



Worst-Case Performance

- **Upper bounds:** simple to obtain
- **Lower bounds:** *a difficult matter...*
- Worst case data may be unlikely to be met in practice
- Unknown "Big-Oh" constants c and n_0 may not be small
- Inputs in practice lead to much lower running times
- **Example:** the most popular fast sorting algorithm, **QuickSort**, has $O(n^2)$ running time in the worst case but in practice the time is $O(n \log n)$

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"Telescoping" a Recurrence

- Recurrence relation and its base condition (i.e., the difference equation and initial condition):

$$T(n) = 2 \cdot T(n-1) + 1; \quad T(1) = 1$$
- Closed (explicit) form for $T(n)$ by "telescoping":

$$\begin{aligned} T(n) &= 2 T(n-1) + 1 \\ T(n-1) &= 2 T(n-2) + 1 \\ &\dots \\ T(2) &= 2 T(1) + 1 \end{aligned}$$

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Average-Case Performance

- Estimate average time for each operation
- Estimate frequencies of operations
- May be a difficult challenge... (take **COMPSCI.320** for details)
- May be no natural "average" input at all
- May be hard to estimate (average time for each operation depends on data)

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"Telescoping" $\equiv$ Substitution

$$\begin{aligned} T(n) &= 2 T(n-1) + 1 \\ 2 T(n-1) &= 2^2 T(n-2) + 2 \\ 2^2 T(n-2) &= 2^3 T(n-3) + 2^2 \\ &\dots \\ 2^{n-1} T(2) &= 2^n T(1) + 2^{n-1} \end{aligned}$$

$$T(n) = 1 + 2 + 2^2 + \dots + 2^{n-1} + 2^n = 2^{n+1} - 1$$

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Recurrent Algorithms

Divide-and-conquer principle:

- to divide a large problem into smaller ones and recursively solve each subproblem, then
- to combine solutions of the subproblems to solve the original problem

Running time: by a **recurrence relation** combining the size and number of the subproblems and the cost of dividing the problem into the subproblems

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Basic Recurrence: 1

$$T(n) = T(n-1) + n \Leftrightarrow T(n) = \frac{n(n+1)}{2}$$

- Closed (explicit) form by "telescoping":

$$\begin{aligned} T(n) &= T(n-1) + n \\ T(n-1) &= T(n-2) + n-1 \\ &\dots \\ T(2) &= T(1) + 2 \\ T(1) &= 1 \end{aligned}$$

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 **1: Explicit Expression for $T(n)$**

$$\begin{aligned}
 T(n) &= T(n-1) + n \\
 &= \overline{T(n-2) + (n-1)} + n \\
 &= \overline{T(n-3) + (n-2)} + (n-1) + n \\
 &\dots = \overline{T(2) + 3} + \dots + (n-2) + (n-1) + n \\
 &= \overline{T(1) + 2} + \dots + (n-2) + (n-1) + n \\
 &= 1 + 2 + \dots + (n-2) + (n-1) + n = \frac{n(n+1)}{2}
 \end{aligned}$$

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 **Basic Recurrence: 2**

- **Repeated halving principle:** halve the input in one step:
 $T(n) = T(n/2) + 1 \Leftrightarrow T(n) \cong \log_2 n$
- “Telescoping” (for $n = 2^m$):

$$\begin{array}{lcl}
 T(2^m) = T(2^{m-1}) + 1 & & T(2^2) = T(2^1) + 1 \\
 T(2^{m-1}) = T(2^{m-2}) + 1 & & T(2^1) = T(2^0) + 1 \\
 \dots & & T(2^0) = 0
 \end{array}$$

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 **Guessing to Solve a Recurrence**

- Infer (guess) a hypothetic solution $T(n)$; $n \geq 0$ from a sequence of numbers $T(0)$, $T(1)$, $T(2)$, ..., obtained from the recurrence relation
- Prove $T(n)$ by math induction:

Base condition: T holds for $n = n_{\text{base}}$, e.g. $T(0)$ or $T(1)$

Induction hypothesis to verify: for every $n > n_{\text{base}}$, if T holds for $n-1$, then T holds for n

Strong induction: if T holds for n_{base} , ..., $n-1$, then...

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 **2: Explicit Expression for $T(n)$**

$$\begin{aligned}
 T(2^m) &= T(2^{m-1}) + 1 \\
 &= \overline{T(2^{m-2}) + 1} + 1 \\
 &\dots = \overline{T(2^1) + 1} + 1 + \dots + 1 \\
 &= \overline{T(2^0) + 1} + 1 + \dots + 1 + 1 \\
 T(2^m) &= m \Rightarrow T(n) = \log_2 n
 \end{aligned}$$

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 **Explicit Expression for $T(n)$**

- $T(1) = 1$; $T(2) = 1 + 2 = 3$; $T(3) = 3 + 3 = 6$;
 $T(4) = 6 + 4 = 10 \Rightarrow$ **Hypothesis:** $T(n) = \frac{n(n+1)}{2}$
- Base condition holds: $T(1) = 1 \cdot 2 / 2 = 1$
- If the hypothetic closed-form relationship $T(n)$ holds for $n-1$ then it holds also for n :

$$T(n) = T(n-1) + n = \frac{(n-1)n}{2} + n = \frac{n(n+1)}{2}$$
- Thus, the expression for $T(n)$ holds for all $n > 1$

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 **Basic Recurrence: 3**

- Scan and halve the input:
 $T(n) = T(n/2) + n \Leftrightarrow T(n) \cong 2n$
- “Telescoping” (for $n = 2^m$):

$$\begin{array}{lcl}
 T(2^m) = T(2^{m-1}) + 2^m & & T(2^2) = T(2^1) + 2^2 \\
 T(2^{m-1}) = T(2^{m-2}) + 2^{m-1} & & T(2^1) = T(2^0) + 2^1 \\
 \dots & & T(2^0) = 1
 \end{array}$$

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3: Explicit Expression for $T(n)$

$$\begin{aligned}
 T(2^m) &= T(2^{m-1}) + 2^m \\
 &= \overline{T(2^{m-2}) + 2^{m-1}} + 2^m \\
 \dots &= \overline{T(2^1) + 2^2} + \dots + 2^{m-1} + 2^m \\
 &= \overline{T(2^0) + 2^1} + 2^2 + \dots + 2^{m-1} + 2^m \\
 T(2^m) &= 2^{m+1} - 1 \Rightarrow T(n) \cong 2n
 \end{aligned}$$

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General “Divide-and-Conquer”

Theorem: The recurrence $T(n) = aT(n/b) + cn^k$; $T(1) = c$ with integer constants $a \geq 1$ and $b \geq 2$ and positive constants c and k has the solution:

$$T(n) = \begin{cases} O(n^{\log_b a}) & \text{if } b^k < a \\ O(n^k \log n) & \text{if } b^k = a \\ O(n^k) & \text{if } b^k > a \end{cases}$$

Proof by telescoping: $n = b^m \Rightarrow T(b^m) = aT(b^{m-1}) + cb^{mk}$

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Basic Recurrence: 4

- “Divide-and-conquer” prototype:
 $T(n) = 2T(n/2) + n \Leftrightarrow T(n) \cong n \log_2 n$
- “Telescoping”: $\frac{T(n)}{n} = \frac{T(n/2)}{n/2} + 1$; $T(1) = 0$
- For $n = 2^m \rightarrow \frac{T(2^m)}{2^m} = \frac{T(2^{m-1})}{2^{m-1}} + 1$

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General “Divide-and-Conquer”

- Telescoping: $T(b^m) = aT(b^{m-1}) + cb^{mk}$
 $aT(b^{m-1}) = a^2T(b^{m-2}) + acb^{(m-1)k}$
 $a^2T(b^{m-2}) = a^3T(b^{m-3}) + acb^{(m-2)k}$
 $\dots = \dots$
 $a^{m-1}T(b) = a^mT(1) + a^{m-1}cb^k$
 $T(b^m) = a^m c + a^{m-1}cb^k + \dots + acb^{(m-1)k} + cb^{mk}$
 $= c \sum_{i=0}^m a^{m-i} b^{ik} = ca^m \sum_{i=0}^m (b^k/a)^i$

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4: Explicit Expression for $T(n)$

$$\begin{aligned}
 T(2^m)/2^m &= T(2^{m-1})/2^{m-1} + 1 \\
 &= \overline{T(2^{m-2})/2^{m-2} + 1} + 1 \\
 \dots &= \overline{T(2^1)/2^1 + 1} + \dots + 1 + 1 \\
 &= \overline{T(2^0)/2^0 + 1} + 1 + \dots + 1 + 1 \\
 &= 0 + 1 + \dots + 1 = m \\
 T(2^m) &= m \cdot 2^m \Rightarrow T(n) = n \log_2 n
 \end{aligned}$$

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Capabilities and Limitations

- Rough complexity analysis cannot result immediately in an efficient practical program but it helps in predicting of empirical running time of the program
- “Big-Oh” analysis is unsuitable for small input and hides the constants c and n_0 crucial for a practical task
- “Big-Oh” analysis is unsuitable if costs of access to input data items vary and if there is lack of sufficient memory
- But complexity analysis provides ideas how to develop new efficient methods

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