Chpater 4. Divide-and-Conquer

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Assignment

- ► Read §4.1, §4.2, §4.3
- ► Problems:
 - ► §4.1 #4
 - ► §4.2 #1, 2, 5
 - ▶ §4.3 #1(a), 1(c), 2

Chapter 4: Divide-and-Conquer

- Chapter 4.1: Multiplying square matrices
- Chapter 4.2: Strassen's algorithm for matrix multiplication
- ► Chapter 4.3: The substitution method for solving recurrences
- Chapter 4.4: The recursion-tree method for solving recurrences
- Chapter 4.5: The master method for solving recurrences
- Chapter 4.6: Proof of the continuous master theorem
- ► Chapter 4.7: Akra-Bazzi recurrences

What is Divide-and-Conquer?

A powerful strategy for designing asymptotically efficient algorithms.

- ▶ We've already seen divide-and-conquer in Merge Sort (Section 2.3.1).
- ► The key idea: solve a problem recursively by breaking it into smaller pieces.
- ► This chapter focuses on algorithm design & solving recurrence relations.

Divide-and-Conquer Paradigm

A recursive algorithm with three main steps:

- 1. **Divide**: Break the problem into smaller subproblems.
- 2. **Conquer**: Solve each subproblem recursively.
- 3. **Combine**: Merge subproblem solutions into a global solution.

The recursion continues until reaching a **base case**, small enough to solve directly.

Why Recurrences?

Recurrences describe the running time of recursive algorithms.

- ► A **recurrence** is an equation for a function defined in terms of smaller inputs.
- Example: Merge Sort's worst-case recurrence from Section 2.3.2.
- Understanding recurrences helps analyze and design efficient algorithms.

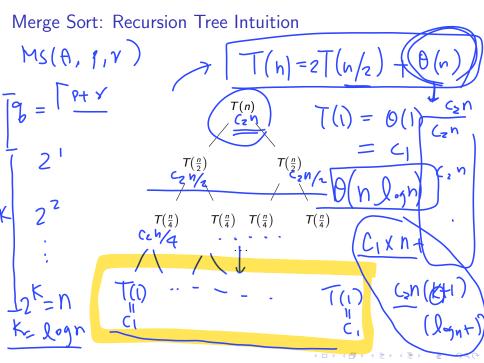
What is an Algorithmic Recurrence?

A recurrence T(n) is algorithmic if:

- 1. $T(n) = \Theta(1)$ for all $n < n_0$ (base case threshold).
- 2. Every recursive path eventually reaches a base case.

These properties ensure the algorithm:

- Runs in finite time.
- Solves at least one valid input of each size $n < n_0$.



Merge Sort Recurrence and Base Case

Recurrence:

$$T(n) = 2 T(\frac{n}{2}) + \Theta(n)$$
, for $n > 1$.

Base Case:

$$T(1) = \Theta(1).$$

Even though sorting a single element is trivial (no comparisons needed), we still incur a *constant cost*:

- ▶ Checking if n = 1.
- Possibly returning or copying the element.
- ► Function-call overhead, etc.

Solution: Recursion-tree analysis,

$$T(n) = \Theta(n \log n).$$

Recurrence Conventions

To simplify recurrence analysis:

- Assume recurrences are algorithmic unless stated otherwise.
- ▶ Ignore floors/ceilings when they don't affect asymptotics.
- If recurrence is an inequality:
 - ▶ Use $O(\cdot)$ for upper bounds (e.g., $T(n) \le 2T(n/2) + \Theta(n)$).
 - ▶ Use $\Omega(\cdot)$ for lower bounds (e.g., $T(n) \ge 2T(n/2) + \Theta(n)$).

Examples of Recurrences

Different divide-and-conquer algorithms yield different recurrences:

- ► $T(n) = 8T(n/2) + \Theta(1) \rightarrow \Theta(n^3)$ (simple matrix multiplication)
- ► $T(n) = 7T(n/2) + \Theta(n^2) \rightarrow \Theta(n^{\log_2 7})$ (Strassen's algorithm)
- $T(n) = T(n/3) + T(2n/3) + \Theta(n) \rightarrow \Theta(n \log n)$
- ► $T(n) = T(n/5) + T(7n/10) + \Theta(n) \rightarrow \Theta(n)$ (Chapter 9)
- ▶ $T(n) = T(n-1) + \Theta(1) \rightarrow \Theta(n)$ (e.g., recursive linear search)

Coming Up: Tools to Solve Recurrences

We'll explore four methods for solving divide-and-conquer recurrences:

- ➤ **Substitution Method** (Section 4.3): Guess-and-prove via induction.
- Recursion-Tree Method (Section 4.4): Sum costs across recursion levels.
- ▶ **Master Method** (Sections 4.5–4.6): Fast asymptotic bounds for T(n) = aT(n/b) + f(n).
- ► Akra-Bazzi Method (Section 4.7): Handles more general cases with calculus.

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Matrix Multiplication Basics



Let $A = (a_{ik})$ and $B = (b_{kj})$ be $n \times n$ matrices.

The (i,j)-th entry of $C = A \cdot B$ is:

$$c_{ij} = \sum_{k=1}^{n} a_{ik} \cdot b_{kj}$$

$$(4.1)$$

Straightforward algorithm runs in $\Theta(n^3)$ time.

Straightforward Triple-Loop Algorithm

MATRIX-MULTIPLY(A, B, C, n)

For
$$i = 1$$
 to n

For
$$j = 1$$
 to n

For
$$k=1$$
 to n

$$\qquad \qquad c_{ij} \leftarrow c_{ij} + a_{ik} \cdot b_{kj}$$

Runs in $\Theta(n^3)$ time.

Divide-and-Conquer Matrix Multiplication

Partition $n \times n$ matrices into $n/2 \times n/2$ submatrices:

$$A = \begin{bmatrix} A_{11} & A_{12} \\ A_{21} & A_{22} \end{bmatrix}, \quad B = \begin{bmatrix} B_{11} & B_{12} \\ B_{21} & B_{22} \end{bmatrix}$$

$$C = \begin{bmatrix} C_{11} & C_{12} \\ C_{21} & C_{22} \end{bmatrix}$$

$$A_{1} = \begin{bmatrix} A_{11} & A_{12} \\ A_{21} & A_{22} \end{bmatrix}$$

$$A_{2} = \begin{bmatrix} A_{11} & A_{12} \\ A_{21} & A_{22} \end{bmatrix}$$

$$A_{3} = \begin{bmatrix} A_{11} & A_{12} \\ A_{21} & A_{22} \end{bmatrix}$$

$$A_{4} = \begin{bmatrix} A_{11} & A_{12} \\ A_{21} & A_{22} \end{bmatrix}$$

$$A_{4} = \begin{bmatrix} A_{11} & A_{12} \\ A_{21} & A_{22} \end{bmatrix}$$

Submatrix Multiplication

```
MM (A,B,n)
                                                       MM (AII, BII, n/2)
MM (AII, Br, n/2)
Compute C = A \cdot B using:
                           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}
```

Requires 8 multiplications of $n/2 \times n/2$ matrices and 4 additions.

MATRIX-MULTIPLY-RECURSIVE (A, B, C, n)

```
MATRIX-MULTIPLY-RECURSIVE (A, B, C, n)
    if n == 1
 2 // Base case.
         c_{11} = c_{11} + a_{11} \cdot b_{11}
         return
5 // Divide.
 6 partition A, B, and C into n/2 \times n/2 submatrices
         A_{11}, A_{12}, A_{21}, A_{22}; B_{11}, B_{12}, B_{21}, B_{22};
         and C_{11}, C_{12}, C_{21}, C_{22}; respectively
    // Conquer.
    MATRIX-MULTIPLY-RECURSIVE (A_{11}, B_{11}, C_{11}, n/2)
    MATRIX-MULTIPLY-RECURSIVE (A_{11}, B_{12}, C_{12}, n/2)
    MATRIX-MULTIPLY-RECURSIVE (A_{21}, B_{11}, C_{21}, n/2)
    MATRIX-MULTIPLY-RECURSIVE (A_{21}, B_{12}, C_{22}, n/2)
    MATRIX-MULTIPLY-RECURSIVE (A_{12}, B_{21}, C_{11}, n/2)
    MATRIX-MULTIPLY-RECURSIVE (A_{12}, B_{22}, C_{12}, n/2)
    MATRIX-MULTIPLY-RECURSIVE (A_{22}, B_{21}, C_{21}, n/2)
    MATRIX-MULTIPLY-RECURSIVE (A_{22}, B_{22}, C_{22}, n/2)
```

Base Case and Partitioning

Base Case (n = 1):

- Each matrix is 1 × 1, so just a single scalar.
- ▶ Computation of $C \leftarrow C + A \times B$ involves:

$$c_{11} \leftarrow c_{11} + a_{11} \cdot b_{11},$$

i.e., one multiplication + one addition.

▶ Therefore, $T(1) = \Theta(1)$.

Partitioning Cost:

- Uses index calculations (no bulk copying).
- ▶ We just compute offsets to define $\frac{n}{2} \times \frac{n}{2}$ submatrices.
- ▶ Hence, partitioning is a constant-time $\Theta(1)$ step, independent of n.

Eight Subproblems and Overall Recurrence

Eight Subproblems:

- ▶ After partitioning, we have 8 recursive calls, each on $\frac{n}{2} \times \frac{n}{2}$ submatrices.
- ▶ Each contributes $T(\frac{n}{2})$ to the running time.
- ▶ Only overhead: a $\Theta(1)$ partition step.

Time Complexity of Recursive Algorithm

$$T(n) = B T(n/2) + O(1)$$

$$(5), \text{ we get:}$$

Let T(n) be the running time.

$$T(n) = 8T(n/2) + \Theta(1)$$

Using the Master Method (Section 4.5), we get:

$$T(n) = \Theta(n^3)$$

Same as the triple-loop algorithm + no speedup yet.

Why Not Faster Than Merge Sort?

Merge Sort:

$$T_{\text{merge}}(n) = 2 T(\frac{n}{2}) + \Theta(n) \implies \Theta(n \log n).$$

- Fewer subproblems per level (only 2).
- ▶ Combine step (merging) costs $\Theta(n)$ each level.

Recursive Matrix Multiply:

$$T(n) = 8 T(\frac{n}{2}) + \Theta(1) \implies \Theta(n^3).$$

- ▶ More subproblems per level (8).
- ▶ Combine step is cheap: $\Theta(1)$ per level.

Conclusion:

- ▶ Having only 2 subproblems yields $\Theta(n \log n)$.
- ► Having 8 subproblems, despite cheaper combine, grows to $\Theta(n^3)$.
- ▶ The large branching factor (8) outweighs the small $\Theta(1)$ combine.



Exercise 4.1-3 (CLRS 4th ed.)

Problem Statement:

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

"MATRIX-MULTIPLY-RECURSIVE" (page 83) partitions matrices A, B, C by index calculation, taking $\Theta(1)$ time. Suppose instead that you *copy* the appropriate elements of A, B, A and C into separate $\frac{n}{2} \times \frac{n}{2}$ submatrices

$$A_{11}, A_{12}, A_{21}, A_{22}, \quad B_{11}, B_{12}, B_{21}, B_{22}, \quad C_{11}, C_{12}, C_{21}, C_{22}$$

respectively, and after the recursive calls, you copy the results from C_{11} , C_{12} , C_{21} , C_{22} back into the appropriate places in C.

Question: How does the recurrence (4.9) change, and what is its solution?

Solution to Exercise 4.1-3

Copying Cost:

- ▶ Copying all relevant submatrices of A, B, and C (and then copying back) touches $\Theta(n^2)$ elements at each level of recursion.
- ▶ Thus, the partition+combine overhead is now $\Theta(n^2)$ instead of $\Theta(1)$.

New Recurrence:

$$T(n) = 8 T(\frac{n}{2}) + \Theta(n^2).$$



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4.2 Strassen's Algorithm for Matrix Multiplication

Matrix multiplication in less than $\Theta(n^3)$ time?

- ▶ Until 1969, many believed n^3 multiplications were necessary.
- ▶ V. Strassen proved a *remarkable* divide-and-conquer method.
- ▶ Strassen's running time: $\Theta(n^{\lg 7}) \approx \Theta(n^{2.81})$.
- ▶ This beats the classical $\Theta(n^3)$ approach.

Main idea:

- ▶ Same *recursive* partitioning of $n \times n$ matrices into $n/2 \times n/2$ blocks.
- But reduce the number of matrix multiplications from 8 down to 7.
- ▶ Pay a small overhead of extra additions (still only a constant factor).

How to Reduce Multiplications?

Motivation from a simple scalar example:

$$x^2 - y^2$$
 (normally needs 2 multiplications)

But recall the identity:

$$x^{2} - y^{2} = (x + y)(x - y),$$

which needs only 1 multiplication $(x + y) \cdot (x - y)$, plus 2 additions.

Why helpful for matrices?

- For scalars, both methods cost 3 operations, so no big deal.
- For large matrices:
 - ▶ Multiplication is $\Theta(n^3)$ (classical).
 - Addition is only $\Theta(n^2)$.
- Replacing one matrix multiplication with a few more additions can lower total cost.

Strassen's Algorithm: Steps 1 and 2

Step 1: Base Case / Partition

- ▶ If n = 1, each matrix is just a single element.
 - ▶ Do 1 scalar multiply + 1 scalar add $(\Theta(1))$.
 - Return.
- ▶ Otherwise, partition A, B, and C each into four $\frac{n}{2} \times \frac{n}{2}$ submatrices.
- ▶ Partitioning by index calculation: $\Theta(1)$.

Step 2: Form S- and P- storage

- ▶ Create 10 *sum/difference* matrices $S_1, ..., S_{10}$ (each $\frac{n}{2} \times \frac{n}{2}$).
- ightharpoonup Zero-initialize 7 product-result matrices P_1, \ldots, P_7 .
- ▶ All told, 17 submatrices, each with $\frac{n}{2} \times \frac{n}{2}$ entries.
- ▶ Cost: $\Theta(n^2)$, since we write all these entries once.

Strassen's Step 2 and Step 3: S and P Matrices

Step 2: Construct 10 matrices S_1, \ldots, S_{10} (each $n/2 \times n/2$)

$$\begin{split} S_1 &= B_{12} - B_{22}, \quad S_2 = A_{11} + A_{12}, \quad S_3 = A_{21} + A_{22}, \\ S_4 &= B_{21} - B_{11}, \quad S_5 = A_{11} + A_{22}, \quad S_6 = B_{11} + B_{22}, \\ S_7 &= A_{12} - A_{22}, \quad S_8 = B_{21} + B_{22}, \quad S_9 = A_{11} - A_{21}, \quad S_{10} = B_{11} + B_{12}. \end{split}$$

Step 3: Recursively compute 7 matrices P_1, \ldots, P_7 (each $n/2 \times n/2$)

$$\begin{split} P_1 &= A_{11} \times S_1, \quad \text{(corresponds to } A_{11}(B_{12} - B_{22})), \\ P_2 &= S_2 \times B_{22}, \qquad \qquad ((A_{11} + A_{12})B_{22}), \\ P_3 &= S_3 \times B_{11}, \qquad \qquad ((A_{21} + A_{22})B_{11}), \\ P_4 &= A_{22} \times S_4, \qquad \qquad (A_{22}(B_{21} - B_{11})), \\ P_5 &= S_5 \times S_6, \qquad \qquad ((A_{11} + A_{22})(B_{11} + B_{22})), \\ P_6 &= S_7 \times S_8, \qquad \qquad ((A_{12} - A_{22})(B_{21} + B_{22})), \\ P_7 &= S_9 \times S_{10}, \qquad ((A_{11} - A_{21})(B_{11} + B_{12})). \end{split}$$

Aligning the C_{11} Expansion (Strassen Step 4)

Update for C_{11} :

$$C_{11} \leftarrow C_{11} + P_5 + P_4 - P_2 + P_6.$$

Expanding each P_i :

$$\underbrace{(A_{11}B_{11} + A_{12}B_{22} + A_{22}B_{11} + A_{22}B_{22})}_{P_{2}} + \underbrace{(A_{22}B_{22} - A_{22}B_{11})}_{P_{4}} - \underbrace{(A_{11}B_{22} + A_{12}B_{22})}_{P_{2}} + \underbrace{(A_{22}B_{22} - A_{22}B_{21} + A_{12}B_{22} + A_{12}B_{21})}_{P_{6}}$$

$$= A_{11}B_{11} + A_{12}B_{21}.$$

Observation: Notice how many terms subtract out in the middle lines. Everything simplifies to exactly $A_{11}B_{11} + A_{12}B_{21}$, which matches the formula for $C_{11} = A_{11}B_{11} + A_{12}B_{21}$.

Final Updates for C_{12} , C_{21} , and C_{22}

1.
$$C_{12} \leftarrow C_{12} + P_1 + P_2$$

 $(A_{11}B_{12} - A_{11}B_{22}) + ((A_{11} + A_{12})B_{22})$
 $= A_{11}B_{12} + A_{12}B_{22}.$

Hence, $C_{12} = A_{11}B_{12} + A_{12}B_{22}$.

2.
$$C_{21} \leftarrow C_{21} + P_3 + P_4$$

$$((A_{21} + A_{22})B_{11}) + (A_{22}(B_{21} - B_{11}))$$

$$= A_{21}B_{11} + A_{22}B_{21}.$$

Hence, $C_{21} = A_{21}B_{11} + A_{22}B_{21}$.

3. $C_{22} \leftarrow C_{22} + P_5 + P_1 - P_3 - P_7$ (omitting intermediate lines)

$$C_{22} = A_{21}B_{12} + A_{22}B_{22}.$$

Strassen's Algorithm: Complexity Summary

Step 1: Base Case / Partition ($\Theta(1)$ cost)

- ▶ If n = 1, just 1 scalar multiply + 1 add $\Rightarrow \Theta(1)$.
- ▶ Otherwise, partition into $\frac{n}{2} \times \frac{n}{2}$ submatrices, also in $\Theta(1)$ time by index calculation.

Step 2: Create S_i and P_i storage ($\Theta(n^2)$ cost)

- ▶ 10 sums/differences S_1, \ldots, S_{10} , plus 7 zero-initialized P_i .
- ▶ Touches n^2 elements total $\implies \Theta(n^2)$.

Step 3: 7 Recursive Multiplications

$$Cost = 7 T\left(\frac{n}{2}\right).$$

(Instead of 8, saving one multiplication in exchange for extra adds.)

Step 4: Combine Results ($\Theta(n^2)$ cost)

▶ Add/subtract P_i 's into C_{ii} submatrices $\implies \Theta(n^2)$.

Overall Recurrence:

$$T(n) = 7 T(\frac{n}{2}) + \Theta(n^2).$$
Master Method yields $T(n) = \Theta(n^{\log_2 7}) \approx \Theta(n^{2.81})$.

Comparing Naive Divide-and-Conquer vs. Strassen

Naive Divide-and-Conquer:

$$T_{\text{naive}}(n) = 8 T(\frac{n}{2}) + \Theta(1).$$

- ightharpoonup \Rightarrow $T_{\text{naive}}(n) = \Theta(n^3)$.
- ▶ 8 subproblems at each level; partition/combine is cheap $(\Theta(1))$.

Strassen's Method:

$$T_{\text{Strassen}}(n) = 7 T\left(\frac{n}{2}\right) + \Theta(n^2).$$

- ightharpoonup \Rightarrow $T_{\mathsf{Strassen}}(n) = \Theta(n^{\log_2(7)}) \approx \Theta(n^{2.81}).$
- Fewer recursive multiplications (7 vs. 8), but more $\Theta(n^2)$ addition overhead.

Conclusion:

- Strassen's clever trade-off yields a strictly faster algorithm asymptotically.
- ▶ Both beat the triple-loop $\Theta(n^3)$ approach, but Strassen's outperforms naive DC.



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4.3 The Substitution Method: Intuition and Setup

The substitution method = guess + induction.

Step 1: Make an educated guess.

We think the recurrence

$$T(n) = 2T(\lfloor n/2 \rfloor) + \Theta(n)$$

might be bounded by $T(n) = O(n \log n)$.

Step 2: Try to prove it by induction.

We assume the bound holds for smaller values:

Assume
$$T(k) \le c k \log k$$
 for all $n_0 \le k < n$.

(Note: the recurrence only needs $T(\lfloor n/2 \rfloor)$, but induction assumes all smaller k.)

Why this assumption?

- ▶ We're trying to show T(n) doesn't grow faster than $n \log n$.
- This assumption lets us plug into the recurrence and test if our guess works.
- ▶ If it fails, we adjust constants (c, n_0) until it holds.

This is how we "substitute" our guess into the recurrence to prove the bound!



Step 2: Substitution into the Recurrence

Assume $n \ge 2n_0$, so the inductive hypothesis applies to $\lfloor n/2 \rfloor$.

Apply the recurrence:

$$T(n) = 2T(\lfloor n/2 \rfloor) + \Theta(n)$$

Apply the inductive hypothesis:

$$T(\lfloor n/2 \rfloor) \le c \lfloor n/2 \rfloor \log(\lfloor n/2 \rfloor)$$

Approximate:

$$\leq c \frac{n}{2} \log \left(\frac{n}{2}\right) = \frac{c n}{2} (\log n - 1)$$

Now plug in:

$$T(n) \le 2 \cdot \frac{c \, n}{2} (\log n - 1) + a \, n = c \, n \log n - c \, n + a \, n \neq c \, n \log n + (a - c) n$$

We want:

$$T(n) \le c n \log n$$

So require:

$$(a-c)n \leq 0 \Rightarrow c \geq a$$

Therefore:

- ▶ Choose $c \ge a$ (where a comes from the hidden constant in $\Theta(n)$) Then for all $n \geq 2n_0$, we have:

$$T(n) \le c \, n \log n$$

Substitution Method: Verifying Base Cases

We showed the inductive step holds for $n \ge 2n_0$. Now verify the base cases: $n_0 \le n < 2n_0$.

Choose $n_0 = 2 \Rightarrow n = 2, 3.$

- ▶ Since T(n) is algorithmic, T(2) and T(3) are constant.
- ► Set $c = \max\{T(2), T(3)\}$
- ► Then:

$$T(2) \le c < 2c \log 2$$
, $T(3) \le c < 3c \log 3$

Conclusion:

$$T(n) \le c n \log n$$
 for all $n \ge 2 \Rightarrow T(n) = O(n \log n)$

Practical Notes on Substitution Method (Base Cases)

Do we always need to write out the base case proof in full?

Not usually. In the algorithms literature:

- People rarely show full base case details.
- ▶ Most divide-and-conquer recurrences bottom out when n is small.
- It's standard to assume:

$$T(n) \le c n \log n$$
 for $n_0 \le n < n'_0$

for some constants n_0 , $n'_0 > n_0$ (e.g., $n'_0 = 2n_0$).

► Then we just choose *c* large enough to make the inequality hold.

Conclusion: The base case is usually routine. Once the inductive step is proven, the full proof is considered complete.

Making a Good Guess for Substitution

How do you guess a solution to a recurrence?

- No general formula it takes intuition, experience, and practice.
- ▶ If a recurrence *resembles* a known one, guess similarly:

$$T(n) = 2T(n/2 + 17) + \Theta(n) \Rightarrow O(n \log n)$$

(because "+17" doesn't matter asymptotically)

- Use bounding technique:
 - Start with a rough range:

$$\Omega(n) \leq T(n) \leq O(n^2)$$

▶ Refine both bounds until they meet at $\Theta(n \log n)$.

Bottom line: Guess, test, refine — and develop your recurrence intuition!

Trick of the Trade: Subtracting a Low-Order Term

Problem: Trying to prove T(n) = O(n) for

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

Guessing $T(n) \le c n$ doesn't work:

$$T(n) \le 2 \cdot c(n/2) + a = c n + a \nleq c n$$

Fix: Strengthen the inductive hypothesis:

$$T(n) \le c \, n - d$$
 for some $d > 0$

Now:

$$T(n) \le 2\left(\frac{c n}{2} - d\right) + a = c n - 2d + a$$

Choose d > a:

$$T(n) \le c n - \text{(something positive)} \Rightarrow T(n) \le c n$$

Insight: Subtracting a small term once for each recursive call helps the inequality close.

Avoiding Pitfalls in the Substitution Method

Don't use asymptotic notation in the inductive hypothesis! Wrong approach:

$$T(n) = 2T(\lfloor n/2 \rfloor) + \Theta(n)$$

Assume
$$T(n) = O(n) \Rightarrow T(n) \le 2 \cdot O(n) + \Theta(n) = O(n)$$

Why it's wrong:

- ▶ The constants inside O(n) and $\Theta(n)$ are hidden and may vary.
- ▶ You lose control over the exact bound required for induction.
- ▶ Can't conclude $T(n) \le c n$ from vague O(n) steps.

Correct approach:

- ▶ Explicitly guess $T(n) \le c n$
- Carry out the proof with real constants.
- At the end, conclude T(n) = O(n) once all constants are handled.



Question?