Introduction to Algorithms and Data Structures

Lecture 10: Divide-conquer-combine and the Master Theorem

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Data structures: reflection

We've looked at ...

- some classic abstract datatypes (lists, stacks, queues, sets, dictionaries)
- various concrete implementations of them (via extensible arrays, linked lists, hash tables, red-black trees . . .)

We've analysed their pros/cons in terms of asymptotic runtimes for operations. (Measured as number of line executions, paying attention to what's allowed as a $\Theta(1)$ time basic memory operation.)

The above datatypes are used frequently in programming – and many other algorithms build on them.

Most of these data structures already provided in standard libraries (e.g. Java API classes).

But understanding of runtime characteristics can help in

- writing efficient programs
- constructing efficient database queries.

Recursion: a recurring theme

As we've seen, many algorithms can be presented as recursive: i.e. they involve subcall to (one or more instances of) same problem.

Examples:

- **Expmod**(a,n,m) involves call to **Expmod**(a, $\lfloor n/2 \rfloor$,m).
- ► Mergesort(A,m,n) calls Mergesort(A,m,p) and Mergesort(A,p,n).
- ► Insert(x,k) (for binary trees) may call Insert(x.left,k) or Insert(x.right,k).

Common pattern:

- ▶ 'Simple' (e.g. small) instances can be dealt with directly.
- ► For larger instances, may do work before/during/after the recursive call(s): we divide into subproblems, conquer these, combine results.

E.g. for Mergesort:

- ▶ divide is simply checking n m > 1 and computing $\lfloor (m + n)/2 \rfloor$.
- **combine** is *merging* the two lists returned by the recursive calls.

Recurrence relations

How can we calculate the (asymptotic) runtime for a recursive algorithm?

Let T(n) be the worst-case runtime e.g. for Mergesort on array segments of size n.

Whatever the function T is, can say that

$$T(n) = T(\lfloor n/2 \rfloor) + T(\lceil n/2 \rceil) + F(n)$$
 for all $n > 1$,

where F(n) is the worst-case time for the divide and combine phases on inputs of size n. Can also say T(1) is a constant C.

This is an example of a recurrence relation.

If we know C and F, can compute T(n) for a specific n, e.g.

$$T(4) = 2T(2) + F(4) = 2(2T(1) + F(2)) + F(4) = 4C + 2F(2) + F(4)$$

But can we 'solve' the rec. rel. to find an explicit formula for T(n)? Or at least, for its asymptotic growth rate?

Recurrence relations for growth rates

$$T(n) = \begin{cases} C & \text{if } n = 1 \\ T(\lfloor n/2 \rfloor) + T(\lceil n/2 \rceil) + F(n) & \text{otherwise} \end{cases}$$

Actually, if we only want the growth rate of T, don't need to know F precisely — knowing its growth rate is enough.

E.g. in Mergesort example, have $F(n) = \Theta(n)$ (time for **Merge** on lists of length n/2).

Leads to the concept of an asymptotic recurrence relation. E.g.

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

Solution we're seeking isn't a precise function, but a growth rate. (Omission of $\lfloor - \rfloor$ and $\lceil - \rceil$ a bit sloppy ... but can be shown these 'don't affect asymptotic solution' in cases like this.)

Recurrence relations ctd.

Asymp. rec. relation for Mergesort again:

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

In Lecture 5 we saw informally that in this case $T(n) = \Theta(n \lg n)$.

Other examples:

Runtime of Expmod(a,n,m) for fixed a,m:

$$T(n) = T(n/2) + \Theta(1)$$
 for $n>1$

► Runtime of **Exp**(a,n) for fixed a (**Expmod** without the **mod**):

$$T(n) = T(n/2) + \Theta(n^2)$$
 for $n>1$

★ Can we solve such recurrences systematically? Is there a general pattern here?

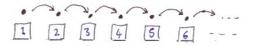
How do we come up with solutions?

Approach 1: Use intuition/experience/numerical data to 'guess' a solution, then verify it using induction.

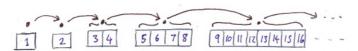
Usual concept of induction needs extending a bit.

We'll use MergeSort as an example.

Ordinary induction:



'Log induction':



Here, log induction on $k \simeq \text{ordinary induction on } \lceil \lg k \rceil$ (recursion depth for MergeSort on array segments of size k).

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Proof by induction on recursion depth

Claim: If $n - m = k \ge 1$, number of comparisons performed by **MergeSort** (A,m,n) is $\le k \lceil \lg k \rceil$.

Proof by complete induction on $\lceil \lg k \rceil$:

Base case: $\lceil \lg k \rceil = 0$, i.e. k = 1.

Then **MergeSort** immediately returns [A(m)] (0 comparisons).

Induction step: Suppose claim holds whenever $\lceil \lg k \rceil \le q$, and now consider some k such that $\lceil \lg k \rceil = q+1$.

Let $p = \lfloor (m+n)/2 \rfloor$, $k_1 = p - m$, $k_2 = n - p$. (So either $k_1 = k_2 = k/2$ or $k_1 = \lfloor k/2 \rfloor$, $k_2 = \lceil k/2 \rceil$.)

In any case, we have $\lceil \lg(k_1) \rceil$, $\lceil \lg(k_2) \rceil \le q$.

So by induction hypothesis:

- ▶ MergeSort (A, m, p) takes $\leq k_1 \lceil \lg(k_1) \rceil \leq k_1 q$ comparisons,
- ▶ MergeSort (A, p, n) takes $\leq k_2\lceil \lg(k_2)\rceil \leq k_2q$ comparisons,
- ▶ the final **Merge** (B, C) takes $\leq k_1 + k_2 = k$ comparisons.

So total number of comparisons is $\leq k_1q + k_2q + k = kq + k = k(q+1) = k\lceil \lg k \rceil$ as required. \square IADS Lecture 10 Slide 8

The Master Theorem

Approach 2: If our recurrence happens to be of the form . . .

$$T(n) = \begin{cases} \Theta(1) & \text{if } n \leq n_0 \\ aT(n/b) + \Theta(n^k) & \text{if } n > n_0 \end{cases}$$

... then there's a Master Theorem that simply gives us the answer. (Also works with 'floors and ceilings' around.)

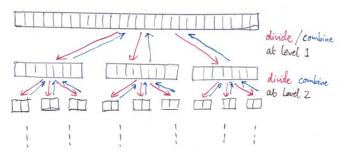
The answer depends on how a compares with b^k (will explain!). Equivalently, how $e = \log_b a$ compares with k.

$$T(n) = \begin{cases} \Theta(n^e) & \text{if } e > k \\ \Theta(n^k \lg n) & \text{if } e = k \\ \Theta(n^k) & \text{if } e < k \end{cases}$$

This applies in many (not all) commonly arising situations. (CLRS 4.5 gives a more general version of the theorem.)

Master Theorem: informal intuition

Think about **total** work done by all divide / combine phases at each recursion level. Does this increase or decrease as we go down?



- Larger a (no. of subproblems) means more work as we descend.
- ▶ But larger b means each subproblem is smaller. If divide/combine work is $F(n) = \Theta(n^k)$, then reducing problem size by factor b will reduce this work by b^k .
- ▶ So break-even point is when $a = b^k$. In this case, amount of work is 'essentially the same' for all levels.

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Optional slide (not covered in video lecture)

A bit more detail for those interested . . .

- If $a < b^k$, then the most work is done at the top level. Thereafter, amount of work roughly decreases in geometric progression, by factor $r = a/b^k < 1$. So total work will be roughly top-level work $(\Theta(n^k))$ times $1 + r + r^2 + \cdots \leq 1/(1-r)$ (constant). Still $\Theta(n^k)$.
- ▶ If $a > b^k$, work increases by $r = a/b^k > 1$ as we descend. Around $\log_b(n)$ levels. So bottom-level exceeds top-level by

$$r^{\log_b(n)} = b^{\log_b(r) \cdot \log_b(n)} = b^{\log_b(n) \cdot \log_b(a/b^k)} = n^{e-k}$$

So total work comes out as $\Theta(n^k).\Theta(n^{e-k}) = \Theta(n^e)$.

▶ If $a = b^k$, all levels are 'essentially the same'. So work is roughly (top-level work × number of levels), i.e. $\Theta(n^k \lg n)$.

Master Theorem in action

► Mergesort recurrence again:

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

Here a=2, b=2, k=1. So $e=\log_b a=1$ and e=k. So we're in the middle case: $\Theta(n \log n)$.

Exp(a,n) for fixed a:

$$T(n) = T(n/2) + \Theta(n^2)$$
 if n>1

Here a = 1, b = 2, k = 2. So $e = \log_b a = 0$ and e < k. Work at top-level dominates: solution is $\Theta(n^2)$.

More examples coming in Tutorial Sheet 4 (for Week 8).

Reading: CLRS Chapter 4 intro and 4.3-4.5.

Today's music: Trad. spiritual, This little light of mine
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Roundup of sorting algorithms

For long lists, Insertsort and Bubblesort aren't serious contenders: both take $\Theta(n^2)$ time on average.

	Mergesort	Heapsort	Quicksort
Average-case time	$\Theta(n \lg n)$	$\Theta(n \lg n)$	$\Theta(n \lg n)$
Worst-case time	$\Theta(n \lg n)$	$\Theta(n \lg n)$	$\Theta(n^2)$
Best-case time	$\Theta(n \lg n)$	$\Theta(n)$ (when input	$\Theta(n \lg n)$
		already sorted)	
Hidden constants	medium	large?	small
Extra space needed	$\Theta(n)$	$\Theta(1)$ (in-place)	$\Theta(1)$ (in-place)
Stable?	Yes	No	No
Memory locality	ok?	poor	good

Theorem: Any general, comparison-based sorting algorithm has worst-case time $\Omega(n | g n)$.

[Proved in CLRS 8.1: boils down to $\lg(n!) = \Omega(n \lg n)$.]

However, Countsort, Radixsort, Bucketsort run in O(n) time on more specialized kinds of inputs. [CLRS 8.2, 8.3, 8.4]