### Divide-and-Conquer

Divide-and conquer is a general algorithm design paradigm:

- **Divide**: divide the input data $S$ into two or more disjoint subsets $S_1$, $S_2$, ...
- **Recur**: solve the subproblems recursively
- **Conquer**: combine the solutions for $S_1$, $S_2$, ..., into a solution for $S$

The base case for the recursion are subproblems of constant size.

Analysis can be done using recurrence equations.

### Merge-Sort Review

- Merge-sort on an input sequence $S$ with $n$ elements consists of three steps:
  - **Divide**: partition $S$ into two sequences $S_1$ and $S_2$ of about $n/2$ elements each
  - **Recur**: recursively sort $S_1$ and $S_2$
  - **Conquer**: merge $S_1$ and $S_2$ into a unique sorted sequence

**Algorithm** `mergeSort(S, C)`

**Input** sequence $S$ with $n$ elements, comparator $C$

**Output** sequence $S$ sorted according to $C$

- If $S.size() > 1$
  - $(S_1, S_2) \leftarrow$ partition($S, n/2$)
  - `mergeSort(S_1, C)`
  - `mergeSort(S_2, C)`
  - $S \leftarrow$ merge($S_1, S_2$)

### Recurrence Equation Analysis

The conquer step of merge-sort consists of merging two sorted sequences, each with $n/2$ elements and implemented by means of a doubly linked list, takes at most $bn$ steps, for some constant $b$.

Likewise, the basis case ($n < 2$) will take at most $b$ steps.

Therefore, if we let $T(n)$ denote the running time of merge-sort:

$$ T(n) = \begin{cases} 
  b & \text{if } n < 2 \\
  2T(n/2) + bn & \text{if } n \geq 2 
\end{cases} $$

We can therefore analyze the running time of merge-sort by finding a closed form solution to the above equation.

That is, a solution that has $T(n)$ only on the left-hand side.
Iterative Substitution

In the iterative substitution, or "plug-and-chug," technique, we iteratively apply the recurrence equation to itself and see if we can find a pattern:

\[ T(n) = 2T(n/2) + bn \]

\[ = 2(2T(n/2^2)) + b(n/2) + bn \]

\[ = 2^2T(n/2^2) + 2bn \]

\[ = 2^3T(n/2^3) + 3bn \]

\[ = 2^4T(n/2^4) + 4bn \]

\[ = \ldots \]

\[ = 2^iT(n/2^i) + ibn \]

Note that base, \( T(n)=b \), case occurs when \( 2^i = n \). That is, \( i = \log n \).

So,

\[ T(n) = bn + bn \log n \]

Thus, \( T(n) = \Theta(n \log n) \).

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The Recursion Tree

Draw the recursion tree for the recurrence relation and look for a pattern:

\[ T(n) = \begin{cases} 
  b & \text{if } n < 2 \\
  2T(n/2) + bn & \text{if } n \geq 2 
\end{cases} \]

- Draw the recursion tree for the recurrence relation and look for a pattern:
- **T**'s size
- **深度**
- **时间**

<table>
<thead>
<tr>
<th>depth</th>
<th>T's size</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>( n )</td>
</tr>
<tr>
<td>1</td>
<td>( n/2 )</td>
</tr>
<tr>
<td>( i )</td>
<td>( n/2^i )</td>
</tr>
</tbody>
</table>

Total time = \( bn + bn \log n \) (last level plus all previous levels)

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Guess-and-Test Method

In the guess-and-test method, we guess a closed form solution and then try to prove it is true by induction:

\[ T(n) = \begin{cases} 
  b & \text{if } n < 2 \\
  2T(n/2) + bn \log n & \text{if } n \geq 2 
\end{cases} \]

**Guess: \( T(n) < cn \log n \).**

**Guess #2: \( T(n) < cn^2 \log n \).**

\[ T(n) = 2T(n/2) + bn \log n \]

\[ = 2(c(n/2) \log(n/2)) + bn \log n \]

\[ = cn(\log n - \log 2) + bn \log n \]

\[ = cn \log n - cn + bn \log n \]

Wrong: we cannot make this last line be less than \( cn \log n \)

So, \( T(n) = O(n \log^2 n) \).

In general, to use this method, you need to have a good guess and you need to be good at induction proofs.
Master Method (Appendix)

Many divide-and-conquer recurrence equations have the form:

\[ T(n) = \begin{cases} 
    c & \text{if } n < d \\
    aT(n/b) + f(n) & \text{if } n \geq d 
\end{cases} \]

The Master Theorem:
1. if \( f(n) = O(n^{\log_b a - \varepsilon}) \), then \( T(n) = \Theta(n^{\log_b a}) \)
2. if \( f(n) = \Theta(n^{\log_b a \log k n}) \), then \( T(n) = \Theta(n^{\log_b a \log^{k+1} n}) \)
3. if \( f(n) = \Omega(n^{\log_b a + \varepsilon}) \), then \( T(n) = \Theta(f(n)) \), provided \( af(n/b) \leq \delta f(n) \) for some \( \delta < 1 \).

Example:

\( T(n) = 2T(n/2) + n \log n \)

Solution: \( \log_b a = 1 \), so case 2 says \( T(n) = O(n \log^2 n) \).

Master Method, Example 1

The form:
\[ T(n) = \begin{cases} 
    c & \text{if } n < d \\
    aT(n/b) + f(n) & \text{if } n \geq d 
\end{cases} \]

The Master Theorem:
1. if \( f(n) = O(n^{\log_b a - \varepsilon}) \), then \( T(n) = \Theta(n^{\log_b a}) \)
2. if \( f(n) = \Theta(n^{\log_b a \log k n}) \), then \( T(n) = \Theta(n^{\log_b a \log^{k+1} n}) \)
3. if \( f(n) = \Omega(n^{\log_b a + \varepsilon}) \), then \( T(n) = \Theta(f(n)) \), provided \( af(n/b) \leq \delta f(n) \) for some \( \delta < 1 \).

Example:

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

Solution: \( \log_b a = 2 \), so case 1 says \( T(n) = O(n^2) \).

Master Method, Example 2

The form:
\[ T(n) = \begin{cases} 
    c & \text{if } n < d \\
    aT(n/b) + f(n) & \text{if } n \geq d 
\end{cases} \]

The Master Theorem:
1. if \( f(n) = O(n^{\log_b a - \varepsilon}) \), then \( T(n) = \Theta(n^{\log_b a}) \)
2. if \( f(n) = \Theta(n^{\log_b a \log k n}) \), then \( T(n) = \Theta(n^{\log_b a \log^{k+1} n}) \)
3. if \( f(n) = \Omega(n^{\log_b a + \varepsilon}) \), then \( T(n) = \Theta(f(n)) \), provided \( af(n/b) \leq \delta f(n) \) for some \( \delta < 1 \).

Example:

\( T(n) = 2T(n/2) + n \log n \)

Solution: \( \log_b a = 1 \), so case 2 says \( T(n) = O(n \log^2 n) \).

Master Method, Example 3

The form:
\[ T(n) = \begin{cases} 
    c & \text{if } n < d \\
    aT(n/b) + f(n) & \text{if } n \geq d 
\end{cases} \]

The Master Theorem:
1. if \( f(n) = O(n^{\log_b a - \varepsilon}) \), then \( T(n) = \Theta(n^{\log_b a}) \)
2. if \( f(n) = \Theta(n^{\log_b a \log k n}) \), then \( T(n) = \Theta(n^{\log_b a \log^{k+1} n}) \)
3. if \( f(n) = \Omega(n^{\log_b a + \varepsilon}) \), then \( T(n) = \Theta(f(n)) \), provided \( af(n/b) \leq \delta f(n) \) for some \( \delta < 1 \).

Example:

\( T(n) = T(n/3) + n \log n \)

Solution: \( \log_b a = 0 \), so case 3 says \( T(n) = O(n \log n) \).
Master Method, Example 4

The form: \[ T(n) = \begin{cases} \ c \ & \text{if } n < d \\ aT(n/b) + f(n) \ & \text{if } n \geq d \end{cases} \]

The Master Theorem:
1. if \( f(n) = O(n^{\log_b a - \varepsilon}) \), then \( T(n) = \Theta(n^{\log_b a}) \)
2. if \( f(n) = \Theta(n^{\log_b a \log^k n}) \), then \( T(n) = \Theta(n^{\log_b a \log^k n}) \)
3. if \( f(n) = \Omega(n^{\log_b a + \varepsilon}) \), then \( T(n) = \Theta(f(n)) \), provided \( af(n/b) \leq \Psi(n) \) for some \( \delta < 1 \).

Example:
\[ T(n) = 8T(n/2) + n^2 \]
Solution: \( \log_b a = 3 \), so case 1 says \( T(n) = O(n^3) \).

Master Method, Example 5

The form: \[ T(n) = \begin{cases} \ c \ & \text{if } n < d \\ aT(n/b) + f(n) \ & \text{if } n \geq d \end{cases} \]

The Master Theorem:
1. if \( f(n) = O(n^{\log_b a - \varepsilon}) \), then \( T(n) = \Theta(n^{\log_b a}) \)
2. if \( f(n) = \Theta(n^{\log_b a \log^k n}) \), then \( T(n) = \Theta(n^{\log_b a \log^k n}) \)
3. if \( f(n) = \Omega(n^{\log_b a + \varepsilon}) \), then \( T(n) = \Theta(f(n)) \), provided \( af(n/b) \leq \Psi(n) \) for some \( \delta < 1 \).

Example:
\[ T(n) = 9T(n/3) + n^3 \]
Solution: \( \log_b a = 2 \), so case 3 says \( T(n) = O(n^3) \).

Master Method, Example 6

The form: \[ T(n) = \begin{cases} \ c \ & \text{if } n < d \\ aT(n/b) + f(n) \ & \text{if } n \geq d \end{cases} \]

The Master Theorem:
1. if \( f(n) = O(n^{\log_b a - \varepsilon}) \), then \( T(n) = \Theta(n^{\log_b a}) \)
2. if \( f(n) = \Theta(n^{\log_b a \log^k n}) \), then \( T(n) = \Theta(n^{\log_b a \log^k n}) \)
3. if \( f(n) = \Omega(n^{\log_b a + \varepsilon}) \), then \( T(n) = \Theta(f(n)) \), provided \( af(n/b) \leq \Psi(n) \) for some \( \delta < 1 \).

Example:
\[ T(n) = T(n/2) + 1 \] (binary search)
Solution: \( \log_b a = 0 \), so case 2 says \( T(n) = O(\log n) \).

Master Method, Example 7

The form: \[ T(n) = \begin{cases} \ c \ & \text{if } n < d \\ aT(n/b) + f(n) \ & \text{if } n \geq d \end{cases} \]

The Master Theorem:
1. if \( f(n) = O(n^{\log_b a - \varepsilon}) \), then \( T(n) = \Theta(n^{\log_b a}) \)
2. if \( f(n) = \Theta(n^{\log_b a \log^k n}) \), then \( T(n) = \Theta(n^{\log_b a \log^k n}) \)
3. if \( f(n) = \Omega(n^{\log_b a + \varepsilon}) \), then \( T(n) = \Theta(f(n)) \), provided \( af(n/b) \leq \Psi(n) \) for some \( \delta < 1 \).

Example:
\[ T(n) = 2T(n/2) + \log n \] (heap construction)
Solution: \( \log_b a = 1 \), so case 1 says \( T(n) = O(n) \).
Iterative “Proof” of the Master Theorem

Using iterative substitution, let us see if we can find a pattern:

\[ T(n) = aT\left(\frac{n}{b}\right) + f(n) \]

\[ = a(aT\left(\frac{n}{b^2}\right)) + f(n/b) + bn \]

\[ = a^2T\left(\frac{n}{b^2}\right) + af(n/b) + f(n) \]

\[ = a^3f(n/b^3) + a^2f(n/b^2) + af(n/b) + f(n) \]

\[ = \ldots \]

\[ = a^{\log_b n}T(1) + \sum_{i=0}^{\log_b n} a^i f(\frac{n}{b^i}) \]

We then distinguish the three cases as:

- The first term is dominant
- Each part of the summation is equally dominant
- The summation is a geometric series

Integer Multiplication

Algorithm: Multiply two n-bit integers I and J.

- Divide step: Split I and J into high-order and low-order bits

\[ I = I_h 2^{n/2} + I_l \]

\[ J = J_h 2^{n/2} + J_l \]

- We can then define \( I*J \) by multiplying the parts and adding:

\[ I*J = (I_h 2^{n/2} + I_l) \ast (J_h 2^{n/2} + J_l) \]

\[ = I_h J_h 2^n + I_h J_l 2^{n/2} + I_l J_h 2^{n/2} + I_l J_l \]

- So, \( T(n) = 4T(n/2) + n \), which implies \( T(n) \) is \( O(n^2) \).

- But that is no better than the algorithm we learned in grade school.

An Improved Integer Multiplication Algorithm

Algorithm: Multiply two n-bit integers I and J.

- Divide step: Split I and J into high-order and low-order bits

\[ I = I_h 2^{n/2} + I_l \]

\[ J = J_h 2^{n/2} + J_l \]

- Observe that there is a different way to multiply parts:

\[ I*J = I_h J_h 2^n + [(I_h - I_l)(J_l - J_h) + I_h J_h + I_l J_l]2^{n/2} + I_l J_l \]

\[ = I_h J_h 2^n + [(I_h J_l - I_l J_l - I_h J_h + I_l J_h) + I_h J_h + I_l J_l]2^{n/2} + I_l J_l \]

\[ = I_h J_h 2^n + (I_h J_l + I_l J_h)2^{n/2} + I_l J_l \]

- So, \( T(n) = 3T(n/2) + n \), which implies \( T(n) \) is \( O(n^{\log_2 3}) \), by

the Master Theorem.

- Thus, \( T(n) \) is \( O(n^{1.585}) \).