a^j f(n/b^j)$

Example: MERGE-SORT on n=64

- The recursion tree has 7 levels
- $\lg 64 = 6$ levels of recursion + 1 bottom level of base cases

Master Method

A "cookbook" for solving recurrences



Master Theorem (v1)

- 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 $af(n/b) \le cf(n)$ for some constant c < 1 and all sufficiently large n, then $T(n) = \Theta(f(n))$.

Intuition: The larger of f(n) and $n^{\log_b a}$ determines the solution of the recurrence

Case 3: Regularity Condition

$$af(n/b) \le cf(n)$$

for some constant c < 1

- Generally not a problem
- It always holds whenever $f(n) = n^k$, so no need to check when f(n) is a polynomial

Proof:

Since $f(n) = n^k$ and $f(n) = \Omega(n^{\log_b a + \epsilon})$, we have $k > \log_b a$. Using a base of b and treating both sides as exponents, we have $b^k > b^{\log_b a} = a$, and so $a/b^k < 1$. Let $c = a/b^k$.

$$af(n/b) = a(n/b)^k = (a/b^k)n^k = cf(n)$$

Divide & Conquer

Using the Master Theorem (v1)

Examples

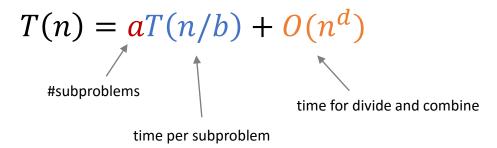
•
$$T(n) = 9T(n/3) + n$$
 $n^{\log_3 9} = n^2 = \Theta(n^2)$
Case 1: $f(n) = O(n^{2-\epsilon})$ where $\epsilon = 1$ so $T(n) = \Theta(n^2)$.

•
$$T(n) = T(2n/3) + 1$$
 $n^{\log_3/2} = n^0 = \Theta(1)$ Case 2: $f(n) = \Theta(1)$ so $T(n) = \Theta(\lg n)$.

$$T(n) = 2T(n/2) + n^3 \qquad n^{\log_2 2} = n^1 = \Theta(n)$$
 Case 3: $f(n) = \Omega(n^{1+\epsilon}) \qquad$ where $\epsilon = 2$ so $T(n) = \Theta(n^3)$.

"Simpler" Master Method

An even simpler "cookbook" for solving recurrences



Master Theorem (v2)

- 1. If $d < \log_b a$, then $T(n) = O(n^{\log_b a})$.
- 2. If $d = \log_b a$, then $T(n) = O(n^d \lg n)$.
- 3. If $d > \log_b a$, then $T(n) = O(n^d)$.

Using the Master Theorem (v2)

Examples

•
$$T(n) = 9T(n/3) + n$$
 $\log_3 9 = 2$
Case 1: $d = 1 < 2$ so $T(n) = O(n^2)$.

•
$$T(n) = T(2n/3) + 1$$
 $\log_{3/2} 1 = 0$
Case 2: $d = 0 = 0$ so $T(n) = O(\lg n)$.

•
$$T(n) = 2T(n/2) + n^3$$
 $\log_2 2 = 1$
Case 3: $d = 3 > 1$ so $T(n) = O(n^3)$.

Binary Search: The "ultimate" D&C algorithm

Find a key k in a large file containing many keys in sorted order.

1	2	3	4	5	6	7
1	2	2	3	4	5	6

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Binary Search: The "ultimate" D&C algorithm

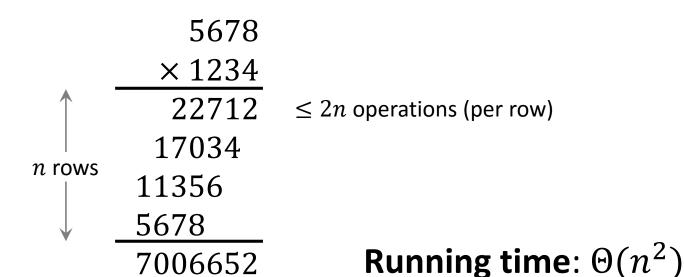
Find a key k in a large file containing many keys in sorted order.

$$T(n) = T(n/2) + 1 \text{ with } T(n) = O(\lg n)$$

Integer Multiplication

- Input: two *n*-digit numbers *x* and *y*
- Output: the product $x \cdot y$

Example: x = 5678 y = 1234



Divide & Conquer

Integer Multiplication

- Input: two *n*-digit numbers *x* and *y*
- Output: the product $x \cdot y$

Example:
$$x = 5678$$
 $y = 1234$

$$y = 10^2 \cdot a + b$$

$$y = 10^2 \cdot c + d$$

$$x \cdot y = (10^{2} \cdot a + b) \cdot (10^{2} \cdot c + d)$$

$$= 10^{4} (ac) + 10^{2} (ad) + (bc) + (bd)$$

Idea: Recursively compute ac, ad, bc, bd

Integer Multiplication

- Input: two *n*-digit numbers *x* and *y*
- Output: the product $x \cdot y$

Example:
$$x = \begin{bmatrix} x_1 x_2 & \dots & x_{n-1} x_n \\ a & b \end{bmatrix}$$
 $y = \begin{bmatrix} y_1 y_2 & \dots & y_{n-1} y_n \\ c & d \end{bmatrix}$ Split numbers at digit $\left[\frac{n}{2}\right]$ $x = 10^{\left[\frac{n}{2}\right]}a + b$ $y = 10^{\left[\frac{n}{2}\right]}c + d$

$$x \cdot y = (10^{\left[\frac{n}{2}\right]}a + b) \times (10^{\left[\frac{n}{2}\right]}c + d)$$

$$x \cdot y = 10^{2 \left[\frac{n}{2} \right]} ac + 10^{\left[\frac{n}{2} \right]} (ad + bc) + bd$$

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

Karatsuba Multiplication

- Input: two *n*-digit numbers *x* and *y*
- Output: the product $x \cdot y$

$$x \cdot y = 10^{2 \left| \frac{n}{2} \right|} ac + 10^{\left| \frac{n}{2} \right|} (ad + bc) + bd$$

Rewrite:
$$(ad + bc) = (a + b)(c + d) - (ac) - (bd)$$

Only three subproblems!

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

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Divide & Conquer

Fibonacci Sequence: 0, 1, 1, 2, 3, 5, 8, 13, 21, 34, 55, 89, ...

A Fibonacci number F(n) is the sum of its two predecessors.

$$F(n) = \begin{cases} 0, & \text{if } n = 0 \\ 1, & \text{if } n = 1 \\ F(n-1) + F(n-2), & \text{otherwise} \end{cases}$$

NAÏVE-FIBONACCI(n)

 $T(n) = O(2^{0.694n})$

1: **if** n == 0

2: return 0

Bad, bad...really bad!

3: **if** n == 1

4: return 1

5: return FIBONACCI(n-1) + FIBONACCI(n-2)

Conclusions

Divide & Conquer...

...is a powerful algorithm design technique

...algorithms can be analysed using recurrences

...often, but not always, leads to efficient algorithms

References

Books

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